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Indonesian Commercial Woods Classification Based on GLCM and K-Nearest Neighbor

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Abstract: ***Currently, the presence of wood is becoming increasingly scarce. In addition, the recognition of wood is still using wood experts, who basing their judgments on the characteristics that can be seen by eye directly such as color, texture and so on. However, wood experts are still few and have a disadvantage that the results obtained are still not sufficiently accurate and time consuming. The purpose of this research is to develop Indonesian commercial woods classification system based on GLCM and k-Nearest Neighbor. Procedures of the wood classification system includes image acquisition using a digital camera, then a preprocessing steps by converting the original image to grayscale image and sharpening the image, after that do texture feature extraction using Gray Level Co-occurrence Matrix (GLCM) with the parameters used are Contrast, Correlation , Energy, Entropy, and Homogeneity, at each direction that are 0°, 45°, 90°, 135°,and the last step is the classification using the k-Nearest Neighbor (k-NN). The testing results show that the testing data can be classified accurately 100% is a testing data derived from the training database with k = 1. In general, the greater the value of k then the classification success rate decreases.***

Keywords: GLCM, Indonesian Commercial Woods, k-Nearest Neighbor, Wood Classification System

I. INTRODUCTION

Wood is part of the trunk or branches and twigs of plants that hardens because of lignification. Wood is used for various purposes, such as making furniture (tables, chairs), paper materials, building materials (doors, windows, roof truss), cooking, making art (sculpture, carving), and others. Currently, the recognition of wood is still using wood experts, who basing their judgments on the characteristics that can be smelled by the nose and seen by eye directly such as color, odor, texture and so on. However, wood experts are still few and have a disadvantage that the results obtained are still not sufficiently accurate and time consuming, which is caused by several factors such as, experience, skills, fatigue and others.

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Along with the development of computer technology, especially in the field of Digital image analysis technology, develop tools to recognition of wood. One such tool for recognition of wood is used the help of image processing. Related research conducted by Bambang S, Elli A. Gojali, Herlan, and Puji L discusses Each type of wood has its own characteristics and can be distinguished by the identification of the wood based on its anatomy. One way is to use computer vision to detect images of macroscopic trees. This method is faster and more accurate for identifying wood species than traditional methods. As the use of smartphones increases around the world, capturing wooden structures with this smart device is very easy and can replace the use of digital microscopes. They propose a method for extracting wood species on an Android smartphone by combining the HOG method and an SVM classifier. They used SVMs to classify the textures of woodextracted from HOG features. In their experiments we used seven wood species. Each wood species has a total of 100 training images and 100 test images. Melanorrhoea wallichii and Agathisendertii have achieved the highest accuracy of 84%. The Agathis endertii species has the highest sensitivity and the value reaches 86%. Moreover, the Melanorrhoea wallichii species has a highest score for specificity and precision[2]. Eko Yudhi P. in "Pengenalan Jenis Kayu Berdasarkan Citra Makroskopik Menggunakan Metode Convolutional Neural Network" discusses choosing the right type of wood can be difficult, as choosing the wrong type of wood can reduce the quality of the processed product as expected. In addition, proper identification of wood can prevent illegal logging, especially for certain types of wood that are increasingly scarce today. One method that can be used to identify the type of wood is image processing based on the characteristics of the wood, such as color, grain orientation, and texture. This research describes the detection of wood-basedimage processing using the Convolutional Neural Network (CNN) method. This method is derived from a neural network that adds an extract layer function that can reduce the free parameters that the system does not need. The wood image data used in this study relates to four types of wood commonly used as raw materials in the manufacture of homes and furniture: Glugu, Teak, Sengon and Waru. The results of this study were able to identify four wood species with 95% accuracy at 600 epochs / iterations, making it a simple, lightweight, and inexpensive wood detection system. [3]. Iwan M. E., Risnandar, Esa P., Bambang S. in "Kayu7net: Identifikasi Dan Evaluasi F-Measure Citra Kayu.

