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FACULTY OF ENGINEERING

Deep Learning-Powered Vision-Based Energy Management System for Next-Gen Built Environment

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June 2023

A thesis submitted in partial fulfilment of the regulations for the Degree of Doctor of Philosophy at the University of Nottingham

Acknowledgement

I would like to acknowledge and give my warmest thanks to Dr John Kaiser Calautit, Prof Jo Darkwa and Dr Christopher Wood for their guidance and supervision throughout this work. The funding for this project was provided by the EPSRC UKRI with project reference 2100822 (EP/R513283/1).

A final thanks to the family and friends who have personally supported me through this work.

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Nomenclature

A	Area (m^2)
D	Depth (m)
H	Height (m)
L	Length (m)
s	seconds (s)
T	Temperature (°C)
U	U-values (W/m^2K)
W	Width (m)

Abbreviations

ACH	Air changes per hour
AI	Artificial intelligence
ANN	Artificial neural network
API	Application programming interface
BEMS	Building energy management system
BES	Building energy simulation
BIM	Building information modelling
BMS	Building management
COCO	Common objects in context
CR	Correct rate
CV	Computer vision
CNN	Convolutional neural network
CO2	Carbon dioxide
DCV	Demand controlled ventilation
DL	Deep learning
DLIP	Deep learning influenced profile
EM	Expectation - Maximization
FC	Fully connected
FN	False negative
FP	False positive
GPR	Gaussian process regression
GPS	Global positioning system
GPU	Graphics processing unit
GRU	Gated recurrent unit
hr	hour
HR	Hit rate
HVAC	Heating, ventilation, and air-conditioning
IAQ	Indoor air quality
IHGP	Internal heat gains profile
IoT	Internet of Things

IoU	Intersection over union
KNN	K-nearest neighbour
LSTM	long short-term memory
ML	Machine learning
MLP	Multilayer perceptron
MPC	Model predictive control
N_{set}	Set number of occupants
NMBE	Normalised mean based error
$O_{ccupancy}$	Number of occupants
px	pixels
PIR	Passive infrared
PGR	Postgraduate research
PMV	Predicted mean vote
PPD	Percentage of dissatisfaction
RBF	Radial basis function
RCNN	Recurrent neural network
ReLu	Rectified Linear Units
Ref	Reference
RFID	Radio frequency identification
RGB	Red, green and blue
RMSE	Root mean square error
RNN	Recurrent neural network
ROI	Region of interest
RPN	Region proposal network
SGDM	stochastic gradient descent along with the momentum
STDV	Standard deviation
SVM	Support vector machine
SVR	Support vector regression
TL	Transfer learning
TN	True negative
TP	True positive
TSP	Temperature setpoint
WGBC	World green building council
WHO	World health organisation
WSN	Wireless sensor network
2D	Two-dimensional
3D	Three-dimensional

Abstract

Heating, ventilation and air-conditioning (HVAC) systems provide thermally comfortable spaces for occupants, and their consumption is strongly related to how occupants utilise the building. The over- or under-utilisation of spaces and the increased adoption of flexible working hours lead to unnecessary energy usage in buildings with HVAC systems operated using static or fixed schedules during unoccupied periods. Demand-driven methods can enable HVAC systems to adapt and make timely responses to dynamic changes in occupancy. Approaches central to the implementation of a demand-driven approach are accurate in providing real-time information on occupancy, including the count, localisation and activity levels. While conventional occupancy sensors exist and can provide information on the number and location of occupants, their ability to detect and recognise occupancy activities is limited. This includes the operation of windows and appliances, which can impact the building's performance.

Artificial intelligence (AI) has recently become a critical tool in enhancing the energy performance of buildings and occupant satisfaction and health. Recent studies have shown the capabilities of AI methods, such as computer vision and deep learning in detecting and recognising human activities. The recent emergence of deep learning algorithms has propelled computer vision applications and performance. While several studies used deep learning and computer vision to recognise human motion or activity, there is limited work on integrating these methods with building energy systems. Such methods can be used to obtain accurate and real-time information about the occupants for assisting in the operation of HVAC systems.

In this research, a demand-driven deep learning framework was proposed to detect and recognise occupancy behaviour for optimising the operation of building HVAC systems. The computer vision-based deep learning algorithm, convolutional neural network (CNN), was selected to develop the vision-based detector to recognise common occupancy activities such as sitting, standing, walking and opening and closing windows. A dataset consisting of images of occupants in buildings performing different activities was formed to perform the training the model. The trained model was deployed to an AI-powered camera to perform real-time detection within selected case study building spaces, which include university tutorial rooms and offices.

Two main types of detectors were developed to show the capabilities of the proposed approach; this includes the occupancy activity detector and the window opening detector. Both detectors were based on the Faster R-CNN with Inception V2 model, which was trained and tested using the same approach. In addition, the influence of different parameters on the performance, such as the training data size, labelling method, and how real-time detection was conducted in different indoor spaces was evaluated. The results have shown that a single response 'people detector' can accurately understand the number of people within a detected space. The 'occupancy activity detector' could provide data towards the prediction of the internal heat emissions of buildings. Furthermore, window detectors were formed to recognise the times when windows are opened, providing insights into the potential ventilation heat losses through this type of ventilation strategy employed in buildings. The information generated by the detector is then outputted as profiles, which are called Deep Learning Influence Profiles (DLIP).

Building energy simulation (BES) was used to assess the potential impact of the use of detection and recognition methods on building performance, such as ventilation heat loss and energy demands. The generated DLIPs were inputted into the BES tool. Comparisons with static or scheduled occupancy profiles, currently used in conventional HVAC systems and building energy modelling were made. The results showed that the over- or under-estimation of the occupancy heat gains could lead to inaccurate heating and cooling energy predictions. The deep learning detection method showed that the occupancy heat gains could be represented more accurately compared to static office occupancy profiles. A difference of up to 55% was observed between occupancy DLIP and static heat gain profile. Similarly, the window detection method enabled accurate recognition of the opening and closing of windows and the prediction of ventilation heat losses.

BES was conducted for various scenario-based cases that represented typical and/or extreme situations that would occur within selected case study buildings. Results showed that the detection methods could be useful for modulating heating and cooling systems to minimise building energy losses while providing adequate indoor air quality and thermal conditions. Based on the developed individual detectors, combined detectors were formed and also assessed during experimental tests and analysis using BES.

The vision-based technique's integration with the building control system was discussed. A heat gain prediction and optimisation strategy were proposed along with a hybrid controller that optimises energy use and thermal comfort. This should be further developed in future works and assessed in real building installations. This work also discussed the limitations and practical challenges of implementing the proposed technology. Initial results of survey-based questionnaires highlighted the importance of informing occupants about the framework approach and how DLIPs were formed. In all, preference is towards a less intrusive and effective approach that could meet the needs of optimising building energy loads for the next-gen built environment.

Chapter 1

1. Introduction

1.1. Research Background

According to the latest projections, the global climate is predicted to continue to change, and the frequency of extreme weather and climate events is expected to increase. This will significantly impact the built environment sector, and new building designs should be able to cope with climate change and meet future energy needs [1]. For instance, heating, ventilation and air-conditioning (HVAC) systems are responsible for over 40% of the energy consumed by buildings in the commercial sector [2]. Reducing the energy demand for HVAC is crucial for overall energy conservation and the reduction of greenhouse gases. Hence, developing technologies or solutions that can minimise its consumption can make a significant impact on achieving ambitious emission reduction targets [3,4]. However, thermal comfort is also a vital factor in the design of buildings and HVAC systems, and it should not be neglected when seeking solutions for reducing building energy consumption [5,6]. To reduce the energy demand as well as enhance occupant comfort, it is essential to use systems and techniques which can automatically control and optimise building operations [7] such as building energy management systems (BEMS) [8]. Many studies [9 - 11] have highlighted that the knowledge of occupancy patterns and activities can assist BEMS to achieve more intelligent, smart buildings through the enhancement of building energy efficiency. Currently, one of the most common types of techniques used to improve buildings is Artificial Intelligence (AI). AI has increasingly become an effective method to aid building and energy-related problems through the provision of smarter solutions for developing more intelligent buildings through a reduction of unnecessary energy loads while simultaneously providing an enhancement towards building thermal comfort.

1.2. Problem Identification

The work presented in this thesis focuses on the development of a novel vision-based deep learning approach for a demand-driven framework that can be integrated with BEMS to accurately predict occupancy behaviour based on common activities with its associated heat gains, along with occupancy actions towards opening and closing of windows that is linked with building ventilation losses. All framework is designed to apply within building spaces such as an office environment to aid the management of HVAC systems and operations, while effectively regulating the building energy performances through the minimisation of unnecessary energy loads while satisfying thermal comfort conditions for occupants.

The current impact and applications of AI within the built environment were reviewed, whereby existing AI techniques applied to buildings aimed to assist the building performance in terms of the performance gap, design, management, and operation. Otherwise designed to enhance building energy efficiency through energy prediction and detection for HVAC systems, which ultimately aims to minimise demands while enhancing response quality and time. Further developments include the proposal in improving the overall building thermal comfort, air quality and occupancy satisfaction. Occupancy detectors based on traditional methods such as environmental and passive infrared sensors and solutions using wireless connectivity were explored. It was understood that they are commonly used to detect and recognise occupancy behaviour within buildings. Within the explored AI techniques, deep learning was suggested as a highly beneficial technique for occupancy detection by integrating the framework onto a camera, forming a type of sensor with the provision of accurate results. The explored frameworks suggest that occupancy detection and recognition-based methods usually do not relate to building energy management and prediction techniques. However, to enable further development towards more intelligent buildings, consideration of framework developments with strategies that acknowledge multiple building applications to balance the several benefits of building design, HVAC systems, and occupancy satisfaction. This significance was developed from evaluating limited solutions covered by deep learning and none from the explored machine learning-based frameworks. In addition, most of the frameworks did not consider the aspects of thermal comfort, which is important to buildings' intended purpose to provide a place of comfort and safety. This suggests the lack of attention towards occupant satisfaction and thermal comfort when proposing new AI-based building energy management techniques. It indicates that only current deep learning-based strategies can be incorporated into multiple aspects of this approach, which provides an enhanced solution to expectantly provide feasible solutions towards the enhancement of more intelligent buildings, giving better environments to fulfil the future needs within the built environment.

The method adopted in this research is based on the application of AI deep learning techniques to form a camera-based detection and recognition system to inform building controls of the true occupancy behaviour based on the understanding of the heat gains and the ventilation heat losses within a building space. Testing of the developed models was performed via experimental tests in selected case study buildings. From conducting a survey, feedback from participants provides a better understanding for further development of the approach and data obtained from the tests were analysed to highlight the importance of the demand for an effective indoor detector. The work also combines the use of building energy simulation (BES) to evaluate the proposed approach under different scenarios of how the proposed framework can be applied to buildings and to also compare with existing system operations. Evaluation targeting the relationship of real-time understanding of occupancy behaviour impacting the HVAC system operations, which ultimately could be a valuable approach to be implemented in various types of building spaces to optimise building energy performances and thermal satisfaction.

1.3. Aims and Objectives

This research aims to develop a demand-driven deep learning-based framework that can be integrated with BEMS to accurately predict occupant behaviour within a building space to aid the optimisation and the management of HVAC systems and operations, while effectively regulating the building energy performances through the minimisation of unnecessary energy loads while satisfying occupancy thermal comfort conditions.

To accomplish this aim, the following objectives were proposed.

1. Comprehensive literature review of the current impact and usage of artificial intelligence-based techniques of deep learning within the built environment. Use existing frameworks to understand the application of various software platforms towards the development of a deep learning framework for occupancy behaviour detection and recognition.
2. Develop a data-driven deep learning framework for the detection and recognition of various occupancy behaviour (napping, sitting, standing, walking and actions towards opening and closing

of windows) within indoor building spaces and validate the deep learning models using various testing datasets based on their suitability for real-time detection.
3. Refinement of the deep learning computer vision method with the evaluation of the impact of different parameters and configurations on the detection performance.
4. Deployment of the developed deep learning model to an AI-powered camera and testing within different experimental tests on several case study buildings and scenarios. Application on several buildings will allow the formation of occupancy and window opening profiles.
5. Assess the impact of the proposed approach on the overall building performance in terms of the building energy loads and occupant satisfaction using the BES tool.
6. Further evaluation of the practical application and challenges of the developed approach such as integration with control systems, the impact of environmental conditions and ethical and privacy issues.

1.4. Overview of the Research Methodology

To address the following objectives given above, the following research methodology was applied. The six objectives stated above correlates to a main step within the research methodology. In all, conducting the steps would ensure the development of a deep Learning-powered vision-based energy management solution.

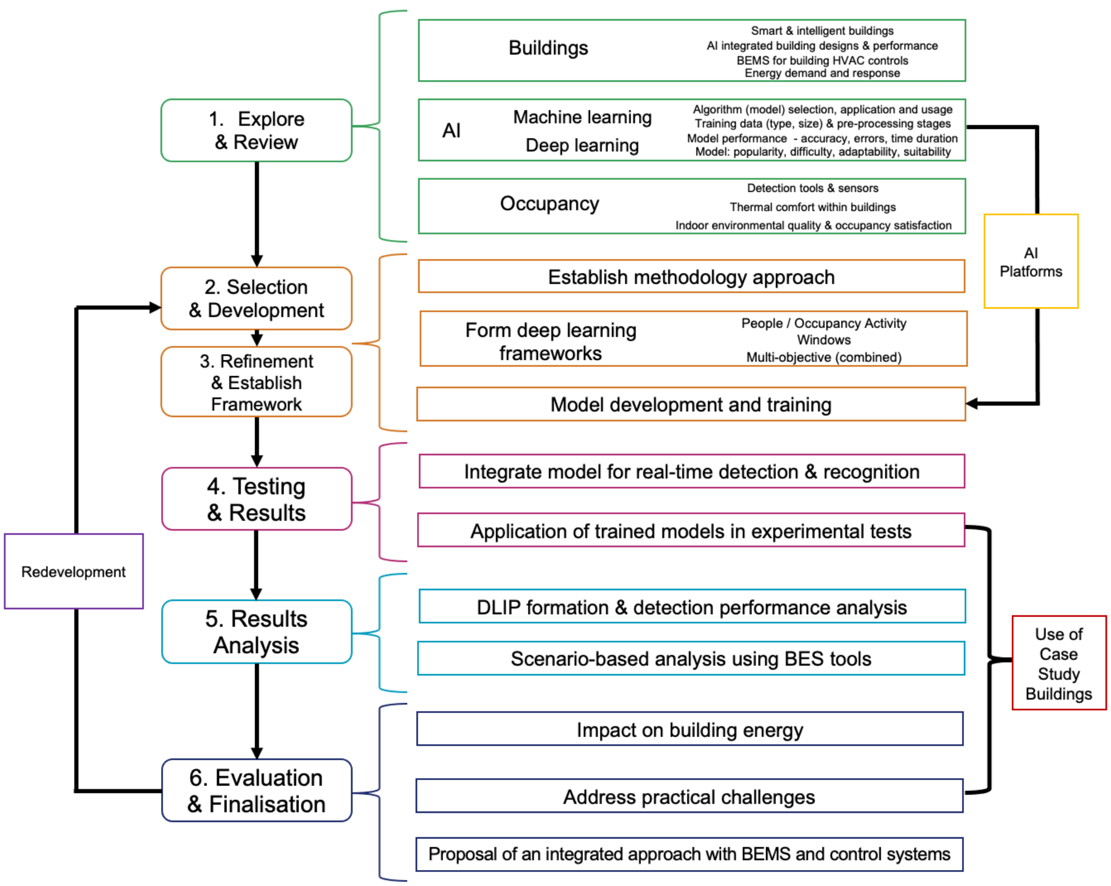


Figure 1-1. Overview of the research methodology.

1.5. Thesis Structure

Chapter 2 introduces the current concerns related to building energy demands and presents the importance of employing artificial intelligence-based techniques to provide better solutions within buildings and energy-related applications. A literature review on the associated topics related to building energy and AI applications was conducted, outlining the research gaps and giving directions for the proposed research framework and design.

Chapter 3 further explores occupancy behaviour and its impact on building and system operations along with the establishment of the method, techniques and strategies used to form the vision-based approach for accurate detection and recognition. Furthermore, the description of the different steps of the framework approach with the workflow process for the model development and analysis with the selected case study buildings used as testbed are presented within this chapter.

Chapter 4 adopts the methods described in Chapter 3 and presents the application of deep learning vision-based methods to form detectors to recognise occupancy behaviour within buildings. A series of models were developed, trained, tested and evaluated using the process given in Chapter 3.

Chapter 5 focuses on the development of window detection models to enable a vision-based solution to understand the conditions of windows within indoor spaces that allow the generation of data in form of DLIPs to suggest potential alterations to the operations of HVAC systems to ensure rooms would not be under/over ventilated and to achieve sufficient indoor air quality.

Chapter 6 combines the individual detection approaches given in Chapters 4 and 5 to form combined detectors. These were tested and evaluated using the same methods as described in Chapter 3, seeking the potential in requiring a multi-objective combined detector to be used to acquire a real-time understanding of indoor spaces that were influenced by occupancy behaviour. Through detection and analysis, the factors that could lead to sufficient dynamic changes in terms of building energy and performance were explored.

Based on the evaluation of the models developed in Chapters 4, 5 and 6, Chapter 7 proposes the techniques and methods used for the next stage of the framework approach. It describes how dynamic changes based on occupancy behaviour can lead to the formation of data from the vision-based detectors to provide specific modifications towards building controls and HVAC systems. Furthermore, the practical challenges impacting the proposed approach through the limitations identified in Chapters 4, 5 and 6 were identified. To enable the proposed approach to become valuable and become implemented on BEMS to achieve more intelligent, smart buildings, this chapter evaluates occupants' feedback on various aspects of the framework from its design to the application, suggesting areas for improvements and to be considered within future developments.

Chapter 8 provides the conclusion to the research study with recommendations for future work.

Chapter 2

2. Review of the Literature and an Outline of the Research Gaps

To address the first objective of this study, this chapter presents a comprehensive literature review of the current impact and usage of AI techniques within the built environment, leading to the outline of the research gaps and giving directions for the proposed research framework and design. Chapter 2.2 explores various building and occupancy-related aspects of the built environment in terms of the applications and use of AI strategies to enhance current building operational methods. Research-based AI strategies for buildings, occupancy detection and occupancy-based comfort were also examined. Further analysis of machine learning-based techniques was made in Chapters 2.3 and 3.4 for deep learning-based techniques. Evaluation of existing framework solutions enabled the identification of ideal processes for future development of AI-based systems. An overall summary of the assessed model framework's feasibility was provided to give an outline of the research gaps with a discussion of the criteria for future development of AI-based applications for the enhancement of buildings.

2.1. Introduction

Developing new technologies and solutions that can minimise its consumption can significantly reduce emissions from the built environment sector. However, thermal comfort and indoor air quality are also important factors that must be considered in the design of buildings and HVAC that should not be neglected when seeking solutions for reducing the building energy demand [12]. Example solutions include the integration of building energy management systems (BEMS) into existing HVAC systems. These are designed to automatically control building operations, including HVAC systems, lighting and equipment [13-15]. According to the report by the American Council for an Energy-Efficient Economy [16], energy savings of 18% for offices and 14% for retail stores can be achieved by employing smart technologies and analytics. BEMS ensures building services, systems, and equipment operate optimally by reducing energy consumption, along with the reduction in operational costs and emissions while providing a better-quality environment for occupants. BEMS are more automated and limits the need for manual procedures in monitoring and controlling HVAC systems. They have a significant role in improving the efficiency of buildings and will be a crucial strategy for developing truly intelligent buildings.

Due to computer and software technology advancements, different sectors are being taken over by automated machines and software, and the field of AI is becoming more important [17]. This has led to smart solutions for buildings that optimise energy performances and reduce resource waste [18, 19] without compromising comfort, health or security [20]. The increasing adoption of the Internet of Things (IoT) and AI technologies for building monitoring and controls will drive the smart building market's growth. More and more academic researchers and building professionals are developing and utilising AI-based solutions for the design and construction [21], operation and maintenance [21, 22] of the built environment. An example is integrating AI algorithms and sensors into the indoor environment to optimise the process in real-time, such as monitoring and controlling the indoor climate. These systems can automatically analyse the data and provide future predictions of the building's behaviour and facilitate and assist decision-making [23, 24]. However, the study by the McKinsey Global Institute [25] presented a statistical comparison of the use of AI within various sectors. It is acknowledged that AI within the building and construction sector has been slow to employ AI and digital tools in comparison to other sectors. Accordingly, there is a need to study AI techniques for enhancing building energy efficiency and solving building-related problems, identifying the reasons for its slow adoption and potential solutions. This stresses the urgency for an in-depth review and exploration of the current use and how it can inform the development of AI solutions for future buildings.

Figure 2-1 summarises the most common AI-based machine and deep learning techniques currently used within the built environment sector, particularly energy efficiency-related applications, which are reviewed in this chapter. In machine learning, data presented in numerical, categorical, time series and text are used as input [26] with the selection of an algorithm as a computational method to 'learn' information directly from data. Deep learning interprets data features and their relationships using neural networks to form a unique model based on a wider range of data, including images, videos, and sounds. To a greater extent, deep learning provides higher accuracy than other methods as the feature extraction process is performed automatically from raw data. However, deep learning would require more data points to improve its accuracy. Several studies have suggested that deep learning surpassed machine learning and other learning algorithms in various applications [27].

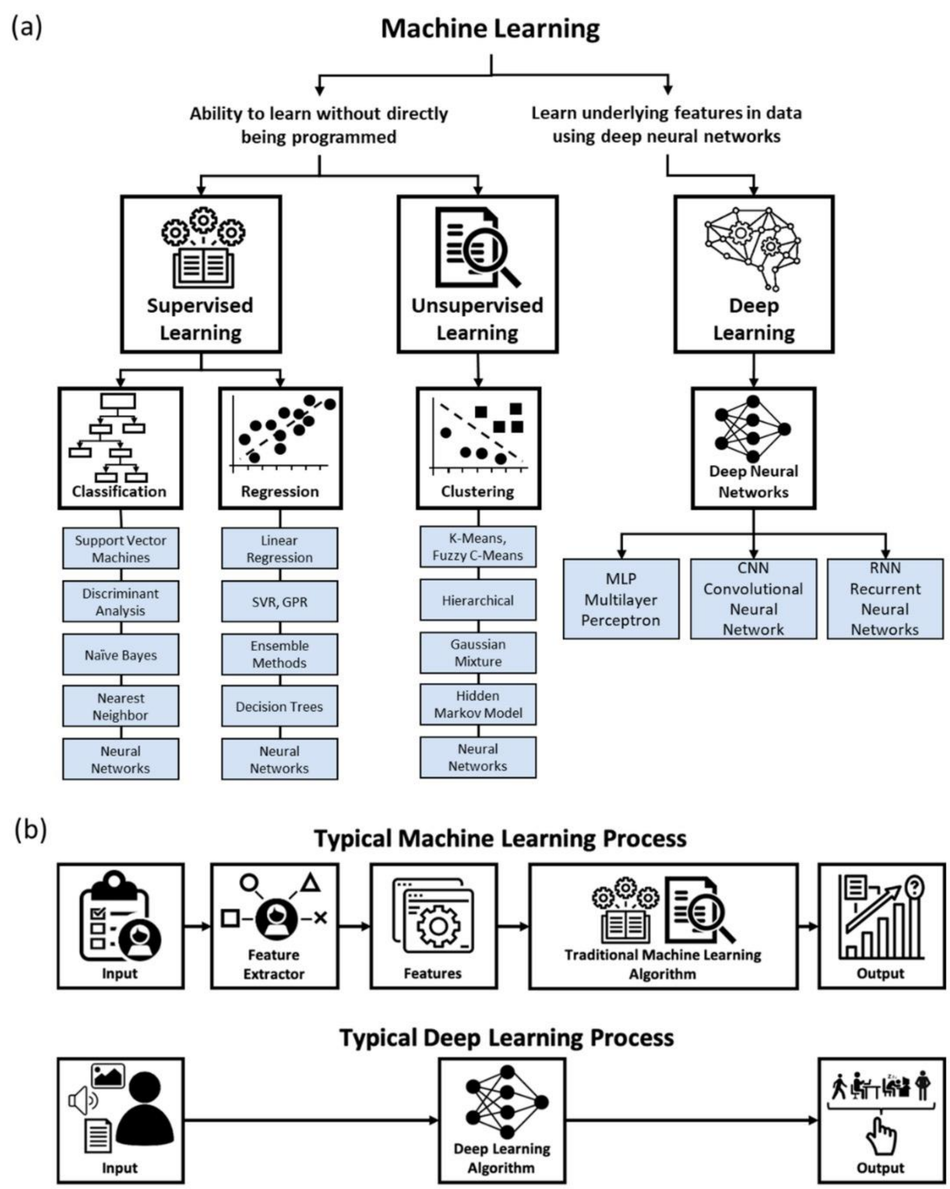


Figure 2-1. (a). AI-based machine learning and deep learning techniques reviewed in this study (b). Comparison of the typical machine learning and deep learning process.

Figure 2-2 presents a summary of the applications of the machine and deep learning-based methods in the design of energy-efficient, comfortable, and healthy buildings evaluated in this chapter. The review focused on building and HVAC systems energy, indoor environment quality and occupancy behaviour, and three types of algorithms: supervised and unsupervised machine learning, and deep learning. The review of different machine learning techniques will help identify the specific techniques that are more suited for each area. This enabled the formation of the connections shown in Figure 2-2, detailed in Chapter 2.3. Each type of machine learning technique was explored based on its application within the built environment with supervised machine learning designed for classification and regression problems that consisted of algorithms that are trained using datasets that are fully labelled, i.e., features' data, providing an answer key that can be used to assess its accuracy. While in unsupervised machine learning, the algorithm attempts to make sense of the unlabeled data by extracting patterns and features on its own without clear instructions on what to do with them. This is useful when fully labelled datasets are not available and, in some cases when the desired outcome or answer is not known. Another subset of machine learning that uses a multi-layered structure of algorithms to create an artificial neural network (ANN) is deep learning. Effectively, deep learning offers several advantages over traditional machine learning methods and, in some cases, outperforms them. It does not require human intervention and can learn from its own mistakes (Figure 2-1b). However, it can be costly in terms of computational power and time. Deep learning is usually applied to problems that require complex and unstructured data such as images, videos, and sound to perform tasks.

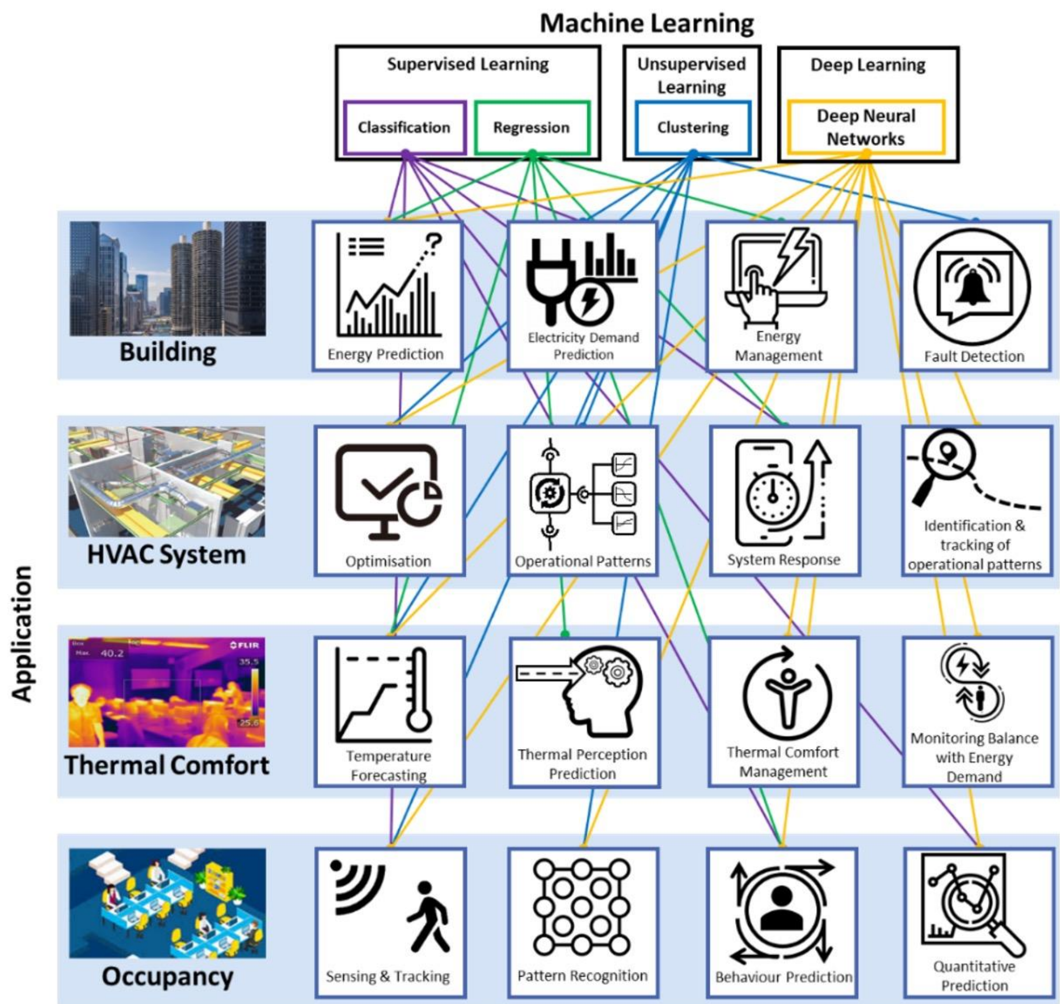


Figure 2-2. Summary of the AI-based methods employed in the design of energy-efficient, comfortable, and healthy buildings reviewed in this study. Connections made correspond to the studies evaluated in Chapter 2.3.

An example is detecting occupants in indoor spaces and using the information to control the operation of HVAC. In recent years, there have been significant developments in deep learning due to the increased available computing power and graphical processing unit (GPU) computing. Compared to supervised and unsupervised machine learning, there is limited research on deep learning techniques for building and energy-related applications; however, deep learning has recently gained more popularity. This stresses the need to review its development and applications in the built environment.

The primary aim of this chapter is to provide a critical summary of the existing literature on machine learning and deep learning methods for the built environment over the past decade, with special reference to holistic approaches. Existing AI-based techniques focusing on the framework, methodology, and performance, including the data acquired, model formation process, accuracy, and speed were explored. The study also includes the different AI-based techniques employed to resolve interconnected problems related to HVAC systems and enhance building performances, including energy forecasting and management, indoor air quality and occupancy comfort/satisfaction prediction, and occupancy detection and recognition.

An extensive literature search was performed to identify publications on existing studies on the application of machine and deep learning methods for the built environment. Peer-reviewed journals, conference papers, technical reports, and books from the last decade (with some exceptions made) were searched using the Scopus and ScienceDirect search engines. The search was carried out using keywords such as ‘artificial intelligence in buildings’, ‘machine learning in the built environment’, and ‘deep learning in the built environment’.

2.2. Applications of Artificial Intelligence within the Built Environment

Artificial intelligence is being adopted widely in various areas to perform tasks more efficiently while reducing the need for human effort. With the ever-increasing computational power and data availability in today’s digital society, significant progress has been made in AI in recent years [28]. Within the construction sector, building information modelling (BIM) is becoming the norm for developing new buildings and facilities. As an enabler of innovation and digitalisation in the sector, BIM provides a foundation for a digital world in which AI can help optimise design, construction, and operation/facility management [29]. For example, with the help of AI, BIM can utilise a large amount of data from previous construction projects and automatically suggest solutions to optimise the design.

AI is driving the development of smart buildings, making them self-learning and adaptive rather than just automated. Smart buildings utilise advanced technologies to automatically control building operations, including HVAC systems, lighting, and security [30, 31]. Figure 2-3 shows the evolution of buildings from conventional to intelligent, along with the integrated systems and techniques such as AI and machine learning which equip buildings with an ability to learn and adapt [32, 33]. Much research has been dedicated to using AI technologies in smart buildings, focusing on improving energy efficiency, thermal comfort, health, and productivity in the built environment. This section explores existing AI-based techniques which aim to achieve energy-efficient, comfortable, and healthy buildings.

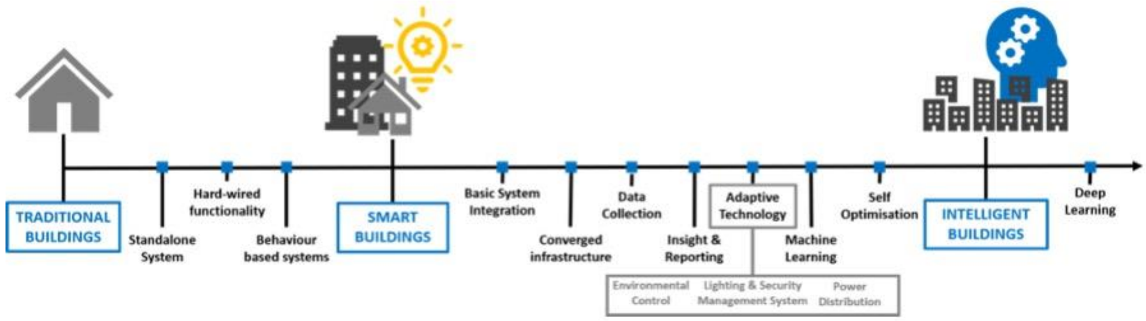


Figure 2-3. Development and evolution of smart and intelligent buildings. Figure adapted from [34].

2.2.1. Building Energy Demand Forecasting

Building energy demand forecasting is vital for optimising building energy performance. It assists in energy planning, management, and conservation to inform strategies for reducing energy consumption and CO2 emissions [35]. Energy forecasting is also used to evaluate building design alternatives and operational strategies to improve demand and supply management [36].

Historical data must be collected to enable performance predictions in building energy usage using AI-based methods, Currently, data are collected via energy meters and sensors. Ahmad et al. and Avancini et al. [37, 38] highlighted the technological advancements in building energy metering and environmental monitoring. Chammas et al. and Terroso-Saenz et al. [39, 40] presented the application of wireless networks, sensors and IoT-based techniques to enable energy monitoring solutions that are low-cost, highly accurate and easy to deploy. However, IoT (Internet of Things) devices can generate vast amounts of data; hence, integration with AI can help deal with such huge volumes [41]. Din et al. [42] identified that machine learning techniques are expected to pave the way for IoT networks, generating sophisticated visions and ideas for IoT systems. Wang and Srinivasan [43] highlighted that AI-based approaches had recently gained popularity due to the ease of use and adaptability to obtain optimal solutions rapidly while requiring less detailed physical parameters and information about the building.

Several works highlighted the importance of different external and internal parameters on prediction performance. Zhao and Liu [44] developed a machine learning-based building energy load forecasting solution with the proposed model achieving a high accuracy prediction of energy loads with a MARE (Mean Average Relative Error) of 2.60% for cooling and 3.99% for heating 1-h (one hour) ahead [45]. The study highlighted the importance of sufficient training of the model and selecting the types of input data to achieve such accuracy. The weather forecast precision affected the proposed model. When an MAE (Mean Average Error) between the actual temperature and the forecasted temperature was 1°C, the MARE of the 24-h ahead loads raises to 2.01% for heating. Hence, dynamic load forecasting for different time horizons from 1 to 24-h ahead could be advantageous to HVAC control system optimisation.

While building engineers and architects commonly use BES to predict the energy consumption of buildings, several factors/issues can lead to low-energy design solutions or performance energy gaps. This includes skills and knowledge of the modeller, use of simplification methods, assumptions, and the tools' quality. Hence, more researchers are attempting to address this using data-driven AI and machine-learning approaches, which do not require detailed information about the building. Singaravel et al. [46] compared

AI methods with BES in terms of accuracy and speed in predicting the building energy demand. Based on the results of 201 cases, the AI model predicted cooling energy with similar accuracy as BES, while it was slightly less accurate in terms of heating energy prediction. However, the AI model significantly reduced simulation time as compared to BES with a reduction in simulation time from 1145 seconds to 0.9 seconds. Finally, they also showed that the deep learning models performed slightly better than simple ANN models. The high-speed prediction compared to BES means more evaluation of design options and optimisation can be carried out or allow real-time predictions.

Table 2-1 presents a summary of the previous works reviewed in this section. This explores the different AI-based techniques used for building energy forecasting and the different building types, energy systems, prediction interval and evaluation metrics used in previous work. The evaluated studies suggest that many methods are evaluated or tested in office and academic buildings. It can also be seen that many works used different types of evaluation metrics to assess and compare the performance of the models. The studies have shown the advantage of AI methods for predicting energy loads compared to conventional BES models. It requires fewer details and information about the building, which reduces the time of developing the model and, in addition, AI-based models are significantly faster. However, it is important to note that the AI-based model's accuracy and reliability rely on the input data, and users must select a suitable learning algorithm for their prediction model. Due to the reliance on historical building data, AI-based models' applications in the design stage are limited. Furthermore, one cannot extrapolate the prediction results once changes are made to the design and operation of a building.

Table 2-1. Summary of AI-based techniques for energy management and predictions in the built environment.

Ref.	Building Type	Energy/ System	Prediction Rate	Evaluation Metrics	Key finding/summary	Performance/Accuracy
[36] Fan et al. 2019	Research Academic	Cooling	Predictions for 24-h ahead	MAE, CV-RMSE	Recurrent models achieved the most accurate predictions without increasing computational load.	RMSE was 30.8% for cooling load prediction
[39] Chammas et al. 2019	Office	Building energy Lighting	Not specified	R^2, RMSE, MAE, MAPE	Multilayer Perceptron (MLP) performed better against four classification models	64% R^2, RMSE 59.84%, MAE 27.28%, MAPE 27.09%.
[44] Zhao and Liu. 2018	Office	Heating Cooling	Predictions for 1-h, 2-h, 2-h, 24-h ahead	MARE, MAE	Dynamic load forecasting for different time horizons to optimise controls of HVAC systems.	1-h ahead: Cooling MARE 2.60%, Heating 3.99%, 24-h ahead MARE increases by 2.01%.
[46] Singaravel at al. 2018	Research Academic	Heating Cooling	Monthly prediction	R^2	Cooling energy prediction using the AI method was significantly faster than BES while providing accurate results.	Building energy simulation required 1145s to simulate while only 0.9s for the AI model.
[47] Pham et al. 2020	Office	HVAC	Predictions for 1 step, 12 steps and 24 steps ahead	MAE, RMSE, MAPE	Random Forest (RF) model was superior to the M5P (M5 Model Tree) and Random Tree (RT) models.	1-step-ahead prediction of RF was 49.21% better in MAE and 46.93% in MAPE than RT. 12 and 24-step-ahead predictions of RF were 49.95% better in MAE and 29.29% in MAPE than M5P.
[48] Kwok and Lee.	Office	Cooling	24h	RMSPE	Occupancy significantly affects cooling load predictions. Understanding	RMSPE 40.376 – 52.047 not employing occupancy factors,

2011					occupancy behaviour improves the predictive accuracy of the models.	RMSPE 14.836 -30.090 not employing occupancy factors
[49] Ding et al. 2011	Office	Heating	Real-time prediction 24-h	MRE R^2	The prediction of the heating load is influenced by exterior variables and interior variables, including occupancy level and lighting/equipment use.	Prediction of heat load with only exterior variable: 84% R^2 Prediction of heat load with exterior and interior variable: 94% R^2
[50] Kumar et al. 2018	-	Heating Cooling	Real-time prediction	MAE	The extreme learning machine (ELM) models learned better and outperformed other popular machine learning approaches.	MAE (kW) 0.0348 and 0.0389 for both cooling and heating, along with the lowest heating load prediction time of 0.06s.
[51] Xu et al. 2019	Multi-building	Building Energy Use	Monthly, Annual	MAPE, RMSE	SNA-ANN model predicted the multi-building energy use with satisfactory accuracy providing an empirical approach to urban building energy use prediction.	MAPE 10.72% RMSE 14.52%, Accuracy of 90.28% for the predicted energy use for all building groups.
[52] Chou and Bui 2014	Residential	Heating Cooling	Not specified	MAPE, RMSE	The ensemble approach and support vector regression (SVR) were the best models for predicting heating and cooling load.	Ensemble approach: MAPE below 4%, 39.0%-65.9% lower RMSE compared to previous works.
[53] Tsanas and Xifara. 2012	Residential	Heating Cooling	Not specified	MAE, MSE, MRE	The heating load can be more accurately estimated than the cooling load.	Heat load estimation with 0.5 points deviation from ground truth, cooling load with 1.5 points deviation from the ground truth.
[54] Zhou and Zheng 2020	Residential, High-rise building	HVAC	Real-time prediction	NMBE, RMSE	Energy peak power reduction of up to 21.9% was achieved using ML for building demand prediction, integrated with a hybrid controller.	NMBE <10% CV-RMSE<30%.

2.2.2. Thermal Comfort, Indoor Air Quality and Environmental Conditions

Building energy forecasting is ultimately dependent upon heating and cooling requirements for a building. As people spend most of their time indoors, comfortable, and healthy spaces must be provided. Thermal comfort can be defined as a condition of mind that expresses satisfaction with the thermal environment (BS EN ISO 7730). Thermal comfort is traditionally evaluated using the predicted mean vote (PMV) method, which considers environmental and personal factors. It is vital in the design of buildings and HVAC systems to strike a balance between providing adequate thermal comfort and reducing the energy consumed [55]. Like in the previous sections which showed the emerging of the developments and adoption of AI methods in energy forecasting and occupancy prediction, recent research has focused on AI methods for predicting and enhancing thermal comfort in buildings.

To address the limitations of the PMV method for thermal comfort assessment in buildings with natural ventilation, Chai et al. [56] employed machine learning algorithms to predict the occupant's thermal comfort and sensation in a naturally ventilated building. The machine learning algorithm used a combination of indoor and outdoor environmental parameters and personal factors as input. The study highlighted the quick ability of machine learning to analyse the input and output parameters relationships. They concluded that the machine learning method performed better than conventional and established models such as PMV. Similarly, Hu et al. [57] used machine learning techniques to develop a learning-based approach for thermal comfort evaluation. The results showed that all the machine learning methods achieved better performance than PMV. Specifically, the proposed method outperformed the PMV by up to 17.8%. While Chaudhuri et al. [58] also employed several classification algorithms for developing a thermal comfort prediction model and showed that the machine learning method outperformed the traditional and modified PMV models, achieving prediction accuracy of up to 81.2%.

Machine learning methods can be integrated with control systems to adjust indoor thermal conditions according to the occupant's thermal preference or comfort requirements while enhancing energy efficiency. Peng et al. [59] used machine learning to develop a framework consisting of multi-learning processes with specified rules for a demand-driven control strategy, which can automatically adapt to occupancy behaviour. The control technique uses the learned occupancy information to operate the cooling system by adjusting the setpoints in real-time. An energy saving of up to 52% was achieved by the proposed control as compared to a conventional method. Yang et al. [60] proposed an optimisation method, which uses model predictive control (MPC) integrated with a machine learning technique to maintain thermal comfort while consuming the least amount of energy. A reduction of up to 58.5% in cooling energy was achieved in an office compared to conventional controls.

Some of the works combined AI-based thermal comfort prediction and management methods. Such studies use thermal comfort prediction as feedback for HVAC control. Lu et al. [61] used a combination of a thermal comfort prediction model based on machine learning algorithms and a reinforcement learning-based temperature set-point control system to develop a data-driven comfort-based controller for HVAC. They concluded that the machine-learning thermal comfort model outperformed that of PMV. While some studies also looked at optimising other parameters such as indoor air quality. Vallaadares et al. [62] developed an HVAC controller based on deep reinforcement learning to reduce energy consumption while maintaining good thermal comfort and air quality in a university building. The results showed that the PMV was maintained within the range of −0.1 to +0.07 while having a 10% lower CO2 level and reducing the energy by up to 4 - 5% compared to a conventional controller.

The study of Gao et al. [63] also employed deep reinforcement learning to optimise the HVAC energy demand and thermal comfort of occupants. The deep neural network method was used to predict the thermal comfort, and the results are then used as input for the controller, which adopts a deep reinforcement learning method. The results showed that the proposed method achieved higher thermal comfort prediction accuracy as compared to other methods such as linear regression and SVM. The study showed the impact on the cooling load of adjusting the thermal comfort threshold and weighting of energy cost, which can be set depending on the priority.

The applications of machine learning and deep learning in thermal comfort studies have been growing, such as in thermal comfort prediction and management [64]. Studies have shown that machine learning outperformed conventional and modified PMV models. However, studies have also suggested the importance of the input parameters and the data size. Machine learning prediction's higher accuracy and speed make it suitable for integration with demand-driven or occupancy-responsive HVAC controls, providing real-time feedback. Several machine learning and deep learning methods were used to develop control strategies to ensure a trade-off between energy efficiency and thermal comfort. Based on the reviewed studies [56-64], a flow chart which summarises the procedure for developing thermal comfort prediction and management models is shown in Figure 2-4. Table 2-2 summarises the AI strategies developed for thermal comfort management and predictions related to the above review.

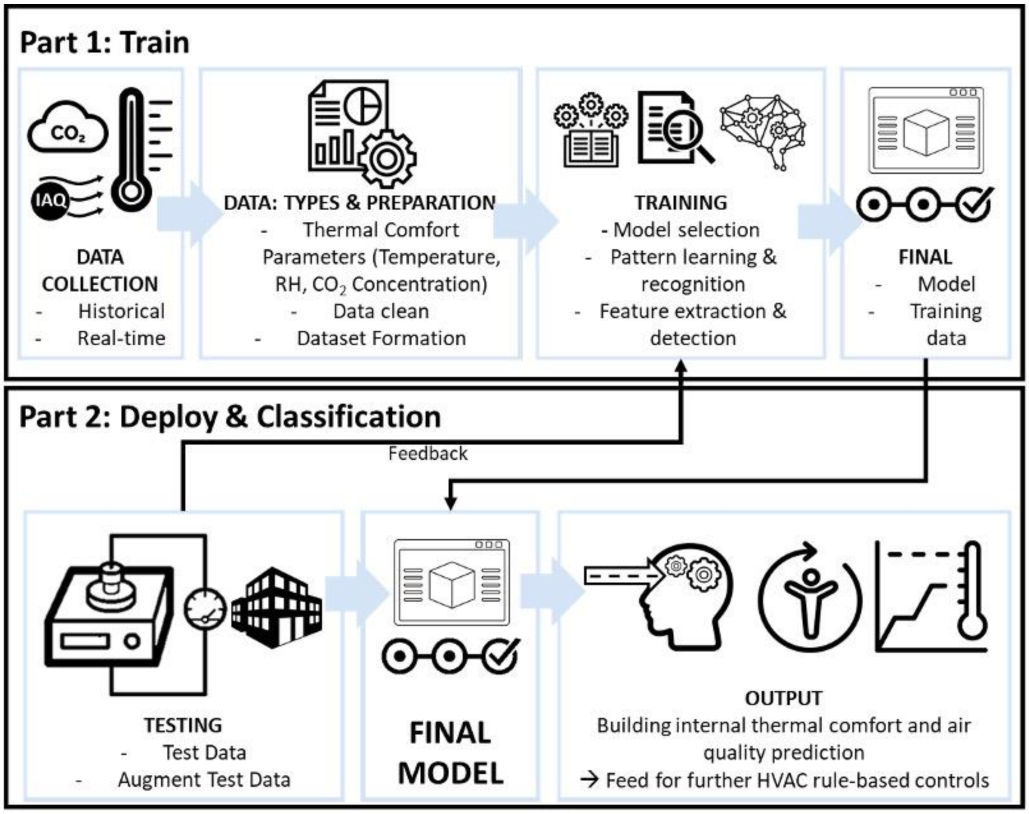


Figure 2-4. Example of a framework strategy for building indoor thermal comfort and air quality prediction.

Table 2-2. Summary of the studies reviewed that used AI for thermal comfort and IAQ prediction and management.

Ref.	Application	Building Type	Technique	System Type	Evaluation Metrics Used	Key Findings	Model Performance /Accuracy
[56] Chai et al. 2020	Thermal comfort prediction	Residential	ML	Natural ventilation	R^2	ML method performed better than conventional PMV.	Thermal comfort model R^2 0.4872
[57 Hu et al. 2018	Thermal comfort prediction and management	Office	ML	Airconditioning	Prediction accuracy %	ML method outperformed the PMV model	The black-box neural network outperformed PMV by up to 17.8%
[58] Chaudhuri et al. 2017	Thermal comfort prediction	Various	ML	Cooling/ Free running	Prediction accuracy %	ML method outperformed traditional and	ML achieved a prediction accuracy of up to 81.2%.

						modified PMV models	
[59] Peng et al. 2018	Thermal comfort prediction and management	Office	ML	Cooling	Not specified	Energy-saving of up to 7–52%.	-
[60] Yang et al. 2020	Cooling and thermal comfort management	Office	ML	Cooling and Ventilatio n	R^2	Energy-saving of up to 58.6% while maintaining thermal comfort level.	Thermal comfort model R^2 0.998
[61] Lu et al. 2017	Thermal comfort prediction and management	Office	ML	Airconditi oning	Recall	The recall of the model with the tree algorithms has increased to 6.3%.	ML methods outperformed the PMV model by up to 6.3%
[62] Valladares et al.	Thermal comfort management	University	DL	Airconditi oning	Not specified	PMV values between −0.1 to +0.07, 4–5% better power usage and 10% lower CO_2.	-
[63] Gao et al. 2019	Energy and thermal comfort management	Laborator y building	DL	Cooling	MSE	The deep neural network method outperformed other AI methods.	MSE 1.16
[65] Cho and Moon et al. 2022	IAQ prediction	School building	DL	Electric Heat Pump with Ventilator	RMSE, R^2	Prediction model sufficiently accurate for integration with a control system in school buildings.	RMSE 0.8816 for CO_2, 0.4645 for PM_{10}, 0.6646 for $PM_{2.5.}$ R^2 1, 0.9991, 0.9979
[66] Kim et al. 2021	IAQ prediction	Not specified	ML	Ventilatio n	MAE	The Decision Tree was found to be almost as accurate as the computationally heavier Random Forest model.	MAE 1.8-14.8 for all the evaluated models
[67] Yu et al. 2021	IAQ prediction and management	University	DL	Airconditi oning and exhaust fan	Not specified	Energy saving of up to 43% while reducing the CO_2 level by 24%	-

In addition to ensuring good thermal comfort in buildings, the provision of good indoor air quality (IAQ) is equally important. A good IAQ is essential to ensure the health and well-being of occupants [68]. Like comfort-based systems, various building ventilation systems and control strategies aim to optimise IAQ with the aid of AI techniques such as predicting concentrations of pollutants and managing the indoor environment. Cho and Moon [65] developed an ANN model to predict indoor pollutant concentrations such as carbon dioxide (CO_2), PM_{10} and $PM_{2.5}$. They developed a prediction model sufficiently accurate for integrating control systems in school buildings. The results showed that the model achieved high accuracy with RMSE (Root mean square error) of 0.8816 for CO2, 0.4645 for PM_{10}, and 0.6646 for $PM_{2.5}$. The study only used simulation results, and field experiments are required to test the approach further. Similarly, Kim et al. [66] predicted the indoor CO2 concentration for the demand-drive and proactive control of ventilation systems. The study employed machine learning models, including ridge regression, decision trees, random forest, and multilayer perceptron. The study found that the random forest model was the most accurate, and the decision tree was almost as accurate but less computationally resource intensive. Hence it is more suitable for lightweight applications.

Several works, such as Valladares et al. [62] and Yu et al. [67] employed AI algorithms to optimise the operation of HVAC in terms of comfort, air quality and energy. In Yu et al. study [67], a control algorithm based on deep reinforcement learning was employed to balance the IAQ, thermal comfort and energy demand of air conditioning and exhaust fan systems. The results showed that the proposed approach achieved an energy saving of up to 43% while reducing the CO2 level by 24%, as compared to an air conditioning system with a fixed temperature schedule. A demand-controlled ventilation system can benefit from using the two AI-based methods here; accurate pollutant prediction and control optimisation models. This would benefit buildings with irregular occupancy by utilising the forecasted pollutant concentration to control the ventilation to minimise or prevent the rapid increase of CO2 levels and operating ventilation systems at max capacity.

While the studies covered are mainly for mechanical systems, AI methods can also be applied in naturally ventilated spaces. For example, camera-based AI techniques can be used to detect occupancy information such as presence, location, activities, and interaction with natural ventilation strategies. Although not as developed as AI methods for thermal comfort optimisation, the applications of machine learning and deep learning in IAQ studies have been recently growing, such as for IAQ prediction and management. This is probably driven by the COVID-19 pandemic and increased awareness of IAQ. Similar to the reviewed thermal comfort prediction and management models, the flowchart in Figure 2-4 gives a typical procedure for the development of AI-based IAQ solutions.

2.3. Machine Learning Approaches for Building-Related Applications

Machine learning is a subset of artificial intelligence. It performs tasks using computer systems that can automatically learn from previous data and improve from experience without following specific instructions [69]. It uses algorithms and statistical models to complete tasks such as modelling, prediction and control [70]. Machine learning has already received much attention in the past decade, but it is expected to continue driving the next big wave of innovations, services, and products in many sectors [25]. As established in Chapter 2.2, machine learning is one of the most common AI techniques adopted to help solve HVAC and building-related problems. Machine learning can answer the demand of the built environment sector for accurate and quick prediction models, necessary for optimising the design and operation of buildings and energy systems which can lower costs and carbon emissions. At the same time, providing an optimum balance between energy demand, comfort and air quality. This section aims to review the studies that employed machine learning techniques for the built environment.

Machine learning consists of three main types of learning; supervised, unsupervised and reinforcement. It can determine non-linear relationships, such as the relation between the cooling load and related factors such as outdoor temperature and occupancy activity, through mapping functions from a dataset. In supervised learning, a pattern is learned from a labelled dataset (input and output data), and the correct output is expected to be predicted when a different input is entered into the model based on this pattern.

Supervised learning algorithms deal with two types of problems: classification and regression problems. Classification algorithms predict a discrete or distinct value, such as when the output is a category, while regression algorithms are used to determine continuous values or quantities. In energy demand forecasting, regression models can be used to understand the factors that drive energy consumption, such as building shape, material, and orientation [70]. Figure 2-5 presents an example workflow diagram for training and deploying supervised machine learning models, influenced by reviewed works in Chapter 2.2, incorporating all the main steps, including data preparation, model selection and development, and the trained model's application.

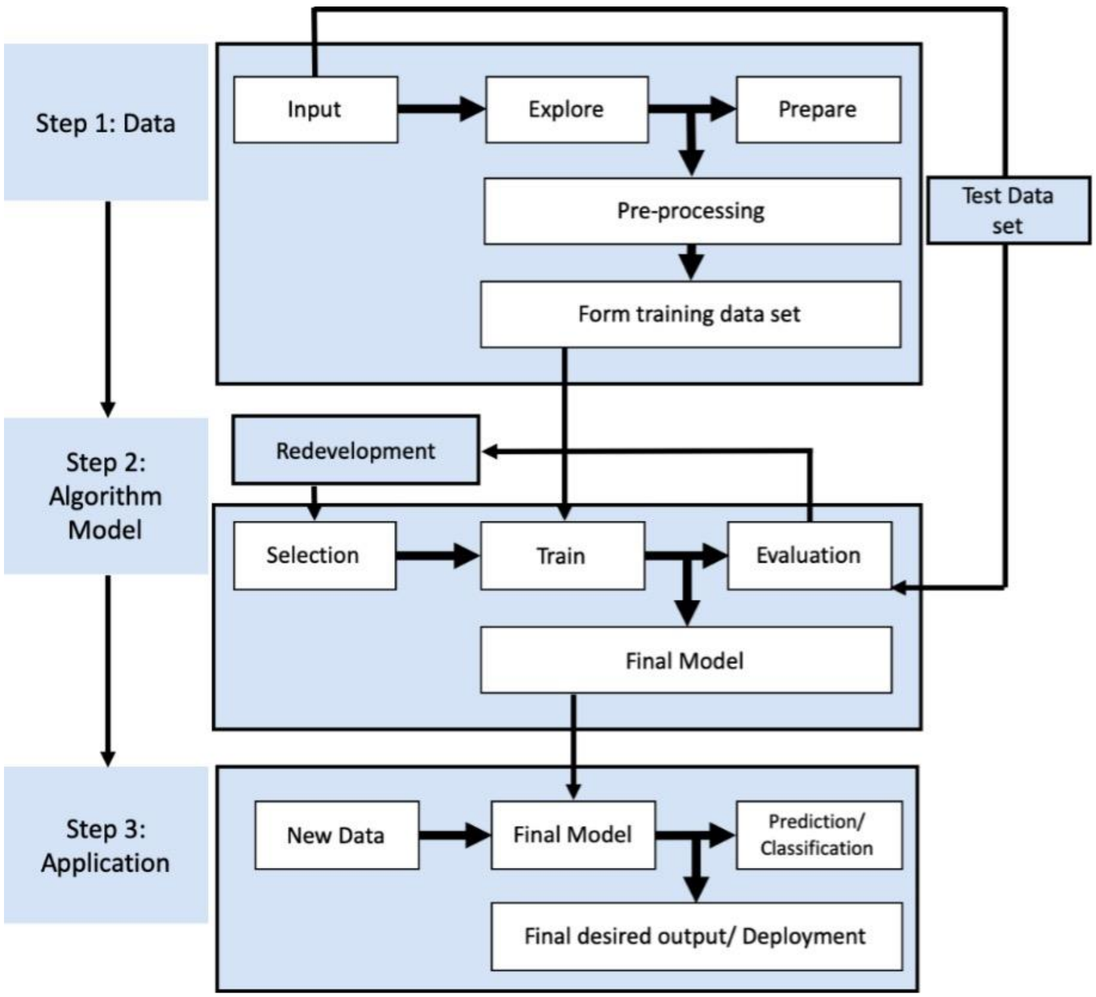


Figure 2-5. An example machine learning framework process.

On the other hand, unsupervised learning is used to identify patterns in unlabelled datasets and predict the output. Unsupervised learning algorithms are typically utilised for tasks including clustering, association, and dimensionality reduction. Clustering, which can find a structure in a collection of unlabelled data, is the most common algorithm for unsupervised learning techniques [70]. It is the most common unsupervised learning method applied to categorising building performance data [71. Supervised and unsupervised learning models are different in how they are trained and in terms of the conditions of the required training data. In some cases, such as [72], a strategy which uses a combination of both learning techniques, also called semi-supervised learning, was used to characterise the energy consumption in smart buildings. This type of algorithm learns from datasets simultaneously containing labelled and unlabelled data. For example, a large quantity of unlabelled data is used to enhance the prediction for the labelled data. It can also work independently, performing classification or clustering tasks separately.

Reinforcement learning [73] algorithms learn to react to an environment independently. It has an agent that learns how to map situations to actions, aiming to maximise a numerical reward (gained from a correct output) signal by trial and error. This way, the algorithm improves over time. Over the years, reinforcement learning methods have been applied to the building sector, particularly in HVAC control systems. It has been applied to find the optimal strategies to help decrease building energy demand. For example, a reinforcement learning-based HVAC control will continuously adapt to the controlled indoor environment using real-time data. This presents advantages compared to conventional approaches such as rule-based and model-predictive controls.

Different machine learning algorithms are suitable for different types of datasets or problems in the field of the built environment and building performance. Also, different models have different impacts on various problems [74]. Hence it is important for modellers to analyse the available data and application when choosing a machine learning model and to determine the data pattern that should be learned. In addition, it is important to assess the necessity of implementing machine learning to solve a specific problem and whether it will be better and more practical than conventional and simpler approaches, considering the modelling effort. The steps required to build, train, and deploy a machine learning model will vary depending on these factors. In general, a typical workflow in built environment studies that use machine learning models consists of three phases; generating data, training the model and deploying the model [75,76].

Data generation involves acquiring input data, which are parameters that impact or correlate with the output data. Methods such as stepwise regression and statistical analysis can be employed to help select useful variables for the prediction. For building performance-related models, inputs could include the climate, building form, occupancy, and material properties, while the outputs are parameters which represent building performance. Depending on the prediction time scale required, the sampling period can be from minutes to years. Then the collected data is pre-processed into a format that is suitable for the training process. This involves techniques which improve the quality of the input data. In the training process, appropriate prediction targets and predicting parameters are selected for the model. The input variables, size of the training data, and performance indicators should be considered when selecting the parameters. Once trained, the model is tested to evaluate its prediction performance and determine its suitability for deployment. As detailed in Table 2-1 and Table 2-2, various performance indicators can be used for evaluation. The following section will further explore the types of machine learning approaches and models applied to buildings to meet one or more of the objectives detailed in Chapter 2.2.

2.3.1. Enhancing Building Performances

Different machine learning models are suitable for several applications related to optimising building performance. The review of the literature showed that it could be challenging to select the most suitable model for solving a problem [77]. The explosive growth experienced by the machine learning research area in the last 10 years has led to hundreds of machine learning algorithms being applied to building performance-related studies. This makes it difficult to find an optimal algorithm for a specific task or case. Hence, several researchers in the field have developed guidelines to encourage best practices in the evaluation and selection of machine learning models [78,79]. However, further developments and more specific guidelines are required for the built environment field [80].

Many studies have employed different machine learning algorithms, with many achieving significantly better performance than conventional methods, such as in building energy forecasting [46] and thermal comfort prediction [61]. Supervised learning models are useful for applications such as building energy demand and IAQ forecasting [70]. While unsupervised learning models are helpful for applications such as load profiling, detection and diagnostics of problems occurring in buildings and occupancy detection [71]. In some cases, a combination of both learning techniques, also called semi-supervised learning, is employed [72] to take advantage of the benefits of both methods. It is useful when learning from large datasets containing labelled and unlabelled samples, performing classification and clustering tasks simultaneously. Although advantageous, it would increase the difficulty of the learning process.

Table 2-3 and Table 2-4 highlighted the unsupervised and supervised machine learning-based algorithms applied to solve building performance-related problems. The literature review shows that current uses of unsupervised machine learning are in enhancing building performance mainly including, HVAC system management, fault detection and diagnosis, and occupancy detection. The most popular among the domain are clustering algorithms, notably the k-means algorithm. Clustering methods can provide information on the underlying data structures that is initially hard to detect [80]. Several works have used unsupervised clustering data methods to enhance the performance of their models. In the study [81, unsupervised learning clustering algorithms are integrated with supervised learning algorithms to enhance the prediction of indoor temperature.

Table 2-3. Examples of unsupervised learning models for enhancing building performance.

Ref.	Model Type	Evaluation	Eval. Metric	Application	Key findings
[81] Mateo et al. 2013	K-means, Fuzzy c-means, Cumulative Hierarchical Tree, DBSCAN, K-medoids	Simulation	MAE	Improving building indoor temperature prediction of linear and non-linear methods.	Clustering techniques did not show significant improvement for linear or non-linear methods.
[82] Carreira et al. 2018	K-Means algorithm	Simulation	CV, STDV	Enables automatic configuration of an HVAC system.	The k-means algorithm helped optimise the HVAC system to minimise energy consumption while maintaining user comfort.
[83] Li et al. 2010	Fuzzy C-mean clustering algorithm	Historical data	MAPE, RMSE	Short-term cooling load forecasting	The clustering technique helped reduce the number of training samples and avoid noise samples.
[84] Liu et al. 2021	Two single-step clustering based on K-Means and DBSCAN	Electricity consumption dataset	Visual comparison, Dunn index	Anomaly detection in building electricity consumption data	The proposed two single-step clustering methods outperformed the k-means and gaussian mixture models in terms of detecting outliers and discovering typical electricity usage characteristics.
[85] Habib et al. 2016	K-Means, Bag of words representation	Building operational data	Cluster evaluation	Detects various operational patterns in a building energy system	The method can automatically find various patterns using as

	with hierarchical clustering				little configuration or field knowledge as possible.
[86] Hong et al. 2015	Gaussian mixture model with partitional clustering	Building sensor information	Classification Accuracy %	Differentiate sensors in buildings by type	The approach can achieve more than 92% accuracy for type classification.
[87] Guo et al. 2013	Hidden Markov Model and a clustering algorithm	Experiment	Not specified	HVAC system fault detection and diagnosis	The method not only identified system faults that were modelled within the training process but also can be applied for diagnosis.
[88] Trabelsi et al. 2013	Hidden Markov Model, Expectation - Maximization (EM) algorithm	Experiment	Classification, Precision, Recall	Recognise human activities from wearables	The proposed method achieved a high classification rate of 91.4% and competitive with a well-known supervised approach.

In the last decade, many works have used supervised learning techniques to conduct various types of building energy use forecasting, including heating and cooling load, thermal comfort prediction and occupancy prediction. Table 2-4 lists some of the typical supervised learning studies in the literature. Most of the studies focused on heating and cooling energy demand, which accounts for a significant portion of the total energy use in buildings and, at the same time, impacts indoor environmental quality. Focusing solely on the studies of energy prediction, it was observed that existing studies have a wide range of prediction time scales from minute to year basis. Ciulla and D'Amico's study [89] employed a multiple linear regression model to conduct an immediate assessment of annual (long-term) heating and cooling building energy requirements, which can be used as a decision support tool for the preliminary evaluation of a building. While it predicted the energy requirements of a building with a high degree of reliability, however, they did not identify that it was not intended to replace a dynamic simulation model. While some of the studies showed the capabilities of supervised learning techniques in short-term predictions. Bilous et al. [90] used a multivariate regression model to predict the hourly indoor air temperature. They used a multivariate regression model which considered various external environmental factors affecting the thermal performance of the building. The results indicated that the model provided high-accuracy predictions with an R-squared (R^2) value of 0.981.

Occupancy detection and prediction is a popular application of supervised machine learning. Such methods can estimate occupancy using data from building sensors, energy meters, Bluetooth and Wi-Fi signals. Ryu and Moon [91] used a decision tree model to detect the occupancy at the current state based on energy consumption and environmental data. Based on the result, the decision tree model could estimate the occupancy at the current state. Depending on the number of predictors used, the RMSE (Root mean squared error) ranged between 0.3673 and 0.2202. While Wang et al. [92] used environmental data, Wi-Fi and fused data combined with machine learning to develop an occupancy prediction. Examined with an on-site experiment, the results suggest that the ANN-based model with fused data has the best performance, while the SVM model is more suitable with Wi-Fi data.

Table 2-4. Examples of supervised learning models for enhancing building performance.

Ref.	Model Type	Evaluation	Eval. Metric	Application	Key findings
[52] Chou and Bui. 2014	Support vector regression (SVR), Ensemble, General linear regression, Classification and regression tree, ANN	Simulation	R^2, MSE, RMSE, MAE, MAPE	Heating and cooling load predictions	The ensemble approach (SVR + ANN) and SVR were the best models for predicting heating and cooling load.
[89] Ciulla and D'Amico 2019	Multiple linear regression	Simulation	R^2, MSE, RMSE, MAE, MAPE	Prediction of annual heating and cooling energy demand	Predicted heating, cooling, and comprehensive energy requirements of a building with a high degree of reliability. R^2 of 0.9 and the MAE and RMSE are lower than 10 kWh/m^2 per year.
[90] Bilous et al. 2018	Multivariate regression model	Simulation	R^2, Fisher's criterion	Prediction of hourly internal air temperature	The model provided high-accuracy predictions with R^2 of 0.981.
[91] Ryu et al. 2016	Decision tree	Experiment	RMSE	Indoor environmental data-driven model for occupancy prediction	The decision tree model could estimate the occupancy state. Depending on the number of predictors used, the RMSE ranged between 0.3673 and 0.2202.
[92] Wang et al. 2018	Combined ANN with an ensemble approach	Simulation	R^2	A novel dynamic forecasting model for building cooling loads that combine ANN with an ensemble approach	The proposed ensemble model greatly improved the forecasting accuracy.
[93] Zhang et al. 2018	Nonlinear ML algorithms, SVR with nonlinear radial basis function (RBF) kernel and neural networks	Experiment	MAE, R^2, Time	Different ML techniques for modelling thermal comfort levels	The nonlinear models performed significantly better than the linear models. The neural network had the best performance.
[95] Wu et al. 2018	Ensemble method	Experiment	R^2, RMSE, MAE, r	An intelligent ensemble ELM method was developed for thermal perception prediction	The proposed ensemble model performed better than ANN and SVM.
[96] Johannesen et al. 2019	Random Forest Regressor, k-nearest neighbour regressor and linear regressor	Energy load dataset	MAPE	Urban area electrical energy demand forecasting	Random Forest Regressor provides better short-term load prediction, and kNN offers relatively better long-term load prediction.
[97] Song et al. 2017	K-means for building energy prediction. ANN for end-user group prediction.	Energy and occupancy dataset	CV-RMSE	Hourly energy prediction considering occupancy characteristics	The prediction accuracy is improved when considering diverse occupancy and its correlation with energy use.
[98] Peng et al. 2017	K-nearest neighbour	Experiment, Application	Not specified	Occupancy information prediction is employed for the control of the cooling system	Average control accuracy of 88.1%. Energy saving of up to 20.3% is achieved with the use of demand-driven control.
[99] Xiong and Yao, 2021	K-nearest neighbour	Experiment	Accuracy %	Thermal comfort model to establish a personalised	The KNN-based thermal comfort model with 1000 sets

				adaptive thermal comfort environment.	of training data can have an accuracy of 88.31%.
[100] Qiong et al. 2017	Support vector machine	Energy load dataset	RMSE, MRE	Prediction model of annual energy consumption of residential buildings	The support vector machine achieved better accuracy and generalisation than evaluated neural network techniques.
[101] Liu et al. 2021	Random forest	Simulation	R^2, RMSE	Prediction model of energy consumption of university buildings	The Random Forest model exhibits notable advantages in building energy consumption prediction compared to SVM

As observed, each machine learning algorithm has its advantages and limitations, and several factors such as the task, data availability, practicability and computational cost must be considered when selecting a suitable model for a project [102,103]. With regards to building performance-related projects, although knowledge of artificial intelligence/machine learning is key, it is also paramount for model developers to know about building engineering/energy systems [80]. This is important when selecting an appropriate prediction target and predicting parameters for the machine learning model.

This section highlighted examples of unsupervised and supervised machine learning-based algorithms applied in building and energy efficiency research. Many studies combined several machine learning methods, with some using a combination of supervised and unsupervised algorithms (also called semi-supervised) to take advantage of the benefits of both approaches. This can be seen in the reviewed works which developed machine learning methods with multiple stages. Furthermore, most of the studies are still at the experimental or testing stage, and there are limited studies which implemented machine learning strategies in actual buildings and conducted the post-occupancy evaluation. Finally, most of the studies are focused on individual buildings or a few building spaces, while there are limited large-scale applications and implementation in other types of buildings such as industrial and retail buildings. This is probably due to the constraints and challenges of data acquisition.

2.3.2. Assessment of the Model Evaluation Methods

As shown in Figure 2-5, the next stage following the training of the machine learning model is the evaluation or experimental stage. At the experimental stage, the performance of the selected machine learning method is evaluated based on how well it performs on new or unseen data. Typically, the development of machine learning methods involves several experiments, including testing of several types of algorithms and optimisation or tuning of the hyperparameters [78, 79]. As detailed in Table 2-1, Table 2-2Table 2-3Table 2-4, various performance metrics or indicators related to model accuracy, sensitivity and robustness are used for model evaluation. These metrics are used to evaluate a model's performance and provide feedback to allow improvements until a desirable performance is achieved [103]. Based on the reviewed literature, the typical evaluation metrics employed [104] include accuracy, mean squared error (MSE), root mean square error (RMSE), mean absolute error (MAE), R squared (R^2), and mean absolute percentage error (MAPE) [45]. The evaluations are carried out using data from simulations, historical data and experiments. It should be noted that the information presented about the evaluation metrics is not meant to assess which is the best evaluation metric, but rather to show that existing studies are using different evaluation methods. This inconsistency makes it challenging to assess or compare the different algorithms and select an optimal method. While most of the studies covered in the review showed that the proposed machine learning methods are suitable and achieved good performance for various building-related applications, it also adds to the challenge of finding an optimal machine learning algorithm. A common approach practised in the literature is the testing of different models on the same data to evaluate the best-performing method. Hence, guidelines on the standardisation of the evaluation methods are required to promote the optimal algorithms selection.

At the application stage, once the model is trained and validated, the machine learning method is then applied to an actual building, for example, its energy management or HVAC control system [98] or used to support the decision-making during the building design process. While this stage is important for further validating the performance of the machine learning method in real implementations, previous works have not paid much attention to this. The review by Wang et al. [80] highlighted that many of the building performance-related machine learning studies are at the experimental stage. This can be observed in Table 2-3 and Table 2-4 indicating most of the studies were either evaluated using simulation results, previously collected datasets, and experiments. Many thermal comfort and occupancy detection studies used experiments to validate the model, while energy prediction studies used historical datasets and simulation results. The use of commercial BES tools such as EnergyPlus and IES VE is commonly compromised to generate training data and prove the theoretical feasibility of the model, which may not be sufficient to put the machine learning model into practice.

Furthermore, Wang et al. [80] also highlighted that most studies did not validate their machine-learning models using real post-building-completion energy or post-occupancy data. Among the rebn viewed studies, the work by Peng et al. [98] implemented the proposed demand-driven strategy for the controls of a cooling system of several offices in a commercial building in Singapore. The two monthly field experiments showed that the proposed strategy could result in energy savings of up to 20.3%. While this study showed the capabilities of the K-nearest neighbour model in occupancy prediction strategy in real offices, the authors did acknowledge the limitations of the experiment. The limited experimental time and a small number of case study offices may restrain the universality of their results.

While modellers aim to develop machine learning models that provide good performances, it does not necessarily mean that it will lead to successful real-world implementations. Future works should consider implementing their proposed machine learning-based strategies in real buildings and systems. More studies should be carried out on the integration of existing machine learning strategies with building management systems and control strategies.

2.4. Deep Learning Approaches for Building-Related Applications

While deep learning is a subset of machine learning, this section focuses on some of the latest advancements and applications of deep learning techniques in the built environment energy prediction and occupancy detection. As defined by LeCun et al. [105], deep learning allows computational models comprised of multiple processing layers to learn data representations with multiple levels of abstraction, imitating the human brain. While it can be considered as a machine learning concept based on artificial neural networks (ANN), deep learning typically contains advanced neurons, which allows deep neural networks to be fed with data in raw form and automatically discover a representation required for the corresponding learning tasks [69]. Such functionalities are not provided by simple ANNs and machine learning algorithms.

Hence, deep learning can address some of the limitations of conventional machine learning methods, including machine learning's inability to process natural data in their raw form, as discussed in the earlier sections. It eliminates some of the data pre-processing tasks typically required in developing machine learning methods, reducing the reliance on expert knowledge (see Table 2-1b). Besides numerical and text data forms, deep learning can also process other forms of data such as images, videos, and sounds. Like machine learning, deep learning can be supervised, unsupervised or reinforcement learning, depending on how the neural network is utilised. For instance, when both input and output are known, such as when performing classification or object detection tasks, supervised learning is used to carry out the prediction task. While unsupervised learning can be used to cluster images based on their similarities.

While machine learning has shown good performance in various applications such as energy forecasting, thermal comfort, and occupancy prediction. The literature has shown that these applications are increasingly making use of deep learning techniques [106, 107]. According to Janiesch et al. [69], deep learning outperforms conventional shallow machine learning algorithms and traditional data analysis methods in numerous applications that require text, images, audio, and video to be processed, such as in natural language processing, image classification, speech recognition and computer vision [105]. It is particularly useful in applications which require handling large and high-dimensional data [108]. The increasing amount of data generated from many sources, the advances in computational power, and the developments of algorithms have led to the increasing popularity of deep learning. However, it also means that deep learning would require high-end machines and could take a long time to train a model. While in applications which deal with low dimensional and small datasets, conventional machine learning is still preferable as it could produce superior and more interpretable results [109].

Deep learning applications have revolutionised many sectors and will continue to do so. While this disruptive technology is becoming more common across a wide range of industries, researchers and practitioners in the built environment sector are striving to keep up with the pace of applying deep learning. Table 2-5 highlights some deep learning-based algorithms applied to solve building performance-related problems. The literature review shows that current uses in enhancing building performance, mainly include energy demand and thermal comfort prediction, and occupancy recognition.

Table 2-5. Examples of deep learning-based methods for enhancing building performance.

Ref.	Model Type	Evaluation	Eval. Metric	Application	Key findings
[36] Fan et al. 2019	Recurrent neural network (RNN)	Building operational data	RMSE, MAE, CV- RMSE	Short-term building energy predictions	Recurrent models achieved the most accurate predictions without increasing computational load. RMSE was 30.8% for cooling load prediction
[106] Kim et al. 2019	Recurrent neural network (RNN), recurrent inception convolution neural network (RICNN)	Smart meter dataset	RMSE, MAPE	A multi-short-term load forecasting model	RICNN model outperforms the benchmarked multi-layer perception, RNN, and 1-D CNN
[107] Cai et al. 2019	Gated RNN, CNN	Electricity dataset	CV, MAPE, Computational efficiency	Day-ahead building-level load forecasts	24-h gated CNN model performed better than

					conventional deep learning models.
[110] Somu et al. 2019	CNN-LSTM	Energy consumption data	RMSE, MAPE, MAE, MSE	Building energy consumption forecast	CNN-LSTM captured the spatio-temporal network characteristics in building energy consumption data
[111] Suryanarayana et al. 2018	Deep neural networks	Heat load dataset	MAPE, F_1 score, F_2	Thermal load forecasting in district heating	Deep neural networks performed better than all linear models although more computationally intensive.
[112] Marino et al. 2016	Long short-term memory (LSTM)	Electricity dataset	RMSE	Building energy load forecasting	LSTM performed well for the one-hour resolution dataset but not for the one-minute resolution data.
[113] Somu et al. 2021	CNN-LSTM	Thermal comfort dataset	Precision, Accuracy, F_1 score	Thermal comfort modelling with a limited dataset	The model proposed provided reasonably accurate predictions and overcome the challenges related to the inadequacy of modelling data.
[114] Gao et al. 2021	Transfer learning-based multilayer perceptron (TL-MLP)	Thermal comfort dataset	Accuracy, F_1 score	Thermal comfort prediction in multiple cities	The Tl-MLP model from the same climate zone exceeded the performance of state-of-the-art methods in accuracy and F1-score.
[115] Deng and Chen 2018	Artificial neural networks (ANN)	Thermal sensation data, behaviour data	MAE, R^2	Thermal comfort prediction in single-occupant and multi-occupant offices	The Comfort zone obtained by the ANN model using thermal sensations was narrower than the comfort zone in ASHRAE Standard 55, while the ANN model using behaviours was wider than the ASHRAE comfort zone.
[116] Anh et al. 2017	Long short-term memory (LSTM), Gated recurrent units (GRU)	Air quality dataset	Accuracy	Indoor air quality prediction using sensors and DL	The GRU model outperformed the LSTM model. The GRU model achieved an accuracy of up to 84.5%
[117] Mutis et al. 2020	Deep neural network	Human action dataset	Accuracy	Indoor air quality control using occupancy information	The model achieved 84% accuracy on the human action dataset using a multi-stream fusion network for recognising activities.
[118] Taheri et al. 2022	Deep recurrent neural networks (DRNN)	HVAC dataset	F1 score, Precision, Accuracy, Recall	Fault detection and diagnostic for variable flow refrigerant system	The DRNN model outperformed random forest and gradient-boosting regression.
[119] Guo et al. 2018	Deep belief network	HVAC dataset	Correct rate (CR), Hit rate (HR)	Fault detection and diagnostic for variable flow refrigerant system	The fault diagnosis correct rate of the optimized model was 97.7%,
[120] Fan et al. 2018	Autoencoder	Building operational data	Accuracy %	Anomaly detection in building energy data	The proposed autoencoder method successfully identified anomalies in building energy data.

While deep learning algorithms can be applied to a range of prediction or classification tasks, like machine learning, modellers should consider several factors when selecting a deep learning model for a project, such as the type of tasks, learning method, data availability, practicability and computational cost. The literature showed that deep learning techniques had been successfully applied in various types of building energy use forecasting. For example, recurrent neural network (RNN) models have shown favourable performance in electric load forecasting [106]. RNN is one of the neural network architectures best suited to tackle datasets with sequential correlations and has demonstrated good performance in processing time-series data such as text and speech. The time series nature of operational data of buildings makes RNN a suitable technique for energy consumption prediction tasks. However, traditional RNN models are not effective in capturing long-term temporal dependencies. Models such as long short-term memory (LSTM) and gated recurrent units (GRU) are used to overcome some of the shortcomings of RNN models. Hence Fan et al. [120] proposed several techniques to enhance the performance of recurrent models in building cooling energy predictions.

Cai et al. [107] compared the performance of RNN and CNN-based algorithms for energy forecasting in commercial buildings. The study developed the gated RNN and CNN specifically for day-ahead building-level load forecasting. The results showed that the gated CNN model outperformed the gated RNN in terms of accuracy and computational efficiency. While CNN is well known for object/image recognition and classification due to their optimal performance, it has also been successfully used in various applications such as building energy prediction tasks which involve time series data [107].

Although most deep learning architectures apply to a range of prediction or classification tasks, some studies have combined deep learning techniques for better performance. In the study by Kim et al. [106], an RNN model was combined with one-dimensional CNN to enhance the performance of a forecast model for short-term loads. The study showed that the proposed model outperformed other models, including multi-layer perception and RNN. In another study by Almalaq and Zhang [108], CNN is combined with LSTM to predict residential energy consumption. The CNN layer extracts the features between multivariate variables affecting energy consumption, while the LSTM models the temporal information and maps time series into separable spaces to generate predictions. The proposed hybrid model accurately predicted the electric energy consumption of residential houses and performed better than other deep learning models such as LSTM and GRU. In some cases, traditional machine learning techniques are combined with deep learning techniques. For example, the study by Somu et al. [110] combined CNN and LSTM with k−means clustering for building energy consumption forecasts. The unsupervised learning clustering method was used to understand the energy consumption trend before data modelling. The results showed the efficiency of the proposed model over the existing building energy consumption forecast models, such as MLP, CNN and LSTM. Furthermore, it showed the capability of the combined CNN and LSTM in capturing the spatio-temporal characteristics in building energy consumption data.

While many of the works in the literature predicted the electricity consumption of buildings, the study by Suryanarayana et al. [111] extended deep learning methods to the field of heat load forecasting. They compared the performance of the deep learning architecture, a deep neural network with linear models in forecasting thermal loads in district heating networks. A deep neural network is a standard neural network with multiple hidden layers (at least 2 hidden layers) between the input and output layers. It extracts uniquely abstract features to model complex non-linear relationships. The results showed that although more computationally intensive, the deep neural network provided the best accuracy among the tested techniques.

Another important application of deep learning is thermal comfort prediction [110, 114] and management [62, 63]. As mentioned earlier, data-driven techniques have shown their advantage over traditional PMV models; however, their application can be hindered by the unavailability or lack of labelled thermal comfort data from occupants. The works by Somu et al. [113] address this issue by implementing a transfer learning-based CNN-LSTM model for predicting thermal comfort in buildings with limited data. Transfer learning takes relevant parts of a pre-trained model and applies them to a new but similar problem. This allows the training of a model using a smaller dataset while using a large amount of relevant data from a previous task. The hybrid model achieved reasonably accurate predictions and overcame the challenges related to the inadequacy of modelling data. It performed better than other methods such as LSTM, CNN, SVM, KNN and traditional PMV.

Gao et al. [114] proposed a transfer learning MLP model for thermal comfort predictions for any building in a similar climate with limited labelled data. Transfer learning allowed the transfer of knowledge from a building in a similar thermal environment or climate to another building for thermal comfort prediction. The proposed model exceeded the performance of state-of-the-art methods in terms of accuracy and F1 score. While transfer learning has been successfully utilised in many real-world applications, it can be a promising technique to scale up the implementation of machine learning and deep learning models in the built environment sector.

As mentioned previously, CNN is one of the most popular deep learning techniques and has shown optimal performance when it comes to object and image recognition tasks. Its advancement has benefitted many areas, including computer vision which is typically used in applications such as image detection and recognition, image and video analysis and natural language processing. While computer vision is not new, it has advanced significantly in the last 10 years since the development of the AlexNet model, which uses CNN. Furthermore, the availability and increase in GPU power have accelerated the development of computer vision solutions. Today, CNN is used in numerous computer vision applications such as facial recognition, augmented reality, pedestrian detection, and autonomous vehicles. The advancement in computer vision has gained the interest of many researchers in several fields, including the built environment.

Deep learning algorithms have recently become the focus of increased attention due to their performance and capabilities. Its popularity has been fuelled by the increasing amount of data generated from many sources, advances in computational power, and the development of algorithms. Deep learning methods have been promising for the development of building energy prediction models due to their powerful learning and prediction abilities. Many of the reviewed studies showed that the methods outperform conventional shallow machine learning algorithms and traditional data analysis methods. Although most deep learning architectures apply to a range of prediction or classification tasks, some studies have combined deep learning techniques for better performance. Such an integrated method typically works in stages, with each stage taking advantage of the abilities of the deep learning/ machine learning method. For example, one method will carry out clustering tasks, and the other will perform prediction tasks. The literature showed that while machine learning has been extensively applied to thermal comfort, indoor air quality prediction, and fault detection and diagnosis, the applications of deep learning in these areas are only starting to pick up steam.

With CNN as one of the most important developments in the field of deep learning, it has shown optimal performance when it comes to object and image recognition tasks. The literature showed that CNN had been successfully used in numerous computer vision applications in the built environment, such as occupancy counting, occupancy activity detection/recognition, equipment usage detection, window detection and fire/smoke detection. The information generated by such methods can be used to automatically adjust the operation of building systems and manage spaces, which can enhance building performance. The literature also highlighted some of the issues that should be resolved before computer vision-based methods can be widely adopted, such as security/privacy issues and the influence of various indoor parameters on performance.

Like in machine learning, each deep learning algorithm has its advantages and limitations, and several factors such as the task, data availability, practicability and computational cost must be considered when selecting a suitable model for a project. As detailed in Table 2-5, various performance metrics or indicators related to model accuracy, sensitivity and robustness are used for model evaluation. However, other performance indicators such as computational efficiency, data requirements and complexity have not been assessed or discussed in many of the reviewed studies. Similar to the review of machine learning methods, most of the studies covered in the review showed that the proposed deep learning methods achieved good performance for various building-related applications. This adds to the challenge of finding an optimal deep-learning algorithm. Some studies have carried out a comparative analysis with an established machine or deep learning algorithms to identify the best-performing model.

The literature also showed that most of the studies are at the experimental stage. This can be observed in Table 2-5 with most of the studies are either evaluated using simulations, previously collected datasets, and experiments. While there is a lack of validation of deep learning models using real post-building-completion energy or post-occupancy data. Future works should consider implementing their proposed deep learning-based strategies in real buildings and systems.

2.5. Summary

The literature review showed that machine learning and deep learning techniques had been successfully applied in various building environment applications, focusing on the improvement of building performance, such as energy-comfort-air quality prediction, and occupancy prediction and detection. Table 2-6 presents a graphical/visual summary of some of the studies covered in the literature review, which categorised them into ‘what type of building system’, ‘which method/solution’, and ‘who benefits’.

While the table does not include all the reviewed studies, it gives an overview of the ideas in the areas where the existing studies are focused. At the same time, it also highlights that most of the studies were focused on optimising the energy efficiency and thermal comfort in a building while less attention was paid to air quality. Although energy use, thermal comfort and IAQ are interrelated, there are limited studies which investigated or considered them all simultaneously. While machine learning and deep learning techniques have important roles in aiding the design and operation of buildings to provide energy-efficient, comfortable, and healthy indoor environments - it requires a holistic approach. For example, while a certain method could minimise energy use and enhance thermal comfort in a building, it may have an adverse effect on other factors such as the IAQ. Future works should consider energy efficiency, thermal comfort, and IAQ aspects and their interactions when developing machine or deep learning-based building strategies.

It can be observed that many of the deep learning and machine learning methods were employed for energy prediction, with most focusing on cooling and/or heating loads while some considered ventilation loads. This demonstrates a gap in the literature on some topics, such as forecasting of lighting energy, plug loads and dehumidification, where more attention should be paid. In addition, most of the studies focused on mechanical HVAC systems while there is less focus on natural ventilation and other passive cooling/heating strategies.

Several studies have coupled different methods to enhance building performance, for example, a detection model is used to obtain occupancy information from a building space, and then the data is fed into a prediction model to estimate the IAQ and thermal comfort in the future. While IAQ and thermal comfort are important indicators of the quality of conditions inside a building, there are also other factors which might influence the indoor environment quality. This includes daylighting, visual comfort, and acoustic conditions – less attention has been paid to these factors in the literature.

Table 2-6. A visual summary of some of the machine learning and deep learning-based studies covered in the literature review.

Reference	**Type**					**Building Energy**		**Indoor Environment Quality (IEQ)**			**Occupancy**		**Benefit Towards**							
													Building		**HVAC**				**Occupancy**
	Heating	**Cooling**	**Air-conditioning**	**Ventilation**	**Thermal Comfort**	**Prediction**	**Management**	**Comfort Prediction**	**IEQ Management**	**Air Quality Prediction**	**Detection**	**Recognition**	**Design**	**Performance**	**Response Time**	**Efficiency**	**System Design**	**Energy Saving**	**Satisfaction**
Fan et al. (2019) [36]																			
Terroso-Saenz et al. (2019) [40]																			
Chammas et al. (2019) [39]																			
Kwok and Lee (2011) [48]																			
Ding et al. (2018) [49]																			
Singaravel et al. (2018) [46]																			
Xu et al. (2019) [51]																			

Tsanas and Zifara (2012) [53]																			
Dong and Lam (2014) [121]																			
Zhao and Liu (2018) [44]																			
Kumar et al. (2018) [50]																			
Pham et al. (2020) [47]																			
Chai et al. 2020 [56]																			
Peng et al. (2018) [59]																			
Yang et al. (2020) [60]																			
Gao et al. (2019) [63]																			
Cho and Moon et al. 2022 [65]																			
Kim et al. (2021) [66]																			
Yu et al. (2021) [67]																			
Mateo et al. (2013) [81]																			
Li et al. (2010) [83]																			
Habib et al. (2016) [85]																			
Carreira et al. (2018) [82]																			
Gull et al. (2021) [72]																			
Ciulla and D'Amico (2019) [89]																			
Bilous et al. (2018) [90]																			
Zhang et al. (2018) [93]																			
Wang et al. (2018) [94]																			
Wu et al. (2018) [95]																			
Ryu and Moon (2016) [91]																			
Wang et al. (2018) [92]																			
Song et al. (2017) [97]																			
Peng et al. (2017) [98]																			
Suryanarayana et al. (2018) [111]																			
Marino et al. (2016) [112]																			
Shaikh and Nor (2018) [19]																			
Deng and Chen (2018) [115]																			
Ahn et al. (2017) [116]																			
Mutis et al. (2020) [117]																			

2.6. Research Gap

Existing AI-based techniques focused on the framework, methodology, and performance of different aspects designed to resolve interconnected problems related to HVAC systems and enhance building performances. Machine and deep learning methods have been successfully applied to building energy prediction. Many studies have shown the advantage of AI methods for predicting energy loads compared to conventional building energy simulation models. It requires fewer details and information about the building, which reduces the time of developing the model and, at the same time, AI-based models are significantly faster. However previous works stressed the importance of selecting suitable input data and learning algorithms. Many studies recommended the integration of occupancy behaviour pattern recognition with the energy load forecasting model to enhance prediction performance. Due to the reliance on historical building data, AI-based models' applications in the design stage are limited. One cannot extrapolate the prediction results once changes are made to the design and operation of a building.

While machine learning has shown good performance in various applications such as energy forecasting, thermal comfort prediction and occupancy detection. The literature has shown that these applications are increasingly making use of deep learning techniques. The increasing amount of data generated from buildings, the advances in computational power, and the developments of algorithms have led to the increased popularity of deep learning. Although most deep learning architectures apply to a range of prediction or classification tasks, some studies have combined deep learning techniques for better performance. In some cases, traditional machine learning techniques are combined with deep learning techniques.

As observed, each machine and deep learning algorithm has its advantages and limitations, and several factors such as the task, data availability, practicability and computational cost should be considered when selecting a suitable model for a project. With regards to building performance-related projects, although knowledge of artificial intelligence/machine learning is key, it is also paramount for model developers to know about building engineering/energy systems. This is important when selecting an appropriate prediction target and predicting parameters for the machine learning model.

Effectively, no work provides a critical summary of the existing literature on the machine and deep learning methods for the built environment over the past decade, with special reference to holistic approaches. The review given in this section indicated the different AI-based techniques employed to resolve interconnected problems related to HVAC systems and enhance building performances, including (1) energy forecasting and management, (2) building design and facilities operations, and (3) indoor air quality and occupancy comfort/satisfaction. However, the frameworks that utilise AI techniques typically only address one of the three objectives. Neural networks were indicated to be incorporated into all categories, which was suggested to be the ideal technique for a range of building-related applications. However, more researchers are adopting deep learning. It was identified to have immense potential for future applications due to its high adaptability in providing solutions that cover multiple aspects including the management of buildings, occupancy detection and thermal comfort prediction. Yet, there are limited studies in the development of deep learning approaches applied to indoor building spaces to resolve energy-related issues in buildings.

Hence, a data-driven deep learning framework for the detection and recognition of occupants as a strategy to enhance more intelligent buildings and provide better solutions to fulfil future needs is desired.

Chapter 3

3. Review of the Literature and an Outline of the Research Gaps on an Innovative Deep Learning-Based Approach for Occupancy Behaviour Detection and Recognition Towards the Enhancement of Building System Operations

This chapter presents a review towards the understanding of occupancy behaviour in buildings. To address the objective of understanding the application of various software platforms towards the development of a deep learning framework for occupancy behaviour detection and recognition, techniques, designs, and solutions for applications within indoor building environments were investigated. The benefits and limitations of traditional sensor-based techniques and the development of deep learning-based solutions are discussed, leading to the identification of the various types of common occupant actions to be recognised by the developed deep learning-based detector.

3.1. Introduction

Building occupancy patterns are rapidly changing, with many occupants in offices adopting flexible working hours which results in variations of the scheduled operating time of conventional HVAC and lighting systems. It leads to unnecessary loads and an increase in building energy usage [122]. Recent studies [10, 11] have shown the benefits of demand-driven control strategies which enable HVAC systems to adapt and make a timely response to the dynamic changes of occupancy instead of using 'static' or 'fixed' occupancy operation schedules, historical load and time factor. For example, when the air-conditioning system for a room is operational, but the room is unoccupied for long periods [123, 124]. This would lead to a significant amount of energy wastage.

Current standards and guidelines such as the ASHRAE 90.1 [125] and ASHRAE 55 [126] suggest a generalised set point range and schedule for room heating and cooling during occupied and unoccupied hours. For example, during occupied hours, it suggests 22 – 27°C for cooling and 17 – 22°C for heating, while during unoccupied hours, it suggests 27 – 30°C for cooling and 14 – 17°C for heating. However, according to Papadopoulos [127], these HVAC setpoint configurations must be revised when applied to commercial buildings. The use of fixed or scheduled set points combined with varying occupancy patterns could lead to rooms frequently being over or under-conditioned. This may lead to significant waste in energy consumption [128] which can also impact thermal comfort and satisfaction [48]. Delzendeh et al. [129] suggested that the impact of occupancy behaviour has been overlooked in current building energy performance analysis tools. This is due to the challenges in modelling the complex and dynamic nature of occupants' patterns, influenced by various internal and external, individual, and contextual factors. Peng et al. [98] collected occupancy data from various offices and commercial buildings and have identified that occupancy patterns vary between different office types. Multi-person office spaces regularly achieve occupancy rates of over 90%. However, private, single-person offices rarely achieve an occupancy rate of over 60%. While equipment or appliances in offices can be kept in operation during the entire working day, irrespective of the occupancy patterns [130]. The study by Chen et al. [131] highlighted that occupancy behaviour is a major contributing factor to discrepancies between the simulated and actual building performance. In current BES programs, the occupancy information inputs are also static and lack diversity which contributes to discrepancies between the predicted and actual building energy performances.

Effectively, seeking a potential solution to overcome such limitations is even more important when COVID-19 restrictions are applied. Many offices follow a staggered shift to reduce workplace congestion [132]. Studies [133] have shown that the daily occupancy rate on average can be below 60% in single-person offices. Hence, accurate identification of occupancy patterns is important for improving the performance of demand-driven control of HVAC systems [134]. Occupancy information sensing can be classified into occupancy counting (number of people), localization (distribution in space) and activity detection. The occupancy information could also be used for controlling other components such as window opening and shading.

3.1.1. Occupancy Activities

The amount of energy consumed by buildings is influenced by various factors, from thermo-physical properties of the building elements to the location, occupancy behaviour and the HVAC systems [135]. Although outdoor environmental conditions significantly impact building energy consumption, the variations in occupancy rates and their behaviour are equally important. The number of occupants, their activity level and how they use the equipment can impact the internal heat gains, indoor environment, and energy demand. Occupants also interact with the building and make personal adjustments such as the thermostat or opening the windows. In practice, conventional HVAC is typically controlled, leading to unnecessary energy usage, such as when spaces are left unoccupied. Similarly, traditional building energy models use ‘static’ and deterministic occupancy inputs, leading to prediction errors. This can result in uncertainties in the building energy prediction, difficulty in sizing and controlling HVAC systems [136], and not meeting the desired indoor conditions and comfort requirements [137]. Hence, occupancy behaviour and its impact on the energy performance of buildings have gained significant interest within the scientific community [138]. This led to the development of advanced occupancy detection techniques and occupancy simulators [139]. The occupancy data can help determine the effects of occupant presence and their activities within buildings, which can be used to optimise HVAC and lighting control [140].

One of the most common methods for occupancy detection is motion or passive infrared (PIR) sensors. They are designed to detect the electromagnetic radiations emitted by occupants within a space [141]. However, it has limitations such as not enabling the identification of the number of occupants and static occupants. It is also sensitive to environmental parameters such as airflow and solar radiation. Comparatively, technologies like radio frequency identification (RFID), wearables, and embedded mobile and Wi-Fi sensors were also proposed by researchers [142] for monitoring the activities of the occupants. However, the main drawback of these technologies is the requirement for occupants to wear or carry a device which could be inconvenient and intrusive. The limitations of these sensing technologies impede the development of demand-driven control solutions for energy and comfort management in buildings. Since many previous works focused on sensing occupancy information through the count of occupants and localization (distribution in space), there is limited research on sensing the actual activities performed by occupants. This is necessary to allow HVACs to dynamically adjust the indoor-outdoor environment changes [143, 144]. It highlights the importance of the exploration and development of strategies such as computer vision and AI that can be implemented into building HVAC systems for higher accuracy monitoring and control [145, 146] and to provide a solution to enhance energy-related applications within the building sector [146].

The use of video or vision-based methods to detect the number and locations of occupants and recognises their activities/ behaviour is promising [59, 142]. It processes images from videos and recognises the person's activity in the video by detecting the person's shape, characteristic or motion. However, it can also encounter issues such as difficulty in identifying a person in complex indoor environments such as open-plan offices where there are many obstacles, including office furniture and equipment. In addition, the activity of occupants may vary significantly in each time frame. Many works [147] have already implemented vision-based deep learning methods to identify human activities and have shown to be capable of learning features from new sensor data and predicting the associated movement. Most of the studies attempted to improve the performance and accuracy of the deep learning model for human presence and detection activity classification rather than using the data to seek solutions toward the minimisation of unnecessary energy loads associated with buildings [148, 149].

3.1.2. Opening and Closing of Windows

The most common methods for window detection are window sensors. It is operated based on a magnet and reed switch with motion or passive infrared (PIR) sensors located on every window of a building. Most of these sensors are used for security and alarm purposes. They have limitations in terms of their sensitivity to environmental parameters including temperature and sound which can result in up to 25.5% of false-positive results [150]. The study by Surantha and Wicaksono [151] improved a traditional home security system by incorporating AI techniques. Initial detection was performed by a PIR sensor, and further recognition was performed using machine learning techniques to provide detection of intruders with up to 89% accuracy. While there are many window detection methods available, there is limited research on the use of window detection to aid demand-driven control solutions for energy and comfort management in buildings. This is necessary to allow building control systems for HVAC systems to adjust to the indoor-outdoor environment changes [143] dynamically. Strategies such as computer vision and AI techniques can be implemented into building controls for higher accuracy monitoring and control [164]. This can also provide solutions to effectively employ natural ventilation in buildings while minimising the associated heat loss [152].

The use of video or vision-based methods to detect occupancy behaviour within a building space is promising [142]. Compared to other shallow learning methods, the use of deep learning techniques can lead to a better performance of detection and recognition through acquiring videos and recognising by detecting the required shape, characteristic or motion [153]. The present work aims to address this by using a vision-based convolutional neural network-based deep learning method. Many works have already implemented vision-based deep learning methods to identify human presence [148] and object classification with high performance and detection accuracies [154]. However, the application of detection and recognition-based techniques for the building sector, especially towards the improvement of building system controls and energy management is limited. Based on the review of previous works on detection methods and the impact of unusual occupancy behaviour on building energy demands, it was observed that there is a necessity for the development of a control and management solution where data is collected and analysed to understand better window operations for enhancing the building operation and energy efficiency. No work has attempted to use computer vision-based window detection and recognition method to provide data that could provide real-time information on the window state or condition for building occupants and building control systems.

