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Oil Palm Fruit Ripeness Detection using Deep Learning

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Abstract: To detect the maturity level of oil palm Fresh Fruit Bunches (FFB) generally seen from the loose fruit that fell to the ground. This method is always used when harvesting swit coconuts. Even though this method is not always valid, because many factors cause the fruit to fall from the bunch. The manual harvesting process can result in the quality of palm oil being not optimal. For this reason, technology is needed that can ensure the maturity level of oil palm FFB. This study aims to detect the maturity of oil palm FFB based on digital images by applying a deep learning algorithm so that the maturity level can be classified into three categories, namely: raw, ripe, and rotten. The deep learning algorithm was chosen because there have been many studies that have proven its high level of accuracy. This research method starts from; preparation of data, designing architectural models and convolutional neural network parameters, testing models, testing images, and analyzing results. From the results of the study, it was found that the convolutional neural network algorithm can be applied to detect the maturity level of oil palm FFB with an accuracy value of 92% for test data, and 76% for model testing.

Keywords: CNN, Deep Learning, Image; Palm Fresh Fruit Bunches; Ripeness.

INTRODUCTION

Palm oil is the main commodity of plantations in North Sumatra Province. In 2020, the number of oil palm plantations in North Sumatra will reach 440 thousand hectares, which can produce 7 million tons of production (Katadata, 2021). One of the largest oil palm producing districts in North Sumatra is Labuhanbatu Regency. BPS data shows that the production of oil palm plantations in Labuhanbatu in 2020 reached 116,853 tons, an increase from the previous year of 14,082 tons (Labuhanbatu, 2021). Oil palm has become the breath of life and the main livelihood of the community in Labuhanbatu Regency (InfoSAWIT, 2022). Not only limited to abundant production, oil palm also affects the Human Development Index (IPM) in Labuhanbatu Regency. In 2020, the HDI in Labuhanbatu Regency reached the highest figure of 72.0, greater than the HDI of other regencies such as Padang Lawas, North Padang Lawas, etc. (Labuhanbatu, 2020).

As the main commodity in Labuhanbatu Regency, the quality of oil palm Fresh Fruit Bunches (FFB) must be maintained, including during the harvest process. The reference when harvesting oil palm FFB in Labuhanbatu is generally by looking at the palm fruit breaking from the bunch. This means that the reference for maturity of the FFB used is when the fruit begins to fall from the mark. This factor is not always valid, because there are many other factors that cause the fruit to fall faster, as a result the harvesting process is not carried out according to the age of harvest so that the quality of the yield of palm oil is not optimal (Sawit, 2018). Therefore, a technology is needed that can ensure the maturity level of the oil palm FFB.

A number of studies have been conducted in an effort to determine the maturity level of oil palm FFB. Among them, by applying the K-Means Clustering method based on RGB and HSV colors, the results showed that the study was able to distinguish between unripe, moderately ripe, and ripe palm fruit with an accuracy rate of 64.58% (Himmah, Widyaningsih, & Maysaroh, 2020). Another study was carried out using an optical probe, the results obtained that the maturity level of oil palm FFB has a correlation with fruit hardness (Sari, Shiddiq, Fitra, & Yasmin, 2019). Detecting the maturity of oil palm FFB has also been applied using the Oriented fast and Rotated Brief (ORB) method, the results obtained cannot be fully applied in the field because the success rate is only 50%.

The current Deep Learning algorithm has the ability to recognize fruit images very well. By applying the Convolutional Neural Network (CNN) method to test 345 images, the results obtained were 97.9% (Maulana &

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Rochmawati, 2020). By applying deep learning based on the color composition of the fruit, the results of the study can classify under-ripe FFB, ripe FFB, FFB, raw, too unripe FFB, upnormal FFB, and empty bunch (Rifqi, 2021). The application of deep learning has shown significant results in recognizing the maturity level of oil palm FFB, as evidenced by a lot of research that has been done (Herman, Susanto, Cenggoro, Suharjito, & Pardamean, 2020).

Based on the background of the problems and phenomena that have been stated, this study aims to detect the ripeness of oil palm fresh fruit bunches by applying a deep learning algorithm with the Convolutional Neural Network method. As for the formulation of the problem in this study, whether the deep learning method can detect the maturity level of oil palm FFB, and what level of accuracy is produced. Hopefully the results of this research can be a reference material for the government and oil palm plantation entrepreneurs in Labuhanbatu Regency to maintain the quality of palm oil for the better..

LITERATURE REVIEW

Deep Learning is one of the fields of Machine Learning that utilizes artificial neural networks to implement problems with large datasets. Deep Learning techniques provide a very robust architecture for Supervised Learning (Shi, Xu, Yao, & Xu, 2019). By adding more layers, the learning model can represent the labeled image data better (Durai & Shamili, 2022). In Machine Learning there are techniques for using feature extraction from training data and special learning algorithms to classify images and to recognize sounds (Carneiro, Magalhães, Neto, Sousa, & Cunha, 2022). However, this method still has some drawbacks both in terms of speed and accuracy (Deng & Yu, 2014). The algorithm used in Feature Engineering can find general patterns that are important to distinguish between classes. In Deep Learning, the CNN or Convolutional Neural Network method is very good at finding good features in the image to the next layer to form nonlinear hypotheses that can increase the complexity of a model. Complex models will of course require a long training time so that in the Deep Learning world the use of GPUs is very common (Danukusumo, 2017).

