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# Classification of Wood Types Based on Wood Fiber Texture Using GLCM - ANN

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## Abstrak

**Di Indonesia, berbagai jenis kayu tumbuh dan berkembang dengan karakteristik dan manfaat yang beragam. Setiap jenis kayu memiliki perbedaan tekstur dan serat, untuk mengklasifikasikannya harus memiliki pengetahuan yang cukup tentang tekstur dan serat kayu. Sistem identifikasi jenis kayu diperlukan untuk membantu proses klasifikasi tersebut. Tujuan dari penelitian ini adalah untuk mengklasifikasikan Kayu Jati, Kayu Sengon, Kayu Mahoni, dan Kayu Gmelina yang banyak diperjualbelikan di Indonesia. Metode klasifikasi yang digunakan dalam penelitian ini adalah Jaringan Syaraf Tiruan dengan ekstraksi Gray Level Co-occurrence Matrix (GLCM). Tahapan pra-pemrosesan meliputi Histogram Equalization, filtering, konversi citra ke dalam bentuk grayscale, dan augmentasi data. Ekstraksi fitur hasil pre-processing menggunakan GLCM yang diambil yaitu kontras, korelasi, energi, homogenitas, dan entropi. Dari hasil penelitian, klasifikasi menggunakan Jaringan Syaraf Tiruan diperoleh akurasi 46%, presisi 43%, recall 42,5%, dan F1-Score 42% dengan sudut kemiringan GLCM 90°. Jadi, metode ini dapat digunakan untuk mengklasifikasikan jenis kayu, namun kurang akurat karena masih terdapat kekurangan pada model.**

**Kata Kunci**: Kayu, Citra Digital, GLCM, *Artificial Neural Ntework*

## Abstract

**In Indonesia, various types of wood grow and develop with various characteristics and benefits. Each type of wood has differences in texture and fiber, to classify it must have sufficient knowledge about the texture and fiber of wood. A wood species identification system is needed to help the classification process. The purpose of this research is to classify Teak Wood, Sengon Wood, Mahogany Wood, and Gmelina Wood which are often sold in Indonesia. The classification method used in this research is Artificial Neural Network with Gray Level Co- occurrence Matrix (GLCM) extraction. Pre-processing stages include Histogram Equalization, filtering, converting images into grayscale form, and data augmentation. Feature extraction of pre-processing results using GLCM is taken, namely contrast, correlation, energy, homogeneity, and entropy. From the research results, classification using Artificial Neural Network was obtained with 46% accuracy, 43% precision, 42.5% recall, and 42% F1-Score with a GLCM inclination angle of 90°. So, this method can be used to classify the types of wood, but it is less accurate because there are still deficiencies in the model.**

**Keywords**: Wood, Digital Image, GLCM, Artificial Neural Network

## Introduction

Indonesia is known for its diverse and abundant natural resources, including its rich forests that produce a lot of wood for industrial purposes, both household industries and large industries globally. In

Indonesia, various types of wood grow and develop with various characteristics and benefits. Revenue from exports of wood products is indeed one of the main sources of income for most countries in Southeast Asia, including Indonesia [1].

Perum Perhutani is a State-Owned Enterprise (BUMN) engaged in the forestry sector. Perum Perhutani's main task is to maintain, manage, and utilize state forests in a sustainable and sustainable manner. The company has an important function in maintaining ecological balance, providing timber resources, and contributing to the economy and welfare of the community [2]. Perum Perhutani is also involved in forest restoration activities, replanting, plant maintenance, forest fire control, and various other activities related to forest management. The main objective is to optimize the utilization of forest resources responsibly for the welfare of the environment and society.

In the 1970s, the beginning of Indonesia's forestry renaissance, the wood species known and utilized for the wood processing industry almost entirely came from one source, namely natural production forests [3]. These wood species are generally characterized by large diameters, straight trunks and excellent wood properties. The types of wood that grow in Indonesia which include commonly traded wood species as many as 10 species, the main types of plant wood as many as 10 species and underutilized wood species as many as 23 species [4].

