Wood Species Classification Based on Wood Porosity Distribution of Macroscopic Image

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***Abstract*— In the context of illegal logging, it is crucial to identify the wood species that are being traded. Wood species classification plays a vital role in inspecting the movement of wood in and out of an area. Furthermore, wood classification is particularly significant to determine the species of the wood test sample to obtain high accuracy. Therefore, the development of automatic wood species classification based on computer vision is highly required. Each wood species possesses unique anatomical characteristics, such as its vessel or pore structure. This research aims to propose an automatic algorithm that can classify wood species based on the porosity distribution of the macroscopic image. This research utilized wood images from six different wood species. The Contour method is used to identify pores first and then many features will be extracted. It will detect the pore size and extract pore features such as the number of pores, size, standard deviation, skewness, kurtosis, and density. By using the macroscopic image of the six wood species, the result showed that 300 data could be extracted and forming a model based on pore features. The accuracy of the wood classification was evaluated using the Random Forest classifier, yielding an accuracy rate of 92.00%. This indicates that the wood porosity distribution features can be effectively utilized for wood species classification.**

Keywords—*wood classification, wood pores, Contour algorithm, Random Forest Classifier*.

I. Introduction

Timber trees play a role in maintaining forest ecosystems which is currently a major concern. Therefore, concrete efforts are required to protect these timber trees. One such effort is safeguarding the forest against illegal logging where timber is traded without proper authorization from the authorities. In the context of illegal logging, it is crucial to identify the wood species that are being traded. Wood species classification plays a vital role in inspecting the movement of wood in and out of an area. Various approaches can be employed for wood species classification and one such method is using computer vision. In wood classification, computer vision methods are employed to achieve more accurate results. These methods utilize wood images as the principle for classification, enabling the extraction of relevant wood features.

In features extraction methods, a variety of wood characteristics can be utilized for classifying wood species. To obtain more relevant features, several studies focus on pore objects [1], [2], [3]. However, the International Association of Wood Anatomists (IAWA) has already compiled an extensive list of pore features in the IAWA Jounal [4]. Regarding the features list from IAWA Journal, there are still many additional features that can be extracted. One such feature is pores size and their distribution. Each pore texture in the macroscopic image is represented by the distribution of the pore. It should be noted that each wood species has a different pores distribution.

This research aims to propose an automatic algorithm that can classify wood species based on the porosity distribution of the macroscopic image. At the first stage, collected wood macroscopic image are ready for the preprocessing stage as wood datasets. In the preprocessing, an image enhancement process is used to improve the wood image by removing the noise that makes the image unclear or damaged. The contour method is used to identify pore first and then many features will be extracted. The contour method will detect the pore size and extract pore features such as the number of pores, size, density, structure, and other features. All these pore features are collected in the pore feature model. Finally, the testing pore feature datasets are prepared to obtain good results from the Random Forest classifier. This phase will also evaluate and analyze the results of the classifier.

The rest of this paper is organized as follows. Section II discusses the related work related to the wood species classification using computer vision method. The discussion of the wood dataset and the proposed research method will be discussed in Section III. Experimental results will be discussed in Section IV with the analysis. The last section is the conclusion of the research result and the future works.

II. Related Works

There are two types of wood classification methods in computer vision. The first method involves using the feature extraction method to identify wood species based on various forms of extraction such as patterns, shapes, or color. Commonly used feature extraction techniques include Local Binary Pattern (LBP) [5], Gray Level Matrix Co-Occurrence (GLCM) [6], Scale Invariant Feature Transform (SIFT) [7], and other methods. Once the features have been extracted, a suitable classifier must be chosen to classify the prepared testing data.

The second type is using the Convolutional Neural Network (CNN). The CNN algorithm consists of deep neural network architecture and trained weights in the architecture. From the studies, the algorithm can be used to classify wood species. Wood species were chosen for this purpose due to their visual similarity on the texture surfaces. In this case, various CNN architectures are used such as VGG [8], ResNET50 [9], Inception [10], and the other architectures. Generally, wood images are inputted into these architectures and undergo various convolution processes with multiple layers to obtain wood features and classify them directly.