3.2. Methodology of the Detection Technique and Strategy

Without monitoring and the exploration of a technique to predict actions or activity performed by occupants, it can cause a domino effect on the associated impact of the temperature and humidity levels of internal space. Effectively, real-time and accurate predictions of the heat emitted by the occupants with various activity levels can be used to estimate better the actual heating or cooling requirements of a space. For example, when the number of people or the overall activity level of the occupants in the space is detected to be increasing, the set point of the heating system can be adjusted to counteract the increase in indoor temperature to reduce the heating energy consumption during the winter while achieving satisfactory comfort levels for occupants. Furthermore, limited studies conducted tests of vision-based deep learning methods in an actual office environment and assessed its performance in terms of energy savings and indoor environment quality. It is important not only to predict occupancy activities but also to quantify the influence on buildings' energy performance. Another drawback of vision-based methods is it interferes with privacy concerns. The approach will address this by developing a system which only outputs heat emission profiles instead of actual occupancy information which can then be inputted into a control system. Finally, the heat emission profiles generated can also be used as input for building energy simulation (BES) tools which can increase the reliability of results since the unpredictability of occupant behaviour is one of the parameters which creates difficulties in BES.

However, there are other occupancy behaviours which also affect building operations. For example, windows are a common natural ventilation strategy employed within most buildings in the UK. Windows can provide significant cooling and ventilation energy savings when used effectively. However, windows can be easily left open and cause unnecessary energy demand. This results in greater amounts of ventilation losses which would lead to greater amounts of energy wastage.

Hence, to develop such computer vision-based detectors for the proposed approach, several defined conditions and techniques must be defined. The following section presents the method used to determine such techniques, strategies and conditions used to establish the framework.

3.2.1. Occupancy Behaviour with Detection Strategies

Conventional occupancy detection methods such as motion sensors can estimate the number of people within the desired space. While recently, more advanced methods such as WiFi-enabled IoT devices are used to identify occupants' activities [155, 156] automatically. This is made feasible by the wide availability of Wi-Fi infrastructure and the occupant's mobile Wi-Fi connected devices [157].

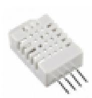
The activity recognition solution proposed by Zou et al. [155] called the 'Deep Hare' was integrated with a deep learning technique to enhance occupancy activity recognition. The approach can distinguish between the different activities performed over time with an accuracy of up to 97.6%. Wang et al. [158] proposed a

Wi-Fi probe-based occupancy detection method, which uses a Markov-based feedback recurrent neural network algorithm. The study showed that it could predict occupancy with accuracies between 80.9% - 93.9%. In a recent study, Wang et al. [124] employed the Wi-Fi probe-based occupancy detection method and showed that it could save up to 26.4% of energy demand, based on experiment and simulation results.

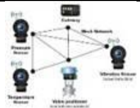
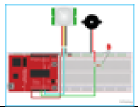
Other methods used more conventional sensors such as radio frequency identification (RFID) and environmental sensors. Carreira et al. [82] used RFID to estimate the occupancy number in a room. Like the previous works, machine learning was incorporated and automatically enabled HVAC management to reduce energy demand while maintaining comfort levels. Jiang et al. [159] estimated the number of indoor occupants in real-time based on the CO2 levels and an extreme machine learning model. The results showed that the proposed method could accurately estimate the occupant number up to 94% based on field tests.

Some researchers employed cameras integrated with AI for sensing occupancy. Zou et al. [148] used existing surveillance video data and a deep-learning approach to measure occupancy for building energy conservation. The experimental results showed an accuracy of up to 95.3% achieved using the approach with low computational requirements. While Diraco et al. [160] used 3D depth sensors to count and localise occupants in buildings while assuring the occupant's privacy as the depth information. Table 3-1 summarises the different occupancy detection techniques developed and used in current research, mainly for building applications. The benefits varied between each type of sensor depending on the desired applications.

Table 3-1. Comparative analysis of existing traditional sensors.

Sensor Types	Specific Sensor Type	Features	Example Applications	Advantages	Limitations	Ref.
Environmental 	Temperature	Detect change in the environment due to the presence and activities of occupants	Enclosed spaces	Low cost Commercially available Non-intrusive	Requires regular calibration	[121, 161]
	Humidity					
	CO_2		Enclosed spaces Small volume spaces		Affected by ventilation Slow response	
Dual-Technology	PIR & Ultrasonic 	Combined PIR and ultrasonic technology minimise false alarm	Classrooms Conference rooms spaces require high detection levels	Self-adaptive to adjust the sensitivity Eliminates false alarm.	Low sensitivity and less coverage compared to microwave-based sensors A limited line of sight of up to 35°	[162]
Passive Infrared (PIR) 		Use IR to detect a difference in heat emitted by moving people and background heat	Enclosed spaces High-ceiling Private offices Computer Room Conference rooms Outdoor spaces	Low cost Commercially available. Non-intrusive Easy detection	Limited to movements Requires direct line of sight Can give false results	[163]
Electromagnetic (EM)	Ultrasonic 	Doppler shift effect Observe frequencies caused by people	Partitioned spaces Restrooms Open offices Enclosed hallways & stairways	Detects minor motion Does not require an unobstructed line of slight	Restricted detection range High levels of vibration or airflow	[164]
	Microwave 	Doppler shift effect Sends microwaves to observe the motion	Large spaces Awkward shaped spaces Spaces requiring fine motion detection	Suitable for various environments, including high heat Low initial cost	Maximum detection range Nuisance switching High operation cost Continuous power draw	[165]

Acoustic and Vibrations	Audio 	Changes in the acoustic wave, propagation path, wave velocity or amplitude	Ambient sensor combination	Low cost readily available Less intrusive	Requires other sensors	[166, 167]
Object Activation	Key cardholder (Energy-saving switch) 	Activates lighting and thermostat controls.	Hotels Apartments (When the room is occupied)	Energy saving Automatic optimisation	Must require a card for activation High installation cost	[168]
Door	Beam Counter 	IR-based electronic device to measure footfall	Retailers Queue management	More accurate than people counting clickers Non-intrusive	It becomes skewed when several were people detected	[169]
Pressure	Pressure Pads 	Monitors occupancy Automatically alarm when detected unexpected activity	Increasing monitoring and protection in homes Car seats Beds	Can only be applied to a specific location	Privacy concerns	[170]
	Air Pressure Change 	Detect change in pressure within the environment due to the presence of occupants	Low occupancy spaces Residential	Non-intrusive Senses movement between spaces	Relationship to occupancy can be indirect	[171]
	Smart Meters 	Detect change in energy consumption patterns Integrate to infer occupancy	HVAC systems Gas, electricity meters	Accurate non-intrusive	It can give false results when some HVAC system is not in use	[172]
Wireless	Bluetooth 	Collects and monitors in real-time Transmit data to the sensor or IoT-based infrastructure	Energy saving Increase building comfort and convenience	Maintenance-free Flexible Easy to install Support intelligent system	Requires integration with other technologies, such as PIR	[173]
	Door Operated Switch 	Wireless IoT Based	Ambient sensor combination	Non-intrusive	Requires other sensors	[174]
	Smart Device Tracking 	Use of IoT-based GPS for asset management and tracking	Workplace Residential	High detection level	Privacy concerns Requires a device to be carried by the occupant	[170]
	Wireless Sensor Network (WSN)	To monitor and record the physical conditions of the environment	Measures environmental conditions like temperature, sound, pollution	Easy-to-use Cross-layer design Adapt to harsh environmental conditions	Must be connected through a specific infrastructure or a central device	[175]

			levels, humidity, wind			
	Sensor Belief Network 	AI-based network of PIR for occupancy sensors	Office Enclosed spaces	High accuracy Missing data entries can be handled successfully	Complex neural network-based model	[176]
Camera	Optical Camera 	Same as the human eye light rays are reflected through the object, through the lens onto the image sensor	Indoor spaces	High level Exact actions are traced and identified	Heavy processing with a complex framework No use when the line of sight is blocked Privacy concerns	[177]
	Thermal Camera 	Infrared lens filter sensor for detection	Surveillance activities Safety	Safe Quiet Minimum risk Doesn't create disruption	High costs High training Applications affected by weather Lack of regulations	[178, 179]
	AI algorithm-based cameras 	Use of AI algorithm-based model integrated with camera devices for detection	Occupancy detection type depends on the selected model design	High detection level and accuracy	Deploy-ability Cost issues (Privacy concerns can be eliminated) High training due to complex AI models	[180]

Newer techniques such as Wi-Fi, wireless sensors and cameras are increasingly being employed in research studies for occupancy studies and, at the same time, integrated with AI techniques. The camera is one of the most popular sensing techniques for indoor environments and human recognition. Similar problems arise from using a camera for detection; however, significant effort has been carried out in recent research to enhance the ability to use the camera through AI adaptation [181].

The utilisation of camera-based techniques for occupancy detection has been increasing recently due to the advancement of deep learning-based techniques [182], such as convolutional neural network (CNN). Deep learning interprets data features and relationships solely using neural networks to form a unique model designed for the desired application, ultimately providing greater flexibility, performance, and accuracy.

The proposed framework process that Ijjina and Chalavadi [181] used for human action recognition emphasises motion in different temporal regions to achieve better discrimination among actions. It suggests the use of video input into a CNN model enables features to be extracted. Within the model, a classifier is trained to recognise human actions to predict recognised activity. The strategy Castro et al. [183] developed to predict occupants' daily activities using egocentric images is similar to [181]; corresponding stages incorporated within the framework were used to develop a workflow to enable activity prediction. Several stages of training were performed to enable in-depth feature extraction refinement before producing the final output classifications. Overall, applying the CNN model alone gave an accuracy of 78.56%, and maximum accuracy of 83.07% could be reached when an ensemble approach was applied. Figure 3-1 provides an example of a workflow process for the development of an AI-based technique for occupancy detection in an indoor environment.

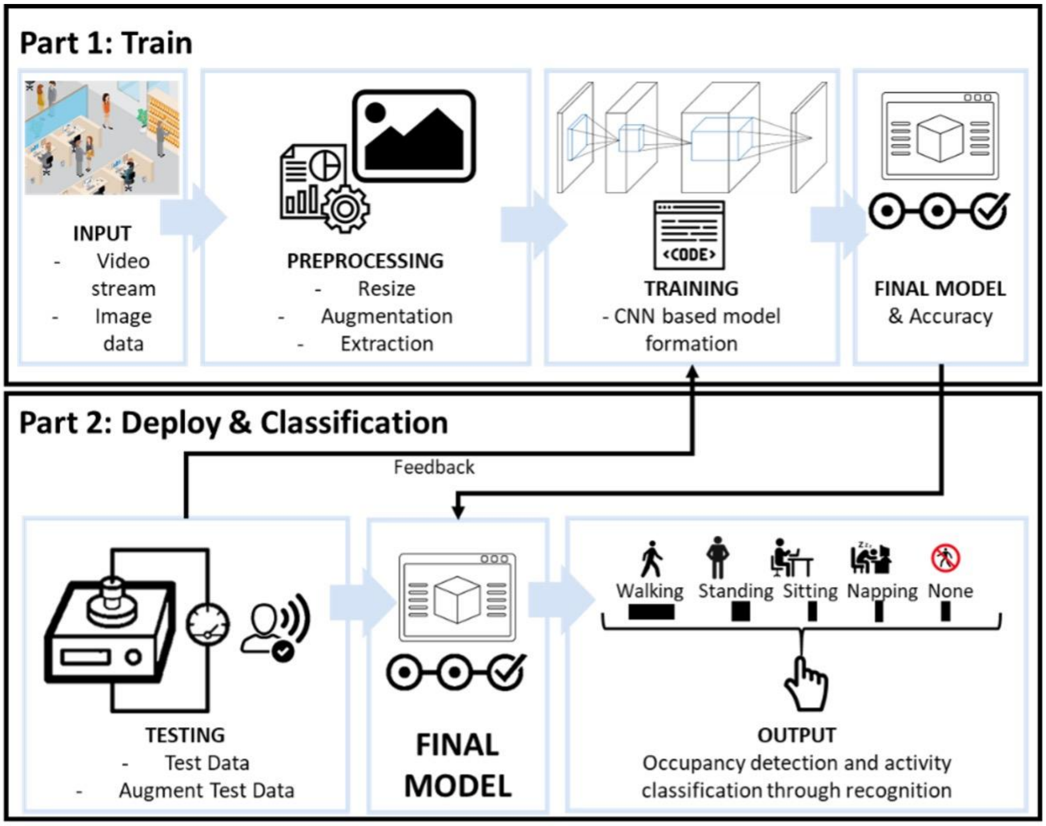


Figure 3-1. Example workflow process of the development of AI-based technique used for occupancy activity detection within an indoor environment.

Based on the review of the literature, different sensors and solutions have different merits and limitations. Through evaluation, camera detection with AI techniques based on the application of deep learning-based methods seems to be a promising approach for indoor occupancy detection. As identified, existing methods mostly utilise the camera for detection and recognition purposes. Most studies have not attempted to integrate the vision-based approach with the HVAC control systems. Furthermore, the impact of the application of such approaches on energy demand and thermal comfort has not been well studied.

3.2.2. Deep Learning Techniques

As explored in Chapter 2.4, deep learning has become an effective tool to help solve building design-related problems and to help improve building HVAC system performance by enhancing building energy predictions [36, 47]. It has been an emerging tool used to develop models that help resolve energy and built environment problems that focus on providing techniques of identification through classification, recognition and predictions [110]. As suggested in Chapter 2, neural network algorithms were explored in machine learning, which indicates that considerations within the neural network architecture are vital to form the basis for deep learning. The term 'deep' refers to the number of layers within the layer, indicating that more layers suggest a deeper network with higher complexity [74]. Neural networks or artificial neural networks (ANN) are computational models inspired by biological neural networks, forming multiple nonlinear interconnected processing layers that process information with dynamic state responses to external inputs [184]. There are many types of neural networks, all designed with unique strengths for their desired purposes. Bacciu et al. [184] suggest the difficulty in selecting the best type to solve the desired problem.

Since the approach is to apply deep learning through a vision-based approach to obtain data upon real-time occupancy behaviour, many studies [185, 186] showed that deep learning models with a CNN-based architecture could perform computer vision tasks with high accuracy. CNN is a class of deep learning networks which is extensively used for image-based classification and recognition applications and was selected as the main technique used in this study. In general, the CNN architecture consists of a feedforward network with the input data such as an image processed through the network. The feature of the data from input images is first extracted within the convolutional layers, and then the spatial volume of the input data is reduced in the pooling layer. Then, the fully connected (FC) layer is used to classify images between different categories by training. A fully connected layer involves weights, biases, and neurons. The output layer then delivers the outcome of the calculations and extractions. For these layers, the configuration is presented in the form of groups, indicated as stacked modules to present the structure of a deep learning model. The rectified linear unit (ReLU) layer consists of advantages due to its simple function and sparse features which can provide benefits towards minimising the training duration. Furthermore, the SoftMax layer provides further constraints to aid the training of the model. Both the ReLU and softmax layers are essential to building CNN architectures for various applications. This includes vision-based applications such as object detection [187] and face recognition [188] and also data analysis and other programmatic marketing solutions [189].

As detailed in [190, 191], the convolutional layers are the first layer to exact features from the input data. It plays a central role in the architecture by utilising techniques to convolve the input data (image). This performs the stages of learning the feature representations while extracting without manual work. Neurons located within each of the convolutional layers are arranged into feature maps. This enables convolution to preserve the relationship between pixels by learning image features using small squares of input data through a mathematical operation. It takes the image matrix and a filter or kernel and passes the result to the next layer through convolutional kernels stride over the whole image, pixel by pixel, to create 3-direction volumes (height, width and depth) of the feature maps. Then, the ReLU layer introduces nonlinearity into the output neuron. An activation function is defined as a piecewise linear function that is used to enable direct output when the input was positive or otherwise as a zero output when a negative input is received. According to LeCun, [105], ReLU has become a default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance. Through this, the volume size will not be affected while the nonlinear properties of the decision function will be enhanced during this process which results in an enrichment of the expressions of an image. Subsequently, the pooling layers enable the reduction in the spatial dimensions of the data (width, height) of the feature maps when the images are too large. For this, the most common spatial pooling type of Max Pooling was selected as it outperforms processing image datasets [192]. It effectively selects the largest element within each receptive field from left to right, so the spatial size of the output is reduced.

Since several convolutional and pooling layers are formed in stacks to enable greater amounts of feature extraction, the FC layers follow on from these layers and interpret the feature representations and perform the function of high-level reasoning to flatten the matrix into a vector form. Combining the features, the FC layers connect every neuron from one layer to every neuron in another layer. This forms the model, and along with the activation function of SoftMax, it enables the classification of the input images, which generates the classified output results of one of the following occupancy activities.

The exceptional image classification performance of CNN [192], along with its flexibility [193] and popularity within the industry [43] influenced the selection of CNN over other neural network techniques when developing the vision-based occupancy detection and recognition solution. Derived from the understanding of the CNN, Figure 3-2 presents the general CNN architecture used for training the vision-based model for detection and the recognition-based deep learning model configured for the training of the model for occupancy behaviour detection and recognition. Further discussion of model configuration is outlined within Chapter 3.3.2.

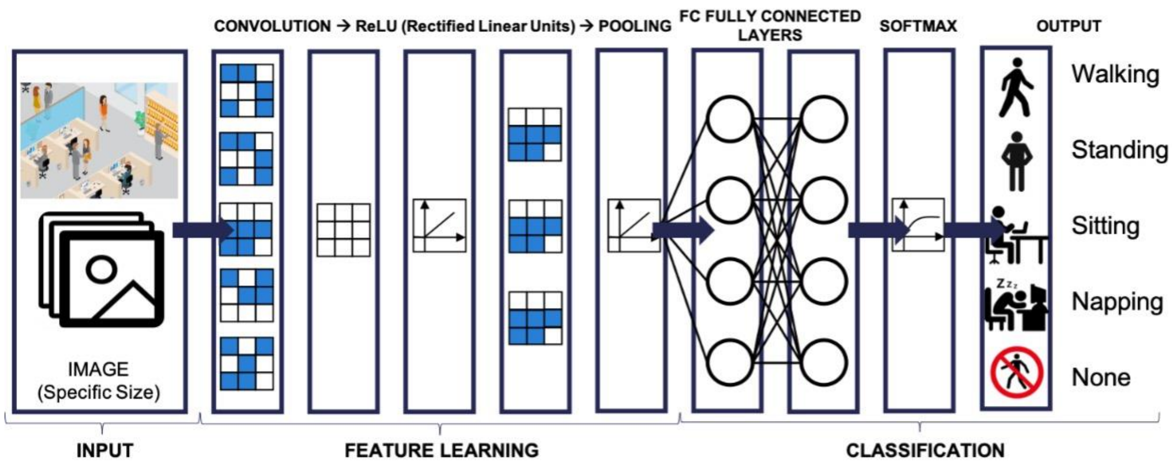


Figure 3-2. General CNN architecture used for the training of a vision-based model for detection and recognition in indoor settings of a building.

In summary, occupancy behaviour in terms of their activities, actions towards window opening and the use of electrical equipment are important towards the impact on building energy demands and system operations. The application of vision-based methods through AI techniques of a CNN-based network enables the development of a detector to provide real-time understanding leading to the proposal of the following framework approach.

3.3. Overview of the Detection, Recognition and Optimisation Framework

This section presents an overview of the research framework. It highlights the overall concept design with a discussion of each part of the framework respectively. This includes the selection of certain techniques and methods applied to establish the proposed approach.

3.3.1. Proposed Approach

Based on the review and the findings made in Chapter 2 and Chapter 3.2, the proposed approach is given in Figure 3-3. By adopting the techniques of deep learning with python and TensorFlow, images were collected and pre-processed to form the CNN models. These were trained and deployed to provide an AI-powered detector whereby suitable responses, specifically the different types of occupancy behaviour would be detected and recognised through the application of a camera-based device. As shown, individual detectors were established with certain ones designed to focus on the common occupancy activities including, napping, sitting, standing, and walking. Another detector focuses on window openings and further detectors for occupants' usage of electrical equipment. Each established model was applied individually and or in various combinations to form multi-detectors which were applied to real-time experimental tests within indoor environments. For each of these, the detection and recognition process enabled the generation of a live feed of the data output results, which were directly used to form the Deep Learning Influenced Profile (DLIP). DLIPs are real-time generated profiles which indicate the output responses from the detection and recognition made through real-time detection. Next, such results would enable the sensors to inform occupants within the selected room that such given occupancy behaviour was performed within the desired space and the profiles would feed into the control system of the HVAC system to inform the building energy management system and controls of the HVAC system to adjust based on the actual building conditions while minimising unnecessary loads. Further discussion of each of these individual processes of the workflow is given below (Chapter 3.3.1-5), with an in-depth investigation of the proposed process shown in the next chapters.

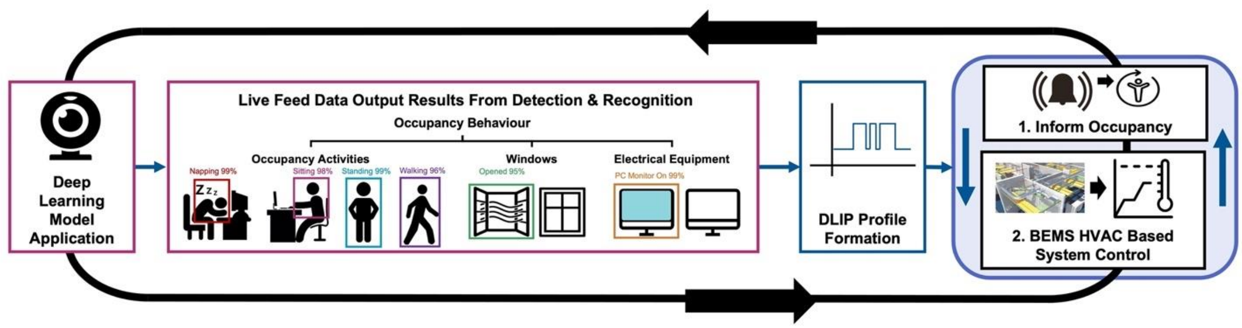


Figure 3-3. General framework approach for occupancy behaviour detection and recognition for building energy systems optimisation.

3.3.2. Model Development and Application Overview

The classification-based algorithm, Convolutional Neural Networks (CNN) is employed to form the deep learning classification detection models (Figure 3-4). It is a form of deep, feed-forward artificial neural network which is most suited to perform modelling for computer vision-related tasks with image datasets [153]. Deep CNNs have been extensively used to form various types of object detection frameworks. It directly learns the automatically designated features to produce a state-of-the-art recognition result, which is ideal for the project's purpose by enabling the actions of detection and recognition. Following a general deep learning workflow [194], this consists of data collection and processing, model training and deployment of the model. Part 1 consists of the process of data collection and model training. Images of various types of occupancy behaviour in indoor settings were collected and processed through pre-processing stages whereby image augmentation occurred through manual labelling of the images. Through the analysis of various types of deep learning models, the most suitable type of CNN-based deep learning model was selected. This was configured specifically for this type of detection approach to provide the model outlined in Figure 3-4. Next, the model was formerly trained to provide the application of the model via the deployment of an AI-based camera to provide real-time detection and recognition of occupancy activities. Conclusively, this was indicated in Part 2 of the workflow. For the training of the models, the same computer with the graphics processing unit (GPU) NVIDIA GeForce GTX 1080 was used.

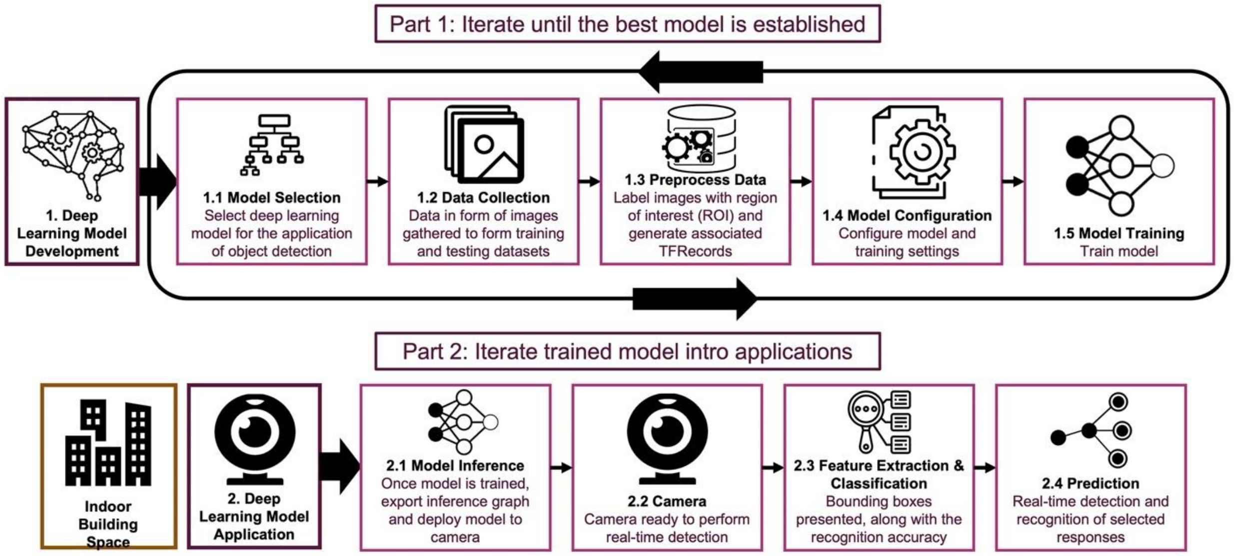


Figure 3-4. Typical deep learning model workflow procedure for the development and application of computer vision-based indoor detectors.

3.3.3. Integration with the Building Control and HVAC System

Using the developed models forming the vision-based detectors to capture the real-time occupancy behaviour, data were generated in form of heat emission profiles known as the Deep Learning Influenced Profiles (DLIP). This allows the output data made from the detection to be valuable for improving indoor thermal comfort, air quality, building energy performance and overall energy savings. Figure 3-5 presents the workflow process of the proposed integrated framework approach based on the application of the developed vision-based detector to provide building heat gain predictions with system optimisations. It consists of using the generated real-time DLIPs to go through the process of 1. Informing occupancy about the indoor conditions while 2. Also informing the BEMS which is implemented in the building to make suitable adjustments to the HVAC system controls. The strict procedure must be directed to the process and the concept given in Figure 3-5 suggests a framework and software infrastructure should be developed for the proposed approach to be fully utilised within buildings. This system will connect the real-time vision-based detector and setpoint optimiser with the demand-driven controls for the HVAC system. The design of this proposed integrated framework is influenced by the detection of the type of occupancy behaviour received as data to determine the optimisation of the system for the variation in the room set point temperatures. Hence, the vision-based approach must be modelled and performed under a series of different building energy performance simulations before determining the associated steps for this integrated optimisation part of the framework.

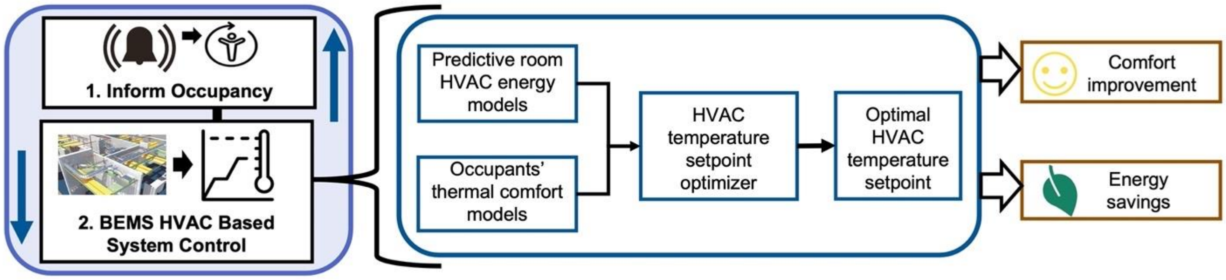


Figure 3-5. The workflow process of the proposed integrated framework approach based on the application of the developed vision-based detector to provide building heat gain predictions with system optimisations.

3.3.4. Model Development and Analysis – Part 1: Detection Performance Analysis

For each of the trained vision-based detectors that were formed from implementing the steps in Figure 3-4, they must undergo a series of performance analyses to help determine their detection ability. First, an initial evaluation of the performance of the model with its detection on still images was conducted. Images assigned in the testing dataset were used to evaluate the detection performance to provide results in the form of a confusion matrix. Values for the terms of true positive (TP: representing the achievement of a correct detection), true negative (TN: representing correctly not providing detection when required), and false positive (FP: representing the number of instances that the prediction was not true, or another instance being wrongly identified as this response, and false negative (FN: representing the number of instances as predicted to be something else, but it wasn't) were achieved. Furthermore, based on the created confusion matrix, common evaluation metrics used to determine the performance of classification results, precision and recall were used to evaluate the accuracy of the algorithm for object detection. This is defined by Eq. (2) and (3) respectively. Precision is the measure of exactness or quality, while recall is a measure of completeness or quantity. However, it is not sufficient to evaluate the detection performance when precision and recall were separately used. With the consideration of a balance between precision and recall, a measure called F_1 Score is formed by combining these two measures and expressed as Eq. (4).

$$\mathrm{Accuracy} = \frac{(\mathrm{TP} + \mathrm{TN})}{(\mathrm{P} + \mathrm{N})} \tag{1}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{2}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{3}$$

$$\mathrm{F_1\ Score} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{4}$$

As the proposed vision-based approach is designed to be implemented in indoor environments of buildings, it was suggested to test the detectors in a series of experimental tests within different case study buildings, allowing the application of the vision-based detector in true indoor conditions and effective analysis of the detection performance to be conducted. Based on the detections achieved during the experimental tests, Figure 3-6 suggests a four-stage performance analysis. Given that during the real-time detection using the trained models, values in terms of the IoU (Intersection over Union) were recorded. This is a value given that corresponds to the recognition ability based on the detection accuracy displayed across each of the bounding boxes that appeared at every instance in terms of the generated IoU values. It is a standard evaluation metric for convolutional neural network detectors used to evaluate how similar a predicted bounding box is to the ground truth box. For such a case, higher prediction accuracy (near 100%) would be achieved when there is a direct overlap between the target mask and the prediction output. Based on the detection performance during the experimental test, an average of the IoUs corresponding to each of the selected response outcomes were evaluated. In addition, the percentage of the time achieving correct, incorrect, and no/missed detections throughout the segments of the experimental tests was analysed. Furthermore, using a similar analysis approach for the model detection on still image detection, the same method of analysis was conducted within segments of the detection made during the given experimental tests. To give the evaluation of the detection performance and classification in form of a confusion matrix and the results for the different common evaluation metrics of precision, recall and the F_1 score.

Besides the in-depth analysis of the detection made during each time frame during the tests, the results gathered to form the DLIPs were also evaluated through the comparison against other profiles to give values for the percentage errors achieved in detection. This includes pre-defined static scheduled profiles that correspond to assumptions related to the understanding of the building operational hours and/ or fixed occupancy rates used within the design of buildings. Furthermore, the generated DLIP were also compared with the Actual Observation profile. This profile represented the ground truth or the actual number of occupants performing the selected activities during the test. Overall, these four performance analyses along with profile comparisons were performed on every set of detection periods during the desired experimental tests to enable verification and clarification of the performance of each of the trained models.

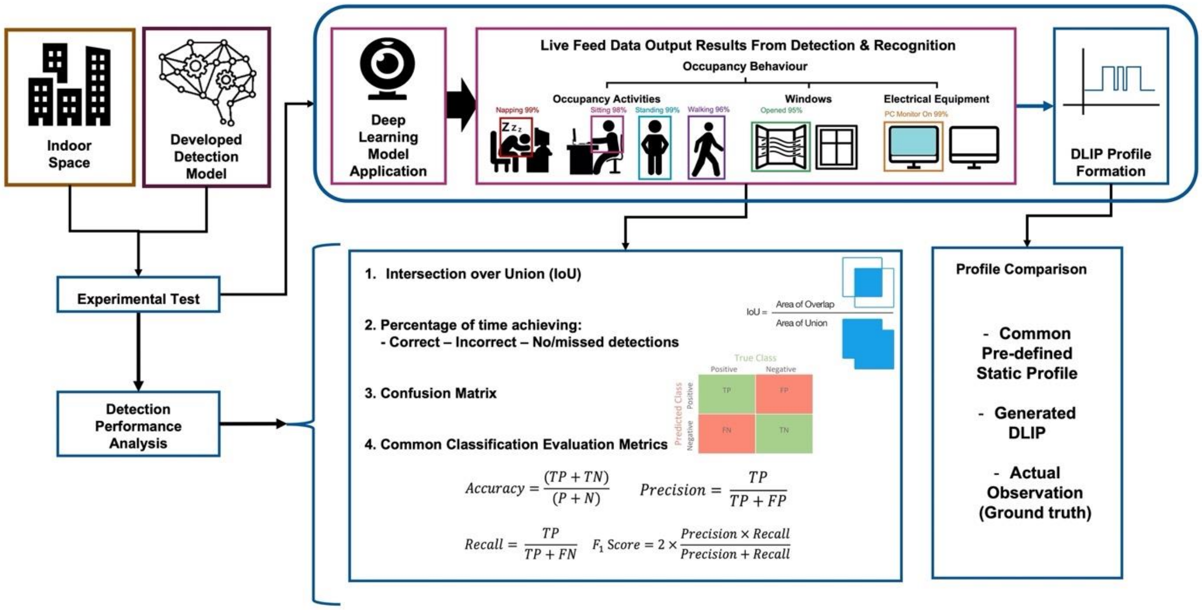


Figure 3-6. Framework process for the analysis of the detection performance during a selected experimental test.

3.3.5. Model Development and Analysis: Part 2: Building Energy Performance Analysis

To assess the impact of the proposed vision-based approach on the effect of the building energy demands and to compare it with the application of existing sensors and/or current buildings where occupancy behaviour is not monitored, the following building energy simulation (BES) workflow process given in Figure 3-7 was applied. Step one includes the data collection and preparation stages to perform such building simulation. The selected case study building correlated to the room that was used to perform the vision-based detection test, whereby sufficient data in terms of detection results were obtained. This was used to model the building geometry along with the creation of suitable building operational profiles for heating, cooling, ventilation, lighting and occupancy. Further details about the selected case study buildings are described in Chapter 3.4 along with specific details about the assigned conditions for building energy simulation are given in the relevant sections of Chapters 4.6 for occupancy activities, Chapters 5.8 and 5.9 for occupancy behaviour towards window openings, Chapter 6.1 and 6.2 for combined detections. Step 2 presents two types of analysis. Type 1 focused on the application with data fed from the conducted experimental tests to provide comparisons with typical pre-defined static scheduled profiles assigned to the given building. Whereas Type 2 was based on a series of common and extreme circumstances for the individually selected buildings along with occupancy behaviour. This type of analysis provides results for analysis in terms of how the system could provide effective responses that aim towards the achievement of a reduction in building energy through operative energy control and management solutions. In all, both types of analysis follow the workflow of requiring conditions defined before the simulation of the different cases. In step three, results were achieved in terms of the internal heat gains (occupancy and/or electrical), heating and cooling loads, ventilation heat losses, and the room CO_2 concentration for evaluations in terms of building energy demands.

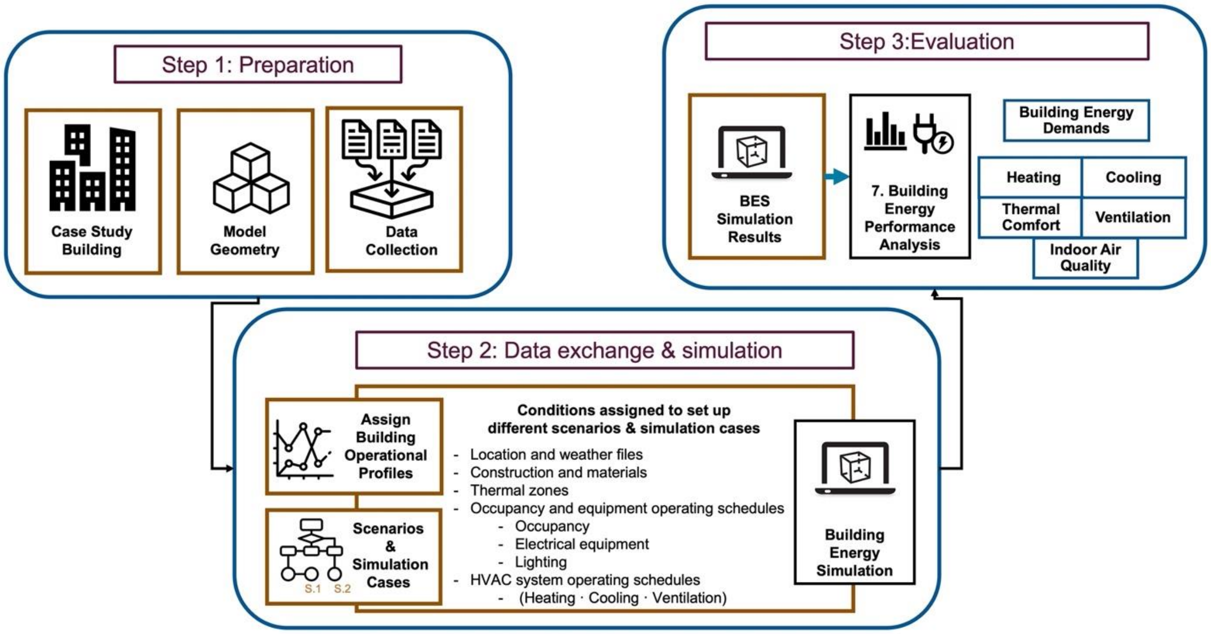


Figure 3-7. Workflow of the application of building energy simulation (BES) to analyse the impact of the application of the vision-based detector.

3.4. Case Study Buildings

To test and evaluate the application of the vison-based approach using the trained models, four different indoor spaces shown in Figure 3-8 were used to support the design and testing of the framework through modelling and simulation using the BES tool Integrated Environment Solutions Virtual Environment (IES VE) [195]. The BES was based on the dynamic thermal simulation of the heat transfer processes between a modelled building and its microclimate. Heat transfer processes of conduction, convection and radiation between each building fabric were modelled and were included within the modelling of air exchange and heat gains, within and around the selected thermal space of the building. Validation of the tool and the theory are fully detailed in [196, 197].

All buildings are located within the Department of Architecture and Built Environment, University Park Campus, University of Nottingham, United Kingdom. The reasons for the choice of these buildings were that sufficient information about the building geometry design, materials and operational features were easily obtained to conduct an accurate model for BES. In addition, occupants were involved in each of the experimental tests. Students and researchers from the university department were invited to participate. Consent from each participant was obtained. They were also informed before the test about the experimental test and had to also complete a survey after participating in the test. Differences between each of these building types led to the possibility of conducting experimental tests in different types of buildings with variations in the number of occupants present.

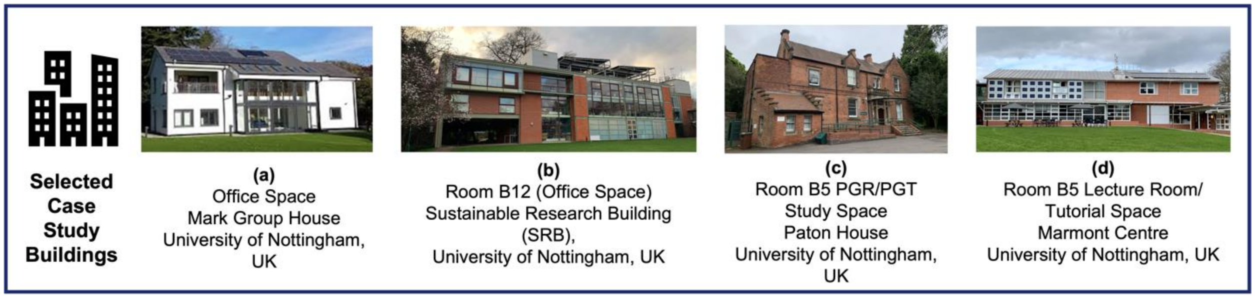


Figure 3-8. The different case study buildings were used within experimental tests and building simulations to assist the evaluation of the proposed vision-based deep learning approach.

Based on the evaluation of the different types of occupancy behaviour and the development of detectors to focus on specific occupancy actions, the observation of the different floor plans for each of these building spaces in Figure 3-9 suggests that specific rooms were more suited to perform experimental tests to evaluate the different detection models. (a) is a small open-plan office space located on the ground floor, Office space (b) is a larger office space compared to (a). Hence, both spaces were used to conduct tests to enable the evaluation of occupancy detection. Due to (b) having a large open plan space; this was also used for multi-objective experimental tests with the detection of occupancy and equipment. Additionally, (c) is a postgraduate research/taught study space. Due to the layout of the room along with high occupant capacity, this was also used to test the developed occupancy detectors. Out of all four spaces, (d) had to largest area, with the largest windows in place. This suggested the use of this selected space for the assessment of the occupancy behaviour towards window openings through the window detection approach. Besides this, (d) is a lecture room/ tutorial space. Hence, it was also used to conduct the experimental test based on both occupancy and window detection. Below presents brief details for each of these buildings.

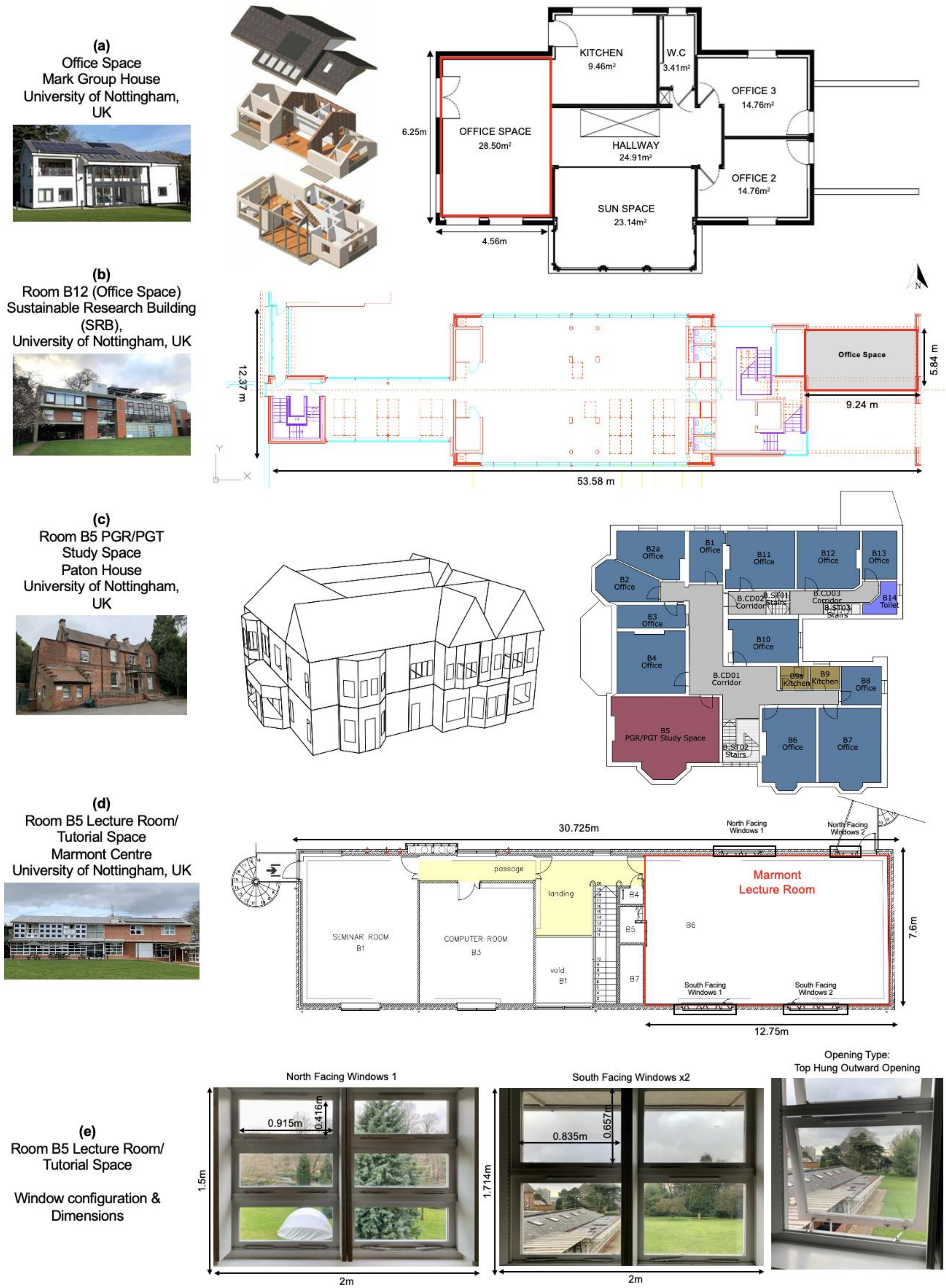


Figure 3-9. Floor plans of all case study buildings.

Mark Group House (office space)
The office space within the Mark Group House (building A), consisted of a 28.5 m^2 floor area and a floor-to-ceiling height of 3.13 m. Each room of the building was represented as thermal zones in BES to set different operation profiles. For the air exchanges, the infiltration rate value was set to 0.1 ach. The U-value of the wall, roof, ground, and window glazing were 0.25, 0.18, 0.15 and 0.71 W/m^2K. The window is triple-glazed with argon filled, along with a solar heat gain coefficient of 0.64, while the visible transmittance was 0.76.

Sustainable Research Building (office space)
An open-plan office on the first floor of the Sustainable Research Building was selected to conduct experimental tests for the detection using the trained models. The building is constructed to a very high standard, achieving a BREEAM rating of Excellent. For this building, the geometry was modelled in the ModelIT tool and some simplifications we carried out such as not including internal features such as furniture and external features such as surrounding buildings and trees. The building was modelled into several zones to allow the setting up and evaluation of each zone. The U-value of the roof and floor were 0.15 W/m^2K, the wall was 0.17 W/m^2K and the windows were 1.92 W/m^2K.

Paton House (PGR/PGT study space)
This building is naturally ventilated with openable windows and a simple heating system to provide essential heating services. The experimental test was conducted in a classroom named the PDR/PGT study space with a floor area of 36.62 m^2 and a floor-to-ceiling height of 3.52 m on the first floor of this building. There are six sliding sash windows which can be opened at the bottom for ventilation. The layout of the first floor is presented in Figure 3-9 and further details on the set-up for the experimental test were presented in the corresponding section. Due to the impact of COVID-19, there was a restriction on the capacity in the room to be set at 11 people at maximum.

Marmont Centre (B5 lecture/ tutorial room)
Furthermore, an architectural engineering lecture room located on the first floor of the Marmont Centre at the University of Nottingham was used. The building is naturally ventilated and integrated with a simple heating system. Like the other three buildings, this was also modelled using Building Energy Simulation (BES) tool IESVE. The selected room has a floor area of 96.9 m^2 with dimensions of 12.75 m x 7.6 m and a floor-to-ceiling height of 2.5 m. As given in Figure 3-9 (c and d), the room consists of four sets of windows with two different window configurations within the lecture room. The north-facing windows are in an arrangement of 2 x 3 with a total of six 0.915 m x 0.416 m (0.38 m^2) glazing panels. The two south-facing windows are in an arrangement of 4 x 4 with a total of 8, 0.835 m x 0.657 m (0.55 m^2) glazing panels. The windows have a top-hung opening strategy, and they are double-glazed with a U-value of 2.20 W/m^2K. For the BES to represent a typical window opening size, an assignment of 50% of the maximum opening area was selected for an opened window, and 0% was assigned for a closed window. From architectural drawings, the building components of the wall, roof, ground, and doors consist of U-values of 0.33, 0.22, 0.32 and 3.00 W/m^2K.

Besides this, each of the experimental tests conducted in these buildings consists of a ‘detection camera’, which is a standard 1080p camera with a wide 90-degree field of view connected to a laptop that runs the trained deep learning model. A specific set-up for the experimental tests was also given and the details are given in the corresponding sections of Chapters 4, 5 and 6.

In addition to the experimental tests within these selected buildings, the BES tool IESVE was used to assess the building energy performances. For the modelling of these four buildings, the Nottingham, UK weather data file was used for all buildings. Overall, simplifications were made to the building and its surroundings. Most of these building operates between the hours of 08:00 to 18:00, with a setpoint temperature maintained at 21°C or 22°C [198]. However, through the input of response data as building profiles, this varied from case to case, which led to the variation in the exact values given in the corresponding simulation sections.

3.5. Ethical Approval

With the proposed approach designed to capture real-time occupancy behaviour within indoor spaces, the overview given in Chapter 3.3 suggests people are required throughout the development and testing stages of the framework. Hence, this research study strongly involves human participants. Therefore, before the testing of the developed computer vision-based indoor detectors following the process shown in Figure 3-3, an ethics application was submitted and approved.

The ethics application form was created to document the ethical issues and the steps taken to ensure participant well-being throughout the study. All associated documents are listed in the appendix section, Appendix B: Ethics Application Documents. The approved ethics application form consisted of the answers to the questions within the ethical issues checklist. Furthermore, the document explaining the description of the study highlighted the design of the study with the framework approach along with the description of the involvement of participants within the study, the equipment used, the procedure of the tests, and how the data was handled and stored. In addition, a poster was created to summarise the description of the study with the bulletin of recruiting participants. Prior to each of the experimental tests, each participant was given the 'Participant Information Sheet' and the 'Participants Consent Form' was completed. The application was reviewed by members of the Faculty of Engineering, University of Nottingham research integrity and research ethics committee, giving the approval as shown.

3.6. Summary

In summary, current sensor-based techniques are limited to the provision of an accurate understanding of occupancy behaviour within indoor spaces and that common occupancy activities and occupancy behaviour occupancy actions towards window openings are important in impacting building system operations. High potential with great interest in using AI vision-based techniques is conveyed. Hence, a three-part framework approach was proposed with the selection of specified model development techniques and conditions. Furthermore, four different indoor spaces were selected for experimental tests and were modelled using BES to support various stages of design, testing and analysis of the framework. The next chapter focuses on the development, testing and analysis of each of the developed vision-based models following the methods described. As indicated in the objectives, data-driven deep learning frameworks for the detection and recognition of various occupancy behaviour (napping, sitting, standing, walking and actions towards opening and closing of windows) within indoor building spaces were developed and validated using various testing datasets based on their suitability for real-time detection. Furthermore, the process given in Figure 3-4 was applied to all developed models to address the objective of continuous refinement of the deep learning computer vision method with the evaluation of the impact of different parameters and configurations on the detection performance.

Chapter 4

4. Occupancy Activity Detection and Recognition

As addressed in Chapter 3.1.1, information on real-time occupancy patterns is central to the development and implementation of a demand-driven control strategy for HVAC systems. Based on the evaluation of the different sensors and technologies used to measure and monitor real-time occupancy which was employed in buildings for automation and controls, temperature and ventilation control, fire detection, and also as part of the building security systems. To some extent, these sensor-based solutions provide accurate detection of occupancy patterns. Strategies based on sensing occupancy information through the count and location of occupants in spaces and aid demand-driven control systems are proposed. However, there is limited research on sensing the actual activities performed by occupants which can affect the indoor environment conditions. The activities of occupants can affect the internal heat gains (sensible and latent heat) in spaces directly and indirectly towards other types of internal heat gains. The real-time and accurate predictions of the heat emitted by the occupants with various activity levels can be used to estimate better the actual heating or cooling requirements of a space. A potential solution is the proposed AI computer vision and deep learning approach used to detect and recognise the activities of occupants.

4.1. Framework for the Detection and Recognition of Occupancy Activity Towards the Optimisaton of Building HVAC Systems

Based on the general framework given in Figure 3-3 and the steps discussed in Chapter 3, Figure 4-1 shows the framework designed to enable the detection and recognition of occupants' activities and generate real-time occupancy data in the form of occupancy heat emission profiles to effectively manage the building energy loads and indoor spaces. The objectives include the development of a suitable deep-learning algorithm using a CNN to train and test a model. The model was deployed to an AI-powered camera to perform real-time detection with the classification of occupant activities forming the DLIPs for each activity, informing adjustments to system controls.

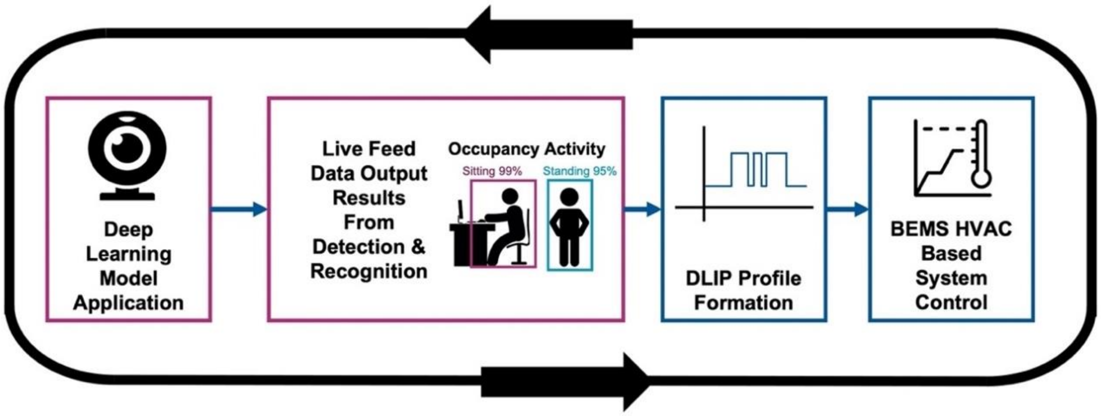


Figure 4-1. Proposed framework for detection and recognition of occupancy activities towards the optimisation of building HVAC systems.

Typical occupancy rates at which heat is given off by human beings vary between the different states of activity. CIBSE Guide A Table 6.3 [199] suggests the following rate of emissions (Table 4-1) for the most common activities performed by occupants within the building types given in Figure 3-9. This includes 'standing', 'sitting', 'walking' and 'napping'. Hence, these were the initial activities that were focused to enable the development of the initial deep learning occupancy activity model to provide prediction related to these output responses. The category of 'none' was also introduced. This enabled the indication of no occupants being present within the desired location of detection.

Table 4-1. Selected heat emission rates of occupants performing activities within an office [199].

	Rate of Heat Emission		
Activity	**Total (W)**	**Sensible (W)**	**Latent (W)**
None	0	0	0
Napping	105	70	35
Sitting	115	75	45
Standing	130	75	55
Walking	145	75	70

4.2. Initial Approach Using MATLAB

This section presents the initial data-driven deep learning framework designed to provide the ability to detect and recognise occupants' activities within buildings. The software and techniques of MATLAB [200] provide tools and functions designed for managing large datasets and specialised toolboxes for neural networks. Furthermore, several existing research [44] used MATLAB as the preferred tool for the main deep learning method. The three-part framework approach discussed in Chapter 3.3 was applied.

4.2.1. Deep Learning Framework

To develop the desired occupancy activity detector, the steps for model development given in Figure 3-4 were followed. Image-based data for these activities were collected. An example of our input dataset images for training purposes is shown in Figure 4-2. For a given short video sequence consisting of multiple frames, the network predicts output labels solely based on the selected response outputs. It should be noted that more responses and predictions would be added in future cases depending on complexity for example when detecting multiple people performing different activities at once.

Figure 4-2. Example dataset images of several human activities. Images obtained via Google image search of the relevant keywords.

The training data set consisted of images categorised with the following responses of ‘standing’, ‘sitting’, ‘walking’, ‘napping’ and ‘none’. Table 4-2 shows the number of images that were used for both training and testing of the model. Since this was the initial development, a smaller number of images was used. However, the number of images within the dataset should follow the Pareto Principle with the suggestion given by Ng [201]. Based on existing methodologies for activity detection such as the method used by Castro [183], it is acknowledged that greater amounts of images would be required for the training of the model. However, this has influenced the use of imageDatastore to collate the training images. This provides a more convenient process to allow images to become easily pre-processed in the next step and also has the benefit of saving memory spaces as MATLAB will only read the images when you need them.

Table 4-2. Description of the image datasets used for the training of the initial occupancy activity detector using MATLAB.

Activity	Number of Images		
	Training	Testing	Total
None (No occupant present)	764	50	814
Napping	330	50	380
Sitting	1025	50	1075
Standing	643	50	693
Walking	460	50	510
Total	3222	250	3472

Pre-processing is a significant stage of the process. It consists of the preparation of the data for it to become ready for training. For this case, all images were resized to the same pixel size of 227 x 227 x 3 and were saved as the same image format within the imageDatastore which enabled the data to be fully prepared for utilisation within the training stages succeeding the selection of the deep learning model and the corresponding network architecture and training options within the use of the deep learning feature in MATLAB.

With images as the desired input data along with the selection of CNN as the main type of model architecture used to develop the detector for detection, recognition and classification, the Deep Learning Toolbox within MATLAB presents a generic process to define the network architecture layers and training options. Specific features designed for performing deep learning such as ‘trainNetwork’, which enables direct training of a CNN network for deep learning classification and regression problems [200] were applied. Based on a feed-forward neural network, CNN utilises the principle of weight sharing.

Figure 4-3 presents an overview of the designed CNN architecture training process. This influenced the use of stochastic gradient descent along with the momentum (SGDM) optimizer within the assigned training layer options and has established the conditions for each of the stages in the CNN architecture. Respectively, for each of the given input training image data, filters were applied within the desired most common layers of convolution, ReLu (Rectified Linear Units) and pooling to perform alterations for the intent of feature learning and to reduce the spatial complexity of the network. By performing analyzeNetwork(net) the following information for each of the desired layers is given in Table 4-3, indicating the description for each of the layers within the deep learning network. It consisted of a total of 15 layers which corresponds directly to the architecture given in Figure 4-3. Following feature learning, classification layers are present to enable the process of performing predictions and generating probabilities for each classification output. This completes the method for the training stages of the deep learning model.

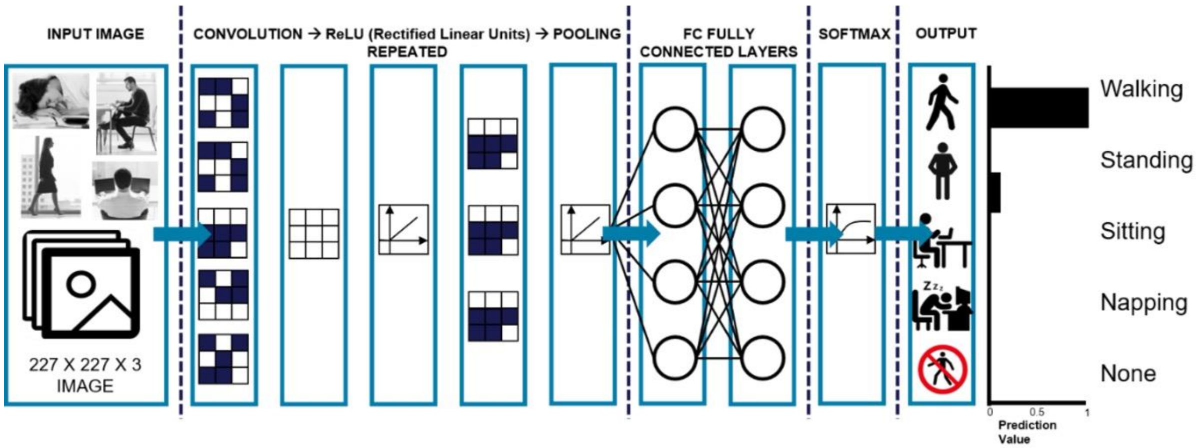


Figure 4-3. CNN model training architecture and configurations applied.

Table 4-3. Description of the CNN model training architecture and configuration.

Image Representation	Layer	Layer Name	Description	Activations	Learnable
	1	Image Input	227x227x3 images with ‘zerocenter’ normalization	227x227x3	-
	2	Convolution 2D	8 3x3x3 convolutions with stride [1 1] and padding ‘same’	227x227x8	Weights 3x3x3x8 Bias 1x1x8
	3	Batch Normalization	Batch normalization with 8 channels	227x227x8	Offset 1x1x8 Scale 1x1x8
	4	ReLU	ReLU	227x227x8	-
	5	Max Pooling 2D	2x2 max pooling with stride [2 2] and padding [0 0 0 0]	113x113x8	-
	6	Convolution 2D	16 3x3x8 convolutions with stride [1 1] and padding ‘same’	113x113x16	Weights 3x3x316 Bias 1x1x16
	7	Batch Normalization	Batch normalization with 16 channels	113x113x16	Offset 1x1x16 Scale 1x1x16
	8	ReLU	ReLU	113x113x16	-
	9	Max Pooling 2D	2x2 max pooling with stride [2 2] and padding [0 0 0 0]	56x56x16	-
	10	Convolution 2D	32 3x3x16 convolutions with stride [1 1] and padding ‘same’	56x56x32	Weights 3x3x316x32 Bias 1x1x32

	11	Batch Normalization	Batch normalization with 32 channels	56x56x32	Offset 1x1x32 Scale 1x1x32
	12	ReLU	ReLU	56x56x32	-
	13	Fully Connected	5 fully connected layers	1x1x5	Weights 5x100352 Bias 5x1
	14	Softmax	Softmax	1x1x5	-
	15	Classification Output	Crossentropyex with 'Napping' and 4 other classes	-	-

4.2.2. Model Application and Experimental Test

The next step given by Figure 3-4 and Figure 4-1 suggests testing the developed model detector based on live detection of all activities performed during an experimental time frame. For this, the office space within the Mark Group House (Figure 3-9a) was used. Figure 4-4a presents the set-up of the equipment. The detection camera' was represented by a standard 1080p camera with a wide 90-degree field of view connected to a laptop that runs the trained deep learning model.

An experimental schedule made for occupant detection whereby an example of the schedule for experimental purposes is given in Figure 4-4b. This enables verification of the results obtained for the DLIP. For the initial test, it was assumed that four occupants were present within the case study building office space and all occupants perform the following activities following the given schedule. Overall, simplifications to the profile were applied as one profile was applied to all occupants to provide an initial analysis of the potential effects of the method on the energy demand. Future cases used for analysis should comprise individual profiles that would be formed following each individual detected occupancy's behaviour and actions.

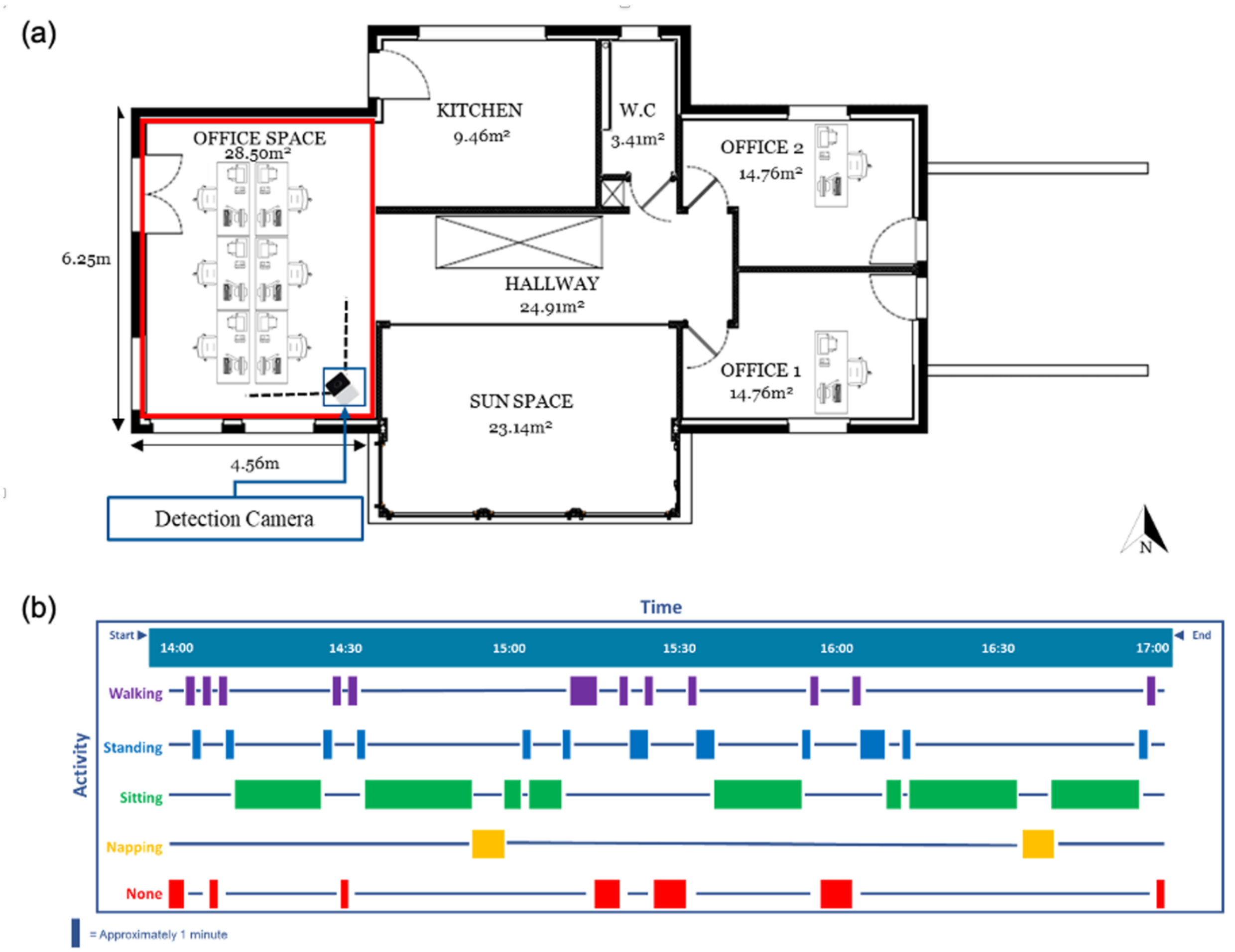


Figure 4-4. (a). Experimental test setup. (b). The activity schedule performed during the three-hour experimental test period.

For each time frame during the detection, generated results provide data in the form of the DLIPs whereby occupant detection results data were coupled with the heat emission data (Table 4-1) to form the profiles. Figure 4-5 provides an example process of the formation of the DLIP formation, showing several snapshots of the recorded frame. It indicates the detection made by the camera through the sample activities and the percentage of prediction accuracy. For each time frame, it should be noted that these sample of detection is presented for visualisation purposes. No images of such detection are stored within the device and only the DLIP is produced.

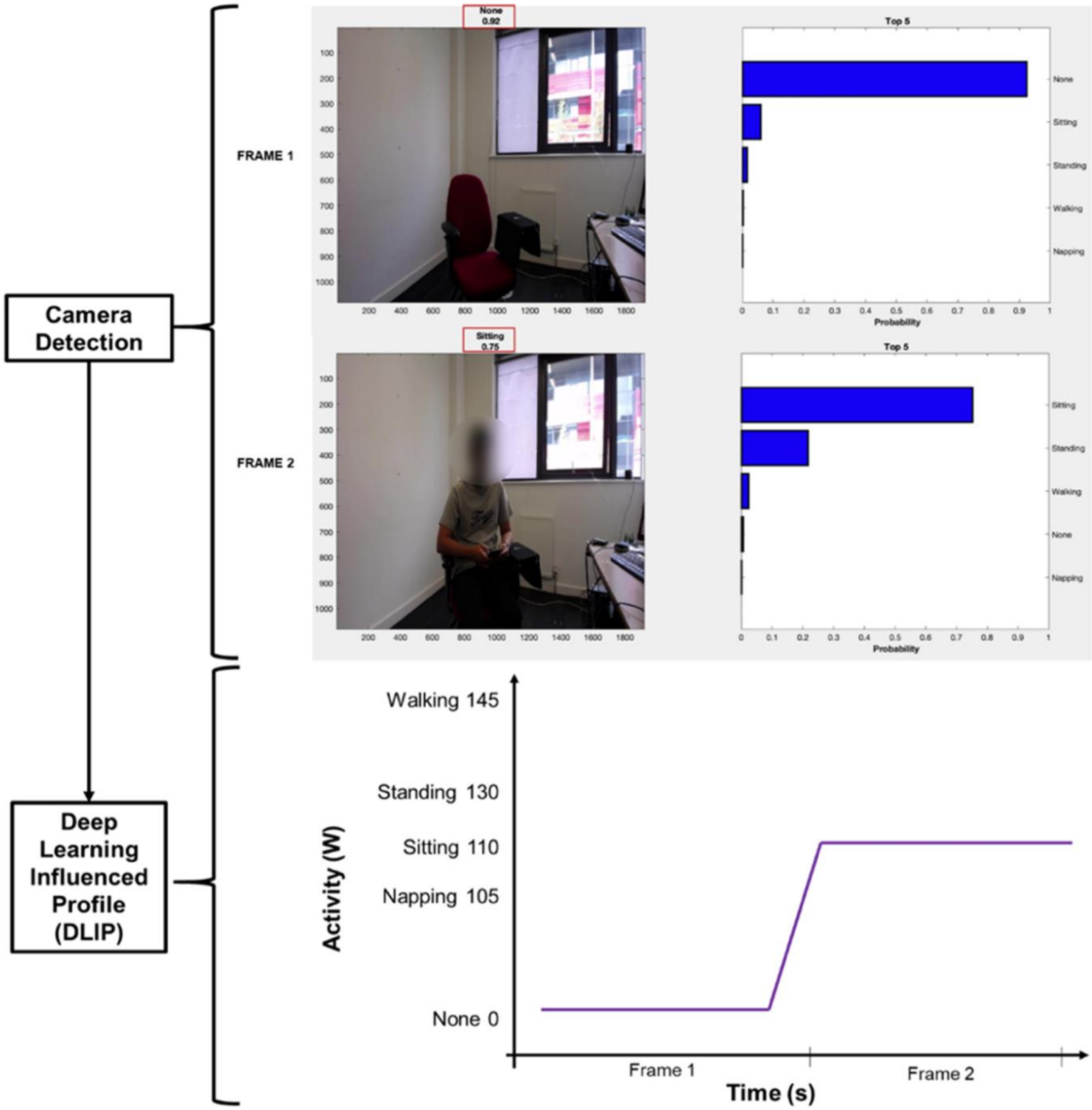


Figure 4-5. Deep Learning Influenced Profile (DLIP) formed from the detection responses from real-time activity detection.

4.2.3. Model Training Results and the Detection Performance on Still Images

This section presents the initial model development results. It includes the accuracy obtained during the training process of the model and the analysis of the experimental results from using the developed deep learning framework applied to the case study building, along with further analysis in terms of energy demands using BES.

The established deep learning model configuration was trained using the graphics processing unit (GPU) NVIDIA GeForce GTX 1080. The training reached a maximum of 1600 iterations, with 80 iterations per epoch. Figure 4-6 presents the graphical results of the training of the model, indicating the total losses reached their minimum level. It also indicates a learning rate of 0.00001 (1e-05) was achieved. Hence, the training options applied were feasible for the development of this type of classification model and an average accuracy of 100% was achieved for the training of this specific CNN activity detection deep learning model.

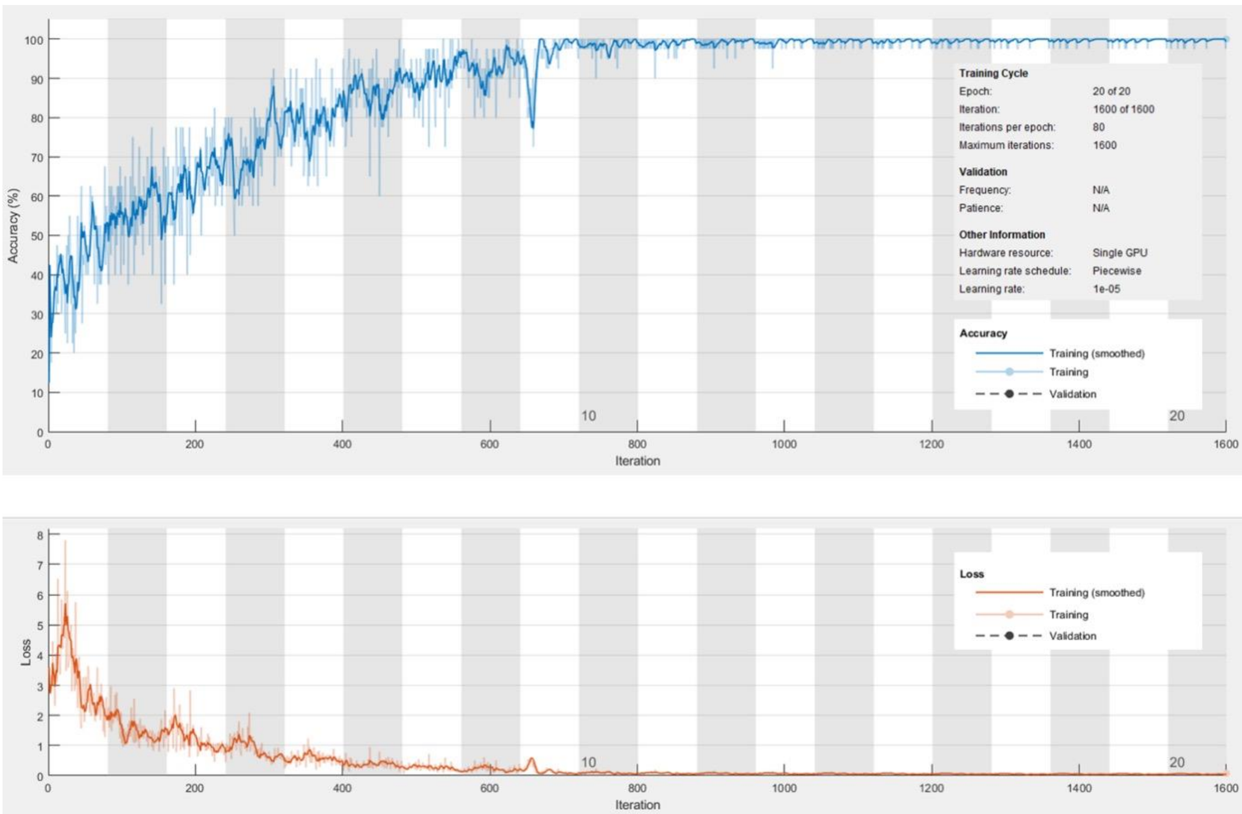


Figure 4-6. Training progress of the initial occupancy activity detector using the MATLAB approach. Graph of the training accuracy curve and loss curve.

To evaluate the feasibility of the model to perform occupant activity detection, validation was initially performed with static image results presented within a confusion matrix (Figure 4-7), indicating an average accuracy of 89.39% achieved from testing 250 images. Observations made for this proposed approach can be used to compare with different modifications applied. This includes inputting more test data and to apply variations in the CNN model's architecture and layers to identify the best design to achieve better performance with the highest accuracy that would complement existing new proposed approaches for similar case problems of human action recognition where the accuracy of 93.37% was obtained [181]. Greater amounts of images will be implemented for testing purposes as the framework is developed further. However, using this evaluation based on static images for validation was not enough. A more substantial and rigorous analysis was made in the next section where an analysis of occupants' behaviour within the office space based on the initial experimental test was made.

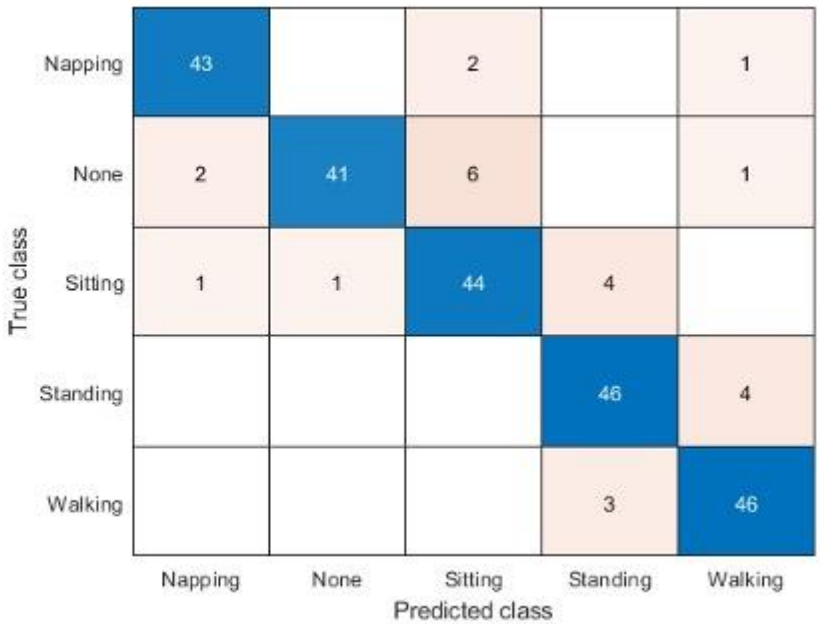


Figure 4-7. Confusion matrix validating the proposed model approach using the images located from the testing dataset that consisted of 250 images.

4.2.4. Detection Performance Analysis Based on the Application of the Trained Occupancy Activity Detector

As given in Figure 4-8 live detection and recognition of the activities by an occupant during the experimental test period between 14:00 – 17:00 at the office space was carried out following the schedule given in Figure 4-4b. It presents the results for each of the recognised activities with a continuous prediction of activity classification between the five response categories to display the predictions within a bar chart. The top prediction represents the detected and recognised activity, whereby a display of the corresponding detection accuracy was shown. It should be acknowledged that the images shown from the live detection are only to present the method of data collection. In practice, these images are not recorded and only the detected activity is outputted along with the accuracy.

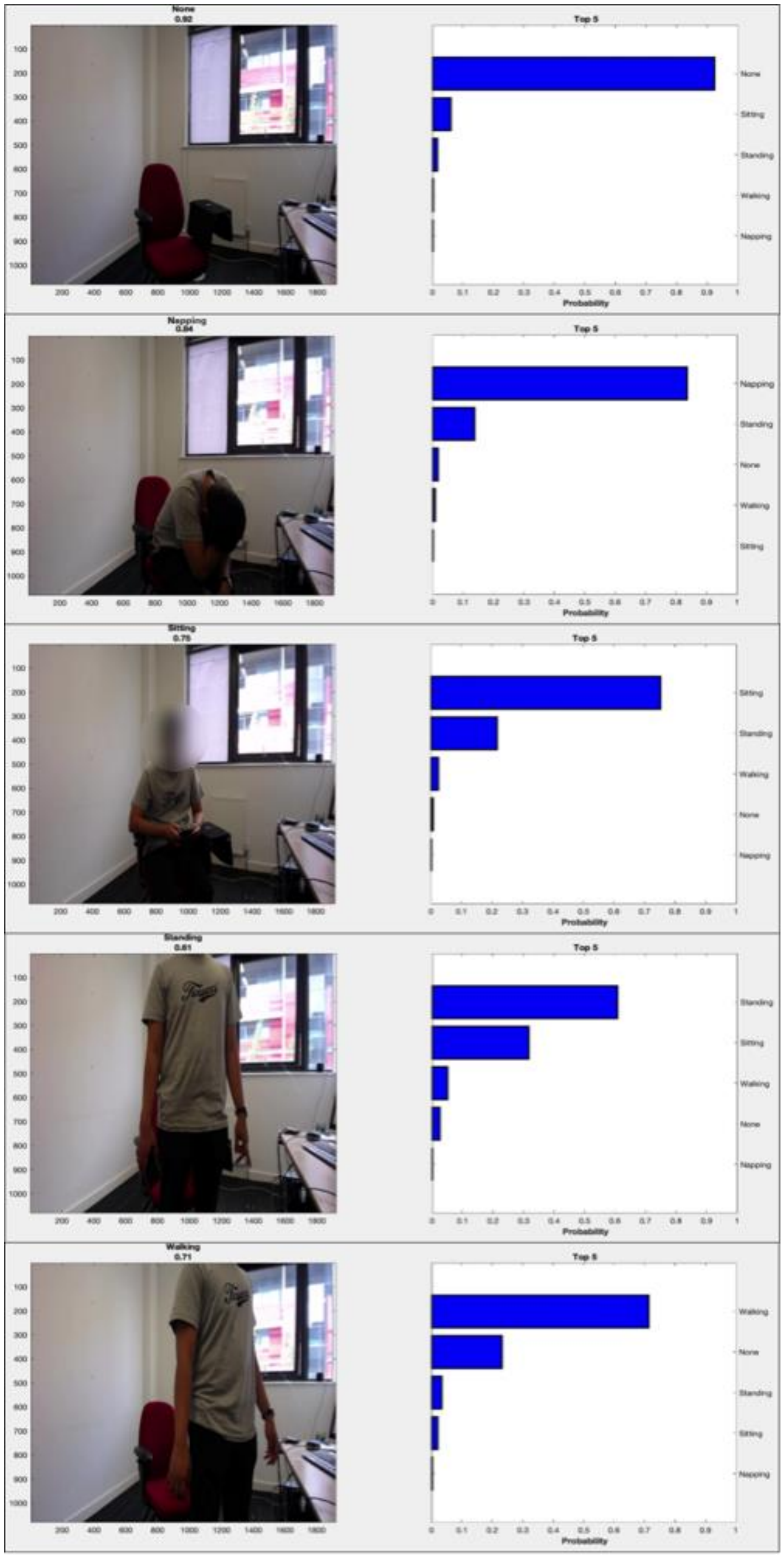


Figure 4-8. Examples of real-time detection and recognition results using the developed occupancy activity detector.

Based on the three-hour experimental test period of the occupant performing various activities, Table 4-4 presents the detection accuracy from the use of the developed deep learning occupancy activity model. The results show the variation in the detection accuracies, with 'none' being the detection of no occupancy being present in the space which provided the highest accuracy with 86.35%. In comparison, standing and walking had the lowest accuracy with 76% and 78.91%. This may be due to the confusion in distinguishing the diversity between standing and walking due to similarities within the human poses. Also, these accuracies show a slight variation with the accuracy obtained based on static images (Figure 4-7) of 93.37%. Therefore, this suggests that slight changes in occupancy movements can affect detection accuracy. In addition, other factors such as the room lighting conditions, and the background environment would also affect it. Hence, further training would be made to improve the detection accuracies to enable more accurate detection of occupancy activities.

Table 4-4. Average detection and recognition accuracy of the different occupancy activities using the trained occupancy detector during the selected experimental tests.

Activity	Deep Learning Detection and Recognition Accuracy
None	86.35%
Napping	81.40%
Sitting	80.43%
Standing	76.00%
Walking	78.91%
Average for all activities	80.62%

For comparison, two typical or "static" office occupancy profiles were created using fixed values of occupant heat gains within the building spaces. Typical Office Profile 1 represents an activity of constant sitting with a standard heat gain of 115 W while Typical Office Profile 2 represents a constant activity of walking assumed in the space, giving a heat gain of 145 W. This condition enables the modelling and analysis of the situation when the maximum heat gain emitted by occupants was assumed. Both occupancy profiles were formed assuming that the occupant was always in the space. These typical occupancy profiles are currently used in HVAC systems operations and in building energy modelling and simulations to present the conditions of occupancy in buildings.

Figure 4-9 presents the four profiles. The Actual Observation Profile corresponds directly to the real activity schedule given in Figure 4-4b. Deep Learning Influenced Profile (DLIP) shows the generated data from utilising the deep learning detection method. The initial results showed that the DLIP can enable the detection of various activities within a space and also provide the identification of times when there are an increase and decrease of activities performed resulting in variation of occupancy heat gains. It is envisioned that the use of DLIP in actual HVAC can ultimately lead to better control of the system, helping detect times requiring less heating for example when there are high occupancy and activity rate and vice versa. The Actual Observation Profile represents the 'true' activity performed by the occupants which was used to assess the accuracy of the DLIP. Based on the comparison between the occupancy profile results, the DLIP still alternates between several detected activities, indicating prediction error. A comparison of the DLIP and the actual observation profile shows a 3.40% difference. This suggests further improvements are required to enhance the accuracy and reliability of the detection model.

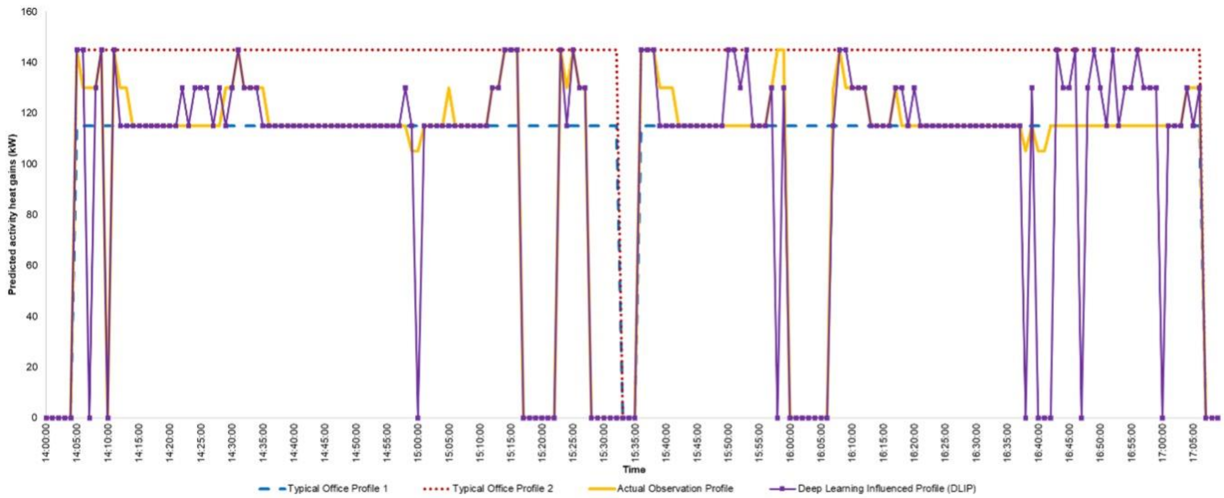


Figure 4-9. Generated occupancy profiles for one occupant between the experimental time frame against Actual Observation Profile and Typical Profiles.

4.2.5. Impact of Occupancy Behaviour on Building Energy Performances

Acknowledging the utilisation of deep learning to perform occupant detection, real-time data achieved would be fed into the creation of new operations for HVAC systems. As suggested BES tool was used to assess the building energy performance through the input of the occupancy response data as building occupancy profiles. The details for the Mark Group House (office space) given in Chapter 3.4 was applied to the modelling of the building.

Table 4-5. Summary of building energy modelling profiles.

Case Number	Case Name	Occupancy Internal Gains (W/Person)	
		Max. Sensible Gain	Max. Latent Gain
1	Typical Office 1	70	45
2	Typical Office 2	75	70
3	Actual Observation	75	70
4	Deep Learning Influenced	75	70

To assess the trained model, the given data (Figure 4-9) obtained during the experimental test was applied to the BES. Essentially, an individual DLIP should be assigned to each occupant. However, for simplifications and the initial analysis of the approach, only one DLIP was generated for further analysis. The building model was simulated for the period between 13:30 - 17:30, which included the three-hour experimental test period. As given in Table 4-5, the different occupancy profiles from Figure 4-9 were assigned to the building model. For the simulation of Case Number 1, fixed values of sensible and latent occupancy gains of 70 W and 45 W were assigned. This follows the Typical Office 1 profile, assuming that the occupant was sitting most of the time during the selected period. For the other simulation cases, maximum sensible and latent occupancy gains of 75 and 70 W were assigned. This enabled the representation of all activities performed within the office space, with walking being the maximum at 100%, followed by standing at 79%, sitting at 64%, napping at 50% and 0% for times when no occupancy was present, (no activity) recorded.

Figure 4-10 presents the BES results of the occupancy sensible gains between 13:30 to 18:30. As observed, the patterns of the occupancy sensible gain for Typical Offices 1 and 2 correspond directly to the static profiles given in Figure 4-8. The results indicate that the typical method (scheduled occupancy profiles) did not effectively represent actual occupancy and building internal gains. An average difference of 29.36% and 32.73% between Typical Office 1 and 2 with Actual Observation was achieved. This was equivalent to a decrease of 0.079 kW and 0.096 kW in heat gains. The difference indicates only a small difference, but the impact would be more significant within larger office buildings and spaces where more occupants are present.

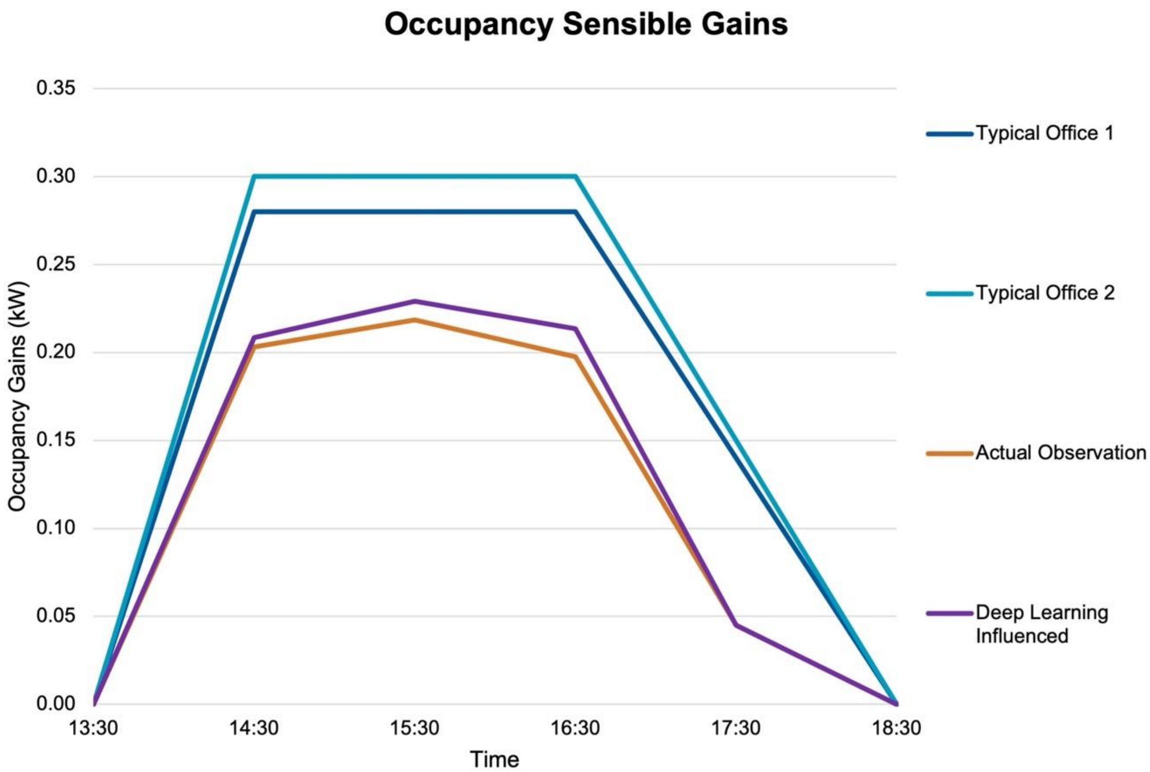


Figure 4-10. Occupancy sensible heat gains for four occupants within the office space; based on typical scheduled profiles, deep learning influenced profile and actual observation.

The results suggest a difference of 27.07% and 30.60% in comparison with the use of static profiles of Typical Office 1 and 2. This suggests that monitoring the occupant activity can help estimate heat gain values more accurately while the typical values or "static" profiles used in current building simulations and guidelines do not provide an accurate estimation of occupancy gains. The average difference between the Actual Observation and DLIP was 3.12%. Although this acknowledges the provision of a good estimation of the occupancy's internal gains. However, further developments are still required to increase accuracy and ability to detect multiple occupants and activities which will show its full capabilities. This shows the ability of the deep learning occupancy activity detection method would be a more effective approach to provide more accurate predictions following real-time occupancy behaviour to provide a better understanding of occupancy gains within the building for effective operations of building energy systems.

In addition to the analysis in terms of sensible gains; latent gains were also analysed based on their significance for building HVAC systems. Figure 4-11 shows a comparison of the latent heat gains results based on the assignment of the different occupancy profiles. In comparison to Typical Office 2 in which a standard scheduled profile of constant maximum occupancy gain for 'walking' was set to display the maximum occupancy gains that would be achieved, the proposed method results suggest an average of 30.60% decrease in latent gains. The variations in latent loads show the influence of the humidity levels of the office space which can ultimately affect the operations of the whole HVAC system for the building. Therefore, this strongly poses the importance of the recognition of occupancy behaviour in terms of the activities they perform in addition to just the number of occupancies in the room.

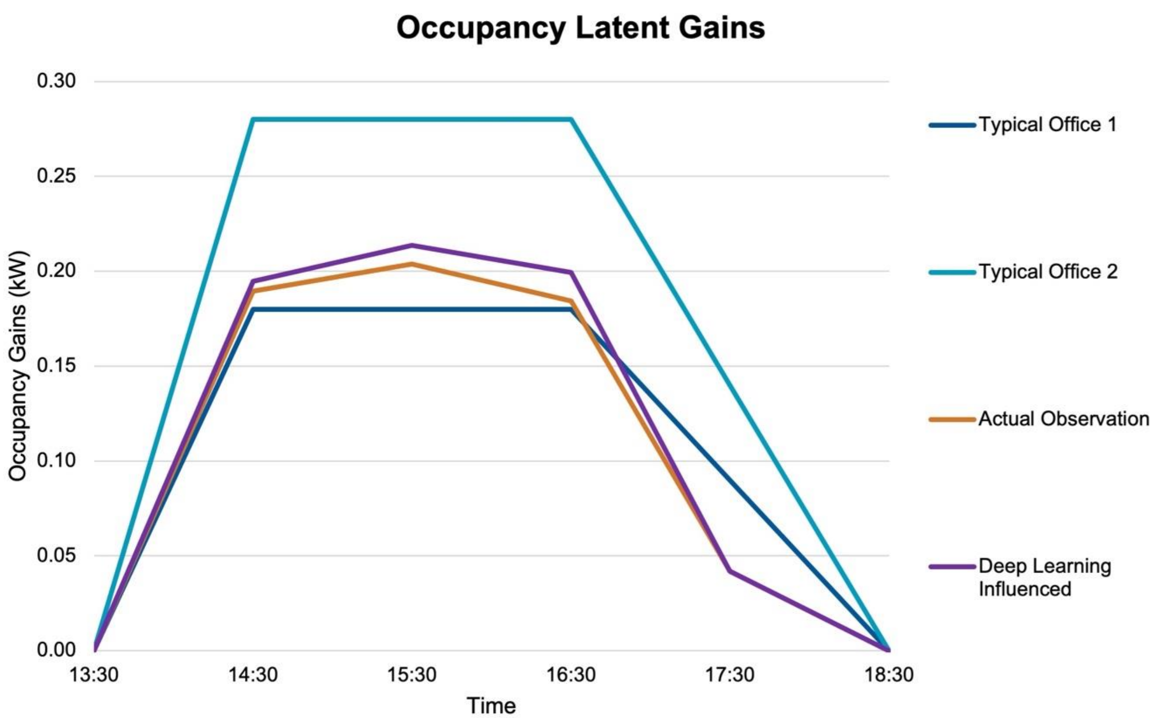


Figure 4-11. Occupancy latent heat gains for four occupants within the office space; based on a typical scheduled profiles, deep learning-influenced profiles and actual observation.

Figure 4-12 shows the effect of the different occupancy profiles on the heating demand for the office space with four occupants on a typical winter's day afternoon. As previously observed, due to changes in occupancy activities following the schedule given in Figure 4-4b, the occupancy gains for the Deep Learning Influenced and the Actual Observation were lower than the results shown by the two Typical Office Profiles. Following this schedule, the activity of sitting was mostly performed, and it was recognised by the deep learning which suggests the actual building heating load be higher. Therefore, more heating was required to enable occupant satisfaction. For the selected period of time, the Actual Observation and proposed method results provided a total heating load of 11.59 kW and 11.56 kW in comparison to Typical Office 2 with 11.24 kW. The indication of an increase in heating was effectively a response to the lower occupancy gains given in Figure 4-9. Therefore, this suggests the deep learning method used to detect various occupancy activities can aid the provision of more accurate building responses in terms of heating and cooling requirements, through a better understanding of real-time occupancy behaviour. Also, if the heating system for larger multiple occupancy office spaces was to be controlled based on the occupancy data, the heating requirement would have to be increased to offset the lower heat gains and provide comfortable conditions in the space. During winter, assuming multiple occupants are emitting continuous and fixed amounts of heat levels in the space will lead to lower heat loads, which is not realistic. This would even be more significant if other heat gains are considered such as lighting and equipment.

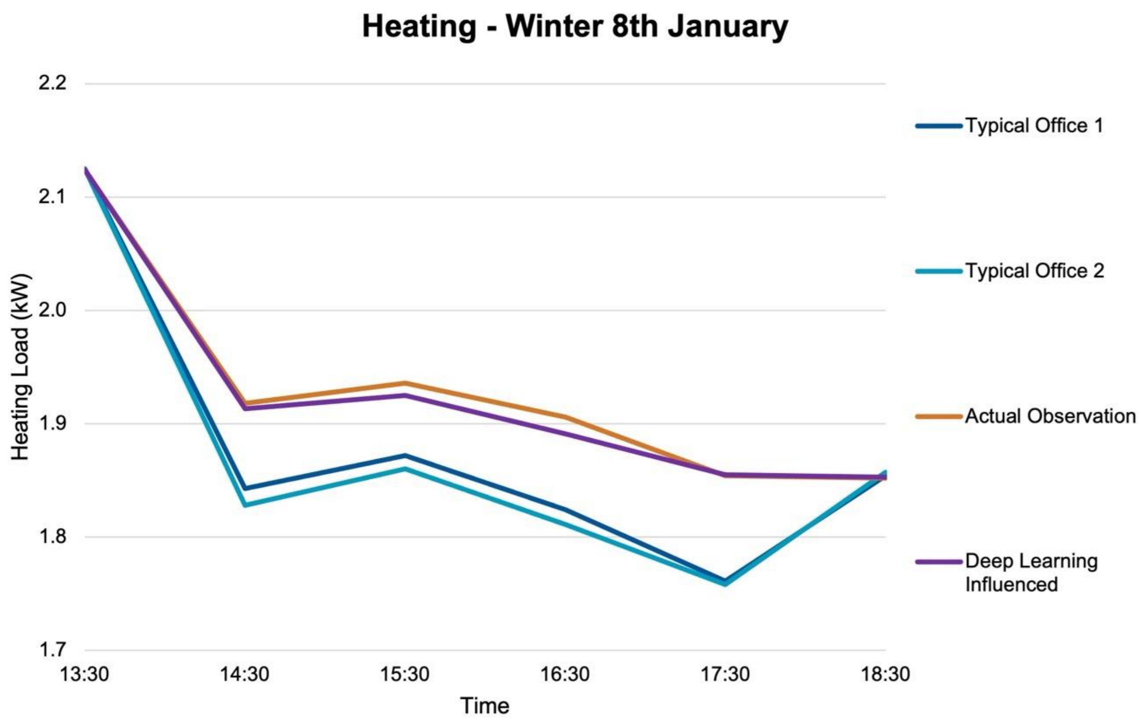


Figure 4-12. Heating load results for a winter day (8th January) within the office space with four occupants; based on the two Typical Office Profiles, DLIP and Actual Observation Profile.

Precise detection of occupants and their activities can also be used to provide a more accurate estimation of building CO2 concentration. According to Pathirana et al., [202] CO2 concentration is an easily measurable parameter which defines the ventilation and air quality within an indoor environment such as a building office space. The information will be useful for modulating ventilation system capacities leading to better indoor environmental quality. Using BES simulation, Figure 4-13 shows the results of CO2 concentration within the office space during the time period. All results suggest the CO2 concentration is below the recommended maximum level of 1000 ppm. This indicates the indoor air quality is satisfactory for the occupants. It also shows that the room CO2 concentration is directly dependent on the number of occupants and activities performed, which highlights the potential of the use of DLIP to provide an accurate estimate of the room CO2 concentrations.

For the selected office space, Figure 4-13 presents the CO2 concentration level with four occupants. The results suggest that the predicted CO2 concentration difference between Typical Office 2 and DLIP could be as high as 242.8 ppm. This shows that using solely the number of people in a space is not sufficient to estimate the CO2 levels. Besides, the movement or activities of occupants in buildings should be considered as this would have a larger impact on the provision of a more accurate estimation of the actual building CO2 concentration levels. This becomes significant especially when a greater number of occupants are in a building space performing a range of different activities. Hence, this suggests that using this deep learning occupancy detection method can inform building ventilation systems to provide the required amounts of fresh and recirculated air, with the ability to reduce unnecessary loads. This leads to the provision of ventilation losses that is only due to occupant's behaviour from their activities performed.