Each type of wood has differences in texture and different fibers, to make a classification of course must have sufficient knowledge about the texture and fiber of wood. For humans who are still laymen, it will certainly be difficult to distinguish with the naked eye. Consequently, a system of categorization techniques was created in order to use the GLCM method to identify wood species. This technique determines the typical amount of grayness in an image by analyzing a single pixel. This research aims to develop a system to classify four types of wood traded in Indonesia, namely Teak Wood, Sengon Wood, Mahogany Wood, and Gmelina Wood. The four types of wood have similar textures and colors that are difficult to distinguish with the naked eye, therefore clustering is needed using the Gray Level Co-occurrence Matrix (GLCM) based Artificial Neural Network (ANN) method so that they can be grouped accurately [5].

Wood identification methods can be learned as science, but the ability to identify wood species can only be obtained through a long, repetitive and continuous training process. Problems that arise if the officer who identifies the wood is not yet skilled, the business process will take longer and of course will increase costs [6]. A wood species identification system is needed to provide a solution to this problem. With regard to wood identification using GLCM-based ANN is a combination of algorithms and feature extraction methods that are appropriate for identifying wood species.

The advantages of Artificial Neural Network in classification include its ability to handle difficult problems even in the presence of imperfect or noisy data. ANN has been proven to be a very effective tool in various applications, especially in data classification. ANNs can learn from given data examples and adapt to complex patterns in the data. This allows them to classify data with a high degree of accuracy even in cases where the relationship between the input and output features is very complex or non-linear [7].

In research [8] using the ANN method to classify the maturity stage of mangosteen fruit using color and texture obtained an accuracy of 90% accuracy in the hidden layer. In research [9] the results of using the Gray Level Co-Occurrence Matrix (GLCM) method in extracting the characteristics of spinach leaves (blitum album) using the Artificial Neural Network method can produce an accuracy rate calculated using the counfusion matrix which is 90%. Research [10] can determine the performance of using the GLCM and ANN methods in identifying the quality of shrimp, that the use of these methods has excellent performance indicated by the acquisition of an accuracy value of 93%. In research [11] shows a comparison in classifying diabetes diagnoses, the accuracy value for the ANN method is 77.60% while the accuracy value for the SVM method is 65.24%. This means that the use of the ANN method is better than SVM to classify someone suffering from diabetes or not.

This research aims to develop a system to classify four types of wood traded in Indonesia, namely Teak Wood, Sengon Wood, Mahogany Wood, and Gmelina Wood. The four types of wood have similar textures and colors that are difficult to distinguish with the naked eye, therefore grouping is needed using the Gray Level Co-occurrence Matrix (GLCM) based Artificial Neural Network (ANN) method so that they can be grouped accurately. It is hoped that this research can contribute to the analysis of wood species and become a strong foundation in classifying wood defects at Perum Perhutani.

## Basic Theory

### Type of Wood

Wood is part of the stem, branch, or twig of a plant that undergoes hardening due to the process of lignification or ossification. The use of wood varies greatly, from cooking purposes to making household furniture such as tables and chairs, building materials such as doors and windows, to papermaking materials [12]. Since long time ago Teak Wood (*Tectona grandis L. f.*) is the most demanded wood because it has an elegant and unique style, strong, stable, durable, and the workmanship is quite easy. Teak wood has characteristics such as colors that vary from golden brown to dark brown, with beautiful and unique fibers [13]. Mahogany wood is a type of wood derived from mahogany trees (*Swietenia spp.*), which is famous for its rich wood color and the beauty of its grain. Mahogany wood has characteristics such as a rich brownish-red color, with attractive wood grain [14]. Gmelina wood is a type of wood derived from the Gmelina Tree (*Gliricidia sepium*), which is also known by other names such as Gliricidia, gamal, or mata-rata. The color of this wood varies from light brown to dark brown, with fine fibers and a slightly rough texture [15]. Sengon wood comes from the sengon tree (*Falcataria moluccana*), which is a type of fast-growing tree and is a member of the Fabaceae family. Sengon wood has characteristics such as fine fibers and colors that tend to be white to yellowish [16].

### Histogram Equaization

Histogram Equalization is a program running on a computer system that is effective in enhancing contrast in the grayscale level range of an image by adjusting the intensity of pixel values in the input image so that the output image has an even distribution of pixel value intensity distribution. Pixel values are depicted in a histogram that represents both the probability and frequency of various gray levels in the image [17].

### Canny Edge Detection

The initial stage in enclosing information in a picture is edge detection, which is the process of creating the edges of image objects. Canny, sometimes referred to as optimal edge detection, is a method that locates edge points, has a low error rate, and returns a single response for each edge [18].

