

**ADVANCED TECHNIQUES FOR
CHARACTERIZING AND PREDICTING
ASPHALT MACROTEXTURE**

By
Shengli Xiang

Supervisors:
Gabriele Albertini
Nick Thom

Thesis submitted to the University of
Nottingham
for the degree of Doctor of Philosophy
Department of Civil Engineering
June 2025

DECLARATION

This is to declare that the contents of this thesis are my own work and were performed at the University of Nottingham from 2020 to 2024. This thesis has not been submitted to any other institution for another degree.

Plagiarism Statement

I hereby declare that the work presented in this thesis is my original research, except where otherwise clearly indicated by appropriate citations and references. I have adhered to the highest standards of academic integrity throughout the research and writing process. All ideas, data, and findings borrowed from other sources, whether published or unpublished, have been appropriately acknowledged through in-text citations and a comprehensive reference list. I have not submitted this work, or any part of it, for any other academic qualification. I understand plagiarism, including using unauthorized assistance, copying, or paraphrasing without proper attribution, is a serious academic offense. I accept full responsibility for the content of this thesis and am prepared to account for any discrepancies or violations of academic integrity that may be identified.

AI Statement

In preparing this thesis, I utilized artificial intelligence tools solely to enhance the quality and clarity of my writing. These tools were employed for grammar and spelling checks, sentence rephrasing for improved readability, and formatting assistance. I have not used AI to generate original ideas, research, analyze data, or formulate conclusions. All research methodologies, data collection, analysis, and interpretations presented in this thesis result from my independent efforts and academic judgment. I have critically reviewed and verified all content generated with the assistance of AI to ensure its accuracy and relevance. This thesis represents my intellectual contribution to the field, and I take full responsibility for its content and integrity.

Abstract

In the realm of asphalt mixture research, traditional texture measurement methods, such as laser scanning and sand patch tests, have long been plagued by high costs, complex operations, and time-consuming procedures. These limitations have hindered the efficient assessment of asphalt surface characteristics crucial for road safety and maintenance. To address these challenges, this thesis embarks on a comprehensive investigation to establish an efficient texture prediction framework by leveraging advanced techniques like X-ray computed tomography (CT), virtual asphalt modeling, and deep learning.

The first study utilizes X-ray CT to delve into the intricate relationship between the void properties of asphalt mixtures and the Mean Profile Depth (MPD_{CT}) of Marshall core samples. Departing from the conventional focus on air void content alone, this research uncovers a strong linear correlation between MPD_{CT} and topological characteristics of voids, including average void diameter (with a correlation coefficient of 0.89). This breakthrough reveals that these properties can serve as more informative predictors of MPD, offering a more nuanced texture control in asphalt design.

Building upon the first study's findings, the second study explores the nonlinear relationship between MPD_{LS} measured via laser scans of asphalt slabs and Mean Texture Depth (MTD_{SPT}) obtained from sand patch tests. By employing the Intersected Stacked Air Voids (ISA) method, this research validates the feasibility of virtual asphalt modeling as an alternative to CT, reducing the reliance on expensive imaging equipment. The study successfully establishes a nonlinear model for MPD_{LS} - MTD_{SPT} , elucidating how maximum aggregate sizes and air void content influence this relationship.

The third study represents a significant leap forward, introducing a deep learning (DL) approach based on Visual Geometry Group (VGG)-based Convolutional Neural Network (CNN) architecture. By training the model on two-dimensional images captured by consumer-grade cameras, this innovative method enables cost-effective and non-contact measurement of asphalt surface texture. The model classifies MPD_{LS} ranges with high accuracy and predicts exact MPD_{VGG} values through regression

analysis, showcasing the potential of digital techniques to replace traditional field measurement methods.

These three studies present a “CT - Virtual - DL” three-tier substitution solution, which has demonstrated the ability to reduce measurement costs by up to 90%. Integrating classification and regression techniques, this efficient framework provides precise and actionable insights, making it applicable across the entire asphalt mixture design, acceptance, and monitoring lifecycle. By advancing from laboratory analyses to real-world pavement assessments, this research paves the way for automated, cost-effective texture evaluations, ultimately enhancing road safety and maintenance strategies through deep learning optimization and non-contact measurement techniques.

Keywords: Asphalt Mixtures, Mean Profile Depth (MPD), Mean Texture Depth (MTD), Volumetric Properties, Topological Properties, X-ray Computed Tomography (CT), Digital Image Processing, Virtual Asphalt, Macrotexture Assessment, Laser Scanning, Sand Patch Test, Nonlinear Relationship, Intersected Stacked Air Voids (ISA) Method, Deep Learning (DL), Visual Geometry Group (VGG), Convolutional Neural Networks (CNNs), Automated Measurement Techniques, Regression Analysis, Image-Based Prediction, Asphalt Surface Characterization, Non-Contact Measurement

Acknowledgments

I want to express my deepest gratitude to my supervisors, Professors Alvaro Garcia Hernandez, Tony Parry, Nick Thom, and Gabriele Albertini, for their unwavering support and guidance throughout my PhD journey. As my first supervisor, Alvaro has been a constant source of creativity and enthusiasm. His willingness to engage in field measurements and explore new machine-learning techniques with me has been invaluable. Tony's friendly demeanor and insightful advice have greatly enriched my research experience.

As I transitioned to working with Gabriele and Nick, I found their patience and constructive feedback incredibly beneficial. They provided invaluable suggestions that have significantly shaped my work. I am incredibly thankful to Dr. Mustafa K Abou Foul, who taught me essential technical skills such as image processing and virtual asphalt methodologies.

I would also like to extend my heartfelt thanks to the technical staff at NTEC, including Jonathan Watson, Richard Blakemore, Martyn Barrett, and Lawrence Pont, for their substantial assistance and support in the laboratory. Their expertise has been crucial to the success of my experiments. Additionally, I am grateful to my colleagues in the research group, including Liyao, Daniel, Mariam, and others, whose camaraderie and assistance were invaluable during this journey.

Furthermore, I wish to acknowledge my peers in the Department of Engineering for their collaboration and support, which made this research more enjoyable. A special thanks to my family for their unwavering love, encouragement, and financial support, which sustained me during the challenging times of my studies. I am grateful to everyone who has contributed to my growth and success.

Lastly, I appreciate the resources the University of Nottingham provided, which made this research possible. Your support has been instrumental in advancing my academic pursuits.

Contents

Abstract	5
Acknowledgments.....	7
List of Figures	17
List of Tables	22
Notations	25
1 Introduction	28
1.1 Research Context and Significance	28
1.1.1 Asphalt Pavements: Fundamental Composition and Functional Requirements.....	28
1.1.2 Critical Role of Surface Texture in Pavement Performance.....	28
1.2 Texture Classification and Current Challenges	28
1.2.1 Multiscale Texture Hierarchy	28
1.2.2 Design Challenges in Texture Control.....	29
1.2.3 Limitations of Conventional Measurement Methods	29
1.3 Innovative Approaches	31
1.3.1 The Intersected Stacked Air Voids (ISA) method	31
1.3.2 Deep Learning (DL) with Convolutional Neural Networks (CNNs).....	32
1.4 Research Aim and Objectives	32
1.4.1 Overarching Aim	32
1.4.2 Stage-Specific Objectives	33

1.4.3	Progressive Research Pipeline	34
1.5	Thesis Structure	35
2	Literature Review	37
2.1	Introduction.....	37
2.2	Materials and Performance of Asphalt Pavements	37
2.3	Asphalt Mixtures: Composition and Structural Components	38
2.3.1	Historical Evolution of Asphalt Compositions	39
2.3.2	Aggregate Structure and Function	39
2.3.3	Bitumen: The Binding Matrix.....	40
2.3.4	Fillers: Microstructural Enhancers.....	40
2.3.5	Common Asphalt Mixture Types in Road Engineering	41
2.4	Asphalt Mixture Design.....	42
2.4.1	Aggregate Selection and Gradation Design.....	43
2.4.2	Binder Selection and Content Optimization	43
2.4.3	Compaction Technology and Its Impact	43
2.5	Volumetric Properties of Asphalt Mixtures	44
2.5.1	Air Void Content (AVC)	45
2.5.2	Voids in Mineral Aggregate (VMA).....	46
2.5.3	Maximum Aggregate Size (MAS)	46
2.5.4	Number of Aggregates (NA)	47
2.5.5	Mastic Content.....	47

2.6	Void Topology and Morphological Characteristics.....	47
2.6.1	Macroporosity	47
2.6.2	Average Void Diameter	48
2.6.3	Connectivity Metrics: Euler Number and Percolation Number.....	49
2.6.4	Tortuosity	50
2.6.5	Void Shape Properties.....	50
2.6.6	Multidimensional Void Parameters in Macrotexture Modeling	52
2.7	Pavement Texture and Its Multifaceted Implications	52
2.7.1	Surface Profile Analysis	53
2.7.2	Hierarchy of Texture Scales.....	54
2.7.3	Texture Parameters and Multidimensional Characterization.....	56
2.7.4	Texture Spectral Analysis Methodology	59
2.7.5	Classification and Characteristics of Asphalt Mixture Macrotexture	65
2.7.6	Texture Measurement Techniques	67
2.7.7	Technical Requirements for Macrotexture in Road Specifications	70
2.8	X-ray Computerized Tomography (CT) in Pavement Materials	72
2.8.1	CT Scanning Principles.....	72
2.8.2	Digital Image Processing	72
2.8.3	Image Segmentation Techniques	73
2.8.4	Technological Advantages and Challenges	75
2.9	Virtual Asphalt Mixture Design.....	76

2.9.1	Finite Element Method (FEM) and Discrete Element Method (DEM) ..	76
2.9.2	Virtual Design and Simulation via Mixlab Software.....	77
2.9.3	Intersected Stacked Air Voids (ISA) Method for Virtual Simulation	79
2.10	Comprehensive Literature Review on AI, ML, and DL	81
2.10.1	Overview of AI, ML, and DL	81
2.10.2	Foundations of Machine Learning and Deep Learning	82
2.10.3	Evolution of Deep Learning.....	83
2.10.4	Prominent Deep Learning Algorithms.....	84
2.10.5	Convolutional Neural Networks	85
2.10.6	The Role and Diversity of Activation Functions	87
2.10.7	The Importance and Evolution of Optimization Algorithms.....	89
2.10.8	VGG Model Hyperparameters.....	90
2.10.9	Integration with Asphalt Pavement Research	92
2.11	Literature Review Gaps and Research Opportunities	93
2.11.1	Current Research Landscape.....	93
2.11.2	Unaddressed Research Gaps	94
2.11.3	Proposed Research Innovations	95
2.11.4	Research Impact.....	96
3	Void Properties and Macrotexture Correlation	97
3.1	Introduction.....	97
3.2	Methodology	97

3.2.1	Sample Fabrication	97
3.2.2	Density and Porosity Measurement	99
3.2.3	CT Data Acquisition	99
3.2.4	Region of Interest (ROI) Defining.....	99
3.2.5	Image Segmentation.....	99
3.2.6	Quantification of Void Topological Properties.....	104
3.2.7	Macrotexture Parameter Measurement	106
3.2.8	Virtual Asphalt Mixture Simulation	106
3.2.9	Statistical Analysis of Structural Relationships	106
3.3	Results and Discussion	108
3.3.1	Influence of CT Image Quantity on Void Properties Measurement	108
3.3.2	Correlations Between Air Void Topological Properties	110
3.3.3	Correlations Between Air Void and VMA Topological Properties.....	115
3.3.4	Impact of Void Properties on Asphalt Macrotexture	116
3.3.5	Multivariate Modeling of MPD_{CT}	119
3.4	Analysis and Discussion	121
3.4.1	Filling Knowledge Gaps in Void-Texture Correlations.....	121
3.4.2	CT Topology Analysis vs. Traditional Volumetric Methods	121
3.4.3	Limitations of Laboratory-Scale CT Analysis.....	122
3.4.4	Foundation for Virtual Texture Prediction	122
3.4.5	Advancing Texture Prediction Beyond Single Parameters.....	122

4	MPD-MTD Modeling via Virtual Asphalt and Experimental Validation.....	124
4.1	Introduction.....	124
4.2	Methodology	125
4.2.1	Materials and Design of Asphalt Slabs	125
4.2.2	Texture Parameter Measurement	125
4.3	Virtual Asphalt Generation Methodology	127
4.3.1	Geometric Modeling via ISA Method	127
4.3.2	Two-Dimensional Void Structure Construction	127
4.3.3	Three-Dimensional Model Extension	129
4.3.4	Validation Against Physical Samples	129
4.4	Virtual Asphalt Measurement Protocols.....	131
4.4.1	Average Void Diameter Quantification	131
4.4.2	MPD Measurement Procedure.....	131
4.4.3	MTD Measurement via Digital Algorithms.....	133
4.4.4	Dataset Validation and Correlation Analysis.....	135
4.5	Results and Discussion	137
4.5.1	Impact of Laser Line Count and Moisture on Measurement Reliability 137	
4.5.2	Nonlinear Correlation Between MPD and MTD	137
4.5.3	Validation of MPD-Void Diameter Linear Relationship.....	142

4.5.4	Comparative Evaluation of 2D vs. 3D MTD _{ISA} Estimation Algorithms	143
4.6	Analysis and Discussion	146
4.6.1	Addressing Literature Gaps and Research Objectives.....	146
4.6.2	Methodological Innovations, Limitations, and Future Directions	147
4.6.3	Cost-Effectiveness and Industry Impact	148
4.6.4	Closing the Research Loop	148
5	Deep Learning for Asphalt Surface Texture Prediction.....	150
5.1	Introduction.....	150
5.2	Data Sources	152
5.2.1	Laboratory-Prepared Asphalt Slab Dataset (Set A)	152
5.2.2	Composite Dataset (Set B).....	152
5.2.3	On-site Road Surface Dataset (Set C).....	152
5.3	Methodology	153
5.3.1	Data Collection and Instrumentation	153
5.3.2	Image Processing Pipeline	153
5.3.3	Classification and Regression Strategies	158
5.4	Deep Learning Model Development.....	160
5.4.1	Classification Model Architecture Design.....	160
5.4.2	Hyperparameter and Architecture Optimization.....	163
5.5	Results and Analysis	164

5.5.1	Parameter Optimization Results and Analysis.....	164
5.5.2	Classification Strategies and Model Performance Analysis	172
5.5.3	Dataset-Specific Performance in Regression Analysis.....	180
5.5.4	Comparative Analysis of Classification, Regression, and Traditional Methods	184
6	Comprehensive Discussion: Integrating CT Mechanisms, Virtual Modeling, and Deep Learning for Asphalt Texture Engineering.....	188
6.1	Research Gaps Addressed and Objectives Fulfilled	188
6.2	Synergistic Integration of Three Research Stages: A Holistic Analytical Framework.....	189
6.3	Theoretical Contributions: A Tripartite Digital Representation Framework	190
6.4	Quantitative Synergy and Industry Impact	190
6.5	Methodological Limitations and Future Directions	191
7	Conclusion.....	193
7.1	Stage 1: CT-Based Void-Texture Mechanism Analysis.....	193
7.2	Stage 2: Virtual Texture Simulation and Validation.....	193
7.3	Stage 3: DL-Driven Automated Texture Recognition	194
7.4	Integrative Framework and Synergistic Impact	195
8	Future Research Directions	196
8.1	Multimodal Data Fusion for Cross-Scale Texture Characterization.....	196
8.2	Environmentally Robust Deep Learning with Domain Adaptation.....	196

8.3	Advanced Virtual Modeling with Realistic Aggregate Morphology....	197
8.4	Lifecycle Texture Degradation Modeling.....	197
8.5	Industry Collaboration and Digital Infrastructure.....	198
	References.....	199
	Forthcoming Publications	227
	Appendices.....	228
	Chapter 3: Void Properties and Macrotexture Correlation.....	228
	Chapter 4: MPD-MTD Modeling via Virtual Asphalt and Experimental Validation	236
	Chapter 5: Deep Learning for Asphalt Surface Texture Prediction	245

List of Figures

Figure 1: Typical Structure of Asphalt Roads (Asphaltadvantages, 2021)	38
Figure 2: Composition of Asphalt Mixture (Kamaluddin, 2008).....	39
Figure 3: Properties of Void Shapes (Norhidayah et al., 2014)	51
Figure 4: Schematic of Surface Texture Depth Definition (ISO, 2019).....	53
Figure 5: Key Parameters of Pavement Surface Profile (ISO, 2019).....	54
Figure 6: Classification of Pavement Texture by Wavelength (Lu & Harvey, 2011).....	55
Figure 7: Schematic of MPD and ETD Calculation Parameters (ISO, 2002)	56
Figure 8: Linear Interpolation of Invalid Data Points (ISO, 2019)	60
Figure 9: Effect of Slope and Offset Suppression (ISO, 2002).....	61
Figure 10: Hanning Window and SCBW Applications (ISO, 2008).....	62
Figure 11: Sand Patch Test for Texture Depth Measurement (Emin Kutay, 2017)	67
Figure 12: CTM for Multi-Directional Profile Scanning (Tatari, Costello, & Wilson, 2016)	68
Figure 13: Ames Engineering Laser Texture Scanner.....	69
Figure 14: Asphalt Mixture CT Slices: (a) Threshold Segmentation (Binary Void-Solid Separation); (b) Weka Segmentation (Three-Phase Classification)	74
Figure 15: Finite Element Analysis of Pavement Model (Pavement Interactive, 2021)	76
Figure 16: Discrete Element Model of Asphalt Mixture (Peng, Harvey, & Sun, 2017)	77
Figure 17: Aggregate Creation and Compaction in Virtual Asphalt	78
Figure 18: 3D Model of Virtual Aggregate Skeleton and Asphalt Mixture in Mixlab	79
Figure 19: Sample Domain Generated by the ISA Method (Chiarelli et al., 2015)	79

Figure 20: 2D to 3D Conversion Process in the ISA Method (Chiarelli et al., 2015)	80
Figure 21: Cylindrical Asphalt Specimens Manufactured via the Marshall Method	98
Figure 22: ROI for Void Topology Analysis. (a) 3D Schematic Representation of ROI. (b) Top View. (c) Side View.	101
Figure 23: Comparison of Original and Segmented Asphalt CT Images. (a) Original CT Slice. (b) Segmented Slice with Color-Coded Components.....	102
Figure 24: Segmentation and 3D Representation of Asphalt Components. (a) Air Voids. (b) Mastic. (c) VMA. (d-f) 3D Structural Representations of Segmented Components.	103
Figure 25: Visualization of an Isolated Void: (a) Planar Representation of an Independent Void. (b) 3D Illustration of the Void with Largest Inscribed Sphere.	105
Figure 26: 3D Model and Sectioned Profiles of Asphalt Surface	107
Figure 27: Example of a Processed Profile for Macrotexture Analysis	107
Figure 28: Average Void Diameter as a Function of Number of CT Images.....	108
Figure 29: Tortuosity Measurements Relative to Number of CT Images	109
Figure 30: 3D Reconstruction of Air Voids in Sample ROI. (a) Sample 5. (b) Sample 11. .	111
Figure 31: Relationship Between Air Void Content and the Euler Number	112
Figure 32: 3D Reconstruction of Air Voids. (a) Sample 5. (b) Sample 9	114
Figure 33: Comparison of MPD_{CT} with Average Void Diameter and Void Perimeter. (a) MPD_{CT} vs. Average Void Diameter (2D). (b) MPD_{CT} vs. Void Perimeter.	117
Figure 34: Illustration of the Relationship Between Surface Texture and Void Dimensions (Diameter and Perimeter)	118
Figure 35: Correlation Between Average Void Diameter, Volume of the biggest Air Void, and MPD_{CT}	120

Figure 36: (a) Laser Texture Scanner Measurement Area (b) Sand Patch Test Area	126
Figure 37: Flowchart of the ISA Algorithm	128
Figure 38: Comparison of CT Scans of Real and Virtual Asphalt Samples.....	130
Figure 39: Rectangular Slice Analysis for MPD_{ISA} Measurement	132
Figure 40: Internal Void Areas Connected to External Edge Profiles.....	132
Figure 41: 3D Structure of Virtual Asphalt Air Voids	134
Figure 42: Impact of Laser Line Count on Texture Representation.....	136
Figure 43: Measurement Differences in Dry vs. Wet Asphalt Surfaces.....	136
Figure 44: Multivariate Regression Model for MTD_{SPT} Prediction	139
Figure 45: Comparison of Measured MTD_{SPT} vs. Predicted MTD_{ISA}	140
Figure 46: Predictive Models for MTD_{SPT} Based on Multiple Parameters	141
Figure 47: Correlation Between MPD and Average Void Diameter.....	143
Figure 48: Correlation between MPD and MTD in Laboratory-Prepared Slabs and Virtual Asphalt Samples	145
Figure 49: Workflow Diagram: From Data Collection to Model Evaluation	151
Figure 50: Imaging and Processing for Sets A and C: Before and After Cropping	154
Figure 51: On-Site Imaging and Processing for Set B: Before and After Cropping	155
Figure 52. Visualization of Image Filling Techniques, with the Red Dashed Line Demarcating the Original Image Area after Offset.....	157
Figure 53: Classification Model Architecture Schematic.....	161
Figure 54: Performance Trends Across Various Model Architectures	166

Figure 55: Learning Rate Impact on Model Performance	168
Figure 56: Momentum Parameter Impact on Model Performance	169
Figure 57: Model Performance Variation Over Training Epochs	170
Figure 58: Resolution Impact on Model Accuracy	170
Figure 59: Non-Overlapping MPD _{LS} Classification Accuracy Across Datasets	175
Figure 60. Overlapping MPD _{LS} Classification Accuracy Across Datasets	179
Figure 61: Predicted MPD _{VGG} vs. True MPD _{LS} Values for Set A.....	181
Figure 62: Predicted MPD _{VGG} vs. True MPD _{LS} Values for Set B	182
Figure 63: Predicted MPD _{VGG} vs. True MPD _{LS} Values for Set C	183
Figure 64: Visual Representation of Domain Configurations with Different Maximum Aggregate Size	241
Figure 65: Comparison of the Extracted ROI from Virtual Asphalt and Real Samples.....	242
Figure 66: Correlation Between MPD and Void Perimeter.....	243
Figure 67: VGG19 Model Architecture Schematic	249
Figure 68: Saliency Map Visuals for Varied MPD _{LS} in Convolutional Network Layers	251
Figure 69: Accuracy Results with Shift Augmentation Techniques	270
Figure 70: Impact of Dropout Regularization on Model Accuracy.....	271

List of Tables

Table 1: Octave and One-Third-Octave Band Standards for Texture Analysis (ISO, 2002) ..	64
Table 2: Initial Texture Depth Requirements for Chipped Hot Rolled Asphalt and Other Surfacing (England, 2020).....	69
Table 3: Pearson Correlation Coefficients for MPD_{CT} , Wavelength, and Topological Properties	114
Table 4: Linear Regression Models for Predicting MPD_{CT}	118
Table 5: Impact of Image Augmentation Techniques on Accuracy	170
Table 6: Accuracy Performance Across Distinct MPD_{LS} Range Classifications for Set A...	173
Table 7: Accuracy Performance Across Distinct MPD_{LS} Range Classifications for Set B...	173
Table 8: Accuracy Performance Across Distinct MPD_{LS} Range Classifications for Set C...	173
Table 9: Accuracy Performance Across Overlapping MPD_{LS} Range Classifications for Set A	177
Table 10: Accuracy Performance Across Overlapping MPD_{LS} Range Classifications for Set B	177
Table 11: Accuracy Performance Across Overlapping MPD_{LS} Range Classifications for Set C	177
Table 12: Composition of Analysed Asphalt Cores	229
Table 13: Analysis of Air Voids and Macrotexture Properties in Asphalt Mixtures	230
Table 14: Pearson Correlation Coefficients Between Air Void (bottom, grey) and VMA Topologies (top, yellow)	232
Table 15: Pearson Correlation Coefficients Between Air Voids and VMA Properties.....	233

Table 16: Linear Prediction Model for MPD _{CT} (Excluding Outliers)	234
Table 17: Linear Prediction Model for Wavelength (Excluding Outliers).....	234
Table 18: Composition and Texture Measurements of Asphalt Slabs	237
Table 19: Data Comparison Between Real CT-Measured Cores and Virtual ISA-Generated Asphalt Mixtures	242
Table 20: Virtual ISA-Generated Asphalt Mixture Data for Slabs	243
Table 21: MPD _{LS} Results from Laser Measurements of Slabs.....	246
Table 22: Characteristics and Data Collection Methods of Asphalt Surface Datasets	247
Table 23: Model Performance Across Various Architectures.....	268
Table 24: Model Performance with Various Normalization Parameters.....	269
Table 25: Comparative Accuracies with Different Regularization Techniques	270
Table 26: Classification Prediction Results of Set A	271
Table 27: Classification Prediction Results of Set B.....	277
Table 28: Classification Prediction Results of Set C.....	287
Table 29: Classification Prediction Results of Combined Set.....	288
Table 30: Non-overlapping Classification of Seven Classes in Set A.....	289
Table 31: Non-overlapping Classification of Seven Classes in Set B.....	290
Table 32: Non-overlapping Classification of Seven Classes in Set C	291
Table 33: Overlapping Classification of Eight Classes in Set A	292
Table 34: Overlapping Classification of Eight Classes in Set B	293
Table 35: Overlapping Classification of Eight Classes in Set C	294

Table 36: Regression Prediction Results of Set A.....	295
Table 37: Regression Prediction Results of Set B.....	296
Table 38: Regression Prediction Results of Set C.....	296
Table 39: Regression Prediction Results of Combined Set.....	297

Notations

2D	–	Two-dimensional
3D	–	Three-dimensional
AI	–	Artificial Intelligence
AC	–	Asphalt Concrete
APT	–	Accelerated Pavement Testing
AVC	–	Air Void Content
AVD	–	Average Void Diameter
CNNs	–	Convolutional Neural Networks
CRMA	–	Cold Recycled Asphalt Mixture
CT	–	Computed Tomography
CTM	–	Circular Track Meter
D	–	Fractal Dimension
DE	–	Differential Evolution
DEM	–	Discrete Element Method
DL	–	Deep Learning
DMRB	–	Design Manual for Roads and Bridges
DNN	–	Deep Neural Networks
DQN	–	Deep Q-Networks
DSMs	–	Digital Surface Models
ELU	–	Exponential Linear Unit
EN	–	Euler Number
ETD	–	Estimate of the MTD
FC	–	Fully Connected Layer
FEM	–	Finite Element Method
F-SMA	–	Fiber-reinforced SMA
GAN	–	Generative Adversarial Networks
GELU	–	Gaussian Error Linear Units
GNN	–	Graph Neural Networks
HMA	–	Hot Mix Asphalt
HRA	–	Hot Rolled Asphalt
IL	–	Investigatory Levels
ISA	–	Intersected Stacked Air Voids

JMAK	–	Johnson–Mehl–Avrami–Kolmogorov
LSTM	–	Long-Short-Term Memory Networks
LTS	–	Laser Texture Scanner
M	–	Macroporosity
MAE	–	Mean Absolute Error
MAS	–	Maximum Aggregate Size
MCHW	–	Manual of Contract Documents for Highway Works
ML	–	Machine Learning
MPD	–	Mean Profile Depth
MPD _{CT}		MPD Based on Computed Tomography Measurement
MPD _{ISA}		MPD Measured by Intersected Stacked Air Voids Method
MPD _{VGG}		MPD Based on VGG Regression Prediction
MSE	–	Mean Squared Error
MTD	–	Mean Texture Depth
MTD _{SPT}		MPD Based on Sand Patch Test
MTD _{ISA}		MPD Measured by Intersected Stacked Air Voids Method
NA	–	Number of Aggregates
OBC	–	Optimal Binder Content
OEM	–	Original Equipment Manufacturer
OGFC	–	Open-Graded Friction Courses
PA	–	Porous Asphalt
PG	–	Performance Grading
PN	–	Percolation Number
PReLU	–	Parametric Rectified Linear Unit
PSD	–	Power Spectral Density
R ²	–	Percentage of Variation in the Response
R ² (adj)	–	Percentage of Adjusted Variation in the Response
R ² (pred)	–	Degree of Prediction of the Regression Model
RAP	–	Reclaimed Asphalt Pavement
ReLU	–	Rectified Linear Unit
ResNet	–	Residual Networks
RMS	–	Root Mean Square
RNN	–	Recurrent Neural Networks

ROI	–	Region of Interest
S	–	Standard Deviation
SAR	–	Surface Area Ratio
SCBW	–	Split Cosine Bell Window
SGC	–	Superpave Gyratory Compactor
SGD	–	Stochastic Gradient Descent
SLP	–	Stationary Laser Profilometer
SMA	–	Stone Mastic Asphalt
SPT	–	Sand Patch Test
SRV	–	Skid Resistance Value
T	–	Tortuosity
TSA	–	Texture Spectral Analysis
UAV	–	Unmanned Aerial Vehicle
V _a	–	Air Voids
VAR	–	Void Aspect Ratio
VAV	–	Volume of the Biggest Air Void
VC	–	Void Circularity
VEM	–	Void Expansion Method
VGG	–	Visual Geometry Group
VM	–	Volume of Mastic
VMA	–	Voids in Mineral Aggregate
VP	–	Void Perimeter
VR	–	Void Roundness
Weka	–	Waikato Environment for Knowledge Analysis
WMA	–	Warm Mix Asphalt
λ	–	Wavelength

1 Introduction

1.1 Research Context and Significance

1.1.1 Asphalt Pavements: Fundamental Composition and Functional Requirements

Asphalt pavements, comprising 91–97% aggregates and 3–9% bituminous binder by mass (Tian, Shukla, Nie, Zhan, & Liu, 2018), rely on aggregate skeleton load resistance and binder cohesion for mechanical integrity (Özgan, Serin, & Kap, 2013). Their performance hinges on surface texture and internal void properties, which govern safety, durability, and operational efficiency.

1.1.2 Critical Role of Surface Texture in Pavement Performance

Surface texture—defined as deviations from an ideal plane (ISO, 2019)—influences multifaceted performance metrics:

- **Safety:** Tire-pavement friction (wet/dry conditions) (Marsac & Delanne, 2004), skid resistance (Noyce, Bahia, Yambo, & Kim, 2005; Pranjić, Deluka-Tibljaš, Cuculić, & Šurdonja, 2020).
- **Sustainability:** Rolling resistance (Sohaney & Rasmussen, 2013), fuel economy (Miller, Swiertz, Tashman, Tabatabaee, & Bahia, 2012), and greenhouse gas emissions (Wang, Harvey, & Kendall 2014).
- **User Experience:** Noise reduction (Praticò, Vaiana, & Iuele, 2013; Praticò, Vaiana, & Fedele, 2015), driving comfort (Delanne & Daburon, 1999; Praticò & Vaiana, 2015).
- **Maintenance:** Wear mechanisms (Domenichini & Martinelli, 2004), particulate emissions (China & James, 2012), and lifecycle costs (Bendtsen, 2004).

1.2 Texture Classification and Current Challenges

1.2.1 Multiscale Texture Hierarchy

Textures are classified by wavelength (ISO, 2019), each impacting pavement performance differently (ISO, 2008).

- **Microtexture ($\lambda \leq 0.5 \text{ mm}$):** Governed by aggregate mineralogy, enhancing low-speed friction (Forster, 1989; ISO, 2002).
- **Macrotexture ($0.5 \text{ mm} \leq \lambda \leq 50 \text{ mm}$):** Dictated by coarse aggregate distribution, critical for high-speed skid resistance, drainage, and noise mitigation (ISO, 2002; Torbruegge & Wies, 2015).
- **Mega-texture ($50 \text{ mm} \leq \lambda \leq 500 \text{ mm}$)/Unevenness ($\lambda \geq 500 \text{ mm}$):** Affect rolling resistance, in-vehicle noise, vehicle wear, and ride quality (McLean & Foley, 1998; ISO, 2002).

1.2.2 Design Challenges in Texture Control

In asphalt design, controlling surface texture remains challenging due to the complex coupling of multiple factors, such as void distribution, aggregate gradation, binder type, and material properties (Chen, Han, Ling, & Su, 2017; Karyawan, Widyatmoko, Ekaputri, & Ahyudanari, 2022). Traditional trial-and-error methods rely on empirical adjustments and numerous rounds of experiments, which are time-consuming and inefficient, as they fail to accurately predict texture changes caused by parametric variations (e.g., binder spread rate, aggregate shape) (Sarsam, 2020; Karyawan et al., 2022).

1.2.3 Limitations of Conventional Measurement Methods

Current texture measurement techniques—predominantly volumetric patch tests (e.g., Sand Patch Test, SPT) and 2D profilometers (e.g., laser scanning)—exhibit critical limitations that hinder their accuracy, efficiency, and applicability in modern pavement engineering:

1.2.3.1 Incomplete Multiscale Characterization and Method-Specific Biases

• 2D Profilometers

While these devices efficiently capture longitudinal texture profiles (e.g., Mean Profile Depth, MPD) over a 100 mm baseline, they are inherently 2D, failing to characterize void properties (e.g., connectivity, tortuosity) and volumetric properties (e.g., air void content, Voids in Mineral Aggregate, VMA) collectively influence macrotexture (Rajaei, Sefidmazgi, & Bahia, 2014; Torbruegge & Wies, 2015). Their reliance on linear scans neglects the 3D interplay between texture peaks, valleys, and internal voids,

which is critical for predicting tire-pavement friction under dynamic loading (Losa, Leandri, & Bacci, 2010; Tomiyama & Moriishi, 2020).

- **Volumetric Patch Methods**

These techniques provide a surrogate 3D metric (Mean Texture Depth, MTD) by approximating surface void volume via granular material spreading (ISO, 2002). However, they are surface-dependent: on non-compact or highly porous surfaces (e.g., open-graded friction courses), sand or glass spheres may infiltrate deeper voids, leading to overestimated MTD_{SPT} values due to uncontrolled particle embedding (Rajaei et al., 2014; ISO, 2019). Manual spreading introduces operator subjectivity, and the method requires closed traffic lanes, making it impractical for high-traffic corridors or large-scale monitoring (Praticò & Vaiana, 2015; Liang, Gu, Chen, Ni, & Zhang, 2020).

- **Correlation Challenges Between MPD and MTD in Texture Prediction**

While prior studies suggest linear correlations between MPD and MTD under controlled conditions (Yaacob, Hassan, Hainin, & Rosli, 2014), material gradation, binder content, and traffic loads introduce nonlinearity, complicating predictive modeling (Wang, Chu, & Fwa, 2022), and existing models struggle to generalize across diverse engineering scenarios.

1.2.3.2 High Equipment Costs and Specialized Operation Requirements

- **Advanced 3D Techniques:**

While technologies like X-ray computed tomography (CT) enable 3D visualization of void networks, it is constrained by sample size and destructive physical coring. Additionally, CT demands high-cost equipment and specialized technical expertise for data reconstruction and topological analysis (Zhang & Li, 1996; Sommacal, Matschinski, Holmes, Drechsler, & Compston, 2023). Similarly, 3D laser scanners capable of capturing megatexture require rigorous calibration, post-processing software, and trained operators to mitigate environmental noise (Hlotov & Marusazh, 2019).

- **Multidimensional Imaging and Multi-View Photography:**

Emerging methods using multi-angle cameras or structured-light systems to reconstruct 3D surface topography offer improved texture characterization but rely on sophisticated

image alignment algorithms and high-resolution cameras, increasing equipment costs compared to 2D profilometers (Liu, Gong, & Zhang, 2015; Liu et al., 2021). These systems also demand complex data fusion workflows, as misalignment between views can introduce artifacts in 3D meshes, compromising texture parameter calculations (Xiang, Zhang, & Wu, 2022).

1.2.3.3 Field Measurement Challenges

- **Environmental Sensitivity**

Both 2D and 3D methods degrade in wet or contaminated conditions: Laser profilometers suffer from specular reflection on water-covered surfaces, while volumetric tests experience particle clumping, rendering data unreliable (Dan, Lu, & Li, 2024). Such limitations restrict their use to dry, clean environments, which are incompatible with real-world pavement monitoring, where weather and debris are omnipresent.

- **Operational Inefficiency**

Traditional methods are labor-intensive: a single Sand Patch Test requires 15–20 minutes per location (ISO, 2002), while 2D profilometry surveys of a 1 km road segment demand 2–3 hours of traffic closure. This inefficiency contrasts with the need for network-level texture mapping, highlighting a critical gap between measurement capabilities and infrastructure management demands (Wang et al., 2022).

1.3 Innovative Approaches

Traditional texture measurement methods are often complex (Liang et al., 2020), costly (Ganji, Golroo, Sheikhzadeh, Ghelmani, & Bidgoli, 2019), and susceptible to human error (Yu, Cao, & Zhao, 2023; Dan et al., 2024), complicating road maintenance and decision-making. To address these limitations, this thesis leverages various transformative technologies:

1.3.1 The Intersected Stacked Air Voids (ISA) method

ISA utilizes geometric principles to create virtual pore networks that simulate the properties of asphalt mixtures. By inputting specific geometric parameters, the ISA method enables the generation of tailored virtual asphalt mixtures, reducing the reliance

on field testing (Chiarelli, Dawson, & Garcia, 2015; Aboufoul, Chiarelli, Triguero, & Garcia, 2019).

1.3.2 Deep Learning (DL) with Convolutional Neural Networks (CNNs)

DL has revolutionized medical imaging (Tajbakhsh et al., 2016; Wu, Lin, Wang, & Wu, 2020), facial recognition (Pai, Balrai, Mogaveera, & Aeloor, 2018), and autonomous driving (Bojarski et al., 2016). CNNs automatically extract hierarchical image features from 2D asphalt surfaces, enabling data-driven classification of MPD_{LS} ranges and regression prediction, overcoming the limitations of traditional methods (Li, Karpathy, & Johnson, 2015; Krizhevsky, Sutskever, & Hinton, 2017).

Among the prominent CNN architectures, the Visual Geometry Group (VGG) model, introduced by Simonyan and Zisserman, enhances CNN architecture with a deep network structure of multiple convolutional, pooling, and fully connected layers using small 3x3 filters (Simonyan & Zisserman, 2014). This architecture improves the extraction and analysis of fine image features and has been applied to various engineering tasks, including pavement defect detection (Mandal, Uong, & Adu-Gyamfi, 2018; Hoang & Tran, 2022; Que et al., 2023). However, prior studies on asphalt surface texture often relied on complex multi-view or three-dimensional data collection (Liu et al., 2021), underscoring the need for simpler and more efficient evaluation models.

These approaches address the critical need for non-invasive, efficient, and environmentally robust texture evaluation, bridging the gap between microscale void properties and macroscale performance metrics.

1.4 Research Aim and Objectives

1.4.1 Overarching Aim

This thesis presents a three-stage research framework to systematically address the challenges in asphalt texture control, integrating microscale void analysis, virtual modeling, and artificial intelligence. By establishing a data-driven pipeline from CT-based mechanism discovery to field-deployable deep learning (DL) tools, the research aims to overcome the limitations of traditional measurement methods and propel the field of asphalt pavement design and monitoring towards intelligence.

1.4.2 Stage-Specific Objectives

1.4.2.1 Fundamental Research: CT-Based Void-Texture Mechanism Analysis

Objective: Decode the quantitative relationship between void topology and surface texture to lay the mechanistic foundation for texture control.

Method:

- X-ray CT scanning is used to characterize 3D void properties (e.g., macroporosity, connectivity, morphological characteristics) and macrotexture (MPD_{CT} , wavelength) in asphalt cores (3–23% void range).
- Multivariate regression analysis establishes statistical correlations between void metrics (e.g., average void diameter) and macrotexture indices (MPD_{CT}).

Impact: Reveal the micro-macro coupling mechanism by linking void morphological features (e.g., spherical vs. elongated voids) to texture formation. Establish a foundation for texture design via void topology.

1.4.2.2 Method Innovation: Virtual Modeling to Replace CT-Based Experiments

Objective: Validate cost-effective virtual asphalt models to simulate texture structure, reducing reliance on high-cost CT scanning and trial-and-error experiments.

Method:

- Validate the nonlinear MPD_{LS} - MTD_{SPT} relationship using laboratory-prepared slabs with varied gradations, binder contents, and air voids (1–27% void range).
- Employ the Intersected Stacked Air Voids (ISA) Approach to reconstruct virtual aggregates and void networks, simulating how maximum aggregate size and void content influence texture depth.

Impact: A geometry-based virtual testing platform that measures the texture-void relationship compared to CT-derived results. The bridge between mechanistic analysis and computational design through virtual validation of mixture designs.

1.4.2.3 Application Translation: Deep Learning for Automated Texture Recognition

Objective: Develop a universally applicable deep learning (DL) tool to enable real-time, non-destructive texture assessment on-site, eliminating dependency on specialized equipment while addressing both rapid screening and precise quantification needs.

Method:

- Curate a multi-source dataset of 4600 asphalt surface images with annotated MPD_{LS} values (collected from lab slabs and field pavements).
- Dual-Model Architecture Development, outperforming traditional measurements in efficiency and operability:
 - Develop a lightweight VGG-based CNN architecture to predict the MPD_{LS} range from 2D images.
 - Leverage a deeper 19-layer VGG architecture to predict exact MPD_{VGG} values from monocular surface images.

Impact:

- The laptop-deployable DL model for asphalt surface texture prediction via smartphone/iPad images. Replace costly professional measuring equipment with "capture-and-predict" workflows, suitable for network-level monitoring and maintenance prioritization.
- This dual-model approach balances computational efficiency (lightweight VGG for rapid range estimation) and precision (VGG19 for sub-millimeter MPD_{VGG} prediction), addressing diverse operational needs in field inspection and laboratory analysis.

1.4.3 Progressive Research Pipeline

- **Stage 1 → Stage 2:** Virtual models replace CT for void analysis. CT-derived void-texture correlations inform the calibration of virtual models, ensuring computational simulations reflect real texture structure.
- **Stage 2 → Stage 3:** DL replaces laser scanning for on-site validation.

Slab datasets augment the DL training pool, enabling the model to generalize across diverse mixtures and compare differences between lab-controlled mixes and real-world pavement.

- **End-to-End Impact:** The pipeline transitions from mechanism discovery (CT) to computational design (virtual models) and finally to operational deployment (DL), creating a closed-loop solution for texture-centric asphalt engineering.

By structuring research around this three-stage framework, the thesis addresses fundamental scientific gaps (void-texture coupling) and practical industry needs (cost, efficiency, scalability), positioning digital tools as indispensable assets for next-generation pavement management.

1.5 Thesis Structure

The thesis is structured as a cohesive three-stage research framework, integrating empirical analysis, computational modeling, and artificial intelligence to address critical gaps in asphalt texture engineering. Each chapter builds upon the previous, forming a closed-loop pipeline from fundamental mechanism discovery to field-deployable solutions.

- **Chapter 2: Literature Review** synthesizes asphalt mixture design, void characterization, void-texture relationships, measurement techniques, digital methodologies, virtual modeling, and DL applications, identifying gaps in void-topology-texture couplings and low-cost assessment tools.
- **Chapter 3: CT-Based Void Analysis** establishes statistical links between void topology (e.g., average void diameter) and MPD_{CT} , validating the critical role of void topological properties in texture-centric asphalt design.
- **Chapter 4: Virtual Texture Simulation** introduces the ISA method to replicate CT-derived AVD - MPD_{CT} correlations, reducing reliance on costly physical testing and optimizing computational design. A log-normal regression model captures the nonlinear MPD_{LS} - MTD_{SPT} relationship, optimizing virtual texture prediction for open-graded mixtures.

- **Chapter 5: DL-Driven Texture Recognition** develops VGG-based CNN architectures for non-destructive texture prediction, replacing specialized scanning equipment with consumer devices. The dual-model architecture uses lightweight VGG for MPD_{LS} range classification and deeper VGG19 for sub-millimeter regression.
- **Chapter 6: Comprehensive Discussion** synthesizes the three-stage research framework, demonstrating how X-ray CT analysis establishes void-texture correlations, virtual modeling validates cost-effective texture prediction, and deep learning enables field-deployable texture assessment via consumer devices. The integrated framework reduces design cycles and cuts equipment costs.
- **Chapter 7: Conclusion** reinforces the three-stage framework's efficacy: Stage 1 decodes void-topology mechanisms via CT, Stage 2 validates virtual texture simulation, and Stage 3 deploys lightweight DL models for field applications. This closed-loop ecosystem bridges microscale void science with macroscale pavement management, enabling evidence-based texture optimization.
- **Chapter 8: Future Research Directions** focuses on multimodal data fusion for cross-scale texture modeling, environment-robust DL via domain adaptation, advanced virtual modeling with realistic aggregates, lifecycle texture degradation prediction, and industry-driven standardization—all aimed at enhancing practical applicability and sustainable infrastructure management.

The thesis innovates a transformative framework integrating CT, virtual modeling, and DL to revolutionize asphalt texture engineering. This work paves the way for intelligent, cost-effective pavement management by addressing fundamental research gaps and enabling scalable field solutions. Future directions aim to refine cross-scale modeling, environmental resilience, and industry integration for sustainable infrastructure development.

2 Literature Review

2.1 Introduction

Asphalt pavements are essential transportation infrastructure components, significantly influencing safety, durability, and operational efficiency through their surface texture and internal void characteristics (Noyce et al., 2005; Pranjić et al., 2020). Surface texture—defined as the deviations from an ideal planar surface (ISO, 2019)—governs critical functional properties such as tire-pavement friction, noise emission, and surface drainage (Praticò & Vaiana, 2015; Song, Yun, Ye, & Gao, 2024). This literature review systematically examines asphalt mixtures, focusing on their volumetric properties, topological features, measurement methodologies, and the role of advanced technologies like DL in texture analysis. This review informs the thesis's research objectives and analytical framework by synthesizing existing research, identifying knowledge gaps, and establishing theoretical foundations.

2.2 Materials and Performance of Asphalt Pavements

Globally, asphalt pavement systems represent a cornerstone of modern transportation infrastructure, facilitating urban development and socioeconomic connectivity. As the uppermost structural layer of roads (Figure 1), asphalt materials dominate pavement construction due to their versatility and performance advantages. Approximately 100 million tons of asphalt are produced annually for road building (Jamshidi, Hamzah, Kurumisawa, Nawa, & Samali, 2016), with over 90% of European road networks and 95% of UK road surfaces utilizing asphalt (Tian et al., 2018; AIA, 2021). Compared to concrete alternatives, asphalt pavements offer distinct benefits: they provide smooth riding surfaces, enhance skid resistance, reduce traffic noise, exhibit long-term durability, and enable full recyclability—qualities that solidify their status as an ideal pavement material for the foreseeable future (AIA, 2021).

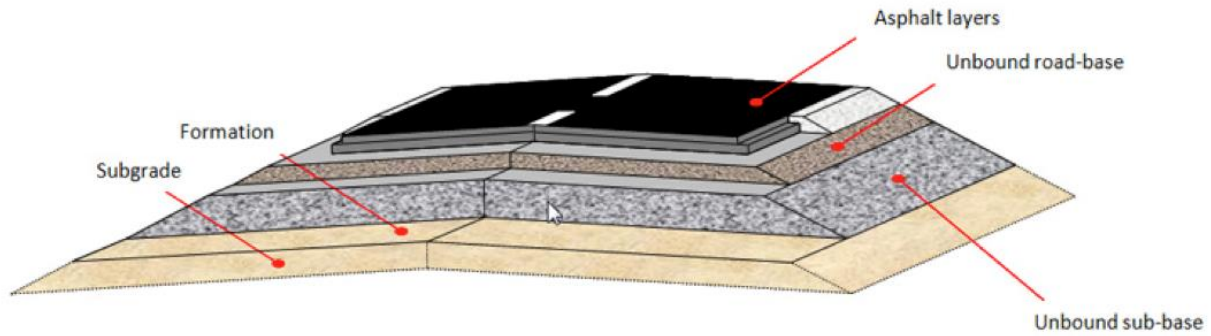


Figure 1: Typical Structure of Asphalt Roads (Asphaltadvantages, 2021)

The functional performance of asphalt pavements hinges prominently on surface texture, defined as "the geometric deviations of the pavement from a true planar surface" (ISO, 2019). This texture directly influences tire-pavement interaction, affecting safety-critical parameters like friction and hydroplaning resistance, as well as environmental factors such as noise propagation (Chen, Roohi Sefidmazgi, & Bahia, 2015; Praticò & Vaiana, 2015). Concurrently, research has established a strong correlation between the air void characteristics of asphalt mixtures [25] and their surface texture (Rajaei et al., 2014). Excessive air void content—often linked to premature pavement distress—impacts mechanical properties and permeability, underscoring the need to investigate the relationship between specific volumetric properties (e.g., void distribution, connectivity) and surface texture (Wang & Ying, 2000). Such analysis clarifies how microstructural features influence macroscale performance, providing a basis for optimizing mixture design and enhancing pavement longevity (Noyce et al., 2005).

2.3 Asphalt Mixtures: Composition and Structural Components

Asphalt mixtures represent heterogeneous multi-phase composite materials, consisting of aggregates and fillers embedded within a binder matrix, with void spaces distributed throughout the microstructure (Wan, Zhang, Wang, Wu, & Wu, 2010; Gu, Wang, & Yang, 2016). This structural configuration endows asphalt pavements with mechanical stability: aggregates resist shear forces, while the binder (bitumen) and fillers provide cohesive strength and durability (Tian et al., 2018). Common aggregate materials include crushed stone, sand, gravel, and industrial byproducts like slag (AIA, 2021).

2.3.1 Historical Evolution of Asphalt Compositions

Early developments in asphalt pavement technology can be traced to the early 19th century in the UK, where coal tar was initially used as a binding agent (Pavement Interactive, 2021). However, safety and environmental considerations led to the adoption of petroleum-derived bitumen as the primary binder by the late 20th century—a material now valued for its full recyclability and consistent performance (AIA, 2021). Modern asphalt mixtures follow a three-component framework (Figure 2) (Tian, 2018): aggregates (91–97% by mass), bitumen (3–9%), and voids (Investopedia, 2021), with optional modifiers (e.g., polymers, fibers, or rubber) incorporated to enhance specific properties such as fatigue resistance or thermal stability (Qian, 2003; Tian, 2010; Li, Li, Fan, Li, & Yan, 2018).

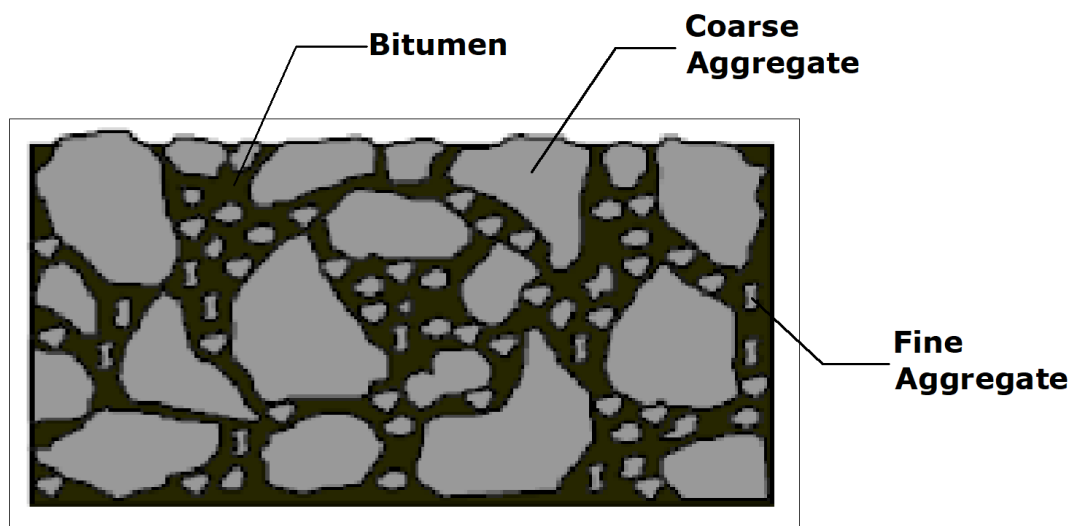


Figure 2: Composition of Asphalt Mixture (Kamaluddin, 2008)

2.3.2 Aggregate Structure and Function

Aggregates serve as the skeletal framework of asphalt mixtures, accounting for most of the material's volume. They include both natural aggregates (e.g., granite, limestone) and synthetic/Recycled materials (e.g., steel slag, recycled concrete), provided they meet strict physical property requirements (e.g., hardness, shape, and gradation) (Collop & Airey, 2009). Through inter-particle frictional resistance, aggregates form a load-bearing structure stabilizing the mixture under traffic loading (Qian, 2003).

- Coarse Aggregates (particles >25 mm, with maximum sizes up to 63 mm) dominate the skeleton structure. Increasing their content or particle size enhances

interlock and load-bearing capacity by expanding contact areas and reinforcing mechanical interconnections (Pan, 2010).

- Fine Aggregates (particles <25 mm) fill voids between coarse particles, densifying the mixture and improving structural homogeneity. The gradation (size distribution) and aggregates' angularity significantly influence macroscopic properties such as compressive strength, fatigue resistance, and surface texture (Pan, 2010).

2.3.3 Bitumen: The Binding Matrix

Bitumen, a viscous, black hydrocarbon-based binder derived from crude oil distillation, acts as an adhesive and lubricant in asphalt mixtures (Zeng & Wu, 2008; Hesami, Jelagin, Kringos, & Birgisson, 2012). Its dual nature—fluid at elevated temperatures (facilitating workability and coating of aggregates) and semi-solid at ambient conditions (providing structural integrity)—is critical for mixture cohesion (Nijboer, 1948; Bitumen, 1990; Chadbourn et al., 1998). Key properties such as viscosity, elasticity, and temperature susceptibility directly impact pavement performance:

- High-temperature fluidity enables uniform aggregate coating and workability during construction (Qian, 2003; Matos, Micaelo, Duarte, & Quaresma, 2014).
- Low-temperature stiffness affects resistance to cracking, while intermediate-temperature behavior governs fatigue life (Miljković & Radenberg, 2015; Pszczola & Szydlowski, 2018). Bitumen classification often relies on penetration tests, which measure its hardness at standard temperatures, guiding selection for specific climatic and traffic conditions (Asphalt Institute, 2014).

2.3.4 Fillers: Microstructural Enhancers

Fillers—fine particulate materials (typically $\leq 10\%$ by mass, with particle sizes <4 mm)—play a pivotal role in optimizing binder-aggregate interactions (Qian, 2003). Though often grouped with aggregates due to their mineral origin, fillers differ in that they lack inter-particle contact and instead form a composite with bitumen to enhance cohesion and stiffness (Dehdezi, Thodesen, Encinas, & Mengede, 2013). Common types include limestone powder, fly ash, and cementitious materials; active fillers (e.g.,

lime or cement) can chemically interact with bitumen, improving water resistance and long-term stability (Dash & Panda, 2018). By reducing voids and reinforcing the binder phase, fillers contribute to the mixture's resistance to deformation and environmental degradation.

2.3.5 Common Asphalt Mixture Types in Road Engineering

Modern road engineering designs asphalt mixtures by considering traffic, climate, and function. Below are typical asphalt mixture types and their engineering characteristics:

2.3.5.1 Asphalt Concrete (AC)

AC, the most widely used pavement material, combines continuously graded aggregates, asphalt, and filler. Based on the maximum density curve theory, its compact design ensures excellent resistance to deformation and water damage, making it suitable for all road types, especially under heavy traffic (Harvey, Deacon, Tsai, & Monismith, 1995; Wang, Hoyos, Wang, Voyiadjis, & Abadie, 2005).

2.3.5.2 Stone Mastic Asphalt (SMA) and Fiber-Reinforced Variants

SMA features a coarse aggregate skeleton (>70% volume) in a rich mastic with high binder content (6–7%), filler, and fibers. This structure offers superior rutting and skid resistance, which is ideal for high-stress areas (Qiu & Lum, 2006; Hainin, Reshi, & Niroumand, 2012). Fiber-reinforced SMA (F-SMA) further enhances binder retention and fatigue resistance, making it a top choice for demanding applications like bridge decks and bus lanes (Sheng et al., 2017; Kumar & Ravitheja, 2019).

2.3.5.3 Porous Asphalt (PA)

PA has 15–25% interconnected voids, enabling stormwater drainage and noise reduction. While effective for urban areas, it requires careful design with high-viscosity binders to balance permeability and durability (Liu & Cao, 2009; Ma, Li, Cui, & Ni, 2018).

2.3.5.4 Open-Graded Friction Course (OGFC)

OGFC, designed for high-speed and wet climates, has 18–25% voids for enhanced skid resistance and drainage. Polymer-modified asphalt boosts its cohesion but needs regular

maintenance to prevent void clogging (Mallick, Kandhal, Cooley Jr, & Watson, 2000; Gu, Watson, Moore, & Tran, 2018).

2.3.5.5 Warm Mix Asphalt (WMA)

WMA reduces production temperatures by 30–50°C using additives, cutting energy use and emissions. It offers mechanical properties similar to Hot Mix Asphalt (HMA) but requires careful mix design to balance workability and long-term durability (Rubio, Martínez, Baena, & Moreno, 2012; Kheradmand, Muniandy, Hua, Yunus, & Solouki, 2014).

2.3.5.6 Hot Rolled Asphalt (HRA)

HRA, a dense and impermeable mixture, uses high-viscosity binders to create a smooth, wear-resistant surface. Ideal for heavy-duty applications, it demands strict temperature control during compaction to avoid cracking (Zoorob & Cabrera, 1997; Subagio, Siswosoebrotho, & Karsaman, 2003).

2.3.5.7 Cold Recycled Asphalt Mixture (CRMA)

CRMA blends reclaimed asphalt with binders at ambient temperatures, providing an eco-friendly solution for base courses and low-traffic roads. Though less strong than hot mixes, its sustainability drives its adoption (Ma, Wang, Zhao, Huang, & Pi, 2015; Kuchiishi, Vasconcelos, & Bariani Bernucci, 2021).

2.4 Asphalt Mixture Design

The Marshall mix design method, initially developed by Bruce Marshall in 1939 and subsequently refined by the U.S. military, remains one of the most globally adopted frameworks for asphalt mixture design (White, 1985). This methodology focuses on determining the optimal binder content to achieve target stability and flow values, balancing mechanical performance with workability (Jiao & Tian, 2009). Core design stages—aggregate selection, gradation determination, binder specification, and volumetric property optimization—are systematically calibrated to meet project-specific performance requirements (Taylor, 2009).

2.4.1 Aggregate Selection and Gradation Design

Aggregates form the load-bearing skeleton of asphalt mixtures, requiring meticulous evaluation of physical properties: hardness, toughness, durability, particle shape, size distribution, and surface texture (Jiang, 1991). Contaminants must be rigorously controlled to avoid compromising interfacial bonding. Gradation—the proportional distribution of particle sizes—dictates the skeleton's interlock efficiency and void structure: continuous gradations promote dense packing (e.g., AC), while gap gradations enable permeable structures (e.g., PA) (Roberts, Kandhal, Brown, Lee, & Kennedy, 1991). Aggregate sources are selected based on mechanical robustness and compatibility with the binder, with gradation curves optimized to achieve target volumetric parameters (e.g., void ratio, mineral aggregate voids).

2.4.2 Binder Selection and Content Optimization

Binder selection follows the Superpave Performance Grading (PG) system, which classifies bitumen based on climatic conditions and traffic demands, integrating viscosity-temperature relationships to ensure rutting and cracking resistance (Certified Material Testing Products, 2021). The optimal binder content (OBC) is determined through an iterative process: initial estimates are derived from empirical charts, followed by preparation of specimens with varying binder contents ($\pm 0.5\%$ around the estimate). Performance tests (e.g., Marshall stability, flow, and volumetric analyses) then validate the OBC, balancing cohesion (to prevent raveling) and lubricity (to facilitate compaction) (Pavement Interactive, 2021).

2.4.3 Compaction Technology and Its Impact

Compaction is a critical process that densifies asphalt mixtures into stable, load-bearing structures by reducing air voids and enhancing particle interlock (Roberts et al., 1991). The degree of compaction directly influences pavement longevity: insufficient compaction accelerates water intrusion and oxidative aging, while excessive compaction causes aggregate breakage, reducing ductility and promoting fatigue cracking (Masad, Jandhyala, Dasgupta, Somadevan, & Shashidhar, 2002; Kakar, Hamzah, & Valentin, 2015). Two primary methods dominate laboratory and field practices, each yielding distinct microstructural characteristics (Hunter, Airey, & Collop, 2004; Iwama, Airey, & Hunter, 2007):

Marshall Compaction

The Marshall method employs a hammer to deliver vertical impacts (50–75 blows per face) to specimens in cylindrical molds at controlled temperatures (Watson, Brown, & Moore, 2005; Pavement Interactive, 2021). While widely used for its simplicity and low cost, this uniaxial impact mechanism produces specimens with higher stiffness and lower density than field conditions, as it does not replicate the shear stresses inherent in roller compaction (Mollenhauer & Wistuba, 2016). Its empirical nature makes it less suitable for performance-based designs requiring realistic stress-strain simulations.

Superpave Gyratory Compactor (SGC)

The SGC method more accurately mimics field compaction by applying axial pressure (600 kPa) and a 1.25° rotational angle at 30 revolutions per minute (Butcher, 1998). This shear-inducing action generates specimens with higher density ($\geq 98\%$ of theoretical maximum), lower air voids, and more representative mechanical properties compared to Marshall specimens (Wu & Zhang, 2011). The reduced binder demand in SGC-prepared mixtures enhances high-temperature stability and fatigue resistance, aligning with modern performance-based design criteria (Zhou, Wang, Zheng, & Bao, 2007; Jiao & Tian, 2009).

These methods highlight the tradeoff between test simplicity and mechanical fidelity. While Marshall compaction suffices for routine quality control, SGC is preferred for advanced mixture designs where realistic simulation of traffic-induced stresses is critical.

2.5 Volumetric Properties of Asphalt Mixtures

Accurate characterization of volumetric properties is fundamental to asphalt mixture design, directly influencing pavement performance indicators such as durability, skid resistance, and fatigue life (Sheng, 1996; Jia & Zhang, 2001; Lin & You, 2001). Key parameters govern the material's microstructural behavior and macroscopic response, including air void content, voids in mineral aggregate (VMA), maximum aggregate size, and mastic content (Hall et al., 2009). These properties guide mixture composition

design and underpin the three-dimensional digital reconstruction of asphalt samples (Wan et al., 2010).

2.5.1 Air Void Content (AVC)

AVC represents the interstitial spaces within the mixture not occupied by aggregates or binder, serving as a critical metric in all asphalt design frameworks. AVC directly impacts permeability, with high voids accelerating water intrusion and oxidative aging, while low voids reduce ductility and increase cracking susceptibility (Pavement Interactive, 2021). AVC is calculated by comparing the bulk density of a sealed specimen to the mixture's theoretical maximum density. Experimental measurements include:

Calculate the density of water as shown in Equation 1 (BS EN, 2012):

$$\text{Equation 1: } \rho_w = 1.00025205 + \frac{7.59 \times t - 5.32 \times t^2}{10^6}$$

Where

ρ_w : Density of water, [mg/m³];

t: Temperature of water, [°C].

Calculate the bulk density of the sealed sample as shown in Equation 2 (BS EN, 2012):

$$\text{Equation 2: } \rho_{bsea} = \frac{m_1}{\frac{m_2 - m_3}{\rho_w} - \frac{m_2 - m_1}{\rho_{sm}}} \times 100\%$$

Where

ρ_{bsea} : Bulk density sealed, [mg/m³];

m_1 : Mass of dry specimen in air unsealed, [g];

m_2 : Mass of dry specimen in air sealed in foil, [g];

m_3 : Mass in water, sealed in foil, [g];

ρ_w : Density of water, [mg/m³];

ρ_{sm} : Relative density of foil, [mg/m³].

Calculate the air void content of the asphalt mixture as shown in Equation 3 (BS EN, 2012):

Equation 3:
$$V_m = \frac{\rho_m - \rho_{bsea}}{\rho_m} \times 100\%$$

Where

V_m : Air void content of the mix, [%];

ρ_m : Maximum density of the mix, [mg/m³];

ρ_{bsea} : Bulk density sealed, [mg/m³].

2.5.2 Voids in Mineral Aggregate (VMA)

VMA refers to the total void space within the aggregate skeleton, encompassing air voids, binder, and fine aggregates not absorbed by the coarse fraction (Gao, 2006). Mathematically, VMA equals the sum of air voids and mastic volume, reflecting the mixture's compaction efficiency and aggregate interlock (Sun, 2016). Its calculation (Equation 4) integrates aggregate specific gravity and bulk density, providing insights into the structural integrity of the skeleton (GlobalGilson, 2021). High VMA indicates a more open aggregate structure, requiring increased binder content to maintain cohesion, whereas low VMA may limit binder retention and compromise durability.

The calculation of VMA is shown in Equation 4 (GlobalGilson, 2021):

Equation 4:
$$VMA = 100 - \frac{G_{mb}P_s}{G_{sb}}$$

Where

VMA: Voids in mineral aggregate (in percent of bulk volume);

G_{mb} : Bulk specific gravity of the asphalt mixture;

P_s : Aggregate (in percent by total weight of the asphalt mixture);

G_{sb} : Bulk specific gravity of the aggregate.

2.5.3 Maximum Aggregate Size (MAS)

MAS is the largest particle size in the aggregate gradation, determined through sieve analysis during mixture design. Common MAS values for standard Marshall specimens include 4 mm, 6.3 mm, 10 mm, 14 mm, 20 mm, and 28 mm; particles ≤ 4 mm are classified as "dust". MAS influences microstructural and functional properties: larger

aggregates enhance load-bearing capacity but may reduce workability, while smaller sizes improve surface texture for skid resistance. Gradation curves are calibrated to balance MAS with other volumetric parameters (e.g., VMA, AV) to meet performance targets (Huang, Cai, Li, Cui, & Wu, 2020).

2.5.4 Number of Aggregates (NA)

NA—the number of particles in a mixture sample—is closely tied to gradation design and aggregate type. In computational studies, particles <2 mm are often excluded to reduce computational complexity, as fine aggregates ≤ 2 mm typically blend with binder to form mastic (Garcia-Hernandez, Wan, Dopazo-Hilario, Chiarelli, & Dawson, 2021). This simplification retains accuracy while optimizing resource use, ensuring practicality in digital modeling and mixture optimization.

2.5.5 Mastic Content

Mastic, composed of bitumen, filler, and fine aggregates not adsorbed by the coarse fraction, is dominated by binder content. It fills voids in the aggregate skeleton, enhancing cohesion and workability. Mastic content directly affects the mixture's viscoelastic properties: higher mastic content improves fatigue resistance but may increase rutting susceptibility, necessitating careful balance with aggregate structure during design. (Gao, 2006; Wan et al., 2010).

2.6 Void Topology and Morphological Characteristics

In porous materials, void topological properties—including macroporosity, average void diameter, connectivity, and tortuosity—are critical indicators for characterizing asphalt mixture microstructure (Garcia, Hassn, Chiarelli, & Dawson, 2015). These properties, quantified using X-ray CT technology, enable in-depth analysis of the relationship between microscale features and macroscale performance (Katuwal, Moldrup, Lamandé, Tuller, & De Jonge, 2015). Below is a synthesis of key topological parameters and their engineering implications:

2.6.1 Macroporosity

Macroporosity is defined as the ratio of void area to the total area of the region of interest (ROI) in cross-sectional CT images, with voids <0.5 mm excluded to minimize

noise-induced errors (Sun, 2016). This metric correlates strongly with laboratory-measured air void content, as both quantify void proportion; however, macroporosity normalizes to the ROI, whereas air void content reflects the entire mixture volume (Aboufoul & Garcia, 2017). Averaging macroporosity across multiple slices yields a representative value for the mixture's overall void structure, which is critical for predicting permeability and fatigue life.

The calculation of macroporosity is shown in Equations 5-7:

Equation 5: Voids volume = Total voids area × Distance between slice

Equation 6: Core volume = Total Area × Total vertical distance

Equation 7:
$$\text{Macroporosity} = \frac{\text{Voids volume}}{\text{Core volume}} \times 100\%$$

Where

Voids volume: Sum of the volume of all voids within the ROI, [mm³];

Total voids area: Sum of the void's areas within the ROI on all imported slices, [mm²];

Distance between slices: Vertical distance between each slice, [mm];

Core volume: Volume of the test piece of the whole imported part, [mm³];

Total area: Sum of the ROI areas on all imported slices, [mm²];

Total vertical distance: Vertical distance of the test piece of the whole imported part, [mm].

2.6.2 Average Void Diameter

The average void diameter is measured using two methodologies:

Three-dimensional thickness algorithm (ImageJ): Computes the largest inscribed sphere diameter within void structures, relying on pixel continuity across CT slices (Kutay, Aydilek, Masad, & Harman, 2007). Smaller vertical distances between slices enhance 3D reconstruction accuracy (Bonej.org, 2021).

The thickness algorithm of the average void diameter is shown in Equation 8 (Aboufoul & Garcia, 2017):

Equation 8:
$$Avd = \frac{\sum_{i=1}^n d_i V_i}{\sum_{i=1}^n V_i}$$

Where

Avd: Average void diameter of void, [mm];

d_i : Diameter of each void within the ROI, [mm];

V_i : Volume of each void within the ROI, [mm³].

Two-dimensional planar analysis: Directly calculates void diameters in individual slices and averages results, mitigating errors from excessive slice spacing (Aboufoul & Garcia, 2017).

The two-dimensional calculation of the average void diameter is shown in Equations 9-10:

Equation 9:
$$\text{Average voids size} = \frac{\text{Voids area}}{\text{Number of voids}}$$

Equation 10:
$$Avd = 2 \times \sqrt{\frac{\text{Average voids size}}{\pi}}$$

Where

Average voids size: Average area of voids on each slice within the ROI, [mm²];

Voids area: Total area of the voids on each slice within the ROI, [mm²];

Number of voids: Number of voids on each slice within the ROI.

2.6.3 Connectivity Metrics: Euler Number and Percolation Number

Euler Number (x): A topological invariant quantifying void connectivity, a function that uses the number of isolated voids (N), the number of redundantly connected voids (C), and the number of fully enclosed sphere voids (H) to calculate Euler number (x) is defined as shown in Equation 11 (Vogel & Roth, 2001). Negative values indicate highly interconnected void networks, enhancing permeability but compromising structural stability (Romero, 2000). Measured via ImageJ's BoneJ plugin (Doubé et al., 2010).

Equation 11:

$$x = N - C + H$$

Percolation Number: The ratio of the biggest air void volume to total void volume. Values approaching 1 signify dominant interconnected voids, directly influencing drainage efficiency and skid resistance durability (Garcia et al., 2015). The biggest air void volume and percolation number can be measured using the particle analysis plugin BoneJ in ImageJ (Doubé et al., 2010).

2.6.4 Tortuosity

Tortuosity measures the tortuousness of fluid flow paths through voids, defined as the ratio of actual flow length to the shortest straight-line distance between void endpoints. Derived from 3D skeleton analysis of stacked CT slices, this parameter governs heat and mass transport properties; higher tortuosity reduces drainage efficiency and accelerates skid resistance degradation in wet conditions (Doubé et al., 2010; Roque & Costa, 2020).

2.6.5 Void Shape Properties

Void morphology—perimeter, aspect ratio, circularity, and roundness—correlates with air void content and aggregate gradation. As porosity increases, voids elongate (higher aspect ratio, lower circularity/roundness), deviating from spherical shapes (Norhidayah, Mahmud, & Ramadhansyah, 2014). These parameters, measured via ImageJ's particle analysis tools, provide mechanistic insights into texture formation: elliptical voids may alter surface roughness distribution, while irregular shapes could weaken aggregate skeleton support (Chen, Han, Ling, & Su, 2019; Garcia, Aboufoul, Asamoah, & Jing, 2019).

The calculation formula of the void shape characteristics is shown in Figure 3 (Norhidayah et al., 2014):

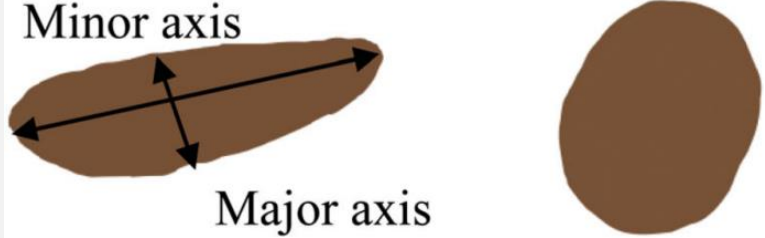
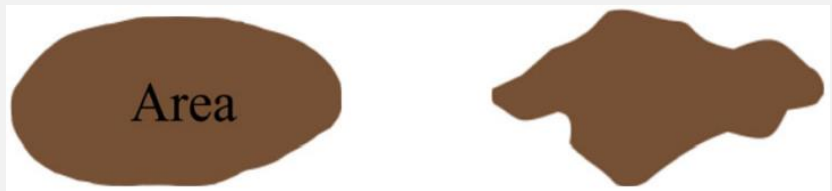
Equations of Void Shape Properties	High	Low
Equation 12: Void aspect ratio = $\left(\frac{\text{Length of major axis}}{\text{Length of minor axis}}\right)$		
Equation 13: Void circularity = $\left(\frac{4\pi \times \text{Area}}{\text{Void perimeter}^2}\right)$		
Equation 14: Voids roundness = $\left(\frac{4 \times \text{Area}}{\pi \times \text{Length of major axis}^2}\right)$		

Figure 3: Properties of Void Shapes (Norhidayah et al., 2014)

2.6.6 Multidimensional Void Parameters in Macrotexture Modeling

Existing studies often focus on isolated void parameters (e.g., laboratory-measured porosity) when linking microstructure to macrotexture, constrained by the need for specialized equipment (e.g., CT scanning) to quantify additional void topology parameters (size, shape, connectivity) (Garcia et al., 2019). This limitation has led to neglect of the synergistic effects of void geometry and connectivity on macrotexture development. For example:

- Negative Euler numbers (complex void networks) correlate with enhanced water ingress and aggregate stripping (Aboufoul & Garcia, 2017).
- High-aspect-ratio voids may indirectly influence MPD by disrupting texture uniformity (Chen et al., 2019).
- Connected void systems could compromise texture stability by weakening load-bearing skeleton integrity (Huang, Liu, Guo, & Wei, 2022).

This research advances current knowledge by integrating multidimensional parameters (void diameter, perimeter, maximum void volume, connectivity) into texture prediction models, unraveling their coupled effects on macroscopic performance and addressing the gap in holistic void-structure analysis.

