Evaluation of Timber Defect Classification Performance using Colour Uniform Local Binary Pattern

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***Abstract*—This study explores timber defect classification using features extracted from Colour Uniform Local Binary Patterns (CULBP) for four timber species: Rubberwood, KSK, Merbau, and Meranti, evaluating eight common defects such as bark pocket, blue stain, borer holes, brown stain, knot, rot, split, and wane. A series of colour feature sets were extracted from individual and combined RGB channels, with classification performed via an Artificial Neural Network (ANN). Results demonstrate that RGB channels without extensive colour normalisation deliver optimal accuracy, achieving 90.2% - higher than all other channels. Compared to previous studies using grayscale images and other LBP variations, our approach outperformed prior models like Daubechies Wavelet and LBP (85%) and basic LBP methods (65.4%), confirming that integrating RGB colour channels significantly enhances classification. Among timber species, Rubberwood achieved the highest accuracy, with particularly strong results for Rubberwood Rot (92.2%) and Merbau Hole (95.6%), underscoring the advantages of colour-based feature extraction in timber defect classifcation.**

***Index Terms*—Automated Visual Inspection, Local Binary Pattern, Timber Defect Classification, Texture Feature, Feature Extraction**

I. Introduction

DIGITAL imaging has undergone significant advancements in recent decades, leading to the acquisition of vast amounts of visual information for quality control improvement [1]–[3]. Automated Visual Inspection (AVI) has opened up new possibilities for various fields, including timber defect analysis. Timber defects pose challenges in industries such as furniture manufacturing, construction, and timber working, as they can affect the quality, durability, and value of timber products [4].

Timber quality is closely related to timber defects. The strength of the timber affects the quality of timber products. The strength of the timber may be weakened by timber defects. Based on the research gathered, the quantity of defects in the timber is used to estimate its quality. We can only guess how long it will take as timber examiners are still engaged in the tedious process of evaluating timber quality by hand without the aid of any tools.

Timber identification systems can be crucial in reducing fraud in the timber markets [5]. Traditionally, timber defect analysis has relied on visual inspection, manual measurement, and subjective grading [4]. However, it is well recognised that manual visual defect inspection in the timber sector requires great deal of time [6]. 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 timber defect analysis. The faster the detection of timber defects is, the faster the quality of the timber will be determined. Any overlooked or flawed products might harm the timber 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 timber to be used in the production of high-quality timber 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 [7].

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. Plus, by using AVI in the timber sector, it is possible to enhance the production line by examining many timber products without

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being constrained by human factors like fatigue, boredom, incompetence, and lack of training [8]–[11].

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 timber surfaces. The features will be divided into several defect classes as we extract them.

Defects on the surface of timber vary in size and form. To identify the defects on the timber 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 [12].

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 timber defect analysis. For example, [6] utilized LBP as a feature extraction technique for timber defect classification and achieved promising results.

Another study by [13] compared different texture feature extraction methods, including LBP, for timber defect classification. In addition, timber defect classification has been evaluated using the variance of LBP by [9]. Plus, LBP is one of the algorithms used to differentiate timber texture by [14], [15]. These studies have demonstrated the effectiveness of LBP in identifying and classifying timber defects.

Despite the existing research on timber 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 timber defects using Colour Uniform LBP. We used comprehensive color normalisation to normalise variation in colours illumination and lighting. We then extract the statistical feature of the colour image using Uniform LBP. The motivation behind this research is to develop a more accurate and efficient method for timber defect analysis, which can contribute to improved quality control and decision-making in industries that rely on timber products.

II. Materials and Methods

A. Approach Overview

This study used the timber defect dataset from the UTeM database [16], where nine different types of timber defects including clear wood had been extracted from amongst the 3600 images of timber defects seen on the four timber species. Four types of timber species are involved in the feature extraction process which are Rubberwood, Merbau, Meranti and KSK. During the collection of samples, the availability of the timber species depended on the type of end products produced by the factories and which were commonly used by different timber industries in Malaysia [17]. As such, the timber samples were limited to certain timber species.

The sawn timbers considered included ungraded, dressed, dried and free of dirt used in rough milling. Timber samples collected were between 45 and 70 mm in width, between 100 and 150 mm in length, and a thickness between 18 and 22 mm. The image of the timber defects of eight types of natural timber defects was knot, blue stain, brown stain, split, bark pocket, borer holes, wane, and rot. The image setting of the timber defect was 24-bit depth, containing 256 intensity levels for each red, green, and blue colour channel.