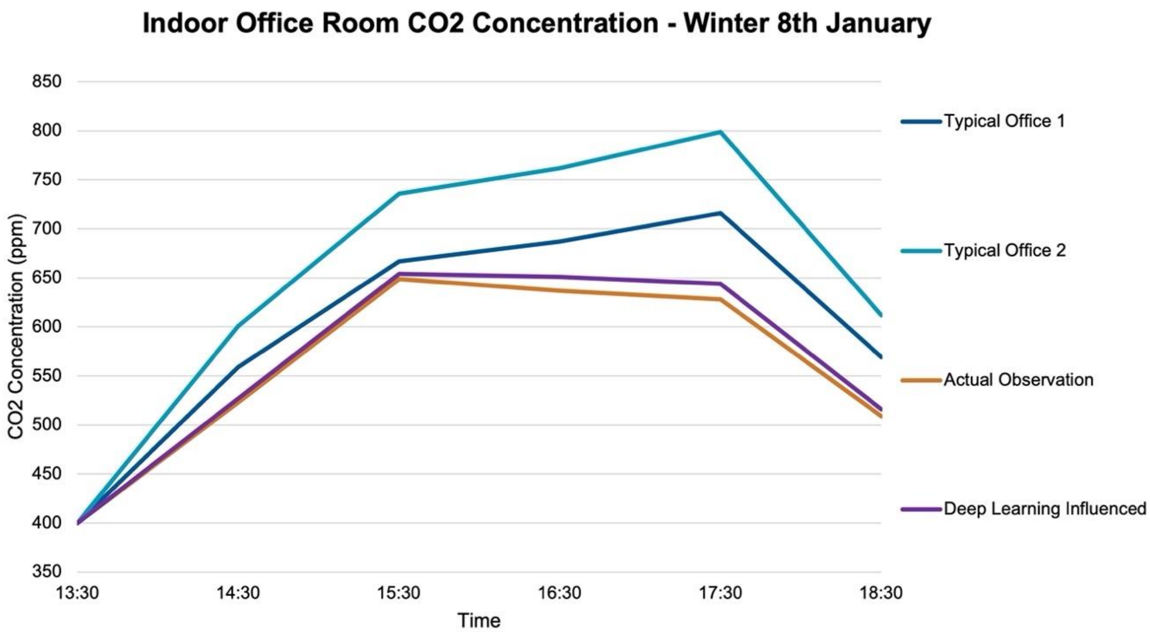


Figure 4-13. CO2 Concentration. CO2 Concentration for a winter day (8th January) at the open-plan office space with four occupants; based on the two Typical Office Profiles, DLIP and Actual Observation Profile.

4.2.6. Summary

The results highlighted the importance of the deep learning model for the formation of more accurate occupancy profiles for better management of the building energy systems. It indicated the potential of the approach to detect and acknowledge the exact number of occupants present in the desired building space along with the common activities performed by them. This framework ultimately enables real-time identification of the changes in heat gains within indoor spaces of a building through the detected occupancy activities. Therefore, this provides a better understanding of the building heating loads, the conditions within the indoor environment and the influence it has on the building design conditions. The proposed method provides an enhanced solution to typical building energy management solutions with the ability to also optimise the indoor thermal conditions to increase occupancy satisfaction.

Based on the results in terms of detection performance shown, a detection accuracy of 80.62% was across all activities. Since only one occupancy response was detected at once in Figure 4-8, it suggests the development of the model towards multiple objects at once. Through a comprehensive literature review of the platforms used for deep learning-based application in Chapter 3, other forms of the deep learning framework toolkits and training platforms can overcome such limitations and provide an alternative solution for the main platform used to construct the desired deep learning model. The following section presents the exploration, development, testing and analysis of an alternative method to form such a vision-based occupancy activity detector.

4.3. Development of the Deep Learning Framework Using TensorFlow Techniques

Through the limitations shown by the results obtained from adopting the MATLAB process given in Chapter 4.2 where a single occupant was detected, an alternative method enabling multiple detections was required to enable further development of an effective detector. Hence, this section presents the development of occupancy activity detectors using Python-based TensorFlow techniques. Similarly, the steps given in Chapters 3.3 and 3.3.2 were followed to give the following workflow in Figure 4-14.

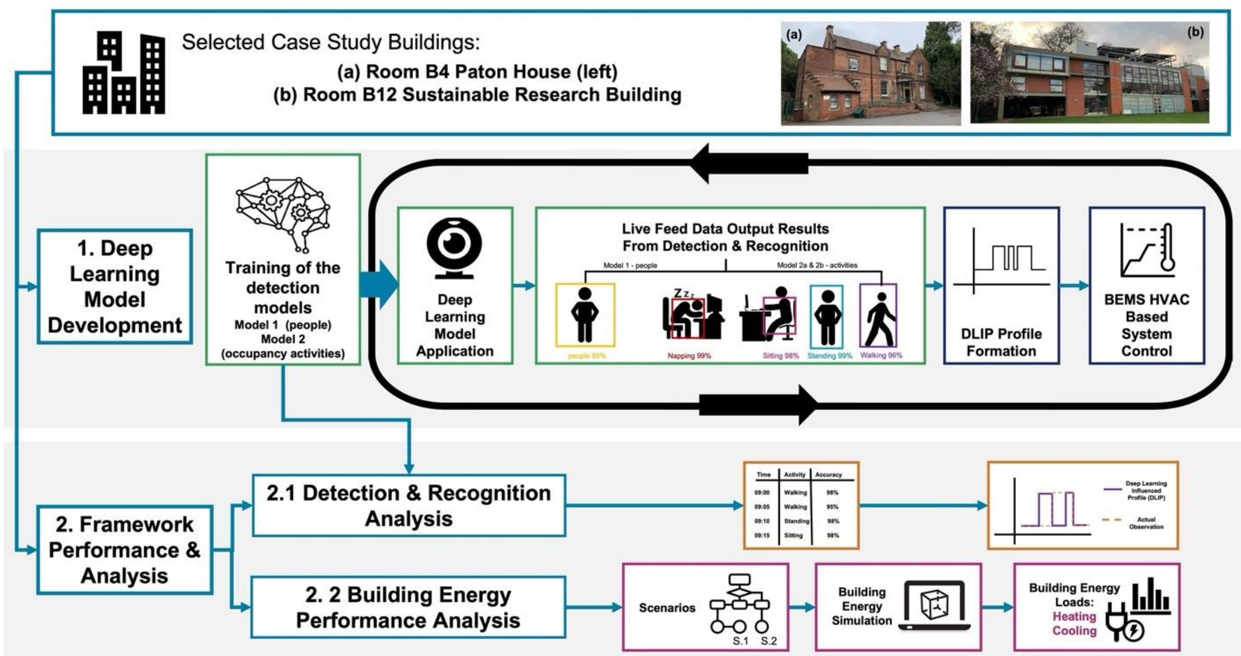


Figure 4-14. The workflow for the development, application and analysis of deep learning vision-based occupancy detector using TensorFlow techniques.

TensorFlow is an end-to-end open-source machine learning platform, it provides an efficient implementation of advanced machine learning algorithms along with the ability to test novel configurations of deep learning algorithms and to demonstrate their robustness. According to previous works, many choose TensorFlow as the desired platform for the development of solutions for building-related applications. This includes [203, 204], where TensorFlow was used to train the desired deep learning model. Vázquez-Canteli et al. [145] fused the TensorFlow technique with building energy simulation (BES) to develop an intelligent energy management system for smart cities and Jo, and Yoon [205] indicated that TensorFlow was used to establish a smart home energy efficiency model. Specifically, the process indicated using TensorFlow was adopted for developing the model for detecting occupancy activities (Figure 4-15).

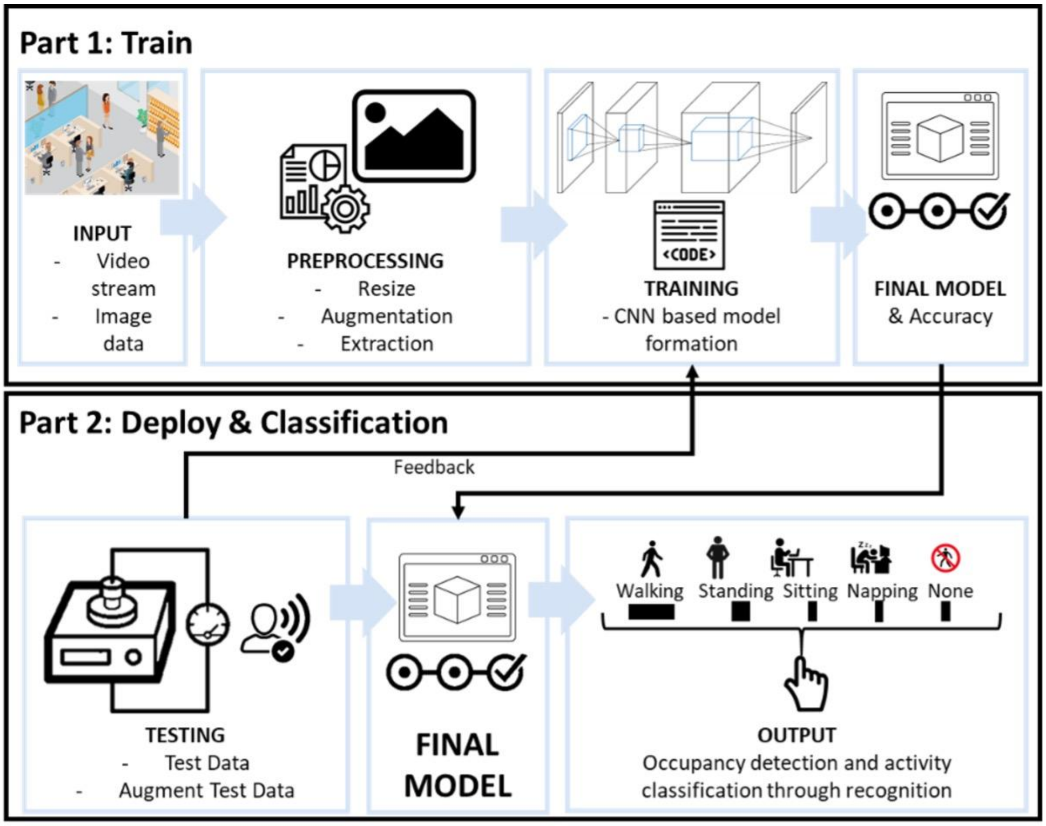


Figure 4-15. Proposed process for forming an occupancy detector.

4.3.1. Model Development and Configurations

Following the model development process in Figure 3-4, images of occupants were collected to form the datasets described in Table 4-6. This was a variation compared to the dataset used for the model presented in Chapter 4.2 as more than one type of model was proposed. This enabled a comparison between the models and help to address any limitations and identify the areas for improvement towards seeking the best solution for an effective vision-based occupancy detector. Model 1 dataset consisted of only one type of response category, 'people' to allow the detection and recognition of the number of people in the space. Whereas two types of datasets were created for occupancy activities, Model 2a and 2b. Dataset 2a consisted of 100 images for each of the activities used in the initial model previously. Whereas the dataset for Model 2b consisted of the more common activities of only 'sitting', 'standing' and 'walking', along with 400 images for each category. For this, the category of 'none' representing no occupants was removed, as it was assumed that if no occupants were present in the space, then no detection is required.

Table 4-6. Training and testing image datasets for the development of occupancy detection models.

Model Name	**Category**	**Dataset Size**					
		N° of Images			**N° of Labels**		
		Training	**Testing**	**Total**	**Training**	**Testing**	**Total**
Model 1	People	40	10	50	168	45	213
Model 2a	None	100	20	120	108	25	133
	Napping	100	20	120	100	20	120
	Sitting	100	20	120	146	26	172
	Standing	100	20	120	131	26	157
	Walking	100	20	120	177	35	212
	Total	500	100	-	662	132	-
Model 2b	Sitting	400	100	500	753	149	902
	Standing	400	100	500	701	134	835
	Walking	400	100	500	1000	177	1177
	Total	1200	300	-	2454	460	-

To establish these image datasets, RBG images were gathered from Google Images. Pre-processing of the gathered images were performed with data augmentation for each image in both the training and testing dataset. This includes ensuring all images were non-identical, or at least with slight variation between each other. For applying the techniques based on the TensorFlow Object Detection API workflow process, images within the dataset did not require to have a restricted size. Therefore, to enable the model to learn all aspects related to the desired response categories, a diverse array of images with high variation in the image pixel densities was collected. The software, LabelImg [206] was used to label all the images located within all datasets manually. This is an open-source graphical image annotation tool which allows images to be labelled with bounding boxes to specifically identify the regions of best interest. A sample of the image gathering and preprocessing stages is shown in Figure 4-16.

Figure 4-16. Example images obtained from Google Images to form the datasets for the training of various occupancy detectors, Model 1 for people detection and Models 2a and b for occupancy activity detection. All images within the datasets were manually labelled as shown using the selected software labelImg [206].

The review of existing models with CNN-based model pipeline and configurations applied to the training of the occupancy detectors given in Chapter 3.2.4 influenced the development of the three occupancy models presented in Table 4-6. For these, the generic architecture of the models directly follows Figure 4-17 along with the application based on the transfer learning approach with a pre-trained object detection model. With the selection of training these models with TensorFlow, the CNN TensorFlow object detection application programming interface (API) was applied to form the base configuration. Furthermore, with the substantial benefits of leveraging pre-trained models through a versatile transfer learning prediction and feature extraction approach, an R-CNN model from the TensorFlow detection model's zoo directory [207] was selected. The TensorFlow detection model's zoo consisted of various forms of networks pre-trained with the Common Objects in Context (COCO) dataset [208]. These pre-trained models are based on the most popular types of R-CNN frameworks used for object detection. Generally, R-CNN works by proposing bounding box object region of interest (ROI) within the input images and uses CNN to extract regions from the image as output classification. As compared with R-CNN, Fast R-CNN runs faster as the convolution operation is performed only once for each image rather than feeding several region proposals to the CNN every time. Both R-CNN and Fast R-CNN employ selective search to look for the region proposals. With regards to this, it commends an effect on the model training computational time and the performance of the network.

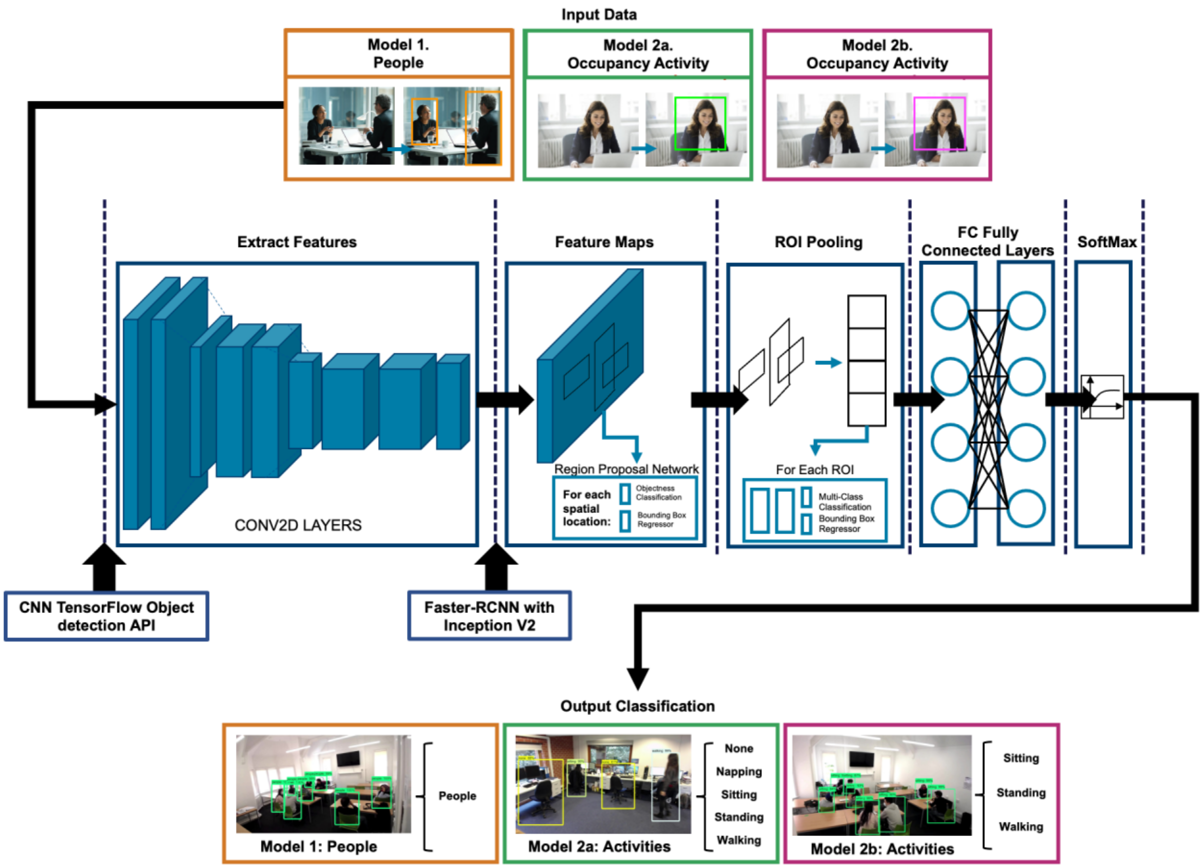


Figure 4-17. CNN-based model configuration used in the training of the different occupancy detection models.

Faster R-CNN uses the region proposal network (RPN) module as the attention mechanism instead of using selective search to learn the region proposals [209]. Ren et al. [187] introduced the Faster R-CNN algorithm. This is similar to Fast R-CNN whereby, it enables input images to feed into the convolution layers and generate a convolutional feature map. Then, the region proposals are predicted by using an RPN layer and reshaped by an ROI pooling layer. The image within the proposed region is then detected by the pooling layer. Overall, all algorithms are suitable to enhance the performance of the network. However, according to the comparison of different CNN-based object detection algorithms [187], Faster R-CNN is much faster than other algorithms, which can be implemented for live object detection [210]. Furthermore, to improve such a Faster R-CNN model, the inception module can aid in the reduction of the required computational time [211] and improves the utilisation of the computing resources inside the network to achieve a higher accuracy [212]. The inception network is presented in many forms. This includes Inception V1 – V4 [211, 213] and also Inception ResNet [214]. Each version is an iterative improvement of the architecture of the previous one.

In this research, the COCO-trained model of Faster R-CNN (With Inception V2) was selected to develop the model for real-time detection and recognition. This was chosen due to the performance of Inception V2 and its widespread use for the development of object detection models such as [187, 214]. Alamsyah and Fachrurrozi [215] used the Faster R-CNN with Inception V2 for the detection of fingertips. Accurate detections of up to 90 – 94% were achieved across all results, including small variations between fingertips. Hence, this suggests the capabilities of Faster R-CNN with Inception V2 to be able to carry out detection tasks even with small changes. Furthermore, the Faster-R-CNN with Inception V2 trained under the COCO dataset achieved an average speed of 58 ms and a mean average precision (mAP) of 28 for detecting various objects from over 90 object categories [207]. Hence, the model summarised in Figure 4-17 with the configured architecture and pipeline of the selected CNN model was used for occupancy activity detection. Inputs from the CNN TensorFlow Object Detection API and the Faster R-CNN with Inception V2 model were also identified.

4.3.2. Formation of the Deep Learning Influenced Profiles (DLIPs) Based on the Detection Results

The proposed framework indicated in Figure 4-1 suggests that once the trained model is applied for detection and recognition within indoor spaces, the output data for each of the detected occupants were used to form the occupancy heat emission profiles (DLIP). Based on the profiles described in Figure 4-8, a similar process is applied to form such profiles from the detections made using the detectors trained using the TensorFlow methods. The process for the DLIP formation involves the output values corresponding with the number of recognised occupants performing each of the selected responses (including the different activities). It was recognised that if such procedures given in Figure 4-8 were applied, the results for the model could not output any sufficient data. Hence, count-based profiles were formed initially formed and they can be further processed to become coupled with the heat emission data-based value for an average adult performing the different activities within indoor spaces such as offices given in Table 4-1. Figure 4-18 presents the DLIP formation process for the three occupancy models.

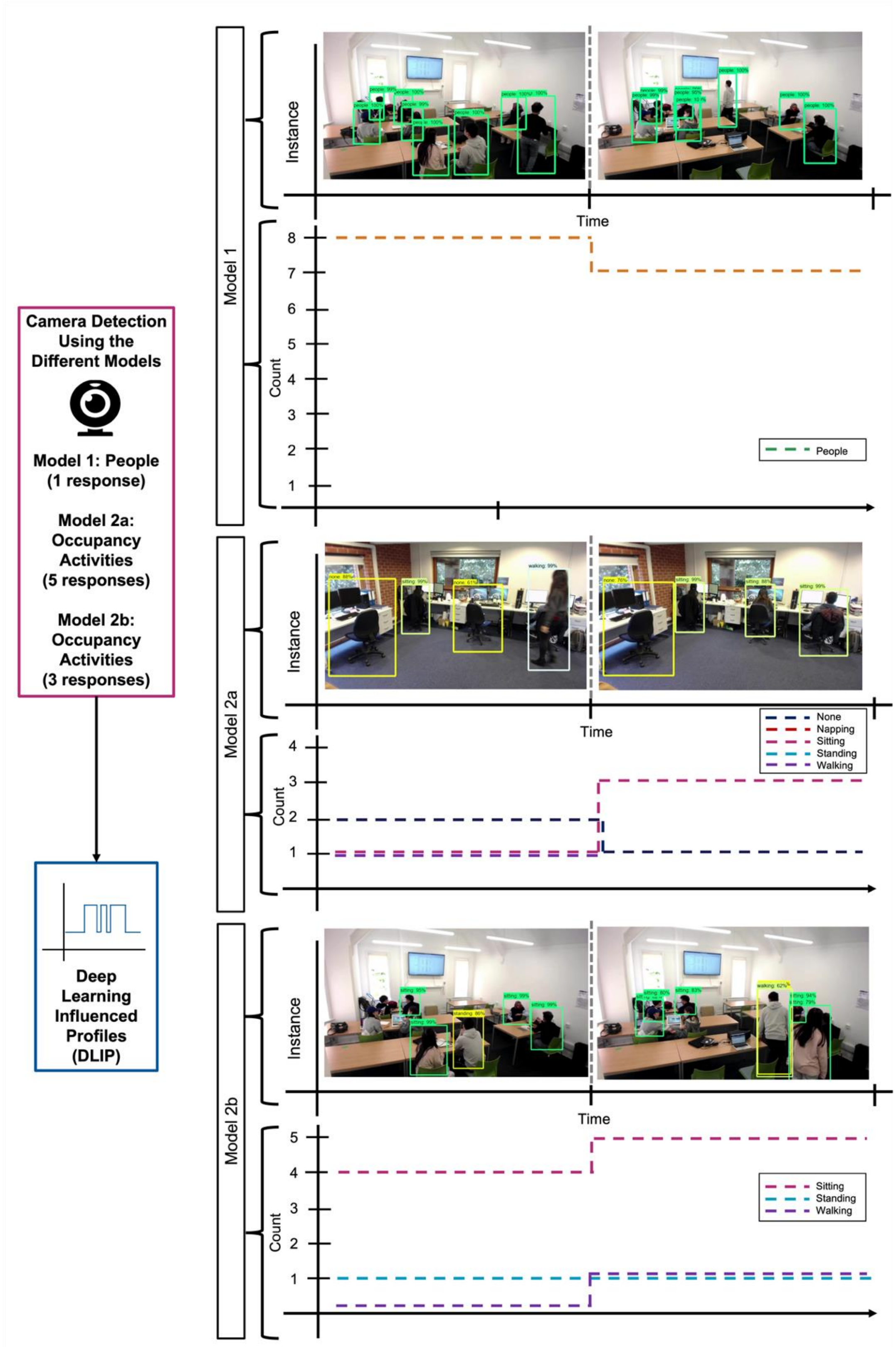


Figure 4-18. Examples of the Deep Learning Influences Profiles (DLIPs) formation under the different time frames for all three occupancy detection models.

4.3.3. Description of the Experimental Test Used to Evaluate the Trained Occupancy Detectors

To test the developed occupancy detection models within ‘real’ situations providing results for the analysis of the detection performance and impact of the framework approach towards building system operations, a selection of buildings was selected to perform various experimental tests. Table 4-7 presents a summary of the experimental tests, whereby descriptions for each of these buildings are given in Chapter 3.4.

Table 4-7. Summary of the experimental tests for the evaluation of the different occupancy detection models.

Experimental Test	Model	Case Study Building	Room Type & Function	Number of Participants	Date/ Time of Test	Purpose of Experimental Test
1	1	Paton House	PGR Study Space	8	May 2021	Testing of the initially developed people detector
2	2a	Sustainable Research Building (SRB)	Open-plan office Space	3	March 2020	Testing of the initially developed occupancy activity detector
3	2b	Sustainable Research Building (SRB)	Open-plan office space	3	March 2020	Testing of an enhanced occupancy activity model with results for scenarios-based analysis
4	2b	Paton House	PGR Study Space	8	May 2021	Comparison of the model application with Model 1

Experimental Test 1 was conducted in Paton House with a maximum of 8 occupants. Figure 4-19a presents the floor plan of the first floor of the building with the room configuration in b)., along with the setup for the experimental tests in c). and d). To enable the capture of the whole test room, cameras with a resolution of 1080p and a wide 90-degree field of view were fixed in the corner of the room and close to the ceiling. It should be noted that this case study building is not intended to evaluate the building itself or its facilities but rather for testing the detection methods in a small-size classroom with occupants performing activities common in this type of space.

Figure 4-19. Paton House at the University of Nottingham applied in Experimental Tests 1 and 4. a). Floor plan of the first floor of the building with the room configuration in (b). Setup for the experimental tests in (c), and (d).

Before the test, a trial with occupants in the space along with two cameras positioned in the selected region of the room was performed. As highlighted in Figure 4-20, the field of vision from Camera A and B both provided the identification of people as ‘People 1 – 8’ for detection performance analysis. However, based on an observational comparison, the position of camera A was not ideal as it was placed behind the door. Hence, Camera B was selected as the desired camera position to be used in the experimental test.

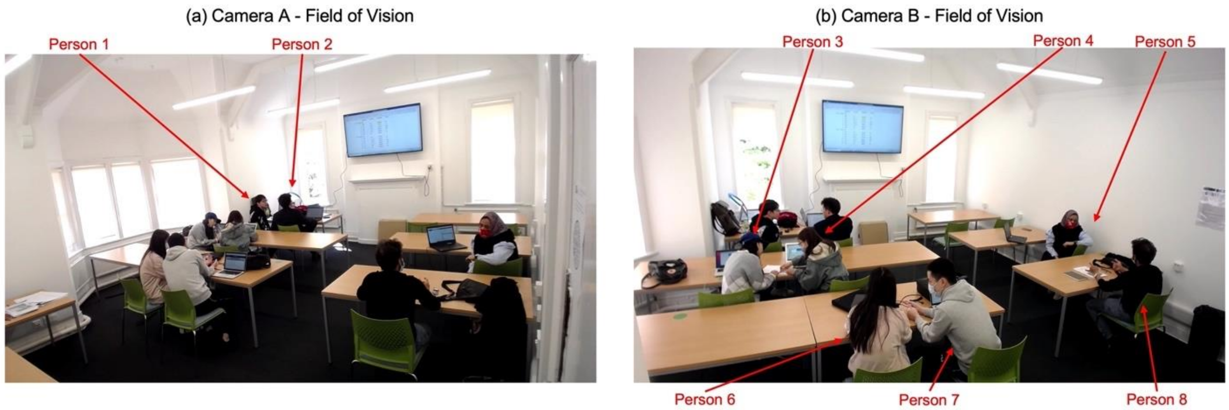


Figure 4-20. Field of vision from Camera A and B with the identification of People as 'People 1 – 8' for detection performance analysis using Model 1 in Experimental Tests 1 and 4.

Figure 4-21 presented the selected case study building used to conduct Experimental Tests 2 and 3 using the occupancy activities Models 2a and 2b. Given the room configuration layouts in Figure 4-21b and c for Experimental Tests 2 and 3, the selected office space was designed to accommodate eleven occupants as a total of eleven office workstations were present. However, for the selected experimental test days, only three occupants were present for the majority of the time. Variation occurs between the experimental test set up as Figure 4-21b for Experimental Test 2 was to provide a direct field of vision (shown by Figure 4-21d) to the selected region whereby occupants were present; whereas Figure 4-21c for Experimental Test 3 acquired a camera position near to the ceiling of the room, achieving a greater field of vision (Figure 4-21e). For easier analysis of the detection performances achieved during both experimental tests, names of Detection A-D and/or Person A-B was assigned to each person, or the region of detections made. Between Experimental Tests 2 and 3, similarity includes the experimental test location. Variations occur between the occupancy detection applied, the occupancy behaviour, the scheduled activity during the test, the indoor-outdoor environmental conditions and also the set-up with the camera position. Overall, this enables effective analysis of the performance of Models 2a and 2b, while also identifying the benefit and limitations of such factors towards the overall and specific aspects of the framework approach.

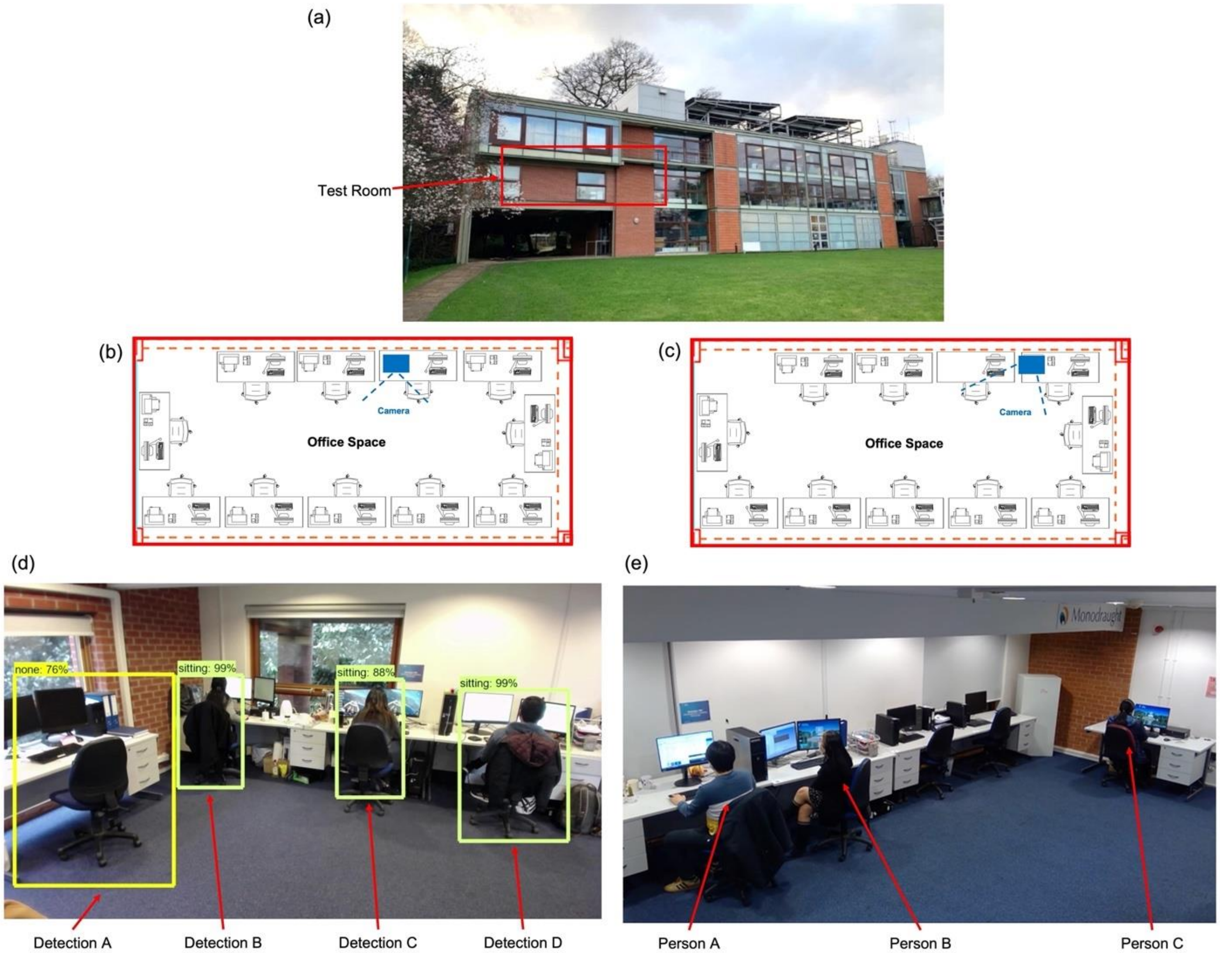


Figure 4-21. The Sustainable Research Building (SRB) at the University of Nottingham used to conduct Experimental Tests 2 and 3. a). Photo of the building with the highlighted test room on the first floor. (b) and (c) presents the floor plan with the configuration of the setup for the experimental tests. (d) and (e) presents the field of vision from the camera located in the room during Experimental Tests 2 and 3.

In addition, an experimental test named, Experimental Test 4 was also conducted in Paton House, following the setup and conditions given in Figure 4-19. This experimental test was designed to assess the application of Model 2B which focused on occupancy activity detection towards the same building and set up as to Experimental Test 1 where occupancy detection was conducted. Such experimental tests provided results which gave a direct comparison with Experimental Test 1 with the identification of the importance of an occupancy detector and an occupancy activity detector. For all four experimental tests, the performance was analysed based on detection performances using the steps mentioned in Chapters 3.3.4 and 3.3.5 giving the results shown in Chapters 4.5 with the corresponding subsections for each experimental test.

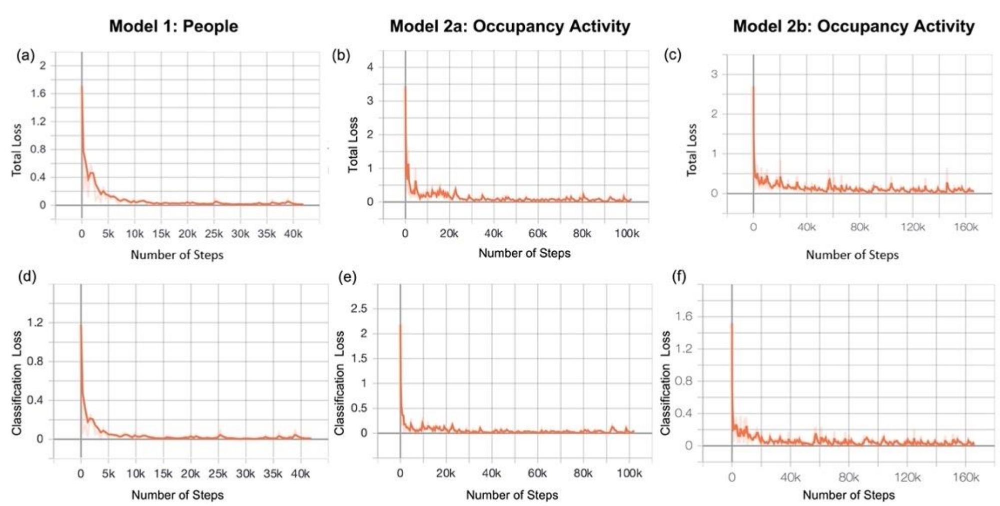
4.4. Application of the Deep Learning Framework Using TensorFlow Techniques

The following section presents the results of the training and testing of the different occupancy detectors based on the models defined in Chapter 4.3.1, Model 1 for people detection, and Models 2a and b for occupancy activity detection. The four-stage performance analysis framework given in Figure 3-6 was applied to provide the results shown in Chapter 4.4.2. This presents the formation of the DLIP for every detection response achieved during the field experimental tests conducted within the selected building following the cases given in Table 4-6.

4.4.1. Occupancy Model Training Results

A summary of the detection model training results is given in Table 4-8. Since Model 1 had a smaller image dataset and only one response assigned, it led to a shorter training duration and fewer training steps than Models 2a and b. As observed in Table 4-8, the total loss versus the training steps plot indicates the complexity of both Model 2 compared to Model 1. Greater fluctuations were seen during the model training. Effectively, based on the loss convergence, all models were sufficiently trained and should be able to carry out the detection tasks.

Table 4-8. Training results for the three occupancy detection models, Model 1, Model 2a and 2b.

Training Conditions	Model 1	Model 2a	Model 2b
Pretrained Model Applied	Faster RCNN with InceptionV2		
Total Steps	41,901	102,194	102,194
Total Duration	2 hours, 54 minutes	6 hours 45 minutes	10 hours, 30 minutes
Average Loss	0.07607	0.141329877	0.13436
Minimum Loss	0.003567	0.01007	0.005654
Total Loss Vs. Training Steps			
Classification Loss Vs. Training Steps			

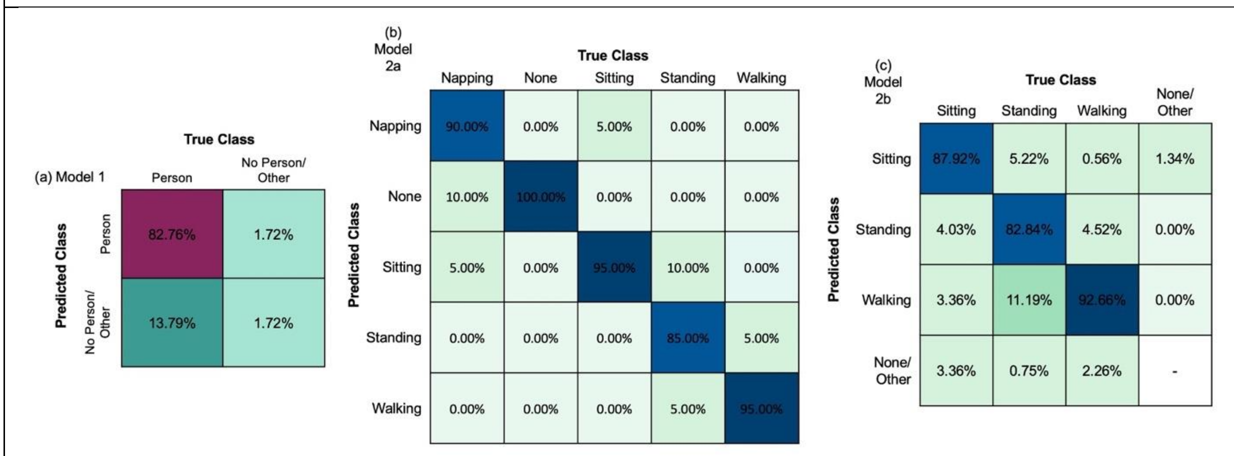
To confirm the completion of the training of the models, initial detection was performed using the test images from the dataset. Results are presented in Table 4-9 with the confusion matrix and the common classification metrics. The confusion matrix presents the ability of the three classification models (Model 1, 2a and 2b) based on their performance on a set of testing datasets whereby the true values are known.

Model 1 was designed to only recognise one type of response (people) via a binary classification problem, while both Model 2a and b had several detection responses. For all models, true positive results were achieved when the classifier correctly recognises the person present in the building space and true negative when it correctly recognises no people in the space. The confusion matrix also indicates the amount of false positive and false negative results achieved, referring to the number of detections that were incorrectly detected. Based on the confusion matrix given in Table 4-9, most categories were correctly detected with true positive detections of over 82.84% for all cases, and an average of 90.12%.

The results for Model 1 suggest the ability of the model to identify occupants present within the building space, providing an effective occupancy count solution. For Model 2a, although the classification for 'none' (when the occupant is absent) achieved the highest performance and 'standing' achieved the lowest. This perhaps is due to the difficulty in recognising the occupancy body form and shape, as it may be confused with the activities of both standing and walking. Hence, when such response category of "none" was removed in Model 2b, the walking activity achieved a higher accuracy (92.66%) compared to the other activities of sitting (87.92%) and standing (82.84%). Effectively, this suggests that the accuracy for detection of both activities of standing and walking were quite similar and presents difficulties in identifying the true activity, leading to the occurrence of walking being incorrectly identified as standing (11.19%). Overall, the results showed the potential of becoming an effective occupancy detector. Further evaluation of the trained models in terms of their ability to classify occupancy and activities using common evaluation metrics, including accuracy, precision, recall and F1 score were used (defined in Chapter 3.3.4) which provided the results given in Table 4-9.

Table 4-9. Performance of all occupancy models based on still images from the testing dataset presented in form of a confusion matrix and the results in terms of common evaluation metrics.

Confusion Matrix



Class	Accuracy	Precision	Recall	F1 Score
Model 1: People				
People	84.48%	0.9796	0.8571	0.9143
Model 2a: Occupancy Activities				
1	96.88%	0.9474	0.9000	0.9231
2	98.94%	0.9524	1.000	0.9758

3	95.88%	0.8636	0.9500	0.9048
4	95.88%	0.9444	0.8500	0.8947
5	97.89%	0.9500	0.9500	0.9367
Average	97.09%	0.9316	0.9300	0.9270
Model 2b: Occupancy Activities				
Sitting	94.04%	0.925	0.8911	0.9077
Standing	91.43%	0.9064	0.8284	0.8657
Walking	92.70%	0.8643	0.9266	0.9047
Average	92.72%	0.8986	0.8820	0.8927

4.4.2. Analysis of the Deep Learning Influenced Profiles (DLIPs) Formed During the Experimental Tests

When the trained model is operated via a camera-based device to form a detector that was placed within an indoor environment, real-time detection and recognition of occupants were made. To avoid privacy issues, this approach does not require the data to be collected and stored in the form of images or videos. Instead, DLIPs were generated and converted to form an occupancy heat emission-based profile which can be used to inform and assist the operations of building system controls and BES models. Figure 4-22 shows the generated DLIPs from using the three occupancy models conducted in all four experimental test cases stated in Table 4-7.

With experimental Tests 1 and 4 based on the same location, setup, and video recording, with the only difference in the detection model used (Model 1 vs. Model 2b), this enabled the results in form of DLIP to provide a direct comparison towards the application of an occupancy detector, recognising the number of occupants in the space (Figure 4-22a) against the understanding of the activities performed by each occupant in Figure 4-22d. Furthermore, generated profiles from the application in Experimental Tests 2 and 3 conducted within the Sustainable Research Building were shown in Figure 4-22b and c. As recordings were taken every one or two seconds during each of the test periods, substantial fluctuations occurred within the generated results indicating prediction error. In addition, the number of occupants performing each activity during different times is unpredictable. Hence, such profiles provide valuable real-time information that could assist the operations of building systems.

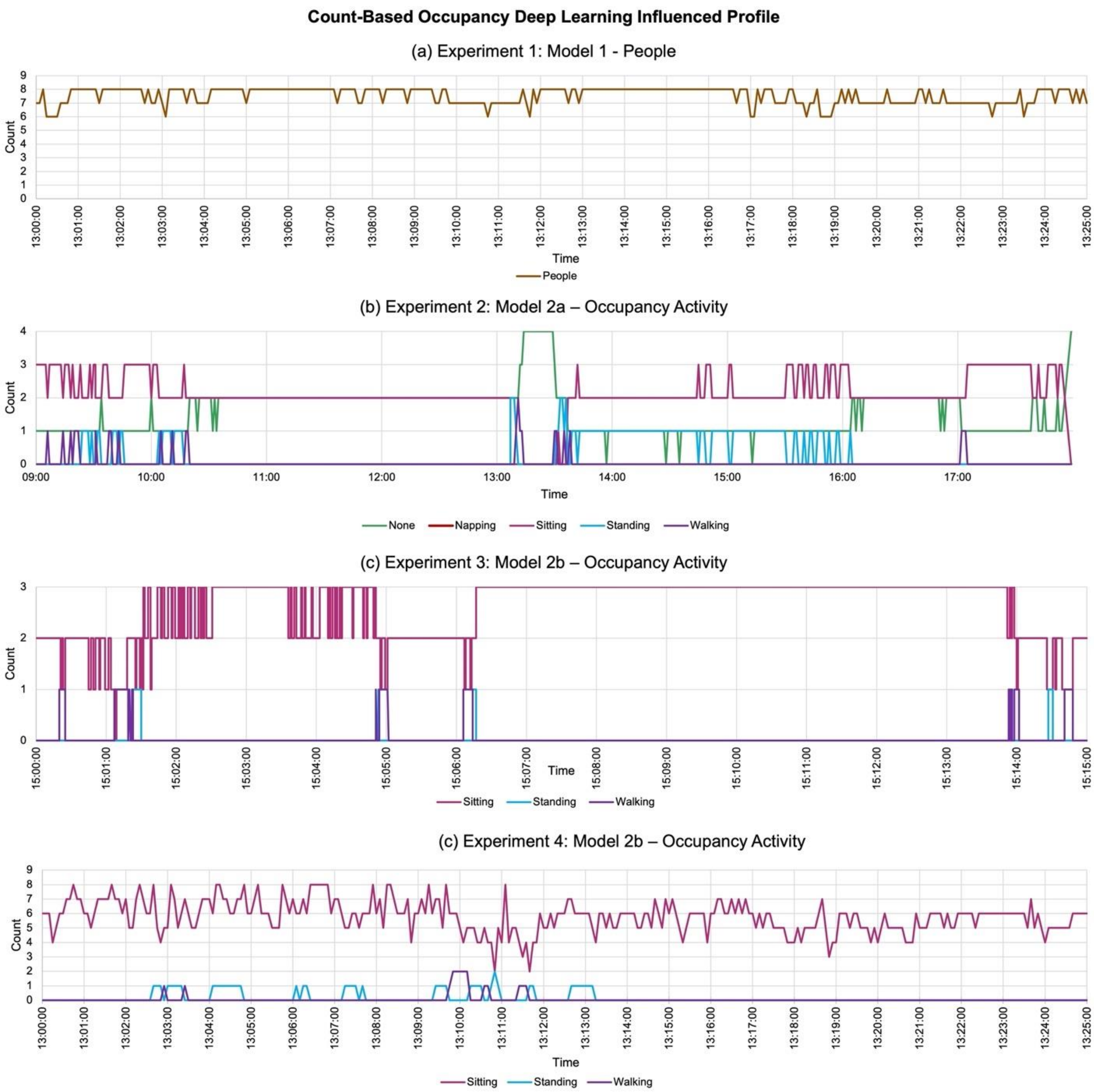


Figure 4-22. Count-based occupancy deep learning influenced profiles (DLIP) generated from the experimental tests performed with the four trained models.

To represent the true occupancy actions/ number of occupants in the building space for the selected duration of the experimental tests, ground truth conditions for occupants were named to form the Actual Observation profile. This was used to further assess the detection performance of the methods. For all generated DLIPs, the comparison with the Actual Observation profiles suggests that the model still alternates between the different activities/ number of occupants recognised in the space due to the occurrence of prediction error, suggesting the opportunities for further improvements to enhance the accuracy, reliability, and stability of the detection model.

As mentioned previously for the occupancy activity detection models, the generated count-based profiles were directly converted to heat-emission-based profiles via the acknowledgement of the standard heat emissions values for each activity detection (stated in Table 4-1). This gives the results for the application of Models 2a, and 2b in Experimental Tests 2, 3, and 4.

Furthermore, static pre-defined occupancy profiles are commonly used in HVAC system operations and in building energy simulations to assume a strict occupancy pattern assigned to people in various indoor spaces. Following the conditions in Table 4-1, Figure 4-23b, c and d presents the 'typical profiles' created to represent a common pre-defined profile. Typical 1 Profile assumes all occupants were constantly sitting (a heat gain of 115 W/person), while the Typical 2 Profile represented the maximum occupancy heat gain (assuming all occupants were constantly walking – 145 W/person) could be achieved. Converting the generated count-based DLIPs to heat emission-based profiles gives the following results shown. It significantly shows a large discrepancy between the profiles.

Based on the detection period of Experimental Test 3, an achievement of up to 37.51% and 50.44% difference was observed between the Typical Profiles 1 and 2 and the actual occupancy heat emission profile. Hence, there was a high discrepancy between the true occupancy activities performed within the building spaces and the use of static profiles. Therefore, this shows the potential of the vision-based deep learning approach for activity recognition to provide a better understanding of the conditions within an indoor space for more effective system controls and operations.

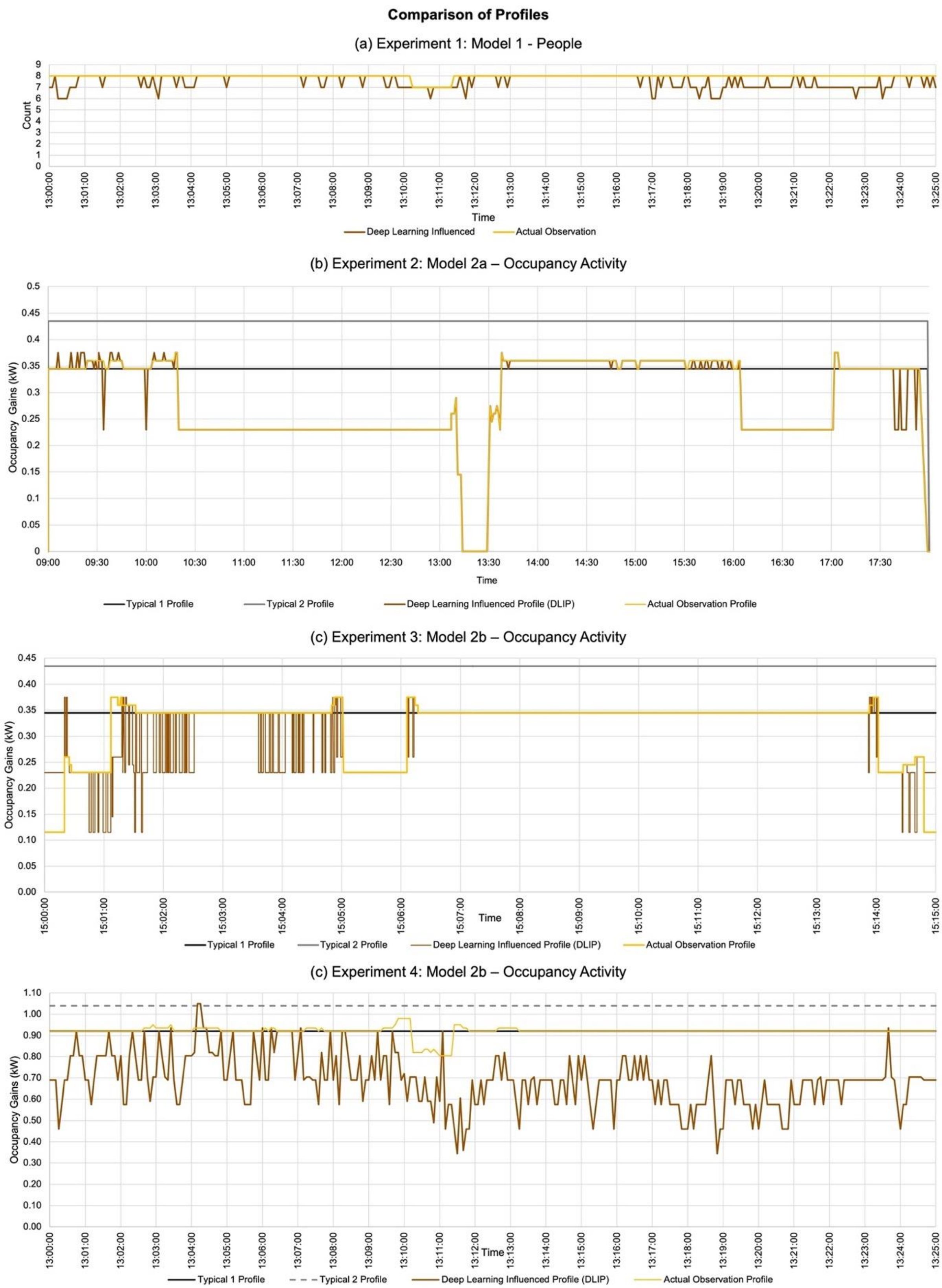


Figure 4-23. Comparison of the generated DLIP Occupancy Profiles with static schedules (typical profiles) and the Actual Observation Profile.

Taking the case of Experimental Tests 1 and 4 which were applied to the same situation, the use of people detection (Model 1) with occupancy activity detection (Model 2b) suggested the results for Model 1 were closer to the Actual Observation (ground truth) due to the limited activities (mostly sitting) performed by the occupants during the experimental test. In addition, Figure 4-23b suggested a difference between the DLIP and the Actual Observation Profiles of only 4.14% for occupancy activities. While Figure 4-23c indicates that the DLIP predicted 29.09% and 10.60% lower occupancy heat gains as compared to Typical Profiles 1 and 2. However, the results also showed that the DLIP still has errors when compared with the Actual Observation Profile with an overall error of 4.14%.

This highlights the importance of developing an accurate and stable occupancy activity detector for effective and valuable building control systems. Furthermore, a greater impact could potentially be observed when such a detection method is implemented within larger indoor spaces with more people performing various occupancy activities. In all, this suggests the importance of adopting such a vision-based approach whereby DLIPs are considered advantageous in comparison to the Typical profiles as it avoided the majority of the high discrepancy indicating the potential of the deep learning-based approach to provide a more accurate understanding of the indoor conditions based on occupancy behaviour within an indoor space for building energy system operations and performances.

4.5. Performance Analysis of the Occupancy Detection Models Applied During Different Experimental Tests

The observation of the results in terms of the formed DLIPs provided some understanding of the performance of each of the developed detectors. However, a detailed analysis of how different indoor conditions could influence the provision of such results cannot be made. Hence, this section provides an in-depth analysis of each of the model's performance during the selected experimental tests highlighted in Table 4-7, using the framework analysis shown in Figure 3-6 with Chapters 4.5.1. – 4.5.4 for Experimental Tests 1 – 4. This assessment enables the identification of the benefits and limitations of each of the configured detection models.

4.5.1. Experimental Test 1 – PGR Study Space (Number of occupants)

Figure 4-24 presents snapshots of the detection and recognition during the experimental test using the occupancy detection Model 1. For the majority of the time, it enabled the detection and recognition of most occupants within the building space. However, some no/false incorrect detections in identifying the occupancy activities occurred directly for the occupants furthest away from the camera and/or obstructed by objects in the room or by other people. Detected occupants were presented via the labelled bounding boxes along with the IoU accuracy shown above. IoU is a standard evaluation metric for CNN detectors used to evaluate how similar a predicted bounding box is to the ground truth box and was defined.

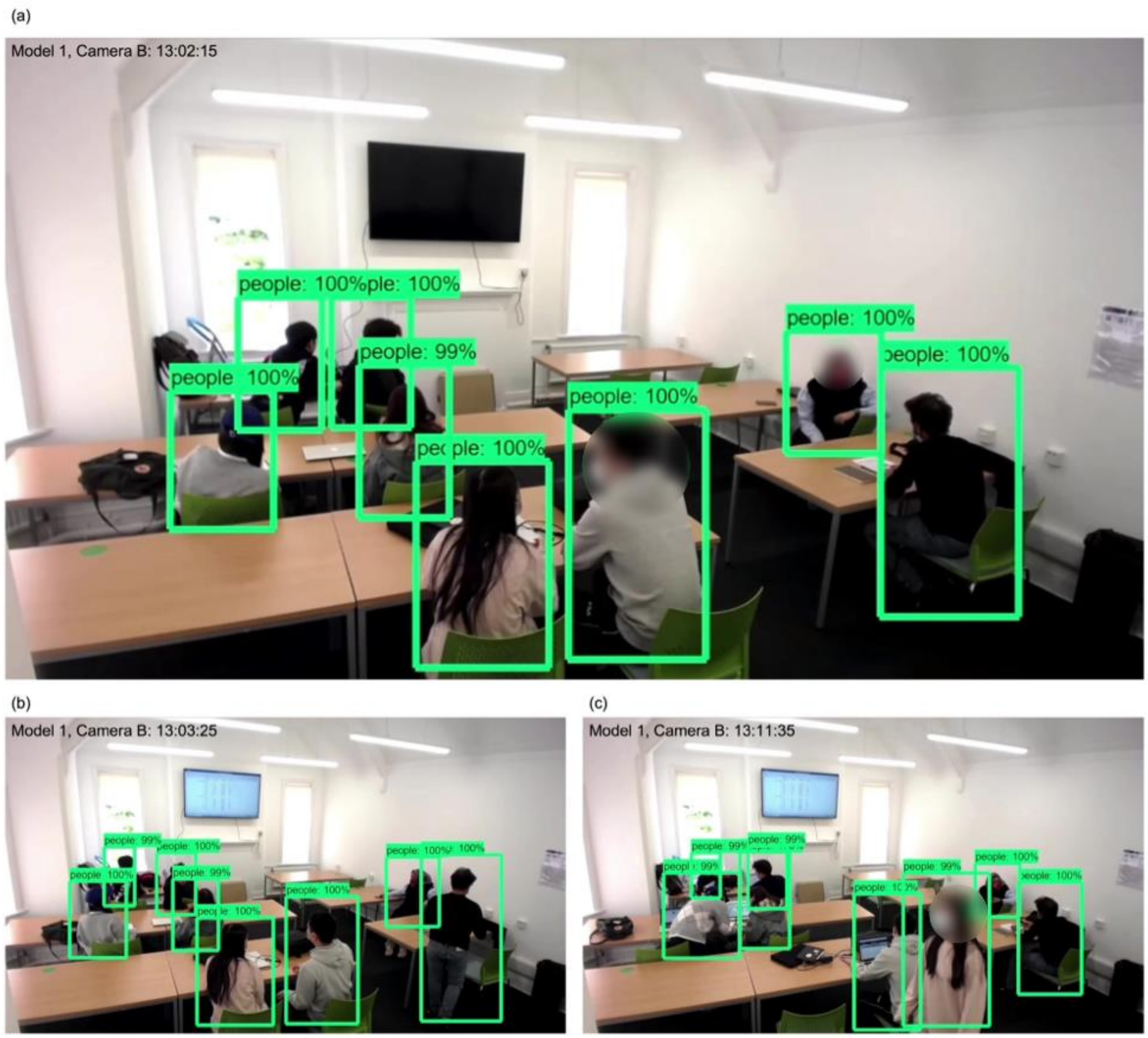


Figure 4-24. Snapshots of occupancy detection and recognition during key stages of the experimental Test 1 using Model 1 (people detector).

Figure 4-25 suggests Model 1 achieved an average detection IoU of 98.85% for all occupants. Despite 'Occupancy 6' within the direct view and angle of the camera, a slightly lower IoU of 93.60% was achieved. This may have resulted from the participant facing opposite the camera in most instances. Future works should take this into account when creating the training dataset. However, the results indicate the ability of the vision-based detection approach to enable real-time identification of the number of occupants present in a building space.

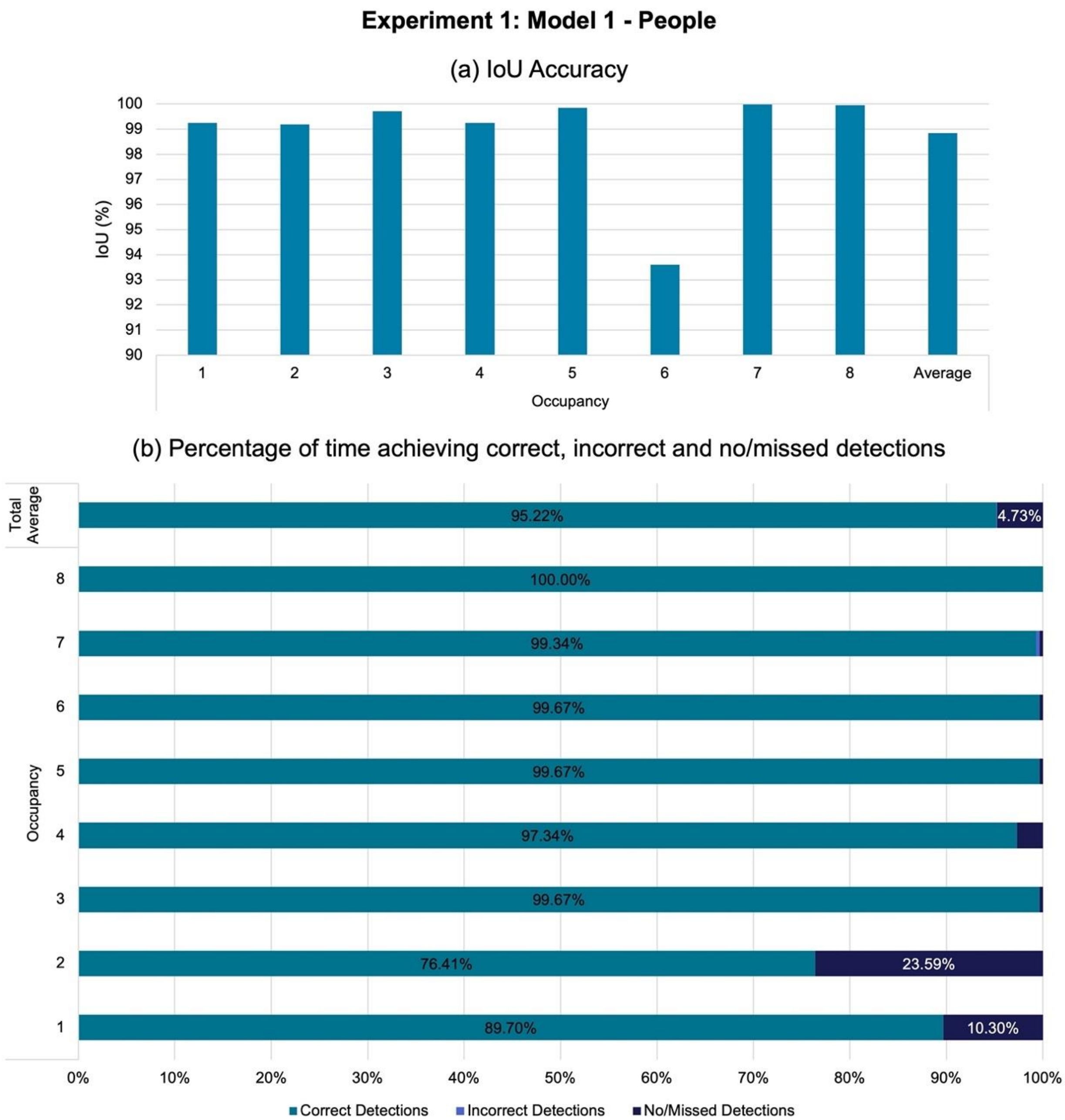


Figure 4-25. (a) Average IoU (%) of the occupants during Experimental Test 1 using occupancy detection Model 1 and (b). The detection performance in terms of the percentage of time achieving correct, incorrect, and no/missed detections.

Table 4-10 presents a detailed summary of the results. It suggests that achieving correct/ incorrect and no detections would have been influenced by the model performance on recognising each occupant within the space. For this model, correct detection of up to 100% could be achieved along with minimal incorrect detections and no/ missed detections also occurred.

Table 4-10. The detection performance in terms of the percentage of time achieving correct, incorrect, and no/missed detections for occupancy Model 1.

Percentage of Time Achieving:			
Model 1: People Detection			
Occupancy	**Correct Detections**	**Incorrect Detections**	**No/ Missed Detections**
1	89.70%	0.00%	10.30%
2	76.41%	0.00%	23.59%
3	99.67%	0.00%	0.33%
4	97.34%	0.00%	2.66%
5	99.67%	0.00%	0.33%
6	99.67%	0.00%	0.33%
7	99.34%	0.33%	0.33%
8	100.00%	0.00%	0.00%
Average	95.22%	0.04%	4.73%

To further evaluate the performance of the detectors during the experimental tests, Figure 4-26 presents the results in the form of the confusion matrix. For Model 1, it verified the results presented in Table 4-10 with the lowest true positive values of 76.41%, and the highest number of false positives of up to 23.59% was for the detection of Occupant 2. In comparison to the detection of the other occupants, more consistent results were achieved, giving minimal false negatives, with no false positives. Overall, an average of 95.23% were achieved for true positives in correctly detecting people within the space. Results given in form of the evaluation metrics were shown in Table 4-11. Model 1 provided an overall accuracy of 95.23% and an F1 score of 0.9756. This indicates the benefits of implementing Model 1 in buildings as an effective solution in predicting the CO2 concentration levels based on the occupancy count. Furthermore, since the category of 'none' representing times when no occupants are present within the space was not classed as one of the detection responses, therefore, no data was given for the times when true positives were active for this.

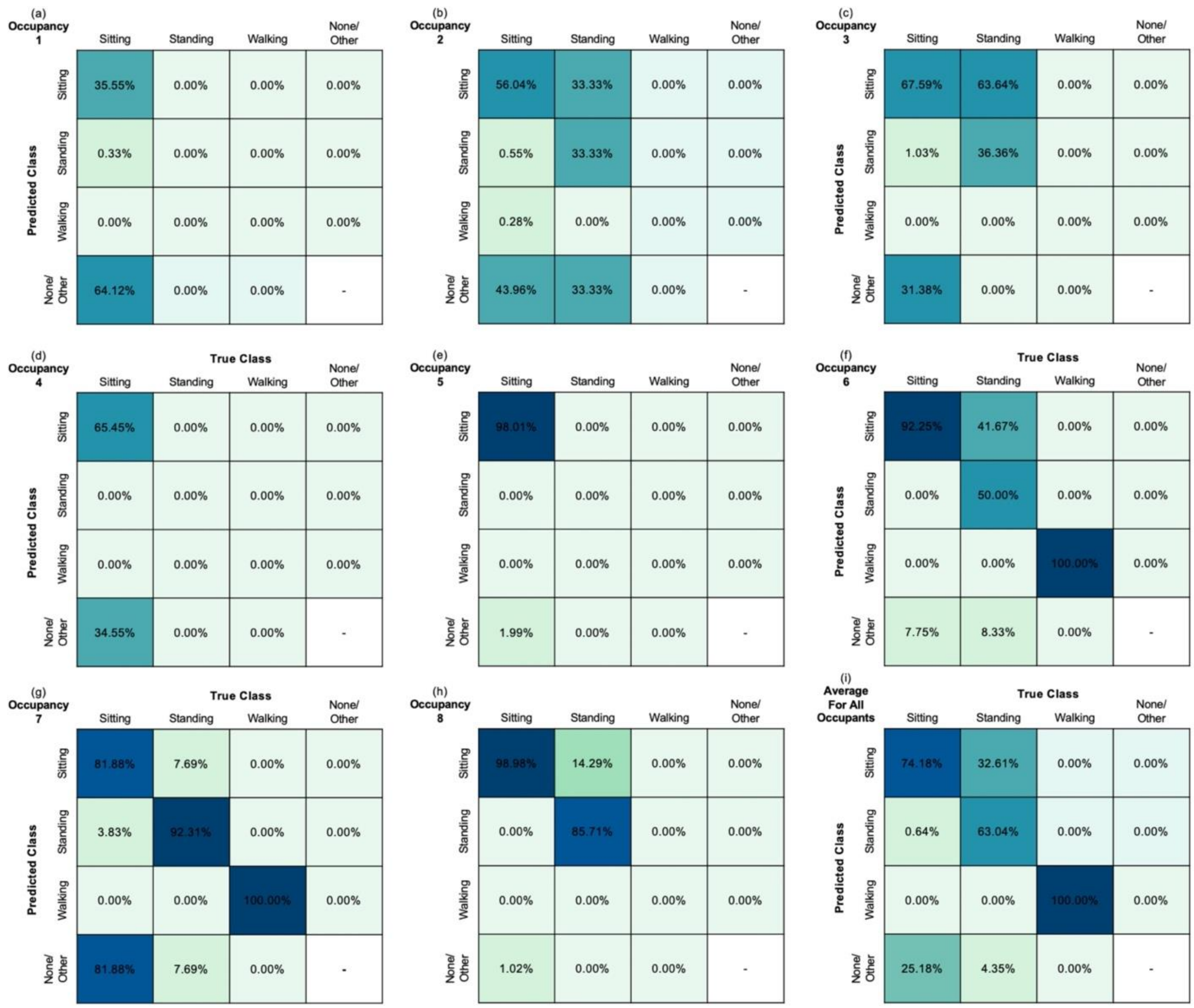


Figure 4-26. Detection performance in form of the confusion matrix for occupancy detection made during Experimental Test 1.

Table 4-11. Detection performance results based on the common classification evaluation metrics from the application of occupancy Model 1 – people detector.

Occupancy	Class	Accuracy	Precision	Recall	F1 Score
1	Person	89.70%	1.000	0.8970	0.9457
2	Person	76.41%	1.000	0.7641	0.8663
3	Person	99.67%	1.000	0.9967	0.9983
4	Person	97.34%	1.000	0.9734	0.9865
5	Person	99.67%	1.000	0.9967	0.9983
6	Person	99.65%	1.000	0.9965	0.9982
7	Person	99.67%	1.000	0.9967	0.9983

8	Person	100.00%	1.000	1.000	1.000
Average	Person	95.23%	1.000	0.9523	0.9756

In summary, this experimental test focused on the application of a vision-based occupancy detector conducted within Paton House. Overall, it provided good detection of the number of occupants within the indoor space as results suggest close prediction with the Actual Observation (ground truth) due to the limited activities (mostly seating) performed by the occupants during the experimental test. This highlights the importance of developing an accurate and stable occupancy activity detector to be effective and valuable for building control systems. It is envisaged that the proposed detection approach could have a greater impact when applied in a larger indoor space and would be impacted when a greater range of different activities was performed by occupants, leading to the evaluation and discussion of the occupancy activity detector implemented in Experimental Tests 2, 3 and 4 shown in Chapters 4.5.2-4.5.4.

4.5.2. Experimental Test 2 – Open-Plan Office Space (Occupancy activity)

Figure 4-27 presents example snapshots at various times of the day from Experimental Test 2 with the detection and recognition of occupants within the selected office space. Based on the setup indicated in Figure 4-21 shows the ability of the proposed approach to detect and recognise occupants. A possibility of up to four output detection bounding boxes was present during this experimental detection, and the accuracy for each detection was also presented above the output bounding boxes. As given in Figure 4-27, these bounding boxes' size and shape varied between each detection interval. It depended on the size of the detected space, the distance of the camera to the detected person and also the occupant's activity. For this model, it included the identification of regions where occupancy could be present, and if no occupants were detected, a bounding box with the response of 'none' were achieved.

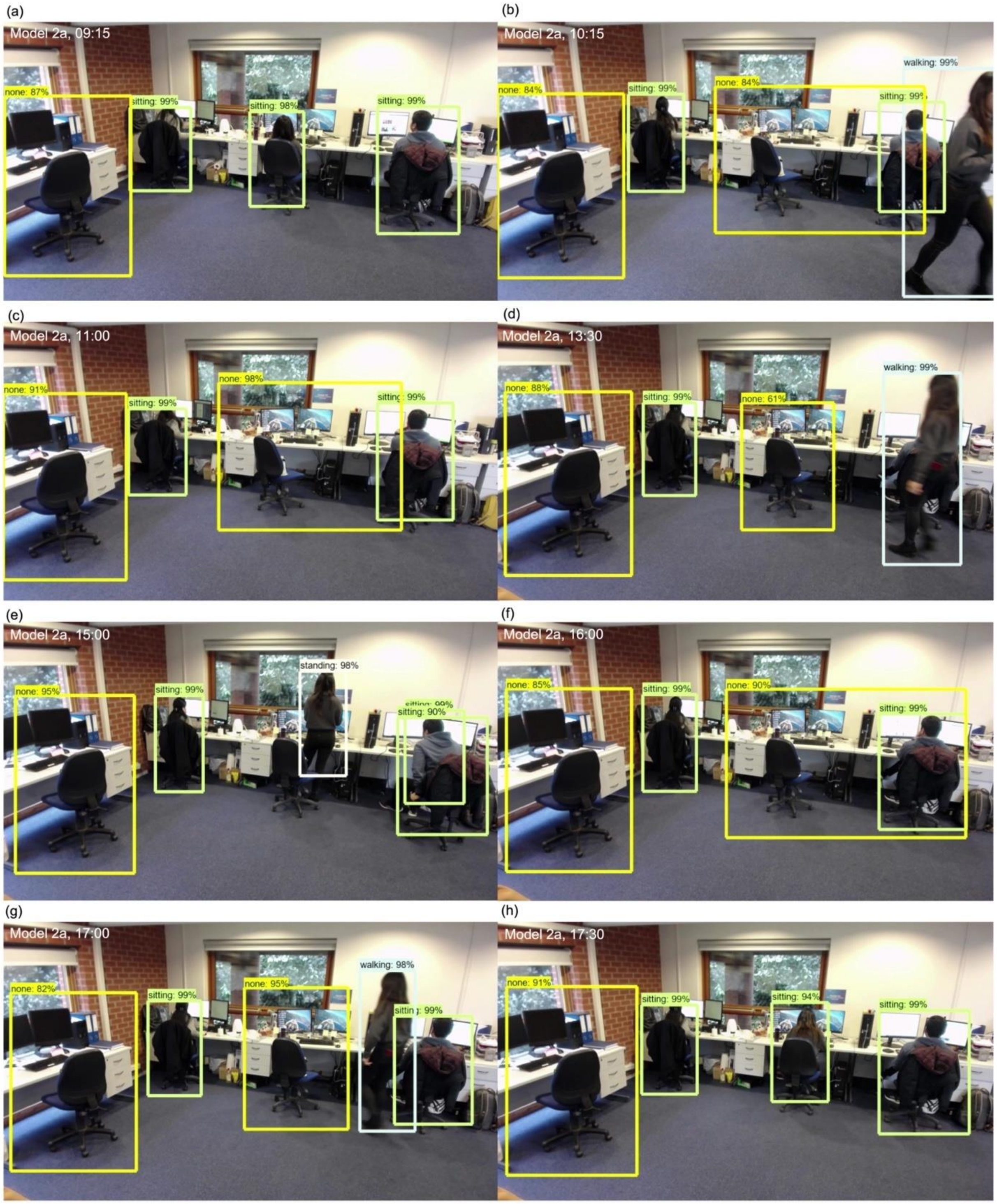


Figure 4-27. Example snapshots at various times of the day of the experimental test of the detection and recognition of occupants within an office space using the deep learning occupancy activity detection approach (Experimental Test 2 using Model 2a).

Figure 4-28a presents the detection performance based on the selected activities. Individual detection accuracies for each activity include walking at 95.83%, standing at 87.02%, sitting at 97.22% and none (when no occupant is present) achieving an accuracy of 88.13%. This shows the capabilities of the deep learning model to recognise the differences between the corresponding human poses for each specific activity. There is some similarity between the action of standing and walking than there is for sitting. Therefore, this suggests the reason to achieve higher accuracy for sitting as compared to standing and walking.

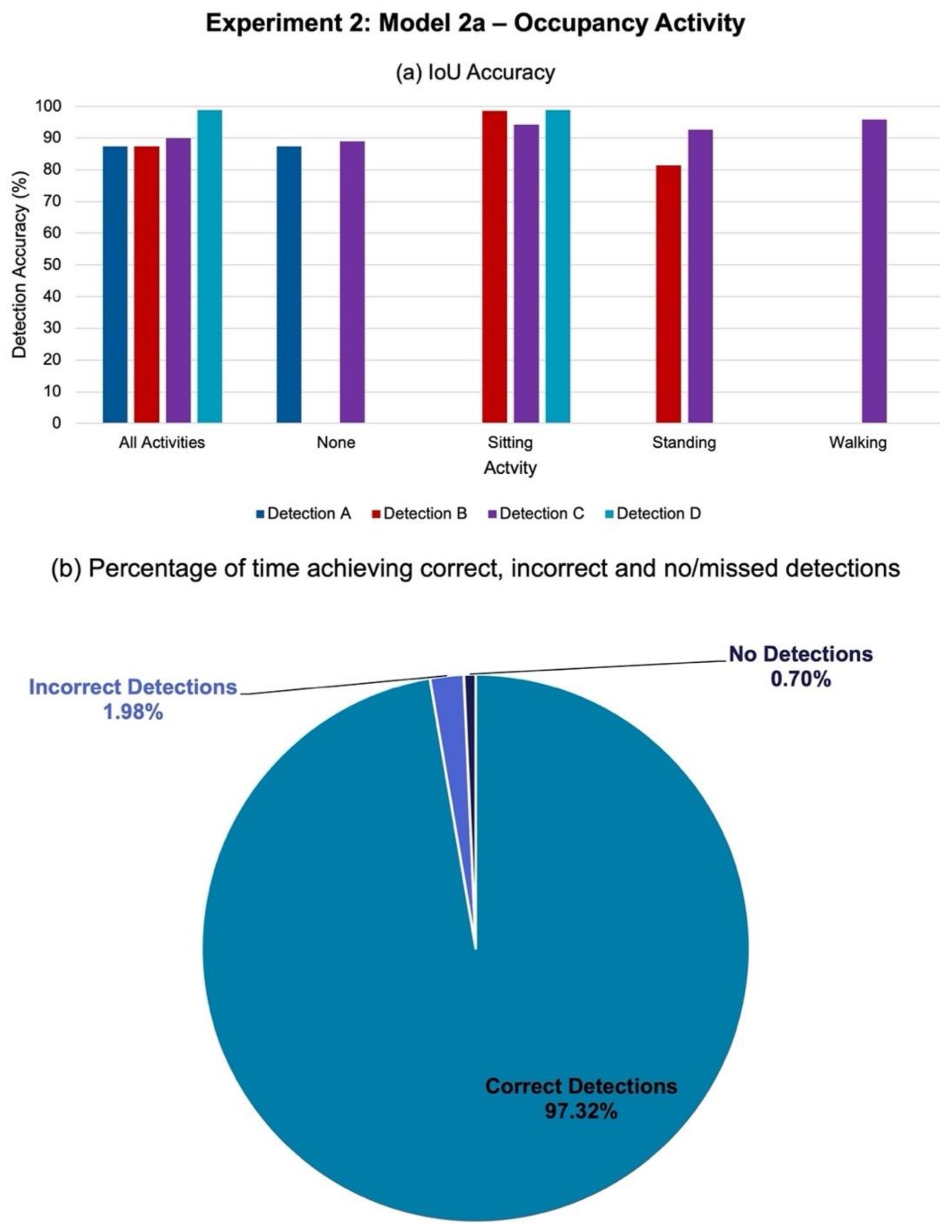


Figure 4-28. Detection performance based on (a). the average IoU (%) across the bounding boxes within the camera detection frame of detections A, B, C and D on each of the selected response outcomes of the detected activities; walking, standing, sitting and none. (b). Overall detection performance during Experimental Test 2a; identifying the percentage of time achieving correct, incorrect and no detections.

This highlights the importance of achieving high accuracy for all activity detections to enable an effective detection approach for building HVAC system controls. Since the following accuracy achieved was only based on small sample size, further model training and testing should be performed to achieve higher detection accuracy for the given occupancy activities to enable further applications of multiple occupancy detection and recognition of a greater number of occupants within different types of office space environments.

Figure 4-28b presents the overall detection performance of the proposed approach during the experimental test. The results showed that the approach provided correct detections 97.32% of the time, 1.98% of the time to achieve incorrect detections and subsequently, 0.70% of the time with no detections. It should be noted that the occupants were asked to carry out their typical office tasks. Overall, this indicates that the selected model provides accurate detections within the desired office space.

Figure 4-29 presents the results in terms of the confusion matrix. For detection A, continuous and accurate detection of ‘non’ was conducted. Both Detection B and D also achieved a rather stable prediction of the occupant performing the activity of sitting. While Detection C achieved the lowest percentage in detections, identifying missed/ incorrect detection between the different activities performed. Effectively, this indicates that the results achieved could be influenced based on each of the individual detections and the type of activity performed by each occupant.

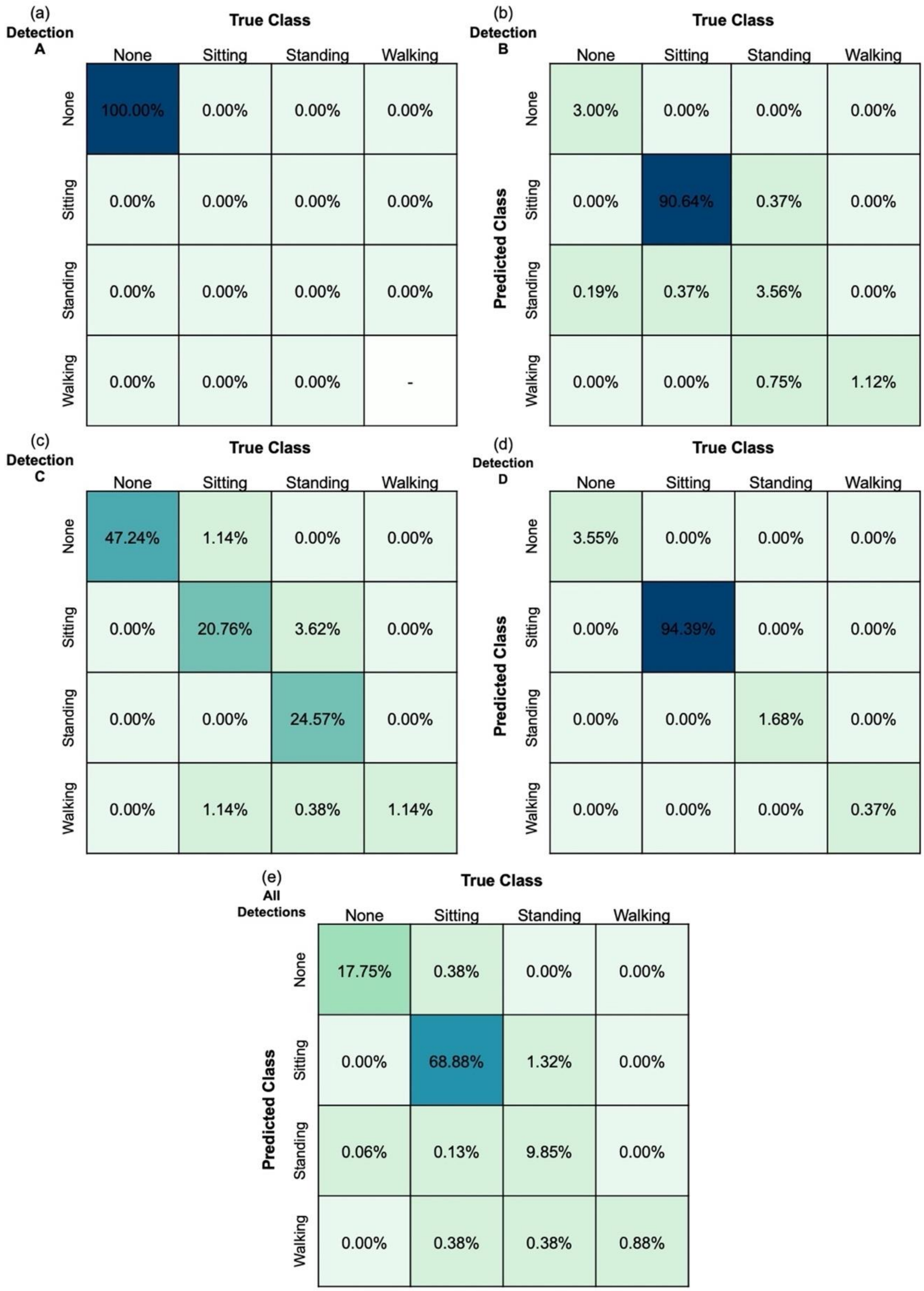


Figure 4-29. Evaluation of detection performance of occupancy activities during Experimental Test 2 using Model 2a in the form of a confusion matrix.

4.5.3. Experimental Test 3 – Open-Plan Office Space (Occupancy activity)

This section presents the detection performance and analysis of the results of occupancy activity detection and recognition made using Model 2b during Experimental Test 3. To enable accurate testing of the developed vision-based detector, a timeline indicating the test's key stages was formed. This allowed the indication of a series of different occupancy activities which were involved, enabling accurate testing of the developed vision-based detector. Examples of the detection images from various stages were presented in Figure 4-30.

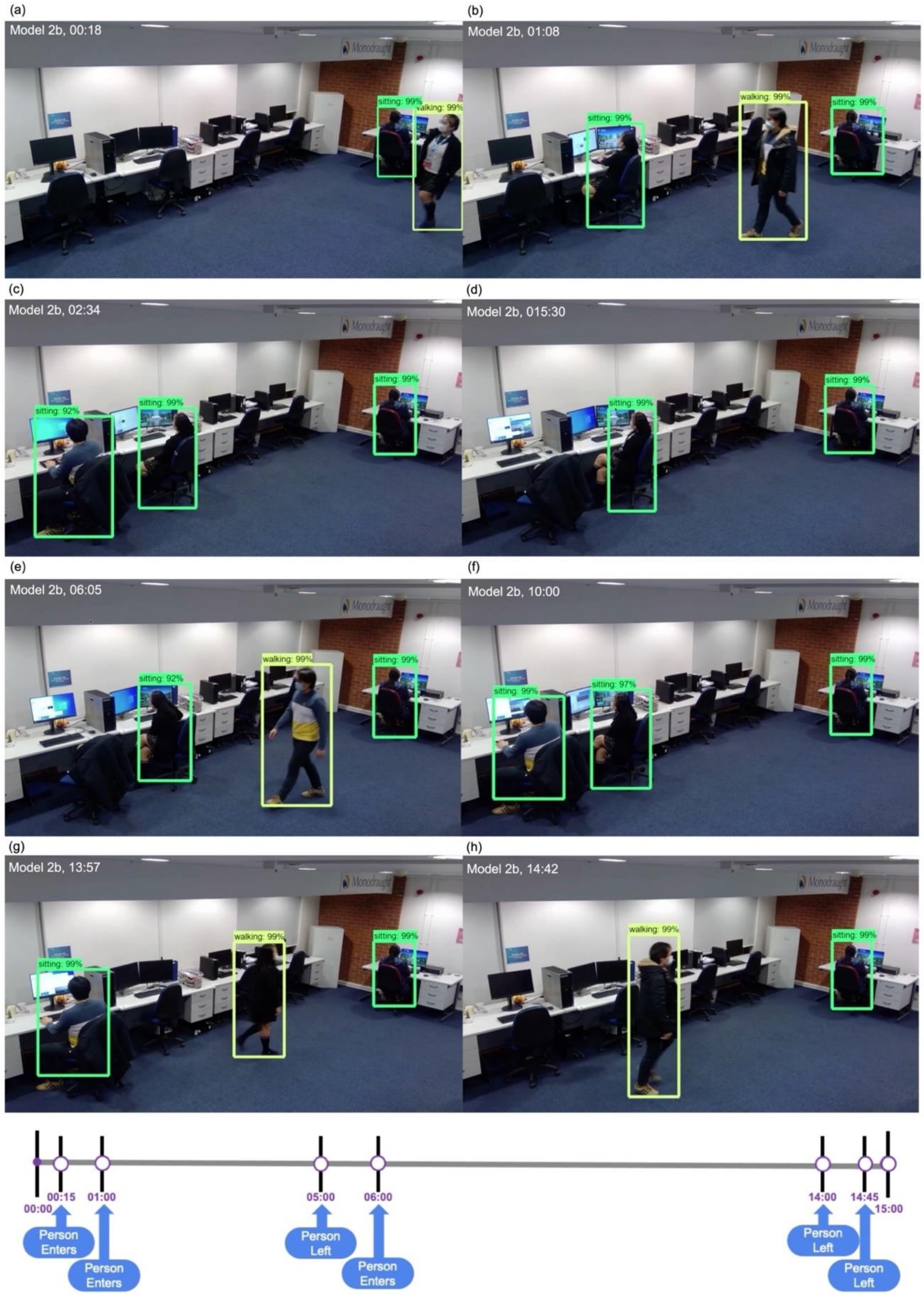


Figure 4-30. Snapshots of various key stages during Experimental Test 3 with the application of occupancy Model 2b.

Figure 4-31a presents the average detection accuracy in terms of the achieved IoU values for each person and activity. It evaluates the detection performance based on the predicted bounding boxes that appeared at every instance. To indicate this, the values were presented above each generated bounding box shown in Figure 4-31a. Overall, it suggests that high confidence is presented for each of the predicted activities, as high percentages were given.

Since the experimental test was conducted for 15 minutes, not all occupants performed all the different activities. However, it still provided enough data to analyse the detection performance. The detection results for Persons A, B and C showed up to 98.47%, 98.80% and 98.46% accuracy on average, respectively. The initial results suggest that the distance between the camera and the object had a negligible effect on the detection accuracy. However, due to the size of the office room, the influence of further distances cannot be evaluated and should be assessed in future works. Overall, the results showed good performance and demonstrated the model's capabilities to recognise the differences between the human poses for each specific activity within an office environment.

While Figure 4-31b presents the results for the detection of occupancy activities classified as correct detection, no detection, or incorrect detection. The detection data was collected every second. It should be noted that the correct detection was achieved when the activity performed by the person was correctly identified and when detection was correctly not made when that activity was not performed. Based on the three activities detected, the best results were achieved for sitting. Due to the similarities between standing and walking poses, the standing activity had incorrect detections for 52.38% of the time, no or missed detections for 9.52% of the time and only correct detection for 38.10% of the time.

Furthermore, to further evaluate the occupancy activity detection performance, the category ‘None’ was added. This indicated that the model was correct in not identifying that activity was performed when an occupant was absent. Correct detection was achieved 83.78% of the time for this category.

Figure 4-31. (a). Average detection accuracy based on the Intersection over Union (IoU accuracy) values that were generated for the different occupancy activities during Experimental Test 3 with Model 2b. (b). The percentage of time achieving correct, incorrect and no/missed detections.

Figure 4-32 presents the generated confusion matrix for each occupant. This helps display how often the approach classifies one activity as another. The columns represent the predicted activities, and the rows represent the actual or correct activities. This table was then used to calculate the TP, TN, FP and FN, which can then be used to measure the precision, recall and F1 score as shown in Chapter 4.2.4. Based on the results, the model performed well when detecting and recognising the sitting activity, with the occasional prediction of the category none or other. In addition, there were times when sitting activity was predicted, even when an occupant was not present. This was considered incorrect detection as it recognised some of the chairs within the detection space as occupants sitting.

While the detection and recognition of standing activity were the poorest. As identified Figure 4-31b, suggests that there was an approximately equal split in achieving correct detection, with it being identified as sitting, and also identified as either walking or not being identified at all. However, the detection of the walking activity showed good performance. The distribution of the results attained for the different responses based on the different factors, including the angle, distance and position relating to the detection camera, shows the approach's ability to achieve good detection performance. Therefore, such conditions reflected upon the associated results in terms of the common evaluation metrics given in Table 4-12. In addition, Person C only performed the activity of sitting, Hence, no data is provided for the other activities.

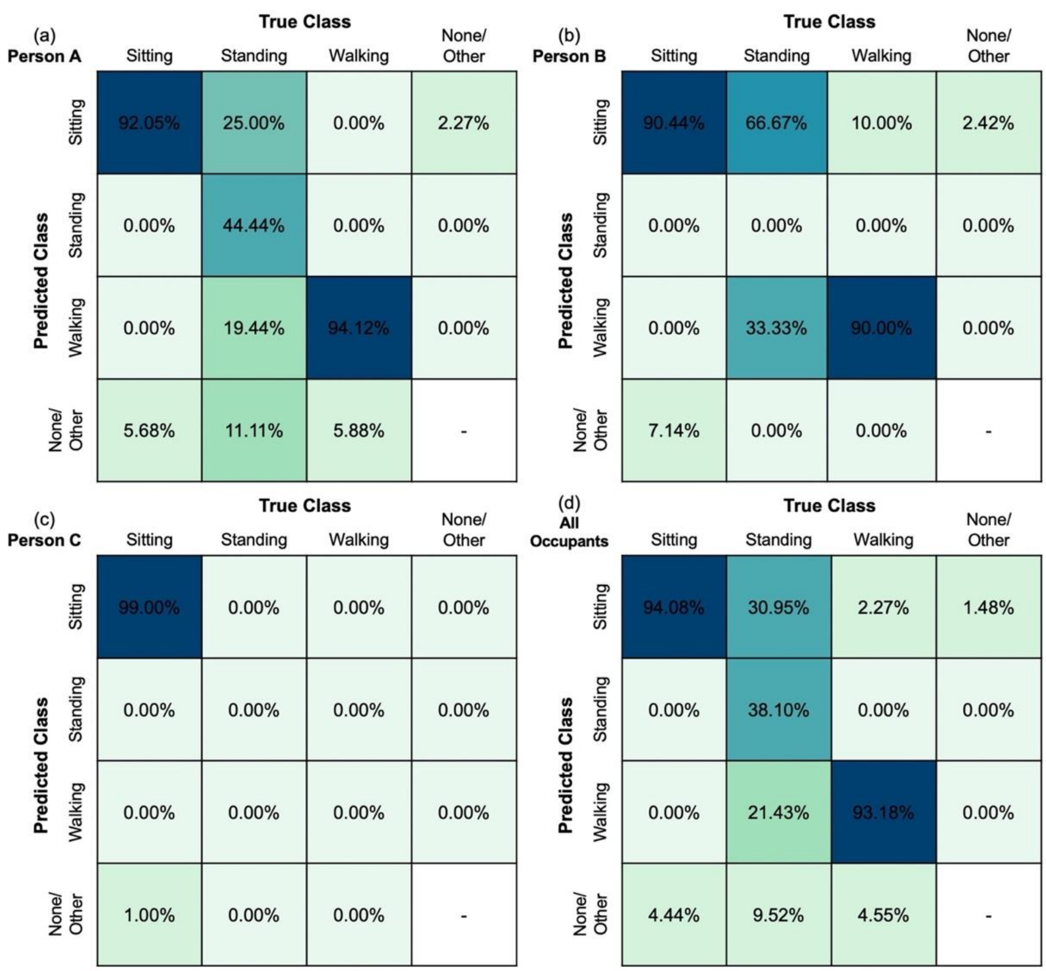


Figure 4-32. Detection of occupancy activities evaluated in the form of the confusion matrix from the application of Model 2b in Experimental Test 3.

Table 4-12. Evaluation of the occupancy activity detection model performance based on common evaluation metrics.

Class	Activity	Accuracy	Precision	Recall	F1 Score
Person A					
1	Sitting	89.02%	0.7715	0.9419	0.8482
2	Standing	81.48%	1.0000	0.4445	0.6154
3	Walking	81.64%	0.8287	0.9412	0.8814
Person B					
1	Sitting	71.26%	0.5335	0.9268	0.6772
2	Standing	66.67%	-	0.0000	0.0000
3	Walking	85.56%	0.7297	0.9000	0.8060
Person C					
1	Sitting	99.00%	1.0000	0.9900	0.9950
2	Standing	N/A	N/A	N/A	N/A
3	Walking	N/A	N/A	N/A	N/A
All Occupants					
1	Sitting	86.95%	0.7305	0.9549	0.8278
2	Standing	79.37%	1.0000	0.3810	0.5518
3	Walking	90.58%	0.8130	0.9318	0.8684
Average for all activities		85.63%	0.8478	0.7559	0.7493

4.5.4. Experimental Test 4 – PGR Study Space (Occupancy activity)

The section presents the detection performance analysis of the application of Model 2b during Experimental Test 4 in the selected building space of the Paton House. Figure 4-33 presents snapshots of the detection and recognition during key stages of the experimental test. Overall, it suggests that some no/false incorrect detections occurred in identifying the occupancy activities. Many of these instances occurred directly for the occupants furthest away from the camera and/or obstructed by objects in the room or by other people.

Figure 4-33. Snapshots of occupancy detection and recognition during key stages of the experimental Test 4 using Model 2b.

Figure 4-34 suggests an overall IoU value of 93.60% was achieved. During the experimental test, the activity of sitting was performed by all occupants. For this activity, consistent IoU was achieved, with an average IoU accuracy of 92.80%. Only some of the occupants performed the standing and walking activities. Hence, further evaluation of other activities must be carried out in future works. The results showed IoU accuracies of 85.25% and 71.25% were achieved for standing and walking activities. Such a lower IoU accuracy was due to the difficulty in detecting and recognising these two types of activities with similar occupancy body forms and shapes. The results in Figure 4-34 also suggest that the IoU accuracy was not highly impacted by the different occupants in the space and their positions in relation to the camera, indicating the detection camera was positioned at a suitable place within the room to capture the activities of most of the occupants.

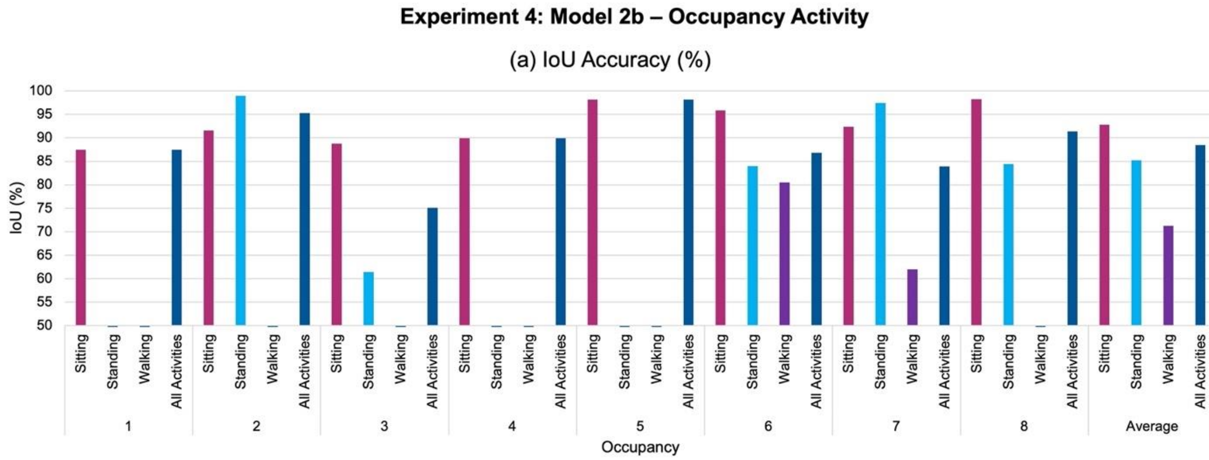


Figure 4-34. Average IoU (%) of the occupants during Experimental Test 4 using Model 2b.

To further summarise the results shown above, results presented in Table 4-13 suggest the achievement of correct, incorrect and no detections would solely be dependent upon each of the individual occupancy behaviour. It should be noted that not all occupants performed all types of activities, hence, N/A was given to some of the categories in Table 4-13. Overall, for all three activities, the percentage of correct detections was the highest, achieving an average of 74.13%, compared to incorrect detections at 1.25% and no/missed detections at 24.63%. The highest no/missed detections were observed for occupant 1, with a no/missed detection rate of 64.12%. This may be due to occupant 1 being the one furthest from the camera, whereby recognition of the activities performed was incorrect or missed.

Table 4-13. Detection performance in terms of the percentage of time achieving correct, incorrect, and no detections for occupancy activities in Experimental Test 3.

Occupancy	Activity	Correct Detections	Incorrect Detections	No/ Missed Detections
1	Sitting	35.55%	0.33%	64.12%
	Standing	N/A	N/A	N/A
	Walking	N/A	N/A	N/A
	All Activities	35.55%	0.33%	64.12%
2	Sitting	56.04%	0.00%	43.96%
	Standing	33.33%	33.33%	33.33%
	Walking	N/A	N/A	N/A
	All Activities	55.81%	0.33%	43.85%
3	Sitting	67.59%	1.03%	31.38%
	Standing	36.36%	63.64%	0.00%
	Walking	N/A	N/A	N/A
	All Activities	66.45%	3.32%	30.23%
4	Sitting	65.12%	0.00%	34.88%
	Standing	N/A	N/A	N/A
	Walking	N/A	N/A	N/A
	All Activities	65.12%	0.00%	34.88%

5	Sitting	98.01%	0.00%	1.99%
	Standing	N/A	N/A	N/A
	Walking	N/A	N/A	N/A
	All Activities	98.01%	0.00%	1.99%
6	Sitting	92.25%	0.00%	7.75%
	Standing	50.00%	41.67%	0.00%
	Walking	100.00%	0.00%	0.00%
	All Activities	91.03%	1.66%	7.31%
7	Sitting	81.88%	3.83%	14.29%
	Standing	92.31%	7.69%	0.00%
	Walking	100.00%	0.00%	0.00%
	All Activities	82.39%	3.99%	13.62%
8	Sitting	98.98%	0.00%	0.00%
	Standing	85.71%	14.29%	0.00%
	Walking	N/A	N/A	N/A
	All Activities	98.67%	0.33%	1.00%
Average	Sitting	74.43%	0.65%	24.80%
	Standing	59.54%	32.12%	6.67%
	Walking	100.00%	0.00%	0.00%
	All Activities	74.13%	1.25%	24.63%

Figure 4-35 provides the associated results in the form of the confusion matrix, with the indication of Model 2b to adequately identify each of the different activities performed by the occupants. The results indicate that the walking activity achieved the greatest number of true positives, with a value of up to 100%. Secondly, it is followed by the sitting activity. This achieved an average of up to 74.18%. The confusion matrix for each occupant suggests that the lower percentage achieved for this activity was due to the occasion of no prediction when this activity was performed. Furthermore, the standing activity was sometimes predicted as sitting and/or no detection of such activity, giving the worst performance compared to the other responses. The overall performance shown in Figure 4-35i was used to calculate the common evaluation metrics, including the accuracy, precision, recall, and the associated F1 scores given in Table 4-14.