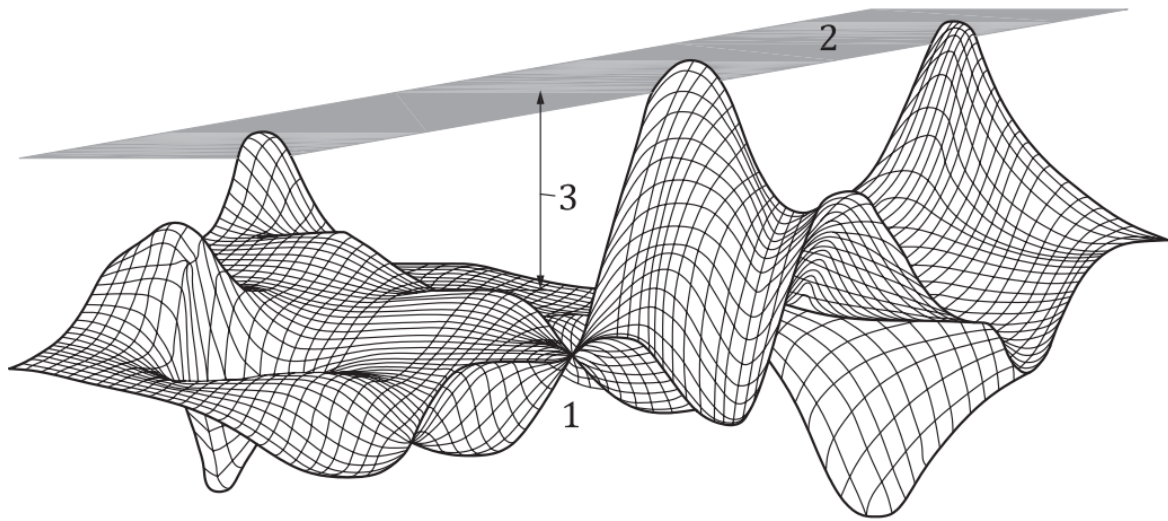
2.7 Pavement Texture and Its Multifaceted Implications

The significance of pavement texture manifests across multiple dimensions, impacting safety, economy, and sustainability (Freitas, Pereira, Antunes, & Domingos, 2008):

- **Usability:** Governs tire-pavement friction for skid resistance (Henry, 2000; Marsac & Delanne, 2004; Kim, Lee, Hyun, & Lee, 2013), and influences driving comfort through vibration mitigation (Delanne & Daburon, 1999).
- **Economy:** Affects vehicle/tire wear rates, (Domenichini & Martinelli, 2004; Praticò & Vaiana, 2015), fuel consumption efficiency (Miller et al., 2012), and long-term maintenance costs (Bendtsen, 2004).
- **Sustainable development:** Linked to particulate emissions during construction (China & James, 2012; Amato et al., 2013), traffic noise pollution (Morgan, 2006;

Lu & Harvey, 2011; Praticò et al., 2013; Praticò & Vaiana, 2015), and lifecycle greenhouse gas emissions (Wang, Harvey, & Kendall, 2014) .

Structurally, pavement texture is defined as the geometric deviation of the surface from a true planar reference, with wavelengths spanning <0.5 m (ISO, 2019). In three dimensions, texture depth quantifies the perpendicular distance from any surface point to the reference plane, typically measured in millimeters. Texture depth is derived from the vertical distance between the surface and a reference plane formed by the three highest texture peaks (Figure 4) (ISO, 2002).



Key

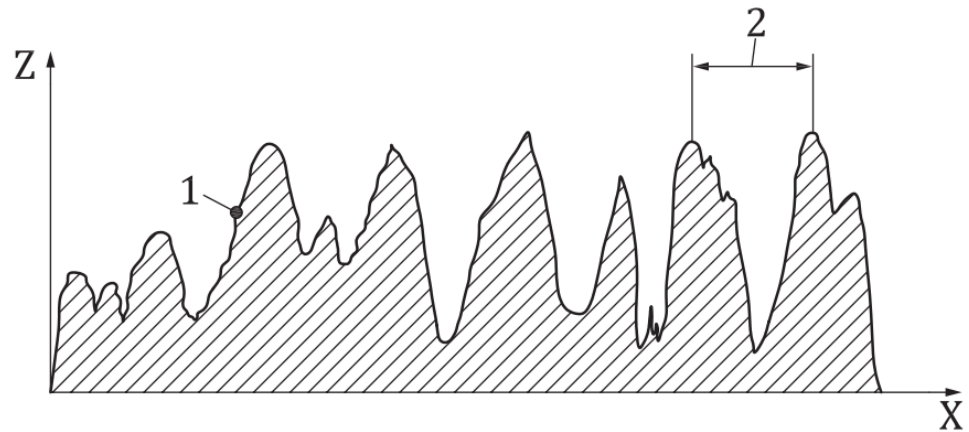
- 1 surface
- 2 plane through the three highest peaks of the surface
- 3 TD

Figure 4: Schematic of Surface Texture Depth Definition (ISO, 2019)

2.7.1 Surface Profile Analysis

The surface profile represents a two-dimensional sampling of texture for quantitative characterization (Figure 5). It consists of a horizontal axis (distance along the surface) and a vertical axis (texture amplitude normal to the surface). Key parameters include:

- **Wavelength:** The spatial period of profile oscillations, measured in meters or millimeters, distinguishing texture features by scale (ISO, 2019).
- **Amplitude:** The vertical deviation magnitude directly correlates with friction and noise generation.



Key

- 1 profile
- 2 texture wavelength
- X distance
- Z vertical displacement

Figure 5: Key Parameters of Pavement Surface Profile (ISO, 2019)

2.7.2 Hierarchy of Texture Scales

Pavement texture is classified into four wavelength-dependent categories (Figure 6) (ISO, 2008; Thigpen, Li, Handy, & Harvey, 2015):

2.7.2.1 Mega-Texture (50 mm–0.5 m)

Mega-texture encompasses macroscopic surface irregularities such as potholes, ruts, and longitudinal cracks. These features arise from design deficiencies, environmental degradation (e.g., freeze-thaw cycles), or cumulative traffic loading (PIARC, 1983). Their presence directly compromises vehicle stability and ride quality, often leading to severe pavement failure.

2.7.2.2 Macrotexture (0.5–50 mm)

Macrotexture governs tire-pavement interaction at high speeds, influencing hydroplaning resistance and noise emissions (Hall et al., 2009; ISO, 2019). It is primarily determined by coarse aggregate gradation and interlock within the asphalt mixture, with optimal performance achieved through angular aggregate shapes and balanced void distribution (Fülöp, Bogardi, Gulyas, & Csicsely-Tarpay, 2000). Most standardized texture measurement techniques (e.g., sand patch test, laser profilometry) target macrotexture due to its dominance in friction modeling (McLean & Foley, 1998).

2.7.2.3 Microtexture (<0.5 mm)

Microtexture refers to the fine-scale roughness of individual aggregate surfaces (Thigpen et al., 2015), providing baseline friction at all speeds by enhancing molecular adhesion between tires and pavement (Forster, 1989; ISO, 2019). This scale is highly susceptible to wear from traffic abrasion and environmental weathering, which can polish aggregate surfaces and reduce skid resistance over time (Corwill, 1989; Ergun, Iyinar, & Iyinar, 2005). Direct measurement of microtexture requires high-resolution imaging (e.g., scanning electron microscopy), as its features fall below the detection limit of conventional profilometers (Chen et al., 2015).

2.7.2.4 Roughness (0.5–50 m)

Roughness encompasses long-wavelength surface undulations, distinct from macrotexture but often correlated with it. Increased aerodynamic drag influences vehicle dynamic loading, water ponding on flat surfaces, and fuel efficiency (Marrakech, 1991; McLean & Foley, 1998). While roughness is typically assessed via inertial profiling, its relationship to macrotexture highlights the need for integrated multiscale texture analysis in pavement design (Ergun et al., 2005).

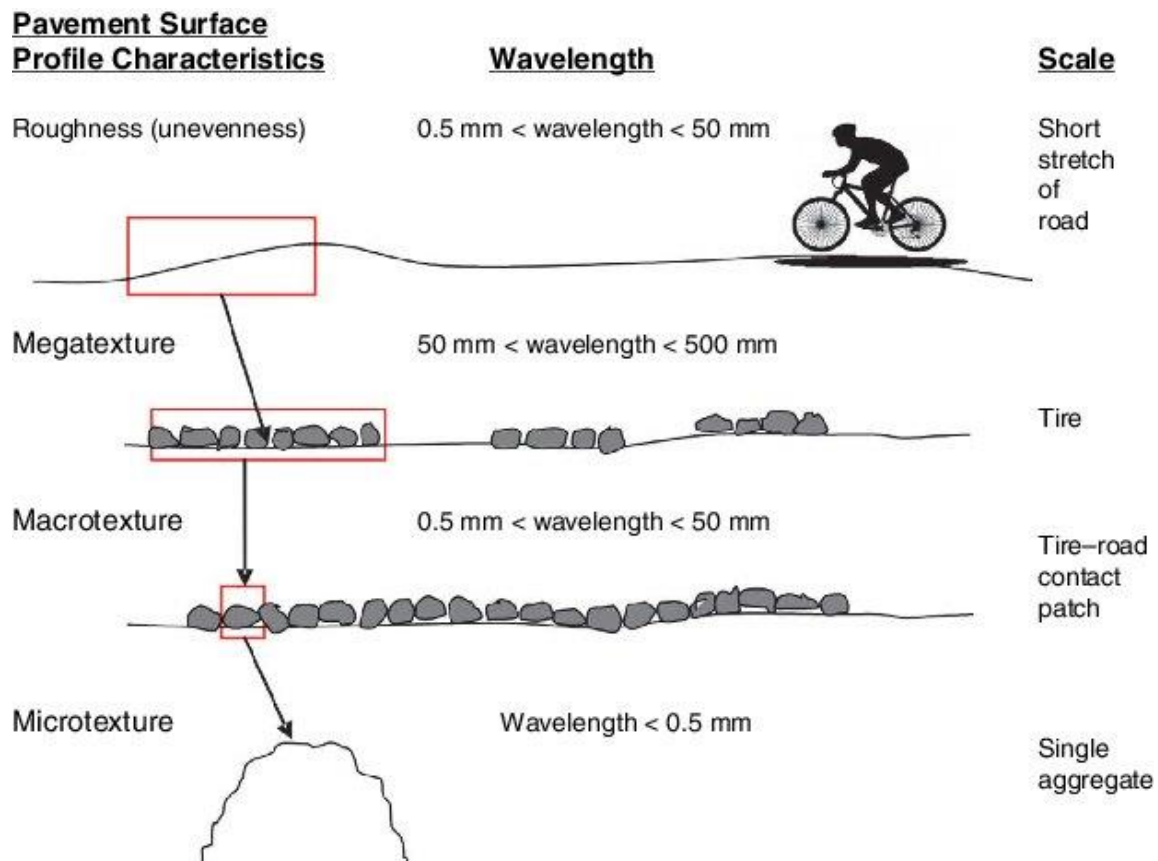


Figure 6: Classification of Pavement Texture by Wavelength (Lu & Harvey, 2011)

2.7.3 Texture Parameters and Multidimensional Characterization

The selection of texture parameters is contingent upon research objectives and measurement methodologies. Most studies prioritize amplitude-based metrics such as MPD, MTD, and Root Mean Square (RMS) (ISO, 1996), while wavelength-specific analysis via Texture Spectral Analysis (TSA) has emerged as a critical tool for friction and noise modeling (Losa & Leandri, 2011; Miller et al., 2012; Chen et al., 2015). This section synthesizes key 2D, 3D, and multi-scale parameters, their engineering applications, and synergistic analytical frameworks.

2.7.3.1 2D Profile Parameters

Mean Profile Depth (MPD)

MPD quantifies the average texture amplitude over a 100 mm baseline, as a proxy for longitudinal friction capacity during braking and acceleration (ISO, 2002; D'Apuzzo, Evangelisti, & Nicolosi, 2020). Higher MPD values correlate with rougher longitudinal textures, which enhance tire-pavement grip, which is particularly critical for curved or inclined road sections. Under wet conditions, MPD influences water film displacement: deeper profiles reduce hydroplaning risk by maintaining continuous tire contact (Čelko, Kováč, & Kotek, 2016). Calculation involves measuring the vertical difference between peak levels and the baseline (Figure 7), with the baseline normalized to zero via slope suppression (ISO, 2002).

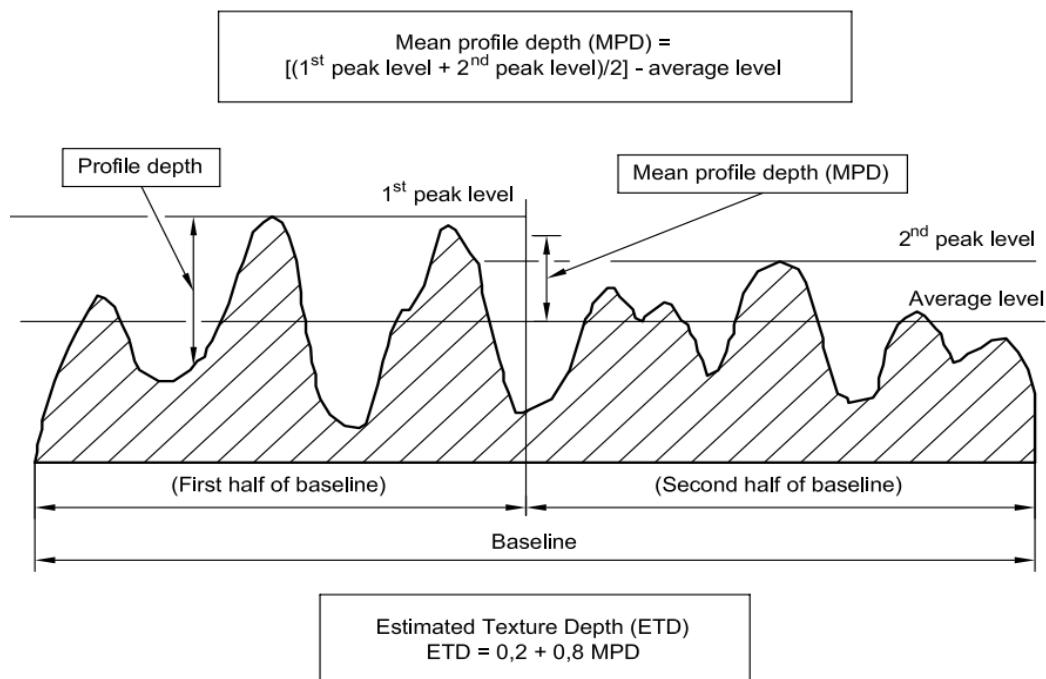


Figure 7: Schematic of MPD and ETD Calculation Parameters (ISO, 2002)

Root Mean Square (RMS)

RMS quantifying the dispersion of profiles deviating from the baseline, sensitive to microtexture variations. Microtexture variations can significantly affect surface properties such as friction at the microscopic level (Kociński et al., 2016). A higher RMS value may indicate the presence of abundant micro-scale asperities or depressions on the pavement surface, which influences the local contact pressure distribution at the tire-pavement interface. This parameter aids in analyzing the microscale frictional behavior between tire tread rubber and pavement aggregates: under dry conditions, higher RMS values may enhance the friction coefficient, whereas under wet conditions, water entrapment in micro-textures associated with elevated RMS could lead to frictional degradation (Gao, Fan, Gao, & Song, 2025) .

RMS is defined as a function of the root mean square value of the ordinate value $Z(x)$ representing the depth of the texture in the evaluation length l , as shown in Equation 15 (ISO, 2002):

Equation 15:
$$\text{RMS} = \sqrt{\frac{1}{l} \int_0^l z^2(x) dx}$$

Wavelength Distribution (λ)

Fourier transform-based spectral analysis decomposes texture into wavelength components (ISO, 2002), linking long waves (50 mm–0.5 m) to macro-deformations (e.g., ruts) and short waves (<0.5 mm) to aggregate surface roughness (Deleanu, Ionescu, Cristea, Suci, & Georgescu, 2022; Liang, Xie, & Wang, 2023). Long-wavelength textures affect tire vibration and rolling resistance, while short-wavelength features dictate micro-adhesion. This dual characterization guides tire design: long-wave-dominated pavements require rigid treads, whereas short-wave-rich surfaces necessitate elastic rubber compounds to optimize contact mechanics (Li, Dong, Wang, & Wang, 2024).

2.7.3.2 3D Areal Parameters

Mean Texture Depth (MTD)

MTD, derived from volumetric analysis, directly correlates with drainage efficiency. Higher MTD values facilitate rapid water evacuation from the tire-pavement interface, critical for preventing hydroplaning in wet climates (Liang et al., 2020). MTD can be estimated from MPD using empirical relationships (Figure 7), bridging 2D and 3D measurements (ISO, 2002). In practice, MTD informs tire groove design: deep-grooved tires are paired with high-MTD pavements for drainage, while low-MTD urban surfaces prioritize noise reduction (Fwa, Kumar, Anupam, & Ong, 2009).

Surface Area Ratio (SAR)

SAR, the actual to projected surface area ratio, characterizes texture complexity. A higher SAR increases real contact area, enhancing dry friction but elevating rolling resistance and fuel consumption (Meng, Xu, Jin, Prakash, & Hu, 2020; Gillespie, 2021; Sun, Premarathna, Anupam, Kasbergen, & Erkens, 2024). In tribological contexts, SAR aids tire wear assessment: degraded treads exhibit reduced SAR, necessitating replacement to maintain frictional performance (Zhang et al., 2024).

Fractal Dimension (D)

D, calculated via the Mandelbrot algorithm, quantifies texture self-similarity across scales. Higher D values indicate multi-scale roughness, stabilizing friction by maintaining contact complexity under varying loads (Pan, Ling, Qu, & Wang, 2021). Conversely, traffic-induced wear reduces D, signaling the need for maintenance to restore frictional properties (Ma, Wang, Zhang, Jelagin, & Hui, 2025).

2.7.3.3 Synergistic 2D-3D Analysis

Integrating 2D profile and 3D areal parameters enables multi-scale evaluation of pavement functionality (Aavik, Kaal, & Jentson, 2013):

- **Skid Resistance Optimization:** Techniques like 3D laser or industrial CT scanning are employed to acquire pavement texture data, validated by 2D profilometers (Chen et al., 2022). Integrating 3D-derived MTD/SAR data with 2D MPD measurements in highway maintenance establishes skid resistance evaluation

models, guiding targeted pavement preservation decisions (Wang, Lai, Zhou, & Xue, 2020). For instance, High MPD/MTD combinations in wet environments ensure effective water removal from the tire-pavement contact area, reducing hydroplaning risk. (Li & Wang, 2016).

- **Noise Control:** Macrotexture (2D MPD) influences high-frequency noise via air turbulence and mechanical interactions between tires and pavement (Dong, Han, Luo, Han, & Xu, 2021), while microtexture (3D SAR) modulates low-frequency noise through contact mechanics and frictional characteristics at the interface (Yang et al., 2025). By carefully designing the pavement texture using a combination of 2D and 3D parameters, minimizing noise emissions in residential areas (Vaitkus et al., 2017; Mikhailenko et al., 2022) .
- **Tire Tread Design:** MPD/MTD simulate contact area dynamics, while SAR/D describe energy dissipation. A rough surface with high MPD and SAR values can increase rolling resistance, leading to higher fuel consumption. On the other hand, a surface with a too smooth texture may not provide enough grip, causing the tires to slip slightly, which can also negatively impact fuel efficiency. Balancing these parameters allows designers to optimize tread patterns for grip and fuel efficiency across diverse pavements (Ilse, 2015; Long & Huang, 2019) .

2.7.4 Texture Spectral Analysis Methodology

Texture spectral analysis (TSA) decomposes pavement profiles into wavelength-specific components using Fourier transform techniques, enabling systematic characterization of texture features. The workflow comprises five sequential stages, each critical for accurate spectral representation:

2.7.4.1 Preprocessing of Texture Profiles

Data Interpolation and Anomaly Removal

The first step involves interpolating missing data points and removing amplitude anomalies from raw profile data. As illustrated in Figure 8, invalid readings (hollow markers) are replaced via linear interpolation between adjacent valid points, described

by Equation 16 (ISO, 2019). This ensures continuity in the profile signal before spectral analysis.

Equation 16:
$$z_i = \frac{z_n - z_m}{n - m}(i - m) + z_m$$

Where

- i: The sample numbers where the value is invalid;
- m: The sample number of the nearest valid value before i;
- n: The sample number of the nearest valid value after i;
- z_i : The interpolated value for sample i;
- z_m : The value of sample m;
- z_n : The value of sample n.

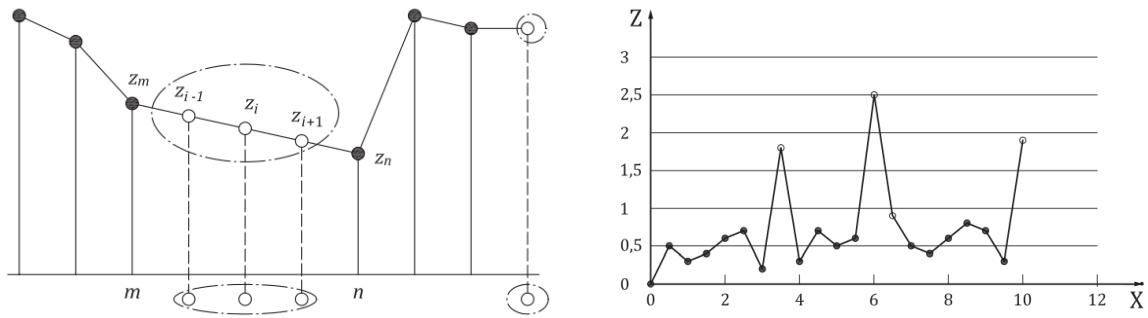


Figure 8: Linear Interpolation of Invalid Data Points (ISO, 2019)

Slope and Offset Suppression

Long-wavelength trends (e.g., pavement curvature) are eliminated through high-pass filtering or least-squares regression, normalizing the baseline to zero (ISO, 2002). Mathematically, the slope b_1 and offset b_0 of the profile z_i are calculated using Equations 17 and 18, respectively, with the corrected signal Z_i derived from Equation 19 (ISO, 2008). This process isolates texture features from global geometry, as demonstrated in Figure 9 (ISO, 2002).

Equation 17:
$$b_1 = \frac{12 \sum_{i=0}^{N-1} i z_i - 6(N-1) \sum_{i=0}^{N-1} z_i}{N(N+1)(N-1)}$$

Where

- b_1 : The slope of the surface profile;
- z_i : The measured signal value for sample i at x_i ;
- N: The number of samples within the evaluated signal.

The calculation of the offset (b_0) of the surface profile is shown in Equation 18 (ISO, 2008):

Equation 18:
$$b_0 = \frac{1}{N} \sum_{i=0}^{N-1} z_i - b_1 \cdot \frac{1}{2} (N - 1)$$

Where

b_0 : The offset of the surface profile.

The calculation of the corrected sample signal value (Z_i) by correcting the slope and offset is shown in Equation 19 (ISO, 2008):

Equation 19:
$$Z_i = z_i - b_1 i - b_0 \quad \text{for } i = 0, \dots, N - 1$$

Where

Z_i : The corrected sampled signal value Z_i .

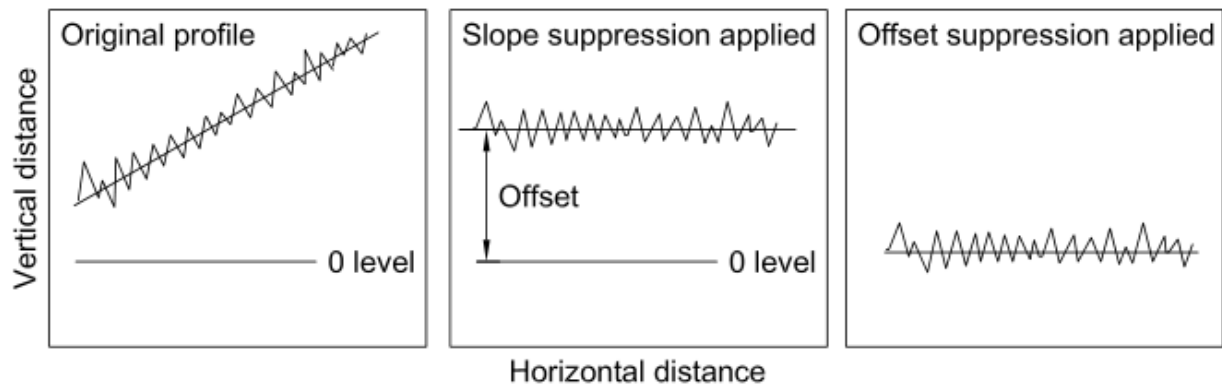


Figure 9: Effect of Slope and Offset Suppression (ISO, 2002)

2.7.4.2 Windowing Techniques

A window function is applied to taper profile edges to zero to mitigate edge effects during the Fourier transform (Figure 10). The Hanning window (Equation 20) and Split Cosine Bell Window (SCBW, Equation 21) are most commonly used. The Hanning window is preferred for its smooth tapering but may attenuate low-frequency components. SCBW is suitable for profiles shorter than 1.0 m, though it risks spectral resolution loss (ISO, 2008).

The Hanning window is defined as shown in Equation 20 (ISO, 2008):

$$\text{Equation 20: } w_{i,H} := \frac{1 - \cos\left(\frac{2\pi i}{N}\right)}{2} = 1 - \cos^2\left(\frac{\pi i}{N}\right) \text{ for } i = 0, \dots, N - 1$$

The function of the SCBW is shown in Equation 21 (ISO, 2008):

$$\text{Equation 21: } w_{i,C} := \begin{cases} \cos^2\left(\frac{5\pi i}{N} - \frac{\pi}{2}\right) & \text{for } 0 \leq i \leq N/10 \\ 1 & \text{for } N/10 \leq i \leq 9N/10 \\ \cos^2\left(\frac{5\pi i}{N} - \frac{9\pi}{2}\right) & \text{for } 9N/10 \leq i \leq N \end{cases}$$

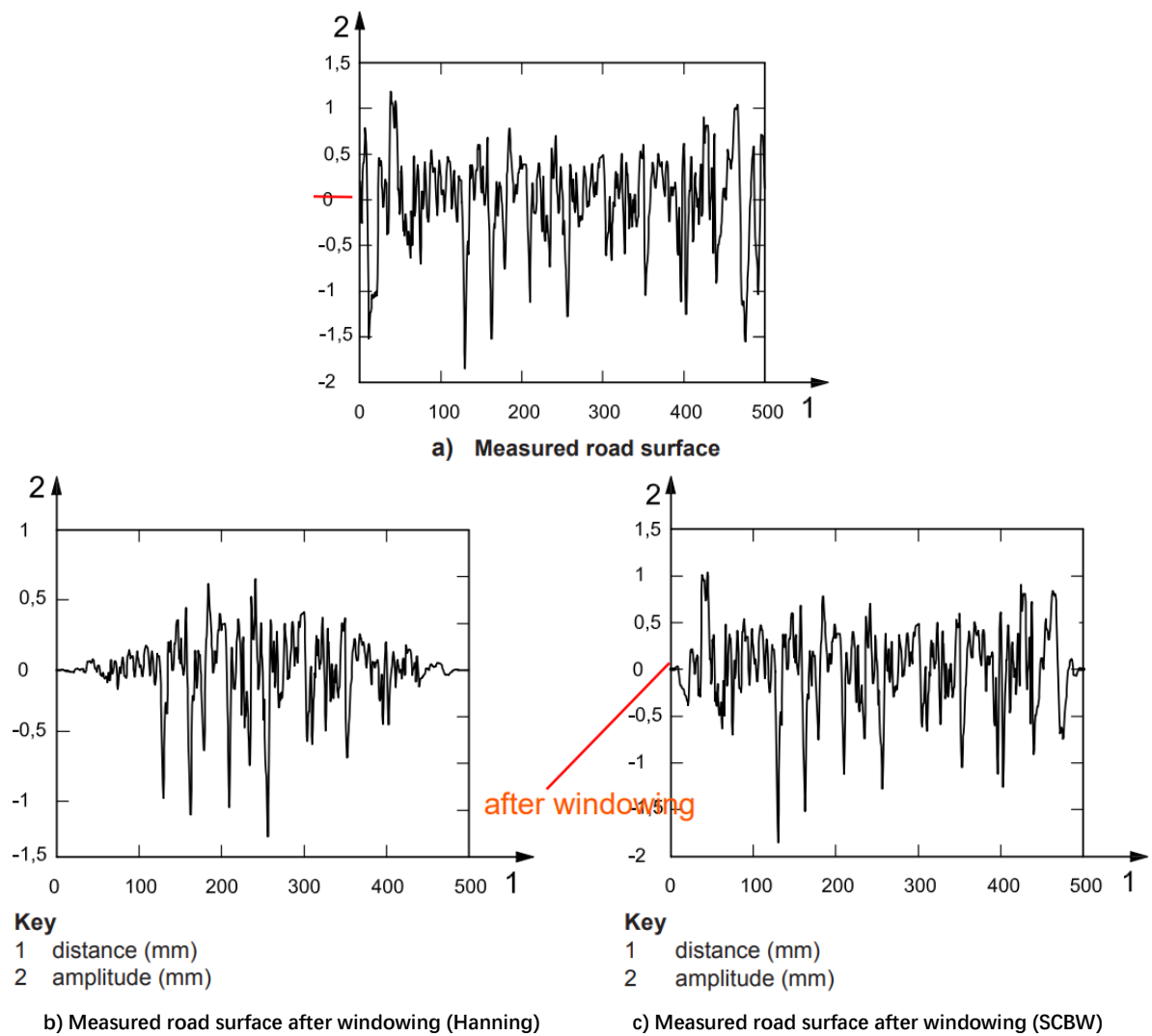


Figure 10: Hanning Window and SCBW Applications (ISO, 2008)

The filter function is multiplied by the corrected sampled signal value Z_i to apply the window, and the product is divided by the integral of the window to avoid signal attenuation. $Z_{i,\text{win}}$ is the signal value after windowing, and N is the number of samples. The application of the Hanning window is shown in Equation 22 (ISO, 2008):

$$\text{Equation 22:} \quad Z_{i,\text{win}} = \frac{w_{i,H} Z_i}{0.6124} \quad \text{for } i = 0, \dots, N - 1$$

The application of the SCBW is shown in Equation 23 (ISO, 2008):

$$\text{Equation 23:} \quad Z_{i,\text{win}} = \frac{w_{i,C} Z_i}{0.9354} \quad \text{for } i = 0, \dots, N - 1$$

The general application equation for determining the windowed profile is shown in Equation 24 (ISO, 2008):

$$\text{Equation 24:} \quad Z_{i,\text{win}} = \frac{w_i Z_i}{\sqrt{\frac{1}{N} \sum_{i=0}^{N-1} w_i^2}} \quad \text{for } i = 0, \dots, N - 1$$

2.7.4.3 Discrete Fourier Transform and Power Spectral Density

The discrete Fourier transform (DFT) converts the spatial domain signal $Z_{i,\text{win}}$ to the frequency domain Z_k (Equation 25), enabling decomposition into wavelength components. Power spectral density (PSD, Equation 26) quantifies energy distribution across frequencies, while narrow-band spectral values $L_{\text{tx},k}$ (Equation 27) isolate contributions from specific wavelength bands (ISO, 2008).

The discrete Fourier transform is used to transform the distance measuring function $Z_{i,\text{win}}$ to the spatial frequency function Z_k , as shown in Equation 25 (ISO, 2008):

$$\text{Equation 25:} \quad Z_k = \frac{1}{N} \sum_{i=0}^{N-1} Z_{i,\text{win}} e^{-j \left(\frac{2\pi k}{N} \right) i} \quad \text{for } k = 0, \dots, N - 1$$

Where

j : the imaginary unit [$j^2 = -1$].

Calculate the Power Spectral Density (PSD) based on the result of the discrete Fourier transform, as shown in Equation 26 (ISO, 2008):

$$\text{Equation 26:} \quad Z_{\text{PSD},k} = \frac{2|Z_k|^2}{\Delta f_{\text{sp}}} \quad \text{for } k = 0, \dots, \left(\frac{1}{2}N - 1\right)$$

The narrow-band spectral value of the profile level $L_{\text{tx},k}$ is calculated as shown in Equation 27 (ISO, 2008):

$$\text{Equation 27:} \quad L_{\text{tx},k} = 10 \lg \left(2 \left| \frac{Z_k}{a_{\text{ref}}} \right|^2 \right) \quad \text{for } k = 0, \dots, \left(\frac{1}{2}N - 1\right)$$

Where

a_{ref} : The reference value of the surface profile amplitude [= 10^{-6} m];

$L_{\text{tx},k}$: The profile level within frequency band f_k with bandwidth Δf_{sp} [dB].

2.7.4.4 Texture Profile Level Analysis

The texture profile level $L_{\text{tx},\lambda}$ (Equation 28) expresses spectral amplitude in decibels via logarithmic transformation, standardizing measurements across scales. Typical values range from 20 to 80 dB, corresponding to micro- to mega-texture features. Analysis employs octave or one-third-octave band standards (Table 1) to classify texture contributions by wavelength (ISO, 2002; ISO, 2008).

$$\text{Equation 28:} \quad L_{\text{TX},\lambda} \text{ or } L_{\text{tx},\lambda} = 10 \lg \frac{a_{\lambda}^2}{a_{\text{ref}}^2} = 20 \lg \frac{a_{\lambda}}{a_{\text{ref}}} \text{ dB}$$

Where

$L_{\text{tx},\lambda}$: The texture profile level in one-third-octave bands (ref. 10^{-6} m), in decibels;

$L_{\text{TX},\lambda}$: The texture profile level in octave bands (ref. 10^{-6} m), in decibels;

a_{λ} : The root mean square value of the vertical displacement of the surface profile, in meters;

a_{ref} : The reference value (= 10^{-6} m);

λ : The subscript indicating a value obtained with a one-third-octave-band or octave-band filter having center wavelength λ .

Table 1: Octave and One-Third-Octave Band Standards for Texture Analysis (ISO, 2002)

Octave bands		One-third-octave bands		Range
Texture wavelength mm	Spatial frequency m ⁻¹	Texture wavelength mm	Spatial frequency m ⁻¹	
		630	1,60	unevenness ↓
500	2,00	500	2,00	↑
		400	2,50	
		315	3,15	
250	4,00	250	4,00	
		200	5,00	
		160	6,30	
125	8,00	125	8,00	
		100	10,0	
		80,0	12,5	
63,0	16,0	63,0	16,0	↓
		50,0	20,0	↑
		40,0	25,0	
31,5	31,5	31,5	31,5	
		25,0	40,0	
		20,0	50,0	
16,0	63,0	16,0	63,0	
		12,5	80,0	
		10,0	100	
8,00	125	8,00	125	
		6,30	160	
		5,00	200	
4,00	250	4,00	250	
		3,15	315	
		2,50	400	
2,00	500	2,00	500	
		1,60	630	
		1,25	800	
1,00	1 000	1,00	1 000	
		0,80	1 250	
		0,63	1 600	↓
0,50	2 000	0,50	2 000	↑
		0,40	2 500	↓
				microtexture

2.7.5 Classification and Characteristics of Asphalt Mixture Macrottexture

Macrottexture morphology, a critical determinant of pavement functional performance, varies systematically with asphalt mixture types. Based on geometric and structural attributes, these distinct categories emerge:

2.7.5.1 Positive Macrotexture

Positive macrotexture manifests as protruding structures on the pavement surface, primarily formed by exposed coarse aggregate angularities. SMA and OGFC typically exhibit this texture type. Its roughness characteristics (e.g., MPD values) effectively enhance friction coefficients in tire-pavement contact zones, particularly by breaking water films under wet conditions to improve skid resistance. Studies show that positive macrotexture's wavelength distribution (0.5-50mm) significantly influences high-speed driving safety (Kane, Riahi, & Do, 2021).

2.7.5.2 Negative Macrotexture

Negative macrotexture is characterized by surface depressions or voids, typified by porous asphalt pavements. While its texture depth is generally greater than positive macrotexture, its friction performance relies more on aggregate surface microtexture than macroscale interlock. The primary functions of negative macrotexture are drainage and noise reduction, as interconnected voids facilitate rapid water infiltration and attenuate tire-generated noise through acoustic absorption. However, long-term durability may suffer from debris accumulation (Vieira, Sandberg, & Erlingsson, 2021).

2.7.5.3 Porous Macrotexture

Porous macrotexture refers to three-dimensional structures formed by interconnected voids, commonly found in permeable pavements and noise-reducing surfaces. Its texture parameters (e.g., void ratio, connectivity) affect drainage efficiency and reduce tire noise through acoustic wave scattering mechanisms. Durability design for porous macrotexture must consider void clogging risks, typically mitigated through regular high-pressure cleaning maintenance (Sandberg, 2021).

2.7.5.4 Open-Graded Macrotexture

An open-graded macrotexture, typified by OGFC, features uniformly distributed voids forming a honeycomb-like surface. This design optimizes hydroplaning resistance through rapid water evacuation and enhances skid resistance at high speeds, though its surface abrasion resistance is lower than that of dense-graded mixtures (Abohamer, Elseifi, Mayeux, Cooper III, & Cooper Jr, 2023; Song et al., 2024).

2.7.5.5 Smooth-Wearing Macrotexture

The smooth-wearing macrotexture characteristic of HRA arises from uniformly graded aggregates and rich mastic content. Its low-amplitude profile ensures smooth ride quality and low noise emissions, but reduced macroscale water displacement may compromise wet skid resistance. Friction in these mixtures relies heavily on aggregate microtexture, making the selection of hard, angular aggregates (e.g., granite) critical for sustaining performance (Rezaei, Harvey, & Lu, 2012; Taher, Aman, & Bujang, 2024) .

2.7.6 Texture Measurement Techniques

Pavement texture characterization relies on diverse measurement methodologies with distinct principles, applications, and limitations. This section categorizes techniques by operational mechanisms, emphasizing their technical features and evolutionary advancements.

2.7.6.1 Volumetric Patch Methods

Volumetric patch methods quantify texture depth by filling surface voids with granular media. The Sand Patch Test (SPT) remains the most widely used variant: a known volume of sand (or glass spheres for improved reproducibility) is spread to form a circular patch, and MTD_{SPT} is calculated from the patch's diameter and material volume (Figure 11) (ISO, 2002). While cost-effective and operationally simple, SPT suffers from operator dependency and environmental biases—porous surfaces may allow media infiltration, skewing results. Its applicability is limited to traffic-closed surfaces, restricting real-time monitoring (Hall et al., 2009; Losa & Leandri, 2011) .

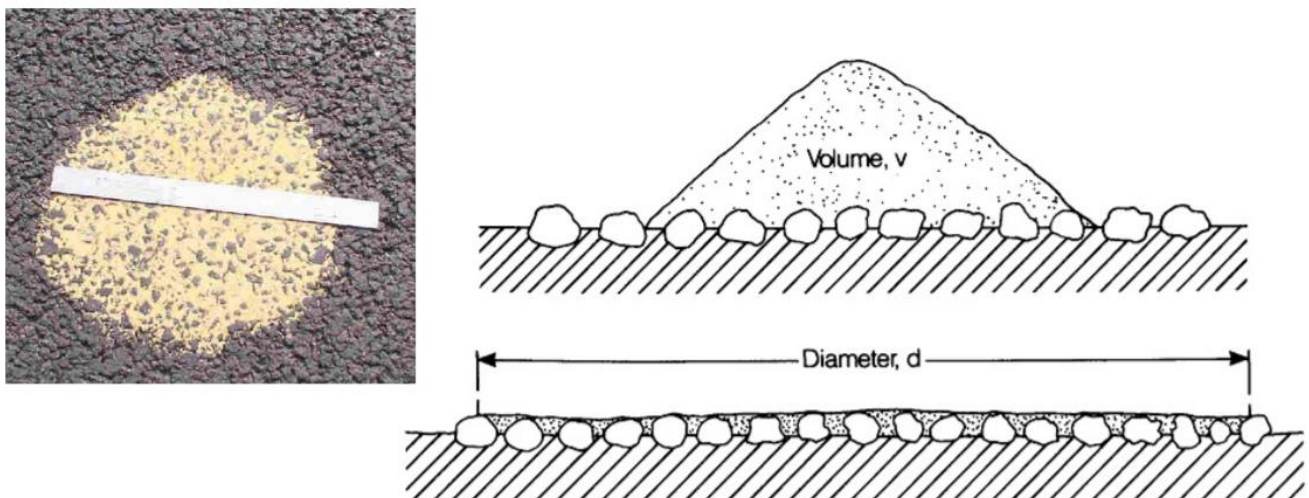


Figure 11: Sand Patch Test for Texture Depth Measurement (Emin Kutay, 2017)

2.7.6.2 Laser Profilometry

Laser-based profilometry enables non-destructive, high-precision texture analysis by capturing 2D profiles or 3D point clouds. Key instruments include:

- **Circular Track Meter (CTM):** This device employs a rotating laser to measure texture profiles across an 11.25-inch diameter circular area, generating eight radial cross-sections (Figure 12). It calculates parameters like MPD and RMS while identifying peak power density, suitable for both laboratory and field applications (Hall et al., 2009; D'Apuzzo, Evangelisti, & Nicolosi, 2012).



Figure 12: CTM for Multi-Directional Profile Scanning (Tatari, Costello, & Wilson, 2016)

- **Stationary Laser Profilometer (SLP):** This instrument acquires linear profiles with submillimeter repeatability. Multidirectional measurements mitigate texture anisotropy biases, enabling spectral analysis (e.g., PSD) to characterize roughness distribution per international standards (ISO, 2002; Miller et al., 2012).
- **Laser Texture Scanner (LTS):** This device captures high-resolution 3D surface data over 100×75 mm areas (Zuniga-Garcia & Prozzi, 2016), facilitating MPD/RMS calculations and 3D model reconstruction (Figure 13) Fisco & Sezen, 2013). Though portable and accurate, its measurement duration and area limit large-scale applications (Serigos, De Fortier Smit, & Prozzi, 2014).



Figure 13: Ames Engineering Laser Texture Scanner

2.7.6.3 Advanced Non-Contact Technologies

Recent innovations in non-contact measurement have expanded texture characterization capabilities:

- **Mobile Laser Profilers:** Systems like the Road Doctor® Survey Van integrate high-speed laser arrays and inertial navigation to generate georeferenced texture maps with submillimeter resolution. These platforms simultaneously measure MPD, PSD, and ride quality parameters, supporting large-scale network surveys. However, their high cost and periodic calibration requirements limit accessibility (De Blasiis, Di Benedetto, & Fiani, 2020; Dutco Tennant, 2022).
- **Unmanned Aerial Vehicle (UAV)-Based LiDAR:** Unmanned Aerial Vehicles equipped with LiDAR sensors enable rapid 3D texture mapping of extensive road networks. By reconstructing Digital Surface Models (DSMs), this technology identifies spatial variability in texture distribution, proving invaluable for post-disaster assessment and maintenance prioritization. Performance is compromised in adverse weather (e.g., rain, fog), requiring robust data filtering algorithms (Gao, Zhang, Sun, Sun, & Zhao, 2018; Yu, Ma, Tian, & Lu, 2021).

- **Structured Light 3D Imaging:** Projects sinusoidal patterns onto surfaces and uses stereo vision to reconstruct 3D topographies with submillimeter precision. It is ideal for analyzing aggregate-scale features (e.g., angularity, microtexture) and has been applied to study friction anisotropy. However, surface reflectivity and lighting inconsistencies may introduce measurement errors (Wu et al., 2019; Cuc, Vinh, & Binh, 2020).

Traditional methods (SPT) provide baseline texture depth, while laser profilometry and advanced 3D techniques enable multi-scale analysis—from macrotexture spectral decomposition to microstructural void characterization. This evolution reflects a shift toward automated, data-driven approaches integrating texture metrics with pavement performance modeling.

2.7.7 Technical Requirements for Macrotexture in Road Specifications

As a core indicator of pavement functional performance, macrotexture is incorporated into road engineering specifications:

2.7.7.1 *Manual of Contract Documents for Highway Works (MCHW)*

Clause 921 of the MCHW mandates the volumetric patch method (BS EN 13036–1) for measuring initial macrotexture on newly constructed asphalt pavements (BSI, 2010). Requirements vary by road type and speed, as outlined in Table 2 (England, 2020; England, 2021):

Table 2: Initial Texture Depth Requirements for Chipped Hot Rolled Asphalt and Other Surfacing (England, 2020)

Speed limit	Road Type	Minimum		Maximum
		Average per 50 m section, mm	Average per 1,000 m section, mm	
≥ 50 miles/ hr (80 km/hr)	Road	1.2	1.5	2.0
	Roundabout	1.0	1.2	1.7
≤ 40 miles/ hr (65 km/hr)	Road	1.0	1.2	1.7
	Roundabout	0.9	1.0	1.5

For high-speed corridors, a minimum average texture depth of 1.2 mm (per 50 m) is required, with section-wide averages (per 1,000 m) ranging 1.5–2.0 mm for HRA surfaces. Lower-speed networks permit slightly reduced thresholds (1.0 mm minimum), reflecting trade-offs between safety and traffic demands.

2.7.7.2 Design Manual for Roads and Bridges (DMRB)

The DMRB framework establishes a risk-based approach to macrotexture design, linking texture parameters to skid resistance through the CS 228 Skidding Resistance standard (England, 2018; England, 2021). Key principles include:

1. Texture-Specific Zoning:

- High-risk zones (e.g., sharp curves, junctions) require enhanced MPD to mitigate hydroplaning, while standard sections prioritize cost-effective texture designs.
- Post-rehabilitation projects must meet or exceed pre-determined MPD thresholds, with periodic monitoring protocols to ensure long-term compliance.

2. Skid Resistance Classification:

- Roads are categorized by geometric and operational risk (e.g., Motorways are in Category A, and junctions are in Category C).
- Investigatory Levels (IL) define acceptable skid resistance coefficients for wet conditions:
 - Motorways (high risk): $IL \geq 0.35$
 - Low-risk roads: $IL \geq 0.30$ (post-engineering assessment)
- This tiered system enables targeted interventions, such as selecting OGFC for high-IL zones to enhance drainage and friction.

DMRB emphasizes proactive texture restoration in maintenance cycles to ensure consistent skid performance. Both MCHW and DMRB underscore the critical role of macrotexture in wet-weather safety. These standards provide a foundational framework for material selection, quality control, and lifecycle management in pavement engineering.

2.8 X-ray Computerized Tomography (CT) in Pavement Materials

X-ray CT represents a non-destructive imaging technique that reconstructs cross-sectional slices of materials using X-ray attenuation, enabling detailed visualization of internal microstructures without sample destruction (Zhang & Li, 1996; Qiao, 2018). While mature in medical diagnostics and geotechnical engineering (Pan, Siewerdsen, La Riviere, & Kalender, 2008; Otani, Watanabe, & Chevalier, 2010), its application to asphalt mixtures and cement-based pavements emerged later, driven by the need for non-destructive microstructural analysis (Wang, Wang, & Chen, 2014).

2.8.1 CT Scanning Principles

CT systems comprise an X-ray source, rotational stage, and detector array. During scanning, collimated X-rays penetrate the specimen, with attenuation dependent on material density: higher-density aggregates absorb more X-rays, appearing brighter in tomographic images, while voids (low density) appear dark (Wan et al., 2010; Qiao, 2018). The exponential attenuation relationship allows computational reconstruction of 2D slices, which are stacked to form 3D models (Gu et al., 2016). With submillimeter resolution, this technology captures heterogeneous structures, such as aggregate distribution, mastic morphology, and void networks.

2.8.2 Digital Image Processing

Digital image processing transforms CT slices into quantitative 3D models, facilitating virtual analysis of asphalt mixture microstructures (Zhang & Duan, 2010). By aligning sequential 2D slices (typically 50–200 μm thick), researchers reconstruct the spatial arrangement of constituent phases—aggregates, mastic, and voids—enabling volumetric property calculations (e.g., air void content, voids in mineral aggregate) and topological characterization (e.g., void connectivity, tortuosity) (Kutay et al., 2007; Qiao, 2018). This non-destructive approach bridges macroscale performance and microscale mechanisms, supporting mixture design and texture prediction advancements (Wan et al., 2010).

2.8.3 Image Segmentation Techniques

Image segmentation is critical for distinguishing asphalt mixture components (aggregates, mastic, voids) in CT images, though its application remains challenging due to overlapping grey values in multi-phase materials (Zhang & Duan, 2010).

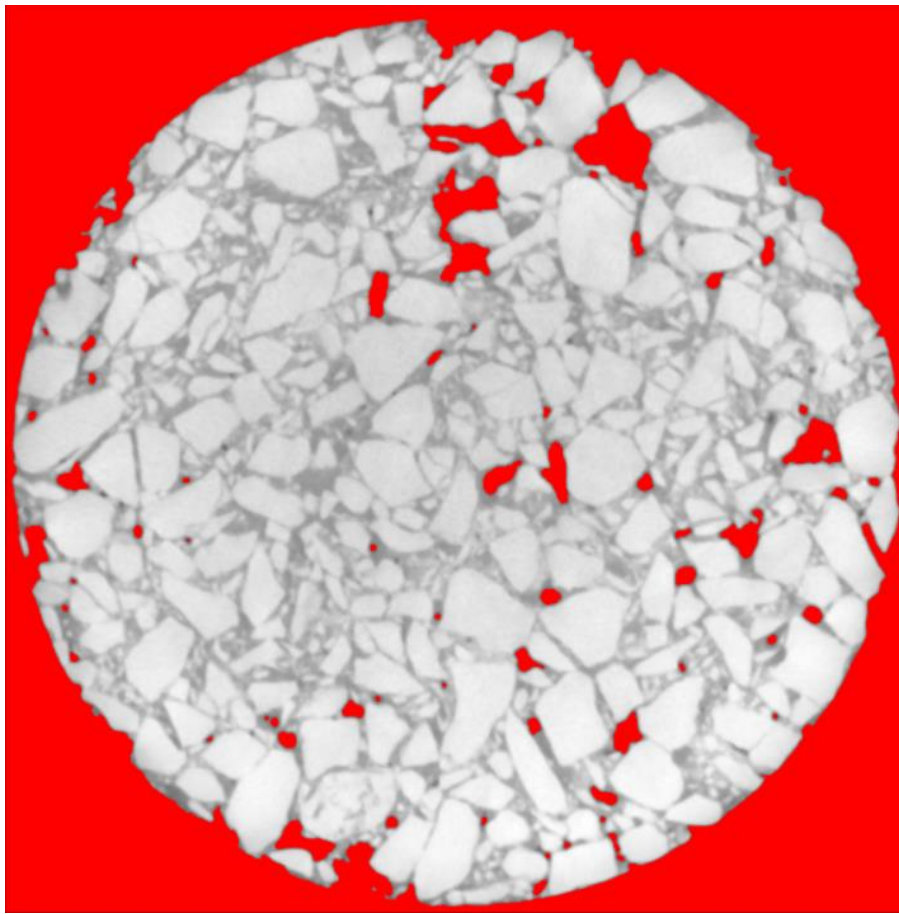
2.8.3.1 Threshold-Based Segmentation

The threshold method leverages grey value differences to separate components, using histograms to define density-dependent intensity ranges (Wan et al., 2010). On the premise that the original CT image reaches a certain quality, the threshold method is the easiest to operate, intuitive, and effective image segmentation method (Zhang & Duan, 2010). For example:

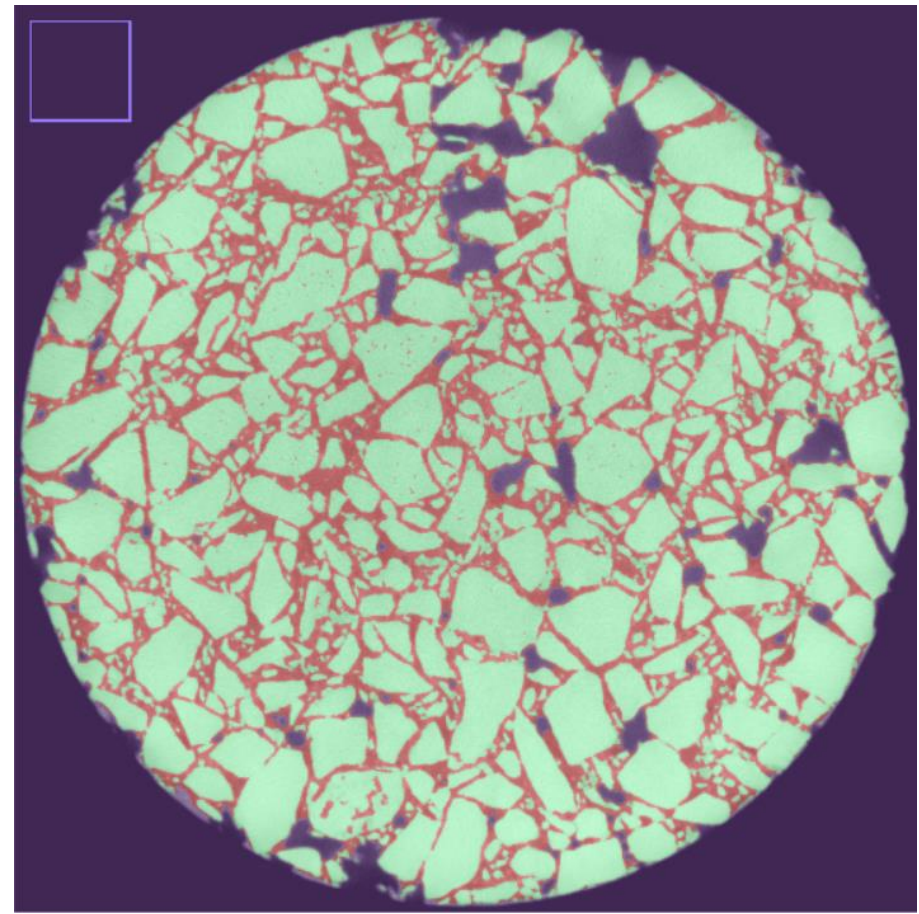
- **Aggregates** (high density): white to light grey
- **Mastic** (intermediate density): medium to dark grey
- **Voids** (low density): black

While intuitive and computationally simple, this method has limitations:

- Single-threshold settings often fail across heterogeneous specimens, as grey values vary with aggregate type and scanning parameters (Figure 14a).
- Segmentation is typically binary (e.g., voids vs. solid phases), requiring multiple passes to separate mastic from aggregates and voids with overlapping grey ranges (Zhang, Duan, Li, Wu, & Wan, 2011).



(a)



(b)

Figure 14: Asphalt Mixture CT Slices: (a) Threshold Segmentation (Binary Void-Solid Separation); (b) Weka Segmentation (Three-Phase Classification)

Weka Segmentation

Waikato Environment for Knowledge Analysis (Weka) segmentation is a plugin for image segmentation. It contains visualization tools and algorithms for data analysis and predictive modeling. It combines machine learning algorithms and image features to support a variety of standard data mining tasks. Weka can analyse and learn the user-labeled image features of different components on one image and automatically segment all the cross-sections (ImageJ Wiki, 2021). This approach:

- Handles complex grey value distributions and can simultaneously segment the three components of the asphalt mixture, reducing manual threshold adjustments (Figure 14(b)).
- It supports batch processing of large CT datasets, though it demands high computational resources and takes a long time.

2.8.4 Technological Advantages and Challenges

CT offers unique benefits for asphalt mixture research:

- **Non-Destructiveness:** Enables longitudinal studies of aged or loaded specimens.
- **Quantitative Analysis:** Provides precise measurements of void topology (e.g., void shape, Euler number, tortuosity) and aggregate interlock.
- **Multiscale Resolution:** Captures features from microtexture (aggregate surface roughness) to macrovoids (connected void networks).

Challenges include:

- **Resolution-Field of View Tradeoff:** High-resolution scans are limited to small specimens.
- **Segmentation Ambiguity:** Mastic-aggregate boundaries are often blurred due to binder coating and filler inclusion.
- **Data Complexity:** Datasets require specialized software for advanced analysis.

2.9 Virtual Asphalt Mixture Design

Against the backdrop of uncertainties in traditional laboratory asphalt mix design, stemming from material variability and external factors, virtual mix design has emerged as a transformative approach in asphalt material research. As digital technology, virtual reality, robotics, and artificial intelligence converge with the asphalt industry, this field is poised to redefine material development paradigms (EAPA, 2021).

The primary advantage of virtual design lies in its ability to precisely control the material design and manufacturing processes while simultaneously recording microscale data at each stage. These data, which reflect the internal structure of asphalt mixtures, significantly influence their macroscopic performance, underscoring the critical role of virtual design in materials science (Hu, Yu, Li, & Song, 2016). By revolutionizing the design and production methodologies, these innovative technologies enhance material development efficiency and mitigate costs and safety risks in the field.

2.9.1 Finite Element Method (FEM) and Discrete Element Method (DEM)

Historically, researchers have predominantly employed two digital techniques—FEM and DEM—to simulate the mechanical behavior and microstructure of asphalt mixtures (Ma, Zhang, Zhang, & Hong, 2016). FEM, grounded in continuum mechanics, treats asphalt mixtures as homogeneous materials (Figure 15) (Papagiannakis, Abbas, & Masad, 2002). While it can model aggregate shapes and textures, it falls short in simulating inter-particle movements and interactions within the mixture (Wang, Kwan, & Chan, 1999).

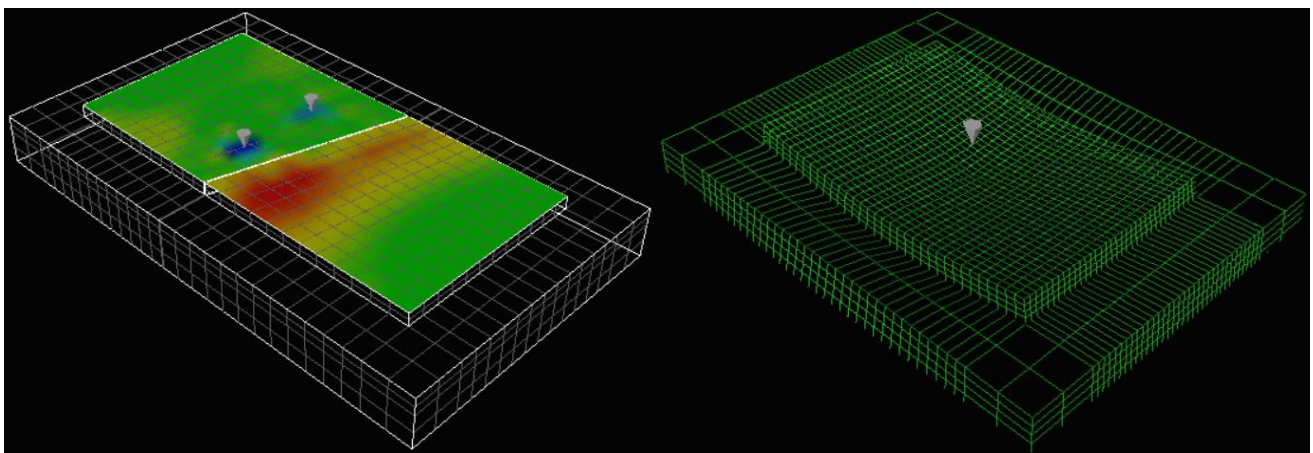


Figure 15: Finite Element Analysis of Pavement Model (Pavement Interactive, 2021)

In contrast, DEM treats aggregate particles as discrete entities, enabling the simulation of their interactions and microscopic motions (Figure 16) (Wang et al., 2014). Leveraging DEM, researchers have developed 2D and 3D models to mimic the random generation of asphalt mixtures and predict physical properties (Aragão, Kim, Lee, & Allen, 2011). Additionally, DEM can replicate diverse compaction processes based on internal microparameters (Tashman, Masad, Peterson, & Saleh, 2000), with the Burgers model commonly used to establish virtual compaction models through contact simulations (Ma, Wang, Zhang, & Zhang, 2017).

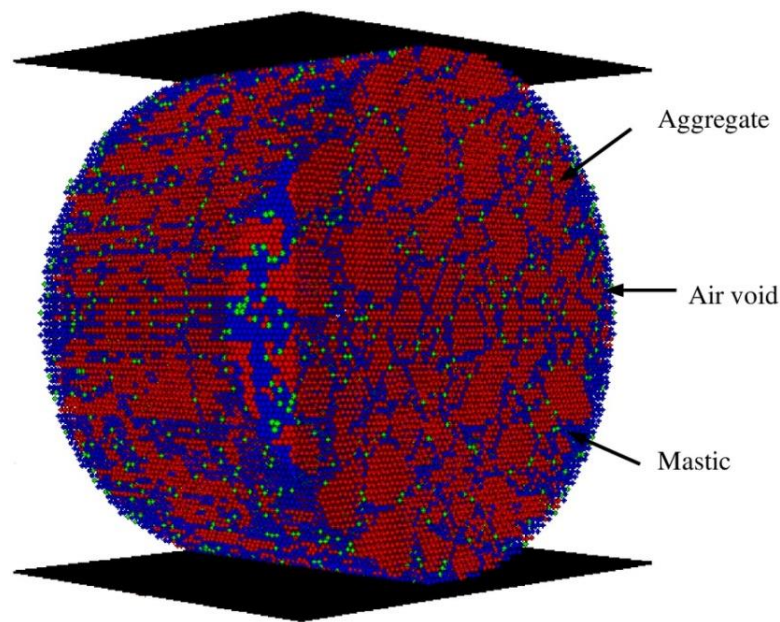


Figure 16: Discrete Element Model of Asphalt Mixture (Peng, Harvey, & Sun, 2017)

2.9.2 Virtual Design and Simulation via Mixlab Software

The core objective of virtual asphalt mixture design is to streamline the creation of virtual specimens and conduct mechanical tests, providing insights into material properties. Accurately capturing the intricate composition and structure of asphalt mixtures is essential for reliable simulations (Wan et al., 2010; Gu et al., 2016).

Mixlab, a software platform built on Unity 3D and powered by the NVIDIA PhysX engine, leverages DEM to enable comprehensive virtual design and 3D structure simulation. It allows users to manipulate material parameters, such as aggregate type and bitumen content, and generates critical microscopic data, including aggregate count, mastic content, and target AVC (Garcia-Hernandez et al., 2021).

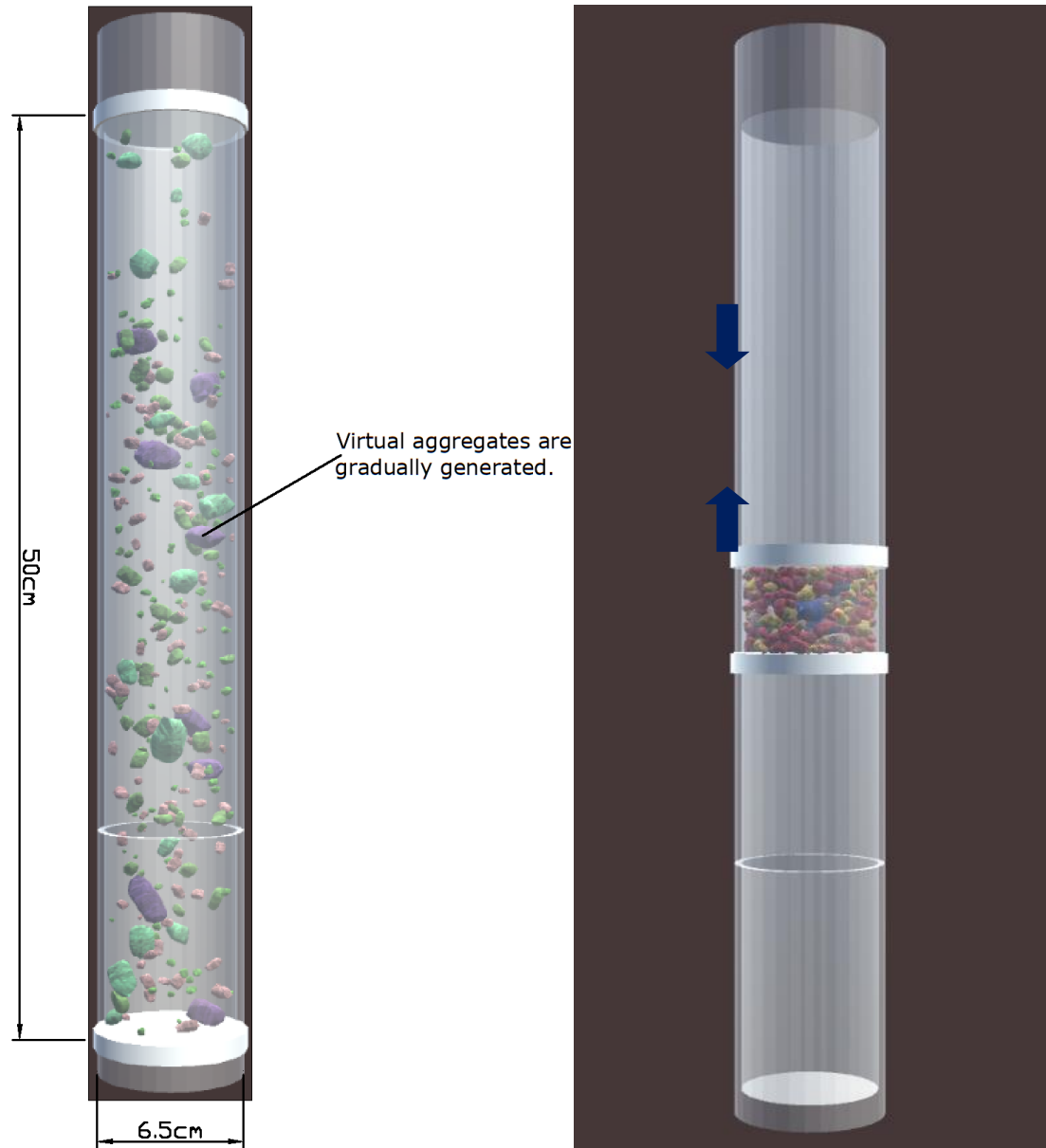


Figure 17: Aggregate Creation and Compaction in Virtual Asphalt

The Mixlab simulation process unfolds in aggregate generation and compaction (Figure 17). First, aggregates are created in a virtual environment with customizable parameters, including size distribution and filler content. Subsequently, virtual pistons apply compression, monitoring porosity changes in real-time (Garcia-Hernandez et al., 2021). This dynamic approach accurately replicates the evolution of material properties during compaction, yielding virtual specimens that closely mimic real-world asphalt mixtures (Figure 18).

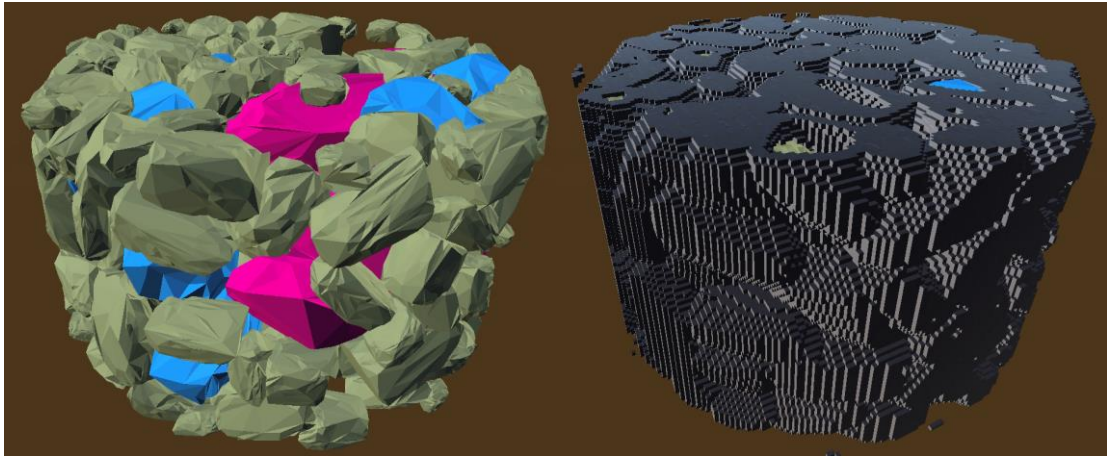


Figure 18: 3D Model of Virtual Aggregate Skeleton and Asphalt Mixture in Mixlab

2.9.3 Intersected Stacked Air Voids (ISA) Method for Virtual Simulation

The ISA method presents a novel geometric approach to generating virtual pore networks in asphalt and granular materials, bypassing the need for physical interaction models. The process commences with creating 2D domains populated with circular or elliptical particles, which are then stacked to form 3D representations of real-world void structures (Chiarelli et al., 2015).

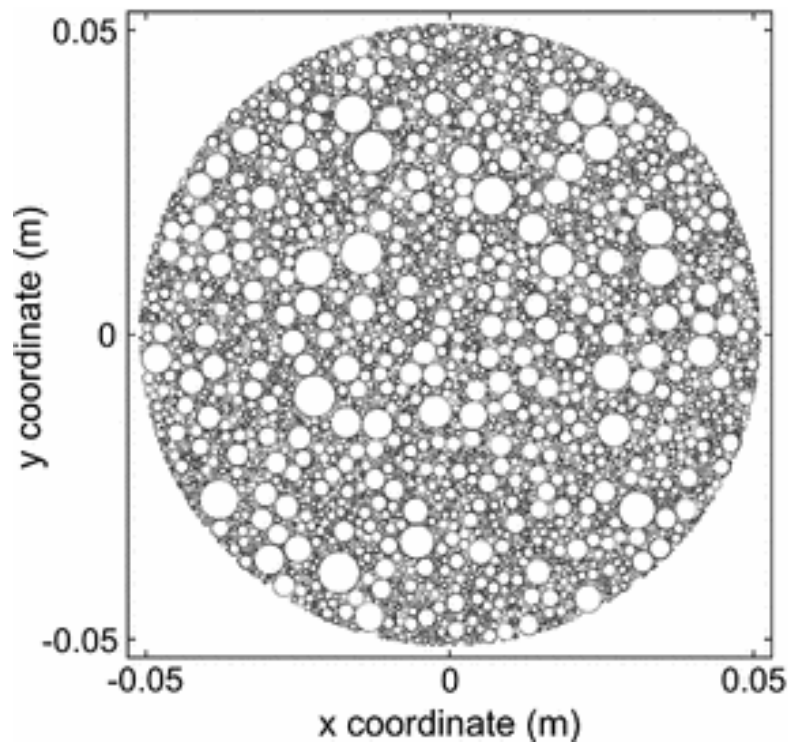


Figure 19: Sample Domain Generated by the ISA Method (Chiarelli et al., 2015)

ISA employs a touch-and-stop packing algorithm, randomly positioning particles within 2D domains and allowing them to grow until contact or overlap occurs (Figure 19). This ensures spatial accuracy and detailed void representation. The transition from 2D to 3D involves converting circles into spheres and stacking layers, effectively simulating granular material characteristics (Figure 20) (Chiarelli et al., 2015).

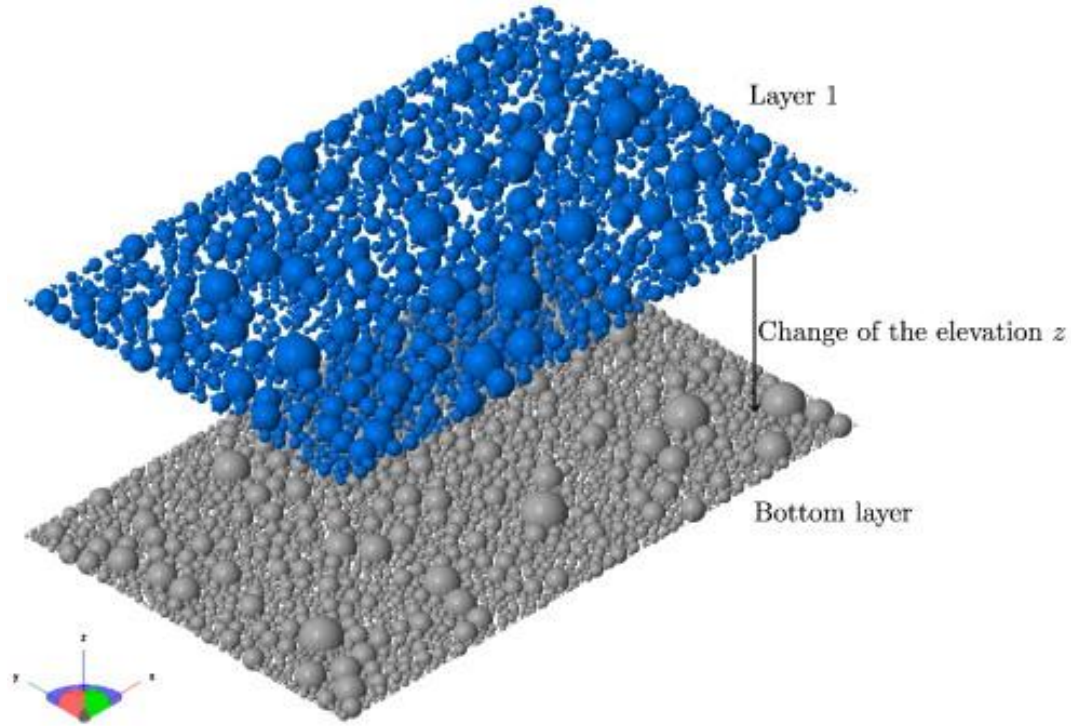


Figure 20: 2D to 3D Conversion Process in the ISA Method (Chiarelli et al., 2015)

The Differential Evolution (DE) algorithm optimizes key parameters, including particle count, target air void content, and growth characteristics to enhance efficiency. By minimizing the error defined in Equation 29, the algorithm achieves configurations that closely match desired asphalt properties, reducing the need for manual adjustments (Storn & Price, 1997; Pham & Karaboga, 2012).

Equation 29:

$$E = (|M_R - M_{OUT}|) + (|A_{vdR} - A_{vdOUT}|) + (|\chi_R - \chi_{OUT}|) + (|T_R - T_{OUT}|)$$

Where

M_R : is the required Macroporosity, [%];

M_{OUT} : is the calculated Macroporosity, [%];

A_{vdR} : is the average void diameter, [mm];

A_{vdOUT} : is the calculated air void diameter, [mm];

χ_R : is the required Euler number;
 χ_{OUT} : is the calculated Euler number;
 T_R : is the required tortuosity;
 T_{OUT} : is the calculated tortuosity.