Fig. 1 illustrates the procedures for extracting the proposed statistical texture features based on Colour Uniform LBP.

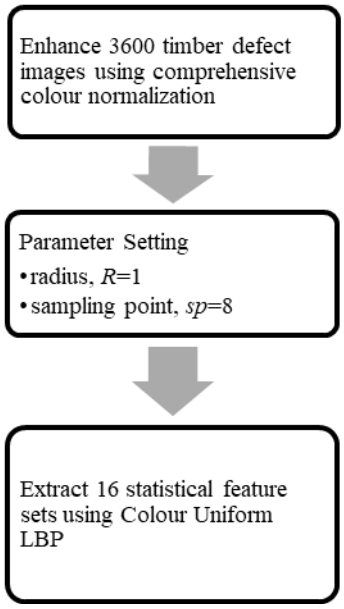

Fig. 1. Procedures for extracting statistical texture features based on Colour Uniform LBP.

First, timber defect images are enhanced using one of colour normalization methods which is comprehensive colour normalization. The basic idea of colour normalization is to remove the effects of illumination and colour variations from an image so that the colour and texture information can be more consistent and reliable. Then, we need to set the parameter setting that will be used which is the radius and the sampling point.

All the steps to derive colour uniform formulation based on a Uniform LBP with appropriate parameters are taken by applying pixel labelling by thresholding formulation of LBP by using single parameter setting; radius, R=1 and sampling point, sp=8. The choice of parameter setting is influenced by previous research on similar dataset [6]. Then, we extracted statistical colour texture features from Colour Uniform LBP for the four timber species which are Rubberwood, Merbau, Meranti and KSK.

Sixteen statistical textures of feature sets have been produced as shown in Table I. Each set consists of 900 samples where 100 samples for nine types of timber defects including clear wood.

TABLE I.
LIST OF STATISTICAL TEXTURE OF FEATURE SETS

Set	Samples	Mapping	No of Features	Colour Channels	Timber Species
S1	900	Uniform LBP	59	Red (R)	Rubberwood
S2	900				KSK
S3	900				Meranti
S4	900				Merbau
S5	900		59	Green (G)	Rubberwood
S6	900				KSK
S7	900				Meranti
S8	900				Merbau
S9	900		59	Blue (B)	Rubberwood
S10	900				KSK
S11	900				Meranti
S12	900				Merbau
S13	900		59+59+59	Red, Green, Blue (RGB)	Rubberwood
S14	900				KSK
S15	900				Meranti
S16	900				Merbau

B. Image Pre-processing

Comprehensive colour normalization plays a crucial role in preparing images for machine learning applications. Images capture the visual world by representing colours using different models. Common models include RGB (Red, Green, Blue) and HSV (Hue, Saturation, Value). Each channel in these models contributes to the final perceived colour.

However, image acquisition and display devices can introduce variations in colour representation. Lighting conditions, camera sensors, and monitor calibration can all lead to inconsistencies. These inconsistencies can affect the performance of machine learning algorithms that rely on accurate colour information. For example, an object recognition model might misclassify a red apple as orange due to variations in lighting.

Comprehensive colour normalization aims to address these inconsistencies and achieve colour constancy. It seeks to transform the colours in an image so that they appear consistent under different lighting conditions or across different devices. This process involves two main steps which are normalization of RGB channels and normalization of colour space.

Normalization of RGB channels step aims to reduce the dependence of pixel values on the overall illumination intensity in the image. Techniques include scaling all channels by a factor or using histogram equalization to create a more uniform distribution of intensity values across channels. On the other hand, normalization of colour space step aims to reduce variations in colour appearance due to the specific colour space used (e.g., RGB, HSV). Techniques include transforming the image to a colour space less sensitive to lighting variations, such as Lab colour space, or applying statistical methods to adjust the colour distribution within the chosen colour space.

According to [18], the function (1) normalizes images for both illumination intensity and illumination color effects. It can be applied to images with an unlimited number of color channels. Ranging from RGB to hyperspectral imagery.

$$NORMALIZED = comprehensive\_colour\_normalization\,(C, T) \quad (1)$$

Where,

C is a $M \times N \times L$ matrix in which $M \times N$ is the spatial domain and L is the colour spectral domain. T is a threshold. The function iterates until the mean square root difference between two consecutive steps is smaller than T. When a threshold is not given, it is set to 10^{-12} by default. For each pixel (i, j) mean$(Mi, Nj, :)$ is approximately 1. For each wavelength or colour (k) mean$(:, :, Lk)$ is approximately 1 as well.

