Wood Types Classification using Back-Propagation Neural Network based on Genetic Algorithm with Gray Level Co-occurrence Matrix for Features Extraction

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***Abstract*—Tree species are very diverse with more than 15,000 species are known, and mostly found in rain forest such as Indonesian rain forest. Species with similar morphological and anatomical features are very difficult to be classified manually. Manual classification for wood production is time and resources consuming, and the result is less accurate. Wood classification have significant effect on the processing and the quality of industrial wood products. Research on the automation of wood type identification has been done but still not able to cover various the type of wood from different tree species. This research is focused on creating a model for identification of some rain forest trees such as teak (*Tectona grandis*), albizia (*Albizia chinensis*), mahogany (*swietenia mahagoni*), and melia (*Melia azedarach*). Classification was performed using back-propagation neural network with genetic algorithm optimization and gray level co-occurrence matrix for feature extraction. Genetic algorithm was used to select which GLCM features function should be used as neural network inputs. IDM, correlation and entropy was chosen the most and by doing so, we are able to achieve higher accuracy compared to the previous model. Furthermore, deeper analysis on the angle of GLCM in wood classification shows that the best accuracy is achieved when the angel is parallel to the wood direction, in our case it is $0°$. This model is found to be an appropriate model for wood image identification enhancement and has a very good accuracy with an average value of 99.14%.**

***Index Terms*—Wood Classification, Back-Propagation Neural Network, Genetic Algorithm, and Gray Level Co-occurrence Matrix**

I. INTRODUCTION

TIMBER is one of forest based commodity that have a big role in global industry and trade. Substantial amount of wood industry like in China, Vietnam, Malaysia, and Indonesia are joining China - ASEAN Free Trade Agreement (CHAFTA) [1]. There are more than 15,000 indigenous species of tree and most of them are originating in the tropical zone. The high diversity of the species, reliable classification of wood types becomes important [2].

Identification on some wood types is complicated because there is several characterization techniques [3]. Wood characteristics are determined by their anatomical and/or chemical composition. The anatomical composition of wood in general is characterized by the size, color, fiber, and pattern. This anatomical composition is often used to specify the wood type. Difficulties often occurs when different tree species have the same wood pattern or different pattern found in the same tree species [4]. Therefore, wood type characterization takes a long time and can only be done by an expert. In summary, tree species with similar morphological and anatomical features are very difficult to classify thus having low accuracy and less reliable. Moreover, there are often misidentification of wood timber by human due to the limited knowledge and experience. Consequently, the time required for identification takes more time and cost inefficient, also often producing inaccurate result [5], [6]. The large number of existing wood types make the process of manually recognizing and identifying the type of wood must be done repeatedly and continuously.

To obtain more information about the intrinsic characteristics of wood types, especially when little information is available about the anatomical or chemical composition of a wood types species, it is necessary to develop and apply a faster and more reliable technique [4]

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II. RELATED WORKS

A. Feature Extraction

One technique that can be used is by using a smart computing approach. Wang Ke-qi used the gaus-MRF theory (G-MRF) to model the texture of Koraiensis wood, Gmelinii, Mandshurica, and Mongolica wood. The results show that different wood textures shows a clear scattered distribution, while the stroke direction is indicated by the maximum value of the G-MRF parameter [7].

Another technique is by using collaborative classification method without image segmentation to sort four wood surface types: radial texture tangential texture, live knot, and dead knot was proposed by Zhang. Theoretical and experimental results show that the direction property of dual-tree complex wavelet can express the complex information of wood surface and the classification done by compressed sensing is proved to be effective [8].

Some researchers used a histogram to extract the features of wood image. Sundaram proves that contrast limited adaptive histogram equalization (CLAHE) is found to be an advanced method for wood image enhancement [9]. Nasirzadeh extracted using the local binary pattern (LBP) histogram. The recognition is performed using chi-square as a dissimilarity measure [10]. Yadav used discrete wavelet transform (DWT), first-order statistics (FOS), four variants of local binary pattern (LBP) histograms, and minimal redundancy maximal relevance (mRMR) [11].