Berbasis Deep Convolutional Neural Network (DCNN)"discusses will help classify some of the wood species traded using Deep Convolutional Neural Networks (DCNN). The novelty of this research lies in the DCNN architecture, Kayu7Net. Kayu7Net Architecture has three convolutional layers in a wood image dataset containing seven species. In the test, the wood image input is changed to 600x600, 300x300, 128x128 pixels, respectively, and repeats up to 50 epochs and 100 epochs, respectively. The proposed DCNN uses the ReLU activation function and batch size 32. ReLUs are more convergent and faster during the iterative process. On the other hand, the four levels of FullyConnected (FC) lead to a more efficient training process. Research results show that the proposed Kayu7Net has 95.54% accuracy, 95.99% precision, 95.54% recall, 99.26% specificity, and finally 95.46% F-measure[5]. Panagiotis B., Kosmas D., loannis B., Nikos G., Panagiotis L. in "Wood species recognition through multidimensional texture analysis" proposes a new approach for automatic detection of wood species by multidimensional texture analysis. Taking advantage of the fact that static wood images contain properties that change periodically and spatially, they introduce a new spatial descriptor that considers each wood image as a collection of multidimensional signals. More specifically, the proposed methodology enables the representation of wood images as concatenated histograms of higher order linear dynamical systems produced by vertical and horizontal image patches. The final classification of images, i.e., histogram representations, into wood species, is performed using a Support Vector Machines (SVM) classifier. For the evaluation of the proposed method, a dataset, namely "WOODAUTH", consisting of more than 4,200 wood images (from cross, radial and tangential sections of normal wood structure) of twelve common wood species existing in Greek territory, was created. [6]. Ohkyung K., Hyung Gu L., Mi-Rim L., Suijin J., Sang-Yun Y., Se-Yeong P., In-Gyu C., Hwanmyeong Y. in "Automatic Wood Species Identification of Korean Softwood Based on Convolutional Neural Networks" discusses a convolutional neural network (CNN) trained in wood species, one of the deep learning techniques, can extract and correctly classify unique feature representations. This is usually better than a classifier built on the features extracted in the manual adjustment process. They have developed an automated system to identify wood species using CNN models such as LeNet and MiniVGGNet and their variants. They used a smartphone camera to get a macroscopic image of a roughly cut surface of a lumber cross section. Five Korean coniferous species (cedar, cypress, Korean pine, Korean red pine, and larch) were classified by the CNN model. The tallest and most stable CNN model was LeNet3. These are two layers added to the original LeNet architecture. The accuracy of species identification by the LeNet3 architecture of five Korean conifers was 99.3%. The results show that automated systems that identify tree species are fast, accurate, and small enough to be used on mobile devices such as smartphones. [7].

II. RESEARCH METHOD

This chapter will explain the stages of Indonesian commercial woods species classification, which is divided into two processes, that is a training process and testing process. Training process and testing process have the same stages. The first stage is image acquisition. The second stage is to perform a preprocessing steps that is by converting original image into a grayscale image and sharpening the grayscale image. The third stage is to perform texture feature extraction using GLCM . The fourth stage is to perform the recognition and classification of wood image and the final is a result that is wood recognized/classified. These stages can be seen in fig. 1.

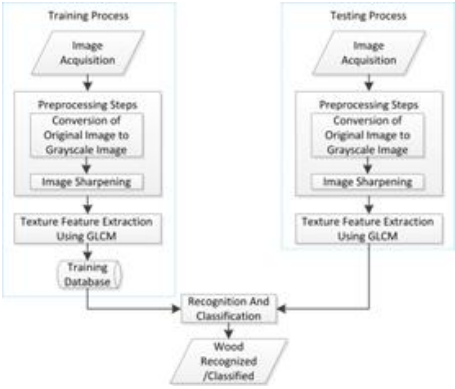

Fig. 1. Research Framework

A. Image Acquisition

The required data in this research are photographic image data of wood were taken using a digital camera. The dimension of a image used is 2048 x 1536 pixels. Image format is JPG in color categories true color. Image data is divided into 6 species of wood that consists of 5 genus, namely bangkirai (Shorea spp.), jati (Tectona.), kamper (Dryobalanops spp.), kempas (Koompassia.), mahoni (Swietenia spp.), and meranti kuning (Shorea spp.). Six sample of Indonesian commercial woods obtained from carpenter with the assumption that the author do not know the wood drying technology used and also do not know wood cleavage method used. Based on the data required for the research, the data samples collected is as follows:

- For the training process using 102 pieces of the image. The composition of the image consists of 17 bangkirai wood images, 17 jati wood images, 17 kamper wood images, 17 kempas wood images, 17 mahoni wood images, and 17 meranti kuning wood images.
- For the testing process is done with 3 scenarios. Each scenario uses 3 testing data for each species of wood so that the total testing data for six species of wood are 18 testing data. The first scenario is that the data used was taken from inside the training data and taken at random. The second scenario is that the data used was taken from outside the training database and retrieved in sequence with number data 18, 19, and 20. The third scenario is that the data used was taken from inside and outside the training database and taken at random. The composition of testing data the third scenario is that 9 data from 6 species of wood taken from the training database and 9 data from 6 species of wood taken from outside the training database.

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B. Preprocessing Steps

This steps aims to improve the quality of the image so as to make subsequent processing easier and more accurate.

- Conversion of Original Image to Grayscale Image
  By converting the original image to The grayscale image is intended to simplify and speed up Further image analysis process .
- Image Sharpening
  The aim of image sharpening is to clarify the edges of objects in the image. Image sharpening operations are essentially the summation of image edges (the result of edge detection) with the original image, so that the edges objeck looks much different from the background and the image seem sharper.
- Feature Extraction
  The feature extraction method used in this research is Gray Level Co-occurrence Matrix (GLCM) [4]. Statistical texture features have proven reliable in classifying the species of wood. Features used in this study is only 5 texture feature namely Contrast, Energy, Homogeneity, Entropy, and Correlation. For each sample image of wood, 5 texture features will be extracted from 4 different direction is horizontal (0°), vertical (90°), and diagonal (45°, 135°). In order to obtain 20 texture features for each wood image (training images and testing images). Distance d is used is 2.

C. Feature Extraction

The feature extraction method used in this research is Gray Level Co-occurrence Matrix (GLCM). Statistical texture features have proven reliable in classifying the species of wood. Features used in this study is only 5 texture feature namely Contrast, Energy, Homogeneity, Entropy, and Correlation. For each sample image of wood, 5 texture features will be extracted from 4 different direction is horizontal (0°), vertical (90°), and diagonal (45°, 135°). In order to obtain 20 texture features for each wood image (training images and testing images). Distance d is used is 2.

D. *k*-Nearest Neighbor

The final stage is the recognition and classification of Indonesian commercial woods species in order to recognized/classified the species of wood. In this research, k-Nearest Neighbor [1].k-nearest neighbor is chosen, one of the reasons is because the average training time is the fastest [8] compared to the others.

E. Application Testing

This stage is the process of checking whether the application is in accordance with the expected results. If there is an error, the application repair process is carried out, followed by checking the database server and continuing to check the connection between the application and the database server if there are still errors.

III. RESULTS AND DISCUSSIONS

A. Image Acquisition

The results of image acquisition can be seen in fig.2 which is 5 original image samples taken from 20 samples contained in database amounting to 6 species of wood.