An integral component of the ISA method is its 3D void identification algorithm. It generates a volumetric grid of points and uses a 3D Boolean matrix to map void spaces, enabling comparisons with real samples via techniques like X-ray CT (Chiarelli et al., 2015). Analyzing void coordination numbers further elucidates pore connectivity, which is crucial for assessing mixture mechanical behavior.

ISA's growth mechanism stands out compared to models such as Johnson–Mehl–Avrami–Kolmogorov (JMAK) and Void Expansion Method (VEM) by continuously introducing new particles to reduce void areas (Andrienko, Brilliantov, & Krapivsky, 1994; Schenker, Filser, & Gauckler, 2010). This approach enhances model realism without the complexity of physical interaction simulations, making ISA a powerful tool for virtual asphalt mixture analysis (Chiarelli et al., 2015).

Multiple studies have successfully employed the ISA method to characterize air void properties in asphalt materials. Given the well-documented interplay between air voids and surface texture in asphalt, where parameters such as void size, connectivity, and distribution directly influence texture formation, the validated accuracy of ISA-generated virtual void models presents a significant opportunity for texture research (Schenker et al., 2010; Chiarelli et al., 2015). By leveraging this method, the intricate relationships between void characteristics and surface texture metrics can be systematically explored, thereby enabling an in-depth understanding and prediction of asphalt surface texture properties.

2.10 Comprehensive Literature Review on AI, ML, and DL

2.10.1 Overview of AI, ML, and DL

Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) are interrelated fields within the broader domain of intelligent systems. AI encompasses technologies that enable machines to perform tasks requiring human-like intelligence,

such as language comprehension and decision-making (Russell & Norvig, 2016). As a subset of AI, ML focuses on developing algorithms that allow systems to learn from data, thereby improving performance without explicit programming (Murphy, 2012). Within ML, DL represents a specialized branch that employs deep neural networks to analyze and learn from large datasets, effectively identifying complex patterns (LeCun, Bottou, Bengio, & Haffner, 1998; Courville, Goodfellow, & Bengio, 2016).

This relationship can be hierarchically structured: AI covers all technologies simulating human intelligence; ML is a data-driven approach to achieve AI; and DL automates feature extraction within ML. The advancements in these technologies have spurred significant innovations across various sectors, including healthcare, finance, and transportation. Understanding these distinctions is essential for navigating the evolving landscape of artificial intelligence (Courville et al., 2016; Russell & Norvig, 2016).

2.10.2 Foundations of Machine Learning and Deep Learning

Key concepts in ML include (Murphy, 2012):

- **Data:** The foundation of ML, comprising various forms such as text, images, and structured datasets, which algorithms utilize for learning and decision-making.
- **Labels:** In supervised learning, data is divided into features (attributes), and labels (targets to predict). For example, image pixel values represent features and object categories serve as labels.
- **Training Data:** ML models learn relationships between features and labels through datasets with known labels.
- **Feature Engineering:** The process of selecting and transforming data attributes to enhance model performance.
- **Models:** Mathematical representations of algorithms capturing relationships between features and labels (e.g., linear regression, neural networks).
- **Training Process:** The iterative optimization of model parameters to improve prediction accuracy.
- **Evaluation and Validation:** These are essential steps for assessing model performance on unseen data using accuracy and F1 score metrics.

Core concepts in DL include (Courville et al., 2016):

- **Neural Networks:** Interconnected artificial neurons organized into layers, simulating human brain function.
- **Deep Learning:** Models with multiple hidden layers that extract intricate features across domains, including image and speech recognition.
- **Convolutional Neural Networks (CNNs):** Specifically designed for image-related tasks, utilizing convolutional layers for automatic feature extraction.
- **Recurrent Neural Networks (RNN):** Tailored for sequential data, effectively capturing temporal dependencies in applications like natural language processing.
- **Deep Learning Frameworks:** Tools like TensorFlow and PyTorch facilitate developing and training deep learning models.

2.10.3 Evolution of Deep Learning

Deep learning has evolved remarkably, punctuated by significant milestones from the 1940s to the present (Schmidhuber, 2022). The journey commenced with McCulloch and Pitts's neural network models in 1943, providing a mathematical basis for understanding neural activity (McCulloch & Pitts, 1943). Subsequent decades introduced pivotal concepts, such as the perceptron in the 1950s (Rosenblatt, 1958) and backpropagation for multilayer perceptrons in the 1980s (LeCun, Touresky, Hinton, & Sejnowski, 1988; LeCun et al., 1989). In 1998, Yann LeCun and colleagues unveiled LeNet-5, establishing fundamental principles like convolution, pooling, and activation functions (LeCun et al., 1998). The emergence of deep belief networks in 2006 marked a renaissance for deep learning (Hinton, Osindero, & Teh, 2006). The transformative impact of deep learning was further solidified by AlexNet's victory in the 2012 ImageNet competition (Krizhevsky, Sutskever, & Hinton, 2012), which achieved groundbreaking results and shifted the narrative from skepticism to widespread recognition of deep learning's superiority over traditional machine learning methods. This success was followed by the introduction of the Transformer model in 2017 (Vaswani, 2017), revolutionizing natural language processing through attention mechanisms and enabling training on vast datasets.

2.10.4 Prominent Deep Learning Algorithms

Since the advent of deep learning in 2006, numerous influential algorithms have transformed the field of artificial intelligence. Below are ten pivotal deep learning algorithms recognized for their innovation, application value, and impact:

1. **Deep Neural Networks (DNN):** Comprising multiple hidden layers, DNNs learn complex feature representations through nonlinear transformations. As network depth increases, they face challenges like the vanishing gradient problem, which affects training stability. Applications include image classification, speech recognition, and natural language processing (Murphy, 2012).
2. **Convolutional Neural Networks (CNN):** Tailored for image data, CNNs employ convolutional layers to capture local features and pooling layers to reduce dimensionality. This architecture excels in tasks like image classification and object detection, although it may struggle with sequential data (LeCun et al., 1998).
3. **Residual Networks (ResNet):** ResNet introduces "residual blocks" with skip connections to alleviate vanishing gradient issues and model degradation, enabling the construction of deep networks. It has demonstrated exceptional performance in image classification and detection tasks (He, Zhang, Ren, & Sun, 2016).
4. **Long-Short-Term Memory Networks (LSTM):** LSTMs enhance traditional RNNs through gating mechanisms that effectively manage long-term dependencies, making them suitable for sequence prediction tasks such as text generation and speech recognition (Hochreiter, 1997).
5. **Word2Vec:** This model converts words into vectors within a continuous vector space, capturing semantic relationships widely used in natural language processing tasks like text classification and sentiment analysis (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013).

6. **Transformer:** Utilizing self-attention mechanisms, the Transformer model captures long-range dependencies in sequential data, significantly enhancing performance in machine translation and text classification (Vaswani, 2017).
7. **Generative Adversarial Networks (GAN):** These networks consist of a generator and a discriminator that compete to produce realistic data. GANs excel in image generation and data augmentation tasks but may face training instability (Goodfellow et al., 2014).
8. **Diffusion models:** These models generate data by progressively adding and removing noise, producing high-quality outputs while ensuring stability during training (Sohl-Dickstein, Weiss, Maheswaranathan, & Ganguli, 2015).
9. **Graph Neural Networks (GNN):** GNNs excel at learning from graph-structured data by iteratively aggregating information from neighboring nodes, making them suitable for applications in social network analysis and molecular structure prediction (Gilmer, Schoenholz, Riley, Vinyals, & Dahl, 2017).
10. **Deep Q-Networks (DQN):** DQNs leverage deep learning within reinforcement learning, utilizing a neural network to approximate Q-values for actions in high-dimensional spaces. They find applications in AI for gaming and robotic control (Mnih et al., 2015).

These algorithms represent the forefront of deep learning innovations, each addressing unique challenges and excelling in various applications.

2.10.5 Convolutional Neural Networks

CNNs are designed explicitly for processing grid-like data, such as images. Biological processes inspire them in the visual cortex of animals, where stimuli activate individual neurons within a limited receptive field. This structure enables CNNs to recognize visual data patterns and features (LeCun et al., 1998).

A typical CNN comprises multiple layers:

- **Input Layer:** Accepts multi-dimensional input, such as RGB images represented as $n \times m \times 3$ tensors.
- **Convolutional Layer:** This layer performs feature extraction by applying filters (or kernels) that slide over the input image, calculating dot products, and producing feature maps. Each filter detects specific features like edges or textures, and the number of filters increases with network depth to capture more complex features (Krizhevsky et al., 2012).
- **Pooling Layer:** Pooling operations, such as max pooling and average pooling, reduce spatial dimensions of feature maps, decrease the number of parameters and computational load while retaining significant information. This layer also introduces translational invariance, allowing the network to recognize objects regardless of their position within the image.
- **Non-linearity Layer:** The ReLU activation function typically introduces non-linearity, enabling the model to learn more complex functions.
- **Fully Connected Layer:** In the final layers, the CNN flattens high-level features into a one-dimensional vector, connecting to fully connected layers akin to traditional neural networks to make predictions based on learned features.

CNNs utilize backpropagation to update weights based on the loss function, applying gradient descent to minimize errors during training (Rumelhart, Hinton, & Williams, 1986). Their architecture renders them particularly effective for image classification tasks, exemplified by successful applications such as the MNIST digit recognition dataset, showcasing their robustness in handling visual data despite variations in appearance (LeCun, 1998).

In summary, CNNs represent a robust architecture for image analysis. They leverage layered structures to automatically extract features efficiently, making them invaluable

for computer vision tasks and beyond. As data complexity increases, the application of CNNs continues to evolve, pushing the boundaries of visual recognition capabilities.

2.10.6 The Role and Diversity of Activation Functions

Activation functions are essential components of artificial neural networks, facilitating learning intricate patterns from data and determining neuron outputs based on their inputs. Their selection is critical for a network's capacity to model complex functions effectively. Below is a refined overview of key activation functions, their characteristics, and their applications:

Sigmoid Function: Maps real-valued inputs to a range between 0 and 1, making it suitable for binary classification tasks. Its smooth, S-shaped curve promotes gradient continuity, enhancing the stability of backpropagation algorithms (Han & Moraga, 1995).

Equation 30:
$$f(x) = \frac{1}{1+e^{-x}}$$

Tanh Function: Similar to the Sigmoid function, it maps inputs to the interval (-1, 1). Due to its broader output range, it is frequently employed in hidden layers, facilitating more effective learning in neural networks (Fan, 2000).

Equation 31:
$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

ReLU (Rectified Linear Unit): ReLU outputs the input directly when positive and zero otherwise. It accelerates training and effectively addresses the vanishing gradient problem associated with Sigmoid and Tanh functions (Agarap, 2018).

Equation 32:
$$f(x) = \max(0, x)$$

Leaky ReLU: An enhancement of ReLU, allowing a small, non-zero gradient for negative inputs, alleviating the "dying ReLU" issue (Xu, Li, Du, Zhang, & Liu, 2020).

Equation 33:
$$f(x) = \max(ax, x)$$

Where a is a small slope (usually close to zero).

Parametric ReLU (PReLU): Builds on Leaky ReLU by allowing the negative slope to be learned during training, providing increased flexibility (Zhang, Pan, Sun, & Tang, 2018).

Equation 34:
$$f(x) = \max(ax, x)$$

Where a is a learnable parameter.

ELU (Exponential Linear Unit): Combines advantages of ReLU while providing a continuous gradient for negative values, contributing to a zero-centered activation distribution (Clevert, 2015).

Equation 35:
$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha(e^x - 1) & \text{if } x \leq 0 \end{cases}$$

Where α is a small positive number, typically equal to 1.

Softmax Function: Commonly utilized in the output layer for multi-class classification, transforming a vector of raw scores into a probability distribution for categorical predictions (Gao & Pavel, 2017).

Equation 36:
$$f(x_i) = \frac{e^{x_i}}{\sum_{j=1}^n e^{x_j}}$$

Where x_i is the i -th element of the input vector and n is the vector length.

Swish Function: Google Brain proposed this self-gated activation function, which integrates linear and non-linear properties and yields improved performance on specific tasks (Mercioni & Holban, 2020).

Equation 37:
$$f(x) = x \cdot \text{sigmoid}(x)$$

Maxout Function: This function outputs the maximum value from a set of linear functions, enhancing the model's expressive capacity (Castaneda, Morris, & Khoshgoftaar, 2019).

Equation 38:
$$f(x) = \max(w_1^T x + b_1, w_2^T x + b_2, \dots, w_k^T x + b_k)$$

Where x is the input vector, w_i and b_i are parameters, and k is group size.

Softplus Function: A smooth approximation of the ReLU function, avoiding non-differentiability at zero while retaining non-linear characteristics (Sun, Yu, Zhang, & Dong, 2020).

Equation 39:
$$f(x) = \ln(1 + e^x)$$

Mish Function: A recent addition that combines benefits from ReLU, tanh, and Softplus, demonstrating promising results across various applications (Zhang & Wang, 2021).

Equation 40:
$$f(x) = x \cdot \tanh(\text{softplus}(x))$$

GELU (Gaussian Error Linear Units): Introduced by Hendricks and Gimpel in 2016, GELU approximates natural neuron behavior and performs significantly in deep neural networks (Hendrycks & Gimpel, 2016) .

Equation 41:
$$f(x) = 0.5x(1 + \tanh\left(\sqrt{\frac{2}{\pi}}(x + 0.044715x^3)\right))$$

2.10.7 The Importance and Evolution of Optimization Algorithms

Optimization algorithms play a crucial role in machine learning by minimizing loss functions and determining optimal parameters, significantly enhancing model performance. They enable the selection of suitable algorithms for specific problems and data while laying the groundwork for developing new models (Alzubaidi et al., 2021).

Gradient Descent is a foundational method for unconstrained minimization among these algorithms. Stochastic Gradient Descent (SGD) improves efficiency by computing gradients using individual samples, making it ideal for large datasets. Momentum SGD further accelerates learning in complex optimization scenarios. Adaptive methods like RMSProp and Adam dynamically adjust learning rates based on gradient information, enhancing stability and performance. Second-order methods, such as Newton's and Conjugate Gradient, converge more rapidly but are computationally intensive. Metaheuristic algorithms like Simulated Annealing and Genetic Algorithms provide global optimization solutions, particularly effective in navigating problems with multiple local optima (Alzubaidi et al., 2021).

In summary, the evolution of optimization algorithms—from basic methods to advanced adaptive techniques—has been vital in advancing machine learning

capabilities and addressing diverse challenges in model training and performance enhancement (Talaoui Khoei, Ould Slimane, & Kaabouch, 2023).

2.10.8 VGG Model Hyperparameters

The VGG model is a widely adopted deep convolutional neural network architecture in computer vision, renowned for its simplicity and effectiveness (Simonyan & Zisserman, 2014). Understanding the hyperparameters of VGG is essential for optimizing the training processes and model performance. The following are key hyperparameters and their implications:

2.10.8.1 Learning Rate

The learning rate is a hyperparameter that controls the rate at which the model parameters are updated. An appropriate learning rate can accelerate the convergence process, while a value that is too high may lead to instability in training or failure to converge (Smith, 2018). Common learning rate scheduling strategies include:

- **Fixed Learning Rate:** The learning rate remains constant throughout the training process.
- **Learning Rate Decay:** The learning rate is gradually reduced as training epochs increase, enhancing convergence capabilities.
- **Adaptive Learning Rate:** Optimizers like Adam dynamically adjust the learning rate based on historical gradient information (Kingma, 2014).

2.10.8.2 Momentum

Momentum is a technique for accelerating the gradient descent process by incorporating a weighted average of past gradients into the parameter updates. This approach helps smooth the updates, reduce oscillations, and speed up convergence. Common momentum values typically range from 0.9 to 0.99 (Sutskever, 2014; Smith, 2018).

2.10.8.3 Batch Size

The batch size is the number of training samples utilized in one iteration for parameter updates. Smaller batch sizes can enhance the model's generalization ability, although they may lead to training instability. Conversely, larger batch sizes can accelerate

training but may result in overfitting. Standard batch sizes generally range from 32 to 256 (Keskar, Mudigere, Nocedal, Smelyanskiy, & Tang, 2016).

2.10.8.4 Normalization

Normalization techniques are crucial for improving convergence speed and stability during training. Standard normalization methods used in VGG include:

- **Batch Normalization:** Normalizes the inputs to each layer, ensuring a mean of 0 and a variance of 1, which accelerates training and improves stability (Ioffe, 2015).
- **Image Normalization:** During preprocessing, image pixel values are scaled to a specific range (e.g., [0, 1] or [-1, 1]) to enhance training efficiency (Finlayson, Schiele, & Crowley, 1998).

2.10.8.5 Regularization

Regularization techniques prevent overfitting and enhance the model's generalization capability. Standard regularization methods used in the VGG model include:

- **L2 Regularization:** Incorporating the L2 norm of the weights into the loss function to restrain model complexity (Cortes, Mohri, & Rostamizadeh, 2012).
- **Dropout:** Randomly deactivating a fraction of neurons during training to reduce reliance on specific neurons and enhance robustness (Srivastava, Hinton, Krizhevsky, Sutskever, & Salakhutdinov, 2014).

2.10.8.6 Epochs

An epoch refers to one complete pass through the entire training dataset. The choice of the number of epochs is crucial, as an appropriate number can improve the model's learning effectiveness, while excessive epochs may lead to overfitting. Common practice is to monitor validation loss and accuracy to determine the optimal number of epochs (Zhuang et al., 2020).

2.10.8.7 Accuracy and Cross-Entropy Loss

Accuracy is the ratio of correctly predicted instances to the total cases, providing a straightforward metric for assessing the model's ability to classify data correctly. Cross-

entropy loss is commonly employed as a loss function in classification tasks, quantifying the dissimilarity between predicted probabilities and the actual class labels. It is particularly effective in scenarios where class probabilities are modeled using softmax functions. The model's accuracy is often evaluated alongside the cross-entropy loss, as a decrease in loss typically correlates with an increase in accuracy, thus serving as an essential measure of model performance (Bishop, 2006).

2.10.8.8 Mean Absolute Error (MAE) and Mean Squared Error (MSE)

MAE and MSE are widely used metrics for evaluating regression model performance. MAE calculates the average of the absolute differences between predicted and actual values, making it less sensitive to outliers. On the other hand, MSE measures the average of the squared differences, emphasizing larger errors, which can be particularly useful when significant inaccuracies are undesirable. While both metrics can yield equivalent values under specific conditions, they generally serve different purposes based on the error characteristics (Hyndman & Koehler, 2006; Botchkarev, 2018).

By carefully tuning these hyperparameters, one can significantly enhance the performance of the VGG model for image classification and other tasks. Understanding the effects of each hyperparameter on the training process guides the selection of optimal model configurations, facilitating the practical application of deep learning.

2.10.9 Integration with Asphalt Pavement Research

Traditional monitoring methods, such as manual inspection and simple physical indexing, are inefficient and inaccurate. Advances in machine learning and neural network technologies have introduced innovative solutions to address these limitations, enabling more efficient and automated pavement analysis.

Machine learning and neural networks have demonstrated substantial advantages in pavement monitoring, enhancing detection accuracy and efficiency through automated analysis. For example, Zheng et al. (2018) employed convolutional neural networks (CNNs) to achieve high-precision prediction of asphalt pavement texture depth, overcoming the subjectivity limitations of traditional methods (Tong, Gao, Sha, Hu, & Li, 2018). Qu et al. (2020) developed a hybrid network combining LeNet-5 and VGG16,

significantly improving the identification of concrete cracks under complex environmental conditions (Qu, Mei, Liu, & Zhou, 2020). Liu et al. (2021) reconstructed 3D pavement textures through multi-view image fusion, providing comprehensive data support for performance evaluation (Liu, Li, Gao, Yuan, Gao, & Chen, 2021). Dan et al. (2024) utilized multi-view stereo technology with a PatchmatchNet model to effectively address the environmental sensitivity of conventional detection methods (Dan et al., 2024). Additionally, Alatoom & Al-Suleiman (2022) used artificial neural networks (ANNs) to predict pavement roughness in real time, outperforming traditional regression models significantly (Alatoom & Al-Suleiman, 2022).

In conclusion, integrating AI, ML, and DL in asphalt pavement research offers excellent potential for improving texture analysis, overcoming traditional limitations, and providing more accurate and reliable predictions for pavement performance. However, further research is needed to realize this potential and ensure the practical application of these technologies in the field. While deep learning has advanced pavement texture analysis, prior studies often rely on complex multi-view imaging systems (Liu et al., 2021; Dan, Bai, Zhu, Liu, & Cao, 2022) or specialized 3D scanning equipment (Mataei, Nejad, & Zakeri, 2022), requiring expensive equipment and complex data processing, limiting practical scalability (Liu et al., 2021; Dan et al., 2024). Thus, there is an urgent need for lightweight, single-view solutions that eliminate reliance on specialized hardware, streamline data acquisition, and enable scalable, cost-effective texture evaluation.

2.11 Literature Review Gaps and Research Opportunities

2.11.1 Current Research Landscape

2.11.1.1 Traditional Void-Texture Studies

The existing literature predominantly focuses on porosity, which is measured through standard laboratory tests when exploring the relationship between asphalt mixture microstructure and surface texture. Quantifying additional internal void topology parameters—including size, connectivity, and shape—requires specialized equipment like X-ray CT scanning. This limitation has led to neglect of the synergistic effects of void geometry and connectivity on macrotexture development (Chen et al., 2019; Huang et al., 2022).

While a strong positive correlation exists between air void content and MPD, research indicates this relationship is inherently non-linear. This complexity underscores the necessity of analyzing additional topological properties to establish direct cause-and-effect links with MPD (Han, Sun, & Fwa, 2021). Without understanding these nuanced interactions, the field lacks a comprehensive mechanistic model for predicting how microscale void features translate to macroscale texture performance, impeding advancements in asphalt design optimization.

2.11.1.2 Virtual Modeling with ISA Method

The Intersected Stacked Air Voids (ISA) method has been successfully validated for simulating void geometry (Schenker et al., 2010; Chiarelli et al., 2015). However, its potential applications remain confined to void property characterization. Current studies have yet to explore or validate the correlations between virtual void models generated by ISA and surface texture parameters. This gap limits the method's utility in predicting texture behavior, preventing integration into virtual texture analysis workflows for asphalt mixture design.

2.11.1.3 Deep Learning (DL) Applications

In DL-based texture analysis, most existing studies rely on 3D laser scans, multi-view imagery, or professional 3D scanners (Liu et al., 2021; Dan et al., 2024). These approaches demand substantial hardware investments and complex data processing pipelines, significantly increasing operational costs and technical barriers. The absence of lightweight DL models that can be deployed on standard laptops, capable of predicting MPD_{VGG} from monocular 2D images captured by smartphones or tablets, severely restricts field-scale accessibility. Such solutions are crucial for streamlining on-site data acquisition and making texture evaluation more cost-effective and operationally feasible.

2.11.2 Unaddressed Research Gaps

1. **Quantitative Void-Texture Relationships:** A significant knowledge gap exists in establishing the mechanistic link between multi-dimensional void parameters (e.g., average void diameter, void perimeter, connectivity) and key macrotexture metrics

(MPD_{CT}, texture wavelength). Current predictive models fail to incorporate topological features, rendering them insufficient for accurately forecasting texture characteristics based on void properties.

2. **Virtual Texture Simulation Validation:** Despite its ability to generate realistic void networks, the ISA method lacks validation for simulating texture depth and distribution against experimental data. Without this validation, the method cannot reliably replace costly CT scans for microscopic analysis in texture-centric asphalt mixture design, hindering the transition to more efficient computational design processes.
3. **Field-Accessible DL Models:** No validated DL framework can predict MPD_{VGG} from standard 2D images captured by consumer devices (e.g., smartphones). Existing solutions' reliance on professional 3D equipment precludes their adoption for routine infrastructure management, creating a critical need for more accessible and practical texture evaluation tools.

2.11.3 Proposed Research Innovations

1. **Multi-Parameter Void-Texture Modeling:** Leverage CT-derived void metrics, including, e.g., average void diameter and void perimeter, to develop advanced regression models for MPD_{CT} prediction. These models will capture the combined effects of void topology on surface texture, enabling a more comprehensive understanding of micro-macro scale interactions.
2. **ISA-Driven Virtual Texture Analysis:** Validate the ISA method's ability to simulate texture depth by cross-correlating virtual void networks with CT-based average void diameter and MPD_{CT} data; experimental MTD_{SPT} and MPD_{LS} data. This validation will establish ISA as a reliable computational alternative to physical CT analysis, facilitating cost-effective virtual testing in asphalt mixture design.
3. **Lightweight Monocular DL Framework:** Develop a VGG-based CNN optimized for smartphone images, enabling sub-millimeter MPD_{VGG} prediction

using standard laptop computational resources. This innovative approach will replace traditional laser profilometry with simplified "capture-and-predict" workflows, eliminating the need for specialized measurement equipment and enhancing field-scale usability.

2.11.4 Research Impact

This research will establish a cohesive pipeline bridging microscale void properties and macroscale texture performance by systematically addressing these identified gaps. The proposed innovations will transform asphalt design practices through data-driven texture optimization, cost-effective virtual testing, and accessible on-site measurement capabilities. These advancements are essential for driving the field towards next-generation intelligent pavement management, enabling more efficient infrastructure monitoring and maintenance.

3 Void Properties and Macrotexture Correlation

3.1 Introduction

This chapter explores the statistical correlations between void volumetric/topological properties and surface macrotexture in asphalt mixtures, providing essential data for validating virtual texture models in subsequent research. Using X-ray CT and digital image processing, void properties (macroporosity, average void diameter, Euler number) were quantified in 19 Marshall-prepared asphalt cores with varying porosities and aggregate sizes. High-resolution CT scans were segmented to isolate voids, mastic, and VMA, and 3D reconstructions were generated from stacked cross-sections. Macrotexture parameters, including MPD_{CT} and dominant wavelength, were derived through precise cutting and data analysis.

Pearson correlations and multivariate regression revealed a strong positive linear relationship ($r^2 = 0.8$) between average void diameter and MPD_{CT} . These findings elucidate micro-macro scale interactions and establish a critical validation basis for virtual modeling studies. By grounding texture prediction in quantified void-macrotexture links, this research advances the development of data-driven approaches for asphalt mixture design.

3.2 Methodology

3.2.1 Sample Fabrication

Nineteen cylindrical specimens (100 mm diameter $\times$ 65 mm height) were prepared using the Marshall compaction method (Figure 21). Given the sample size constraints of X-ray CT scanning (typically limited to diameters <150 mm for high-resolution imaging), Marshall cores were selected as they balance representative volume with CT's spatial resolution requirements. Raw materials included granite/limestone aggregates and 60/40 penetration-grade bitumen, with systematically varied gradations and binder contents to achieve target air voids (3.96–22.23%) and maximum aggregate sizes (6.3–20 mm). Detailed compositions are in Table 12 (Appendix).



Figure 21: Cylindrical Asphalt Specimens Manufactured via the Marshall Method

3.2.2 Density and Porosity Measurement

Aggregate density was assumed to be 2.7 g/cm³, and bitumen density was 1.03 g/cm³. Maximum mixture density followed BS EN 12697-5:2018 (BSI, 2018), while bulk density used foil sealing per BS EN 12697-6:2020 (BSI, 2020). Porosity was calculated from bulk/maximum density ratios, as specified by BS EN 12697-8:2018 (BSI, 2018). Traditional volumetric methods quantify overall air void content but cannot resolve 3D void topology—an advantage of CT scanning, detailed in 3.2.3.

3.2.3 CT Data Acquisition

Dry cores underwent 2-hour 360° scans on a Phoenix v|tomex|L scanner (290 kV, 2700 μ A), generating 16-bit TIFF stacks at 90.54 μ m resolution. Images were cropped to 1150 $\times$ 1150 pixels to minimize cone-beam artifacts. Unlike traditional methods, CT enables quantification of void connectivity, shape anisotropy, and tortuosity, which are critical for linking microscale void topology to macrotexture.

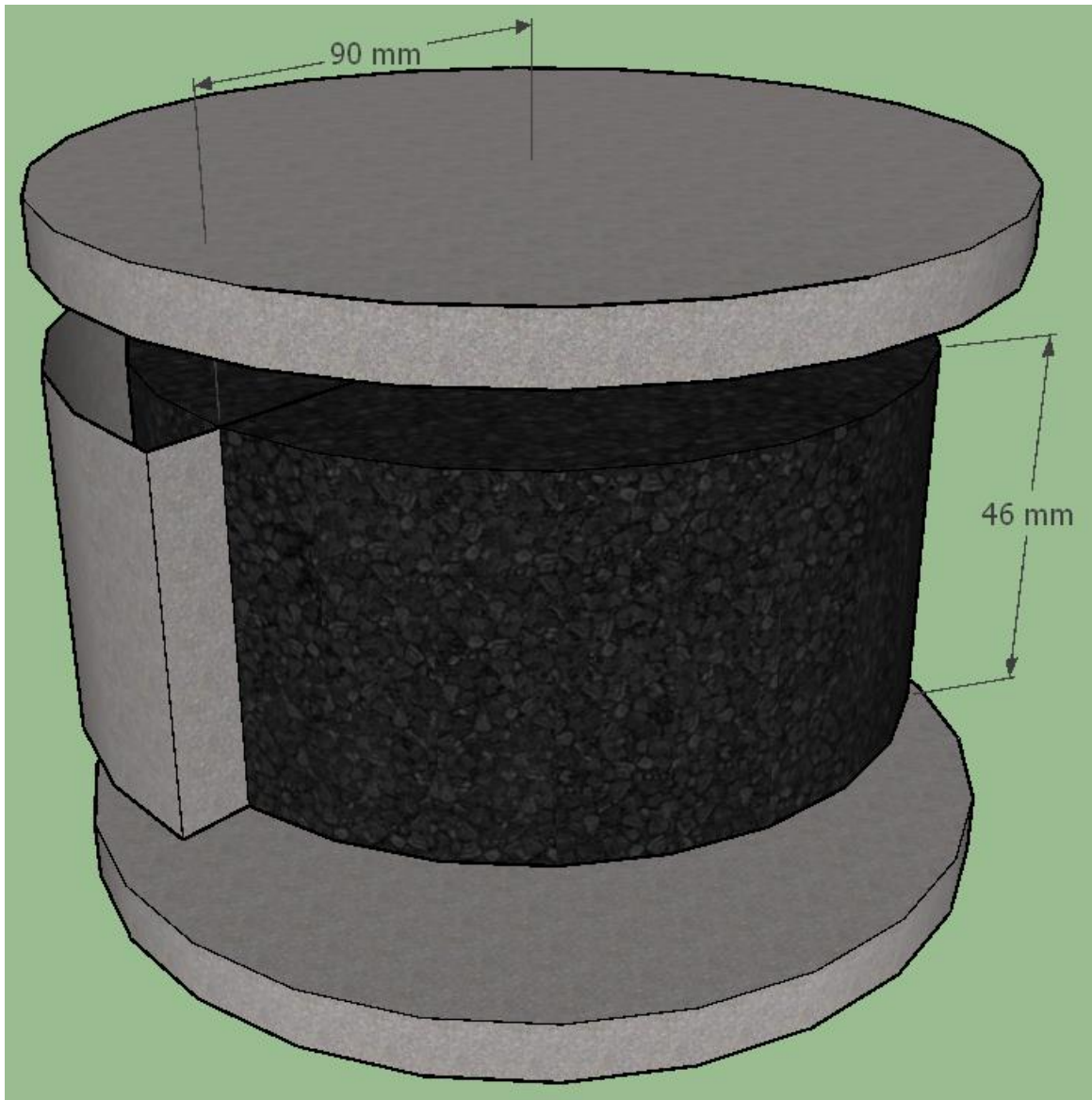
3.2.4 Region of Interest (ROI) Defining

CT images were processed using ImageJ to quantify void topological properties within the mixtures. As shown in Figure 22, a central cylindrical ROI (90 mm in diameter, 46 mm in height) was selected for analysis. For each asphalt core, void topological properties were measured across 170 clear, complete cross-sectional slices of this ROI, with a vertical interval of 0.27 mm between consecutive slices.

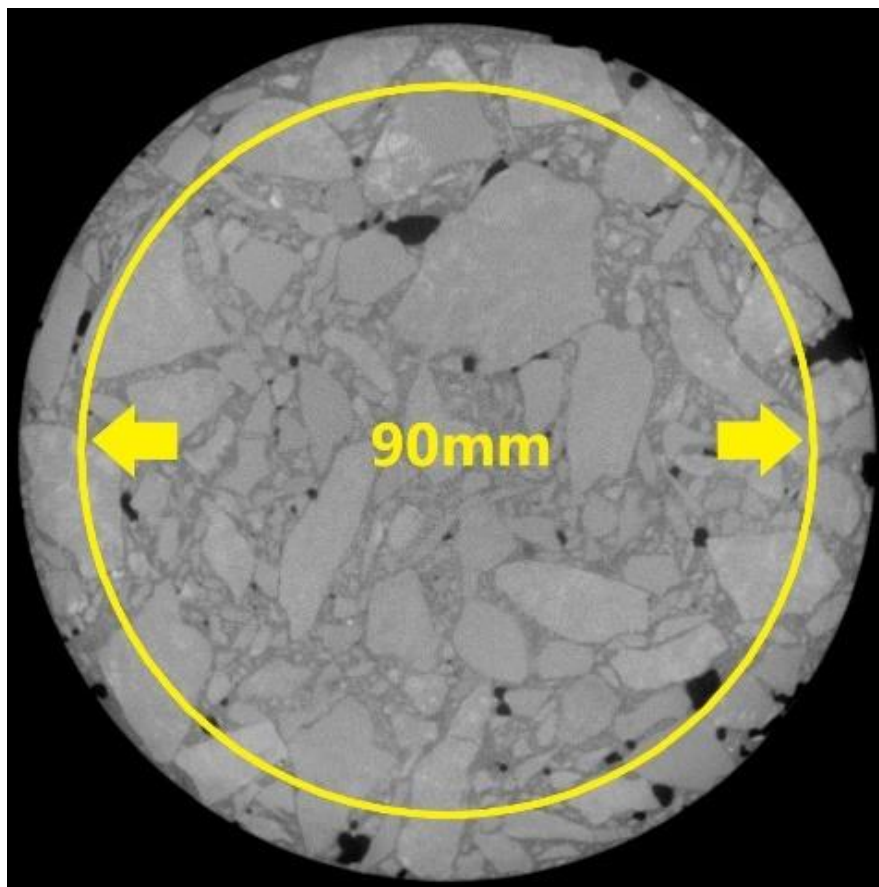
3.2.5 Image Segmentation

X-ray CT generates grayscale images where material phases (aggregates, mastic, voids) are distinguishable by intensity differences. However, overlapping grayscale ranges between mastic and aggregates complicate threshold-based segmentation, as shown in Figure 23(a) (a representative raw CT slice of asphalt). The Trainable Weka Segmentation plugin (Arganda-Carreras et al., 2016)—an AI-driven ImageJ tool—enhanced segmentation accuracy. This plugin leverages machine learning to analyze material-specific image features, enabling precise differentiation of phases. Post-segmentation, Figure 23(b) demonstrates clear color coding: aggregates (green), mastic (red), and voids (purple), facilitating component isolation for further analysis via threshold adjustments.

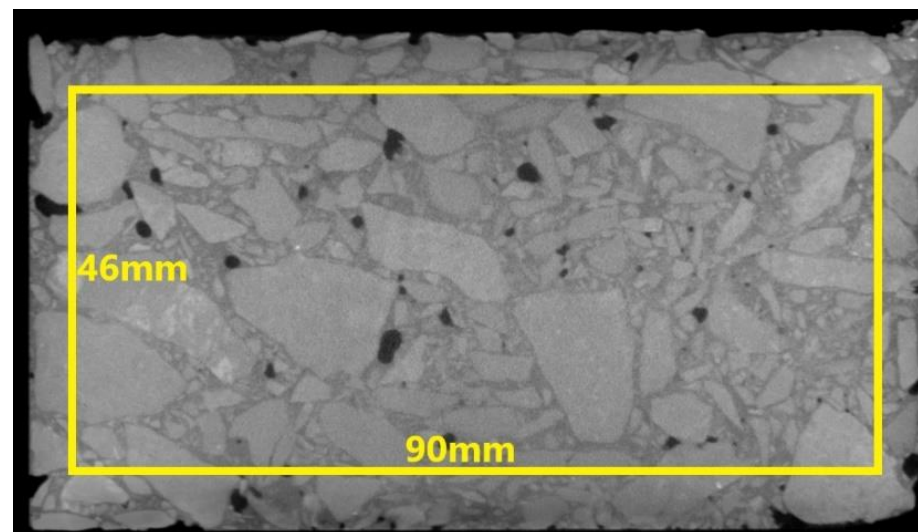
Figure 24 illustrates the segmentation of air voids (V_a), mastic, and voids in mineral aggregate (VMA) within the ROI of the same core. Panels (a), (b), and (c) show 2D segmentations of V_a , mastic, and VMA, respectively (black regions denote the target phase). Mastic is the composite of bitumen and particles <2 mm (Gao et al., 2018). Panels (d), (e), and (f) present 3D reconstructions of these phases, generated by stacking 170 slices to visualize their spatial distribution throughout the core.



(a)

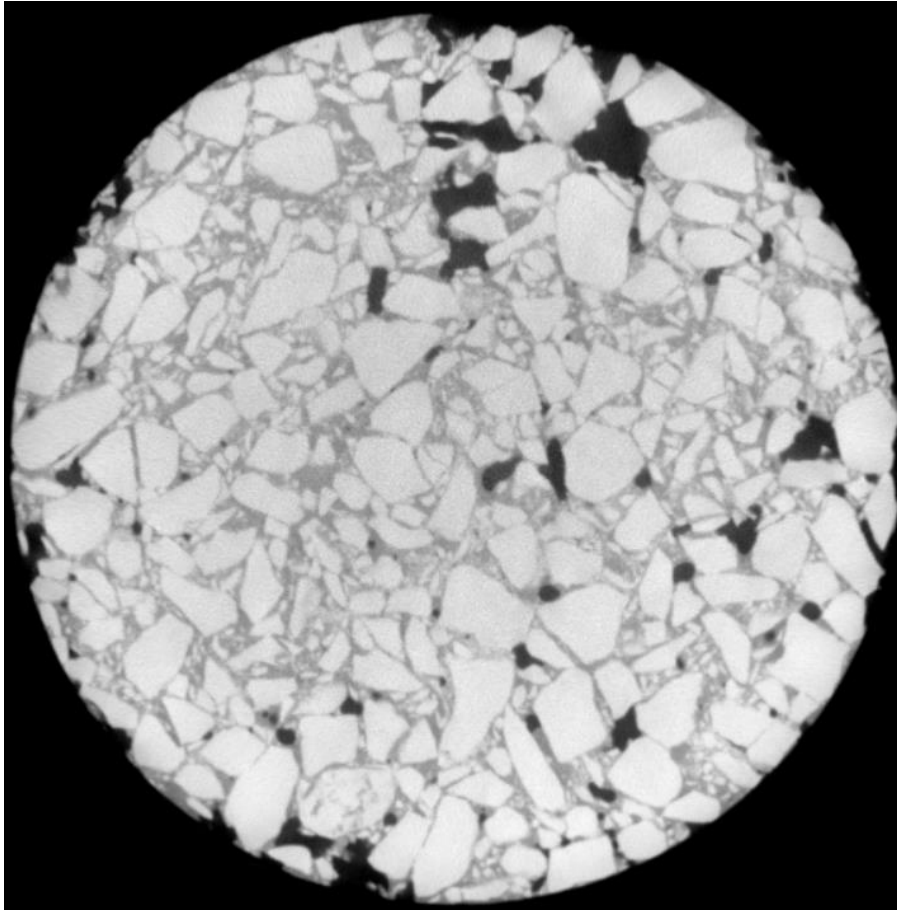


(b)

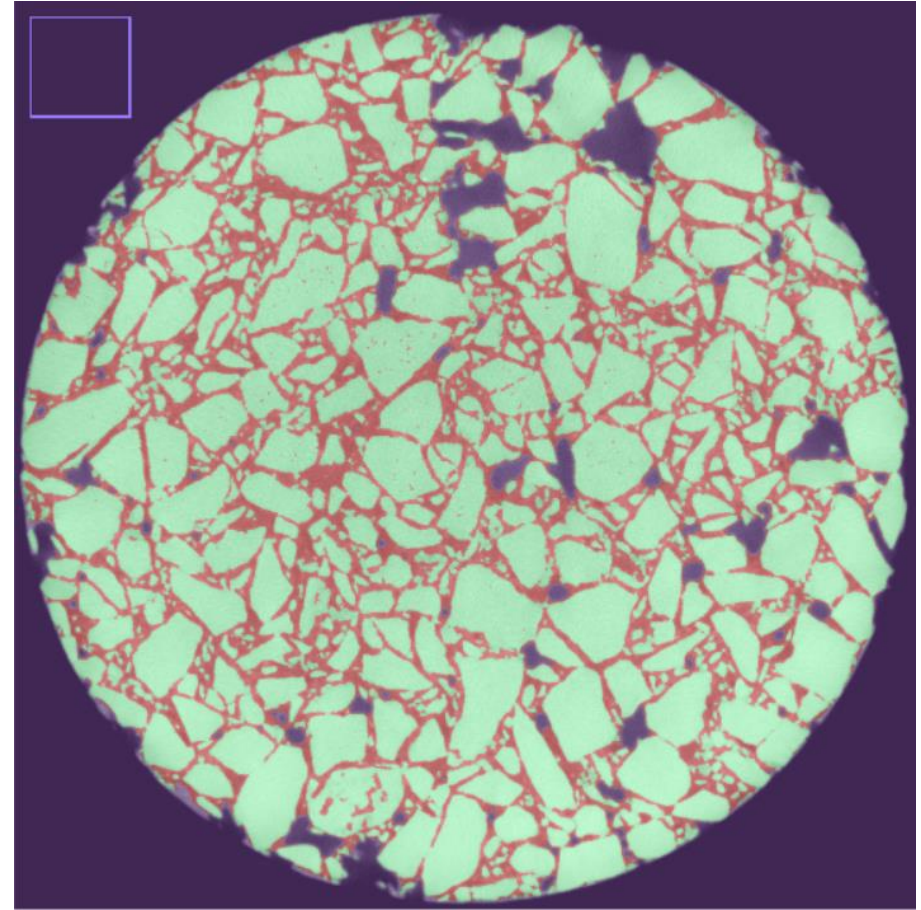


(c)

Figure 22: ROI for Void Topology Analysis. (a) 3D Schematic Representation of ROI. (b) Top View. (c) Side View.



(a)



(b)

Figure 23: Comparison of Original and Segmented Asphalt CT Images. (a) Original CT Slice. (b) Segmented Slice with Color-Coded

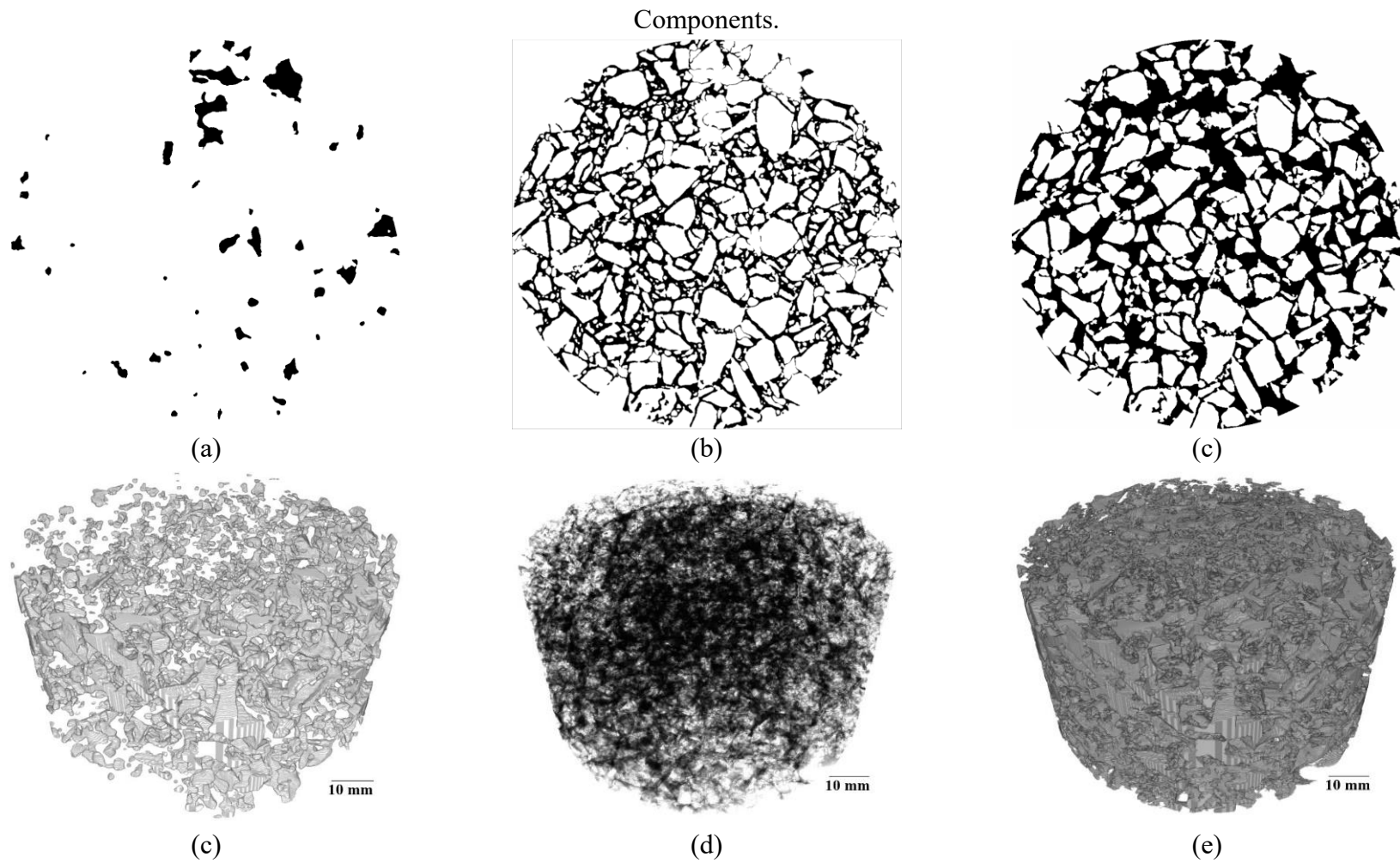


Figure 24: Segmentation and 3D Representation of Asphalt Components. (a) Air Voids. (b) Mastic. (c) VMA. (d-f) 3D Structural Representations of Segmented Components.

3.2.6 Quantification of Void Topological Properties

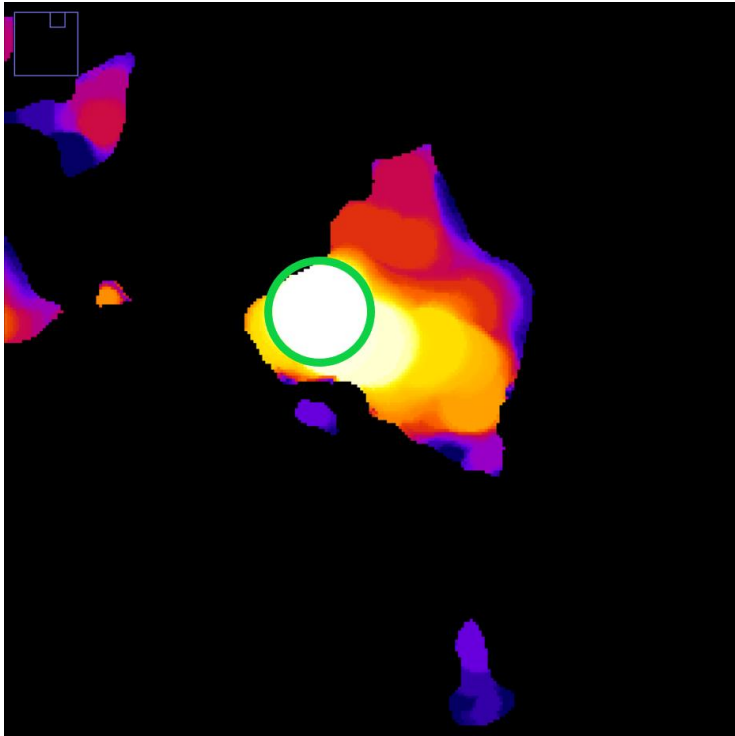
Topological properties of V_a and VMA were quantified separately using ImageJ (Schneider, Rasband, & Eliceiri, 2012). Parameters included macroporosity (Katuwal et al., 2015), average void diameter (Katuwal et al., 2015), Euler number (Romero, 2000), volume of the biggest air void (Garcia et al., 2015), percolation number (Garcia et al., 2015), and tortuosity (Roque & Costa, 2020), measured via specialized ImageJ plugins. Macroporosity was equated to air void content derived from CT measurements.

The 3D average void diameter was calculated using the BoneJ plugin in ImageJ (Doubé et al., 2010), which approximates each void as the largest inscribed sphere. This method relies on slice continuity; thus, a high number of slices (minimizing vertical spacing) was critical for accuracy. A complementary 2D planar algorithm was applied to mitigate errors from incomplete 3D reconstruction due to slice spacing.

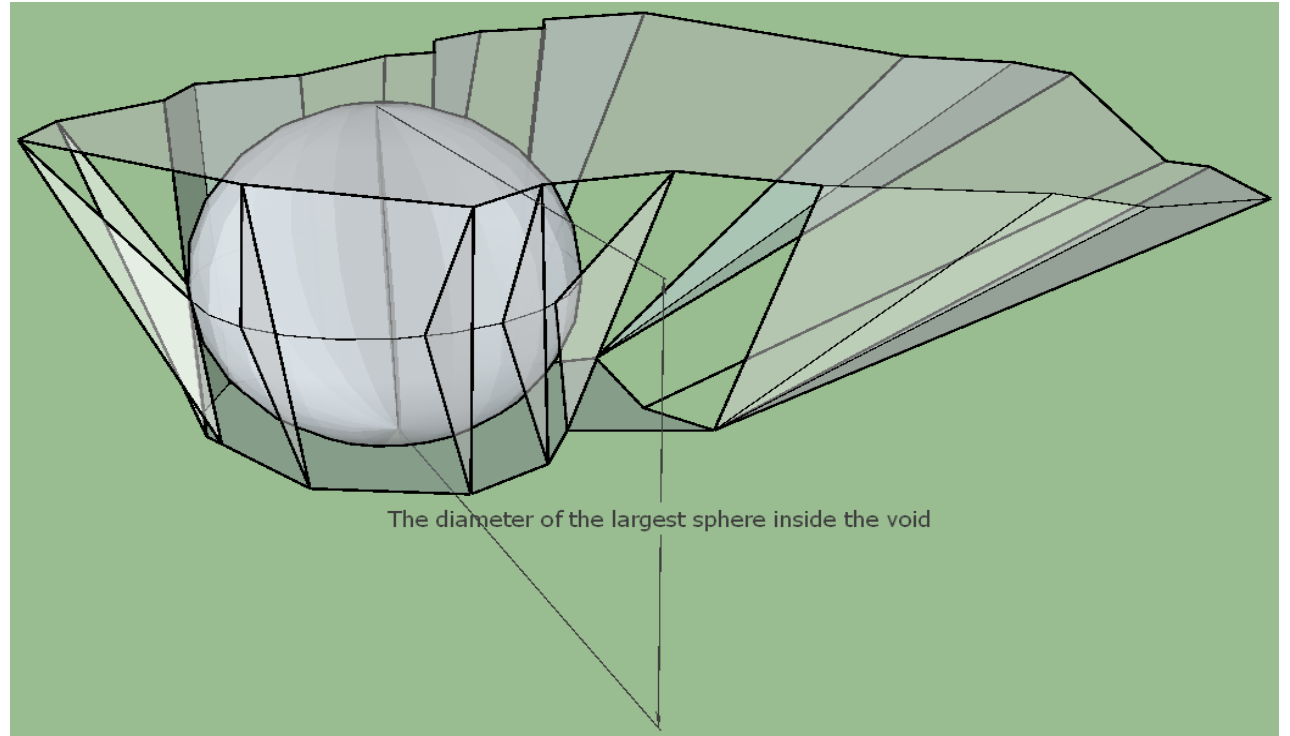
Figure 25(a) shows a 2D planar view of an isolated void (BoneJ output), where internal regions are shaded by depth: brighter areas represent deeper, more transparent void regions, with the brightest point marking the center of the largest inscribed sphere. Figure 25(b) provides a 3D rendering of the same void, with the inscribed sphere's diameter defining the 3D void diameter.

The Analyze Particles plugin (Schneider et al., 2012) was used to calculate the average 2D area of V_a and VMA across all slices, with results averaged over the total number of images. Notably, 3D diameter (from inscribed spheres) is systematically smaller than 2D planar diameter (calculated by treating irregular voids as circles).

Void shape properties (perimeter, circularity, aspect ratio, roundness) were measured for V_a and VMA using ImageJ's particle analysis function (Norhidayah et al., 2014). These parameters are detailed in the literature review (Aboufoul & Garcia, 2017) and are not elaborated further here.



(a)



(b)

Figure 25: Visualization of an Isolated Void: (a) Planar Representation of an Independent Void. (b) 3D Illustration of the Void with Largest Inscribed Sphere.

3.2.7 Macrotexture Parameter Measurement

3.2.7.1 3D Model Reconstruction

MPD and wavelength characterize vertical and horizontal variations in surface profiles, respectively (ISO, 2019). For macrotexture analysis, two 3D surface models (top and bottom) were generated per asphalt core using CT data: 150 consecutive raw CT images of the surface were processed in ImageJ to reconstruct 3D structures, followed by surface repair in Autodesk Netfabb to produce final models (Figure 26(a)). Each model was sectioned into four 45°-spaced profiles (Figure 26(b)), yielding eight profiles per core (four from the top, four from the bottom). These profiles were converted to 2D coordinate samples using ImageJ.

3.2.7.2 Profile Processing

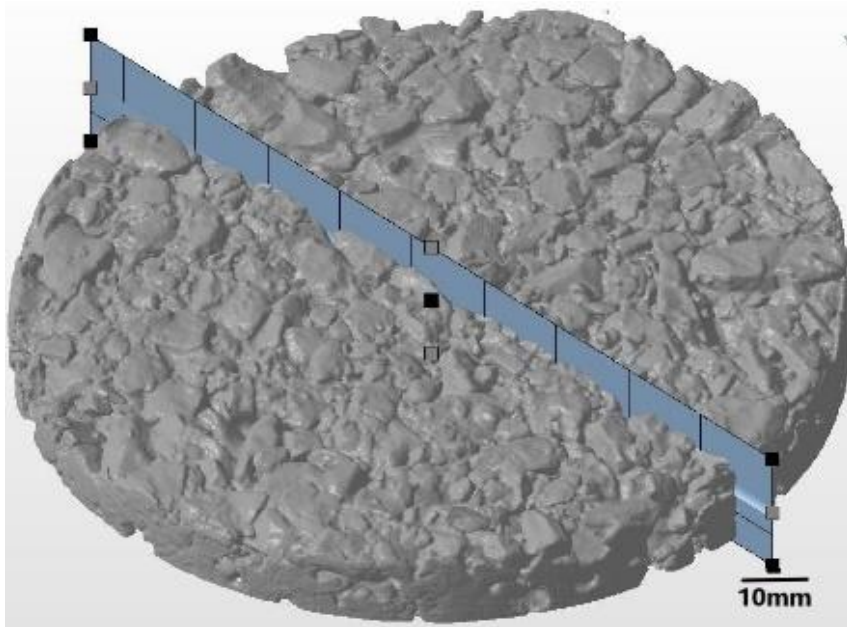
Profiles were processed according to ISO 13473-1:2019 (ISO, 2019) to measure MPD_{CT} and λ . Missing values (“dropouts”) were interpolated linearly between adjacent valid points. To align with laser scanning standards, sampling intervals were standardized to ~0.5 mm (ISO, 2019). Figure 27 illustrates a processed profile after dropout correction, resampling, slope/offset suppression, and windowing, enabling subsequent MPD_{CT} and wavelength measurements.

3.2.8 Virtual Asphalt Mixture Simulation

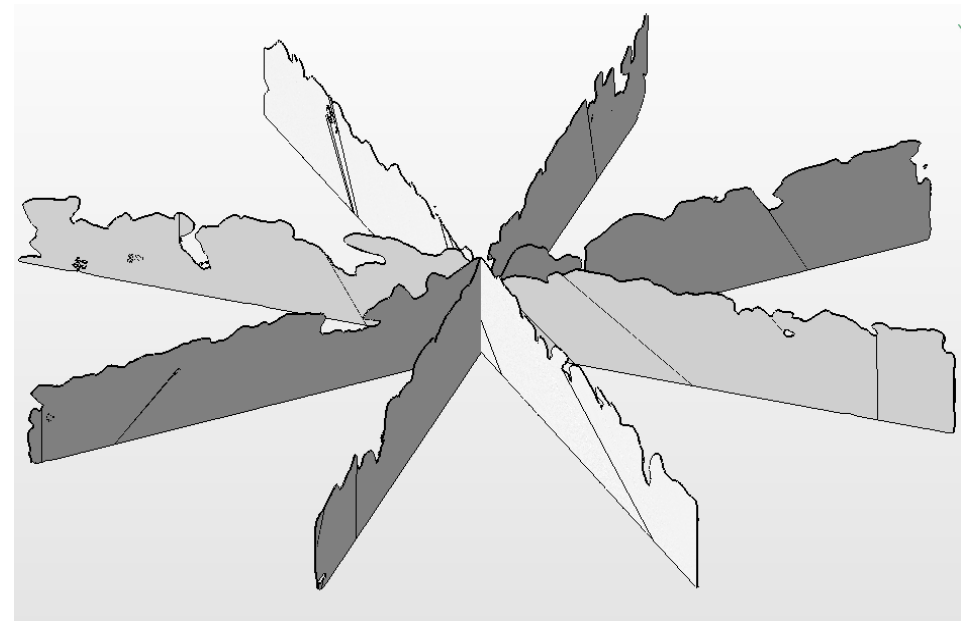
To expand the dataset for texture correlation analysis, nineteen virtual asphalt mixture skeletons were generated via software simulation. These virtual mixtures replicated the aggregate gradations and binder contents of the physical specimens, enabling estimation of aggregate and mastic content. The simulation methodology is described in detail elsewhere (Garcia-Hernandez et al., 2021).

3.2.9 Statistical Analysis of Structural Relationships

Statistical relationships between macrotexture, V_a , and VMA topological properties were investigated to elucidate their interdependencies and influences on pavement performance. Pearson correlation coefficients and linear regression fits were computed using Minitab. Nonlinear regression and multivariate surface plots were generated in MATLAB to visually resolve complex parameter interactions, supporting data-driven insights for material design optimization.



(a)



(b)

Figure 26: 3D Model and Sectioned Profiles of Asphalt Surface

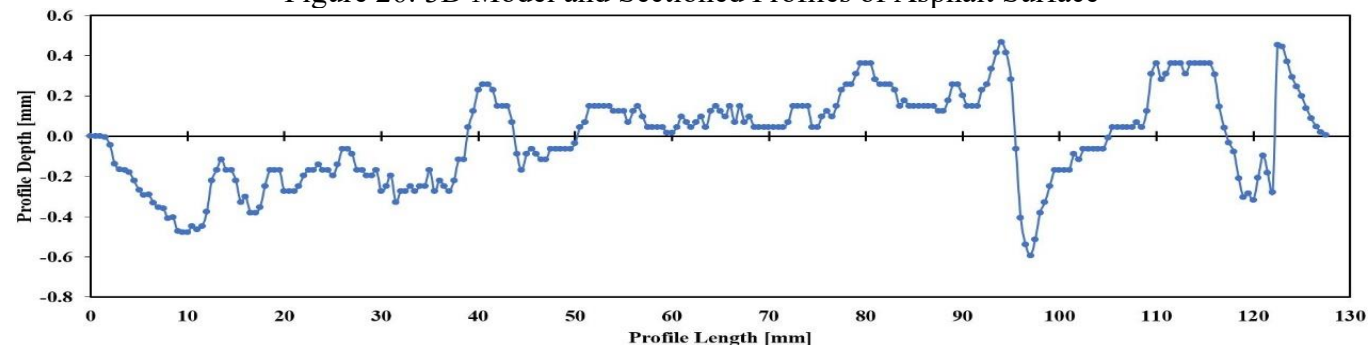


Figure 27: Example of a Processed Profile for Macrotexture Analysis

3.3 Results and Discussion

Table 13 (Appendix) shows the air void topologies, VMA, and macrotexture properties for the mixtures analysed.

3.3.1 Influence of CT Image Quantity on Void Properties Measurement

Three asphalt samples were analyzed to evaluate the impact of CT slice count on void property measurements. Using BonJ's 3D algorithm for average void diameter and dedicated plugins for tortuosity, increasing the slice count (50~600 slices) improved the continuity of the void structure representation. As shown in Figure 28, the average void diameter increased with more slices, reflecting more accurate 3D reconstructions, which are critical for capturing elongated or interconnected voids. Conversely, fewer slices introduced discontinuities, leading to underestimated diameters due to incomplete void representation.

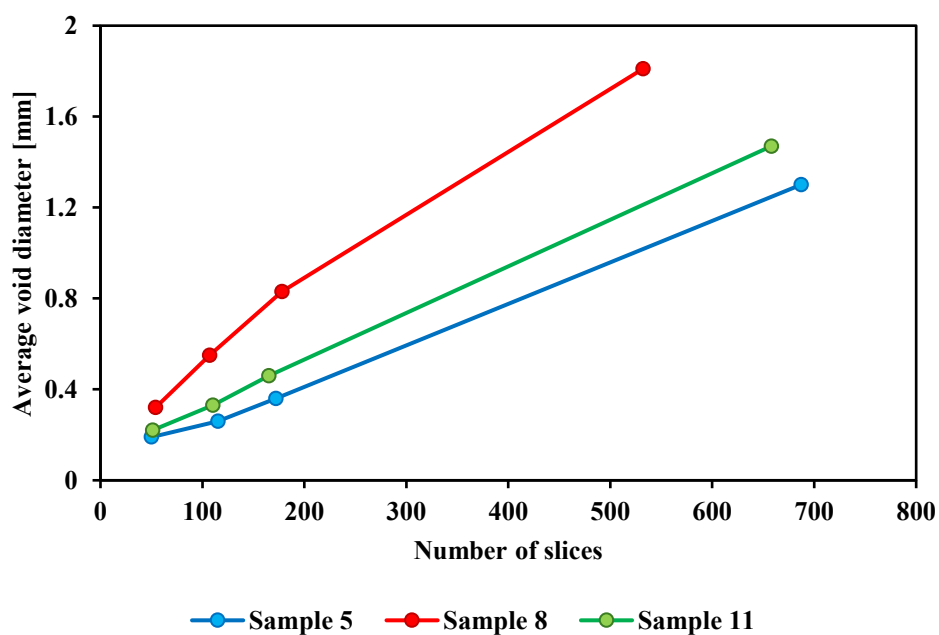


Figure 28: Average Void Diameter as a Function of Number of CT Images

Tortuosity measurements (Figure 29) showed a decreasing trend for samples with higher air void content (Samples 8 and 11), indicating that sparser slicing (e.g., 50 slices) exaggerated void displacement and missed critical connections. In contrast, denser slicing (e.g., 170 slices) provided smoother, more realistic void trajectories. Sample 5, with low air void content (1.41%), exhibited stable tortuosity, suggesting that isolated

voids are less sensitive to slice density. These findings highlight the need for standardized slicing protocols in CT-based void analysis, balancing accuracy (≥ 170 slices) with practicality, especially for mixtures with interconnected void networks.

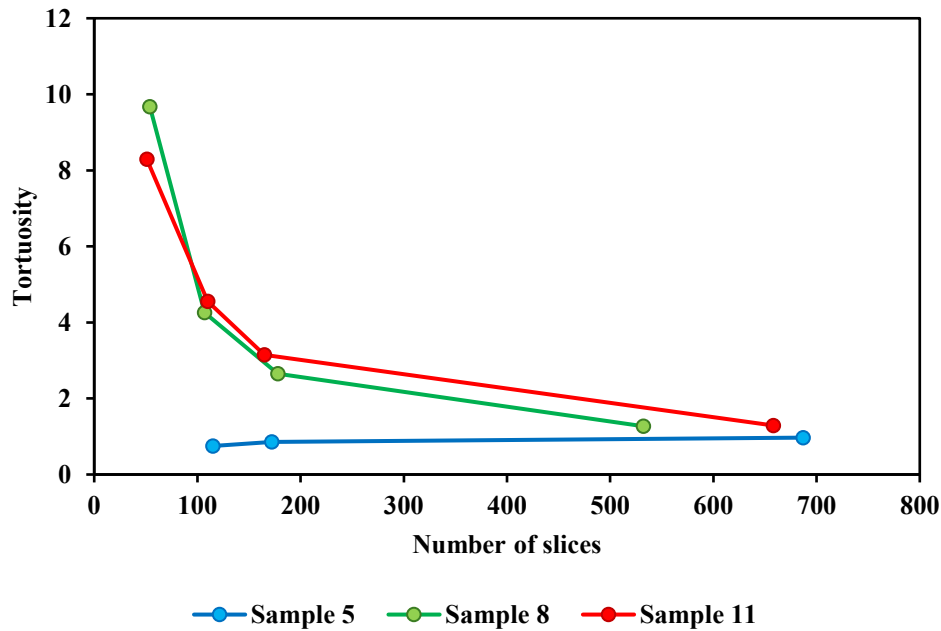


Figure 29: Tortuosity Measurements Relative to Number of CT Images

This study investigated additional parameters, including macroporosity, Euler number, and void shape characteristics, to assess their sensitivity to variations in CT image count. Results showed these parameters were modestly influenced by image quantity, though the magnitude of variation remained notably smaller compared to average void diameter and tortuosity metrics.

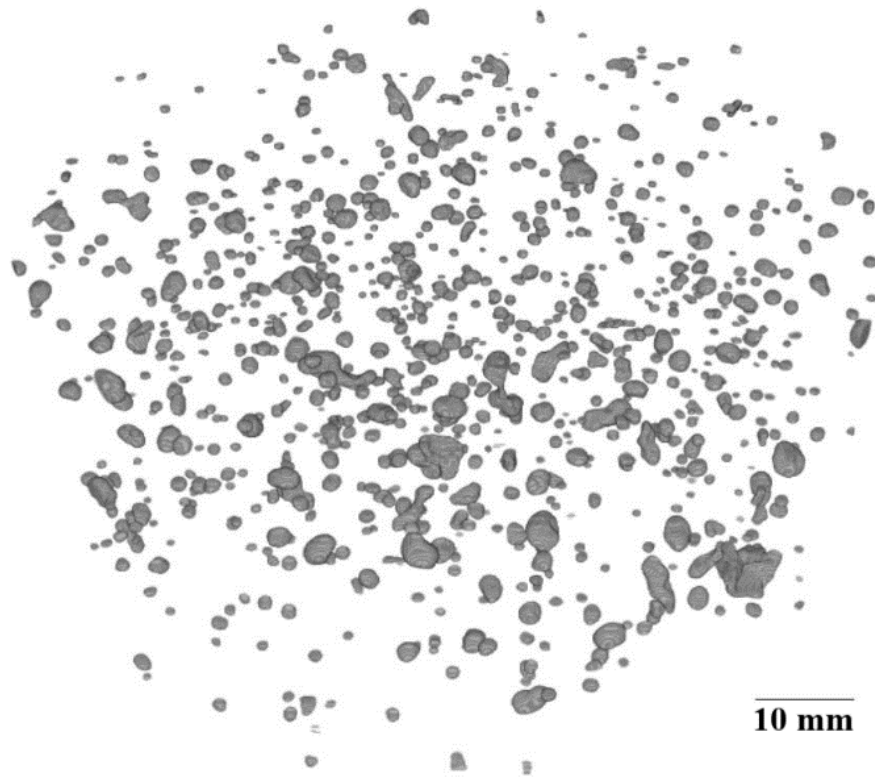
These findings emphasize the critical role of selecting appropriate CT image counts when characterizing void properties in asphalt mixtures. The observed correlation between image quantity, average void diameter accuracy, and tortuosity highlights the need for meticulous experimental design. Increasing slice numbers facilitated more comprehensive void structure reconstruction, a key requirement for materials science and engineering applications. Future research could benefit from exploring a broader spectrum of asphalt mixtures and image counts to validate these relationships further. It is essential to recognize that excessive image acquisition is not always advantageous, as higher quantities demand significant time, computational resources, and advanced

equipment. Standardizing CT slice count (170 slices in this study) ensures reliable void characterization for quality control, enabling consistent texture-performance correlations in mix design.

3.3.2 Correlations Between Air Void Topological Properties

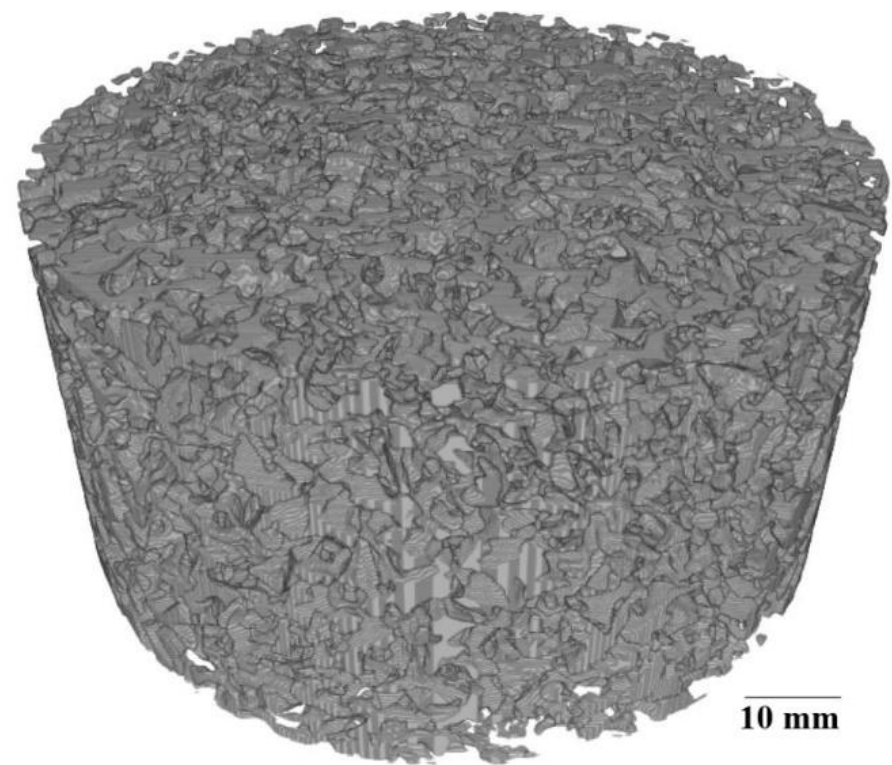
Table 14 (Appendix) presents Pearson correlation coefficients between air void (V_a) and voids in mineral aggregate (VMA) topological properties, revealing strong links between air void content (AVC) and indicators of void connectivity. The volume of the biggest air void (VAV, $r = 0.90$) and percolation number (PN, $r = 0.85$) showed pronounced positive correlations with AVC, indicating void coalescence into interconnected networks as AVC increases (Garcia et al., 2015). This aligns with percolation theory, where higher void content promotes the formation of a dominant void network, as demonstrated by 3D reconstructions in Figure 30: Sample 5 (1.41% AVC) exhibits isolated spherical voids, while Sample 11 (22.23% AVC) features a continuous void network with a VAV of 60,459.42 mm³, accounting for 99% of total void volume. This indicates that in the 22.23%-porosity sample, nearly all air voids form a fully connected network, a finding closely aligned with prior research (Aboufoul & Garcia, 2017).

Notably, the lowest measured VMA macroporosity across all samples—23.1%—approximates this critical porosity threshold, implying complete connectivity of VMA within the core structure. For all analyzed mixtures, the biggest individual VMA volume equals the total VMA volume, causing percolation numbers to approach unity. Consequently, as shown in Table 14 (Appendix), correlation coefficients for this parameter with other VMA properties could not be computed due to the lack of variability. The direct proportionality between VMA content and total volume also explains the strong correlation between VMA's macroporosity (equivalent to VMA content) and the biggest VMA volume (equal to total VMA volume).



Sample 5	
AVC	1.41%
VAV	41 mm ³
PN	0.02
EN	1076

(a)



Sample 11	
AVC	22.23%
VAV	60459.42 mm ³
PN	0.99
EN	-5377

(b)

Figure 30: 3D Reconstruction of Air Voids in Sample ROI. (a) Sample 5. (b) Sample 11.

The Euler number (EN), a key metric of void connectivity, transitions from positive (EN = 1076 for isolated voids) to negative (EN = -5377 for interconnected voids) as AVC exceeds 10–15% (Figure 31), a threshold identified in this study. This transition signifies the shift from discrete voids to a percolating network, consistent with prior research (Aboufoul & Garcia, 2017). Voids at this threshold balance drainage (via interconnected pathways) and structural integrity (via residual aggregate skeleton), informing optimal void content targets for specific pavement functions (e.g., high-speed vs. low-traffic roads).