Both types of wood classification mentioned above extract all surface areas in the wood image without considering whether the resulting features are important or not. This approach also extracts many unimportant, such as lines or holes caused by knife cuts during the image acquisition process, camera light points detected in the wood image and other tissues that are not the main features of wood classification. Consequently, this inefficient extraction makes the classification process take a long time. In this research, the classification approach is based on the main features of pores. Each wood species has different sizes, numbers, structures, and densites of pores. By highlighting these pores distribution, feature extraction can be performed to achieve higher accuracy and faster classification.

III. The Proposed Porosity Distribution Method

The objective of this research is to propose a new model complete feature extraction, which utilizes wood porosity distribution and aims to obtain comprehensive features for the classification process. To accomplish the wood porosity distribution and wood species classification, several stages were undertaken as depicted in Fig. 1.

A. Wood Dataset

The wood datasets for this research were obtained from the Xylarium Indonesia, National Research and Inovation Agency (BRIN), Republic of Indonesia. The wood block sample can be seen on Fig. 2. In the experiments, macroscopic wood images of cross section surface from six wood species were used: Jati (*Tectona grandis L),* Sengon (*Falcataria moluccana)*, Kecapi (*Sandoricum kutjapi*), Kupang (*Ormosia macrodisca Baker*), Tenggayun (*Parartocarpus venenosus*), and Puspa (*Schima wallichii Korth*). Fig.3 shows the six wood images used in this experiment. The wood datasets were also divided into training and testing sets for classifier. For the training and testing process, 50 wood images from each species were prepared to obtain the pore features.

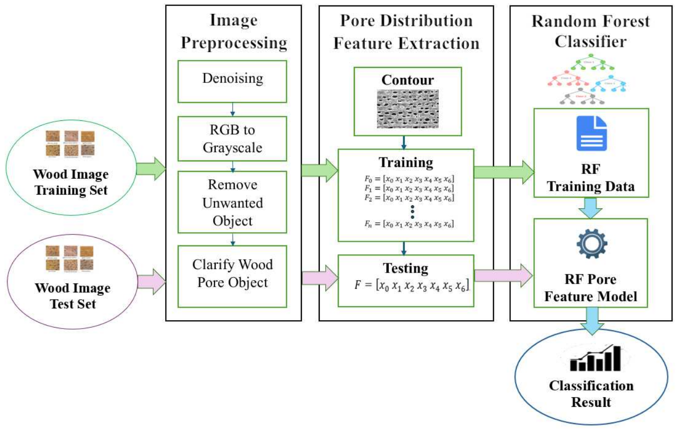

Fig. 1. The proposed method for the wood species classification using porosity distribution

Fig. 2. The example of wood block samples.

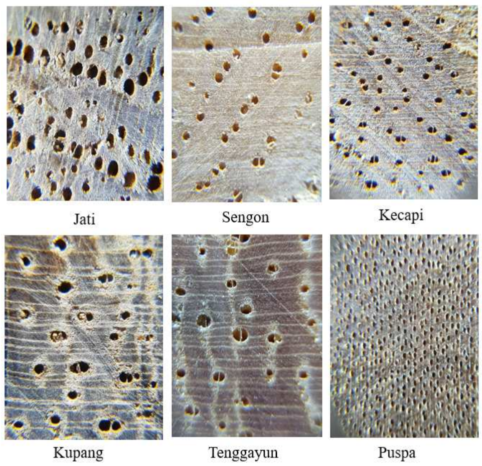

Fig. 3. The six species wood images carried out in this initial experiment.

B. Image Prepocessing

The wood datasets preprocessing was carried out on the collected datasets to refine them to meet research requirement. Considering the macroscopic image of the wood dataset, the image preprocessing procedure to obtain clear and sharp pores is illustrated in Fig. 4.