By reducing colour variations, comprehensive colour normalization can significantly improve the performance of machine learning algorithms. They become less sensitive to lighting changes and better able to focus on the actual object features relevant to the task. However, it's important to consider the specific application and data characteristics when choosing a normalization technique. Over-normalization can introduce artefacts or reduce colour information relevant to the task. Additionally, some methods rely on specific assumptions about the image content, which might not always hold true.

Comprehensive colour normalization is a powerful tool for image pre-processing in machine learning. By understanding the principles behind colour representation and variations, appropriate normalization techniques can be applied to improve the robustness and accuracy of our models.

C. Feature Extraction

In the realm of artificial intelligence, particularly for tasks like image recognition and texture analysis, feature extraction plays a crucial role. Extracting meaningful features from images allows machine learning models to understand the underlying patterns and relationships within the data. One powerful technique for texture analysis is the Uniform Local Binary Pattern (ULBP).

ULBP operates at the local level, analyzing small image patches around each pixel. For each pixel, it compares its intensity with the intensity of its neighbours in a circular pattern. This comparison is performed using a binary threshold (typically 0). If the intensity of the neighbour is greater than the center pixel, a 1 is assigned; otherwise, a 0. By rotating this circular neighbourhood and repeating the comparison, a binary string is generated for each pixel, representing the local spatial pattern of intensities.

ULBP focuses on patterns where the binary string transitions between 0 and 1 (or vice versa) at most twice. These uniform patterns are less susceptible to noise and rotations compared to non-uniform patterns. Finally, these binary strings are converted into a histogram, capturing the frequency of each unique pattern within the image patch. This histogram becomes the feature vector that represents the texture information of that particular patch. Transition count calculation can be obtained using (2):

$$U\left(LBP_{P,R}\right) = |\, s(g_{P-1} - g_c) - s(g_0 - g_c)\,| + \sum_{i=1}^{P-1} |\, s(g_i - g_c) - s(g_{i-1} - g_c)\,| \quad (2)$$

There are $P(P-1)+3$ different P-bit output labels; 8 sampling points produce 59 labels, where 58 are uniform and 1 is non-uniform.

By applying ULBP across the entire image and creating a feature map of these histograms, we obtain a rich representation of the image's texture variations. This feature map can then be fed into machine learning models. The simplicity and effectiveness of ULBP make it a valuable tool for extracting informative features from images, particularly those rich in texture.

III. RESULT AND DISCUSSION

A. Impact of Pre-processing on Timber Defect Classification Performance

The pre-processing technique that we used is colour normalization. Colour normalization techniques can involve adjusting lighting conditions or digitally manipulating images to achieve a consistent colour standard. Fig. 2 reveals the impact of applying pre-processing (comprehensive colour normalisation) on timber defect classification accuracy. The findings are surprising. Fig. 2 shows that a slightly higher classification accuracy percentage of four timber species can be achieved without pre-processing compared to with pre-processing.

Rubberwood achieves the highest classification accuracy without and with pre-processing result which are 90.2% and 87.5%, respectively across others timber species. Meranti and Merbau also show highest classification accuracy in without pre-preprocessing, 85.6% and 82.2% respectively compared to with pre-processing results which are 81.6% and 78.1% respectively. In contrast, KSK showing with pre-processing result achieved 85.3% compared with 84.2% in without pre-processing.

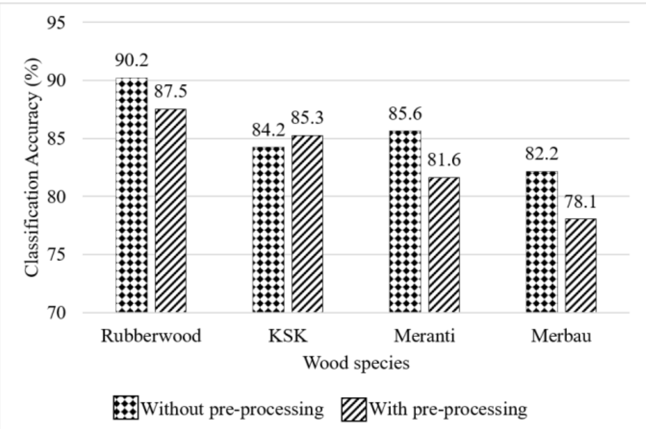

Fig. 2. Classification performance across with and without pre-processing for each timber species.

