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MANGROVE FRUIT RIPENESS CLASSIFICATION USING DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Mangrove is a community of plants that live between the sea and land which is affected by tides. Indonesia has the largest mangrove forest in the world and also has the largest biodiversity and most varied structure. In general, mangrove plants have several benefits, such as preventing coastal erosion, preventing seepage of seawater to land which can cause groundwater turns into turbid condition, as a place to live and a source of food for several species of animals. Mangrove plants consist of several parts, from the stem of the tree leaves, flowers and fruit. To get the optimal mangrove plants, it is necessary to have fruit which is optimal based on the ripeness level. In general, by assessing the ripeness of mangroves is only by looking manually with the eyes, so that the accuracy of mangrove fruit ripeness valuations isn't high because of they only see with eyes. Many mangrove farmers think that mangrove want to plant in case of rehabilitation, already have a good level of ripeness, but after replanted, the result isn't appropriate. To overcome this case, this study utilizes digital image processing using the Deep Convolutional Neural Network method to help the communities and farmers in recognizing the ripeness level of mangrove fruit. The image processing techniques used in this study are Grayscaling, Adaptive Threshold, Sharpening, and Smoothing. After tested in this study, it was concluded that the method applied can determine the ripeness of mangroves well and the accuracy obtained is equal to 99.1%.

Keywords: *Mangrove, Grayscaling, Sharpening, Adaptive Threshold, Deep Convolutional Neural Network*

1. INTRODUCTION

Indonesia has the largest mangrove forests in the world and also has the greatest biodiversity and the most varied structures. Indonesia is recorded to have at least 202 species of mangroves, including 89 species of trees, 5 types of palms, 19 types of climbers, 44 types of soil herbs, 44 species of epiphytes and 1 type of fern. Of these 202 species, 43 species (including 33 tree species and several types of shrubs) were found to be true mangroves, while other species were found around mangroves and are known as follow-up mangrove species [1].

Mangrove is a collection of or individual plants that live and also form a community that is in the tidal area. Mangrove is also a model of forest that lives naturally under the influence of the ebb and flow of sea water. Mangroves can be inundated during high tide and free from inundation during low tide. Mangrove forests are divided into 8 different families. Mangroves grow in tropical and subtropical coastal areas around the world. Generally, this area is between latitudes 25 degrees north and 25 degrees south, but its geography varies greatly depending on the local climate. The mangrove forest itself is dominated by species in the form of trees or shrubs which have the ability to continue to grow in salty waters.

Despite having a fairly wide distribution area, tropical mangroves are among those with the most species. Because Southeast Asia is in the tropics, one third of the world's mangrove area is in Southeast Asia. Of that amount, around 80 percent are in Indonesian territory. This then makes Indonesia has the most extensive mangrove areas in the world. Besides that, there are many important functions for nature, including physical functions such as protecting the coastline from abrasion, biological functions such as fish, shrimp and other aquatic biota hatcheries, economic functions as a source of fuel, aquaculture and salt production. Mangrove plants consist of several parts, starting from tree trunks, leaves, flowers and fruit. In general, now, to assess the ripeness of mangrove fruit is only done manually, so that the accuracy of assessing the level of mangrove fruit ripeness is not high because it is only seen with the eye. Many mangrove farmers think that the mangrove fruit they want to plant in the case of rehabilitation, has a good level of ripeness, but after replanting, the results obtained are not suitable. With a low level of accuracy for assessing the ripeness of a mangrove fruit, an application is needed to make it easier to find out which mangrove fruit is at a ripeness level that matches its characteristics.

There is only one way to know the level of fruit ripeness manually, namely by checking the physical characteristics (shape, size). One way to determine the level of ripeness of a fruit in the field of informatics is the use of image processing.

