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Wood Classification using Convolutional Neural Networks and Vessel Features on Cross Section Images

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Abstract: Wood identification can be considered as one of the essential tasks for experts on wood anatomy. The task of wood identification is not only required by wood anatomists, but it is also needed in other fields, such as custom ports, forest survey, and wood industries. However, the availability of wood identification is limited due to the number of wood anatomists. A computer vision-based algorithm is proposed to perform wood classification to resolve the existing problems. The algorithm uses an image of wood surfaces to determine the wood species. A trained identification model is applied to classify the wood name based on a Convolutional Neural Network (CNN) algorithm. The images were acquired using a smartphone camera and additional loupe mounted on the camera lens. The paper focuses on twelve (12) wood species that have a visual similarity appearance. Two classification models based on a convolutional neural network have been developed and used to obtain an acceptable accuracy on the observed wood species. The first model, Model-1, is created by stacking the convolutional and flattening layers. Meanwhile, the second model, Model-2, combines the unsupervised clustering technique and the CNN algorithm. The results show that both models can perform well, indicated by an F_1 score 0.90, at five species. The F_1 scores of the three species are still found to be close to 0.50. Specific techniques need to be explored and applied for these species. The methods might improve the classification performance.

Keywords: macroscopic images, convolutional neural network, wood classification

1. Introduction

Indonesia is known as a tropical country that has many kinds of wood species. The Indonesian forest is also recognised as the third largest area of tropical forest in the world. The forest area covers almost half of the Indonesian land area. It is estimated that 4,000 wood species are growing in Indonesia [1]. However, only a quarter of the total species are actively commercialised. The wood species is distinguished based on its name and characteristics. These characteristics, including its utilisation, are considered to determine its commercials price. By the government, this price value will be derived to determine the fee tariff. Therefore, it is crucial to identify the wood species to minimise the fee losses accurately. Not only for fees or tax collections but wood identification is also required in forensic investigation. Some criminal cases used the wood made objects as a part of illegal actions. Thus, the crime investigator would need information about the wood object characteristics to reconstruct the events. Furthermore, the student capability of wood identification is required to train their knowledge and experience in wood anatomy.

Wood identification is performed by visually observing the structure of wood anatomy. The unique structure of the wood surface is used as a physical feature to distinguish the species. The procedure of wood identification can be categorised into two types, namely microscopic and macroscopic observation. In the microscopic examination, a thin slice of wood specimen needs to be prepared. Additional liquid and treatment might also required to enhance the visual appearance. The sample is then observed under microscopic lens at a high magnification level. Additional camera is often mounted to the microscope to digitised the image. Conversely, the macroscopic assessment is more simpler than the microscopic. Firstly, the examiner must make a small cut in the cross-section plane of the wood surface.

As widely known, wood surfaces are defined as three

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directions, i.e. radial, tangential, and cross-section surfaces. The small cut is applied to the cross-section surface because it can give a clear surface pattern of wood vessels. The wood anatomists usually observe and examine the wood cross-section pattern to classify the species. Several characteristics need to be found and considered to decide either species or genus of the observed wood. The structural elements of wood surfaces mostly are unique and can be used as distinguishable features. This result cannot be strongly found in the radial and tangential surfaces. However, the feature dimension is tiny to be seen by the bare eye. Therefore, a handheld magnifying loupe is typically used by the examiner to observe the wood surface. The examiner uses a loupe equipped with a light source to observe and identify the wood. Using a magnification level lower than the microscopic assessment, the examiner should find the unique wood feature through the loupe view.

According to the procedure explanations of micro and macroscopic assessments, it can be seen that both procedures have to be conducted by a qualified person. They should have enough experience and good knowledge in wood anatomy. Because the person must locate the wood features and then decide what is the wood species. In terms of accuracy and availability, it will depend on the presence of the examiner. Other issues related to the reliability of human assessment are also needed to be concerned. The identification results conducted by an experienced examiner might be severed by incorrectness due to intra and inter-rater variation of visual evaluation. Therefore, a classification algorithm based on computer vision is proposed to minimise the identification problems on current procedures. The magnified image from the loupe could be directly acquired by many kinds of cameras, such as smartphones or tiny camera sensors of the single-board computer. The arrangement of the loupe and camera lens of the smartphone can produce an image with appropriate resolution.

An algorithm based on a Convolutional Neural Network (CNN) is used to perform the classification. The CNN was firstly coined by Yann LeCun *et al.* and implemented as a digits classifier [2]. The CNN architecture, namely LeNet, has been trained to recognise the handwritten digits on the binary images. The algorithm consists of deep neural network architecture and trained weights in the architecture. In this paper, the algorithm has been prepared for covering the identification of twelve species. The species is selected since it has visual similarity on the texture surfaces. This paper aims to present particular methods for decreasing misclassification results. The process is applied to a set of species with misclassification at a high rate.

The paper organisation consists of five sections. The first section introduces background, problem, and objective of the research reported in the paper. The second section describes previous research works that are related to the article. Most of the earlier investigations related to computer vision applications for wood identification are discussed in this section. The third section describes the development and implementation of identification algorithms. There are three different methods applied to find the best solution for resolving misclassification cases. The methods and their results are given sequentially. In the following section, section 4, the results from the previous section are summarised and analysed. The optimum solution is decided in this section. Finally, the fifth section will conclude and end the paper. An acknowledgement statement is included at the end of the article.

