



**TEXTURE REPRESENTATION FOR WOOD DEFECT IMAGE
CLASSIFICATION USING ENHANCED COLOUR UNIFORM
LOCAL BINARY PATTERN**

**RAHILLDA NADHIRAH NORIZZATY BINTI
RAHIDDIN**

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

DOCTOR OF PHILOSOPHY

2025



Faculty of Information and Communications Technology

**TEXTURE REPRESENTATION FOR WOOD DEFECT IMAGE
CLASSIFICATION USING ENHANCED COLOUR UNIFORM
LOCAL BINARY PATTERN**

اونيورسيتي تيكنيكل مليسيا ملاك
Rahillda Nadhirah Norizzaty Binti Rahiddin
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

Doctor of Philosophy

2025

**TEXTURE REPRESENTATION FOR WOOD DEFECT IMAGE
CLASSIFICATION USING ENHANCED COLOUR UNIFORM LOCAL BINARY
PATTERN**

RAHILLDA NADHIRAH NORIZZATY BINTI RAHIDDIN



Faculty of Information and Communications Technology

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2025

DECLARATION

I declare that this thesis entitled “Texture Representation for Wood Defect Image Classification Using Enhanced Colour Uniform Local Binary Pattern“ is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



Signature :

Name : Rahillda Nadhirah Norizzaty Binti Rahiddin

Date : 22 June 2025

اونيورسيٲى ٲيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Doctor of Philosophy.



Signature :

Supervisor Name : Ts. Dr. Ummi Raba'ah Binti Hashim

Date :
4/7/2025

اونيورسيتي تيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

DEDICATION

This thesis is dedicated to the unwavering pillars of my life, the root of my strength, and the spirit within, and above all, to the Divine. First and foremost, all praise and gratitude belong to Allah (SWT), the Almighty, the Most Merciful, for His infinite blessings, strength, guidance, and wisdom throughout this journey. Without His divine grace and benevolence, this accomplishment would not have been possible. To my beloved parents, Rahiddin Muda and Mazlinda Minhat, whose boundless love, tireless sacrifices, and constant belief in my potential fueled every step of this arduous journey. Your encouragement was my bedrock, and your unwavering support, both emotional and practical, made this dream a reality. I am eternally grateful for everything you've given me. To my dear grandparents, Kpt(B) Hj Minhat Manas and Hjh Zainon Hitam, your wisdom, life lessons, and unwavering support have always been a quiet source of strength. Thank you for your endless love and for instilling in me the values that have guided me through every challenge. To my PhD supervisors, Ts. Dr. Ummi Raba'ah Binti Hashim and Ts. Dr. Kasturi A/P Kanchymalay, your intellectual guidance, insightful critiques, and unwavering patience were invaluable. Thank you for challenging me to think deeper, for fostering my scientific curiosity, and for believing in my ability to navigate the complexities of this research. Your mentorship has profoundly shaped my academic and personal growth. And to my friend, Khoo Ghee Yeaw, thank you for the laughter, the much-needed distractions, and the constant reminders that there is life beyond the research. Your camaraderie and support were a vital source of strength and sanity throughout this demanding period. Finally, this dedication is also for myself. For the resilience, perseverance, and unwavering determination that carried me through moments of doubt and countless hours of work. For believing in this journey and seeing it through to completion.