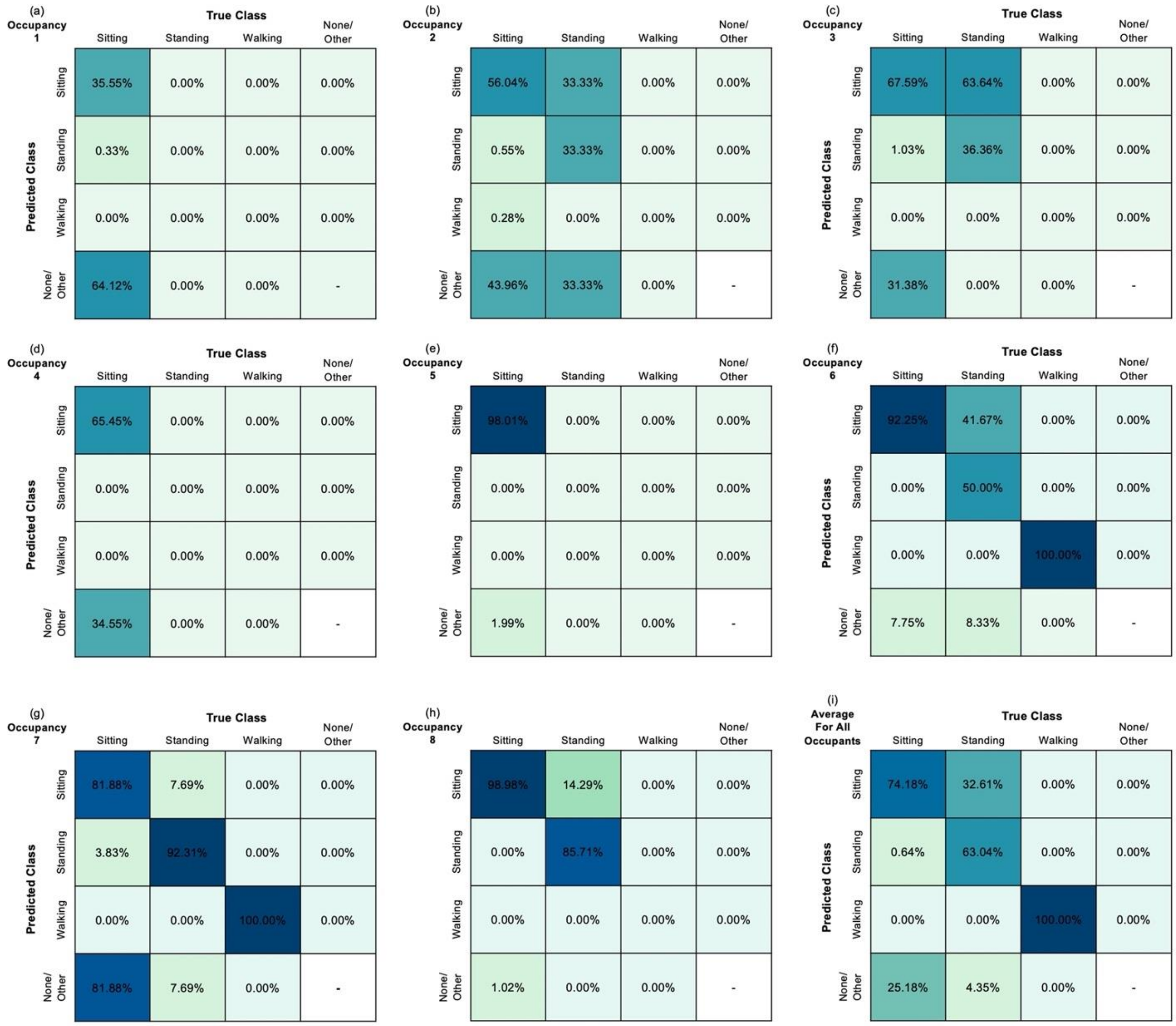


Figure 4-35. Detection performance results for Model 2b (occupancy activity detector) in the form of a confusion matrix.

The associated evaluation metrics results are shown in Table 4-14. This model provided an accuracy of 89.37% with an F1 score of 0.8298. Since multiple responses were selected for this model, further development is required to ensure a consistent level of detection accuracy could be achieved across the different occupancy activities. Furthermore, compared with Model 1 applied in Experimental Test 1, both models were only tested on a single experimental test, further analysis is required to evaluate whether both models can effectively assist the operations of building HVAC systems and enhance the building energy performances through further testing on different indoor spaces and variation in variation occupancy conditions. Overall, Model 1 may be effective in predicting the CO2 concentration levels based on the occupancy count, while Model 2b would be more suitable for evaluating the heat gains from occupants or predicting the activity rate for thermal comfort calculations in real time.

Table 4-14. Detection performance results based on common classification evaluation metrics from the application of Model 2b in Experimental Test 4.

Occupancy	Class	Accuracy	Precision	Recall	F1 Score
1	Sitting	35.55%	1.0000	0.3556	0.5245
	Standing	N/A	N/A	N/A	N/A
	Walking	N/A	N/A	N/A	N/A
	All Activities	35.55%	1.0000	0.3556	0.5245
2	Sitting	61.35%	0.6270	0.5604	0.5918
	Standing	66.67%	1.0000	0.3334	0.5001
	Walking	N/A	N/A	N/A	N/A
	All Activities	64.01%	0.8135	0.4469	0.5460
3	Sitting	51.98%	0.5150	0.6759	0.5846
	Standing	67.67%	0.9725	0.3636	0.5293
	Walking	N/A	N/A	N/A	N/A
	All Activities	59.83%	0.7438	0.5198	0.5570
4	Sitting	64.65%	1.0000	0.6545	0.7912
	Standing	N/A	N/A	N/A	N/A
	Walking	N/A	N/A	N/A	N/A
	All Activities	64.65%	1.0000	0.6545	0.7912
5	Sitting	98.01%	1.0000	0.9801	0.9800
	Standing	N/A	N/A	N/A	N/A
	Walking	N/A	N/A	N/A	N/A
	All Activities	98.01%	1.0000	0.9801	0.9800
6	Sitting	83.53%	0.6888	0.9225	0.7887
	Standing	83.33%	1.0000	0.5000	0.6667
	Walking	100.00%	1.0000	1.0000	1.0000
	All Activities	88.95%	0.8963	0.8075	0.8185
7	Sitting	91.40%	0.9141	0.8188	0.8638
	Standing	96.16%	0.9602	0.9231	0.9413
	Walking	100.00%	1.0000	1.0000	1.0000
	All Activities	95.85%	0.9581	0.9140	0.9350
8	Sitting	92.35%	0.8738	0.9898	0.9282
	Standing	92.86%	1.0000	0.8571	0.9231
	Walking	N/A	N/A	N/A	N/A
	All Activities	92.61%	0.9369	0.9235	0.9257
Average	Sitting	80.64%	0.6975	0.7418	0.7190
	Standing	87.47%	0.9899	0.6304	0.7703
	Walking	100.00%	1.0000	1.0000	1.0000
	All Activities	89.37%	0.8958	0.7907	0.8298

In summary, four experimental tests were conducted in two locations with detections using three different occupancy detection and recognition models. Results suggest Model 1 provided accurate detection with a high possibility of determining the number of occupants present in a building space. Experimental Tests 2, 3, and 4 indicated the ability of Models 2a and 2b to recognise occupancy performing different activities within a building space. A comparison between the application of Model 1 for people detection and Model 2b for occupancy activity was given in Figure 4-36 and Video 1. The same video recording was applied during both Experimental Tests 1 and 4 in Paton House, the University of Nottingham to allow the identification of the benefits and limitations of both types of models applied to the same indoor setting. Based on the comparison shown and the detailed analysis given in Chapters 4.5.1. and 4.5.4, it suggests that the selection of the model to be applied is dependent upon the purpose required. However, overall to improve building energy performances, the generation of the DLIP, whereby constant data about the number of occupants performing each of the selected activities is envisioned to provide more valuable data about occupants within a building space regarding heat emission for more effective HVAC system operations. This highlights the importance of developing an accurate and stable occupancy activity detector to become effective and valuable for building control systems. It is envisaged that the proposed detection approach could have a greater impact when applied in a larger indoor space with more occupants and different types of activities.

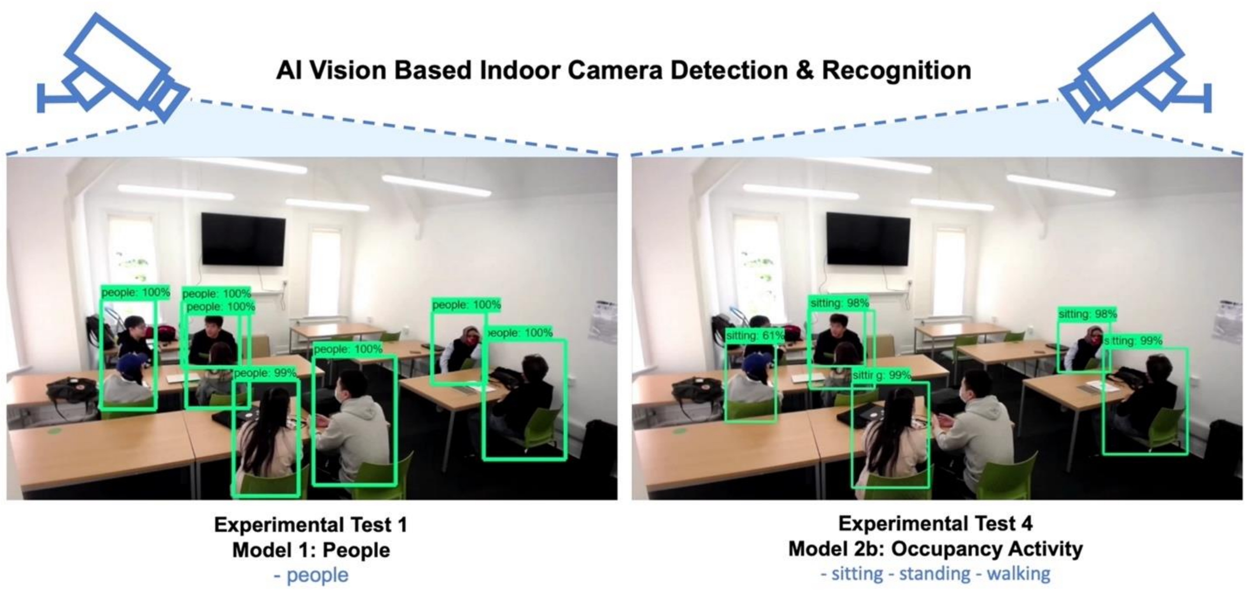


Figure 4-36. Comparison between the application of Model 1 for people detection and Model 2b for occupancy activity detection during experimental tests 1 and 4. Refer to Video 1 to see the example of detection and recognition conducted using the same video recorded during Experimental Tests 1 and 4 in Paton House, University of Nottingham.

4.6. Evaluation of the Proposed Approach Using Building Energy Simulation

This chapter presents the evaluation of the proposed vision-based occupancy detection and recognition approach via assessments of the applications of the different trained models (Model 1, Model 2a and 2b) using building energy simulations. The methods presented in Chapter 4.2.5 with the workflow process shown in Figure 3-7 were applied. As mentioned, two types of BES were conducted. Chapter 4.6.1 focuses on the ‘Type 1’ assessment based on the impact of the detection performance using the vision-based approach on building energy via comparisons of the generated DLIPs from the experimental tests with constant static predefined scheduled profiles. Whereas Chapter 4.6.2 presents the ‘Type 2’ analysis, focusing on scenario-based situations. Furthermore, Chapter 4.6.3 provides a further investigation of the impact on building system operations and strategies by seeking ways in which the vision-based occupancy detector could assist the operations of building HVAC systems to ensure that sufficient interior thermal conditions and air quality were attained while reducing unnecessary building energy loads to improve building energy performances.

4.6.1. Impact of the Detection Performance using the Vision-based Approach on Building Energy

The generated DLIP during Experimental Test 2 using Model 2a in Figure 4-22b and its comparison with constant static profiles in Figure 4-23b, suggested a 37.38% and 50.25% difference between the Typical Office Profiles 1 and 2 and the Actual Profile, indicating a large discrepancy between the true occupancy activities performed within the building spaces and the scheduled occupancy profiles. This highlights the importance of the vision-based detector. Hence, using these different profiles, the following section presents an analysis of the impact of the proposed deep learning activity detection approach on building energy consumption during a typical winter working day. By applying the knowledge of the building geometry and conditions, along with the experimental test conditions given in Chapters 3.3.5, 3.4 and 4.5.2, the building space was modelled.

Table 4-15 summarises the simulation cases and the associated occupancy and building profiles used for the simulation and analysis. The different variations in occupancy profiles were created to compare the DLIP and to evaluate the impact of the use of control strategies, informed by real-time multiple occupancy activity detections on building energy performance. Cases 1 and 2 follow the current building operational systems based on the use of static or fixed control setpoints. Typical office 1 assumes that the occupants are sitting most of the time during the selected period (sedentary activity), and Typical office 2 assumes that the occupants are walking most of the time during the selected period. For the simulation cases, maximum sensible and latent occupancy gains of 75 W and 70 W were assigned. This enabled the representation of all activities performed within the office space, with walking being the maximum at 100%, followed by standing at 79%, sitting at 64%, napping at 50%, and no activities (none) would present at 0%. Furthermore, the occupancy density of 1 was assigned to each of the DLIP and actual observation profiles. However, for the typical office profiles, it was acknowledged that the maximum number of occupants present within the room on the selected day would be three, so this was assigned as the maximum occupancy density for these cases. Furthermore, a description of the building's heating, cooling and ventilation conditions are also shown in the corresponding table.

Table 4-15. Summary of the occupancy and building energy modelling profiles used for the simulation of different conditions to identify the impact of the vision-based approach towards building energy.

<table>
<tr><th rowspan="3">Name</th><th rowspan="3">Profile Description</th><th colspan="2">Occupancy</th><th rowspan="2">Heating</th><th rowspan="2">Ventilation</th></tr>
<tr><th colspan="2">Internal Gains [Table 4-1]</th></tr>
<tr><th>Max. Sensible Gain (W/Person)</th><th>Max. Latent Gain (W/Person)</th><td rowspan="5">Standard Constant Heating with the setpoint at 21°C</td><td rowspan="5">Standard constant ventilation following a typical office schedule</td></tr>
<tr><td>Typical 1</td><td>Constant sitting between 09:00 – 18:00 (Typical 1 Profile, Figure 4-23b)</td><td>70</td><td>45</td></tr>
<tr><td>Typical 2</td><td>Constant walking between 09:00 – 18:00 (Typical 2 Profile, Figure 4-23b)</td><td>75</td><td>70</td></tr>
<tr><td>Actual Observation</td><td>Based on actual observation of Detection A, B, C, D (Actual Observation Profile, Figure 4-23b)</td><td>75</td><td>70</td></tr>
<tr><td>Deep Learning Influenced</td><td>Based on DLIP Detection A, B, C, D (DLIP, Figure 4-23b)</td><td>75</td><td>70</td></tr>
</table>

The following provides an analysis of the impact of the proposed deep learning activity detection approach on building energy consumption during a typical winter working day. The generated DLIPs are compared with the static scheduled profiles.

Figure 4-37 presents the building energy simulation (BES) results of the occupancy sensible and latent gains. Typical 1 and 2 results followed the assigned static scheduled occupancy profiles. Based on the simulated conditions, it can be observed that the typical office profiles over-predicted the occupancy heat gains within the room. The DLIP results provided a better estimation of the occupancy internal heat gains. The occupancy heat gains were high from 09:00 – 10:00 when there was an increase in activity movement in the space. Lower occupancy heat gains were observed between 13:15 – 13:30 as most of the occupants had left the office space during this time. This shows the potential of the deep learning method in providing a more accurate estimation of the internal heat gains. Additionally, Figure 4-37b shows the predicted latent heat gains. The accurate prediction of the latent heat gains is important for the estimation of the required dehumidification load and can further reduce unnecessary energy usage. This is important for buildings located in tropical or humid climates as it can lead to heavy usage of air-conditioning systems. The method should be further evaluated by incorporating it into buildings with different climates. Furthermore, Figure 4-37c summarises the total sensible and latent occupancy heat gains. Based on the simulated conditions, the occupancy heat gains predicted by using the Typical 1 and 2 profiles suggests an overestimation of 22.9% and 54.9% as compared with the Actual Observations. This is equivalent to 83.2 kWh and 199.8 kWh. In comparison, there was a 1.13% (4.1 kWh) difference between the DLIP method and Actual Observations.

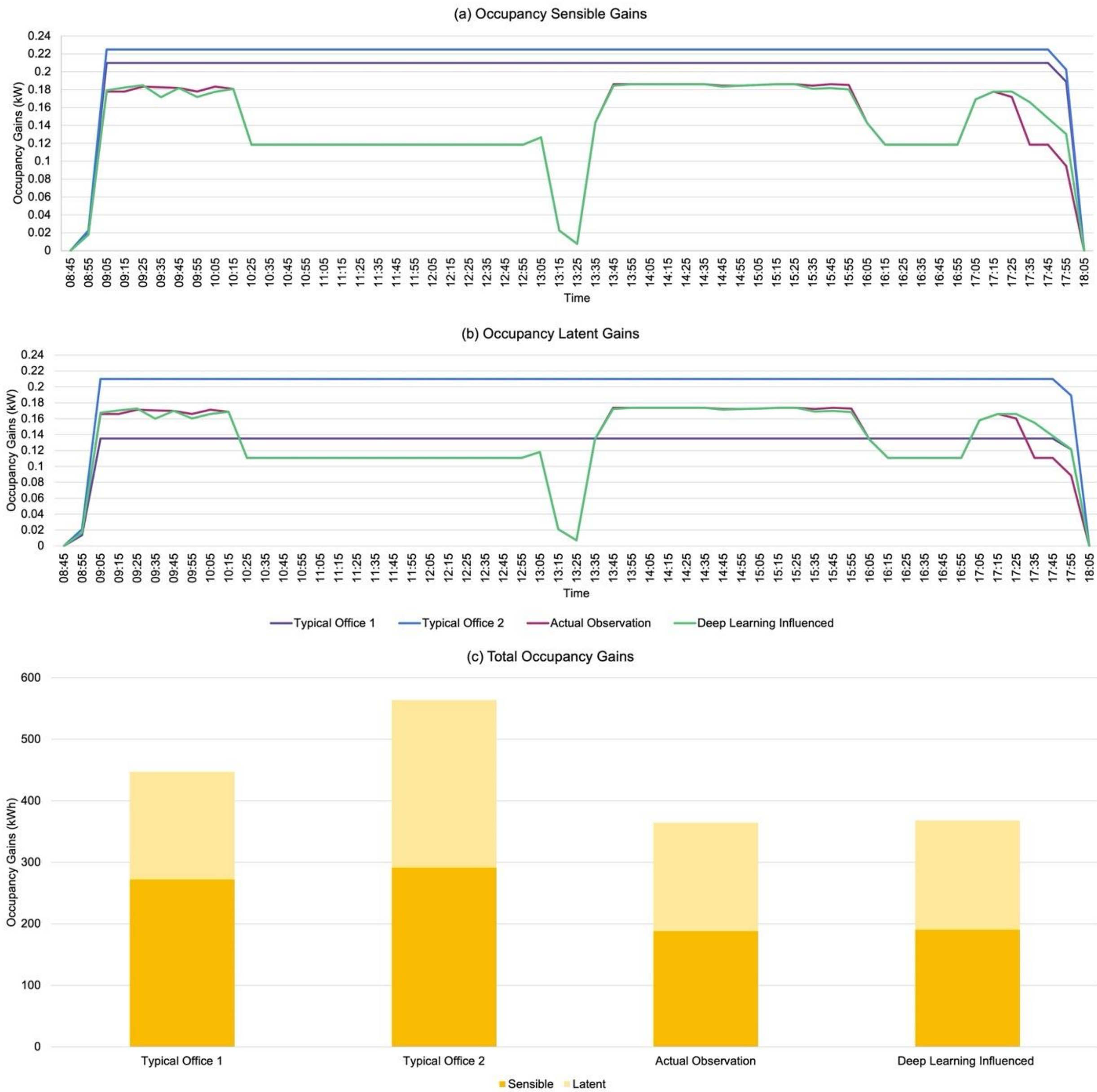


Figure 4-37. Comparison of the (a). Sensible heat gains, (b). Latent heat gains and (c). Total occupancy gains were achieved when different occupancy profiles were assumed within the operations of the building's HVAC system. (Within the office space during the detection period of 09:00 – 18:00).

Comparing the simulation results of the BES model with different occupancy profiles, Figure 4-38 shows the heating demand for office space during a typical cold period in the UK. Figure 4-38a presents the heating load across time, and Figure 4-38b compares the total heating loads for the selected day. The predicted heating load for the model with the DLIP profile was 375.5 kW and was very similar to the Actual Observation profile. While the model with Typical Office 1 and 2 profiles had a heating load of 372.0 kW and 371.8 kW. As expected, the DLIP and actual heat gains in the space were lower than static profiles, which assumed constant activities in the space, and hence the heating requirement will be higher to provide comfortable indoor conditions.

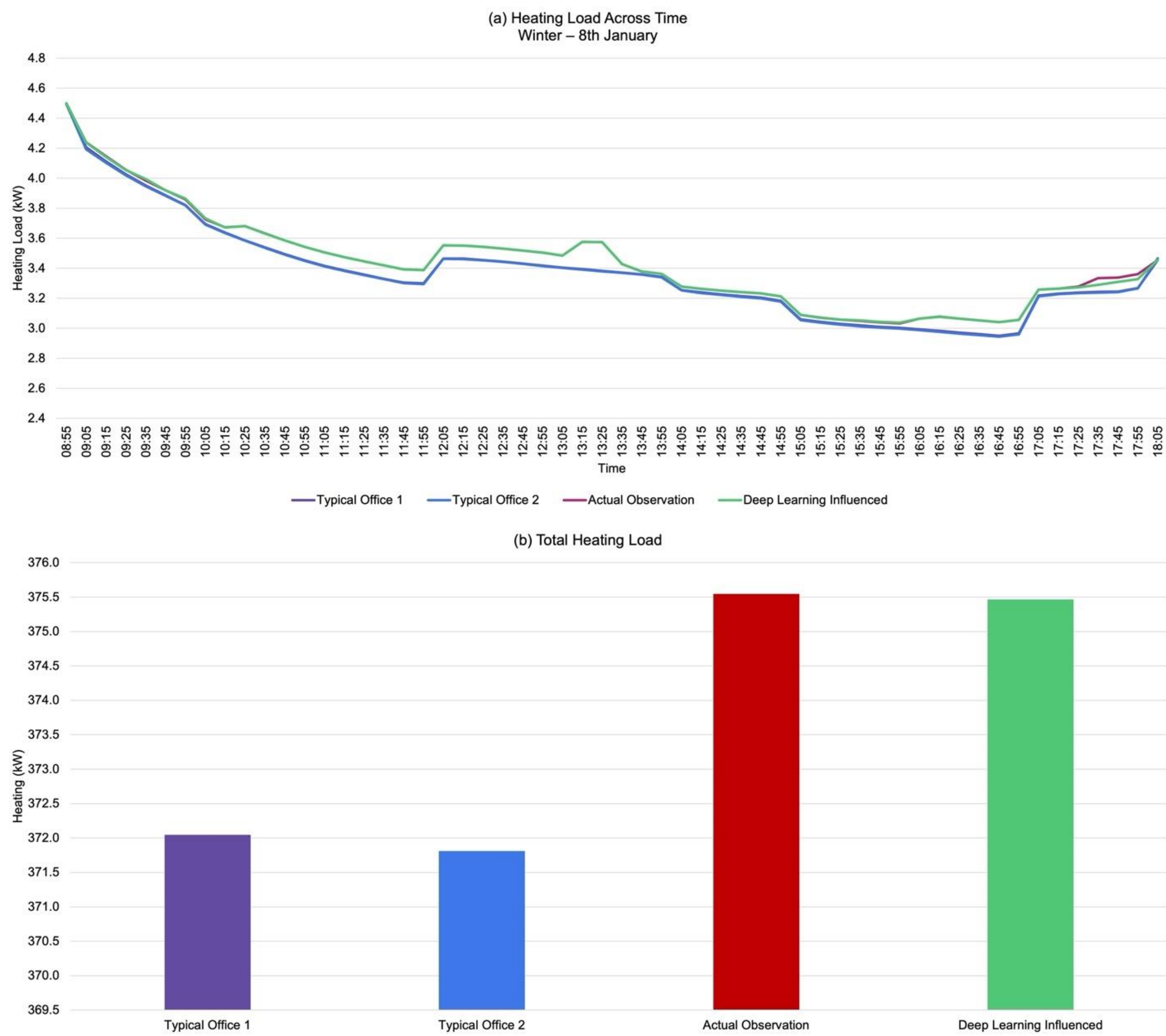


Figure 4-38. Comparison of the (a). Heating across time and, (b). The total heating load was achieved when different occupancy profiles were assumed within the operations of the building's HVAC system.

Overall, such results suggest that the use of static or scheduled occupancy profiles currently used in most building HVAC systems operations and in building energy modelling and simulations presents an over or underestimation of the occupancy heat gains and could lead to substantial inaccurate heating and cooling energy predictions. Solely based on these initial BES results and set conditions, a difference of up to 55% was observed between DLIP and static occupancy heat gain profiles, this is equivalent to 8.33 kW.

4.6.2. Scenario-Based Simulations and Analysis

Since occupancy behaviour and actions are unpredictable, the results achieved in Chapter 4.6.1 cannot be entirely used to represent all buildings and office spaces, the following section presents the analysis of the approach on a series of different scenario-based cases, replicating situations that would typically occur within the same indoor environment.

Applying the same case study building, different scenario-based cases were created Figure 4-39, Table 4-16). Each case (Deep Learning Scenario-based Case 1 – 4) represented a different variation in occupancy activity patterns within the office space. These were compared with Typical Office 1 and 2 static profiles, which represented the application of typical predefined, or fixed schedules. The two fixed occupancy profiles are presented in Figure 4-39 (a1 and a1'). Since it was assumed that there would normally consist of up to 8 people working within the office space, a constant number of 8 people was assumed during the working hours. Typical Office 1 assumed that the occupants are performing sedentary activities within the office space. While Typical Office 2 assumed a higher activity rate by the occupants. The scenario-based profiles assigned for the Deep Learning Scenario-Based 1, 2, 3, and 4 cases assumed more realistic occupancy patterns within the office space. The description of occupancy patterns for each of these scenarios is detailed under each of the given profiles in Figure 4-39a2-a5.

Furthermore, heating and cooling profiles were assigned to maintain indoor temperatures within a suitable range to provide occupants with thermal comfort. As mentioned in Chapter 3.1, current standards and guidelines including ASHRAE 55 [125] and ASHRAE 90.1 [126] suggest a generalised setpoint temperature is currently applied within most buildings and rooms. This includes occupied hours with a temperature range of 22 – 27°C for cooling and 17 – 22°C for heating. For unoccupied hours, temperatures of 27 – 30°C for cooling and 14 – 17 °C for heating were also advised. Moreover, CIBSE Guide A Table 1.5 [198] suggests office buildings maintained at an operative room temperature of 21 – 23°C during the winter and 22 – 25°C in the summer. Hence, all cases applied in this section were simulated with the room heating setpoint temperature of 21°C – 22°C during the building's operational hours. In addition, a temperature of 15°C was set for the unoccupied hours, and a cooling setpoint temperature of 25°C was assigned. For both the Typical Office 1 and 2 cases, building operational hours of 06:00 – 18:00 were assumed. However, for the Deep Learning Scenario-Based Cases, the HVAC systems' operation would be based on the detected occupancy level, as indicated in Figure 4-39b2-b5 and Figure 4-39c2-c5. The ventilation profiles (Figure 4-39d1-d5) were also based on the occupancy patterns. Table 4-16 summarises the occupancy and HVAC operation profiles for the simulation of the scenario-based cases. Each scenario was performed for a day during a typical office week during both heating and cooling seasons.

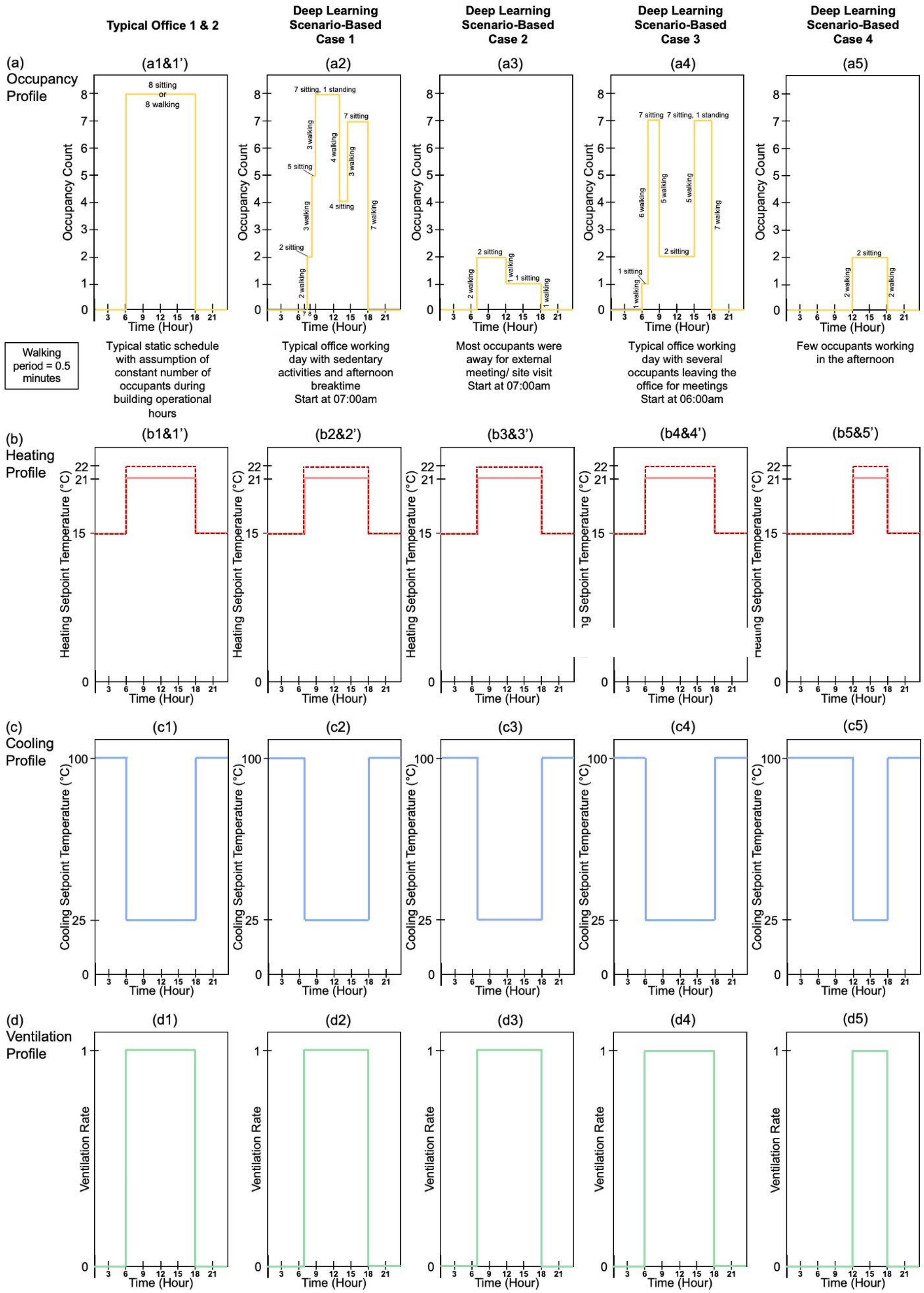


Figure 4-39. Occupancy and HVAC profiles for the scenario-based simulation cases.

Table 4-16. Summary of the occupancy and HVAC operation profiles for the simulation of the scenario-based cases.

	Cases					
	Typical Office 1	**Typical Office 2**	**Deep Learning Scenario 1**	**Deep Learning Scenario 2**	**Deep Learning Scenario 3**	**Deep Learning Scenario 4**
Description	The deep learning method is not applied. Static scheduled profiles assumed		The deep learning occupancy detection model used. Heating, cooling and ventilation profiles are dependent on the assigned occupancy profile			
Occupancy Profile	Figure 4-39 (a1): Typical Office 1 (Constant Sitting)	Figure 4-39 (a1'): Typical Office 2 (Constant Walking)	Figure 4-39 (a2) Deep Learning Scenario-Based Profile	Figure 4-39 (a3) Deep Learning Scenario-Based Profile	Figure 4-39 (a4) Deep Learning Scenario-Based Profile	Figure 4-39 (a5) Deep Learning Scenario-Based Profile
Number of occupants present in the room	8	8	Varies according to the occupancy profile (achieved by the application of the deep learning detection approach)			
Occupancy Internal Gains	For sitting: Maximum sensible gain: 70W/person Maximum latent gain: 45 W/person	Maximum sensible gain: 75 W/person Maximum latent gain: 70 W/person (To meet the maximum total of 145 W/person for the activity of walking)				
Heating Profile	Simulation A: Heating setpoint temperature: 21°C during operational hours					
	Figure 4-39 (b1)	Figure 4-39 (b1)	Figure 4-39 (b2)	Figure 4-39 (b3)	Figure 4-39 (b4)	Figure 4-39 (b5)
	Simulation B: Heating setpoint temperature: 22°C during operational hours					
	Figure 4-39 (b1')	Figure 4-39 (b1')	Figure 4-39 (b2')	Figure 4-39 (b3')	Figure 4-39 (b4')	Figure 4-39 (b5')
Cooling Profile	Figure 4-39 (c1)	Figure 4-39 (c1)	Figure 4-39 (c2)	Figure 4-39 (c4)	Figure 4-39 (c4)	Figure 4-39 (c5)
Ventilation Profile	Figure 4-39 (d1)	Figure 4-39 (d1)	Figure 4-39 (d2)	Figure 4-39 (d4)	Figure 4-39 (d4)	Figure 4-39 (d5)
Ventilation Conditions	Infiltration Rate: 0.5 ACH Maximum conditions: 10 L/s					

The following presents the simulation results. Figure 4-40 provides the predicted daily occupancy sensible and latent heat gains. Typical Office 1 and 2 results showed the predicted occupancy heat gains when static or fixed occupancy profiles were set. This verified the findings made in Chapter 4.6.1 whereby the use of such profiles can lead to unrealistic and less diverse variation in occupancy heat gains. The four Deep Learning Scenario-Based cases suggest the occupancy gains were directly related to the number of occupants and the type of activities performed by each occupant during the day. For Case 4 when the room was unoccupied for the majority of the time and only a small number of occupants were present for a few hours, it led to the lowest occupancy heat gains (1.40 kWh). However, if such a situation happens and the building was operated based on the assumption corresponding to the occupancy profiles for Typical Office 1 or 2, it can lead to an overestimation by up to 9.60 kWh and 12.50 kWh.

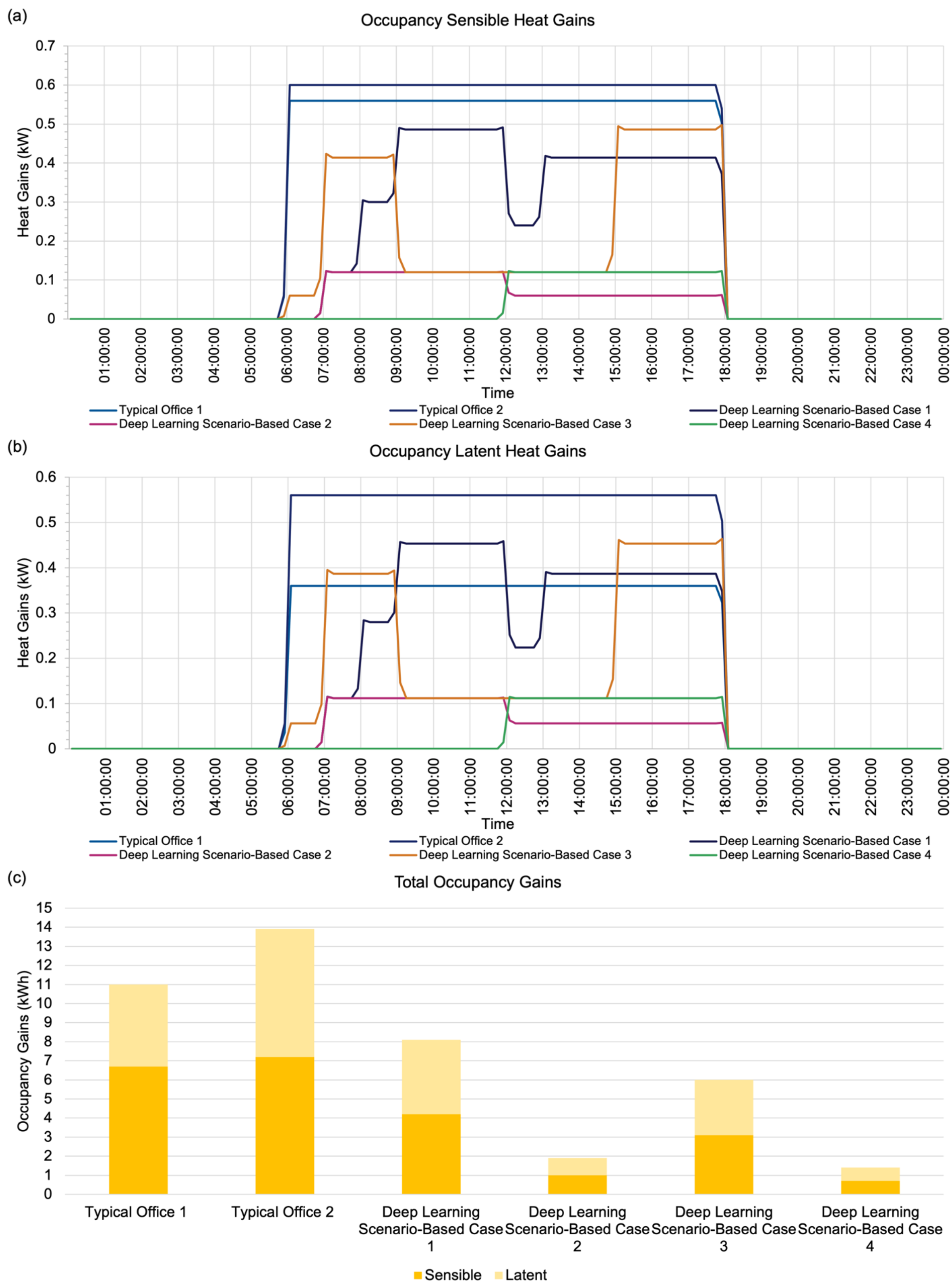


Figure 4-40. Comparison of the occupancy heat gain profiles generated using the proposed occupancy activity framework approach and the typically scheduled profiles. Variation of gains across time, (a). occupancy sensible heat gains, (b). occupancy latent heat gains and (c). the total occupancy gains.

The following results present the heating demand for the simulation cases for a typical winter day, Wednesday 8th January. Given that the simulations were performed with two different heating setpoint temperatures during the building operational hours, Figure 4-41a shows that the heating load for all cases would increase by an average of 2.62 kWh when the heating setpoint was set at 22°C as compared to 21°C. Therefore, changing the room set point temperature by 1°C can change the total heating demand by up to 15.40%. Depending on the occupancy level, slight adjustments to the setpoint can be done to significantly affect the energy demand of the building.

Figure 4-41b and c present the distribution of the predicted daily heating load. The results in Figure 4-41a indicated that the Deep Learning Scenario-based Cases had a higher heating load than the Typical Office 1 and 2. It indicated that the use of the detection approach led to a reduction in occupancy heat gains, which impacted the heating load. Case 2 achieved the highest heating load with 18.90 kWh and 21.60 kWh for the two setpoint temperatures. This was due to the low number of occupants present and lower emission rate activities (mostly sitting), resulting in low occupancy heat gains. In comparison, Case 1 had the highest amount of occupancy heat gains and heating loads of 15.7 kWh and 18.4 kWh. While the lowest heating demand was observed for Case 4, which had no occupants in the morning and hence the heating setpoint was automatically lowered to 15°C when using the proposed control strategy.

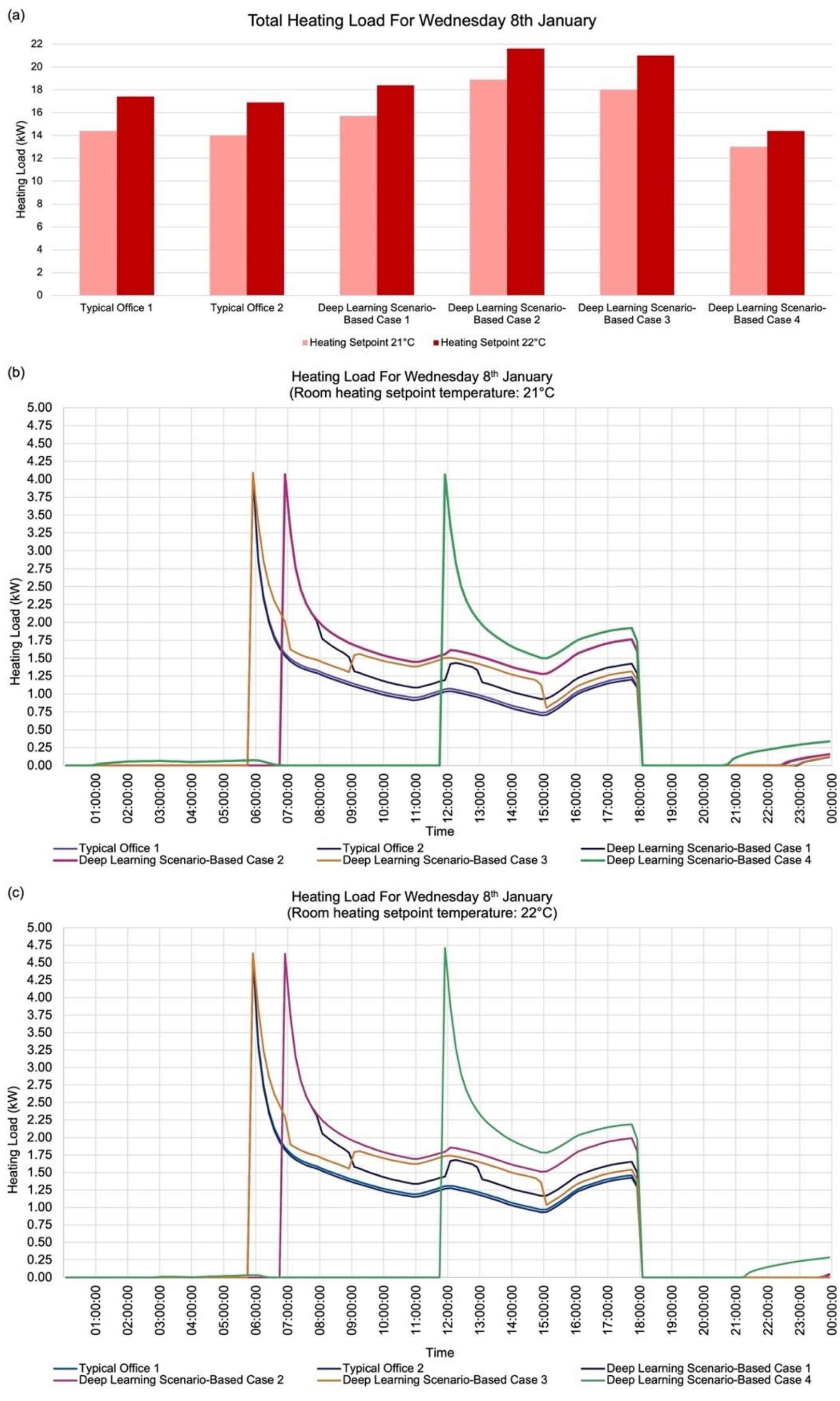


Figure 4-41. (a). Comparison of the total heating load achieved under the different deep learning scenario-based cases compared to the typical occupancy profiles, with room heating setpoint at 21°C and 22°C. (b). and (c). Variation of heating load across time for all simulated cases when a room heating setpoint temperature of 21°C and 22°C was assigned.

Figure 4-42 provides an estimation of the cooling loads for the various simulation cases during a typical day in the cooling season, Wednesday 14th May. Since the cooling setpoint temperature was maintained at 25°C during building operational hours (Figure 4-39), Figure 4-42a suggests the changes in the heating setpoint of 21°C and 22°C presented minimal variations in the total cooling loads, with only an increase by an average of 0.05 kWh, which is equivalent to a change of 0.26%. As shown, the total cooling loads were 20.90 kWh and 21.00 kWh for Typical Office 1 and 21.50 kWh for Typical Office 2. Overall, using typical profiles for occupancy would result in a higher cooling load than the deep learning approach-based cases. Higher amounts of cooling are required when there is a higher occupancy heat gain in the space. For example, Deep Learning Scenario 1 achieved the highest occupancy gains. This resulted in the highest cooling load with 18.80 kWh.

Like the evaluation for heating, the lowest cooling loads were achieved by Case 4 as the deep learning detection approach assisted the cooling system's operations. Based on the response to the detections made, the cooling setpoint temperature becomes 25°C once occupants were present within the space. Hence, no cooling was required before noon, and only after this time, cooling up to a peak of 3.879 kW was required to provide a thermally comfortable environment for occupants.

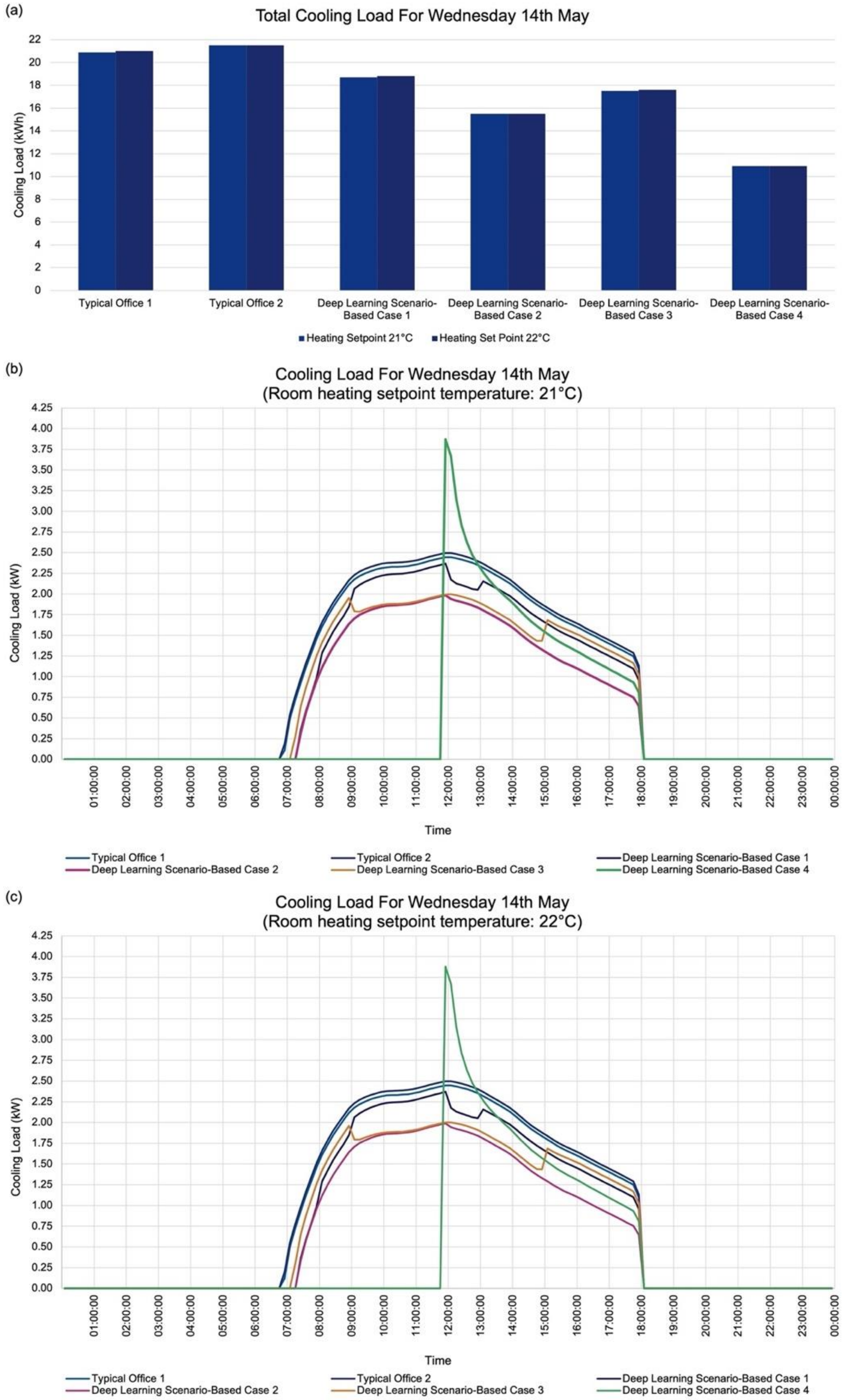


Figure 4-42. (a). Comparison of the total cooling load achieved under the different deep learning scenario-based cases compared to typical occupancy profiles, with room heating setpoint at 21°C and 22°C. (b). and (c). Variation of cooling load across time for all simulated cases when a room heating setpoint temperature of 21°C and 22°C was assigned.

Performing BES with various scenario-based cases enabled the assessment of the deep learning approach and provided insights into how the proposed detection method can enable HVAC systems to adapt and respond to occupancy's dynamic changes. Results indicate that the deep learning approach can reduce the under or over-estimation of occupancy heat gains. Compared with static profiles, when occupancy activities were monitored, it influences occupancy gains and ultimately results in a greater variation in the building energy demands. Results in terms of both heating and cooling loads were highly dependent on the occupancy profiles. Using the deep learning approach through the scenario-based cases suggests the heating, cooling, and ventilation profiles assigned would operate based on the response to the detections made to reduce unnecessary building energy loads effectively.

Improvements to the current approach are required before the integration with controls of building HVAC systems. Future works include developing a streamlined framework-based solution to define the required HVAC control system conditions based on real-time detection data responses. This includes the most suitable indoor/ room setpoint temperature that should be assigned to HVAC systems to provide adequate thermal conditions based on the real-time understanding of the utilisation of the space by occupants.

4.6.3. Impact Towards Building Systems Operations and Strategy

Based on the findings made in Chapters 4.6.1. and 4.6.2, suggests the potential of the application of a real-time occupancy detection approach to assist the operations of buildings. With occupancy behaviour being critical to the performance of buildings, indoor conditions are equally important. The achievement of good IAQ is directly and strongly related to the well-being, health, and comfort of occupants in indoor spaces. Poor indoor air quality could significantly increase health risks and reduce the productivity of occupants. This is a critical issue as people spend about 80–90% of their time in indoor spaces, either at home, in offices, or other types of buildings. Especially, children, the elderly, and people with pre-existing medical issues are among those who spend practically all of their time inside [216]. Moreover, one of the top five threats to public health is indoor air pollution [217]. According to the report produced by World Health Organization (WHO), it claimed over 3.8 million deaths in 2021 as being caused by indoor air pollution [218]. Additionally, according to the World Green Building Council (WGBC), better IAQ (lower CO2 and pollutant concentration) due to high ventilation rates can improve productivity by 8-11% [219]. Furthermore, enhancing IAQ could not only improve occupant health, well-being, and comfort but also contribute to significant economic benefits at a country level.

In addition, this could also result in increased ventilation heat loss in cold climates and conditions or ventilation heat gain in hot climates [220] due to the great temperature difference between indoor and outdoor air. This causes unnecessary energy consumption and wastage and compromises the HVAC efficiency; therefore, minimising ventilation heat loss/gain in cold/hot climates can significantly reduce the heating and cooling demands. This is further exacerbated when the ventilation system is operated using fixed or static schedules and when spaces are partially occupied or unoccupied for significant periods, leading to unnecessary over-ventilation and -conditioning of spaces. During the pandemic, occupancy levels and patterns in buildings such as offices have varied greatly due to social distancing requirements, self-isolation, lockdown, and more employees getting accustomed to working remotely [221]. Although employees started to return to the office when restrictions were lifted, the pandemic has made businesses rethink their workplace strategies with many moving towards flexible workspace models after seeing its benefits [222]. This also means that the design and operation of HVAC systems require rethinking to adapt to the change in occupancy.

A potential solution is the use of demand-driven or occupant-centric control measures, such as demand-controlled ventilation (DCV) which varies the ventilation of a space according to the pollution level or occupancy [223, 224]. There has been a rise in studies on occupant- or human-centred control strategies for HVAC systems [225]. Such strategies actively reflect real-time occupancy information and behaviour in the control of building systems. Bringing the concept of occupancy behaviour detection within indoor spaces as discussed in this chapter, this section aims to provide a scenario-based analysis that envisions the operations of DCV systems that could ensure that sufficient interior thermal conditions and air quality were attained to help reduce unnecessary building energy loads to improve building energy performance.

Figure 4-43 presents the proposed vision-based approach framework for demand-based ventilation control. The occupancy detection model is implemented in a conditioned space to generate and collect real-time data on occupancy information with the use of an AI-enabled camera. Then a real-time occupancy profile will be generated based on the obtained information and inputted into the BEMS to adjust the HVAC system operations automatically to provide demand-based ventilation. This specific analysis focused on a classroom in a university building (Figure 3-8 Figure 3-93-9) as the case study room for the evaluation of the developed approach.

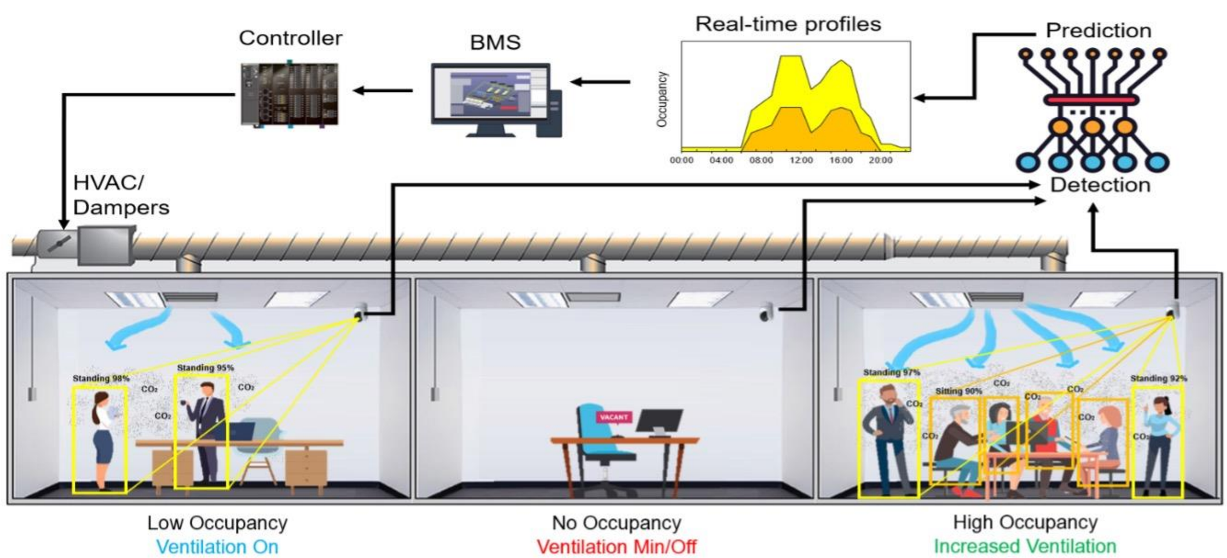


Figure 4-43. Framework for the application of the vision-based occupancy detection approach towards demand-based ventilation controls.

To evaluate the impact of using the proposed approach on indoor CO2 concentration and building energy performance, the case study building was modelled with the use of different ventilation scenarios by a BES tool and the details of the simulation and conditions are given in this section. Four ventilation scenarios were employed for the BES models to estimate the effectiveness of using the outcomes from this approach. For each scenario, four weekdays of a typical week (Monday – Thursday) in the heating and cooling season were chosen and simulated. Scenario A represented the situation where no ventilation occurred within the conditioned space, meaning all windows were always closed, and the mechanical ventilation was always off. It was assumed as the worst case for IAQ. For Scenario B, as presented in Figure 4-44a, the windows in the space were maximally opened for natural ventilation during working hours (8:00 – 18:00). Since the windows installed in the room are sash windows, each window contains only one movable panel, 50% of the window area is the maximum open area for natural ventilation supply. Both Scenario C and Scenario D used mechanical ventilation to control indoor CO2 concentration. According to CIBSE Guide A [198], the fresh air ventilation rate required for each person was 10 L/s in this study to fit between medium and moderate IAQ standards. For Scenario C, as the room's maximum capacity is 11 people, the maximal ventilation rate of 110 L/s was constantly supplied to the room, as shown in Figure 4-43b, to provide the best air quality during working hours. While, for Scenario D, the ventilation rate was applied based on the scenario-based occupancy profile which illustrated the actual occupancy variation in the case study room given in Figure 4-45. In other words, the ventilation rate varied with the number of people present in the room for the whole day which could be predicted by the deep learning detection model. Figure 4-44c demonstrated the detection-based mechanical ventilation profile (Scenario D).

Although it would lead to significant ventilation heat loss, Scenario B can be applied or occur during the heating season. For example, some buildings in the university will have openable windows which will be opened by the building users during the occupancy period. This is a result of the COVID-19 pandemic which has recently brought indoor air quality up front and increased awareness of the importance of ventilation to reduce the spread of COVID-19. At the same time, there are instances when building users have left windows open after leaving the space, during the winter which can then cause significant ventilation heat loss in the buildings. This scenario was considered as although it satisfied the fresh air requirements, it resulted in increased energy demands to heat the space to the desired comfort level. The air changes per hour (ACH) were estimated by the building energy simulation tools, which take a value of 5 ach to model ventilation by window opening. In practice, this would vary throughout the day depending on several factors and could be evaluated later when the proposed approach is combined with a window detection model.

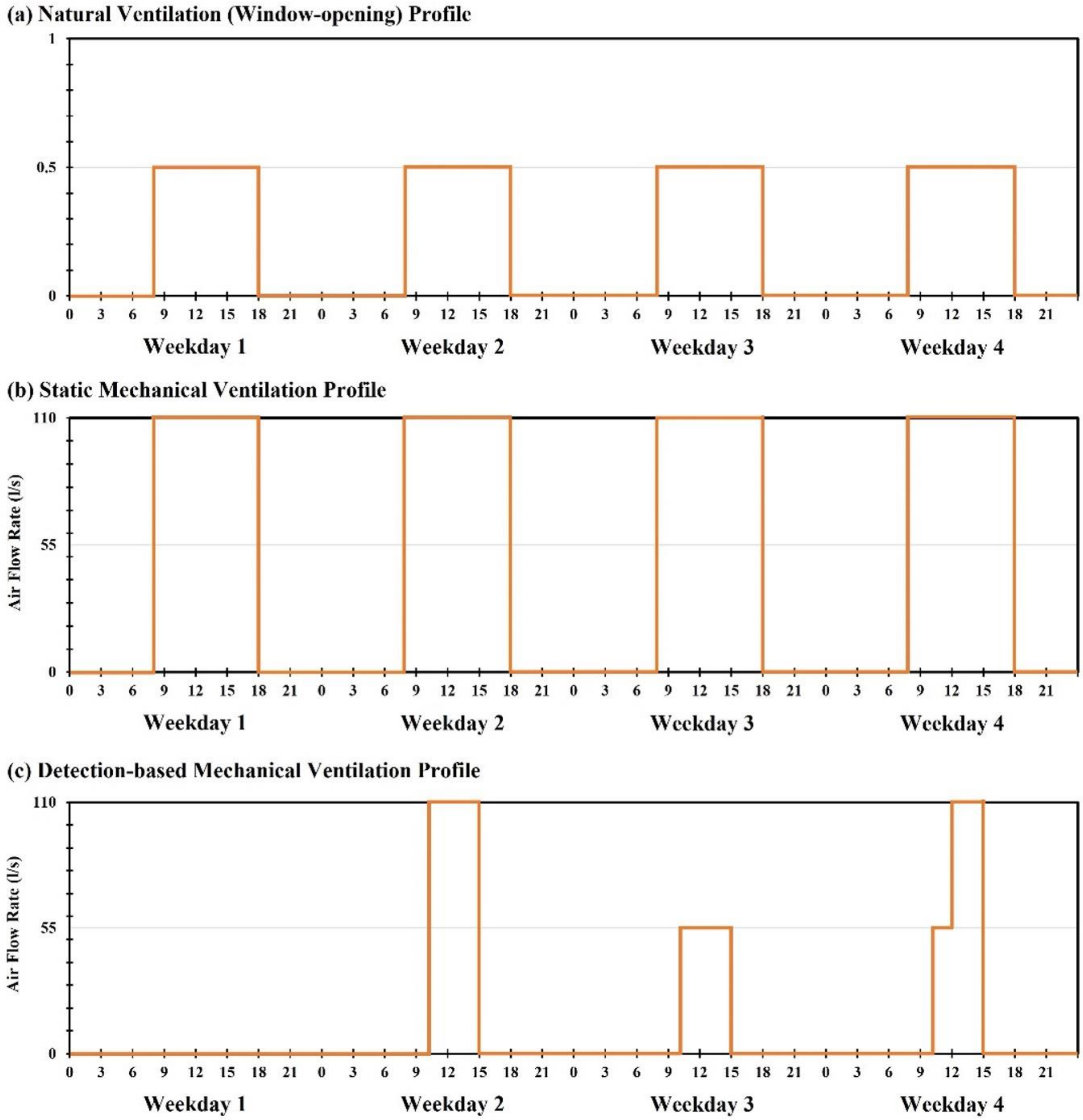


Figure 4-44. Scenario-based ventilation profiles applied to BES simulation. (a). Scenario B (natural ventilation), (b). Scenario C (static mechanical ventilation), and (c). Scenario D (detection-based mechanical ventilation) profiles.

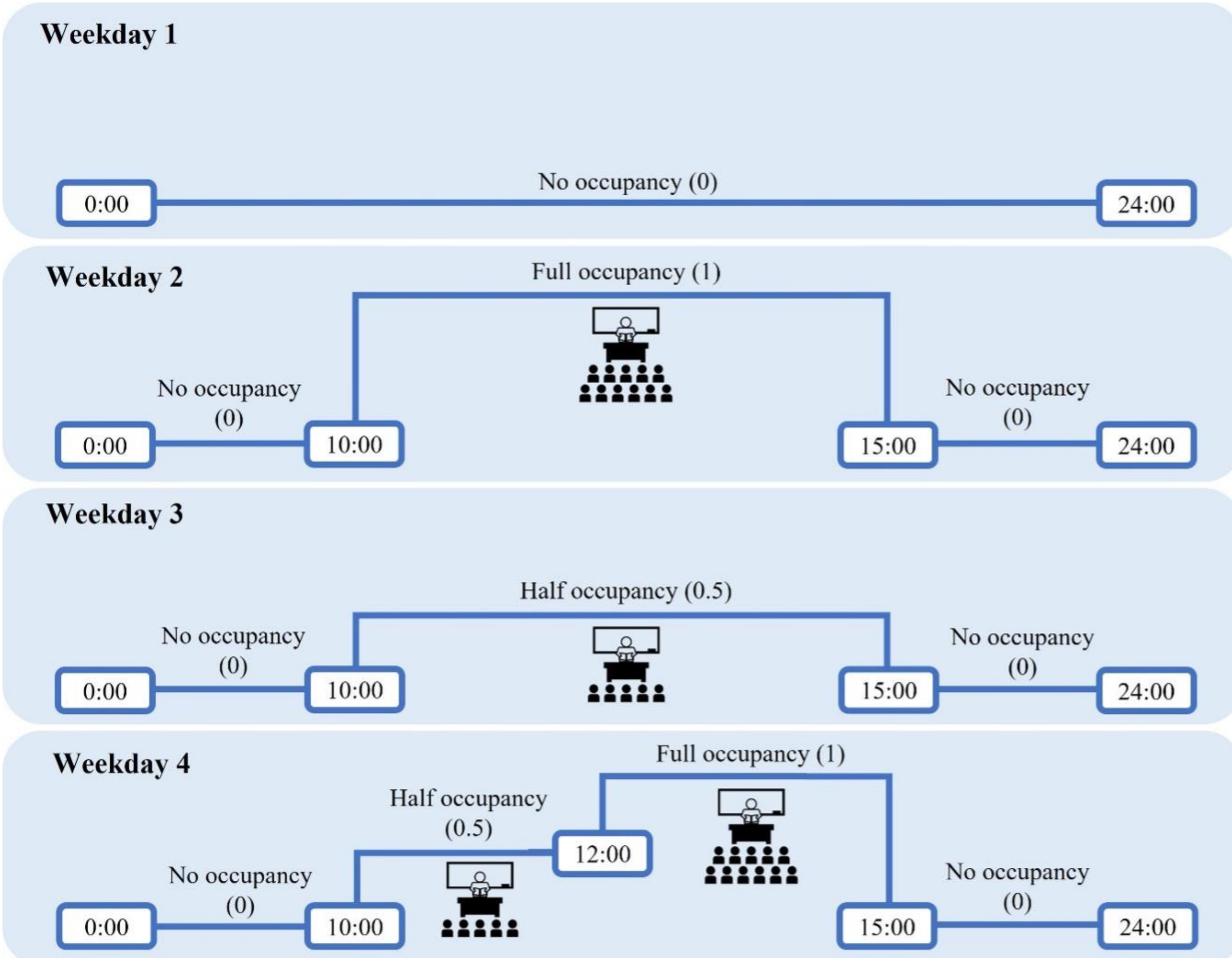
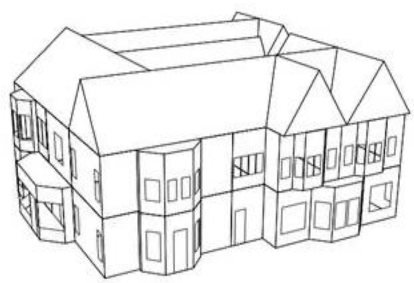


Figure 4-45. A four-day scenario-based occupancy profile applied to the investigation of the proposed occupancy approach toward the impact on the operations of the demand-controlled ventilation (DCV) system.

Similarly, building simulation using IESVE was employed. Simplifications to the selected case study building, Paton House were applied. Further details about the building and its surroundings were presented in Chapter 3.4 and some features were excluded such as vegetation, surrounding buildings, and interior furniture. For this simulation analysis, the people in the space were assumed to be constantly sitting during the occupied period. The heating and cooling temperatures during the building's operational period were set to be 21℃ and 25℃ according to ASHRAE standards [125, 126]. The details of each scenario and building simulation setups are provided in Table 4-17.

Table 4-17. Overview of the scenarios for the ventilation-based BES with the selected case study building for the analysis of the impact on DCV.

	Scenario A: No Ventilation	**Scenario B: Natural Ventilation (Window-opening)**	**Scenario C: Static Mechanical Ventilation**	**Scenario D: Detection-based Mechanical Ventilation**
Profile	Windows were always closed, and mechanical ventilation was off.	The windows were half-open during working hours.	A maximum ventilation rate of 110 L/s was applied during working hours.	The ventilation rate was applied based on the number of occupants present
Building Model				
Overall U-value	External wall (brick + gypsum plaster): 1.42 W/m^{2}K External floor (cast concrete + air cavity + timber + carpet): 0.95 W/m^{2}K External roof (clay tiles + timber frame + gypsum plaster): 1.46 W/m^{2}K Door (timber): 2.33 W/m^{2}K Window (single glazing): 5.20 W/m^{2}K			
Infiltration	0.5 ACH			
Weather File	Nottingham			
Occupancy Gains	Max sensible gain: 75 W/person Max latent gain: 70 W/person			
Lighting	10 W/m^2			
Heating Profile	21°C during building operational hours (8:00 – 18:00)			
Cooling Profile	25°C during building operational hours (8:00 – 18:00)			

The following presents the results of the proposed CNN-based occupancy detection on the impact on DCV with the discussions based on the IAQ and energy performances. The room IAQ can be assessed by the CO2 concentration. According to ASHRAE standard [226], a room with lower than 1000 ppm can be considered with fairly good air exchange. When the CO2 level is higher than 1000 ppm, it indicates that the room is polluted, indicating poor conditions for well-being, health, and productivity. While using different ventilation methods to maintain an adequate supply of fresh air could result in a remarkable difference in ventilation heat gain or loss depending on the indoor-outdoor conditions. This correspondingly affects the building energy consumption required to keep a good thermal comfort level for occupants. Thus, a balance between CO2 level and building energy demand should be achieved. The following shows the analysis of the impact of the proposed approach on the CO2 level and building energy performance within the conditioned spaces based on the comparison with other commonly used ventilation scenarios. Building energy simulation was carried out to assess the CO2 concentration and ventilation heat gains within the selected case study room.

Figure 4-46Figure 4-48 presented the simulation results in terms of CO2 concentration and ventilation gains from using different ventilation scenarios for four weekdays during the heating season (15-18th December) and the warm period (12-15th May) in the selected case study room. Scenario A-D represented the situations for no ventilation, natural ventilation, static mechanical ventilation, and detection-based mechanical ventilation, respectively. As shown in the figures, the CO2 concentration varied with the occupancy profile given in Figure 4-45. The ventilation heat losses changed in response to the ventilation profiles (Figure 4-44) and the variation in external temperature. The losses were greater during the cold days and less on the warmer winter days.

As illustrated in Figure 4-46 for the heating period, although Scenario A achieved a minimum ventilation heat loss, it caused a maximum CO2 level of over 3000 ppm within the test room. This suggests the necessity of ventilation to improve the IAQ. For Scenario B which provided natural ventilation by opening the windows, the lowest CO2 level was achieved during the occupied period. However, a remarkable ventilation heat loss was produced due to the large indoor-outdoor temperature difference in winter. The lower the outdoor temperature is, the higher the ventilation heat loss is within the space. This caused extreme discomfort and therefore an enormous increase in heating demand to maintain a comfortable indoor temperature. It indicates that during the cold period, in terms of thermal comfort and building energy efficiency, natural ventilation by opening windows is not a suitable ventilation strategy. For mechanical ventilation (Scenario C and D), both scenarios could provide low CO2 levels with less ventilation heat losses. However, in comparison to Scenario C which supplied a static airflow rate during the building operation period, Scenario D provided the dynamic airflow rate based on the variation of occupancy rate and led to a ventilation loss reduction of up to 54.56 % (32.89 kW). In comparison with Scenario B, up to 90.96 % (266.98 kW) reduction of ventilation heat loss was achieved by Scenario D. It highlighted that using Scenario D could reduce the unnecessary energy demand for heating and system operation. It suggested that providing the real-time occupancy information collected from the proposed detection approach to the building ventilation system to achieve demand-driven controls could offer an opportunity to significantly improve the building's energy efficiency while maintaining a good IAQ for occupants.

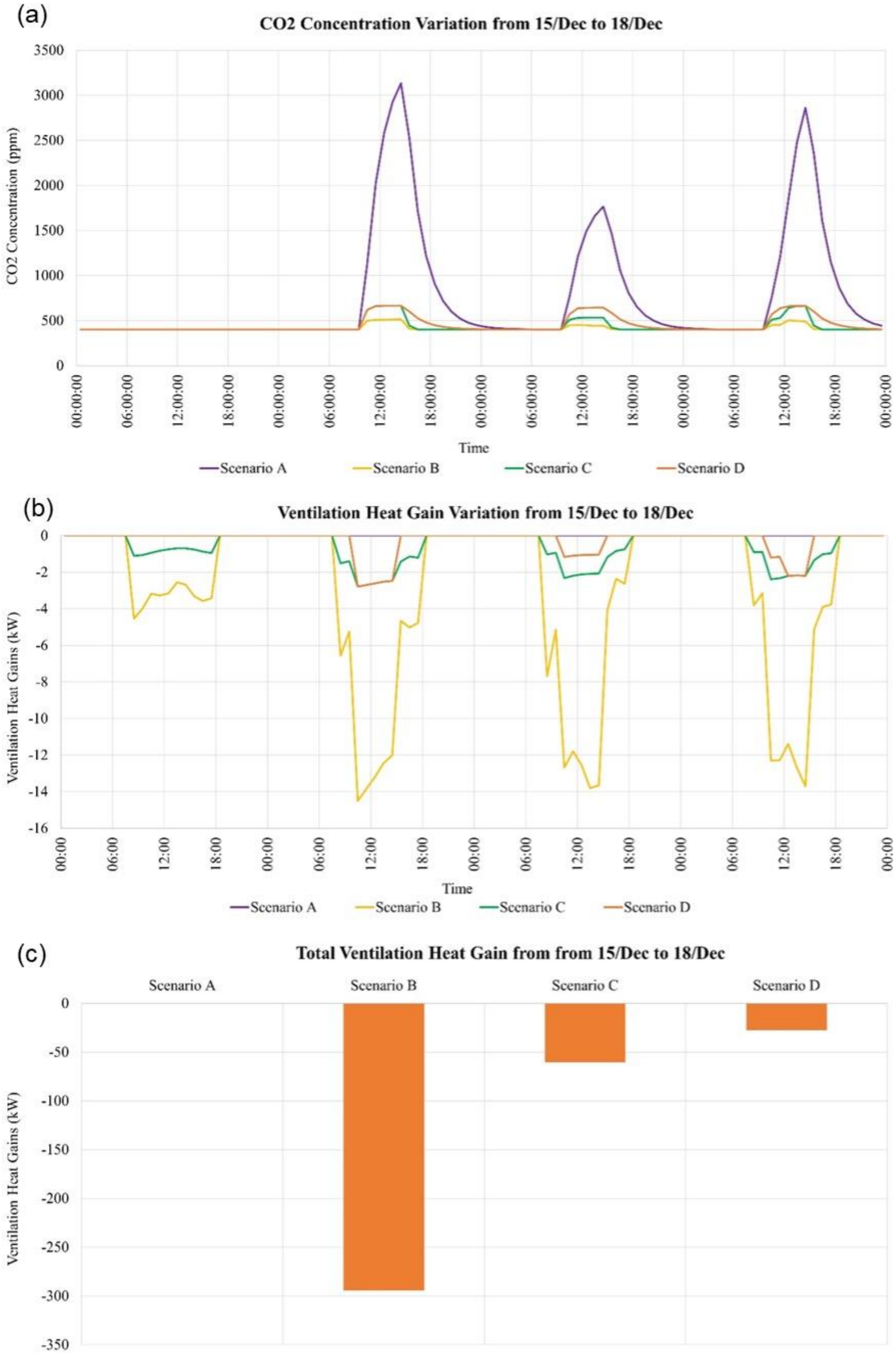


Figure 4-46. Results for the application of the different ventilation scenarios based on the potential application of the vision-based occupancy detection approach for DCV. (a). CO2 level, (b). Ventilation heat gains variation, and (c). Total ventilation heat gains during the heating season. Note that a negative result denotes ventilation heat loss.

The simulation results of using different ventilation scenarios for four days during the warm period (12-15th May) in the case study room are shown in Figure 4-47. Similarly, Scenario A achieved the minimum ventilation heat loss while causing the highest CO2 concentration, which indicated that the indoor air was highly polluted. Scenario B resulted in the lowest CO2 level during most of the occupied period and the maximum ventilation heat gain of 13.93 kW due to the higher outdoor temperature in summer. For mechanical ventilation, both scenarios could provide low and similar CO2 levels. Scenario C generated a ventilation heat gain of 4.49 kW while Scenario D generated a ventilation heat loss of 1.32 kW during the four weekdays. Up to 5.81 kW difference of ventilation heat gain was created between Scenario C and D. It indicated that using Scenario D could provide real-time demand-driven controls for a good IAQ and also reduce the cooling energy demand in summer. However, because the UK has a temperate climate, the summer is generally warm and wet. The variations of the external air temperature and room air temperature using four scenarios for the four weekdays are presented in Figure 4-48. The peak outdoor air temperature was about 27 ℃ and during most of the days in summer was lower than 25 ℃. According to CIBSE Guide A [198] the general comfort temperature range is 20 - 26 ℃. It demonstrated that the cooling demand for the case study room was minor. In addition, room air temperatures using four scenarios during the occupied period were within the comfort temperature range. However, due to the use of natural ventilation, using Scenario B could reduce energy use while still maintaining a comfortable indoor environment. This highlighted the benefits of employing natural ventilation in the building's energy cost, greenhouse gas emissions, and air quality.

Based on the simulation results in the selected case study room, Scenario B-D could maintain the CO2 level below 1000 ppm. In the cold period, up to 90.96% and 54.56% reduction of ventilation heat loss could be potentially achieved by the demand-driven mechanical ventilation using real-time occupancy detection (Scenario D) in comparison with natural ventilation (Scenario B) and mechanical ventilation with a static airflow rate (Scenario C). In the cooling season, using Scenario D could reduce the ventilation heat gain to minimize the building energy demand for cooling and system operation. It indicated that the proposed approach could provide demand-driven ventilation controls based on the real-time changes of occupancy to improve the IAQ and address the problem of under or over-estimation of the building energy consumption when using the static or fixed profiles. This highlighted the benefits of employing deep learning and computer vision techniques to monitor occupancy behaviour in real-time for the effective operation of the HVAC according to occupants' actual needs. However, as the cooling demand was minor in the UK due to its mild weather, using natural ventilation is another beneficial option to further reduce the energy cost in buildings with windows or vents. Thus, an alert system which can inform people to open or close the windows will be integrated with the proposed approach to optimize building energy efficiency and keep the space well-ventilated.

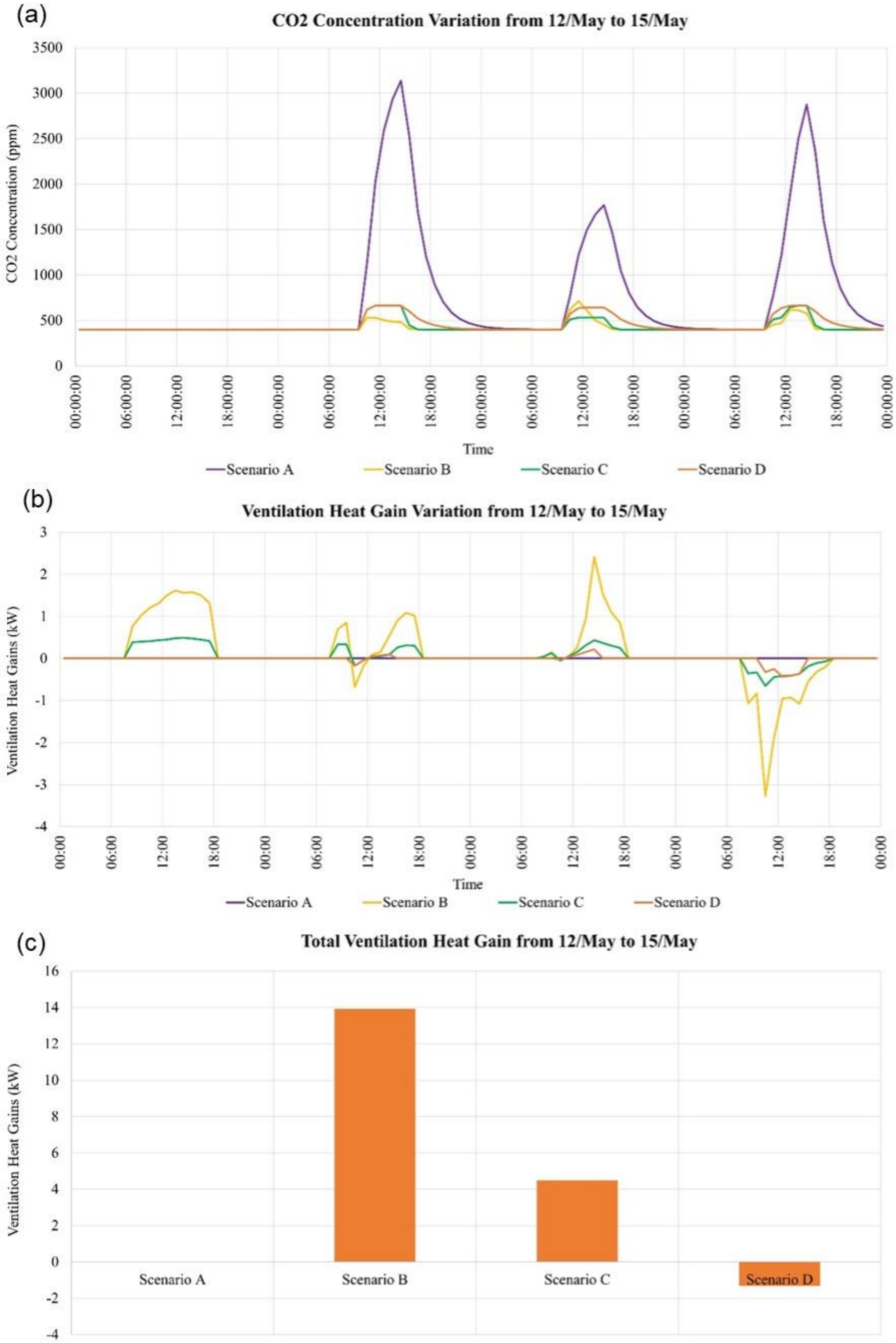


Figure 4-47. Results for the application of the different ventilation scenarios based on the potential application of the vision-based occupancy detection approach for DCV. (a). CO2 level, (b). Ventilation heat gains variation, and (c). Total ventilation heat gains during the warm period. Note that a negative result denotes ventilation heat loss.

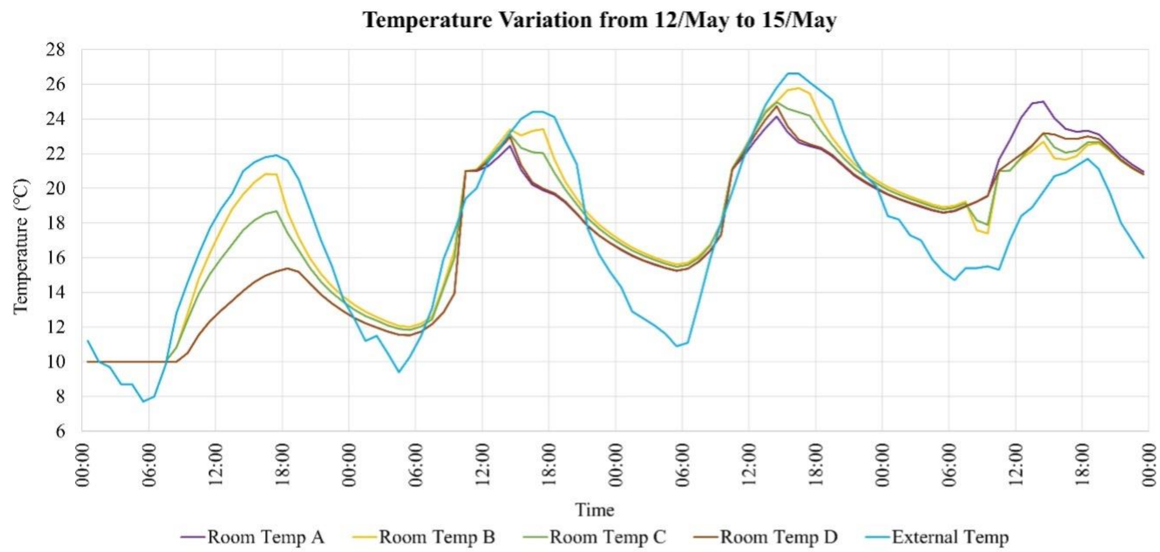


Figure 4-48. Comparison of the external air temperature and room air temperature when using Scenario, A-D for the four weekdays during the warm period for identification of the potential use of the occupancy detection framework approach.

In summary, scenario-based modelling of the case study building under four ventilation scenarios during heating and cooling seasons was carried out using BES provided results that demonstrated the proposed approach could provide DCV to improve the IAQ and address the problem of under- or over-estimation of the ventilation energy consumption when using the static or fixed profiles. It gave insights into the way that the proposed approach can enable the adjustment of HVACs based on occupants' dynamic changes and also indicated the potential of this approach in the enhancement of indoor air quality and energy efficiency. This highlighted the benefits of employing deep learning and computer vision techniques to monitor occupancy behaviour in real-time for the effective operation of the HVAC according to occupants' actual requirements. Furthermore, it leads to the next section focusing on the development of a vision-based detector enabling the recognition of window openings to assist the operations of naturally ventilated buildings.

4.7. Summary

To conclude and summarise the proposed occupancy detection approach toward the enhancement of building systems and operations, the findings in this section suggest the possibility of using selected deep learning vision-based approach to achieve a real-time understanding of occupancy actions within indoor building spaces. This includes the number of people within the space using the 'people detector' and the activities performed by occupants with an 'occupancy activity detector'. Such variations are all dependent upon the input image data and the number of selected responses for the designed detector. Through the formation of the DLIPs with its comparison with constant static pre-scheduled profiles and the actual occupancy conditions, the BES results suggest the demand for such a real-time understanding of occupancy behaviour allows accurate adjustments on the HVAC operations.

Chapter 5

5. Window Detection and Recognition

Chapter 3.1.2 identified the actions of manual adjustments and opening of windows by occupants will lead to substantial building heat loss and consequent energy consumption. Hence, it resulted in the demand for the development of a possible control strategy that can detect and recognise the period and amount of window opening in real-time. In addition, it also enables adjustments in the operations of the building HVAC systems to minimise energy wastage and maintain indoor environment quality and thermal comfort. Chapter 4.6 introduced a proposed DCV approach via monitoring and understanding occupancy behaviour within indoor spaces. Hence, this chapter presents the initial exploration and development of a window detector following a similar method applied to the occupancy detector and framework approach in Chapter 4.

5.1. Framework for the Detection and Recognition of Window Opening Towards the Optimisation of Building HVAC Systems

Figure 5-1 presents the proposed framework approach for the detection and recognition of window openings towards the optimisation of building HVAC systems. This is designed to control the unnecessary or over-ventilation of the space or times when the fresh air is more than what is required to ensure adequate indoor air quality.

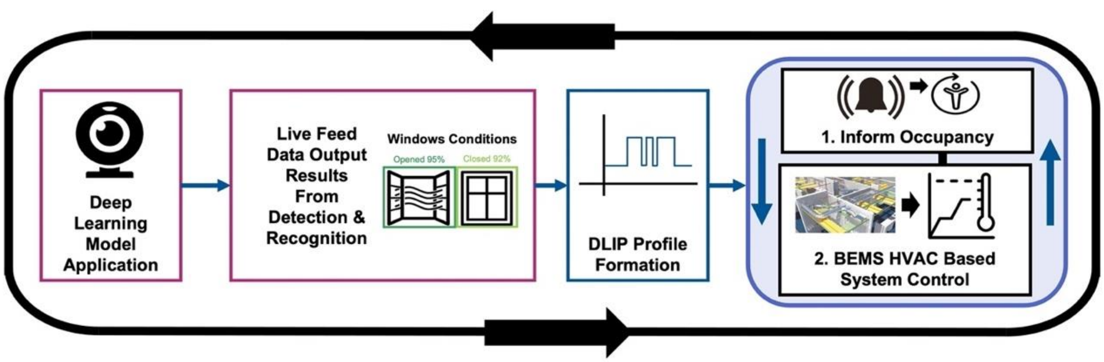


Figure 5-1. The proposed framework approach for the detection and recognition of window openings for the optimisation of building HVAC systems.

5.2. Deep Learning Method for Forming the Window Detector: Technique and Process

Window detection model configurations were established using a similar approach following the steps shown in Chapter 3.3 as given in Figure 5-2. Different window detection models were individually trained using the classification-based algorithm Convolutional Neural Networks (CNN) and were evaluated based on real-time detection and recognition experiment tests (Chapters 5.5 and 5.6). Particular focus was given to the data set used and the labelling of the training data. For each detection model, a series of evaluation metrics were used to evaluate the performance of the trained models on the detection of the same window in the selected case study building. Using the deep learning influenced profiles (DLIP) generated from the real-time detection (Chapter 5.7), building energy simulation (BES) was also performed to predict the potential impact of the model framework performance on the ventilation heat loss and building energy demands (Chapter 5.8 and 5.9).

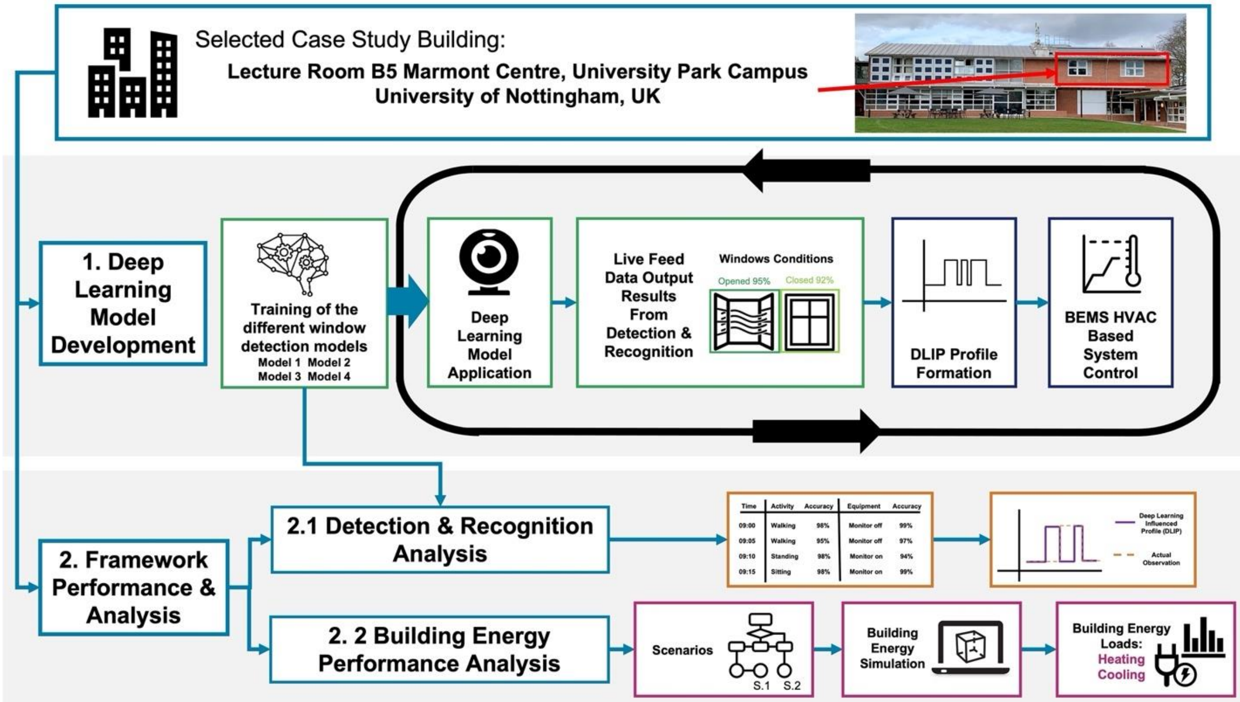


Figure 5-2. The workflow process for the development, application and analysis of deep learning vision-based window detector using TensorFlow techniques.

5.2.1. Model Development and Configurations

Four different window detection model configurations were established and compared in the present study. Table 5-1 summarises the specification of each model with varying types (opened and/or closed) and several datasets. Models 1 and 2 consisted of two response categories: 'Open' and 'Closed' windows, while Models 3 and 4 consisted of only one detection response 'Open' windows. Model 1 represents the base model trained with the lowest number of images within the dataset. This will show the capabilities of the model to detect and recognise window openings with a limited amount of data. The number of images in Model 2 is increased while having the same types of categories and images. This will allow the evaluation of the influence of the number of images in the training datasets on detection performance. Models 3 and 4, which only detect 'open' windows, will have a lower number of training and testing images.

Table 5-1. Description of the training and testing image dataset for the different window detection models.

Model Name	**Category**	**Dataset Size**					
		No. of Images			**No. of Labels**		
		Training	**Testing**	**Total**	**Training**	**Testing**	**Total**
1	Closed	100	25	125	164	36	200
	Open	100	25	125	108	27	135
	Total	200	50	-	272	63	-

2	Closed	1000	250	1250	2185	576	2761
	Open	1000	250	1250	899	157	1056
	Total	2000	500	-	3084	733	-
3	Open	500	125	625	865	191	1056
	Total	500	125	-	865	191	-
4	Open	666	160	826	1398	318	1716
	Total	666	160	-	1398	318	-

Pre-processing was conducted, which involved the preparation of the data for the model training. The main tasks include manual labelling of each of the images within the training and testing datasets using the software LabelImg [206]. Different methods of labelling were used for Models 1, 2, 3 and 4. Figure 5-3presents example images indicating the types of images collected and how they were labelled. Bounding boxes were drawn manually around each image's selected region of interest. As shown in Figure 5-3, Models 1 and 2 labelling method consists of the selection of the regions around the full area of the windows for both open and closed windows. For Models 3 and 4, only open windows were considered for detection and recognition. Model 3 followed the same labelling method for open windows as Models 1 and 2. While for Model 4, bounding box regions were assigned around the opening gaps of the windows. In most cases, multiple numbers of labels were assigned to each image. The justification for only detecting open windows in Models 3 and 4 and opening gaps in Model 4 will be further discussed when evaluating the results.

Figure 5-3. Example images of windows obtained from Google Images that were used to form the different image datasets for the various window detection models.

Figure 5-4 presents the CNN-based model configuration used to train the different models, following the model development and application workflow process given in Figure 3-4 and the generic CNN model shown in Figure 3-2. To assist in the development of the neural network for training, the TensorFlow Object Detection API was used. This framework platform provides pre-trained models to be used through a transfer learning approach that enables the development of an effective vision-based detector [207]. Existing models provided in the TensorFlow Detection Model were explored to establish the model configuration as highlighted in Figure 5-4. Through the assessment of the different models provided in terms of the model description, the speed and the COCO mAP given for the different SSD MobileNet and Faster R-CNN-based networks, the Faster R-CNN (With Inception V2) was selected. The time required for the training of the models would vary due to the differences in the input data and the desired detection output responses, and each of these trained detectors can be deployed to an AI-powered camera. Overall, the same model architecture and configuration as the ones used for the development of the occupancy detection models were applied.

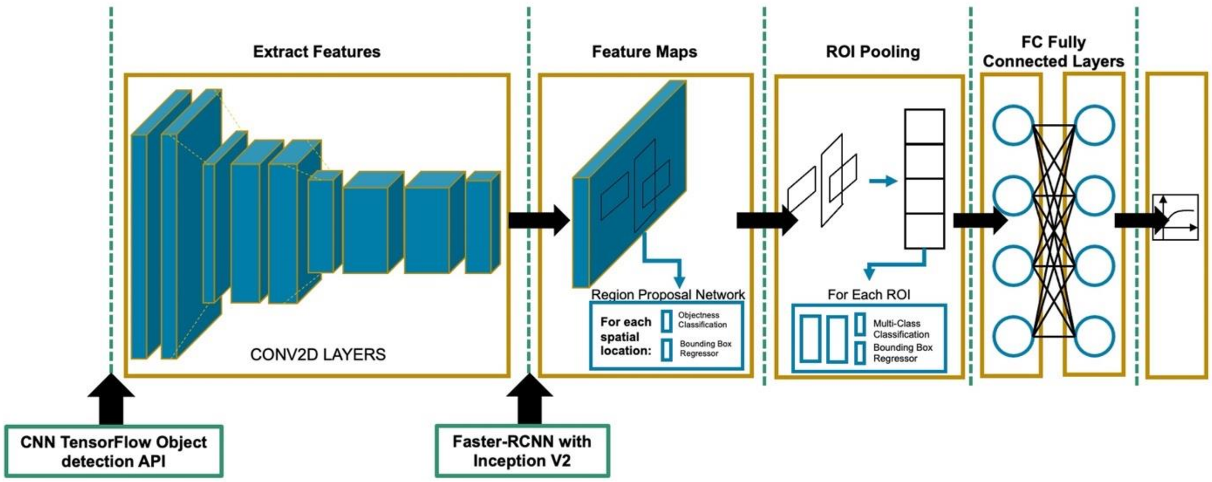


Figure 5-4. CNN-based model configuration used to train the four window detection models.

5.3. Model Applications

Once the model was trained to a sufficient level where losses did not decrease any further, the associated inference graph was exported. Directly, the model was prepared for real-time application via detection whereby the models were deployed to form vision-based detection cameras. The following section presents the details of the various experimental tests conducted within the selected case study building. Similar to occupancy detection, real-time detection of windows enables the recording of data in form of DLIPs. The following discusses how the DLIP for windows were formed.

5.3.1. Experimental Tests and the Case Study Building

To evaluate the performance of the different window detector configurations, a lecture room within a case study building was selected to perform experimental tests, which allowed real-time-based detection and recognition. This is the Marmont Centre at the University of Nottingham (University Park Campus, UK) (Figure 5-5a). Details about the building construction, materials and features are detailed in Chapter 3.4. This building is used mainly for teaching architecture and engineering students. It has several teaching spaces, a laboratory and a café. The teaching spaces include a lecture and seminar room, each with 30 - 40 students. Students also use both rooms as workspaces during non-lecture hours and can have variable occupancy throughout the day. Both rooms have large openable windows and are often used by the students to ventilate the space. Some windows are left open in some cases, which leads to a significant waste of heating energy during cold periods. Like most buildings in the University, the windows are manually operated and do not have any sensors to detect and prevent such issues. Such a space could benefit from the installation of a window detector. Figure 5-5b presents the setup for the experimental tests. A 90-degree field of view camera was used for the detection, positioned towards the 'South Facing Windows 1' located near the room's ceiling. Figure 5-5c presents the floor plan of the first floor, along with the arrangement of the experimental setup.

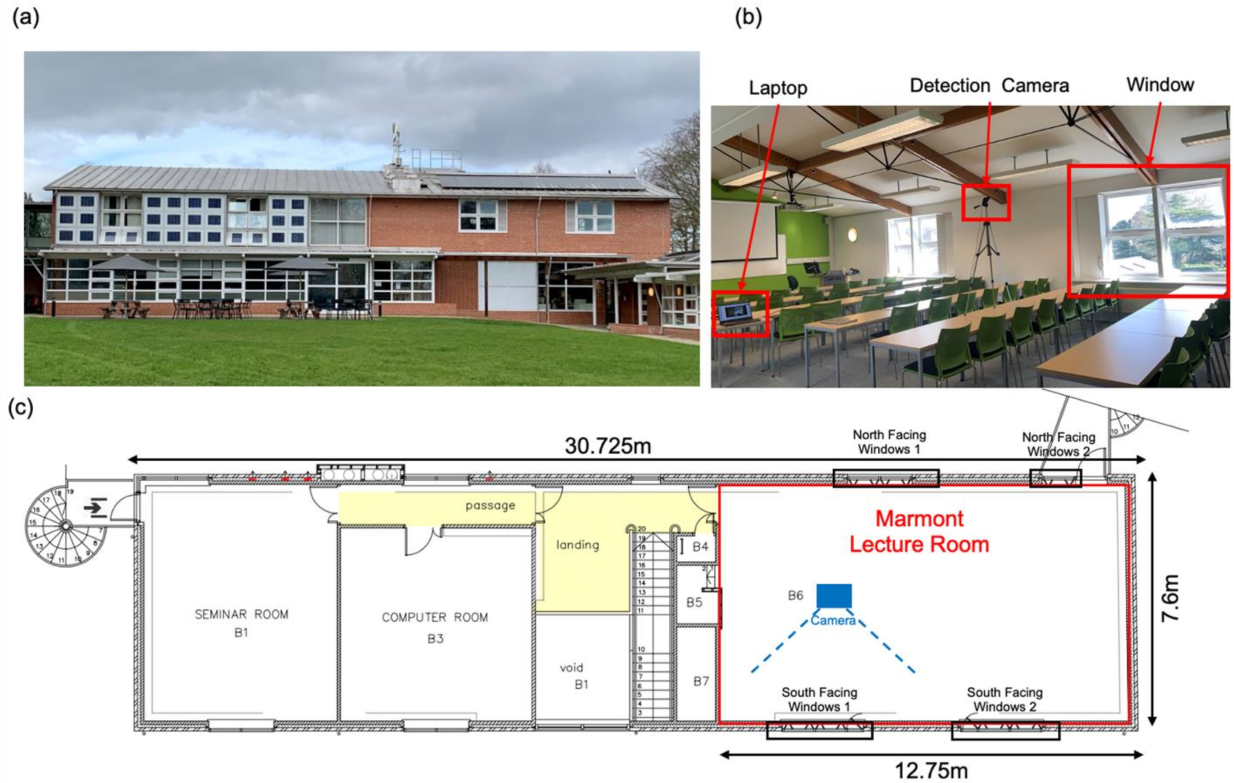


Figure 5-5. (a). Marmont centre at the University of Nottingham, UK. (b). Set up for the experimental tests 1 - 5, with the floor plan of the first floor of the building in Figure (c).

In summary, a total of six experimental tests were conducted within the building with the setup shown in Figure 5-5. Experimental Tests 1 – 4 were assumed to be the same, allowing a recorded video that enabled accurate detection performance analysis between each of the developed models (Models 1, 2, 3 and 4) via the techniques of 'offline' video feed tests. Corresponding results for such comparison are presented in Chapter 5.5. While Experimental Tests 5a and 5b adopted Model 4 and consisted of two separate 15-minute tests focusing on a scenario whereby an occupant is taking action towards changes in the window opening. Effectively, Experimental Tests 5a and 5b were conducted to provide BES analysis to show the significance and the impact of window openings through comparison with constant static and actual window profiles towards building energy performances and to also provide scenario-based analysis in terms of common/ extreme conditions to present possible adjustments towards system controls to enhance indoor air quality and ventilation conditions once the window status was acknowledged.

5.3.2. Formation of the Window-based Deep Learning Influenced Profiles (DLIPs)

For Experimental Tests 1 – 4 to assist in the performance evaluation of all the trained window detectors (Models 1 - 4), a scenario where an occupant would operate the windows within the selected building space was recorded. This ensured that the same scene or segment of occupancy actions towards the opening/ closing of the windows were used to evaluate each detection model configuration. Furthermore, it also ensured that other factors such as slight variation in the actions performed by the occupant, indoor lighting conditions and glare did not influence the results, providing a fair comparison between the model's detection and recognition abilities.