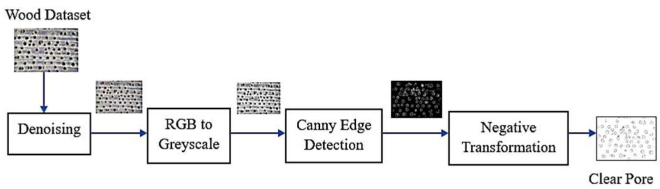

Fig. 4. The wood image preprocessing procedure

Wood image denoising is performed to clear the wood dataset and obtain a recovery image for the next stage of processing. In this proposed system, the nonlocal mean algorithm is utilized to denoise the wood image. The main principle of the nonlocal means algorithm involves averaging the colors of multiple sub-windows in the image that similar to the pixel neighbourhood, thereby replacing the pixel's color. To facilitate the extraction process, the wood color image is converted to grayscale image as color is not required for pore detection. Moreover, grayscale image is generally used to simply the algorithm and eliminates the computational complexities. Unwanted objects are removed to get existing pores objects. One method to get pores objects is Canny edge detection. Since the output of the Canny process is on a black background, a negative transformation is needed to restore the grayscale colors to their original color state. Fig. 5 shows the result of the preprocessing and is ready for the extraction stage.

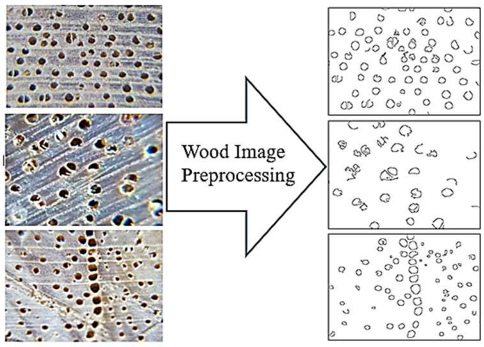

Fig. 5. Examples of wood images after undergoing the preprocessing process.

C. Pores Features Extraction

In this research, the Contour algorithm is used to identify wood pores in cross-section surfaces image. The purpose of Contour detection attempts to extract curves or circle which represent object shape from the wood image. Contour is applied to represent and bound the shape of the abject [11]. Contour detection attempts to extract curves or circle which represent object shape from the image then it useful tool for shape analysis and object detection. The function to predict the posterior probability is defined first by [12] with the function $Pb(x, y, \theta)$. θ parameter is the orientation at each image pixel of x and y. This function is defined by measure the variation in texture, colour, and brightness of the local image. The *Pb* contour detection is the oriented gradient $G(x, y, \theta)$ computation from the image intensity (I) [13]. By placing a circular disc, this computation will proceed at location (x, y) and split into two half discs by dimeter at θ direction. Furthermore, the histogram of the intensity values of the pixels of I is covered for each half-disc. If the range between the two half-disc histogram g and h is notated by x^2, then the gradient magnitude G at location (x, y) can be calculated as follows:

$$x^2(g,h) = \frac{1}{2}\sum_i \left(\frac{(g(i)-h(i))^2}{g(i)+h(i)}\right). \qquad (1)$$

In addition to calculating the distance between two half-discs, it is also necessary to calculate the diameter of the detected pores. This diameter can be derived from the equivalent diameter. Equivalent diameter (*ED*) is the circle diameter that the region is the same as the contour area and can be obtained as follows:

$$ED = \sqrt{\frac{4\ x\ Contour\ Area}{\pi}}. \qquad (2)$$

The implementation of contour provides detected wood pores and their properties, such as dimensions, location, and total number. The circle radius represents the pore's dimensions. The pore's location is measured based on the centroid coordinate of the detected circle. The pores number is counted from the detected pores in a single image. Fig. 6 shows the wood image after being extracted by the Contour algorithm for six wood species.