2. Previous Works

Erick Mata-Montero *et al.* applied a convolutional neural network algorithm to classify wood species. The algorithm is obtained by modifying the top layer of the ResNet50 model. A dataset of 41 different forest species of Brazilian flora is used to train the proposed algorithm. The research can achieve an accuracy of 98%, which is stated better than previous investigations [3]. One of the investigations was conducted by Pedro Luiz de Paula Filho *et al.*[4]. In this work, a total of 15 texture descriptors are extracted from the image dataset. The dataset is then used by Erick Mata-Montero *et al.*, as reported in [3]. The extracted features are classified by using SVM (Support Vector Machine) to provide the name of the wood species. The best identification accuracy (97.64%) is obtained by combining several feature extraction methods, such as Local Binary Pattern (LBP), Gabor filter, and Fractal. Classification models for wood identification have been developed by applying convolutional neural networks. The model is trained through the transfer learning method. Ten species of neotropical wood of the Meliaceae family, including CITES-listed *Swietenia macrophylla*, *Swietenia mahoni*, *Cedrela fissilis*, and *Cedrela odorata*, are observed in the research. The classification based on species and genus group is studied. The classification accuracies ranging from 87.4 to 97.5% are obtained in the study. Ravindran *et al.* found that the wood classification based on its genus can provide better results than species-based classification [5]. CNN is used to classify defects on wood surfaces. Two deep learning models are implemented in the research. The models are LeNet, VGG-19, and Densenet 121 [6]. Ting He *et al.* proposed a method based on a fully convolutional neural network (Mix-FCN) to detect the location of wood defects. A specialised image acquisition device collects the images with equipped cameras from two view directions, top and bottom views. The method is also able to classify the types of defects from the given wood surface images. Six types of wood defects can be identified by the proposed method at an accuracy of 99.14%. By applying this method, the wood defects are quickly located and classified [7]. Juraj˘Steve *et al.* developed a method for classifying wood fibres. The technique is used to classify four wood fibre categories: groundwood, sulphate pulp, whatman paper, and rag. The fibre is photographed at a magnification of 40× by using a microscope mounted on a digital camera. Helmholtz colour coordinate is used as a representative parameter of the fibres. The linear and quadratic discriminatory analysis is performed to classify the fibre category [8]. Seng *et al.* have studied a method for wood identification. Their research used an image dataset of 27 wood classes acquired using a standard single-lens reflex digital camera. The images were collected from small wood blocks obtained from a timber industry corporation. The dataset consists of 13,216 image patches at size 50×50 pixels. A classification model based on a convolutional neural network is used to train the dataset. The wood images are not directly loaded to the model. The red, green, and blue channels are transformed into six layers by multiplying two colour channels. The architecture comprises three convolutional layers and two fully connected layers, with Relu and Softmax activation used in these layers, respectively. The proposed method can achieve the highest accuracy at 93.94% [9]. Lainez *et al*. have applied a deep learning-based algorithm for identifying commercial Peruvian timber species. Seven species have been studied in the research. Wood images are acquired from tangential surfaces by using a digital handheld microscope. Two convolutional layers and two flatten layers are combined to build a convolutional neural network model. The best performance is obtained at image input size of 128×128. High accuracies can be found at six species, meanwhile low accuracy is only found in species of *Ceibapentandra* (L.) Gaertn. This exception occurred due to limited dataset availability on this species [10]. Figueroa-Mata *et al*. have applied a convolutional neural network algorithm to identify wood species. Popular architectures, such as LeNet and ResNet50, have been used and modified to achieve the best accuracy. The highest accuracy of 98.03% can be reached by applying the pre-trained weight of Imagenet [11]. The deep learning approach has been applied to classify 25 infrequent wood species of Yunnan [12]. A total of 120 wood images are collected for each species. The best result was found by implementing transfer learning technique on the RestNet50 architecture. Zhu *et al.* combined several models to obtain a high performance in wood classification [13]. The models were faster region-based convolutional neural networks (Faster RCNN), the sopisticated spatial pyramid pooling (SPP), and the multi-scale of feature pyramid networks (FPN). This model combination achieved an accuracy of 83.8%. The classification test analysed 1,216 wood images of 10 wood species.

3. Methodology

A. Data Collection

The wood images are collected from the wood specimen of Xylarium Bogoriense, Forest Products Research and Development Center, Bogor. The images are photographed using a smartphone camera and an additional loupe lens. An additional lens is mounted in front of the smartphone camera. The magnification of the extra lens is 60×, whereas the digital magnification of the smartphone camera is set to 3.5×. The combination of these magnification levels gives a total value of 210×. A small scratch is required on the wood surface. The scratching aims to open the wood pores and obtain a clean surface. The wood surface is then photographed by combining a smartphone and the additional lens. A total of 12 wood species were selected in this classification study. The common name of the wood is listed in Table I. Macroscopic images of the chosen wood species are depicted in Figure 1.