The detection and recognition responses were obtained and recorded every two seconds, generating the Deep Learning Influenced Profile (DLIP). Figure 5-6 presents an example of the process of generating the DLIP using the different detection model configurations for the selected case study building and experimental test. Models 1 and 2 would generate 2 profiles based on two responses, open and closed windows, whereas Models 3 and 4 would only generate a profile for open windows only. The formed DLIPs would be assessed and compared with typical static profiles of 'constant open and closed' profiles, together with the true 'actual observation' of the window conditions to evaluate the overall performance of each window detector.

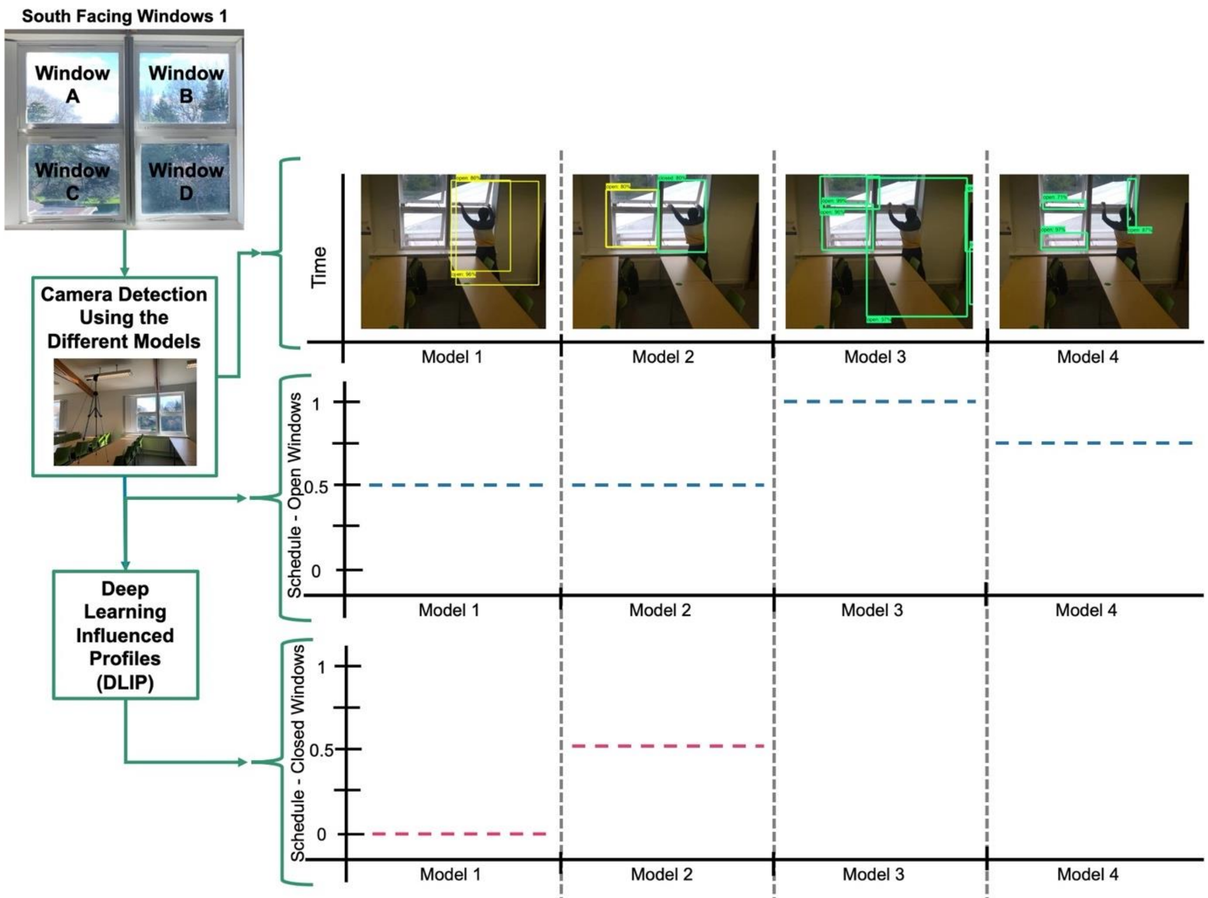
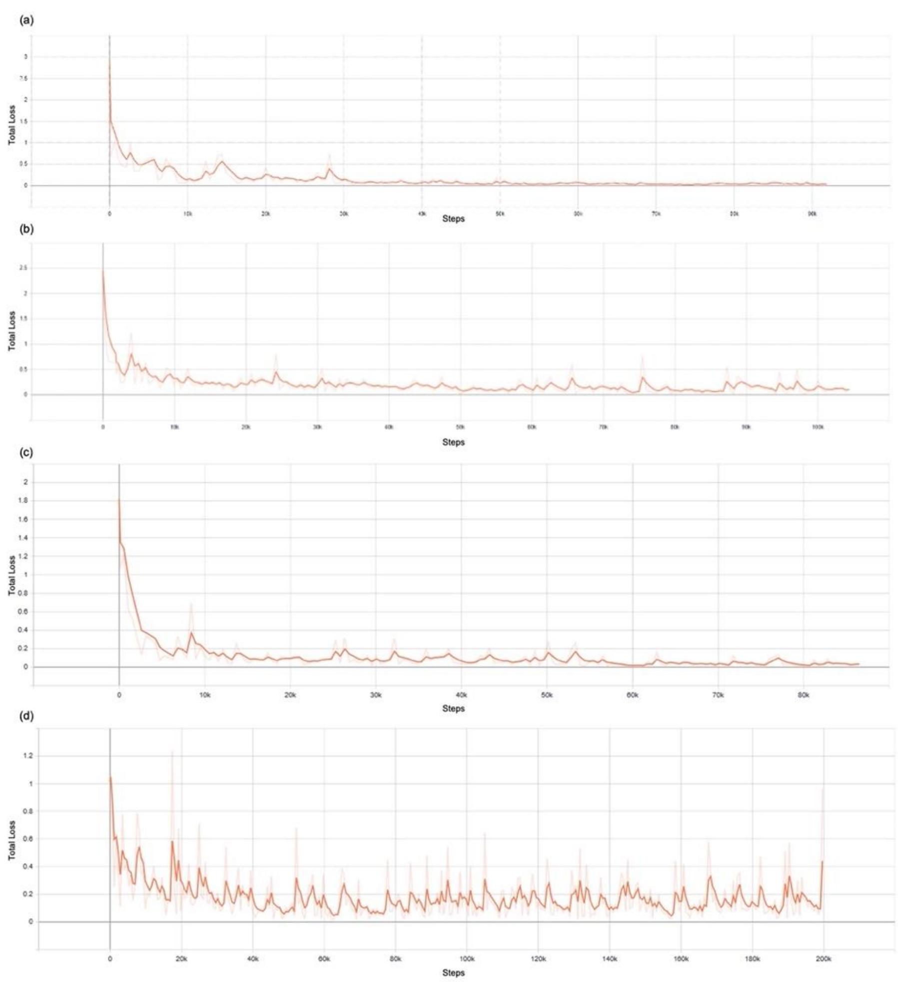


Figure 5-6. Example of the process of real-time detection, recognition and formation of the deep learning influenced profiles (DLIP) using different window detectors (Models 1, 2, 3, and 4).

5.4. Window Model Training Results

All models were trained until converged, as detailed in Table 5-2, and the duration varied across the different detection model configurations. This is due to the differences in the pre-processing approach and size of the model's training datasets of the different window detectors.

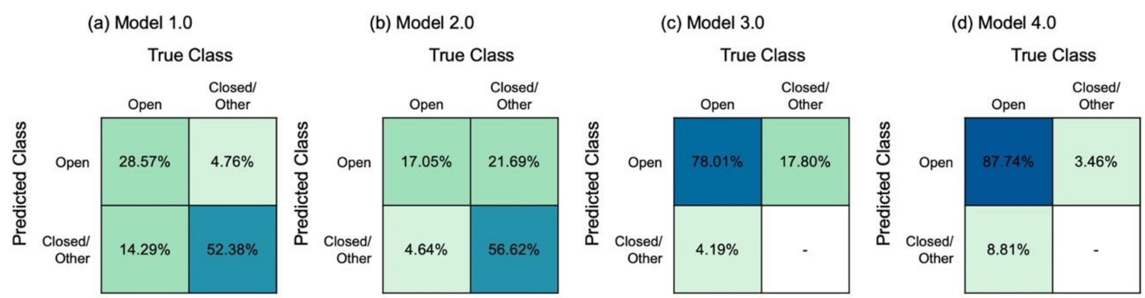
Table 5-2. Training results for the different window detection models.

Training Conditions and Results	Model			
	(a) 1	(b) 2	(c) 3	(d) 4
Pre-trained Model Used	Faster RCNN with InceptionV2			
Total Steps	91,842	104,396	86,523	199,630
Training Duration	6 hours, 1 minute, 49 seconds	7 hours, 19 minutes, 2 seconds	5 hours, 29 minutes, 49 seconds	11 hours, 29 minutes, 46 seconds
Maximum Loss	2.876961	2.037059	1.821876	1.236806
Minimum Loss	0.005654	0.000113	0.010038	0.01519
Total loss versus the number of training steps				

With the same baseline CNN model configuration (Figure 5-4) applied to the training of all four models, the following presents an initial analysis of the trained model performances through the detection and recognition ability of the still images located in the test dataset (Table 5-1). To provide an effective analysis of the initial model performances, results were presented in form of a confusion matrix and the common classification metrics. The same images were given in all the testing datasets, and these were similar to the images used for the training of the detection models.

The variation in the labelling techniques and response selection before the training of the models was reflected in the results given in Table 5-3. With Models 1 and 2 consisting of the two response categories of 'Open' and 'Closed', it presented an overall F1 score of 0.7981 and 0.6878, indicating the occurrence of false positives and false negatives in detecting the window conditions was high, suggesting high possibility in incorrect detections when two response identification categories were required. Contrastingly, Model 3 was trained to only recognise opened windows and had a higher F1 score of 0.8765. Furthermore, with Model 4 designed to recognise the opening gaps of windows, it achieved an overall F1 score of 0.9346 with the highest potential in recognising opened windows. To further evaluate the performance of each model, all models were applied under an experimental test in a selected case study building and analysis in terms of its detection and recognition ability and its impact on building energy was further explored in the following sections.

Table 5-3. (a). Detection performance results are based on the still images from the test dataset, presented in the form of a confusion matrix and assessed in terms of common evaluation metrics.

<table>
<tr><th colspan="5">Confusion Matrix</th></tr>
<tr><td colspan="5">


</td></tr>
<tr><th>Classification</th><th>Accuracy</th><th>Precision</th><th>Recall</th><th>F1 Score</th></tr>
<tr><th colspan="5">(a) Model 1</th></tr>
<tr><th>Open</th><td>80.95%</td><td>0.8572</td><td>0.9167</td><td>0.7500</td></tr>
<tr><th>Closed</th><td>80.95%</td><td>0.7857</td><td>0.666</td><td>0.8461</td></tr>
<tr><th>Average for both types</th><td>80.95%</td><td>0.8215</td><td>0.7914</td><td>0.7981</td></tr>
<tr><th colspan="5">(b) Model 2</th></tr>
<tr><th>Open</th><td>73.67%</td><td>0.4401</td><td>0.7861</td><td>0.5643</td></tr>
<tr><th>Closed</th><td>73.67%</td><td>0.9243</td><td>0.723</td><td>0.8113</td></tr>
<tr><th>Average for both types</th><td>73.67%</td><td>0.6822</td><td>0.7546</td><td>0.6878</td></tr>
<tr><th colspan="5">(c) Model 3</th></tr>
<tr><th>Open</th><td>78.01%</td><td>0.8142</td><td>0.9490</td><td>0.8765</td></tr>
<tr><th colspan="5">(d) Model 4</th></tr>
<tr><th>Open</th><td>87.73%</td><td>0.9621</td><td>0.9088</td><td>0.9346</td></tr>
</table>

5.5. Detection Performance of Models Based on Experimental Tests 1 – 4

This section presents the analysis of the detection performance conducted using the developed window models 1 - 4 during Experimental Tests 1 – 4. It should be noted that these experimental tests were based on one recorded video obtained during a recording taken in the selected case study building to allow direct and accurate analysis, identifying the differences between the developed models and their performance in real indoor situations. These screenshots and video recordings captured are for visual purposes only. None of these forms of data is stored within the developed vision-based detectors.

5.5.1. Real-Time Window Detection

The real-time detection and recognition of the open windows in the case study lecture room/ tutorial room (Marmont Centre) with the comparison of the different window detection model configurations are presented in Figure 5-7, with Video 2. Figure 5-8 shows an example of the output of the detection and recognition performed on the video recorded. A clear variation can be observed between the different models' recognition of the open windows. The differences between the methods of labelling and the selected response outcomes resulted in the different forms of the bounding boxes around the detected windows. It shows that the size and shape of these bounding boxes varied between each detection interval and the desired response associated with the model configuration applied. For most of the detection period, Model 1 recognised that all four windows were one standalone window, and only one detection response of either open or closed was given. Whereas Model 2, which was trained with a greater number of images, could recognise windows separately and had fewer false/incorrect detections; however, the model was not accurate and reliable in identifying all four windows and their actual conditions. This clearly shows the importance of the data set size when training the window detection model.

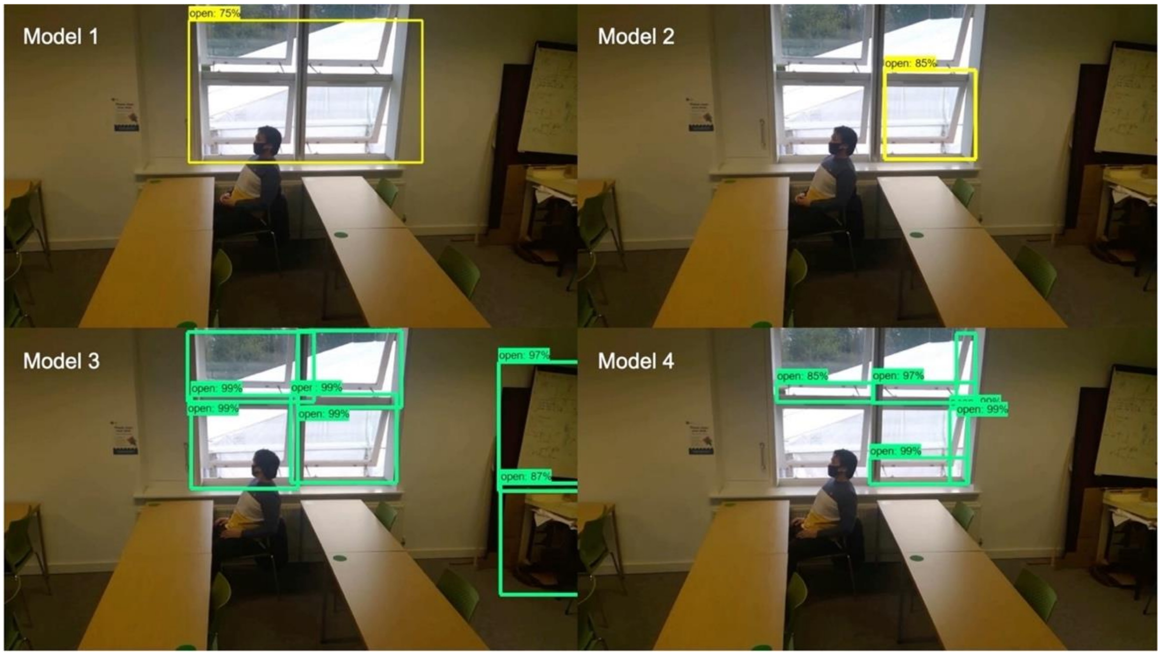


Figure 5-7. Comparison of the detection of open windows using the different models. (see Video 2).

A different approach was taken when designing Models 3 and 4 window detectors. Both approaches only detected and recognised open windows. This simplified the detection method and reduced the training data preparation task, with only open windows required to be labelled. Although the detection of closing/closing of windows could potentially be useful in some applications, detecting open windows only could be adequate for notifying/alerting users or automatically adjusting the HVAC. For most instances, Model 3 provided detection responses similar to Model 2 with correct identification of the four separate windows. However, the person and objects outside the window region were sometimes detected as open windows.

Model 4 was able to detect open windows more accurately and reliably by focusing only on the openings or gaps of the windows. In some cases, two bounding boxes were assigned to a detected open window, increasing the chances of each window being detected and recognised. As observed, bounding boxes could be assigned to the vertical or the horizontal opening gaps. Since the size of the windows could be larger compared to objects such as occupancy body size and size of objects/furniture within a room, this approach could reduce the occurrence of obstruction impacting detection performance and leading to incorrect and no detection. This also raises the possibility of estimating the window opening size, which can be developed in future works.

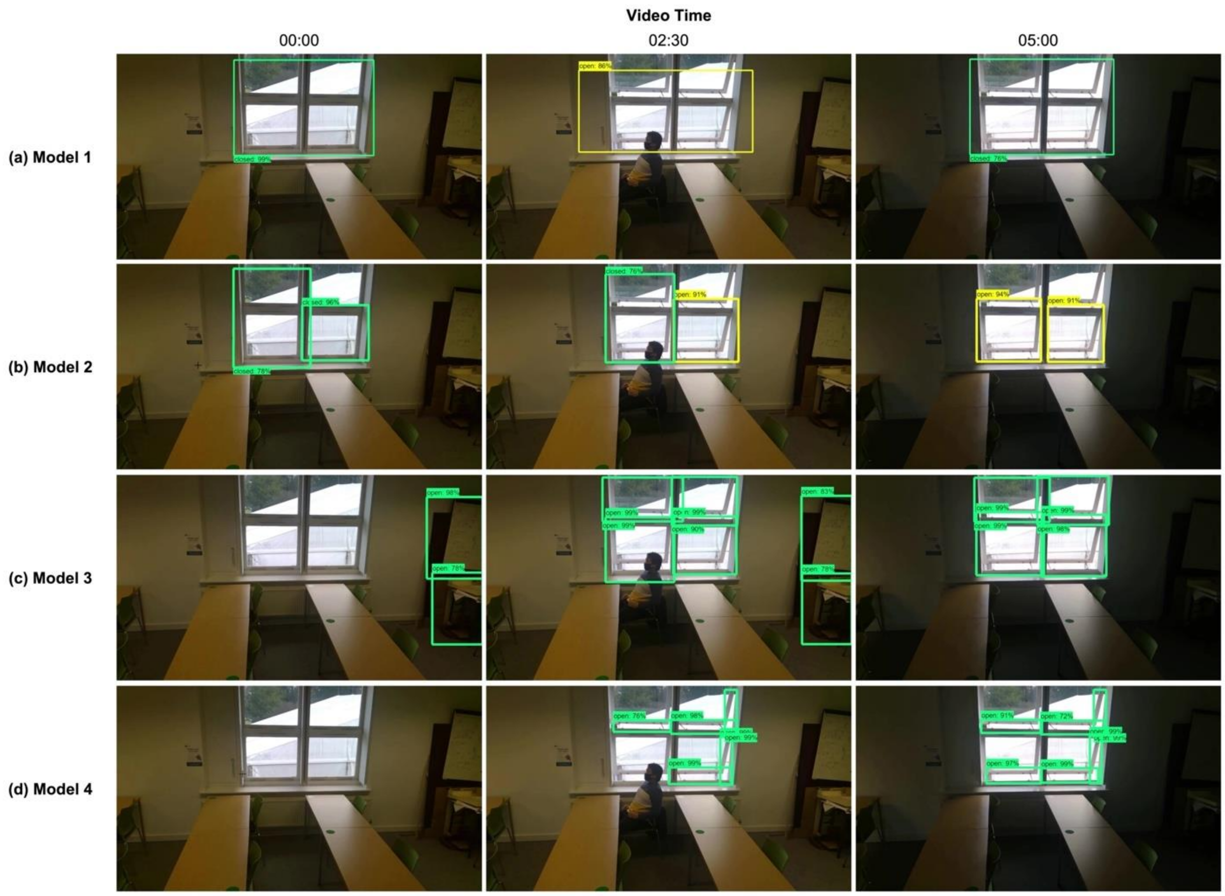


Figure 5-8. Snapshots of window detection and recognition during various key stages of the experimental test using the different window detectors.

5.5.2. Window Detection Performance Analysis

The following section analyses the detection and recognition performance and identifies the benefits and limitations of each of the window detection model configurations. Figure 5-9 compares the average IoU for each configuration. Overall, Model 1 had the lowest number of images within the dataset and achieved an average IoU of 97.68% for open windows and 82.90% for closed. Model 2 achieved an average IoU of 86.2% for open, and 86.84% for closed. Although Model 1 had a higher IoU for the open window condition, which shows how accurate a detector is on a particular dataset, it did not reflect in the real-time detection and recognition observed in Video 2 and Figure 5-8.

With the selected window configuration, it was assumed that the window on the top left was Window A, the top right was Window B, the bottom left was Window C and the window on the bottom right was Window D. As shown in Figure 5-9, Model 3 achieved a more consistent detection IoU between all the windows with an average IoU of 96.82%. The results also followed a similar trend to Model 1, with Windows A and B achieving higher IoU than Windows C and D. This is probably due to the occupant's presence obstructing the lower windows. Despite achieving the highest detection IoU, this model also identified other objects within the building space as the selected response, this is not included in the results shown. Such errors in detection were avoided through the labelling method used in Model 4, giving an overall IoU of 95.12%. Despite the lower IoU achieved for Window A with an IoU of 85.74%, consistent IoU were achieved for Windows B, C and D, indicating the labelling method can avoid problems related to obstruction.

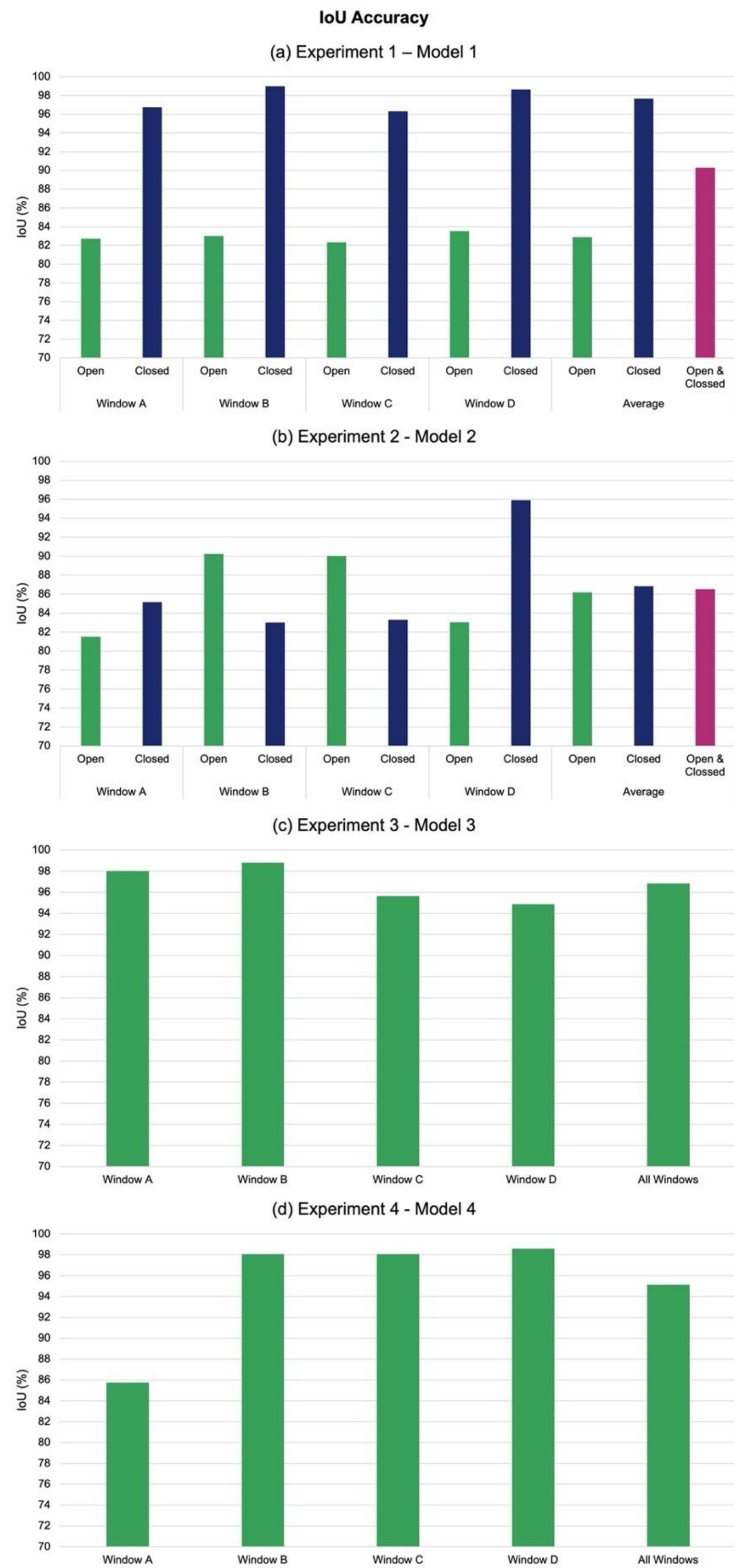


Figure 5-9. Average IoU (%) of the windows during the experimental test based on the application of Models 1 – 4.

Table 5-4Table 5-5Table 5-5 presents the detection performance for Models 1, 2, 3 and 4 regarding the percentage of time achieving correct, incorrect, and no detections. This will provide a greater understanding of the detection performances of the different model configurations. Based on Model 1 results, a consistently low percentage of time achieving correct detection across all four windows and for both window condition responses, an average of 28.73% of the time achieving correct detections. Both incorrect and missed detections were mainly due to the open windows being identified as closed. Model 1 had an average incorrect detection of 9.44%, with Window C receiving the highest number of incorrect detections. While the most no/missed detections were for opened Window A.

Table 5-4. Comparison of Window Models 1 and 2 performances in terms of the percentage of time achieving correct, incorrect, and no detections.

Percentage of Time Achieving (%)	Open and Closed Windows										
	Window A		Window B		Window C		Window D		All Windows		
	Open	Closed	Open	Closed	Open	Closed	Open	Closed	Open	Closed	Combination of Both
Model 1											
Correct Detections	29.14%	28.48%	27.15%	29.14%	29.80%	28.48%	28.48%	29.14%	28.64%	28.81%	57.45%
Incorrect Detections	16.56%	0.00%	15.23%	3.97%	17.88%	0.00%	14.57%	3.97%	16.06%	1.99%	18.05%
No/Missed Detections	20.53%	5.30%	15.89%	8.61%	20.53%	3.31%	17.22%	6.62%	18.54%	5.96%	24.50%
Model 2											
Correct Detections	3.31%	1.99%	2.65%	2.65%	22.52%	15.89%	43.05%	39.07%	17.88%	14.90%	32.78%
Incorrect Detections	0.00%	0.00%	0.00%	0.00%	11.26%	0.00%	1.32%	0.66%	3.15%	0.17%	3.31%
No/Missed Detections	62.91%	31.79%	55.63%	39.07%	34.44%	15.89%	15.89%	0.00%	42.22%	21.69%	63.91%

Table 5-5. Comparison of Window Models 3 and 4 performances in terms of the percentage of time achieving correct, incorrect, and no detections.

Percentage of Time Achieving (%)	Open Windows				
	Window A	Window B	Window C	Window D	All windows
Model 3					
Correct Detections	98.68%	62.25%	93.38%	68.21%	80.63%
Incorrect Detections	1.32%	37.75%	6.62%	31.79%	19.37%
No/Missed Detections	0.00%	0.00%	0.00%	0.00%	0.00%
Model 4					
Correct Detections	82.12%	100.00%	63.58%	98.01%	85.93%
Incorrect Detections	2.65%	0.00%	4.64%	0.00%	1.82%
No/Missed Detections	15.23%	0.00%	31.79%	1.99%	12.25%

Model 2 achieved a higher percentage in terms of the time it achieved correct detections, an average of 32.78%, and a lower number of incorrect predictions. However, it led to a high number of no/missed detections up to 63.91% of the time. This shows that both model configurations will not be suitable for the required detection of the windows in the lecture room, as it will lead to many incorrect notifications/alerts and incorrectly adjust the heating of the room. Although the model could potentially be improved by using a larger dataset for training, the detection method in Models 3 and 4 led to higher detection performance (Table 5-3), while using a small dataset for training. A significantly higher average of correct detections was achieved, 80.63% for Model 3 and 85.93% for Model 4.

Figure 5-10 and 5-11 presents the case study test results in the form of a confusion matrix. As discussed previously, Model 1 was not able to adequately identify each of the individual windows, and as expected, it led to relatively low percentages for true positives compared to false positives and false negative results (shown in Figure 5-8a-e). For Model 2, similar results were achieved specifically for Windows A and B.

Model 3 indicated good performance, in particular, the detection of Windows A and C with relatively high true positive results of up to 92.08%. However, it indicated lower performance for Windows B and D with false positive values of 41.3% and 34.53%, giving an overall percentage of 76.17% for true positives on all four windows. Model 4 presented the best performance with the highest number of true positives (up to 100%), and only a lower value was achieved for Window C (50%), which may have been affected by the occupant obstructing the window openings. An overall value of 78.43% was achieved for true positives for Model 4.

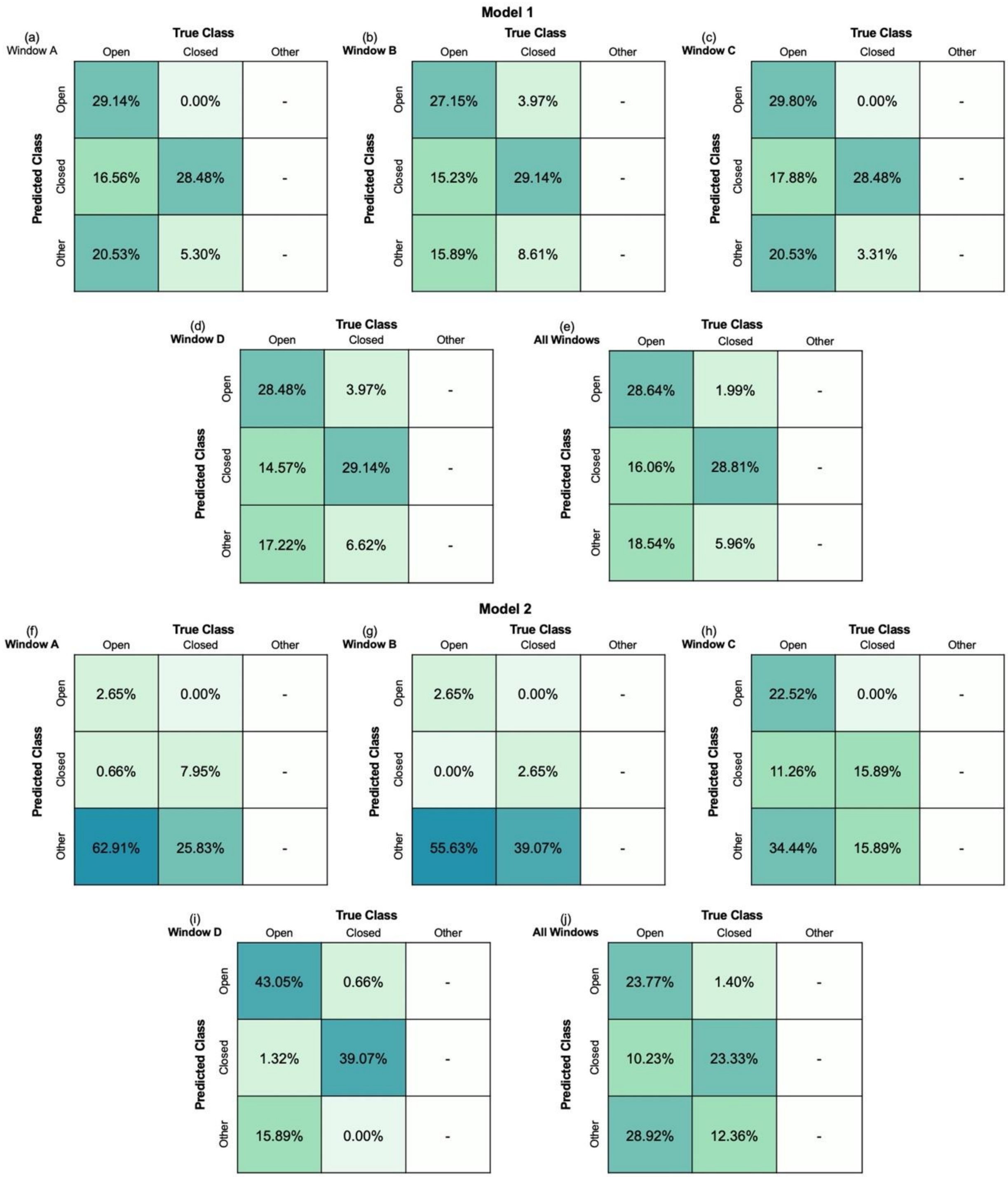


Figure 5-10. Detection performance results for Window Models 1 and 2 in the form of a confusion matrix.

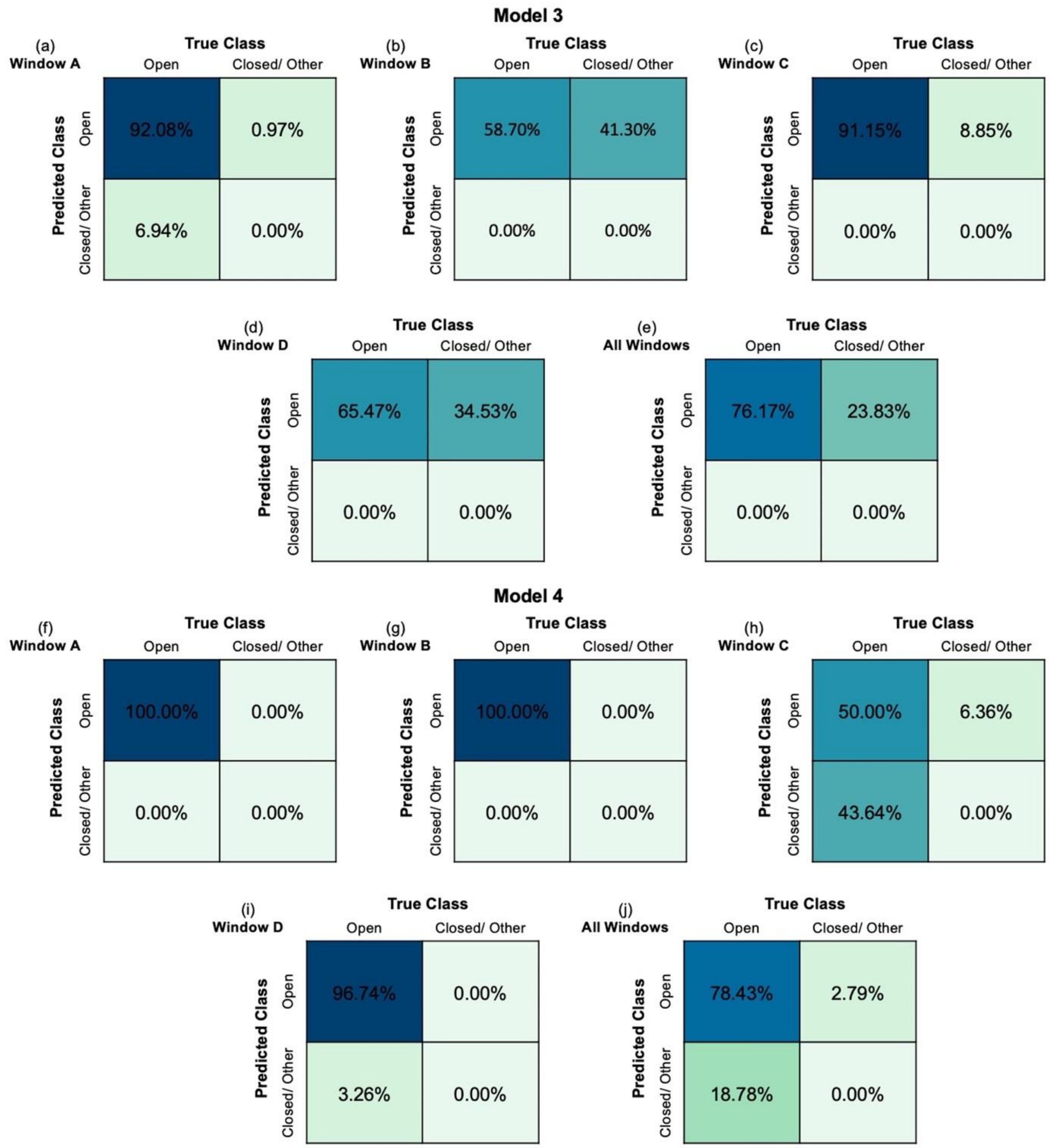


Figure 5-11. Detection performance results for Window Models 3 and 4 in form of a confusion matrix.

Table 5-6 and 5-7 presents the results in terms of the common evaluation metrics, including the accuracy, precision, recall, and the associated F1 score that was based on the occurrence of the labelled instances for each of the windows. Overall, Model 4 provided the best performance with the highest accuracy of 78.43% and an F1 score of 0.8791. Model 1 had the poorest performance based on quantitative and qualitative results. It could not detect the four windows separately, whereby the windows were assumed as one in most instances. Unanticipated results were obtained with Model 2 as given by the results in terms of the IoU

(Figure 5-9), which was also seen in Table 5-3, the addition of more images to the training dataset did not lead to improved detection performance. Yet overall, it had a better performance compared to Model 1 in detecting and recognising the individual windows, but it did not perform well in terms of detecting all windows. As for Model 3, having only one selected response outcome enabled better identification of the separate windows. However, this model was limited and, in some cases, identified other objects as opened windows, such as the drawing board. Model 4 was able to detect open windows more accurately by focusing only on the openings or gaps of the windows.

Table 5-6. Evaluation of Window Models 1 and 2 performances based on common classification evaluation metrics.

Window	**Class**	**Window**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Model 1						
A	1	Open	62.91%	1.0000	0.4400	0.6111
	2	Closed	78.14%	0.6323	0.8431	0.7227
	Average for both types		70.53%	0.8162	0.6416	0.6669
B	1	Open	64.91%	0.8724	0.4659	0.6075
	2	Closed	72.19%	0.6568	0.6985	0.6770
	Average for both types		68.55%	0.7646	0.5822	0.6423
C	1	Open	61.59%	1.0000	0.4369	0.6081
	2	Closed	78.81%	0.6143	0.8959	0.7289
	Average for both types		70.20%	0.8072	0.6664	0.6685
D	1	Open	64.24%	0.8777	0.4725	0.6143
	2	Closed	74.84%	0.6667	0.7335	0.6985
	Average for both types		69.54%	0.7722	0.6030	0.6564
Model 2						
A	1	Open	36.43%	1.0000	0.0400	0.0770
	2	Closed	72.98%	0.9244	0.2353	0.3752
	Average for both types		54.71%	0.9622	0.13765	0.2261
B	1	Open	44.37%	1.0000	0.0455	0.0870
	2	Closed	60.93%	1.0000	0.0635	0.1195
	Average for both types		52.65%	1.0000	0.0545	0.1033
C	1	Open	54.30%	1.0000	0.3301	0.4964
	2	Closed	72.85%	0.5853	0.5	0.5393
	Average for both types		63.58%	0.7927	0.4151	0.5179
D	1	Open	82.81%	0.9849	0.7144	0.8281
	2	Closed	98.02%	0.9673	0.9834	0.9753
	Average for both types		90.42%	0.9761	0.8489	0.9017

Table 5-7. Evaluation of Window Models 3 and 4 performances based on common classification evaluation metrics.

Window	Class	Window	Accuracy	Precision	Recall	F1 Score
Model 3						
A	1	Open	98.02%	0.9802	1.0000	0.9900
B			58.70%	0.5870	1.0000	0.7398
C			91.15%	0.9115	1.0000	0.9537
D			65.47%	0.6547	1.0000	0.6547
Model 4						
A	1	Open	100.00%	1.0000	1.0000	1.0000
B			100.00%	1.0000	1.0000	1.0000
C			50.00%	0.8872	0.5340	0.5000
D			96.74%	1.0000	0.9674	0.9834

5.6. Detection Performance of Models Based on Experimental Tests 5a and b

Based on the results given in Chapter 5.5 for Experimental Tests 1 – 4, suggest the possibility of using Model 4 for the most accurate window detection and recognition. Hence, this led to further tests using this model in Experimental Tests 5a and 5b. Firstly, Figure 5-12 shows the real-time detection and recognition results for the different windows located in the room. Through the detection of the north-facing window, along with the south-facing window 1 from two different camera angles and lighting conditions, it was observed that windows that were opened were identified. Further training would be made to improve the detection accuracy and to reduce the possibility of achieving false detections. Effectively, further improvements towards the model's ability to detect other window types are required. Hence, both Experimental Test 5a and 5b still focused on the detection of the south-facing windows.

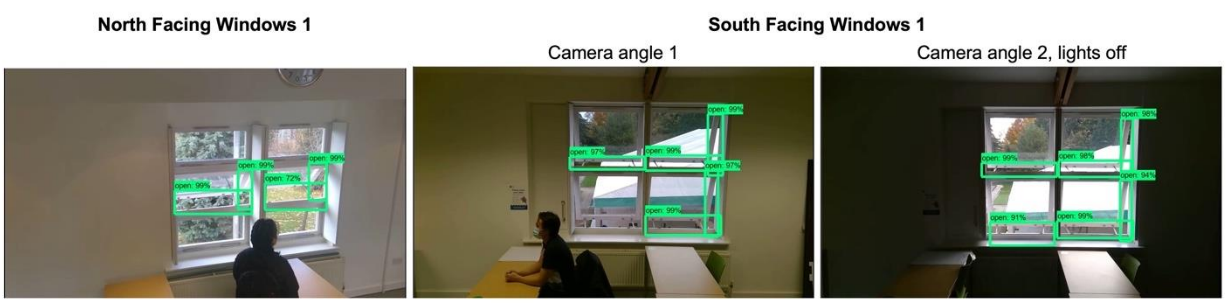


Figure 5-12. Detection and recognition result on different windows in the selected Marmont Lecture Room.

To show the capability of the proposed approach using Model 4, two real-time experimental detection tests, Experimental Test 5a and 5b were performed within the Marmont Lecture room. The test was based on the same set-up given in Figure 5-5 and each test was performed for 15 minutes following the scenario given in Figure 5-13 to highlight a typical scenario of the interaction of occupancy behaviour impacting the window conditions. Similarly, both experimental tests had the camera positioned at the height and angle replicating typical occupancy sensors, by locating the camera near the ceiling of the room.

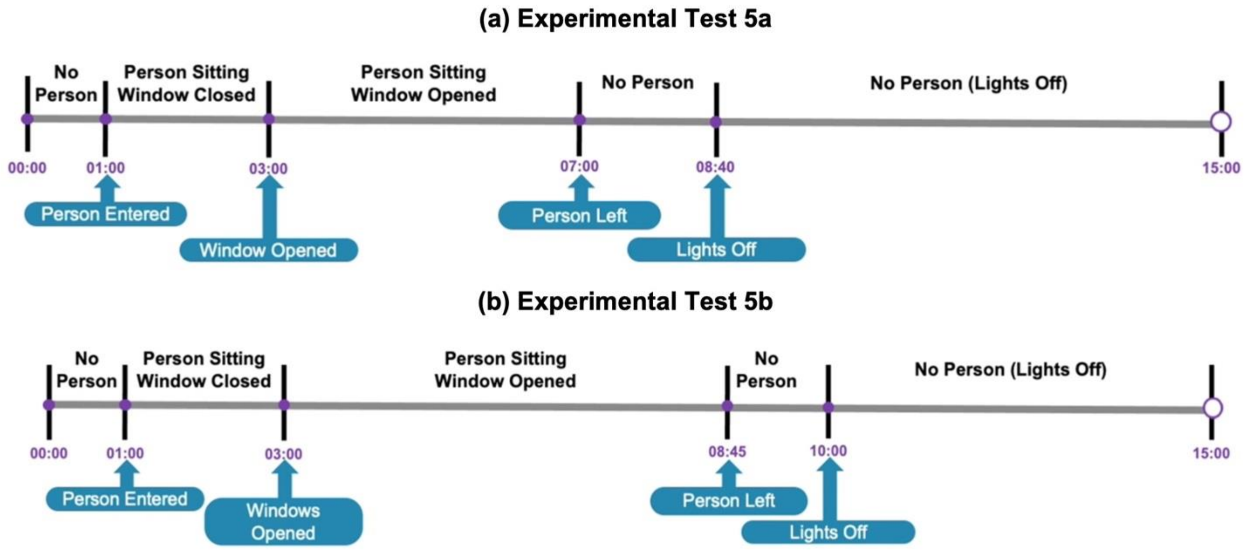


Figure 5-13. Window detection experimental tests 5a and b scenarios.

5.6.1. Real-Time Window Detection and Recognition

Figure 5-14 and 5-15 both provide examples of window detection and recognition during Experimental Test 5a and 5b that were based on the key stages as highlighted by the timelines given in Figure 5-13. The results showed its capabilities in detecting opened windows during times when there is no one near/beside the window and the action of a person opening a window and times when a person is sitting near to the window. It also showed its capabilities when artificial lighting is switched off. As given by the snapshots, the size and shape of these bounding boxes varied between each detection interval. It was dependent on the size of the detected space, and the distance of the camera from the detected window, and it was also dependent upon the influence of the presence of a person which can be considered as an obstructing object.

In addition, the method in the labelling of the gaps of opened windows within the images in the training dataset resulted in instances of windows achieving two bounding boxes assigned to one window. For example, this was presented in all the detections highlighted in Figure 5-14, with one horizontal and one vertical bounding box assigned. Otherwise, in instances such as the top left window shown in Figure 5-15, only one bounding box was present as the vertical gap within the window was not clearly shown.

Hence, the proposed method of detecting window opening gaps potentially reduces the occurrence of issues such as obstruction as typically, the size of the windows will be larger in comparison to objects such as occupancy body size and size of general objects within a room. This suggests the full window would be unlikely to be always blocked. Furthermore, a window should not be blocked as this could lead to other issues such as daylighting and visual comfort within buildings.

Figure 5-14. Snapshots of various key point stages during the application of the window detection approach (Model 4) during Experimental Test 5a.

Figure 5-15. Snapshots of various key point stages during the application of the window detection approach (Model 4) during Experimental Test 5b.

5.6.2. Window Detection Performance Analysis

Based on the detections shown in Chapter 5.6.1, the following shows the analysis of the model detection and recognition performance throughout different segments during the experimental tests conducted within the case study building.

Figure 5-16 presents the average IoU detection accuracy for both experiments. No results were obtained for parts 1 and 2 of both experiments, as all windows were identified as not being opened. For the other parts, it indicated an average detection accuracy of 98.19% was achieved for Experimental Test 5a, and 96.67% for Experimental Test 5b. A threshold limit with a minimum detection accuracy of 60% was set to only enable the display of detections when the accuracy is above this value. This mitigates any form of uncertain predictions. Stable performance was achieved, as minimal variations were presented within the accuracies between parts 3, 4 and 5 in both experimental tests (the different parts correspond to the different segments of the timelines shown in Figure 5-13).

The highest prediction accuracy was achieved in part 3. This was when the windows were opened, and minimal movement was performed by the person. Similar results were achieved in part 4, and only a slight decrease in accuracy values was achieved when the lights were switched off in part 5. Overall, the results suggest that the developed model can detect multiple numbers of windows under various room conditions. However, this is only based on the initial detection at the selected period of time. Hence, further model training and testing would be performed to achieve higher detection accuracies for various types of windows.

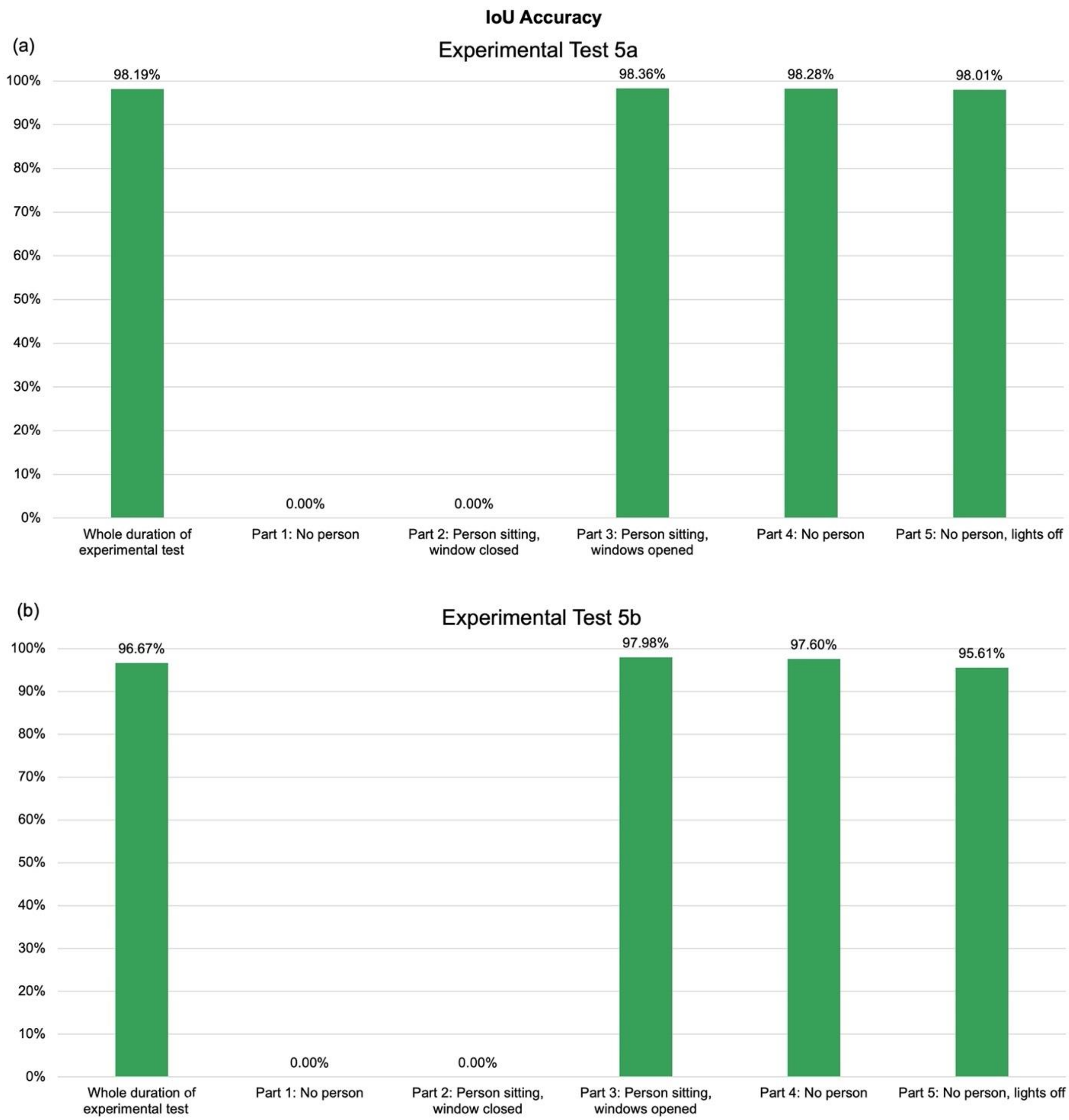


Figure 5-16. Average IoU detection accuracy based on the displayed bounding box during real-time predictions in (a). Experimental Test 5a and (b). Experimental Test 5b.

Figure 5-17 presents the overall detection performance of the proposed approach during the two experimental tests. For Experimental Test 5a, Figure 5-17a suggests the approach provided correct detections for an average of 99.61% of the time, 0.28% of the time to achieve incorrect detections and subsequently, 0.11% of the time with no detections. Similarly, for Experimental Test 5b, Figure 5-17b suggests it achieved correct detection 97.56% of the time, 1.94% of the time to achieve incorrect detections and no detections occurred for 0.50% of the time. Obtaining a correct detection represents the instance when the opened windows were correctly identified as open, and for the times when detection was correctly not made when windows were closed. Generally, the performance of the model was better in Experimental Test 5a than in Experimental Test 5b.

Based on the breakdown of the detection performance for each of the five parts of each of the experimental tests, part 2 achieved the most amount of incorrect detection, 1.25% of the time. This could be because the person was within the detection frame and displaying false results in suggesting windows being identified as opened when they were not. Similarly, this may also cause the result of incorrect detection in part 3 of detection performance during Experimental Test 5b, with incorrect detections recorded for 3.13% of the time and no detection for 1.88% of the time.

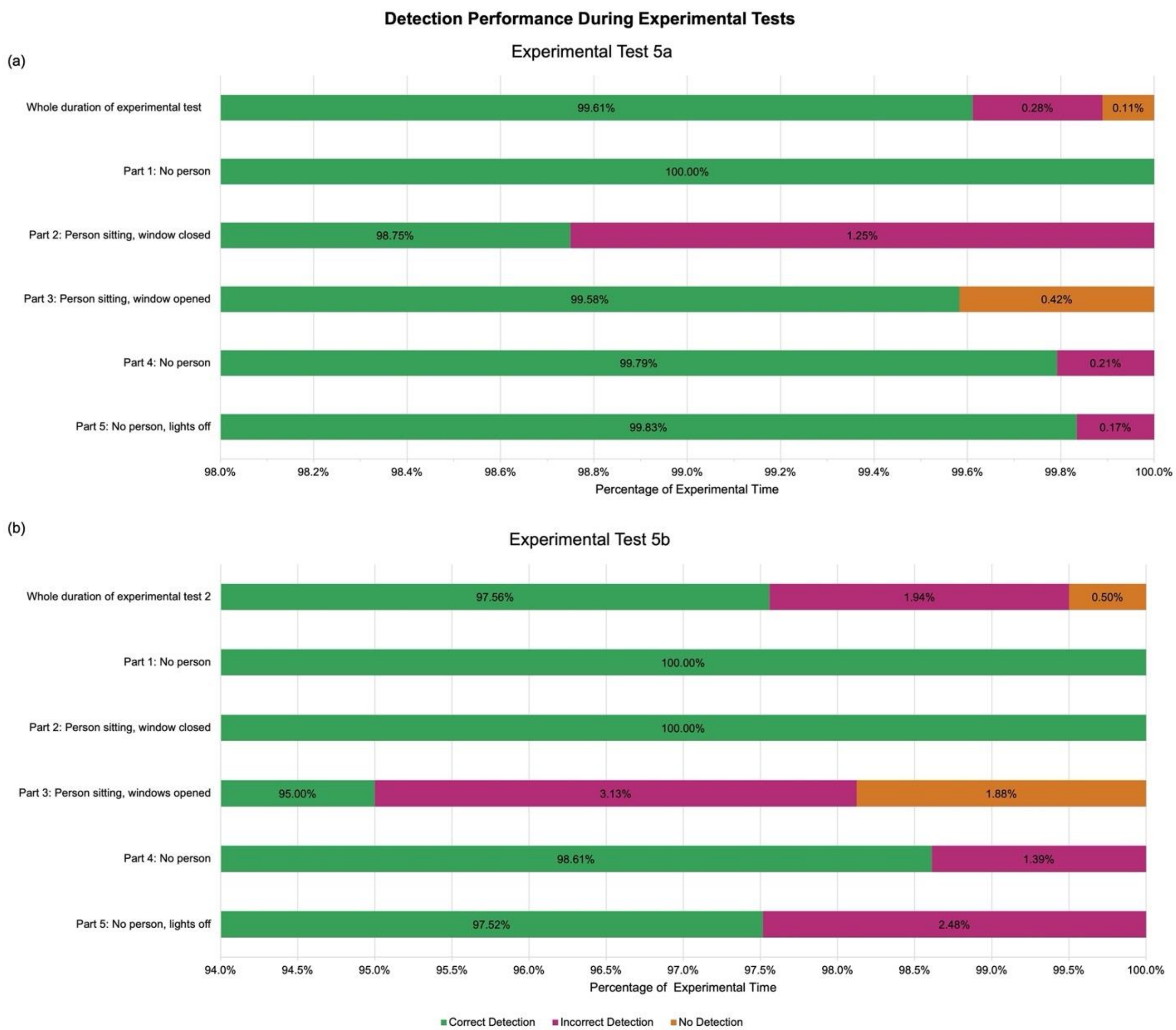


Figure 5-17. Detection performance during a). Experimental Test 5a and b). Experimental Test 5b. Identification of the percentage of time achieving correct, incorrect, and no detections during the whole duration of each test and for each of the sections.

Figure 5-18 presents the results for the different parts of the experimental tests in the form of a confusion matrix based on the prediction response label of ‘open’ displayed on the detected windows. Since no windows were opened in parts 1 and 2 of both tests, no results were given for the majority of the confusion matrix displayed. However, for part 2 in Experimental Test 5a, three labels were present in identifying windows as opened, when they were not. This resulted in the only value displayed in this matrix. Similar to the results shown in Figure 5-17 of the overall detection performance, the results shown in the confusion matrix for parts 3, 4, and 5 for both experimental tests, suggest that most labels were correctly assigned to the opened windows. Only the occasional instances when the opened windows were not identified, so no labels were assigned. Also, times when labels were assigned to windows that were closed.

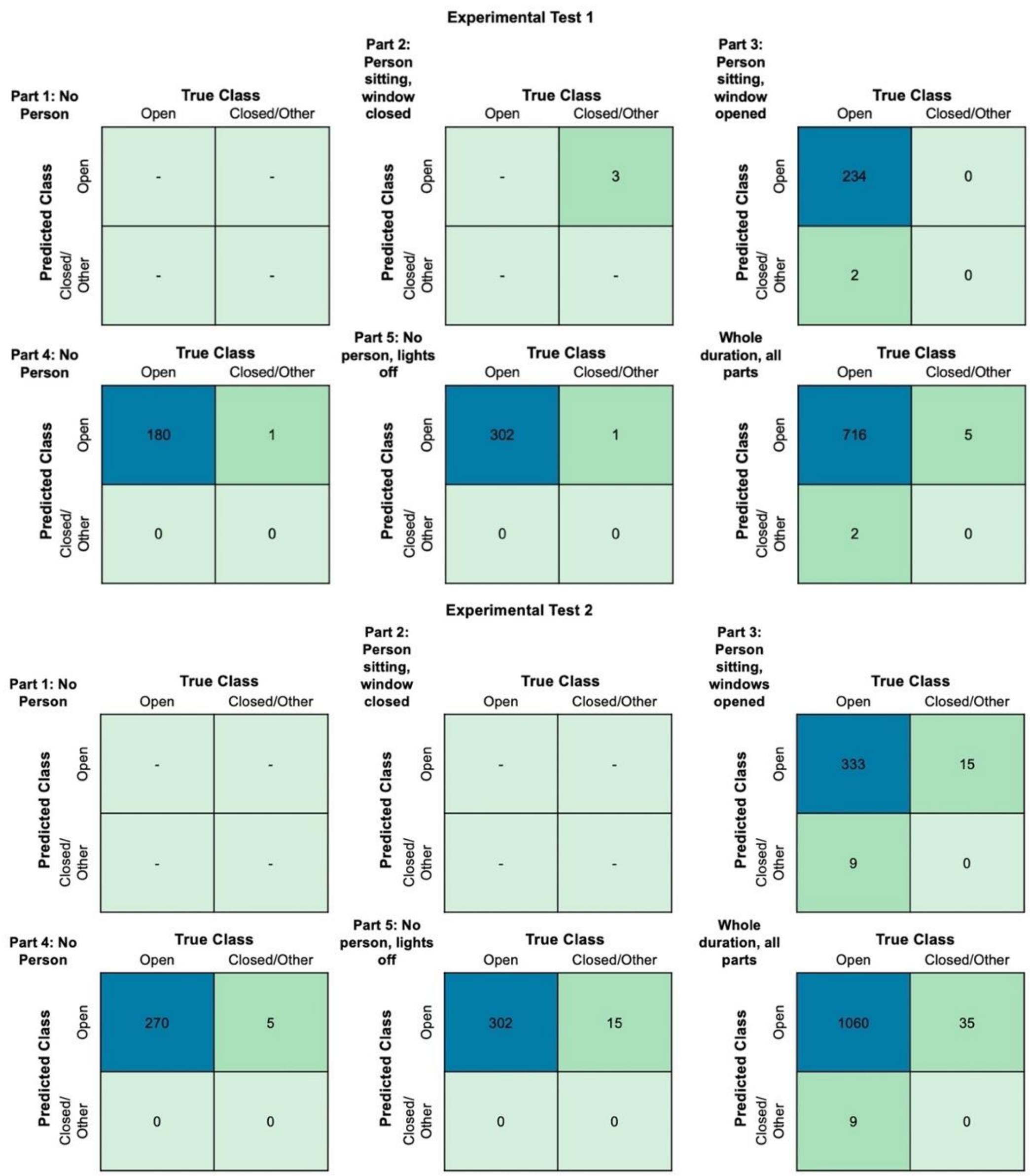


Figure 5-18. Experimental Test 5a and b detection performances evaluated in the form of the confusion matrix based on the labels identified. From clockwise, no person, a person sitting with windows closed, a person sitting with windows opened, no person, no person with lights off, entire duration.

The confusion matrix results displayed in Figure 5-18 for each part enabled the evaluation of the results in the form of the different classification evaluation metrics, as shown in Table 5-8. An accuracy of over 99% accuracy with an F1 score of 0.9951 was achieved for the performance during experimental test 5a and an accuracy of 96% with an F1 score of 0.9797 for experimental test 5b.

Table 5-8. Evaluation of the model performance during Experimental Test 5a and b, based on common evaluation metrics.

Section	Accuracy	Precision	Recall	F_1 Score
Experimental Test 5a				
Part 1: No person	N/A	N/A	N/A	N/A
Part 2: Person sitting, the window closed	N/A	N/A	N/A	N/A
Part 3: Person sitting, windows opened	99.15%	1.0000	0.9915	0.9957
Part 4: No person	99.45%	0.9945	1.0000	0.9972
Part 5: No person, lights off	99.67%	0.9967	1.0000	0.9983
The whole duration of experimental test 1	99.03%	0.9931	0.9972	0.9951
Experimental Test 5b				
Part 1: No person	N/A	N/A	N/A	N/A
Part 2: Person sitting, the window closed	N/A	N/A	N/A	N/A
Part 3: Person sitting, windows opened	93.28%	0.9569	0.9737	0.9652
Part 4: No person	98.18%	0.9818	1.0000	0.9908
Part 5: No person, lights off	95.27%	0.9527	1.0000	0.9758
The whole duration of experimental test 2	96.01%	0.9680	0.9916	0.9797

5.7. Comparison of the Deep Learning-Influenced Window Profiles with Actual Observation

Based on the detection given in Video 2, Figure 5-19 presents the generated DLIP of the opening patterns for the selected windows in the Marmont Room during the experimental tests using the different models. The Actual Observation Profile defined the 'actual' window condition and was used to assess the performance of each model. The DLIP was based on a modulating number of detected opened windows, with the value of 1 representing the times when all four windows within the detection frame were identified as open. For all models, the generated DLIP still alternates between the values of the window profile schedule, indicating prediction error. Therefore, further improvements are required to enhance the detection model's accuracy, reliability, and stability. Comparing the results based on these four models applied to the experiment test indicates that Model 4 provides the least amount of variation in terms of errors in predictions, providing the most accurate results compared to the actual observation profile.

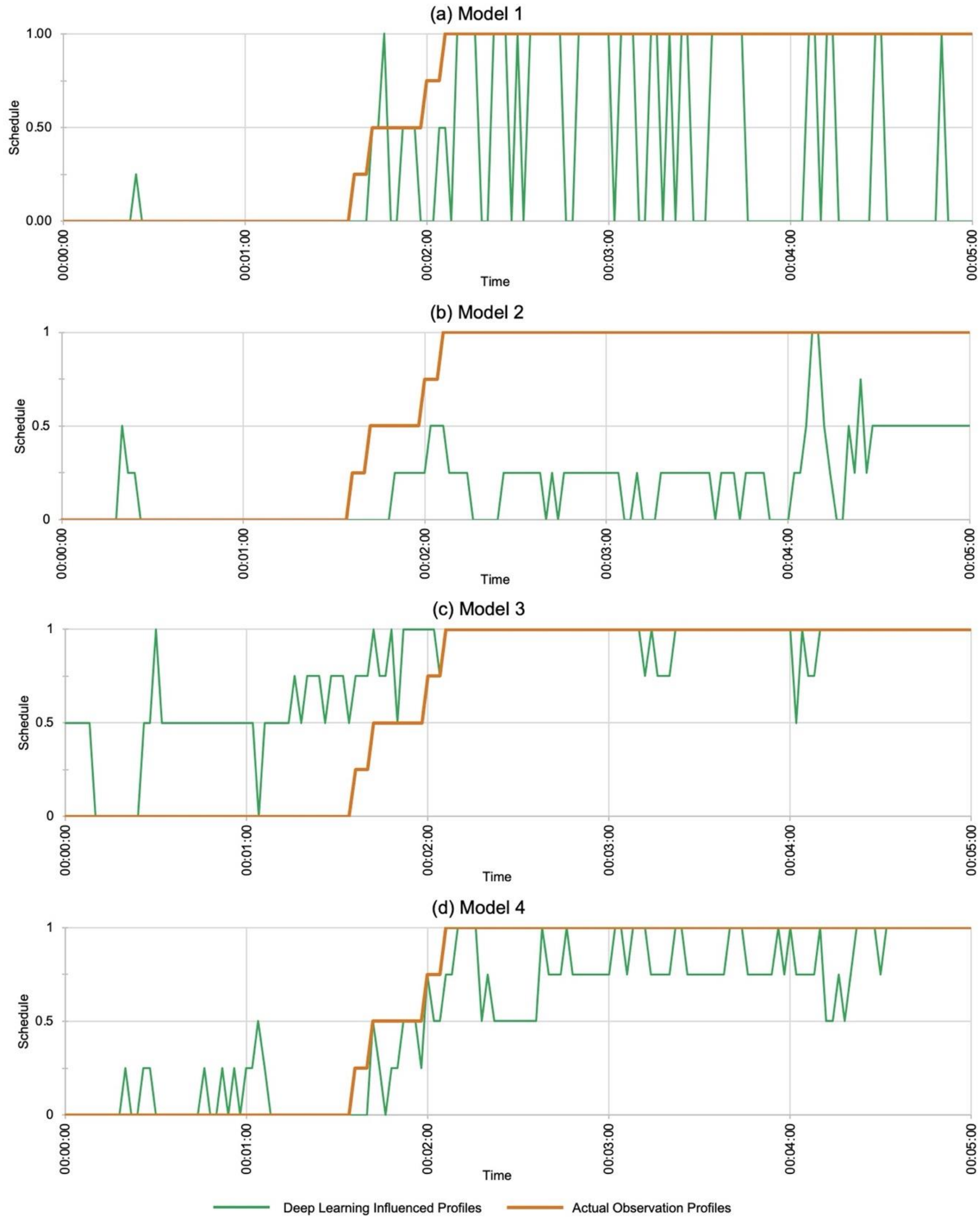


Figure 5-19. Deep learning-influenced window profiles (DLIPs) were generated from the application of the different models during the experimental test plotted against the Actual Observation Profile.

Correspondingly, Figure 5-20 presents the generated DLIPs of the opening patterns for the selected windows in the Marmont Room during a). Experimental tests 5a and b). Experimental test 5b. Similarly, the DLIP still alternates between the values of the window profile schedule, indicating a prediction error.

Therefore, further improvements are required to enhance the accuracy, reliability and stability of the detection model.

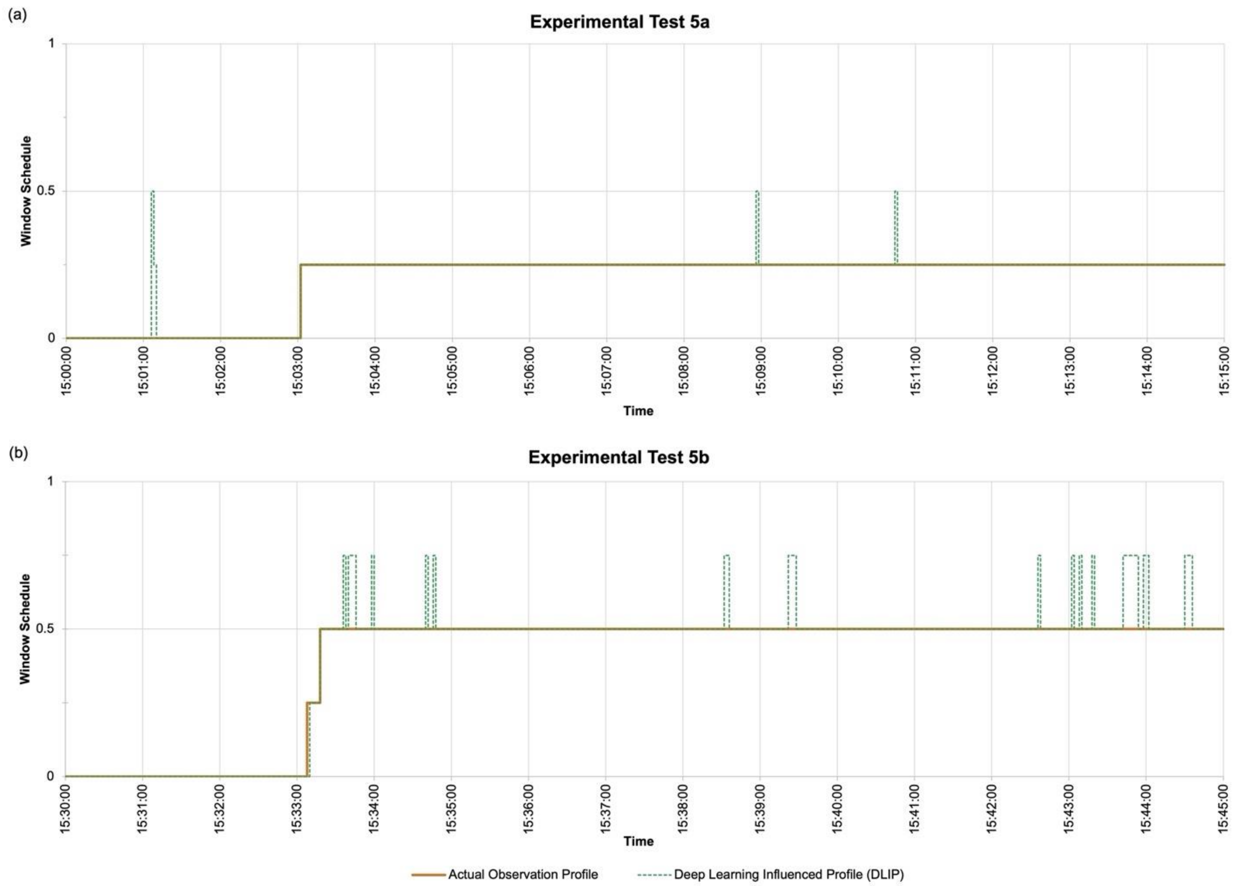


Figure 5-20. Generated DLIPs based on the window detection results performed in Experimental Tests 5a and b, along with the corresponding actual window conditions.

5.8. Evaluation of the Window Detection Framework Approach Using Building Energy Simulation

The comparison of the DLIP with the actual observation in Chapter 5.7 presented an initial analysis towards the effectiveness of each of the window models. To further assess the model performances and to suggest how the framework would be operated under various window conditions, the following section presents the use of building energy simulation to analyse the impact of the application of the different window profiles through various simulation cases.

5.8.1. Impact of the Window Detection Performance on Building Energy and Ventilation Heat Losses

Building energy simulation (BES) was used to predict the potential impact of the detection method on ventilation heat loss and building energy demands. The case study building model was set to operate between 09:00 – 17:00. The base building model employed an HVAC system operating with a conventional control system, which used a fixed operation schedule (Figure 5-21d-e). Additionally, scheduled-based profiles for windows (fully opened and closed), occupancy, and lighting were set, as shown in Figure 5-21a, d and e. The occupancy was assumed to be 40 people, and the lighting was 10 W/m^2 during the building operation period. Scenario-based simulations were carried out to evaluate the impact of the vision-based detector on the ventilation heat loss and heating energy demand. While it is ideal that the profiles are generated using the detection method (following the process shown in Figure 5-6). are directly inputted into the BES model, the minimum simulation time step in IESVE is 10 minutes. Hence, smaller time steps would be necessary for the direct input of these profiles. This is because the detection and recognition responses were obtained and recorded every two seconds. Future works should consider employing other methods which can capture the detail of the detection operation in simulations. However, for comparison, the generated profiles were extended to an entire class period. This means every detection is now equivalent to 1 min in the simulation. While this does not directly correspond to the real-time detections, it would still allow us to evaluate the impact of detections (correct, incorrect and missed detections) on the predicted ventilation heat loss. While occupancy can also be detected using a similar approach as the window detector, this was not evaluated in this study.

Table 5-9 summarises all the different combinations of assigned profiles used for all the simulation cases.

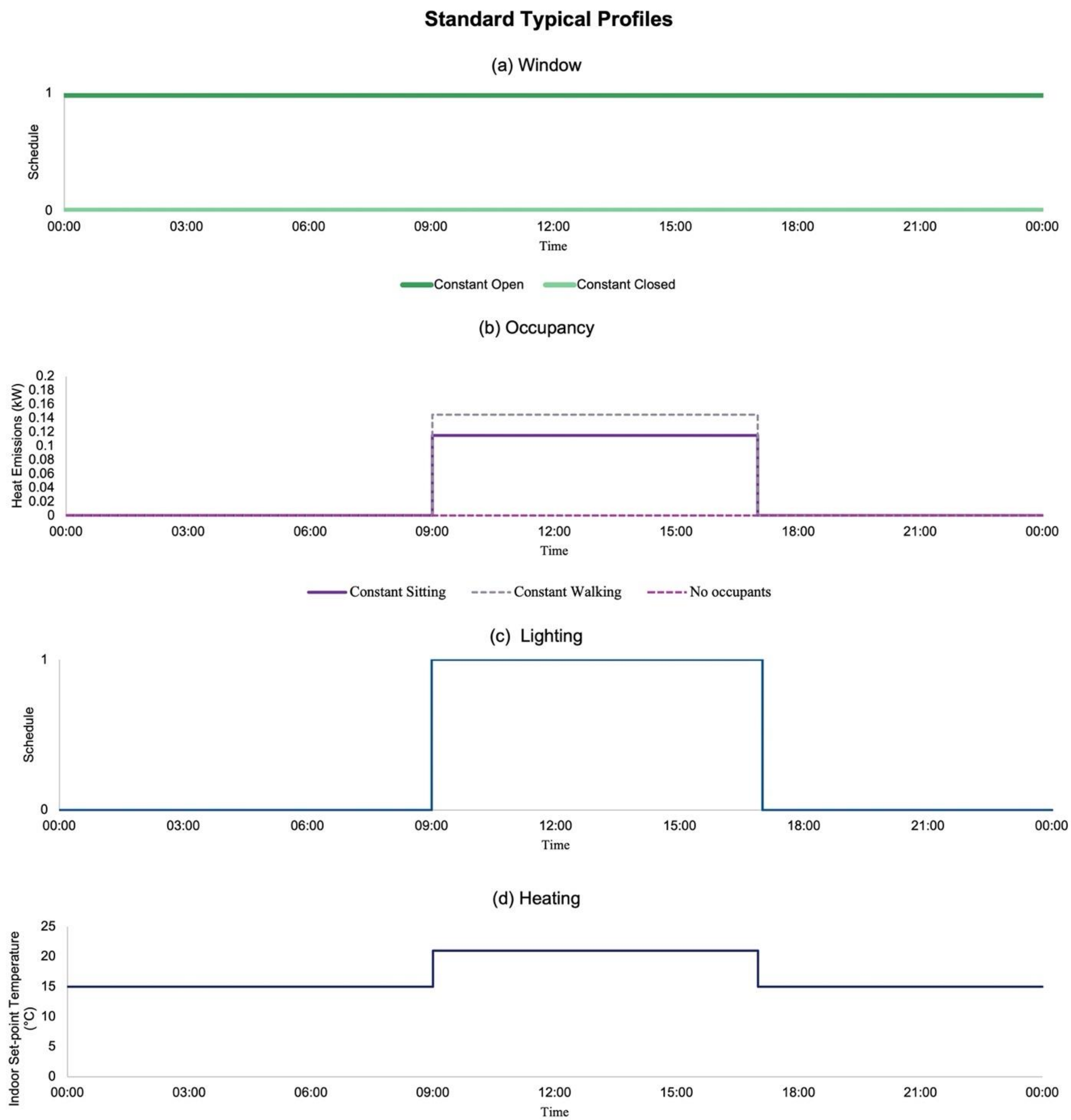


Figure 5-21. Predefined constant 'static' profiles for occupancy, windows, lighting, heating and cooling were used for the assessment of the results from window detection building energy performances.

Table 5-9. Summary of the profiles assigned to the different simulation cases to evaluate the impact of window detection on building energy.

<table>
<tr><th colspan="2" rowspan="2">Simulation Cases</th><th colspan="4">Assigned Profiles</th></tr>
<tr><th>Window (Figure 5-21a)</th><th>Occupancy (Figure 5-21b)</th><th>Lighting (Figure 5-21c)</th><th>Heating (Figure 5-21d)</th></tr>
<tr><td rowspan="2">Fixed Profiles</td><td>1</td><td>Constant open</td><td rowspan="2">Constant sitting during operational hours</td><td colspan="2" rowspan="2">Standard typical</td></tr>
<tr><td>2</td><td>Constant closed</td></tr>
<tr><td>Deep Learning-Influenced Profiles</td><td>1, 2, 3, 4</td><td>DLIP profiles (extended to full class period)</td><td rowspan="2">Actual (extended to full class period)</td><td colspan="2">Actual (extended to full class period)</td></tr>
<tr><td colspan="2">Actual Observation</td><td>Actual (extended to full class period)</td><td colspan="2">Actual (extended to full class period)</td></tr>
</table>

The following section analyses the impact of the application of the window detection model on the building energy performance, specifically evaluating the heating load and the ventilation heat losses through the window openings. While Model 1 and, to some extent, Model 2 were highly inaccurate and not well suited for the required application, both models are still evaluated here to show their impact on energy performance. As mentioned previously, the generated profiles were extended to an entire class period in the simulation. This was due to the limitation of the BES tool. While this does not directly correspond to the real-time detections, it would still allow us to evaluate the impact of detections (correct, incorrect, and missed detections) on the predicted ventilation heat loss. Figure 5-22 presents the predicted hourly ventilation heat loss for all the simulated scenario cases during a typical winter/heating day in the selected case study building. The results were related to the simulated window opening profiles and the airflow conditions across the four windows during the selected time and day. The maximum and minimum ventilation heat losses were obtained in the simulations, which assumed the window to be either constantly open or closed. These were used for comparison purposes. Compared with the "actual" profile results, using fixed or static profiles to simulate the window conditions is insufficient and can lead to inaccurate prediction of ventilation heat loss. As observed in Figure 5-22, higher detection accuracy led to better prediction of the ventilation heat losses. The percentage differences between the results of Models 1, 2, 3 and 4 and the actual profile were 22.83%, 105.38%, 22.07% and 19.60%. While Model 1's performance as a detector was poor, it could still provide a reasonable prediction of heat loss, particularly during the occupancy period. While Model 2, which had difficulties detecting all the open windows, did not perform as well as the others.

Figure 5-23 shows the results of the heating energy load in the simulated space. To maintain the room within the setpoint temperature of 21°C during the occupancy period, a high amount of heating energy would be required at the start of the class during the heating period at 10:00. This immediately decreased once the occupants start to go into the room and generate the internal heat gains. Similar to the findings in Figure 5-23, Model 4 achieved the closest prediction of heating energy load (as compared to the actual profile), while Model 2 had the worst performance. As observed, Model 2 underpredicted the heating energy demand as it mostly recognises only one of the four windows open during the occupancy period.

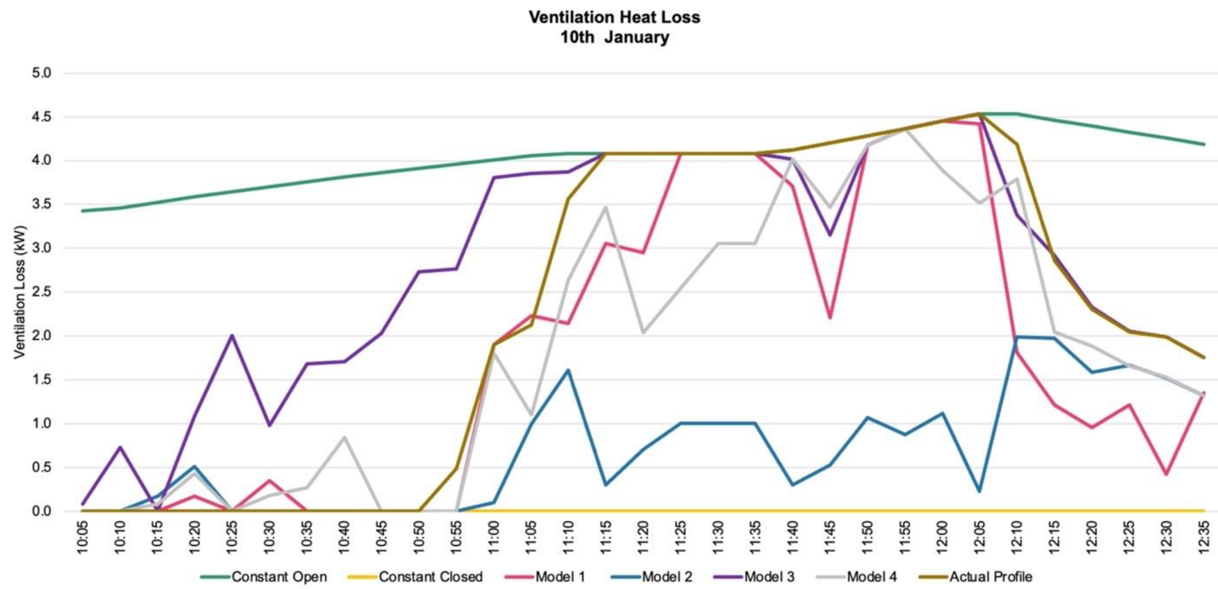


Figure 5-22. Ventilation heat loss predictions based on the simulation of the predefined fixed profiles (Constant open and constant closed), along with the window detections using Models 1 – 4, and the Actual Observation profiles.

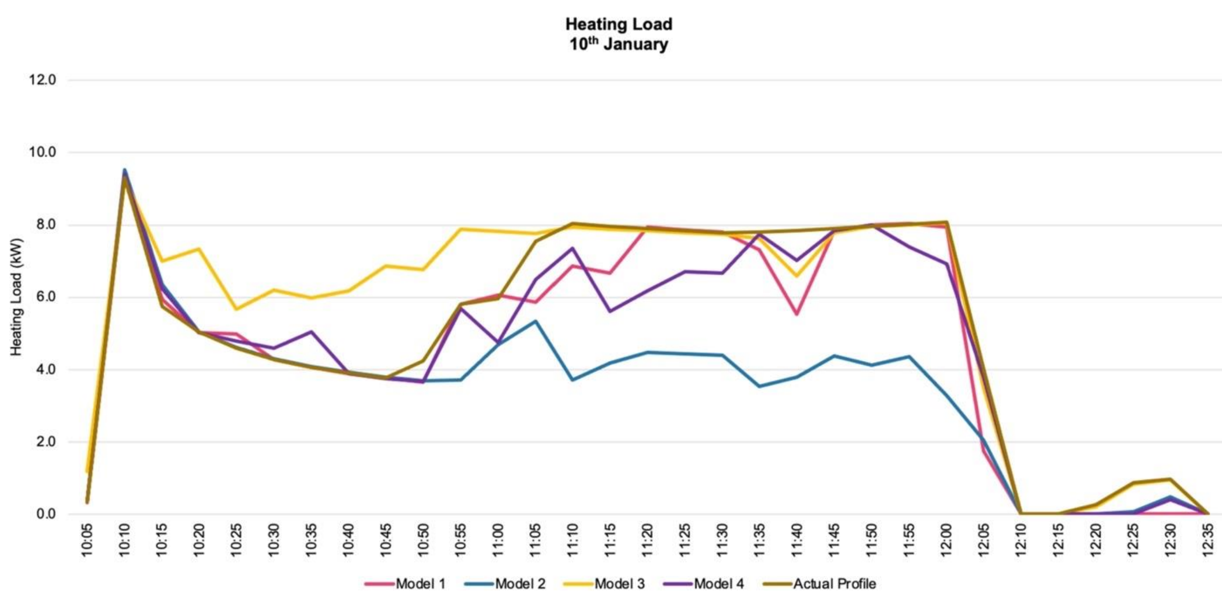


Figure 5-23. Building heating load prediction based on the simulation of predefined fixed profiles, along with the window detection and Actua Observation profiles.

Based on these results, the detection and recognition ability of the models ultimately influenced the prediction of the ventilation heat loss and heating demand. While the model configuration had a significant impact on the detection performance, other factors, such as the lighting conditions and obstructions, also affected the performance. This led to variations in the detection performance and predictions thought the detection period. The results highlighted the importance of the data set size and labelling method on the performance of the window detector. Model 4 provided the best detection performance, resulting in the most accurate prediction of ventilation heat loss. However, further evaluation and validation of the detection method should be conducted. The model's performance under different room settings and environmental conditions should be explored. Practical aspects, including people blocking the detector view and/or windows within the selected room, leading to inaccurate detection and recognition, should be addressed. For example, the device can provide alerts or sound notifications when the detector view is obstructed.

5.9. Scenario-Based Simulation and Analysis

During the winter seasons in cold or temperate climate locations such as the UK, high amounts of energy would be wasted due to windows being left open while building heating systems would still be in operation. An example is the selected lecture room within the Marmont Centre, which was used to conduct all experimental tests, where it relies on conventional control systems for the HVAC. Typical 'static' or fixed operation schedules were used. However, this cannot adjust according to the actual requirements of the space.

The following presents the set-up of test scenarios used to investigate the impact on building energy demand when the deep learning approach is applied. The scenario consists of the schedules indicated in Figure 5-24. The four-day period, Friday to Monday timeline provides a sample structure of how the room is occupied during a typical weekend during the winter months, between Friday 10th and Monday 13th of January. Specifically, the heating season was selected for analysis as parameters such as outdoor airflow and temperature must be considered when designing the control strategy i.e., night cooling and passive cooling.

The room was timetabled to have a lecture session on Friday (day 1) from 14:00-16:00 and another session from 10:00–12:00 on Monday (day 4). At these times, it was assumed that the building had maximum occupancy with 40 students present. Furthermore, the room was assumed to be unoccupied for the rest of the time. These occupancy-based conditions were presented as the scenario-based occupancy profile in Figure 8c.

For all scenarios (S1 – S3), it was assumed that only the highlighted south-facing windows in Figure 5-24 were opened by occupants during the lecture session at 15:00 on Friday (Day 1). For Scenario 1, the window was left open until 10:00 am on Monday when a person who attended the session decided to close these windows. In scenario 2, the window detection strategy is employed which is assumed to have the ability to inform the occupants or building manager. This was highlighted in Figure 5-2 as the first response when windows are detected as opened when they are not intended to be in this state. For this scenario, the opened windows were detected, and it informed the occupants/building manager to close the windows at 17:00. Scenario 3 adopts an approach in which the opened windows were continuously detected after alerting the occupant/ building manager and hence adjustments were made to the setpoint temperature.

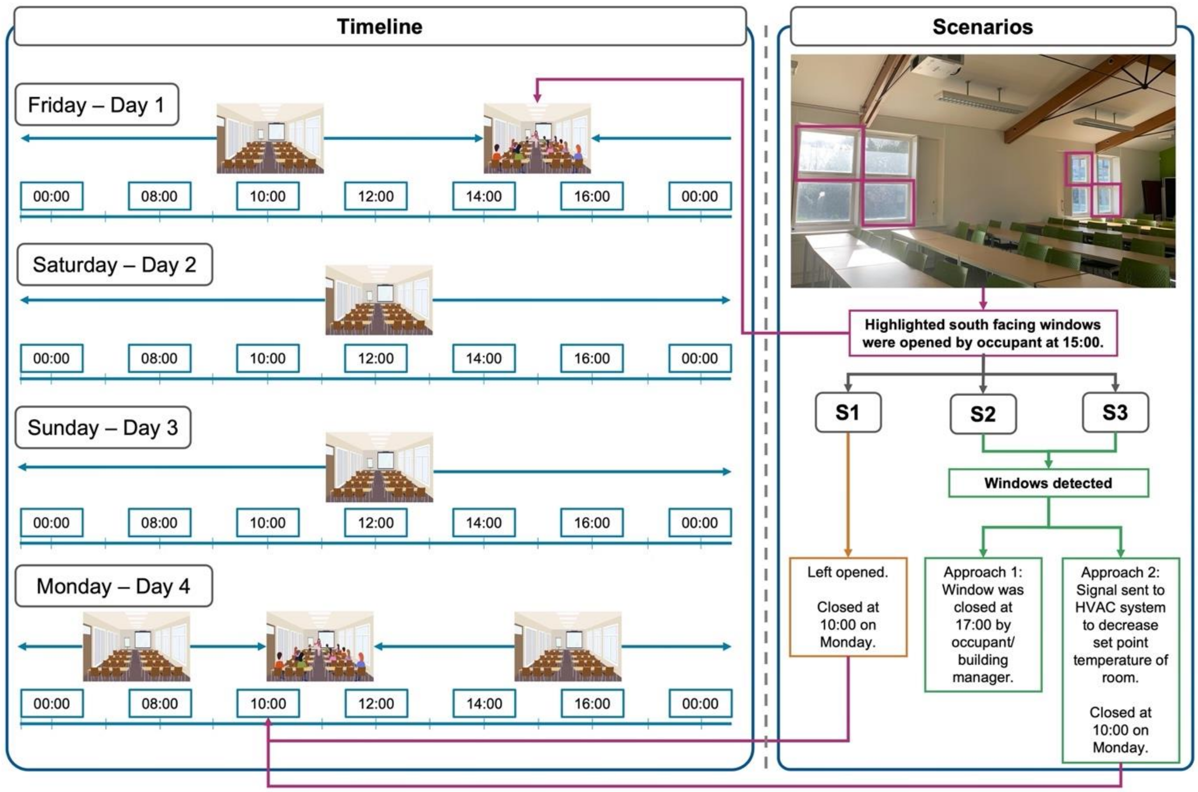


Figure 5-24. Description of the scenario schedules for the simulation and analysis.

Figure 5-25 presents the window operation and heating setpoint profiles used within BES. The static profiles are presented in Figure 5-26a and are incorporated within the scenario-based building energy modelling. The comparison of the static profiles with the DLIP would provide an understanding of the difference between actual window conditions and the use of static profiles. Based on the scenarios described above, Figure 5-26b presents the corresponding window profiles. The set indoor room temperature was also based on ASHRAE guidelines [125, 126]. For occupied hours, it advised a temperature of 22 – 27°C for cooling and 17 – 22°C for heating, while during unoccupied hours it suggested 27 – 30°C for cooling and 14 – 17°C for heating.

Effectively, as given in Figure 5-25d, a generalised room setpoint temperature of 21°C was set during the typical occupied hours of 09:00 – 17:00 and 15°C during the unoccupied hours. It should be noted that occasionally students may occupy this room on both Saturdays and Sundays. Hence, the standard heating profile shows the same profiles for all four days. However, due to the approach given for Scenario 3, it, therefore, follows the heating profile indicated in Figure 5-25e.

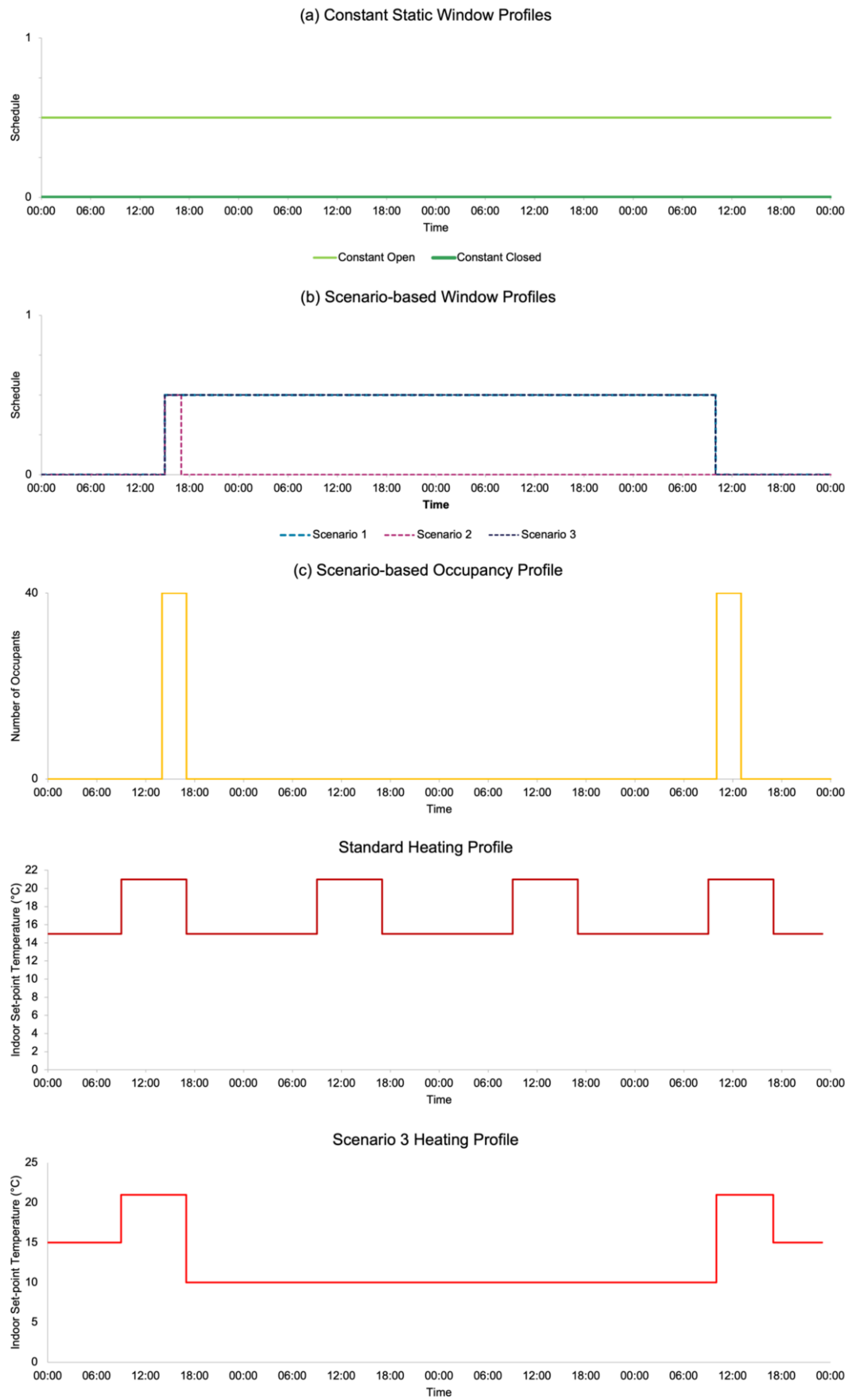


Figure 5-25. Window and building energy modelling profiles applied to BES for analysis.

The modelling of the windows consisted of an exposed wall type exposure, with a top-hung window opening. Following Figure 3-9 the windows were assigned an openable area of 50% and a maximum openable angle of 45°. The degree of the opening was assigned with a modulating profile corresponding to the window profiles created (Figure 5-25a and b). Table 5-10 summarises the simulation cases and the associated window and heating profiles used.

Table 5-10. Summary of the building energy performance simulation scenario cases.

<table>
<tr><th rowspan="2">Simulation Case</th><th colspan="3">Assigned Profiles</th></tr>
<tr><th>Window</th><th>Heating</th><th>Occupancy</th></tr>
<tr><td>Constant Open</td><td>Constant open (Figure 5-25a)</td><td rowspan="4">Standard (Figure 5-25d)</td><td rowspan="5">Scenario-based (Figure 5-25c)</td></tr>
<tr><td>Constant Closed</td><td>Constant closed (Figure 5-25a)</td></tr>
<tr><td>Scenario 1</td><td rowspan="3">Scenario-based (Figure 5-25b)</td></tr>
<tr><td>Scenario 2</td></tr>
<tr><td>Scenario 3</td><td>Scenario 3 (Figure 5-25e)</td></tr>
</table>

Based on the proposed research method shown in Figure 5-2, this section presents the analysis of the framework performance based on different scenarios-based situations. BES was conducted to provide the following discussion in terms of heating demand and ventilation heat losses.

Figure 5-26 presents the heating results for the four days under the different simulation cases. Based on the use of 'static' profiles for the window operation in the BES, the maximum (constant open) and minimum (constant closed) the heating load can be achieved depending on the window opening. When the windows were constantly closed, the high number of occupants present within the room led to high internal occupancy heat gains which led to the lower heating requirement for these periods of time.

Figure 5-26b shows the results for the heating load for the three scenarios. For Scenario 1 the results suggest the heating load would be similar to constant opening as the windows were kept open from 15:00 on Friday (day 1) to 10:00 on Monday (day 4). The only differences occurred at the times before the window was opened on Friday (day 1) and after it was closed on Monday (day 2). The opened windows resulted in a high increase in heating loads due to the continuous heating of the room to reach the desired setpoint temperatures (Figure 5-25d).

For Scenario 2, the deep learning method was used to assist in the detection of the opened windows and notification was given to either the occupants or the building manager. Prior to the closure of the window one hour after the lecture was finished (at 17:00), the same amount of heating load as Scenario 1 was required. However, once the windows were closed, it resulted in a significant decrease in the heating load. In this case, heating was not required for the rest of the day. Instead, heating was only required for the periods when the room had a set point temperature of 21°C.

Scenario 3 was simulated using the same window profiles as Scenario 1 (Figure 5-25b) since the windows were kept open from Friday night to Monday morning. Instead of a standard heating profile based on the typical room occupied hours, a different heating profile given in (Figure 5-25e) was used to model the situation where the deep learning detection method assisted the building controls through sensing the opened windows which therefore informed the operations of the building HVAC systems. Due to it being the end of the office day and no occupants present after 17:00, the second approach given in the deep learning framework shown in Figure 5-2 was followed. The sensors from the detection model informed the building energy management system controls and influenced the building HVAC system to reduce the heating setpoints until Monday.

Figure 5-26 also presents the corresponding heating load results for Scenario 3. By comparing the results across all three scenarios, similar heating loads were achieved on day 1 and since the room setpoint temperature was changed to 10°C for the times when the window was detected as opened, it resulted in the requirement of no heating. Furthermore, a high peak in an increase of heating demand was presented a 10:00 on Monday (day 4) as the room setpoint was then changed to 21°C. However, the requirement of a high heating load only occurred for a short period of time as occupants were present within the room.

Figure 5-26c presents the total heating demand between the scenario simulation days. It suggested the room with windows assumed to be constantly opened required a heating load of 606.6 kWh. This is based on a worst-case scenario which indicates the maximum amount of heating that is essential to maintain the room at 21°C during occupied hours. In comparison, for constantly closed windows, heating of 91.4 kWh was needed. This was due to no ventilation heat losses through windows. It should be noted that the occupancy profile was assigned in the model and hence the occupancy heat gains led to the requirement for less heating.

Furthermore, Scenarios 1, 2 and 3 achieved a total heating load of 238.5 kWh, 99.3 kWh and 68.0 kWh. Given scenario 2, heating after 17:00 was decreased by approximately 7 kW (during the next hour) as the occupancy/building manager was informed about the opened windows, which prevented the windows from being left open.

Additionally, Scenario 3 consisted of the DLIP data to inform the HVAC system to provide lower indoor temperatures during unoccupied times. This was shown by the achievement of decreased heating loads to the minimum. With the setpoint temperature of the room being dependent on the window conditions, building demands can be effectively reduced.