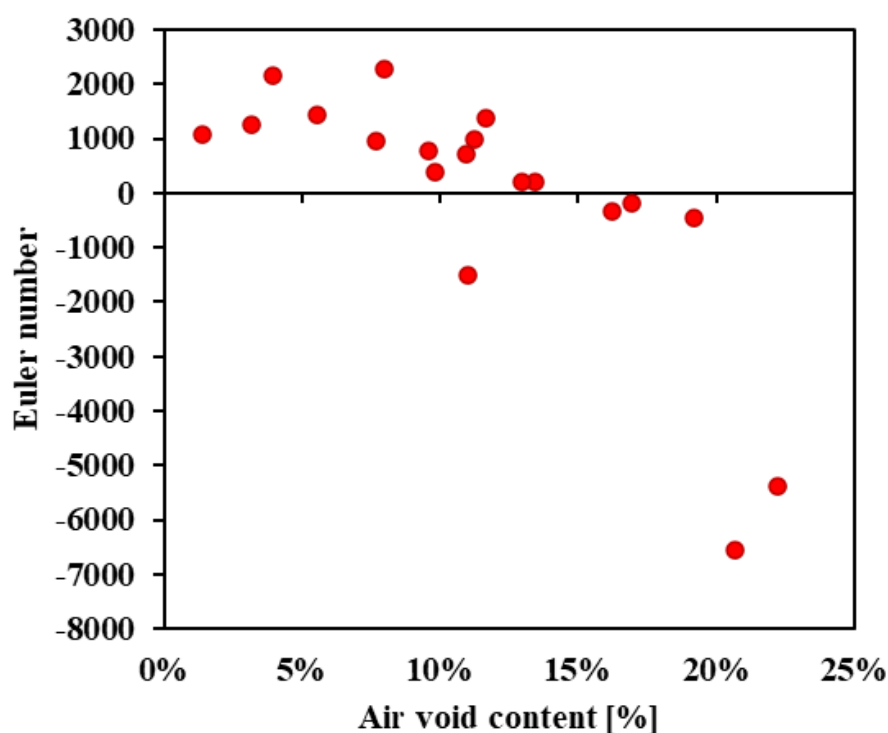


Figure 31: Relationship Between Air Void Content and the Euler Number

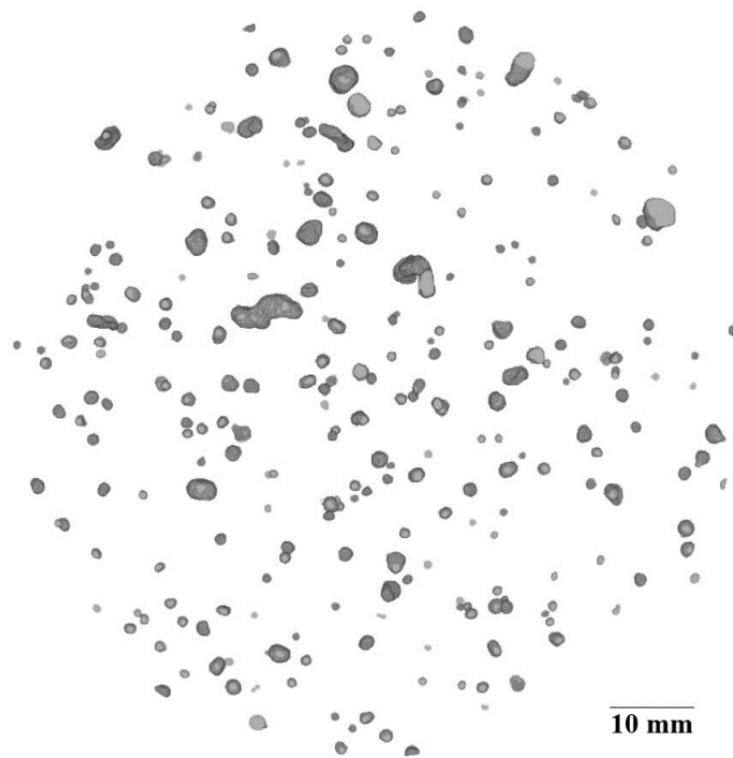
The negative correlation between AVC and EN ($r = -0.76$) highlights that interconnected voids reduce the number of individual void particles, enhancing network complexity and surface texture development. Strong negative correlations are also observed between Euler number and the biggest air void volume ($r = -0.82$) and percolation number ($r = -0.73$). This relationship arises because higher air void connectivity reduces the count of isolated void particles, decreasing the Euler number while fostering the development of extensive interconnected void systems. As air void content increases, enhanced connectivity expands the network's area, perimeter, and

characteristic diameters, naturally elevating the prominence of the biggest air void volume and percolation number metrics (Kassem, Masad, Lytton, & Chowdhury, 2011).

Most isolated air voids exhibit spherical morphologies in low-porosity asphalt, as shown in Figure 32(a). As void content and connectivity increase, void shapes evolve into more elongated forms, accompanying increases in the biggest void volume, percolation numbers, and aspect ratios, while circularity decreases. Figure 32(b) illustrates how larger void entities develop irregular geometries. Significant correlations were identified between air void content and shape metrics: perimeter ($r = 0.74$), aspect ratio ($r = 0.74$), circularity ($r = -0.89$), and roundness ($r = -0.77$).

Gradation designs incorporating larger aggregates led to reduced aggregate counts, yielding a moderately negative correlation ($r = -0.73$) between aggregate number and maximum aggregate size—variations in mixture gradations likely moderated this relationship. Mastic fills the spaces within the aggregate skeleton and voids. As air void content increases, mastic volume decreases, establishing a negative correlation ($r = -0.72$) between these parameters. Higher mastic content directly influences void morphology, promoting more circular ($r = 0.72$) and rounded ($r = 0.73$) void shapes—findings consistent with recent research that underscore mastic's critical role in shaping void structural characteristics within asphalt mixtures (Diab & Enieb, 2018).

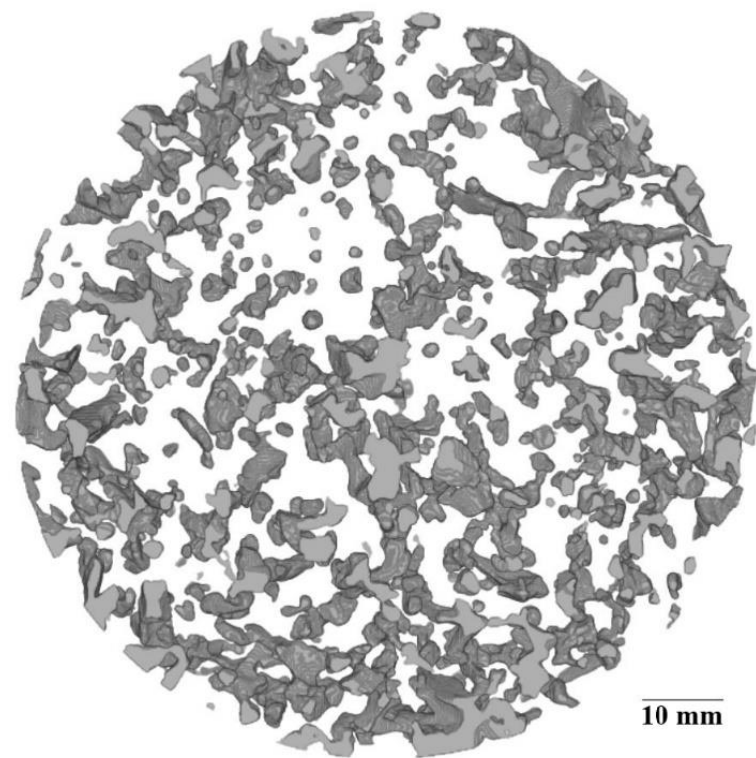
Unlike traditional studies relying on simple porosity measurements, this research integrates multi-scale topological parameters (connectivity, shape, tortuosity), providing a more nuanced understanding of how void networks influence texture. For example, the aspect ratio of voids ($r = 0.74$ with air void content) reveals that higher void connectivity promotes elongated voids, increasing surface irregularity and MPD_{CT} , which are key for designing anti-skid pavements.



Sample 5

AVC	1.41%
VP	4.65 mm
VAR	1.38
VC	0.87
VR	0.77

(a)



Sample 9

AVC	13.44%
VP	11.68 mm
VAR	2.01
VC	0.61
VR	0.56

(b)

Figure 32: 3D Reconstruction of Air Voids. (a) Sample 5. (b) Sample 9

3.3.3 Correlations Between Air Void and VMA Topological Properties

Table 15 (Appendix) presents Pearson correlation coefficients between the topological properties of V_a and those of the VMA for the analyzed mixtures. Notably, no significant correlation emerged between these two property sets. A strong correlation was initially hypothesized between V_a 's macroporosity and VMA content, given the influence of air voids and mastic on VMA formation. However, the relatively low correlation coefficient ($r = 0.154$) indicates the absence of a straightforward linear relationship. This suggests that while air void characteristics impact VMA properties, the underlying relationship likely involves complex non-linear interactions or confounding variables such as aggregate gradation and mastic composition (Hu, Qian, Wang, & Oeser, 2015).

Table 3: Pearson Correlation Coefficients for MPD_{CT} , Wavelength, and Topological Properties

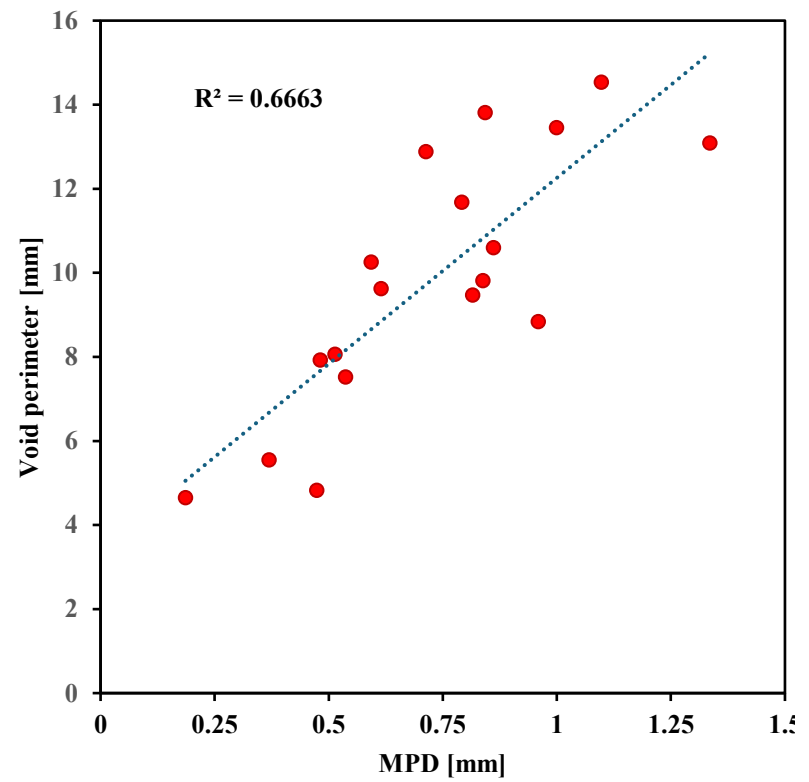
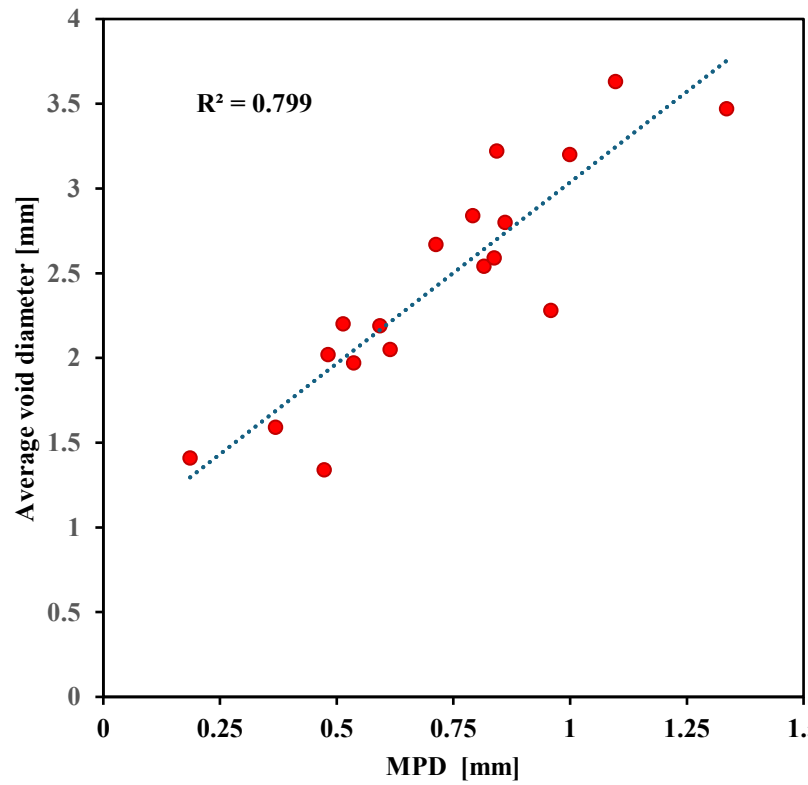
	MPD_{CT}		λ	
MPD_{CT}	1.00			
λ	0.42		1.00	
AVC	0.44		-0.21	
NA	-0.56		-0.24	
VM	-0.54		0.00	
MAS	0.411		0.25	
	V_a	VMA	V_a	VMA
M	0.35	-0.43	-0.19	-0.30
AVD	0.89	-0.22	0.29	-0.17
EN	-0.08	0.41	0.19	0.08
VAV	0.24	-0.43	-0.27	-0.30
PN	0.33	NaN	-0.23	NaN
T	0.28	0.03	-0.08	0.14
VP	0.82	-0.08	0.15	-0.23
VAR	0.59	0.62	0.07	-0.03
VC	-0.55	0.06	0.03	0.06
VR	-0.59	-0.73	-0.04	-0.17

3.3.4 Impact of Void Properties on Asphalt Macrotexture

Table 3 displays Pearson correlation coefficients for the relationships between MPD_{CT} , wavelength, and properties of V_a and VMA. MPD_{CT} positively correlates with air void content, whereas mastic volume correlates negatively with aggregate count. This behavior arises because macrotexture reflects the surface expression of internal void structures: higher air void content tends to deepen surface texture, as prior research highlights the critical role of void architecture in shaping mixture surface characteristics (Han et al., 2021). Conversely, mastic and fine aggregates can fill surface imperfections during compaction, reducing MPD_{CT} and contributing to the observed weak correlations.

The strongest positive linear relationship occurs among V_a properties between MPD_{CT} and average void diameter ($r = 0.89$). As illustrated in Figure 33(a), modeling isolated air voids as spheres links their diameter directly to the vertical height of surface depressions—larger voids correspond to greater MPD_{CT} . Void perimeter ($r = 0.82$, Figure 33(b)) further amplifies this effect, as irregular void edges increase profile roughness. By quantifying the direct geometric contribution of void boundaries to macrotexture, this study links void area to texture depth. The interdependence of surface texture, void diameter, and perimeter is further detailed in Figure 34. This 3D-based finding underscores the importance of volumetric void geometry: Larger voids directly translate to deeper surface depressions, enhancing tire-pavement friction, enhancing tire-pavement contact and frictional performance, which is critical for wet-weather safety.

For VMA properties, MPD_{CT} shows a high negative correlation with VMA roundness ($r = -0.73$). This likely stems from more rounded VMA indicating fewer inter-void connections and less mastic filling between aggregates, contributing to a coarser texture. The negative correlation between VMA content and MPD_{CT} supports this mechanism. Conversely, MPD_{CT} correlates positively with VMA aspect ratio ($r = 0.62$), suggesting that elongated VMA shapes reflect denser aggregate packing and lower air void content, reducing texture depth.



(a) (b)
Figure 33: Comparison of MPD_{CT} with Average Void Diameter and Void Perimeter. (a) MPD_{CT} vs. Average Void Diameter (2D). (b) MPD_{CT} vs. Void Perimeter.

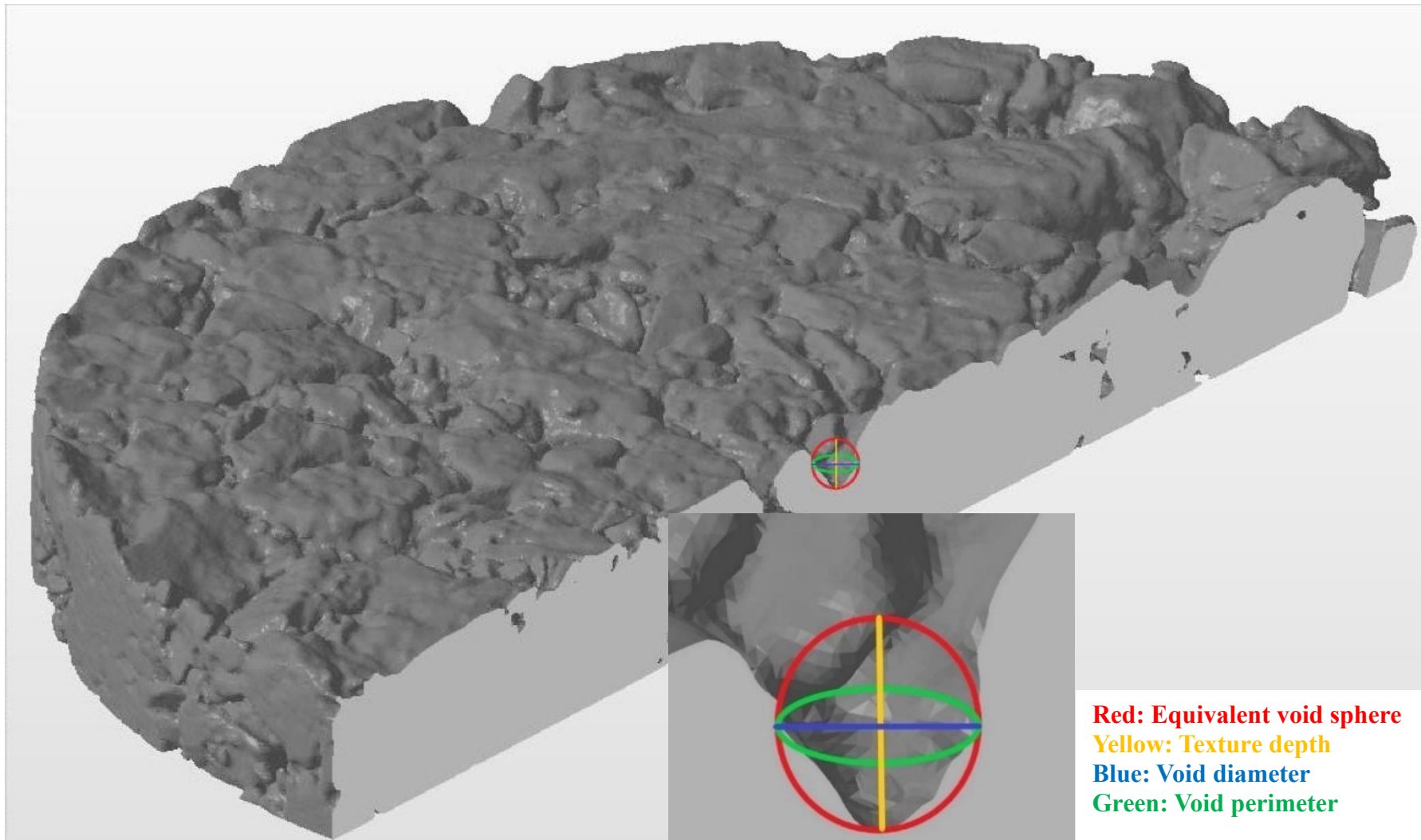


Figure 34: Illustration of the Relationship Between Surface Texture and Void Dimensions (Diameter and Perimeter)

Wavelength exhibits weaker correlations with all analyzed properties, with the strongest associations observed for V_a average void diameter ($r = 0.29$) and VMA macroporosity ($r = -0.30$). Longer void diameters increase the span of surface depressions, driving wavelength growth. However, wavelength correlations remain less pronounced than those for MPD_{CT} , likely because the analysis focuses on dominant wavelengths that may not fully capture the horizontal complexity of texture profiles (Yan, Ran, Sandberg, Zhou, & Xiao, 2020).

By prioritizing void diameter and perimeter in mix design, engineers can tailor asphalt surfaces to meet specific performance needs: e.g., larger voids for high-speed highways to enhance drainage and skid resistance, versus more minor, more rounded voids for urban roads to reduce noise and wear.

3.3.5 Multivariate Modeling of MPD_{CT}

Table 4 presents linear regression models for predicting MPD_{CT} using variables with the highest correlation coefficients from Table 3. These models incorporate multiple input factors to enhance predictive performance. Table 16 (Appendix) shows the multivariate MPD_{CT} linear prediction model with one texture measurement outlier removed, and Table 17 (Appendix) shows the multivariate linear prediction model for wavelength.

Table 4: Linear Regression Models for Predicting MPD_{CT}

Fitting parameters					Variables from V_a						
Model	S(N)	R^2	R^2 (adj)	R^2 (pred)	AVD	EN	VAV	PN	VP	VAR	VC
1	0.168	0.666	0.646	0.577					X		
2	0.130	0.799	0.786	0.734	X						
3	0.124	0.83	0.807	0.742	X		X				
4	0.125	0.828	0.805	0.743	X			X			
5	0.114	0.866	0.837	0.779	X			X		X	
6	0.114	0.866	0.837	0.783	X			X			X
7	0.112	0.880	0.843	0.788	X		X		X		X
8	0.111	0.881	0.844	0.793	X			X	X		X
9	0.113	0.886	0.838	0.796	X	X		X	X		X

The left side of Table 4 details model fitting parameters, while the right side lists associated variables. More minor standard deviation (S) values and higher adjusted R^2 (R^2 (adj)) and predicted (R^2 (pred)) values indicate superior model accuracy. The results demonstrate the feasibility of predicting MPD_{CT} through linear equations using Va's topological properties as inputs, highlighting the utility of multivariate approaches for characterizing material properties in asphalt mixtures (Albayati & Sukhija, 2024).

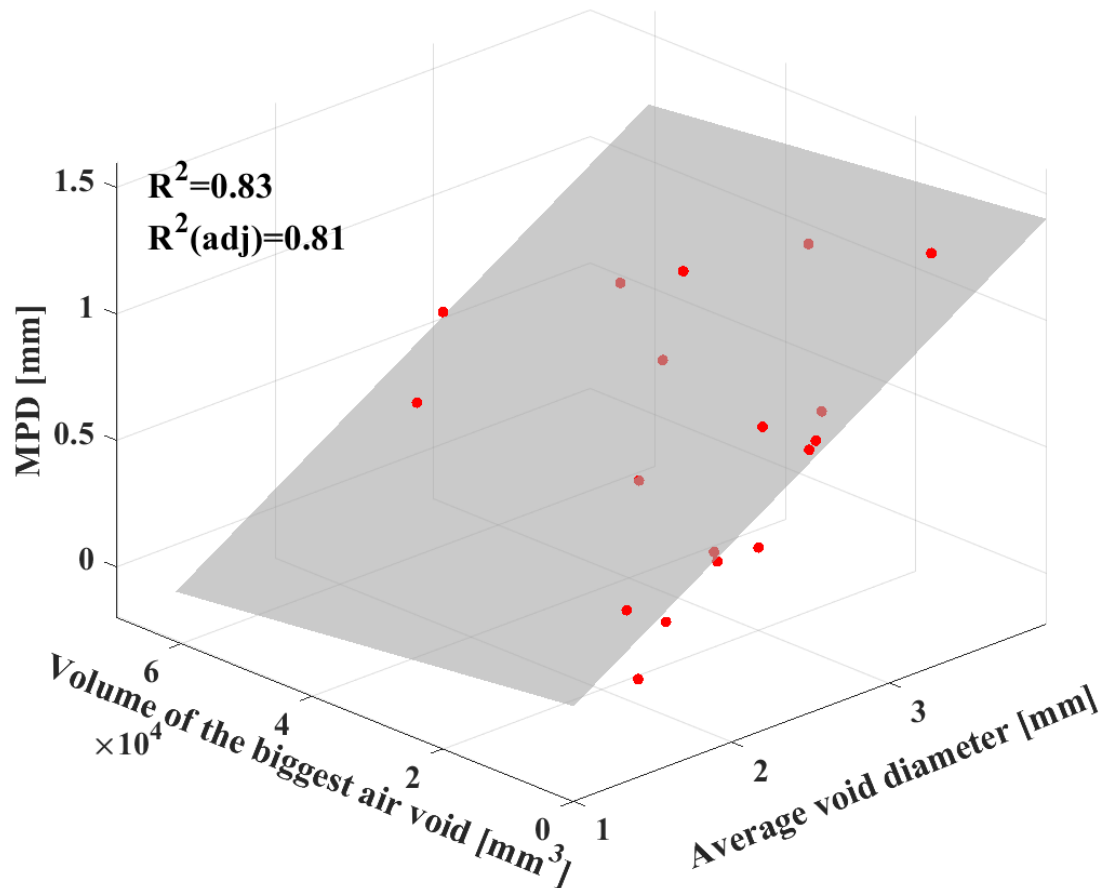


Figure 35: Correlation Between Average Void Diameter, Volume of the biggest Air Void, and MPD_{CT}

Figure 35 illustrates the incremental improvement from single to multi-parameter models, where adding connectivity metrics (e.g., VAV). Average void diameter alone achieves high prediction accuracy ($R^2 = 0.80$). Further, incorporating connectivity-related parameters improves predictive power. For example, Model 7, integrating AVD, VAV, VP, and VC, improved prediction accuracy by 8% compared to AVD-only models. This aligns with prior research showing that connectivity metrics significantly enhance prediction accuracy for porous material (Chen, You, Yang, Garcia, & Rose,

2021). These models enable texture prediction from mix design parameters, reducing reliance on costly physical testing.

Gradation and compositional factors also play critical roles in MPD_{CT} predictions, including (i) aggregate geometry, (ii) compaction method, (iii) mastic content, and (iv) aggregate size distribution. For example, aggregate angularity and size distribution have been shown to influence void structure and, consequently, MPD_{CT} (Hu, Liu, Wang, & Oeser, 2018). However, many specific effects remain underexplored, necessitating future studies with expanded datasets to validate and refine these predictive models.

3.4 Analysis and Discussion

3.4.1 Filling Knowledge Gaps in Void-Texture Correlations

This study addresses a critical gap in prior research. While traditional studies focused on AVC with weak MPD_{CT} correlations ($r = 0.44$), this work reveals that AVD exhibits a far stronger linear relationship with MPD_{CT} ($r = 0.89$, $R^2 = 0.8$). This disparity highlights the limitation of relying solely on volumetric void measurements (e.g., AVC from standard lab tests), which fail to capture topological properties (shape, connectivity) essential for texture prediction (Wang, Xie, Gao, Liu, & Tang, 2021). By contrast, CT-based 3D void analysis quantifies parameters like void perimeter ($r = 0.82$ with MPD_{CT}) and aspect ratio ($r = 0.59$), enabling mechanistic insights into micro-macro texture coupling—findings that directly address the literature’s neglect of void topology’s synergistic effects (Chen et al., 2019; Huang et al., 2022).

3.4.2 CT Topology Analysis vs. Traditional Volumetric Methods

Traditional volume-based porosity measurements cannot resolve void shape (e.g., spherical vs. elongated) or connectivity (EN), which this study shows influence MPD_{CT} non-linearly. For example, voids in Sample 11 (22.23% AVC) form a connected network ($EN = -5377$), yielding 70% deeper MPD_{CT} than Sample 5 (1.41% AVC, $EN = 1076$) (Figure 30). CT’s ability to characterize such topological features bridges the gap between microscale void properties and macrotexture, outperforming traditional methods that treat voids as uniform pores (Zhang & Li, 1996; Sommacal et al., 2023).

3.4.3 Limitations of Laboratory-Scale CT Analysis

While CT enables high-resolution void characterization, its application is constrained by:

- **Sample Representativeness:** Marshall cores (100 mm diameter) exhibit surface texture discrepancies (e.g., top-bottom MPD_{CT} variation) due to compaction-induced void distribution biases, differing from the field pavements.
- **Cost Limitation:** Single CT scans (90.54 μm resolution, 2-hour acquisition) cost >£200, precluding large-scale routine testing.
- **Size Constraints:** CT's spatial resolution limits analysis to small cores, necessitating destructive sampling for field pavement evaluation.

These limitations underscore the need for virtual modeling (Stage 2 of this research, Chapter 4), where CT-derived AVD-MPD_{CT} correlations ($R^2 = 0.8$) validate the Intersected Stacked Air Voids (ISA) method's ability to simulate texture-void relationships computationally, reducing reliance on costly CT scans (Schenker et al., 2010; Chiarelli et al., 2015).

3.4.4 Foundation for Virtual Texture Prediction

The strong AVD-MPD_{CT} linearity established here provides critical validation for Stage 2's (Chapter 4) virtual modeling: By validating whether the AVD-MPD_{CT} relationships derived from CT scans align with those of virtual asphalt mixtures generated by the ISA method, subsequent research can confirm the texture quantification capability of virtual asphalt. This transition from CT-based mechanism discovery to virtual validation addresses the literature's gap in ISA's texture prediction capability, forming a scalable pipeline for data-driven asphalt design.

3.4.5 Advancing Texture Prediction Beyond Single Parameters

This study overcomes prior single-parameter limitations by integrating multi-dimensional void metrics into MPD_{CT} regression models (R^2 up to 0.88). For instance, Model 7 (incorporating AVD, VAV, VP, VC) improves prediction accuracy by 8% versus AVD-only models (Table 4), demonstrating that holistic void characterization is essential for reliable texture forecasting. These findings directly support the thesis's aim of transforming texture control through data-driven, multi-stage research.

In summary, this chapter's CT-based analysis resolves key void-texture relationships, exposes traditional method limitations, and furnishes the empirical basis for virtual modeling—thereby bridging the gap between microstructural mechanisms and digital texture prediction tools.

4 MPD-MTD Modeling via Virtual Asphalt and Experimental Validation

4.1 Introduction

The correlation between MPD and MTD in asphalt pavements is central to performance-based design, yet existing models struggle to capture its nonlinearity across diverse void conditions (Yaacob et al., 2014; Wang et al., 2022). Building directly on Chapter 3's discovery of a strong linear relationship between AVD and MPD_{CT} ($R^2 = 0.8$), this chapter aims to:

1. Validate whether virtual asphalt models replicate the AVD- MPD_{CT} correlation established via X-ray CT.
2. Quantify the MPD_{LS} - MTD_{SPT} relationship across 60 laboratory-fabricated slabs with controlled gradation and void properties.
3. Demonstrate that virtual mixtures generated by the Intersected Stacked Air Voids (ISA) method can reliably simulate texture depth, eliminating reliance on destructive CT scans.

Sixty asphalt slabs with varied gradations, binder contents, and porosities were prepared to investigate how void topology modulates the MPD_{LS} - MTD_{SPT} relationship. Laser texture scanning and Sand Patch Test (SPT) were used to characterize macrotexture, while the ISA method generated virtual void networks matching the physical specimens' AVD and connectivity (Schenker et al., 2010; Chiarelli et al., 2015). By verifying that virtual models adhere to the CT-derived AVD- MPD_{CT} mapping, this study establishes ISA's capability to quantify texture depth without physical testing. This breakthrough overcomes the high cost and destructiveness of CT.

The findings reveal that at low AVC, MPD_{LS} - MTD_{SPT} correlations remain linear, whereas interconnected void networks ($AVC > 10\%$) induce nonlinear MTD_{SPT} amplification. This is consistent with Chapter 3's observation that void connectivity alters surface texture expression. By embedding these empirical relationships into virtual modeling workflows, this research bridges the gap between microscale void properties and macroscale texture performance, positioning ISA as a scalable tool for data-driven mixture design and network-level texture prediction.

4.2 Methodology

4.2.1 Materials and Design of Asphalt Slabs

Under strictly controlled laboratory conditions, 60 asphalt slabs measuring approximately 30 cm x 30 cm x 5 cm were prepared using a laboratory roller compactor. The slab geometry offers two key advantages: (1) uniform compaction that replicates field pavement texture profiles; (2) a large surface area (900 cm²) enabling comprehensive texture measurements. Variables including gradations (maximum aggregate size: 6.3–20 mm), binder contents (4–7%), and air voids (0.96–26.51%) were systematically varied to generate diverse texture profiles. Detailed compositions and texture metrics are listed in Table 18 (Appendix).

4.2.2 Texture Parameter Measurement

4.2.2.1 Laser Texture Scanning

An AMES 9400HD laser scanner captured 100 mm × 70 mm surface profiles with submillimeter precision. For each slab, a minimum of 24 scans were performed across non-completely overlapping zones to account for texture heterogeneity—a capability enabled by the slab’s large surface area. MPD_{LS} was calculated as the average of ten equidistant profiles per scan, ensuring representativeness (Figure 36(a)). This multi-location scanning strategy surpassed the spatial limitations of core samples, which typically pose challenges for laser scanning.

4.2.2.2 Sand Patch Test (SPT)

At the slab center, SPT was conducted by spreading a defined sand volume to form a circular patch, with diameter measurements used to compute MTD_{SPT} (Figure 36(b)) (ASTM, 2006). However, notable discrepancies in MTD_{SPT} arise when applying SPT to porous slabs, primarily due to sand leakage into void structures—a limitation consistent with prior studies (Noyce et al., 2005; Praticò, & Vaiana, 2015). To address this variability, triplicate measurements were conducted for each specimen, and average values were used to enhance the reliability of the results. While SPT offers simplicity and field applicability, its outcomes remain sensitive to operator technique and ambient conditions.



(a)



(b)

Figure 36: (a) Laser Texture Scanner Measurement Area (b) Sand Patch Test Area

4.2.2.3 Comparative Analysis

A comparative analysis of MPD_{LS} and MTD_{SPT} was undertaken to assess measurement accuracy and methodological differences, drawing on established methodologies from literature (ASTM, 2015; Plati, Pomoni, & Stergiou, 2017). This evaluation incorporated additional variables—including air void content and maximum aggregate size—to explore their combined effects on macrotexture metrics. By integrating these parameters, the study aimed to refine predictive models linking MPD_{LS} to MTD_{SPT} , leveraging their observed correlations to improve estimation precision for pavement surface texture.

4.3 Virtual Asphalt Generation Methodology

4.3.1 Geometric Modeling via ISA Method

The ISA method was employed to replicate the maximum aggregate size and target AVC of laboratory-prepared asphalt specimens, specifically the Contact-Stop Fill Algorithm (Chiarelli et al., 2015). This geometric modeling approach, independent of physical mechanisms (Aboufoul et al., 2019), enables systematic simulation of void structures to evaluate MPD_{ISA} and MTD_{ISA} . However, it's important to note that the ISA method simplifies aggregate geometry by using spheres to represent particles, inherently overlooking real-world aggregates' angularity and irregular shapes. This simplification may indirectly introduce errors in void shape representation, potentially affecting the accuracy of virtual asphalt texture measurements.

4.3.2 Two-Dimensional Void Structure Construction

The ISA method initiates with a random, non-overlapping placement of 2D particles (circular/elliptical aggregates) within a defined rectangular domain (Aboufoul et al., 2019). Key input parameters—domain dimensions, nucleation center count, maximum particle size, and target AVC—were derived from physical sample data. Particle growth proceeded iteratively: starting with an initial radius of 0.1 mm, each particle expanded until it contacted neighboring particles, reached domain boundaries, or attained the specified maximum radius. New particle generations were introduced using rejection sampling to ensure non-overlapping centers, maintaining randomness and uniform distribution (Chiarelli et al., 2015). This process continued until the cumulative non-

particle area matched the target AVC, as visualized in Figure 37. By repeating this cycle, virtual asphalt structures with predefined void contents were systematically generated.

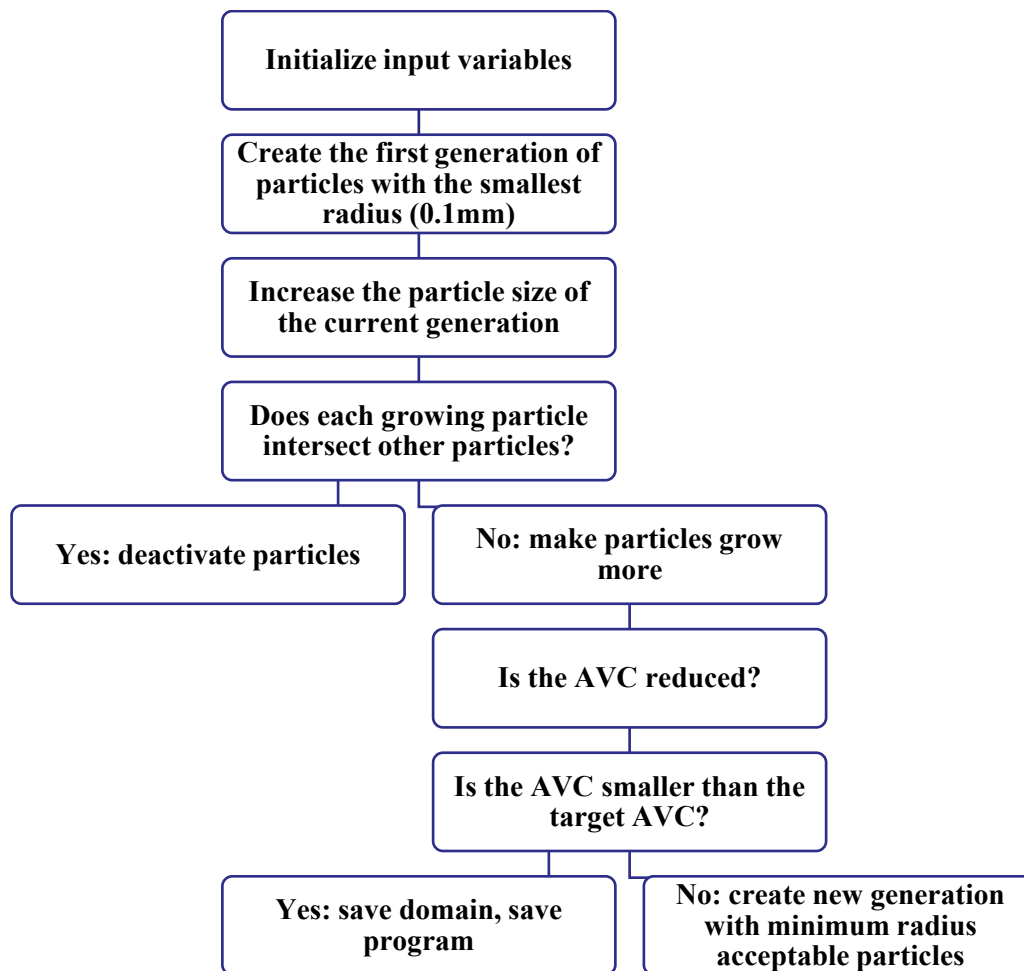


Figure 37: Flowchart of the ISA Algorithm

While idealized circular particles represent aggregate components, real-world aggregates exhibit irregular shapes. Intersecting particles were combined to form complex solid structures resembling natural aggregate packing to mimic this. Though geometrically abstract, these structures represent the material phase of the mixture, with the study focusing on the surrounding void spaces (Chiarelli et al., 2015). However, due to the initial spherical approximation of aggregates, the resulting void shapes may deviate from those in actual asphalt, which could impact the correlation between virtual voids and surface texture. Figure 64 (Appendix) illustrates domain configurations at varying maximum particle radii, maintaining consistent AVC across aggregate size scenarios.

4.3.3 Three-Dimensional Model Extension

Each 2D domain was converted to a 3D model by extruding circular particles into spherical volumes (Chiarelli et al., 2015). Spherical layers were vertically stacked at intervals matching the slice spacing from CT scans of physical samples, creating a staggered multilayer structure (Aboufoul et al., 2019). A 3D point grid with predefined resolution was then overlaid to identify void spaces: grid points not intersecting spherical particles were classified as voids (value = 0). At the same time, material phases (aggregates/binder) were denoted as solid (value = 1), forming a Boolean matrix (Chiarelli et al., 2015; Aboufoul et al., 2019). This process enabled quantitative characterization of void geometry and connectivity.

4.3.4 Validation Against Physical Samples

Despite its geometric foundation and inherent simplifications, the ISA method reproduces real asphalt void structures (Aboufoul et al., 2019). Figure 38 compares CT slices of physical specimens ((a), (b), (c)) with equivalent virtual samples ((d), (e), (f)) matched by maximum aggregate size and AVC. Visual inspection confirms substantial similarity in void shape and size distributions, validating the method's ability to simulate realistic microstructures. However, the potential void shape errors introduced by the spherical aggregate approximation may still affect the accuracy of texture-related predictions.

This virtual asphalt generation framework allows precise replication of mixture void architectures, enabling MPD_{ISA}/MTD_{ISA} evaluations without reliance on extensive physical testing. Bridging geometric modeling and texture analysis provides a scalable platform for exploring how gradation and void properties influence asphalt macrotexture, overcoming limitations of traditional experimental approaches.



(a) AVC=7.68%



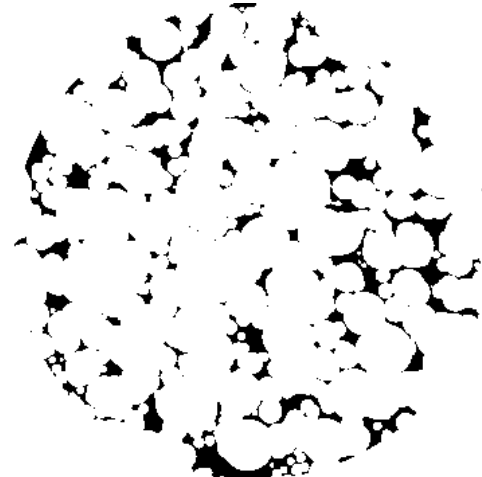
(b) AVC=13.44%



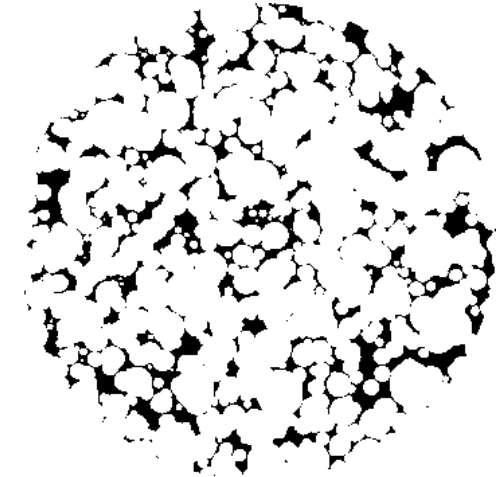
(c) AVC=19.19%



(d) AVC=7.62%



(e) AVC=13.49%



(f) AVC=19.13%

Figure 38: Comparison of CT Scans of Real and Virtual Asphalt Samples

4.4 Virtual Asphalt Measurement Protocols

4.4.1 Average Void Diameter Quantification

Virtual asphalt slices were systematically processed to measure average void diameter to extract a 90 mm-diameter circular ROI at the geometric center. This ROI served as the analytical focal zone, where void count and area were quantified to compute the average void diameter using established geometric relationships (Schneider et al., 2012). This method mirrored the CT scan-based measurement protocol applied to physical samples, ensuring procedural consistency and result comparability.

Figure 65 (Appendix) visualizes the ROI extraction from virtual and real asphalt specimens, demonstrating the virtual model's fidelity in replicating real-world void distributions. By investigating the linear relationship between MPD_{ISA} and average void diameter in virtual samples and contrasting it with laboratory-derived correlations, this study validated the virtual model's ability to reproduce the fundamental texture-void associations identified in Chapter 3.

4.4.2 MPD Measurement Procedure

MPD_{ISA} was evaluated using two vertical rectangular slices at 1/3 and 2/3 heights of the virtual structure. Eight surface profiles were extracted from these slices, with measurements averaged to ensure representativeness. Using ImageJ software (Schneider et al., 2012), the topmost reading from each profile, corresponding to the laser-scanned surface texture, was retained (Figure 39). Profiles were processed following ISO 13473-1 (2019) standards: missing data imputation, resampling at 0.5 mm intervals, slope/offset correction, and windowing to isolate MPD_{ISA} (ISO, 2019). This protocol mimicked CT scanning workflows, ensuring compatibility with texture analysis in Chapter 3.

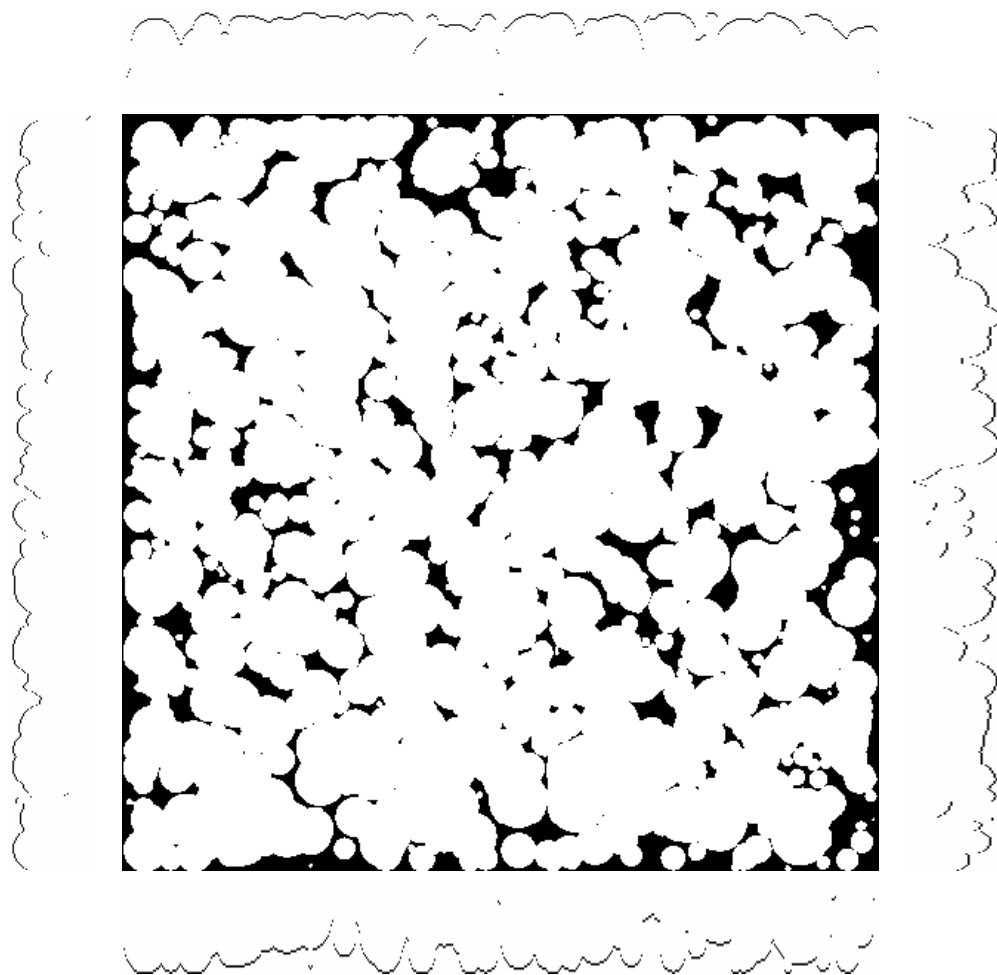


Figure 39: Rectangular Slice Analysis for MPD_{ISA} Measurement

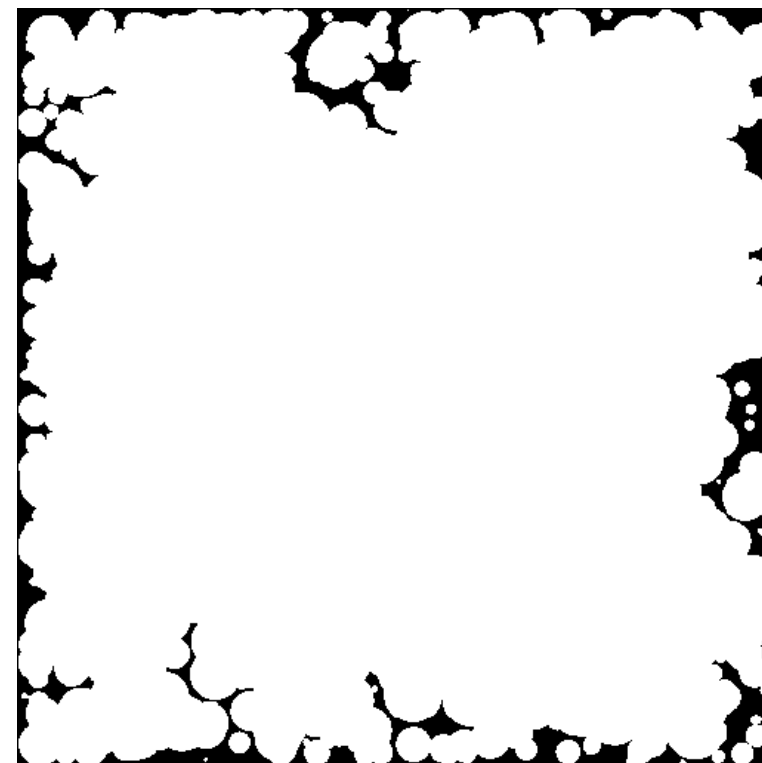


Figure 40: Internal Void Areas Connected to External Edge Profiles

4.4.3 MTD Measurement via Digital Algorithms

Two digital approaches were developed to replace physical SPT for virtual MTD_{ISA} measurement:

- **2D Approximation:** Using the same vertical slices as MPD_{ISA} analysis, void regions directly connected to the specimen's external edges were identified (Figure 40). Texture depth was calculated by the ratio of the area of these connected voids to the surface profile length, with results averaged across eight profiles to minimize bias. This approach is suitable for low-void scenarios with minimal connectivity.
- **3D Volumetric Method:** Leveraging the BoneJ plugin in ImageJ (Doube et al., 2010), a 3D void network was reconstructed by stacking 2D slices (Figure 41). The biggest connected void volume—accessible surface-connected voids—was divided by the total external surface area to derive MTD_{ISA} , providing a volumetric interpretation of texture depth consistent with SPT principles. This approach addressed 3D void complexity but required caution with external void contributions, which could overestimate MTD_{ISA} in low-void samples due to boundary effects.

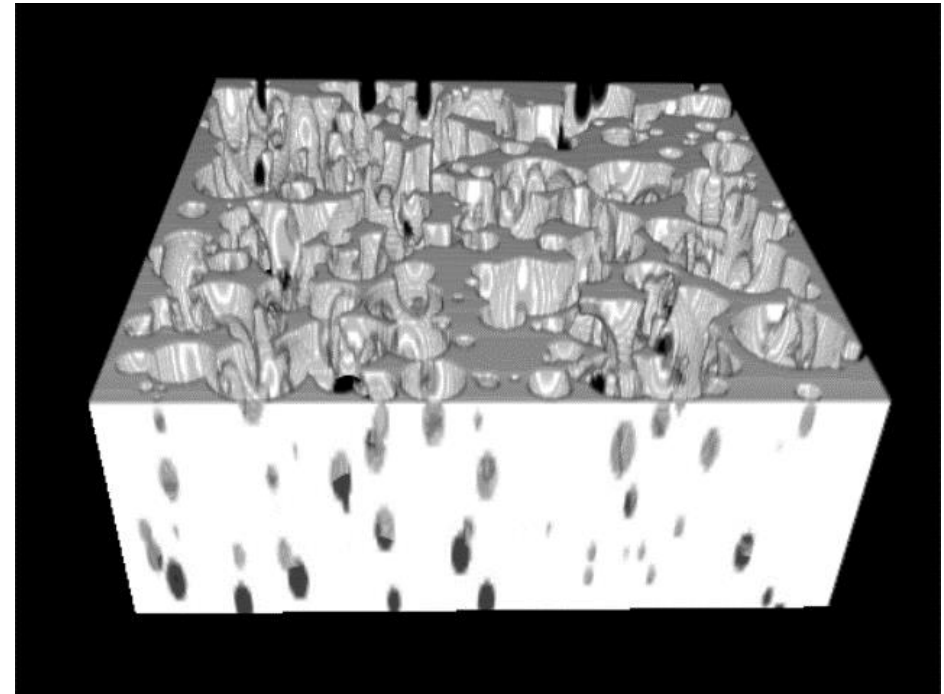
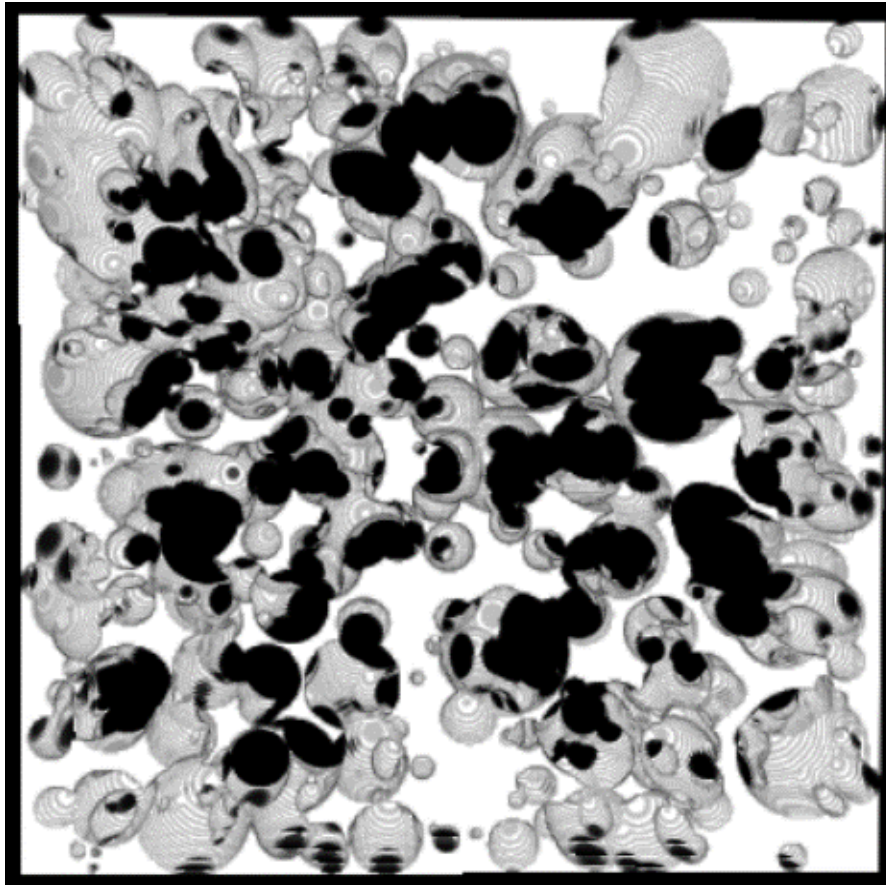


Figure 41: 3D Structure of Virtual Asphalt Air Voids

4.4.4 Dataset Validation and Correlation Analysis

A comprehensive virtual dataset was generated, including Marshall core-simulated mixtures and 60 virtual slabs corresponding to physical specimens. This dataset served two key purposes:

1. **MPD-Void Diameter Validation:** By verifying the linear correlation established in Chapter 3 within virtual samples, the study confirmed that virtual asphalt faithfully reproduces the fundamental texture-void relationship, validating its use for MPD_{ISA} characterization.
2. **MPD-MTD Feasibility Study:** Virtual slabs enabled systematic exploration of how gradation and void properties influence the MPD_{ISA} - MTD_{ISA} correlation, overcoming the limitations of physical testing, such as time-consuming sample preparation and texture control challenges. This approach facilitated analysis of complex nonlinear interactions that are difficult to isolate experimentally, offering a scalable platform for data-driven texture prediction.

These digital measurement techniques eliminate reliance on destructive sampling and labor-intensive physical testing, enabling efficient, repeatable characterization of asphalt macrotexture. By bridging geometric modeling with empirical texture metrics, this framework establishes virtual asphalt as a robust tool for advancing pavement material design and performance evaluation.

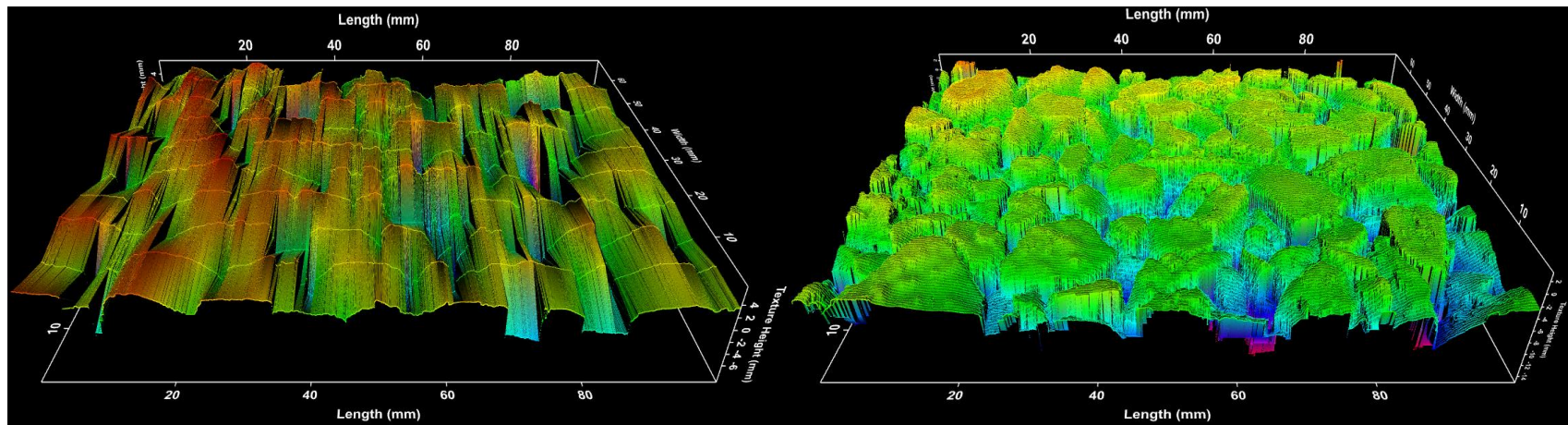


Figure 42: Impact of Laser Line Count on Texture Representation

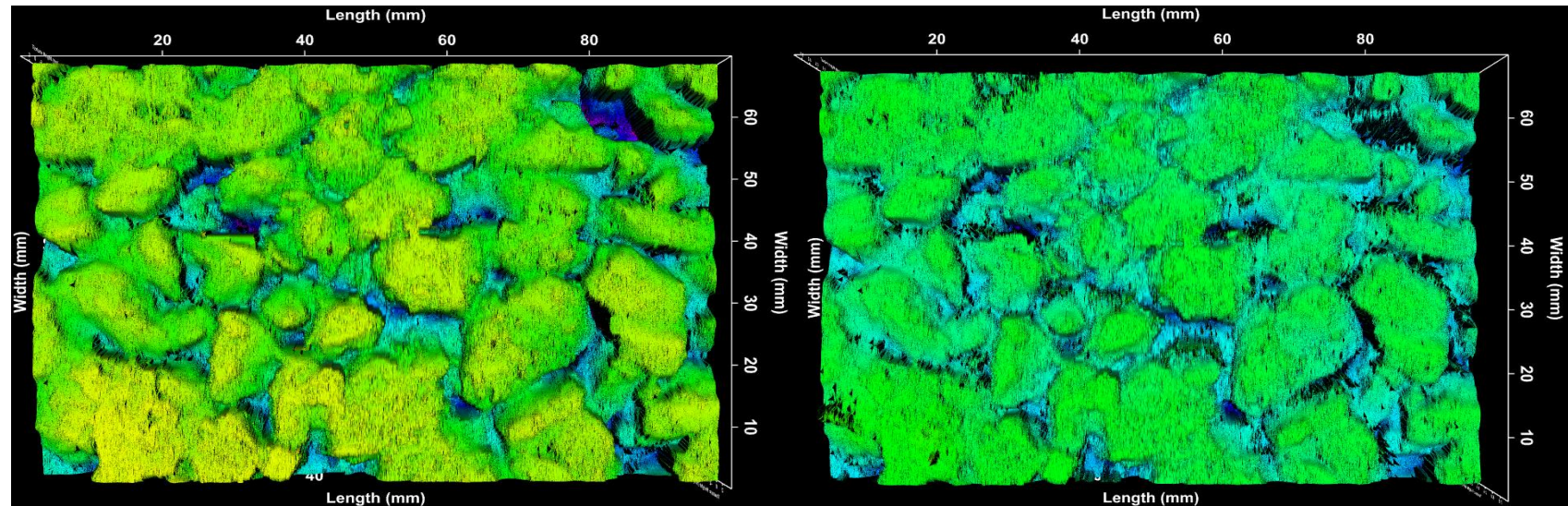


Figure 43: Measurement Differences in Dry vs. Wet Asphalt Surfaces

4.5 Results and Discussion

4.5.1 Impact of Laser Line Count and Moisture on Measurement Reliability

This study systematically investigated the influence of laser scanning configuration and surface moisture on MPD_{LS} measurements. As illustrated in Figure 42, 150-line laser scans captured finer texture details compared to 10-line scans. However, the resulting MPD_{LS} values were nearly identical, with 2.234 mm for 150-line scans and 2.276 mm for 10-line scans. Given the negligible impact on accuracy and the significant time savings, a 10-line scanning configuration was adopted for subsequent experiments, effectively balancing measurement efficiency and reliability.

Figure 43 demonstrates the pronounced differences in MPD_{LS} measurements between dry and wet asphalt surfaces. The dry surface exhibited an MPD_{LS} of 1.683 mm, while the damp surface showed an MPD_{LS} of 1.434 mm. These findings underscore the substantial impact of moisture on measurement accuracy, echoing the challenges commonly encountered in traditional pavement measurement methodologies. As noted in previous literature (Praticò & Vaiana, 2015), environmental factors such as weather conditions can significantly affect pavement assessments, highlighting the importance of controlling for such variables in texture measurement studies.

4.5.2 Nonlinear Correlation Between MPD and MTD

The data analysis in Table 18 (Appendix) revealed a complex, nonlinear relationship between MPD_{LS} and MTD_{SPT} , which is modulated by the maximum aggregate size. This nonlinearity can be attributed to the hierarchical void architecture within asphalt mixtures. Larger aggregates facilitate the formation of macropores, creating interconnected pathways that enhance sand penetration during the SPT. In contrast, MPD_{LS} remains relatively insensitive to such three-dimensional void complexity, focusing primarily on surface profile characteristics. Figure 44(a) visually represents this association through color-coded maximum aggregate sizes, demonstrating how coarser aggregates alter the MPD_{LS} – MTD_{SPT} relationship.

Model Development and Mechanistic Insight

A multivariate regression model was developed to characterize this intricate interaction, integrating MAS and MPD_{LS} as predictors of MTD_{SPT} . The resulting three-dimensional

surface, depicted in Figure 44(b), captures the interactive effects of these parameters, enabling the estimation of MTD_{SPT} based on measurable geometric properties. The predictive equation employs a log-normal formulation:

Equation 42:

$$MTD = 376.23 \times 10^{(-0.085(\log(Max. aggregate size)+3.57)^2 - 2.26(\log(MPD)-1.19)^2)}$$

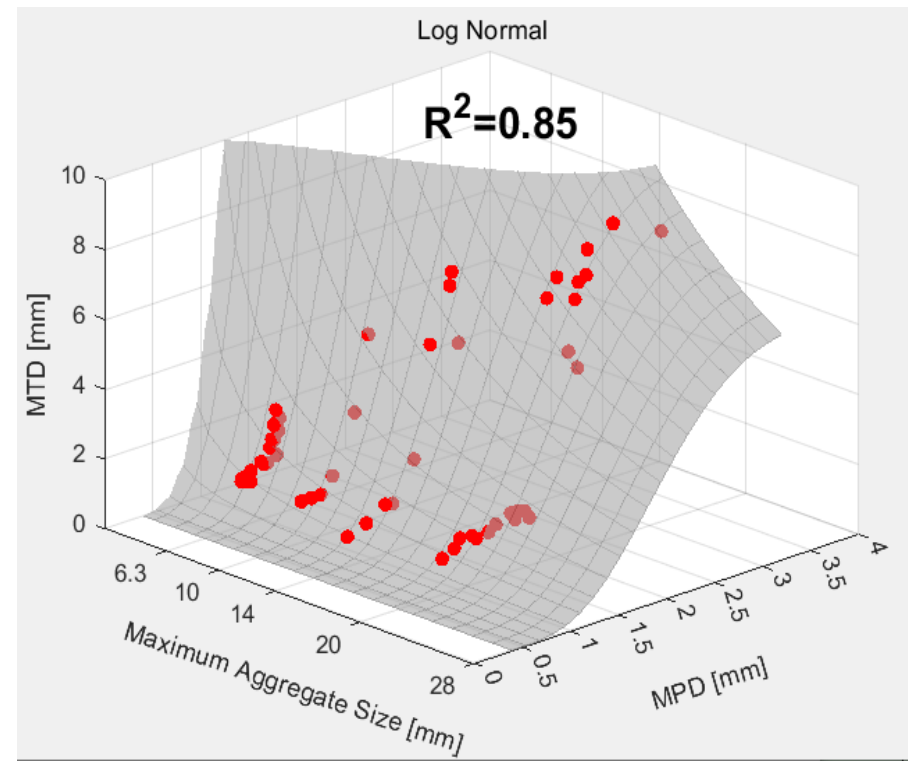
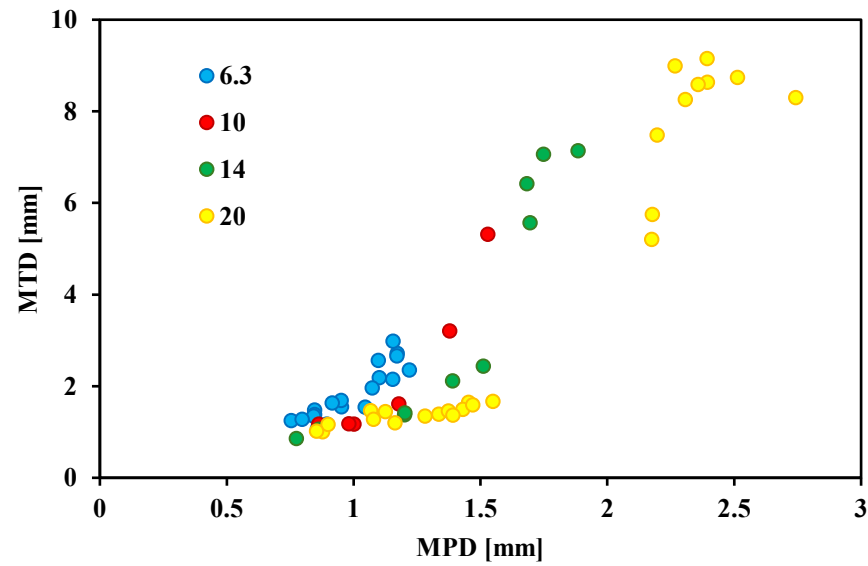
Both theoretical principles and empirical fit support this choice. The multiplicative effects of aggregate gradation and void morphology align with the geometric constraints of the aggregate skeleton on sand particle diffusion paths, a phenomenon well-documented in granular material studies (Bendat & Piersol, 2011; Cao, Jin, Changjun, & Feng, 2017). The model explains 85% of the variability in MTD_{SPT} ($R^2 = 0.85$), with logarithmic transformations stabilizing the variance and improving the model's resistance to outliers (Kumar, 2024). By incorporating MAS as a regulatory variable, this framework uniquely captures the nonlinear amplification of texture depth by coarse aggregates. It is particularly well-suited for open-graded or high-void mixtures where traditional linear models often prove inadequate.

Prediction Accuracy and Methodological Contrasts

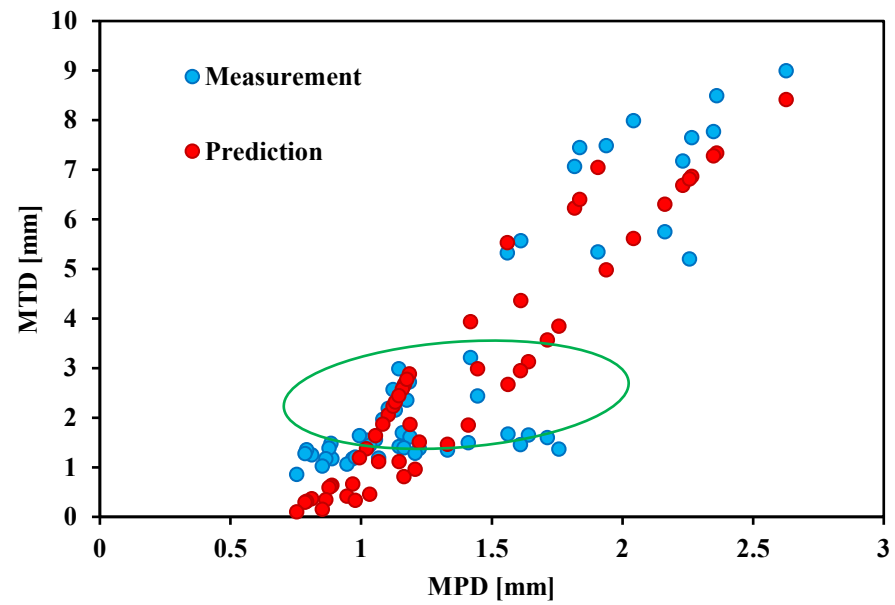
Figure 45(a) highlights the discrepancies between experimentally measured MTD_{SPT} values and model predictions, with errors becoming more pronounced in low- MPD_{LS} intervals corresponding to low air void content. While MPD_{LS} and MTD_{SPT} exhibit an approximately linear relationship under certain conditions, the established ASTM equation (ASTM, 2015) for estimating MTD_{SPT} from Equation 43 shows varying degrees of accuracy. As illustrated in Figure 45(b), the fitting of this equation is reasonable when the air void content is below 10%. However, as void connectivity increases, the SPT measures a disproportionately faster growth in MTD_{SPT} than MPD_{LS} . This divergence can be attributed to SPT's reliance on volumetric void networks, in contrast to MPD_{LS} 's surface-centric measurement approach. The amplifying effect of three-dimensional void structures on sand penetration aligns with previous research (Noyce et al., 2005; Vilaça, Fonseca, Pinho, & Freitas, 2010), which has noted the limited applicability of the SPT to porous mixtures.

Equation 43:

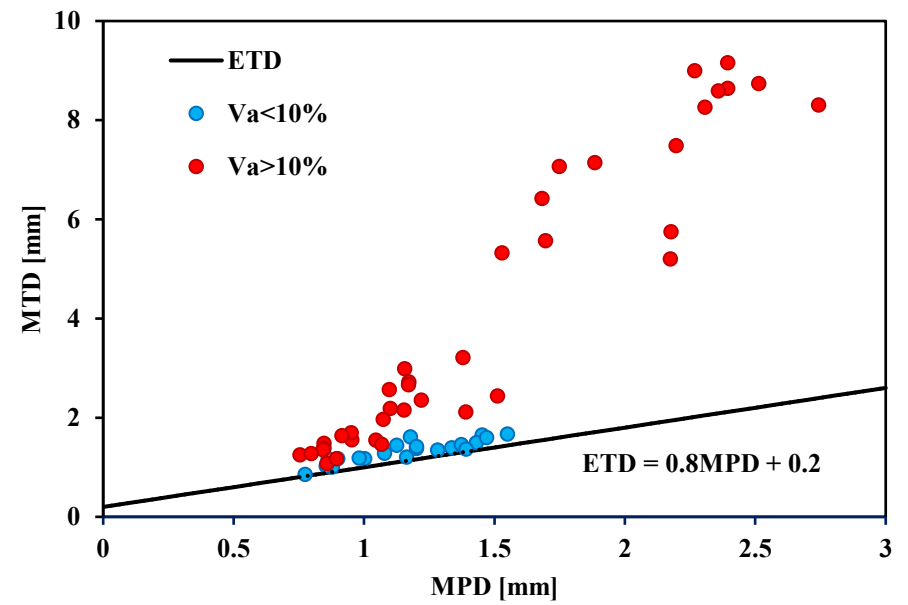
$$ETD = 0.2 + 0.8MPD$$



(a) (b)
Figure 44: Multivariate Regression Model for MTD_{SPT} Prediction



(a)



(b)

Figure 45: Comparison of Measured MTD_{SPT} vs. Predicted MTD_{ISA}

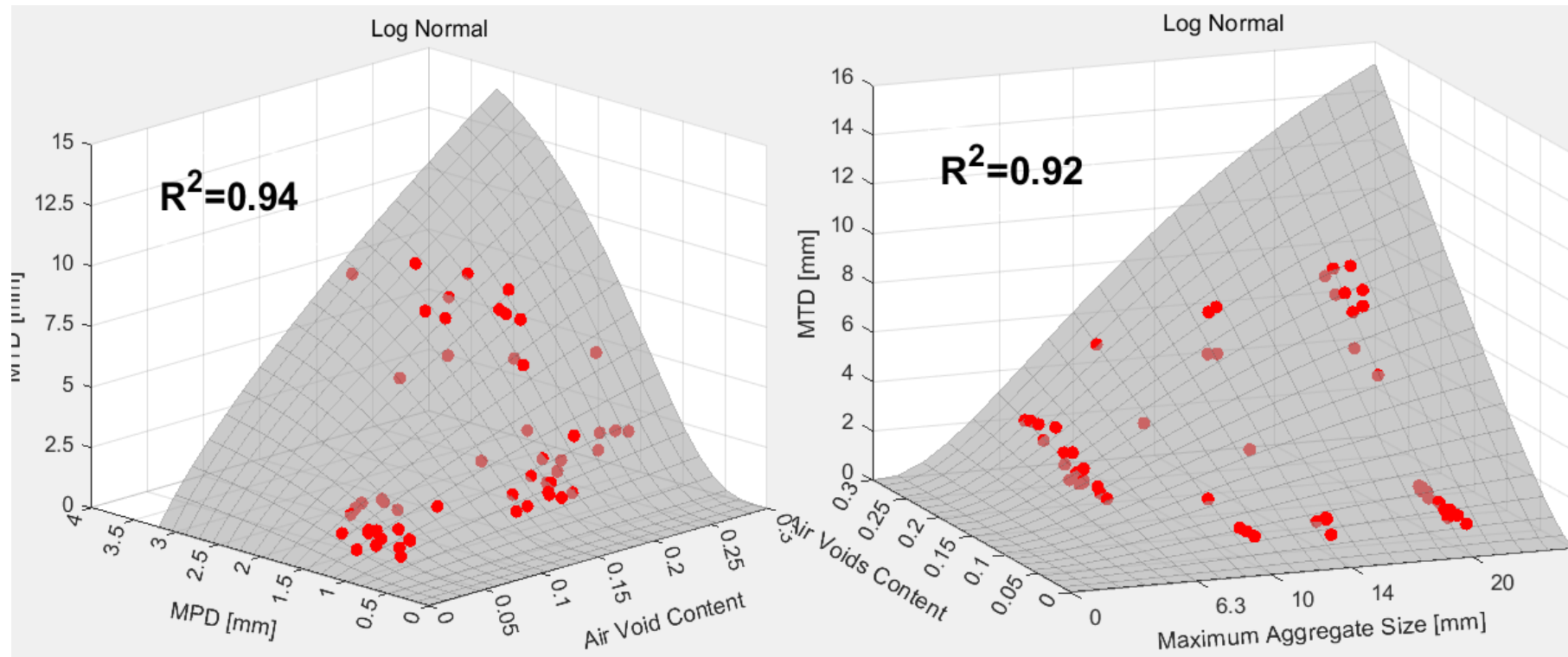


Figure 46: Predictive Models for MTD_{SPT} Based on Multiple Parameters

Enhanced Multivariate Predictive Models

Incorporating air void content into the regression framework significantly improved prediction accuracy, yielding an R^2 value of 0.94 for the MPD_{LS} -AVC-MTD_{SPT} model. This is higher than 0.92 the MAS-AVC-MTD_{SPT} model achieves, as shown in Figure 46. These results emphasize the critical role of void connectivity in mediating the relationship between texture depth and other mixture properties. Higher void content increases the complexity of void networks and their interaction with measurement methods, underscoring the importance of considering multiple parameters in texture prediction models. The superior explanatory power of these multi-parameter models reinforces their utility in asphalt mixture design, enabling engineers to account for both geometric (aggregate size, MPD) and volumetric properties (AVC) when optimizing gradations and binder contents. By integrating these variables, the models provide a comprehensive framework for predicting MTD across diverse mixture types, effectively bridging the gap between laboratory measurements and real-world pavement performance.

