Wood Type Identification System using Naive Bayes Classification

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***Abstract*—Wood, a forest product and natural resource, is a raw material used to make household goods. Some types of wood have almost the same pattern or structure. Wood quality varies greatly depending on the tree species and the environmental conditions in which it grows. This makes it challenging to identify the type of wood, especially for wooden furniture users. Therefore, wood classification is essential to ensure that the wood used meets the required quality standards and requirements. Automatic classification of wood using image processing has several advantages and can make it easier for humans. One of the image processing methods for wood classification is the Naïve Bayes method. Feature extraction technique using GLCM using contrast, correlation, energy, and homogeneity attributes. The GLCM methods can be combined to create a system design to distinguish five wood species using an image-based wood type identification system. The study results have successfully designed a system to determine five types of wood using the framework of an image-based wood type identification system. An application system has been produced to distinguish five types of wood using the framework of an image-based wood type identification system with the GLCM feature extraction method and the Naive Bayes classification method. The application system successfully identified wood species with a test accuracy rate of 88%.**

Keywords*—Naive Bayes, Wood Classification, GLCM, MATLAB

I. Introduction

Today's technology continues to develop, especially computerization for automation processes. This encourages constructing a system that can identify wood types, namely Teak, Mahogany, Mendi, and Sengon, using computers to help humans distinguish Mahogany, Mendi, and Sengon Teak [1]. The four types of wood are popular and commonly used for household furniture [2]-[4]. Generally, users of wood furniture as home furniture choose wood based on certain types that refer to the appearance of texture and color, mostly still done by humans [5]. Human identification of wood species needs to be more accurate due to time constraints and other things. The limited ability of humans to analyze wood by sight is generally less sensitive to small changes that occur gradually [6]-[9].

Errors often arise when manually identifying wood types, often due to a lack of experience and knowledge about wood [10]. Moreover, the direct visual examination of wood reveals nearly indistinguishable patterns and textures, necessitating prolonged and repetitive identification procedures to ensure accuracy [11]. The development of technology capable of analyzing wood textures to differentiate and classify wood types has become imperative. One such advancement involves the creation of technology for the automatic classification of wood types used in household furniture [12]-[15]. Consequently, there is a pressing need for an automated system for identifying wood types, which can significantly mitigate the inaccuracies of manual wood identification methods.

Naive Bayes are machine learning models that distinguish objects based on specific features [16]-[17]. In simple terms, Naïve Bayes assumes that the presence of a particular feature in the class is not related to the presence of other features [18]-[19]. This algorithm is easy to create and valuable when faced with large datasets. A simple example of this algorithm is that a fruit can be categorized as a watermelon if it is green, round, and 10 in diameter. These features can depend on each other for their existence [20]-[23].

However, each independently contributes to the likelihood that the fruit under consideration is watermelon. Therefore, this algorithm has the term "Naïve" in its name [24]-[25]. This study classifies Teak, Mahogany, Munggur, Albasia, and Trembesi wood types based on wood texture by implementing digital image processing using GLCM texture feature extraction and Naive Bayes algorithm to generate GLCM characteristic extraction parameter values as Naive Bayes input to identify wood types. The GLCM method itself is a method that can provide important information about image texture [26]. This image texture information is used as input data in classifying wood types using the MLP algorithm. MLP is a machine learning method that presents working principles that almost resemble the nervous system in humans [27]-[28].

II. Methods

A. System Design

The research objects studied in this study amounted to five types of wood. In this study, they are classifying wood types using Bayes Classification. In identifying wood, this study uses the GLCM (Gray Level Cooccurrence Matrix) method as a characteristic extraction [29]. The wood to be identified as many as five types of wood are Albasia, Teak, Mahogany, Munggur, and Trembesi. The type of wood is usually determined based on the size, color, pattern, and texture of the wood itself. Each type of wood has diverse physical properties. This study designed a system to classify Albasia, Teak, Mahogany, Munggur, and Trembesi wood types based on the texture of each type of wood [30]-[31].

First, start and then collect a dataset of different types of wood images. In this study, there were five types of wood, and the number of wood images was 100, so there was a total of 500 images. Then divide the dataset into two parts, namely training data and test data. Training data in this study there were 400 images and 100 images for test data. Furthermore, the data training process is by converting ordinary photo images taken from microscopic cameras into gray scaling to convert them into gray images and segmentation.

The next stage is extracting features on the training data using image processing algorithms and, in this stage, using the Gray Level Co-occurrence Matrix (GLCM) method. Next, the stage of training the data is classifying the training data to build a wood classification model. Using the Naïve Bayes classification method will get the training results at this stage.

Next, test the test data prepared by taking test data and training process data for further classification. The classification stage uses the Naïve Bayes classification method to test the system using unknown wooden drawings. The system output is the type of wood produced from the classification of wood drawings [32].