Timber species have inherent variations in colour due to factors like growth conditions and natural pigments. Some timber types may have more naturally consistent colouring, requiring minimal processing for successful work. Other timber species might have a wider range of colour variations, needing more extensive colour normalization to achieve uniformity. Pre-processing may have a more significant impact on timber species with a high degree of colour variation.

From a purely functional standpoint, colour variations within a timber species might not significantly affect its workability. Species suitability for processing is likely determined by more fundamental properties like timber density, hardness, and grain structure. Timber species have inherent characteristics that determine their ease of processing. Some timbers are naturally hard and dense, requiring more aggressive processing techniques like milling or planing. Conversely, softer timbers may be easier to work within their natural state.

There could be other factors besides colour consistency that influence the successful processing of different timber species. For example, the hardness, density, and grain structure of the timber can all play a role in how easily it can be worked. Additionally, the intended application of the timber might also be a consideration. Certain applications may have stricter colour consistency requirements than others.

It is also important to consider the cost-effectiveness of pre-processing. If the benefit of colour normalization for a particular timber type is minimal, then the additional processing step might not be worthwhile. If the primary concern is structural integrity and the timber has minimal colour variation, then colour normalization might not be necessary. However, for aesthetic purposes or applications requiring consistent colour, pre-processing might be crucial.

B. Classification Performance Across Features Extracted from Various Colour Channels

From the previous experiments, it is found that applying comprehensive colour normalisation had minimal impact on timber defect classification accuracy. Therefore, in the next experiments, the pre-processing step is omitted. Next, we further analysed the classification performance across features extracted from individual colour channels which are red, green, blue, and RGB. This is to gain a deeper understanding of how colour information contributes to our classification model's performance. This involved feeding the model data from each channel separately on the test set and evaluating its performance using metrics like accuracy, precision, recall, and F1-score.

The results as shown in Fig. 3 revealed interesting insights. The model performed significantly better when using data from the RGB channel, achieving an average classification accuracy of 87.8%. This suggests that information within this channel plays a crucial role in distinguishing between the target classes. Conversely, the performance on the remaining individual channels like Red, Green, and Blue was considerably lower. Red colour channel achieves 86.2% of classification accuracy, green and blue colour channels achieved 84.8% and 83.4% classification accuracy, respectively. This implies that these channels contain less discriminative information for our specific classification task.

These findings highlight the importance of RGB feature extraction tasks. The timber species' features of interest likely possess distinct colour characteristics primarily captured within this channel. However, the lower performance on other channels raises questions about potential biases. The model might be relying heavily on the dominant channel due to training data skewed towards certain colour profiles or inherent biases within the model architecture itself.

Moving forward, we can leverage these insights to improve the overall performance and robustness of the model. We can explore creating new features that combine information from specific channels to enhance its ability to utilize colour data effectively. Additionally, data augmentation techniques can be employed to enrich the training data with variations in colour profiles, potentially mitigating biases and improving performance across all channels. Finally, investigating alternative model architectures less susceptible to colour-based biases could be another avenue for future exploration. By delving into the role of individual colour channels, we gain valuable tools to refine our model and achieve more accurate and robust classifications.

C. Classification Performance from Previous Studies

We further discuss the previous studies using different colour channels and feature extraction using LBP variants. Table II. shows the list of feature sets used for performance comparison. It appears that LBP is a texture analysis method that has been shown to be effective in a variety of tasks, including defect detection in timber.

TABLE II.
LIST OF FEATURE SETS USED FOR PERFORMANCE COMPARISON

Feature Set from Previous Studies				
Dataset	Colour Channels	Statistical Features based on Local Binary Pattern Variants	Related Work	Reference
D1	Greyscale	Basic LBP, Rotation Invariant LBP, Rotation Invariant Uniform LBP, and Uniform LBP.	Wood defect detection	[19]
D2	Greyscale	Basic LBP	Wood defect identification	[6]
D3	Greyscale	Daubechies Wavelet (DW) and LBP	Wood identification	[20]
Proposed Feature Set				
Dataset	Colour Channels	Statistical Features based on Local Binary Pattern	Notes	
D4	Red, Green, Blue and RGB	Uniform LBP	Features extracted from individual colour channel and combination of colour channels.	