4.5.3 Validation of MPD-Void Diameter Linear Relationship

Figure 47 illustrates the correlation between MPD and average void diameter for real and virtual asphalt mixtures. The blue data points represent physical cores characterized via X-ray CT scanning in Chapter 3. In contrast, the orange points correspond to virtual mixtures generated using the ISA method. In Table 19 (Appendix), the comparative analysis of average void diameter and MPD data from real cores and virtual mixtures further validates this linear relationship. Both datasets exhibit a strong linear correlation, confirming that average void diameter, regardless of the measurement methodology, significantly influences surface texture depth (Alawneh & Soliman, 2023). This consistency validates the hypothesis that larger voids directly increase MPD by enhancing surface profile amplitude. Additionally, the correlation between MPD and void perimeter for physical cores and virtual asphalt mixtures exhibits a similarly close linear relationship, as shown in Figure 66 (Appendix).

Notably, although the real and virtual results are in close agreement, minor discrepancies exist. Several virtual samples display slightly enlarged average void diameters, which can be attributed to the stochastic nature of particle placement in the ISA method. This method's random nucleation and growth processes introduce

variability in void size distributions. Despite these nuances, the robust linear trend across both datasets underscores the feasibility of using ISA-generated virtual asphalt for MPD_{ISA} characterization. This approach offers a reliable alternative to destructive CT-based measurements, reducing the need for extensive physical sampling and costly equipment. Future research should focus on minimizing these stochastic variations, for example, by refining particle growth algorithms or incorporating real aggregate shape distributions to enhance the fidelity of virtual models. Integrating advanced imaging techniques such as X-ray microtomography with the ISA method could improve the balance between microstructural realism and computational efficiency (Chiarelli et al., 2015; Jin et al., 2022).

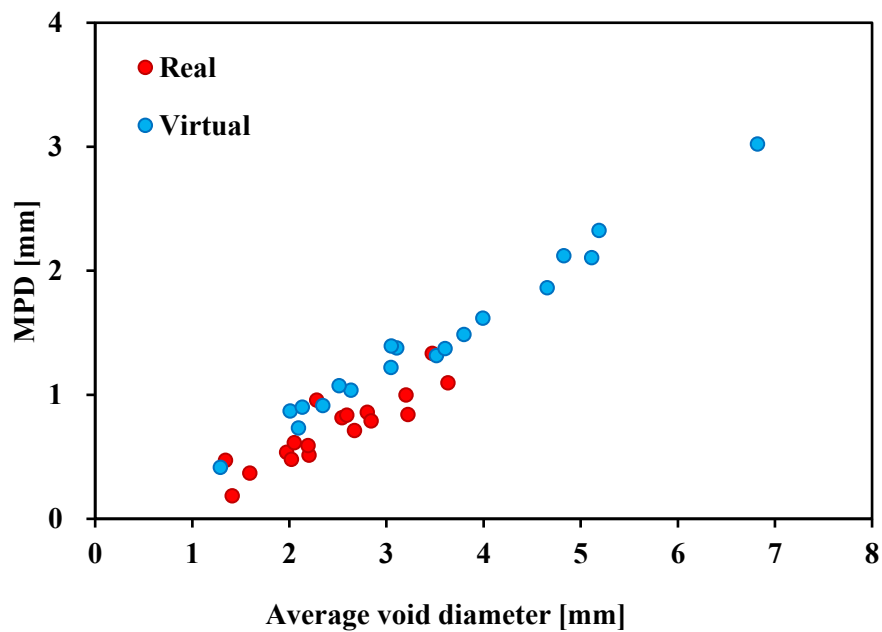


Figure 47: Correlation Between MPD and Average Void Diameter

4.5.4 Comparative Evaluation of 2D vs. 3D MTD_{ISA} Estimation Algorithms

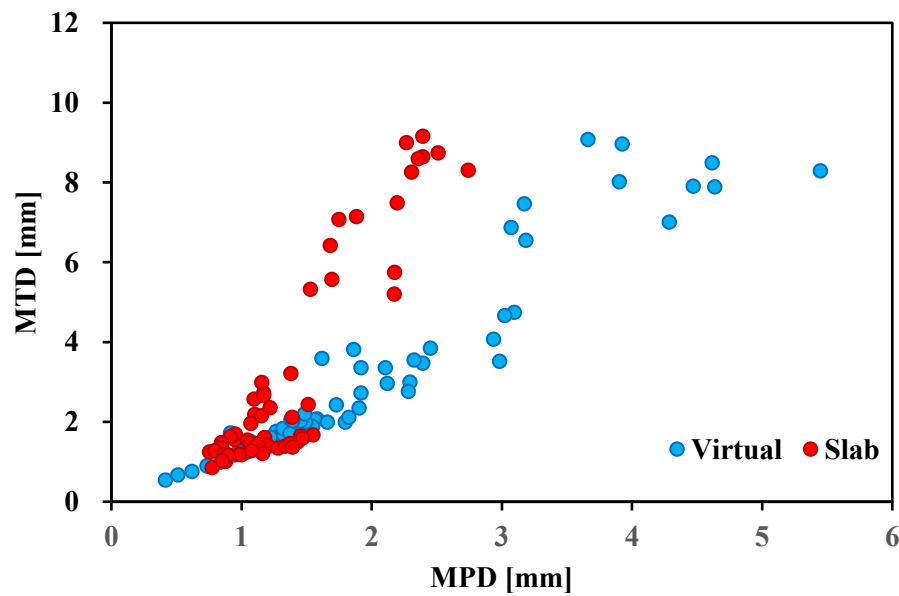
Table 20 (Appendix) presents the texture measurement data of virtual asphalt mixtures created based on slab data. Figure 48 contrasts MTD predictions from laboratory-measured and virtual asphalt samples using two digital algorithms, revealing distinct error profiles influenced by void complexity and geometric simplifications inherent in the ISA method.

4.5.4.1 2D Algorithm: Limitations in Complex Void Networks

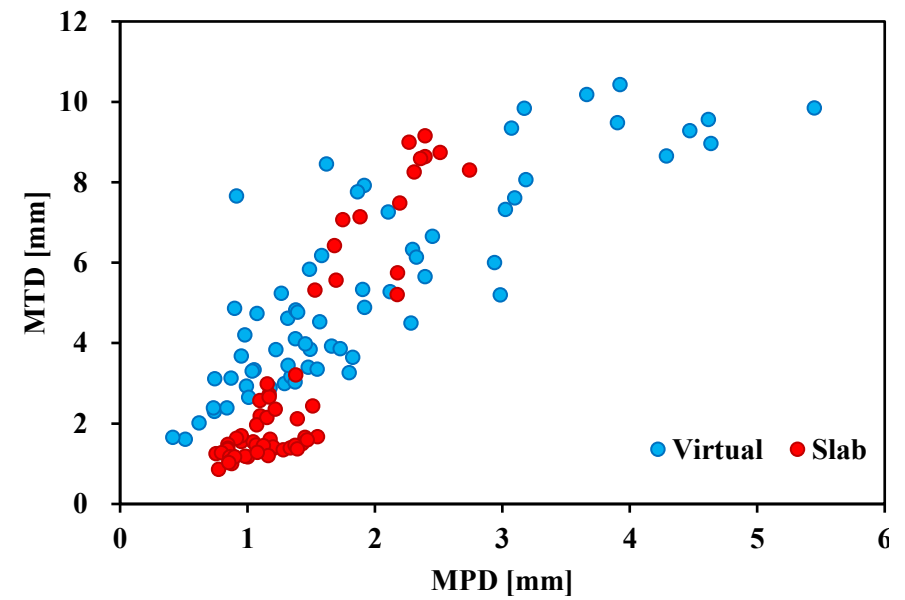
The 2D approach, as depicted in Figure 48(a), estimates MTD_{ISA} by dividing the connected void area with the surface profile by the surface profile's length. This method closely aligns with experimental results for low- MPD_{LS} , low-void mixtures with predominantly isolated voids, as its planar analysis effectively captures the simplified void area (Ma, Zhang, Zhang, Zhao, & Huang, 2016). However, as air void content increases and voids form interconnected 3D networks, the 2D algorithm significantly underestimates MTD_{ISA} . This limitation stems from neglecting vertical void depth and through-thickness connectivity, exacerbated by the ISA method's initial approximation of aggregates as spherical particles. Since real aggregates' angularity affects void interconnections, the resulting void shape errors compound the 2D algorithm's inability to quantify volumetric void space accurately, leading to incomplete texture depth calculations (You, Adhikari, & Dai, 2010). Figure 48(a) illustrates this divergence: at high MPD_{LS} values indicative of complex void structures, virtual 2D MTD_{ISA} estimates fall short of experimental measurements, highlighting the algorithm's sensitivity to 3D void complexity.

4.5.4.2 3D Volumetric Algorithm: Trade-offs in Void Volume Calculation

The 3D algorithm, depicted in Figure 48(b), calculates MTD_{ISA} by normalizing the largest connected void volume by the external surface area, offering improved consistency with experimental data for high-void mixtures. By accounting for through-thickness connectivity, this method better captures the volumetric characteristics of interconnected voids, a critical advantage over 2D analysis. However, it introduces systematic overestimation in low-void scenarios. The 3D algorithm's reliance on external void volume calculations amplifies errors caused by boundary effects: flat surface textures can generate artificially large "external voids" at the specimen edges, disproportionately inflating MTD_{ISA} values (Ren et al., 2024). Additionally, the spherical approximation of aggregates in the ISA method indirectly impacts 3D void volume accuracy, as it fails to replicate the interlocking and void formation influenced by real aggregate shapes. Figure 48(b) demonstrates this bias, with inflated MTD_{ISA} predictions in low- MPD_{LS} intervals where void networks are less complex and boundary-related artifacts dominate volume assessments (Liang, Pagano, Oddone, Cong, & De Blasiis, 2024).



(a) Two-dimensional algorithm



(b) Three-dimensional Algorithms

Figure 48: Correlation between MPD and MTD in Laboratory-Prepared Slabs and Virtual Asphalt Samples

4.5.4.3 Methodological Recommendations

Given these complementary strengths and limitations, a hybrid approach is recommended:

- **2D Analysis:** Ideal for low-void, low-MPD_{LS} mixtures with isolated voids, where the planar representation adequately approximates real-world void geometry area.
- **3D Analysis:** Preferred for high-void, high-MPD_{LS} scenarios, despite its boundary-related biases, as it captures the volumetric complexity essential for accurate texture depth estimation.

Future research should focus on developing adaptive algorithms that dynamically select between 2D and 3D frameworks based on real-time void connectivity metrics. Additionally, incorporating more realistic aggregate shapes into the ISA method could mitigate void shape errors, enhancing the accuracy of both 2D and 3D MTD_{ISA} estimations. Validating these algorithms against physical samples with known void architectures, such as those created via 3D printing (Aboufoul et al., 2019; Daminabo, Goel, Grammatikos, Nezhad, & Thakur, 2020), will refine virtual texture prediction models for asphalt mixture design.

4.6 Analysis and Discussion

4.6.1 Addressing Literature Gaps and Research Objectives

This study effectively addresses several critical gaps identified in the literature review. Firstly, it validates the ISA method for texture prediction, a significant advancement as previous studies had only utilized ISA for void geometry analysis (Schenker et al., 2010; Chiarelli et al., 2015). By demonstrating that virtual asphalt can replicate the CT-derived MPD_{CT}—void diameter linear relationship ($R^2 = 0.8$), this research provides a reliable computational alternative to expensive and destructive CT-based measurements, reducing the reliance on physical sampling and specialized equipment.

Secondly, quantifying the nonlinear MPD_{LS} – MTD_{SPT} relationship resolves the ambiguity in previous research regarding the interaction between these texture metrics. The developed multivariate regression models, which incorporate multiple parameters such as maximum aggregate size, MPD_{LS}, and air void content, offer a more

comprehensive understanding of how void properties influence surface texture depth. This is a significant improvement over traditional linear models (ASTM, 2015), which often fail to capture the complexity of texture behavior in diverse asphalt mixtures.

Regarding research objectives, this study stage successfully validates the cost-effective virtual asphalt models for simulating texture structure. The hybrid 2D/3D MTD_{ISA} estimation algorithms and the validated MPD_{ISA} -void diameter relationship in virtual models provide a robust framework for texture prediction. This reduces the time and cost associated with physical testing and enables engineers to explore a broader range of mixture designs, facilitating data-driven decision-making in asphalt pavement engineering.

4.6.2 Methodological Innovations, Limitations, and Future Directions

4.6.2.1 Innovative Contributions

This research introduces several key methodological innovations. The successful validation of the ISA method for texture prediction marks this approach's first application in this context. The study establishes ISA as a viable alternative for CT in texture-centric design by cross-correlating virtual and physical MPD -void diameter relationships. Virtual models reduce the need for extensive physical testing, as demonstrated by replacing a large dataset of physical cores and slabs with digital simulations.

The development of hybrid 2D/3D MTD_{ISA} estimation algorithms addresses the limitations of single-method approaches. The 2D algorithm is effective for low-void mixtures, while the 3D algorithm excels in high-void scenarios. This dual strategy improves the overall accuracy of MTD_{ISA} prediction, providing a more comprehensive assessment of asphalt surface texture.

Limitations and Future Directions

Despite these advancements, the study also identifies several limitations. The simplification of aggregate geometry in the ISA method, which uses spherical particles, introduces void shape errors. Incorporating real aggregate morphology through techniques such as 3D scanning could significantly refine texture predictions in future research (Lugo et al., 2008; Jin et al., 2022).

Additionally, the ISA method overlooks construction-induced void variations, such as those resulting from roller compaction density gradients. This oversight leads to noticeable MPD_{ISA} discrepancies in high-void virtual slabs. Future work should focus on integrating compaction parameters, such as roller pass count and temperature, into the virtual modeling process to better mimic field conditions and improve the accuracy of virtual texture predictions.

4.6.3 Cost-Effectiveness and Industry Impact

Traditional texture characterization methods are associated with high costs and time-consuming procedures. Physical testing, including sample mixing, compaction, and CT scanning, typically requires 2 - 3 days per slab and involves significant expenses for materials, laboratory equipment, and specialized scanning services.

In contrast, virtual asphalt modeling offers a cost-effective alternative. Digital simulations require only computational resources and can produce results within a much shorter timeframe (approximately 1 hour per simulation). This efficiency allows engineers to explore more gradation scenarios than physical testing, as evidenced by validating 19 virtual mixtures against CT data.

The validated MPD_{ISA} -void diameter relationship provides a computational shortcut for texture optimization. Embedding this relationship into the ISA method allows mixture designers to predict MPD_{ISA} from void parameters without resorting to physics testing. This marks a significant paradigm shift from empirical trial-and-error approaches to data-driven design, enabling more efficient and economical pavement mixture design processes.

4.6.4 Closing the Research Loop

This chapter plays a crucial role in connecting the three stages of the research. The findings from the CT-based mechanism discovery in Stage 1 (Chapter 3) serve as the foundation for validating the virtual asphalt models in Stage 2 (Chapter 4). The confirmed MPD_{ISA} —void diameter linear relationship is a benchmark for ensuring that the virtual models accurately replicate real-world texture—void relationships, effectively replacing destructive CT scanning with computational analysis.

The experimental data generated in this stage (Chapter 4), including laser-scanned MPD_{LS} from the 60 laboratory-fabricated slabs, directly contributes to developing the deep learning framework in Stage 3 (Chapter 5). Since virtual asphalt cannot currently generate photorealistic surface images, the laser scan data and slab photographs provide the essential training inputs for the VGG-based CNN, enabling the prediction of MPD_{VGG} from 2D images.

Methodologically, Chapter 4's virtual modeling approach builds on the CT-validated void-topology-texture mappings from Chapter 3. In contrast, Chapter 5's deep learning approach leverages the high-precision laser scanning protocol established in Stage 2, transforming lab measurements into field-deployable "capture-and-predict" workflows. This seamless integration of microscale void analysis, virtual simulation, and AI-driven field assessment creates a comprehensive research pipeline, paving the way for a new era of intelligent pavement texture engineering.

5 Deep Learning for Asphalt Surface Texture Prediction

5.1 Introduction

Deep learning, particularly convolutional neural networks (CNNs), offers a transformative approach to asphalt surface texture analysis, overcoming the limitations of traditional manual and 2D profilometry methods. Unlike conventional techniques that rely on empirical correlations or labor-intensive measurements, CNNs automatically extract hierarchical features from asphalt surface images, enabling data-driven predictions of MPD_{VGG} with sub-millimeter precision. This chapter presents a systematic framework for MPD_{VGG} prediction using a VGG-based CNN, integrating classification and regression strategies to address categorical texture assessment and continuous value prediction. By leveraging three diverse datasets—laboratory slabs from Chapter 4 (Set A), composite samples (Set B), and in-service road surfaces (Set C)—this study demonstrates the model’s adaptability across controlled and real-world conditions, while highlighting the critical role of data preprocessing and architectural optimization. Key innovations include a novel overlapping interval strategy in classification tasks and a high-precision regression framework, enhancing the model’s capability to provide intuitive texture categorization and exact MPD_{VGG} predictions. The study highlights the DL model’s potential to replace labor-intensive traditional methods, offering scalable, data-driven insights for pavement assessment.

A detailed workflow (Figure 49) outlines the process from multi-source data collection to model validation, with subsequent sections detailing methodology, experimental design, and performance evaluation.

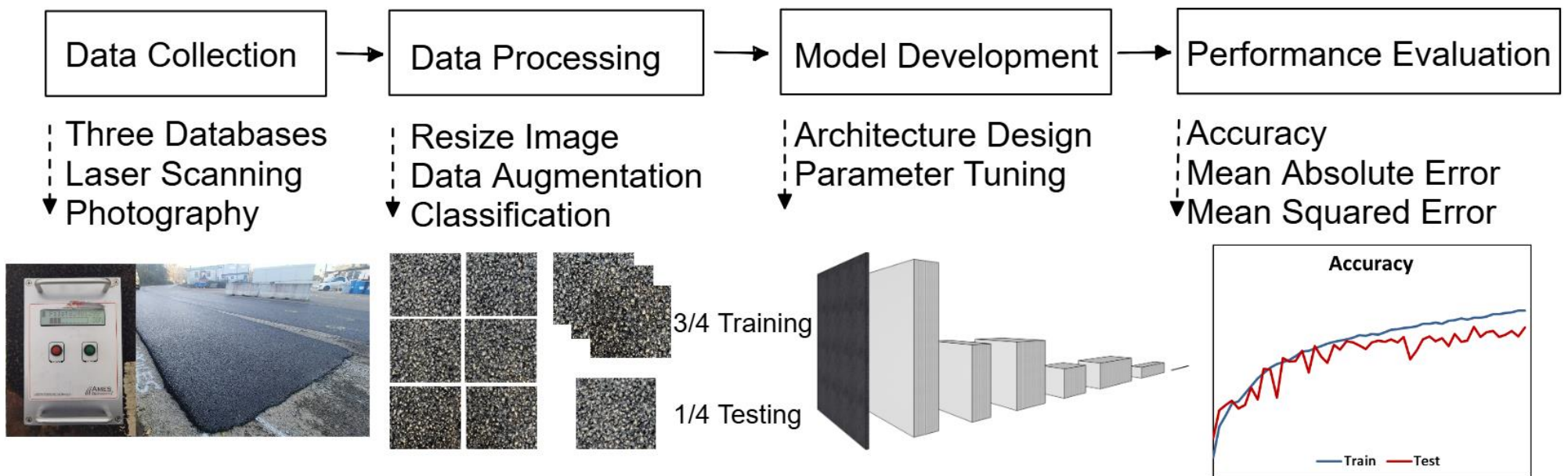


Figure 49: Workflow Diagram: From Data Collection to Model Evaluation

5.2 Data Sources

Three datasets were employed to train and validate the CNN model, each capturing distinct surface conditions:

5.2.1 Laboratory-Prepared Asphalt Slab Dataset (Set A)

Set A consists of 60 asphalt slabs (30×30×5 cm) fabricated under controlled conditions, with systematically varied gradation and porosity (Table 18, Appendix). Laser scanning (10×7 cm) and high-resolution photography (3840×2592 pixels, 15 cm height) were used to collect 1,788 image-MPD_{LS} pairs (Table 21, Appendix). Images were captured from consistent angles to align with scanned regions, ensuring spatial correspondence between visual and topographic data. The uniform lighting and controlled material properties make this dataset ideal for baseline model training, as it minimizes extraneous variability.

5.2.2 Composite Dataset (Set B)

Set B integrates 855 samples from diverse environments: newly constructed roads, parking lots, semi-closed areas, and additional lab slab imagery (different photography from Set A). Images were acquired at 40 cm height with a 4032×3024 resolution, capturing a broader 45×35 cm area. The wider field of view challenges the model to generalize across spatial scales. This dataset introduces natural variability in lighting, debris, and early-age texture, reflecting pre-service and low-speed load pavement conditions. Including lab and field samples allows for cross-environmental validation of model robustness.

5.2.3 On-site Road Surface Dataset (Set C)

Set C comprises 2,004 images from in-service roadways, acquired under natural weather conditions (sunlight, shadow, moisture) at standardized conditions matching Set A (15 cm height, 3840×2592 resolution, 10×7 cm scan area). The dataset captures wear-induced features such as aggregate polishing, moisture-induced texture degradation, and surface contamination, providing a rigorous test of model performance in operational environments.

Key characteristics are summarized in Table 22 (Appendix).

5.3 Methodology

5.3.1 Data Collection and Instrumentation

Surface topography was measured using an AMES 9400HD laser scanner (10×7 cm fixed area), while visual data were captured via consumer-grade devices: Huawei P40 Pro (Sets A, C) and iPad Pro (Set B) cameras. This choice of everyday consumer electronics, readily available and requiring no specialized training, addresses traditional laser profilometry's high cost and operational barriers. Using distinct devices (smartphone vs. tablet) across datasets demonstrates the model's robustness to camera hardware variations, a critical factor for field deployability. Laboratory imaging was conducted under controlled lighting, whereas field data included unconstrained environmental conditions (natural lighting, weather, debris) to reflect real-world operational scenarios.

5.3.2 Image Processing Pipeline

5.3.2.1 Spatial Alignment

For Sets A and C, raw images were cropped to 2600×1900 pixels to align with laser-scanned regions, ensuring spatial consistency between visual and topographic data (Figure 50). Set B required additional processing: each 4032×3024 pixel image was segmented into six 1344×1512 pixel sub-regions to mitigate variability in capture scale, yielding 4,622 samples (Figure 51).



(a)



(b)

Figure 50: Imaging and Processing for Sets A and C: Before and After Cropping



(a)

(b)

Figure 51: On-Site Imaging and Processing for Set B: Before and After Cropping

5.3.2.2 Data Augmentation

Effective data preprocessing is critical for enhancing deep learning model performance. The following strategies were implemented to optimize dataset quality and diversity:

Geometric Transformations

- **Image Rotation:** Images were rotated at 90°, 180°, and 270° intervals, generating four times the original dataset size. This augmentation improves models' invariance to texture orientation, ensuring consistent performance regardless of image capture angle (Chollet, 2021).
- **Random Shifts and Flips:** Fifty percent probability of horizontal flips and random width/height shifts (up to 10% of image dimensions) were applied to simulate real-world positional variations. Three filling techniques were used for shifted regions (Figure 52):
 - **Nearest:** Uses neighboring edge pixels, suitable for preserving sharp texture boundaries.
 - **Reflect:** Mirrors edge pixels, ideal for maintaining texture continuity.
 - **Wrap:** Loops pixel values from opposite edges, reducing boundary artifacts.

These methods enhance the model's robustness to partial texture visibility and alignment errors (Ioffe, 2015).

Spatial and Intensity Normalization

- **Image Rescaling:** All images were resized to 200×200 pixels to balance computational efficiency and feature retention. This reduction in spatial dimensions decreased training time while preserving critical details like aggregate morphology and void patterns (Chollet, 2021).
- **Pixel Value Normalization:** RGB pixel values were normalized from [0, 255] to [0, 1] using ImageDataGenerator, stabilizing gradient updates during training and improving convergence speed (Ioffe & Szegedy, 2015).

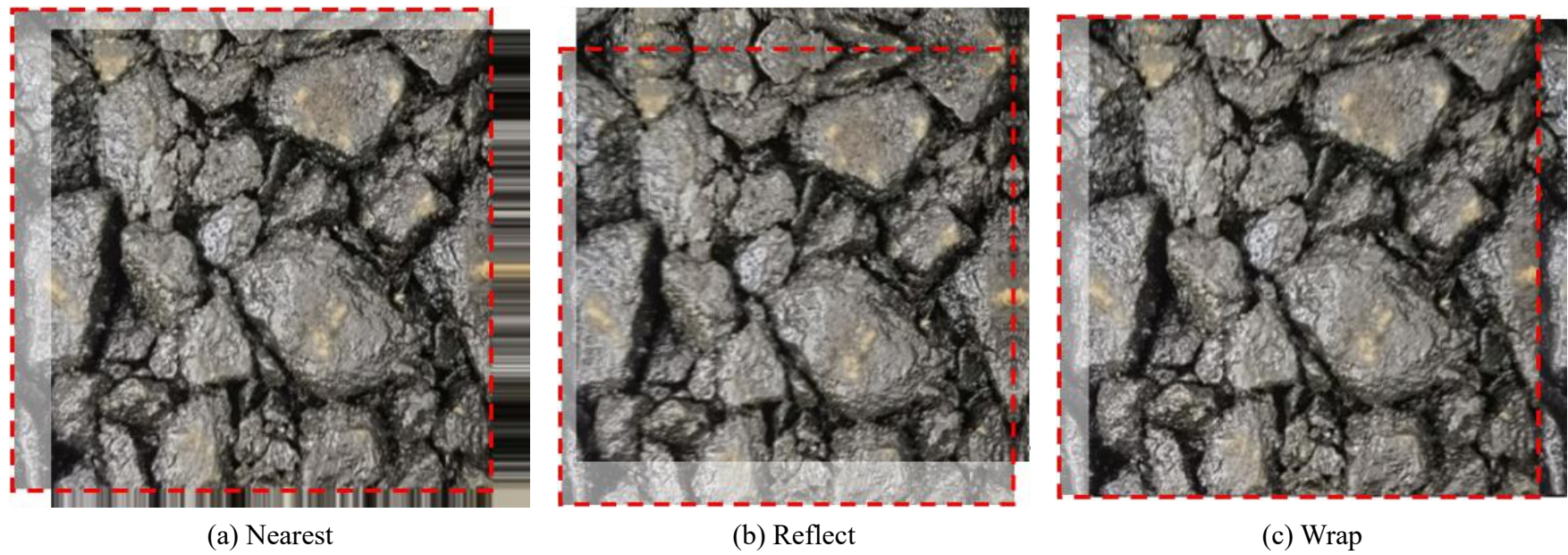


Figure 52. Visualization of Image Filling Techniques, with the Red Dashed Line Demarcating the Original Image Area after Offset

5.3.2.3 Dataset Expansion and Diversity

By combining cropping and rotations, and removing some unusable images, the adequate dataset size increased significantly:

- **Set A:** From 1,788 to 7,152 samples.
- **Set B:** From 855 to 20,068 samples.
- **Set C:** From 2,004 to 8,016 samples.

This expansion mitigated the data shortage and imbalance for some classes. It exposed the model to diverse texture manifestations and was beneficial for rare high-MPD_{LS} classes with limited real-world data.

5.3.3 Classification and Regression Strategies

5.3.3.1 Categorization Framework

Two distinct categorization strategies were employed to systematically analyze the relationship between MPD_{LS} and asphalt surface features: non-overlapping and overlapping interval classification. These approaches address the challenge of converting continuous MPD_{LS} measurements into discrete classes for CNN training while balancing granularity and model robustness.

Non-Overlapping Interval Classification

Initially, traditional non-overlapping categorization schemes were evaluated, where each MPD_{LS} range is strictly exclusive. For example, classes were defined as "<0.8 mm," "0.8–1.0 mm," "1.0–1.2 mm," etc., with clear boundaries that do not intersect. This strategy simplifies model training by assigning each image to a single class, aligning with conventional pavement texture grading standards (England, 2020).

However, non-overlapping intervals introduce boundary ambiguity: images near class thresholds (e.g., MPD_{LS} = 1.2 mm) may exhibit transitional features of adjacent classes but are forced into a single category. This can lead to misclassification, particularly in datasets with high texture variability. To mitigate this, class boundaries were initially aligned with empirical pavement performance thresholds, such as those distinguishing low-, medium-, and high-texture surfaces, as shown in Table 2.

Overlapping Interval Classification

A novel overlapping interval strategy was developed for the training phase to address the limitations of rigid class boundaries. Adjacent MPD_{LS} ranges were allowed to partially overlap (e.g., "0.8–1.2 mm" and "1.0–1.4 mm"), enabling images near boundaries to be trained across two classes. This approach leverages transitional features (e.g., gradual changes in aggregate exposure or void connectivity) that are otherwise ignored in non-overlapping schemes.

Crucially, the test set maintained strict non-overlapping intervals to ensure unbiased performance evaluation. For example, a training image with MPD_{LS} = 1.1 mm might be labeled for both "0.8–1.2 mm" and "1.0–1.4 mm" classes, while the test set would assign it to "1.0–1.2 mm" (non-overlapping). This strategy enhances model generalization by exposing it to shared features across class boundaries, reducing sensitivity to minor measurement variations or image noise.

Experimental Design and Validation

- **Boundary Selection:** Class limits were informed by both statistical analysis of dataset MPD_{LS} distributions and engineering standards (England, 2020). For instance, "1.2–1.5 mm" matched minimum texture depth requirements for high-speed road surfaces (Table 2).
- **Data Partitioning:** Within each MPD_{LS} class (whether overlapping or not), 75% of images were allocated to the training set, with 25% reserved for testing. This ratio balanced statistical significance with model generalization.
- **Performance Metrics:** Accuracy was used to compare strategies. As demonstrated in the results, overlapping intervals consistently improved accuracy compared to non-overlapping schemes, reflecting the model's enhanced ability to handle transitional textures.

5.3.3.2 Regression Methodology

A regression framework was developed in parallel with classification to predict continuous MPD_{VGG} values from images directly, bypassing predefined classes. This

method utilizes the VGG19 architecture with a linear output layer (Figure 67, Appendix) (Simonyan & Zisserman, 2014), trained on a dataset annotated with exact MPD_{VGG} measurements. Key advantages include:

- **Granular Precision:** Avoids information loss from categorical discretization, enabling sub-millimeter predictions.
- **Flexibility:** Adaptable to any MPD value without predefining class boundaries, critical for rare or extreme texture cases.
- **Loss Function:** MAE provides interpretable absolute error values. MSE emphasizes larger errors through squaring, aiding in detecting systematic biases (Botchkarev, 2018; Terven, Cordova-Esparza, Ramirez-Pedraza, & Chavez-Urbiola, 2023).

5.4 Deep Learning Model Development

5.4.1 Classification Model Architecture Design

This study's foundational code for the CNN model originates from Jason Brownlee, PhD's 2021 article (Brownlee, 2019). The original code, designed for binary image classification of dogs and cats, is the basis for the asphalt texture prediction framework presented here. Simplified VGG-style CNN architecture from the original work was adapted and optimized for asphalt surface analysis, with modifications tailored to capture texture-void relationships in asphalt mixtures.

As described in Brownlee's tutorial, the initial model employed a hierarchical structure of convolutional and pooling layers to extract visual features (Brownlee, 2019). This research streamlined the architecture to balance feature extraction capability with computational efficiency for asphalt texture data, as illustrated in Figure 53. Key adjustments included reducing the weight layers and optimizing hyperparameters to handle the smaller dataset size and structured texture patterns inherent in asphalt surfaces, while retaining the core VGG design principles of 3×3 convolutional filters and ReLU activation (Simonyan & Zisserman, 2014).

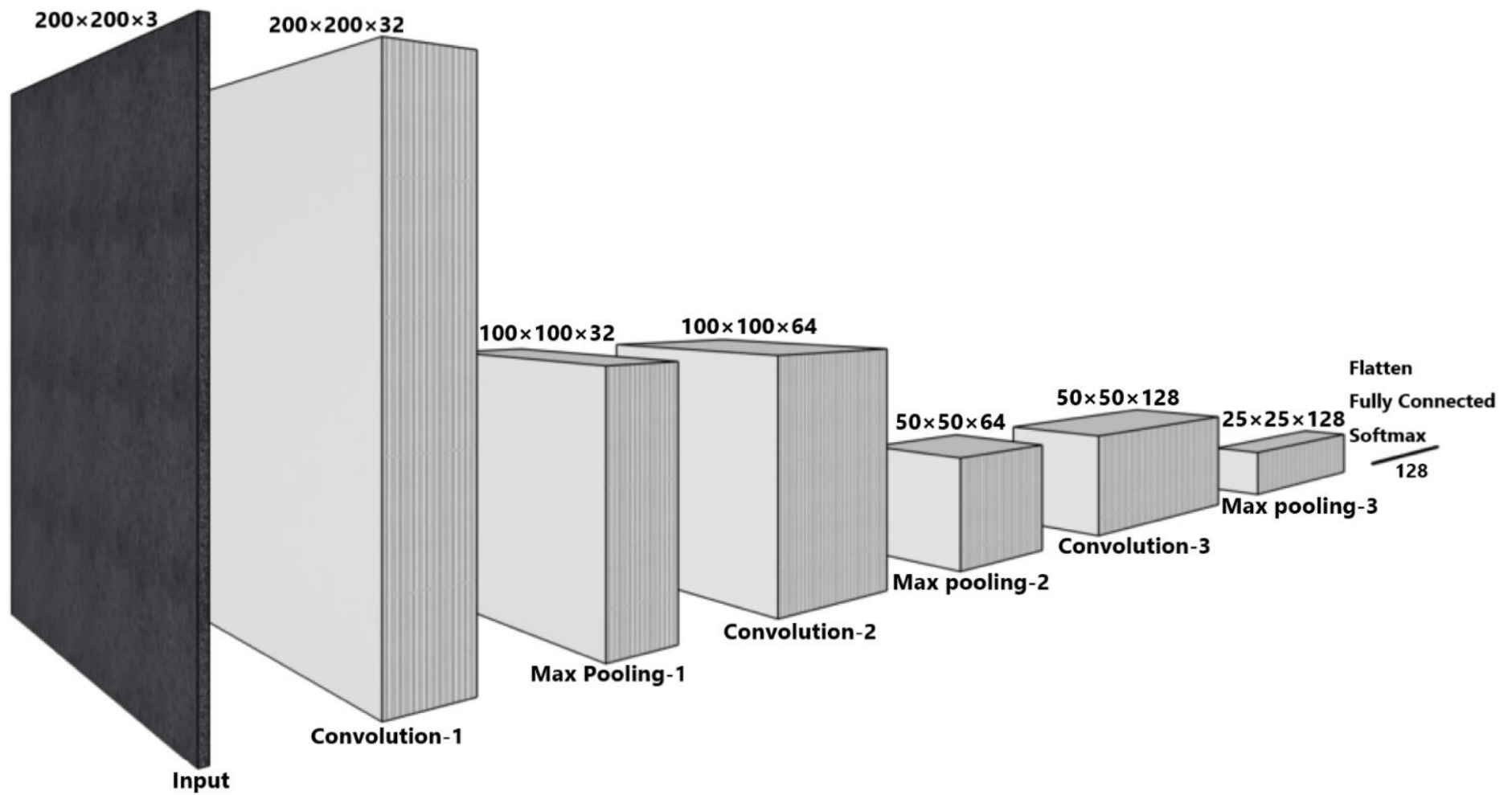


Figure 53: Classification Model Architecture Schematic

The architecture emphasizes hierarchical texture analysis while minimizing parameter redundancy:

1. **Convolutional Layers:** Three layers with 32, 64, and 128 filters (3×3 kernels) progressively capture fine-grained features. ReLU activation introduces non-linearity, enabling the model to learn complex relationships between pixel intensities and texture depth.
2. **Max-Pooling Layer:** 2×2 pooling after each convolution reduces spatial dimensions by 50%, retaining dominant features while reducing computational load.
3. **Fully Connected Layer:** A 128-neuron layer processes flattened feature maps, learning abstract representations of texture-void relationships.
4. **Output Layer:** SoftMax activation for classification tasks (multi-class MPD_{LS} ranges) or linear activation for regression (continuous MPD_{VGG} prediction) (Simonyan & Zisserman, 2014; Goodfellow et al., 2016).

The original code from Brownlee's study is provided in the Appendix, alongside the adapted code used for asphalt MPD_{VGG} prediction. These modifications demonstrate the versatility of transfer learning in adapting computer vision models from natural image classification to material science applications, highlighting the potential of CNNs for automated asphalt texture analysis.

Saliency Map Analysis (Figure 68, Appendix, attention: Red>Green>Blue) revealed stage-specific feature learning, validating its ability to associate microstructural features with texture.

- Layer 1: Focuses on large aggregate contours and primary void boundaries.
- Layer 2: Captures mid-scale roughness and particle interactions.
- Layer 3: Identifies small voids and texture valleys, critical for MPD_{LS} differentiation.

This hierarchical processing highlights void geometry as a key predictor of surface texture depth.

5.4.2 Hyperparameter and Architecture Optimization

A systematic optimization framework using the controlled variable method was employed to refine the CNN model for asphalt texture analysis. Key parameters were evaluated individually while maintaining consistency in other configurations, ensuring robust performance optimization (Arnold, Biedebach, Küpfer, & Neunhoffer, 2023).

5.4.3.1 Architecture Design

VGG-style CNN architectures with varying depths (2–16 layers) were tested, including custom and pre-trained (VGG16) models (Simonyan & Zisserman, 2014). Configurations were systematically adjusted for the number of convolutional layers (32–512 filters), max pooling layers, and fully connected neurons, balancing feature extraction and computational efficiency.

5.4.3.2 Hyperparameter Calibration

- **Learning Rate:** Logarithmic values (10^{-5} to 10^{-1}) were tested via SGD to optimize convergence stability (LeCun, Bottou, Orr, & Müller, 2002).
- **Momentum:** Values (0 to 0.99) were evaluated to enhance gradient smoothing and training speed (Sutskever, Martens, Dahl, & Hinton, 2013; Smith, 2018).

5.4.3.3 Training Protocol

- **Epochs:** 30, 50, and 100 epochs were compared to balance accuracy and computational cost.
- **Resolution:** Image sizes (50×50 to 400×400 pixels) were assessed to retain texture detail while minimizing overhead.

5.4.3.4 Data Preprocessing

- **Augmentation:** Rotational replication (90° increments), random horizontal flipping, and mirroring expanded dataset diversity (Ioffe, 2015).
- **Normalization:** To stabilize training, pixel values were scaled to $[0, 1]$ using factors (1/127.5, 1/255, 1/512) (LeCun et al., 2002; Goodfellow et al., 2016).

5.4.3.5 Regularization Evaluation

L2 weight decay and Dropout (0.2–0.5 rates) were tested to mitigate overfitting, but minimal performance gaps in initial trials negated their necessity (Cortes et al., 2012; Srivastava et al., 2014).

5.4.3.6 Final Optimized Configuration

Through systematic evaluation, the optimal parameters were determined:

Classification

- **Architecture:** 4-layer VGG-style CNN (3 conv layers: 32→64→128 filters; 1 FC layer: 128 neurons).
- **Hyperparameters:** SGD optimizer (learning rate=0.001, momentum=0.9).
- **Training:** 50 epochs, 200×200 pixel input resolution.
- **Preprocessing:** Rotational/flip augmentation, 1/255 pixel normalization.
- **Regularization:** Not applied, due to minimal overfitting risks.

Regression

- **Architecture:** 19-layer VGG-style CNN (16 conv layers: Two 64→Two 128→Four 256→Four 512→Four 512 filters; 3 FC layer: 4096, 4096, and 1000 neurons).
- **Hyperparameters:** Adam optimizer (learning rate=0.0001, clipnorm=1.0).
- **Training:** 50 epochs, 200×200 pixel input resolution.
- **Preprocessing:** Rotational/flip augmentation, 1/255 pixel normalization.

This methodology ensures the model is efficient and generalizable for asphalt texture analysis, with validated parameters supporting robust performance across datasets.

5.5 Results and Analysis

5.5.1 Parameter Optimization Results and Analysis

All parameter evaluations were conducted on Dataset B, a composite dataset of seven non-overlapping MPD_{LS} classes, ensuring consistent classification boundaries across experiments. This controlled framework enabled a systematic assessment of

architectural and hyperparameter impacts on model performance for asphalt texture analysis.

5.5.1.1 Model Architecture Impact

We examined the impact of different VGG model architectures, including non-pre-trained models with varying weight layers and a pre-trained VGG16 model (Simonyan & Zisserman, 2014). Results showed that increasing weight layers improved accuracy but heightened the risk of overfitting.

VGG-style networks with 2–16 layers were tested using Dataset B’s seven-class MPD_{LS} taxonomy. As shown in Figure 54 and Table 23 (Appendix), increasing layers improved accuracy but exacerbated overfitting:

- **Shallow Models (2–4 Layers):** A four-layer model (3 conv layers, 1 FC layer) achieved 61.25% accuracy with a 7.09% training-test gap, efficiently capturing texture-void relationships without excessive complexity.
- **Deeper Models (5+ Layers):** While a seven-layer model reached 65.65% accuracy, its 15.08% gap indicated severe overfitting. The pre-trained VGG16 model struggled with asphalt’s uniform textures, highlighting domain-specific limitations of generic deep networks (Qu et al., 2020).

The four-layer architecture emerged as optimal, aligning with prior research on simplified CNNs for material science (Howard et al., 2017). It offers an efficient layer structure with high precision, low computational demand, and strong generalizability. Deeper networks introduced diminishing returns due to asphalt’s structured texture patterns, which lack the high-frequency variation of natural images.

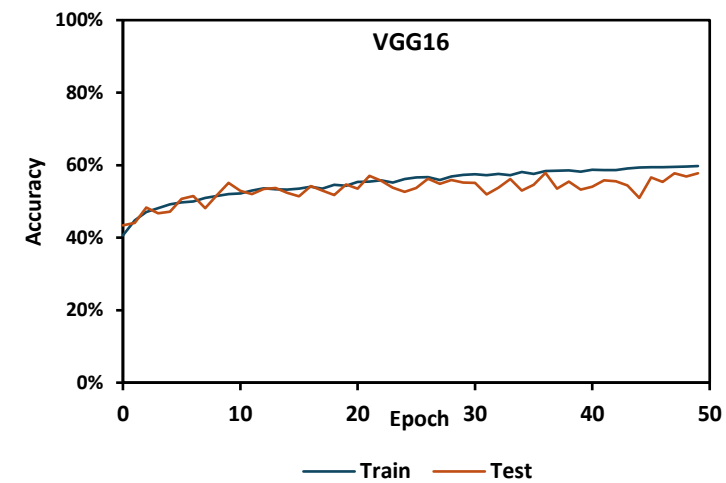
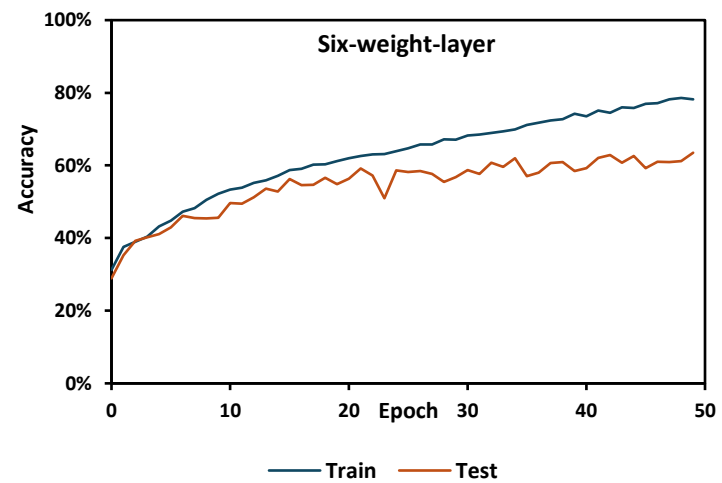
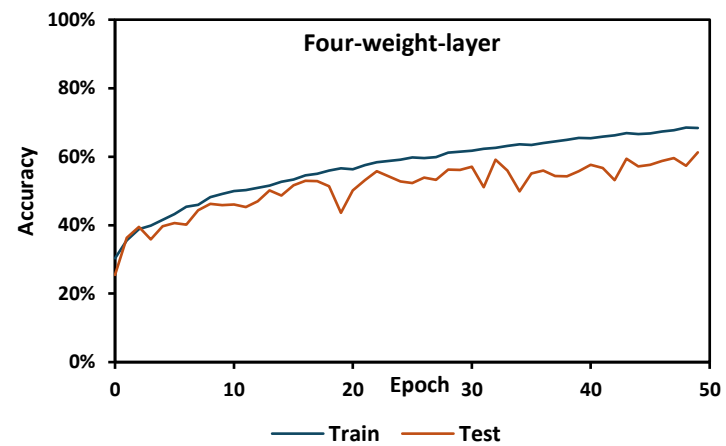
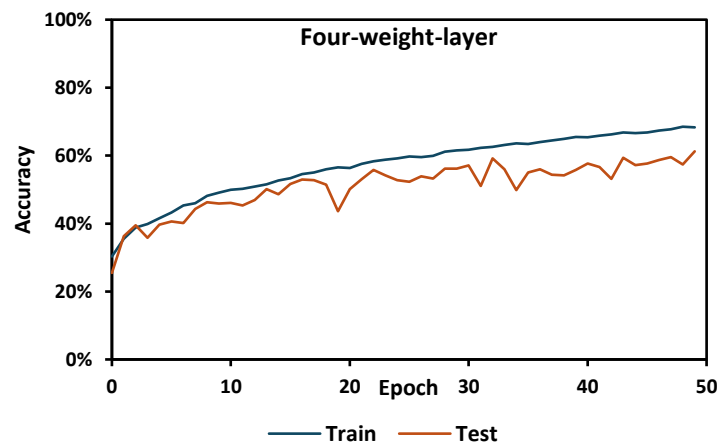


Figure 54: Performance Trends Across Various Model Architectures

5.5.1.2 Learning Rate and Momentum Effects

A logarithmic grid search over Dataset B's seven classes identified 0.001 as the optimal learning rate, balancing convergence speed and stability (Figure 55). Momentum values were tested at fixed learning rates, with 0.9 achieving the highest accuracy (61.25%) by smoothing gradient updates and reducing oscillations (Figure 56). Higher momentum (0.99) caused overshooting, while lower values (0.5) slowed convergence.

The selected parameters (learning rate=0.001, momentum=0.9) reflect a compromise between rapid learning and error minimization, consistent with SGD best practices in CNN training (Smith, 2017).

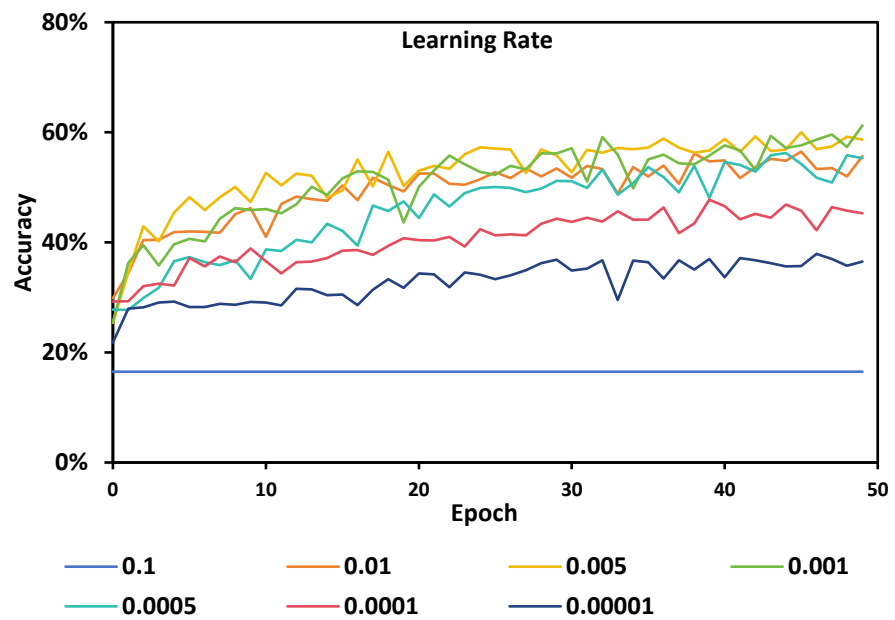
5.5.1.3 Training Epochs and Resolution Trade-offs

Training epochs were evaluated using Dataset B to balance accuracy and computational cost (Shafi & Assad, 2023):

- **50 Epochs:** Achieved 61.25% accuracy with minimal overfitting (Figure 57).
- **100 Epochs:** Slightly higher accuracy (62.85%) came with doubled training time and a widened accuracy gap, indicating incipient overfitting.

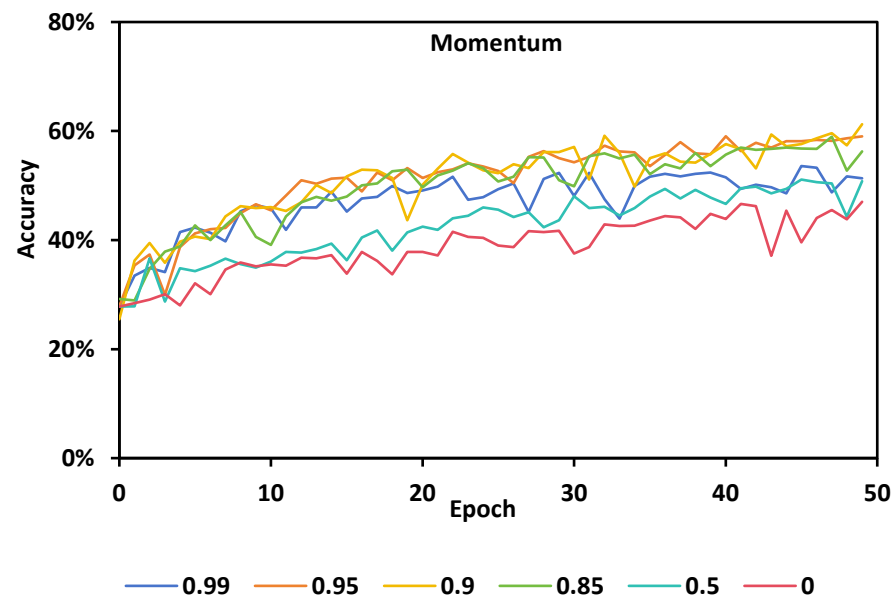
Image resolution tests on Dataset B revealed a threshold at 200×200 pixels: below this, accuracy dropped sharply due to feature loss, while higher resolutions (e.g., 400×400) offered no significant gains (Figure 58) (Koziarski & Cyganek, 2018). This aligns with the 0.4 mm/pixel resolution, capturing critical macrotexture features.

Fifty epochs and 200×200 pixels represent an optimal balance for practical deployment, prioritizing efficiency without sacrificing accuracy.



Learning rate	Momentum	Accuracy
1	0.9	16.49%
0.1		16.49%
0.01		55.66%
0.005		58.68%
0.001		61.25%
0.0005		55.29%
0.0001		45.29%
0.00001		36.51%

Figure 55: Learning Rate Impact on Model Performance



Learning rate	Momentum	Accuracy
0.001	0.99	51.34%
	0.95	59.00%
	0.90	61.25%
	0.85	56.28%
	0.50	50.80%
	0.00	47.02%

Figure 56: Momentum Parameter Impact on Model Performance

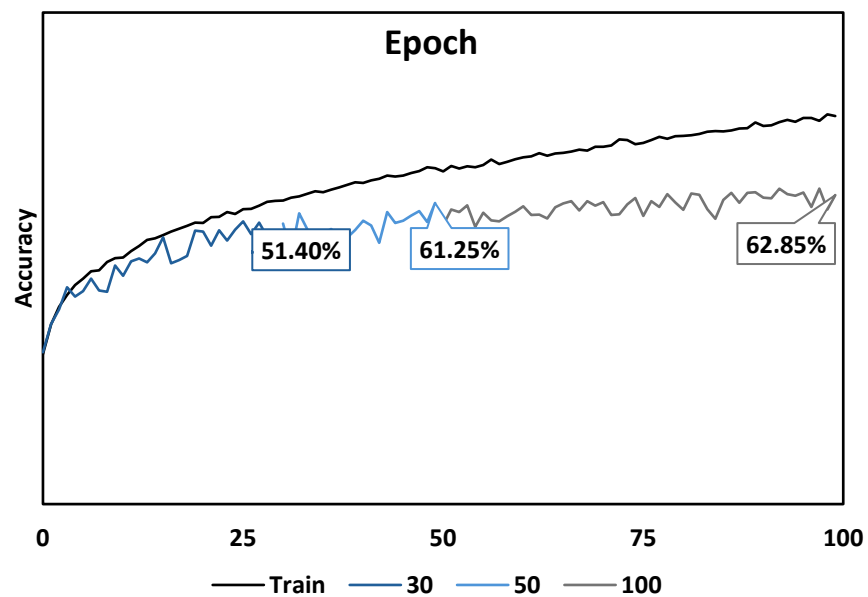


Figure 57: Model Performance Variation Over Training Epochs

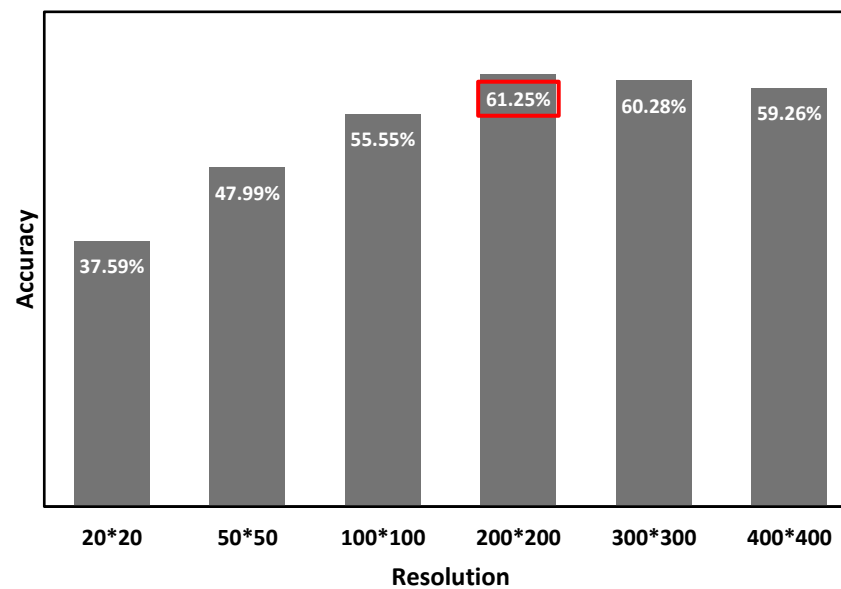


Figure 58: Resolution Impact on Model Accuracy

5.5.1.4 Data Augmentation Efficacy

Augmentation techniques were evaluated on Dataset B to address dataset limitations:

- **Rotational Replication:** Tripling the dataset size via 90° rotations improved accuracy from 49.57% to 58.46% (Table 5), highlighting the impact of data volume (Perez, 2017).
- **Horizontal Flipping:** Introducing a 50% flip rate further boosted accuracy to 61.25% by enhancing positional invariance (Table 5).
- **Random Shifts:** Testing random width/height shifts (10% max displacement) with 'nearest', 'reflect', and 'wrap' padding methods improved generalization, though excessive shifts degraded accuracy (Figure 69, Appendix) (Alrasheedi, Zhong, & Huang, 2023). The accuracy differences among filling methods were minor, likely due to consistent asphalt surface post-filling.
- **Normalization:** Since digital images utilize 8-bit color channels, each channel's value ranges from 0 to 255. Scaling pixel values to [0, 1] using 1/255 outperformed other factors, stabilizing gradient flow during training (Table 24, Appendix) (Ioffe & Szegedy, 2015).

Table 5: Impact of Image Augmentation Techniques on Accuracy

Number of Images		Action	Accuracy
Training	Test		
3464	1158		49.57%
13856	4632	Rotate copy	58.46%
13856	4632	Rotate copy, Training set horizontal flip (50%)	61.25%
27712	9264	Rotate copy, Mirror copy	62.36%

Rotational and flip augmentations provided the best cost-benefit ratio, while random shifts offered marginal gains. The 'nearest' padding method emerged as most effective for preserving texture integrity. Excessive operations (e.g., mirroring) increased computational load without proportional gains (Shorten & Khoshgoftaar, 2019).

5.5.1.5 Regularization Considerations

L2 regularization and Dropout were tested on Dataset B but showed limited utility (Table 25, Appendix):

- **L2 (=0.01):** Reduced the training-test gap from 7.09% to 1.84% but sacrificed accuracy from 61.25% to 51.68% due to weight suppression (Bishop, 2006).
- **Dropout (0.2–0.5 rates):** Maintained consistency but did not improve performance.

Further experiments showed that the five-weight-layer network increased accuracy to 62.8% compared to the four-weight-layer model's 61.25%, though Figure 70 (Appendix) revealed significant overfitting. Applying Dropout resulted in 54.25% accuracy at 50 epochs, improving to 61.72% at 100 epochs, which is still below the original model's performance and requires extended training.

While regularization enhanced generalization metrics, the 7.09% accuracy gap in the four-layer model after 50 epochs indicated minimal overfitting, within acceptable limits for practical applications. Prioritizing predictive accuracy over marginal gap reduction, the study opted against regularization, as the accuracy loss from weight suppression (up to 10%) outweighed the benefits of reduced overfitting.

5.5.2 Classification Strategies and Model Performance Analysis

5.5.2.1 Impact of Classification Strategies on Accuracy

This section evaluates the efficacy of non-overlapping and overlapping MPD_{LS} classification strategies across three datasets, contextualizing their performance within each dataset's unique characteristics. The findings underscore the importance of dataset diversity and the application of tailored classification strategies to enhance model performance (Pelletier, Jeffries, Song, & Hemmerling, 2022).

Non-Overlapping Interval Segmentation

Non-overlapping classification partitions MPD_{LS} into discrete, mutually exclusive ranges (e.g., 0.8–1.0 mm, 1.0–1.2 mm), creating clear but rigid boundaries. Clear class boundaries enabled better feature recognition across classes (Lei, He, Yuan, & Tao, 2023). As shown in Tables 6–8, accuracy improved with fewer, wider classes due to

increased per-class sample size and reduced feature ambiguity (Hinton & Salakhutdinov, 2006):

- **Set A (Lab Data):** Accuracy rose from 49.88% (9 classes) to 79.86% (3 classes), driven by controlled lighting and uniform texture in laboratory slabs, which minimized intra-class variability.
- **Set B (Composite Data):** Similar trends were observed, with accuracy increasing from 48.86% to 79.92%, demonstrating consistency across the newly asphalt features. However, slightly lower accuracy reflected the dataset's mix of lab slabs and field images with natural lighting variations compared to Set A.
- **Set C (Field Data):** Accuracy remained lowest (15.55% → 44.88%), as real-world factors like wear, debris, and uneven illumination introduced noise, making texture classification challenging (Liu & Panagiotakos, 2022).

Enhancements could involve expanding the dataset to represent road conditions better. Adopting a wider capture angle, as seen in dataset B, could increase the field of view, reducing the impact of minor irregularities and environmental factors. This approach would capture more surface information, averaging noise from varying conditions for a more reliable classification model. Similar strategies have proven effective in various image classification tasks, emphasizing capturing representative data (Chen et al., 2021; Zhang, Li, & Wang, 2023).

Additionally, dividing datasets with identical class quantities but different MPD_{LS} boundary values can yield distinct data groupings. Appendix Tables 26 to 29 detail more results of non-overlapping classification methods, while Table 29 presents the training outcomes integrating the three datasets.

Table 6: Accuracy Performance Across Distinct MPD_{LS} Range Classifications for Set A

Number of ranges	1	2	3	4	5	6	7	8	9	Accuracy
9	<0.8	0.8-1.0	1.0-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2.0	2.0-2.5	>2.5	49.88%
8	<0.8	0.8-1.0	1.0-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2.0	>2.0		54.10%
7	<0.8	0.8-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	>2.0			55.74%
6	<1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	>2.0				62.53%
5	<1.0	1.0-1.3	1.3-1.6	1.6-2.0	>2.0					67.92%
4	<1.0	1.0-1.5	1.5-2.0	>2.0						77.05%
3	<1.0	1.0-2.0	>2.0							79.86%

Table 7: Accuracy Performance Across Distinct MPD_{LS} Range Classifications for Set B

Number of Ranges	1	2	3	4	5	6	7	8	9	Accuracy
9	<0.6	0.6-0.8	0.8-1.0	1.0-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2.0	>2.0	48.86%
8	<0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	>2.5		58.03%
7	<0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	>2.0			61.25%
6	<0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2.0	>2.0				63.95%
5	<0.8	0.8-1.2	1.2-1.6	1.6-2.0	>2.0					71.81%
4	<0.8	0.8-1.2	1.2-1.7	>1.7						74.18%
3	<1.2	1.2-1.7	>1.7							79.92%

Table 8: Accuracy Performance Across Distinct MPD_{LS} Range Classifications for Set C

Number of Ranges	1	2	3	4	5	6	7	8	9	10	11	Accuracy
11	<0.6	0.6-0.8	0.8-1.0	1.0-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2.0	2.0-2.2	2.2-2.4	>2.4	15.55%
8	<0.6	0.6-0.9	0.9-1.2	1.2-1.5	1.5-1.8	1.8-2.1	2.1-2.4	>2.4				31.69%
7	<0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	>2.0					40.55%
6	<1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	>2.0						44.88%

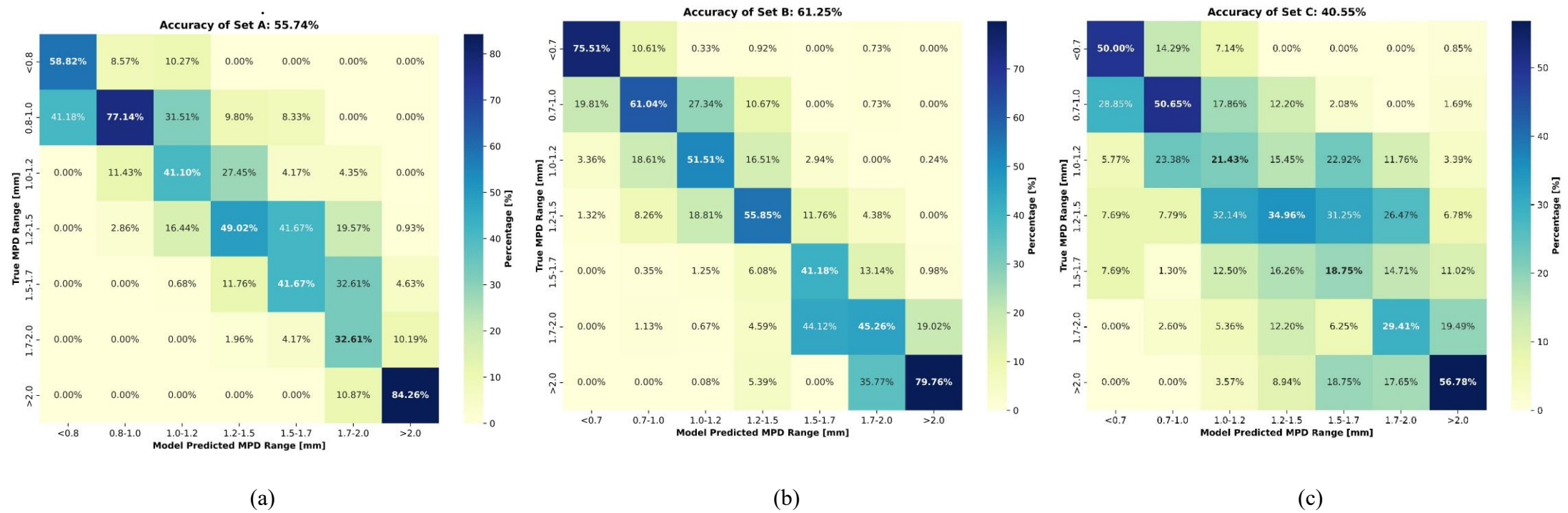


Figure 59: Non-Overlapping MPD_{LS} Classification Accuracy Across Datasets

Figure 59 illustrates the accuracies of each class from three datasets using a seven-class scheme. Appendix Tables 30 to 32 present each dataset's specific recognition accuracies for different MPD_{LS} ranges. Higher accuracies were observed for classes with the most distinct features, such as those with the lowest and highest MPD_{LS} (e.g., MPD_{LS} <1 mm, MPD_{LS} >2 mm), making identifying them more accessible. The recognition range is mainly distributed in the target class and its adjacent MPD_{LS} ranges on both sides, reaffirming the model's potential in differentiating texture features across classes. Non-overlapping strategies struggled with boundary cases, where adjacent classes shared visual features like medium-sized voids and irregular aggregates. Figure 59(c) shows a significant misclassification rate at class boundaries in Set C, as the model could not leverage transitional features (Xin & Wang, 2019).

Overlapping Interval Classification

To address boundary ambiguity, overlapping intervals (e.g., 0.8–1.2 mm and 1.0–1.4 mm) were introduced during training, allowing images to contribute to multiple classes. This strategy improved accuracy by leveraging shared features at class boundaries:

Adjacent classes like "1.0–1.2 mm" and "1.2–1.4 mm" share visual continuity in aggregate distribution and void edge roughness (Figure 65a). For example, an MPD_{LS} = 1.2 mm image may exhibit both "medium voids" (1.0–1.2 mm) and "irregular contours" (1.2–1.4 mm), enabling the model to learn cross-class features (Vuttipittayamongkol, Elyan, & Petrovski, 2021).

Performance Gain (Tables 9-11):

- **Set A:** Accuracy increased from 56.98% (10 non-overlapping classes) to 85.81% (6 overlapping classes), reflecting the model's ability to utilize controlled transitional features. The highest accuracy was achieved due to minimal noise and consistent feature representation.
- **Set B:** Improved from 61.55% (10 non-overlapping classes) to 84.13% (6 non-overlapping classes), demonstrating robustness to semi-controlled environmental variations (Ahmed, Issac, & Das, 2024). Moderate accuracy reflected a balance between a larger sample size and semi-controlled (new surface) conditions.

- **Set C:** Rose from 31.30% (10 non-overlapping classes) to 63.19% (6 non-overlapping classes), highlighting the strategy's effectiveness in mitigating real-world feature variability ([141] Lowest accuracy stemmed from complex backgrounds (e.g., water stains, polished aggregates) and ambiguous void and aggregate structures.

As illustrated in Figure 60, datasets A and B achieved high accuracy with eight classes after overlapping, reaching 84.54% and 80.85%, respectively. Appendix Tables 33 to 35 present each dataset's specific recognition accuracies for different MPD_{LS} ranges. This indicates that overlapping strategies activated shared feature detectors for texture across adjacent classes, reducing boundary misclassification compared to non-overlapping schemes. This finding supports the notion that overlapping strategies can effectively mitigate the challenges posed by similar feature representation in adjacent classes (Ahmed et al., 2024).

Table 9: Accuracy Performance Across Overlapping MPD_{LS} Range Classifications for Set A

Number of Ranges	1	2	3	4	5	6	7	8	9	10	Accuracy
10	<0.9	0.8-1.1	1.0-1.3	1.2-1.5	1.4-1.7	1.6-1.9	1.8-2.1	2.0-2.3	2.2-2.5	>2.4	56.98%
8	<1.0	0.8-1.2	1.0-1.4	1.2-1.6	1.4-1.8	1.6-2.0	1.8-2.5	>2.0			84.54%
7	<1.0	0.8-1.2	1.0-1.4	1.2-1.7	1.4-2.0	1.8-2.5	>2.0				77.67%
6	<1.2	1-1.5	1.2-1.7	1.5-2.0	1.7-2.4	>2.0					85.81%

Table 10: Accuracy Performance Across Overlapping MPD_{LS} Range Classifications for Set B

Number of Ranges	1	2	3	4	5	6	7	8	9	10	Accuracy
10	<0.7	0.6-0.9	0.8-1.1	1.0-1.3	1.2-1.5	1.4-1.7	1.6-1.9	1.8-2.1	2.0-2.3	>2.2	61.55%
8	<1.0	0.8-1.2	1.0-1.4	1.2-1.6	1.4-1.8	1.6-2.0	1.8-2.5	>2.0			80.85%
6	<1.2	1.0-1.5	1.2-1.7	1.5-2.0	1.7-2.4	>2.0					84.13%

Table 11: Accuracy Performance Across Overlapping MPD_{LS} Range Classifications for Set C

Number of Ranges	1	2	3	4	5	6	7	8	9	10	Accuracy
10	<0.7	0.6-0.9	0.8-1.1	1.0-1.3	1.2-1.5	1.4-1.7	1.6-1.9	1.8-2.1	2.0-2.3	>2.2	31.30%
9	<0.9	0.8-1.1	1.0-1.3	1.2-1.5	1.4-1.7	1.6-1.9	1.8-2.1	2.0-2.3	>2.2		38.58%
8	<1.0	0.8-1.2	1.0-1.4	1.2-1.6	1.4-1.8	1.6-2.0	1.8-2.5	>2.0			49.80%
7	<1.0	0.8-1.2	1.0-1.5	1.2-1.7	1.5-2.0	1.7-2.2	>2.0				56.69%
6	<1.2	1.0-1.5	1.2-1.7	1.5-2.0	1.7-2.2	>2.0					63.19%

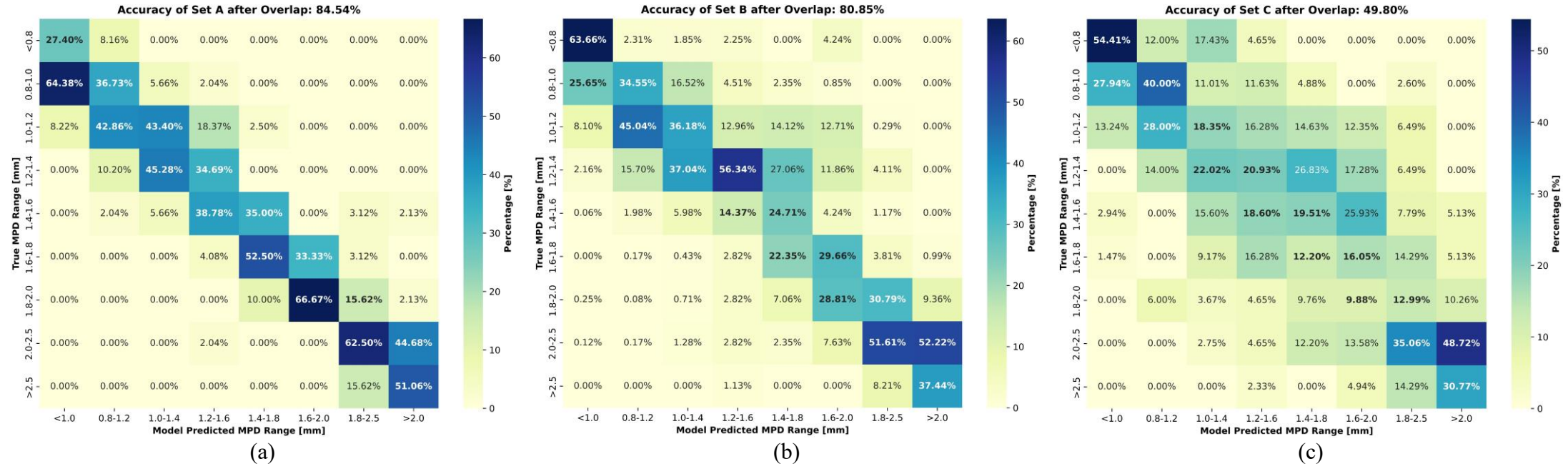


Figure 60. Overlapping MPD_{LS} Classification Accuracy Across Datasets

5.5.3 Dataset-Specific Performance in Regression Analysis

A VGG19-based regression model was evaluated across datasets to predict continuous MPD_{VGG} values (Simonyan & Zisserman, 2014), highlighting the impact of data quality on precision. Appendix Tables 36 to 39 present the specific regression prediction results of the three datasets under different settings, and Table 39 presents the training outcomes integrating the three datasets.