ABSTRACT

Wood defect classification remains a critical challenge in the timber industry due to natural variations in defect appearance, illumination inconsistencies, and texture complexity across wood species. Traditional manual inspection methods for assessing wood quality are time-consuming, subjective, and prone to human error, limiting their reliability for large-scale industrial applications. While computational approaches have been developed to automate defect detection, existing methods struggle with distinguishing defect classes due to grayscale-based texture extraction, sensitivity to lighting conditions, and excessive feature generation that leads to overfitting. Previous research has primarily relied on Basic Local Binary Patterns (LBP) to extract surface texture features, treating defects as localized structural variations. However, LBP operates on grayscale images, resulting in the loss of colour-based information, which is essential for distinguishing defects from clear wood regions. Additionally, LBP exhibits sensitivity to illumination changes, meaning classification performance varies under different lighting conditions, leading to inconsistencies in defect identification. High-resolution images introduce further complexity, as LBP generates excessive features, increasing the risk of overfitting and poor generalization in classification models. This study aims to address these limitations by proposing an enhanced feature representation that utilizes Colour Uniform Local Binary Patterns (CULBP) combined with comprehensive colour normalization to mitigate the effects of varying lighting conditions and improve classification robustness. The methodology extracts texture and colour features from images of four wood species which are Rubberwood, Kembang Semangkuk (KSK), Merbau, and Meranti and evaluates classification accuracy across multiple defect types, including bark pocket, blue stain, borer holes, brown stain, knot, rot, split, and wane. A succession of colour feature sets was derived from individual and combined RGB channels, with classification performed using an Artificial Neural Network (ANN). Results indicate that RGB channels, without substantial colour normalization, achieve the highest classification accuracy at 90.2%, surpassing previous grayscale-based methods such as Daubechies Wavelet and Basic LBP (85%) and Basic LBP alone (65.4%). Among the evaluated species, Rubberwood exhibited the highest accuracy, with particularly strong results for Rubberwood Rot (92.2%) and Merbau Hole (95.6%), demonstrating the advantages of colour-based feature extraction in defect classification. By integrating multi-channel texture and colour features, this study provides a more robust defect classification framework, addressing key challenges related to illumination sensitivity, texture inconsistencies, and excessive feature extraction. The findings highlight the importance of systematic preprocessing using colour normalization and statistical validation using Multivariate Analysis of Variance (MANOVA) to improve classification performance. These advancements offer a scalable solution for industrial wood quality assessment, contributing to enhanced defect recognition and efficiency in the timber industry.

**PERWAKILAN TEKSTUR UNTUK PENGELASAN IMEJ KECACATAN KAYU
MENGUNAKAN CORAK PERDUAAN TEMPATAN SERAGAM WARNA YANG
DIPERTINGKAT**