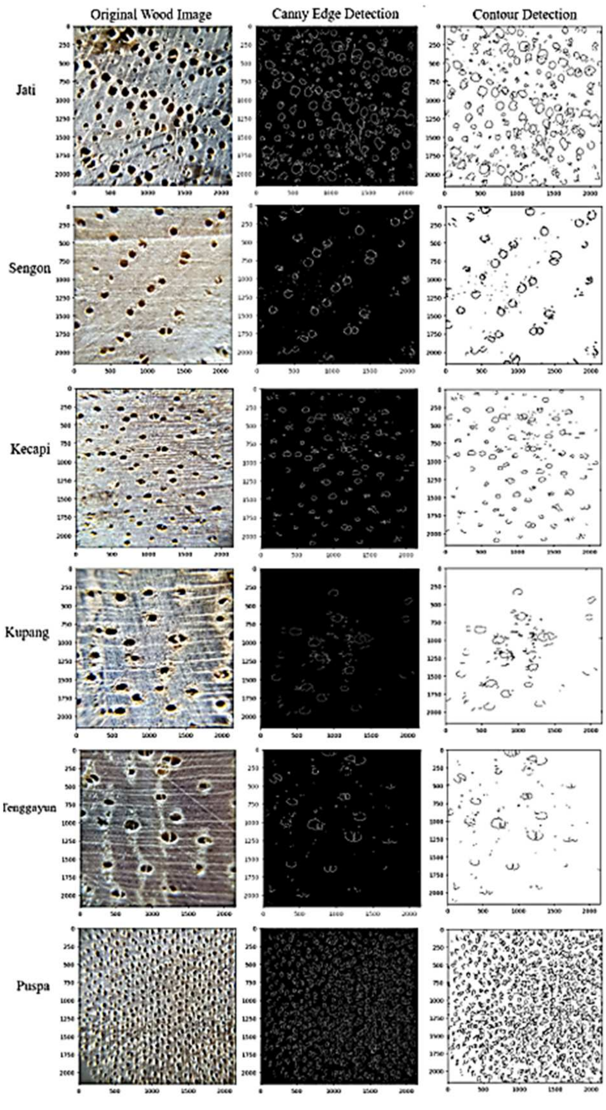

Fig. 6. The six wood image after being extracted by Contour algorithm.

D. Pores Distribution Calculation

The pore can be seen since its roundness and close to the circle shape in the Contour algorithm. The total number of detected wood pores in the image region is represented by N and the pores diameter represented by D [14]. Furthermore, from the number of detected wood pores in one region, statistically the distribution of pores can be calculated. This distribution parameters of the Contour algorithm can be described as follows:

a. Number of the Wood Pores (N)

The number of the wood pores is considered as the first parameter (x_1).

$$x_1 = N \quad (3)$$

b. Average Diameter (AD)

The Average Diameter parameter is obtained by averaging the wood pores diameter which has been detected in the wood image and represented by x_2. All the detected pores are considered in determining the parameter and if each detected pores are represented by D_i, then the average diameter of detected pores can be calculated as follows:

$$x_2 = \frac{\sum_{i=1}^{N} D_i}{N} \quad (4)$$

c. Standard Deviation (SD)

The Standard Deviation parameter measures the dispersion of detected pores relative to their mean and it can be calculated as the square root of the variance of pores. This parameter (x_3) represents the uniformity of the wood pores in the form of their diameter and can be obtained as follows:

$$x_3 = \sqrt{\frac{\sum_{i=1}^{N}(D_i - x_2)^2}{N}}. \quad (5)$$

d. Skewness (SK)

The skewness parameter is used to represent the tendency of pore size. The skewness value will be negative if most of the detected pore diameters are greater than the average pore diameter. Conversely, a positive skewness is obtained if most detected pore diameters are smaller compared to the average pore diameter. The skewness parameter (x_4) can be calculated as follows:

$$x_4 = \sqrt{\frac{\sum_{i=1}^{N}(D_i - x_2)^3 / N}{(x_3)^{\frac{3}{2}}}}. \quad (6)$$

e. Kurtosis (KT)

The kurtosis parameter gives the information about the shape (tailedness) of the pore distribution in the wood image region. From the kurtosis parameter, there are three types of kurtoses: leptokurtic, platykurtic, and mesokurtic. The higher the kurtosis value, the sharper the curve. The kurtosis reference value is 3. If the kurtosis value exceeds 3, the pore distribution has a relatively high peak. This distribution curve is called leptokurtic. Meanwhile, the platykurtic has a kurtosis value lower than 3 where the pores distribution almost flat peaks. While the kurtosis value equals 3. It indicates a normal pores distribution curve and calls as mesokurtic. The wood kurtosis distribution parameter (x_5) is defined as follows:

$$x_5 = \frac{\sum_{i=1}^{N}(D_i - X_2)^4}{N . {x_3}^4}. \quad (7)$$

f. Density (DT)

The density parameter is calculated by dividing the number of detected pores by the total region of the wood image. The region is calculated by multiplying the image's width (w) and height (h). The region can be considered as a pixel if there is no scale ratio variation. The wood density parameter (x_6) is calculated as follows:

$$x_6 = \frac{x_1}{(w * h)} \quad (8)$$

From the previously discussed extraction results of the six feature parameters, the pore distribution features are then collected in a pore feature set, denoted as F. The quantity of each parameter is used to compute for each wood species with the formula as follows:

$$F = [x_0, x_1, x_2, x_3, x_4, x_5, x_6], \quad (9)$$

where x_0 represent wood species, x_1 represent the number of the wood pores, x_2 represent the average diameter of the detected pores, x_3 represent the standard deviation of the pore, x_4 represent the skewness of the pore distribution, x_5 represent the kurtosis of the pore distribution, and x_6 represent the density of the pores in wood image region.