Until now, there has been no research on the classification of mangrove fruit ripeness levels and no research on fruit ripeness level classification using the Deep Convolutional Neural Network method, but there are several studies that raise topics for other fruit ripeness classifications. Research was held to examined the classification of the ripeness level of Fuji apples [2], examination of the passion level of fruit ripeness using K-means Clustering, and ANN model [3]. Furthermore, research by [4] examined the classification of apple ripeness based on color through digital images using the Artificial Neural Network method. Another study by [5] examined the ripeness level of mango fruit using the Support Vector Machine method. Another study was conducted by [6] with the title Forest Species Recognition using Deep Convolutional Neural Networks. This study proposes a Deep Convolutional Neural Network algorithm to identify tree species with input data in the form of macroscopic and microscopic images. Other several research regarding mangrove is specified to image zonation classification using satellite image [7][8], whereas we also conducted our previous research which using machine learning to classify mangrove sprout [9].

Based on several research described ahead, we can get research gap, where mangrove image for fruit, sprout, a whole mangrove tree, and type of mangrove, are not yet to be classified using machine learning. Thus, in order to help farmer, we need to retrieve the best machine learning method that can be easily implemented in mobile application, so mangrove farmer can use it easily.

2. PREVIOUS RESEARCH

Previously, research on the classification of mangrove fruit ripeness has never been carried out, and no one has also conducted research on fruit classification using the Deep Convolutional Neural Network method, but there are several studies that raise topics to classify other fruit ripeness. As has been researched by [2] who examined the classification of the level of ripeness in Fuji Apple. In this study, the method used is fuzzy logic. Here the researchers changed the type of Fuji Apple image from RGB to Grayscale. After that, the Fuji Apple was extracted using MATLAB to get several categories, namely raw, half-ripe, and ripe. In this study, the accuracy of 100% for raw apples, 100% for ripe apples, and 66.67% for half ripe apples. However, the data in this study is still small, namely only 19 data. If more data is collected than before, the accuracy for half-ripe apples could be even higher.

In a study conducted by [3] examined the ripeness level of passion fruit. This study uses the K-Means Clustering and Artificial Neural Network methods. The results of this study were the level of fruit ripeness which was divided into 3, namely ripe, close to ripe, and unripe. The data input in this study was the passion fruit video there are 6 different sides. This study used 75 videos of passion fruit as training data and 20 videos of passion fruit as testing data with a duration of 5 seconds per video. In this study, the accuracy rate obtained reached 90%. However, the classification approaching ripe and not ripe experiences an error because the color of the fruit is not too different.

Research by [4] discusses the classification of apple ripeness based on color through digital images using the Artificial Neural Network method. In this study, the training data used was 80% of the total image, while the other 20% was used for testing data. In this study, the accuracy rate obtained was more than 90%. The total data used is 600 data. If the data collected is greater than before, the accuracy that will be obtained will be even higher.

Another study by [5] examined the ripeness level of mango fruit using the Support Vector Machine method. In this study, 5 different varieties of mango were used, so that a total of 1350 mangoes were collected with a total image data of 16400 images, an average of 3280 images for each variety and 820 for each group or class. The accuracy obtained in this study reached 96%.

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Other studies conducted a study entitled Forest Species Recognition using Deep Convolutional Neural Networks. This study proposes a Deep Convolutional Neural Network algorithm to identify tree species with input data in the form of macroscopic and microscopic images. The accuracy results obtained are 95.77% for macroscopic images and 97.32% for microscopic images. This study shows that the Deep Convolutional Neural Network algorithm can improve the accuracy of previous studies using the Support Vector Machine (SVM) classification method with an accuracy of 95.5%. Seeing the good performance of the Deep Convolutional Neural Network, the authors try to use it in this study [6].

Based on the above research, this study aims to predict the ripeness level of mangrove fruit with the results of the ripeness level divided into 3, namely close to ripe, half ripe, and unripe from digital image processing. Based on previous research, to obtain higher accuracy, this research will be conducted using the Deep Convolutional Neural Network method.

Deep Convolutional Neural Network which usually written as DCNN is one of Deep Learning methods with high performance accuracy in image processing. DCNN has a nature to do fusion between feature extraction and engine classifier in one flow. DCNN will receive raw image as an input and will propagate image feature extraction and produce output in the end, which is the big difference compared to convolutional classifiers [10].