### Data Augmentation

Data augmentation is a method that helps practitioners greatly expand the variety of data used for training models without needing to gather new data. Common techniques for data augmentation include cropping, padding, and horizontal flipping, which are often employed to train large networks. Despite this, many methods rely primarily on these fundamental types of augmentation. [19].

### Grey Level Co-occurance Matrix

The term "cooccurrence" refers to the frequency with which one pixel value level occurs adjacent to another within a given pixel distance $(d)$ and angular orientation $(\theta)$. Pixels are used to describe distance, and degrees are used to express orientation. Four angular directions 0°, 45°, 90°, and 135° with 45° angular intervals are used to construct orientation. In the meantime, 1 pixel is typically used as the separation between pixels [20]. Figure 1 can be used to depict the four directions.

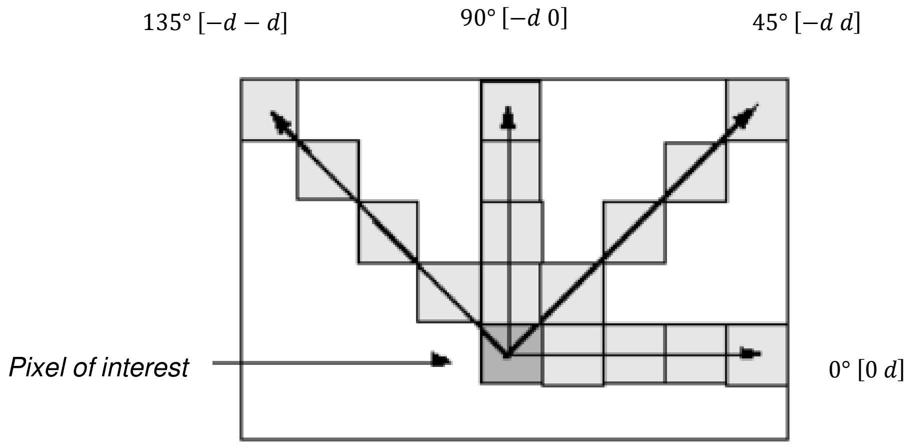


**Figure 1.** Four-way Degree of Grey

The shape of the co-occurrence matrix is square when the number of entries in the matrix is equal to the square of the number of pixel intensity levels in the image. The probability of a pixel of value $(i)$ neighboring a pixel of value $(j)$ at a distance $(d)$ and orientation $(180 - \theta)$ is contained at each point $(i, j)$ in the oriented cooccurrence matrix. The steps in creating a cooccurrence matrix are:

1. Create a matrix work area.
2. Ascertain the spatial correlation between neighboring pixels and reference pixels about the pixel distance $(d)$ and angle value $(\theta)$.
3. Calculates the cooccurrence sum and populates it in the matrix work area.
4. Sum the cooccurrence matrix with its transpose to make it symmetric.
5. Normalise the matrix to convert it to probability form.

Cooccurrence refers to the frequency with which one level of pixel value is adjacent to another level in terms of both distance $(d)$ and angular orientation $(\theta)$. Orientation is formed in the right angular direction with 45° intervals, namely 0°, 45°, 90°, and 135°. While the distance between pixels is usually set by 1 pixel, 2 pixels, 3 pixels and so on.

For example, a 4 x 4 matrix has grey levels from 0 to 6. The cooccurrence matrix will be calculated with a value of $d = 1$ and $\theta = 0°$. The number of times a pair $(i, j)$ appears is calculated for the entire matrix.

### Extraction of GLCM Features

After obtaining the GLCM cooccurrence matrix, proceed to find the value of the GLCM features. In this research, the GLCM features used include energy, contrast, correlation and homogeneity features. The following is an explanation of each feature [21].