E. Random Forest Classifier

The pore distribution features are input into machine learning algorithm to carry out the training and testing process. In this research, Random Forest is used to classify these features. Random forest is an algorithm that contains a collection of decision trees and built in bootstrap samples [15]. Ensemble is the process of collection trees in the Random Forest [16]. Ensemble has two methods: bagging and boosting. By this ensemble learning method, this classifier can carry out the classification process using collection decision tree during training stage and making prediction of individual tree [17]. Fig. 7 shows the illustration of how Random Forest works. $tree_1$, $tree_2$, …, $tree_B$ are the random decision trees. These trees correspond to k_1, k_2, …k_B. Class k is the output of this classifier and selected from k_1, k_2, …k_B with the majority of the votes [18].

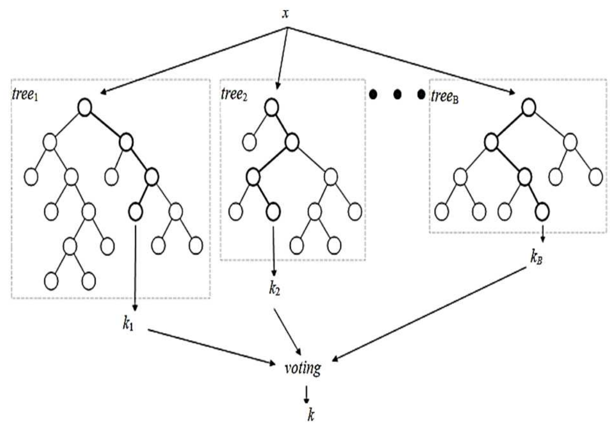

Fig. 7. General architecture of Random Forest [18].

When it comes to handling pore distribution features, the Random Forest classifier performs a training process on these features. Additionally, these features serve as both the training and test set for the random forest. It is important to carefully determine the number of training and test set to achieve accurate results from the classification system.

IV. Experimental Result and Analysis

In this research, Python programming is used to implement the Contour algorithm and the Random Forest classifier. Two functions are utilized to detect and draw wood pores. The *findContours()* function is employed to identify wood pores in a wood image. This method works by examining boundary pixels that share the same color or intensity. To mark the wood pores object, the *drawContours()* function is utilized.

After drawing the detected pores, the next step is to extract the observed pore distribution using the aforementioned parameters. This value is denoted by *N*. One other important point is the diameter of the detected pore (*D*). The pores diameter can also be a feature in wood species classification. Each wood species has a different number of pores, making it possible to determine the quantity of pores in an image or region using a Contour algorithm. Furthermore, by analyzing the number of detected wood pores (*N*) and their average diameter (*AD*), it is possible to statistically calculate the pores distribution features using the aforementioned parameters. Table I provides an example of pores distribution feature obtained from the Contour algorithm for six different wood species in a single image.

TABLE I. THE EXAMPLE OF PORE DISTRIBUTION FEATURES FOR ONE IMAGE OF THE SIX WOOD SPECIES

Wood Species	Pores Number (N)	Average Pores Diameter (D)	Standard Deviation	Skewness	Kurtosis	Density
Jati	73	79.9178	12.7516	-1.4123	2.1117	0.0000156
Sengon	35	77.7143	9.6393	-0.0354	-0.8233	0.0000075
Kecapi	57	53.9298	6.5951	-0.8460	-0.4291	0.0000122
Kupang	23	86.0870	3.6793	-0.3755	0.5680	0.0000049
Tenggayun	19	87.6316	3.1307	0.3459	3.3190	0.0000041
Puspa	248	29.5363	2.1928	0.1401	-0.7058	0.0000532

As shown in Table I, the pores feature distribution describes the six parameter features in one wood image for each species. The largest average pore diameter is Tenggayun with 87.6316. Meanwhile, the Puspa has the smallest diameter with 248 pores in one region of the wood image. Compared to other species, Puspa has a higher number of pores. The Standard Deviation parameter measures the dispersion of detected pores relative to their mean value. This indicates that Jati has various pores diameters, resulting in greater inaccuracy with respect to the mean value. On the other hand, Puspa has smaller pores diameter, and it means the pores diameters are similar in value or closer to the mean.