Our research motivation can be described as a purpose to determine the level of mangrove fruit ripeness, so that mangrove farmers are not wrong in choosing the fruit used for replanting. Previous research has been done for mangrove sprouts before [9]. Until now, farmers who have assessed the ripeness level of mangrove fruit are still being carried out in plain view so that the accuracy of assessing the ripeness level of mangrove fruit is not according to the desired ripeness level. Therefore, an approach is made to this problem in order to classify the level of ripeness of mangrove fruit. Based on specified benefit we can see the gap of the research such as we need to find any machine learning approach that can identified mangrove fruit ripeness accurately and precisely.

3. METHODOLOGY

The research stages carried out in this study consisted of image acquisition, image pre-processing, image segmentation, image post-processing, and classification using a Deep Convolutional Neural Network. The general architecture that describes the stages carried out can be seen in Figure 1.

3.1 Image Acquisition

This stage is the stage of collecting mangrove fruit image data which is the initial input to this system. Mangrove fruit image data is divided into two, namely training data and testing data. The image is taken using a DSLR camera with a camera resolution of 18 MP without using a flash. The image

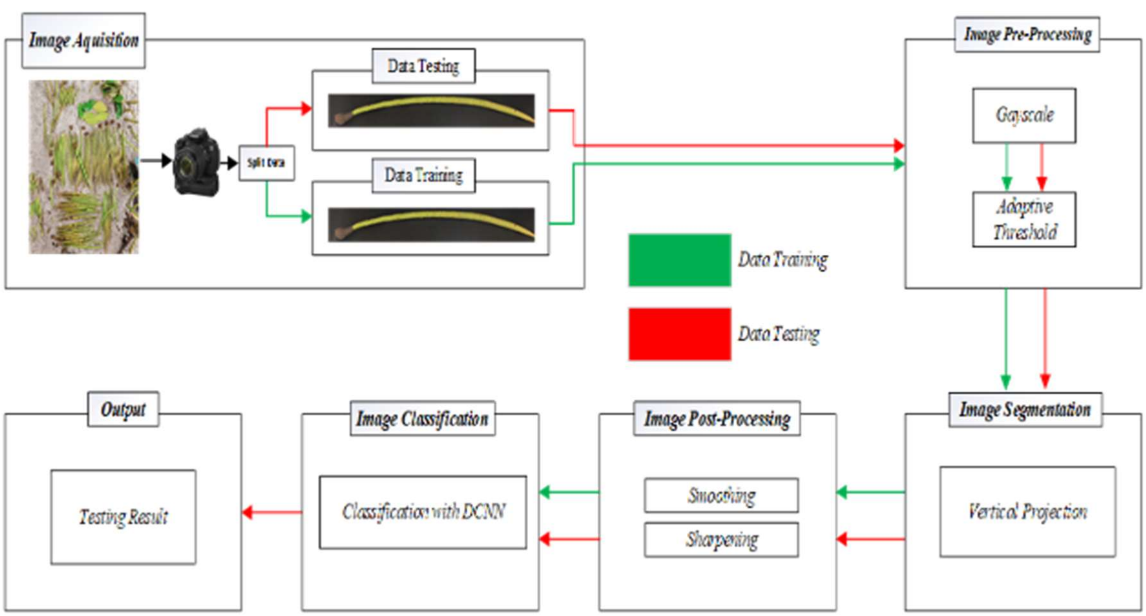

Figure :1 General Architecture

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taken must use a black background. The data used in this study was taken from several mangrove forests in North Sumatra. The image used in this study has the extension .JPG or .JPEG with a size of 720 × 84 pixels.

The characteristic that distinguishes mangrove fruit is unripe, half ripe, and near ripe, namely the appearance of a ring that is located between the head of the mangrove fruit and the body of the mangrove fruit, or what is often called the propagule. Examples of mangrove fruit image data can be seen in Figure 2 and Figure 3.

Figure 2: Image of unripe mangrove fruit

Figure 3: Image of near ripe mangrove fruit

3.2 Image Preprocessing

The preprocessing stage is the stage where the image is processed to produce a better image for processing at the next stage. This preprocessing stage consists of gray-scaling and thresholding.