1. Energy

   Energyindicates a measure of the concentration of intensity pairs in the cooccurrence matrix. The energy value increases when the pixel pairs that qualify the cooccurrence intensity matrix are concentrated at a few coordinates and decreases when they are spread out.

$$f_1 = \sum_i \sum_j P(i,j)^2 \tag{1}$$

2. Correlation
   Correlation is a representation of the linear relationship in the degree of a grayscale image. Correlation ranges from -1 to 1.
   $$f_2 = \sum_i \sum_j P(i,j) \frac{(i-\mu i)(j-\mu j)}{\sigma i \sigma j} \tag{2}$$
3. Contrast
   The picture matrix elements' dispersion (moment of inertia) is indicated by contrast. They have a high contrast value if they are far from the main diagonal. In terms of visuals, the contrast value is a measurement of the difference in an image region's shades of grey.
   $$f_3 = \sum_i \sum_j (i,j)^2 P_d(i,j) \tag{3}$$
4. Homogenity
   Homogeneity represents a measure of the similarity of the variation value of the image intensity. If all pixel values have uniform values then homogeneity has a maximum value.
   $$f_4 = \sum_i \sum_j \frac{P_d(i,j)}{i+|i-j|} \tag{4}$$

Where:

$i$ = i-th row matrix, i = 1, 2, ..., i
$j$ = j-th row matrix, j = 1, 2, ..., j
$p_{i,j}$ = Pixel value in matrix pair (i,j) = (1,1), (1,2), ..., (i,j)
$\mu_i$ = Calculation of the average value of row i, i = 1, 2, ..., i
$\mu_j$ = Calculation of the average value of row j, j = 1, 2, ..., j
$\sigma_i$ = Variance of matrix i
$\sigma_j$ = Variance of matrix j

**K-fold Cross Validation**

In machine learning, K-fold Cross Validation is a technique used to evaluate model performance and make sure the model successfully generalizes to new data. It addresses the issue of overfitting that can arise when a model is evaluated on just one dataset. The dataset is divided into K segments of identical size for K-fold cross validation, and the testing and training procedures are performed K times. [22].

**Artificial Neural Network**

The Artificial Neural Network (ANN) approach uses the human brain's nerve system to solve problems. There are many different kinds of network architecture, including Single Layer, Multi Layer, and Recurrent. The input layer, hidden layer, and output layer are the three network layers that make up the Multi Layer Networks architecture. The hidden layer is situated between the output and input layers [23]. The structure of Multi Layer Networks is composed of three layers: the input layer, the hidden layer, and the output layer, as shown in Figure 2 below:

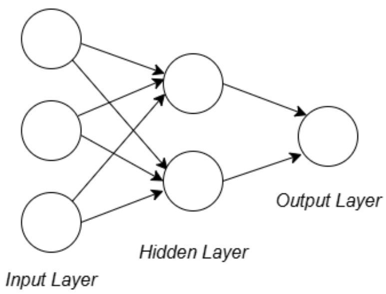


**Figure 2.** Architecture of Artificial Neural Network

An artificial neural network is made up of several neuron groups organized into three layers, which are as follows:

1. Input Layer, which functions as a link between the network and the data used. These neurons do not do anything to the data, only forward the data to the next layer.
2. Hidden Layer, functions as a modifier of input received from the input layer which will then be connected to the output unit. Hidden layer is located between the input and output layer. Using the following formula, each neuron in the hidden layer will determine the sum of the products between the input values $(x_i)$ and the weights $(\omega_i)$, plus the bias $(b)$.

$$z = \sum_{i=1}^{n} \omega_i x_i + b` \quad (5)$$

Where:
$z$ = Total number of inputs of the neuron
$\omega_i$ = Weight connected to input-$i$
$x_i$ = Input value to input-$i$
$b$ = Bias

a. Sigmoid

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (6)$$

Where:
$\sigma(z)$ = Output of the sigmoid function
$z$ = Total input to the neuron (sum of the weights and inputs)
$e$ = Euler's number, which is a mathematical constant of about 2.71828

b. ReLU

$$f(z) = max(0, z) \quad (7)$$

Where:
$f(z)$ = Output of the ReLU function
$z$ = Total input to the neuron (sum of weights and inputs)

3. Output Layer, has a function as a layer that provides output as a result of the process that has been carried out.

**Confussion Matrix**

A table called a confusion matrix is frequently used in machine learning to assess how well categorization models perform. In this research, test data will be used to evaluate the classification model that has been used. The Confusion Matrix, which comprises accuracy, precision, recall, and F1-score, will be calculated to test the model. The success rate of the classification process is known as accuracy. Precision quantifies the degree of accuracy with which our model produces favorable predictions. Recall is the chance of cases with positive categories that are correctly predicted to be positive. F1-score is an evaluation matrix that is useful in dealing with the weaknesses of recall and precision [24].