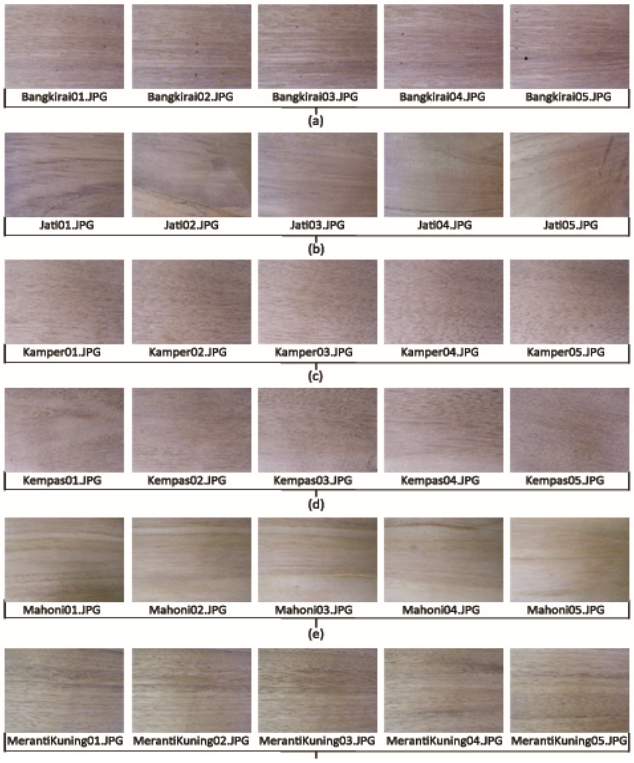

Fig. 2.Five Sample Original Image of Each Indonesian Commercial Woods Species: (a) Bangkirai, (b) Jati, (c) Kamper, (d) Kempas, (e) Mahoni, and (f) Meranti Kuning

B. Preprocessing Steps

- Conversion of Originl Image to Grayscale Image
  The results of conversion process of original images to grayscale image can be seen in fig. 3 Result image of the conversion process appear to change to grayscale with texture remains.

Fig. 3.(a) Original Image and (b) Grayscale Image

- Image Sharpening
  The aim of image sharpening is to clarify the edges of objects in the image. The results of image sharpening process can be seen in fig. 4.

Fig. 4.(a) Grayscale Image and (b) Result image of the Sharpening Process

C. Feature Extraction

The next step is to perform feature extraction is a process before performing classification. Feature extraction is a very important part of pattern classification. To identify the texture of the image, do modeling texture as the gray level variation of two-dimensional arrays. This array is called Gray Level Co-occurrence Matrix. The results values of feature extraction using GLCM from the training data using 102 pieces of data then look for the ranges value and average value for each species of wood image.

- Contrast Analysis

  After getting the range and average values further will be look for the narrowest and the widest range shown in Table 1. The smallest and the largest average shown in Table 2.

Table- I: Value of The Narrowest and Widest Range in Contrast Parameters

Direction	The Narrowest Range	The Widest Range
0°	Mahoni (0.12152-0.2058)	Bangkirai (0.07834-0.24842)
45°	Mahoni (0.18922-0.40443)	Kempas (0.25002-0.79832)
90°	Mahoni (0.17383-0.3754)	Kempas (0.20328-0.78701)
135°	Mahoni (0.19999-0.3731)	Kempas (0.2068-0.79538)

Table- II: Value of The Smallest and Largest Average in Contrast Parameters

Direction	The Smallest Average	The Largest Average
0°	Meranti Kuning (0.12964)	Kempas (0.21021)
45°	Jati (0.22399)	Kempas (0.4387)
90°	Jati (0.20622)	Kamper (0.4151)
135°	Jati (0.22039)	Kamper (0.43493)

- Correlation Analysis

  After getting the range and average values further will be look for the narrowest and the widest range shown in Table 3. The smallest and the largest average shown in Table 4.

Table-III: Value of The Narrowest and Widest Range in Correlation Parameters

Direction	The Narrowest Range	The Widest Range
0°	Kamper (0.82107-0.88742)	Kempas (0.70293-0.89925)
45°	Meranti Kuning (0.6531-0.88311)	Kempas (0.40245-0.80941)
90°	Meranti Kuning (0.66862-0.9082)	Jati (0.52491-0.91421)
135°	Meranti Kuning (0.65902-0.89322)	Jati (0.52012-0.90307)

Table- IV: Value of The Smallest and Largest Average in Correlation Parameters

Direction	The Smallest Average	The Largest Average
0°	Kempas (0.80586)	Mahoni (0.86785)
45°	Kempas (0.60723)	Jati (0.75775)
90°	Kempas (0.63962)	Jati (0.77712)
135°	Kempas (0.62335)	Mahoni (0.76295)

- Energy Analysis

  After getting the range and average values further will be look for the narrowest and the widest range shown in Table 5. The smallest and the largest average shown in Table 6.