3.2.1 Gray-scaling

Gray-scaling is a process for converting an image into a degree of grayscale image that can be easily processed by a computer [11]. The first stage of preprocessing is grayscaling. At this stage, the image that was originally an RGB (color image) image is converted into a gray image (grayscale image). One representation of grayscale images is X-ray [12]. Grayscaling aims to facilitate the detection of mangrove fruit species in the image. In this study, the grayscaling used is grayscaling with the luminosity method. The conversion of RGB images to gray is carried out on both types of images, namely training images and testing images. The conversion of an RGB image into a gray image using the luminosity method can be done using Equation (1). The grey-scaling process are shown in figure 4 and figure5.

$$GI = 0.2989R + 0.5870G + 0.1140B \quad (1)$$

Where:
GI = intensity's value in Greyscale Image
R = Red Intensity value on RGB Image
G = Green Intensity value on RGB Image
B = Blue Intensity value on RGB Image

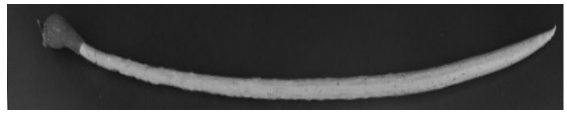

Figure 4 : Image of unripe mangrove fruit after greyscaling

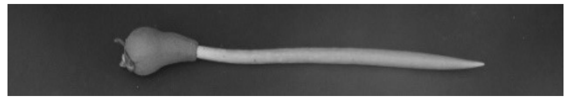

Figure 5: Image of near ripe mangrove fruit after greyscaling

3.2.2 Adaptive Thresholding

The thresholding process is a process that aims to produce a binary image. Binary image is an image that has two gray level values, namely black and white. In general, the process of developing grayscale images to produce binary images can be seen in Equation (2).

$$g(x,y) = \begin{cases} 1, f(x,y) \geq T \\ 0, vice\ versa \end{cases} \quad (2)$$

Where :
f(x,y) : grey scale image
g(x,y) : binary image
T : threshold value

After carrying out the grayscaling process, the next step is thresholding. This process aims to separate the mangrove fruit from the background behind it. There are 2 types of threshold, namely global thresholding and locally adaptive thresholding [10]. This study applies an adaptive threshold where the adaptive threshold works by using a local threshold that is calculated adaptively based on the statistics of neighboring pixels. To use an adaptive threshold, it can be done using Equation (3). Figure 6 shows the image of mangrove fruit after adaptive thresholding process.

$$T = \frac{\sum_{(y,x)\in W} f(i,j)}{N_W} - C \quad (3)$$

Where :
W : Windows of an Image
Nw : Number of Pixel in Image Window
C : Constant

Figure 6 : Image of mangrove fruit after adaptive thresholding

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3.2.3 Image Segmentation

The next stage after the pre-processing process is image segmentation. Image segmentation is used to cut or crop the mangrove fruit image into parts which will be classified later. To perform segmentation, this study applies a vertical projection.

3.2.4 Vertical projection

In this study, the segmentation process used is vertical projection. Vertical projection is used to determine which boundaries the mangrove fruit image will be cropping. At this stage, you will see the position where the initial mangrove image was detected. After getting the initial position where the mangrove fruit image is, then at that point the image will be cut or cropping to the required limit. Image segmentation results can be seen in Figure 7.

Figure 7: Segmented Image

3.3 Image Post-Processing

The next stage is post-processing, where the image will be added with 2 more processes to get the characteristics of the mangrove fruit image. After obtaining the desired characteristics, the mangrove fruit image is ready to be classified. In this study, the post-processing processes used were smoothing and excessive sharpening. Image postprocessing is done to change image to become numerical array to bbe process in the computer [13].