Other approaches that have been done by many researchers for feature extraction are scale-invariant feature transform (SIFT) algorithm [12], gabor filters [13], and gray level co-occurrence matrix (GLCM) [2], [4], [5], [14], [15], [16], [17]. GLCM is robust to the rotation that can be captured at any orientation of same resolution. One of implementation of GLCM proposed by Mohan as a features selection technique. In his research, GLCM were used to obtain three features: entropy, standard deviation, and correlation. The classification feature used to classify the wood species is correlation. The experimental results show that the proposed method can achieve the recognition rate more than 95% [2]. GLCM is a feature selection algorithm that many researchers rely on today, but to identify the type of wood is not enough just by extracting features but should be equipped with a classification process.

Several wood type classification which using GLCM as the extraction of features are described below. Kobayashi proposed k-nearest neighbor (k-NN) algorithm combined with cross-validation. It is applied for the classification and evaluation of the wood image. The data input with a variation in image qualities (resolution, gray level, and image size) was investigated using this novel system, and achieving accuracy greater than 98% when the input images had a certain quality level [17]. Another classification model proposed by Yusof by using gabor image as feature extraction for GLCM and multi-layer neural network back-propagation (MLBP) for classification [4]. Another classification model was used by Park by using k-NN for classification, GLCM as feature extractor, and binary gravitational search algorithm (BGSA) as the optimizer for GLCM's feature selection and parameters. The proposed approach reduces the classification time [16].

Wang used SVM classifier to the experiment of the wood recognition. About 91.7% recognition rates are acquired through feature extractions of 24 wood species with 480 samples. In order to extract features from the wood stereogram images, GLCM was used to calculate statistics of texture features [14]. Some researchers also used neural networks for wood classification image [18], [19], [20] . The neural networks have been successfully applied in several studies. Nisgoski [3] in his research about identifying some Brazilian wood species proved that the artificial neural network was more efficient than the soft independent modeling of class analogies (SIMCA) classification and has a good potential to be applied for species discrimination. According to Singh, a back-propagation neural network (BPNN) and wavelet transform provide a better discrimination between images and increasing the accuracy of the classification [20]. Yuwono showed learning vector quantization neural network (LVQ-NN) with binary-based features capable of producing sufficient accuracy results for the process of identifying the quality of wood from coconut tree [6]. Pramunendar compared the BPNN and SVM methods based on the GLCM feature. The result shows that BPNN is able to work better than the SVM algorithm on classifying the coconuts wood dataset [5].

Based on the state of the art described above, it can be concluded that GLCM and BPNN are reliable algorithms to extract features and classify wood. Nevertheless, BPNN has disadvantages because some hyperparameters need to be manually adjusted, such as momentum, learning rate level, and training cycle [6]. Therefore, some researchers suggest the use of optimization algorithms such as genetic algorithm (GA) to adjust hyperparameters automatically. Zhao used a genetic algorithm to solve the optimum radians height so that the spectral reflectance curves had the best classification information for wood species. Experiments on five common wood species in North-East China shows an overall 95% accuracy at optimum recognition velocity [18]. Instead of using genetic algorithms or neural network alone, Santosa proved that the genetic algorithm neural network (GANN) is able to improve classification results [21]. However, this approach is done for numerical data in the case of concrete mix design strength predictions that are very different from image processing. Ramchoun proved that GA was able to improve the performance of multi-layer perceptron (MLP) to classify wine, iris, seeds and medical data (cancer, thyroid). However, the ability of GA to optimize NN to classify wood types needs to be tried [22].

Very limited quantities of tropical wood, including wood from teak (Tectona grandis), albizia (Albizia chinensis), mahogany (swietenia mahagoni), and melia (Melia azedarach) have not been receiving a lot of studies. In order to identify teak, mahogany, albizia, and melia, and improve the performance of BPNN in classifying wood types, this research uses BPNN which is optimized by GA and using GLCM to extract wood texture features. Besides that, relating to the unique wood texture, the effect of GLCM angle is also observed on the wood image classification. With this approach, it is expected that a new state of the art model for tropical wood classification of teak, mahogany, albizia, and melia will obtain better accuracy.