Table II. compared feature sets from three previous studies (D1, D2, and D3) with a proposed feature set (D4). All the previous studies used grayscale images, except for the proposed feature set (D4), which uses red, green, blue, and RGB colour channels. The proposed research is investigating the potential of using colour information to improve defect detection accuracy.

Emphasised is a detailed analysis of the feature sets from the previous studies (D1, D2, and D3). D1 uses a variety of LBP variants, including basic LBP, rotation-invariant LBP, uniform LBP, and non-uniform LBP which gives the impact of different LBP variants on defect detection accuracy [19]. Basic LBP is a simple operator that captures the local spatial patterns of pixels in an image. Rotation-invariant LBP is a variant of basic LBP that is more robust to image rotations. Uniform LBP is a variant of LBP that only considers local patterns that are relatively uniform. Non-uniform LBP captures all local patterns, regardless of uniformity.

Next, D2 uses only basic LBP. The feature set simple, and they have found that basic LBP performed well for their task [6]. Besides, D3 uses DW in conjunction with LBP. DW are a mathematical tool that can be used to decompose an image into different frequency bands. By combining DW with LBP capture more information about the texture of the timber, which is helpful for defect detection [20].

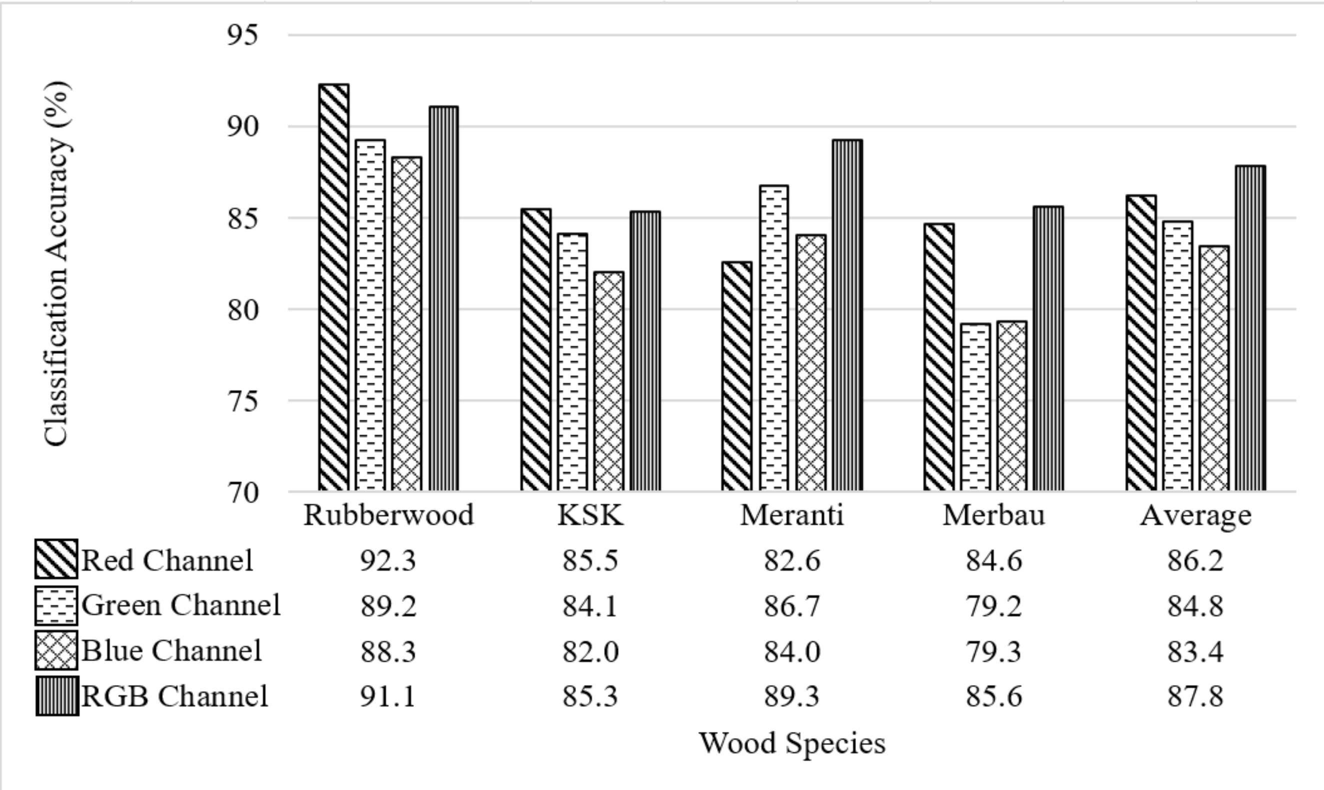

Fig. 3. Classification performance of features extracted across colour channels.