3.3.1 Smoothing

After applying cropping to the mangrove fruit image, the image will go through the smoothing stage. There are various kinds of filtering methods, namely mean filtering, median filtering, and max filtering. Median filter is one method that can be used to remove noise [14]. In this research, the method used is median filtering. In this study, the median filtering was carried out using the OpenCV library. Median formula can be described in Equation 4 below.

$$y(n) = med\ [x(n-k), x(n-k+1), \dots, x(n), \dots, x(n+k-1), x(n+k) \quad (4)$$

Where:
y(n) = output value
x(n) = input value
Images that have not been applied to the smoothing process and those that have been applied to the smoothing process can be seen in Figure 8 and Figure 9.

Figure 8: Magrove fruit image before smoothing process

Figure 9: Mangrove fruit image after smoothing process

3.3.2 Excessive sharpening

Sharpening is a basic image enhancement technique in image processing and computer vision. This process aims to improve the edges, texture, and detail of the image. Image sharpening is also widely used in medical image processing, electronic printing, and industrial inspection, among others [15]. Sharpening calculations can be seen in Equation (5)

$$\sum_{p \in f} \left(\mu(p) - f(p)\right)^2 + \lambda\left(\left(f_x(p) - g_{x,t}(p)\right)^2 + \left(f_y(p) - g_{y,t}(p)\right)^2\right) \quad (5)$$

Where:
μ(p) = pixel's value from original image
f(p) = pixel's value from processed image.

After the noise in the image has been reduced in the smoothing process, the image will be sharpened to get the details of the ring that will be characterized so that it can be classified accurately. Images that

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have not gone through the excessive sharpening stage and those that have gone through the excessive sharpening stage are shown in Figure 10 and Figure 11.

Figure 10: Mangrove fruit before sharpening process

Figure 11: Mangrove fruit after sharpening process

3.3.3 Resizing

After the sharpening process is done, the next step is resizing. The resizing stage is needed to change the image whose initial size is 640 × 480 pixels to 256 × 256 pixels. This resizing stage is needed to meet system requirements because the method used in this study accepts input with a size of 256 × 256 pixels. The method used for this resizing process is the bilinear interpolation method. The bilinear interpolation method will adjust the color value of each pixel according to the 4 closest pixels. Using the 4 closest pixels, bilinear interpolation sets the new pixel value by taking the average of the weighted values. The resizing process will be represented in Figure 12.

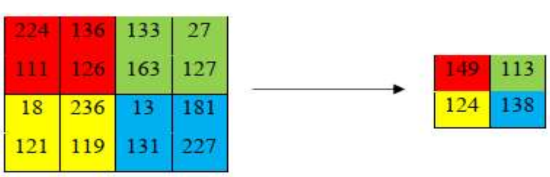

Figure 12: Example of resizing process

Figure 12 shows the resizing process from a 4×4 pixel image to a 2×2 pixel image. By taking the average value of the 4 closest pixels, the value for each new pixel is obtained as follows:

P1 = (224 + 136 + 111 + 126) / 4 = 149

P2 = (133 + 27 + 163 + 127) / 4 = 113

P3 = (18 + 236 + 121 + 119) / 4 = 124

P4 = (13 + 181 + 131 + 227) / 4 = 138

3.4 Convolutional Neural Network

Convolutional Neural Network is a type of neural network which generally has 3 types of layers, namely Convolutional Layer, Pooling Layer, and Fully-connected Layer. Convolutional Neural Network is designed to process two-dimensional data. Unlike the case with the Multi-Layer Perceptron where the data processed is one-dimensional data. The Convolutional Layer is a core part of the Convolutional Neural Network which has local connections and the same characteristic weight. The purpose of this layer is to learn how to represent a feature from the input that is given. Through this layer, features will be extracted and then proceed to the next layer with the aim of extracting more complex features [16]. Convolution is a mathematical term that means applying one function to the output of another function repeatedly. The purpose of convolution on image data is to extract features from the input image. The linear transformation of the input data according to the spatial information in the data is the result of a convolution process. The weights at that layer specify the convolution kernel used, so that the convolution kernel can be trained based on the input on the CNN. An overview of the Convolutional Neural Network can be found in Figure 13.