Fig. 1 shows a flow for training methods on training data. The input used comes from image data in the form of images with objects containing wood. Furthermore, the wood image will be processed in the initial data processing stage to produce an image with wooden objects. The initial processing of data is to equalize the color of wooden objects. After going through the initial processing stages of the data, the image results will then be processed to obtain feature extraction using GLCM. After that, get each of the values of the training data.

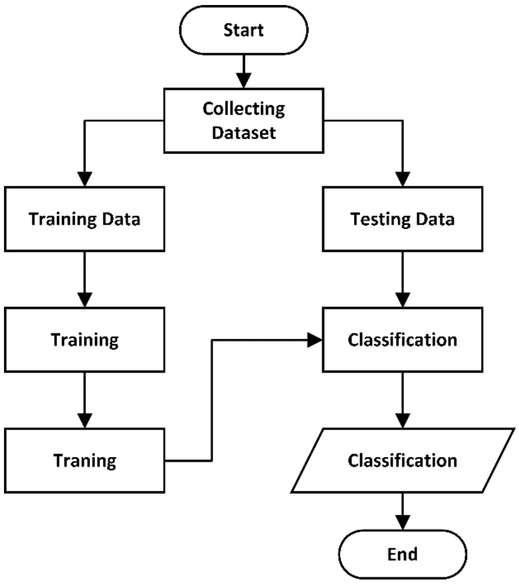


Fig. 1. Identification system flowchart

B. Features of Feature Extraction

In this subsection, we will explain the coding feature of the feature extraction used. The feature extraction feature consists of RGB and GLCM. RGB consists of red, green, and blue features. GLCM consists of contrast, correlation, energy, and homogeneity.

1) Gray Level Co-Occurrence Matrix (GLCM)

The extraction of GLCM textile features produces several features: contrast, correlation, energy, and homogeneity. Contrast is a feature that represents differences in color levels or grayscale that appear in an image. Correlation represents the linear relation of degrees of the grayish image. Energy represents a measure of uniformity in a snap. Homogeneity represents the homogeneity of variation in an image [33]. Fig. 2 is coding to find the GLCM value.

```
GLCM = graycomatrix(Img_gray,'offset',[0
1; -1 1; -1 0; -1 -1]);
stats =
graycoprops(GLCM,{'Contrast','Correlation'
,'Energy','Homogeneity'});
Contrast = mean(stats.Contrast);
Correlation = mean(stats.Correlation);
Energy = mean(stats.Energy);
Homogeneity = mean(stats.Homogeneity);
```

Fig. 2. Coding looking for GLCM values

GLCM is a texture analysis method used in digital image processing to extract features from an image. GLCM is a matrix that describes the relationship between the grayness of adjacent pixels in n image. It is calculated by counting the number of times a pair of pixels with a particular spatial relationship occurs in an image with a specific combination of grayish levels. GLCM is used to extract texture features such as contrast, correlation, energy, and homogeneity, which can be used for image classification and segmentation [34]-[36].

GLCM constructs a two-dimensional matrix of n x n size, where n is the number of grayish levels in the image. Each matrix element represents the number of occurrences of pixel pairs with a certain distance and direction on the image. Each component of the matrix contains information about the corresponding brightness and pixel orientation values in the image. GLCM describes the frequency with which pairs of two pixels of a certain intensity appear in a certain distance and direction in an image.

2) Naive Bayes

Naive Bayes is a classification algorithm based on Bayesian probability theory. This algorithm predicts classes from data by calculating the probability of any given class and then selecting the class with the highest probability as the class predicted from that data. This algorithm is considered relatively simple but works well for various classification problems, such as text classification, image recognition, etc. Naïve Bayes, derived from the name "Naïve," refers to the assumption that each feature in the data is treated independently and uncorrelated, making it easier to calculate probabilities [37].

Naive Bayes classifier is one classification method that can recognize objects with a minimum dataset. Naive Bayes is a suitable method for binary and multiclass classification. This method, also known as the Naïve Bayes Classifier, implements the technique of classifying future supervised objects by assigning class labels to instances/records using conditional probabilities [38]-[39]. Conditional probability is a measure of the probability of an event occurring based on other events that have (assumed, alleged, stated, or proven to have happened). Equation (1) is the probability density formula, Equation (2) is the Formula for finding the Naïve Bayes value, and equation (3) is the Formula for finding the end of value [40]. P(x) is the probability density, C_i is the index value, t_f is the value of the feature, π is 3.14, σ is the standard deviation, x is the input value, μ is the mean of class, e is natural value and C_i^* is Final grade of classification.