ABSTRAK

Pengelasan kecacatan kayu kekal sebagai cabaran kritikal dalam industri perkayuan disebabkan oleh kepelbagaian semula jadi dalam bentuk kecacatan, ketidakseragaman pencahayaan dan kerumitan tekstur merentas spesies kayu. Kaedah pemeriksaan manual secara tradisional untuk menilai kualiti kayu memakan masa, subjektif, dajin terdedah kepada kesilapan manusia, menghadkan kebolehpercayaan untuk aplikasi industri berskala besar. Walaupun pendekatan pengiraan telah dibangunkan untuk mengautomasikan pengesanan kecacatan, kaedah sedia ada bergelut dengan membezakan kelas kecacatan disebabkan oleh penyarian tekstur berasaskan skala kelabu, kepekaan kepada keadaan pencahayaan dan penjanaan ciri yang berlebihan yang membawa kepada pemasangan berlebihan. Penyelidikan sebelum ini terutamanya bergantung pada Corak Binari Tempatan Asas (LBP) untuk menyari ciri tekstur permukaan, merawat kecacatan sebagai kepelbagaian struktur setempat. Walau bagaimanapun, LBP beroperasi pada imej skala kelabu, mengakibatkan kehilangan maklumat berasaskan warna, yang penting untuk membezakan kecacatan daripada kawasan kayu yang jelas. Selain itu, LBP mempamerkan kepekaan terhadap perubahan pencahayaan, bermakna prestasi pengelasan berbeza-beza di bawah keadaan pencahayaan yang berbeza, yang membawa kepada ketidakseragaman dalam pengecaman kecacatan. Imej resolusi tinggi memperkenalkan kerumitan lagi, kerana LBP menjana ciri yang berlebihan, meningkatkan risiko pemasangan berlebihan dan generalisasi yang lemah dalam model pengelasan. Kajian ini bertujuan untuk menangani batasan ini dengan mencadangkan rangka kerja perwakilan ciri yang dipertingkatkan yang menggunakan Corak Perduaan Tempatan Seragam Warna (CULBP) digabungkan dengan normalisasi warna yang komprehensif untuk mengurangkan kesan keadaan pencahayaan yang berbeza-beza dan meningkatkan keteguhan pengelasan. Metodologi menyari ciri tekstur dan warna daripada imej empat spesies kayu iaitu Kayu Getah, Kembang Semangkuk (KSK), Merbau, dan Meranti dan menilai ketepatan pengelasan merentas pelbagai jenis kecacatan, termasuk poket kulit kayu, noda biru, lubang pengorek, noda coklat, simpul, reput, belah dan pudar. Susunan set ciri warna diperolehi daripada saluran RGB individu dan gabungan, dengan pengelasan dilakukan menggunakan Rangkaian Neural Buatan (ANN). Keputusan menunjukkan bahawa saluran RGB, tanpa normalisasi warna yang ketara, mencapai ketepatan pengelasan tertinggi pada 90.2%, mengatasi kaedah berasaskan skala kelabu sebelumnya seperti Daubechies Wavelet dan LBP Asas (85%) dan LBP Asas sahaja (65.4%). Di antara spesies yang dinilai, Kayu Getah mempamerkan ketepatan tertinggi, dengan keputusan yang sangat kukuh untuk Kayu Getah Reput (92.2%) dan Merbau Lubang Penggerek (95.6%), menunjukkan kelebihan penyarian ciri berasaskan warna dalam pengelasan kecacatan kayu. Dengan menyepadukan ciri tekstur dan warna berbilang saluran, kajian ini menyediakan rangka kerja pengelasan kecacatan yang lebih mantap, menangani cabaran utama yang berkaitan dengan kepekaan pencahayaan, ketidakseragaman tekstur dan penyarian ciri yang berlebihan. Penemuan ini menyerlahkan

kepentingan prapemprosesan sistematik menggunakan normalisasi warna dan pengesahan statistik menggunakan Analisis Varian Pelbagai (MANOVA) untuk meningkatkan prestasi pengelasan. Kemajuan ini menawarkan penyelesaian berskala untuk penilaian kualiti kayu perindustrian, menyumbang kepada peningkatan pengiktirafan kecacatan dan kecekapan dalam industri perkayuan.



ACKNOWLEDGEMENT

In the Name of Allah, the Most Gracious, the Most Merciful, First and foremost, I would like to take this opportunity to express my sincere acknowledgement and deepest gratitude to my supervisor Ts. Dr. Ummi Raba'ah Binti Hashim and co-supervisor Ts. Dr. Kasturi A/P Kanchymalay from the Faculty of Information and Communication Technology for their insightful comments, remarks, support, and encouragement towards the completion of this doctorate thesis. Special thanks to my family members who have supported me throughout this journey, I will be forever grateful. Lastly, thank you to everyone who had been associated to the crucial parts of the realization of this project. Not forgetting, my humble apology as it is beyond my reach personally mentioned those who are involved directly or indirectly one to one.

اونیورسیتی تکنیکل ملیسیا ملاک
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

TABLE OF CONTENTS

	PAGE
DECLARATION	
DEDICATION	
ABSTRACT	i
<i>ABSTRAK</i>	ii
ACKNOWLEDGEMENT	iv
TABLE OF CONTENTS	v
LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF ABBREVIATIONS	x
LIST OF SYMBOLS	xi
LIST OF APPENDICES	xiii
LIST OF PUBLICATIONS	xiv
 CHAPTER	
1. INTRODUCTION	1
1.1 Background	1
1.2 Problem Statement	4
1.3 Research Question	9
1.4 Research Objective	9
1.5 Scope of Research	10
1.6 Thesis Outline	10
 2. LITERATURE REVIEW	13
2.1 Introduction	13
2.2 Malaysian Wood Species	14
2.3 Overview Wood Process	18
2.4 Variation of Wood Defects	24
2.5 Automated Visual Inspection (AVI)	26
2.5.1 Introduction of AVI	26
2.5.2 Related Works on AVI	28
2.5.3 AVI in Wood Industry	32
2.6 Feature Extraction of Defect Images	35
2.6.1 Related Works and Discussion on Feature Extraction of Wood Defects	36
2.6.2 Related Works on LBP	42
2.6.3 Related Works on Colour LBP	50
2.7 Statistical Texture Feature based on Local Binary Pattern (LBP)	56
2.7.1 Basic LBP	56
2.7.2 Uniform LBP	61
2.7.3 Uniform LBP for Colour Images	63
2.8 Conclusion	64
 3. METHODOLOGY	69