After the pore distribution feature analysis is successful, these features can be inputted to the Random Forest classifier as a training dataset in a comma separated values (CSV) format. The image dataset of each species was successfully extracted using the Contour algorithm to produce six features from 50 images for each species. For this research, 210 data were used for training and 90 data for final testing. The extracted data is saved in CSV format as shown in Fig. 8. Therefore, 300 data are generated for either training or testing process in Random Forest classifier.

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SPECIES,N,AD,SD,SK,KT,DT
Jati,73,79.9178,12.7516,-1.4123,2.1117,0.0000156
Jati,75,79.7870,12.7516,-1.4122,2.2117,0.0000161
Jati,34,40.7140,17.2217,-1.3018,1.6364,0.0000300
Jati,69,79.8970,13.3597,-1.3370,1.6590,0.0000150
Jati,73,80.0270,12.9063,-1.2769,1.6304,0.0000156
Jati,77,79.5840,13.1350,-1.2067,1.5634,0.0000165
Jati,75,79.4130,13.1077,-1.1204,1.4035,0.0000161
Jati,90,78.7330,15.2769,-4.0063,1.0687,0.0000001
Jati,67,77.2540,13.0689,-1.0407,1.0609,0.0000144
Jati,67,77.8810,11.8813,-0.7503,0.1601,0.0000144
Sengon,35,77.7143,9.6393,-0.0354,-0.8233,0.0000075
Sengon,32,77.1250,10.1972,-0.2647,-0.7032,0.0000069
Sengon,30,77.4333,10.3679,-0.3317,-0.6907,0.0000064
Sengon,53,30.0312,10.2311,-0.2437,-0.7312,0.0000111
Sengon,35,76.6000,10.9684,-0.4898,-0.2998,0.0000075
Sengon,35,74.8571,11.0829,-0.2823,-0.4555,0.0000075
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Fig. 8. The example of extracted data result in CSV format

The Random Forest classifier trains the the extracted data and form multiple decision trees to obtain a majority vote in the classification process. In this research, 100 decision trees are used. Fig. 9 shows the decision tree visualization of the first tree in Random Forest, followed by the subsequent trees. For evaluation, Fig. 10 presents the confusion matrix from the testing process in the Random Forest classifier. The confusion matrix shows a classification accuracy of 92.00%. This indicates that the pore distribution features can be utilized for wood species classification.