TABLE I. LIST OF OBSERVED WOOD NAMES IN THE EXPERIMENT

No	Code	Common Name	Total Images
1	W01	*Kayu kereta*	161
2	W02	*Menjalin*	167
3	W03	*Kenanga*	154
4	W04	*Tembesu*	203
5	W05	*Tenggayun*	168
6	W06	*Berangan*	165
7	W07	*Kedongdong hutan*	240
8	W08	*Bipa*	163
9	W09	*Kelumpang*	174
10	W10	*Terap*	168
11	W11	*Jabon*	186
12	W12	*Balsa*	179

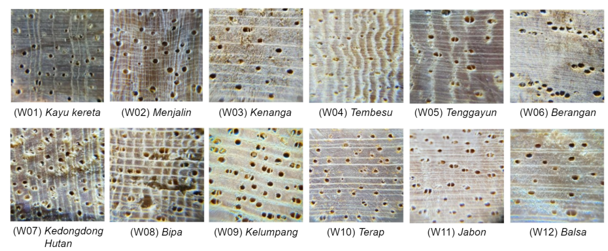


Figure 1. Macroscopic images of the observed wood species.

As understood in wood anatomy, a wood block consists of three main surfaces. The surfaces are defined as radial, tangential, and cross-section surfaces. The radial surface is a surface which divides the wood log at vertical direction. The tangential surface is located perpendicular with the radial surface. Lastly, the cross-section surface is a cutting surface at horizontal direction. This surface will cut wood vessels along the wood log. Location of each surface types are described in Figure 2. Here, only images of cross-section surfaces will be considered to use as input data for the proposed method. The cross section surface is selected to represent the wood characteristic. The texture of the cross section part has a unique pattern. We can use the texture to distinguish wood species.

The dataset is divided into three groups, training, validation, and testing. The training and validation groups are used to iterate the proposed model. The testing group will not be used in the training stage. The proportion between these groups is around 70:20:10 for training, validation, and testing datasets, respectively. The paper implements two methods that have been used to identify wood species. The design and identification results of these methods are presented in the following subsections. The respective form and its results are described separately in different

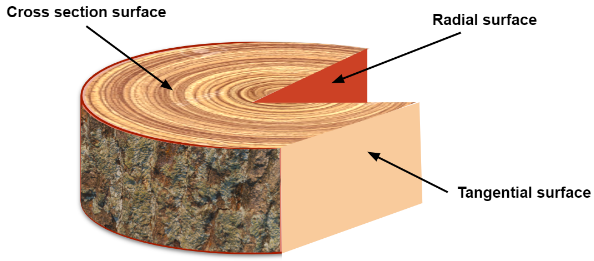


Figure 2. Categorisation of wood surfaces. The images are acquired from the cross section surface

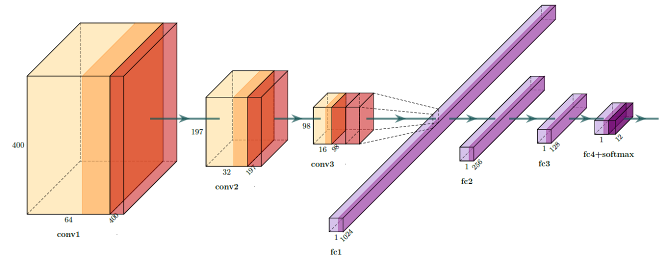


Figure 3. The architecture of the Model-1 for wood identification.

subsections.

B. Performance Parameters

The testing result of the proposed algorithm is evaluated by computing the performance parameters. Four classification descriptions are counted by referring to a confusion matrix. The classification descriptions are True Positive (*TP*), True Negative (*TN*), False Positive (*FP*), and False Negative (*FN*). Assumes a particular species, namely X will be predicted from various species. *TP* is obtained when we give an *X* species to the classifier, and then the classifier will predict *X*. *FP* is found when the classifier predicts non *X* species as an *X* species. Conversely, *FN* is given when the classifier foresees an X species as a non *X* species. The last case possibility is *TN*. The *TN* is acquired if the classifier determines any non *X* species as a non *X* species.

These four variables are then used to compute performance parameters, such as *Precision*, *Recall*, and F_1 score. *Precision* gives a fraction of how many classified items are belong to *X* species. *Recall* defines a fraction of how many *X* species could be found from the existing *X* items. Finally, both parameters, *Precision* and *Recall*, are combined to yield a F_1 score. The final F_1 score depends on the *Precision* and *Recall* values. Therefore, the F_1 score is used to evaluate the classification performance in each species. These three parameters are formulated in Equation 1, 2, and 3 respectively.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$F_1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

Meanwhile, accuracy is not considered in this paper. As formulated in Equation 4, the accuracy will accumulate the overall values of the confusion matrix [14]. A separated accuracy determination at single species is not available. Therefore, the performance analysis of a single species cannot be performed as in the previous three performance parameters (Equation 1 to 3).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