3.1	Introduction	69
3.2	Research Design	70
3.2.1	Research Framework	70
3.2.2	Operational Framework	72
3.2.3	Overall Research Plan	90
3.3	Summary	92
4.	RESULT AND DISCUSSION	95
4.1	Introduction	95
4.2	Feature Extraction using Colour Uniform LBP	96
4.3	Evaluation of Feature Quality	97
4.3.1	Exploratory Feature Analysis using Multivariate Intra-Class and Inter-Class Distance Between <i>Clear Wood</i> and Defects	98
4.3.2	Confirmatory Feature Analysis using MANOVA	101
4.4	Performance Validation	103
4.4.1	Classification Performance Across Wood Species and Image Pre-processing	104
4.4.2	Classification Performance Across Feature Extracted from Various Colour Channels	106
4.4.3	Classification Performance Across Wood Defects	112
4.5	Discussion	119
5.	CONCLUSION AND RECOMMENDATIONS FOR FUTURE RESEARCH	121
5.1	Introduction	121
5.2	Summary of the Research Objectives	121
5.2.1	Objective 1 - To propose feature representation of wood defect based on statistical texture features using enhanced Colour Uniform LBP with comprehensive colour normalization.	122
5.2.2	Objective 2 - To propose the wood defect class discrimination based on the proposed colour texture feature using statistical analysis of intra-class and inter-class distance and MANOVA.	122
5.2.3	Objective 3 - To evaluate the classification performance of the proposed Colour Uniform LBP feature across multiple defects and multiple wood species.	123
5.3	Research Contributions	125
5.4	Limitations of The Present Study	127
5.5	Future Works	127
5.5.1	Image Pre-processing Technique	128
5.5.2	Feature Extraction	128
5.5.3	Colour Channels	129
5.6	Summary	130
	REFERENCES	131
	APPENDICES	148

LIST OF TABLES

TABLE	TITLE	PAGE
Table 2.1	The wood species in Malaysia (MTC, 2016)	15
Table 2.2	Special characteristics of four wood species (MTC, 2016)	16
Table 2.3	List of major wood defects (Hashim et al., 2015a)	25
Table 2.4	Examples of binary patterns and decimal numbers	58
Table 3.1	Samples of the nine classes of wood defect images (Hashim et al., 2015a)	75
Table 3.2	List of statistical texture features set	80
Table 3.3	Confusion matrix	89
Table 3.4	Overall research plan	90
Table 4.1	List of statistical texture features set	96
Table 4.2	Example of extracted features (one sample per defect class, $R=1$, $sp=8$) (<i>BS=Blue Stain</i> , <i>BR=Brown Stain</i> , <i>HL=Borer Holes</i> , <i>KN=Knot</i> , <i>PC=Bark Pocket</i> , <i>RT=Rot</i> , <i>SP=Split</i> , <i>WN=Wane</i> , <i>CL=Clear Wood</i>) (Wood species – Merbau, LBP variant – Rotation Invariant Uniform LBP)	97
Table 4.3	Pillai's Trace value across multiple quantization levels and displacements	102
Table 4.4	List of feature sets used for performance comparison	107
Table 4.5	Confusion matrices for Rubberwood, KSK, Meranti and Merbau (Colour Channel – RGB)	117