III. Research Methods

GA-based BPNN is used to classify wood types automatically. This study has three stages which consists of data collection, data pre-processing, and experiment (feature extraction, classification, evaluation and validation) as shown on figure 1. The whole process will affect the results of the classification performance performed.

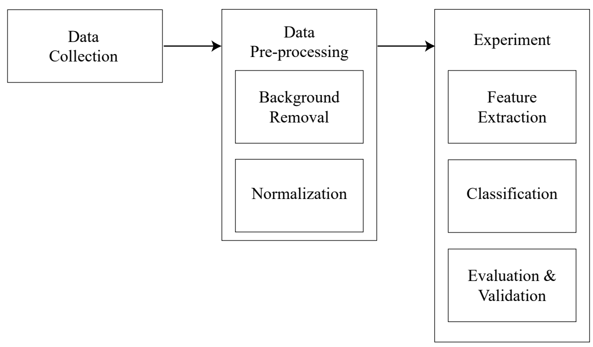
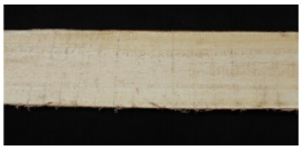


Fig. 1: Stage of Experiment

(a) Teak



(b) Albizia

(c) Mahogany

(d) Melia

Fig. 2: Types of Wood

A. Data Collection

This study uses four types of commercial wood namely teak, mahogany, albizia, and melia. The data is taken from CV Majawana and cooperating with Wood Industry Education (PIKA) Semarang. The data primarily consists of 400 data from 4 kinds of wood as an example shown at figure 2, so each type of wood contains 100 image data. All of the wood image was taken horizontally as shown on figure 2

B. Preprocessing Data

The collected original images were preprocessed by giving the value 0 for background. The background removal process began with a blurring process using matrix blur to remove the noise on the image. After that, the wood edges were detected by using sobel filter. Because some edges were cut off, morphological (close and open) operations were performed to connect the unconnected edges.

The next stage is the normalization process. Normalization is a process that adjusts the series of pixel intensity values, particularly when the contrast level of the images is low due to clarity. In this work, a minmax normalization method adjusts the range of pixel intensity values for better clearness [23]. Normalization process was done to match the color domain used. The original RGB image was converted to 4 channels image with the grayscale channel and each individual channels of RGB. The image size was not changed because GLCM features extraction does not require the same image size.

C. Experiment

1) GLCM Feature Extraction: Texture analysis depends on the characteristics of the observed texture features. Different texture features have different characteristics and approaches. Wood texture is varying depending on the species. GLCM is able to describe wooden texture variations [5], [21], [22] therefore, it can be used for feature extraction from wood image textures.

GLCM is a co-occurrence matrix that represents the neighbor relationship between pixels in images pixels in various orientation directions and spatial [21], [22]. There are 4 computing directions in GLCM, i.e. $\delta = 0°, \delta = 45°, \delta = 90°, \delta = 135°$ as shown on Figure 3.

In addition, GLCM has several measuring function that can be used to extract features from an image data. Following are the frequently used GLCM features [5, 22]:

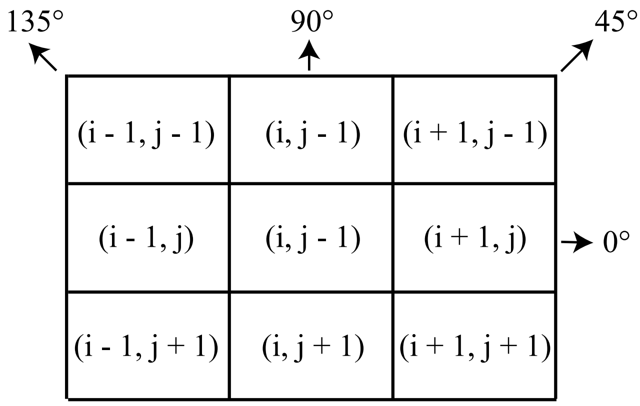


Fig. 3: Angle of Co-occurrence Matrix

a) Angular Second Moment (ASM) is a measure of homogeneity of an image. ASM will be of high value if the pixel value in the homogeneous image is high.