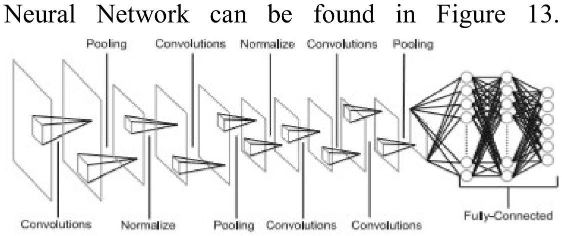

Figure 13: Convolutional Neural Network

The pooling layer is an advanced stage of the convolutional layer. Pooling layer is a resizing process or it can be called a process for resizing different input images. Pooling commonly used is max pooling and average pooling. This layer consists of a filter and a stride of a certain size. As in Figure 14, in max pooling, the maximum value in the filter area will be selected at the time of shift, whereas in average pooling, the average value in the filter will be selected, the goal is to help reduce the number of parameters and calculation time needed when training the network.

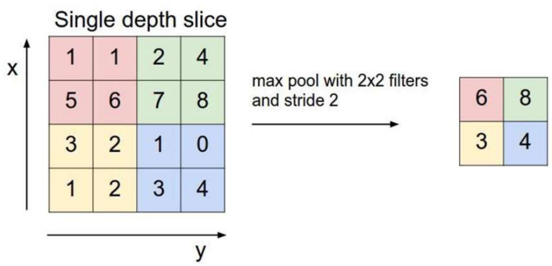

Figure 14. Pooling Layer Process

The last layer is the fully connected layer. This layer takes all the neurons in the previous layer (Convolutional Layer and MAX Pooling Layer) and connects them to every single existing neuron [17]. In this layer, a flatten process or reshape the feature map is carried out into a vector so that it can be used as input for this layer, because the feature map produced in the previous layer is still in the form of a multidimensional array.

3.5 Deep Convolutional Neural Network

The term deep learning has the meaning of adding accuracy to the training process by adding a hidden layer to the neural network so that the resulting output is more detailed. Deep Convolutional Neural Network (DCNN) shows outstanding performance in the field of image recognition, this is supported by DCNN's excellent performance in extracting high-level features. The Convolutional Layer and MAX Pooling Layer used in DCNN have proven to be very effective in recognizing various shapes. DCNN is able to carry out all stages of image recognition, namely the feature extraction and classifier stages simultaneously because DCNN receives raw images as input, so it does not require separate feature extraction and pre-processing stages as in the Conventional Classifier [18].

3.6 Classification

After the image has been processed in the previous stages. The next stage is to classify. In this study, the method used for the classification process is the Deep Convolutional Neural Network method. DCNN is able to carry out all stages of image recognition, namely the feature extraction and classifier stages simultaneously because DCNN accepts the raw image as input, so it does not require separate feature extraction and preprocessing stages like in the Conventional Classifier [18].

3.6.1 Model making

At this stage of making this model, there are several things that need to be done, including determining the number of hidden layers, the number of neurons, activation functions, optimizer, batch size, and epochs.

3.6.2 Determination of hidden layer

Determination of the optimal number of hidden layers is done by trial and error. The number of hidden layers used is from 2 to 10 hidden layers.

3.6.3 Determination of number of neurons

In determining the number of neurons in the hidden layer to be used, there are no special calculations. In this study, the number of neurons used in the three fully-connected layers were 900, 90, and 3 neurons.

3.6.4 Determination of activation forum

The calculation result between input, weight, and bias will be calculated again using the equation of the activation function. It aims to get the output from each layer. In this study using 2 types of activation functions, which in the convolutional layer use the relu activation function and for the output layer use the softmax activation function.

3.6.5 Determination of optimizer

Optimizer is an algorithm used to determine the optimal weight. In this study, the optimizer used is the RMSProp optimizer.

3.6.6 Determination of batch size

The batch size is used to determine the number of observations made before changing the weight which is determined based on the computer specifications used. In this study, the batch size used is the default batch size, which is 32.

3.6.7 Determination of epoch

Epoch is the amount of literacy done during the system training process. Epoch has an effect on training results where the greater the epoch, the higher the level of training results. In this study, the number of epochs we used is 100 epochs.