LIST OF FIGURES

FIGURE	TITLE	PAGE
Figure 2.1	Wood process	18
Figure 2.2	System structure of AVI	33
Figure 2.3	Wood inspection using AVI	35
Figure 2.4	RGB image and grey level image (Ojala et al., 1994)	57
Figure 2.5	Local Binary Pattern (LBP) form a pixel neighbourhood. (a) 3x3 pixel of the grey level image. (b) Coordinate of the pixel in the image. (c) 3x3 greyscale neighbourhood. (d) Comparison between the neighbour pixels and the centre pixel. (e) Threshold neighbourhood differences. (Ojala et al., 1994).	58
Figure 2.6	Histogram of LBP. From regions or grids of image and generate a histogram of each region. Then, combination of histograms into one histogram of the whole image (Ojala et al., 1994).	59
Figure 2.7	Examples of the extended LBP operator: circular (8, 1), (16, 2) and (24, 3) neighbourhoods. (Huang et al., 2011)	60
Figure 2.8	58 unique uniform patterns (Inen et al., 2011)	63
Figure 3.1	Research framework	71
Figure 3.2	Operational framework	73
Figure 3.3	Procedures for extracting statistical texture features based on Colour Uniform LBP	76
Figure 4.2	Mean intra-class distance between clear wood samples and mean inter-class distance between clear wood and wood defect samples without image pre-processing	100
Figure 4.3	Intra-class distance between <i>clear wood</i> samples and inter-class distance between <i>clear wood</i> and defect samples (S11: Wood species – Meranti and colour channel – Blue)	101
Figure 4.4	Classification performance across with and without pre-processing for each wood species.	105
Figure 4.5	The classification accuracy of four datasets	109

Figure 4.6	Classification performance across colour channels for each wood species.	111
Figure 4.7	Classification performance across wood defects for each wood species.	113



LIST OF ABBREVIATIONS

ANOVA	-	Analysis of Variance
AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
AVI	-	Automated Visual Inspection
CNN	-	Convolutional Neural Network
FN	-	False Negatives
FP	-	False Positives
GLCM	-	Gray Level Co-occurrence Matrix
GLDM	-	Grey Level Dependence Matrix
HSV	-	Hue, Saturation, Value
LBP	-	Local Binary Pattern
MANOVA	-	Multivariate Analysis of Variance
MD	-	Mahalanobis Distance
MGR	-	Malaysian Grading Rules
MITB	-	Malaysian Timber Industry Board
RGB	-	Red, Green, and Blue
TN	-	True Negatives
TP	-	True Positives
UTeM	-	Universiti Teknikal Malaysia Melaka

LIST OF SYMBOLS

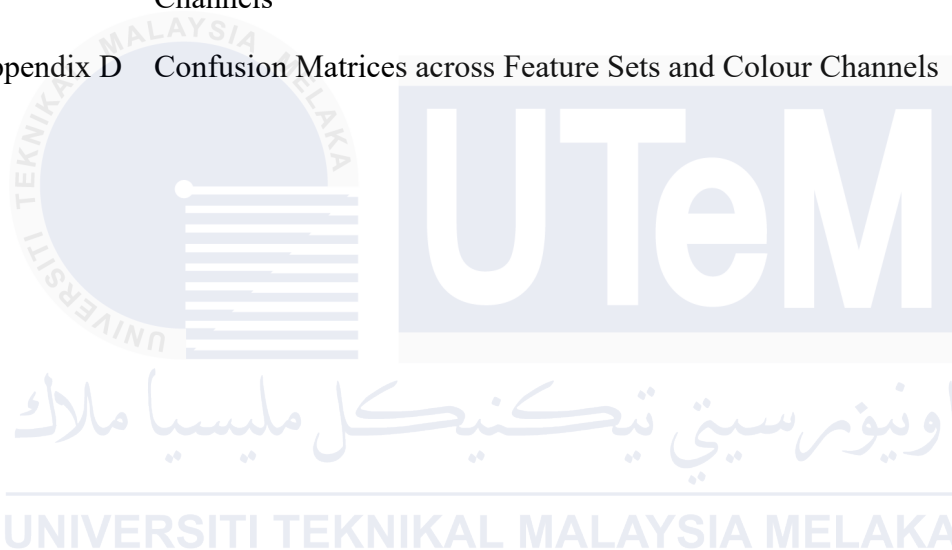
$+$	-	Plus
$-$	-	Minus
\times	-	Multiplication Sign
$\%$	-	Percentage
$=$	-	Equal
x_c	-	Subscript
2^i	-	Superscript
(x)	-	Parentheses
\sum	-	Summation
$\begin{Bmatrix} 1 \\ 0 \end{Bmatrix}$	-	Cases (two conditions)
\geq	-	Greater Than or Equal To
$<$	-	Less Than
$ x $	-	Cardinality
$\frac{1}{N}$	-	Stacked Fraction
\in	-	Element Of
$\sqrt{\quad}$	-	Square Root
$\begin{bmatrix} & \\ & \end{bmatrix}$	-	2 By 2 Matrix in Brackets
d'	-	Single-Quote
\bar{A}	-	Vector
\vdots	-	Vertical Ellipsis