C. The First Method: Model 1

A simple CNN architecture is developed to classify the wood images according to their species. The net architecture consists of three convolutional and four flatten1-dimensional layers. In the first convolutional layer, 64 filters are applied to the input image at size 400×400. All three colour channels are considered in this first convolution layer. To refer to this architecture in the paper, then it will be named Model-1. Max-pooling filter at size 2×2 is then applied to the convoluted images. This filter reduces the original image size to half of the previous size. In the second layer, a total of 32 convolutional filters is applied to output images of the first convolutional layer. The subsequent max-pooling layer is also applied to the output of the second convolutional layer. This second max-pooling reduces image dimension to 25% of its original size. The third convolutional layer with 16 filters is then implemented to the max-pooling output. The filtered images of the third layer are then given to double max-pooling layers. The output of these two max-pooling layers is then flattened into a one-dimensional layer. The initial size of the flattened layer is 1,024. The following layer sizes are then reduced to smaller sizes, 256 and 128. Finally, the flattened layer is ended with the size of 12. This size is selected based on the number of species that will be classified in this work. Figure 3 displays the structure of Model-1 architecture. The architecture is trained by implementing functions and tools given by TensorFlow libraries. Programming codes are written using Python language.

A set of 15 images for each species are used as tested images. The confusion matrix is used to summarise the classification results of the Model-1 architecture. Two versions of confusion matrices are depicted in Figure 4 and Figure 5. Three performance parameters, namely Precision, Recall, and F_1-score, represent the algorithm objectiveness. The parameter values for each species are listed in Table 2. Parameter F_1 is used as a performance reference because the score is computed by considering two performance

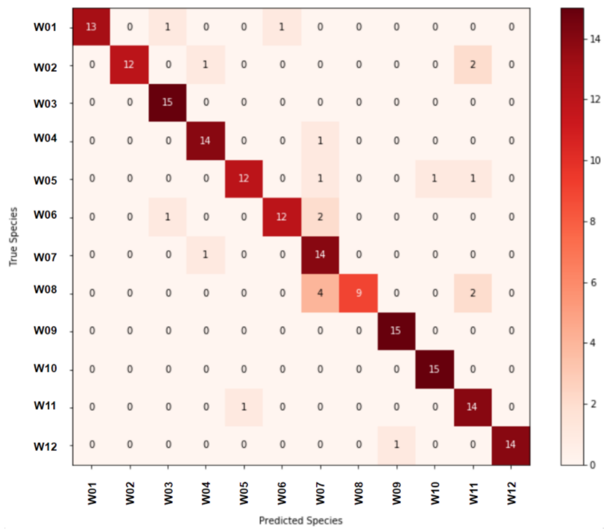


Figure 4. The actual confusion matrix was obtained from the Model-1 implementation.

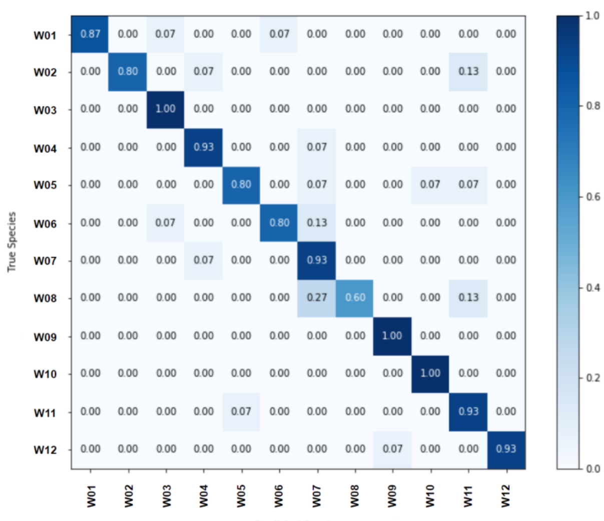


Figure 5. The normalised confusion matrix was obtained from the Model-1 implementation.

parameters, Precision and Recall. According to F_1 scores in Table 2, several species show good performances. Here, the F_1 can be stated as acceptable if its score is not less than 0.85. Therefore, the results of nine species can be accepted. The commercial names are used in this paper to simplify in referring a particular species. The wood with highest F_1-score are *Kelumpang* (W09: 0.97), *Terap* (W10 : 0.97), and *Balsa* (W12: 0.97). The lowest F_1-score, 0.75, is found at the wood of *Bipa*. Nine wood types can successfully achieve an F_1-score higher than 0.85.

D. The Second Method: Model-2 Combination of Unsupervised Clustering and CNN Algorithm

The second method is applied in this research work. The technique consists of a combination of unsupervised clustering and the CNN algorithm. The objective of this method is to reduce misclassification among the species. The original class will be initially clustered into some subgroups. The CNN is then applied to these clustered subgroups. Unsupervised classification k-Means clustering is selected to classify the dataset into these subgroups. The optimum weights will vary according to the type and number of classes in each subgroup. Therefore, the CNN algorithm will be applied to the smaller class dataset. In general, the proposed method consists of the following main steps:

TABLE II. PERFORMANCE RESULTS OF MODEL-1 ALGORITHM

No	Code	Name	Precision	Recall	F_1
1	W01	*Kayu kereta*	1.00	0.87	**0.93**
2	W02	*Menjalin*	1.00	0.80	**0.89**
3	W03	*Kenanga*	0.88	1.00	**0.94**
4	W04	*Tembesu*	0.88	0.93	**0.90**
5	W05	*Tenggayun*	0.92	0.80	**0.86**
6	W06	*Berangan*	0.92	0.80	**0.86**
7	W07	*Kdg.hutan*	0.64	0.93	0.76
8	W08	*Bipa*	1.00	0.60	0.75
9	W09	*Kelumpang*	0.94	1.00	**0.97**
10	W10	*Terap*	0.94	1.00	**0.97**
11	W11	*Jabon*	0.74	0.93	0.82
12	W12	*Balsa*	1.00	0.93	**0.97**

1) Apply Hough circle transform,
2) Cluster the dataset into two or three groups, and
3) Train the clustered group independently.

As displayed in Figure 6, several parameters are given to the k-Means clustering algorithm. Here, the parameters are determined from the wood vessel characteristics. Perceived on cross section, a tree trunk consists of bark, cambium, wood, and pith. The wooden part functions as a reinforcement and conduction of food from soil to the tree leaves [15]. It is made up of a variety of fibrous elements, vascular elements of varying sizes and configurations, and axial parenchyma cells in a variety of patterns and numbers [16]. Vessels are specialized conducting cells that are stacked one on top of the other to form vessels in hardwoods [16]. According to the [17], IAWA Committee developed vessel characteristics classification qualitatively and quantitively. Qualitatively, hardwood vessels were grouped based on the wood porosity, vessel arrangement, and vessel grouping. The porosity differentiates the wood into ring-porous, semi-ring-porous, and diffuse-porous. In the vessel arrangement, the vessels are also organized in tangential bands, diagonal and/or radial pattern, and dendritic pattern. Meanwhile, in vessel grouping, wood is distinctive observed as exclusively solitary vessels (90% or more), vessels in radial multiples of four or more common, and vessel clusters common. Another structure of vessel that is important in the wood identification is the angular outline of solitary vessel. Quan-

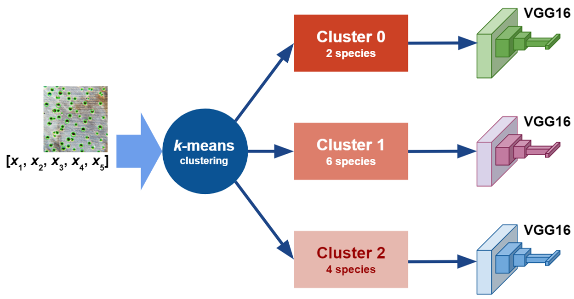


Figure 6. Combination of *k*-Means (unsupervised) clustering and three VGG16 models.

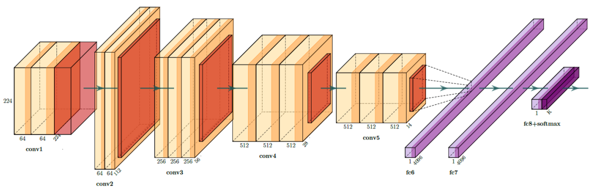


Figure 7. The architecture of VGG16.

titative vessel characteristics at cross section are tangential diameter of vessel lumina which are grouped into four classes (50 µm; 50–100 µm; 100–200 µm, and 200 µm). The tangential diameter of the vessel lumina, excluding the wall, is measured at the widest part of the opening. Another feature of vessel characteristic is vessel frequency (vessels per square millimetre), which are classified clearly at 5 vessels per square millimetre, 5–20 vessels per square millimetre, 20–40 vessels per square millimetre, 40–100 vessels per square millimetre, and 100 vessels per square millimetre. All the vessels are counted as individuals even in a radial multiple.

These wood vessels are extracted by applying the Hough circle transform. Three clustered dataset is then trained through VGG16 architectures. The dataset will be trained independently. The detail of each step is described in the following subsection.

1) Circle Hough Transform

Hough transform is applied to find wood vessels at cross-section surfaces. The implementation of Hough filters provides detected wood vessels and their properties, such as dimension, location is measured based on the centroid coordinate of the detected circle. The vessel number is counted from the detected vessels in a single image. Statistical formulas are used to extract representative values of wood characteristics. The parameters can be described as follows:

(a) **Number of the wood vessel**. Implementation of Hough transform can detect wood vessel existence on the wood surface. The wood vessel can be seen since its roundness is close to the circle shape detector of Hough transform. The total number of the detected wood vessels in the image area is denoted by N. The number of the wood vessel is considered as the first parameter.

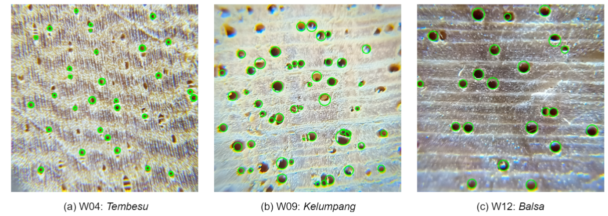


Figure 8. Detected wood vessels using Hough Transform.

$$x_1 = N \tag{5}$$

For example, the numbers of detected wood vessels in Figure 8 are (a) 30, (b) 50, and (c) 20 vessels. The smallest vessel number can be found in *Balsa* (Figure 8 (c)) among these three images.