Table- V: Value of The Narrowest and Widest Range in Energy Parameters

Direction	The Narrowest Range	The Widest Range
0°	Kamper (0.20566-0.28577)	Kempas (0.18936-0.4142)
45°	Kamper (0.13576-0.2409)	Kempas (0.13176-0.35481)
90°	Kamper (0.13723-0.25447)	Kempas (0.13663-0.37732)
135°	Kamper (0.13639-0.25212)	Kempas (0.13528-0.38635)

Table-VI: Value of The Smallest and Largest Average in Energy Parameters

Direction	The Smallest Average	The Largest Average
0°	Kamper (0.24318)	Meranti Kuning (0.32218)
45°	Kamper (0.18078)	Jati (0.2726)
90°	Kamper (0.18556)	Jati (0.28067)
135°	Kamper (0.18127)	Jati (0.27419)

- Entropy Analysis

  After getting the range and average values further will be look for the narrowest and the widest range shown in Table 7. The smallest and the largest average shown in Table 8.

Table- VII: Value of The Narrowest and Widest Range in Entropy Parameters

Direction	The Narrowest Range	The Widest Range
0°	Kamper (1.58676-1.94495)	Kempas (1.24636-2.02371)
45°	Jati (1.44243-1.8404)	Kempas (1.40906-2.36576)
90°	Jati (1.38481-1.8229)	Kempas (1.34359-2.33107)
135°	Jati (1.44921-1.84366)	Kempas (1.31971-2.34092)

Table-VIII: Value Of The Smallest and Largest Average in Entropy Parameters

Direction	The Smallest Average	The Largest Average
0°	Meranti Kuning (1.4696)	Kamper (1.76594)
45°	Jati (1.63757)	Kamper (2.06005)
90°	Jati (1.60694)	Kamper (2.0381)
135°	Jati (1.63136)	Kamper (2.05845)

- Homogeneity Analysis

  After getting the range and average values further will be look for the narrowest and the widest range shown in Table 9. The smallest and the largest average shown in Table 10.

Table-IX: Value of The Narrowest and Widest Range in Homogeneity Parameters

Direction	The Narrowest Range	The Widest Range
0°	Mahoni (0.89763-0.93925)	Bangkirai (0.88822-0.96084)
45°	Mahoni (0.81362-0.90549)	Bangkirai (0.79333-0.93569)
90°	Mahoni (0.82534-0.91313)	Kempas (0.74423-0.89927)
135°	Mahoni (0.82545-0.90013)	Kempas (0.74196-0.89722)

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Table-X: Value of The Smallest and Largest Average in Homogeneity Parameters

Direction	The Smallest Average	The Largest Average
0°	Kempas (0.89926)	Meranti Kuning (0.93592)
45°	Kempas (0.81974)	Jati (0.8927)
90°	Kempas (0.82858)	Jati (0.90053)
135°	Kempas (0.82249)	Jati (0.89419)

D. *k*-Nearest Neighbor

At this stage aims to recognize and classify wood testing images test in accordance with the species of wood. In this research, the classification method used is the *k*-nearest neighbor witheuclidean distance. Data used for *k*-nearest neighbor is the training data and testing data. For the testing process is done with 3 scenarios. Each scenario uses 3 testing data for each species of wood so that the total testing data for six species of wood are 18 testing data. This scenario is done for determine level of accuracy for each scenario on each parameter *k*.

- **Evaluation Results**
  Ratio accuracy of the classification process result by using the *k*-nearest neighbor can be seen in Table 11.

Table- XI: Ratio Accuracy of The Classification Process Result

Scenario	Classification Accuracy Ratio			
	k=1	*k*=3	*k*=5	*k*=7
Scenario 1 (Testing Data Were Taken Inside from Training Database)	100.00%	66.67%	61.11%	55.56%
Scenario 2 (Testing Data Were Taken Outside from Training Database)	33.33%	27.78%	27.78%	22.22%
Scenario 3 (Testing Data Were Taken Inside and Outside from Training Database)	66.67%	55.56%	50.00%	50.00%

Looking result from the table 11 the overall can be concluded that:

- Testing data can be classified appropriately and accurately is a testing data derived from the training database with $k = 1$.
- In general, the greater value of k then classification success rate of getting decreased. This is because the larger the value of k, then boundary region decision is also getting wider. The wider area of the decision boundary, then the possibility of error higher. If the value of $k = 1$, then the taken is the nearest training data.
- Percentage success scenario 3 is greater than scenario 2 because in scenario 2 testing data derived from outside the training database, which means derived from the same wood but has a different texture because capturing images of different locations on the same species, while the scenario 3 testing data derived from outside and inside, which means There are some data that have the same texture with the data in the training database

E. Display in GUI Form

Open main_menu.fig, after that run, then Indonesian Commercial Woods Species Recognition and Classification System Based on Texture application will start up and display the main page is the main menu page which can be seen in fig.5.

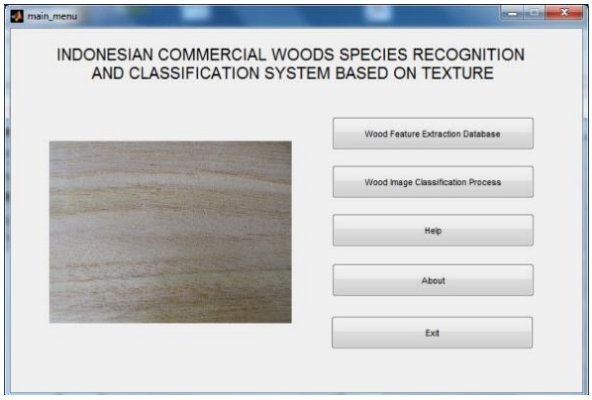

Fig.5.Main Menu Page View

There are five buttons on this page, namely:

A. Wood Feature Extraction Database button for display and add the training database that is used to classify wood image.
B. Wood Image Classification Process button for the recognition and classification wood image.
C. Help button contains a description of how to use this application.
D. About button contains information from this application.
E. Exit button is used to exit the application.

If user presses Wood Feature Extraction Database button then will display is wood_database.fig that is a page to display and add the training database that is used to classify wood image. See fig.6.

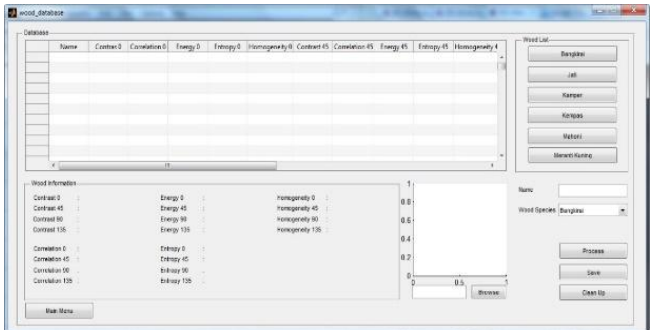

Fig.6.Wood Feature Extraction Database Page View

On this page there is a table that is used to display training database that contains the name and value of the image feature extraction of wood image. Beside table, there are 6 button is Bangkirai, Jati, Kamper, Kempas, Mahoni and Meranti Kuning is used to display data in a table according to the species of wood. Furthermore, if user wants to add data in training database then the first step is to choose a wood image, select image type is entered in accordance with the species of wood, press the Process button, and press the Save button. If the user wants to classify the image of the wood on the main menu button is selected is Wood Image Classification Process button, choose the wood image, select image type is entered in accordance with the species of wood, press the Process button, and press the Classification button it will make the process of classification wood image and it will look like the fig.7. Note that this application uses the parameter k = 1 as the default.

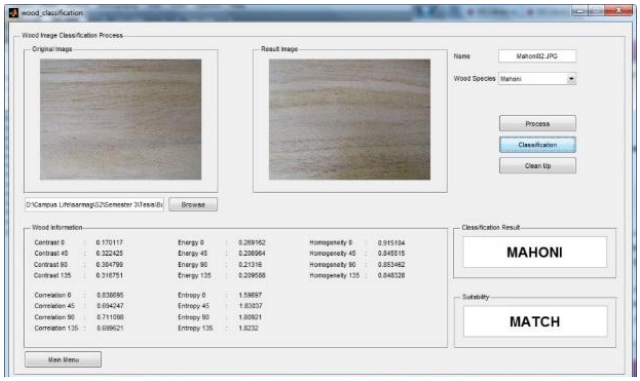

Fig.7.Wood Image Classification Process Page View After Pressing Classification Button

If user want to display information containing details on how to use this application, then press the Help button which will run is help.fig to look like fig.8.