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\sigma)^2}{2\sigma^2}} \tag{1}$$

$$C_i = P(C_i) \prod_{f=1}^{f} P(t_f | c_i) \tag{2}$$

$$C_i^* = arg\ maximal\ C_i \tag{3}$$

III. RESULT AND DISCUSSION

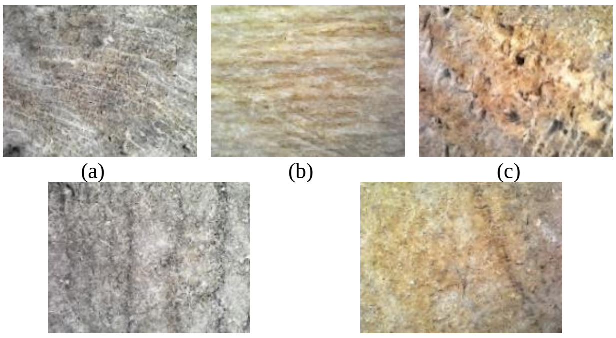
A. Data

We utilized primary data for this study, which was manually collected using a microscope camera. The data comprises photographs of wood samples captured through a digital microscope camera connected to the default Windows 10 camera application on a laptop. The data collection process involved using a Digital Microscope 1600 camera and a resolution 480x360. Light intensity was provided by the built-in light of the microscope camera, and the data collection occurred indoors between 10:00 AM to 1:00 PM WIB. The objects being imaged were horizontally cut sections of trees. Our classification focused on five wood species: Albasia, Teak, Mahogany, Munggur, and Trembesi. A total of 500 wood photo data points were collected, with each wood type consisting of 100 photos, resulting in a comprehensive dataset of 400 training and 100 test images, as detailed in Table 1.

Table 1. Details of research wood data

No	Types of Wood	Training data	Test data
1	Albasian wood	80	20
2	Teak Wood	80	20
3	Mahogany Wood	80	20
4	Munggur Wood	80	20
5	Tremebsi Wood	80	20

The resulting dataset was acquired once all wood types were captured using a digital microscope camera. The wood data employed for this study encompasses five distinct wood types: Albasia, Teak, Mahogany, Munggur, and Trembesi. The subsequent section provides an illustrative representation of wood data obtained through the digital microscope camera. Fig. 3 shows example images of each of the five types of wood.



(d) (e)

Fig. 3. (a) Albasian wood (b) Teak wood (c) Mahogany wood (d) Munggur wood (e) Tremebsi wood

B. Testing Data With GUI

To utilize the GUI program, click the "Open Image" button, then select the "Test data" folder. Proceed to choose and press the desired image for identification. Once selected, the image's filename and the original version will appear in the GUI. Following this, activate grayscale mode by pressing the "Grayscale" button, displaying the grayscale image. Utilize the "Feature Extraction" button to find the feature extraction value and the "Classification" button to classify the selected image, with results in the green box. To identify another image, press "Reset" to restore the GUI's initial state. Refer to Fig. 4 for the GUI layout.

Fig. 4. GUI initial view, sistem identifikasi kayu menggunakan klasifikasi naive bayes (Wood Type Identification System using Naive Bayes Classification), pengolahan (processing), buka citra (open the image), esktaksi ciri (feature extraction), klasifikasi (classification), hasil klasifikasi (classification result), nilai ekstraksi ciri (feature extraction value), ciri (feature), nilai (value)

The test set with 20 images representing five different wood types was used. The complete test involves 100 wood images subjected to identification using a GUI program. The outcomes of the test are documented in Table 2. Based on the test scenario's results, it can be deduced that the naïve Bayes method can be classified with an accuracy rate of 88%. After examining 100 data instances, the results encompass 88 accurate cases of identification and 12 examples of incorrect titles. The test findings indicate that Albasia wood images exhibit the highest accuracy level, while Mahogany and Trembesi wood images are mostly recognizable with only a single misclassification. On the other hand, Teak and Munggur wood images display error rates in their identification.

Table 2. Test result

Types of Wood	Albizia	Teak	Mahogany	Munggur	Trembesi
Albizia	20	0	0	0	0
Teak	0	15	0	0	5
Mahogany	0	0	19	0	1
Munggur	5	0	0	15	0
Trembesi	1	0	0	0	19
Accuracy= 88%					

IV. CONCLUSIONS

The research findings lead to the following conclusions. An application system has been developed to effectively differentiate between five distinct types of wood, employing an image-based wood type identification framework that integrates the Gray-Level Co-occurrence Matrix (GLCM) feature extraction method and the naïve Bayes classification technique. The system's performance has been assessed and demonstrated through accurate wood type identification, achieving an impressive test accuracy rate of 88%. Several constructive suggestions arise from this research for potential enhancements. Exploring alternative characteristic extraction methods could elevate accuracy levels during training and testing. Additionally, incorporating or augmentation of the Hue-Saturation-Value (HSV) color space might offer avenues to enhance accuracy further. Moreover, adding supplementary training data, specifically from each wood type, can strengthen accuracy during training and testing processes. These proposed refinement avenues underscore the research domain's dynamic nature and offer avenues for continued advancement in wood type identification systems.

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