3.6.8 Training process

Training is the implementation stage of the Deep Convolutional Neural Network model that has been created. All images that have been processed in the previous steps will be input from the input layer which will later be included in the convolutional layer. The first step is to give input, weight and bias values which are given randomly. The number of neurons in the input layer is adjusted to the parameters used from the data used. Next is the calculation of the hidden layer output matrix which is the processing result of the input that neurons have received in the hidden layer from neurons in the input layer. After the calculation of the hidden layer output matrix has been completed, the next step is calculating the weight. The result of this process is a

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matrix that represents the weight of each neuron from the output layer. All results from this training process will be saved into a file with the extension .h5 which will be used during the testing process.

3.6.9 Testing process

Testing is the testing phase of a model that has been formed in the previous training process. This stage was carried out to determine how effective the Deep Convolutional Neural Network method was applied to the mangrove fruit image classification system.

3.6.10 Output

The final output of the system is information in the form of accuracy and loss obtained in the training process and the results of the classification of mangrove fruit ripeness carried out in the testing process.

4. TEST AND RESULT

The data used in this study were taken from three places in the North Sumatra region, namely in Percut Sei Tuan, at Kampung Nipah Mangrove Beach, and lastly at Mangrove Ecotourism, Sicanang Belawan. Data collection was carried out 7 times at different times. Mangrove fruit image data was collected using a DSLR camera with a resolution of 18 MP. The amount of data collected is 3900 images with a size of 720 × 84 pixels. Of the 3900 images, 3000 images were used for training, and 900 images were used for testing by dividing into 3 categories, namely unripe, half ripe, and close to ripe.

4.1 Training

The training process in the mangrove fruit maturity classification system uses the Deep Convolutional Neural Network method, it can be obtained a training accuracy value with an average of 100% after going through the system training process with an average time of 84 seconds / epoch, so it takes 2 hours 33 minutes to train 3000 images of 100 epochs.

In the 10th epoch, training accuracy is still quite good, above 95%. Then in the 20th to 50th epoch, the training data accuracy is in the range of 96-98%. In the 70th, 80th, 90th and 100th epochs the accuracy of the training data has reached 99% and has reached the convergence limit. Likewise with the training lost result, the graphic trend also follows the training accuracy results. The results of training loss and training accuracy can be seen in Figure 15 and Figure 16.

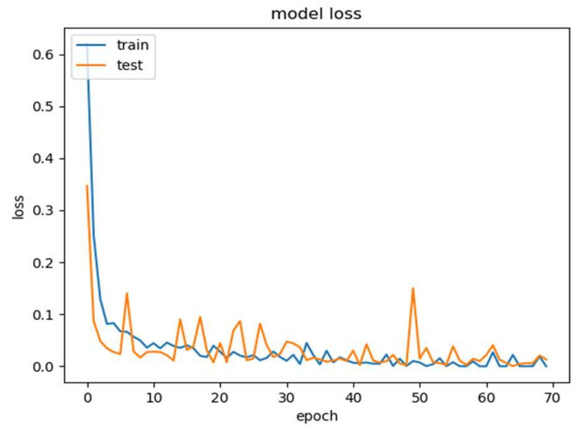

Figure 15: Training loss result

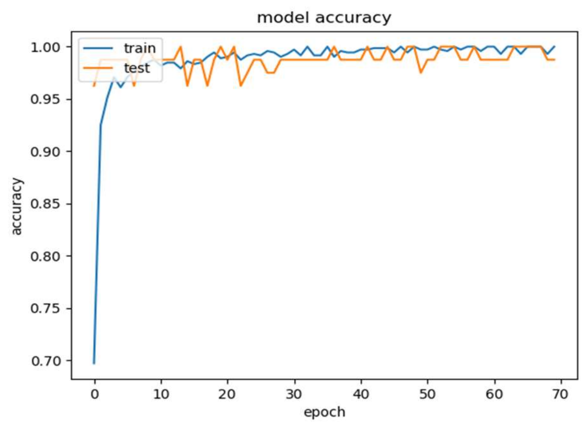

Figure 16: Training accuracy result

4.2 Testing

The testing phase is carried out after the system has passed the implementation stage according to the procedure described in the previous section. Data testing was carried out on 900 mangrove fruit images taken from several areas in the field. The 900 images are divided into 3 categories as describes before, each with a total of 300 images. The results of testing the mangrove fruit maturity classification system using the Deep Convolutional Neural Network method can be seen in Figures 17, 18, and 19.