$$precission = \frac{TP}{TP+FP} \times 100\% \quad (8)$$

$$recall = \frac{TP}{TP+FN} \times 100\% \quad (9)$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

$$F1 - score = \frac{2 \times precission \times recall}{precission + recall} \quad (11)$$

Retrieved from:

$TP =$ True Positive (Number of positive samples correctly classified by the model)

$TN =$ True Negative (Number of negative samples correctly classified by the model)

$FP =$ False Positive (Number of negative samples misclassified as positive by the model)

$FN =$ False Negative (Number of positive smples incorrectly classified as negative by the model)

## Methods

### Data Source

The data used is primary data taken by the author using an Iphone 6s smartphone camera on Thursday, February 29, 2024 at the Wuluhan Timber Stockpile (TPK), Jember Regency. The data taken is image data from 4 types of wood, namely Teak Wood, Mahogany Wood, Gmelina Wood, and Sengon Wood with data format (.jpg). Has a total of 139 data with a combination of 41 Teak Wood image data, 42 Mahogany Wood image data, 24 Gmelina Wood image data, and 32 Sengon Wood image data.

### Steps

The flowchart used in this research is as follows:

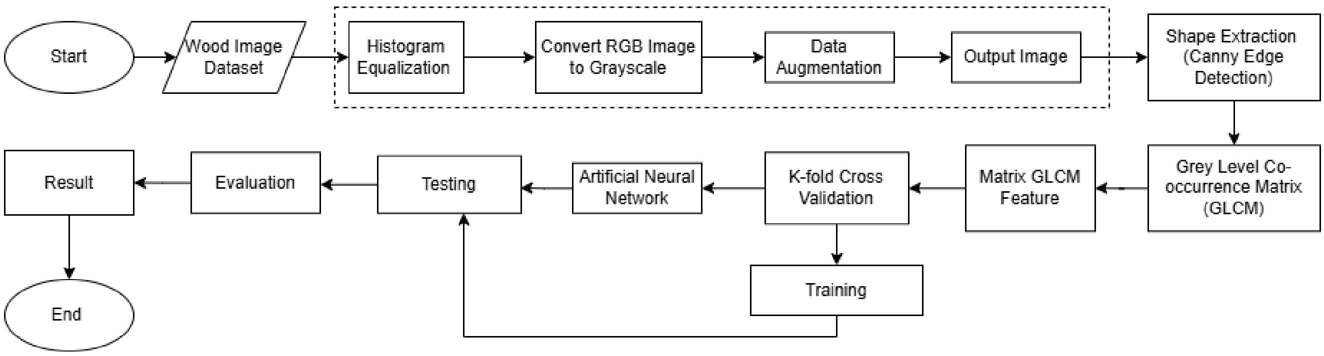


**Figure 3.** Flowchart

The stages of analysis that can be carried out are as follows:

a. Prepare research data.
b. Data pre-processing which consists of performing histogram equalization, converting images into grayscale form, and data augmentation until new data appears.
c. Performing shape extraction using Canny Edge Detection to detect the edges of objects in the image.
d. Perform image extraction using Gray Level Co-occurrence Matrix (GLCM) to obtain GLCM Feature Matrix values consisting of Energy, Contrast, Homogeneity, Entropy, and Correlation variables. In addition, variables such as Perimeter, Area, Aspect Ratio, Bounding Rectangle Width, Bounding Rectangle Height, Diss_sim, Energy_sobel, Corr_sobel, Diss_sim_sobel Homogeneity_sobel, Contrast_sobel, Entropy_sobel are also obtained.
e. K-Fold Cross Validation is used in the data division process to obtain training and testing data.
f. Training the data to get the best model for classification
g. Testing the data that has been created using training data
h. Interpretation of classification results and model output.
i. Summarizing the results of data testing.

## Results and Discussion

## Pre-processing

First step in the data acquisition process is data pre-processing. Data pre-processing is adjusted to the sequence of available data obtained and is good for processing to the next stage. In the pre-processing process starts from data filtering, histogram equalization, then converting the image into grayscale form, then the data augmentation process into 556 images. The results of pre-processing can be shown in Figure 4 and Figure 5. Figure 4 shows the improvement of image quality using histogram equalisation and Figure 5 is the result of converting the image into grayscale.