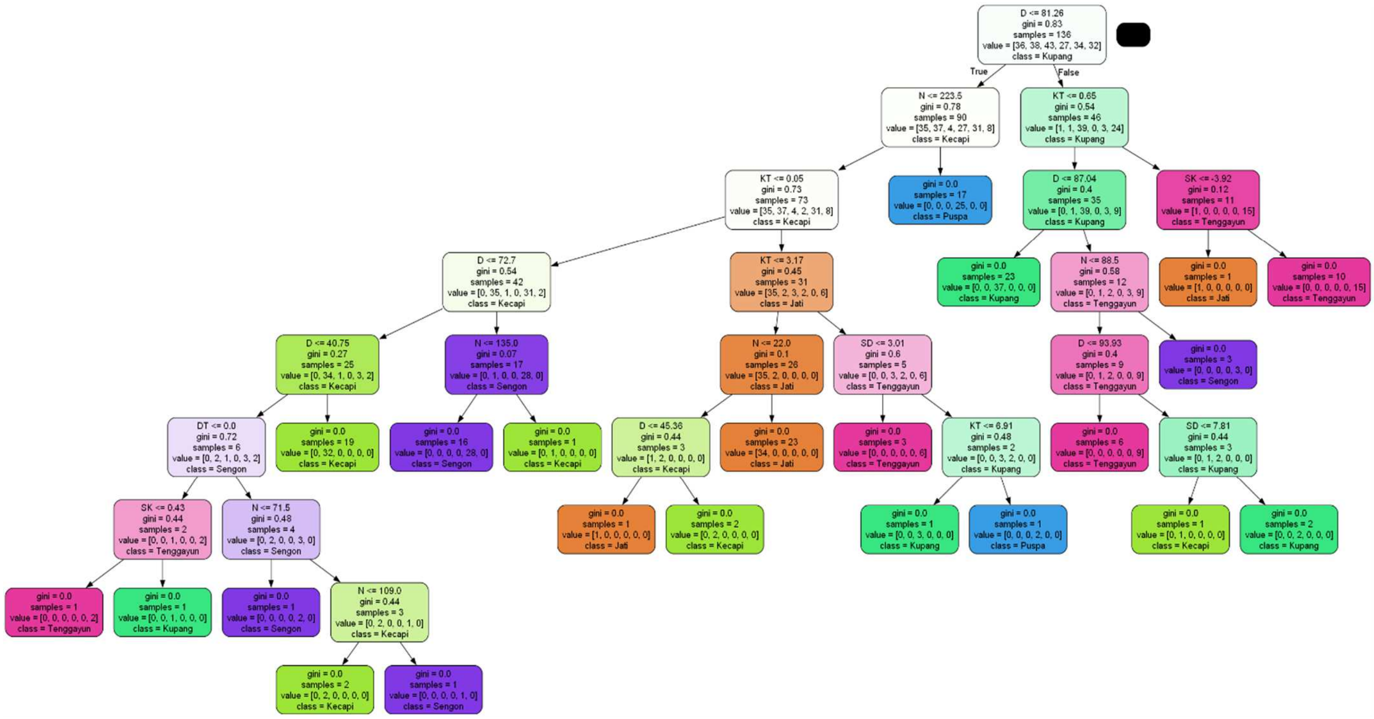

Fig. 9 The example of the first decision tree visualization for the Random Forest classification.

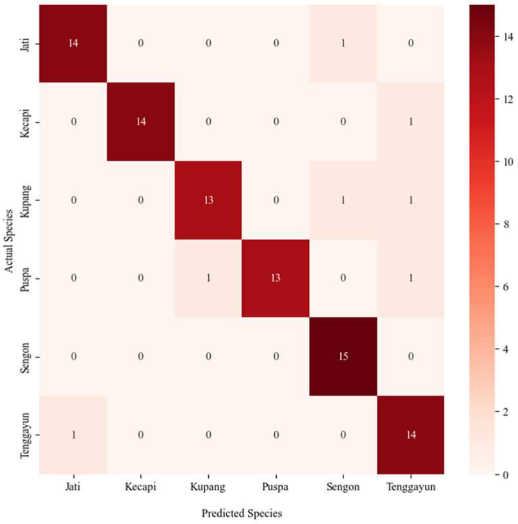

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Fig. 10 The confusion matrix of the Random Forest classifier report

Table II presents the classification report for important metrics such as precision, recall, and F1-Score.

TABLE II. THE METRIC OF THE CLASSIFICATION RESULT

Wood Species	Precision	Recall	F1-Score
Jati	0.93	0.93	0.93
Sengon	0.88	1.00	0.94
Kecapi	1.00	0.93	0.97
Kupang	0.93	0.87	0.90
Tenggayun	0.82	0.93	0.87
Puspa	1.00	0.87	0.93

Based on the accuracy and metric result, it is evident that there are several errors in the feature result. The reason behind this is the incomplete pores detection in macroscopic wood images. Some portions of the pores remain undetected due to unclear image acquisition. As a result, it becomes crucial to include a preprocessing stage to ensure a clear and accurate process.

V. CONCLUSION

The automatic algorithm presented for classifying wood species based on the porosity distribution of the macroscopic wood image uses a Contour algorithm. The results obtained from six different wood species showed that 300 data can be extracted and used to generate feature models. The accuracy of the wood classification was evaluated using the Random Forest classifier, yielding an accuracy rate of 92.00%. This indicates that the pore distribution features can be effectively utilized for wood species classification.

For further work, the results of this pores distribution analysis can be combined with other features. Moreover, further studies should be conducted to utilize a feature extraction method, as it will allow for the identification of all the pore features in macroscopic wood images, as suggested by references in the IAWA Journal.

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