...	-	Midline Horizontal Ellipsis
B/W	-	Linear Fraction
λ_i	-	Lambda



LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Intra-class Distance and Inter-class Distance	148
Appendix B	One-way MANOVA Results	165
Appendix C	Detailed Classification Accuracy across Feature Sets and Colour Channels	176
Appendix D	Confusion Matrices across Feature Sets and Colour Channels	182



LIST OF PUBLICATIONS

The followings are the list of publications related to the work on this thesis:

Rahiddin, R.N.N., Hashim, U.R., Salahuddin, L., Kanchymalay, K., Wibawa, A.P., and Chun, T.H., 2022. Local Texture Representation for Timber Defect Recognition based on Variation of LBP. *International Journal of Advanced Computer Science and Applications*, 13 (10), pp.443–448.

Rahiddin, R.N.N., Hashim, U.R. ah, Kanchymalay, K., Salahuddin, L., Ali, M., and Wibawa, A.P., 2025. Evaluation of Timber Defect Classification Performance using Colour Uniform Local Binary Pattern. *IAENG International Journal of Computer Science*, 52 (1), pp.201– 207.



CHAPTER 1

INTRODUCTION

1.1 Background

Malaysia appreciates its forests due to their important socioeconomic and environmental benefits. Traders guaranteed that the raw materials used to create Malaysian wood goods came from sustainably managed forests. The biggest expanses of natural land ecosystems in Malaysia are found in its forests. They are a significant source of biodiversity as a result. Manufacturing process has to be made efficient, hence, requires a reliable quality control procedure to support the increasing rate of production. Digital imaging has undergone significant advancements in recent decades, leading to the acquisition of vast amounts of visual information for quality control improvement (Khan, 2018). Automated Visual Inspection (AVI) has opened up new possibilities for various fields, including wood defect analysis. Wood defects pose challenges in industries such as furniture manufacturing, construction, and woodworking, as they can affect the quality, durability, and value of wood products (Qu et al., 2020).

Wood quality is closely related to wood defects. The strength of the wood affects the quality of wood products. The strength of the wood may be weakened by wood defects. Based on the research gathered, the quantity of defects in the wood is used to estimate its quality. The duration remains uncertain, as wood examiners are still engaged in the tedious process of evaluating wood quality manually, without the aid of any tools. Wood identification systems can be crucial in reducing fraud in the wood markets (Riana et al., 2021). Traditionally, wood defect analysis has relied on visual inspection, manual

measurement, and subjective grading (Qu et al., 2020). However, it is well recognised that manual visual defect inspection in the wood sector requires great deal of time (Ibrahim et al., 2021). These methods also provide an inaccurate and unreliable result because it is prone to human mistake, such as when headache symptoms are acute and eye fatigue. Therefore, there is a need for more efficient and objective techniques for wood defect analysis. The faster the detection of wood defects is, the faster the quality of the wood will be determined. Any overlooked or flawed products might harm the wood business, jeopardising safety measures and raising the risk that money would be lost settling failure or liability claims. Before a product passes on to the shipping stage, product quality control is crucial in preventing errors and defects in the manufacturing process.