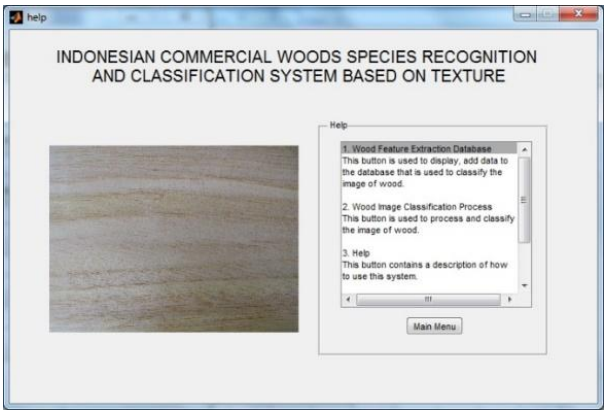

Fig.8.Help Page View

If user want to display the information of this application then press About button to look like fig. 9.

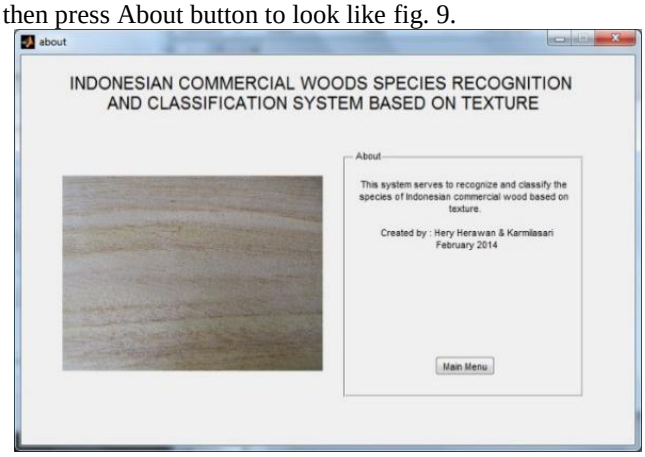

Fig.9.About Page View

If the user wants to exit the application, then on press the Exit button then will display a exit confirmation dialog box to look like the fig. 10.

Fig. 10.Exit Confirmation View

IV. CONCLUSION AND FUTURE RESEARCH

The author has succeeded in designing and developing a recognition and classification system of Indonesian commercial woods species based on texture image. Conclusions obtained by the authors of the research are testing data can be classified appropriately and accurately is a testing data derived from the training database with k = 1. In general, the greater value of k then classification success rate of getting decreased. Percentage success scenario 3 is greater than scenario 2 because in scenario 2 testing data derived from outside the training database. For the future, this system can be developed and enhanced by the addition of several features. For Wood Feature Extraction Database page can added feature delete and search the data in the database. For Wood Image Classification Process page can be added features can be classify the testing images are more than 1. Diversity of species of wood used can be added. Number of wood samples used can be added. In addition, the classification method used can be tested using other methods such as Neural Network (NN) and Support Vector Machine (SVM).

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Hery Herawan, is a lecturer in the Information Technology at Gunadarma University, Depok, West Java, Indonesia. Completed a Bachelor's degree in Information Technology, a master's degree in Management Information System concentration Information System Software, all of which were completed at Gunadarma University. He has more than 5 years of experience teaching and making tests related to algorithms and programming, computer science, and information technology. His interests include in image processing, project management, software development life cycle, artificial intelligent, machine learning, cloud services and its application in various fields, such as online media, online video sharing, financial services, news portal, and other fields.

Karmilasari, is a lecturer in the Information Technology department at Gunadarma University, Indonesia. Completed a Bachelor's degree in Information Systems, a master's degree in Management and a doctorate in information technology, all of which were completed at Gunadarma University. Her interest include in image processing and its application in various fields, such as medical, biometrics, plants and other objects.