Set A (Laboratory-Prepared Slabs)

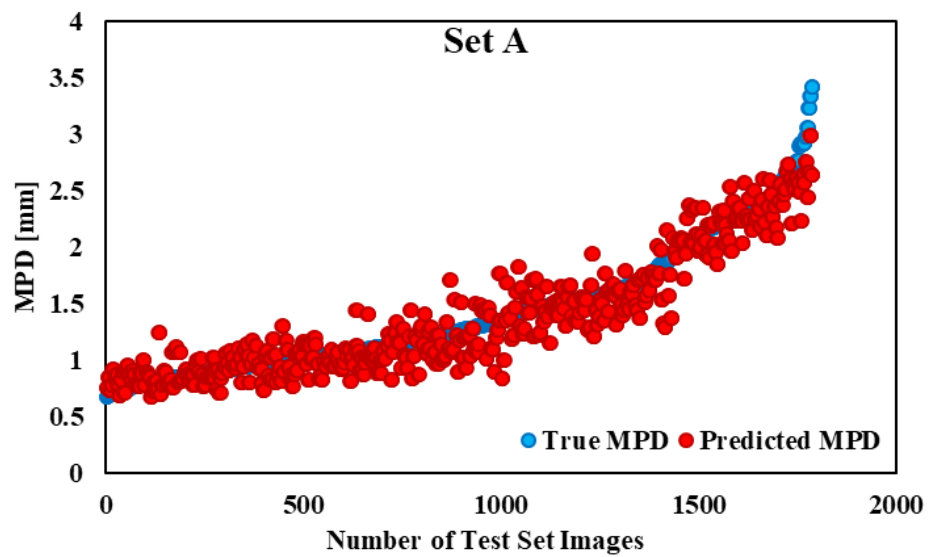
- **Training / Test images:** 5,364/1,788
- **Characteristics:** Uniform material properties, controlled lighting, and minimal noise.
- **Performance:** Achieved $MAE = 0.136$ mm and $MSE = 0.033$ mm² (Figure 61), with predictions tightly clustered around the 45° line. The model effectively captured consistent texture-feature relationships in lab conditions.

Set B (Composite Data)

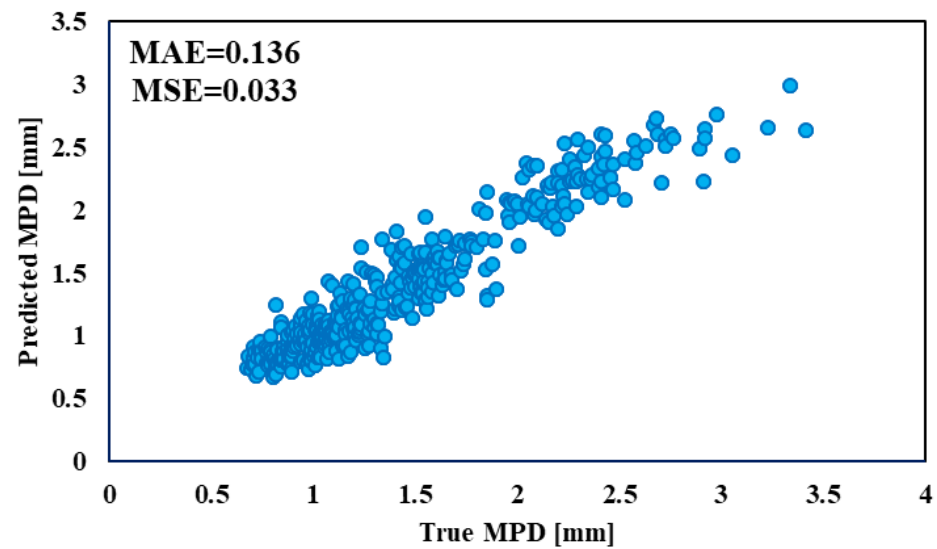
- **Training / Test images:** 15,052/5,016
- **Characteristics:** Mixture of lab slabs, parking lot, and new field pavements, with natural and lab lighting.
- **Performance:** $MAE = 0.138$ mm, $MSE = 0.041$ mm² (Figure 62). Higher MPD_{LS} ranges (>1.7 mm) showed deviations due to inconsistent aggregate exposure in different types of surface images, though a larger sample size improved overall reliability.

Set C (In-Service Road Surfaces)

- **Training / Test images:** 5,984/2,032
- **Characteristics:** Aged textures, variable lighting, and wear-induced feature degradation (e.g., polished aggregates, moisture damage).
- **Performance:** $MAE = 0.320$ mm, $MSE = 0.171$ mm² (Figure 63). Wear had blurred texture features leading to higher prediction errors, reflected the model's struggle to handle complex, noisy textures typical of real-world pavements (Liu & Panagiotakos, 2022).

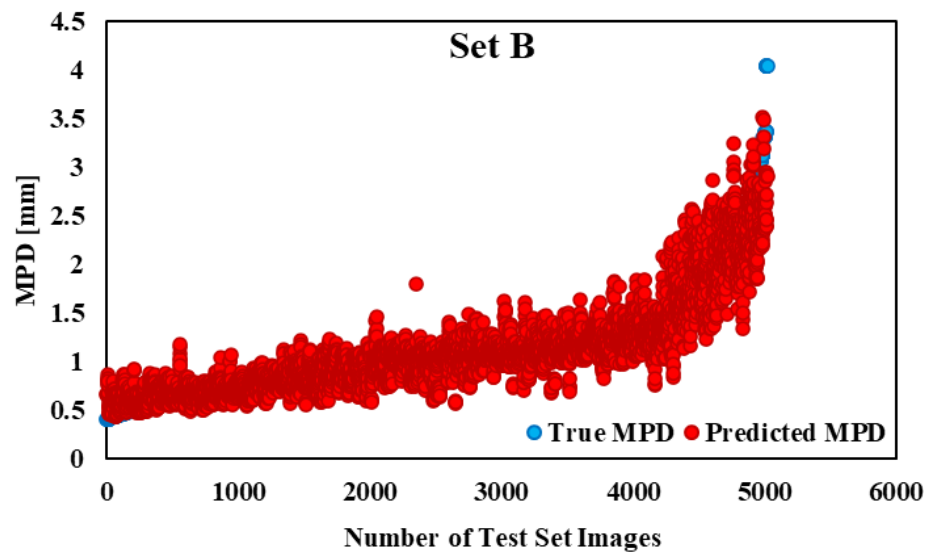


(a)

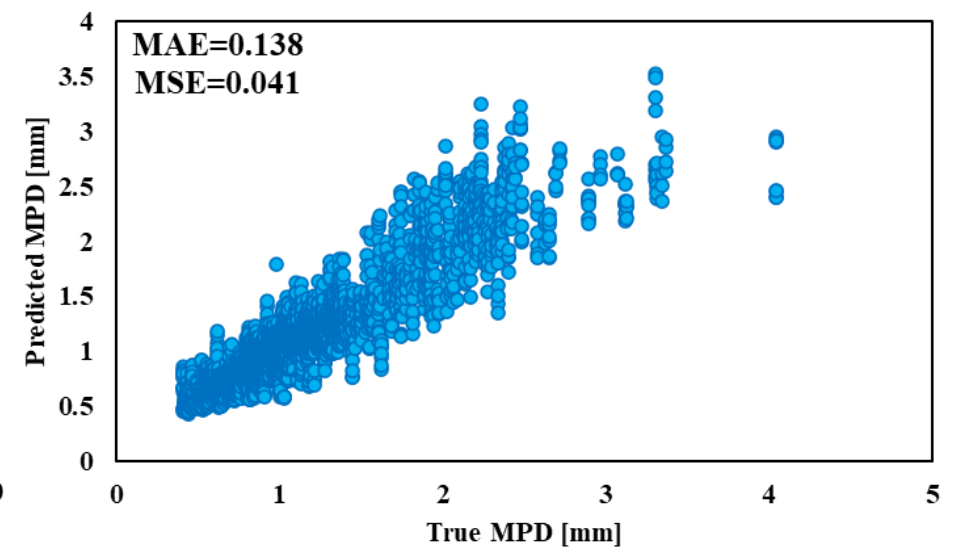


(b)

Figure 61: Predicted MPD_{VGG} vs. True MPD_{LS} Values for Set A

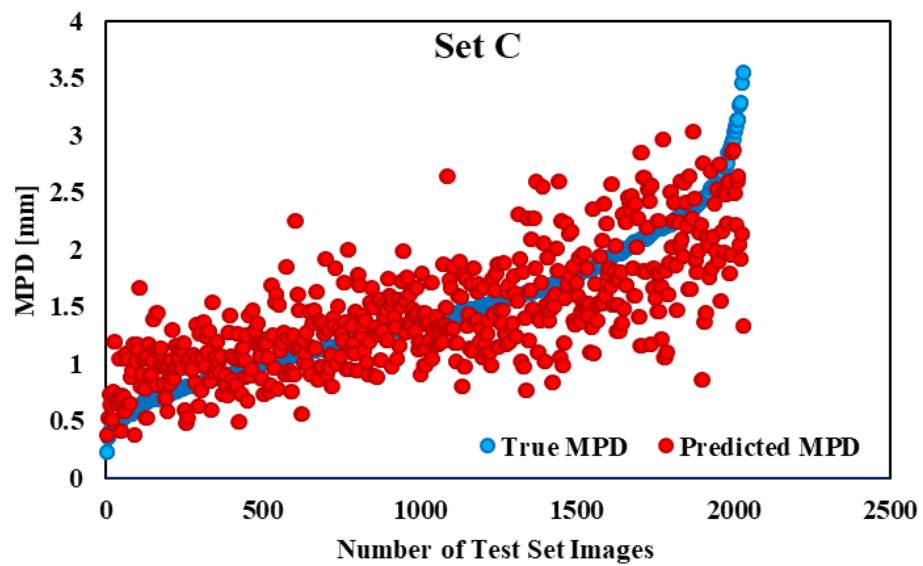


(a)

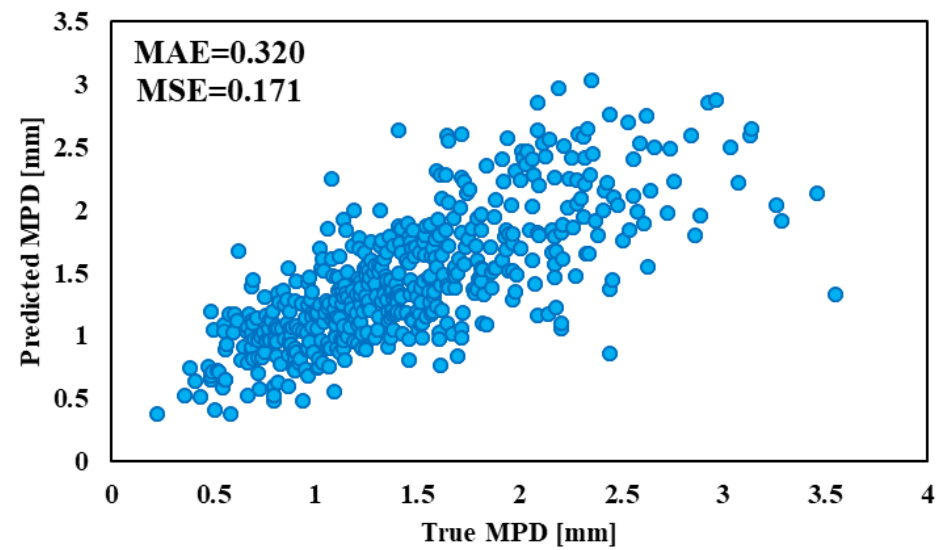


(b)

Figure 62: Predicted MPD_{VGG} vs. True MPD_{LS} Values for Set B



(a)



(b)

Figure 63: Predicted MPD_{VGG} vs. True MPD_{LS} Values for Set C

The findings affirm that regression performance correlated strongly with dataset homogeneity: controlled datasets (Set A) enabled precise feature learning and MPD_{VGG} prediction, while field datasets (Set C) required more sophisticated preprocessing or domain adaptation to mitigate variability. Future research should focus on collecting more diverse data or training separate models tailored for specific road surface conditions to enhance the model's applicability to real-world scenarios. This approach will improve the model's robustness and prediction accuracy across various applications.

5.5.4 Comparative Analysis of Classification, Regression, and Traditional Methods

5.5.4.1 Addressing Literature Gaps and Research Objectives

By developing the VGG-based CNN that predicts MPD_{VGG} from smartphone images, the research overcomes prior reliance on professional 3D scanners (Liu et al., 2021; Dan et al., 2024). The model reduces equipment costs and eliminates the need for specialized training, aligning to create accessible texture evaluation tools.

5.5.4.2 Overlapping vs. Non-Overlapping Classification Strategies

The overlapping interval classification strategy significantly outperformed non-overlapping schemes in handling transitional texture features. By allowing adjacent classes (e.g., 0.8–1.2 mm and 1.0–1.4 mm) to share training data (e.g., 1.0–1.2 mm), the model learned to leverage visual continuity in aggregate distribution and void edge roughness. For example, in Set A, accuracy increased from 54.1% (8 non-overlapping classes) to 84.5% (8 overlapping classes) (Tables 6 and 9), directly addressing the boundary misclassification rate observed in non-overlapping schemes. This improvement is rooted in the model's ability to recognize shared features like medium-sized voids and irregular contours in boundary cases, as visualized in saliency maps (Figure 68).

In contrast, non-overlapping classification struggled with rigid boundaries, particularly in complex datasets like Set C, where real-world variability (e.g., lighting, wear) amplified feature ambiguity. The 31.7% accuracy in Set C with eight non-overlapping classes (Table 8) highlighted the limitations of discrete categorization in noisy environments. In contrast, overlapping intervals improved accuracy to 49.8% (Table 11), demonstrating robustness against feature shift caused by environmental factors.

5.5.4.3 Classification vs. Regression: Trade-offs and Use Cases

Classification excels in rapid pavement screening, such as evaluating whether new roads meet design texture standards (e.g., Set B's 79.92% accuracy with 3 classes, Table 7). Regression, however, is indispensable for engineering tasks requiring precise MPD values, like mixture design optimization. In Set A, regression achieved an MSE of 0.033 mm², reflecting the model's ability to capture controlled texture features. In comparison, Set C's higher MSE (0.171 mm²) underscored the challenge of generalizing to aged, heterogeneous surfaces.

5.5.4.4 Advantages Over Traditional Measurement Methods

Compared to labor-intensive traditional techniques (e.g., laser scanning, sand patch tests), the proposed deep learning framework offers three key improvements:

- **Accessibility:** Domestic smartphone cameras (e.g., Huawei P40 Pro in Sets A/C, Table 22) and a laptop are used instead of specialized equipment, reducing costs while maintaining spatial alignment with scanned regions (Figure 50).
- **Scalability:** Processes thousands of images in minutes, versus hours for manual methods. For example, Set B's 5016 test samples (Table 22) were analyzed in less than 5 minutes based on the trained model, enabling rapid network-wide pavement assessment.
- **Reduced Skill Dependence:** This method eliminates subjective judgments in texture grading. Traditional methods require trained technicians to interpret profilometry data. In contrast, the model autonomously extracts hierarchical features (e.g., Layer 3 focusing on small voids, Figure 68), achieving 84.54% accuracy with 8 classes in controlled conditions without human intervention.

5.5.4.5 Dataset-Driven Insights into Model Robustness

- **Set A (Controlled Lab Data):** Uniform lighting and material properties enabled the model to achieve the highest accuracy (84.54% classification, MAE=0.136 mm regression), validating its fundamental capability to link visual features to MPD_{LS}.

- **Set B (Composite Field Data):** Despite containing natural variability (e.g., debris, lighting), its large sample size (20,068 samples) and 84.13% accuracy (Table 10) demonstrated that increased data size can mitigate environmental noise, even with varying capture heights (15 cm vs. 37 cm, Table 22).
- **Set C (In-service Road Surfaces):** The lowest accuracy (63.19% classification, MAE=0.320 mm regression) highlighted the need for domain-specific adaptations. Real-world wear (e.g., polished aggregates) introduced feature degradation, necessitating larger datasets or transfer learning from Set A/B to improve generalization.

5.5.4.6 Limitations and Future Directions

Current Constraints:

- **Field Image Complexity:** Complex field conditions in Set C (in-service roads) caused 0.320 mm MAE, 2.3× higher than Set A. Data augmentation or environment-specific models are needed to mitigate environmental noise.
- **Data Imbalance:** Data imbalance: The dataset exhibits inconsistent sample sizes across different classes, primarily due to the randomness in field data collection locations and the uncontrollable nature of pavement texture.
- **Model Diversity:** Limited comparison to alternative architectures (e.g., ResNet) hinders optimal design. Future work should evaluate hybrid frameworks for sequential texture analysis.

To address real-world challenges, future research should:

- **Environment-Specific Models:** Develop sub-models for scenarios like wet/aged pavements or specific aggregate types, leveraging Set C's wear data to train weather-resistant architectures.
- **Hybrid Frameworks:** Combining classification for rapid screening and regression for detailed texture quantification could optimize workflow efficiency.

Classification could flag pavements needing maintenance, such as using overlapping intervals to flag high-risk areas (e.g., $MPD_{LS} < 1.0$ mm), while regression provides precise MPD_{VGG} values for repair planning.

- **Data Expansion:** Integrate diverse image sources (e.g., drone, vehicle camera) to create balance and multi-modal datasets, enhancing model resilience to capture scale variations (e.g., Set B's 45×35 cm vs. Set A's 16×10 cm capture areas, Table 22). This study establishes a robust framework for the ongoing refinement of the model through a diverse and continuous inflow of image data from various sources, thereby facilitating the development of a large-scale monitoring network for real-time, rapid assessment of pavement conditions.

The dual classification-regression framework offers a versatile solution for asphalt texture analysis, with overlapping intervals addressing boundary ambiguity and regression enabling precise continuous prediction. Building upon the high prediction accuracy achieved in Set A and Set B, the model demonstrates efficacy for texture assessment in newly paved surfaces, aligning with quality control and acceptance requirements. Compared to traditional methods, this approach is cost-effective, scalable, and adaptable to diverse environments, though real-world applications require tailored strategies for aged or complex pavements. This research paves the way for automated, AI-driven pavement management systems that balance interpretability and precision by prioritizing data diversity and model customization. Future deployments could focus on developing environment-specific sub-models while leveraging the current framework's strengths in new pavement evaluation, thereby streamlining infrastructure maintenance workflows.

6 Comprehensive Discussion: Integrating CT Mechanisms, Virtual Modeling, and Deep Learning for Asphalt Texture Engineering

6.1 Research Gaps Addressed and Objectives Fulfilled

The three-stage research framework systematically addresses critical gaps in the literature:

1. **Quantitative Void-Texture Relationships (Chapter 3):** Stage 1 (CT analysis) established a strong linear correlation ($r^2 = 0.8$) between AVD and MPD_{CT} , resolving the mechanistic gap in prior studies that relied on simple porosity measurements (Chen et al., 2019; Huang et al., 2022). By quantifying void topology (e.g., size, connectivity, shape), this stage revealed how elongated voids (aspect ratio, $r = 0.74$) directly deepen surface texture, enabling predictive models that empower asphalt designers to achieve target texture specifications by controlling void properties during mixture design.
2. **Virtual Texture Simulation Validation (Chapter 4):** Stage 2 validated the ISA method, showing that virtual asphalt replicates CT-derived AVD- MPD_{CT} correlations. This addressed the literature's gap in ISA's texture prediction capability (Schenker et al., 2010), reducing reliance on costly CT scans (e.g., £200 per scan vs. computational cost for virtual models). The hybrid 2D/3D MTD_{ISA} algorithms further bridged the nonlinear MPD_{LS} - MTD_{SPT} relationship, critical for open-graded mixtures. Enabling virtual asphalt design workflows where controlling void properties (e.g., AVD) directly predicts and achieves target texture performance.
3. **Field-Accessible DL Models (Chapter 5):** Stage 3 developed two VGG-based CNN architectures capable of sub-millimeter MPD_{VGG} prediction (MAE = 0.136 mm in controlled laboratory conditions) using smartphone-acquired images, fundamentally overcoming prior research dependencies on professional 3D scanners and complex multi-view data collection protocols (Liu et al., 2021; Mataei et al., 2022). The model's classification accuracy is 84.5% (8 overlapping

classes) in controlled datasets and 63.19% (6 overlapping classes) in field conditions. This breakthrough eliminates the need for specialized equipment, high-resolution multi-angle imaging systems, or structured-light scanning setups, instead leveraging standard consumer-grade cameras to enable accessible texture assessment.

6.2 Synergistic Integration of Three Research Stages: A Holistic Analytical Framework

The three research stages form a cohesive, hierarchical framework spanning physical experimentation, virtual simulation, and field deployment. This synergy is crucial for translating microscale void-topology insights into practical, real-world texture management solutions.

Physical Layer (Stage 1) to Virtual Layer (Stage 2): X-ray CT analysis in Stage 1 established a robust linear correlation ($r^2 = 0.8$) between AVD and MPD_{CT} , revealing the fundamental relationship between void geometry and surface texture. These empirical findings served as a calibration benchmark for the ISA method in Stage 2. For instance, virtual slabs with an AVD of 1.45 mm accurately replicated an MPD_{ISA} of 0.42 mm, within a 13% error margin compared to CT-measured values, validating the ISA method's ability to simulate real-world texture-void relationships.

Virtual Layer (Stage 2) to Application Layer (Stage 3): The laser-scanned MPD_{LS} data from 60 laboratory slabs in Stage 2 constituted the controlled training dataset (Set A) for the DL models in Stage 3. This dataset enabled the models to learn consistent texture features under standardized conditions before being compared to diverse field data (Sets B and C). The overlap of slab datasets across stages ensured continuity in texture-void relationship modeling, facilitating the development of a reliable "capture-predict" workflow.

Closed-Loop Framework: The research pipeline transitions from physical CT analysis in Stage 1 to non-destructive virtual testing in Stage 2 and culminates in field monitoring via lightweight DL models in Stage 3. This progression creates a scalable,

cost-effective solution that overcomes the limitations of traditional methods, such as reliance on CT (Stage 1) and Laser Scanning (Stage 2).

6.3 Theoretical Contributions: A Tripartite Digital Representation Framework

This study introduces a novel "void topology - virtual texture - digital detection" framework, transcending traditional single-scale research approaches:

1. **Physical Layer (Stage 1):** X-ray CT offers high-precision void topology analysis, elucidating the microscale mechanisms linking void properties to surface texture, providing a theoretical foundation for subsequent stages.
2. **Virtual Layer (Stage 2):** The ISA method revolutionizes asphalt mixture design by generating digital twins, reducing the demand for physical testing. The validated MPD_{ISA} -void diameter relationship in virtual models confirms their efficacy for texture optimization, enabling iterative design without extensive physical prototyping.
3. **Application Layer (Stage 3):** The lightweight DL model processes 2,000 images in 10 minutes, facilitating network-level texture screening with 90%-time savings compared to traditional laser scanning. Its dual classification-regression architecture balances rapid screening and precise prediction, enabling widespread adoption in field applications.

6.4 Quantitative Synergy and Industry Impact

The integrated framework delivers substantial improvements over traditional methods:

- **Design Cycle Reduction:** Traditional texture optimization via CT and lab testing takes 2–3 days per sample. The new approach reduces this to 2 hours through virtual modeling, achieving a 90% efficiency gain.
- **Cost Savings:** CT scans cost more than £100 per hour, while virtual simulations incur only computational expenses. The DL model eliminates 90% of equipment

costs by leveraging smartphones and tablets instead of £10,000 laser scanners, significantly improving texture monitoring efficiency.

- **Practical Application:**

- Quantifying multiple void properties significantly improves texture prediction accuracy, elevating the coefficient of determination from 0.66 in single-parameter models to 0.88 in multivariate models. This advancement supports safety-critical applications, such as wet-skid resistance design, enabling more precise control over asphalt texture during the design phase. The texture-centric asphalt design process can be expedited when integrated with virtual digital measurement techniques, reducing time and cost.
- In addition, the developed DL model demonstrates strong classification performance for MPD_{LS} levels. It achieves an accuracy of 84.54% on Set A, which comprises new laboratory-fabricated slabs, and 80.85% on Set B, which contains substantial data from newly constructed pavements. Given these results, the current DL model is well-suited for application in the MPD_{LS} inspection and acceptance of freshly constructed pavements, providing a reliable and efficient alternative to traditional measurement methods.

6.5 Methodological Limitations and Future Directions

Despite significant advancements, each stage presents specific challenges:

- **Stage 1:** CT scans for large samples are destructive and limited to small cores, failing to represent field-scale texture variations. Future research could integrate micro-CT with 3D pavement sections to enhance sample representativeness.
- **Stage 2:** The ISA method assumes spherical aggregates, neglecting particle angularity. Incorporating 3D-scanned aggregate shapes could improve void shape accuracy and reduce MPD_{ISA} prediction errors, which currently overestimate MTD_{ISA} by 15%. Additionally, the virtual measurement method for MTD_{ISA} should be further optimized to enhance its accuracy and reliability in simulating real-world texture depth.

- **Stage 3:** Field images (Set C) exhibit reduced accuracy due to weather, wear, debris, and data imbalance. Future work should develop environment-specific sub-models using transfer learning and address class imbalance through synthetic data generation or class-weighted training.

This comprehensive framework integrates microscale void science, computational modeling, and deployable DL, marking a paradigm shift in asphalt texture engineering and paving the way for intelligent, data-driven pavement management.

7 Conclusion

This thesis presents a three-stage research framework integrating X-ray CT analysis, virtual modeling, and DL to revolutionize asphalt texture engineering. The cohesive pipeline—from microscale void mechanism discovery to field-deployable intelligent tools—addresses critical gaps in traditional texture characterization, enabling data-driven pavement management.

7.1 Stage 1: CT-Based Void-Texture Mechanism Analysis

This stage decoded the quantitative relationship between void topology and surface texture, establishing a strong linear correlation ($R^2 = 0.8$) between AVD and MPD_{CT} , decoding the topological drivers of surface texture. Key contributions include:

- **Standardized Imaging:** The differing numbers of CT images used cause variability in measuring void properties, highlighting the need for standardized imaging protocols to ensure consistency.
- **Void Topology Insights:** Independent voids typically exhibit spherical shapes, which cannot continually expand spherically as air void content increases due to constraints from the coarse aggregate skeleton. Elongated voids (aspect ratio, $r = 0.74$) directly deepen texture, while Euler number transitions from positive to negative at 10–15% AVC, marking the shift to interconnected void networks.
- **Predictive Modeling:** Multivariate regression models incorporating void diameter, perimeter, and connectivity improved MPD_{CT} prediction accuracy from $R^2 = 0.66$ to 0.88, outperforming single-parameter approaches.
- **Downstream Impact:** The validated AVD- MPD_{CT} relationship provided essential calibration for Stage 2's virtual asphalt models, ensuring computational simulations mirror real-world texture-void dynamics.

7.2 Stage 2: Virtual Texture Simulation and Validation

This stage validated the ISA method, demonstrating its capability to replicate CT-derived texture-void correlations. Key outcomes include:

- **Virtual Asphalt Feasibility:** ISA-generated void networks replaced costly CT scans, enabling virtual void structures and texture quantification.
- **Nonlinear MPD_{LS}-MTD_{SPT} Modeling:** A log-normal regression model ($R^2 = 0.85$) captured the nonlinear influence of aggregate size and void connectivity on texture depth, outperforming traditional linear models in open-graded mixtures. The comparative analysis of 2D versus 3D algorithms highlighted the strengths and limitations of each, underscoring the necessity for tailored approaches based on specific conditions.
- **DL Training Groundwork:** Laser-scanned MPD_{LS} data from 60 laboratory slabs formed the controlled training dataset (Set A) for Stage 3's DL models, enabling feature learning under standardized conditions.

7.3 Stage 3: DL-Driven Automated Texture Recognition

This stage developed lightweight VGG-based CNNs that can be deployed on a laptop to achieve sub-millimeter MPD_{VGG} prediction from consumer device images, overcoming dependencies on professional equipment. Key achievements include:

- **Classification Excellence:** Classification accuracy improved by reducing class count and expanding the MPD_{LS} range. 84.54% accuracy in lab datasets (Set A) and 80.85% in new pavement data (Set B) using overlapping interval strategies, addressing boundary ambiguity in texture categorization.
- **Regression Precision:** The regression analysis confirmed the model's capacity to predict exact MPD_{VGG} values, which complemented the classification approach. Sub-millimeter MAE (Set A=0.136 mm, Set B=0.138 mm) from smartphone and tablet images, reducing equipment costs by 90% compared to laser profilometry.
- **Practical Deployment:** The model's high accuracy in new pavement datasets (Sets A/B) enables application in quality control, streamlining inspection workflows.

7.4 Integrative Framework and Synergistic Impact

The three stages form a closed-loop ecosystem:

1. **CT Mechanisms → Virtual Validation:** Stage 1's void-topology insights calibrate ISA models to simulate texture-void relationships computationally.
2. **Virtual Models → DL Training:** Stage 2's slab datasets enhance DL generalization across mixture types.
3. **DL Deployment → Field Application:** Stage 3's "capture-predict" workflow achieves 90% time/cost savings over traditional methods, enabling network-level texture monitoring.

8 Future Research Directions

The proposed future research agenda builds directly on the limitations identified in the three-stage framework, aiming to enhance practical applicability, model robustness, and industry integration. Each direction is rooted in technical gaps and aligned with real-world engineering needs.

8.1 Multimodal Data Fusion for Cross-Scale Texture Characterization

Challenge: Inconsistencies between lab-scale CT analysis and field-scale texture variation.

Approach:

- Integrating LiDAR 3D point clouds (capturing macrotexture) with micro-CT void parameters to construct hybrid models.
- Develop transfer learning frameworks to bridge microscale void topology (Stage 1) and macroscale texture features (Stage 3), validated against field profilometry data (Rahman, Bhasin, & Smit, 2021).

The goal is to reduce the accuracy gap in texture prediction by capturing horizontal texture complexity, enabling cross-scale validation from void geometry to pavement performance.

8.2 Environmentally Robust Deep Learning with Domain Adaptation

Challenge: Reduced DL accuracy in field conditions (MAE = 0.320 mm in Set C due to wear/debris).

Technical Path:

- **Adaptive Sub-Models:** Train environment-specific networks for wet/aged pavements using:
 - Transfer learning from controlled datasets (Sets A/B) with domain adaptation loss (e.g., Maximum Mean Discrepancy).
 - Synthetic data augmentation (rain/snow/grime simulations) to expand training diversity.

- **Hardware Optimization:** Deploy lightweight models on edge devices (e.g., edgeTPU) to mitigate real-time noise in field images.

Target: Lower MAE in field datasets by integrating weather-resistant feature extraction modules.

8.3 Advanced Virtual Modeling with Realistic Aggregate Morphology

Challenge: The ISA method's spherical aggregate assumption introduces MTD_{ISA} overestimation in low-void mixtures.

Innovations:

- Incorporate 3D-scanned aggregate shapes (using X-ray micro-CT) into ISA to refine the void topology simulation (Wang, Huang, Li, You, & Chen, 2014).
- Develop hybrid 2D/3D MTD_{ISA} algorithms that dynamically switch between planar and volumetric analysis based on void connectivity metrics.
- Validate against 3D-printed asphalt samples with controlled void architectures to reduce prediction errors.

Impact: Improve virtual texture prediction accuracy, enabling cost-effective replacement of 90% of physical CT scans in mixture design.

8.4 Lifecycle Texture Degradation Modeling

Challenge: Lack of dynamic texture evolution prediction under traffic/weather loads.

Framework:

- Mechanistic-Empirical Integration: Embed void properties into finite element models with traffic load data (e.g., axle counts, speed profiles) (Zaltuom, 2018).
- Temporal Prediction: Use DL (e.g., LSTM) networks to model MPD degradation curves, trained on:
 - Longitudinal data from accelerated pavement testing (APT) facilities.
 - CT scans of aged cores (5–10 years in service) to link void coarsening with texture loss.

Deliverable: Predict MPD degradation with high accuracy over 10-year intervals, enabling proactive maintenance scheduling.

8.5 Industry Collaboration and Digital Infrastructure

Implementation Strategy:

- **Automotive Partnerships:** Collaborate with original equipment manufacturers (OEMs) to integrate in-vehicle cameras (e.g., Tesla Autopilot cameras) for real-time texture monitoring (Ranft & Stiller, 2016).
- **National Database Initiative:** Establish a cloud-based pavement texture database of different pavements using different image acquisition methods (e.g., manual, vehicle-mounted, drone-mounted), supporting machine learning-driven performance modeling.
- **Standardization:** Develop ASTM protocols for image-based texture assessment, specifying: Image capture method.

Outcome: Create a national-scale texture monitoring network, reducing infrastructure maintenance costs.

This research roadmap addresses technical limitations through interdisciplinary integration—combining materials science, computational modeling, and AI—while prioritizing industry adoption. The proposed directions aim to transform asphalt texture engineering from reactive testing to proactive, data-driven management, supporting sustainable infrastructure development.

References

- [1] Aavik, A., Kaal, T., & Jentson, M. (2013). Use of pavement surface texture characteristics measurement results in Estonia. In *The XXVIII International Baltic Road Conference. Vilnius, Lithuania*.
- [2] Abohamer, H., Elseifi, M. A., Mayeux, C., Cooper III, S. B., & Cooper Jr, S. (2023). Effects of Air Void Content, Crumb Rubber, and Pozzolanic Fillers on OGFC Laboratory Performance. *Transportation Research Record*, 2677(11), 338-350.
- [3] Aboufoul, M., & Garcia, A. (2017). Factors affecting hydraulic conductivity of asphalt mixture. *Materials and Structures*, 50(2), 1-16.
- [4] Aboufoul, M., Chiarelli, A., Triguero, I., & Garcia, A. (2019). Virtual porous materials to predict the air void topology and hydraulic conductivity of asphalt roads. *Powder Technology*, 352, 294-304.
- [5] Agarap, A. F. (2018). Deep learning using rectified linear units (relu). *arXiv preprint arXiv:1803.08375*.
- [6] Ahmed, Z., Issac, B., & Das, S. (2024). Ok-NB: An Enhanced OPTICS and k- Naive Bayes Classifier for Imbalance Classification with Overlapping. *IEEE Access*.
- [7] AIA The Asphalt Industry Alliance. (2021). *Faqs - AIA The Asphalt Industry Alliance*. [online] Available at: <<https://www.asphaltuk.org/faqs/>>.
- [8] AIA The Asphalt Industry Alliance. (2021). *Why Asphalt? - AIA The Asphalt Industry Alliance*. [online] Available at: <<https://www.asphaltuk.org/uk-asphalt/>>.
- [9] Alatoom, Y. I., & Al-Suleiman, T. I. (2022). Development of pavement roughness models using Artificial Neural Network (ANN). *International Journal of Pavement Engineering*, 23(13), 4622-4637.
- [10] Alawneh, M., & Soliman, H. (2023). Using imaging techniques to analyze the microstructure of asphalt concrete mixtures: Literature review. *Applied Sciences*, 13(13), 7813.
- [11] Albayati, A., & Sukhija, M. (2024). Univariate and Multivariate Exploration of Resilient Modulus for Warm Mix Asphalt Mixtures. *Journal of Testing and Evaluation*, 52(4), 2538-2558.
- [12] Alrasheedi, F., Zhong, X., & Huang, P. C. (2023). Padding module: Learning the padding in deep neural networks. *IEEE Access*, 11, 7348-7357.
- [13] Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ...

- & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of big Data*, 8, 1-74.
- [14] Amato, F., Pandolfi, M., Alastuey, A., Lozano, A., González, J. C., & Querol, X. (2013). Impact of traffic intensity and pavement aggregate size on road dust particles loading. *Atmospheric Environment*, 77, 711-717.
- [15] Andrienko, Y. A., Brilliantov, N. V., & Krapivsky, P. L. (1994). Pattern formation by growing droplets: The touch-and-stop model of growth. *Journal of statistical physics*, 75, 507-523.
- [16] Aragão, F.T.S., Kim, Y.R., Lee, J. and Allen, D.H. (2011). Micromechanical model for heterogeneous asphalt concrete mixtures subjected to fracture failure. *Journal of Materials in Civil Engineering*, 23(1), pp.30-38.
- [17] Arganda-Carreras, I., Kaynig, V., Rueden, C., Schindelin, J., Cardona, A., & Seung, H. S. (2016). Trainable_Segmentation: Release v3. 1.2. DOI: <https://doi.org/10.5281/ZENODO.59290>.
- [18] Arnold, C., Biedebach, L., Küpfer, A., & Neunhoeffler, M. (2023). The role of hyperparameters in machine learning models and how to tune them. *Political Science Research and Methods*, 1-8.
- [19] Asphalt Institute (2014). MS-2 Asphalt Mix Design Methods. 7th editio.
- [20] Asphaltadvantages.com. (2021). *Asphalt Advantages | What Is Asphalt?*. [online] Available at: <<http://www.asphaltadvantages.com/en/about/how-asphalt-made/>>.
- [21] ASTM E1845-15. (2015). Standard practice for calculating pavement macrotexture mean profile depth.
- [22] ASTM. (2006). Standard test method for measuring pavement macrotexture depth using a volumetric technique. *Designation: E 965-96*.
- [23] Bendat, J. S., & Piersol, A. G. (2011). *Random data: analysis and measurement procedures*. John Wiley & Sons.
- [24] Bendtsen, H. (2004). Rolling resistance, fuel consumption: a literature review- Danish Road Institute Technical note 23.
- [25] Bishop, C. M. (2006). Pattern recognition and machine learning. *Springer google schola*, 2, 1122-1128.
- [26] Bitumen, S. (1990). The Shell bitumen handbook. Shell Bitumen UK.
- [27] Bojarski, M., Del Testa, D., Dworakowski, D., Firner, B., Flepp, B., Goyal, P., ... & Zieba, K. (2016). End to end learning for self-driving cars. *arXiv preprint arXiv:1604.07316*.

- [28]Bonej.org. (2021). *bonej.org: User Guide - Thickness*. [online] Available at: <<https://bonej.org/thickness>>.
- [29]Botchkarev, A. (2018). Performance metrics (error measures) in machine learning regression, forecasting and prognostics: Properties and typology. *arXiv preprint arXiv:1809.03006*.
- [30]British Standards Institution (BSI). (2010). *Road and airfield surface characteristics. Test methods - Measurement of pavement surface macrotexture depth using a volumetric patch technique* (BS EN 13036-1:2010) [Standard].
- [31]British Standards Institution. (2018). Bituminous mixtures—test methods for hot mix asphalt—Part 5: determination of the maximum density, BS EN 12697-5-2018.
- [32]British Standards Institution. (2018). Bituminous mixtures—test methods for hot mix asphalt—Part 8: determination of void characteristics of bituminous specimens, BS EN 12697-8-2018.
- [33]British Standards Institution. (2020). Bituminous mixtures—test methods for hot mix asphalt—Part 6: determination of bulk density of bituminous specimens, BS EN 12697-6-2020.
- [34]Brownlee, J. (2019). How to Classify Photos of Dogs and Cats (with 97% accuracy). *MachineLearningMastery.com*.
- [35]BS EN 12697-6. (2012). British Standard Institute (BSI) Bituminous mixtures, test methods for hot mix asphalt: determination of bulk density of bituminous specimens.
- [36]Butcher, M. (1998). Determining gyratory compaction characteristics using servopac gyratory compactor. *Transportation Research Record*, 1630(1), pp.89-97.
- [37]Cao, P., Jin, F., Changjun, Z., & Feng, D. (2017). Investigation on statistical characteristics of asphalt concrete dynamic moduli with random aggregate distribution model. *Construction and Building Materials*, 148, 723-733.
- [38]Castaneda, G., Morris, P., & Khoshgoftaar, T. M. (2019). Evaluation of maxout activations in deep learning across several big data domains. *Journal of Big Data*, 6, 1-35.
- [39]Čelko, J., Kováč, M., & Kotek, P. (2016). Analysis of the pavement surface texture by 3D scanner. *Transportation research procedia*, 14, 2994-3003.
- [40]Certified Material Testing Products. (2021). *Why & How To Perform The Marshall Stability Test On Asphalt*. [online] Available at:

<<https://www.certifiedmtp.com/blog/why-how-to-perform-the-marshall-stability-test-on-asphalt/>>.

- [41] Chadbourn, B.A., Newcomb, D., Voller, V., Desombre, R.A., Luoma, J.A., & Timm, D.H. (1998). An asphalt paving tool for adverse conditions.
- [42] Chen, D. , Han, S. , Ling, C. , & Su, Q. . (2017). Prediction of asphalt mixture surface texture level and its distributions using mixture design parameters. *International Journal of Pavement Engineering*, 1-9.
- [43] Chen, D., Han, S., Ling, C., & Su, Q. (2019). Prediction of asphalt mixture surface texture level and its distributions using mixture design parameters. *International Journal of Pavement Engineering*, 20(5), 557-565.
- [44] Chen, D., Roohi Sefidmazgi, N., & Bahia, H. (2015). Exploring the feasibility of evaluating asphalt pavement surface macro-texture using image-based texture analysis method. *Road Materials and Pavement Design*, 16(2), 405-420.
- [45] Chen, L., Li, S., Bai, Q., Yang, J., Jiang, S., & Miao, Y. (2021). Review of image classification algorithms based on convolutional neural networks. *Remote Sensing*, 13(22), 4712.
- [46] Chen, S., Liu, X., Luo, H., Yu, J., Chen, F., Zhang, Y., ... & Huang, X. (2022). A state-of-the-art review of asphalt pavement surface texture and its measurement techniques. *Journal of Road Engineering*, 2(2), 156-180.
- [47] Chen, S., You, Z., Yang, S. L., Garcia, A., & Rose, L. (2021). Influence of air void structures on the coefficient of permeability of asphalt mixtures. *Powder Technology*, 377, 1-9.
- [48] Chiarelli, A., Dawson, A. R., & Garcia, A. (2015). Generation of virtual asphalt mixture porosity for computational modelling. *Powder Technology*, 275, 351-360.
- [49] Chiarelli, A., Dawson, A. R., & Garcia, A. (2015). Stochastic generation of virtual air pores in granular materials. *Granular Matter*, 17, 617-627.
- [50] China, S., & James, D. E. (2012). Influence of pavement macrotexture on PM10 emissions from paved roads: A controlled study. *Atmospheric Environment*, 63, 313-326.
- [51] Chollet, F. (2021). *Deep learning with Python*. Simon and Schuster.
- [52] Clevert, D. A. (2015). Fast and accurate deep network learning by exponential linear units (elus). *arXiv preprint arXiv:1511.07289*.
- [53] Collop, A. C., & Airey, G. D. (2009). ‘Chapter 22: Asphalts: an introduction’, in ICE Manual of Construction Materials. ICE Publishing, pp. 259–261.

- [54]Cortes, C., Mohri, M., & Rostamizadeh, A. (2012). L2 regularization for learning kernels. *arXiv preprint arXiv:1205.2653*.
- [55]Corwill, D.M. (1989). May. Antiskid properties of road surfacing. In Proc., Int. Symp. on Road Development and Safety.
- [56]Courville, A., Goodfellow, I., & Bengio, Y. (2016). Deep learning. *Nature*, 29(7553), 1-73.
- [57]Cuc, N. T. K., Vinh, N. V., & Binh, C. X. (2020). Multiple plane fitting algorithm to evaluated the accuracy of 3D point cloud using structured light measurement. *J. Sci. Technol*, 12-17.
- [58]D'Apuzzo, M., Evangelisti, A. and Nicolosi, V. (2012). Preliminary findings for a prediction model of road surface macrotexture. *Procedia-Social and Behavioral Sciences*, 53, pp.1109-1118.
- [59]D'Apuzzo, M., Evangelisti, A., & Nicolosi, V. (2020). An exploratory step for a general unified approach to labelling of road surface and tyre wet friction. *Accident Analysis & Prevention*, 138, 105462.
- [60]Daminabo, S. C., Goel, S., Grammatikos, S. A., Nezhad, H. Y., & Thakur, V. K. (2020). Fused deposition modeling-based additive manufacturing (3D printing): techniques for polymer material systems. *Materials today chemistry*, 16, 100248.
- [61]Dan, H. C., Bai, G. W., Zhu, Z. H., Liu, X., & Cao, W. (2022). An improved computation method for asphalt pavement texture depth based on multiocular vision 3D reconstruction technology. *Construction and Building Materials*, 321, 126427.
- [62]Dan, H. C., Lu, B., & Li, M. (2024). Evaluation of asphalt pavement texture using multiview stereo reconstruction based on deep learning. *Construction and Building Materials*, 412, 134837.
- [63]Dash, S. S., & Panda, M. (2018). Influence of mix parameters on design of cold bituminous mix. *Construction and Building Materials*, 191, 376-385.
- [64]De Blasiis, M. R., Di Benedetto, A., & Fiani, M. (2020). Mobile laser scanning data for the evaluation of pavement surface distress. *Remote Sensing*, 12(6), 942.
- [65]Dehdezi, P.K., Thodesen, C., Encinas, C.C., & Mengede, M. (2013). Effects of Fillers on the Rheological/Mechanical Performance of Mastics/Asphalt Mixes. In *Proceedings of the international conferences on the bearing capacity of roads, railways and airfields*, pp. 721-733.

- [66] Delanne, Y., & Daburon, P. (1999). Unevenness and vibrational comfort of light cars. In *Environmental Impact of Road Unevenness, International Symposium, 1999, Oporto, Portugal*.
- [67] Deleanu, L., Ionescu, T. F., Cristea, G. C., Suciu, C. C., & Georgescu, C. (2022). 3D texture parameters for wear scars after severe regime. *Industrial Lubrication and Tribology*, 74(3), 324-334.
- [68] Diab, A., & Enieb, M. (2018). Investigating influence of mineral filler at asphalt mixture and mastic scales. *International Journal of Pavement Research and Technology*, 11(3), 213-224.
- [69] Domenichini, L., & Martinelli, F. (2004). Influence of the road characteristics on tyre wear. In *Symposium on Pavement Surface Characteristics [of Roads and Airports], 5th, 2004, Toronto, Ontario, Canada*.
- [70] Dong, S., Han, S., Luo, Y., Han, X., & Xu, O. (2021). Evaluation of tire-pavement noise based on three-dimensional pavement texture characteristics. *Construction and Building Materials*, 306, 124935.
- [71] Doube, M., Kłosowski, M. M., Arganda-Carreras, I., Cordelières, F. P., Dougherty, R. P., Jackson, J. S., ... & Shefelbine, S. J. (2010). BoneJ: free and extensible bone image analysis in ImageJ. *Bone*, 47(6), 1076-1079.
- [72] Dutco Tennant. (2022). *Advanced Road Scan System | ROAD DOCTOR® SURVEY VAN*.
- [73] EAPA. (2021). *Overview - EAPA*. [online] Available at: <<https://eapa.org/innovation-2/>>.
- [74] Emin Kutay, M. (2017). *Embedment Acceptance Testing for Chip Seals*.
- [75] England, H. (2018). *DESIGN MANUAL FOR ROADS AND BRIDGES*. TSO.
- [76] England, H. (2020). Manual of contract documents for highway works volume 1 specification for highway works. *Series 900 Road Pavements–Bituminous Bound Materials*.
- [77] England, H. (2021). *CS 228 Skidding resistance (Revision 2)* [Technical report].
- [78] England, H. (2021). *MANUAL OF CONTRACT DOCUMENTS FOR HIGHWAY WORKS*. STATIONERY OFFICE BOOKS.
- [79] Ergun, M., Iyınam, S. and Iyınam, A.F. (2005). Prediction of road surface friction coefficient using only macro-and microtexture measurements. *Journal of transportation engineering*, 131(4), pp.311- 319.
- [80] Fan, E. (2000). Extended tanh-function method and its applications to nonlinear

- equations. *Physics Letters A*, 277(4-5), 212-218.
- [81] Finlayson, G. D., Schiele, B., & Crowley, J. L. (1998). Comprehensive colour image normalization. In *Computer Vision—ECCV'98: 5th European Conference on Computer Vision Freiburg, Germany, June, 2–6, 1998 Proceedings, Volume I 5* (pp. 475-490). Springer Berlin Heidelberg.
- [82] Fisco, N. and Sezen, H. (2013). 'Comparison of surface macrotexture measurement methods', *Journal of Civil Engineering and Management*, 19(SUPPL.1), pp. 153–160. doi: 10.3846/13923730.2013.802732.
- [83] Forster, S.W. (1989). Pavement microtexture and its relation to skid resistance. *Transportation Research Record*, 1215, pp.151-164.
- [84] Freitas, E. F., Pereira, P. A., Antunes, M. L., & Domingos, P. (2008). Analysis of test methods for texture depth evaluation applied in Portugal.
- [85] Fülöp, I.A., Bogardi, I., Gulyas, A. and Csicsely-Tarpay, M. (2000). Use of friction and texture in pavement performance modeling. *Journal of Transportation Engineering*, 126(3), pp.243-248.
- [86] Fwa, T. F., Kumar, S. S., Anupam, K., & Ong, G. P. (2009). Effectiveness of tire-tread patterns in reducing the risk of hydroplaning. *Transportation research record*, 2094(1), 91-102.
- [87] Ganji, M. R., Golroo, A., Sheikhzadeh, H., Ghelmani, A., & Bidgoli, M. A. (2019). Dense-graded asphalt pavement macrotexture measurement using tire/road noise monitoring. *Automation in Construction*, 106, 102887.
- [88] Gao, B., & Pavel, L. (2017). On the properties of the softmax function with application in game theory and reinforcement learning. *arXiv preprint arXiv:1704.00805*.
- [89] Gao, J., Fan, J., Gao, C., & Song, L. (2025). Friction Prediction in Asphalt Pavements: The Role of Separated Macro-and Micro-Texture Parameters Under Dry and Wet Conditions. *Lubricants*, 13(4), 138.
- [90] Gao, J., Wang, H., Bu, Y., You, Z., Hasan, M. R. M., & Irfan, M. (2018). Effects of coarse aggregate angularity on the microstructure of asphalt mixture. *Construction and Building Materials*, 183, 472-484.
- [91] Gao, R., Zhang, X., Sun, Q., Sun, M., & Zhao, Q. (2018). Road pavement monitoring and roughness assessment based on UAV LiDAR data. *Journal of Basic Science and Engineering*, 26(4), 681-696.

- [92] Gao, Z. (2006). Talking about the Porosity of Asphalt Mixture. *Science and Technology Information* (24), 75-75.
- [93] Garcia, A., Aboufoul, M., Asamoah, F., & Jing, D. (2019). Study the influence of the air void topology on porous asphalt clogging. *Construction and Building Materials*, 227, 116791.
- [94] Garcia, A., Hassn, A., Chiarelli, A., & Dawson, A. (2015). Multivariable analysis of potential evaporation from moist asphalt mixture. *Construction and Building Materials*, 98, 80-88.
- [95] Garcia-Hernandez, A., Wan, L., Dopazo-Hilario, S., Chiarelli, A., & Dawson, A. (2021). Generation of virtual asphalt concrete in a physics engine. *Construction and Building Materials*, 286, 122972.
- [96] Gillespie, T. (Ed.). (2021). *Fundamentals of vehicle dynamics*. SAE international.
- [97] Gilmer, J., Schoenholz, S. S., Riley, P. F., Vinyals, O., & Dahl, G. E. (2017). Neural message passing for quantum chemistry. In *International conference on machine learning* (pp. 1263-1272). PMLR.
- [98] GlobalGilson.com. (2021). *Marshall Test Method: Everything You Need To Know*. [online] Available at: <<https://www.globalgilson.com/blog/asphalt-marshall-test-method>>.
- [99] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press.
- [100] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. *Advances in neural information processing systems*, 27.
- [101] Gu, F., Watson, D., Moore, J., & Tran, N. (2018). Evaluation of the benefits of open graded friction course: Case study. *Construction and Building Materials*, 189, 131-143.
- [102] Gu, Y., Wang, J., & Yang, X. (2016). Three Dimensional Reconstructing of Asphalt Mixture for Discrete Element Method Based on X-ray Tomography. *Highway*, 61(4), 182-186.
- [103] Hainin, R., Reshi, W. F., & Niroumand, H. (2012). The importance of stone mastic asphalt in construction. *Electronic Journal of Geotechnical Engineering*, 17(49), 56-74.
- [104] Hall, J.W., Smith, K.L., Titus-Glover, L., Wambold, J.C., Yager, T.J. and Rado, Z. (2009). Guide for pavement friction. Final Report for NCHRP Project, 1, p.43.
- [105] Han, J., & Moraga, C. (1995). The influence of the sigmoid function

- parameters on the speed of backpropagation learning. In *International workshop on artificial neural networks* (pp. 195-201). Berlin, Heidelberg: Springer Berlin Heidelberg.
- [106] Han, S., Sun, P., & Fwa, T. F. (2021). Relationships between internal structure and surface texture of asphalt mixtures. *Road Materials and Pavement Design*, 22(4), 894-909.
- [107] Harvey, J. T., Deacon, J. A., Tsai, B. W., & Monismith, C. L. (1995). Fatigue performance of asphalt concrete mixes and its relationship to asphalt concrete pavement performance in California.
- [108] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).
- [109] Hendrycks, D., & Gimpel, K. (2016). Gaussian error linear units (gelus). *arXiv preprint arXiv:1606.08415*.
- [110] Henry, J. J. (2000). *Evaluation of pavement friction characteristics* (Vol. 291). Transportation Research Board.
- [111] Hesami, E., Jelagin, D., Kringos, N., & Birgisson, B. (2012). An empirical framework for determining asphalt mastic viscosity as a function of mineral filler concentration. *Construction and Building Materials*, 35, pp.23-29.
- [112] Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. *science*, 313(5786), 504-507.
- [113] Hinton, G. E., Osindero, S., & Teh, Y. W. (2006). A fast learning algorithm for deep belief nets. *Neural computation*, 18(7), 1527-1554.
- [114] Hlotov, V., & Marusazh, K. H. (2019). Accuracy investigation of point clouds with Faro Focus 3d S120 terrestrial laser scanner. *Geodesy, Cartography and Aerial Photography*, 90(90), 41-49.
- [115] Hoang, N. D., & Tran, V. D. (2022). Computer vision based asphalt pavement segregation detection using image texture analysis integrated with extreme gradient boosting machine and deep convolutional neural networks. *Measurement*, 196, 111207.
- [116] Hochreiter, S. (1997). Long Short-term Memory. *Neural Computation MIT-Press*.
- [117] Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). MobileNets: efficient convolutional neural networks for

- mobile vision applications (2017). *arXiv preprint arXiv:1704.04861*, 126.
- [118] Hu, B., Yu, J., Li, L. and Song, Q. (2016). Macroscopic and Mesoscopic Compactive Study of Warm Mix Asphalt. *Highway Engineering*, (01 2016), 24-27.
- [119] Hu, J., Liu, P., Wang, D., & Oeser, M. (2018). Influence of aggregates' spatial characteristics on air-voids in asphalt mixture. *Road Materials and Pavement Design*, 19(4), 837-855.
- [120] Hu, J., Qian, Z., Wang, D., & Oeser, M. (2015). Influence of aggregate particles on mastic and air-voids in asphalt concrete. *Construction and Building Materials*, 93, 1-9.
- [121] Huang, W., Cai, X., Li, X., Cui, W., & Wu, K. (2020). Influence of nominal maximum aggregate size and aggregate gradation on pore characteristics of porous asphalt concrete. *Materials*, 13(6), 1355.
- [122] Huang, W., Liu, C., Guo, W., & Wei, Y. (2022). A Surface Texture Prediction Model Based on RIOHTrack Asphalt Pavement Testing Data. *Applied Sciences*, 12(20), 10539.
- [123] Hunter, A.E., Airey, G.D., & Collop, A.C. (2004). September. Effect of asphalt mixture compaction on aggregate orientation and mechanical performance. In *Proceedings of the 8th Conference on Asphalt Pavements for Southern Africa (CAPSA'04)*, 12, pp.16.
- [124] Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International journal of forecasting*, 22(4), 679-688.
- [125] Ilse, M. (2015). Evaluation of tire/surfacing/base contact stresses and texture depth. *International Journal of Transportation Science and Technology*, 4(1), 107-118.
- [126] ImageJ Wiki. (2021). *Trainable Weka Segmentation*. [online] Available at: <<https://imagej.net/plugins/tws/>>.
- [127] International Organization for Standardization. (1996). *Geometrical Product Specifications (GPS)--surface Texture: Profile Method--rules and Procedures for the Assessment of Surface Texture*. ISO.
- [128] Investopedia. (2021). *Bitumen*. [online] Available at: <<https://www.investopedia.com/terms/b/bitumen.asp>>.
- [129] Ioffe, S. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*.
- [130] Ioffe, S., & Szegedy, C. (2015). Batch normalization: Accelerating deep

- network training by reducing internal covariate shift. In *International conference on machine learning* (pp. 448-456). pmlr.
- [131] ISO 13473-1. (2019). 'Characterisation of pavement texture by use of surface profiles - Part 1: Determination of mean profile depth'.
 - [132] ISO 13473-2. (2002). 'Characterisation of pavement texture by use of surface profiles - Part 2: Terminology and basic requirements related to pavement texture profile analysis'.
 - [133] ISO 13473-3. (2002). 'Characterisation of pavement texture by use of surface profiles - Part 3: Specification and classification of profilometers'.
 - [134] ISO 13473-4. (2008). 'Characterisation of pavement texture by use of surface profiles - Part 4: Spectral analysis of surface profile'.
 - [135] Iwama, M., Airey, G.D., & Hunter, A.E. (2007). June. Influence of asphalt mixture compaction method and specimen size on internal structure and mechanical properties. In *Proceedings of the International Conference on Advanced Characterisation of Pavement and Soil Engineering Materials*, Athens, pp. 1063-1073.
 - [136] Jamshidi, A., Hamzah, M. O., Kurumisawa, K., Nawa, T., & Samali, B. (2016). Evaluation of sustainable technologies that upgrade the binder performance grade in asphalt pavement construction. *Materials & Design*, 95, 9-20.
 - [137] Jia, Y., & Zhang, Q. (2001). Discussion on Domestic Marshall Mixture Design Method [J]. *Highway*, 2001 (8), 84 - 90.
 - [138] Jiang, F. (1991). *Roller Compacted Concrete*. China Railway Publishing House.
 - [139] Jiao, T., & Tian, C. (2009). Approach to Design and Experimental Methods of Asphalt Mixture Stability. *Northern Communications*, (6), 35-37.
 - [140] Jin, C., Feng, Y., Yang, X., Liu, P., Ding, Z., & Oeser, M. (2022). Virtual design of asphalt mixtures using a growth and contact model based on realistic aggregates. *Construction and Building Materials*, 320, 126322.
 - [141] Johnson, J. M., & Khoshgoftaar, T. M. (2019). Survey on deep learning with class imbalance. *Journal of big data*, 6(1), 1-54.
 - [142] Kakar, M. R., Hamzah, M. O., & Valentin, J. (2015). A review on moisture damages of hot and warm mix asphalt and related investigations. *Journal of Cleaner Production*, 99, 39-58.

- [143] Kamaluddin, N. A. (2008). *Evaluation of Stone Mastic Asphalt Using Palm Oil Fuel Ash as Filler Material* (Doctoral dissertation, Universiti Teknologi Malaysia).
- [144] Kane, M., Riahi, E., & Do, M. T. (2021). Tire/road rolling resistance modeling: Discussing the surface macrotexture effect. *Coatings*, 11(5), 538.
- [145] Karyawan, I. D. M. A. , Widyatmoko, I. , Ekaputri, J. J. , & Ahyudanari, E. . (2022). Texture and skid resistance of asphalt concrete surface course incorporating geopolymers artificial aggregates.
- [146] Kassem, E., Masad, E., Lytton, R., & Chowdhury, A. (2011). Influence of air voids on mechanical properties of asphalt mixtures. *Road Materials and Pavement Design*, 12(3), 493-524.
- [147] Katuwal, S., Moldrup, P., Lamandé, M., Tuller, M., & De Jonge, L. W. (2015). Effects of CT number derived matrix density on preferential flow and transport in a macroporous agricultural soil. *Vadose Zone Journal*, 14(7).
- [148] Keskar, N. S., Mudigere, D., Nocedal, J., Smelyanskiy, M., & Tang, P. T. P. (2016). On large-batch training for deep learning: Generalization gap and sharp minima. *arXiv preprint arXiv:1609.04836*.
- [149] Kheradmand, B., Muniandy, R., Hua, L. T., Yunus, R. B., & Solouki, A. (2014). An overview of the emerging warm mix asphalt technology. *International Journal of Pavement Engineering*, 15(1), 79-94.
- [150] Kim, H. B., Lee, S. W., Hyun, T. J., & Lee, K. H. (2013). Measurement of texture depth of pavement using portable laser profiler. *Journal of the Eastern Asia Society for Transportation Studies*, 10, 1576-1589.
- [151] Kingma, D. P. (2014). Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*.
- [152] Kociński, M., Materka, A., Lundervold, A., Salvesen, H., Ytre-Hauge, S., & Haldorsen, I. (2016). Texture analysis of 2D spatial distribution of blood pharmacokinetic model parameters for endometrial carcinoma classification. In *2016 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA)* (pp. 91-96). IEEE.
- [153] Koziarski, M., & Cyganek, B. (2018). Impact of low resolution on image recognition with deep neural networks: An experimental study. *International Journal of Applied Mathematics and Computer Science*, 28(4), 735-744.
- [154] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. *Advances in neural information*

processing systems, 25.

- [155] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. *Communications of the ACM*, 60(6), 84-90.
- [156] Kuchiishi, A. K., Vasconcelos, K., & Bariani Bernucci, L. L. (2021). Effect of mixture composition on the mechanical behaviour of cold recycled asphalt mixtures. *International Journal of Pavement Engineering*, 22(8), 984-994.
- [157] Kumar, N. K., & Ravitheja, A. (2019). Characteristics of stone matrix asphalt by using natural fibers as additives. *Materials today: proceedings*, 19, 397-402.
- [158] Kumar, R. (2024). From Gaussian to lognormal: improving material property modeling for precise structural predictions. *Applied Physics A*, 130(11), 841.
- [159] Kutay, M. E., Aydilek, A. H., Masad, E., & Harman, T. (2007). Computational and experimental evaluation of hydraulic conductivity anisotropy in hot-mix asphalt. *International Journal of Pavement Engineering*, 8(1), 29-43.
- [160] LeCun, Y. (1998). The MNIST database of handwritten digits. <http://yann.lecun.com/exdb/mnist/>.
- [161] LeCun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W., & Jackel, L. D. (1989). Backpropagation applied to handwritten zip code recognition. *Neural computation*, 1(4), 541-551.
- [162] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11), 2278-2324.
- [163] LeCun, Y., Bottou, L., Orr, G. B., & Müller, K. R. (2002). Efficient backprop. In *Neural networks: Tricks of the trade* (pp. 9-50). Berlin, Heidelberg: Springer Berlin Heidelberg.
- [164] LeCun, Y., Touresky, D., Hinton, G., & Sejnowski, T. (1988). A theoretical framework for back-propagation. In *Proceedings of the 1988 connectionist models summer school* (Vol. 1, pp. 21-28).
- [165] Lei, S., He, F., Yuan, Y., & Tao, D. (2023). Understanding deep learning via decision boundary. *IEEE Transactions on Neural Networks and Learning Systems*.
- [166] Li, F. F., Karpathy, A., & Johnson, J. (2015). Convolutional neural networks for visual recognition. Available in <http://cs231n.github.io/convolutional-networks>.

- [167] Li, H., Dong, Y., Wang, T., & Wang, J. (2024). Research on tire pattern parameters based on multi-objective optimization. *Journal of Mechanical Science and Technology*, 38(2), 775-786.
- [168] Li, L., & Wang, K. C. (2016). Geometric texture indicators for safety on AC pavements with 1 mm 3D laser texture data. *International Journal of Pavement Research and Technology*, 9(1), 49-62.
- [169] Li, Y., Li, Z., Fan, X., Li, T., & Yan, G. (2018). Effect of Regenerant on Marshall Stability of Asphalt Mixtures. *Journal of Hebei Institute of Architectural Engineering*, 36 (3), 25-27.
- [170] Liang, H., Pagano, R. G., Oddone, S., Cong, L., & De Blasiis, M. R. (2024). Analysis of Road Surface Texture for Asphalt Pavement Adhesion Assessment Using 3D Laser Technology. *Remote Sensing*, 16(11), 1943.
- [171] Liang, J., Gu, X., Chen, Y., Ni, F., & Zhang, T. (2020). A novel pavement mean texture depth evaluation strategy based on three-dimensional pavement data filtered by a new filtering approach. *Measurement*, 166, 108265.
- [172] Liang, J., Gu, X., Chen, Y., Ni, F., & Zhang, T. (2020). A novel pavement mean texture depth evaluation strategy based on three-dimensional pavement data filtered by a new filtering approach. *Measurement*, 166, 108265.
- [173] Liang, X. Y., Xie, B. L., & Wang, D. Y. (2023). Study on the influence of surface texture characteristics on pavement vibration noise. *Journal of Wuhan University of Technology*, 45(5), 57–null.
- [174] Lin, X., & You, G. (2001). The Quick - confirmation Ways of Designing Target Proportioning of Bituminous Mixture [J]. *East China Highway*, 2001 (2): 3 - 8.
- [175] Liu, C., Li, J., Gao, J., Yuan, D., Gao, Z., & Chen, Z. (2021). Three-dimensional texture measurement using deep learning and multi-view pavement images. *Measurement*, 172, 108828.
- [176] Liu, F., & Panagiotakos, D. (2022). Real-world data: a brief review of the methods, applications, challenges and opportunities. *BMC Medical Research Methodology*, 22(1), 287.
- [177] Liu, Q., & Cao, D. (2009). Research on material composition and performance of porous asphalt pavement. *Journal of materials in civil engineering*, 21(4), 135-140.

- [178] Liu, Y., Gong, H., & Zhang, Z. (2015). Real-Time 3-D Surface Reconstruction from Multiple Cameras. In *International Symposium on Visual Computing* (pp. 93-101). Cham: Springer International Publishing.
- [179] Long, J., & Huang, C. Q. (2019). Parametric design of tires based on CATIA. *Tire Industry*, 4.
- [180] Losa, M., & Leandri, P. (2011). The reliability of tests and data processing procedures for pavement macrotexture evaluation. *International Journal of Pavement Engineering*, 12(1), 59-73.
- [181] Losa, M., Leandri, P., & Bacci, R. (2010). Empirical rolling noise prediction models based on pavement surface characteristics. *Road Materials and Pavement Design*, 11(sup1), 487-506.
- [182] Lu, Q., & Harvey, J. T. (2011). Laboratory evaluation of open-graded asphalt mixes with small aggregates and various binders and additives. *Transportation Research Record*, 2209(1), 61-69.
- [183] Lugo, A., Allex, E., Arámbula, E., Spinel, C., Alvarez Lugo, A., Mercado, E., & Caro Spinel, S. (2008). X-ray computed tomography and aggregate image system (AIMS) for studying hot mix asphalt and aggregates. *Ifoldr Import 2019-10-08 Batch 5*.
- [184] Ma, T., Wang, H., Zhang, D. and Zhang, Y. (2017). Heterogeneity effect of mechanical property on creep behavior of asphalt mixture based on micromechanical modeling and virtual creep test. *Mechanics of Materials*, 104, pp.49-59.
- [185] Ma, T., Wang, H., Zhao, Y., Huang, X., & Pi, Y. (2015). Strength mechanism and influence factors for cold recycled asphalt mixture. *Advances in Materials Science and Engineering*, 2015(1), 181853.
- [186] Ma, T., Zhang, D. Y., Zhang, Y., Zhao, Y. L., & Huang, X. M. (2016). Microstructure modeling and virtual test of asphalt mixture based on three-dimensional discrete element method. *Journal of Central South University*, 23(6), 1525-1534.
- [187] Ma, T., Zhang, D., Zhang, Y. and Hong, J. (2016). Micromechanical response of aggregate skeleton within asphalt mixture based on virtual simulation of wheel tracking test. *Construction and Building Materials*, 111, pp.153-163.
- [188] Ma, X., Li, Q., Cui, Y. C., & Ni, A. Q. (2018). Performance of porous asphalt mixture with various additives. *International Journal of Pavement*

Engineering, 19(4), 355-361.

- [189] Ma, Z., Wang, H., Zhang, Y., Jelagin, D., & Hui, B. (2025). Study of the surface texture evolution and friction degradation in asphalt pavements during wear process. *Wear*, 564, 205714.
- [190] Mallick, R. B., Kandhal, P. S., Cooley Jr, L. A., & Watson, D. E. (2000). Design, construction, and performance of new-generation open-graded friction courses.
- [191] Mandal, V., Uong, L., & Adu-Gyamfi, Y. (2018). Automated road crack detection using deep convolutional neural networks. In *2018 IEEE International Conference on Big Data (Big Data)* (pp. 5212-5215). IEEE.
- [192] Marrakech, R.A. (1991). Permanent International Association of Road Congress 1991 Report. In 21th World Road Congress, 1991.
- [193] Marsac, P., & Delanne, Y. (2004). Prediction of tire-wet road friction from road surface microtexture and tire rubber properties. In *Symposium on Pavement Surface Characteristics [of Roads and Airports], 5th, 2004, Toronto, Ontario, Canada*.
- [194] Masad, E., Jandhyala, V. K., Dasgupta, N., Somadevan, N., & Shashidhar, N. (2002). Characterization of air void distribution in asphalt mixes using X-ray computed tomography. *Journal of materials in civil engineering*, 14(2), 122-129.
- [195] Mataei, B., Nejad, F. M., & Zakeri, H. (2022). Automatic pavement texture measurement using a new 3D image-based profiling system. *Measurement*, 199, 111456.
- [196] Matos, P., Micaelo, R., Duarte, C., & Quaresma, L. (2014). Influence of bitumen and filler on the selection of appropriate mixing and compaction temperatures. *International Journal of Pavement Research and Technology*, 7(4), pp.237-246.
- [197] McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, 5, 115-133.
- [198] McLean, J. and Foley, G. (1998). 'Road surface characteristics and condition: Effects on road users', Research Report ARR, (314), pp. 1–55.
- [199] Meng, Y., Xu, J., Jin, Z., Prakash, B., & Hu, Y. (2020). A review of recent advances in tribology. *Friction*, 8, 221-300.
- [200] Mercioni, M. A., & Holban, S. (2020). P-swish: Activation function with learnable parameters based on swish activation function in deep learning. In *2020 International Symposium on Electronics and Telecommunications (ISETC)* (pp. 1-

4). IEEE.

- [201] Mikhailenko, P., Piao, Z., Kakar, M. R., Bueno, M., Athari, S., Pieren, R., ... & Poulikakos, L. (2022). Low-Noise pavement technologies and evaluation techniques: a literature review. *International Journal of Pavement Engineering*, 23(6), 1911-1934.
- [202] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. *Advances in neural information processing systems*, 26.
- [203] Miljković, M., & Radenberg, M. (2015). Characterising the influence of bitumen emulsion on asphalt mixture performance. *Materials and Structures*, 48(7), pp.2195-2210.
- [204] Miller, T., Swiertz, D., Tashman, L., Tabatabaee, N., & Bahia, H. U. (2012). Characterisation of asphalt pavement surface texture. *Transportation research record*, 2295(1), 19-26.
- [205] Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Hassabis, D. (2015). Human-level control through deep reinforcement learning. *nature*, 518(7540), 529-533.
- [206] Mollenhauer, K., & Wistuba, M.P. (2016). Influence of asphalt compaction procedure on 3D deformation properties. *International journal of pavement engineering*, 17(1), pp.5-12.
- [207] Morgan, P. (Ed.). (2006). Guidance manual for the implementation of low-noise road surfaces. *benefits*, 769, 66.
- [208] Murphy, K. P. (2012). *Machine learning: a probabilistic perspective*. MIT press.
- [209] Nijboer, L.W. (1948). Plasticity as a factor in the design of dense bituminous road carpets. Elsevier Pub. Co.
- [210] Norhidayah, A. H., Mahmud, M. Z. H., & Ramadhansyah, P. J. (2014). Air void characterisation in porous asphalt using X-ray computed tomography. In *Advanced Materials Research* (Vol. 911, pp. 443-448). Trans Tech Publications Ltd.
- [211] Noyce, D. A., Bahia, H. U., Yambo, J. M., & Kim, G. (2005). Incorporating road safety into pavement management: maximising asphalt pavement surface friction for road safety improvements. *Draft Literature Review and State Surveys*,

Midwest Regional University Transportation Center (UMTRI), Madison, Wisconsin.

- [212] Otani, J., Watanabe, Y., & Chevalier, B. (2010). Introduction of X-ray CT application in geotechnical engineering—theory and practice. In *IOP Conference Series: Materials Science and Engineering* (Vol. 10, No. 1, p. 012089). IOP Publishing.
- [213] Özgan, E., Serin, S., & Kap, T. (2013). Multi-faceted investigation into the effects of hot-mix asphalt parameters on Marshall Stability. *Construction and Building Materials*, 40, 419-425.
- [214] Pai, V. K., Balrai, M., Mogaveera, S., & Aeloor, D. (2018). Face recognition using convolutional neural networks. In *2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 165-170). IEEE.
- [215] Pan, W., Ling, L., Qu, H., & Wang, M. (2021). Analysis of complex modal instability of a minimal friction self-excited vibration system from multiscale fractal surface topography. *European Journal of Mechanics-A/Solids*, 87, 104226.
- [216] Pan, X. (2010). Marshall Test Research on Large-Sized Asphalt Mixture. *China New Technology and New Products* (15), 122-123.
- [217] Pan, X., Siewerdsen, J., La Riviere, P. J., & Kalender, W. A. (2008). Anniversary Paper: Development of x-ray computed tomography: The role of Medical Physics and AAPM from the 1970s to present. *Medical physics*, 35(8), 3728-3739.
- [218] Papagiannakis, A.T., Abbas, A. and Masad, E. (2002). Micromechanical analysis of viscoelastic properties of asphalt concretes. *Transportation Research Record*, 1789(1), pp.113-120.
- [219] Pavement Interactive. (2021). *Marshall Mix Design - Pavement Interactive*. [online] Available at: <<https://pavementinteractive.org/reference-desk/design/mix-design/marshall-mix-design/>>.
- [220] Pavement Interactive. (2021). *Pavement History - Pavement Interactive*. [online] Available at: <<https://pavementinteractive.org/reference-desk/pavement-types-and-history/pavement-history/>>.
- [221] Pavement Interactive. (2021). *Rigid Mechanistic Models - Pavement Interactive*. [online] Available at: <<https://pavementinteractive.org/reference-desk/design/structural-design/rigid-mechanistic-models/>>.
- [222] Pelletier, E. D., Jeffries, S. D., Song, K., & Hemmerling, T. M. (2022).

Comparative Analysis of Machine-Learning Model Performance in Image Analysis: The Impact of Dataset Diversity and Size. *Anesthesia & Analgesia*, 10-1213.