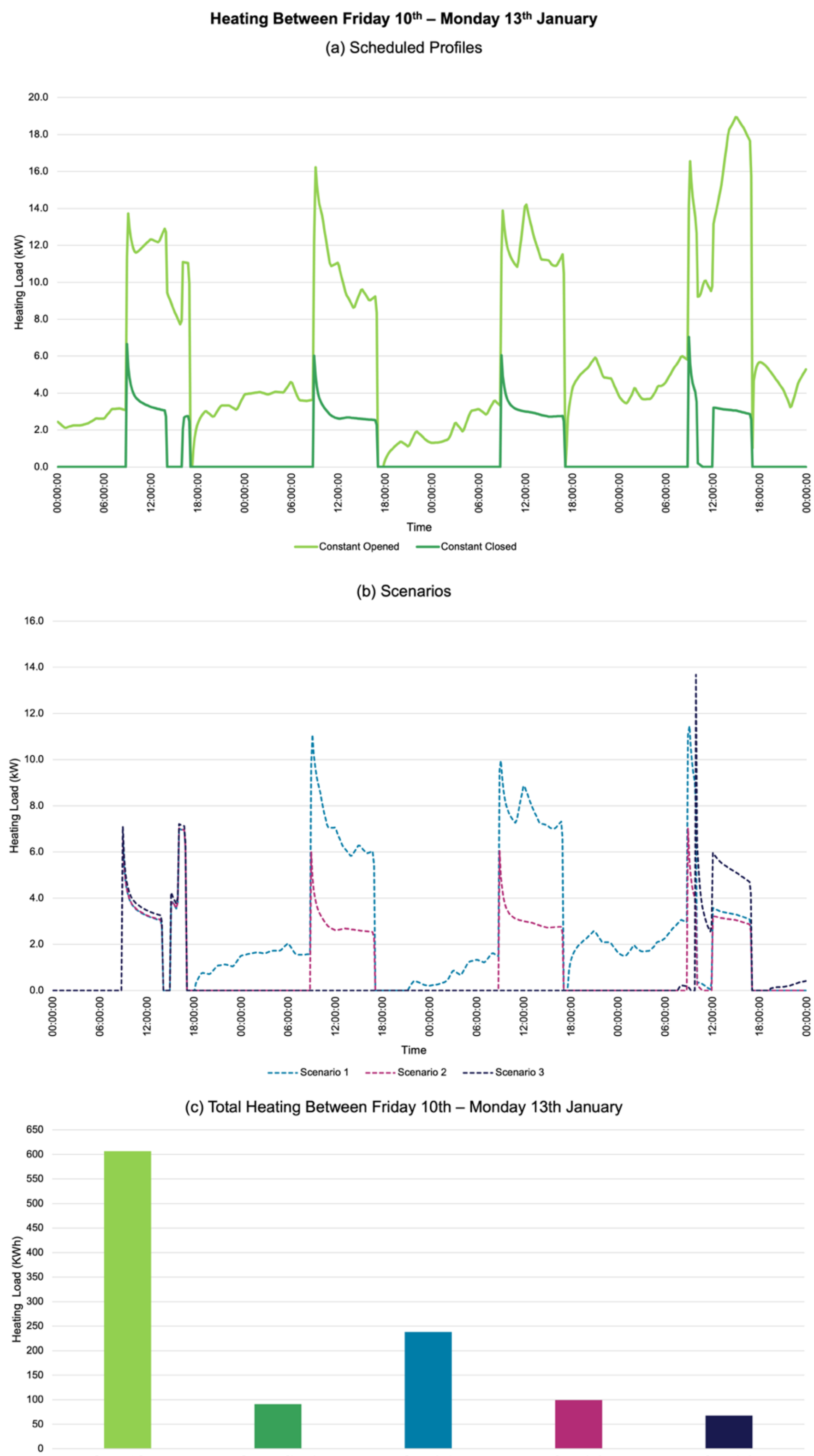


Figure 5-26. Heating load results for a weekend (Friday 10th – Monday 13th January) achieved using building energy simulation cases of (a). The constantly scheduled window profiles and (b). the three different scenario-based cases. (c). A comparison between the total heating loads.

Figure 5-27a indicates the ventilation heat losses within the room throughout the four days. The losses are influenced by the outdoor air conditions on the selected day and also directly by the window profiles given. Given the constant open and constant closed results, generally shows the maximum and minimum possible losses.

The results for scenarios 1, 2, and 3 were directly influenced by the window profiles given in Figure 5-25b which indicates the importance of knowing whether windows are either opened or closed, as it can significantly affect the ventilation conditions within an indoor environment. Therefore, this justifies the importance of the deep learning detection method. Figure 5-27b shows the total ventilation heat losses for each scenario. The ventilation heat loss achieved was solely based on the consideration of the window opening behaviour. However, other contributing factors such as the wind direction, and velocity, would also have a large impact on the indoor air quality, airflow performance and also the number of ventilation losses via the opened windows. These contributing factors would be considered within the future development of the approach towards the design of the response system that would be integrated with building controls to enable the achievement of effective operations of building HVAC systems.

Effectively, the results show the assumption of windows being constantly opened can provide an over-prediction of the heating load by up to 208% or that the assumption of windows being constantly closed can result in an under-prediction by up to 57%. The scenario-based analysis suggests situations such as Scenario 1 where windows were left during the entire period led to a total heating load of 239 kWh. In Scenario 2, the deep learning method was used to assist in the detection of the opened windows and notification was given to either the occupants or the building manager who closed the windows one hour after the lecture was finished. This resulted in the total heating load decreasing by up to 139 kWh. In Scenario 3, adjusting the setpoints based on the detection data led to a much higher reduction in heating loads.

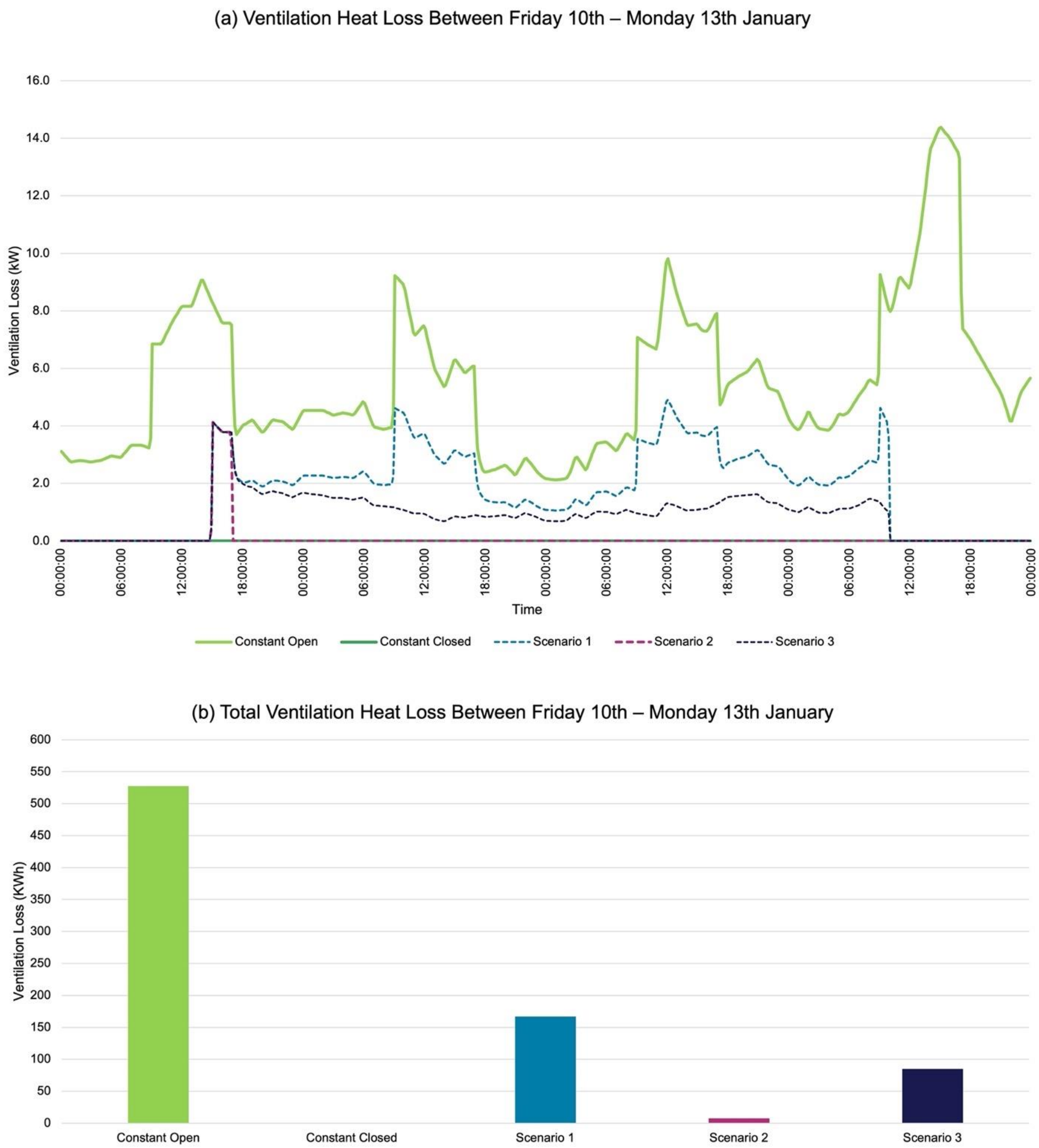


Figure 5-27. (a). Building ventilation heat loss (Friday 10th – Monday 13th January) predicted based on BES cases of assigning constantly scheduled window profiles and the three different scenario-based cases. (b). A comparison between the building ventilation losses.

Following the workflow process of the proposed integrated framework approach for system optimisation in Figure 3-5, suggests the potential in considering the exploration of how the information of the window condition can also be used to provide users and/or controls towards the opening designs (for the case of automatically controlled windows) to optimise the indoor air quality and comfort during occupied periods. Further developments will be carried out in the proposed future works as the deep learning framework can be optimised by adding more training data to improve the detection accuracy with modifications to the deep learning model architecture. Moreover, a streamlined transfer of the data obtained from the deep learning model to the building profile generator would be necessary. It would provide a direct and automated adjustment of setpoints for the HVAC system based on the detection results. Whereby, the framework would be enhanced to enable direct detection of windows that feeds data to an actual building control system.

5.10. Summary

Overall, the results for all four different window detection models (Models 1, 2, 3, and 4) suggest the possibility of using a detection approach to understand window conditions across time. The detection enables the prediction of the ventilation heat loss towards the overall building energy performance. Such variation in detection accuracy was based on the model configuration, the camera position, and the influence of environmental factors. This led to variation in the detection and prediction, with some instances achieving better results than other moments during the day. Furthermore, it also indicates the ability to provide a better understanding of indoor conditions (acknowledging the times when high amounts of heat gains/ losses occur through variation in occupancy behaviour) to assist the operations of building systems. Based on the comparison of the models, it suggests Model 4 achieves the best detection performance, resulting in the most accurate energy prediction. However, greater verification of the detection ability will be explored through further investigation of the model's performance under different room settings and environmental conditions.

It is envisioned that the generation of DLIPs with HVAC can ultimately lead to better control of the system, helping detect times requiring less heating and/or cooling for example when windows are intentionally left or closed. Therefore, the DLIP can aid the identification of times when such occupancy behaviour occurs to result in variation of occupancy heat gains based on the occupancy activity detection and to also notify occupants about the window conditions and inform the building control system to monitor the HVAC system thermal set-point conditions.

Chapter 6

6. Multi-objective Combined Approach with Occupancy, Windows, and Equipment Detection

The exploration, development and analysis of the potential individual occupancy and window detection framework approach led to the investigation of the combined approach to further enhance the effectiveness towards improving building energy system operations through optimisation. This chapter introduces two different multi-objective detection frameworks concentrating on the understanding and recognition of various occupancy behaviour and actions to assist the buildings. Chapter 6.1 focuses on an occupancy activity with electrical equipment detection to provide a better understanding of building internal heat gains, while Chapter 6.2 explores the occupancy activities with window openings. This was designed to acquire a real-time understanding of occupants' behaviour towards the actions of opening/ closing windows for the control of building ventilation heat losses.

6.1. Combined Approach - Occupancy and Equipment

Acknowledging that building occupants generate heat depending on the level of activity. This increases the internal heat gains and affects the energy consumption of heating or cooling systems, depending on indoor-outdoor conditions [227]. Effectively, occupants can also affect the internal heat gains by using equipment and appliances in the building [128]. Like the occupancy levels, equipment usage in offices such as computers and laptops can also be varied, depending on several factors. For example, the occupants may leave their computers 'on' when taking breaks or leaving the office [48]. This could lead to uneven heat gain distribution and cause difficulties in the design and efficient operation of HVAC. Hence, the techniques for the development of the vision-based model for occupancy activity recognition were employed to form equipment detectors.

6.1.1. Framework for Combining Occupancy and Equipment Detection

An overview of the proposed method is summarised in Figure 6-1. Similar to previous framework approaches, an office building at the university was selected to test the coupled detection approach. Presented in this figure, the approach can be split into two parts; 1. implementation of the proposed deep learning framework and 2. framework performance analysis. In the first part (highlighted in green), an appropriate model was selected, and this was modified and used to develop the models for occupancy and equipment usage detection. The deep learning detection models were deployed to an AI-enabled camera and tested within the chosen office space. In this study, the two models were tested separately to perform a detailed evaluation of the performance of each method. It is envisioned that in future works, both methods will be combined and deployed to a single device to carry out both occupancy and equipment detection. The detection output will be used to generate heat gain profiles for occupancy and equipment, also called here deep learning-influenced profiles (DLIP). This information could then be used by the controller or control system to automatically adjust the HVAC operations. To assess its feasibility and analyse its potential impact on building energy use, Part 2.1 presents the analysis of detection performance and recognition accuracies, and Part 2.2 presents the use of scenarios and BES software. Hence, the same case study office space of B12 in the Sustainable Research Building, University of Nottingham as previous individual detection models were tested under experimental tests in this selected location was performed.

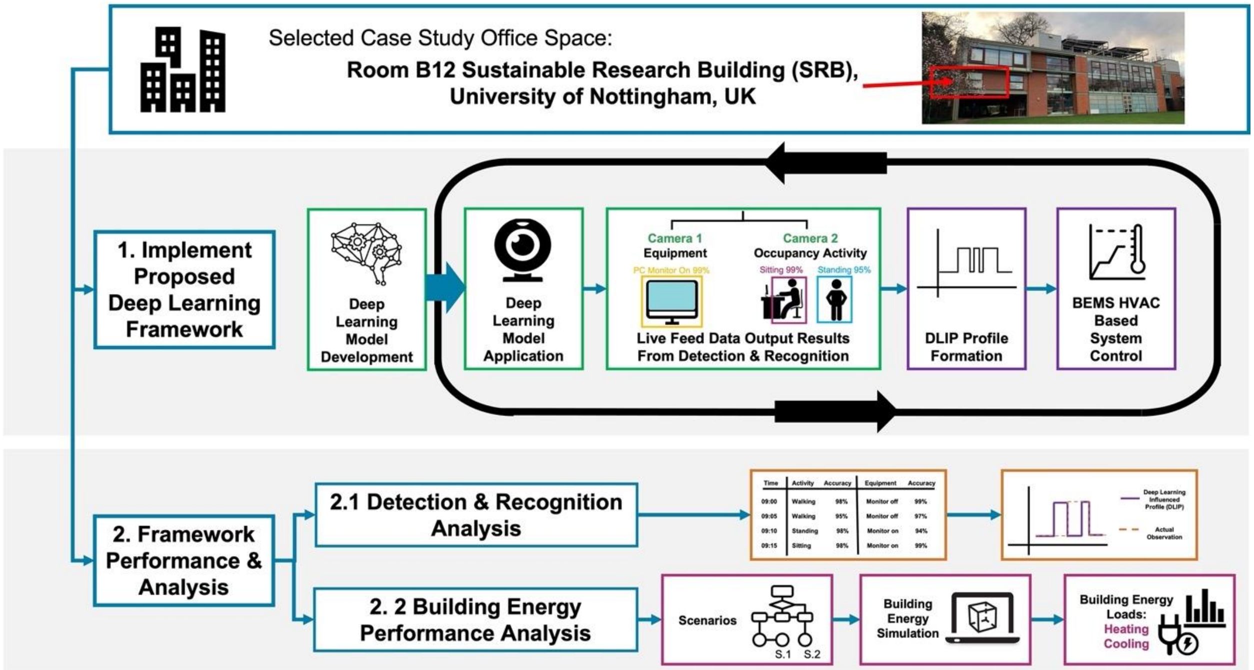


Figure 6-1. Approach to develop, test and analyse a combined occupancy activity and electrical equipment detection framework.

6.1.2. Deep Learning Method

To develop the deep learning model with the data collection and model training procedure, the same methods described in Chapter 3.3 were applied. Relevant input data with images selected to form the datasets for training and testing were collected. Images were labelled manually by using the software LabelImg whereby labelling of the objects via assigning bounding boxes in images and the creation of XML files that describe the objects in the images which assist the detector to recognise the objects. After labelling, the associated XML files to each of the images in the dataset were converted to form TFRecord files to provide a summary of the data which would be utilised for model training. Table 6-1 presents the summary of the image datasets and two experimental tests were highlighted. Specifically, the selection of the models used to form these combined detectors was solely based on the occupancy detection models developed form in Chapter 4, along with its previous evaluation of the detection performances. Effectively, Experimental Test 1 focused on the application of a smaller dataset and both models were trained separately. Both were tested separately using a camera for each type of detection, allowing the generation and recording of results for BES analysis based on the comparison of the application of static profiles of both equipment and occupancy versus the generation of real-time DLIPs.

Furthermore, the experimental test consists of the application of the trained models to be separately trained but coupled together to allow combined detections during the tests. For this experiment, detection performances were also evaluated based on each of the detection responses achieved and further scenario-based energy analysis under common situations within the selected building space was performed. This enabled insights towards the understanding of how multi-objective combined detection could assist building system operations, influencing energy performances and occupancy satisfaction. Descriptions about each of the image datasets and the model architecture can be shown in the assigned sections of Chapter 4 for occupancy activity and the given reference for electrical equipment.

Table 6-1. Summary of the image datasets used to train both the occupancy activity and equipment detectors.

Type	**Model Name**	**Response Categories**	**Training Dataset**		**Reference**
			Number of images	**Total number images**	
Experimental Test 1					
Occupancy Activity	Model 2a	None	100	400	Chapter 4.4.1, Table 4-6
		Sitting	100		
		Standing	100		
		Walking	100		
Equipment	1	PC Monitor	400		[228]
Experimental Test 2					
Occupancy Activity	Model 2b	Sitting	400	1200	Chapter 4.4.1, Table 4-6
		Standing	400		
		Walking	400		
Equipment	1	PC Monitor	400		[229]

6.1.3. Scenarios and Experimental Test Setup

Since the Sustainable Research Building (University of Nottingham, UK) was previously used to test the formed detection models, it was also chosen as the case study building used to support various stages of the analysis of this combined occupancy activity and equipment approach. Figure 6-2 presents the setup for the two experimental tests conducted to test the developed combined detectors. Slight variation occurred in the positioning of the camera between the two tests as Experimental Test 1 consisted of a more direct view towards the coverage of four desk areas, while the positioning in Experimental Test 2 replicated the location where typical sensors would be placed, nearer to the ceiling and corner of the room. For both experimental tests, each monitor was assumed to have a heart rate of approx. 50 W and each monitor was connected to a desktop computer with the assumption of a heat rate of approximately 200 W. Furthermore, according to Table 4-1, occupancy profiles were set with a sensible heat gain (70 W/person) and latent heat gain (45 W/person). Further details about the building and the conditions set for the BES are given in Chapter 3.4.

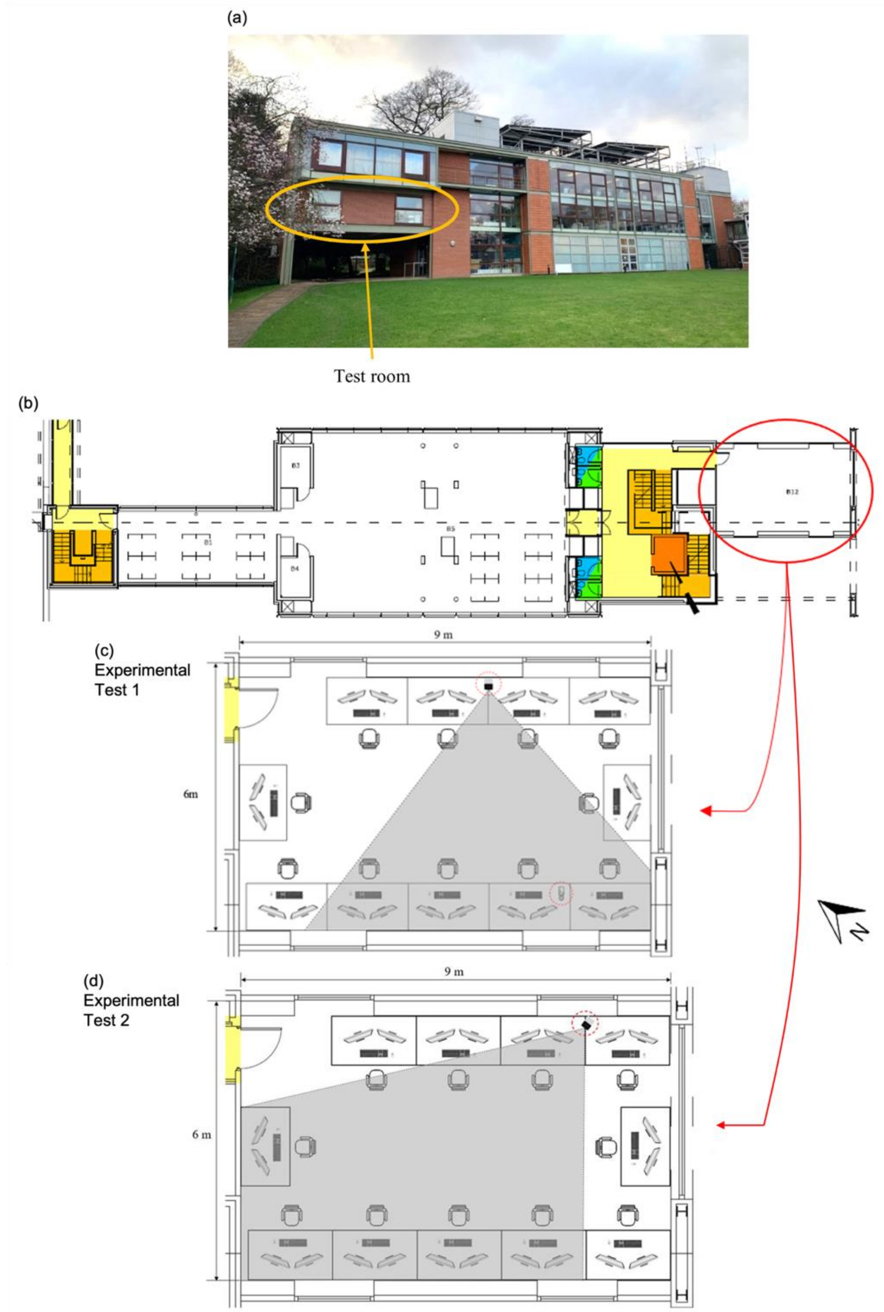


Figure 6-2. (a). Sustainable Research Building at the University of Nottingham, UK. (b). Floor plan of the first floor of the building with (c). Set up for the Experimental Tests 1 and 2 in (d).

Figure 6-3 presents the formation process of the DLIPs for a combined detector of both occupancy activity and equipment. It was assumed that such a process would be conducted when both models were deployed to form the vision-based AI cameras, allowing detection and recognition of the desired responses. Figure 6-3a presents the set-up with the field of vision achieved via Experimental Test 1. For this test, separate cameras were used for each type of detection, while Figure 6-3b presents the combined detection of both sets of responses using one camera as a combined detection applied in Experimental Test 2. The DLIPs were generated based on real-time detections and count-based recordings for the number of activities and PC monitors were recognised.

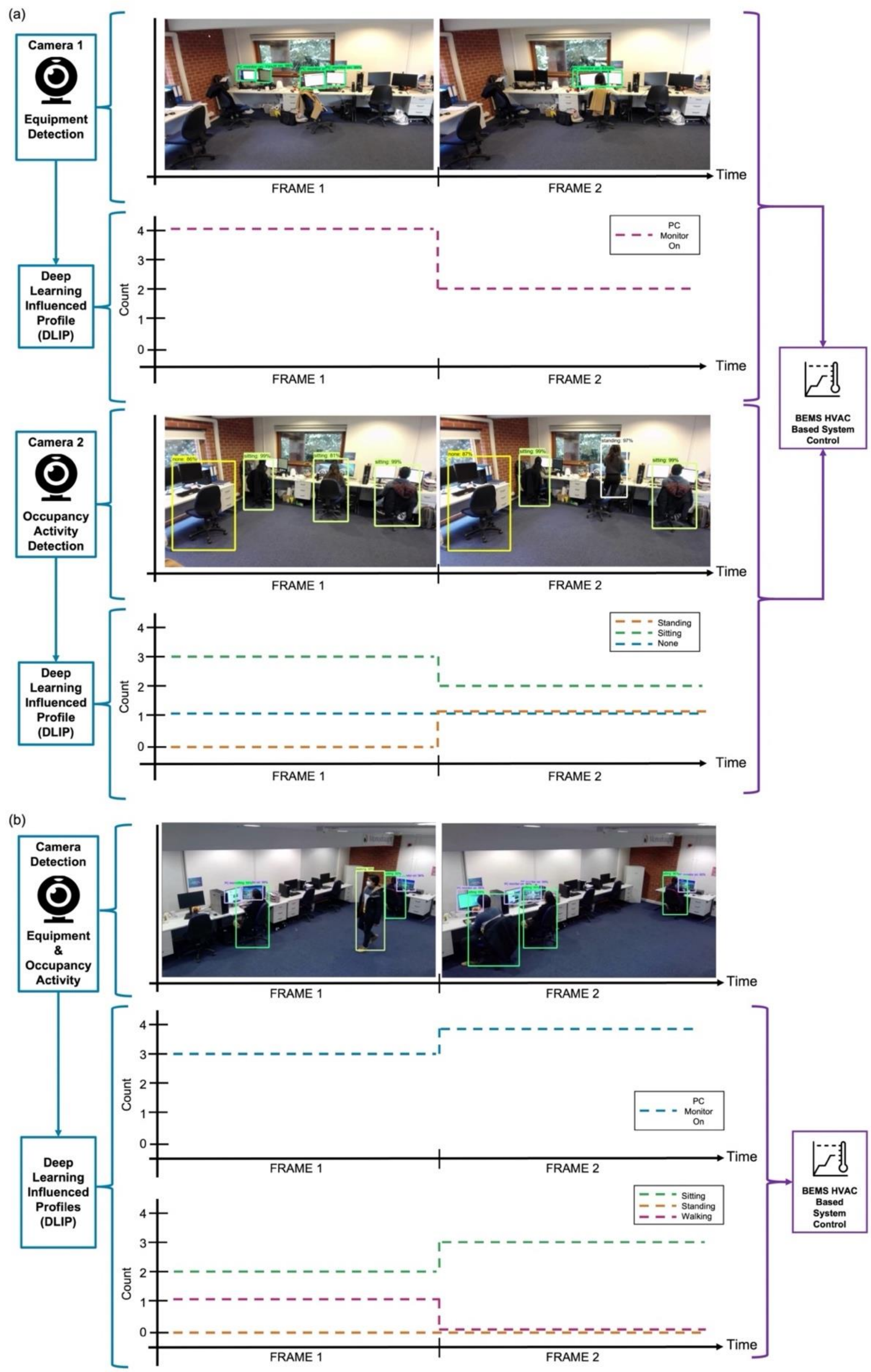
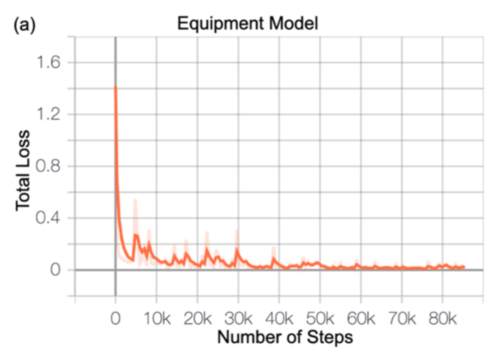


Figure 6-3. Preview of the desired detection made in (a.) Experimental Test 1 and (b.) Experimental Test 2 for combined occupancy activity and equipment detection, along with the DLIP formation.

6.1.4. Training Performances of the Equipment and Occupancy Detection Models

Same occupancy detection models as the ones trained and presented in Chapter 4 were employed within this combined approach. Details for the model training are given in Chapter 4.4.1, while the following presents the training results for the equipment model as given by [229] in Table 6-2. Both models applied the Faster RCNN with the InceptionV2 model for training. Presented by the total loss versus the number of training step graphs suggests the convergence of the loss function implies that the model has been adequately trained. The results provide benchmark data for comparing the performance of future frameworks which would use more training and test data and different models.

Table 6-2. Training results for the Equipment Model given by Wei et al. [229].

Training Conditions and Results	Equipment Model
Model Used	Faster RCNN with InceptionV2
Total Steps	85,422
Training Duration	5 hours 3 minutes, 51 seconds
Average Loss	0.0577
Minimum Loss	0.003516
Total loss versus the number of training steps	

Furthermore, following the same procedure applied to the training of the occupancy and window detection models, the detection performance of the application of the equipment model on still images was conducted. The equipment detection was trained to detect and provide recognition responses of PC monitors ON. Based on the images within the test dataset, a total of 150 prediction labels should be assigned to these images. The results suggest 125 labels (83.33% of the total number of labels) were correctly assigned to PC monitors ON. This influenced the provision of the overall model performance giving an average detection accuracy of 83.33%. Moreover, 12 labels were identified as "PC monitor on" when they were turned off and 13 labels were not identified as "PC monitor on" when they were in use. Based on these results, an overall F_1 score of 0.9091 was achieved, suggesting the model can provide adequate detection and recognition of PC monitors [229].

6.1.5. Experimental Test 1 Detection Performance – Separate detections

This section presents the detection performance achieved using the initially proposed combined vision-based deep learning method during Experimental Test 1 which was conducted in the selected office space in the Sustainable Research Building. Given the example detection shown in Figure 6-4a and c, separate detections of both equipment and occupancy were made using the two cameras. It also shows the ability to detect and recognise the equipment and occupants in the space. For both cases, output detection bounding boxes were present during the detection, and the accuracy for each detection was also presented above.

During the experimental test, the occupancy and equipment detection models were operated while occupants were doing their daily work as usual. If the computers are in use, then the model will respond as 'pc monitor on'. The overall equipment detection performance is shown in Figure 6-4b. It shows that 80.80% correct detection could be achieved by this approach during the initial experimental test. While the errors including incorrect detection and no detection were 15.24% and 3.94% of the detection period. Overall, the proposed model can perform the equipment detection task with good accuracy within the case study office building. For the performance of occupancy activity detection and recognition, Figure 6-4c indicates correct detections 97.32% of the time, incorrect detections 1.98% of the time and no detections 0.70% of the time. In detail, in terms of the selected detection response categories of individual activities, walking achieved an accuracy of 95.83%, standing with 87.02%, 97.22% for sitting, and none achieved an accuracy of 88.13%. This shows the capabilities of the deep learning model to recognise the differences between the corresponding human poses for each specific activity. This further verifies the ability of the developed model as initially presented in Chapter 4.

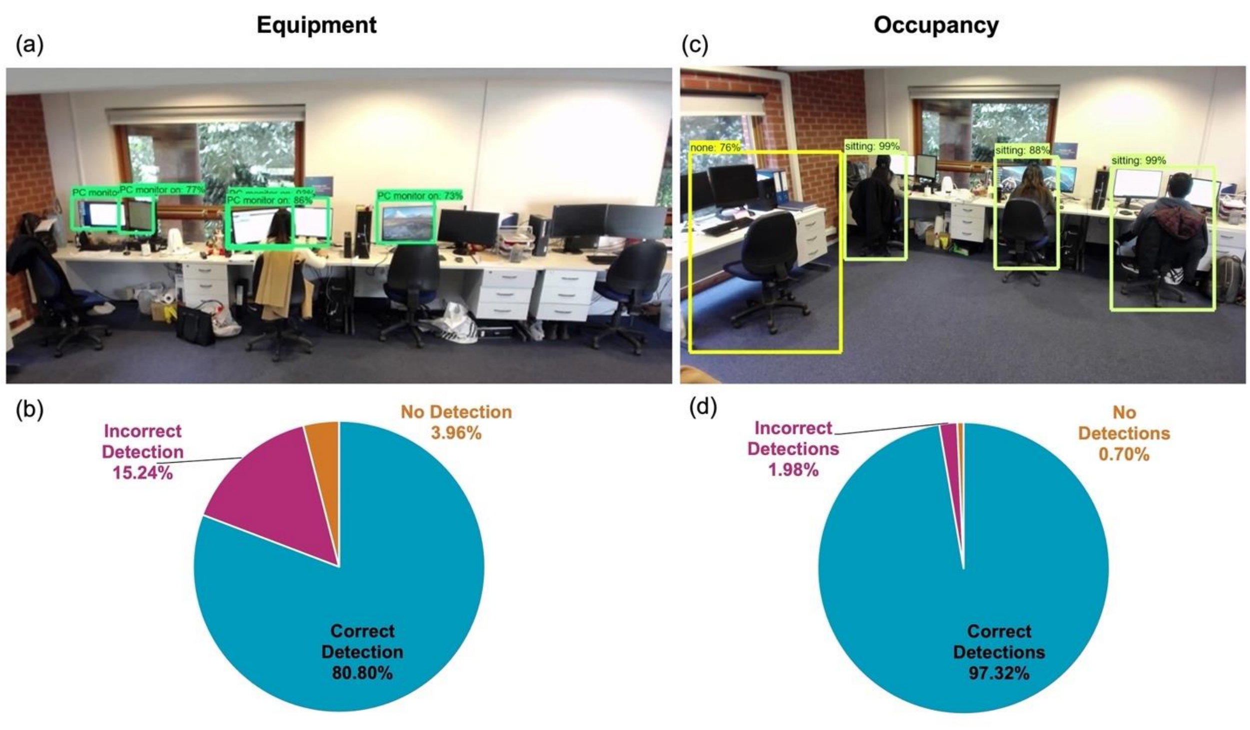


Figure 6-4. Example of the detection result with performance based on the occurrence of correct detection, incorrect detection and no detection during Experimental Test 1. (a). and (b). for equipment detection – PC monitors, (c). and (d)., for occupancy activity.

Following the procedure of the framework approach given in Figure 6-1, Figure 6-5 shows the generated count-based DLIPs achieved during Experimental Test 1. Both DLIPs provided informative data showing the number of detected occupants performing each of the activities and the number of equipment in use across the whole detection period. This contributes towards a better understanding of the occupants and the equipment usage within the office space in comparison to conventional sensors used within buildings. Furthermore, to enable the data to assist building system controls and building energy performance simulations, both the profiles for equipment and occupancy were converted to heat emissions-based DLIP. This is further discussed in Chapter 6.2.7. This will allow the evaluation of the impact of the application of such a combined, multi-objective deep-learning detection approach.

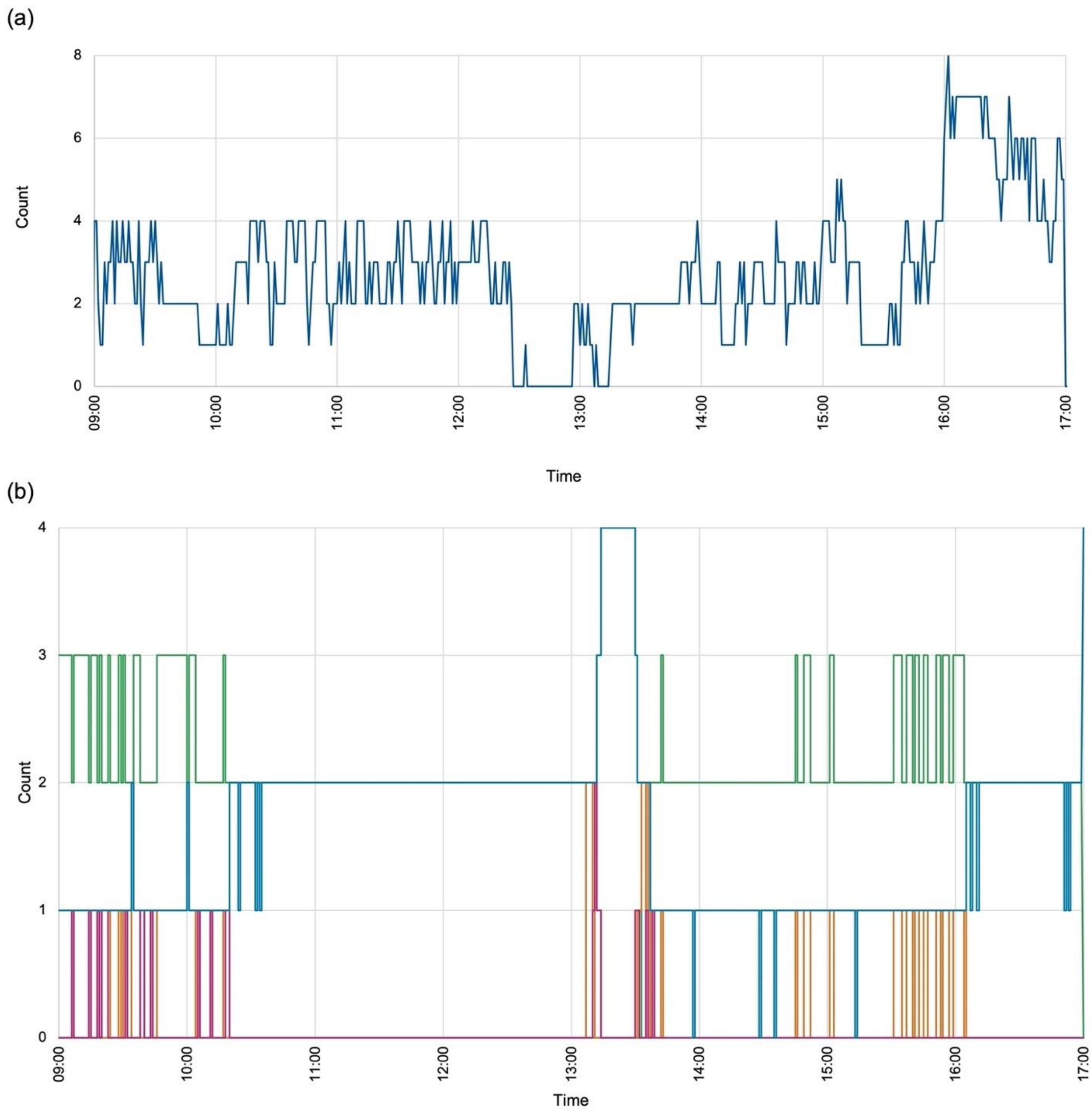


Figure 6-5. Formed count-based DLIPs from the detection of (a). equipment, and (b). within the case study office during Experimental Test 1.

Using the data presented in Figure 6-5, along with the typical values of heat gain of computers and occupants performing different activities, the following heat emissions-based profiles were formed (Figure 6-6). The typical equipment profile and equipment heat emissions-based DLIP were also plotted in Figure 6-6. The comparison of the profiles suggests that the proposed approach could enable the detection of the usage of equipment and various activities and the identification of the times when the equipment usage or occupancy activities increased and decreased, which influence the internal heat gains. Based on the detection period, up to 65.75% difference between the typical equipment heat emission profile and the actual equipment heat emission profile was observed. While up to 37.51% and 50.44% difference was observed between the Typical Occupancy Profiles 1 and 2 and the actual occupancy heat emission profile. Hence, there was a high discrepancy between the true equipment usage and occupancy activities performed within the building spaces, and the use of static profiles. Therefore, this shows the potential of the vision-based deep learning approach for both equipment and activity recognition for providing a better understanding of the conditions within an indoor space for more effective system controls and operations.

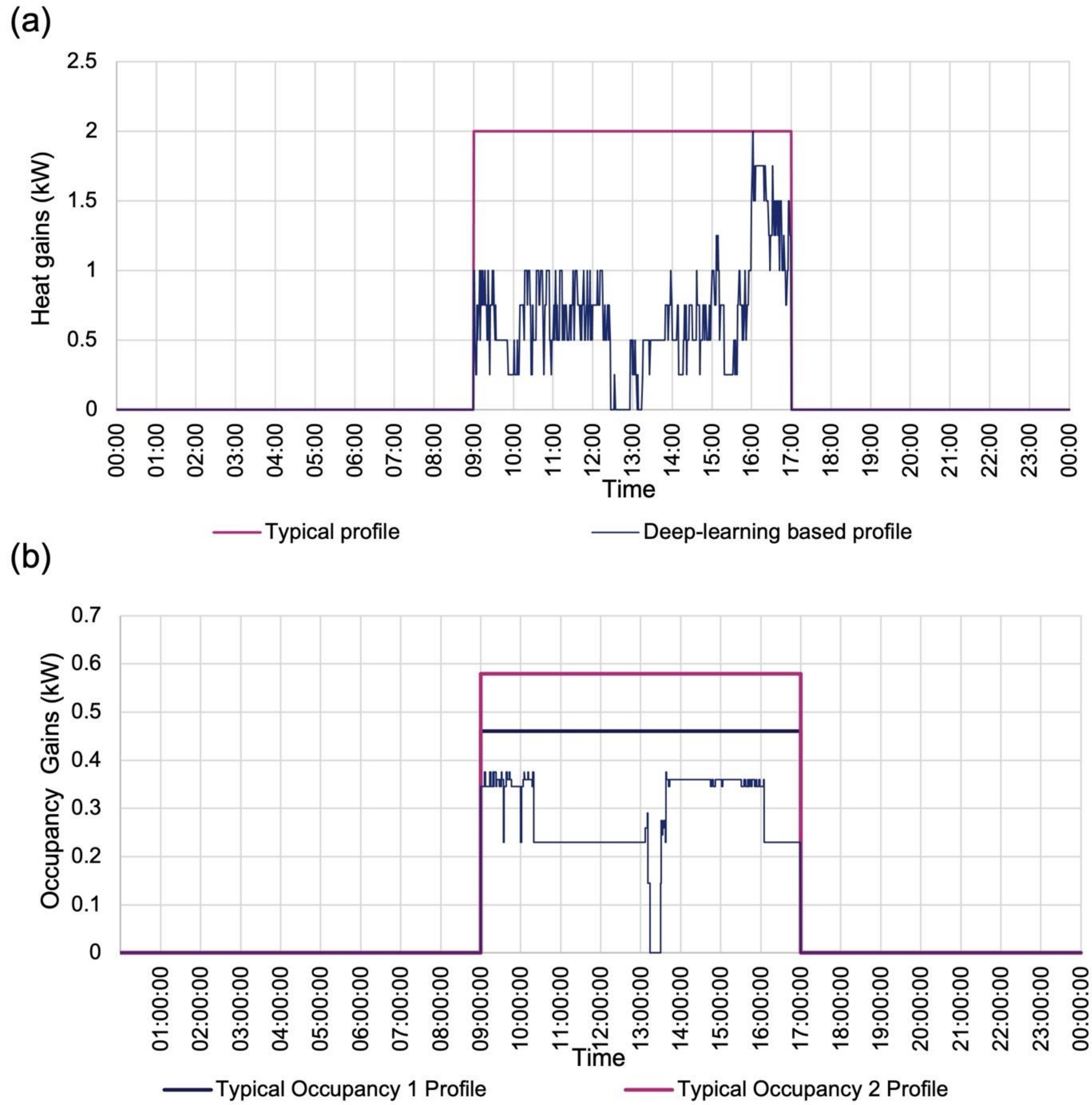


Figure 6-6. Heat emission-based deep learning profile, (a). equipment, and (b). occupancy. DLIP plotted against typical profiles for comparison.

6.1.6. Experimental Test 2 Detection Performance – Combined Detections

This section presents the performance achieved during Experimental Test 2. This experimental test was designed to test the performance when both models were integrated, giving combined detections at every time step. As highlighted by the timeline shown in Figure 6-7, the test consisted of occupants performing all the selected occupancy activities, and the PC monitors were presented as both on and off. Furthermore, as shown by the preview from the detection camera in Figure 6-7, the camera was located close to the space's ceiling at the height and angle.

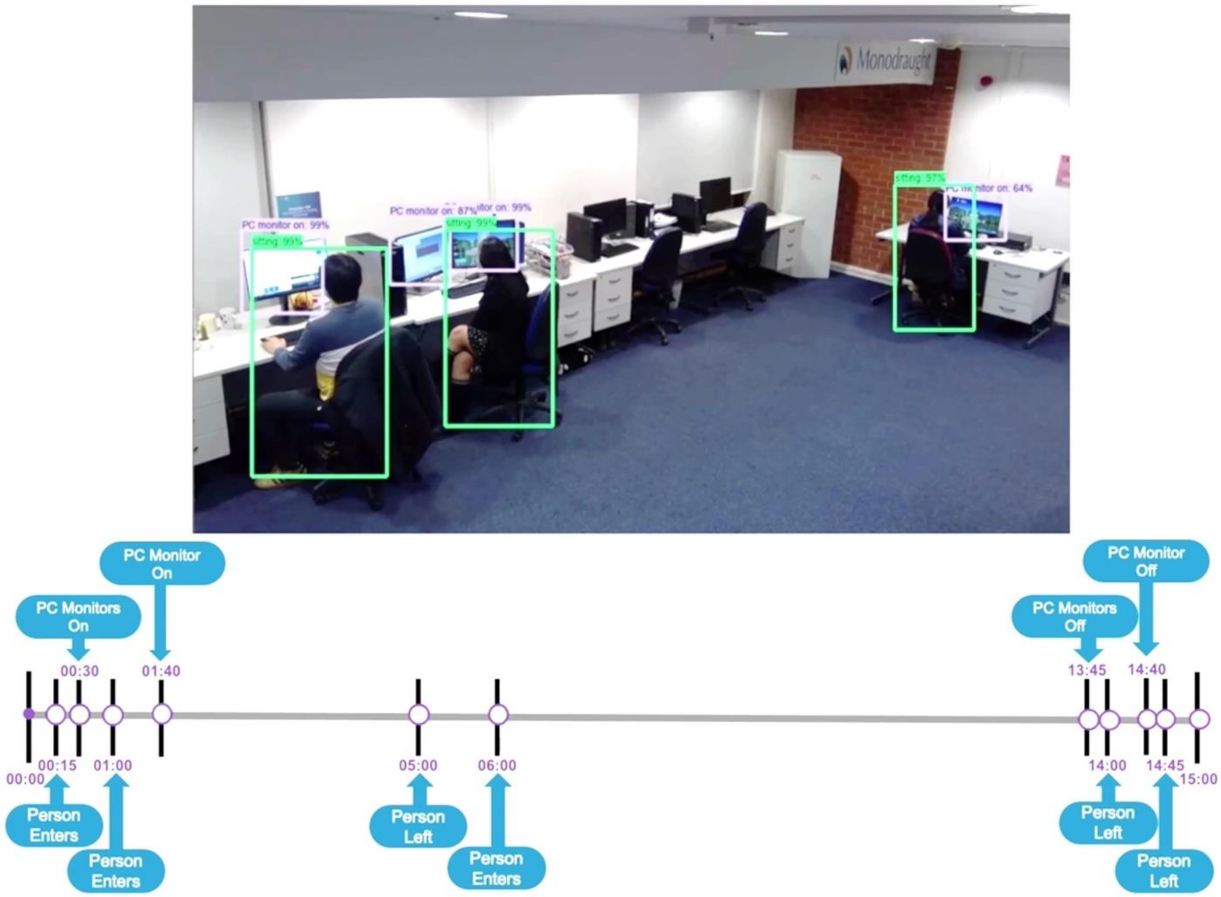


Figure 6-7. Timeline of Experimental Test 2 to focus on the real-time detection and recognition of equipment and occupancy activity.

According to the experimental detection test carried out within the selected case study office space, Figure 6-8 shows snapshot images from the various key stages highlighted by the timeline in Figure 6-7. As previously given by the evaluation of the model's capability to detect through sources of still images in Chapter 6.2.4., Figure 6-8 presents further verification of the model's capability to detect both occupants and equipment within an actual office space in real-time. Bounding boxes were presented as an output of the detection and recognition response. Above each of the boxes, it shows the detection accuracy. Furthermore, both the appearance and the bounding boxes' shapes and sizes varied between each of the detection intervals.

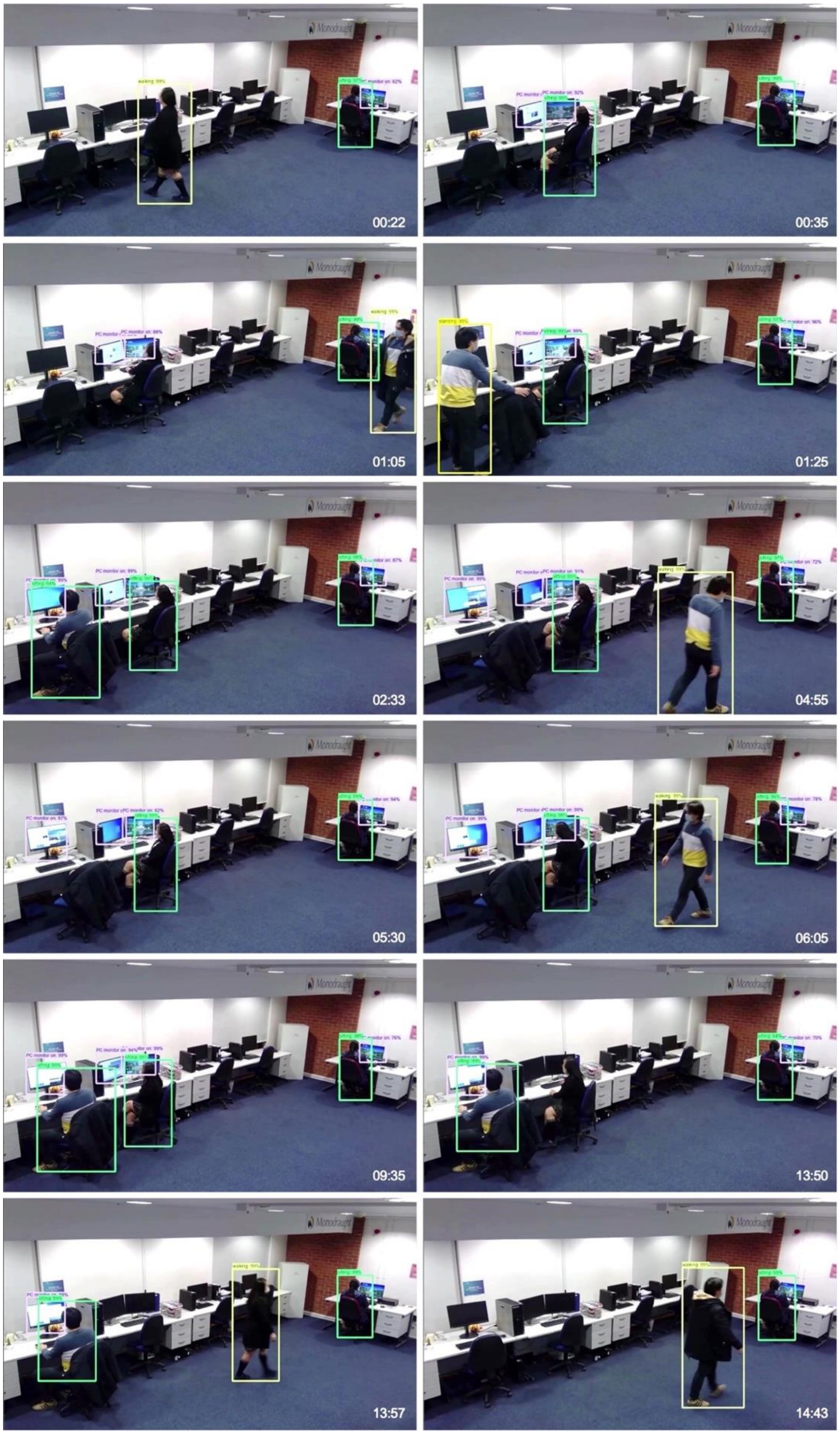


Figure 6-8. Example snapshots of various key point stages during the application of the combined deep learning detection approach during Experimental Test 2.

To evaluate the performance of detection and recognition ability of the PC monitors during Experimental Test 2, for analysis, the PC monitors that appeared in the detection camera screen from left to right were each given the names of PC Monitor A, B, C and D. Similarly, the occupants were also noted as Person A, B and C. Figure 6-9Figure 6-10 present the overall detection performance, with Figure 6-9 for equipment (PC monitor on) and Figure 6-10 for occupancy activity. The detection labelled assigned at every second during the experimental test was classified as a correct detection, no detection, or incorrect detection. Because the performance of PC monitors was influenced by the detection camera's distance from the PC monitors, Figure 6-9 was evaluated based on each PC monitor. The aspect for the achievement of a correct detection includes the times when the PC monitor was on and correctly identified, and the times when detection was not implemented when the monitors were off. However, as evaluated by the stable bounding box detection accuracy across all occupants and activities, the results given in Figure 6-10 are based on each activity and not each person. Additionally, for occupancy activity, correct detection was given when the device correctly recognised the activity performed by the occupant and when detection was not implemented as the occupant was not performing that activity.

Figure 6-9 presents the breakdown of each of the monitors' detection performance and suggests the results partially succeed in the evaluation made about the bounding box detection accuracy. PC Monitor D achieved the lowest amount of correct detections due to its distance from the detection camera. PC Monitors A, B and C achieved correct detections 82.80%, 99.22% and 90.46% of the time. Since there was constant obstruction of Monitor A and C by Person A and B, it may have influenced Monitor B to achieve the highest value. Overall, it showed that correct detections for PC monitors were recorded for an average of 78.39% of the time, no detections for 21.59% of the time, and subsequently incorrect detections for 0.03% of the time.

For occupancy activities, the results presented in Figure 6-10 suggest an overall achievement of correct detections for 93.60% of the time, no or missed detections for 4.22% of the time and incorrect detections for 2.18% of the time. Based on the three activities, the best results were achieved for the activity of sitting as this action is very different to the activities of standing and walking. Effectively, the body poses when people are standing and walking are similar, which influenced the activity of standing to achieve low correct detection. Furthermore, a category entitled ‘None’ was added for this evaluation of occupancy activity detection performances. This category demonstrated that no activity was identified by the model when occupants were not present. This was achieved 83.78% of the time. Accordingly, it was incorrect by displaying a detection of any form of activity when there was no activity conducted for 16.22% of the time.

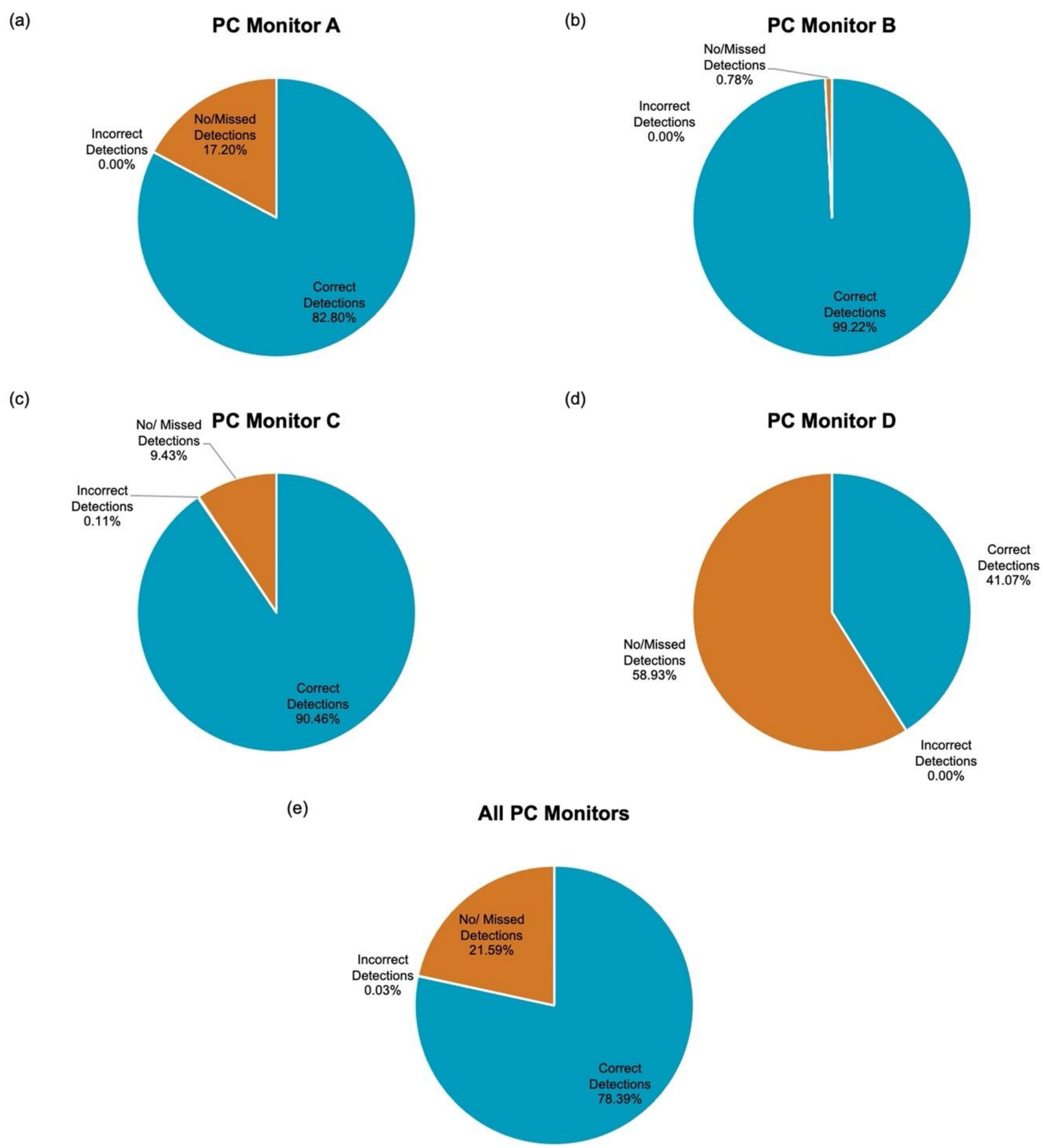


Figure 6-9. The performance of equipment (PC monitors on) during Experimental Test 2 for combined detections.

Figure 6-10. The detection performance of occupant activities during Experimental Test 2 for combined detections.

Below provides a further evaluation of the detection performance during the test according to the analysis using the classification evaluation metrics. Figure 6-11 shows the different PC monitors' results based on the prediction response label of ‘PC monitor on’, and Figure 6-12 presents the results for the different occupants based on the selected activities. Given in the following confusion matrix, are displayed in the form of percentage values due to the unbalanced number of labels for each response as different activities were performed at various times during the experimental test.

Alike, the results presented in Figure 6-9 of the overall detection performance for PC monitors, the confusion matrix results suggest that the best performance was achieved when detecting PC monitor B with the highest percentage of true positives, succeeding by PC Monitor C, A and then D. The confusion matrix indicated by Figure 6-11e suggests that overall, there was some occurrence of false negatives, where the PC monitors were detected as off or other when the monitors were on. Additionally, the minimal occurrence of true negative results was achieved.

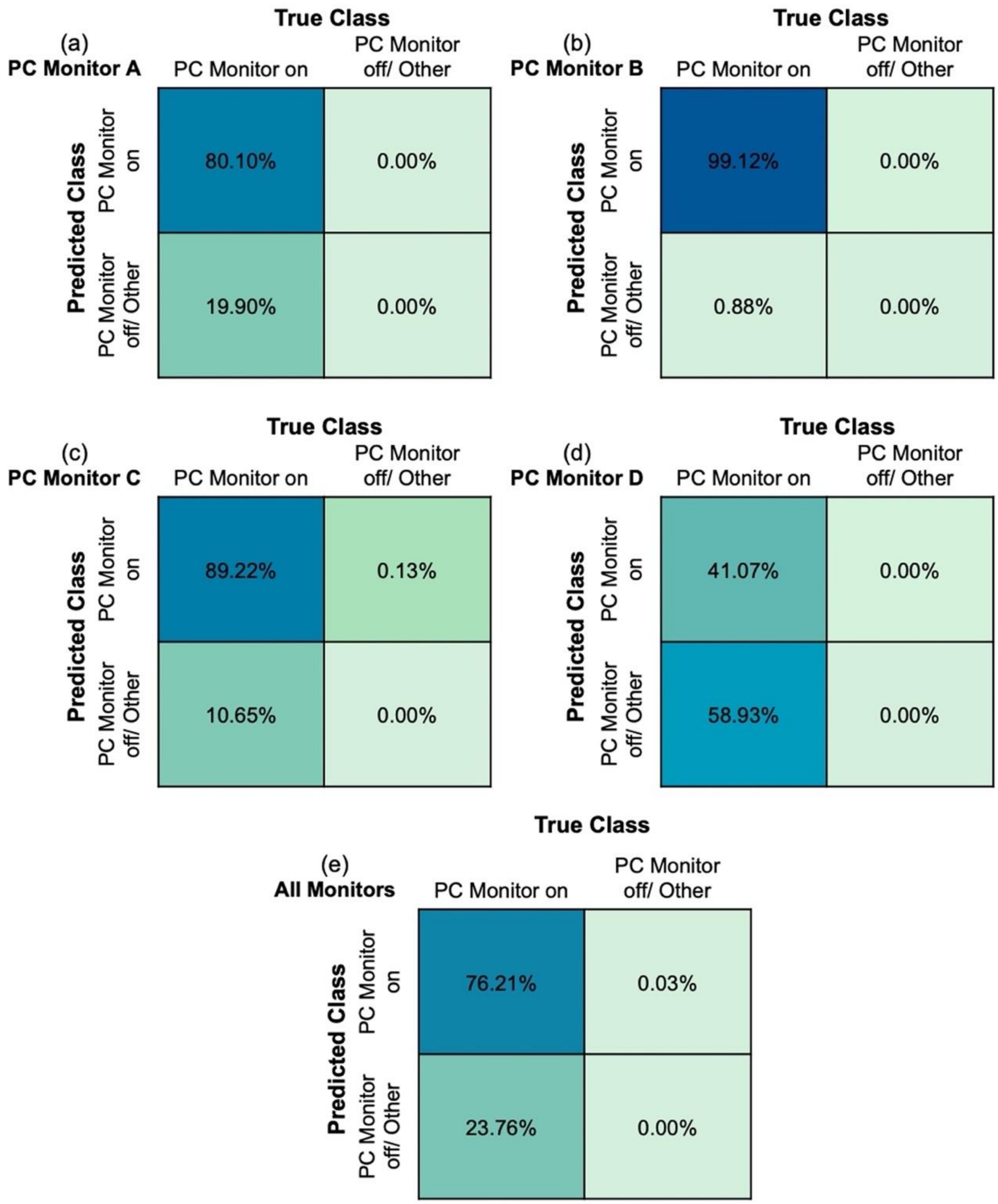


Figure 6-11. The performance of equipment (PC monitor on) detection based on the percentages of labels identified during Experimental Test 2.

According to the confusion matrix results illustrated above, results based on different evaluation metrics were obtained (Table 6-3 and Table 6-4) to further evaluate the detection performance. The average accuracy of 76.21% with an F_1 score of 0.8650 was achieved for PC monitors. The best performance was achieved by Monitor B with an accuracy of 99.12% and an F_1 score of 0.9956 and the lowest performance was Monitor D with an accuracy of 41.07% and an F_1 score of 0.5822. Hence, the results in Table 6-3 for the different PC monitors reinforce the evaluation made and indicate that most of the detection response labels were correctly assigned to the PC monitors.

Table 6-3. Performance based on the evaluation metrics for the equipment model during Experimental Test 2.

Class	Equipment: PC monitor on	Accuracy	Precision	Recall	F1 Score
1	Monitor A	80.10%	1.0000	0.8010	0.8895
	Monitor B	99.12%	1.0000	0.9912	0.9956
	Monitor C	89.22%	0.9986	0.8934	0.9430
	Monitor D	41.07%	1.0000	0.4107	0.5822
	All PC Monitors	76.21%	1.0000	0.7621	0.8650

The confusion matrix given in Figure 6-12 presents the detection performance of each of the activities performed by each person. It verifies that Person A and B performed all three activities during the experimental test, while Person C only performed the activity of sitting. Based on the detection and recognition of all occupants, high performance was achieved for the activity of sitting, with only the occasional no predictions made that was highlighted within the response category of none or other and times. Additionally, there were times when sitting predictions were made when actual occupants were not present. This was considered an incorrect detection since some of the chairs were identified as occupants performing the activity of sitting.

Furthermore, the accuracy of the detection of the activity of standing was the lowest. Contrastingly, walking activity achieved a good performance. Therefore, solely based on this experimental detection test using the developed detection model, the results suggest the activity of standing can be confused with the identification of it as sitting or walking. However, both activities of sitting and walking were less likely to be incorrectly recognised. Hence, there are limitations to the current model and could be further enhanced to improve the detection performances.

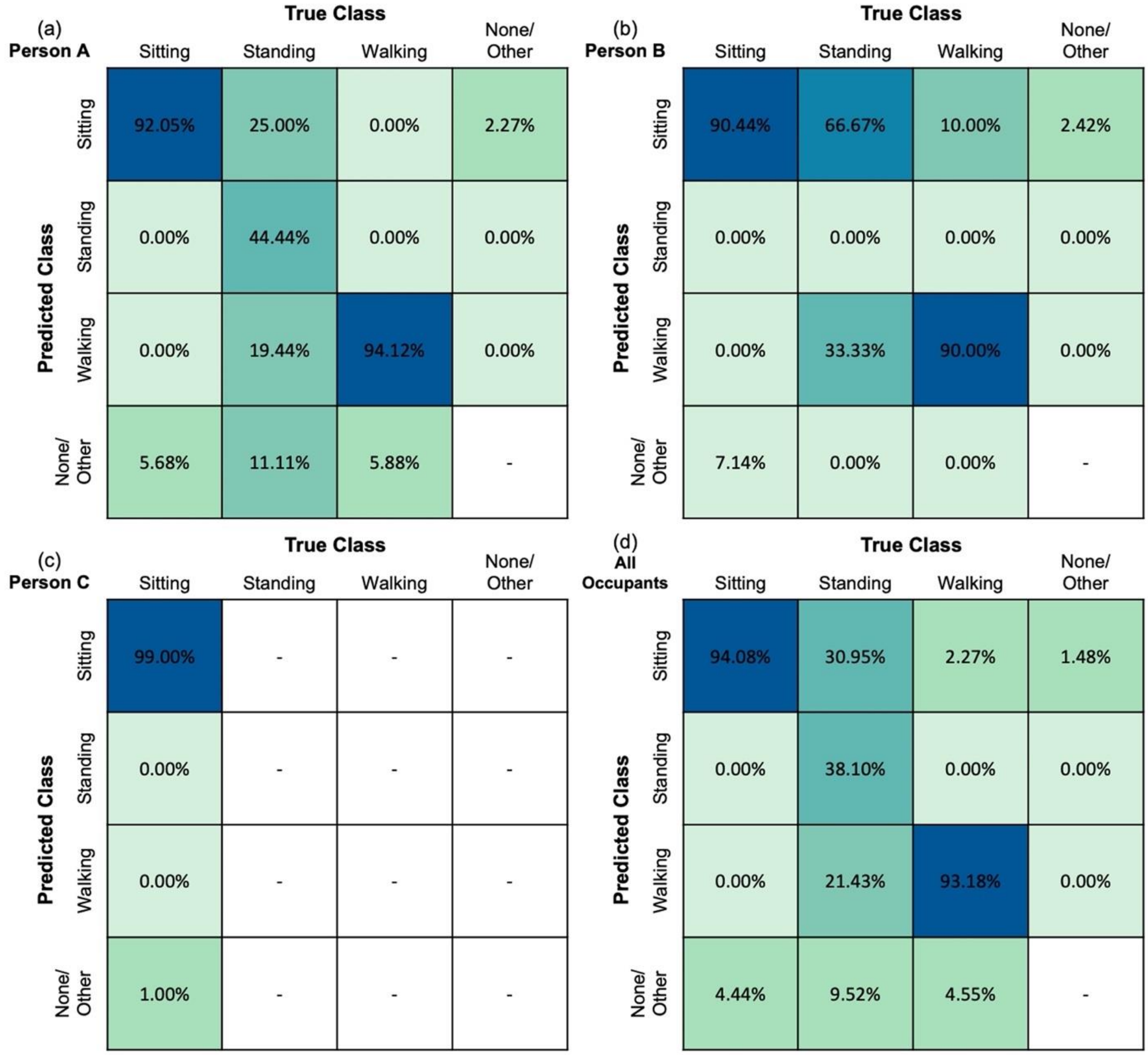


Figure 6-12. Detection performances of occupancy activities based on the percentages of labels identified during Experimental Test 2 using the combined detector.

Similar to Table 6-3, the results in Table 6-4 present the evaluation of the occupancy activity model performance with the use of the common evaluation metrics. The results reflect the evaluation made, presenting sitting and walking with higher accuracy and F_1 scores than standing. Since Person C did not perform the activities of standing and walking. Hence, no data is presented in the table.

Table 6-4. Performance evaluation based on the evaluation metrics for the occupancy activity model applied during Experimental Test 2.

Class	Activity	Accuracy	Precision	Recall	F1 Score
Person A					
1	Sitting	89.02%	0.7715	0.9419	0.8482
2	Standing	81.48%	1.0000	0.4445	0.6154
3	Walking	81.64%	0.8287	0.9412	0.8814

Person B					
1	Sitting	71.26%	0.5335	0.9268	0.6772
2	Standing	66.67%	-	0.0000	0.0000
3	Walking	85.56%	0.7297	0.9000	0.8060
Person C					
1	Sitting	99.00%	1.0000	0.9900	0.9950
2	Standing	N/A	N/A	N/A	N/A
3	Walking	N/A	N/A	N/A	N/A
All Occupants					
1	Sitting	86.95%	0.7305	0.9549	0.8278
2	Standing	79.37%	1.0000	0.3810	0.5518
3	Walking	90.58%	0.8130	0.9318	0.8684
Average for all activities		85.63%	0.8478	0.7559	0.7493

In summary, the real-time application of the deep learning-based models in the selected office during the desired Experimental Test 2 presents an overall performance accuracy of 76.21% for equipment and 85.63% for occupancy activities. The distribution of the results was obtained from different responses according to the various factors of PC monitors and occupants, such as the angle and position relating to the camera. In comparison to the occupancy counting method developed in the study [224] which performed better for a smaller office with less than 5 occupants, the proposed method, which can recognize occupants' activities and interaction with appliances and equipment, can be implemented in large-size offices accurately. While the detection accuracy of the proposed model was lower than the relevant studies [147, 148 230, 231], which suggests that further improvements are required to achieve higher performance for the current approach.

According to the real-time experimental detection using the deep learning models, detection and response achieved provided time-stamped data in the form of both equipment (PC monitor on) and occupancy activities, giving the generated count-based deep learning influenced profiles (DLIP) presented in Figure 6-13 and Video 3, describing the provided video of the experimental test and profile generation. The formation of such profiles is based on the process described in Figure 6-3b. Profiles presented in Figure 6-14a for equipment (PC monitor on) and Figure 6-14b for occupancy activities provide informative data about the amount of equipment in use and the occupants who were detected and performing each of the activities during the experimental test's detection period.

Figure 6-13. Preview of the video showing the application of the proposed combined detection model applied in Experimental Test 2 with the generation of the Deep Learning Influenced Profiles (DLIPs), see Video 3.

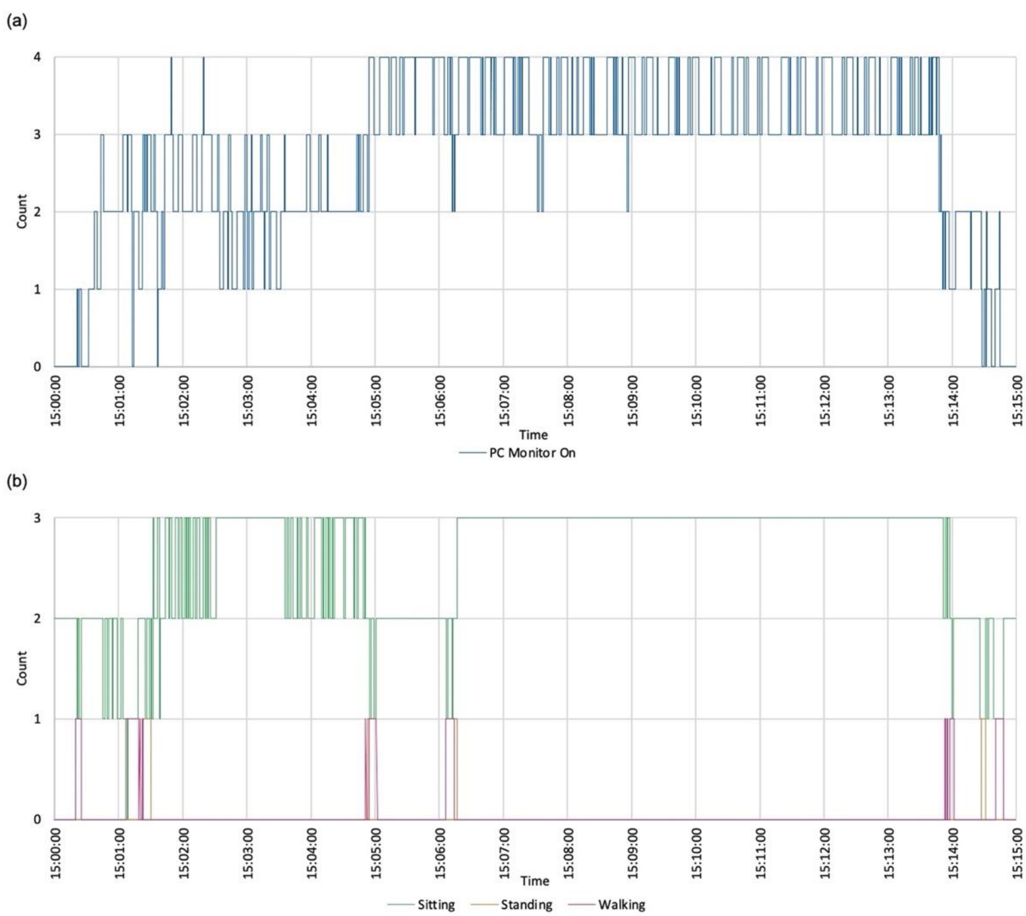


Figure 6-14. Count-based deep learning profiles for the detected (a). equipment, and (b). occupancy obtained from Experimental Test 2.

To enable the real-time profile-based data to assist in building energy simulation and building energy system controls, the heat emission-based DLIPs were formed based on the equipment and occupancy profile indicated in Figure 6-3. The generated DLIPs were compared with the static profiles and the Actual Observation Profile corresponding to the 'true' operation of the occupants' PC monitor and activity.

Compared with the use of the typical profiles, the DLIP predicted up to 54.4% lower equipment heat gains from the PC monitor detection and up to 29.1% lower occupancy heat gains. This indicates the advantage of using such a deep learning-based approach to better understand the occupants and the equipment used within the office space. It identifies the times when the equipment used is increased or decreased, or occupants' activities are varied, which can affect the overall building HVAC system operations through the influence of the variations within the building's internal heat gains. However, since the generation of the data for these profiles is highly dependent on the detection performance, the DLIP still alternates between different responses as shown in Figure 6-14. This resulted in the differences between the DLIP and the Actual Observation Profiles with up to 24.6% for PC monitors and only 4.14% for occupancy activities. Although there were variations between the DLIP and the Actual Observation Profile, it still provided DLIPs which were considerably advantageous in comparison to the Typical profiles as it avoided the majority of the high discrepancy indicating the potential of the deep learning-based approach to provide a more accurate understanding of the conditions within the conditioned space for building energy system operations.

6.1.7. Analysis of the Combined Approaches Towards Building Energy Using Building Energy Simulation (BES)

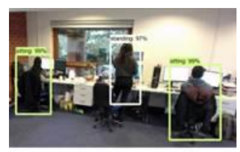
To show the importance of requiring both types of detection, this section presents the use of BES to provide a comparison towards a better understanding of the performance of building energy. The indoor building conditions based on the selected case study building; Sustainable Research Building were described in Chapter 3.3.5. Table 6-5 summarises the test scenarios set up for each of the energy simulation cases. Based on the detections made in Experimental Test 1 detect mentioned in Chapter 6.2.5. with the generated profiles shown in Figure 6-6.

Corresponding to the deep learning detection period, four different scenarios were generated following a typical office day profile with the building assumed to be operated during the hours of 09:00 – 17:00. Effectively, each scenario consists of different variations in equipment and occupancy profiles to enable the evaluation of the impact of the use of control strategies, informed by real-time multiple detections on building energy demand.

Scenario 1 follows the conventional method using static or fixed control setpoints. Scenarios 2 and 3 present the use of a single deep learning model, either the equipment or the occupancy. Additionally, Scenario 4 presents the application of both deep learning methods. For the simulation cases, maximum occupancy sensible and latent occupancy gains of 75 and 70W were assigned. This enables the representation of all activities performed within the office space, with walking being the maximum at 100%, followed by standing at 79% sitting at 64%, and no activities would present 0%. (This corresponds to the conditions applied in Chapter 4).

To ensure the achievement of adequate thermal comfort conditions within the building, a constant HVAC set point temperature was assigned to the building space. The set temperature values were based on ASHRAE [125, 126]. For occupied hours, it advised a temperature of 22 – 27°C for cooling and 17 – 22°C for heating. Effectively, a generalised room setpoint temperature of 22°C was set during the typical occupied office hours of 09:00 – 17:00, and no heating was assigned to the building during the unoccupied hours. Furthermore, maximum ventilation rates were assumed during the occupied hours.

Table 6-5. Summary of the test scenario cases with the assigned building, equipment and occupancy building energy simulation modelling profiles and conditions.

	Scenario 1: Constant Typical	**Scenario 2: Equipment Detection Only**	**Scenario 3: Occupancy Detection Only**	**Scenario 4: Coupled**
Image Representation				
Scenario Description	The deep learning method is not applied	Deep learning equipment detection model used	Deep learning occupancy detection model used	Both equipment and occupancy detection models used
Equipment Profile	Typical Static Profile (Figure 6-6a)	Equipment Deep Learning Influence Profile	Constant Typical (Figure 6-6a)	Equipment Deep Learning Influence Profile
Number of PC Monitor turned on (Equipment)	8	Varies according to the actual equipment usage	8	Varies according to the actual equipment usage and occupancy
Occupancy Profile	Constant Typical Occupancy 2 (Figure 6-6b)	Constant Typical Occupancy 2 (Figure 6-6b)	Occupancy Deep Learning Influence Profile	Occupancy Deep Learning Influence Profile
Number of occupants present in the room	3	3	Varies according to the actual occupancy	Varies according to the actual occupancy

Occupancy Internal Gains	The deep learning method is not applied	Deep learning equipment detection model used	Deep learning occupancy detection model used	Both equipment and occupancy detection models used
Heating Profile	Constant Heating (Room set point temperature, 22°C during office hours)			
Cooling Profile	Constant Cooling (Room set point temperature, 22°C during office hours)			
Ventilation Profile	Constant Typical (Maximum ventilation conditions during office hours)			

The following presents the BES results with an analysis of the potential impact of the proposed deep learning detection approaches on building energy performance. The analysis was based on the comparison of the different Scenarios 1 - 4 (as described in Table 6-5).

Both office equipment usage and occupancy activities can influence internal heat gains. This results in the variation of the indoor air temperature and humidity and hence can influence the indoor thermal environment and the requirement for heating, cooling and ventilation. Figure 6-15a and b present the comparison of the equipment and occupancy gains achieved for a typical day under the four different scenarios. Scenario 1 results suggest the benchmark values based on the assignment of typically scheduled or static profiles. The Scenario, 1 equipment gains, corresponded directly with the total heat gains for the typical or static profile (Figure 6-6), giving a total equipment heat gain of 96.0 kW. Additionally, the occupancy gains were directly related to the occupancy gains indicated by the Typical Occupancy 2 Profile, giving a total occupancy gain of 20.88 kW. These values were greater than the gains predicted using the deep learning approach. As observed, when both equipment and occupancy deep learning methods were used (Scenario 4), the total equipment heat gain was 32.88 kW, and total occupancy heat gain was 14.05 kW, 65.76% and 32.74% lower as compared to Scenario 1. Hence, this shows that the typical or static profiles can overestimate or underestimate the heat gains. Therefore, this shows the benefits of using the deep learning approach for demand-driven HVAC control systems.

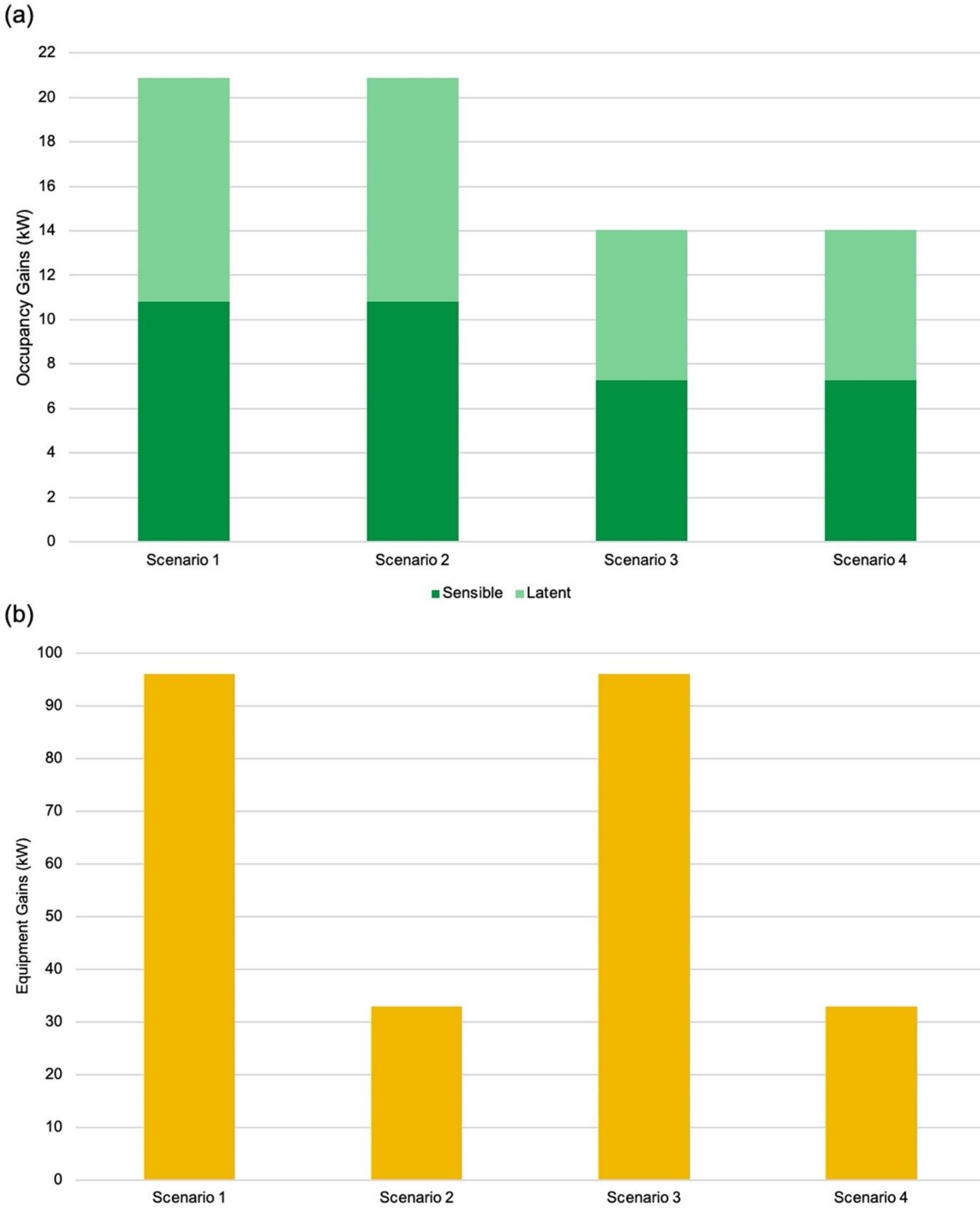


Figure 6-15. Predicted (a). equipment, and (b). occupancy (sensible and latent) gains within the case study building office space based on Scenarios 1 – 4.

Figure 6-16 presents the sum of the equipment heat gains, occupancy sensible and latent heat gains predicted for the different scenarios. Due to the working environment being an office space with a greater number of office equipment emitting larger amounts of heat gains and with a low number of occupants present in the room and mostly sitting for a majority of the time, it was observed that the equipment heat gains are more significant than occupancy heat gains.

A total internal heat gain value of 116.88 kW was predicted for Scenario 1. Scenario 2, which employed equipment detection, showed a significant reduction (63.13%) as compared to Scenario 1. While Scenario 3, which had occupancy activity detection, indicated a total internal heat gain of 110.05 kW. This shows that based on the conditions simulated and the selected case study, the detection of occupancy movement did not have a significant impact as compared to the application of equipment detection. However, its usage could be more advantageous in an indoor environment with lots of occupancy movement and heavy occupancies such as shopping malls or indoor gyms.

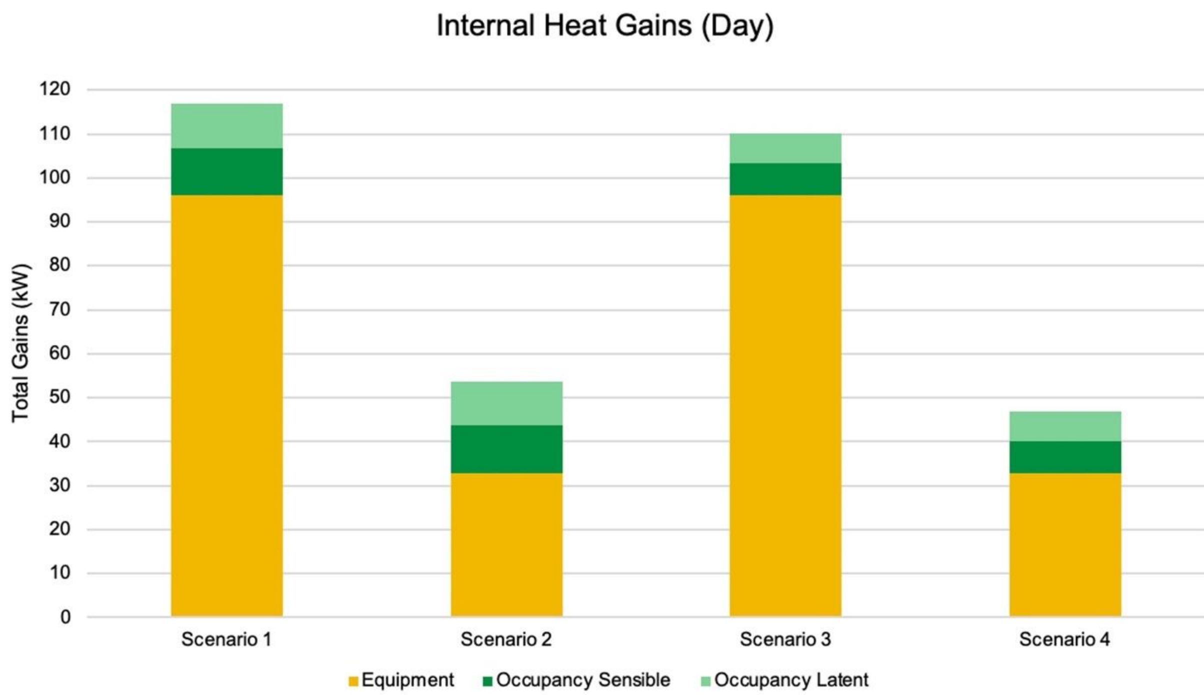


Figure 6-16. Total internal heat gains achieved based on Scenarios 1 – 4 utilising both the occupancy and electrical equipment detection strategies.

6.1.8. Further Scenario-Based Analysis for Combined Occupancy Activity and Equipment Detection Towards Building Performance and Operations

With the identification of the importance of achieving accurate detection and recognition within indoor spaces can lead to effective estimations of the internal heat gains, this section provides further analysis of the impact on energy performance and system operations via the different scenario-based conditions and the application of the profiles generated in the Combined Experimental Test 2 in Chapter 6.1.6.

The conditions applied to the model and setup are discussed in Chapter 3.4. For this, Table 6-6 provides a summary of the setup for building simulation cases. Each scenario simulated 4 days (Wednesday – Saturday) of a typical office week during the heating and cooling season.

Table 6-6. Overview of the scenarios for the BES model to further analyse the impact of combined occupancy and equipment detection towards building energy.

	Scenario 1: Constant Typical	**Scenario 2: Equipment Detection Only**	**Scenario 3: Occupancy Detection Only**	**Scenario 4: Coupled**
Image Representation				
PC Monitor on Profile	Static Profile (Figure 6-17b)	Equipment DLIP (Figure 6-17d)	Static Profile (Figure 6-17b)	Equipment DLIP (Figure 6-17b)
Number of PC Monitor turned on (Equipment)	8 during each weekday and 4 during the weekend	Varies according to the equipment usage	8 during each weekday and 4 during the weekend	Varies according to the equipment usage and occupancy
	For each PC, it represents 2 PC monitor-on and 1 computer-on Maximum conditions: 4 PCs = (8 PC Monitors turned on, 4 Computers)			
Occupancy Profile	Static Profile (Constant sitting) (Figure 6-17a)	Static Profile (Constant sitting) (Figure 6-17a)	Occupancy DLIP (Figure 6-17c)	Occupancy DLIP (Figure 6-17c)
Number of occupants present in the room	8 during each weekday and 4 during the weekend	8 during each weekday and 4 during the weekend	Varies according to the actual occupancy	Varies according to the actual occupancy
Occupancy Internal Gains	Max sensible gain: 75W/person Max latent gain: 70W/person			
Heating Profile	22°C during building operational hours [125, 126]			
Cooling Profile	22°C during building operational hours [125, 126]			

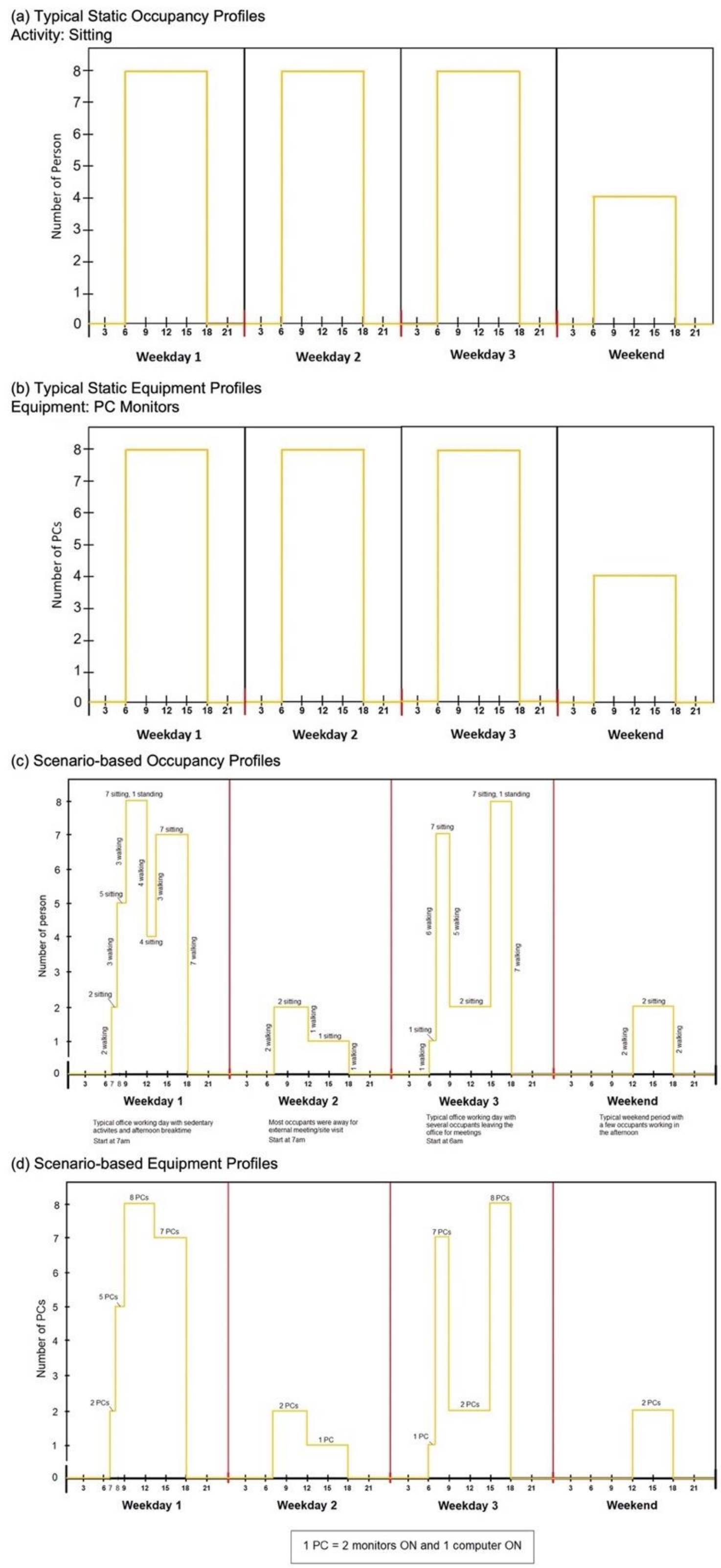


Figure 6-17. Profiles applied to the scenario-based BES simulations. Static (a). Occupancy and (b). equipment profiles. Scenario-based (c). occupancy, and (d). equipment profiles representing a typical office week (Wednesday – Saturday).

Scenario 1 represents the conventional method where static or fixed control setpoints are used. The typical occupancy and equipment profile for PC monitors given in Figure 6-17a and b were assigned to this simulation case. Effectively, during the operational hours of the building, the most common occupancy activity in an office space, 'sitting' was assumed to be performed by eight occupants during the weekday and four people performing this on the weekend. Correspondingly, for electrical equipment, eight PC monitors were assumed to be turned on throughout the operational hours during the three weekdays, and four PC monitors were on during the weekend.

Scenarios 2 and 3 present the application of only one of the deep learning detection approaches with Scenario 2 for equipment only, Scenario 3 for occupancy activity only and scenario 4 when both detections were applied. For these scenarios, Figure 6-17c and d present the assigned occupancy and equipment profiles. To provide a more realistic scenario, different profiles were created for each of the days, and a brief description of each is given in Figure 6-17.
The activity of occupants and the utilisation of equipment generate internal heat gains. The variations in occupants' activities and equipment usage affect the amount of heat generated within a space and further influence the HVAC system operation strategy due to the change in heating, cooling and ventilation demands within the conditioned spaces.

Figure 6-18 shows the distribution of occupancy and equipment gains over time for the four typical days under different scenarios. The results of employing Scenario 1 present the heat gains using fixed or static profiles that were typically used for building heating, cooling and ventilation design. With the comparison of Scenario 1, the other scenarios, which employed the deep learning method to assess real-time occupancy and/or equipment profiles, generated great differences in heat gains especially on the days with similar profiles as Weekday 2. It also suggests that the requirements of building services are varied to achieve a comfortable indoor environment.

To present the heat gain difference under four scenarios, the total equipment gains, occupancy sensible gains, and occupancy latent gains for four days were plotted in Figure 6-19. Equipment gains are the major contributors to the total heat gains as there were only a few people whose main activity in the office space was sitting while a large amount of equipment was set up which caused more heat emission from equipment. As Scenario 1 results represent the benchmark values, it shows that the total heat gain using the fixed or static profiles for four days was 139.4 kW. This value was larger than the results of the other scenarios which were assisted by the deep learning method for an accurate estimation. As compared to Scenario 1, Scenario 2, 3, and 4 created remarkable differences of 38.74%, 15.21%, and 53.95% respectively. As can be seen, the lowest predicted total heat gains were when using the deep learning method for both equipment and occupancy gain estimations (Scenario 4). It indicated that an under or over-estimation of occupancy and equipment heat gains could occur when using scheduled or static profiles. Therefore, incorporating the deep learning method into an HVAC system can help it predict the real-time heat gains and achieve efficient controls while meeting the actual requirements. In addition, based on the simulation results, in comparison to Scenario 1, Scenario 2 which used equipment detection only generated a larger difference than Scenario 3, which used occupancy detection only. It implies that the detection of usage of equipment has a greater influence on heat gain estimation in the office space in the selected case study building because of the relatively low number and less movement of occupants.

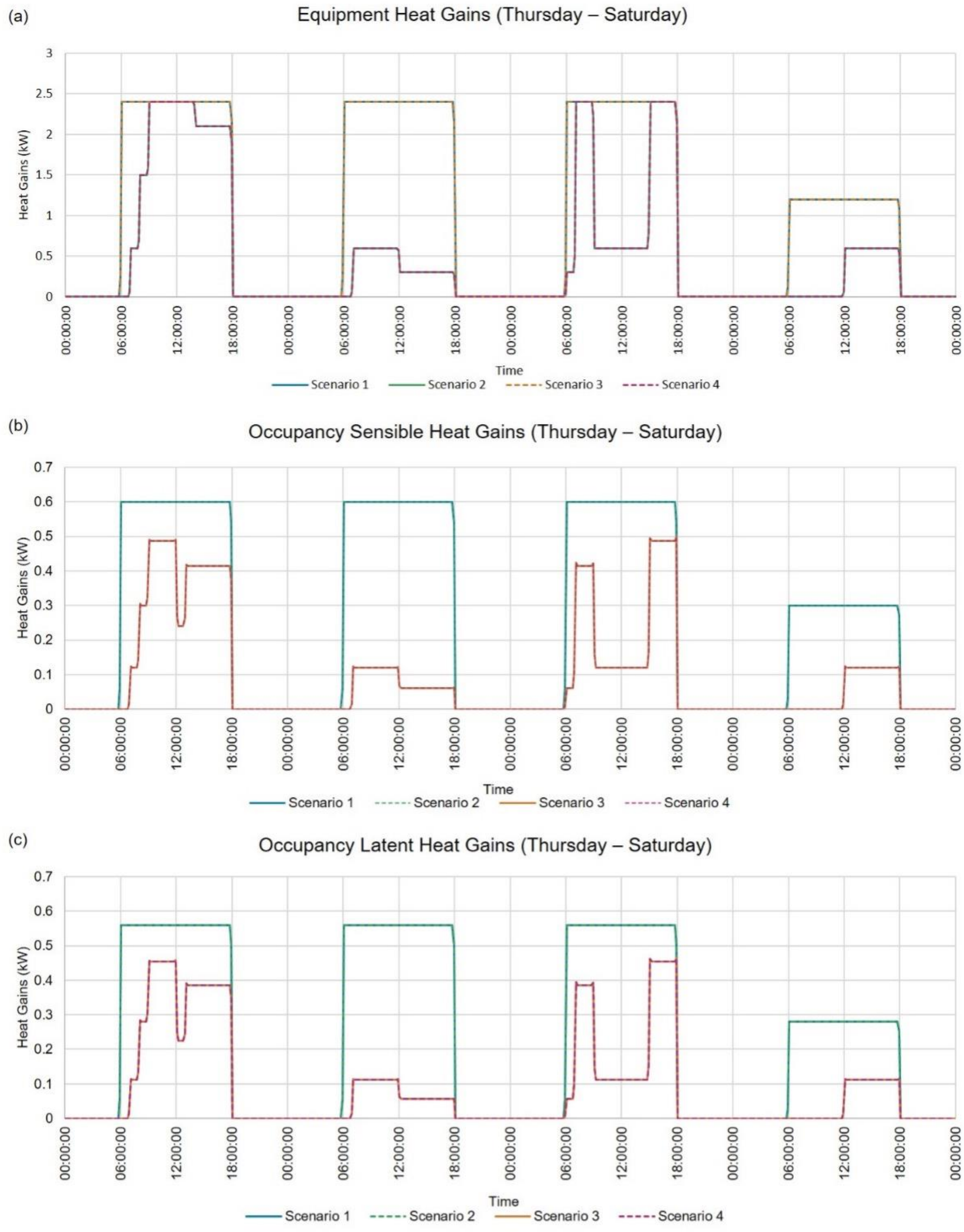


Figure 6-18. (a). Equipment, (b). occupancy sensible, and (c). occupancy latent heat gain distributions under Scenarios 1-4 for four days.

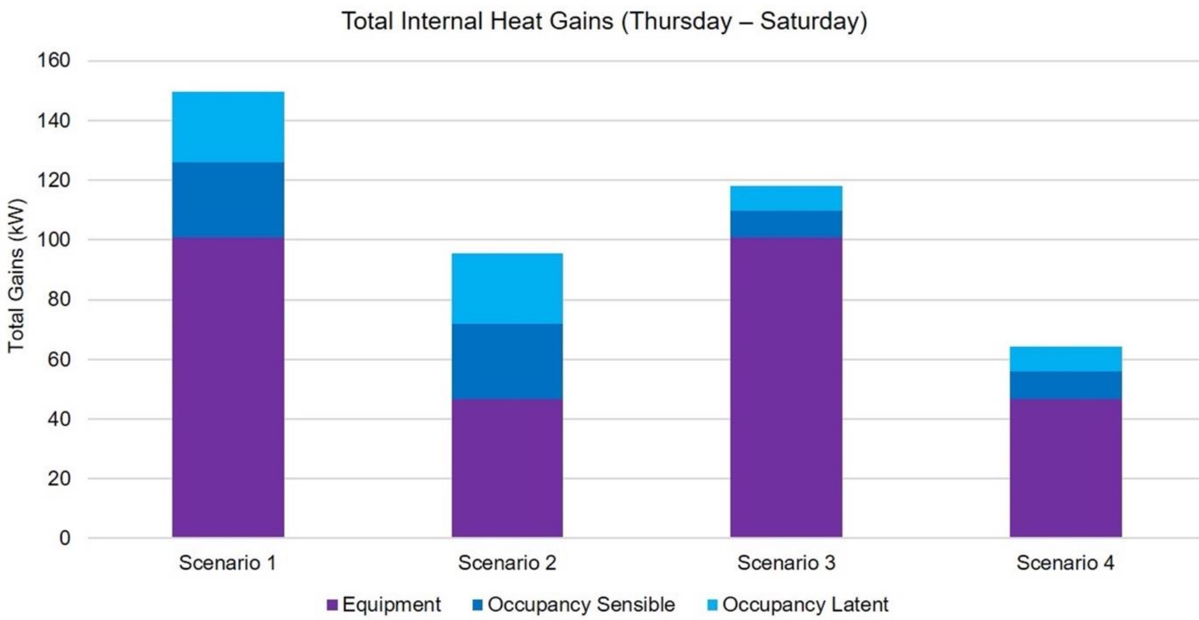


Figure 6-19. Total internal heat gains under Scenario 1-4 for combined occupancy and detection approaches.