Test are carried out with a different number of fully connected layers starting from 2, 4, 6, to 8 layers. Testing with different numbers of fully connected layers aims to get the most optimal accuracy. The following are the test results with the number of different fully connected layers, which can be seen in Table 1.

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Figure 17: Unripe result

Figure 18: Half ripe result

Figure 19: Close to ripe result

Table 1: Training Result.

Number of training data	Number of testing data		Fully-connected Layer	Accuracy
	True	False		
3000	799	101	2	88.78%
3000	832	68	4	92.44%
3000	832	67	6	92.67%
3000	892	8	8	99.1%

Based on the results of tests that have been carried out using the Deep Convolutional Neural Network method, it is possible to obtain training accuracy values with an average of 100% after going through the system training process with an average time of 84 seconds / epoch, so it takes 2 hours 33 minutes to train 3900 images as many as 100 epochs. The following results of the confusion matrix in system testing can be seen in Table 2.

Table 2: Confusion Matrix.

	Unripe	Half ripe	Close to ripe	Total
Unripe	296	4	0	300
Half ripe	0	300	0	300
Close to ripe	0	4	296	300
Total	296	308	296	900

The accuracy in this testing process reaches 99.1%, where the accuracy calculation is obtained using Equation (6).

$$Accuracy = \frac{\text{correctly classified images}}{\text{total of images}} \text{ x } 100\% \quad (6)$$

From the above calculations, it can be seen that the level of accuracy obtained from this study can reach 99.1% which is a fairly high level of accuracy but not perfect. There are several factors that cause this system to be imperfect, namely the presence of light bias from around it which causes the image to not be segmented perfectly so that the Deep Convolutional Neural Network is not correct in classifying the level of mangrove fruit ripeness. An example of an image of mangrove fruit that failed to classify can be seen in Figure 20.

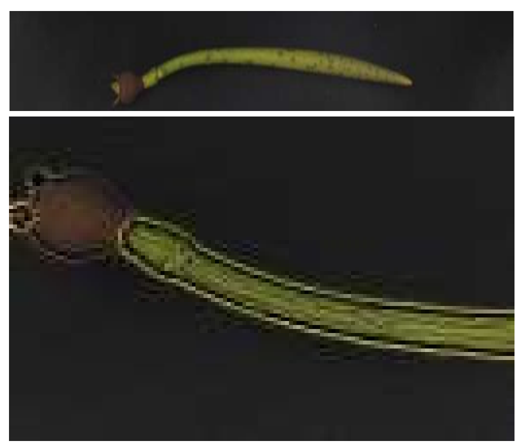

Figure 20: Example of image that failed to be classified

Since our research and study does not have any apple to apple data comparison, we can only assume our work into several result from our previous research. From our previous study, which classify mangrove sprout using multilayer perceptron [9], we only get 91% in testing accuracy. Compared to this research that reach 99%. This results is very important research in order to develop mangrove image identification in mobile application. If we talked about novelty we can claim that there is no other

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image classification research in mangrove like we do here.

5. CONCLUSION

The Deep Convolutional Neural Network (DCNN) method is able to classify mangrove fruit ripeness very well with an accuracy of 99.1%. We can answer our research questions, that DCNN method is very suitable for our purpose. However, the process of capturing images using a DSLR camera is very influential on the image. If the image is taken incorrectly and the light around it is not bright enough, it will cause noise and the captured image will be dark, so that the image details are less prominent. This will disrupt the segmentation and classification process. The amount of layer data used affects the training process. The greater the number of layers used in the training process, the better accuracy of the system being created. Using this DCNN method with several image pre-processing phase will give very good result to be implemented in mobile device for mangrove activist to do mangrove planting.

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