- [223] Peng, Y., Harvey, J. T., & Sun, L. J. (2017). Three-dimensional discrete-element modeling of aggregate homogeneity influence on indirect tensile strength of asphalt mixtures. *Journal of Materials in Civil Engineering*, 29(11), 04017211.
- [224] Perez, L. (2017). The effectiveness of data augmentation in image classification using deep learning. *arXiv preprint arXiv:1712.04621*.
- [225] Pham, D., & Karaboga, D. (2012). *Intelligent optimisation techniques: genetic algorithms, tabu search, simulated annealing and neural networks*. Springer Science & Business Media.
- [226] PIARC. (1983). 'Technical Committee Report on Surface Characteristics', in Proceedings of the XIXth World Road Congress,. Sidney, Australia.
- [227] Plati, C., Pomoni, M., & Stergiou, T. (2017). Development of a mean profile depth to mean texture depth shift factor for asphalt pavements. *Transportation Research Record*, 2641(1), 156-163.
- [228] Pranjić, I., Deluka-Tibljaš, A., Cuculić, M., & Šurdonja, S. (2020). Influence of pavement surface macrotexture on pavement skid resistance. *Transportation research procedia*, 45, 747-754.
- [229] Praticò, F. G., & Vaiana, R. (2015). A study on the relationship between mean texture depth and mean profile depth of asphalt pavements. *Construction and Building Materials*, 101, 72-79.
- [230] Praticò, F. G., Vaiana, R., & Fedele, R. (2015). A study on the dependence of PEMs acoustic properties on incidence angle. *International Journal of Pavement Engineering*, 16(7), 632-645.
- [231] Praticò, F. G., Vaiana, R., & Iuele, T. (2013). Acoustic absorption and surface texture: an experimental investigation. In *INTER-NOISE and NOISE-CON Congress and Conference Proceedings* (Vol. 247, No. 8, pp. 465-473). Institute of Noise Control Engineering.
- [232] Pszczola, M., & Szydlowski, C. (2018). Influence of bitumen type and asphalt mixture composition on low-temperature strength properties according to various test methods. *Materials*, 11(11), p.2118.
- [233] Qian, D. (2003). Stability of Asphalt Pavement and Its Influencing Factors. *Contemporary Construction*, 1.

- [234] Qiao, D. (2018). Analysis and Research on Void Feature of Gussasphalt Mixture by CT Scanning Technology. *Highway Traffic Technology*, 34(005), 27-31, 37.
- [235] Qiu, Y. F., & Lum, A. K. (2006). Design and performance of stone mastic asphalt. *Journal of transportation engineering*, 132(12), 956-963.
- [236] Qu, Z., Mei, J., Liu, L., & Zhou, D. Y. (2020). Crack detection of concrete pavement with cross-entropy loss function and improved VGG16 network model. *Ieee Access*, 8, 54564-54573.
- [237] Que, Y., Dai, Y., Ji, X., Leung, A. K., Chen, Z., Jiang, Z., & Tang, Y. (2023). Automatic classification of asphalt pavement cracks using a novel integrated generative adversarial networks and improved VGG model. *Engineering Structures*, 277, 115406.
- [238] Rahman, S., Bhasin, A., & Smit, A. (2021). Exploring the use of machine learning to predict metrics related to asphalt mixture performance. *Construction and Building Materials*, 295, 123585.
- [239] Rajaei, M., Sefidmazgi, N. R., & Bahia, H. (2014). 'Establishment of relationship between pavement surface friction and mixture design properties', Transportation 72 Research Record. National Research Council, pp. 114–120. doi: 10.3141/2457- 12.
- [240] Ranft, B., & Stiller, C. (2016). The role of machine vision for intelligent vehicles. *IEEE Transactions on Intelligent vehicles*, 1(1), 8-19.
- [241] Ren, Z., Yan, E., He, B., Crispino, M., Huang, L., & Tan, Y. (2024). Unraveling the nexus between internal structural variability and macro-texture in asphalt mixtures: a mesoscopic investigation. *Materials and Structures*, 57(3), 48.
- [242] Rezaei, A., Harvey, J. T., & Lu, Q. (2012). Investigation of Noise and Ride Quality Trends for Asphaltic Pavement Surface Types: Five-Year Results.
- [243] Roberts, F. L., Kandhal, P. S., Brown, E. R., Lee, D. Y., & Kennedy, T. W. (1991). Hot mix asphalt materials, mixture design and construction.
- [244] Romero, P. (2000). *Laboratory Evaluation of the PQI Model 300. Project Report. Multiple State Pooled Fund Study*. DTFH61-00-P-00549.
- [245] Roque, W. L., & Costa, R. R. (2020). A plugin for computing the pore/grain network tortuosity of a porous medium from 2D/3D MicroCT image. *Applied Computing and Geosciences*, 5, 100019.
- [246] Rosenblatt, F. (1958). The perceptron: a probabilistic model for information

- storage and organization in the brain. *Psychological review*, 65(6), 386.
- [247] Rubio, M. C., Martínez, G., Baena, L., & Moreno, F. (2012). Warm mix asphalt: an overview. *Journal of cleaner production*, 24, 76-84.
- [248] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *nature*, 323(6088), 533-536.
- [249] Russell, S. J., & Norvig, P. (2016). *Artificial intelligence: a modern approach*. Pearson.
- [250] Sandberg, U. (2021). Why do clogged porous asphalt pavements give better traffic noise reduction than a dense-graded asphalt pavement?. In *INTER-NOISE and NOISE-CON Congress and Conference Proceedings* (Vol. 263, No. 4, pp. 2020-2031). Institute of Noise Control Engineering.
- [251] Sarsam, S. I. . (2020). Influence of surface texture on interface bond shear strength of asphalt concrete. *Civil Engineering Beyond Limits*, 1(3), 8-14.
- [252] Schenker, I., Filser, F. T., & Gauckler, L. J. (2010). Stochastic generation of particle structures with controlled degree of heterogeneity. *Granular matter*, 12, 437-446.
- [253] Schmidhuber, J. (2022). Annotated history of modern ai and deep learning. *arXiv preprint arXiv:2212.11279*.
- [254] Schneider, C. A., Rasband, W. S., & Eliceiri, K. W. (2012). NIH Image to ImageJ: 25 years of image analysis. *Nature methods*, 9(7), 671-675.
- [255] Serigos, P.A., De Fortier Smit, A. and Prozzi, J.A. (2014). Incorporating surface microtexture in the prediction of skid resistance of flexible pavements. *Transportation Research Record*, 2457(1), pp.105-113.
- [256] Shafi, S., & Assad, A. (2023). Exploring the relationship between learning rate, batch size, and epochs in deep learning: an experimental study. In *Soft Computing for Problem Solving: Proceedings of the SocProS 2022* (pp. 201-209). Singapore: Springer Nature Singapore.
- [257] Sheng, J. (1996). Discussion on the Density, Voids and Compactness of Asphalt Mixture [J]. *Highway*, 1996 (6), 29 - 41.
- [258] Sheng, Y., Li, H., Guo, P., Zhao, G., Chen, H., & Xiong, R. (2017). Effect of fibers on mixture design of stone matrix asphalt. *Applied Sciences*, 7(3), 297.
- [259] Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation for deep learning. *Journal of big data*, 6(1), 1-48.
- [260] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for

- large-scale image recognition. arXiv preprint arXiv:1409.1556.
- [261] Smith, L. N. (2017). Cyclical learning rates for training neural networks. In *2017 IEEE winter conference on applications of computer vision (WACV)* (pp. 464-472). IEEE.
- [262] Smith, L. N. (2018). A disciplined approach to neural network hyper-parameters: Part 1--learning rate, batch size, momentum, and weight decay. *arXiv preprint arXiv:1803.09820*.
- [263] Sohaney, R. C., & Rasmussen, R. O. (2013). *Pavement texture evaluation and relationships to rolling resistance at MnROAD* (No. MN/RC 2013-16). Department of Transportation, Research Services Section.
- [264] Sohl-Dickstein, J., Weiss, E., Maheswaranathan, N., & Ganguli, S. (2015). Deep unsupervised learning using nonequilibrium thermodynamics. In *International conference on machine learning* (pp. 2256-2265). PMLR.
- [265] Sommacal, S., Matschinski, A., Holmes, J., Drechsler, K., & Compston, P. (2023). Detailed void characterisation by X-ray computed tomography of material extrusion 3D printed carbon fibre/PEEK. *Composite Structures*, 308, 116635.
- [266] Song, L., Yun, D., Ye, W., & Gao, J. (2024). Characteristics of open-graded friction course macrotexture and macrostructure and its effect on skid resistance under rainfall. *Materials*, 17(18), 4658.
- [267] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1), 1929-1958.
- [268] Storn, R., & Price, K. (1997). Differential evolution—a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization*, 11, 341-359.
- [269] Subagio, B. S., Siswosoebrotho, B. I., & Karsaman, R. H. (2003). Development of laboratory performance of Indonesia rock asphalt (ASBUTON) in hot rolled asphalt mix. *Proc Eastern Asia Soc Transport Stud*, 4.
- [270] Sun, K., Yu, J., Zhang, L., & Dong, Z. (2020). A convolutional neural network model based on improved softplus activation function. In *International Conference on Applications and Techniques in Cyber Intelligence ATCI 2019: Applications and Techniques in Cyber Intelligence 7* (pp. 1326-1335). Springer International Publishing.

- [271] Sun, L. (2016). *Structural behavior of asphalt pavements: Intergrated analysis and design of conventional and heavy duty asphalt pavement*. Butterworth-Heinemann.
- [272] Sun, Z., Premarathna, W. A. A. S., Anupam, K., Kasbergen, C., & Erkens, S. M. (2024). A state-of-the-art review on rolling resistance of asphalt pavements and its environmental impact. *Construction and Building Materials*, 411, 133589.
- [273] Sutskever, I. (2014). Sequence to Sequence Learning with Neural Networks. *arXiv preprint arXiv:1409.3215*.
- [274] Sutskever, I., Martens, J., Dahl, G., & Hinton, G. (2013). On the importance of initialization and momentum in deep learning. In *International conference on machine learning* (pp. 1139-1147). PMLR.
- [275] Taher, M. N. M., Aman, M. Y., & Bujang, H. (2024). The effect of aggregate micro and macro texture on pavement skid resistance of Malaysia road network. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1347, No. 1, p. 012054). IOP Publishing.
- [276] Tajbakhsh, N., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., & Liang, J. (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning?. *IEEE transactions on medical imaging*, 35(5), 1299-1312.
- [277] Talaei Khoei, T., Ould Slimane, H., & Kaabouch, N. (2023). Deep learning: Systematic review, models, challenges, and research directions. *Neural Computing and Applications*, 35(31), 23103-23124.
- [278] Tashman, L.S., Masad, E., Peterson, B. and Saleh, H. (2000). Internal structure analysis of asphalt mixes to improve the simulation of superpave gyratory compaction to field conditions. *J. Assoc. Asphalt Paving Technol.*, 70, 605–645.
- [279] Tatari, A., Costello, S. B., & Wilson, D. J. (2016). ASSESSMENT OF RECYCLED AGGREGATE FOR USE IN THE PAVEMENT SURFACE LAYER.
- [280] Taylor, R. (2009). ‘Chapter 26: Asphalt mixture design’, in ICE manual of Construction Materials, pp. 297–306. doi: 10.1680/mocm.35973.0297.
- [281] Terven, J., Cordova-Esparza, D. M., Ramirez-Pedraza, A., & Chavez-Urbiola, E. A. (2023). Loss functions and metrics in deep learning. A review. *arXiv preprint arXiv:2307.02694*.

- [282] Thigpen, C. G., Li, H., Handy, S. L., & Harvey, J. (2015). Modeling the impact of pavement roughness on bicycle ride quality. *Transportation Research Record*, 2520(1), 67-77.
- [283] Tian, H. (2010). The Study on Marshall Stability and Splitting Test of Fiber Reinforced Asphalt Mixtures. *Shanxi Communications Science and Technology*, 2(1), 9-12.
- [284] Tian, P., Shukla, A., Nie, L., Zhan, G., & Liu, S. (2018). Characteristics' relation model of asphalt pavement performance based on factor analysis. *International Journal of Pavement Research and Technology*, 11(1), 1-12.
- [285] Tomiyama, K., & Moriishi, K. (2020). Pavement Surface Evaluation Interacting Vibration Characteristics of an Electric Mobility Scooter. In *Proceedings of the 9th International Conference on Maintenance and Rehabilitation of Pavements—Mairepav9* (pp. 893-900). Springer International Publishing.
- [286] Tong, Z., Gao, J., Sha, A., Hu, L., & Li, S. (2018). Convolutional neural network for asphalt pavement surface texture analysis. *Computer-Aided Civil and Infrastructure Engineering*, 33(12), 1056-1072.
- [287] Torbruegge, S., & Wies, B. (2015). Characterization of pavement texture by means of height difference correlation and relation to wet skid resistance. *Journal of traffic and transportation engineering (English edition)*, 2(2), 59-67.
- [288] Vaitkus, A., Andriejauskas, T., Vorobjovas, V., Jagniatinskis, A., Fiks, B., & Zofka, E. (2017). Asphalt wearing course optimization for road traffic noise reduction. *Construction and Building Materials*, 152, 345-356.
- [289] Vaswani, A. (2017). Attention is all you need. *Advances in Neural Information Processing Systems*.
- [290] Vieira, T., Sandberg, U., & Erlingsson, S. (2021). Negative texture, positive for the environment: effects of horizontal grinding of asphalt pavements. *Road Materials and Pavement Design*, 22(1), 1-22.
- [291] Vilaça, J. L., Fonseca, J. C., Pinho, A. C. M., & Freitas, E. (2010). 3D surface profile equipment for the characterization of the pavement texture—TexScan. *Mechatronics*, 20(6), 674-685.
- [292] Vogel, H. J., & Roth, K. (2001). Quantitative morphology and network representation of soil pore structure. *Advances in water resources*, 24(3-4), 233-242.

- [293] Vuttipittayamongkol, P., Elyan, E., & Petrovski, A. (2021). On the class overlap problem in imbalanced data classification. *Knowledge-based systems*, 212, 106631.
- [294] Wan, C., Zhang, X., Wang, S., Wu, W., & Wu, Z. (2010). Reconstruction of 3D digital specimen of asphalt mixture based on X-CT technology. *Journal of Highway and Transportation Research and Development*, 11.
- [295] Wang, H., Huang, Z., Li, L., You, Z., & Chen, Y. (2014). Three-dimensional modeling and simulation of asphalt concrete mixtures based on X-ray CT microstructure images. *Journal of Traffic and Transportation Engineering (English Edition)*, 1(1), 55-61.
- [296] Wang, H., Wang, J. and Chen, J. (2014). Micromechanical analysis of asphalt mixture fracture with adhesive and cohesive failure. *Engineering Fracture Mechanics*, 132, pp.104-119.
- [297] Wang, L., Hoyos, L. R., Wang, J., Voyiadjis, G., & Abadie, C. (2005). Anisotropic properties of asphalt concrete: characterization and implications for pavement design and analysis. *Journal of materials in civil engineering*, 17(5), 535-543.
- [298] Wang, T., Chu, L., & Fwa, T. F. (2022). Improved numerical method for determination of pavement mean texture depth from 3-dimensional digital image. *Construction and Building Materials*, 358, 129447.
- [299] Wang, T., Harvey, J., & Kendall, A. (2014). Reducing greenhouse gas emissions through strategic management of highway pavement roughness. *Environmental Research Letters*, 9(3), 034007.
- [300] Wang, X., & Ying, P. (2000). Research on the air voids of asphalt mixture. *Journal of Chongqing Jiaotong University*, 19(4), 18-21.
- [301] Wang, Y., Lai, X., Zhou, F., & Xue, J. (2020). Evaluation of pavement skid resistance using surface three-dimensional texture data. *Coatings*, 10(2), 162.
- [302] Wang, Z., Xie, J., Gao, L., Liu, Y., & Tang, L. (2021). Three-dimensional characterization of air voids in porous asphalt concrete. *Construction and Building Materials*, 272, 121633.
- [303] Wang, Z.M., Kwan, A.K.H. and Chan, H.C. (1999). Mesoscopic study of concrete I: generation of random aggregate structure and finite element mesh. *Computers & structures*, 70(5), pp.533-544.

- [304] Watson, D.E., Brown, E.R., & Moore, J. (2005). Comparison of Superpave and Marshall mix performance in Alabama. *Transportation research record*, 1929(1), pp.133-140.
- [305] White, T. D. (1985). Marshall procedures for design and quality control of asphalt mixtures. In *Association of asphalt paving technologists proc.* Vol. 54.
- [306] Wu, F., Li, J., Yang, H., Yang, P., Liu, J., Liang, X., & Yuan, B. (2019). Research of pavement topography based on NURBS reconstruction for 3D structured light. *Optik*, 194, 163074.
- [307] Wu, S., & Zhang, H. (2011). Comparative analysis of Marshall compaction and rotation compaction test results. *Urban Construction Theory Study: Electronic Version* (35).
- [308] Wu, Y., Lin, L., Wang, J., & Wu, S. (2020). Application of semantic segmentation based on convolutional neural network in medical images. *Sheng Wu Yi Xue Gong Cheng Xue Za Zhi= Journal of Biomedical Engineering= Shengwu Yixue Gongchengxue Zazhi*, 37(3), 533-540.
- [309] Xiang, Z., Zhang, Q., & Wu, Z. (2022). 3D shape measurement and texture mapping method based on structured light projection. *Opto-Electronic Engineering*, 49(12), 220169-1.
- [310] Xin, M., & Wang, Y. (2019). Research on image classification model based on deep convolution neural network. *EURASIP Journal on Image and Video Processing*, 2019(1), 1-11.
- [311] Xu, J., Li, Z., Du, B., Zhang, M., & Liu, J. (2020). Reluplex made more practical: Leaky ReLU. In *2020 IEEE Symposium on Computers and communications (ISCC)* (pp. 1-7). IEEE.
- [312] Yaacob, H., Hassan, N. A., Hainin, M. R., & Rosli, M. F. (2014). Comparison of sand patch test and multi laser profiler in pavement surface measurement. *Jurnal Teknologi*, 70(4).
- [313] Yan, Y., Ran, M., Sandberg, U., Zhou, X., & Xiao, S. (2020). Spectral techniques applied to evaluate pavement friction and surface texture. *Coatings*, 10(4), 424.
- [314] Yang, S., We, Y., Ye, Z., Liu, H., Yang, B., Liu, W., & Wang, L. (2025). Characterization and modeling of textured cement concrete pavement surfaces for tire-pavement noise prediction. *Applied Acoustics*, 227, 110183.
- [315] You, Z., Adhikari, S., & Dai, Q. (2010). Air void effect on an idealised asphalt

- mixture using two-dimensional and three-dimensional discrete element modelling approach. *International Journal of Pavement Engineering*, 11(5), 381-391.
- [316] Yu, D., Cao, Y., & Zhao, Q. (2023). Detection and Analysis of Asphalt Pavement Texture Depth Based on Digital Image Analytics Technology. *International Journal of Pavement Research and Technology*, 1-10.
- [317] Yu, J., Ma, L., Tian, M., & Lu, X. (2021). Registration and Fusion of UAV LiDAR System Sequence Images and Laser Point Clouds. *Journal of Imaging Science & Technology*, 65(1).
- [318] Zaltuom, A. M. (2018). A review study of the effect of air voids on asphalt pavement life. In *Proceedings of First Conference for Engineering Sciences and Technology* (Vol. 2, pp. 618-625).
- [319] Zeng, M., & Wu, C. (2008). Effects of type and content of mineral filler on viscosity of asphalt mastic and mixing and compaction temperatures of asphalt mixture. *Transportation research record*, 2051(1), pp.31-40.
- [320] Zhang, C., & Li, L. (1996). Application of X-CT Technique to Reservoirs Research.
- [321] Zhang, F., & Wang, X. (2021). Object tracking in siamese network with attention mechanism and Mish function. *Academic Journal of Computing & Information Science*, 4(1), 75-81.
- [322] Zhang, M., Li, J., Yin, H., Wang, X., Qin, Y., Yang, Z., ... & Xu, L. (2024). Pilot analysis of tire tread characteristics and associated tire-wear particles in vehicles produced across distinct time periods. *Science of the Total Environment*, 932, 172760.
- [323] Zhang, Q., Li, H., & Wang, Q. (2023). Wide-angle rectification via content-aware conformal mapping. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 17357-17365).
- [324] Zhang, T., & Duan, Y. (2010). The research of different segmentation methods based on CT scan images of asphalt mixtures [J]. *Guangdong Highway Communications*, 3.
- [325] Zhang, X. N., Duan, Y. H., Li, Z., Wu, W. L., & Wan, C. (2011). Classification of asphalt mixture materials based on X-ray computed tomography. *Journal of South China University of Technology*, 39(3).
- [326] Zhang, Y. D., Pan, C., Sun, J., & Tang, C. (2018). Multiple sclerosis identification by convolutional neural network with dropout and parametric

- ReLU. *Journal of computational science*, 28, 1-10.
- [327] Zhou, J., Wang, X., Zheng, C., & Bao, X. (2007). Comparison of Superpave and Marshall Methodology on Asphalt Mixture Design. *Journal of Wuhan University of Technology*, 29 (9), 68-70.
- [328] Zhuang, F., Qi, Z., Duan, K., Xi, D., Zhu, Y., Zhu, H., ... & He, Q. (2020). A comprehensive survey on transfer learning. *Proceedings of the IEEE*, 109(1), 43-76.
- [329] Zoorob, S. E., & Cabrera, J. G. (1997). Design and construction of a road pavement using fly-ash in hot rolled asphalt. In *Studies in environmental science* (Vol. 71, pp. 149-165). Elsevier.
- [330] Zuniga-Garcia, N., & Prozzi, J. A. (2016). *Contribution of micro-and macro-texture for predicting friction on pavement surfaces* (No. CHPP Report-UTA# 3-2016).

Forthcoming Publications

1. Relationship Between the Void Properties and Surface Macrostructure of Asphalt Mixture (in preparation).
2. Exploring the Correlation Between Mean Profile Depth and Mean Texture Depth in Asphalt Slabs: An Experimental and Virtual Modeling Approach (in preparation).
3. A Deep Convolutional Neural Network for Image-Based Asphalt Surface Texture Recognition (in preparation for "Automation in Construction").

Appendices

Chapter 3: Void Properties and Macrotexture Correlation

Methodology Summary

1. Sample Preparation and CT Scanning

- **Marshall Core Fabrication:** 19 cylindrical specimens (100 mm diameter $\times$ 65 mm height) with controlled air voids (3.96–22.23%) and maximum aggregate sizes (6.3–20 mm) were compacted using the Marshall method. Materials included granite/limestone aggregates and 60/40 penetration-grade bitumen.
- **CT Data Acquisition:** Dry cores were scanned on a Phoenix v|tomex|L scanner (290 kV, 2700 μ A) at 90.54 μ m resolution, generating 16-bit TIFF stacks. Images were cropped to 1150 $\times$ 1150 pixels to reduce cone-beam artifacts.

2. Image Segmentation and Void Topology Analysis

- **ROI Definition:** A central cylindrical ROI (90 mm diameter, 46 mm height) was selected and analyzed using ImageJ across 170 cross-sectional slices (0.27 mm interval).
- **Phase Segmentation:** The Trainable Weka Segmentation plugin (ImageJ) was used to classify aggregates (green), mastic (red), and voids (purple) in CT slices. By stacking 170 slices, 3D reconstructions of voids, mastic, and VMA were generated.
- **Topological Property Quantification:**
 - **The average void diameter** can be calculated in 3D via the BoneJ plugin by approximating voids as inscribed spheres, whereas macroporosity, void circularity, perimeter, and aspect ratio were derived from planar area analyses. The sphere-based AVD exhibited significant variability with changes in the number of CT slices, necessitating the adoption of planar area algorithms for more stable measurements.
 - **Euler number and percolation number** were measured using ImageJ's Analyze Particles function to assess void connectivity.

- **Tortuosity:** Evaluated via 3D void trajectory analysis.

3. Macrotexture Measurement

- **3D Surface Reconstruction:** Top/bottom surfaces of cores were reconstructed from 150 CT slices using ImageJ and Autodesk Netfabb. Four 45°-spaced profiles were extracted per surface, yielding eight profiles/core.
- **MPD_{CT} Calculation:** Profiles were processed per ISO 13473-1:2019: dropout interpolation, resampling at 0.5 mm, slope suppression, and windowing to compute MPD_{CT} and dominant wavelength.

4. Statistical Analysis

Pearson Correlation & Regression: Minitab was used to analyze relationships between void properties (AVD, perimeter, etc.) and MPD_{CT}. Multivariate regression models in MATLAB incorporated AVD, void perimeter, and connectivity metrics to predict MPD_{CT} (Single parameter: $R^2=0.8$, Multi-parameter: R^2 up to 0.88).

Table 12: Composition of Analysed Asphalt Cores

Sample number	Material	Aggregate percentage [%]						Bitumen [%]	Air void content [%]
		20mm	14mm	10mm	6.3mm	Dust	Filler		
1	Limestone	0.0	0.0	0.0	42.9	51.1	6.0	7.0	3.96
2	Granite	0.0	0.0	0.0	44.4	49.6	6.0	7.0	7.97
3	Limestone	0.0	0.0	0.0	49.0	51.0	0.0	6.0	11.68
4	Granite	0.0	0.0	0.0	47.2	52.8	0.0	5.3	20.68
5	Limestone	0.0	0.0	56.4	0.0	37.6	6.0	6.0	1.41
6	Granite	0.0	0.0	59.4	5.4	26.2	9.0	6.5	5.56
7	Granite	0.0	0.0	51.9	14.8	25.3	8.0	7.3	9.56
8	Limestone	0.0	0.0	72.4	4.5	23.1	0.0	7.0	11.24
9	Granite	0.0	0.0	57.6	10.1	28.3	4.0	5.7	13.44
10	Granite	0.0	0.0	63.2	13.5	18.3	5.0	5.5	19.19
11	Granite	0.0	0.0	70.8	4.7	24.5	0.0	5.5	22.23
12	Granite	0.0	64.4	0.0	4.7	26.9	4.0	5.2	7.68
13	Limestone	0.0	59.4	14.5	3.2	22.9	0.0	5.0	10.94
14	Granite	0.0	60.0	15.0	5.0	20.0	0.0	5.0	16.93
15	Granite	18.7	18.5	13.3	9.5	34.0	6.0	7.0	3.18
16	Granite	25.0	45.0	0.0	10.0	13.0	7.0	5.7	9.81
17	Limestone	18.7	18.6	13.6	9.2	33.9	6.0	4.0	10.98
18	Granite	25.0	45.0	0.0	10.0	13.0	7.0	5.6	12.98
19	Limestone	20.0	20.0	15.0	15.0	30.0	0.0	7.0	16.21

Table 13: Analysis of Air Voids and Macrotexture Properties in Asphalt Mixtures

Sample number	Air Voids										Voids in Mineral Aggregate										VM	NA	MPD _{CT}	λ
	M	AVD	EN	VAV	PN	T	VP	VAR	VC	VR	M	AVD	EN	VAV	PN	T	VP	VAR	VC	VR				
1	1.2	1.3	2167	109	0.0	1.1	4.8	1.7	0.8	0.7	38.0	7.1	-65956	111243	1.0	1.0	52.1	2.4	0.4	0.5	99131	6539	0.5	6.3
2	8.1	2.0	2268	1977	0.1	1.9	7.5	1.9	0.7	0.6	42.5	10.2	-81210	124155	1.0	1.0	60.5	2.5	0.4	0.5	87517	6350	0.5	5.0
3	9.9	2.0	1368	2676	0.1	3.1	7.9	1.9	0.7	0.6	33.6	4.8	-91258	98158	1.0	1.0	46.2	2.4	0.3	0.5	64498	7263	0.5	4.0
4	17.3	2.1	-6567	49433	1.0	1.8	9.6	2.1	0.5	0.5	35.3	4.7	-125115	103290	1.0	1.0	47.5	2.4	0.3	0.5	45987	6533	0.6	4.0
5	0.6	1.4	1076	41	0.0	1.0	4.7	1.4	0.9	0.8	43.9	21.0	-24859	128357	1.0	1.0	101.8	2.4	0.4	0.5	107149	3346	0.2	2.5
6	4.5	2.2	1429	735	0.1	1.8	8.1	1.9	0.7	0.6	29.1	3.5	-76662	84941	1.0	1.1	27.3	2.4	0.3	0.5	68112	3465	0.5	12.5
7	8.1	2.8	779	5586	0.2	2.3	10.6	1.9	0.7	0.6	33.8	6.2	-43399	98587	1.0	1.0	54.8	2.5	0.4	0.5	70918	3980	0.9	4.0
8	5.2	2.3	1000	2050	0.1	2.7	8.8	2.0	0.6	0.6	32.7	7.4	-47087	95594	1.0	1.0	58.6	2.6	0.3	0.5	73933	2971	1.0	5.0
9	12.4	2.8	191	30912	0.9	4.2	11.7	2.0	0.6	0.6	31.1	4.2	-54622	90816	1.0	1.0	34.6	2.5	0.3	0.5	52430	3954	0.8	5.0
10	16.8	3.2	-449	46612	1.0	2.0	13.8	2.1	0.6	0.6	34.6	5.9	-39415	101038	1.0	1.0	50.5	2.6	0.4	0.5	49621	3602	0.8	2.5
11	20.9	2.7	-5377	60459	1.0	1.4	12.9	2.2	0.5	0.5	35.5	6.1	-64923	103745	1.0	1.0	57.4	2.5	0.3	0.5	38169	3573	0.7	4.0
12	5.7	2.5	954	1204	0.1	1.9	9.5	2.0	0.7	0.6	23.1	3.4	-67836	67433	1.0	1.1	27.2	2.7	0.3	0.5	49028	2357	0.8	6.3
13	5.1	2.6	710	1401	0.1	1.9	9.8	2.0	0.6	0.6	30.2	8.3	-30729	88408	1.0	1.1	67.8	2.8	0.4	0.5	64429	2312	0.8	3.15
14	13.3	3.2	-196	36468	0.9	2.3	13.5	2.1	0.6	0.5	32.0	12.3	-48071	93523	1.0	1.1	79.6	2.9	0.3	0.5	44550	2295	1.0	4.0
15	1.1	1.6	1246	130	0.0	2.1	5.6	1.7	0.8	0.6	26.8	7.6	-60656	78278	1.0	1.2	71.8	2.6	0.2	0.5	68093	3276	0.4	3.15
16	6.8	3.5	385	4999	0.3	1.9	13.1	2.1	0.6	0.6	30.8	10.1	-26178	90013	1.0	1.1	73.4	2.6	0.4	0.5	64047	1846	1.3	16.0
17	7.6	2.2	-1499	18828	0.9	3.5	10.3	2.4	0.5	0.5	36.9	10.4	-51873	107978	1.0	1.0	69.5	2.5	0.4	0.5	70878	3287	0.6	4.0
18	12.3	3.6	216	27711	0.8	2.9	14.5	2.0	0.6	0.6	30.3	7.5	-27056	88621	1.0	1.1	58.4	2.7	0.3	0.5	48987	1815	1.1	6.3
19	14.6	4.0	-339	24781	0.6	2.6	17.2	2.0	0.6	0.6	48.2	24.7	-14411	140843	1.0	1.0	96.9	2.5	0.4	0.5	82149	3495	0.6	5.0

Air void content, %, (AVC); Number of Aggregates (NA); Volume of Mastic, mm³, (VM); Maximum Aggregate Size, mm, (MAS); Macroporosity, %, (M); Average Void Diameter, mm, (AVD); Euler Number (EN); Volume of the biggest Air Void, mm³, (VAV); Percolation

Number, %, (PN); Tortuosity (T); Void Perimeter, mm, (VP); Void Aspect Ratio, %, (VAR); Void Circularity, %, (VC); Void Roundness, %, (VR).

Table 14: Pearson Correlation Coefficients Between Air Void (bottom, grey) and VMA Topologies (top, yellow)

VMA V_a	AVC	NA	VM	MAS	M	AVD	EN	VAV	PN	T	VP	VAR	VC	VR
AVC	1.00	0.00	-0.72	-0.05	0.09	-0.10	-0.13	0.09	NA	-0.36	-0.07	0.15	0.03	-0.20
NA	0.00	1.00	0.28	-0.73	0.38	-0.18	-0.72	0.38	NA	-0.43	-0.25	-0.72	0.02	0.42
VM	-0.72	0.28	1.00	-0.13	0.59	0.54	0.22	0.59	NA	-0.25	0.44	-0.45	0.48	0.70
MAS	-0.05	-0.73	-0.13	1.00	-0.16	0.36	0.61	-0.16	NA	0.56	0.43	0.48	-0.11	-0.19
M	0.96	0.07	-0.69	-0.08	1.00	0.75	0.18	1.00	NA	-0.69	0.61	-0.49	0.72	0.84
AVD	0.58	-0.54	-0.50	0.51	0.58	1.00	0.58	0.75	NA	-0.23	0.90	-0.03	0.55	0.68
EN	-0.76	-0.07	0.57	0.05	-0.73	-0.16	1.00	0.17	NA	0.02	0.59	0.47	0.44	0.02
VAV	0.90	-0.02	-0.67	-0.04	0.92	0.43	-0.82	1.00	NA	-0.69	0.61	-0.49	0.72	0.84
PN	0.85	-0.12	-0.65	0.14	0.85	0.51	-0.73	0.94	1.00	NA	NA	NA	NA	NA
T	0.23	-0.07	-0.29	0.27	0.23	0.37	0.06	0.12	0.35	1.00	-0.16	0.41	-0.73	-0.47
VP	0.74	-0.44	-0.56	0.45	0.74	0.97	-0.36	0.62	0.68	0.38	1.00	0.16	0.35	0.47
VAR	0.74	-0.20	-0.68	0.29	0.65	0.56	-0.54	0.56	0.68	0.51	0.68	1.00	-0.26	-0.72
VC	-0.89	0.16	0.72	-0.23	-0.82	-0.63	0.67	-0.75	-0.82	-0.44	-0.78	-0.96	1.00	0.57
VR	-0.77	0.14	0.73	-0.23	-0.68	-0.57	0.49	-0.57	-0.66	-0.54	-0.69	-0.98	0.95	1.00

Table 15: Pearson Correlation Coefficients Between Air Voids and VMA Properties

Pearson' s correlation coefficients (19 mixtures)											
Air voids VMA	Macroporosit y	Average void diameter (2D)	Average void diameter (3D)	Euler number	Volume of the biggest air void	Percolation number	Tortuosity	Void perimeter	Voids Aspect ratio	Voids circularity	Voids roundness
Macroporosit y	0.154	-0.029	-0.207	-0.085	0.121	0.094	-0.139	0.068	-0.173	0.031	0.226
Average void diameter (2D)	-0.074	0.193	0.152	0.097	-0.062	-0.025	-0.132	0.195	-0.238	0.127	0.316
Average void diameter (3D)	0.267	0.803	0.767	0.063	0.191	0.27	0.169	0.748	0.152	-0.259	-0.125
Euler number	-0.153	0.528	0.648	0.35	-0.127	-0.022	0.085	0.418	-0.082	0.065	0.133
Volume of the biggest air void	0.154	-0.029	-0.208	-0.085	0.12	0.094	-0.138	0.067	-0.172	0.03	0.224
Tortuosity	-0.355	-0.002	0.182	0.242	-0.311	-0.267	0.052	-0.108	-0.081	0.186	0.04
Void perimeter	-0.103	0.12	0.1	0.02	-0.031	0.007	-0.184	0.127	-0.189	0.11	0.279
Voids Aspect ratio	0.041	0.48	0.568	0.13	0.081	0.147	0.037	0.387	0.241	-0.213	-0.265
Voids circularity	0.066	0.239	0.206	0.102	-0.028	0.019	-0.026	0.236	-0.052	-0.004	0.131
Voids roundness	-0.114	-0.298	-0.384	-0.016	-0.116	-0.15	-0.159	-0.228	-0.405	0.303	0.475

Table 16: Linear Prediction Model for MPD_{CT} (Excluding Outliers)

MPD model's evaluation (Excluding 20-10)												
Model	S(N)	R ²	R ² (adj)	R ² (pred)	Air voids							
					Air voids content	Number of aggregate	Mastic (Vitural)	Average void diameter	Euler number	Volume of the biggest air void	Percolation number	Void perimeter
1	0.229716	0.3603	0.3204	0.1807		X						
2	0.170387	0.6481	0.6261	0.5608								X
3	0.120338	0.8245	0.8135	0.756				X				
	0.191133	0.5848	0.5295	0.4093		X	X					
4	0.105993	0.8723	0.8553	0.7697	X			X				
5	0.111971	0.8575	0.8385	0.7623				X		X		
6	0.110162	0.8621	0.8437	0.7698				X			X	
7	0.108082	0.8672	0.8495	0.7849				X				X
8	0.109395	0.8731	0.8459	0.7821		X		X				X
9	0.104737	0.8836	0.8587	0.7882				X	X			X

Table 17: Linear Prediction Model for Wavelength (Excluding Outliers)

λ model's evaluation (Excluding 20-10)																	
Model	S(N)	R ²	R ² (adj)	R ² (pred)	Air voids												
					Air voids content	Number of aggregate	Mastic (Vitural)	Mastic (CT)	Maximum aggregate size	Macroporosity	Average void diameter	Euler number	Volume of the biggest air void	Percolation number	Void perimeter	Voids Aspect ratio	Voids circularity
1	4.29227	0.3394	0.2981	0.0867					X								
2	4.49767	0.2747	0.2293	0.0961											X		
3	4.32575	0.3291	0.2871	0.1701							X						
4	4.2767	0.3852	0.3032	0.1511		X	X										
5	4.33484	0.3683	0.2841	0.1705	X						X						
6	4.22461	0.4001	0.3201	0.1783		X					X						
7	4.1714	0.4151	0.3371	0.2265				X			X						
8	4.14619	0.4221	0.3451	0.2563						X	X						
9	4.32047	0.3725	0.2889	0.172							X	X					
10	4.24082	0.3954	0.3148	0.202							X		X				
11	3.75568	0.5575	0.4626	0.2568						X	X						X
12	3.49027	0.6451	0.5359	0.3596				X	X						X		X
13	3.57683	0.6273	0.5126	0.3921				X		X	X						X
14	3.54679	0.6617	0.5208	0.3311				X	X	X	X						X
15	3.53118	0.6647	0.525	0.3705				X	X		X				X		X

Chapter 4: MPD-MTD Modeling via Virtual Asphalt and Experimental Validation

Methodology Summary

1. Physical Asphalt Slab Preparation

Slab Fabrication: 60 slabs (30×30×5 cm) were compacted with varied gradations (6.3–20 mm MAS), binder contents (4–7%), and air voids (0.96–26.51%) using a laboratory roller compactor.

2. Texture Measurement

- **Laser Scanning:** AMES 9400HD scanner captured 100×70 mm profiles at submillimeter precision. MPD_{LS} was calculated from 10 equidistant profiles/scan.
- **Sand Patch Test:** MTD_{SPT} was measured by spreading sand to form circular patches, with the diameter used to compute depth (ASTM E965-96). Triplicate measurements were averaged to reduce error.

3. Virtual Asphalt Generation (ISA Method)

- **2D Void Network Construction:**
 - Random placement of non-overlapping circular/elliptical aggregates in a rectangular domain.
 - Particles grew iteratively until contacting neighbors or reaching a max radius (0.1 mm initial radius).
 - Rejection sampling ensured non-overlapping nucleation centers until the target AVC was met.
- **3D Model Extension:** 2D domains were extruded into spherical volumes, stacked vertically with CT-matched slice spacing, and converted to Boolean matrices (voids = 0, material = 1).

4. Virtual Texture Quantification

- **AVD Measurement:** A 90 mm-diameter ROI was extracted from virtual slices; the void area/count was used to compute AVD via ImageJ.

- **MPD_{ISA} Simulation:** Vertical slices at 1/3 and 2/3 heights were processed per ISO 13473-1:2019 to extract MPD_{ISA} from 8 profiles/slab.
- **MTD_{ISA} Algorithms:**
 - **2D Approach:** Connected void area/surface profile length.
 - **3D Volumetric Method:** Largest connected void volume/external surface area (BoneJ plugin).

5. Nonlinear MPD_{LS}-MTD_{SPT} Modeling

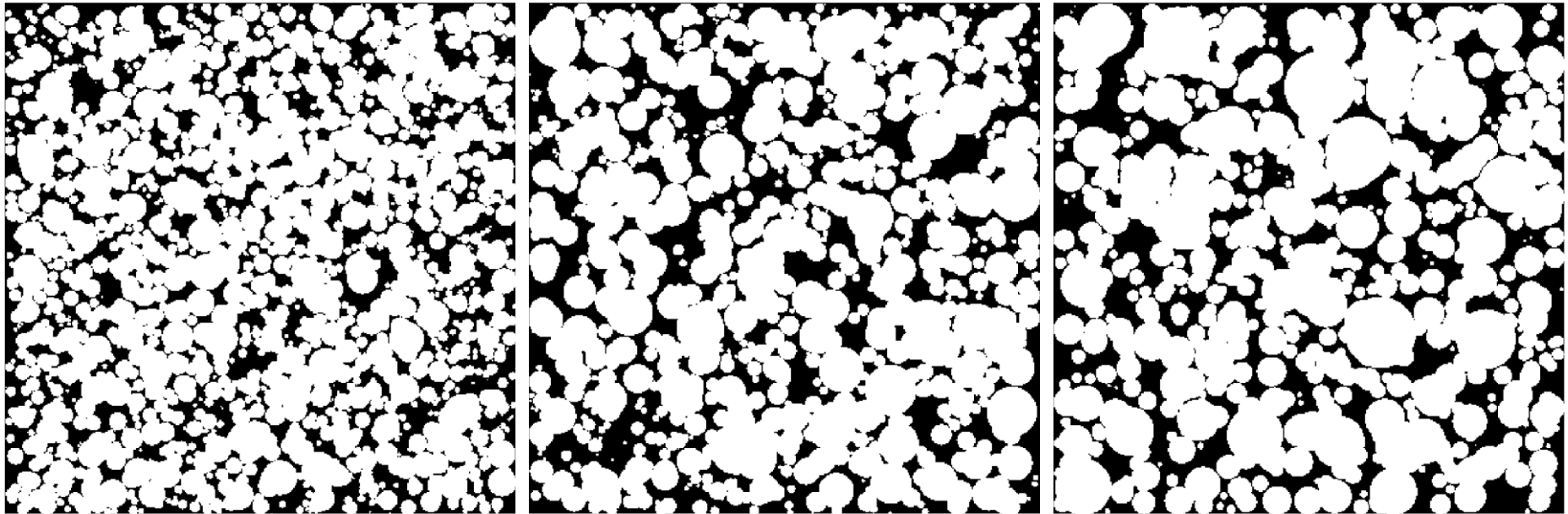
Multivariate Regression: A log-normal model integrated MAS and MPD_{LS} to predict MTD_{SPT} ($R^2 = 0.85$, validated against 60 slabs). Combined with air void content, R^2 is further improved to 0.94.

Table 18: Composition and Texture Measurements of Asphalt Slabs

Code	Binder percentage [%]	Aggregate percentage [%]						Fiber [%]	Maximum aggregate size [mm]	Air voids [%]	MTD _{SPT} [mm]	MPD _{LS} [mm]
		20mm	14mm	10mm	6.3mm	dust	filler					
20-703	5.3	0	0	0	85	15	0	NO	6.3	14.64	1.074	0.858
20-708	5.3	0	0	0	85	15	0	NO	6.3	23.28	2.186	1.101
20-721	5.3	0	0	0	88.2	9.8	2	NO	6.3	24.04	2.721	1.172
20-722	5.3	0	0	0	78.4	19.6	2	NO	6.3	18.38	1.551	0.953
21-249	7.0	0	0	0	79.9	14.1	6	NO	6.3	15.08	1.546	1.046
21-250	4.0	0	0	0	83.3	14.7	2	NO	6.3	26.10	2.567	1.097
21-251	7.0	0	0	0	81.6	14.4	4	NO	6.3	17.19	1.964	1.073
21-252	7.0	0	0	0	85	15	0	NO	6.3	20.21	2.151	1.154
21-256	6.0	0	0	0	90	10	0	NO	6.3	25.27	2.660	1.170
21-257	5.3	0	0	0	70	30	0	NO	6.3	17.86	1.249	0.754
21-258	5.3	0	0	0	80	20	0	NO	6.3	20.07	1.693	0.951
21-259	5.3	0	0	0	75	25	0	NO	6.3	19.39	1.172	0.895
21-260	5.3	0	0	0	86.4	9.6	4	NO	6.3	21.45	2.985	1.156
21-261	5.3	0	0	0	84.6	9.4	6	NO	6.3	18.90	2.355	1.220
21-262	5.3	0	0	0	76.8	19.2	4	NO	6.3	18.24	1.634	0.915
21-263	4.0	0	0	0	75.2	18.8	6	NO	6.3	17.21	1.480	0.846
21-264	5.3	0	0	0	73.5	24.5	2	NO	6.3	17.25	1.385	0.846
21-265	5.3	0	0	0	72	24	4	NO	6.3	14.67	1.350	0.843
21-266	5.0	0	0	0	70.5	23.5	6	NO	6.3	13.65	1.276	0.797

20-874	6.0	0	0	58.8	0	39.2	2	NO	10	4.86	1.172	0.862
20-875	7.0	0	0	57.6	0	38.4	4	NO	10	2.59	1.172	1.002
20-876	7.0	0	0	60	10	30	0	NO	10	9.65	1.612	1.178
20-877	7.0	0	0	49	9.8	39.2	2	NO	10	3.79	1.182	0.981
21-247	5.5	0	0	75	7	18	0	NO	10	19.36	3.210	1.379
21-248	4.3	0	0	91	0	9	0	NO	10	26.51	5.320	1.529
20-704	5.0	0	60	15	5	20	0	NO	14	15.99	2.117	1.391
20-709	5.0	0	60	15	5	20	0	NO	14	15.50	2.437	1.512
21-468	6.6	0	55	22	15	8	0	NO	14	20.45	5.567	1.695
21-469	6.6	0	55	22	15	8	0	NO	14	21.74	7.066	1.748
21-470	6.6	0	55	22	15	8	0	NO	14	21.85	7.140	1.885
21-471	6.6	0	55	22	15	8	0	NO	14	20.57	6.420	1.683
21-2309	6.4	0	5	55	16	14	10	0.4	14	3.85	1.377	1.201
21-2310	6.4	0	5	55	16	14	10	0.4	14	3.19	0.856	0.774
21-2313	6.4	0	5	55	16	14	10	0.4	14	5.38	1.062	0.863
21-2314	6.4	0	5	55	16	14	10	0.4	14	3.98	1.417	1.202
20-705	7.0	20	20	15	15	30	0	NO	20	10.16	1.465	1.068
20-706	7.0	19.6	19.6	14.7	14.7	29.4	2	NO	20	5.18	1.007	0.878
20-707	7.0	18.8	18.8	14.1	14.1	28.2	6	NO	20	4.86	1.168	0.899
20-710	7.0	20	20	15	15	30	0	NO	20	5.06	1.446	1.125
20-711	7.0	19.6	19.6	14.7	14.7	29.4	2	NO	20	2.29	1.346	1.282

20-712	7.0	18.8	18.8	14.1	14.1	28.2	6	NO	20	0.96	1.204	1.163
20-713	4.0	60	20	10	0	10	0	NO	20	22.38	9.155	2.393
20-714	4.0	50	30	10	0	10	0	NO	20	20.76	7.486	2.196
20-715	4.0	40	40	10	0	10	0	NO	20	21.12	8.257	2.307
20-716	4.5	59.25	19.25	9.25	0	9.25	3	NO	20	19.36	8.739	2.513
20-717	4.5	49.25	29.25	9.25	0	9.25	3	NO	20	18.17	8.639	2.394
20-718	4.5	39.25	39.25	9.25	0	9.25	3	NO	20	18.50	8.995	2.267
20-719	5.0	58.5	18.5	8.5	0	8.5	6	NO	20	16.64	8.304	2.742
20-720	5.0	48.5	28.5	8.5	0	8.5	6	NO	20	16.65	8.590	2.358
21-253	7.0	19.2	19.2	14.4	14.4	28.8	4	NO	20	3.39	1.390	1.336
21-254	5.0	38.5	38.5	8.5	0	8.5	6	NO	20	17.91	5.750	2.177
21-255	5.0	60	10	10	5	9	6	NO	20	14.34	5.203	2.174
21-2311	5.1	5	15	20	28	24	8	NO	20	3.79	1.024	0.854
21-2312	5.1	5	15	20	28	24	8	NO	20	4.31	1.280	1.078
22-1	6.0	5	51	17	3	14	10	YES	20	8.15	1.652	1.453
22-2	6.0	5	51	17	3	14	10	YES	20	7.82	1.495	1.430
22-3	6.0	5	51	17	3	14	10	YES	20	5.15	1.458	1.373
22-4	6.0	5	51	17	3	14	10	YES	20	6.67	1.368	1.391
22-5	6.0	5	51	17	3	14	10	YES	20	7.75	1.669	1.549
22-6	6.0	5	51	17	3	14	10	YES	20	6.91	1.595	1.469

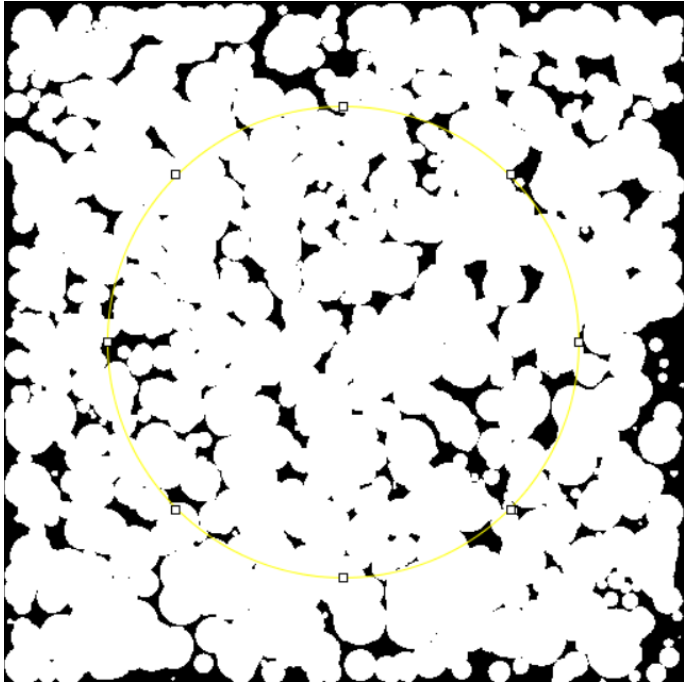


AVC=15.47%

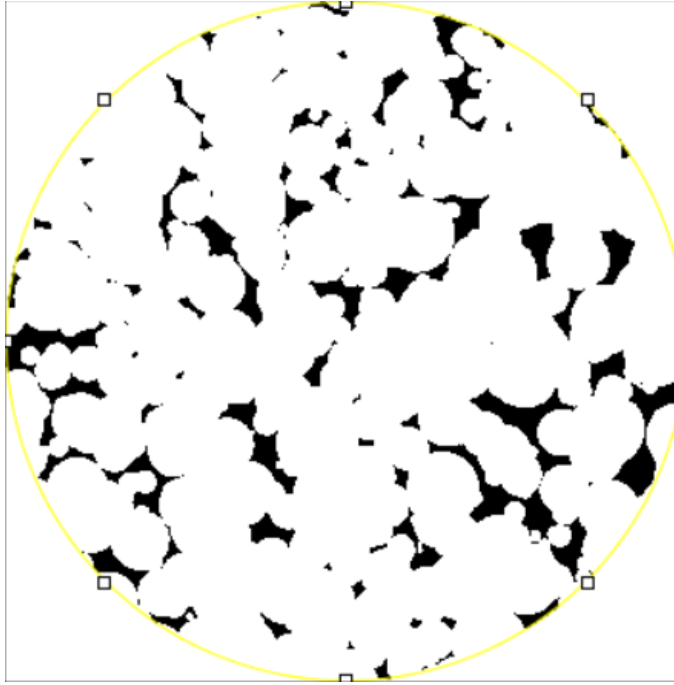
AVC=14.96%

AVC=18.73%

Figure 64: Visual Representation of Domain Configurations with Different Maximum Aggregate Size



Virtual



Real

Figure 65: Comparison of the Extracted ROI from Virtual Asphalt and Real Samples

Table 19: Data Comparison Between Real CT-Measured Cores and Virtual ISA-Generated Asphalt Mixtures

Code	Maximum aggregate size	Real		Virtual		Real					Virtual					Void area connected		MTD [mm] 2D			Average void diameter				Volume of the biggest air void	Area	MTD 3D					
		Air void content	Average void diameter	Air void content	Average void diameter	Top	Bottom	Average	Max	Min	MPD [mm]					Overall average	Image 1	Image 2	Profile length	Image 1	Image 2	Average	2	Total								
											Side 1	Side 2	Side 3	Side 4	Average													Side 1	Side 2	Side 3	Side 4	Average
20-589	6	3.96%	1.34	4.10%	1.45	0.480	0.467	0.474	0.56	0.373	0.427	0.310	0.395	0.497	0.407	0.366	0.482	0.398	0.446	0.423	0.415	274.710	285.033	520.2	0.528	0.548	0.538	0.76	1.29	6127.762	7.112	1.66
20-627	6	7.97%	1.97	7.47%	2.02	0.591	0.482	0.537	0.658	0.41	0.913	0.758	0.828	1.025	0.881	0.755	0.728	0.953	1.014	0.863	0.872	624.838	559.098	520.2	1.201	1.075	1.138	1.52	2.01	11158.984	6.858	3.13
20-602	6	11.68%	2.02	11.77%	2.06	0.538	0.425	0.481	0.662	0.352	0.977	1.071	0.869	0.792	0.927	0.776	0.701	0.899	1.118	0.874	0.900	611.160	564.128	520.2	1.175	1.084	1.130	1.73	2.13	16067.189	6.35	4.86
20-540	6	20.68%	2.05	20.80%	2.04	0.703	0.526	0.615	0.88	0.483	0.957	0.876	0.811	0.829	0.868	0.883	1.038	0.981	0.937	0.960	0.914	810.579	979.937	520.2	1.558	1.884	1.721	2.14	2.34	21246.828	5.334	7.66
20-636	10	1.41%	1.41	4.33%	1.92	0.213	0.159	0.186	0.241	0.146	0.774	0.729	0.681	0.812	0.749	0.753	0.647	0.741	0.740	0.720	0.735	463.870	463.354	520.2	0.892	0.891	0.891	1.22	2.09	14846.533	11.938	2.39
21-51	10	5.56%	2.2	5.95%	2.29	0.636	0.393	0.514	0.896	0.325	1.430	1.134	1.053	0.942	1.140	0.924	0.797	1.104	0.917	0.936	1.038	676.967	615.031	520.2	1.301	1.182	1.242	1.56	2.63	20095.112	11.684	3.31
21-54	10	9.56%	2.8	9.24%	2.84	1.008	0.715	0.861	1.454	0.595	1.478	1.241	1.088	1.258	1.266	1.678	1.450	1.110	1.236	1.369	1.317	944.063	965.934	520.2	1.815	1.857	1.836	2.67	3.51	25599.003	10.668	4.61
20-249	10	11.24%	2.28	11.24%	2.26	0.953	0.965	0.959	1.198	0.766	0.902	0.986	1.015	1.206	1.027	1.409	1.115	1.012	0.955	1.123	1.075	753.999	809.999	520.2	1.449	1.557	1.503	2.12	2.51	23786.2	9.652	4.74
21-59	10	13.44%	2.84	13.39%	2.84	0.781	0.802	0.791	0.892	0.659	1.521	1.214	1.306	1.726	1.442	1.669	1.593	1.319	1.542	1.531	1.486	1271.417	1016.966	520.2	2.444	1.955	2.200	3.13	3.80	28515.065	9.398	5.83
21-58	10	19.19%	3.22	19.26%	3.16	0.899	0.787	0.843	0.995	0.653	1.553	1.961	1.813	1.871	1.800	1.531	2.062	2.028	2.086	1.927	1.863	2039.739	1931.997	520.2	3.921	3.714	3.818	4.29	4.65	30753.816	7.62	7.76
20-577	10	22.23%	2.67	22.16%	2.68	0.692	0.734	0.713	0.879	0.597	1.455	1.683	1.688	1.813	1.660	1.400	1.798	1.646	1.475	1.580	1.620	1838.062	1895.997	520.2	3.533	3.645	3.589	3.64	3.99	33513.725	7.62	8.45
21-63	14	7.68%	2.54	7.66%	2.56	0.876	0.755	0.816	1.111	0.58	1.339	1.239	0.978	1.201	1.189	1.727	1.397	1.041	0.856	1.255	1.222	805.870	872.837	520.2	1.549	1.678	1.614	2.47	3.04	28883.282	14.478	3.84
21-567	14	10.94%	2.59	10.20%	2.59	0.821	0.854	0.838	1.295	0.544	1.332	1.351	1.325	1.455	1.366	1.675	1.289	1.251	1.355	1.393	1.379	1014.321	1119.805	520.2	1.950	2.153	2.051	2.87	3.10	34426.108	13.716	4.82
20-262	14	16.93%	3.2	17.12%	3.20	0.827	1.173	1.000	1.264	0.616	1.888	2.745	1.968	2.177	2.195	2.179	2.281	1.856	1.752	2.017	2.106	1798.965	1696.836	520.2	3.458	3.262	3.360	4.85	5.11	44141.883	11.684	7.26
20-284	20	3.18%	1.59	3.88%	2.61	0.352	0.386	0.369	0.518	0.273	1.273	1.664	1.202	1.106	1.311	1.586	1.308	1.382	1.468	1.436	1.374	874.192	911.418	520.2	1.680	1.752	1.716	2.04	3.60	36419.725	23.114	3.03
21-67	20	9.81%	3.47	9.80%	3.47	1.752	0.920	1.336	2.287	0.63	1.806	1.874	2.345	2.093	2.030	2.769	1.940	2.298	1.846	2.213	2.121	1585.094	1500.965	520.2	3.047	2.885	2.966	3.85	4.83	54429.895	19.812	5.28
20-42	20	10.98%	2.19	10.45%	2.44	0.362	0.823	0.593	0.972	0.293	1.229	1.250	1.339	1.277	1.274	1.555	1.430	1.539	1.541	1.516	1.395	1043.030	1059.998	520.2	2.005	2.038	2.021	2.55	3.05	48551.069	19.558	4.77
21-384	20	12.98%	3.63	12.67%	3.64	1.213	0.982	1.098	1.332	0.793	2.536	2.276	1.841	2.435	2.272	2.047	2.655	2.481	2.337	2.380	2.326	1628.707	2062.133	520.2	3.131	3.964	3.548	3.81	5.19	56766.862	17.78	6.14
20-10	20	16.21%	3.95	16.16%	3.91	0.990	0.283	0.637	1.224	0.225	3.936	1.849	2.907	2.329	2.755	3.570	2.482	3.243	3.873	3.292	3.024	2556.383	2297.037	520.2	4.914	4.416	4.665	6.70	6.82	61958.391	16.256	7.33

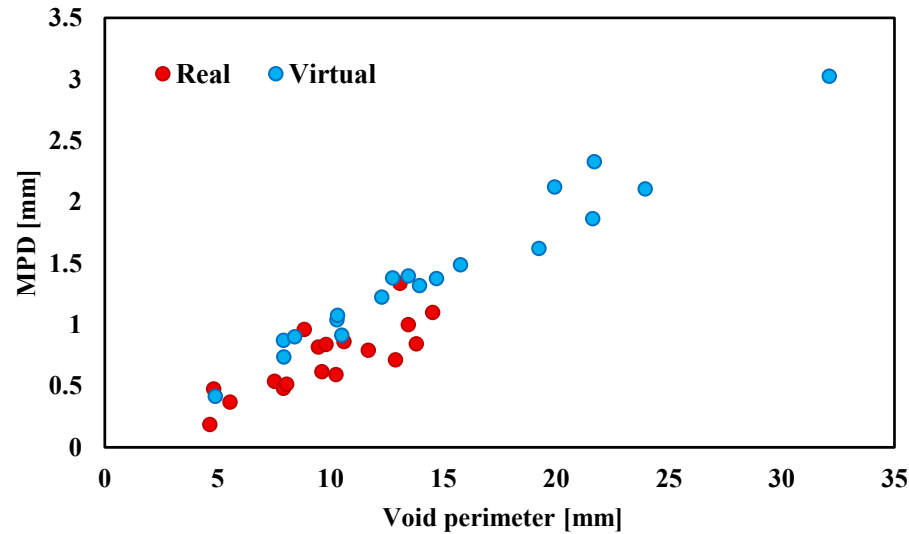


Figure 66: Correlation Between MPD and Void Perimeter

Table 20: Virtual ISA-Generated Asphalt Mixture Data for Slabs

Maximum aggregate size	Air void content	Average void diameter	MPD [mm]											Void area connected to the surface			MTD [mm] 2D				Average void diameter				Volume of the biggest air void	Height	MTD 3D
			Side 1	Side 2	Side 3	Side 4	Average	Side 1	Side 2	Side 3	Side 4	Average	Overall average	Image 1	Image 2	Profile length	Image 1	Image 2	Average	Air voids	Total	Middle (-3+2)					
6	4.46%	1.65	0.641	0.503	0.559	0.551	0.564	0.449	0.458	0.416	0.519	0.461	0.512	370.515	323.032	520.2	0.712	0.621	0.667	4.96%	1.42	1.05	6148.56	7.366	1.60		
6	5.15%	1.81	0.581	0.607	0.603	0.625	0.604	0.527	0.600	0.755	0.659	0.635	0.620	393.548	397.160	520.2	0.757	0.763	0.760	5.83%	1.63	1.27	7705.41	7.366	2.01		
6	6.62%	1.93	0.675	0.825	0.702	0.831	0.758	0.669	0.691	0.830	0.733	0.731	0.744	462.902	465.806	520.2	0.890	0.895	0.893	7.13%	1.93	1.43	11931.2	7.366	3.11		
6	7.75%	2.10	1.151	0.926	1.086	0.776	0.985	0.798	0.954	1.007	0.920	0.920	0.952	609.031	614.321	520.2	1.171	1.181	1.176	8.21%	2.15	1.71	13608.1	7.112	3.68		
6	9.60%	2.26	0.853	1.082	0.872	0.873	0.920	1.013	1.202	1.087	0.859	1.040	0.980	598.450	711.676	520.2	1.150	1.368	1.259	9.75%	2.37	1.99	15001.9	6.858	4.21		
6	11.69%	2.44	1.248	1.234	1.061	1.246	1.197	1.029	1.228	1.668	1.424	1.337	1.267	884.837	949.159	520.2	1.701	1.825	1.763	11.84%	2.72	2.31	17133.9	6.35	5.24		
6	14.14%	2.71	1.592	1.713	1.422	1.662	1.597	1.476	1.593	1.557	1.637	1.566	1.581	1180.514	979.805	520.2	2.269	1.884	2.076	14.23%	3.25	2.82	17964.3	5.588	6.18		
6	18.72%	3.01	1.870	2.321	1.782	2.500	2.118	1.423	1.964	1.324	2.156	1.717	1.917	1707.158	1786.642	520.2	3.282	3.435	3.358	18.99%	4.34	3.91	17799.5	4.318	7.92		
10	3.88%	1.88	0.704	0.805	0.828	0.800	0.784	0.548	0.553	0.858	0.835	0.698	0.741	500.902	442.902	520.2	0.963	0.851	0.907	4.20%	1.87	1.38	13967.8	11.684	2.30		
10	4.19%	2.01	0.784	0.923	0.691	0.826	0.806	0.746	1.106	0.788	0.851	0.873	0.839	499.483	534.902	520.2	0.960	1.028	0.994	4.66%	2.09	1.61	14519	11.684	2.39		
10	5.30%	2.27	0.932	0.976	0.876	0.947	0.933	0.962	1.017	1.349	0.883	1.053	0.993	607.676	653.418	520.2	1.168	1.256	1.212	5.70%	2.49	2.00	17791.6	11.684	2.93		
10	6.38%	2.42	1.219	0.970	1.094	0.914	1.049	1.023	1.292	0.954	0.961	1.057	1.053	639.160	669.805	520.2	1.229	1.288	1.258	6.82%	2.81	2.23	19850.3	11.43	3.34		
10	7.51%	2.68	1.400	1.156	1.562	1.209	1.332	1.471	1.371	1.448	1.391	1.420	1.376	925.353	1012.901	520.2	1.779	1.947	1.863	8.10%	3.25	2.72	23873.2	11.176	4.11		
10	8.96%	2.94	1.415	1.819	1.363	1.436	1.508	1.625	1.749	1.654	1.477	1.626	1.567	1053.933	1077.095	520.2	2.026	2.071	2.048	9.29%	3.69	3.22	25128.3	10.668	4.53		
10	11.18%	3.07	2.304	1.825	1.774	1.884	1.947	1.880	1.207	1.837	2.522	1.862	1.904	1173.933	1266.320	520.2	2.257	2.434	2.345	11.11%	3.95	3.55	27465.7	9.906	5.33		
10	13.39%	3.49	2.300	1.779	1.887	2.740	2.176	2.214	2.326	2.940	2.414	2.295	2.295	1432.771	1680.900	520.2	2.754	3.231	2.993	13.88%	4.81	4.39	28444.7	8.636	6.33		
10	21.68%	4.09	2.962	3.061	2.614	2.577	2.803	3.898	3.556	2.223	3.688	3.341	3.072	3714.509	3432.445	520.2	7.141	6.598	6.869	19.88%	6.32	5.97	19764.6	4.064	9.35		
14	4.11%	2.28	0.945	0.875	0.962	1.120	0.976	1.035	1.070	0.988	1.081	1.043	1.009	660.515	612.902	520.2	1.270	1.178	1.224	3.81%	2.47	2.00	22761.9	16.51	2.65		
14	4.52%	2.45	1.276	1.153	0.921	0.969	1.080	1.093	1.149	1.516	1.342	1.275	1.177	682.644	719.160	520.2	1.312	1.382	1.347	4.56%	2.74	2.28	24812.9	16.51	2.89		
14	5.24%	2.67	1.280	1.211	1.721	2.017	1.557	1.077	1.309	1.472	1.724	1.396	1.476	828.514	892.966	520.2	1.593	1.717	1.655	5.59%	3.16	2.63	28748.6	16.256	3.40		
14	5.82%	2.87	1.576	1.602	1.716	1.473	1.592	1.731	1.713	1.102	1.459	1.501	1.547	923.482	1032.579	520.2	1.775	1.985	1.880	7.11%	3.82	3.31	27458.2	15.748	3.35		
14	6.64%	2.99	1.779	1.988	1.901	1.362	1.758	1.464	1.606	1.487	1.701	1.564	1.661	1078.191	994.192	520.2	2.073	1.911	1.992	6.73%	3.79	3.43	31122.4	15.24	3.93		
14	9.04%	3.58	2.429	1.369	1.599	2.134	1.883	2.265	1.450	1.588	2.511	1.954	1.918	1320.126	1513.158	520.2	2.538	2.909	2.723	8.29%	4.39	3.97	36826.9	14.478	4.89		
14	10.76%	3.79	2.145	2.568	2.236	2.763	2.428	2.835	1.720	2.387	2.495	2.359	2.394	1775.158	1837.738	520.2	3.412	3.533	3.473	10.04%	4.82	4.36	39575.7	13.462	5.65		
14	12.97%	4.31	3.080	2.305	2.228	2.289	2.475	2.230	2.902	2.466	2.115	2.428	2.452	1879.287	2119.093	520.2	3.613	4.074	3.843	11.67%	5.95	5.70	40426.4	11.684	6.65		
14	16.02%	4.39	2.121	3.659	3.563	2.628	2.993	2.117	3.202	4.081	3.411	3.203	3.098	2431.092	2508.447	520.2	4.673	4.822	4.748	16.48%	7.55	7.49	39199.2	9.906	7.61		
20	4.19%	2.63	1.517	1.316	1.448	1.243	1.381	1.001	1.020	1.431	1.356	1.202	1.292	930.643	801.289	520.2	1.789	1.540	1.665	3.95%	3.12	2.62	35174.2	22.606	2.99		
20	4.38%	2.93	1.805	1.729	1.726	1.782	1.760	1.473	1.976	1.783	2.108	1.835	1.798	1047.998	1028.643	520.2	2.015	1.977	1.996	3.79%	3.32	2.87	38353	22.606	3.26		
20	4.54%	2.50	1.423	1.519	1.388	1.250	1.395	1.465	1.130	1.185	1.368	1.287	1.341	935.934	853.160	520.2	1.799	1.640	1.720	5.46%	3.43	2.76	35970	21.844	3.17		
20	4.74%	3.06	1.784	1.663	1.718	2.248	1.853	2.129	1.845	1.618	1.602	1.799	1.826	1047.675	1149.417	520.2	2.014	2.210	2.112	4.48%	4.02	3.57	43357.1	22.86	3.65		
20	5.72%	3.45	1.417	1.628	1.560	1.733	1.584	1.912	1.991	2.051	1.542	1.874	1.729	1301.675	1224.256	520.2	2.502	2.353	2.428	5.42%	4.28	3.72	44907.5	22.352	3.86		
20	5.80%	2.46	1.438	1.154	1.446	1.419	1.364	1.453	1.225	1.389	1.035	1.276	1.320	883.418	868.579	520.2	1.698	1.670	1.684	5.30%	2.96	2.55	37787.4	21.082	3.45		
20	6.16%	3.60	2.099	2.540	3.026	3.305	2.743	2.038	2.296	1.445	1.508	1.822	2.282	1508.965	1369.546	520.2	2.901	2.633	2.767	7.04%	5.27	4.82	49937.3	21.336	4.50		
20	6.77%	2.52	1.622	1.550	1.389	1.539	1.525	1.335	1.715	1.280	1.509	1.460	1.492	1065.869	1007.288	520.2	2.049	1.936	1.993	6.83%	3.26	2.81	41619.2	20.828	3.84		
20	7.18%	3.97	1.474	2.528	4.464	3.183	2.912	2.197	3.446	3.876	2.703	3.056	2.984	1788.061	1870.061	520.2	3.437	3.595	3.516	6.34%	5.46	5.12	54929.7	20.32	5.20		
20	7.48%	2.42	1.440	1.558	1.488	1.504	1.497	1.238	1.467	1.952	0.992	1.412	1.455	1033.869	1064.643	520.2	1.987	2.047	2.017	8.82%	3.38	3.03	42037.6	20.32	3.98		
20	10.91%	4.63	3.237	1.776	2.639	3.810	2.865	2.833	2.610	3.150	3.451	3.011	2.938	1945.996	2289.157	520.2	3.741	4.401	4.071	10.13%	7.27	7.04	61098.3	19.558	6.01		
20	15.97%	5.52	3.565	6.713	4.541	3.038	4.464	3.688	6.746	2.907	3.105	4.111	4.288	3768.767	3519.606	520.2	7.245	6.766	7.005	12.74%	8.14	7.98	49149.9	10.922	8.65		
20	17.86%	5.96	4.716	4.839	4.015	5.395	4.741	4.239	5.790	3.245	4.862	4.534	4.638	4200.250	4008.766	520.2	8.074	7.706	7.890	14.58%	9.55	9.35	46194.6	9.906	8.96		
20	18.19%	4.93	3.338	3.179	4.488	1.785																					

Chapter 5: Deep Learning for Asphalt Surface Texture Prediction

Methodology Summary

1. Dataset Collection

- **Set A (Lab Slabs):** 1,788 images/MPD_{LS} pairs from 60 slabs, captured by Huawei P40 Pro (3840×2592 pixels, 15 cm height).
- **Set B (Composite):** 855 images from lab slabs, parking lots, etc., acquired via iPad Pro (4032×3024 pixels, 40 cm height), segmented into 4,622 sub-regions.
- **Set C (Field Roads):** 2,004 images from in-service roads, the same as Set A's camera/height.

2. Data Preprocessing

- **Spatial Alignment:** Cropping to 2600×1900 pixels (Sets A/C) or 1344×1512 sub-regions (Set B).
- **Augmentation:**
 - Geometric: 90° rotations, fifty percent horizontal flips, random shifts (10% max), with nearest padding.
 - Intensity: Pixel values normalized to [0, 1] (1/255 scaling).
- **Resolution:** All images resized to 200×200 pixels for computational efficiency.

3. Model Architecture and Training

- Classification Model (VGG-style CNN):
 - Layers: 3 conv (32→64→128 filters) + 1 FC (128 neurons), softmax output.
 - Optimizer: SGD (lr=0.001, momentum=0.9), 50 epochs.
- Regression Model (VGG19):
 - Layers: 16 conv (2*64→2*128→4*256→8*512 filters) + 3 FC (4096, 4096, 1000 neurons), linear output.
 - Optimizer: Adam (lr=0.0001, clipnorm=1.0), 50 epochs.

4. Classification Strategies

- **Non-overlapping Intervals:** Discrete MPD_{LS} ranges (e.g., <0.8 mm, 0.8–1.0 mm) for straightforward grading.
- **Overlapping Intervals:** Adjacent ranges (e.g., 0.8–1.2 mm, 1.0–1.4 mm) during training to leverage transitional features, with strict non-overlapping test sets.

5. Performance Evaluation

- **Metrics:**
 - Classification: Accuracy, confusion matrices.
 - Regression: Mean Absolute Error, Mean Squared Error.
- **Key Findings:**
 - Overlapping intervals improved accuracy by 20–30% vs. non-overlapping.
 - Regression MAE: 0.136 mm (Set A), 0.320 mm (Set C), reflecting real-world variability.