(b) **Average diameter**. This parameter is obtained by averaging the wood vessel diameter. The x_2 denotes the average vessel diameter. The diameter of each detected wood vessel is represented by D_i. All of the detected vessels are considered in the parameter determination. The equation can be written as follows

$$x_2 = \frac{\sum_{i=1}^{N} Di}{N} \tag{6}$$

The average vessel diameters of Figure 8 can be described as follows: (a) 24.967, (b) 65.480, and (c) 88.045 pixels. As seen in Figure 8, the wood vessel with a large diameter is dominant at *Balsa* wood. Therefore, compared to *Tembesu* and *Kelumpang*, *Balsa* can have the largest diameter of the wood vessel.

(c) **Standard deviation**. The parameter is computed by applying the standard deviation formula to the detected wood vessel. The equation might represent the uniformity of the wood vessel in terms of its diameter size. The equation is shown in Equation 7. The average value is provided from the previous equation, *i.e.* Equation 6.

$$x_3 = \sqrt{\frac{\sum_{i=1}^{N} (D_i - x_2)^2}{N}} \tag{7}$$

Standard deviation values of Figure 8 are given as follows: (a) 40.861, (b) 555.071, and (c) 274.617. Based on these values, it can be stated that *Kelumpang* has the most diversity in terms of vessel size. Small and large vessel sizes are found in the surrounding surfaces.

(d) **Skewness**. The skewness parameter can be derived from Equations 2 and 4. The parameter is used to represent the tendency of vessel size. The skewness value will be negative if most of the wood vessel diameter is greater than the average size. Conversely, the positive skewness is attained if most vessel diameters are smaller compared to the average vessel diameter

$$x_4 = \sqrt{\frac{\sum_{i=1}^{N}(D_i - x_2)^3/N}{[x_3]^{\frac{3}{2}}}} \tag{8}$$

Here, the skewness values of Figure 8 are (a) 0.002, (b)0.006, and (c)0.032. According to these values, *Tembesu* has a different characteristic compared to the two other species. Its vessel diameter is mostly smaller than the average diameter. It can be depicted in Figure 8 (a), small vessels are more dominant, covering the wood surface.

(e) **Wood vessel density**. The density is determined by dividing the number of vessels, x_1, detected in the total area of the image. The area is calculated by multiplying the image's width (w) and height (h). Since there is no scale ratio variation, the unit of the area is retained as a pixel.

$$x_5 = \frac{x_1}{(w \times h)} \tag{9}$$

The vessel density of species at Figure 8 can be listed as follows: (a) 0.00016, (b) 0.00027, and (c) 0.00016. By referring to these results, it can be described that the densest vessel belongs to *Kelumpang*. In the same image sizes, this wood image contains 50 wood vessels. It is the largest number compared with two other wood species. The vessel density is linearly proportional to the number of wood vessels. These five parameters are then applied as representative features of wood species in *k*-Means clustering implementation.

2) Clustering of Three Sub Group

The dataset of 12 species is initially clustered into three sub groups. Based on *k*-Means results, two boundaries for separating three clustered can be created. According to the result of *k*-Means clustering on 12 species, the species members in each sub group can be described as follows:(1) Sub group 0 (2 members): *Kelumpang* and *Balsa*; (2) Sub group 1 (6 members): *Kayu kereta*, *Menjalin*, *Kenanga*, *Tembesu*, *Tenggayun*, and *Jabon* (3) Sub group 2 (4 members): *Berangan*, *Kedondong hutan*, *Bipa*, and *Terap*. The CNN algorithm based on VGG16 architecture is applied to the dataset in each sub group, namely 0, 1, and 2. The algorithm is used separately to obtain unique weights for each sub group. Therefore, the final weights among these sub groups would not be similar. As conducted in previous section, the test images from all species are applied to the second method (See Figure 6).

The weights in sub group 0, 1, and 2 are trained independently. The values of five parameters are extracted from the input image. The algorithm will decide the input image to a certain sub group based on result of the *k*-Means classifier. Once, the sub group can be decided, the whole image could be analysed by the VGG16 model of the selected sub group.

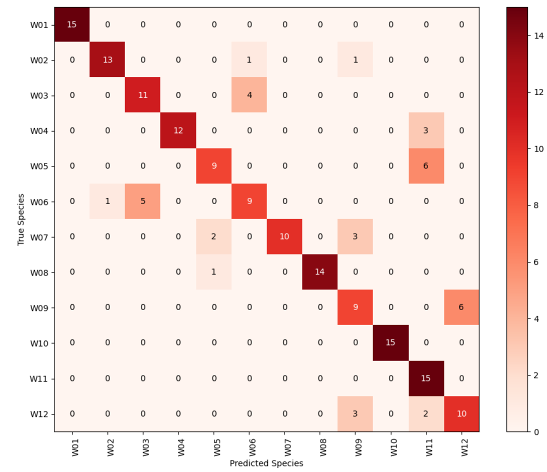


Figure 9. The actual confusion matrix was determined by Model-2.