$$ASM = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{P(i,j)\}^2 \tag{1}$$

$P(i,j)$ = Co-occurrence value of i and j
G = Color intensity

b) Contrast is the difference of intensity between one pixel and the adjacent pixels. Contrast will be zero for a constant image.

$$Contrast = \sum_{n=0}^{G-1} n^2 \{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} P(i,j)\}, |i-j| = n \tag{2}$$

c) Correlation is the linear dependency between pixels in certain positions against other pixels. Higher values are obtained in the same gray-level area.

$$Correlation = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{(i \times j) P(i,j)\} - \mu_i' \mu_j'}{\sigma_i' \sigma_j'} \tag{3}$$

with:

$$P_x(i) = \sum_{j=0}^{G-1} P(i,j) \tag{4}$$

$$P_y(j) = \sum_{i=0}^{G-1} P(i,j) \tag{5}$$

$$\mu_i' = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} i \times P(i,j) \tag{6}$$

$$\mu_j' = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} j \times P(i,j) \tag{7}$$

$$\sigma_i' = \sum_{i=0}^{G-1} P_x(i) - \mu_i' \tag{8}$$

$$\sigma_j' = \sum_{j=0}^{G-1} P_y(j) - \mu_j' \tag{9}$$

d) Local Homogeneity, Inverse Difference Moment (IDM). IDM is also influenced by the homogeneity of the image.

$$IDM = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{1}{1+(i-j)^2}P(i,j) \quad (10)$$

e) The other of feature called entropy, if the value of entropy gets smaller, then the pixel distribution is not uniform. If the value of entropy gets bigger, then the pixel distribution is more uniform

$$Entropy = \sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(P(i,j)\times log(P(i,j))) \quad (11)$$

P(i, j) in the equation 1 until 11 is a co-occurrence value of i and j, and G is a color intensity.

In this study, five GLCM features functions are applied to four angles, i.e. angle $0°, 45°, 90°, 135°$. Thus in total 20 features for each channel was obtained. Since one image consists of 4 channels, namely grayscale color, R layer on RGB, G layer on RGB, and B layer on RGB, one image will have in a total of 80 features that will be observed in depth. Because most of the woods in industrial sites tends to be cut parallel to the tree rather than perpendicular to the tree, the pattern of the woods are mostly stripes rather than blobs. Our hypothesis is that some of the angles of GLCM will have more impacts to the accuracy than the other.

2) Classification: In order to re-examine the state-of-the-art before, a classification experiment was performed using BPNN. The next step will be to test the assumption that the BPNN's ability to classify teak, mahogany, albizia, and melia wood types can be improved by using GA as a new state of the art. BPNN is an artificial neural network algorithm that is mostly used for image processing. BPNN takes a long time in the training process but has an excellent level of accuracy [5]. BPNN consists of training and testing phases. This model has at least three layers, namely input, hidden, and the output layer.

The input layer receives the multivariate type data from an external source, then the input data is processed into a hidden layer and output layer. In experiments, the BPNN model varies greatly. It can have more than two hidden layers with varying number of neurons each. BPNN needs to be initialized with some parameters such as number of layers, bias values, learning rate, momentum, training cycle, and activation function. BPNN distributes input values to hidden layers and outputs through 12 to 13. Prediction error is calculated by equation 14. When prediction errors are obtained, BPNN propagate backward to update the weights by equations 17 and 18.

$$y = b_i n + \sum_{i=0}^{n} x_i w_{i,j} \quad (12)$$

$$z = b_h id + \sum_{i=0}^{n} y_i v_{i,j} \quad (13)$$

$$\delta_z = (t_k - z_k) f'_z \quad (14)$$

$$\Delta_v = \sum_{i=0}^{m} \delta_z w_{i,j} \quad (15)$$

$$\Delta_w = \alpha \delta_y z \quad (16)$$

$$w_{new} = w_{old} + \Delta_w \quad (17)$$

$$v_{new} = v_{old} + \Delta_v \quad (18)$$

where

x, y, z = input, hidden, and output values
b = bias value
v, w = weights of input-hidden and hidden-output values
δ = prediction error