It has been shown that the feature sets from the previous studies (D1, D2, and D3) demonstrated the potential of using LBP for timber defect detection. The use of different LBP variants and the combination of wavelets with LBP suggest that there is still room for exploration in terms of optimizing the feature set for this study.

Complementary to this, D4 proposed using Uniform LBP on RGB images. This is a significant departure from the previous studies, which all used grayscale images. By using RGB images, the proposed feature set can capture colour information, which is helpful for defect detection. For example, some timber defects manifest as colour variations, such as discoloration or streaks. Uniform LBP is a good choice for capturing these types of colour patterns. The proposed feature set is based on the idea that using features extracted from individual colour channel and combination of colour channels which achieved good results but with RGB images potentially improve defect detection accuracy. This is a reasonable hypothesis, and it shows the proposed feature set performs in comparison to the previous studies.

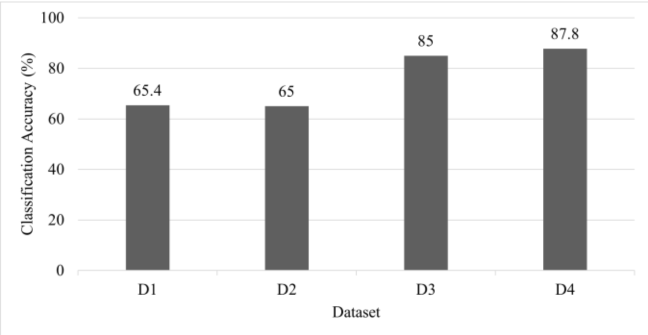

Fig. 4. Performance comparison of datasets.

The Fig. 4. shown three existing feature sets (D1, D2, D3) used in previous research on timber defect identification. The classification accuracies for D1 achieved 65.4%, 65% and 85% for D2 and D3, simultaneously. From these results, we can observe that D3 achieves highest accuracy among existing sets. Dataset D3, which utilizes a combination of DW transform and LBP features, achieves the highest classification accuracy (85%) for timber defect identification. The result shows that incorporating both spatial frequency information from the wavelet transform and textural information from LBP can be effective in capturing relevant features for the task.

Both D1 (65.4%) and D2 (65%) exhibit lower accuracies compared to D3. This could be due to several reasons. D1 and D2 solely rely on LBP variants for feature extraction, potentially missing out on the complementary information that the wavelet transform provides in D3. Additionally, the specific LBP variants used in D1 and D2 might be less suited for capturing the distinguishing characteristics of timber defects compared to the combination used in D3.

Fig. 4. also presents a proposed feature set (D4) for timber defect identification. The classification accuracy of 87.8% for D4. This is the highest accuracy among all the datasets. The proposed feature set (D4) utilizes colour information by using RGB images, whereas the previous sets (D1, D2, D3) relied solely on greyscale images. Additionally, LBP features are computed independently for each colour channel (red, green, blue). The improvement in accuracy from D3 (85%) to D4 (87.8%) illustrates that colour features are helpful in distinguishing between timber defects and defect-free regions.

Subsequently, Fig. 4. indicates that the proposed method employs Uniform LBP, a variant also used in D1. This suggests that even though D4 incorporates colour information, texture features extracted using Uniform LBP play a significant role in achieving good classification accuracy.

D. Classification Performance across Timber Defects

Firstly, let's address the classification performance across various timber species as shown in Fig. 5. Ideally, we would expect to see a high average accuracy across all timber species (Rubberwood, KSK, Meranti, Merbau) for each defect type. However, Fig. 5 shows that the performance can vary depending on the timber species and the specific defect. For instance, some entries, like Rubberwood Rot (Avg: 92.2%) and Merbau Hole (Avg: 95.6%), showcase exceptional accuracy across multiple algorithms. This concludes that the algorithms effectively capture the visual characteristics associated with these defects in those timber species.