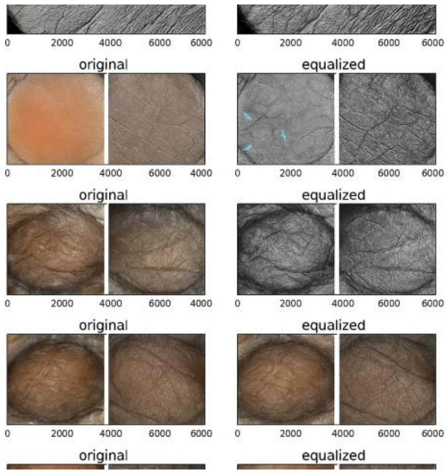


**Figure 4.** Result of Histogram Equalization

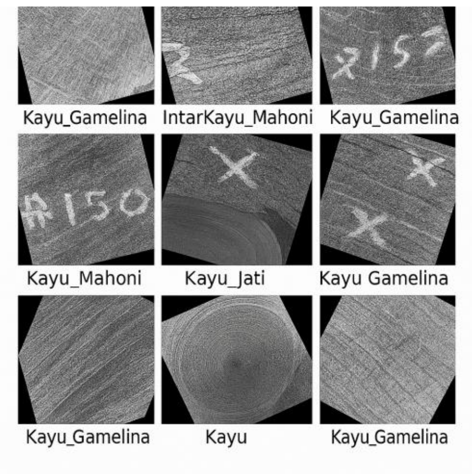


**Figure 5.** Result of Greyscale

## Canny Edge Detection

In this phase, the image can be retrieved in grey scale, then processed for object edge detection in each image. The results of object edge detection are obtained variables including Perimeter, Area, Aspect Ratio, Bounding Rectangle Width, and Bounding Rectangle Height.

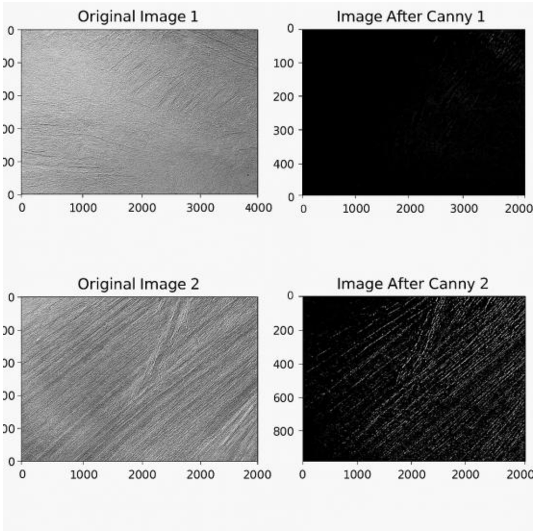


**Figure 6.** Result of Canny Edge Detection

Based on Figure 6, the Canny Edge Detection sample identification is obtained as in Table 1.

**Table 1.** Canny Edge Detection Sample Data

| Perimeter | Area | Aspect Ratio | Bounding Rectangle Width | Bounding Rectangle Height | Class |
|---|---|---|---|---|---|
| 15.313708 | 6.0 | 1.250000 | 5.0 | 4.0 | Sengon |
| 162.769552 | 3.0 | 8.111111 | 73.0 | 9.0 | Mahogan y |
| 136.024385 | 24.0 | 1.900000 | 57.0 | 30.0 | Teak |
| 149.154328 | 3.5 | 3.368421 | 64.0 | 19.0 | Mahogan y |
| 248.534051 | 30.0 | 1.321429 | 37.0 | 28.0 | Sengon |

## Image Extraction using GLCM

In this phase, the data is processed using the GLCM method to obtain Contrast, Correlation, Energy, Homogeneity, and Entropy values. The sample results of this GLCM feature extraction can be presented in Table 2. To acquire classification results, the obtained statistical data will be processed using the Artificial Neural Network model classifier.