The next stage was doing classification using BPNN with GA. GA used to improve performance of classification. GA is an adaptive and consistent method for solving optimization problems. GA consists of several stages, namely encoding technique, early population generation, selection, crossover, mutation, and eliminations. GA starts from creating alternative solutions (population). Each solution is represented as an individual or a chromosome. GA was created by John Holland in the 1960s and 1970s, GA uses a natural analogy based on natural selection. There are six major components in the genetic algorithm

a) Encoding technique. Arrange the gene code in the form of a series of bits, for example 100011. The gene is the encoding of the chosen GLCM features for classification process.
b) Early population generation. Make individuals through random processes or through certain methods.
c) Selection. Select the individual to be used in the process of crossing and mutation. This option is used to find good prospective parents. The initial stage in selection is to find the fitness value. Higher fitness values of individuals are more likely to be chosen and used in later stages.
d) Recombination or Crossover. Involving two parents to form a new individual. This stage generates a new point in the search space that will be ready for testing.
e) Mutations. Replace entries in the population so that the missing chromosome that did not appear at the initial population can occur.
f) Eliminations. Eliminate some of the population by certain method i.e. elitism.

In this research, the testing experiment was done on various parameters of BPNN such as momentum, learning rate, and training cycle. After the parameters were obtained, some of the inputs were excluded by GA. This process was done by setting the weight to be zero where GA decided that excluding some inputs will increase the accuracy.

3) Evaluation and Validation: Evaluation and validation were performed using the k-fold cross-validation estimator. Value of cross-validation that was used is 2 to 10. To train and test the classification result experiments were conducted 2 to 10 times then the average score was calculated.

To assess the proposed models performance, confusion matrix was used (see Table I). By using confusion matrix, classification accuracy can be calculated with equation 19.

TABLE I:
CONFUSION MATRIX

	Actual			
Prediction	**Teak**	**Mahogany**	**Albizia**	**Melia**
Teak	$Teak^{+}$	$Teak^{-}$	$Teak^{-}$	$Teak^{-}$
Mahogany	$Mahogany^{-}$	$Mahogany^{+}$	$Mahogany^{-}$	$Mahogany^{-}$
Albizia	$Albizia^{-}$	$Albizia^{-}$	$Albizia^{+}$	$Albizia^{-}$
Melia	$Melia^{-}$	$Melia^{-}$	$Melia^{-}$	$Melia^{+}$

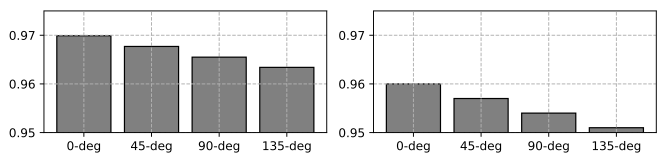
$$Accuracy = \frac{Teak^{+} + Mahogany^{+} + Albizia^{+} + Melia^{+}}{|prediction|} \tag{19}$$

IV. RESULT AND DISCUSSION

A. Effect of GLCM Angle on Classification of Wood Types

The spatial distribution of wood texture has particular characteristics. In general, the use of wood in the industry for both the home furniture industry and building construction industry tends to be cut in parallel with the tree so that the parallel textures are mostly visible instead of the perpendicular textures to the tree. The texture that is parallel to the trees tend to be a collection of parallel lines instead of a collection of circles marking the development of the cambium which can only be found if the cut was made perpendicular to the tree. Figure 2 shows the direction of the lines pattern found on teak tree, mahogany, albizia, and melia.

The image shown on figure 2, all the woods are placed horizontally making GLCM texture analysis at $0°$ will have more significant results than the other angle. This is proven through the test results below. Testing is done by measuring the level of accuracy using confusion matrix and kappa.



(a) Accuracy (b) Kappa

Fig. 4: Classification Results based on Computing Direction

Based on the results shown in figure 4, the highest level of accuracy is achieved at a $0°$ angle of 96.99%. Kappa accuracy testing also consistently shows the highest level of accuracy achieved at a $0°$ angle of 96%. The interesting thing about this experiment at an angle of $90°$ the accuracy placed third, lower than the $0°$ and $45°$ angle. This fact can be explained by the following figure.