In this section, the energy consumption of the case study building under four different simulation cases (Scenarios 1-4) in heating and cooling seasons was analysed. Figure 6-20 shows the heating results for the four selected days in the heating season. The heating load variation across the simulation days was presented in Figure 6-20a. For Scenario 1 and 2, due to the use of a typical occupancy profile, the office was assumed to be occupied from 6:00 to 18:00. Hence, the heating was provided with a setpoint temperature of 22°C during the pre-scheduled period. For Scenarios 3 and 4, the heating was provided based on the actual occupied period because of the use of the deep learning detection method. It could mitigate the waste of energy for unnecessary heating during the unoccupied period, especially on weekends. Moreover, it is apparent that equipment and occupancy gains directly affect the heating demand over time. Lower heat gains were estimated, and higher heating was required to provide a comfortable indoor environment.

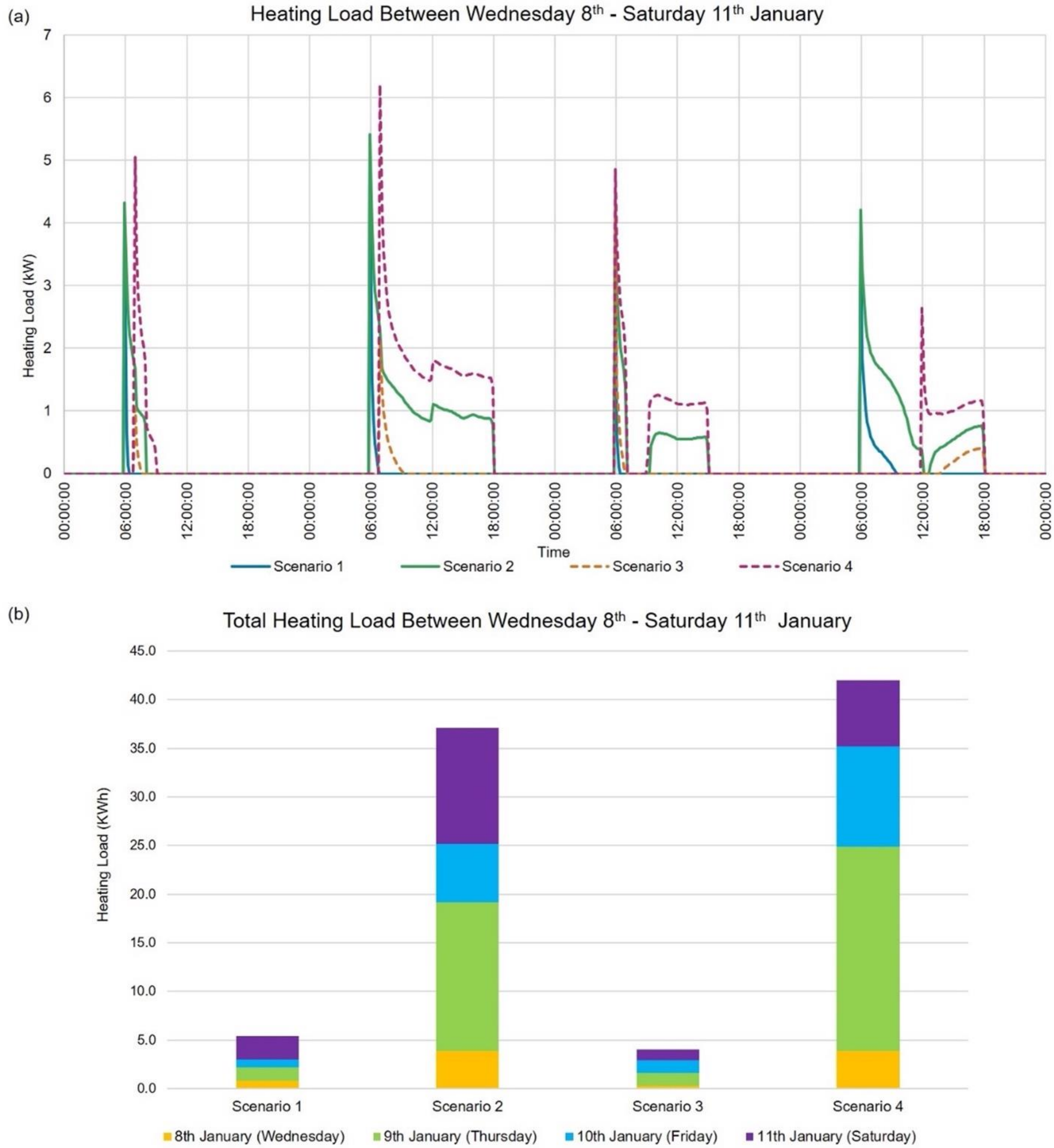


Figure 6-20. (a). Distribution of heating loads and (b). total heating loads for four days during the heating season under Scenario 1-4.

Figure 6-20b presents the simulation result of total heating demand for the selected four days in the heating season under Scenario 1-4 giving a total heating load of 5.4 kWh, 37.1 kWh, 4 kWh, and 42 kWh. It indicated that under Scenario 4, which predicted the lowest heat gains, maximum heating was required among all simulation scenarios to achieve thermal comfort during the heating period. It should be noted that the heat gains predicted for Scenario 1 were higher than that for Scenario 3, while the heating loads for Scenario 1 were also greater. The reason is in Scenario 3 the heating was provided based on the actual occupied period due to the use of a deep learning-generated occupancy profile, while in Scenario 1 the provision of heating followed the static profile. The unnecessary heating provided during the unoccupied time was reduced in Scenario 3. It highlighted that following the profiles generated by deep learning detection techniques could potentially mitigate the building energy use by making the HVAC system adapt to the actual demands while maintaining a better indoor environment.

Figure 6-21 shows the cooling results for the four selected days in the cooling season. The cooling load distribution across the simulation days was presented in Figure 6-21a. For Scenario 1 and 2, due to the use of a typical occupancy profile, the cooling was provided with a setpoint temperature of 25°C from 6:00 to 18:00 in the office. The cooling was provided based on the actual occupied period under Scenarios 3 and 4. This method could avoid providing unnecessary cooling in the conditioned space and further reduce the building energy consumption. In addition, the cooling demands were influenced by the variations in internal heat gains. Lower heat gains caused lower cooling loads. Figure 6-21b presents the total cooling demand in the cooling season. As shown, the total heating loads for selected days based on four scenarios were 132.7 kWh, 85 kWh, 117.3 kWh, and 72.5 kWh respectively. Scenario 4 which employed both detection profiles estimated the lowest cooling load among all the scenarios and was 45.37% lower than Scenario 1 which employed fixed or static profiles. The results also indicated that deep learning techniques for occupancy and equipment detection could affect building energy consumption by providing accurate profiles to achieve demand-driven controls.

According to the simulation results for selected four days within the case study building, up to 53.95% reduction of internal heat gains could be potentially achieved with the use of both occupancy and equipment detection profiles in comparison with the use of predefined typical or static schedules. This highlighted the importance of monitoring occupancy behaviour and electrical equipment usage and the benefits of using the deep learning detection method to monitor real-time occupants' activities and equipment usage and effectively operate the HVAC system based on the actual requirements. It can create a large potential to reduce unnecessary building energy consumption while maintaining a comfortable indoor environment.

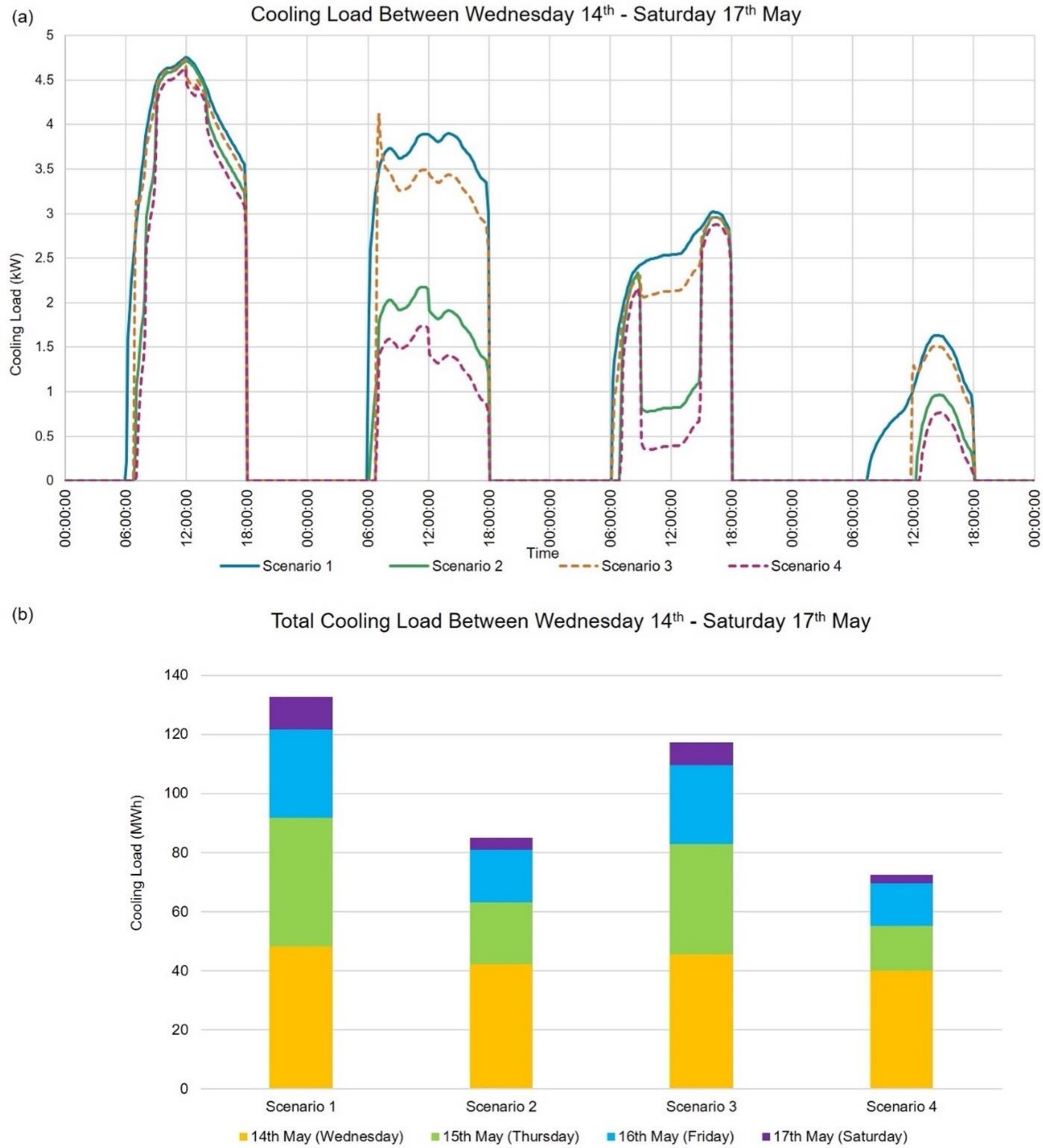


Figure 6-21. (a). Distribution of the cooling loads and (b). the total cooling loads for four days during the cooling season under Scenario 1-4.

Effectively, using a combined occupancy activity and equipment usage detection approach based on computer vision and deep learning methods can provide efficient building energy controls. This approach can perform real-time detection and recognition tasks for multiple occupants' activities and equipment conducted within an indoor space. Adopting the Faster R-CNN model along with image-based datasets enabled the detection and recognition using a camera. The performance of this model was assessed through the use of different evaluation metrics. The two experimental tests in Chapters 6.1.5 and 6.1.6 indicate the proposed model can perform occupancy and equipment detection and recognition tasks with high accuracy. To investigate the impact of the proposed approach on building energy performance, the case study building was modelled and simulated in BES with the different scenarios in Chapters 6.1.7 and 6.1.8. These results highlighted the importance of monitoring real-time occupancy behaviour and electrical equipment usage and the benefits of using deep learning detection methods to provide profiles to HVAC systems to achieve demand-driven controls that can minimise unnecessary building energy consumption while maintaining a comfortable indoor environment.

To optimise the proposed approach, further improvements needed to be carried out in future works. The deep learning model can be optimised by modifying the model's architecture and adding more data to minimise the error rate. A lower error rate can conduct a more accurate estimation of energy demand. Therefore, a better indoor environment condition will be provided for occupants. Moreover, it is necessary to develop a strategy which can streamline the real-time data from the deep learning model to the HVAC system to achieve demand-driven controls by automatically adjusting the setpoints.

6.2. Combined Approach – Window and Occupancy

With the occupancy activity and window detection and recognition approaches individually explored in Chapters 4 and 5, this section presents the investigation of a combined framework design. This includes a real-time detection and recognition framework design focused on occupancy activities and conditions of windows being opened or closed by occupants within a building space. Similar to the concepts applied to the individual framework designs and the combined design for occupancy activity and equipment, the proposed approach is designed to provide a real-time prediction of the internal heat gains and detection of the status of windows (open/close) for building control systems. This can enable the adjustment of the operations of building HVAC systems to ensure that adequate indoor thermal conditions and air quality are achieved while minimising unnecessary building energy loads. A model based on a Faster R-CNN model was trained for the detection and recognition of occupancy activities and window status using a camera. Validation of the approach was conducted using a set of testing data, and the accuracy and suitability for live detection were evaluated. Similarly, field experiments were carried out within a case study university lecture room to test the capabilities of the proposed approach. Using building energy simulation (BES), the case study building was simulated with different scenario-based operation profiles to assess the indoor air quality and potential energy savings that can be achieved.

6.2.1. Framework for Combining Occupancy Activity and Window Detection

The proposed research approach is given in Figure 6-22. As highlighted, a case study lecture room within a university building was selected to assist in the testing and evaluation of the application of the approach. Furthermore, the key stages of the method were outlined. This includes the steps of developing and implementing the proposed vision-based deep learning framework in Part 1 and the analysis of the utilisation of the deep learning model for real-time detections from the experimental test and under scenario-based situations using BES in Part 2.

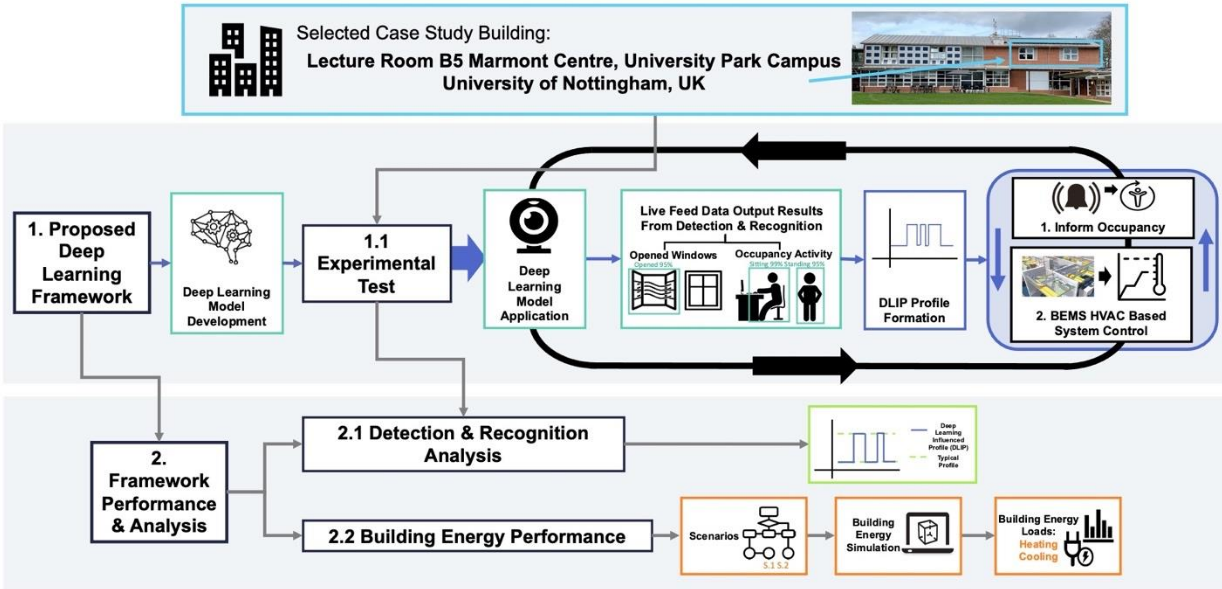


Figure 6-22. The workflow process for the development, application and analysis of deep learning vision-based window and occupancy detector using TensorFlow techniques.

To test this framework approach, a case study building was selected and applied to support various stages of the model development. The same case study building along with the same experimental test setup as to the selected space used in Chapter 5 for individual window detection approaches was applied. This includes the setup shown in Figure 5-5b.

6.2.2. Deep Learning Method

Table 6-7 presents the description of the datasets in terms of the number of images and labels assigned. Overall, the same workflow process was applied. This consists of gathering the images to form the datasets and manually labelling images. Figure 6-23 presents an example of the types of images gathered and how they were manually labelled to highlight each image's specific region of interest. The number of labels assigned to each image was also solely based on the content of each image. For most cases, multiple labels were assigned by highlighting a bounding box around each occupant and on each of the gaps of the windows across all sides of the window.

Figure 6-23. Example images were gathered from Google Images to form the image datasets (training and testing) for both categories of occupancy activities and windows, along with examples of how images were manually labelled to highlight the specific region of interest.

For the occupancy activity dataset, 'sitting, standing and walking' activities were selected as the desired model detection responses. The present model assumes that no occupant is present within the space when no detection is made. It should be noted that the image dataset and the trained model are identical to the reference model of Model 2b for Occupancy activity as developed in Chapter 4 and Model 4 in Chapter 5. To form this combined detector, these two separately trained models were combined.

As shown by the example in Figure 6-23, the images within the dataset do not have to include the whole (full) window. Instead, it consisted of images that only presents 'opened windows' which presented opening types/designs of side-hung, top-hung and pivot (vertical, horizontal). The reason why only these types of open window images were selected was to demonstrate a different method of labelling. The labelling method assigned bounding boxes to regions where it showed window opening gaps. The change in the types of images for the window dataset and the labelling method increased the number of images used giving a total of 826 images given in Table 6-7.

Table 6-7. Description of the training and testing image dataset for the window and occupancy detection models.

Reference Model	Category	Number of Images			Number of Labels		
		Training	**Testing**	**Total**	**Training**	**Testing**	**Total**
Occupancy Activities							
Occupancy Activity Model 2b	Sitting	400	100	500	753	149	902
	Standing	400	100	500	701	134	835
	Walking	400	100	500	1000	177	1177
	Total	1200	300	-	2454	460	-
Windows							
Window Model 4	Open	666	160	826	1398	318	1716

Once the images were gathered and pre-processed, a suitable framework platform was selected to configure and train the CNN-based model. Likewise, the TensorFlow Object Detection API [207] was used to develop the occupancy activity and window detector via a transfer learning approach. A model selected from the TensorFlow detection model zoo was used to assist the pipeline configuration of the model used to train the desired detector. The COCO-trained model of Faster R-CNN (With Inception V2) was selected. Two models were configured and trained separately, forming Model A for occupancy activity detection and Model B for window detection. Figure 6-24 presents the overall architecture and the pipeline configuration of the models used. Once these models were successfully trained, they were combined and deployed in an AI-powered camera.

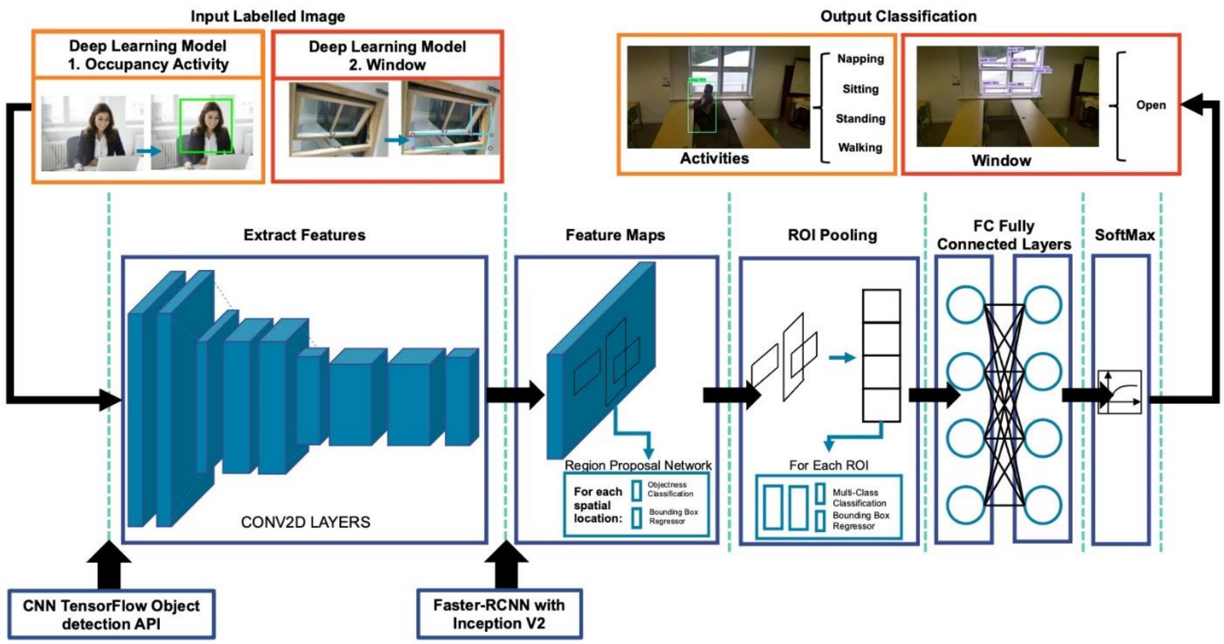


Figure 6-24. Architecture and configuration of the convolutional neural network (CNN) based models used to develop the occupancy activity and window multi-detector.

As presented in Figure 6-22, along with the set-up shown in Figure 5-5, a 15-minute experimental test during a typical winter's day afternoon (at 15:00) was performed within the selected room. The experiment is divided into 5 parts. The test started with Part 1 (1-minute duration), which consisted of all windows being closed and no occupants being present within the room. Next, Part 2 (15:01 – 15:03) consisted of a person entering the room and performing a series of activities that included sitting, standing, and walking. Within Part 3 (15:03 – 15:08), the person continued to perform the following activities and decided to open all 4 windows. Towards the end of Part 3, the person decided to leave the room, and all windows were left open. Hence, in Part 4 (15:08 – 15:11), the windows were all opened, and no occupant was present in the room. Furthermore, Part 5 consisted of the same situation as part 4; however, for this section, the lights were switched off. During the experimental test, continuous real-time detection provided response output, including sitting, standing, walking, and open window. It was assumed that when none of these responses was made, windows were closed, and no occupancy was present in the room.

Figure 6-25 presents the formation process of the DLIP using the real-time detection data of both occupancy activities and windows. As shown in the snapshots of the recorded frame indicating the detection and recognition made, along with the IoU accuracy, a separate profile was generated for each category. Same count-based profiles for occupancy activities were generated, which were then used to estimate the heat emission rates of occupants performing different activities. As described in Chapter 5.3.2, a modulating profile was generated for windows, which corresponds to the total number of open windows detected. As shown in Figure 6-25, the method of labelling the opened windows, resulted in instances when two overlapping bounding boxes were assigned to one window. Hence, a rule was set to ensure that a single window opening would only be detected once.

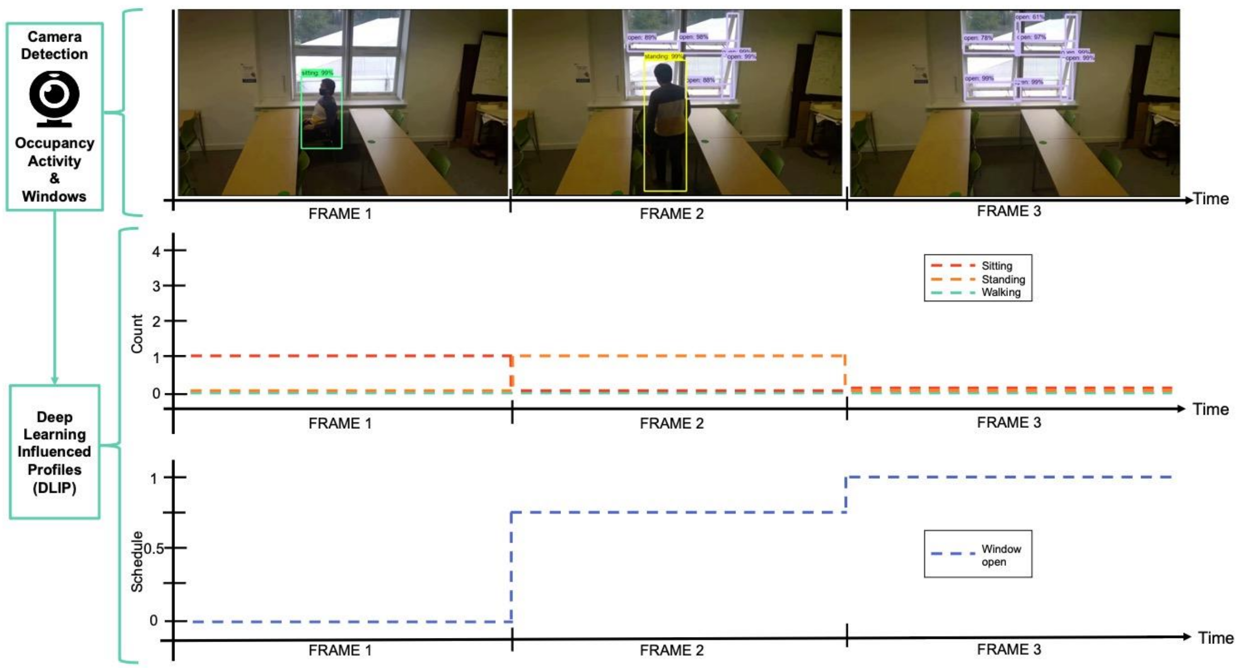


Figure 6-25. Real-time detection and formation of the deep learning influenced profiles (DLIP) for the combined detection of occupancy activities and windows.

6.2.3. Performance Analysis of the Combined Window and Occupancy Detection Model

Individual training results of each of the models and the initial performance of each of these models (Model 2b for occupancy activity and Model 4 for windows) were given in Chapters 5 and 6. This section presents the model performance under the selected experimental tests whereby the combined approach was tested and evaluated. Similar to the previous analysis as mentioned in Chapter 3.3.3, the detection performance analysis was evaluated based on the IoU, correct, incorrect and no detections, along with the presentation of the detection instances in form of the confusion matrix, giving values in terms of the common evaluation metrics.

Video 4 indicated by Figure 6-26 presents a preview of the real-time detection and recognition using the integrated vision-based detection approach within the case study lecture room. Figure 6-27 presented a series of results for each of the key stages of the test, Part 1 – Part 5. The results showed the capabilities of the approach to provide a combined detection of occupancy activities and window conditions.

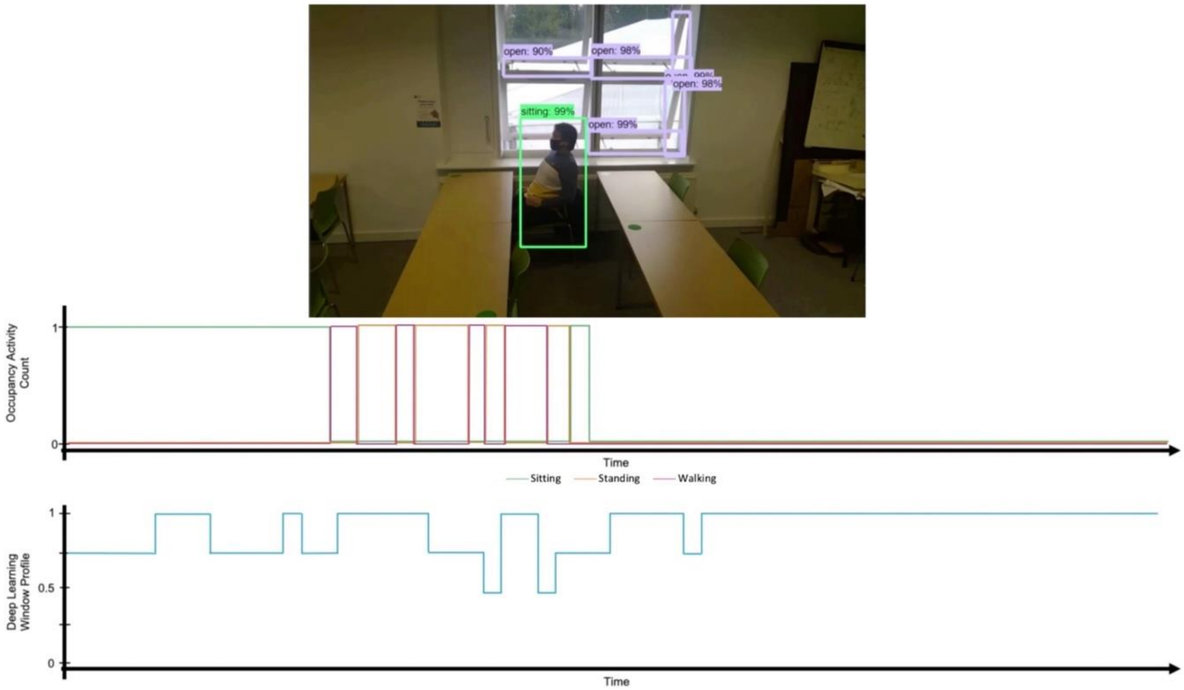


Figure 6-26. Preview of the video showing the application of the proposed combined occupancy activity and window detection model in the test with the DLIP generation, see Video 4.

During the real-time detection, bounding boxes were assigned across the desired object that was recognised, and the detection accuracy based on the IoU value was presented. Since this is a vision-based approach that requires a camera to perform the following detections, limitations in terms of obstruction can ultimately affect the performance of such an approach. Furthermore, the labelling of the images of the gaps of opened windows in the training dataset resulted in instances of windows achieving two overlapping bounding boxes assigned to one window. This was shown in Figure 6-27, with overlapping horizontal and vertical bounding boxes.

Figure 6-28 presents the generated DLIP for occupancy activities and window conditions during the experimental test. The profile details the activities perfo∂rmed by the detected occupant, which was utilised to predict the internal heat gains from occupancy and form a heat emission profile. In Figure 6-28b, it compares the DLIP against other profiles, including two static scheduled profiles assuming fixed occupancy rates and the Actual Observation profile, representing the ground truth or actual activities performed by the occupant during the test. Figure 6-28c presents the comparison between the predicted and actual conditions (open or close) of the windows. The results show that there were some errors when comparing the DLIP against the actual conditions. The error was 8.20% for occupancy activity detection and 20.98% for window detection. This suggests that further development is necessary to improve the detection performance.

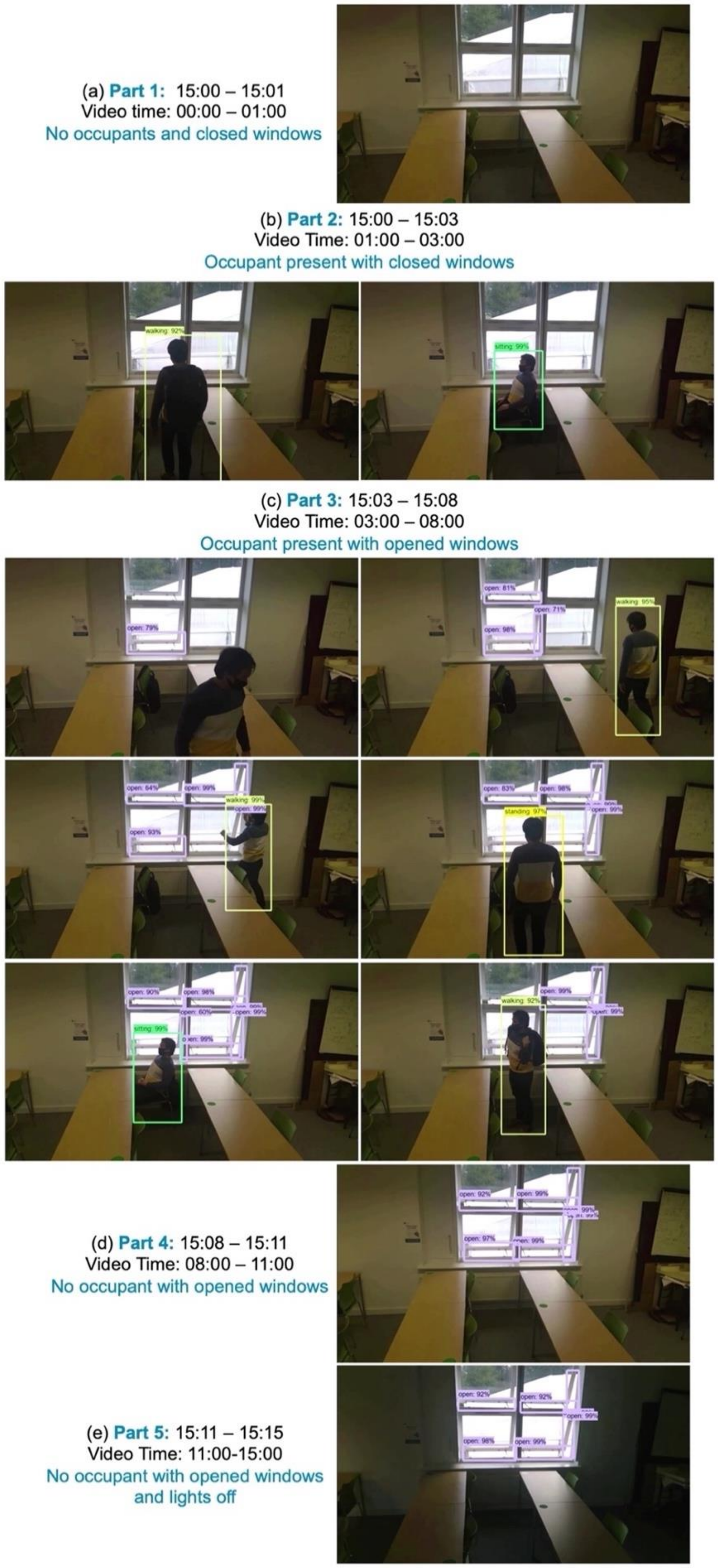


Figure 6-27. Key stages of the occupancy activity and window detection during the experimental test.

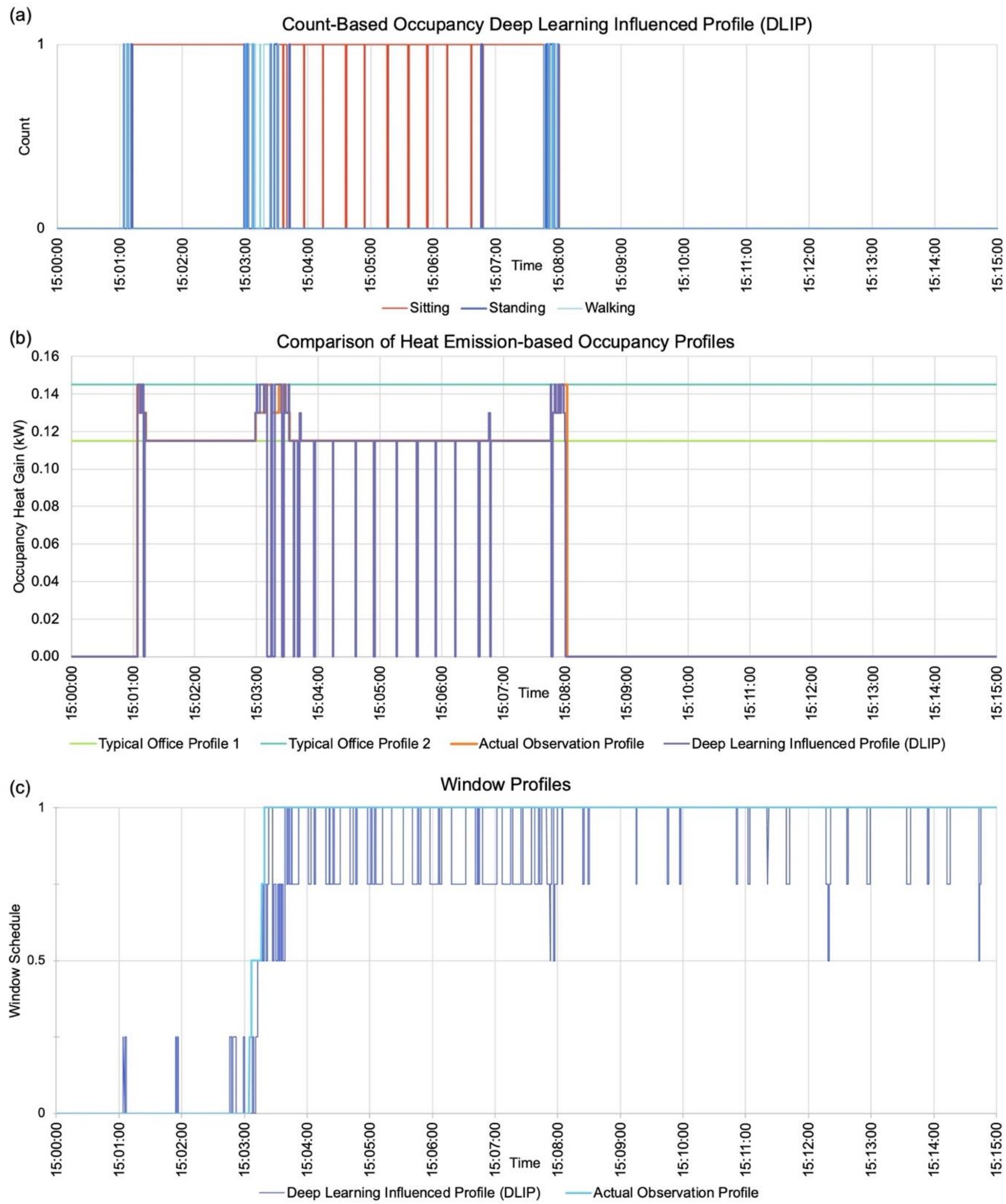


Figure 6-28. Generated (a) count-based occupancy deep learning influenced profile (DLIP) during the experimental test. (b). Comparison between heat emissions DLIP and the static scheduled and the actual observation profiles. (c). Generated DLIP for windows during the experimental test plotted against the Actual Observation Profile.

6.2.4. Scenario-Based Simulations and Analysis

As detailed in Figure 6-22, the case study building was modelled, and BES was performed to evaluate the effect on the building energy demand of the proposed combined detection approach. The following section presents the description and set up of scenario-based simulation cases.

Figure 6-29 shows the selected lecture room in the Marmont Centre and the activity schedule during a typical four-day period (Friday to Monday) between Friday 10th and Monday 13th January. It was assumed that a timetabled lecture was held on day 1 (Friday between 14:00 – 16:00) with full occupancy (up to 40 people), and another session was held on day 4 (Monday between 10:00 – 1200) with only half the number of occupants present (up to 20 people). The room was unoccupied during the other periods.

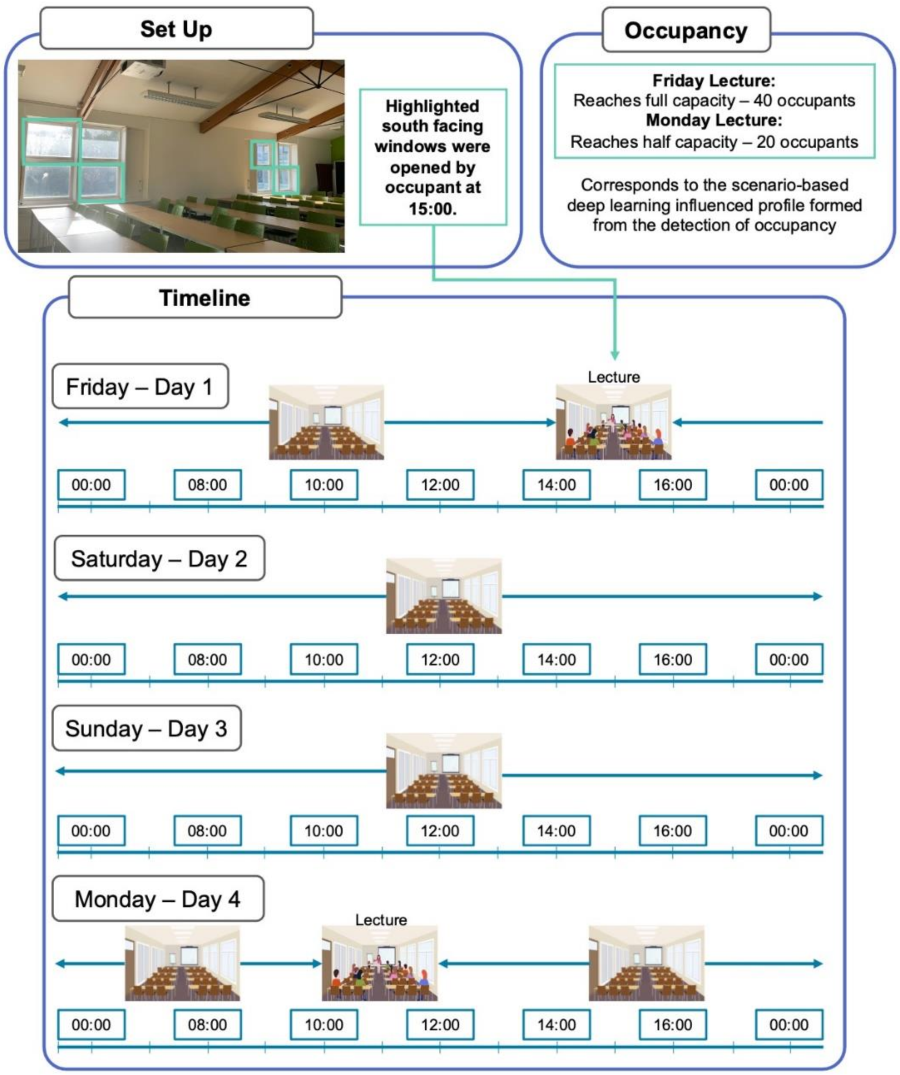


Figure 6-29. Timeline of the activities performed by the occupants within the selected lecture room during a typical week.

A total of five different cases were presented as described in Figure 6-30. This enabled the analysis of the different system responses that could assist the HVAC control system provide adequate indoor thermal comfort and air quality while improving the building energy performance. As mentioned previously, many HVAC systems are operated based on predefined or fixed schedules that are usually based on the building operational hours and recommended setpoint temperature [125, 126]. Hence, for the present study, heating setpoint temperatures of 21°C and 15°C for occupied and unoccupied hours were set. Additionally, for most buildings, the number of occupants within the building and the window conditions are usually not known. Hence, to represent such situations, Case A was created with 6 different combinations of using constant 'static' profiles for occupancy, windows, heating and cooling. For these cases, occupants were either; 1. Assumed to be not present in the room, 2. Present in the room and mainly performing sedentary activities during building operational hours and 3. Present in the room and mainly performing high-intensity activities to represent the maximum occupancy conditions. Additionally, it was assumed that windows were either constantly opened or closed during occupied hours.

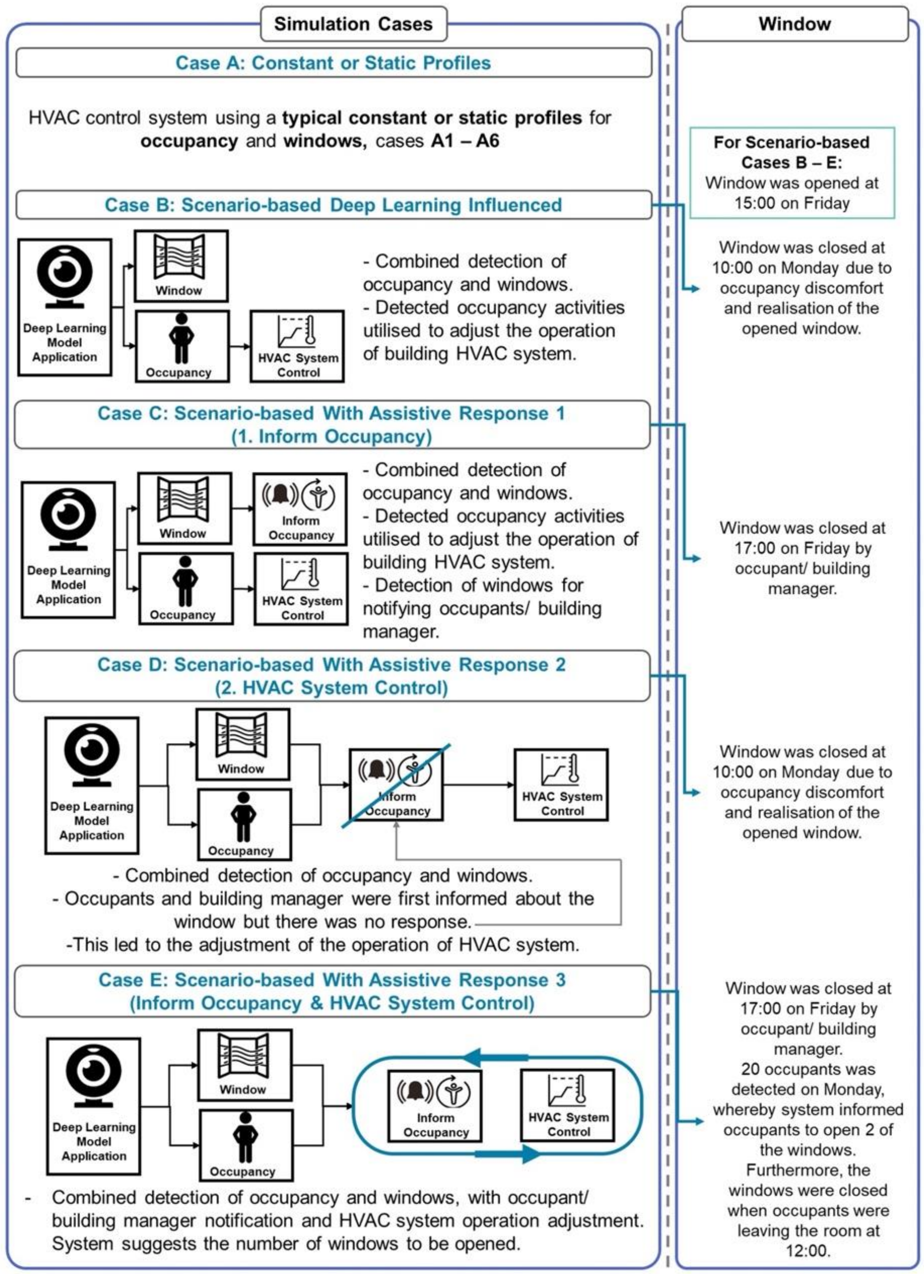


Figure 6-30. Description of the five simulation cases based on the different system responses.

The vision-based detection approach was implemented in scenario cases B, C, D and E. For the occupancy, the Scenario-based Deep Learning Influenced Occupancy Profile (Figure 6-31b) was set, and Figure 6-31c and d present a more detailed version of the profile with the number of occupants detected and the activities performed on both lecture days. Furthermore, only the south-facing windows were assumed to be left open by occupants during the lecture session at 15:00 on Friday (Day 1).

Case B represented the situation when both occupants' activities and window conditions were detected and recognised using the integrated vision-based approach. The detection of occupancy activities aided the adjustments of the operations of the building HVAC. The heating setpoint temperature of 21°C was only set when occupants were detected in the lecture room. The windows were detected to be opened at around 15:00 on Day 1. However, no response-based adjustments were made. Hence, the windows were left open until 10:00 am on Monday, when a person who attended the session decided to close these windows.

Similar to Case B, both occupants' activities and window conditions were detected in Case C, and the building HVAC operation was adjusted based on the occupancy level. In addition, the building users were informed about the window condition. For this, the windows left open after the lecture on Day 1 (Friday) were detected, and the building manager was informed and closed the windows at 17:00 (1 hour after the end of the lecture).

In Case D, the building users or manager did not respond to the notification made, and the building HVAC controls made a direct response by switching off the heating system when no people and opened windows were detected. This is indicated by the heating profile shown in Figure 6-33c.

In Case E, the system response was further improved. In addition to the adjustment of the HVAC operation and informing building users about window conditions, the approach suggests the number of windows that should be opened depending on the number of occupants within the room and the indoor room temperature.

Hence, for this case, the same scenario-based conditions as for Case C were assumed for occupants, windows, heating, and cooling windows during day 1 (Friday). However, on Monday (day 4), only half of the occupants were present in the room. The system suggested that only a certain number of windows be opened and was later closed just before all the occupants left the room at noon. For all cases, the corresponding profiles are highlighted in Figure 6-31, Figure 6-32 and Figure 6-33. A summary of the scenario cases is detailed in Table 6-8.

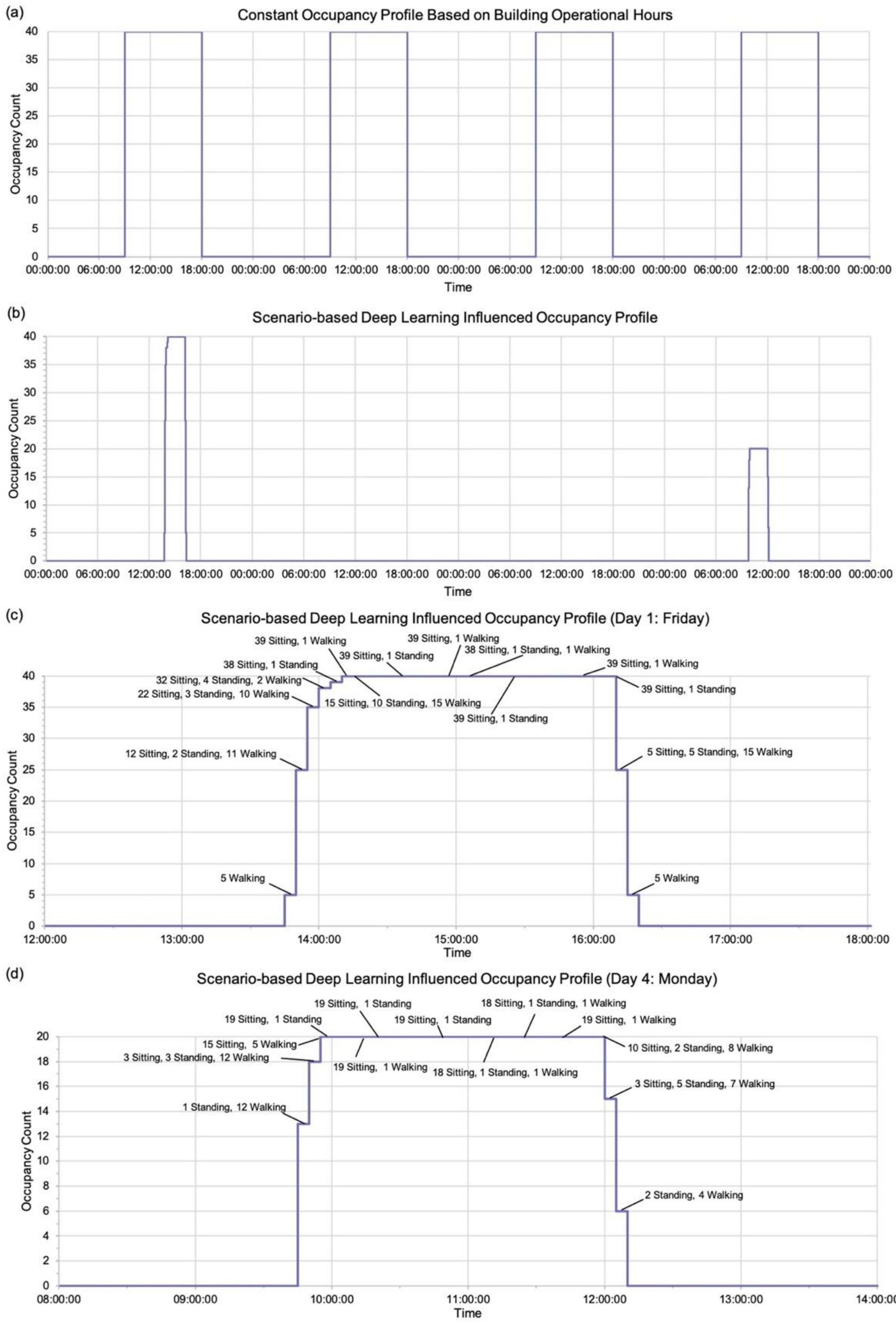


Figure 6-31. Occupancy profiles used within BES. (a). Typical, constant static occupancy profile that is based on building operational hours. (b). Scenario-based deep learning influenced the occupancy profile that corresponds to the timeline given in Figure 6-29. (c). and (d). A more detailed view of (b), with the description of occupancy behaviour during day 1 (Friday) and day 4 (Monday).

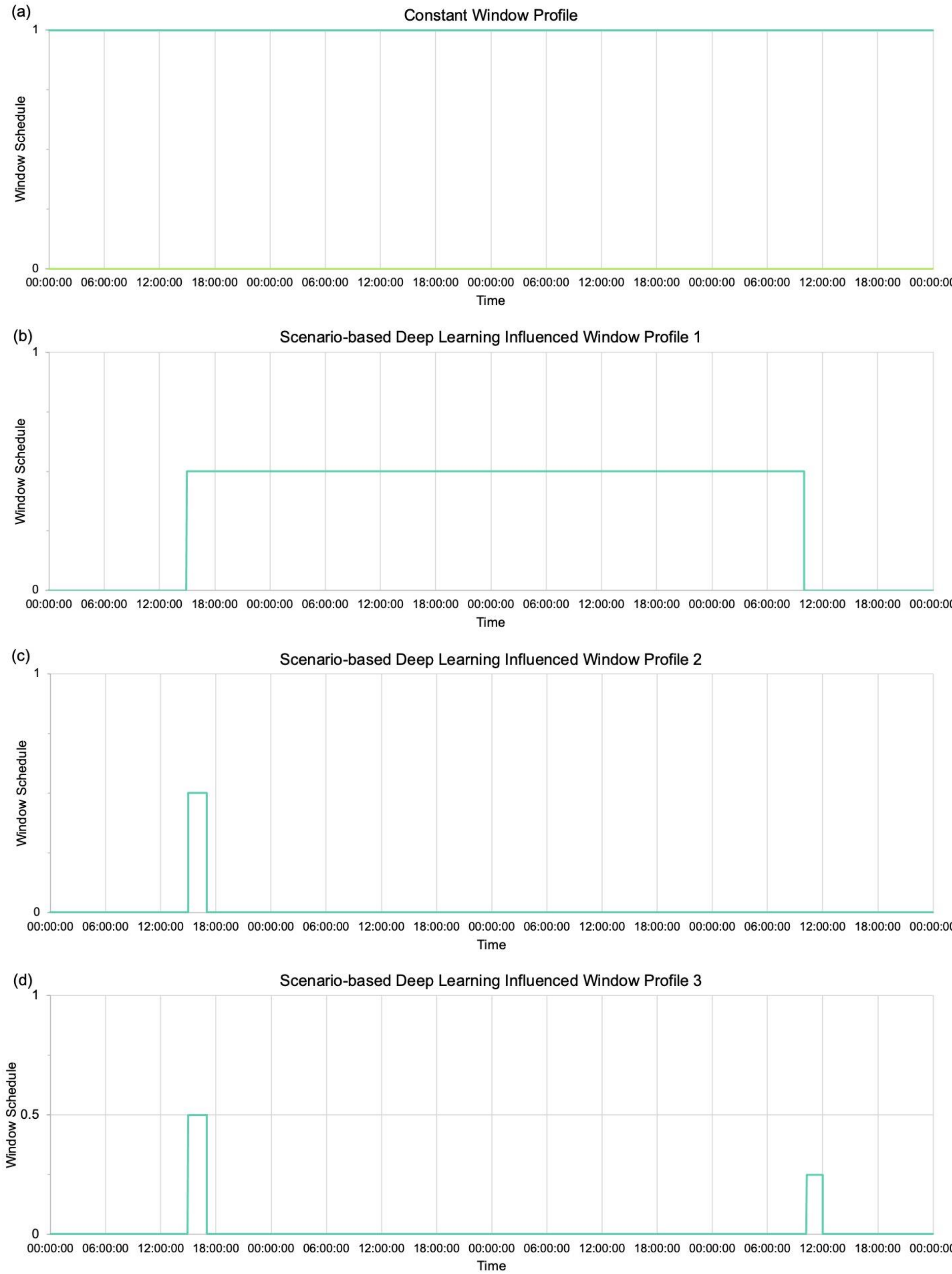


Figure 6-32. Window profiles used within BES. (a). Typical, constant open and closed window profiles. (b)., (c). and (d). Scenario-based deep learning influenced occupancy profile that corresponds to cases highlighted in Figure 6-30a and Table 6-8.

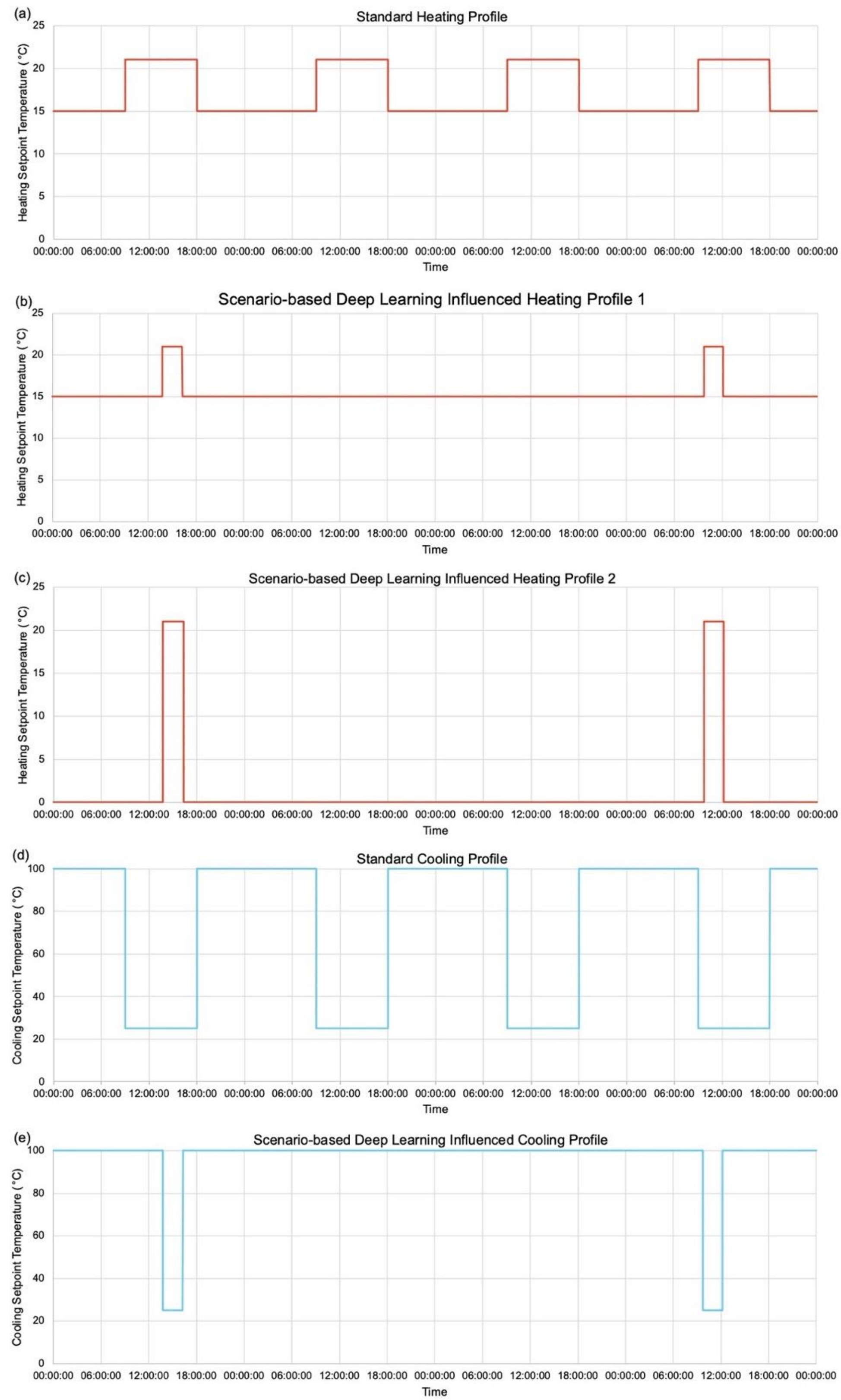


Figure 6-33. The heating and cooling profiles used in the scenario cases as highlighted in Table 6-8.

Table 6-8. Summary of the profiles assigned to the scenario cases as described in Figure 6-30.

<table>
<tr><th colspan="2" rowspan="2">Simulation Case</th><th colspan="4">Assigned Profiles</th></tr>
<tr><th>Occupancy</th><th>Window</th><th>Heating</th><th>Cooling</th></tr>
<tr><td rowspan="6">A: Typical</td><td>A1</td><td rowspan="2">None</td><td>Constant closed (Figure 6-32a)</td><td rowspan="6">Standard (Figure 6-33a)</td><td rowspan="6">Standard (Figure 6-33d)</td></tr>
<tr><td>A2</td><td>Constant open (Figure 6-32a)</td></tr>
<tr><td>A3</td><td rowspan="2">Constant low activity level during building operational hours (Figure 6-31a)</td><td>Constant closed (Figure 6-32a)</td></tr>
<tr><td>A4</td><td>Constant open (Figure 6-32a)</td></tr>
<tr><td>A5</td><td rowspan="2">Constant high activity level during building operational hours (Figure 6-31a)</td><td>Constant closed (Figure 6-32a)</td></tr>
<tr><td>A6</td><td>Constant open (Figure 6-32a)</td></tr>
<tr><td colspan="2">B</td><td rowspan="4">Scenario-based DL Influenced (Figure 6-31b, c & d)</td><td>Scenario-based DL Influenced 1 (Figure 6-32b)</td><td rowspan="2">Scenario-based DL Influenced 1 (Figure 6-33b)</td><td rowspan="4">Scenario-based DL Influenced (Figure 6-33e)</td></tr>
<tr><td colspan="2">C</td><td>Scenario-based DL Influenced 2 (Figure 6-32c)</td></tr>
<tr><td colspan="2">D</td><td>Scenario-based DL Influenced 1 (Figure 6-32b)</td><td>Scenario-based DL Influenced 2 (Figure 6-33c)</td></tr>
<tr><td colspan="2">E</td><td>Scenario-based DL Influenced 3 (Figure 6-32d)</td><td>Scenario-based DL Influenced 1 (Figure 6-33b)</td></tr>
</table>

First, results in terms of occupancy gains (Figure 6-34) were generated. This verified the results presented from the similar BES made in Chapter 6.2.7. and suggests the results for Typical Office 1 and 2 provided benchmark values to represent static occupancy profiles employed in conventional control systems. Typical Office 1 assumed occupants to be carrying out sedentary activities, while Typical Office 2 assumed that the occupants were more active. For both cases, overall heat gains of 165.6 kWh and 208.8 kWh were predicted. Figure 6-34a presents the distribution of heat gains across the simulated period. With the lecture room unoccupied for most of the time and only a small number of occupants present for a few hours, hence a lower total occupancy heat gain (16.6 kWh) was predicted using the DLIP. This shows that if the HVAC was assumed to be operated using static occupancy profiles, it could lead to a significant overestimation of the indoor heat gains. This shows the importance of employing strategies which can recognise whether a room is occupied or unoccupied, along with the knowledge of the type of activities performed by occupants at a given time.

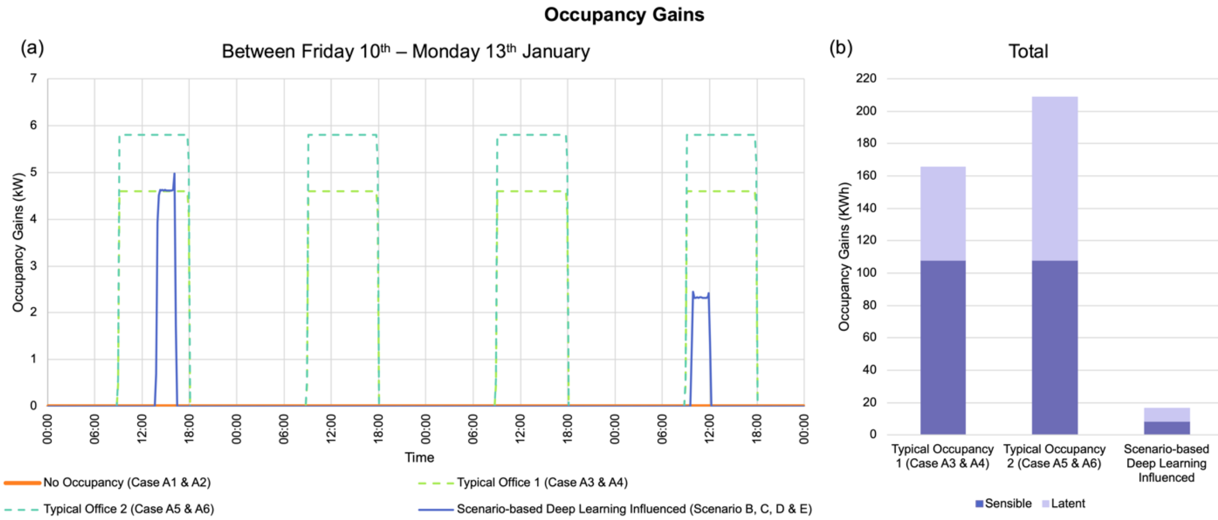


Figure 6-34. Comparison of the (a). occupancy heat gains across time and (b). the predicted total sensible and latent occupancy heat gains based on the scheduled profiles and scenario-based DLIP.

Figure 6-35a presents the total ventilation heat loss, and Figure 6-35b shows the distribution of the ventilation heat loss for all cases during the 4 days. The ventilation heat loss was influenced by the indoor-outdoor conditions and the number of opened windows. The constant open and closed results show the maximum and minimum heat loss. The results for Case B, C, D and E, were directly influenced by the window profiles given in Figure 6-32, which shows the advantage of knowing whether windows are either opened or closed, as it can significantly affect the conditions within an indoor environment.

Case B and D had higher ventilation heat losses (90 kWh and 77.9 kWh) as the windows were left open after the lecture on Friday (day 1) afternoon. Using the proposed approach, the open windows were detected, and the building manager was alerted and managed to close the windows, which led to the lowest ventilation heat loss (6.8 kWh) during the 4 days. A slightly higher ventilation heat loss (10.4 kWh) was predicted for Case E as the windows were suggested to be opened by the system during the lecture on Day 4 to improve indoor air quality. Although the windows were left open in Case D, unnecessary energy demand can be minimised by adjusting the setpoints or turning off the heating system after the system detected no response.

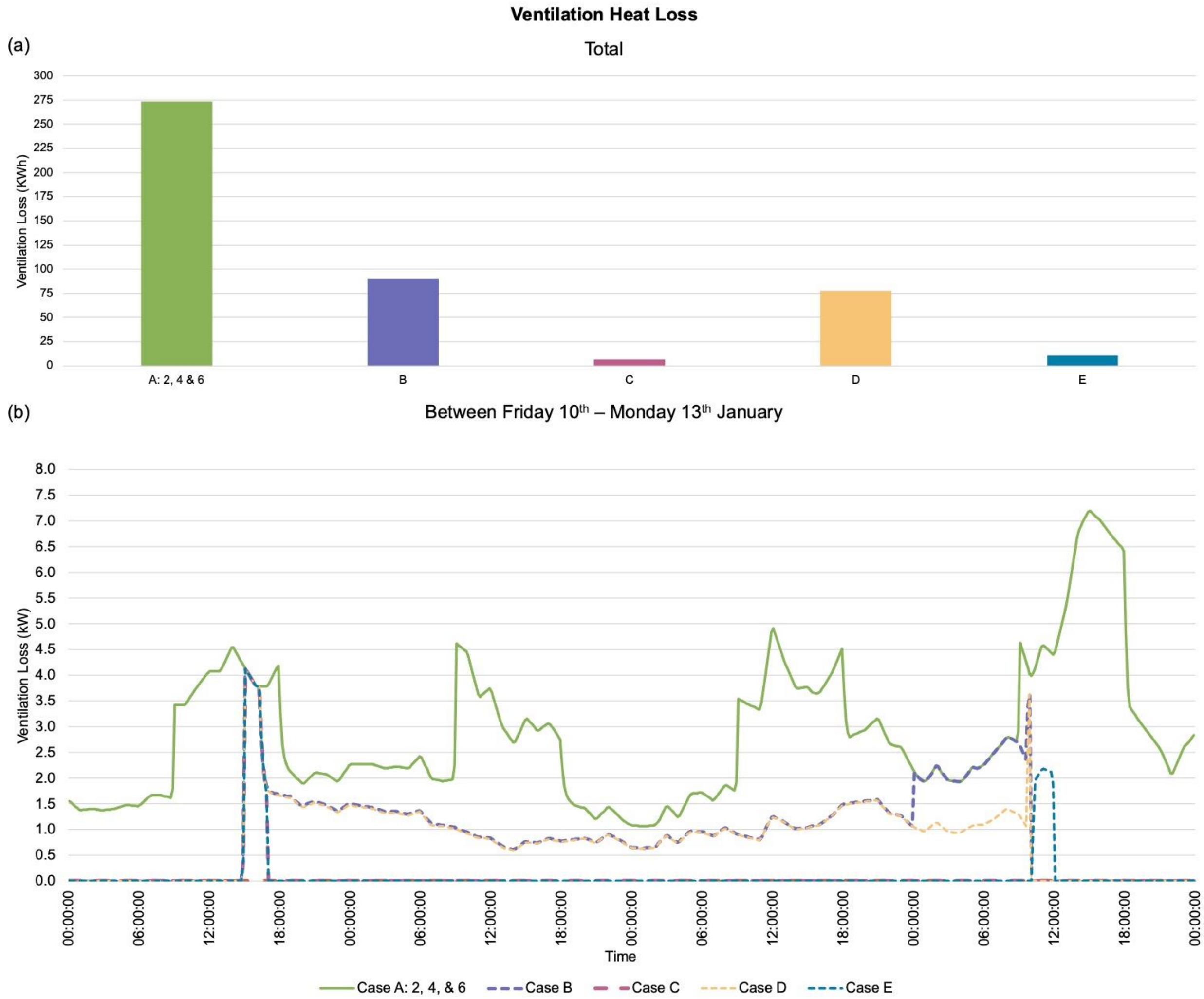


Figure 6-35. Total building ventilation heat loss prediction for all simulated cases (Case A, B, C, D and E), with (a). and (c). presenting total heat losses for all cases under the 4-day scenario. (b). and (d). indicating the variation in heat losses across time.

The results of the heating energy demand based on the different scenario cases are presented in Figure 6-36. This presents the predicted results for Cases A1 – A6, which employed fixed scheduled profiles for occupancy and windows. For all cases, the building HVAC system was operated based on an indoor setpoint temperature of 21°C during operational hours.

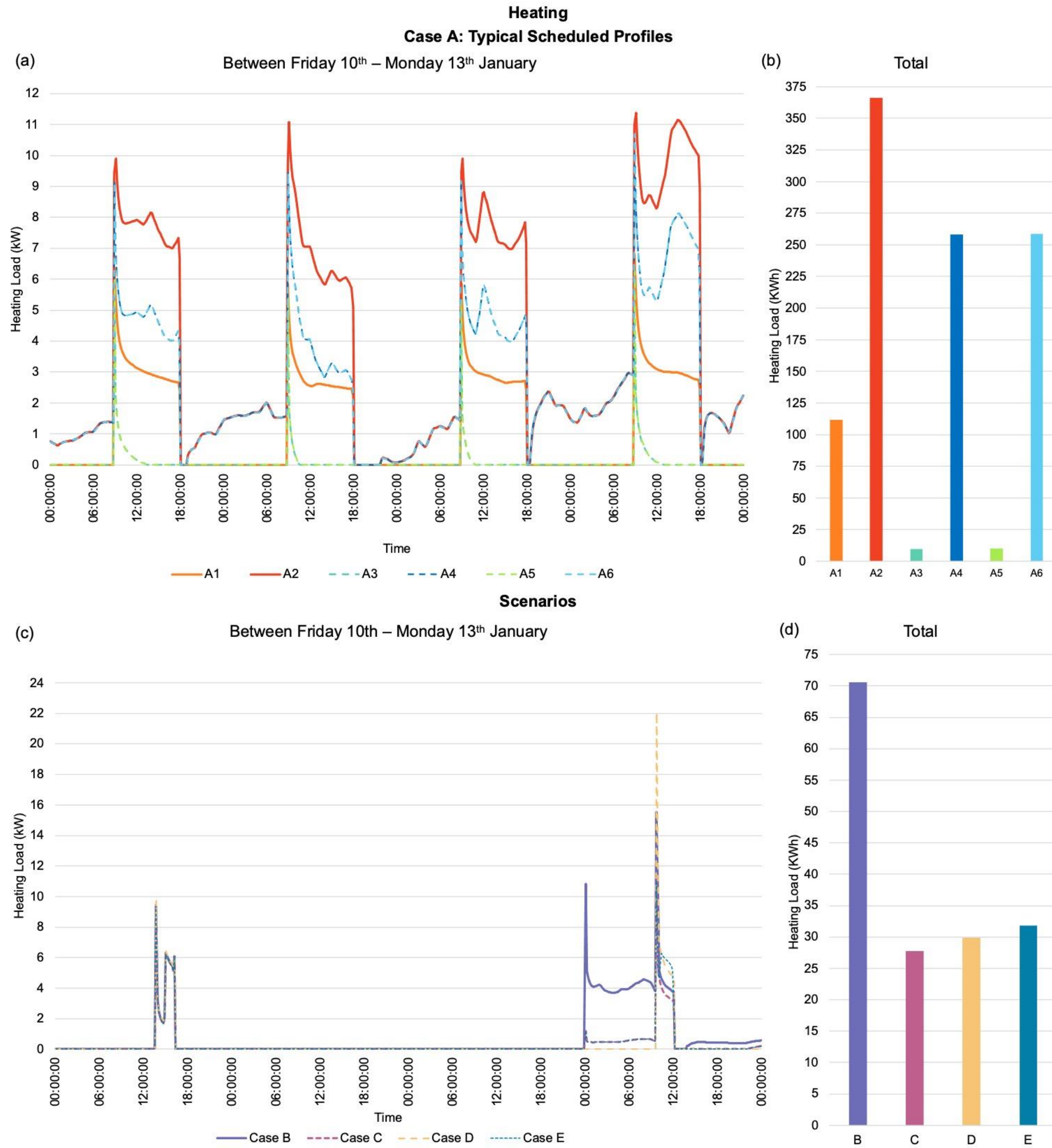


Figure 6-36. Total building heating load prediction for Case A and the different scenario-based cases (Case B, C, D and E), with (a). and (c). presenting the variation in loads across time. (b). and (d). presents the total heating load for all cases under the 4-day scenario.

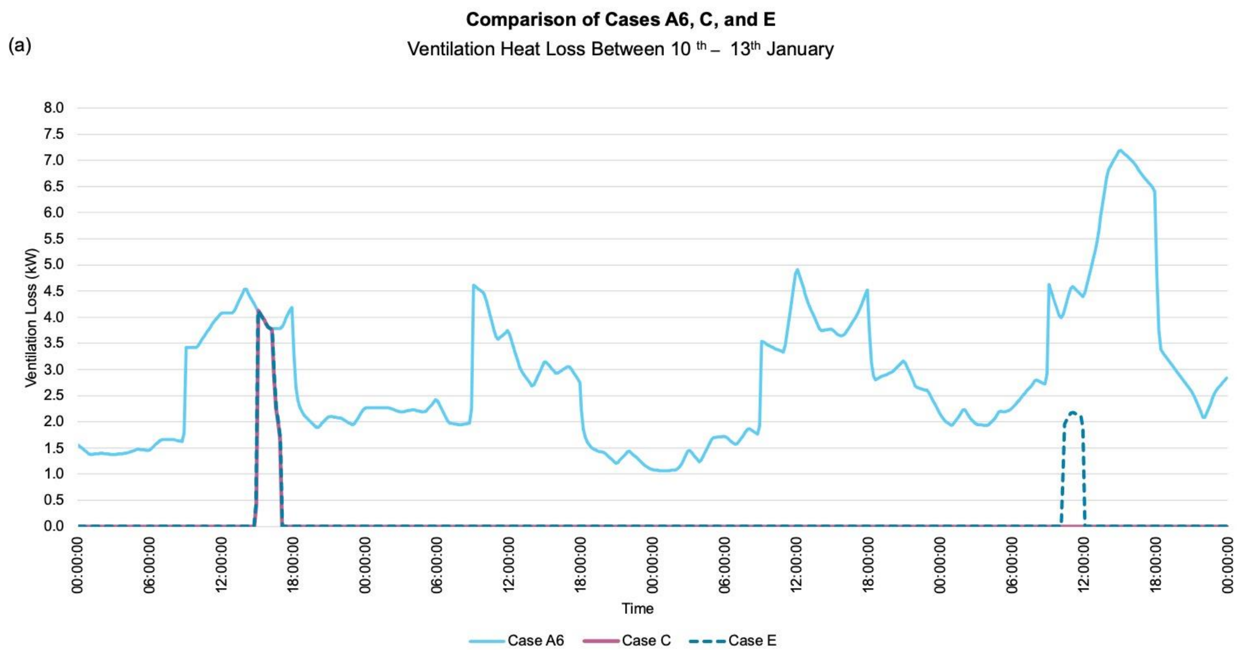
The constant open and constant closed results generally show the maximum and minimum possible heating demand. When the windows were constantly closed, the number of occupants present within the room influenced the internal occupancy heat gains, affecting the heating requirement. However, the results show that its impact is not as significant as the ventilation heat loss from the windows. Figure 6-36c and d present the results for Cases B, C, D, and E.

For Case B, the opened windows at 15:00 on day 1 were detected, but no adjustments to the building HVAC operations were made. As a result, on Monday (day 4), the room temperature reached below 15°C (the set temperature during unoccupied hours); hence constant heating occurred during Monday morning, and more heating occurred when the occupants were detected within the room on Monday (day 4) at 09:45. Case C employed the detection approach, which provided notifications or alerts to the building users or manager. For this case, heating was not required until Monday (day 4), when occupants were present in the room for the lecture. Hence a total heating load of 27.8 kWh was predicted.

In Case D, no changes were made even after the system provided notifications, and the windows were left open from Friday night to Monday morning. When the system detected that the windows were left open for some time, the heating was turned off until Monday morning, when occupants were detected in the space.

In Case E, a balance between energy reduction and good indoor air quality was aimed to be provided; it informs the occupants and makes adjustments to the HVAC system operations to minimise unnecessary heating demand and maintain the indoor air quality. The heating load achieved across were identical to Case C. However, on Monday, when there is half occupancy in the room, it was suggested that the occupant open two of the windows to ensure that good IAQ is maintained (Figure 6-37), which then led to the increased heating energy demand of up to 31.8 kWh.

The indoor air quality can be assessed in terms of the room CO2 concentration levels. Generally, CO2 levels in rooms below 1,000 ppm were assumed to be fairly adequate, and anything above this level would indicate the room is highly polluted [226]. This can affect occupancy productivity and human health [232, 233]. Figure 6-37b presents a comparison of the distribution of the CO2 concentration across the 4-day scenario for the three selected cases. Although a lower ventilation heat loss was achieved for Case C during the lecture period on Day 4, it also led to very high CO2 concentration levels peaking at 2,288 ppm when the occupants did not open the windows. In Case E, both the number of occupants and windows open were considered in the decision-making process of the control system. It assumed that 2 windows were opened during the lecture period as per the recommendation by the system. This resulted in the CO2 concentration reducing from 2,288 ppm to approximately 1,000 ppm. Although the air quality is still poor, it can be further reduced by suggesting to the users to have more windows to be opened.



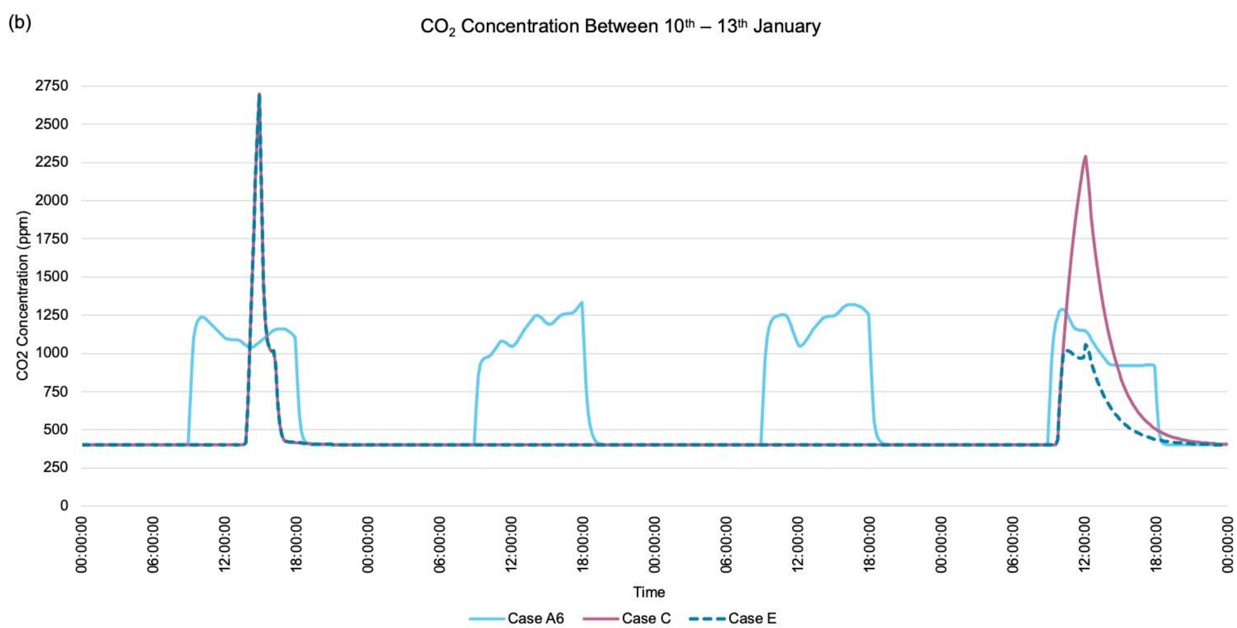


Figure 6-37. Variation in (a). ventilation heat losses and (b). CO2 concentration across time during the 4 days comparing Cases A6, C and E.

6.3. Summary with the Proposal of a Demand Data-Driven Control Approach

Effectively, the development and findings made in Chapter 6.2 about the combined occupancy activity and window detection and recognition approach suggest the potential of enabling real-time monitoring of the number of occupants, activity performed by the occupants and the number of opened/ closed windows. The provision of accurate prediction of the indoor internal heat gains and the levels of the room CO2 concentration to inform the system and occupants to open/ close a specific number of windows and/ or to enable the demand-controlled heating system to provide the requirements when required.

Following the scenario-based BES conducted the findings suggest the demand for accurate HVAC systems to adapt and respond to occupancy's dynamic changes. The basis of the framework was presented, yet further development should be explored. A framework and software infrastructure [234] should be developed for the proposed approach to be fully utilised within buildings. This system will connect the real-time vision-based detector and setpoint optimiser with the demand-driven controls for the HVAC system. This will ensure that the HVAC is operated according to the real-time building or space requirements. The potential of a co-simulation approach using BES [235, 236] should also be explored in future works. Using Case E as an example to demonstrate such a decision support system, this approach will combine the two vision-based approaches for detecting occupancy activity and windows to assist the alert and control system in determining the window and HVAC setpoint adjustments required to ensure adequate indoor air quality is achieved and minimise the unnecessary ventilation heat loss. Figure 6-38 shows a simple example of the decision-making process based on the application during the heating season. Depending on the selected building space, integrated with the vision-based occupancy and window detector, a set number of occupants will be defined to decide if the windows should be opened or closed and/or if adjustment to the HVAC setpoint is required. $N_{occupancy}$ represents the number of occupants detected using the vision-based approach, and N_{set} represents a set number of occupants. It should be noted that the control flow process shown here is simplified and does not take into account the number of windows detected, which can be included in the decision-making process to maximise natural ventilation while minimising heat loss. Additional steps can be added to the control flow process, informing the building users about the optimum number of windows to open or close; this will be developed in future works. Furthermore, more scenario-based analysis is §buildings.

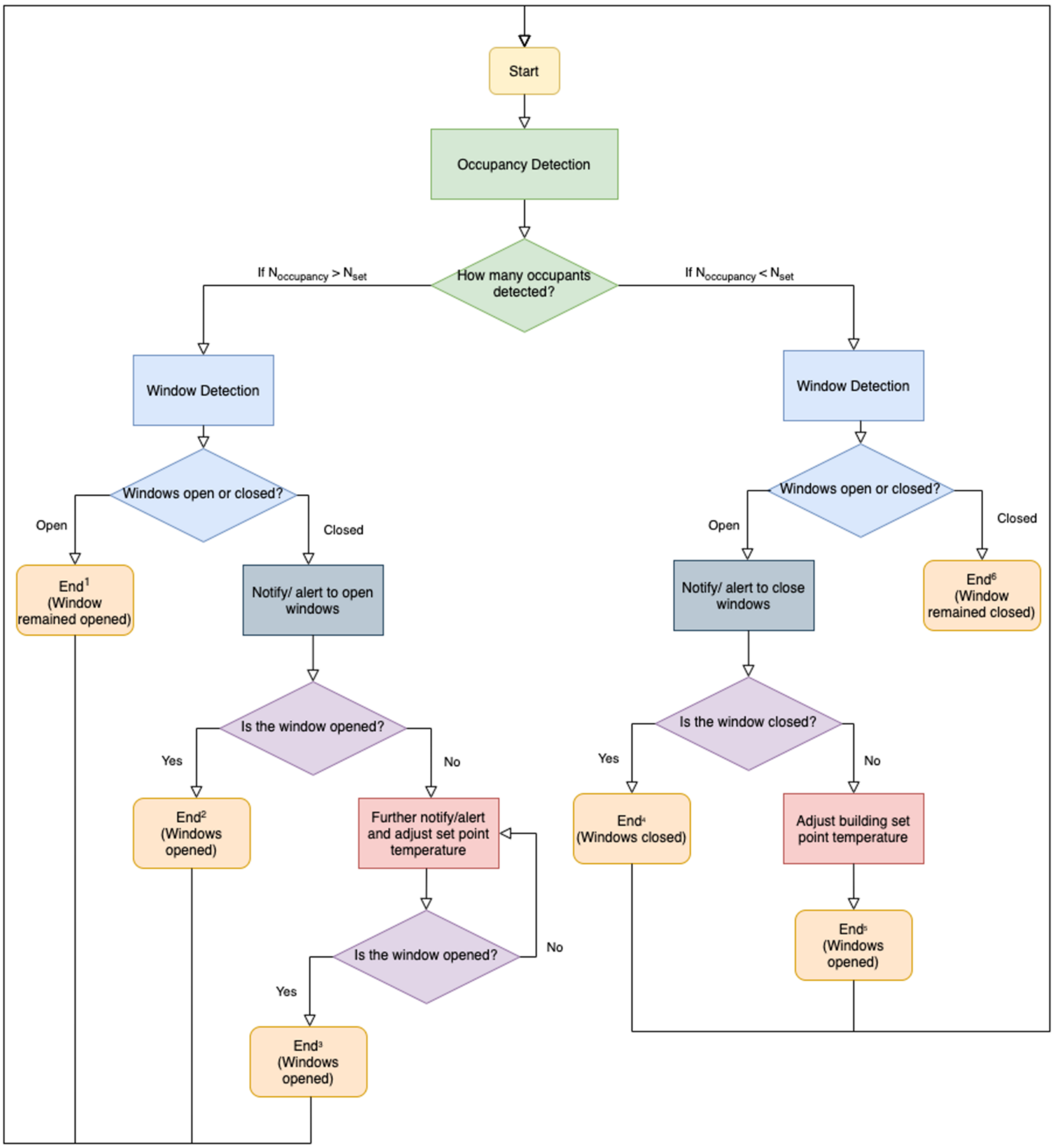


Figure 6-38. An example flow chart demonstrating the decision-making process of the proposed integrated control system.

In summary, Figure 6-39 with Video 5 presents the potential workflow process of adapting the deep learning vision-based detection and recognition approach towards the formation of a demand data-driven process to enable effective management of building energy. Cameras are placed within indoor spaces and real-time detections and recognitions were made. Simultaneously, data are generated in for of DLIPs, providing information towards HVAC adjustments to ensure adequate indoor conditions are provided while minimising building energy. To ensure that this framework can be fully implemented and integrated with building energy management systems, further work is necessary. This includes exploring other types of model configurations and evaluating the influence of the training data on its detection performance. A setpoint optimiser will be integrated into the framework to automatically adjust the HVAC operation according to the detection data and requirements of the space. Further testing is required in different types of spaces and scenarios, for example, in spaces with high occupancy and movement. Such limitations and proposed future works are discussed in Chapter 7.

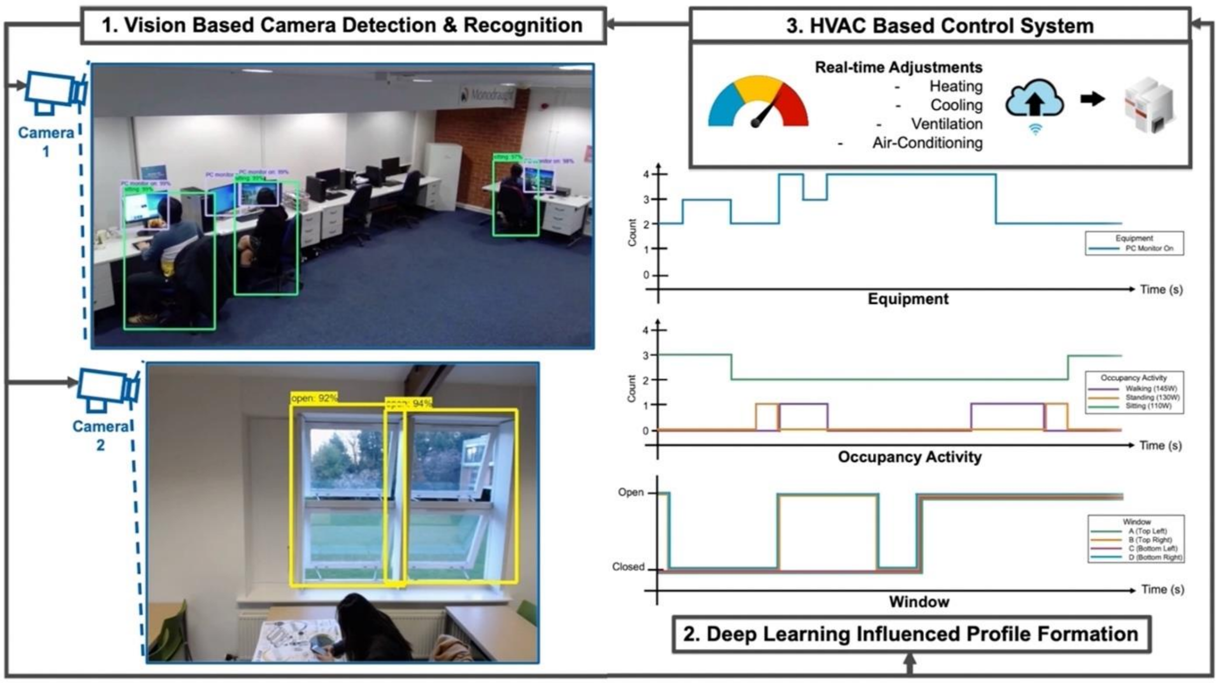


Figure 6-39. Potential workflow process of a demand data-driven vision-based approach for management of building energy, see Video 5.

Chapter 7

7. Practical Challenges of the Integration of the Vision-based Technique with a Building System

The integration of a vision-based technique with building control systems was first discussed in Chapter 3 (detailed in Figure 3-5) as a framework and software infrastructure that should be developed for the proposed approach to be fully utilised within buildings. Through BES simulations performed with various scenario-based cases that were evaluated in Chapters 4, 5, and 6, it suggests the system to connect real-time vision-based detector with a setpoint optimiser from the building HVAC control system to enable effective controls forming an integrated optimisation part of the framework approach.

Furthermore, to ensure such vision-based method and integrated control system-based approach becomes a viable solution that could be implemented in buildings, limitations identified during the development and experimental process must be addressed. To address this objective, this chapter presents the identification of the practical challenges impacting the proposed approach. This includes the conditions which led to poor performances and the aspects that could be improved through the proposal of different areas that require further development. In addition, it is important to acknowledge occupants' opinions and their current intentions regarding how it would be a viable solution to become implemented within indoor spaces. Hence, a survey was created to gather occupants' points of view on all aspects of the framework design. Based on the feedback received, it outlines the areas to be further explored.

7.1. Integration with Building Control System: The Proposed Approach

Once data is obtained using the vision-based approach and the formation of the real-time DLIP, the next step of the workflow process for the framework approach is the integration of the vision-based technique with prediction and optimisation strategies to allow adjustment within the building control systems. The aim is to explore the possibility of employing the vision-based detection approach with the generated DLIP to give a real-time internal heat gains profile (IHGP) to select an optimal HVAC temperature setpoint (HVAC TSP) designed to reduce building HVAC energy consumption and occupants' thermal dissatisfaction. Figure 3-5 outlines the proposed workflow process for heat gain prediction and optimisation of HVAC setpoint for BEMS control systems.

7.1.1. Development Process of a Heat Gain Prediction and Optimisation Strategy

Similar to the development of the vision-based detectors, case study buildings will be used to support the development and testing stages of forming the prediction and optimisation model for the application within BEMS control systems. Following a vision-based camera detection conducted within a selected case study building, such as the office space in the Sustainable Research Building, University of Nottingham, UK, count-based DLIPs would be generated, giving a real-time IHGP (internal heat gain prediction) based on the understanding of the number of activities performed by occupants in the building space. The generated IHGP would be used for two purposes. Firstly, it was used to verify the predictive room HVAC loads models and secondly, it would be used to predict room HVAC loads when optimising the TSP for the

HVAC system. Figure 7-1 shows how the data would be obtained from the simulations used to develop the predictive room HVAC loads and thermal comfort models. In these scenarios, fixed IHGP will be adopted. The data from scenarios 51-60 will be used to verify the developed predictive models. In scenarios 51-60, the generated IHGP from the vision-based cameras will be used in simulations. The simulated results will then be compared with the results from the predictive models that also used the real-time IHGP. Based on simulation data from scenarios 1-50, two thermal comfort models would be developed.

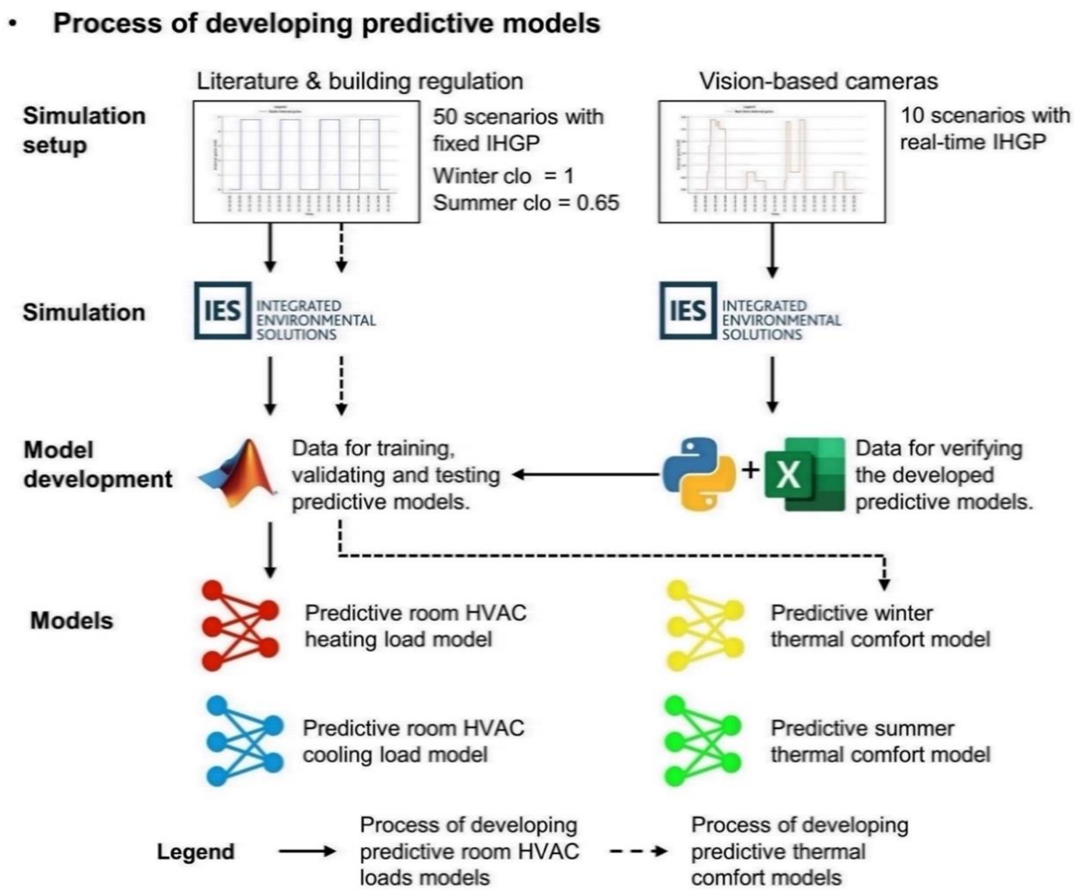


Figure 7-1. Process of developing the predictive models for the establishment of an optimisation approach for the building HVAC temperature setpoint value.

Next, the HVAC TSP would be optimised via the optimisation rules applied. The first optimisation rule relates to the situation when the cameras detect and recognise that no occupants were within the conditioned space, which therefore leads to switching off the HVAC system to save energy. When occupants were present and were identified by the cameras, corresponding heating or cooling would be provided. Under such a situation, optimisation rule 2 would be applied. This is designed to lower the building HVAC energy consumption without sacrificing occupants' thermal satisfaction. Ultimately, Figure 7-2 shows how the proposed integrated framework works. As shown, real-time online work was achieved by using vision-based cameras and HVAC TSP optimiser, while prerequisite work included the development of predictive models.

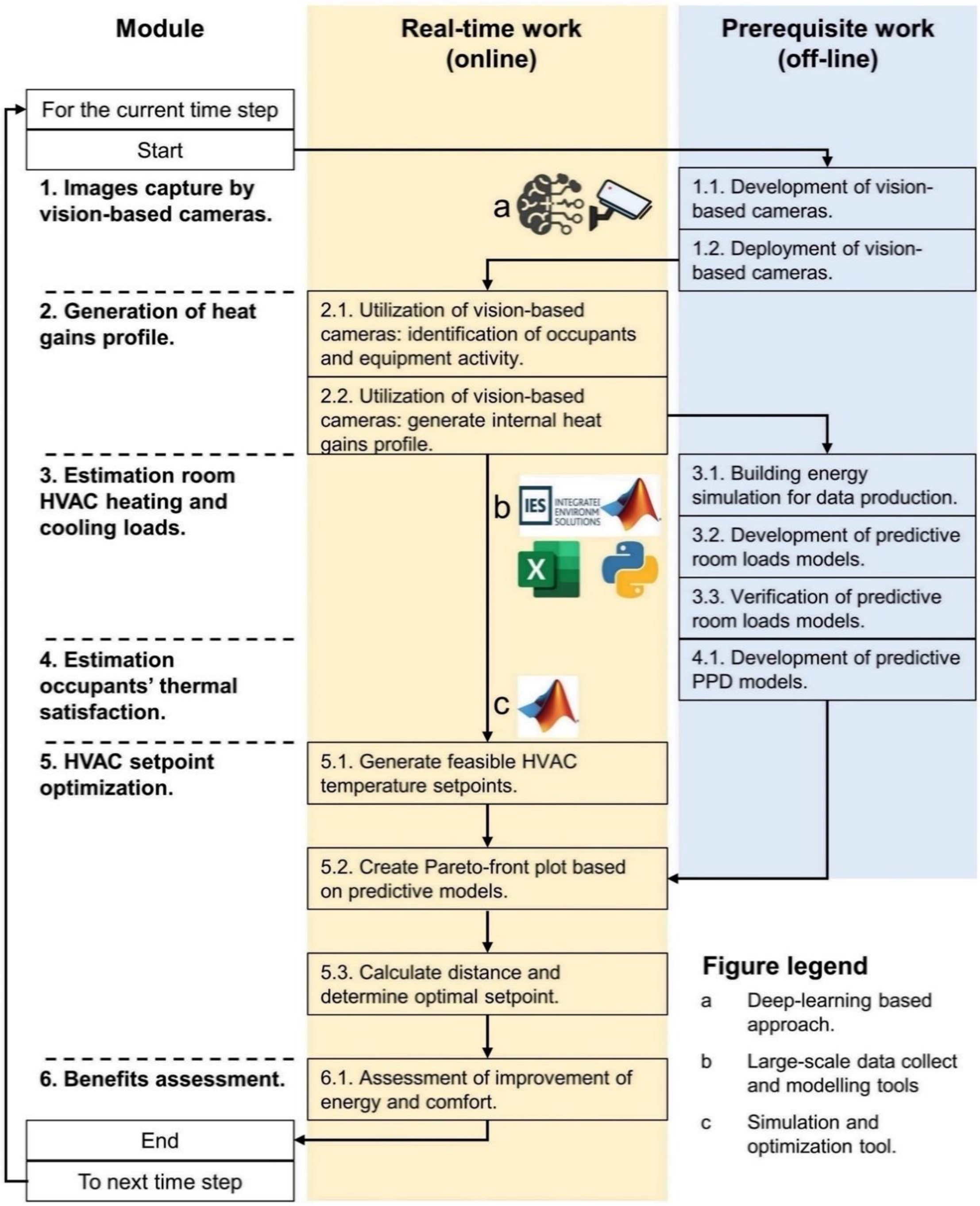


Figure 7-2. A schematic diagram of the proposed integrated framework for the building HVAC system setpoint optimisation.