On the other hand, entries like KSK Split (Avg: 65.1%) and Meranti Knot (Avg: 71.0%) reveal lower accuracy across the board, suggesting these defects might be more challenging to classify for certain timber species. This could be due to factors like inherent variations in how these defects manifest across different timber types. In addition, the presence of class imbalance in the training data where some defect and timber species are less frequent also can be the challenging factor to classify the timber defects.

IV. Conclusion

This study emphasizes the efficacy of Colour Uniform LBP in enhancing timber defect classification, especially when extracting features from RGB channels without color normalization. The RGB-based method achieved the best overall accuracy (87.8%), surpassing prior research using grayscale images and other LBP variants, such as Daubechies Wavelet and LBP methods, which reached a maximum of 85%. Notably, defects like Rubberwood Rot and Merbau Hole showed high accuracy rates, whereas defects like KSK Split and Meranti Knot proved more challenging. This comparison illustrates that using color channels in defect classification offers substantial improvement over grayscale approaches, supporting the utility of color-based feature engineering to strengthen model performance. Future research should focus on alternative feature extraction architectures to address color-based biases, ultimately advancing the robustness and accuracy of timber defect classification models in industry applications.

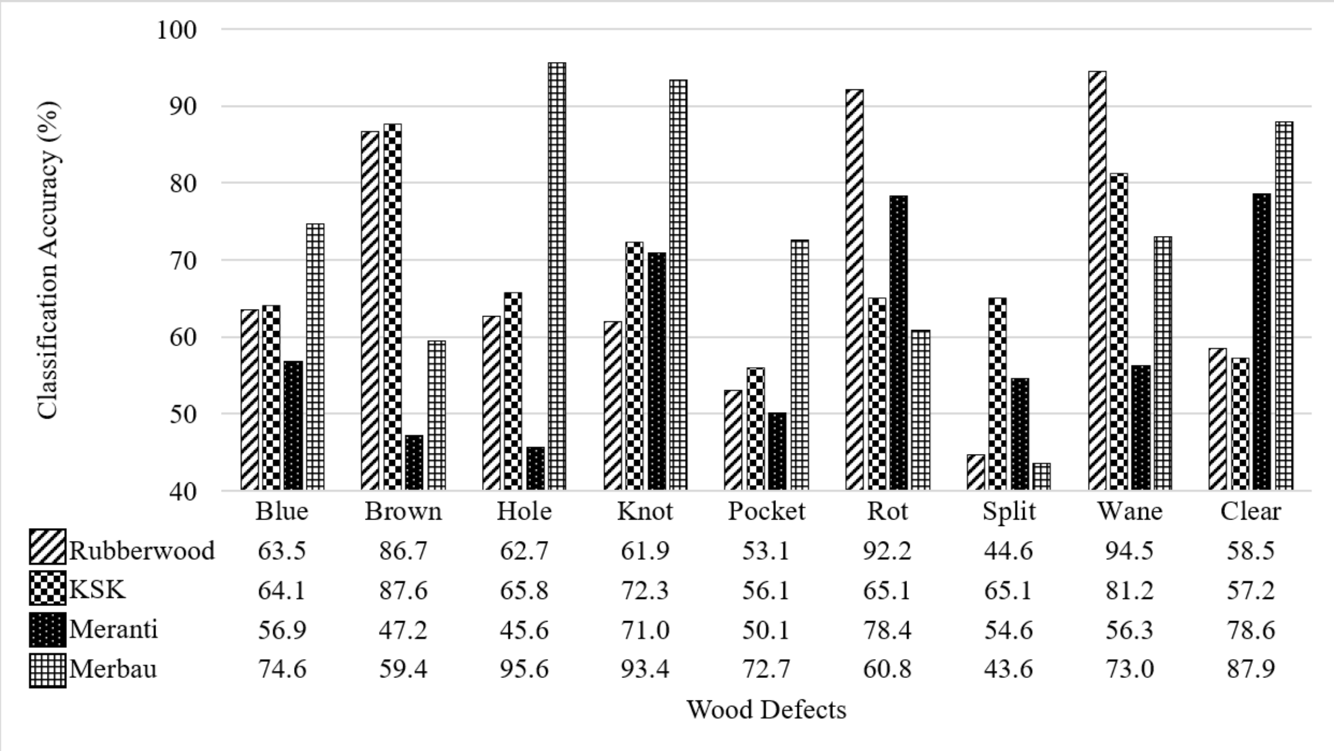

Fig. 5. Classification performance across timber defects.

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