In case of all of the data is taken in similar manner as the examples on figure 2, using $0°$ as the computing direction for GLCM is the best option as we can observe the result of the classification. By using $0°$, the highest accuracy of 96.99% is achieved. Consistently the highest kappa value is also achieved using $0°$. Interestingly, $90°$ placed on the third, lower than $0°$ and $45°$. As for the reason, it is how the GLCM feature extraction works.

Fig. 5: Pixel color Gradation of the Sample Image

The pixel color gradation of the sample image on figure 5, in the direction of the $0°$ angle shows lower level variation compared to the gradation in the direction of $90°$. This is in accordance with the direction of wood strokes in our dataset which in general which have the low variation in the direction of $0°$ angle and higher variation in the vertical direction of the wood. The conclusion that can be obtained from this experiment is that for the texture analysis of wood images the angle of GLCM which is very important in the classification is the direction of the wood in the dataset. In our case since all the woods placed horizontally, $0°$ makes a perfect sense. Further important study is the analysis of wood cross-sectional images, which in this study have not been carried out because it requires taking a cross-section image of the wood. There is a possibility other or several angle of GLCM plays an important role in the classification of wood based on a cross-section, not only the parallel direction of the wood.

B. Effects of GLCM feature function at 0 degree angle

GLCM feature functions also observed further. Not all features (ASM, contrast, IDM, Entropy, and Correlation) has significant impact for the classification results. Here, GA is used to select which features should be used in 0^{o}. After training process, IDM, entropy, and correlation has the most significant impact on the results based on the accuracy. Both IDM and entropy calculate the homogeneity of the image while correlation not only calculate the homogeneity of the image but also the spatial information of the homogen pixels. From the result, by selecting these features can improve the accuracy of the classification. Thus it is recommended to use these features for further research in teak, mahogany, albizia, and melia wood classification.

C. Classification Using BPNN

State-of-the-art model states that GLCM and BPNN are reliable algorithms to extract features and classify wood. Replication of the model needs to be done to test the state of the art in the identification of teak, mahogany, albizia, and melia. This research uses MATLAB and RapidMiner to conduct this experiments. All extraction processes were performed in MATLAB and classification processes were

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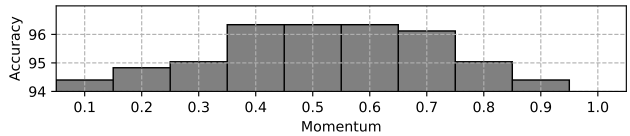

Fig. 6: BPNN Accuracy Based on Momentum Parameter Variations from 0.1 to 1

performed in RapidMiner. The results of the test are shown on figure 6

Figure 6 shows the differences in momentum parameter variation with the range of values from 0.1 to 1. The experimental results show that the setting of the momentum parameters with values 0.4, 0.5 and 0.6 yields the same accuracy. To get the optimal accuracy, new settings based on the same range with the cycles value of 100 and Learning Rate of 0.1, also momentum between 0.45, 0.55, and 0.65 was done and shown in figure 7.

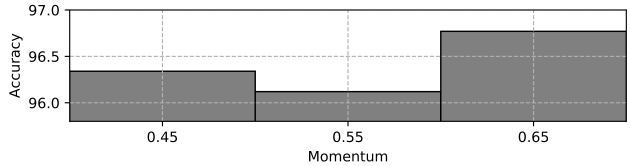

Fig. 7: BPNN Accuracy Based on Momentum Parameter Variations between 0.45, 0.55, and 0.65

The results show that the best accuracy is indicated by the momentum parameter = 0.65 with an accuracy of 96.77%. After the best momentum parameters were obtained, variation of learning rate parameters were tested. Figure 8 shows that higher learning rate leads to poorer accuracy. The best accuracy results obtained at learning rate 0.1 with an accuracy of 96.77%.