No.	Code	Binder percent	20mm	14mm	10mm	6.3mm	dust	filler	Fiber	Maximum aggregate	Air voids	MTD	MPD range	MPD mean	Test before	Central mean
Aggregate percentage (%)																
1	20-703	5.3	0	0	0	85.5	9.5	0	0	6.3	14.64%	1.074	0.268	0.888		0.804
2	20-703	5.3	0	0	0	85.5	9.5	0	0	6.3	14.64%	1.074	0.268	0.888		0.804
3	20-721	5.3	0	0	0	24.04%	72.1	0	0	6.3	24.04%	1.185	0.155	0.703	1.104	1.155
4	20-722	5.3	0	0	0	78.4	19.6	2	0	6.3	18.38%	1.651	0.219	0.953	1.055	0.929
5	21-249	7.0	0	0	0	79.9	14.1	5.46	6	0	6.3	15.06%	0.406	1.045	1.020	0.983
6	21-250	4.0	0	0	0	85.3	14.2	2.567	2	0	6.3	26.10%	0.257	1.090	1.097	1.122
7	21-251	7.0	0	0	0	81.6	14.4	4	0	6.3	17.19%	1.954	0.237	1.073	1.083	1.071
8	21-252	7.0	0	0	0	81.6	15	2.151	0	0	6.3	20.31%	0.154	1.164	1.162	1.044
9	21-256	5.3	0	0	0	26.27%	10.0	0	0	6.3	26.27%	1.185	0.155	0.703	1.104	1.155
10	21-257	5.3	0	0	0	70	30	0	0	6.3	17.86%	1.249	0.225	0.754	0.811	0.766
11	21-258	5.3	0	0	0	80	20	0	0	6.3	20.07%	1.693	0.326	0.951	1.157	0.917
12	21-259	5.3	0	0	0	75	25	0	0	6.3	19.39%	1.172	0.313	0.895	0.888	0.909
13	21-260	5.3	0	0	0	86.4	9.6	4	0	6.3	14.5%	2.985	0.287	1.156	1.144	1.208
14	21-261	5.3	0	0	0	86.4	9.4	6	0	6.3	18.99%	2.355	0.38	1.220	1.175	1.231
15	21-262	5.3	0	0	0	86.4	9.4	6	0	6.3	18.99%	2.355	0.38	1.220	1.175	1.231
16	21-263	4.0	0	0	0	75.2	18.8	6	0	6.3	17.21%	1.480	0.275	0.846	0.884	0.924
17	21-264	5.3	0	0	0	75.2	24.5	2	0	6.3	17.25%	1.385	0.247	0.846	0.877	0.849
18	21-265	5.3	0	0	0	72.4	24	4	0	6.3	14.67%	1.350	0.269	0.843	0.791	0.824
19	21-266	5.0	0	0	0	70.5	23.5	6	0	6.3	13.65%	1.276	0.233	0.797	0.785	0.833
20	21-874	6.0	0	0	0	58.8	0	39.2	2	0	4.86%	1.172	0.233	0.862	0.865	0.861
21	21-875	7.0	0	0	0	58.8	0	39.2	2	0	4.86%	1.172	0.233	0.862	0.865	0.861
22	21-876	7.0	0	0	0	58.8	0	39.2	2	0	4.86%	1.172	0.233	0.862	0.865	0.861
23	21-877	7.0	0	0	0	58.8	0	39.2	2	0	4.86%	1.172	0.233	0.862	0.865	0.861
24	21-878	7.0	0	0	0	58.8	0	39.2	2	0	4.86%	1.172	0.233	0.862	0.865	0.861
25	21-879	7.0	0	0	0	58.8	0	39.2	2	0	4.86%	1.172	0.233	0.862	0.865	0.861
26	21-880	7.0	0	0	0	58.8	0	39.2	2	0	4.86%	1.172	0.233	0.862	0.865	0.861
27	21-881	7.0	0	0	0	58.8	0	39.2	2	0	4.					

Table 22: Characteristics and Data Collection Methods of Asphalt Surface Datasets

Features	Set A	Set B	Set C
Data Source	60 Laboratory-prepared asphalt slabs	Newly laid roads not yet in use, parking lots, semi-closed areas around buildings, and asphalt slabs	In-service roads
Lighting	Consistent lighting conditions in the laboratory	Natural weather and light conditions. Laboratory light	Natural weather and light conditions
Data Collection Method	Laser scanning and photography		
Data Standardization	The capture area is consistent with the scanning area.	Ensured consistency through additional image processing steps	The capture area is consistent with the scanning area.
Number of Samples	1788	855	2004
Laser Scanning Area	10x7 cm		
MPD_{LS} Range	0.6-3.3 mm	0.4-4.1 mm	0.1-4.4 mm
Camera	Huawei P40 Pro	iPad Pro	Huawei P40 Pro
Image Capture Size	Approximately 16x10 cm	Approximately 45x35 cm	Approximately 16x10 cm
Image Capture Height	15 cm	37 cm	15 cm
Image Resolution	3840x2592	4032x3024	3840x2592
Image Cropping Size	Approximately 2600x1900	1344x1512	Approximately 2600x1900
Data Augmentation	Rotation copy: 7152	Segmentation: 5017 Rotation copy: 20068	Rotation copy: 8016
Model Deployment Laptop	Intel 8th-generation i7 CPU, 32 GB of RAM, NVIDIA RTX 2070 graphics card		

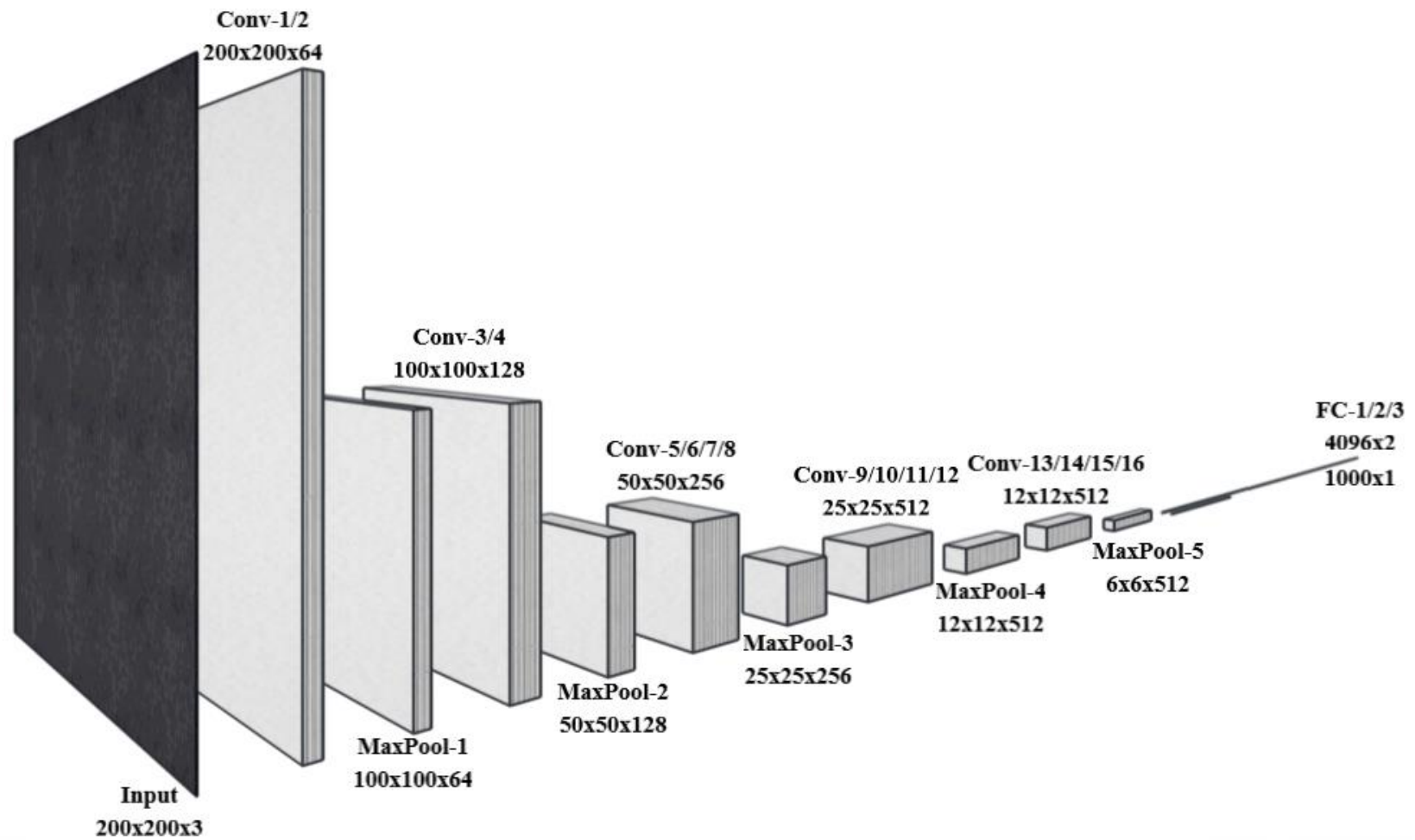
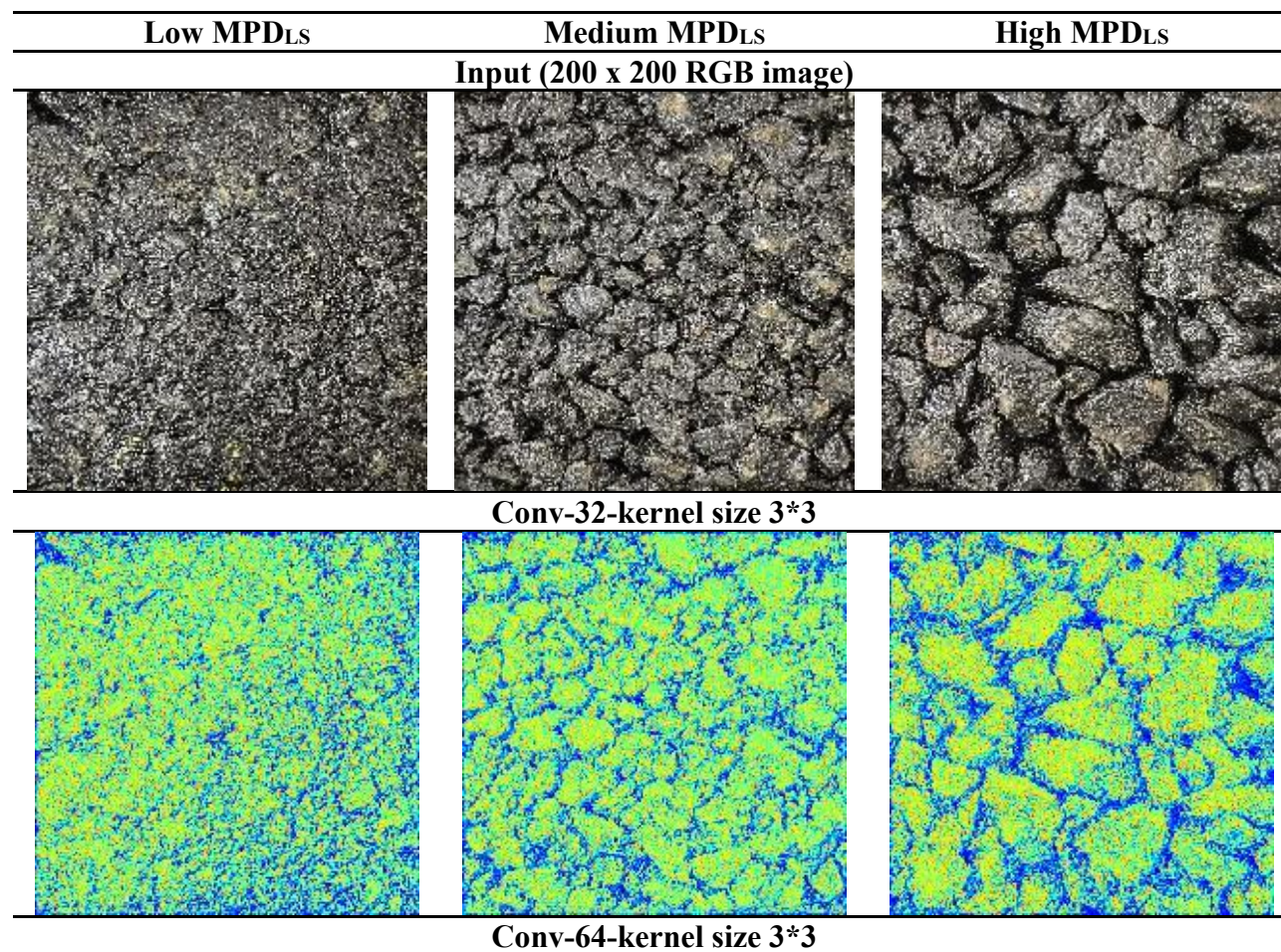


Figure 67: VGG19 Model Architecture Schematic



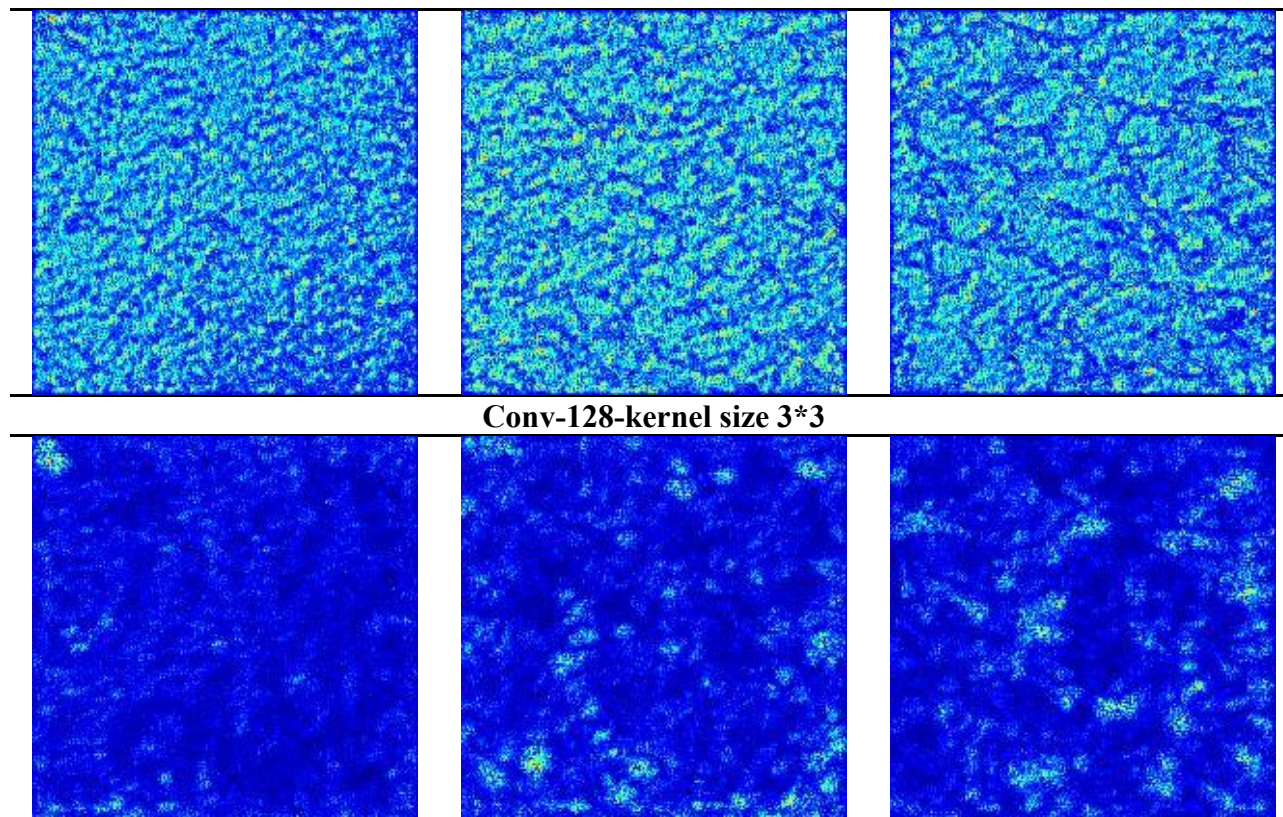


Figure 68: Saliency Map Visuals for Varied MPDs_{LS} in Convolutional Network Layers

Dr. Jason Brownlee's Python code for classification based on the VGG3 model

```
# baseline model with data augmentation for the dogs vs cats dataset
import sys
from matplotlib import pyplot
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Conv2D
from keras.layers import MaxPooling2D
from keras.layers import Dense
from keras.layers import Flatten
from keras.optimizers import SGD
from keras.preprocessing.image import ImageDataGenerator

# define cnn model
def define_model():
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same', input_shape=(200, 200, 3)))
    model.add(MaxPooling2D((2, 2)))
    model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
    model.add(MaxPooling2D((2, 2)))
    model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))
    model.add(MaxPooling2D((2, 2)))
    model.add(Flatten())
    model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
    model.add(Dense(1, activation='sigmoid'))
    # compile model
    opt = SGD(lr=0.001, momentum=0.9)
    model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
    return model
```

```

# plot diagnostic learning curves
def summarize_diagnostics(history):
    # plot loss
    pyplot.subplot(211)
    pyplot.title('Cross Entropy Loss')
    pyplot.plot(history.history['loss'], color='blue', label='train')
    pyplot.plot(history.history['val_loss'], color='orange', label='test')
    # plot accuracy
    pyplot.subplot(212)
    pyplot.title('Classification Accuracy')
    pyplot.plot(history.history['accuracy'], color='blue', label='train')
    pyplot.plot(history.history['val_accuracy'], color='orange', label='test')
    # save plot to file
    filename = sys.argv[0].split('/')[-1]
    pyplot.savefig(filename + '_plot.png')
    pyplot.close()

# run the test harness for evaluating a model
def run_test_harness():
    # define model
    model = define_model()
    # create data generators
    train_datagen = ImageDataGenerator(rescale=1.0/255.0,
        width_shift_range=0.1, height_shift_range=0.1, horizontal_flip=True)
    test_datagen = ImageDataGenerator(rescale=1.0/255.0)
    # prepare iterators
    train_it = train_datagen.flow_from_directory('dataset_dogs_vs_cats/train/',
        class_mode='binary', batch_size=64, target_size=(200, 200))
    test_it = test_datagen.flow_from_directory('dataset_dogs_vs_cats/test/',
        class_mode='binary', batch_size=64, target_size=(200, 200))

```

```
# fit model
history = model.fit_generator(train_it, steps_per_epoch=len(train_it),
                             validation_data=test_it, validation_steps=len(test_it), epochs=50, verbose=0)
# evaluate model
_, acc = model.evaluate_generator(test_it, steps=len(test_it), verbose=0)
print('> %.3f % (acc * 100.0))
# learning curves
summarize_diagnostics(history)

# entry point, run the test harness
run_test_harness()
```

Python Code for Asphalt Surface Classification Based on VGG Model

```
import sys
import time
import pandas as pd
from matplotlib import pyplot
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.callbacks import Callback

# Callback for displaying training progress
class TrainingProgress(Callback):
    def __init__(self, total_epochs):
        super(TrainingProgress, self).__init__()
        self.total_epochs = total_epochs
        self.start_time = time.time()

    def on_epoch_end(self, epoch, logs=None):
        elapsed_time = time.time() - self.start_time
        remaining_time = elapsed_time * (self.total_epochs - (epoch + 1)) / (epoch + 1)
        percent_complete = (epoch + 1) / self.total_epochs * 100
        print(f'Epoch {epoch + 1}/{self.total_epochs} complete. {percent_complete:.2f}% done. Estimated time remaining: {remaining_time / 60:.2f} minutes.')

# Define cnn model
def define_model():
    model = Sequential()
    model.add(Conv2D(32, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same', input_shape=(200, 200, 3)))
```

```

model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))

model.add(MaxPooling2D((2, 2)))
model.add(Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'))

model.add(MaxPooling2D((2, 2)))
model.add(Flatten())
model.add(Dense(128, activation='relu', kernel_initializer='he_uniform'))
model.add(Dense(8, activation='softmax'))
opt = SGD(learning_rate=0.001, momentum=0.9)
model.compile(optimizer=opt, loss='categorical_crossentropy', metrics=['accuracy'])
return model

# Plot diagnostic learning curves
def summarize_diagnostics(history, output_path):
    # plot loss
    pyplot.figure(figsize=(8, 6))
    pyplot.subplot(211)
    pyplot.title('Cross Entropy Loss')
    pyplot.plot(history.history['loss'], color='blue', label='train')
    pyplot.plot(history.history['val_loss'], color='orange', label='test')
    pyplot.legend(loc='upper right')

    # plot accuracy
    pyplot.subplot(212)
    pyplot.title('Classification Accuracy')
    pyplot.plot(history.history['accuracy'], color='blue', label='train')
    pyplot.plot(history.history['val_accuracy'], color='orange', label='test')

```

```

pyplot.legend(loc='lower right')

# Adjust the spacing between the plots
pyplot.subplots_adjust(hspace=0.3)

# save plot to file
pyplot.savefig(output_path + 'plot.png', dpi=300)
pyplot.close()
# save history data to Excel
pd.DataFrame(history.history).to_excel(output_path + 'history_data.xlsx')

# run the test harness for evaluating a model
def run_test_harness():
    # define model
    model = define_model()
    # create data generators
    train_datagen = ImageDataGenerator(rescale=1.0/255.0,
                                       width_shift_range=0.1, height_shift_range=0.1, horizontal_flip=True)
    test_datagen = ImageDataGenerator(rescale=1.0/255.0)
    # prepare iterators
    train_it = train_datagen.flow_from_directory('MPD:/train/',
                                                class_mode='categorical', batch_size=20, target_size=(200, 200))
    test_it = test_datagen.flow_from_directory('MPD:/test/',
                                              class_mode='categorical', batch_size=20, target_size=(200, 200))

    epochs = 50 # Total number of epochs
    progress_callback = TrainingProgress(total_epochs=epochs)

    # fit model
    history = model.fit(train_it,

```

```

        steps_per_epoch=len(train_it),
        validation_data=test_it,
        validation_steps=len(test_it),
        epochs=epochs,
        verbose=0,
        callbacks=[progress_callback])

# evaluate model
_, acc = model.evaluate(test_it, steps=len(test_it), verbose=0)
print('> %.3f % (acc * 100.0))

# learning curves
output_path = 'MPD:/ /'
summarize_diagnostics(history, output_path)

# save model
model.save(output_path + 'model_name.h5')

# Entry point, run the test harness
run_test_harness()

```

Python Code for MPD_{LS} Classification Prediction Model Validation

```
import os
import numpy as np
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.models import load_model

# Load model
model_path = 'MPD:/output_path/model_name.h5'
model = load_model(model_path)

# Load images
images_dir = 'MPD:/test'
image_paths = [os.path.join(images_dir, f) for f in os.listdir(images_dir) if f.endswith('.jpg')]

# Initialize a dictionary to store the count for each class
# Note: Adjusting the keys to start from 1 instead of 0
class_count = {i+1:0 for i in range(6)} # Adjusted here

# Loop over all images
for image_path in image_paths:
    # Load image
    image = load_img(image_path, target_size=(200, 200))
    image = img_to_array(image)
    image = np.expand_dims(image, axis=0)
    image = image.astype('float32')
    image = image / 255.0

    # Predict class
    result = model.predict(image)
```

```
predicted_class = result.argmax(axis=-1)[0] + 1 # Incrementing here to make classes start from 1

# Increment count for the predicted class
class_count[predicted_class] += 1

# Print class count
for class_id, count in class_count.items():
    print("Class ", class_id, ": ", count, "images")
```

Python Code for Regression Prediction of MPD_{VGG} Based on VGG19

```
import os
import numpy as np
import re
import time
import pandas as pd
from matplotlib import pyplot
from tensorflow.keras.preprocessing.image import ImageDataGenerator, img_to_array, load_img
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dense, Flatten
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import Callback, ReduceLROnPlateau
from tensorflow.keras.utils import Sequence

class TrainingProgress(Callback):
    def __init__(self, total_epochs):
        super().__init__()
        self.total_epochs = total_epochs
        self.start_time = time.time()

    def on_epoch_end(self, epoch, logs=None):
        elapsed_time = time.time() - self.start_time
        remaining_time = elapsed_time * (self.total_epochs - (epoch + 1)) / (epoch + 1)
        percent_complete = (epoch + 1) / self.total_epochs * 100
        print(f'Epoch {epoch + 1}/{self.total_epochs} complete. {percent_complete:.2f}% done. Estimated time remaining: {remaining_time / 60:.2f} minutes.')

def define_model():
    model = Sequential([
        Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same', input_shape=(200, 200, 3)),
```

```

Conv2D(64, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
MaxPooling2D((2, 2)),
Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(128, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
MaxPooling2D((2, 2)),
Conv2D(256, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(256, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(256, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(256, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
MaxPooling2D((2, 2)),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
MaxPooling2D((2, 2)),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
Conv2D(512, (3, 3), activation='relu', kernel_initializer='he_uniform', padding='same'),
MaxPooling2D((2, 2)),
Flatten(),
Dense(4096, activation='relu', kernel_initializer='he_uniform'),
Dense(4096, activation='relu', kernel_initializer='he_uniform'),
Dense(1000, activation='relu', kernel_initializer='he_uniform'),
Dense(1, activation='linear')
])

opt = Adam(learning_rate=0.0001, clipnorm=1.0)
model.compile(optimizer=opt, loss='mean_squared_error', metrics=['mae'])
return model

```

```

class CustomImageGenerator(Sequence):
    def __init__(self, directory, batch_size=32, target_size=(200, 200), shuffle=True, augment=False):
        self.directory = directory
        self.batch_size = batch_size
        self.target_size = target_size
        self.shuffle = shuffle
        self.augment = augment
        self.image_filenames = os.listdir(directory)
        self.indexes = np.arange(len(self.image_filenames))
        self.datagen = ImageDataGenerator(
            rescale=1.0/255.0,
            width_shift_range=0.1,
            height_shift_range=0.1,
            horizontal_flip=True) if self.augment else ImageDataGenerator(rescale=1.0/255.0)
        if self.shuffle:
            np.random.shuffle(self.indexes)

    def __len__(self):
        return int(np.floor(len(self.image_filenames) / self.batch_size))

    def __getitem__(self, index):
        batch_indexes = self.indexes[index*self.batch_size:(index+1)*self.batch_size]
        batch_filenames = [self.image_filenames[k] for k in batch_indexes]
        X, y = self.__data_generation(batch_filenames)
        return X, y

    def on_epoch_end(self):
        self.indexes = np.arange(len(self.image_filenames))
        if self.shuffle:

```

```

        np.random.shuffle(self.indexes)

    def __data_generation(self, batch_filenames):
        X = np.empty((len(batch_filenames), *self.target_size, 3))
        y = np.empty((len(batch_filenames)), dtype=float)
        for i, filename in enumerate(batch_filenames):
            file_path = os.path.join(self.directory, filename)
            image = load_img(file_path, target_size=self.target_size)
            image_array = img_to_array(image)
            X[i,] = image_array
            true_mpd_match = re.match(r'(\d+\.\d+)', filename.split(' ')[0])
            if true_mpd_match:
                true_mpd = float(true_mpd_match.group(1))
            else:
                raise ValueError(f"Unable to extract MPD value from filename: {filename}")
            y[i] = true_mpd

        if self.augment:
            X = np.array([self.datagen.random_transform(img) for img in X])

        X /= 255.0
        return X, y

    def run_test_harness():
        model = define_model()
        train_gen = CustomImageGenerator(directory='MPD:/train/', batch_size=20, augment=True)
        test_gen = CustomImageGenerator(directory='MPD:/test/', batch_size=20)

        epochs = 50
        lr_reducer = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=10)

```

```

progress_callback = TrainingProgress(total_epochs=epochs)

history = model.fit(train_gen, steps_per_epoch=len(train_gen), validation_data=test_gen, validation_steps=len(test_gen), epochs=epochs,
verbose=0, callbacks=[progress_callback, lr_reducer])

loss, mae = model.evaluate(test_gen, steps=len(test_gen), verbose=0)
print(f'> Loss: {loss:.3f}, MAE: {mae:.3f}')

output_path = 'MPD:/ /'
summarize_diagnostics(history, output_path)
model.save(output_path + 'model_name.h5')

def summarize_diagnostics(history, output_path):
    pyplot.figure(figsize=(8, 6))
    pyplot.subplot(211)
    pyplot.title('Mean Squared Error Loss')
    pyplot.plot(history.history['loss'], color='blue', label='train')
    pyplot.plot(history.history['val_loss'], color='orange', label='test')
    pyplot.legend(loc='upper right')
    pyplot.subplot(212)
    pyplot.title('Mean Absolute Error')
    pyplot.plot(history.history['mae'], color='blue', label='train')
    pyplot.plot(history.history['val_mae'], color='orange', label='test')
    pyplot.legend(loc='lower right')
    pyplot.subplots_adjust(hspace=0.3)
    pyplot.savefig(output_path + 'plot.png', dpi=300)
    pyplot.close()
    pd.DataFrame(history.history).to_excel(output_path + 'history_data.xlsx')

if __name__ == '__main__':

```

```
run_test_harness()
```

Python Code for MPD_{VGG} Regression Prediction Model Validation

```
import os
import re
import pandas as pd
import numpy as np
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing.image import load_img, img_to_array

# Load model
model = load_model('MPD:/output_path/model_name.h5')

# Define image preprocessing function
def preprocess_image(image_path, target_size=(200, 200)):
    img = load_img(image_path, target_size=target_size)
    img_array = img_to_array(img) / 255.0 # Normalize
    img_array = np.expand_dims(img_array, axis=0) # Increase batch dimension
    return img_array

# Batch prediction and save results
def batch_predict_save(directory):
    results = []
    for filename in os.listdir(directory):
        if filename.lower().endswith(".jpg") or filename.lower().endswith(".png"): # Make sure to process image files
            image_path = os.path.join(directory, filename)
            preprocessed_image = preprocess_image(image_path)
            predicted_mpd = model.predict(preprocessed_image)[0][0]
            # Use regular expressions to extract the MPD value before the brackets
            true_mpd_match = re.match(r'(\d+\.\d+)', filename)
            if true_mpd_match:
                true_mpd = float(true_mpd_match.group(1))
```

```

        else:
            true_mpd = None # If unable to extract, set to None
            results.append({'Filename': filename, 'True MPD': true_mpd, 'Predicted MPD': round(predicted_mpd, 3)})

# Save results to Excel
results_df = pd.DataFrame(results)
results_df['True MPD'] = results_df['True MPD'].apply(lambda x: "{:.3f}".format(x) if x is not None else None) # Ensure that True MPD
is rounded to three decimal places
results_df.to_excel(os.path.join(directory, 'prediction_results.xlsx'), index=False)

# Call function
test_directory = 'MPD:/test' # Update to your test directory
batch_predict_save(test_directory)

```

Table 23: Model Performance Across Various Architectures

Configuration	Convolution	Max pooling	Fully Connected	Accuracy	Gap
2 weight layers	Conv-32*1	1	FC-64	43.18%	5.05%
3 weight layers	Conv-32*1 Conv-64*1	2	FC-128	54.53%	6.83%
4 weight layers	Conv-32*1 Conv-64*1 Conv-128*1	3	FC-128	61.25%	7.09%
5 weight layers	Conv-32*1 Conv-64*1 Conv-128*1 Conv-256*1	4	FC-256	62.80%	12.01%
6 weight layers	Conv-32*1 Conv-64*1 Conv-128*1 Conv-256*1 Conv-512*1	5	FC-1024	63.49%	14.74%
7 weight layers	Conv-32*1 Conv-64*1 Conv-128*1 Conv-256*1 Conv-512*1 Conv-1024*1	6	FC-2048	65.65%	15.08%
VGG16 (16 weight layer)	Conv-64*2 Conv-128*2 Conv-256*3 Conv-512*6	5	FC-4096 FC-4096 FC-1000	57.77%	1.98%

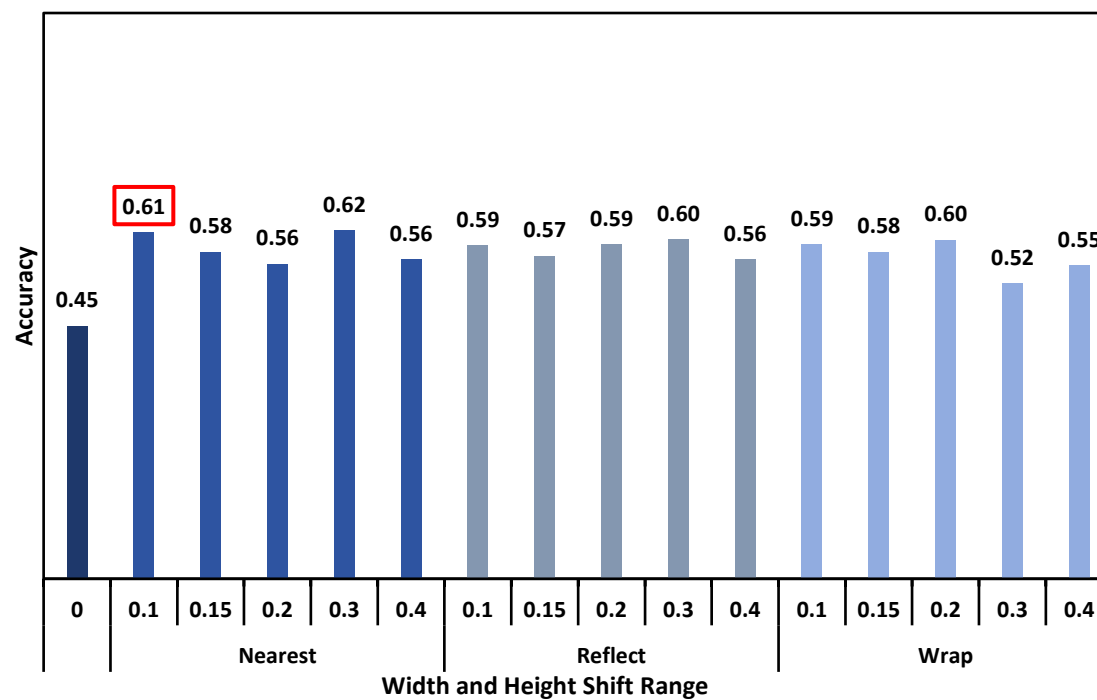


Figure 69: Accuracy Results with Shift Augmentation Techniques

Table 24: Model Performance with Various Normalization Parameters

Rescale	Accuracy
1/127.5	59.07%
1/255.0	61.25%
1/512.0	57.23%

Table 25: Comparative Accuracies with Different Regularization Techniques

L2	Regularization Dropout	Training Accuracy	Test Accuracy	Difference
		68.34%	61.25%	7.09%
0.001		65.77%	57.23%	8.54%
0.005		57.73%	52.42%	5.31%
0.01		53.52%	51.68%	1.84%
	Conv-0.2, FC-0.5	51.07%	51.14%	-0.08%
0.01	Conv-0.2, FC-0.5	36.29%	36.38%	-0.08%

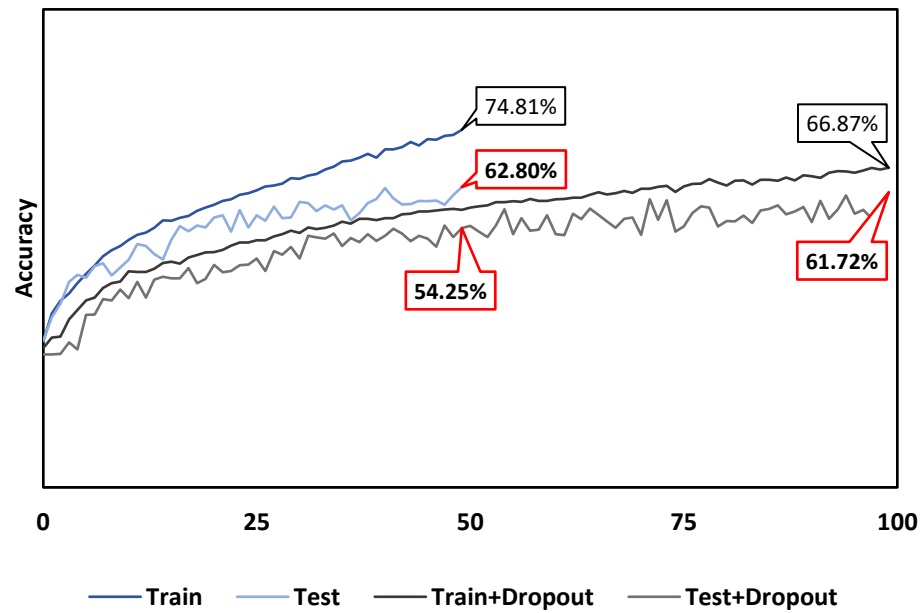


Figure 70: Impact of Dropout Regularization on Model Accuracy

Table 26: Classification Prediction Results of Set A

Number of images																							
Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3	4	5	6	7	8	9
1788	1361	427	9	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	39.813	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
1788	5444	427	9	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	49.883	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
1788	1361	1708	9	VGG3	3	3	1	0.001	0.9	Test	0.1 (Train)	Train	50	41.92	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
1788	5444	1708	9	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	48.155	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
1788	5444	1708	9	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	47.775	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
1788	5432	1720	9	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	45.349	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
1788	5432	1720	9	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	42.791	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3	4	5	6	7	8	
1788	1361	427	8	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	37.705	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<	
1788	1361	427	8	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	48.946	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5444	427	8	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	54.098	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	1361	1708	8	VGG3	3	3	1	0.001	0.9	Test	0.1 (Train)	Train	50	48.478	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5444	1708	8	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	53.63	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5444	427	8	VGG3	6	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	51.991	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5444	427	8	VGG4	8	4	1	0.001	0.9	Train	0.1 (Train)	Train	50	51.522	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5444	427	8	VGG5	10	5	1	0.001	0.9	Train	0.1 (Train)	Train	50	47.775	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	10288	792	8	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	41.288	0.6-1	0.8-1.2	1-1.4	1.2-1.6	1.4-1.8	1.6-2	1.8-2.5	2.0-3.5	
1788	5444	1708	8	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	51.991	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5432	1720	8	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	48.605	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5432	1720	8	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	48.372	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<	
1788	5432	1720	8	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	55.349	-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-	
1788	5432	1720	8	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	59.302	-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-	

Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3	4	5	6	7
1788	1361	427	7	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	55.504	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<
1788	5444	427	7	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	59.485	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<
1788	1361	1708	7	VGG3	3	3	1	0.001	0.9	Test	0.1 (Train)	Train	50	34.426	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<
1788	5444	1708	7	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	52.927	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<
1788	9720	749	7	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	46.328	0.6-1	0.8-1.2	1-1.4	1.2-1.6	1.4-1.8	1.8-2.5	2.0-3.5
1788	5432	1720	7	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	58.782	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
1788	5432	1720	7	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	61.358	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
1788	5432	1720	7	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	55.738	0.4-0.8	0.8-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
1788	5432	1720	7	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	58.782	0.4-0.8	0.8-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
1788	5444	1708	7	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	54.567	0.4-0.8	0.8-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
1788	5444	1708	7	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	46.838	0.4-0.8	0.8-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
1788	5432	1720	7	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	45.433	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<
1788	5432	1720	7	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	58.782	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<
1788	5444	1708	7	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	57.143	<1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2<

Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3	4	5	6
1788	1361	427	6	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	59.251	<1	1-1.2	1.2-1.5	1.5-1.7	1.7-2	2<
1788	5444	427	6	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	62.529	<1	1-1.2	1.2-1.5	1.5-1.7	1.7-2	2<
1788	5444	1708	6	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	61.124	<1	1-1.2	1.2-1.5	1.5-1.7	1.7-2	2<
1788	5444	1708	6	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	62.763	<1	1-1.2	1.2-1.5	1.5-1.7	1.7-2	2<
1788	1361	427	6	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	61.124	<0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2	2<
1788	5444	427	6	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	63.466	<0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2	2<
1788	5444	1708	6	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	64.871	<0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2	2<
1788	5444	1708	6	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	66.745	<0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2	2<

Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3	4	5
1788	1361	427	5	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	56.44	<1	1-1.3	1.3-1.6	1.6-2	2<
1788	5444	427	5	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	70.258	<1	1-1.3	1.3-1.6	1.6-2	2<
1788	5444	1708	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	68.618	<1	1-1.3	1.3-1.6	1.6-2	2<
1788	5444	1708	5	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	62.998	<1	1-1.3	1.3-1.6	1.6-2	2<
1788	1361	427	5	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	60.656	<1	1-1.4	1.4-1.8	1.8-2.2	2.2<
1788	5444	427	5	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	66.042	<1	1-1.4	1.4-1.8	1.8-2.2	2.2<
1788	5444	1708	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	66.511	<1	1-1.4	1.4-1.8	1.8-2.2	2.2<
1788	5444	1708	5	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	64.871	<1	1-1.4	1.4-1.8	1.8-2.2	2.2<
1788	1757	538	5	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	60.409	<1	1-1.5	1.2-1.7	1.5-2	2<
1788	7028	538	5	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	57.621	<1	1-1.5	1.2-1.7	1.5-2	2<
1788	7028	2152	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	60.223	<1	1-1.5	1.2-1.7	1.5-2	2<
1788	1757	538	5	VGG16	3	3	1	0.001	0.9				10	47.026	<1	1-1.5	1.2-1.7	1.5-2	2<
1788	5444	427	5	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	66.979	<1	1-1.2	1.2-1.5	1.5-2	2<
1788	5444	1708	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	67.916	<1	1-1.2	1.2-1.5	1.5-2	2<
1788	5444	1708	5	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50		<1	1-1.2	1.2-1.5	1.5-2	2<
1788	5380	445	5	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	66.067	<0.8	0.8-1.1	1.1-1.5	1.5-2	2<
1788	5380	1780	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	70.562	<0.8	0.8-1.1	1.1-1.5	1.5-2	2<
1788	5380	1780	5	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50		<0.8	0.8-1.1	1.1-1.5	1.5-2	2<
1788	5444	1708	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	64.637	0.4-0.8	0.8-1.2	1.2-1.6	1.6-2.0	2.0-
1788	5444	1708	5	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	69.789	0.4-0.8	0.8-1.2	1.2-1.6	1.6-2.0	2.0-
1788	5444	1708	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	72.365	0.4-0.8	0.8-1.2	1.2-1.7	1.7-2.0	2.0-
1788	5444	1708	5	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	72.6	0.4-0.8	0.8-1.2	1.2-1.7	1.7-2.0	2.0-

Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3	4	5
1788	1361	427	4	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	70.258	<1	1-1.5	1.5-2	2<	
1788	5444	427	4	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	77.049	<1	1-1.5	1.5-2	2<	
1788	5444	1708	4	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	79.157	<1	1-1.5	1.5-2	2<	Ro
1788	5444	1708	4	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	71.429	<1	1-1.5	1.5-2	2<	Ro
1788	5444	427	4	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	77.049	<1	1-1.4	1.4-1.8	1.8<	
1788	5444	1708	4	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	77.518	<1	1-1.4	1.4-1.8	1.8<	Ro2
1788	5444	1708	4	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	72.365	<1	1-1.4	1.4-1.8	1.8<	Ro2
1788	5444	1708	4	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	75.176	0.4-0.8	0.8-1.2	1.2-1.7	1.7-	Ro3
1788	5444	1708	4	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	77.049	0.4-0.8	0.8-1.2	1.2-1.7	1.7-	Ro3

Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3
1788	1361	427	3	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	79.157	<1	1-2	2<
1788	5444	427	3	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	75.878	<1	1-2	2<
1788	5444	427	3	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	79.859	<1	1-2	2<
1788	5444	1708	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	88.29	<1	1-2	2<
1788	5444	1708	3	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	81.499	<1	1-2	2<
1788	5444	1708	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	82.904	<1	1.0-1.7	1.7-
1788	5444	1708	3	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	80.796	<1	1.0-1.7	1.7-
1788	5444	1708	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	83.841	-1.2	1.2-2.0	2.0-
1788	5444	1708	3	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	82.201	-1.2	1.2-2.0	2.0-
1788	5444	1708	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	87.354	-1.5	1.5-2.0	2.0-
1788	5444	1708	3	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	86.183	-1.5	1.5-2.0	2.0-
1788	5444	1708	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	80.796	-1.2	1.2-1.7	1.7-
1788	5444	1708	3	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	79.859	-1.2	1.2-1.7	1.7-
1788	5432	1720	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	78.372	-0.9	0.9-1.5	1.5-
1788	5432	1720	3	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	75.349	-0.9	0.9-1.5	1.5-
1788	5444	1708	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	72.6	-1	1.0-1.5	1.5-
1788	5444	1708	3	VGG3(32M64 M128MF128F 128F128)	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	77.283	-1	1.0-1.5	1.5-

Raw	Train	Test	Classes	Model	Convolut ional layer	Pooling layer	Fully connecte d layer	Learning rate	moment um	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2
1788	1361	427	2	VGG3	3	3	1	0.001	0.9		0.1 (Train)	Train	50	93.443	<1.5	1.5<
1788	5444	427	2	VGG3	3	3	1	0.001	0.9	Train	0.1 (Train)	Train	50	93.443	<1.5	1.5<
1788	5444	1708	2	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	92.974	<1.5	1.5<

Table 27: Classification Prediction Results of Set B

Number of images			Classes	Model	SGD		Cut	Pre-process image sizes	image sizes	Rotate	Dropout	Rescale	Width and height shift range	Flip	Batch	Epochs	Accuracy	1	2	3	4	5	6	7	8	9
Raw	Train	Test			Learning rate	momentum																				
793	13814	4664	9	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	54.288	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
793	13814	4664	9	VGG3	0.001	0.9	1344*1512	400*400	400*400	Both		1/255	0.1 (Nearest)	True	20	50	53.109	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	3464	1158	9	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	41.364	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	3464	1158	9	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	46.028	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	3464	1158	9	VGG3	0.001	0.9	1344*1512	400*400	300*300	Both		1/255	0.1 (Nearest)	True	20	50	46.978	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	3464	1158	9	VGG3	0.001	0.9	1344*1512	400*400	400*400	Both		1/255	0.1 (Nearest)	True	20	50	43.092	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	13856	4632	9	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	49.352	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	13856	4632	9	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	48.856	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	13856	4632	9	VGG3	0.001	0.9	1344*1512	400*400	300*300	Both		1/255	0.1 (Nearest)	True	20	50	51.921	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	13856	4632	9	VGG3	0.001	0.9	1344*1512	400*400	400*400	Both		1/255	0.1 (Nearest)	True	20	50	52.461	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	13856	4632	9	VGG3(32 M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	52.202	0.4-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	13856	4632	9	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	55.052	0.4-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5-
855	13856	4632	9	VGG3(32 M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.866	0.4-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5-

Raw	Train	Test	Classes	Model	Learning rate	momentum	Cut	Pre-process image sizes	image sizes	Rotate	Dropout	Rescale	Width and height shift range	Flip	Batch	Epochs	Accuracy	1	2	3	4	5	6	7	8
855	13856	4632	8	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	53.692	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-
855	13856	4632	8	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.031	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-
855	13856	4632	8	VGG3	0.001	0.9	1344*1512	400*400	300*300	Both		1/255	0.1 (Nearest)	True	20	50	56.952	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-
855	13856	4632	8	VGG3(32 M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.758	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-
855	13856	4632	8	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	56.434	0.4-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
855	13856	4632	8	VGG3(32 M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.377	0.4-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-
Raw	Train	Test	Classes	Model	Learning rate	momentum	Cut	Pre-process image sizes	image sizes	Rotate	Dropout	Rescale	Width and height shift range	Flip	Batch	Epochs	Accuracy	1	2	3	4	5	6	7	
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	54.555	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-	
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.348	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-	
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	300*300	Both		1/255	0.1 (Nearest)	True	20	50	57.081	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-	
855	13856	4632	7	VGG3(32 M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.939	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-	
855	3464	1158	7	VGG3	1	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	16.494	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	
855	3464	1158	7	VGG3	0.1	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	16.494	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	
855	3464	1158	7	VGG3	0.01	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	51.986	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	
855	3464	1158	7	VGG3	0.005	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	52.591	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	
855	3464	1158	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	30	43.696	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	
855	3464	1158	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	49.568	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	
855	3464	1158	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	100	53.627	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	

855	3464	1158	7	VGG3	0.0005	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	44.646	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.0001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	36.788	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.00001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	30.311	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.000001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	27.461	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.001	0.99	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	51.641	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.001	0.95	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	52.763	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.001	0.85	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	46.2	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.001	0.5	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	40.415	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	3464	1158	7	VGG3	0.001	0	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	37.047	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	20*20	Both		1/255	0.1 (Nearest)	True	20	50	37.586	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	50*50	Both		1/255	0.1 (Nearest)	True	20	50	47.992	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	55.548	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/ 64/128/128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.248	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	300*300	Both		1/255	0.1 (Nearest)	True	20	50	60.276	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	400*400	Both		1/255	0.1 (Nearest)	True	20	50	59.262	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	1	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	16.494	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.1	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	16.494	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.01	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	55.656	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.005	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.679	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.0005	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	55.289	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.0001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	45.294	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.00001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	36.507	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.000001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	28.282	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-

855	13856	4632	7	VGG3	0.001	0.99	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	51.339	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.95	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.003	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.85	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	56.282	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.5	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	50.799	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	47.021	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	30	51.403	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	100	62.845	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255		True	20	50	45.272	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	True	20	50	44.711	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.15 (Nearest)	True	20	50	57.772	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.2 (Nearest)	True	20	50	55.656	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.3 (Nearest)	True	20	50	61.55	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.4 (Nearest)	True	20	50	56.412	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Reflect)	True	20	50	58.916	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.15 (Reflect)	True	20	50	57.06	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.2 (Reflect)	True	20	50	59.154	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.3 (Reflect)	True	20	50	59.974	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.4 (Reflect)	True	20	50	56.412	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Wrap)	True	20	50	59.132	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.15 (Wrap)	True	20	50	57.772	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.2 (Wrap)	True	20	50	59.909	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.3 (Wrap)	True	20	50	52.202	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.4 (Wrap)	True	20	50	55.462	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	False	20	50	58.463	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	27712	9264	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	All	20	50	62.36	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/127.5	0.1 (Nearest)	True	20	50	59.067	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/512	0.1 (Nearest)	True	20	50	57.232	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	10	50	59.866	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	32	50	56.282	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	64	50	49.309	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	128	50	51.468	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-

855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both	L2(0.01),Dropout0.2+0.5	1/255	0.1 (Nearest)	True	20	50	36.377	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both	L2(0.01)	1/255	0.1 (Nearest)	True	20	50	51.684	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both	L2(0.005)	1/255	0.1 (Nearest)	True	20	50	52.418	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both	L2(0.001)	1/255	0.1 (Nearest)	True	20	50	57.232	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both	Dropout 0.2+0.5	1/255	0.1 (Nearest)	True	20	50	51.144	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG1(32//32)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	27.807	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG1(32//64)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	43.178	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG1(32//64)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	True	20	50	27.807	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG2(32//64//64)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	53.778	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG2(32//64//128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	54.534	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG2(32//64//128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	True	20	50	40.609	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//64)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	57.858	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//256)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	52.763	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//256)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.708	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//256)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	True	20	50	46.891	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//512)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.047	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//1024)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.586	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//2048)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.226	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32//64//128//4096)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.233	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG4(32//64//128//256//256)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.802	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG4(32//64//128//256//256)	0.001	0.9	1344*1512	400*400	200*200	Both	L2(0.001)	1/255	0.1 (Nearest)	True	20	50	61.572	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG4(32//64//128//256//256)	0.001	0.9	1344*1512	400*400	200*200	Both	Dropout 0.2+0.5	1/255	0.1 (Nearest)	True	20	50	54.253	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG4(32//64//128//256//256)	0.001	0.9	1344*1512	400*400	200*200	Both	Dropout 0.2+0.5	1/255	0.1 (Nearest)	True	20	100	61.723	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-

855	13856	4632	7	VGG4(32/64/128/256/ /512)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.457	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG4(32/64/128/256/ /512)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	True	20	50	49.784	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG5(32/64/128/256/ 512//1024)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.493	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG5(32/64/128/256/ 512//1024)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	True	20	50	53.562	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/64/128/256/ 512/1024//2048)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	65.652	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/64/128/256/ 512/1024//2048)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	False	20	50	52.051	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/64/128/256/ 512/1024//2048)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0	True	20	50	56.174	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/32/64/64/12 8/128//128)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.01	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/32/64/64/12 8/128//256)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.766	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/32/64/64/12 8/128//512)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.953	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/32/64/64/12 8/128//1024)3Maxpo ol	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.895	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG10(32/32/64/64/1 28/128/256/256//512/5 12//512)5Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	64.745	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(128/64/32//128)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	57.211	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//25 6)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.175	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//51 2)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.65	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//10 24)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	64.054	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//20 48)3Maxpool	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.86	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG16	0.001	0.9	1344*1512	400*400	224*224	Both		1/255	0.1 (Nearest)	True	20	15	40.868	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG16	0.001	0.9	1344*1512	400*400	224*224	Both		1/255	0.1 (Nearest)	True	20	50	57.772	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-

855	13856	4632	7	VGG3(32/64/128//128/128)3Maxpool/2FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.449	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128//128/256)3Maxpool/2FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.593	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128//256/256)3Maxpool/2FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.824	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128//512/512)3Maxpool/2FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.601	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128//64/64/64)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.427	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128//128/128/128)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.169	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128//128/256/256)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.406	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128//256/256/256)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.68	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//256/512)3Maxpool/2FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.528	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//512/512)3Maxpool/2FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	64.335	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//256/256/256)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.132	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(64/128/256//512/512/512)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	64.853	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/32/64/64/128/128/128/128)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.083	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/32/64/64/128/128/256/256)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.687	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(32/32/64/64/128/128/512/512)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.774	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG6(64//128//256/256/512/512//1024)4Maxpool/1FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.55	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG9(32/32/32//64/64/64//128/128/128//128/128/128)3Maxpool/3FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	55.138	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128/128)	Auto	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.225	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128/128)	Adam 0.001		1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.154	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3(32/64/128/128)	RMSprop 0.001		1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	46.546	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	ResNet50	0.001	0.9	1344*1512	400*400	224*224	Both		1/255	0.1 (Nearest)	True	20	50	36.161	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	EfficientNetB0	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	27.807	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	LeNet-5(6M16MF120F84)2CM2F	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	56.649	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	AlexNet(96M256M384/384/256MF4096F4096)5C3M2F	0.01	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	27.807	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	AlexNet(96M256M384/384/256MF4096F4096)5C3M2F	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	57.168	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-

855	13856	4632	7	ResNet(F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.73	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	MobileNet(F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	53.195	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	EfficientNet(F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.83	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	16632	1856	7	VGG3(32/64/128//128)3Maxpool/1FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.716	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	16632	1856	7	VGG3(32/64/128//128 /128/128)3Maxpool/3 FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.584	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	15712	2776	7	VGG3(32/64/128//128)3Maxpool/1FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.033	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	15712	2776	7	VGG3(32/64/128//128 /128/128)3Maxpool/3 FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.284	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	14788	3700	7	VGG3(32/64/128//128)3Maxpool/1FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.297	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	14788	3700	7	VGG3(32/64/128//128 /128/128)3Maxpool/3 FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	66.297	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	12948	5540	7	VGG3(32/64/128//128)3Maxpool/1FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	59.495	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	12948	5540	7	VGG3(32/64/128//128 /128/128)3Maxpool/3 FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	62.22	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	12016	6472	7	VGG3(32/64/128//128)3Maxpool/1FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	56.289	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	12016	6472	7	VGG3(32/64/128//128 /128/128)3Maxpool/3 FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	57.494	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	11092	7396	7	VGG3(32/64/128//128)3Maxpool/1FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	56.287	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	11092	7396	7	VGG3(32/64/128//128 /128/128)3Maxpool/3 FC	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.87	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
855	13856	4632	7	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	60.363	0.4-0.8	0.8-1	1-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2-
855	13856	4632	7	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	61.939	0.4-0.8	0.8-1	1-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2-

Raw	Train	Test	Classes	Model	Learning rate	momentu m	Cut	Pre- process image sizes	image sizes	Rotate	Dropout	Rescale	Width and height shift range	Flip	Batch	Epochs	Accuracy	1	2	3	4	5	6
855	13856	4632	6	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	59.542	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-
855	13856	4632	6	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	58.614	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-
855	13856	4632	6	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.968	0.4-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-
855	13856	4632	6	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	60.687	0.4-0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2.0	2.0-
855	13856	4632	6	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	63.946	0.4-0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2.0	2.0-
855	13856	4632	6	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	67.293	0.4-0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2.0	2.0-
855	13856	4632	6	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	64.249	0.4-1	1-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2-
855	13856	4632	6	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	68.243	0.4-1	1-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2-

Raw	Train	Test	Classes	Model	Learning rate	momentu m	Cut	Pre- process image sizes	image sizes	Rotate	Dropout	Rescale	Width and height shift range	Flip	Batch	Epochs	Accuracy	1	2	3	4	5
855	13856	4632	5	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	67.098	0.4-0.8	0.8-1.2	1.2-1.6	1.6-2.0	2.0-
855	13856	4632	5	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	71.805	0.4-0.8	0.8-1.2	1.2-1.6	1.6-2.0	2.0-
855	13856	4632	5	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	74.439	0.4-0.8	0.8-1.2	1.2-1.6	1.6-2.0	2.0-
855	13856	4632	5	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	68.782	0.4-0.8	0.8-1.2	1.2-1.7	1.7-2.0	2.0-
855	13856	4632	5	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	70.941	0.4-0.8	0.8-1.2	1.2-1.7	1.7-2.0	2.0-
855	13856	4632	5	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	73.273	0.4-0.8	0.8-1.2	1.2-1.7	1.7-2.0	2.0-
855	13856	4632	5	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	67.854	0.4-1.0	1.0-1.3	1.3-1.6	1.6-2.0	2.0-
855	13856	4632	5	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	69.041	0.4-1.0	1.0-1.3	1.3-1.6	1.6-2.0	2.0-

Raw	Train	Test	Classes	Model	Learning rate	momentum	Cut	Pre-process image sizes	image sizes	Rotate	Dropout	Rescale	Width and height shift range	Flip	Batch	Epochs	Accuracy	1	2	3	4
855	13856	4632	4	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	71.762	0.4-0.8	0.8-1.2	1.2-1.7	1.7-
855	13856	4632	4	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	74.18	0.4-0.8	0.8-1.2	1.2-1.7	1.7-
855	13856	4632	4	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	75.216	0.4-0.8	0.8-1.2	1.2-1.7	1.7-
855	13856	4632	4	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	75.95	0.4-1.0	1.0-1.5	1.5-2.0	2-
855	13856	4632	4	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	75.756	0.4-1.0	1.0-1.5	1.5-2.0	2-
Raw	Train	Test	Classes	Model	Learning rate	momentum	Cut	Pre-process image sizes	image sizes	Rotate	Dropout	Rescale	Width and height shift range	Flip	Batch	Epochs	Accuracy	1	2	3	
855	13856	4632	3	VGG3	0.001	0.9	1344*1512	400*400	100*100	Both		1/255	0.1 (Nearest)	True	20	50	76.662	0.4-1.0	1.0-1.7	1.7-	
855	13856	4632	3	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	76.511	0.4-1.0	1.0-1.7	1.7-	
855	13856	4632	3	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	79.231	0.4-1.0	1.0-1.7	1.7-	
855	13856	4632	3	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	81.218	0.4-1.2	1.2-2.0	2.0-	
855	13856	4632	3	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	83.053	0.4-1.2	1.2-2.0	2.0-	
855	13856	4632	3	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	91.861	0.4-1.5	1.5-2.0	2.0-	
855	13856	4632	3	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	92.617	0.4-1.5	1.5-2.0	2.0-	
855	13856	4632	3	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	79.922	0.4-1.2	1.2-1.7	1.7-	
855	13856	4632	3	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	83.117	0.4-1.2	1.2-1.7	1.7-	
855	13856	4632	3	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	78.346	0.4-0.9	0.9-1.5	1.5-	
855	13856	4632	3	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	82.362	0.4-0.9	0.9-1.5	1.5-	
855	13856	4632	3	VGG3	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	78.951	0.4-1.0	1.0-1.5	1.5-	
855	13856	4632	3	VGG3(32M64M128 MF128F128F128)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	78.843	0.4-1.0	1.0-1.5	1.5-	
855	13856	4632	3	VGG3(32M64M128 M256)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	79.62	0.4-1.0	1.0-1.5	1.5-	
855	13856	4632	3	VGG3(64M128M256 M512)	0.001	0.9	1344*1512	400*400	200*200	Both		1/255	0.1 (Nearest)	True	20	50	80.527	0.4-1.0	1.0-1.5	1.5-	

Table 28: Classification Prediction Results of Set C

Raw	Train	Test	Classes	Model	Convolutional layer	Pooling layer	Fully connect ed layer	Learning rate	momentum	Rotate	Width and height shift range	Flip	Epochs	Accurac y	1	2	3	4	5	6	7	8	9
2004	5984	2032	11	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	15.55	-0.6	0.6-0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2.0	2-2.2
2004	5984	2032	9	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	25.394	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
2004	5984	2032	9	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	28.74	<0.8	0.8-1	1-1.2	1.2-1.4	1.4-1.6	1.6-1.8	1.8-2	2-2.5	2.5<
2004	5984	2032	8	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	34.252	-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-	Ro
2004	5984	2032	8	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	32.874	-0.7	0.7-1.0	1.0-1.3	1.3-1.6	1.6-1.9	1.9-2.2	2.2-2.5	2.5-	Ro
2004	5984	2032	8	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	31.69	-0.6	0.6-0.9	0.9-1.2	1.2-1.5	1.5-1.8	1.8-2.1	2.1-2.4	2.4-	
2004	5984	2032	7	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	40.55	-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	Ro	
2004	5984	2032	7	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	38.78	-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-	Ro	
2004	5984	2032	7	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	35.04	-0.6	0.6-1	1-1.2	1.2-1.5	1.5-1.7	1.7-2	2-		
2004	5984	2032	6	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	43.504	<0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2	2<	Ro		
2004	5984	2032	6	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	43.307	<0.8	0.8-1.1	1.1-1.4	1.4-1.7	1.7-2	2<	Ro		
2004	5984	2032	6	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	44.88	-1	1-1.2	1.2-1.5	1.5-1.7	1.7-2	2-			
2004	5984	2032	5	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	52.953	-0.8	0.8-1.2	1.2-1.7	1.7-2.0	2.0-	Ro			
2004	5984	2032	5	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	51.575	-0.8	0.8-1.2	1.2-1.7	1.7-2.0	2.0-	Ro			
2004	5984	2032	4	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	52.362	<1	1-1.5	1.5-2	2<	Ro				
2004	5984	2032	4	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	56.496	<1	1-1.5	1.5-2	2<	Ro				
2004	5984	2032	3	VGG3	3	3	1	0.001	0.9	Both	0.1 (Train)	Train	50	63.583	-1.2	1.2-2.0	2.0-	Ro					
2004	5984	2032	3	VGG3	3	3	3	0.001	0.9	Both	0.1 (Train)	Train	50	63.583	-1.2	1.2-2.0	2.0-	Ro					

Table 29: Classification Prediction Results of Combined Set

	Raw	Train	Test	Classes	Model	Convolutional layer	Pooling layer	Fully connected layer	Learning rate	momentum	Rotate	Width and height shift range	Flip	Epochs	Accuracy	1	2	3	4	5	6	7
GA+GB	2643	19288	6352	7	VGG3	3	3	1	0.001	0.9	Both	.1 (Train)	Train	50	59.21	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
GA+GB	2643	19288	6352	7	VGG3 (32 M64M128 MF128F1 28F128)	3	3	3	0.001	0.9	Both	.1 (Train)	Train	50	56.313	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
GA+GC	3792	11416	3752	7	VGG3	3	3	1	0.001	0.9	Both	.1 (Train)	Train	50	47.122	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
GA+GC	3792	11416	3752	7	VGG3 (32 M64M128 MF128F1 28F128)	3	3	3	0.001	0.9	Both	.1 (Train)	Train	50	47.335	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
GB+GC	2859	19840	6664	7	VGG3	3	3	1	0.001	0.9	Both	.1 (Train)	Train	50	52.896	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
GB+GC	2859	19840	6664	7	VGG3 (32 M64M128 MF128F1 28F128)	3	3	3	0.001	0.9	Both	.1 (Train)	Train	50	54.652	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
GA+GB+GC	4647	25272	8384	7	VGG3	3	3	1	0.001	0.9	Both	.1 (Train)	Train	50	50.954	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-
GA+GB+GC	4647	25272	8384	7	VGG3 (32 M64M128 MF128F1 28F128)	3	3	3	0.001	0.9	Both	.1 (Train)	Train	50	56.011	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-

Table 30: Non-overlapping Classification of Seven Classes in Set A

5444	Number of training set	344	944	1204	1068	516	360	1008			
55.738	Number of categories	1	2	3	4	5	6	7	Correct number of images	Number of test set	Accuracy
	7	0.4-0.8	0.8-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-			
	0.4-0.8	40	12	60					40	112	35.71%
	0.7-1.0	28	108	184	20	8			108	348	31.03%
	1.0-1.2		16	240	56	4	8		240	324	74.07%
	1.2-1.5		4	96	100	40	36	4	100	280	35.71%
	1.5-1.7			4	24	40	60	20	40	148	27.03%
	1.7-2.0				4	4	60	44	60	112	53.57%
	2.0-						20	364	364	384	94.79%
									952	1708	55.74%
		40	108	240	100	40	60	364			
		68	140	584	204	96	184	432			
		58.82%	77.14%	41.10%	49.02%	41.67%	32.61%	84.26%			

Table 31: Non-overlapping Classification of Seven Classes in Set B

13856	Number of trainin g set	2376	4072	2920	2108	376	760	1244			
61.248	Number of categor ies	1	2	3	4	5	6	7	Correct number of images	Number of test set	Accuracy
	7	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-			
	0.4-0.7	629	122	4	8		1		629	764	82.33%
	0.7-1.0	165	702	327	93		1		702	1288	54.50%
	1.0-1.2	28	214	616	144	1		1	616	1004	61.35%
	1.2-1.5	11	95	225	487	4	6		487	828	58.82%
	1.5-1.7		4	15	53	14	18	4	14	108	12.96%
	1.7-2.0		13	8	40	15	62	78	62	216	28.70%
	2.0-			1	47		49	327	327	424	77.12%
									2837	4632	61.25%
		629	702	616	487	14	62	327			
		833	1150	1196	872	34	137	410			
		75.51%	61.04%	51.51%	55.85%	41.18%	45.26%	79.76%			

Table 32: Non-overlapping Classification of Seven Classes in Set C

5984	Number of trainin g set	496	964	836	1220	696	676	1096			
40.551	Number of categor ies	1	2	3	4	5	6	7	Correct number of images	Number of test set	Accuracy
	7	0.4-0.7	0.7-1.0	1.0-1.2	1.2-1.5	1.5-1.7	1.7-2.0	2.0-			
	0.4-0.7	104	44	16				4	104	168	61.90%
	0.7-1.0	60	156	40	60	4		8	156	328	47.56%
	1.0-1.2	12	72	48	76	44	16	16	48	284	16.90%
	1.2-1.5	16	24	72	172	60	36	32	172	412	41.75%
	1.5-1.7	16	4	28	80	36	20	52	36	236	15.25%
	1.7-2.0		8	12	60	12	40	92	40	224	17.86%
	2.0-			8	44	36	24	268	268	380	70.53%
									824	2032	40.55%
		104	156	48	172	36	40	268			
		208	308	224	492	192	136	472			
		50.00%	50.65%	21.43%	34.96%	18.75%	29.41%	56.78%			

Table 33: Overlapping Classification of Eight Classes in Set A

10288	Number of trainin g set	1288	2148	1988	1376	924	568	988	1008			
	Number of categor ies	1	2	3	4	5	6	7	8	Correct number of images	Number of test set	Accuracy
	8	0.6-1	0.8-1.2	1-1.4	1.2-1.6	1.4-1.8	1.6-2	1.8-2.5	2.0-3.5			
	0.6-0.8	80	32							80	112	71.43%
	0.8-1.0	188	144	12	4					332	348	95.40%
	1.0-1.2	24	168	92	36	4				260	324	80.25%
	1.2-1.4		40	96	68					164	204	80.39%
	1.4-1.6		8	12	76	56	0	8	4	132	164	80.49%
	1.6-1.8				8	84	4	8		88	104	84.62%
	1.8-2.0					16	8	40	4	48	68	70.59%
	2.0-2.5				4	0	0	160	84	244	248	98.39%
	2.5-3.5							40	96	96	136	70.59%
										1444	1708	84.54%
		268	312	188	144	140	12	200	180			
		292	392	212	196	160	12	256	188			
		91.78%	79.59%	88.68%	73.47%	87.50%	100.00%	78.13%	95.74%	86.86%		

Table 34: Overlapping Classification of Eight Classes in Set B

23860	Number of trainin g set	6448	5764	4732	2308	928	936	1500	1244			
	Number of categor ies	1	2	3	4	5	6	7	8	Correct number of images	Number of test set	Accuracy
	8	0.4-1	0.8-1.2	1-1.4	1.2-1.6	1.4-1.8	1.6-2	1.8-2.5	2.0-4.1			
	0.4-0.8	1030	28	13	8		5			1030	1084	95.02%
	0.8-1.0	415	418	116	16	2	1			833	968	86.05%
	1.0-1.2	131	545	254	46	12	15	1		799	1004	79.58%
	1.2-1.4	35	190	260	200	23	14	14		460	736	62.50%
	1.4-1.6	1	24	42	51	21	5	4		72	148	48.65%
	1.6-1.8		2	3	10	19	35	13	2	54	84	64.29%
	1.8-2.0	4	1	5	10	6	34	105	19	139	184	75.54%
	2.0-2.5	2	2	9	10	2	9	176	106	282	316	89.24%
	2.5-4.1				4			28	76	76	108	70.37%
										3745	4632	80.85%
		1445	963	514	251	40	69	281	182			
		1618	1210	702	355	85	118	341	203			
		89.31%	79.59%	73.22%	70.70%	47.06%	58.47%	82.40%	89.66%			

Table 35: Overlapping Classification of Eight Classes in Set C

10888	Number of trainin g set	1460	1540	1664	1588	1344	1004	1192	1096			
	Number of categor ies	1	2	3	4	5	6	7	8	Correct number of images	Number of test set	Accuracy
	8	-1	0.8-1.2	1-1.4	1.2-1.6	1.4-1.8	1.6-2	1.8-2.5	2.0-			
	-0.8	148	24	76	8					148	256	57.81%
	0.8-1.0	76	80	48	20	8		8		156	240	65.00%
	1.0-1.2	36	56	80	28	24	40	20		136	284	47.89%
	1.2-1.4		28	96	36	44	56	20		132	280	47.14%
	1.4-1.6	8		68	32	32	84	24	8	64	256	25.00%
	1.6-1.8	4		40	28	20	52	44	8	72	196	36.73%
	1.8-2.0		12	16	8	16	32	40	16	72	140	51.43%
	2.0-2.5			12	8	20	44	108	76	184	268	68.66%
	2.5-				4		16	44	48	48	112	42.86%
										1012	2032	49.80%
		224	136	176	68	52	84	148	124			
		272	200	436	172	164	324	308	156			
		82.35%	68.00%	40.37%	39.53%	31.71%	25.93%	48.05%	79.49%			

Table 36: Regression Prediction Results of Set A

	Raw	Train	Test	Model	Convolutional layer	Pooling layer	Fully connected layer	Learning rate	momentum	clipnorm	Batch size	Image size	Rotate	Rescale	Width and height shift range	Flip	Epochs	Loss	Mae
GA	1788	1341	447	VGG3	32/64/128	3	128	0.001	0.9		20	200					50	0.123	0.263
	1788	1341	447	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	200	Both	1/255	0.1	Train	50	0.038	0.147
	7152	5364	1788	VGG3	32/64/128	3	128	0.001	0.9		20	200	Both				10	0.066	0.205
	7152	5364	1788	VGG3	32/64/128	3	128	0.001		1	20	200	Both				50	0.058	0.186
	7152	5364	1788	VGG3	32/64/128	3	128	0.001		1	20	200	Both				100	0.057	0.184
	7152	5364	1788	VGG3	32/64/128	3	128	0.001		1	20	200	Both	1/255	0.1	Train	50	0.041	0.157
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.001		1	20	200	Both	1/255	0.1	Train	50	0.041	0.149
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.001		1	20	400	Both	1/255	0.1	Train	50	0.04	0.16
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.0001		1	20	800	Both	1/255	0.1	Train	50	0.039	0.155
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.1		1	20	200	Both	1/255	0.1	Train	50	0.317	0.455
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.01		1	20	200	Both	1/255	0.1	Train	50	0.049	0.174
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.0005		1	20	200	Both	1/255	0.1	Train	50	0.039	0.15
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.0001		1	20	200	Both	1/255	0.1	Train	50	0.036	0.148
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.00005		1	20	200	Both	1/255	0.1	Train	50	0.039	0.155
	7152	5364	1788	VGG6	32/64/128	3	128/128/128	0.00001		1	20	200	Both	1/255	0.1	Train	50	0.044	0.163
	7152	5364	1788	VGG8	32/64/128/256/512	5	512/512/512	0.001		1	20	200	Both	1/255	0.1	Train	50	0.037	0.143
	7152	5364	1788	VGG15	32*2/64*2/128*2/256*3/512*3	5	1024/1024/1024	0.001		1	20	200	Both	1/255	0.1	Train	50	0.036	0.143
	7152	5364	1788	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	200	Both	1/255	0.1	Train	50	0.034	0.142
	7152	5364	1788	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.03	0.128

Table 37: Regression Prediction Results of Set B

	Raw	Train	Test	Model	Convolutional layer	Pooling layer	Fully connected layer	Learning rate	momentum	clipnorm	Batch size	Image size	Rotate	Rescale	Width and height shift range	Flip	Epochs	Loss	Mae
GB	5017	3763	1254	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.274	0.38
	5017	3763	1254	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.091	0.214
	20068	15052	5016	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.041	0.138

Table 38: Regression Prediction Results of Set C

	Raw	Train	Test	Model	Convolutional layer	Pooling layer	Fully connected layer	Learning rate	momentum	clipnorm	Batch size	Image size	Rotate	Rescale	Width and height shift range	Flip	Epochs	Loss	Mae
GC	2004	1496	508	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.001		1	20	200	Both	1/255	0.1	Train	50	0.154	0.292
	2004	1496	508	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	200	Both	1/255	0.1	Train	50	0.157	0.297
	8016	5984	2032	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	200	Both	1/255	0.1	Train	50	0.166	0.309
	8016	5984	2032	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.161	0.297

Table 39: Regression Prediction Results of Combined Set

	Raw	Train	Test	Model	Convolutional layer	Pooling layer	Fully connected layer	Learning rate	momentum	clipnorm	Batch size	Image size	Rotate	Rescale	Width and height shift range	Flip	Epochs	Loss	Mae
GA+GB	27220	20416	6804	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.047	0.149
GA+GC	15168	11348	3820	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.09	0.22
GB+GC	28084	21036	7048	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.071	0.182
GA+GB+GC	35236	26400	8836	VGG19	64*2/128*2/256*4/512*4/512*4	3	4096/4096/1000	0.0001		1	20	Preprocessing 200	Both	1/255	0.1	Train	50	0.063	0.176