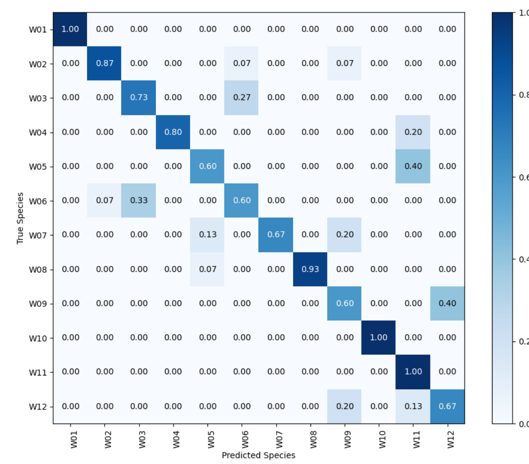


Figure 10. The normalised confusion matrix was obtained by Model-2.

The confusion matrix of the second method is summarised in Figure 9 and 10. Both representations, actual and normalised confusion matrices, are presented in these figures. Based on the confusion matrix values, three performance parameters are then computed. These parameters are Precision, Recall, and F_1-score. The parameters are calculated independently for each species. The calculation results are listed in Table III. According to the F_1-score of the tested species, six species can achieve F_1-score not less than 0.85. Those species are: W01-*Kayu kereta* (1.00), W02-*Menjalin* (0.95), W04-*Tembesu* (0.91), W07-*Kedondong hutan* (0.85), W08-*Bipa* (0.93), and W10-*Terap*

TABLE III. PERFORMANCE RESULTS OF MODEL-2 ALGORITHM (COMBINATION OF *K*-MEANS AND VGG16)

No	Code	Name	Precision	Recall	F_1
1	W01	*Kayu kereta*	1.00	1.00	**1.00**
2	W02	*Menjalin*	0.97	0.93	**0.95**
3	W03	*Kenanga*	0.77	0.77	0.77
4	W04	*Tembesu*	1.00	0.83	**0.91**
5	W05	*Tenggayun*	0.80	0.53	0.64
6	W06	*Berangan*	0.69	0.73	0.71
7	W07	*Kdg.hutan*	1.00	0.73	**0.85**
8	W08	*Bipa*	1.00	0.87	**0.93**
9	W09	*Kelumpang*	0.55	0.60	0.57
10	W10	*Terap*	1.00	1.00	**1.00**
11	W11	*Jabon*	0.59	1.00	0.74
12	W12	*Balsa*	0.62	0.67	0.65

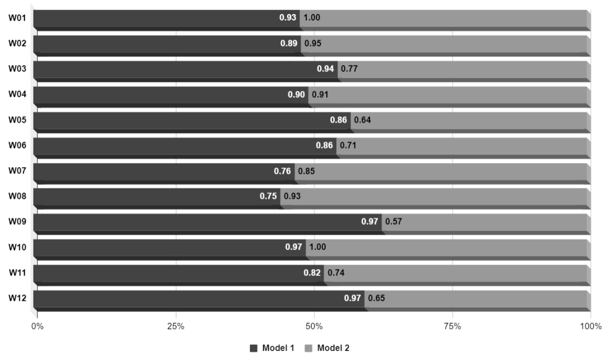


Figure 11. F_1-score comparison determined by Model-1 vs Model-2.

(1.00).

4. RESULT AND DISCUSSION

The proposed method is tested by using a set of testing images. These images are not included during the training process. Therefore, the data has never been used as a training and validation dataset. As presented in the previous section, two performance tables have been displayed. By comparing the results shown in Table II and Table III, it can be stated that the Model-1 algorithm can provide a better result since the species number with a high F_1-score at Model-1 is more significant compared to the number obtained by the Model-2. The Model-1 provides eight species, whereas, in the Model-2, only six species can get high F_1-scores. This fact proves that the Model-1 algorithm is more robust compared to the Model-2. The F_1-score comparison between both algorithms can be shown in Figure 11.

Four species - *Kayu kereta*, *Menjalin*, *Tembesu*, *Terap* – can provide good performance in both models. Their average F_1 score is higher than 0.90. The medium and large vessel sizes dominate the wood textures. The vessel positions are also found in the regular wood lines pattern. The vessels appearance is also clear and discernible. The pattern of wood lines and vessel variation is unique. Therefore, these species can provide high performance in the classification stages. Figure 12 depicts the surfaces of those four wood species.

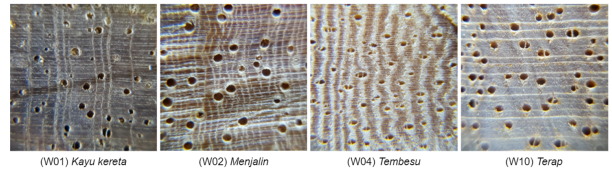


Figure 12. Four species have high F_1 scores in Model-1 and 2.