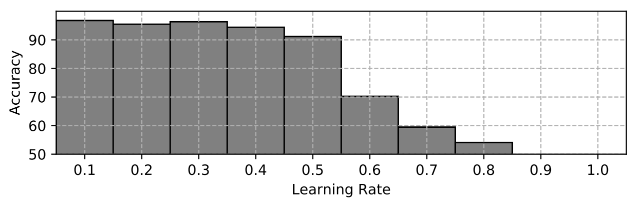

Fig. 8: BPNN Accuracy Based on Learning Rate Parameter Variations

In addition to momentum and learning rate, the training cycle parameters are tested with a range of 100 to 10,000 cycles. The results on figure show that the parameters with the cycle as much as 600 times produce 97.63% accuracy as shown on figure 9.

D. Classification Using BPNN with GA optimization

In order to improve the ability of the previous model classification, this study offers a new model involving GA. GA is used to select among GLCM features (ASM, IDM, contrast, correlation, and entropy) to be used for classification process. The parameters obtained from the experiments above (cycle, learning rate, and momentum) is used as a

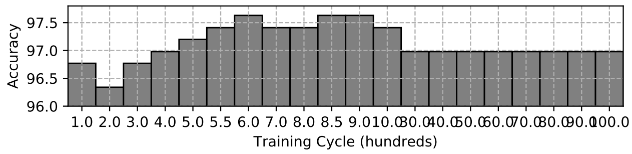

Fig. 9: BPNN Accuracy Based on Training Cycle Parameter Variations

reference for improving the model's ability using GA. The GA parameters which were tested are population size and maximum generation parameters. Experiments are intended to get the best performance results.

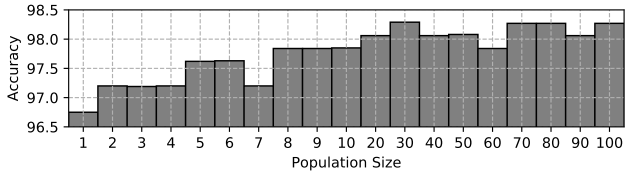

Fig. 10: Accuracy based on Varying the Population Size

Figure 10 shows the results of population size parameters using range 0 to 100. The best results are seen in population size 30 with an accuracy of 98.29%.

The next stage is to experiment with the number of generations ranging from 1 to 10. The results show that the 9th generation produces the best performance with a performance outcome of 99.14% as shown on figure 11.

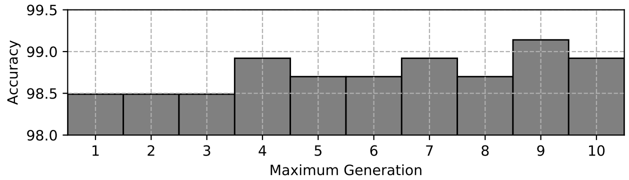

Fig. 11: Accuracy based on Varying the Maximum Generation

When compared with previous research using BPNN, GA is very influential in increasing the ability to classify teak, mahogany, albizia and melia tree. This can be seen from the results of testing accuracy 97.63% compared to 99.14%.

V. CONCLUSION

In this study, it shows that the use of 80 combined-feature extracted based on GLCM is functioning properly. State-of-the-art testing research shows that the performance of the BPNN method in the classification of wood types produce good accuracy value. The test results indicate that the combination of parameters such as momentum, learning rate, and training cycle influencing the accurate result. Accuracy results that were obtained are 97.63%.

The new state-of-the-art obtained from this study is a classification method of teak, mahogany, albizia, and melia that are able to achieve higher accuracy by using feature extraction based on the best GLCM angle for this particular case. The best results of BPNN GA combination resulted from the accuracy of 99.14% with training cycle parameter of 600, the learning rate of 0.1, momentum of 0.65, the population size of 30, and maximum generation of 9. GA chose IDM, entropy, and correlation are features that impact the accuracy results the most. Thus we encourage to use these three features for classifying teak, mahogany, albizia, and melia classification.

Apart from those results, we also experiment on the angle of GLCM which turns out that the angle that is parallel to the wood image gives the highest accuracy, in our case it is $0°$. Further studies for the perpendicular cut of the wood is needed. There is a possibility of certain or several angles of GLCM plays an important role in the classification based on wood cross-sectional texture rather than $0°$ angle.

Based on our findings, further research can be focused on using IDM, entropy, and correlation for the GLCM feature extraction process and the GLCM angle that is parallel to the wood image.

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