Next, optimal heating and cooling HVAC TSPs would be generated as a result of linking HVAC temperature setpoints to internal heat gains, heating and cooling TSPs varied with time. The performance comparison between the application of the fixed HVAC TSPs and optimal HVAC TSPs would be expressed, identifying whether it satisfies occupants' thermal demand most of the time.

Furthermore, the performance of both the prediction and the optimisation models would be assessed. This includes the comparison of the goodness of fitting between the predicted models of heating and cooling under the different scenarios. In addition, the utilisation of such a profile would reduce HVAC systems' operation time and eliminate discomfort problems to indicate potential energy saving without compromising occupants' thermal satisfaction.

7.1.2. Further Development of the Integrated Approach Based on Window Detection

With occupants having the flexibility in opening or closing windows based on their sense of thermal satisfaction in addition to requirements of indoor air quality, the demand in reducing HVAC energy consumption without sacrificing the thermal satisfaction offered by the HVAC system can hardly be met. Window opening behaviour and its impact on building ventilation heat losses are based on the proposed approach identified in Chapter 7.1. and 7.2 suggests the framework could be extended to include the detection of window openings. Especially, during winter times in the UK, opening windows can cause a rapid decline in indoor air temperature and increase building ventilation heat loss and HVAC energy consumption. As explored, the vision-based detection approach can directly identify the opening of windows, better than predicting the opening of windows. At the same time, it could identify occupants within the space and predict occupancy activities and heat gains.

7.1.3. Proposal of a Hybrid Controller Based on Window Detection Responses for the Optimisation of Building Energy and Indoor Conditions

Applying the vision-based technique in identifying the real-time window conditions, a controller for governing the opening of windows to reduce building ventilation heat losses and lower occupants' thermal dissatisfaction should be developed. Effectively, all the proposed three controllers (vision-based occupancy, equipment and window detector (Chapter 6), the proposed combined heat gain controller (Chapter 7.1) along with a formed ventilation prediction model, to provide a hybrid controller that optimises energy use and thermal comfort.

Figure 7-3 illustrates how the hybrid controller works. Firstly, a vision-based detection camera was developed and installed within a selected indoor space to test the performance in terms of detecting the windows (open/close). The vision-based detection approach can generate real-time profiles of heat gains from occupants and profiles of window openness ratio, respectively. Secondly, three predictive models would be developed based on simulation data to forecast real-time building ventilation heat loss, predicted mean vote (PMV) and predicted percentage of dissatisfaction (PPD), respectively. The occupancy-based on-off controller switched heating systems on when occupants were within the investigated room. The energy-comfort-based temperature setpoint controller determined an optimal temperature setpoint by balancing the trade-off relationship between building ventilation heat loss and occupants' thermal satisfaction. When occupants are not within the room and windows are open, the window openness controller will close/suggest closing windows to lower unintended building ventilation heat loss. Thirdly, the hybrid controller was used to enhance occupants' thermal satisfaction whilst reducing building ventilation heat loss.

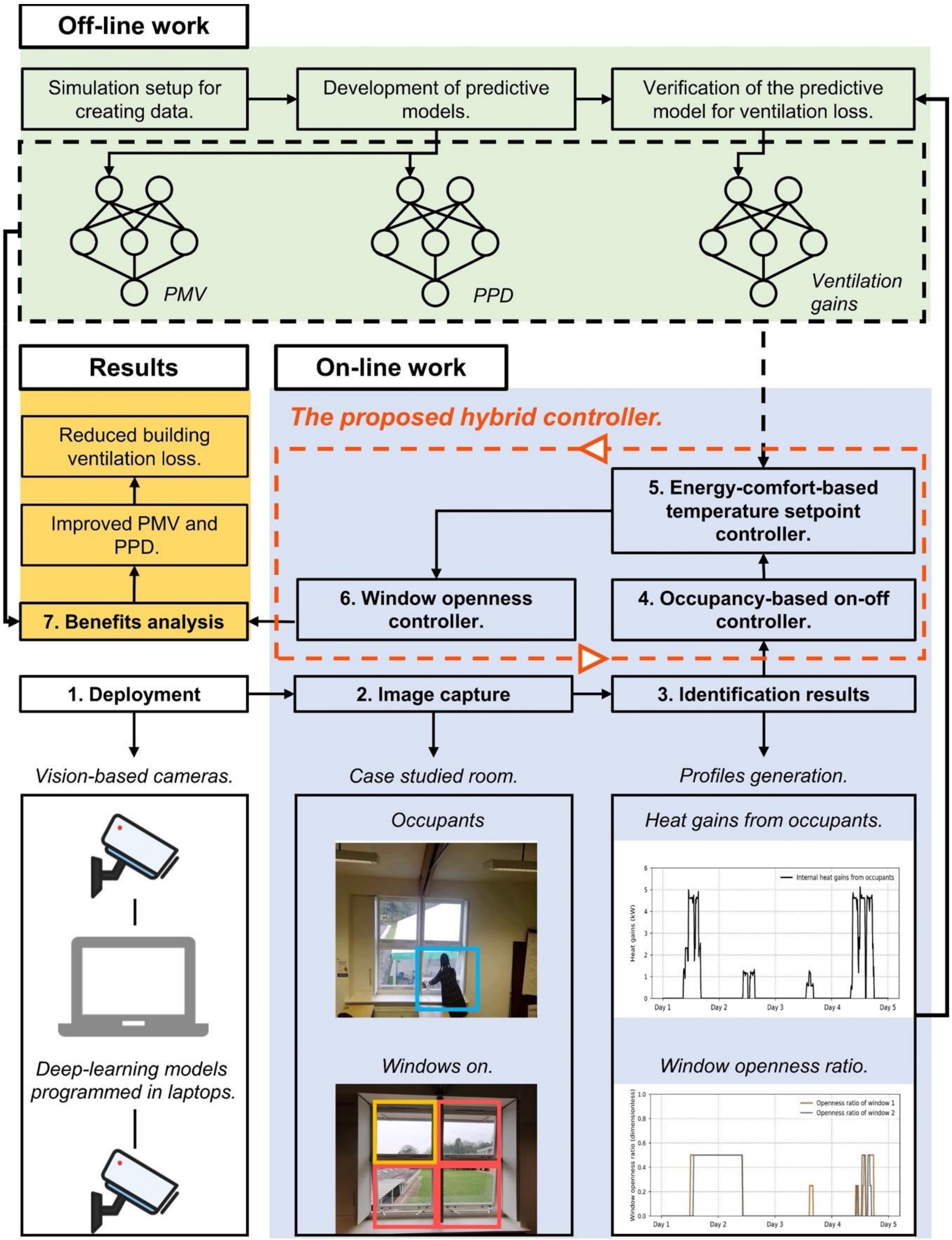


Figure 7-3. Schematic of the proposed hybrid controller connecting the vision-based approach of window and occupancy detection and recognition with system optimisation.

As shown, three data-driven predictive models were established. The first predictive model was used to forecast building ventilation heat loss. The second and third models were used to forecast the level of occupants' thermal satisfaction, quantified by using two indicators, which were PMV and PPD, respectively. These pre-defined scenarios consist of variations within the HVAC heating setpoint temperature, profiles of heat gains from occupants and profiles of window openness ratio. (For example, the profiles given in Figure 6-31- Figure 6-33). The data from the scenarios were used to train, validate and test the predictive models.

7.1.4. Development Process of a Hybrid Controller

The proposed hybrid controller composed of three sub-controllers with the optimisation rules defined in Table 7-1 along with the integration of these controllers with vision-based detection cameras is shown in Figure 7-4.

Table 7-1. The proposed three optimisation rules applied to the developed hybrid controller.

Controller	Controlling Variable	Control Aim	Control Method
1	HVAC on-off status	Minimise thermal discomfort issues and reduce energy wastage.	Turn on HVAC systems if occupants are present.
2	HVAC setpoint temperature	Reduce ventilation heat loss and increase thermal comfort.	Determine the optimal HVAC heating setpoint.
3	Window openness ratio	Reduce unnecessary ventilation heat loss.	Close windows.

Controller 1 is designed to be applied when vision-based cameras identify the detected spaces to be occupied. Under such a situation, heating would be provided to improve the level of occupants' thermal satisfaction. Controller 2 will be used when occupants were in the room and windows were detected as opened. Under such a situation, the HVAC setpoint temperature shall be optimised to reduce ventilation heat loss without sacrificing occupants' thermal comfort. Effectively, the HVAC setpoint temperature will be optimised by using a performance indicator. Controller 3 was adopted when occupants were not in the room while the windows remained open, for example, when the occupants left the windows open after leaving the space. Under such a situation, windows shall be closed to reduce ventilation heat loss.

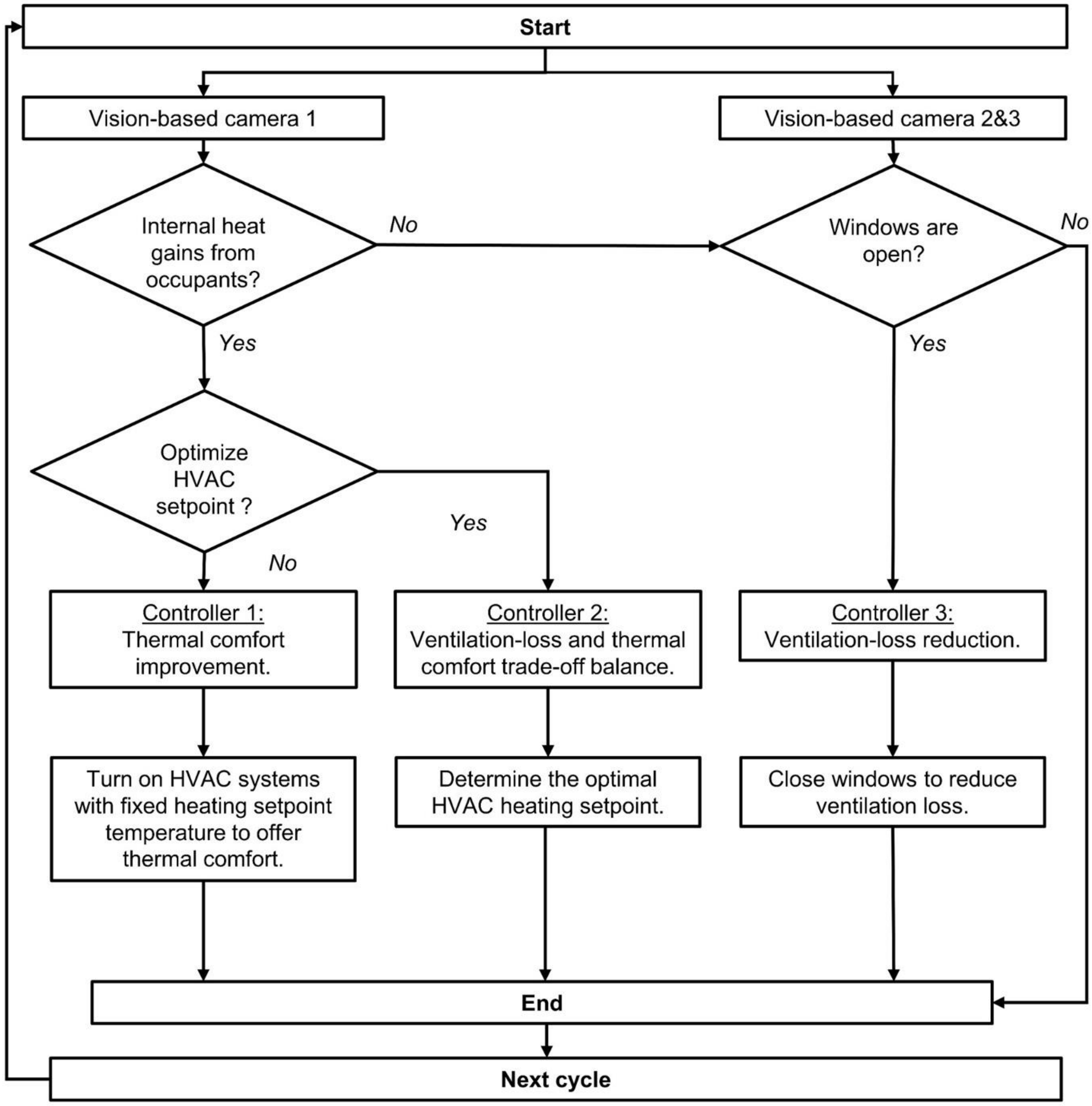


Figure 7-4. Coupling the proposed controllers with vision-based detection cameras to form an optimisation strategy using both window and occupancy detection and recognition.

7.2. Practical Challenges Impacting the Proposed Approach

The developed deep learning vision-based models presented in Chapters 4, 5 and 6 were analysed via BES which outlined the possibility of it being a viable solution to provide real-time understanding of occupancy behaviour within indoor spaces. However, the analysis suggests various limitations within the initial development and outlines several areas whereby the approach could be improved. This chapter presents the identification of the practical challenges impacting the proposed approach. This includes the conditions which led to poor performances and the aspects that could be improved through the proposal of different areas that require further development. Furthermore, with the proposed approach aimed to improve indoor thermal conditions for occupants along with the optimisation of building energy, it is important to acknowledge occupants' opinions and their current intentions regarding how it would be a viable solution to become implemented within indoor spaces. Hence, a survey was created to gather occupants' points of view on all aspects of the framework design. Based on the feedback received, it outlines the areas to be further explored.

As presented in Figure 3-4, along with the series of different model developments and experimental tests conducted in Chapters 4, 5 and 6, it suggests the method used to develop the deep learning models are not restricted to training, testing and evaluating the model once. Instead, continuous development is required. Specifically, possible solutions seeking to enhance the model detection performance, the effective application within various indoor spaces, and the ability to develop towards the integration building control solution were required. However, the performance of the developed vision-based detectors was undoubtedly impacted by both controllable and uncontrollable factors. Assessment of all types are factors were required to provide an effective detector to be used within indoor spaces, giving an acceptable framework design for effective performances for the desired purposes.

7.2.1. The Impact of Various Conditions Within Selected Case Study Buildings

Controllable factors which can be modified to enhance the performance includes the steps highlighted in Figure 3-4. Many of these have been applied within the process of development and testing of the different models given in the associated chapters of Chapters 4, 5, and 6. In terms of the model development, configuration and design, with variations that include the dataset size, selected images, labelling techniques employed, the training configuration and the selected model pipeline configuration.

Collectively, the types of images selected for each type of image dataset used for the training of the models would largely impact the overall detection and recognition ability. Hence, through the development of the given models in Chapters 3, and 4, various models were tested out with different response categories. Furthermore, the number of images used to train the models would affect the model performances. Comparisons were shown within Table 4-6 between Model 2a and 2b for occupancy activities. Model 2b was an enhanced version of model 2a, whereby four times as many images were used within the dataset. Through the experimental test conducted and the evaluation of its detection performances, this was modified and was eliminated to the three main response categories (sitting, standing and walking), compared to (none, sitting, standing and walking). A similar development was applied to the window models in Chapter 5. Throughout the chapter, four different models were developed and compared. In addition, changes in the labelling techniques and the response categories were made.

As identified in Figure 3-4, another aspect which could be applied to the development includes modifications to the CNN model training configuration and model pipeline used. This consists of the exploration of the impact of variations within the model pipeline configurations and the evaluation of its corresponding detection performances. Acquiring a higher training and framework accuracy requires a sufficient balance between the amount of training data, the complexity of training layers along with model selection and configuration. Similar to the training used in this initial research framework, where a transfer learning approach could be further studied. A fine-tuning method could be used to analyse the effect of the various types of TensorFlow models applied for training the detection model [207]. This includes the most common TensorFlow object detection models of MobileNet, inception V2 and ResNet50. Using the different training models, training performance could be further compared, along with the analysis of the accuracy of each response to the detection element.

Throughout Chapters 4 and 5 for the development of the different detection models, along with the combined integration forming combined detectors in Chapter 6, various case study buildings with different indoor environments were used to test the approach. Results suggested all models provided variations in performances when under the different building spaces due to the impact of various environmental conditions. Conducting these experimental tests observed that factors such as the position of cameras and the room environmental conditions, lighting conditions and obstruction would affect the detection accuracy. Since incorrect detection can lead to inaccurate estimation of parameters such as occupancy number and position, therefore, future works should consider the investigation towards the impact of environmental conditions towards the detection accuracy of the monitored spaces. The environmental conditions which could be explored include the impact of indoor-outdoor lighting conditions, any obstruction towards the desired detection element and variations in the detection within different environments. Real-time live detection would be performed under various environmental conditions, and the detection results would be used to form real-time DLIPs. Results would therefore aid the identification of how conditions such as low lighting levels and times with lots of glare through windows would have a significant effect as the detection of occupants as their actions would not have been identified accurately, presenting unreliable results. Figure 7-5 presents the current detection performance without the exploration of the impacts of such environmental conditions. The images suggest the importance of the optimisation of the deep learning model and adapting to the ability to perform extensive detection under more infrequent conditions to enhance the desired approach further.

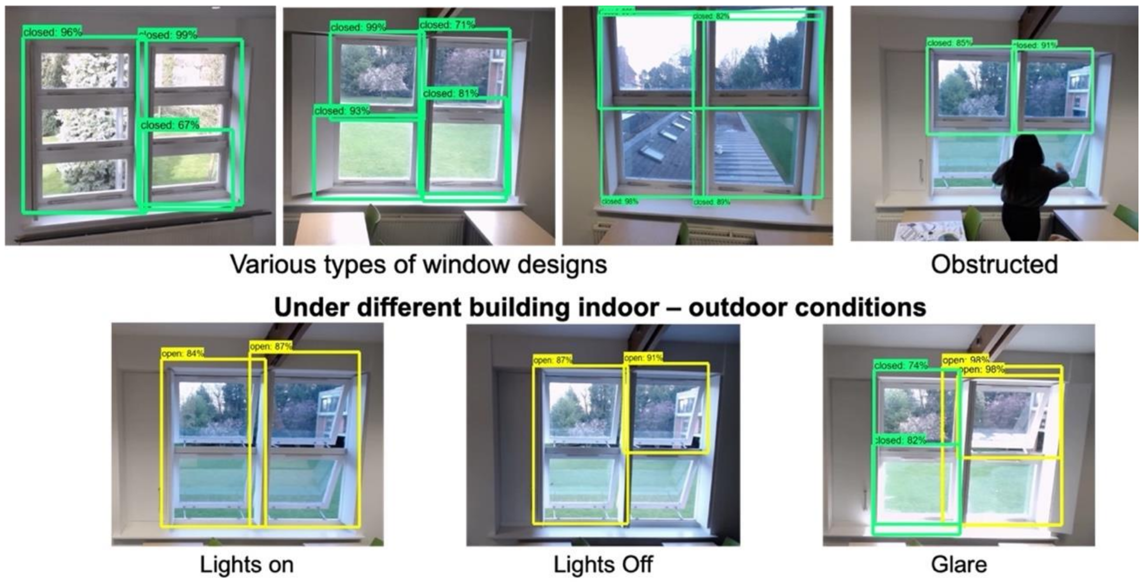


Figure 7-5. Example images suggest future studies focus on a series of different indoor-outdoor conditions towards the enhancement of the detection performance for window detection.

In addition to the identification of the impact of environmental conditions on the model's ability in detection and recognition, it was also identified that the experimental tests conducted so far were limited to indoor spaces of lecture rooms, university tutorial rooms and office spaces. Hence, to enable the vision-based strategy to work within various indoor spaces, it is suggested to further conduct field or pilot testing of the detection and recognition prototype along with the proposed system and framework application derived in Chapter 7 in different building spaces, specifically focusing on indoor spaces with more occupancy footfall such as warehouses and shopping centres.

To confirm the demand for testing within other types of indoor spaces, the occupancy detection model 1 developed in Chapter 4.3 was applied to perform detection and recognition on a pre-recorded video via a video feed test. A video capturing a scene whereby workers were working within a warehouse environment [237] was used. Figure 7-6 provides the associated results in terms of the key stages of the detection results and the corresponding DLIP for people detection and recognition were plotted in the graph shown in Figure 7-7, compared with the 'Actual Observation', highlighting the ground truth results of the actual number of occupants present within the space over the video recording period. Based the given results, shows the ability to detect some of the people, however many were not detected and recognised. Unrecognition of the people may be impacted by the distance between the camera position and the detected sources. Hence, developing a sufficient model that could provide effective detections within any indoor environment, would require modifications to the model design along with further testing.

Figure 7-6. Key stages of occupancy detection using Model 1 during a video feed test of a warehouse building.

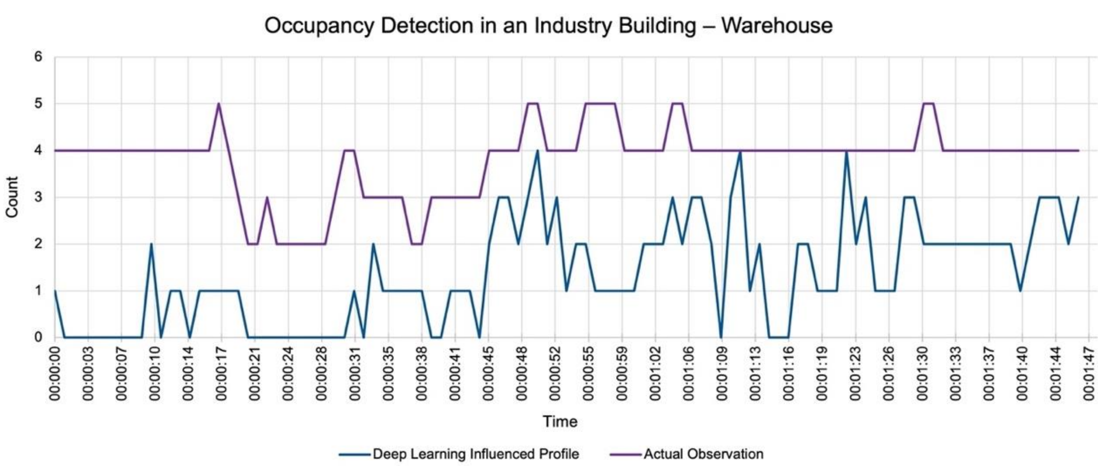


Figure 7-7. Generated DLIP Vs. the Actual Observation Profile achieved using Occupancy Model 1 with the detection in a warehouse building.

7.2.2. Survey and Evaluation of the Proposed Vision-Based Detection Approach

To acknowledge occupants' opinions and their points of view on all aspects of the proposed deep learning vision-based approach and on the current intentions of how it would be implemented within indoor spaces, a survey was created. Questions from the survey were asked during one of the experimental test days. The following section presents the information consisted within the survey, how it was conducted, along with the analysis of the feedback received.

A four-part survey with seven questions was created. Figure 7-8 and 7-9 presents the questions consisted within the survey. This survey was conducted directly after a presentation was given to the participants before a selected experimental test. The participants were informed about the highlights of involving AI techniques within building system controls to assist towards building energy reductions while aiming to enhance comfort conditions. Hence, part 1 of the survey consisted of the participant's consent. As this survey included their own opinions as feedback responses to the framework approach, survey responses with all participants' consent (all boxes ticked) were incorporated within the feedback analysis.

Part 2 of the survey consisted of questions related to the aspects of privacy issues. With the application of computer vision techniques considered an invasive method due to the constant capturing of occupants within a building space, the detections and recognitions made will be filtered immediately towards generating data in form of the DLIP. Hence, no raw footage will be seen by anyone or stored and so no invasion of privacy is incurred. Examples of such processes were explored in Chapters 4, 5, and 6. Effectively, the corresponding explanation was given to the participants which led to requiring them to respond to the questions in part 2.

Furthermore, to implement such a vision-based approach within indoor spaces of various types of buildings, the camera used for detection would be visually seen by occupants. Hence, Part 3 consists of questions related to the camera design. Four different existing camera designs were selected and presented in the survey to provide participants to express their preference towards their most preferred camera style. In addition, Part 4 of the survey presents questions related to the alert system. This is designed to achieve responses towards the design of the response and optimisation stage of the framework approach as expressed in Figure 3-5.

Survey Date: Tuesday 30th November 2021, Coates C19 09:00

Survey on The Application of a Deep Learning Vision-Based Detector Within the Indoor Built Environment

Part 1: Participant Consent

(Please tick the boxes if you give consent to the following:)

☐ I have observed the presentation by Paige Tien on 30th November.

☐ I understand the purpose of the research project and my involvement in it.

☐ I understand that while information gained during the study may be published, I will not be identified, and all personal results will remain confidential.

Part 2: Privacy Issues

Cameras will be installed in buildings to enable the application of such vision-based approach to achieve real-time monitoring of the building HVAC system operations based on the real-time dynamic changes of occupant behaviour. This includes occupancy activities, use of electrical equipment and/or adjustments towards window opening.

Q. How concerned are you when seeing a room with camera/s being used to monitor the indoor space?

☐ Highly likely ☐ Very likely ☐ Neutral ☐ Unlikely ☐ Very Unlikely

Q. Will you still be concerned after knowing that the camera does not take any form of recordings?

☐ Yes, still very concerned ☐ Somewhat concerned ☐ Not concerned

Reason: ____

Part 3. Camera Design

Q. Which form of camera design do you most prefer/ most comfortable with it being placed in a room? Please rank the following camera designs to your preference.

(1) CCTV camera style	(2) Camera design 1	(3) Camera design 2	(4) Implemented within other room sensor devices
			

- Most preferred: _________ Reason: ____________________________
- 2nd Preference: _________
- 3rd Preference: _________

Figure 7-8. Survey on the application of a deep learning vision-based detector within the indoor built environment - Page 1.

Survey Date: Tuesday 30th November 2021, Coates C19 09:00

- Least preferred: __________

Part 4: Alert System

Through the application of the detection approach, specific indoor conditions will trigger the system to alert occupants for them to change/adjust certain indoor or HVAC operational settings.

For example: On a hot summer day with a large number of occupants and equipment within the space, the system will send a notification to inform the need of opening more windows which can provide passive cooling and improve IAQ. Another example is when several windows were left open during a cold winter period, the system can alert the building manager to clost them to avoid ventilation heat loss.

Q. How do you feel about having an alert system within the indoor space?

☐ Very Satisfied ☐ Satisfied ☐ Neither satisfied nor dissatisfied ☐ Dissatisfied ☐ Very Dissatisfied

Q. Please rate your preference on the design of the alert system.

(1) Sound-based notification

- **Depending on the response/action required for occupants to make, a different sound will be projected to the room.**

  ☐ Yes ☐ No

  Reason for choice: ____________________

(2) Visual-based or over head display notifications

- **A small device will be placed in the room. It will present text or animation to alert occupants.**

  ☐ Yes ☐ No

  Reason for choice: ____________________

(3) Combination of both types (sound & visual-based notification)

☐ Yes ☐ No ☐ Maybe

Reason for choice: ____________________

If you have any other concerns or comments on the framework designs, please state it below. Many thanks.

____

____

Thank you for participating.

Very much appreciated.

Paige Tien (BEE PhD Researchers)

paige.tien@nottingham.ac.uk

Figure 7-9. Survey on the application of a deep learning vision-based detector within the indoor built environment - page 2.

Feedback obtained from the completed surveys by the participants was gathered to present the results given in Figure 7-10. A neutral response was the majority selected as the result for question one on the concern of having a camera being placed within indoor spaces to monitor indoor spaces. This indicates that the occupants are neither concerned about the overall application of a camera for such an approach. Yet, more percentage of responses selected were very unlikely (9.09%) and unlikely (25%) compared to highly likely (2.27%) and very likely (15.91%), indicating that based on the interviewed occupants that overall, it would not be a concern. Based on the response achieved for question 2 with 47.73% of the participants will not feel concerned when occupants are fully informed about the framework approach and how DLIPs is formed to eliminate the concerns related to data being stored in the forms of images/ recordings.

For the camera design question (question 3), the most preferred type would be the sensor style. This is the style that the detection camera is implemented within other room sensor devices. The camera is hardly seen as is hidden within such a sensor device. Most participants' reasons for the choice are due to the design being more discrete, small design, and less noticeable, and so that they don't feel like they are being watched. They also suggest that with the design not being CCTV alike, it could reassure that this is a device that is different to CCTVs and so that it could ensure them that they are not being watched. Yet, the second most popular choice is the CCTV style. This indicates that 22.73% of the participants would select this design instead. This suggests that they would rather select a more commonly seen, traditional style device, giving them a safer feeling as its design is similar to a normal CCTV camera most reasons were due to them wanting to see the camera, positioned in the room.

Questions 4, 5, 6 and 7 were from part 4 of the survey focused on the alert system. As shown in Figure 7-9, a short description with an example was given to express the methods within the control system part of the framework approach based on the content given in Figure 3-5. Given the response to question 4, most of the participants suggest that they neither feel satisfied nor dissatisfied about having an alert system within the indoor space assigned to this framework, along with most of them would feel satisfied compared to dissatisfied. This gives initial reassurance towards the designing and development of the optimisation and response system based on an alert approach. Next, questions 5, 6 and 7 were designed to ask participants towards the design of the alert system that they would like to have from the vision-based device. Comparing the results from questions 5 and 6, many responses indicated that they would not mind a sound-based notification, while some chose the visual-based or overhead display notification from the alert system. The feedback received on both questions with their reasons for choice covered most of the benefits and limitations arising from both types of approaches. This includes the sound-based approach having the benefit of occupants from across the building space being able to hear the alert regardless of what they are doing.

However, some response includes fearing of a sudden loud noise, which could be controlled, ensuring the sound would not be too loud. Furthermore, the occurrence rate of such notification can be disruptive and may cause an irritative nuisance if constant noise is given. For the vision-based display notification, it opted as many responses suggest that is their preferred option due to the design would be ideal when you're at home or in office spaces whereby TV monitors or computer devices are used so that the notification can be visually seen on the screens. However, the greatest limitation of this type of response would be the notification could be easily misread and/or missed. Hence, through the response to question 7, most of the participants preferred a combined alert system, whereby it can give more information, and become more useful and noticeable as there would be less chance of the alert being missed. Furthermore, if combined have a choice between two types of alert notification applied, depending on room type/ situation. Effectively, it can directly inform occupants in certain areas of the building spaces. A response suggestion also includes the combination of the alert notification with a mobile device so that occupants would have both types of notification via their mobile phones. Overall, the response acquired from the survey conducted suggests the design and the framework approach requires to be less intrusive giving the most effective approach and comfortable design that satisfies most of the occupants. Hence, results and feedback from this survey will be considered within the future works of the development of the desired framework approach.

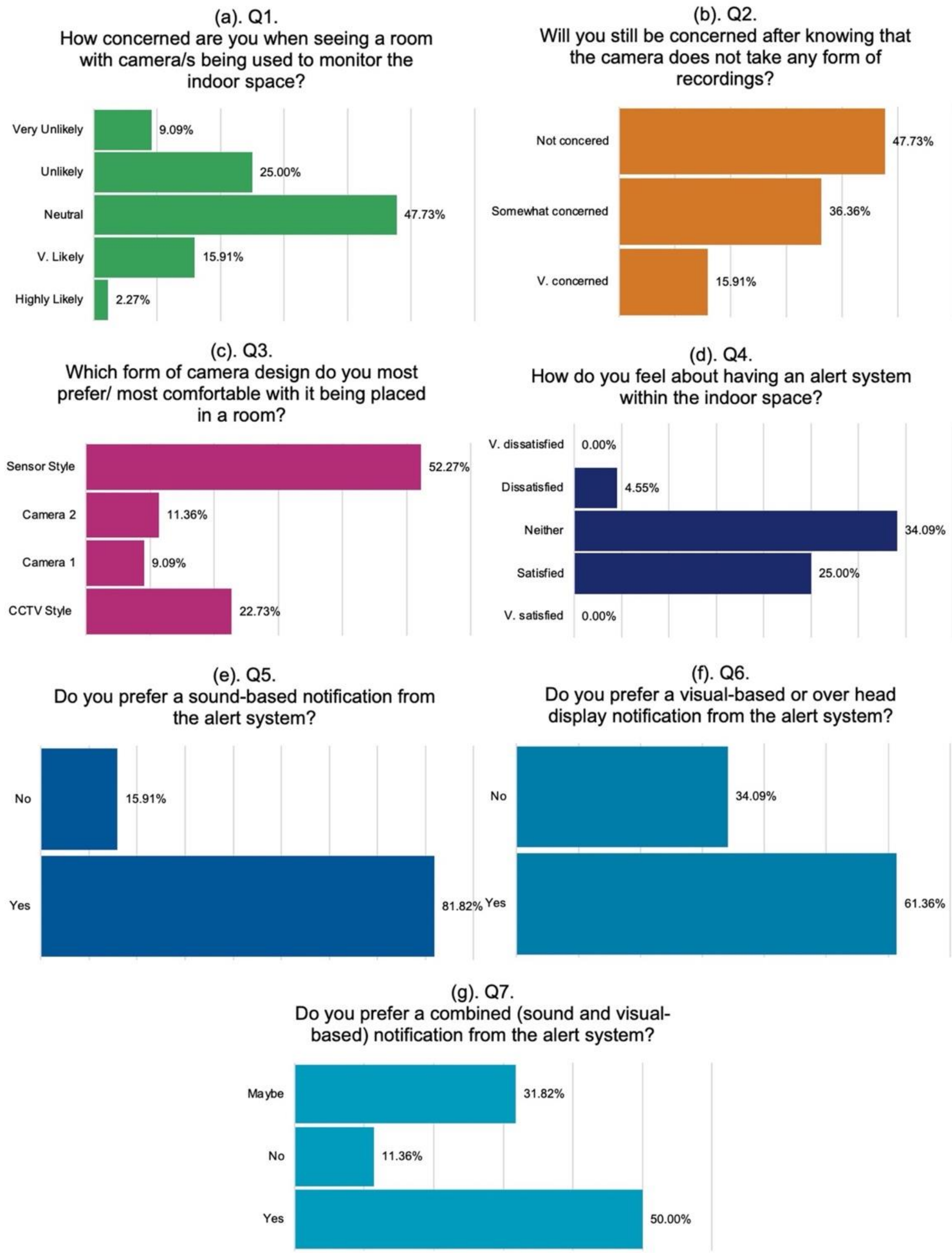


Figure 7-10. Survey responses.

7.3. Summary

Effectively, this chapter presented the proposal of a building control system approach to integrate the deep learning vision-based technique to enable the optimisation of building HVAC systems. It was first explored to adapt prediction and optimisation strategies to allow adjustment within the building control systems based on the real-time internal heat gains profile (IHGP). Later, with the suggestion of the importance of ventilation heat losses through manual window openings, a predictive mode-based hybrid controller was formed. Its design compromises of an occupancy-based on-off controller, energy-comfort-based temperature setpoint controller and window openness controller coupled together designed to lower building ventilation heat loss and occupants' thermal dissatisfaction, while giving fast response and low computation and time cost. Furthermore, it is now recommended to experimentally test the benefits of using the proposed controllers in real buildings in future works.

The second part of this chapter addressed the objectives of identifying various practical challenges and factors impacting the proposed approach. The type and size of the image dataset used to train the model along with the model configuration significantly affected the detection ability. Hence, multiple variations to the model were formed giving, different detectors specifically for different purposes. Conducting detection tests within experimental tests within selected case study buildings, suggests an achievement of a poorer detection performance compared to the detections made on still images from the testing dataset. This suggests many environmental conditions including lighting and glare, along with the differentiation between the images of the selected response given in the training dataset with the actual shape/form of the selected object required to be recognised. Hence, this indicates the requirement for modifications to the model design along with further testing in a wider range of case study buildings.

A survey was conducted to understand occupants' opinions and suggestions on the proposed framework design with aspects related to the design, ethical and privacy issues. Overall, out of the 40 surveyed people, they suggest that the use of a camera for such an approach would not be a privacy concern. However, it should highly insist that occupants would be fully informed about the framework approach and how DLIPs is formed to eliminate the concerns related to data being stored in the forms of images/ recordings. In all, the feedback received would be considered within the future works of the development of the desired framework approach.

Chapter 8

8. Conclusions and Future Works

8.1. Conclusions

Based on the understanding of occupancy behaviour within indoor spaces, it suggests the demand for an effective approach to regulate building energy performances and minimise unnecessary energy loads while aiming to enhance indoor thermal comfort conditions for occupants. To meet the first objective on the understanding of the current impact and usage of AI within the built environment, a comprehensive literature review was conducted, and it led to the research work to provide a development of a demand-driven deep learning vision-based framework for the optimisation and management of HVAC systems and operations. The thesis conclusions are presented thereafter, numerically linked to the defined objectives as presented in Chapters 1.3.

Various AI-based machine learning and deep learning methodologies and techniques are applied to design framework solutions to enhance building operations and performances through different aspects of energy and occupancy-based related strategies. Each research-based framework follows a generic workflow procedure for both classification and predictions of building and energy-related parameters but with an independent approach towards its specific intention. Each research proposal focuses on one aspect of energy and building-related concerns. This is to either enhance building energy forecasting for HVAC systems, advance building performances, or improve overall building thermal comfort and occupancy satisfaction. Neural networks were indicated as a more flexible solution compared to machine learning techniques that employ traditional algorithms from categories of supervised learning and unsupervised learning.

To provide a better understanding of how buildings are operated and how occupancy behaviour in buildings influences energy usage, current applications include the use of environmental and passive infrared sensors. More recently, AI-based solutions have become a popular technique as deep learning methods were indicated to have higher flexibility as they could be used for energy forecasting and to also apply CNN for occupancy detection, giving accurate recognition and classifications. Platforms designed to configure and train deep learning convolutional neural networks (CNN) models were explored and the application of such techniques were selected to form vision-based detectors through the integration of the framework onto a camera, providing a detection and recognition-based method for building energy management and prediction. Overall, deep learning was employed as the main technique used within the proposed framework approach aiming to enhance intelligent buildings to provide better environments that could fulfil future needs within the built environment.

Occupants' behaviour can significantly impact the operation of HVAC and building energy demand. HVAC, which uses conventional control strategies or fixed setpoint schedules could not adjust to the conditioned spaces' actual requirements. For the majority of the time, indoor spaces that are not fully occupied or completely unoccupied lead to the appearance of being over-conditioned and may lead to a substantial waste of energy. To understand the impact of occupancy behaviour towards building energy performances, the parameter of internal heat gains must be monitored. In addition, through the understanding of ventilation heat losses can contribute towards over 40% of the building energy at times windows were left unintendedly opened within a naturally ventilated room, both factors were considered. Hence, the adaptation of deep learning techniques within the proposed framework approach enabled the 'capturing' of the performed activity which then generates output data in form of the Deep Learning Influenced Profiles (DLIPs). The format of the formed DLIPs depended on the trained models based on the type and the number of selected detection responses. A series of detectors were formed and compared. This includes a 'people' detector to provide an accurate understanding of the impact of the number of occupants in a room. Occupancy activity detectors formed DLIPs that were directly related to the generic heat emissions suggested for each of the activities (sitting, standing, walking, and napping). Furthermore, based on a window detection approach, predictions were based on building ventilation heat losses.

Based on Objective 2 on the development of the data-driven deep learning framework that allows the establishment of vision-based detectors, images were collected to form a series of different image training and testing datasets. For each image, the pre-processing stage was performed by manual labelling of the desired region of interest (ROI). To achieve high accuracy and eliminate the time needed to train the models from scratch, a transfer learning approach using pre-trained CNN given in by the TensorFlow detection model zoo was applied. For all models, the COCO-trained model of Faster R-CNN with Inception V2 was selected and fine-tuned. The training was performed using the same computer with the graphics processing unit (GPU) NVIDIA GeForce GTX 1080 applied. In all, a total of seven models were trained, tested, and evaluated.

A workflow process was established and was followed by each of these trained models to assess the detection ability. It consisted of an initial evaluation of the performance of the model with its detection on still images located from the testing dataset to give results in form of a confusion matrix along with results in terms of the common evaluation metrics (accuracy, precision, recall and the F_1 score). Next, experimental tests were conducted within selected case study buildings to test the models under real-life situations. During all tests, continuous detections were made, and results were recorded in form of DLIPs. The generated results were analysed based on the IoU (Intersection over Union) accuracy, the percentage of the time achieving correct, incorrect, and no/missed detections throughout specific timed segments. Similarly, a confusion matrix was also formed based on the detection results and evaluations given on the common evaluation metrics. Succeeding in an in-depth analysis for each experimental test conducted using these models gave suggestions for refinement to the model configuration, dataset size and features along with suggestions for further improvements. Hence, one 'people' detector, two 'occupancy activity' detectors and four 'window' detectors were developed and analysed. After evaluation of each of these individual detection models, the models that provided the most assuring occupancy activity detector and window detector were applied and further explored into the formation of combined detectors. Effectively, such work conducted towards the model development and testing applied addresses Objective 3 and 4.

Training of a detector with one selected response of 'people' gave a count-based occupancy detector. The formed DLIP indicated the number of people present within the detected space. Based on the performance during Experimental Test 1, an average detection IoU of 98.85% was achieved for all occupants. Furthermore, given by 8 occupants within the test, correct detection was achieved over 76.41% of the time. The results in terms of the common evaluation metrics suggest an overall accuracy of 95.23% and an F1 score of 0.9756. This indicates the development of an effective occupancy detector which can be used to predict CO2 concentration levels based on the occupancy count. However, limitations occur. Such occupancy detectors cannot provide sufficient information for the optimisation of building systems. Hence, occupancy activity models were developed. Given that two models were developed, Model 2a and b had variations in the number of images within the training and testing datasets. Model 2b consisted of the more common activities of only 'sitting', 'standing' and 'walking'. An experimental test within one case study office space (Experimental Tests 2 and 3) was applied to give a direct comparison of the performance of both models. Since the experimental test conducted for Model 2b was conducted on a different day proceeded from the analysis made on Model 2a, hence there was a variation in the positioning of the detection camera. Overall, Model 2a achieved an average detection accuracy of 92.20% for all activities. Walking at 95.83%, standing at 87.02%, sitting at 97.22% and none (when no occupant is present) achieving an accuracy of 88.13%. The need to detect times when no occupant is present may have influenced the over-detection accuracy. Hence, this response category was removed in the formation of Model 2b. For this, if no occupants were present in the space, then no detection is required. Additionally, with the model selected to test within an office space, the response category of 'napping' was also removed as compared to the other selected activities, this is not a common activity that would be performed in the given building space. High percentages were presented for each of the predicted activities based on the application of Model 2b.

Both models showed the capabilities of recognising the differences between the corresponding human poses for each specific activity. Although there is some similarity between the action of standing and walking than there is for sitting. Therefore, this suggests the reason to achieve higher accuracy for sitting as compared to standing and walking. An average IoU accuracy of 98.58% was achieved. The results suggest that the distance between the camera and the object had a negligible effect on the detection accuracy. However, due to the size of the office room, the influence of further distances cannot be evaluated and should be assessed in future works.

The distribution of the results attained for the different responses based on the different factors, including the angle, distance and position relating to the detection camera, shows the approach's ability to achieve good detection performances. Overall, the results showed good performance and demonstrated the model's capabilities to recognise the differences between the human poses for each specific activity. For both DLIPs in the same format were formed for both models. However, based on the analysis of the generated DLIPs in comparison to the 'actual observation' profile which represented the true activities performed by occupants during the tests, it suggests fluctuations occurred, indicating prediction error.

With the modifications to Model 2b based on the evaluations made from the test conducted using Model 1, Model 2b outperformed Model 2a. To verify this, Model 2b was further tested using a different case study building under an experimental test with a greater number of people present in the space. Results suggest an overall IoU accuracy of 93.60%. Similar to the results for Model 2a in Experimental Test 2 and Model 2b in Test 3, a lower IoU accuracy was achieved for the activity of standing and/or walking compared to the activity of sitting suggesting the difficulty in recognising the occupancy body form and shape, as it may be confused with the activities of both standing and walking. Model 2b provided an accuracy of 89.37% with an F1 score of 0.8298. Since multiple responses were selected for this model, further development is required to ensure a consistent level of detection accuracy could be achieved across all the different occupancy activities and become an effective tool to assist in the evaluation of the heat gains from occupants or predicting the activity rate for thermal comfort calculations in real-time.

The same deep learning method and techniques were applied for the forming of the window detectors. Four window detection models were developed. All were tested through the application via a video feed test of a selected case study building. Models 1 and 2 consisted of selecting two response categories of both 'open' and 'closed' windows, with Model 1 as the initial dataset and Model 2 as an enhanced version with a greater number of images consisted within the image datasets. Models 3 and 4 focused on one detection response of 'Open' with Model 3 compromising on the same labelling techniques as Models 1 and 2. While Model 4 employed a different labelling process, with the bounding boxes explicitly assigned to the opening gaps of the windows. All models were trained using the same CNN-based model configuration and evaluated on the application of an experimental test performed within a selected case study building space.

The detection performance evaluation suggests that Model 1 provided the lowest detection ability. For most instances, it could not detect each of the windows separately to distinguish the difference between opened and closed windows. Model 2 was able to detect the windows individually at times. Having only one selected-response outcome for Model 3 enabled better identification of the separate windows. This model had the limitation of identifying other objects as opened windows. Using a different labelling technique for Model 4 aided the improvement of the detection and recognition ability, giving the best performance for Model 4. Based on the application of Model 1, a consistently low percentage of time of up to 28.73% achieved correct detection. Most of the time, incorrect and missed detections were obtained. Model 2 achieved a higher percentage in terms of the time it achieved correct detections (32.78%), and a lower number of incorrect predictions. However, it led to a high number of no/missed detections up to 63.91% of the time. This resulted in the development and testing of a detector with a single response for opened windows in Models 3 and 4. Model 3 achieved a more consistent detection IoU between all the windows with an average IoU of 96.82%. However, this model also identified other objects within the building space as the selected response. Hence, such errors in detection were avoided through the labelling method used in Model 4, giving an overall IoU of 95.12%. In comparison, a significantly higher amount of time achieving correct detections was obtained for Model 4 with 85.93% of the time. This suggests Model 4 provides the most accurate window detection through the labelling adopted to enable a focus on the openings or gaps of the windows.

DLIP for windows were formed during the experimental tests for all window detections. The profiles were based on a modulating number of detected opened windows. The results reflected upon the detection performance for each of the models as the generated DLIP still alternates between the values of the window profile schedule, indicating prediction error. Therefore, with the comparison to the actual observation of the true window conditions, Model 4 provided the most accurate result.

Objective 5 was presented to ensure effective detectors that could provide accurate real-time understanding of how buildings are utilised and or impacted by occupancy behaviour. Hence, build energy simulation (BES) was used to predict the potential impact on ventilation heat loss and building energy demands. Based on the selected case study buildings and experimental tests used to conduct the detection performance analysis, these were further modelled to provide profiles for energy analysis. DLIPs for occupancy and windows were inputted into the BES. Comparison of the use of static or scheduled occupancy profiles currently used in most building HVAC systems operations and in building energy modelling and simulations presents an over or underestimation of the occupancy heat gains and could lead to substantial inaccurate heating and cooling energy predictions. Solely based on these BES results and the set conditions, a difference of up to 55% was observed between occupancy DLIP and static heat gain profile. The higher difference in gains was achieved when a more accurate occupancy detector is employed, giving a lower difference between the DLIP method and Actual Observations. Similarly, window DLIPs enable a direct prediction of ventilation heat losses.

BES was conducted for various scenario-based cases that represented typical and/or extreme situations that would occur within selected case study buildings. Scenarios based on variations in the number of occupants performing different activities in a given space can result towards HVAC systems adapting and responding to occupancy's dynamic changes. Results in terms of both heating and cooling loads were highly dependent on the occupancy profiles, leading to the indication of HVAC systems to vary indoor set point temperatures to ensure the ability to minimise building energy losses while providing adequate indoor air quality and thermal conditions.

Based on the individual detectors, combined detectors were also formed. The same procedure was applied towards the development, training and testing of these. Detection performances reflected upon the performance given by the individual detectors. Proposing combined detectors through BES further indicates the importance of forming multi-detectors to acquire accurate real-time dynamic changes.
For the proposed approach to be fully utilised within buildings, a framework infrastructure should be developed to integrate the vision-based technique with a building control system to ensure HVACs operate according to the real-time building or space requirements. A heat gain prediction and optimisation strategy were proposed. Using the vision-based camera detection, real-time IHGP (internal heat gain prediction) based on the understanding of the number of activities performed by occupants in the building space was used to verify the predictive room HVAC loads models and secondly, it would be used to predict room HVAC loads when optimising the TSP for the HVAC system. Next, the performance of both the prediction and the optimisation models would be assessed through a comparison of the goodness of fitting between the predicted models of heating and cooling under the different scenarios. In addition, the utilisation of such a profile would reduce HVAC systems' operation time and eliminate discomfort problems to indicate potential energy savings without compromising occupants' thermal satisfaction. Furthermore, the strategy was suggested to be further developed to propose a hybrid controller. The hybrid controller is proposed to include all the proposed vision-based controllers, along with the combined heat gain controller, along with the formed ventilation prediction model, to provide a hybrid controller that optimises energy use and thermal comfort. In all, the proposal of the given integration approach should be further explored in future works and assessed towards the formation of a streamlined framework approach that connects to a building control system to allow the developed vision-based approach to assist the defining of the required HVAC control system conditions to provide the correct requirements corresponding to the varied room conditions.

The potential application of the development framework approach was assessed based on the described experimental tests conducted within selected case study buildings. As mentioned in Objective 6, the practical challenges impacting the proposed approach must identified. This includes the type and size of the image dataset used to train the model along with the model configuration significantly affecting the detection ability, which led to variations in the different trained models. Furthermore, the set up along with the indoor-outdoor environmental conditions such as lighting and glare impacting during the experimental test would affect the performance. Since these are uncontrollable factors that would generally arise in all buildings, the detection models must be effectively trained to adapt to such situations.

Since the framework approach is designed to be implemented within indoor spaces of buildings and to provide a continuous capturing of occupancy behaviour, occupants' opinion and suggestion related to the design and application is important. A survey was conducted, and the feedback suggests they have no concern about having a camera implemented within the room. However, it should highly insist that occupants would be fully informed about the framework approach and how DLIPs is formed to eliminate the concerns related to data being stored in the forms of images/ recordings. Also, they preferred a design that is close to a more commonly seen, traditional style device, giving them a safer feeling as its design is similar to a normal CCTV camera. As for their opinions on the idea of the alert system used as a response to the optimisation system, some preferred sound-based systems and some preferred a visual-time system to provide notification to the occupants. Overall, key considerations include the need of forming a less intrusive effective approach and comfortable design that satisfies most of the occupants. All feedback received would be considered within the future works of the development of the desired framework.

8.2. Recommendations for Future Works

Improvements to the current approach are required before the integration building HVAC system controls. Future works include further modification to the dataset, an attempt to try out different deep learning CNN-based methods for training the models to form detectors, testing under a wider range of indoor environments and to also perform the proposed steps given in Chapter 7 to form a controller to enable the vision-based technique to integrate with building energy systems via the process of an optimisation strategy.

Further improvements are required to enhance the detection model's accuracy, reliability, and stability. As shown by the development of different detection models in this present study suggests improvements are important to form a more stable detector, eliminating prediction errors to provide accurate information about the conditions within an indoor space. Furthermore, modifications include the exploration of different pre-trained CNN-based models to be applied to the training of the detectors. In this research, the Faster RCNN with Inception V2 model was selected. However, other object detection algorithms are suggested as popular forms of CNN models used to train detection models. For example, the R-FCN (Region-based fully convolutional networks), the SSDs (Single shot multibox detector), the FPN (Feature pyramid networks), and different variations of the YOLO region-based algorithms could be used towards the formation of accurate detectors.

Testing of the trained models was performed under selected indoor spaces within case study buildings at the University of Nottingham, University Park Campus, United Kingdom. During these tests, a limited number of occupants as participants were involved and the building types selected were limited to office spaces and lecture rooms. To fully test the performance of these models and to identify the model's ability for accurate occupancy detection, larger spaces such as factories, shopping centres, and busier indoor spaces with high footfall should be selected as potential environments for model testing.

Considering the practical challenges impacting the proposed approach whereby indoor-outdoor conditions linked to lighting and glare led to variations in each model's performance. These uncontrollable factors must be addressed by seeking solutions to acknowledge such conditions and incorporate them as a consideration within the improvement of the detectors. This may link to steps that have already been performed to improve models, which can be re-applied further. This includes the enhancement towards the image datasets used, and the methods of labelling applied during pre-processing stages.

The exploration towards the formation of combined detectors suggests the importance of acquiring one multi-detector that provides a full understanding of the dynamic changes within the indoor space. Hence, the ability to combine individual detectors could be further explored with the potential exploration into developing models that focuses on the detection of other types of occupancy activity and or/ their behaviour towards various actions depending on the building type and location of where this system could be implemented.

In addition, the process of integrating the vision-based technique with a building control system through BEMS is equally important. This is the stage in which the output data achieved from the detection becomes valuable for improving indoor thermal comfort, air quality, building energy performance and overall energy savings. Hence, the procedure with the approach suggesting a streamlined framework-based solution to define the required HVAC control system conditions based on real-time detection data responses should be further explored and developed from the initial proposal given in Chapter 7. This includes the most suitable indoor/ room setpoint temperature that should be assigned to HVAC systems to provide adequate thermal conditions based on the real-time understanding of the utilisation of the space by occupants.

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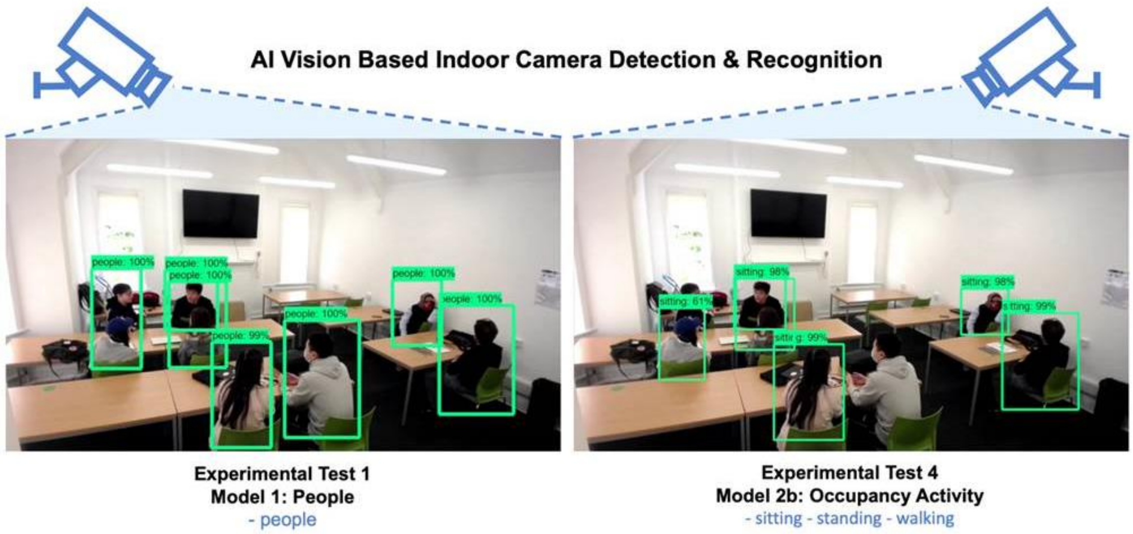
236. Schiera, D.S., Barbierato, L., Lanzini, A., Borchiellii, R., Pons, E., Bompard, E.F., Patti, E., Machii, E., Bottaccioli, L. A distributed platform for multi-modelling co-simulations of smart building energy behaviour. 2020 IEEE International Conference on Environment and Electrical Engineering and 2020 IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe), 2020, 1-6.

237. Tamez, C. Allied Security Links Warehouse Megapixel Camera Image. Available from: https://www.youtube.com/watch?v=CxpRrRBxl4Q [accessed on 20th September 2022].

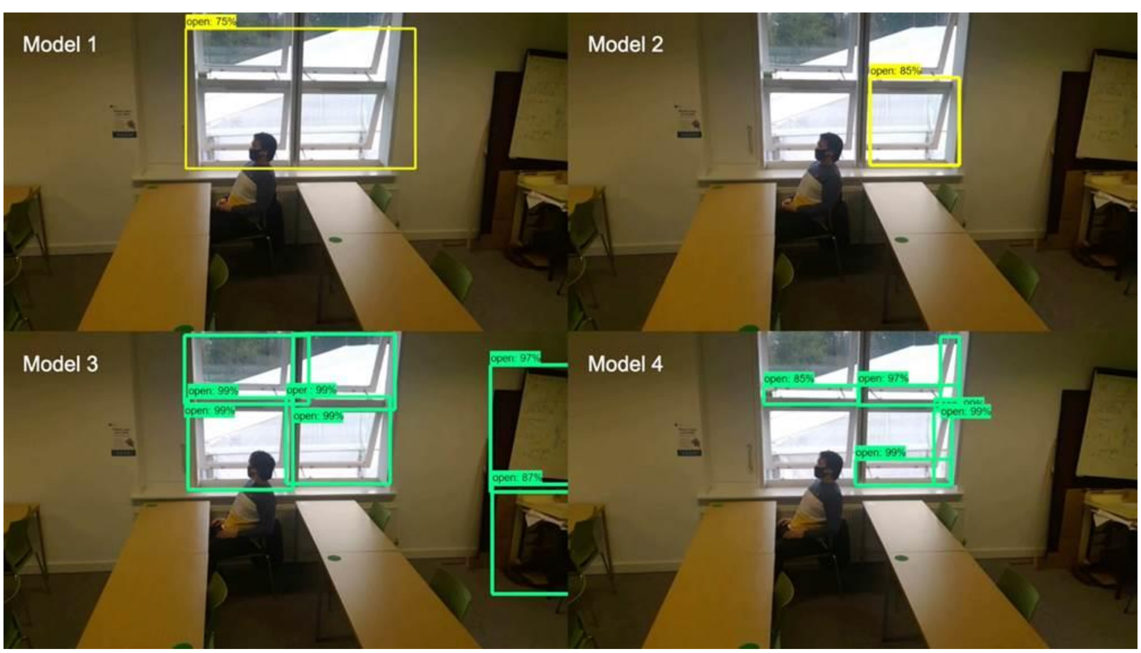
Appendices

Appendix A: Videos

The following presents a list of all the videos discussed within the thesis. Please refer to the attached links to view the full video.

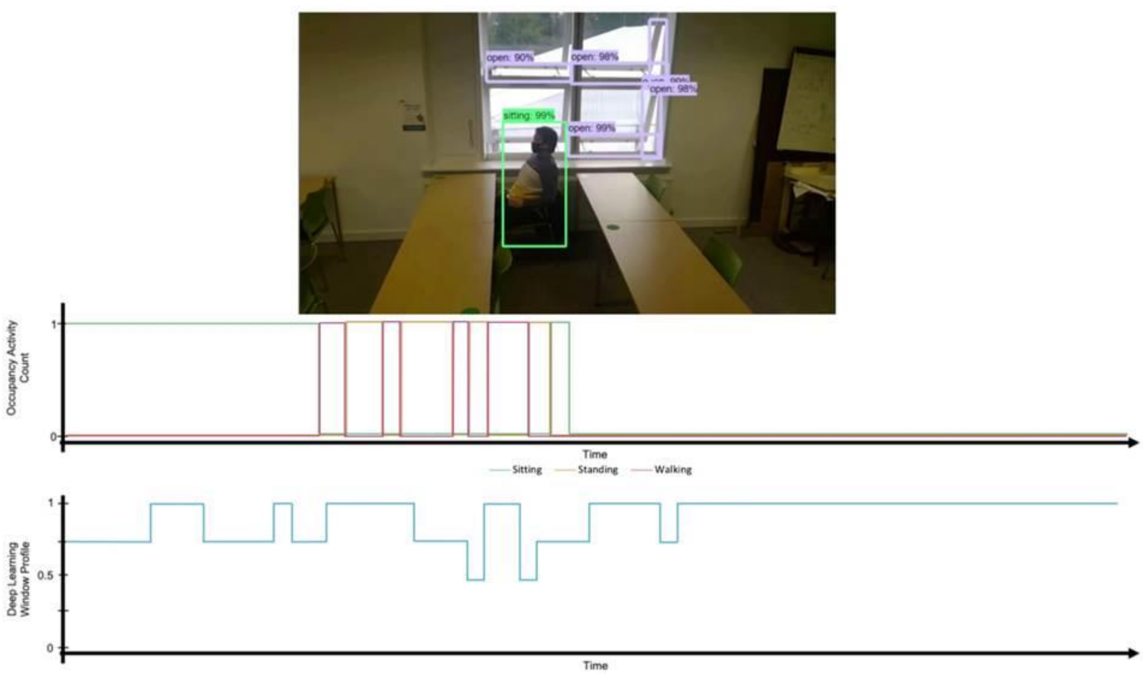


Video 1 – Preview given in Figure 4-36. This video presents the comparison between the application of Model 1 for people detection and Model 2b for occupancy activity detection during experimental tests 1 and 4. Video 1 consists of an example detection and recognition conducted using the same video recorded during Experimental Tests 1 and 4 in Paton House, University of Nottingham.

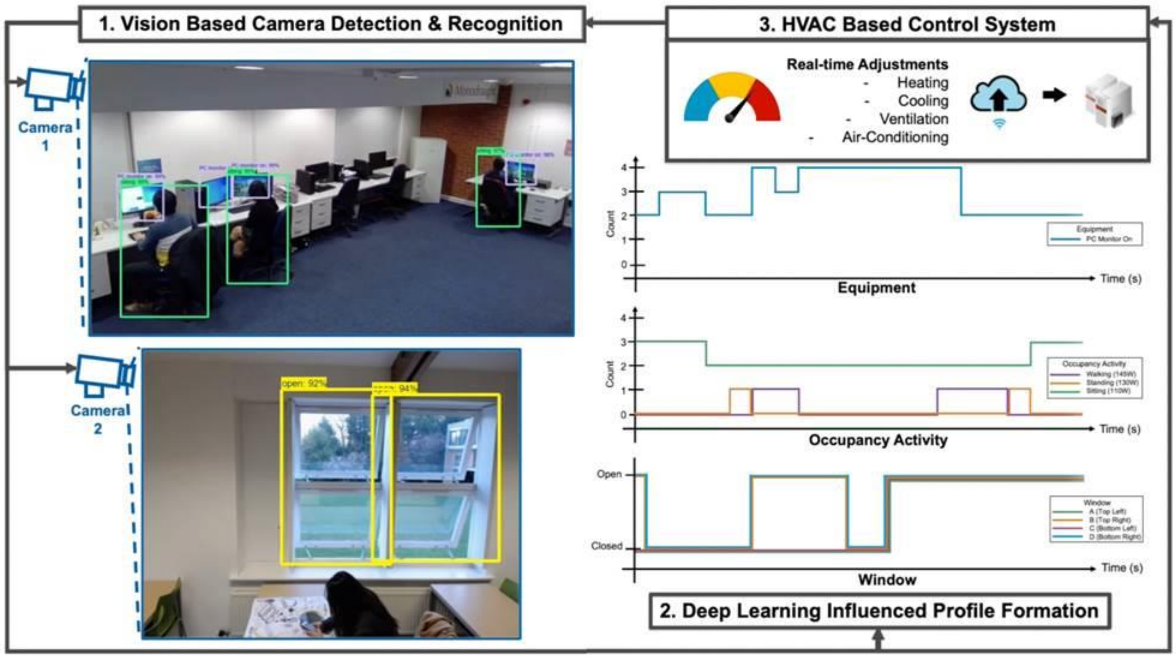


Video 2 – Refers to Figure 5-7. The video consists of a comparison of the detection and recognition performance achieved with the application of the four window detectors.

Video 3 – Links to Figure 6-13 showing the application of the proposed combined occupancy activity and equipment detection model in the test with the DLIP generation.



Video 4 – Refer to Figure 6-26 presenting a preview of the video showing the application of the proposed combined occupancy activity and window detection model in the test with the DLIP generation.



Video 5 - Figure 6-39 presents the potential workflow process of a demand Data-driven vision-based approach for the management of building energy.

Appendix B: Ethics Application Documents

The following presents the documents submitted within the ethics application along with the reviewer's approval.

Ethics Application Form

2019-2020

Faculty of Engineering
Application for approval of research study involving human participants

ALL applicants must provide the following information
The applicant must be the person who will conduct the investigations; each application must be made by one applicant:

- usually the student in the case of taught or research courses,
- usually the researcher (the member of university research or academic staff) who will conduct the study in the case of funded research projects,
- usually the principal investigator in the case of applications for ethics approval in advance of submission of a research proposal

If the applicant is an Undergraduate or Postgraduate taught or research student please complete the information below. The application must be approved by a Supervisor.

Name of student:	*Paige Wenbin Tien*	Student No:	*14342365*
Course of study:	*PhD Building Technology*	Email address:	*paige.tien@nottingham.ac.uk*
Supervisor:	*Dr John Calautit*	PGR ■	PGT ☐
		MSc ☐	UG ☐

If the applicant is a member of university research or academic staff, please complete the information below:
For research staff, the application must be approved by the Principal Investigator

Name:		Principal Investigator (Budget Holder)	Professor Jo Darkwa
Email address:		PI Signature:	

Title of investigation: Testing of a vision-based deep learning occupancy activity and heat gains detection framework for various workspace environments

Planned date for study to begin ......01/08/20.......... Duration of Study ......5 days........

Please state whether this application is:

■ New ☐ Revised ☐ A renewal ☐ For a continuation study

Selection of review process

Please indicate whether the application is required to go forward to the ethics committee for formal review, or, in the case of projects completed by ***taught undergraduate and postgraduate students only***, whether the application can be approved by the supervisor under the expedited review process*.

■ Formal review, application will be submitted to ethics committee

☐ Expedited review, application is approved by supervisor*
* This option can only be selected if the Supervisor is a member of the Faculty Ethics committee

Approval by supervisor: expedited review

I approve the application as supervisor of this project, under the expedited review procedure.

Name of supervisor..................Dr John Calautit......... Signature............... John Calautit ...... Date......30/06/2020..............

2019-2020

Ethical Issues Checklist

The purpose of this Checklist is to facilitate the review process and to identify any ethical issues that may concern the Committee. It is meant to be an aid to both the researcher and the Committee. Listed below are areas which require some justification and attention on your part in specifying your study protocol. Please answer each question honestly, giving full details where required. Answering "YES" to any of the questions will not necessarily lead to a negative response to your application but it will draw issues to your attention and give the reviewers the opportunity to ensure appropriate steps are being taken. In expedited review, supervisors should ensure that for any questions where the answer "YES" has been given, appropriate measures have been taken to maintain ethical compliance.

Applicant's full name Paige Tien

You must complete ALL of this section before submitting your application

1 Who is the population to be studied?

The population to be studied includes adult academic staff members and students within the faculty of engineering, department of architecture and the built environment. The provisional sample size of participants required is a maximum of 10 people.

2 Please give details of how the participants will be identified, approached and recruited. (Include any relationship between the investigator and participants e.g. instructor-student).

Participants will be invited in person and by email invitations. They would select their preferred time from a list of experimental time slots. The email will include a brief introduction to the aims and objectives of the research, requirements for data collection and expected outputs prior to the experiment before the test period. Each participant will be informed about the participant's information sheet to enable them to make an informed decision about their participation, stating their rights to refuse or opt out of the research at any point in time. This information will also be provided to respective gatekeepers, to make them aware of the rights of participants who may be their subordinates in the organization. These rights would also be included in consent forms which participants will sign in advance of participation in the research. Participants would not be offered any financial incentive for their participation in this research. They are volunteers without payment.

3 Will the population studied include any vulnerable members of the public?
Note: for the purpose of ethics approval this includes participants who are under 18, people who are disabled or in poor health, and also those who are non-English speakers and may not be able to understand the consent forms. (If YES, please give further details)

YES ☐ **NO** ■

4 Will it be possible to associate specific information in your records with specific participants on the basis of name, position or other identifying information contained in your records?

YES ☐ **NO** ■

5 What steps have you taken to ensure confidentiality of personal information and anonymity of data both during the study and in the release of its findings?

In accordance with the principles set out in the ESPRC data policy framework, respondents and organisations would be anonymised in academic and non-academic publications. Any data published would be related to non-identifiable characteristics of organisations and individuals (e.g. company size, industry, employee position). Pseudonyms would be used as substitutes for firm names to ensure anonymity. Consent would be sought from respondents and organisations in instances where identity disclosure would be beneficial to project objectives (e.g. impact case studies, media publications in print and video).

Data are collected through continuous text-based data loggings during the experimental test period. The data would only consist of detection response categories: sitting, standing, walking, and opened and closed windows which are present in the form of profile graphs. Hence, no personal information will be recorded.

6 Describe what data will be stored, where, for what period of time, the measures that will be put in place to ensure security of the data, who will have access to the data, and the method and timing of disposal of the data.

During the duration of the study, all physical hard documents will be kept in a locked filing cabinet in my office at the Sustainable Research Building, University of Nottingham. This data will be scanned and will be stored digitally on to the research computer in the Sustainable Research Building on University Park Campus. During the study, screen recordings from the application of the Deep Learning Detection Model will be recorded and saved to the research computer in room B12, Sustainable Research Building. Screen recordings are taken to record the process of the application of the trained deep learning model during the study tests, whereby recognition of the occupancy behaviour has been made. It also provides a form of data which enables the verification of the detection output given by the trained detector. This associated data will also be compiled and saved to the same research computer. At the end of Paige Wenbin Tien's research project, Paige Wenbin Tien will pass along all data to the Academic Supervisor of the project, Dr John Kaiser Calautit. Dr John Kaiser Calautit will store all hard copies within his locked filing cabinet at Mark Group House and store electronic data on his password protected university computer in the Mark Group House. In accordance with the Data Protection Act, the data will be kept securely for seven years following publication of results. After this time, the hard copies will be shredded, and the raw data electronic files will permanently be deleted by Dr John Kaiser Calautit.

		YES	NO
7	Will persons participating in the study be subjected to physical or psychological discomfort, pain or aversive stimuli which is more than expected from everyday life? (If YES, please give further details)	☐	■
8	Will participants engage in strenuous or unaccustomed physical activity? (If YES, please give further details)	☐	■
9	Will the investigation use procedures designed to induce participants to act contrary to their wishes? (If YES, please give further details)	☐	■
10	Will the investigation use procedures designed to induce embarrassment, humiliation, lowered self esteem, guilt, conflict, anger, discouragement or other emotional reactions? (If YES, please give further details)	☐	■
11	Will participants be induced to disclose information of an intimate or otherwise sensitive nature? (If YES, please give further details)	☐	■
12	Will participants be deceived or actively misled in any manner? (If YES, please give further details)	☐	■
13	Will information be withheld from participants that they might reasonably expect to receive? (If YES, please give further details)	☐	■
14	Will the research involve potentially sensitive topics? (If YES, please give further details)	☐	■
15	Will data be collected which requires potentially invasive procedures (eg attaching electrodes to the skin) and/or other health-related information to be identified (eg heart rate). If yes please give details	☐	■

If you require space for additional information, please add it here and identify the question to which it refers:

2019-2020

Checklist of information to include with your application:
Please tick the boxes below to confirm that you have included the following information with your submission. Failure to include the required information may result in your ethics application and approval for start of your research to be delayed.

- A brief description of the study design:
  - number and type of participants
  - number and duration of activities participants will be involved in
  - equipment and procedures to be applied
  - information about how participants will be recruited
  - whether participants will be paid (state how this will be done)
  - plans to ensure participant confidentiality and anonymity
  - plans for storage and handling of data
  - information about what will happen to the data after the study
  - information about how any data and images may be used
  - state whether it will be possible to identify any individuals.

- Copies of any information sheets to be given to participants (include recruitment information (e.g. adverts, posters, letters, etc)

- A copy of the participant consent form

- Copies of data collection sheets, questionnaires, etc

I confirm that all of the above is included in the application:

As the applicant I confirm that I have read and understand the Ethical requirements for my study and have read and complied with the University of Nottingham Code of Research Conduct and Research Ethics.

Signature of applicant .... Date ......30/06/2020..............................

As supervisor, I confirm that I have checked the details of this application.

Signature of supervisor .... Dr John Calautit .... John Calautit .... Date ....30/06/2020...........................

NB The signature of the supervisor on this part of the application DOES NOT indicate supervisor approval for expedited review. If supervisor approval is granted then the front page of the application MUST be signed for approval to be confirmed.

Description of Study

University of Nottingham
UK | CHINA | MALAYSIA

Faculty of Engineering
Sustainable Research Building
University of Nottingham
Nottingham
NG7 2QQ

DESCRIPTION OF THE STUDY

1. DESIGN

This study aims to aid the testing of a vision-based deep learning occupancy activity and heat gains detection framework approach to aid demand-driven HVAC systems operations and performances. Figure 1 presents a flowchart outlining the detection and data logging process used in this study to test the approach for the main research framework given in Figure 2. This study consists of a trained deep learning model deployed to an AI-powered camera to enable the detection and recognition of the occupancy activity and heat gains within a building space. The participants will be invited to perform 'typical' office-based activities. This includes activities following the five output responses of the framework design. Activities include sitting, standing, walking, the opening and closing of windows. They will be advised to behave like how they usually would in a workspace environment. Their actions would be detected throughout the experiment using the device, and data will be stored on the connected computing device. The AI-powered camera detects occupant activity and generates data in the form of deep learning-influenced profiles (DLIP). No videos are recorded in the proposed approach.

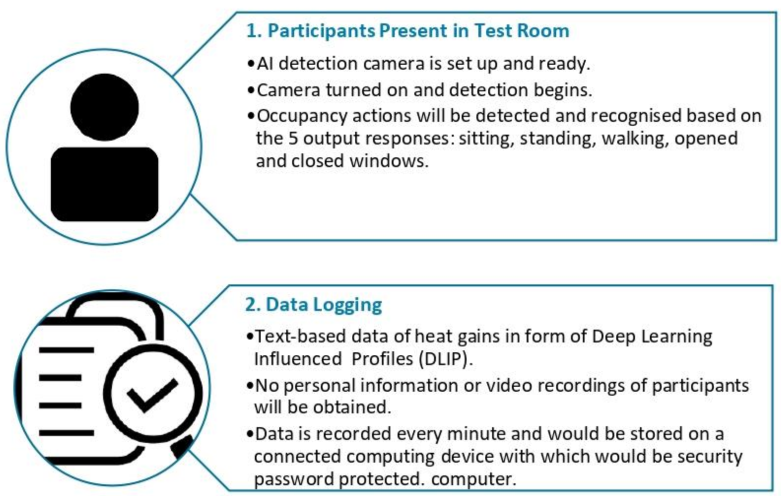


Figure 1. Flowchart process outlining the detection and data logging process of the present study.

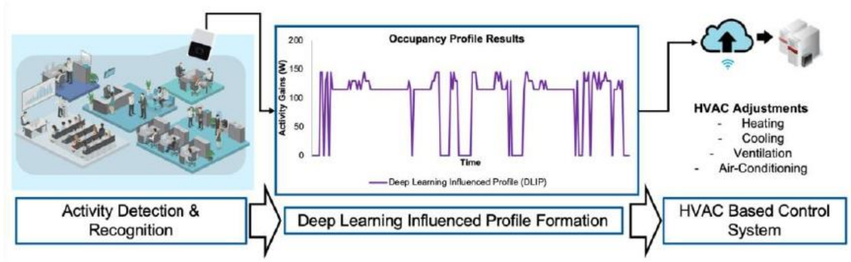


Figure 2. Overview of the framework process.

2. PARTICIPANTS

Up to 10 participants will be invited to this experiment over the age of 18, including males and females. Researchers within the faculty of engineering, department of architecture and the built environment will be recruited. Each participant will take part in at least one of the experimental test sessions indicated within the available timeslots given. Participants will be recruited in person and by email invitations. A poster will be used to describe the nature of the study and will be approached and invited to take part in this study. Participants will not be informed of the purpose of this experiment; however, they will be informed after the study has been completed what it is that we are investigating. This is a voluntary study, and the participants will, therefore, not be paid. Participants would perform their 'typical' office-based activities. They will be advised to behave like how they normally would in a workspace environment. Participants are not constrained to certain actions to be performed at a specific scheduled time. However, they are only advised to perform some (preferably all) of the 'typical' activities. This should at least consist of the following activities: sitting, standing, walking, and opening and closing the window. Note that the participant is not required to be in the experimental detection room for the full duration. Therefore, participants can have breaks and leave the room for a certain period (e.g. 10 minutes and 30 minutes breaks). However, the detection will be continuously running with data logging of the five activities or the half or full-day test duration. Data are collected through continuous text-based data loggings during the experimental test period. The data would only consist of detection response categories in terms of, sitting, standing, walking and opened and closed windows. Hence, no personal information will be recorded.

3. EQUIPMENT AND PROCEDURE

Equipment:

- Test Room: office-based workspace environment with the presence of an openable window
- Typical office equipment set-up
- Desk and chair
- PC with webcam to run the deep learning model and the data logger

Procedure:

1. Participants will be invited to participate in the study. They will be sent the participant information sheet to give them an overview of the process and if they still which to participate, a time slot will be arranged for a time agreeable for both the participant and the researchers.

2. At the prearranged time the participant will make their way to the experiment study location. They will be welcomed and asked to re-read the participant information form and then sign the consent form if they agree to participate in the study. The participants will be provided with a copy of the completed consent form, either by email or hard copy as they prefer. Participants will be reminded that they can stop and leave the study at any time without any explanation if desired.

3. The participant is asked to make themselves feel comfortable at the assigned workspace desk. They are advised to work on their tasks using the given computer.

4. The researcher (Paige Wenbin Tien) will have all the detection equipment set up in the test room and would be ready for detection before the participants' arrival. Once the participant is ready, the AI-powered camera will be turned on and detection begins. Continuous data logging of the occupancy heat gains data in the form of graphs is being logged.

5. The participant is advised to continue with their normal office space-based activities, i.e working on the computer, and moving in, out and around the room during the agreed time duration.

6. The test will end at the end of the agreed participation time duration from a timeslot of either 1 office day or ½ an office day by the participant. The participant will be asked to complete the post-study consent form, thanked for their time, led to the door and told they are free to leave.

4. DATA HANDLING AND STORAGE

This study utilises a camera-based device to obtain data in response to occupancy activities within a building space. However, it should be noted that no personal information is obtained, and no image or video recordings will be conducted. During the duration of the study, all physical hard documents will be kept in a locked filing cabinet in my office at the Sustainable Research Building, University of Nottingham. This data will be stored digitally with password protection on to the research computer in the Sustainable Research Building on University Park Campus. During the study, data recordings from the application of the Deep Learning Detection Model will be saved to the research computer in room B12, Sustainable Research Building. This associated data will also be compiled and saved to the same research computer. At the end of Paige Wenbin Tien's research project, Paige Wenbin Tien will pass along all data to the Academic Supervisor of the project, Dr John Calautit. Dr John Calautit will store the all hard copies within his locked filing cabinet at Mark Group House and store electronic data on his password-protected university computer in the Mark Group House. By the Data Protection Act, the data will be kept securely for seven years following the publication of results. After this time, the hard copies will be shredded, and the raw data electronic files will permanently be deleted by Dr John Calautit.
Data collected from this study is to be used in the following forms:

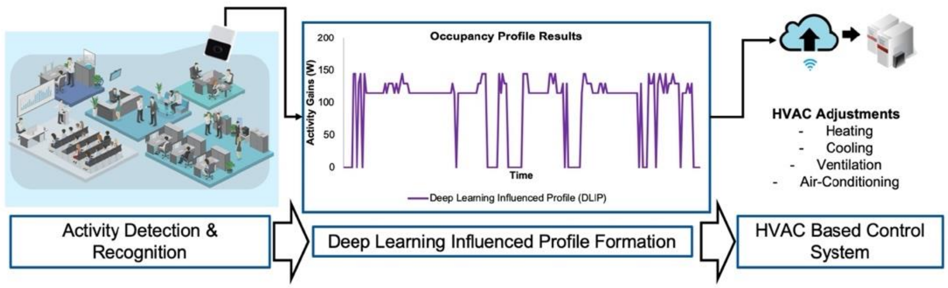
1. To be included as a core experimental study in Paige Wenbin Tien's (student number: 14342365) PhD thesis.
2. To be included within journal and conference publications led by Paige Wenbin Tien and Dr John Calautit, citing all authors who contributed to the work.

Poster

Faculty of Engineering
Sustainable Research Building
University of Nottingham
Nottingham
NG7 2QQ

PARTICIPANT NEEDED

For a research study on the testing of a vision-based deep learning occupancy activity and heat gains detection framework



What does the study involve?

You will be taking part in testing a vision-based deep learning occupancy activity and heat gains detection framework by performing various 'typical' office-based activities. You will be asked to behave like how you would in a workspace environment; doing your 'normal' activities. It should include activities such as sitting, standing, walking, and opening and closing the window. Your actions would be recorded throughout the experiment as the device is developed to detect the activities in a particular space and generates occupancy profiles that will be used to predict the internal heat gains. This can be inputted into the control system for demand-controlled heating and cooling systems.

What participation criteria must I meet to qualify?

We are looking for participants:

i. Over the age of 18.
ii. Speak fluent English.
iii. Willing to perform a series of typical activities that would be performed within a general workspace environment, such as an office.
iv. Willing to participate in the presence of other participants.
v. Willing to interact with other participants to help create a more realistic workspace environment.

How long will this study take?

If you choose to take part, you will be asked to choose a 1 office day or ½ an office-day time slot in which you can come to meet the researchers in the Sustainable Research Building (SRB) on the University Park campus.

Note that the participant is not required to be in the experimental detection space for the full duration. Therefore, participants can have breaks and leave the room for a certain period (e.g. 10 minutes and 30 minutes breaks). Also, participants are welcome to bring their own laptops so they can continue to do their work. However, the detection will be continuously running, and data logging are recorded for the full day.

Will the research be of any personal benefit to me?

You are voluntarily participating in this study. We cannot promise the study will help you personally, but the information we get from this study may help gain a better insight into a better understanding of occupancy behaviour within buildings to aid energy-based HVAC systems operations and performances through the development of a method for predicting indoor occupancy heat gains.

Are there any possible disadvantages or risks in taking part?

There are not any risks associated with taking part in this study as participants are informed to behave like how they normally would in an office-based workspace environment. Participants are not constrained to certain actions or behaviour to be performed at a specific scheduled time. However, they are only advised to perform some (preferably all) of the 'typical' activities, that were mentioned above during the experimental test period.

How do I take part?

Please email: paige.tien@nottingham.ac.uk

Participant Information Sheet

Faculty of Engineering
Sustainable Research Building
University of Nottingham
Nottingham
NG7 2QQ

PARTICIPANT INFORMATION SHEET

Project Title: Testing of a vision-based deep learning occupancy activity detection and heat gains prediction framework at various workspace environments
measures

Researcher: Paige Wenbin Tien [paige.tien@nottingham.ac.uk]
Supervisor: Dr John Kaiser Calautit [john.calautit1 @nottingham.ac.uk]

Thank you for agreeing to take part in this research study on the testing of a vision-based deep learning occupancy activity detection and heat gains prediction framework at various workspaces. Before you begin, we would like you to understand why the research is being done and what it involves for you.

The Study

This study aims to help test a vision-based deep learning occupancy activity detection and heat gains prediction detection framework. During the test, your heat gains within the selected workspace environment, known as the detection space, will be predicted by the developed. You will be asked to perform your 'normal activities' which should include activities such as sitting, standing, walking, and opening and closing the window. You have been invited because you meet the criteria the researchers of this project are looking for participants:

i. Over the age of 18.
ii. Speak fluent English.
iii. Willing to perform a series of typical activities that would be performed within a general workspace environment, such as an office.
iv. Willing to participate in the presence of other participants.
v. Willing to interact with other participants to help create a more realistic workspace environment.

We would like to remind you that this study is optional, and it is up to you to decide whether or not to take part. If you do decide to take part, you will be asked to sign a consent form. Following this, the researcher will lead the participant to the experimental test room. Once the participants are ready, the detection device connected to a trained deep learning model operated with the connection to a laptop or PC will be switched on. It begins when the detection device starts recognising activities within the space and logging heat gains data in the form of graphs. Participants are suggested to act like they normally would in a typical office-based workspace environment, with activities including sitting, standing, walking, and opening and closing the windows.

Will the research be of any personal benefit to me?

You are voluntarily participating in this study. We cannot promise the study will help you personally, but the information we get from this study may help gain a better insight into a better understanding of occupancy behaviour within buildings to aid energy-based HVAC systems operations and performances through the development of a method for predicting indoor heat gains.

Are there any possible disadvantages or risks in taking part?

There are not any risks associated with taking part in this study as participants are informed to behave like how they normally would in an office-based workspace environment. Participants are not constrained to certain actions or behaviour to be performed at a specific scheduled time. However, they are only advised to perform some (preferably all) of the 'typical' activities, that were mentioned above during the experimental test period.

What will happen to the information I provide?

We will follow ethical and legal practices and all information will be handled in confidence. The data collected for the study will be looked at and stored by authorised persons from the University of Nottingham who are organising the research. They may also be looked at by authorised people from regulatory organisations to check that the study is being carried out correctly. All will have a duty of confidentiality to you as a research participant, and we will do our best to meet this duty.

What if there is a problem?

If you have any queries or complaints, please contact the student's supervisor /chief investigator in the first instance.

What if I have other questions?

If you have any questions or concerns, please don't hesitate to ask. The researchers can be contacted before and after your participation at the email addresses above.

Participant Consent form

PARTICIPANT CONSENT FORM

Project Title: Testing of a vision-based deep learning occupancy activity and heat gains detection framework for various workspace environments

Researcher: Paige Wenbin Tien

Supervisors: Dr John Kaiser Calautit, Jo Darkwa and Christopher Wood

I undersigned as a research participant confirmed that: (please sign your initials as appropriate)

☐ I have read the Participant Information Sheet and the nature and purpose of the research project have been explained to me. I understand and agree to take part.

☐ I understand the purpose of the research project and my involvement in it.

☐ I understand that I may withdraw from the research project at any stage and that this will not affect my status now or in the future.

☐ I understand that while information gained during the study may be published, I will not be identified, and all personal results will remain confidential.

☐ I understand that the anonymised data are approved for use in secondary studies.

☐ I understand that data will be stored in a locked filing cabinet, and digital data will be stored only on a password-protected computer and on a secure server. Only researchers and supervisors can get access to the data. At the end of the researcher student's project, all data from the study will be passed on to the academic supervisor and the supervisor will then have responsibility for the storage of the data. By the Data Protection ACT, the data will be kept securely for seven years following the publication of results. After this time, electronic files will be deleted, and any hard copies will be destroyed.

☐ I understand that I may contact the researcher or supervisor if I require further information about the research.

Signed ………………………………………………………… (Research participant)

Print name …………………………………………………… **Date** ………………………………

Signed ………………………………………………………… (Researcher)

Print name …………………………………………………… **Date** ………………………………

Contact details

Researcher: paige.tien@nottingham.ac.uk Supervisor: john.calautit1@nottignham.ac.uk

This form will be printed and originally signed in DOUBLE COPIED: the experimenter will retain one copy and the subject will retain one copy.

POST-STUDY PARTICIPANT CONSENT FORM

Project Title: Testing of a vision-based deep learning occupancy behaviour detection framework at various workspace environments

Researcher: Paige Wenbin Tien

Supervisors: Dr John Kaiser Calautit, Jo Darkwa and Christopher Wood

I the undersigned as a research participant confirmed that (please sign your initials as appropriate)

☐ This is the end of my participation in the following experiment.

Signed ………………………………………………………… (Research participant)

Print name ……………………………………………………… **Date** ………………………………

Signed ………………………………………………………… (Researcher)

Print name ……………………………………………………… **Date** ………………………………

Ethics Committee Review and Decision Form

Ethics Committee Reviewer Decision

This form must be completed by each reviewer. Each application will be reviewed by two members of the ethics committee. Reviews may be completed electronically and sent to the Faculty ethics administrator from a University of Nottingham email address, or may be completed in paper form and delivered to the Faculty of Engineering Research Office.

Applicant full name   Paige Tien

Reviewed by:

Name   B18

Signature (paper based only) ……………………………………………………………………………………

Date 12/07/2020

- [x] Approval awarded - no changes required
- [ ] Approval awarded - subject to required changes (see comments below)
- [ ] Approval pending - further information & resubmission required (see comments)
- [ ] Approval declined – reasons given below

Comments:

Please note:

1. The approval only covers the participants and trials specified on the form and further approval must be requested for any repetition or extension to the investigation.
2. The approval covers the ethical requirements for the techniques and procedures described in the protocol but does not replace a safety or risk assessment.
3. Approval is not intended to convey any judgement on the quality of the research, experimental design or techniques.
4. Normally, all queries raised by reviewers should be addressed. In the case of conflicting or incomplete views, the ethics committee chair will review the comments and relay these to the applicant via email. All email correspondence related to the application must be copied to the Faculty research ethics administrator.

Any problems which arise during the course of the investigation must be reported to the Faculty Research Ethics Committee

Appendix C: Published Work and Declaration

Published Journal Papers

1. Tien, P.W., Wei, S., Darkwa, J., Wood, C. and Calautit, J.K., 2022. Machine Learning and Deep Learning Methods for Enhancing Building Energy Efficiency and Indoor Environmental Quality–A Review. Energy and AI, 10, p.100198. https://doi.org/10.1016/j.egyai.2022.100198
   This review study provided an analysis of the research development in artificial intelligence-based strategies for applications related to occupancy aspects of the built environment that were intended to assist the enhancement of current building operational methods. All content presented in the paper is given in Chapters 2, 3.1 and 3.2.
2. Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J. and Wood, C., 2020. A vision-based deep learning approach for the detection and prediction of occupancy heat emissions for demand-driven control solutions. Energy and Buildings, 226, p.110386 https://doi.org/10.1016/j.enbuild.2020.110386
   This paper presents the concept of using AI deep learning techniques to optimise building energy performance. It compiles the initial approach with the application of MATLAB techniques. This paper directly relates to the method and discussion given in Chapter 4.2.
3. Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J. and Wood, C., 2021. Occupancy heat gains detection and prediction using a deep learning approach for reducing building energy demand. Journal of Sustainable Development of Energy, Water and Environment Systems, 9(3), pp.1-31. http://dx.doi.org/10.13044/j.sdewes.d8.0378
   This paper presents further development of the occupancy detection and recognition approach as presented in Chapter 4. It consists of the application of Python with Tensorflow through the TensorFlow Object Detection API as discussed in Chapter 4.3. Using the initially trained detection model, a focus on the analysis of the detection performance (Chapters 4.4. and 4.5) and the impact towards building energy performances were performed.
4. Tien, P.W., Wei, S., Chow, T.W., Darkwa, J., Wood, C. and Calautit, J.K., 2022, July. Enhancing the detection performance of a vision-based occupancy detector for buildings. In Proceedings of the Institution of Civil Engineers-Engineering Sustainability (Vol. 40, pp. 1-14). Thomas Telford Ltd. https://doi.org/10.1680/jensu.22.00013
   The development of the different occupancy detection models described and analysed in Chapters 4.3, 4.4 and 4.5 are related to the investigation presented in this paper.
5. Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J. and Wood, C., 2021. Vision-based human activity recognition for reducing building energy demand. Building Services Engineering Research and Technology, 42(6), pp.691-71. https://doi.org/10.1177/01436244211026120
   This paper focused on the use of building energy simulations to assess the potential conditions required within HVAC system setpoint temperatures to cope with the detected dynamic changes in occupancy activities. The work follows the method presented in Chapter 3.3.5, with the results and discussion in Chapter 4.6.2.
6. Wei, S., Tien, P.W., Chow, T.W., Wu, Y. and Calautit, J.K., 2022. Deep learning and computer vision-based occupancy CO2 level prediction for demand-controlled ventilation (DCV). Journal of Building Engineering, 56, p.104715. https://doi.org/10.1016/j.jobe.2022.104715
   This paper explored the importance of occupancy detection towards achieving accurate data for a better understanding of the conditions in terms of indoor air quality and the building ventilation energy demand. Content in this paper is highlighted within Chapter 4.6.3.

7. Tien, P.W., Wei, S., Chow, T.W., Darkwa, J., Wood, C. and Calautit, J.K., 2022. Enhancing the detection performance of a vision-based window opening detector. Cleaner Energy Systems, November 2022, 3, 100038. https://doi.org/10.1016/j.cles.2022.100038
   This paper focused on the development of the most effective window detection model. In total, four different window detection models were developed, compared, and analysed under a series of experimental tests. All content presented in this paper is given in Chapter 5.
8. Tien, P.W., Wei, S., Liu, T., Calautit, J., Darkwa, J. and Wood, C., 2021. A deep learning approach towards the detection and recognition of the opening of windows for effective management of building ventilation heat losses and reducing space heating demand. Renewable Energy, 177, pp.603-625. https://doi.org/10.1016/j.renene.2021.05.155
   All discussion and findings given in the paper relate to Chapters 5.6. and 5.8. This includes the process of forming the different window detectors, testing of the vision-based approach and also the use of building energy simulations for analysis in terms of the potential in requiring accurate data to assist the operations of HVAC systems.
9. Tien, P.W., Wei, S. and Calautit, J., 2021. A Computer Vision-Based Occupancy and Equipment Usage Detection Approach for Reducing Building Energy Demand. Energies, 14(1), p.156. https://doi.org/10.3390/en14010156
   This paper focused on the development of the approach for the detection of both occupancy activity and electrical equipment. Insights of real-time detection within a selected case study office building were explored as described in Chapter 6.1. In addition, building energy simulation under scenario-based conditions was performed.
10. Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J. and Wood, C., 2022. Real-time monitoring of occupancy activities and window opening within buildings using an integrated deep learning-based approach for reducing energy demand. Applied Energy, 308, p.118336. https://doi.org/10.1016/j.apenergy.2021.118336
    Content from this paper forms Chapter 6.2 of this study. It focused on the investigation of forming combined detections of both occupancy and window detection models together to further develop the vision-based approach to assist energy reduction and system optimisation.
11. Wang, Z., Calautit, J., Wei, S., Tien, P.W. and Xia, L., 2022. Real-time building heat gains prediction and optimization of HVAC setpoint: An integrated framework. Journal of Building Engineering, 49, p.104103. https://doi.org/10.1016/j.jobe.2022.104103
    This paper relates to the content given in Chapter 7.3, where it provides a framework approach in heat gain prediction with a proposed optimisation strategy to be further developed and processed to allow effective controls for building HVAC systems as a response to the data obtained from real-time detection related to the internal heat gains.

Published Conference Papers

1. Tien, P.W., Mohammadi, M., Zhong, F., Calautit, J.K., Darkwa, J., Wood, C. Deep learning-based occupancy behaviour approach towards the improvement of the indoor air quality within building spaces. CUE2021 The 7th Applied Energy Symposium 2021: Low carbon cities and urban energy systems., Set. 4 - 8, 2021, Matsue, Japan (Virtual).
2. Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J, Wood C. A computer vision deep learning method for the detection and recognition of manual window openings for effective operations of HVAC systems in buildings. Imaginable Futures: Design Thinking, and the Scientific Method. 54th International Conference of the Architectural Science Association 2020, Ali Ghaffarianhoseini, et al (eds), pp. 21–30. Published by the Architectural Science Association (ANZAScA), 2020.
3. Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J, Wood C. Deep Learning Occupancy Activity Detection Approach for Optimising Building Energy Loads. International Conference on Applied Energy 2020. Proceedings of the 12th International Conference on Applied Energy, Dec. 1 - Dec. 10, 2020, Bangkok / Virtual.
4. Tien, P.W., Wei, S., Calautit, J.K., Darkwa, J, Wood C. Detection of window opening using a deep learning approach for effective management of building ventilation heat losses. Proceedings of BSO-V 2020 5th IBPSA-England Building Simulation and Optimization Virtual Conference 21-22nd September 2020 Loughborough, UK.
5. Tien, P.W., Calautit, J. K., Darkwa, J., Wood, C., Wei, S., Pantua C.A.J., Xu, W. A Deep Learning Framework for Energy Management and Optimisation of HVAC Systems, IOP Conference Series: Earth and Environmental Science, Volume 463, International Conference on Sustainable Energy and Green Technology 2019 11-14 December 2019, Bangkok, Thailand https://doi.org/10.1088/1755-1315/463/1/012026
6. Tien, P. W., Wei, S., Calautit, J.K., Darkwa, J., Wood, C. A New Deep Learning Approach for Energy Management and Optimisation of HVAC Systems for the Built Environment, International Conference on Applied Energy 2019, Volume 2: Proceedings of 11th International Conference on Applied Energy, Part 1, Sweden, 2019.

Declaration

I declare that the thesis has been composed by myself and that the work has not been submitted for any other degree or professional qualification. I confirm that the work submitted is my own, except where work which has formed part of jointly authored publications has been included. My contribution to this work and those of the other authors have been explicitly indicated below.

I confirm that appropriate credit has been given within this thesis where reference has been made to the work of others. The work presented in Chapters 3, 4, 5, and 6 was previously published in eleven separate journals by author Paige Wenbin Tien and co-authors John Kaiser Calautit, Jo Darkwa, and Christopher Wood and this study was conceived by all of the authors.

Declaration in Chapter 2

The work presented in this chapter was previously published as a review paper in the journal, Energy and AI with the title, 'Machine Learning and Deep Learning Methods for Enhancing Building Energy Efficiency and Indoor Environmental Quality–A Review' by author Paige Wenbin Tien and co-authors Shuangyu Wei, Jo Darkwa, Christopher Wood and John Kaiser Calautit. I played a major role in the conceptualisation, formal analysis, investigation, data curation, writing - original draft, and visualisation and this study was conceived by all the authors.

Declaration in Chapter 4

The work presented in Chapter 4 was previously published in a series of different journals. This includes the paper entitled 'A vision-based deep learning approach for the detection and prediction of occupancy heat emissions for demand-driven control solutions' in the Energy and Buildings journal, the paper 'Occupancy heat gains detection and prediction using deep learning approach for reducing building energy demand' in the Journal of Sustainable Development of Energy, Water and Environment Systems, the paper 'Enhancing the detection performance of a vision-based occupancy detector for buildings', in the Proceedings of the Institution of Civil Engineers-Engineering Sustainability, and the paper 'Vision-based human activity recognition for reducing building energy demand. Building Services Engineering Research and Technology' in the Building Services Engineering Research and Technology journal. For all four papers, Paige Wenbin Tien was the corresponding author while co-authors include, Shuangyu Wei, Tin Wai Chow, Jo Darkwa, Christopher Wood and John Kaiser Calautit. I played a major role in the conceptualisation, methodology, software, validation, formal analysis, investigation, data curation, writing - original draft, and visualisation. Furthermore, some work described in Chapter 4.6.3 was presented in the previously published paper entitled 'Deep learning and computer vision-based occupancy CO2 level prediction for demand-controlled ventilation (DCV)' in the Journal of Building Engineering. For this paper, I took the roles of conceptualisation, software, data curation and writing – review & editing.

Declaration in Chapter 5

The work presented in this chapter was previously published in two different journals. This includes the paper entitled 'Enhancing the detection performance of a vision-based window opening detector' in the Cleaner Energy Systems and the paper entitled 'A deep learning approach towards the detection and recognition of the opening of windows for effective management of building ventilation heat losses and reducing space heating demand' in the Renewable Energy journal. For both, Paige Wenbin Tien was the corresponding author and I took the roles of conceptualisation, methodology, software, validation, formal analysis, investigation, data curation, writing – the original draft, and visualisation. For both, co-author includes, Shuangyu Wei, Tianshu Liu, John Kaiser Calautit, Jo Darkwa and Christopher Wood.

Declaration in Chapter 6

The work presented in this Chapter was previously published in two journal papers. This includes the paper entitled 'A Computer Vision-Based Occupancy and Equipment Usage Detection Approach for Reducing Building Energy Demand' in Energies and the paper 'Real-time monitoring of occupancy activities and window opening within buildings using an integrated deep learning-based approach for reducing energy demand' in Applied Energy. Paige Wenbin Tien was the corresponding author, while co-authors include, Shuangyu Wei, John Kaiser Calautit, Jo Darkwa and Christopher Wood. For both papers, I played a major role in the conceptualisation, methodology, software, validation, formal analysis, investigation, data curation, writing - original draft, and visualisation.

Declaration in Chapter 7

Some work described and presented in this chapter was previously published in the Journal of Building Engineering as 'Real-time building heat gains prediction and optimization of HVAC setpoint: An integrated framework' by author Zu Wang and co-authors John Kaiser Calautit, Shuangyu Wei, Paige Wenbin Tien and Liang Xia. I played a major role in the conceptualisation, formal analysis, investigation, writing - original draft, writing - review & editing and this study was conceived by all the authors.