**Table 2.** Sample GLCM Image Extraction Data

| No. | Feature Extraction | | | | | Class |
|---|---|---|---|---|---|---|
| | Contrast | Correlation | Energy | Homogeneity | Entropy | |
| 1. | 808.499060 | 0.211292 | 0.012504 | 0.062421 | 0.969434 | Sengon |
| 2. | 353.761477 | 0.462951 | 0.046783 | 0.146811 | 0.811722 | Mahogany |
| 3. | 93.649172 | 0.243025 | 0.126065 | 0.262724 | 0.599576 | Teak |
| 4. | 67.121969 | 0.424018 | 0.080326 | 0.255675 | 0.465888 | Mahogany |
| 5. | 606.144922 | 0.143890 | 0.013582 | 0.057179 | 0.898977 | Sengon |

## Model Evaluation

The data entered for this process are features that have been extracted using the GLCM method. Next, the data is divided using K-Fold Cross Validation. This research uses k-fold = 10, because the test results show that k-fold = 10 is better than k-fold = 5. Following that, the classification results will yield percentages for accuracy, precision, recall, and F1-Score after being confirmed using a confusion matrix. This classification experiment was conducted by varying the degree of the GLCM.

**Table 3.** Result

| Class | K-Fold | Degree | Precision | Recall | F1-Score | Accuracy |
|---|---|---|---|---|---|---|
| Jati | 5 | 0° | 43% | 37% | 39% | 33% |
| | | 45° | 36% | 46% | 41% | 42% |
| | | 90° | 42% | 59% | 49% | 41% |
| | | 135° | 44% | 53% | 48% | 43% |
| Sengon | 5 | 0° | 56% | 39% | 46% | 33% |
| | | 45° | 46% | 44% | 45% | 42% |
| | | 90° | 39% | 42% | 41% | 41% |
| | | 135° | 38% | 48% | 43% | 43% |
| Mahoni | 5 | 0° | 21% | 38% | 27% | 33% |
| | | 45° | 51% | 49% | 50% | 42% |
| | | 90° | 53% | 30% | 38% | 41% |
| | | 135° | 44% | 43% | 44% | 43% |
| Gmelina | 5 | 0° | 21% | 17% | 19% | 33% |
| | | 45° | 29% | 23% | 26% | 42% |
| | | 90° | 26% | 29% | 28% | 41% |
| | | 135° | 44% | 20% | 28% | 43% |
| Jati | 10 | 0° | 42% | 59% | 49% | 43% |
| | | 45° | 44% | 33% | 38% | 38% |
| | | 90° | 44% | 61% | 51% | 46% |
| | | 135° | 40% | 32% | 36% | 37% |
| Sengon | 10 | 0° | 43% | 33% | 38% | 43% |
| | | 45° | 29% | 55% | 37% | 38% |
| | | 90° | 44% | 24% | 31% | 46% |
| | | 135° | 32% | 37% | 34% | 37% |
| Mahoni | 10 | 0° | 45% | 36% | 40% | 43% |
| | | 45° | 61% | 38% | 47% | 38% |
| | | 90° | 51% | 54% | 53% | 46% |
| | | 135° | 44% | 41% | 43% | 37% |
| Gmelina | 10 | 0° | 41% | 45% | 43% | 43% |
| | | 45° | 21% | 29% | 27% | 38% |
| | | 90° | 33% | 31% | 32% | 46% |
| | | 135° | 25% | 33% | 29% | 37% |
| Jati | 10 | 0° | 42% | 59% | 49% | 43% |
| | | 45° | 21% | 29% | 27% | 38% |
| | | 90° | 33% | 31% | 32% | 46% |
| | | 135° | 25% | 33% | 29% | 37% |

From the experimental results, Table 3 shows that the best results are obtained at 90° GLCM. True Negative (TN), False Positive (FP), False Negative (FN), and True Positive (TP), which are shown in the table, are the best model findings.

## Conclusion

From the results of the study, it can be seen that the use of Artificial Neural Network method and GLCM feature extraction with k-fold = 10 produces better classification results than k-fold = 5, which is able to produce an accuracy value calculated using a confusion matrix of 46%, precision 43%, recall

42.5%, and F1-Score 42% with a GLCM inclination angle of 90°. From the accuracy value obtained in this study, it can be concluded that the Artificial Neural Network method in this study is not good at classifying 4 types of wood.

Based on the research that has been done, the author suggests that for data collection the wood image to be used has the same felling age so that the colour has not faded and is still clearly visible. The device used is expected to be able to take clear images according to the standard so that the texture of the wood can be read clearly. As for the image capture technique, it is hoped that the image data will be taken per section of the same size to facilitate research to produce a better accuracy value.

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