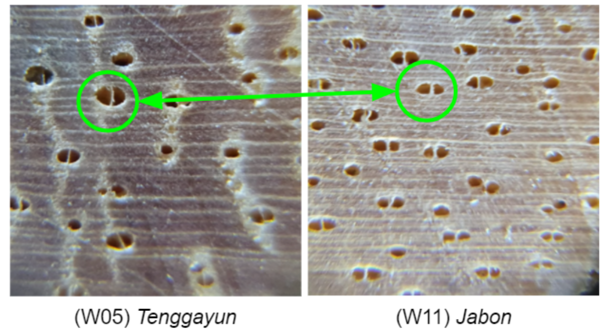


Figure 13. Shape similarity of the wood vessels.

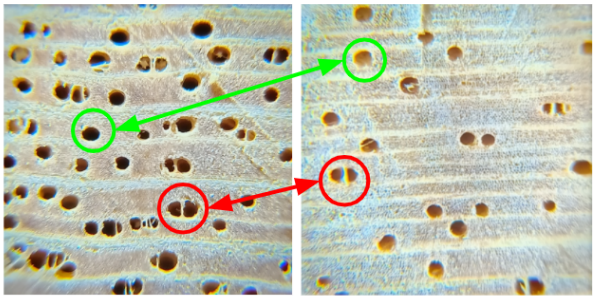
Two wood pairs are not accurately classified. The first pair is between *Tenggayun* and *Jabon*. Meanwhile, the second pair is between *Kelumpang* and *Balsa*. Figure 13 depicts the similarity of the wood vessel shape of *Tenggayun* and *Jabon*. The vessel is divided into two symmetrical cavities. As shown by the figure, the vessel size and distribution of both are not much distinct. Therefore, Model-2 will be influenced by the existing wood similarity.

Misclassification due to similarity of texture appearance is also found in the wood of Kelumpang and Balsa. These woods have two similar vessel types. The first type is the vessel with a single cavity and the second type is the vessel filled by symmetric two radial multiples. Both vessel types from two different species are grown in equal size and distribution. This condition can cause a classification error when Model-2 is implemented in the wood dataset.

The misclassification cases of *Kelumpang-Balsa* and *Tenggayun-Jabon* happen internally in sub group 0 and 1 respectively. It can be deduced that the *k*-Means clustering has correctly grouped the wood species according to textural properties. However, the VGG16 classification of subgroups 0 and 1 are not yet accurate to distinguish the wood species. Improvement on the CNN architecture of subgroups 0 and 1 needs to be applied.

5. CONCLUSION

Twelve wood species are classified by applying convolutional neural network-based architecture, namely Model-1. In the second model, Model-2, unsupervised clustering and



(W09) *Kelumpang* (W12) *Balsa*

Figure 14. Wood vessel similarity between Kelumpang and Balsa.

VGG16 classifier are implemented to improve the classification. The Model-1 is constructed by stacking several convolutional and flattening layers. Model-2 couples the unsupervised clustering technique and the CNN algorithm. The experiment results found that both models could perform well. The models provide an F_1 score 0.90 for five species. The F_1 scores of the three species are still low. More texture parameters should be included in the classification algorithm. Those parameters such as wood vessel shape, texture colour, and growth ring orientation. In some cases, the wood vessel could be encircled with a unique pattern.

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TABLE IV. Comparison of wood identification methods using vision modalities

Author	Year	Method	Wood Object	Acc.(%)	Prec.(%)	Recall(%)	F_1
Jasim *et al.* citation	2014	LDA+*k*-NN	Indonesia, 9 species	92.42	-	-	-
Oliveira *et al.* [4]	2014	Color Feature,GLCM,GF,LBP,Fractal,Edges+SVM	Brazilian Flora, 41 species	97.77	-	-	-
Tevek *et al.* [8]	2016	Helmholtz Color Coordinates	Wood Fibers, 4 types	50.00	-	-	-
Mata-Montero *et al.* [3]	2018	CNN (ImageNet)	Brazilian Flora, 41 species	98.00	-	-	-
Ravindran *et al.* [5]	2018	CNN (VGG16)	Neotropical Species, 10 species	97.50	-	-	-
Jung *et al.* [6]	2018	CNN (LeNet,VGG-19,Densenet121)	Wood Industrial Images, 4 defect classes	99.80	-	-	-
Seng *et al.* [9]	2018	CNN (RGB Channels)	Sarawak Timber Industry, 27 class images	93.94	-	-	-
Lainez *et al.* [10]	2018	CNN (VGG16)	Peru, 7 species	94.05	90.00	-	-
Figueroa *et al.* [11]	2018	CNN (ResNet50)	Brazilian Flora, 41 species	98.30	-	-	-
He *et al.* [7]	2019	Mix-FCN (VGG16)	Wood Defects, 6 types	99.14	-	-	-
Sun *et al.* [12]	2021	RLK (ResNet50, LDA and KNN)	China, 25 species	99.6	-	-	99.40
Zhu *et al.* [13]	2021	Faster RCNN+SPP+FPN	China, 10 species	83.8	77.79	-	-
Our method (Model-1)	2021	Convolutional Neural Networks	Indonesian, 12 species	88.33	90.50	88.25	88.50
Our method (Model-2)	2021	Unsupervised clustering+CNN	Indonesian, 12 species	80.56	83.25	80.50	81.00

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