When determining the quality of wood to be used in the production of high-quality wood products and for providing reliable results in the quality control process, automated vision-based inspection systems can provide more accurate results, detect flaws and defects in less time, and deliver more reliable results (Qayyum et al., 2016). Application and use of an AVI process, which consists of automated image acquisition and enhancement, segmentation, feature extraction, and classification features, would not only help to improve the inspection process but would also result in a decrease in labour costs because the features from the images divided into areas of interest and background in the AVI would already be present. Plus, by using AVI in the wood sector, it is possible to enhance the production line by examining many wood products without being constrained by human factors like fatigue, boredom, incompetence, and lack of training (Abdullah et al., 2020).

Feature extraction plays a crucial role in pattern recognition and image analysis. It involves extracting meaningful information from images to represent their distinctive

characteristics. By extracting relevant features, it becomes possible to classify and analyse images more effectively. It is a procedure used before the identification of defects on wood surfaces. Defects on the surface of wood vary in size and form. To identify the defects on the wood surface, the feature extraction technique is used. Consequently, to locate the appropriate features to be utilised to detect a defect, it is very essential to define and develop a quality feature set. The detection procedure might be executed with great accuracy and reliability by choosing the ideal collection of features (Packianather and Kapoor, 2015).

The Local Binary Pattern (LBP) technique is a widely used method for texture analysis and pattern recognition. It encodes the local texture information of an image by comparing each pixel with its neighbouring pixels. LBP has been proven to be robust, computationally efficient, and capable of capturing important texture patterns. Several studies have explored the use of LBP for wood defect analysis. For example, Ibrahim et al. (2021) utilized LBP as a feature extraction technique for wood defect classification and achieved promising results. Another study by De Sa et al. (2022) compared different texture feature extraction methods, including LBP, for wood defect classification. These studies have demonstrated the effectiveness of LBP in identifying and classifying wood defects.

Despite the existing research on wood defect analysis using LBP, there is still a research gap in terms of specific applications and optimization of the technique. This study aims to address this gap by focusing on the feature extraction of wood defects using LBP. The motivation behind this research is to develop a more accurate and efficient method for wood defect analysis, which can contribute to improved quality control and decision-making in industries that rely on wood products.

1.2 Problem Statement

The Automated Visual Inspection (AVI) of wood defects has gained significant attention in recent years, driven by the increasing need for reliable and efficient quality control in the wood industry. Traditional methods relying on manual inspection suffer from subjectivity, time constraints, and human fatigue, making them less effective in large-scale production environments (Hwang et al., 2021). Consequently, researchers have explored machine learning-based approaches that leverage image processing techniques for automated defect detection.

Among the various texture-based feature extraction methods, Local Binary Patterns (LBP) have emerged as a popular choice due to their computational efficiency and robustness (Kumar et al., 2024). However, the conventional grayscale LBP approach struggles with illumination variations and fails to capture essential chromatic information needed for reliable classification in wood defect classification (Feng et al., 2019; Pati et al., 2025). These challenges, including sensitivity to illumination changes and the loss of valuable colour information, have motivated the need for a more advanced feature extraction framework integrating colour features and normalization techniques (Vácha and Haindl, 2024).

Existing research has demonstrated the effectiveness of LBP in analyzing texture patterns for classification tasks, particularly in detecting surface defects. LBP operates by encoding pixel intensity differences into binary patterns, which are then used to construct histograms representing the texture characteristics of an image. While this method has been successfully applied in various domains, its primary limitation lies in its grayscale dependency. Wood defects often exhibit intricate colour variations that cannot be accurately