Convolutional Neural Network (CNN) is a method for processing data in the form of several arrays, for example a color image consisting of three 2D arrays containing pixel intensities in three colors. Convolutional Neural Networks (ConvNets) are a more specialized application of Artificial Neural Networks (ANN) and are currently claimed to be the best model for solving object recognition problems (Goodfellow, Bengio, & Courville, 2016). Input from CNN is an image with a certain size. The first stage in CNN is the convolution stage. Convolution is done by using a kernel of a certain size. The number of kernels used depends on the number of features produced. The output of this stage is then subjected to an activation function, which can be a tanh function or a Rectifier Linear Unit (ReLU). The output of the activation function then goes through a sampling or pooling process. The output of the pooling process is an image that has been reduced in size, depending on the pooling mask used. This process is repeated several times until sufficient feature maps are obtained to proceed to the fully connected neural network, and from the fully connected network is the output class (LeCun, Kavukcuoglu, & Farabet, 2010). The purpose of doing convolution on image data is to extract features from the input image. Convolution will produce a linear transformation of the input data according to the spatial information in the data. The weight on this layer specifies the convolution kernel used, so that the convolution kernel can be trained based on input on CNN (Suartika E. P, I Wayan, Wijaya Arya Yudhi, 2016).

METHOD

In this study, the method used to identify images of palm fruit with the Convolutional Neutral Network (CNN) algorithm which is one of the methods in Deep Learning which is well known for being able to classify image data well. The process for processing the CNN algorithm is assisted by the Jupyter Notebook software with the Python 3.6 programming language and the Tensorflow package. The way the work is done is to recognize objects or images as input and the expected output is the level of accuracy of object recognition.

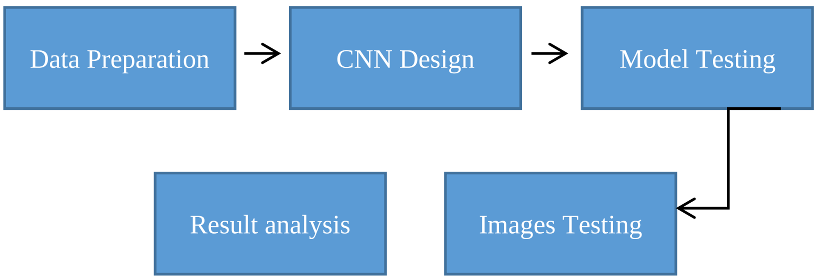

Fig 1. Research Flowchart

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Table 1 shows the research variables along with an explanation of each variable.

Table 1. Research variable

Images	Variable	Descriptions
	Crude Palm	Crude palm is a category of oil palm fruit that is not ready to be processed. The characteristic of the fruit is that the skin color is still black.
	Ripe Palm	Ripe palm is a category of oil palm fruit that is ready to be processed. The characteristic of the fruit is the color of the skin is red or orange.
	Rotten Palm	Rotten palm oil is a category of oil palm fruit that is too late to ripen. Its characteristics are blackish brown skin color.

Data Preparation

The dataset consists of 400 images which are divided into 2 parts, the distribution process uses the Train Test Split technique provided by the Sklearn package, then the data is divided into 80% training data and 20% testing data. Training data is a collection of data that will be used to create a model to be built, testing data is used to test the model that has been created. Then the architectural design is carried out starting from determining the network depth, layer arrangement, and selecting the type of layer that will be used to obtain a model based on the input dataset.

Previously the dataset will be divided into several parts, namely 80% training data and 20% testing data. Then each image of oil palm fruit will be changed and stored with a size of 128x128 pixels with channel size 3, input shape size 128x128x3, batch size 16 and epoch 10 to then be used as a dataset. The image is then augmented before entering the network.

CNN Design

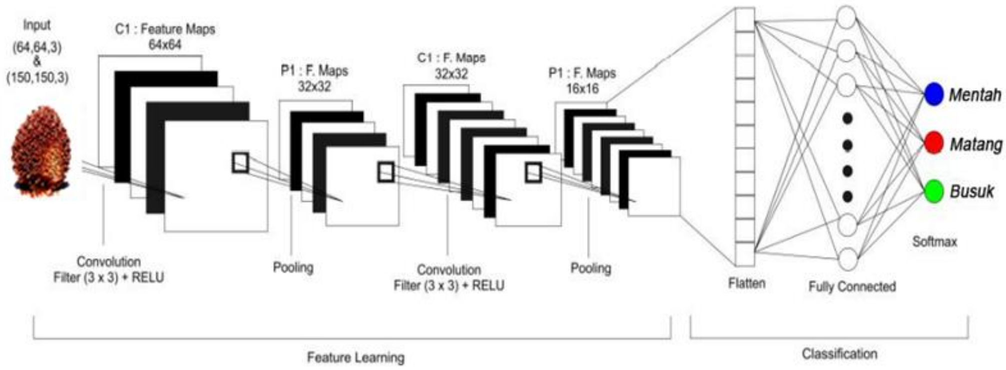

Fig 2. Flowchart Training

Based on the picture, the first convolution process uses 64 filters and a kernel with a 3x3 matrix. Then the pooling process is carried out using a pooling size of 2x2 with a mask shift of two steps. Then in the second convolution stage by using the number of filters as many as 32 and the kernel with a 2x2 matrix. Then proceed with flattening, which is changing the output of the convolution process in the form of a matrix into a vector

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which will then be forwarded to the classification process using MLP (Multi-Layer Perceptron) with a predetermined number of neurons in the hidden layer. The class of the image is then classified based on the value of the neurons in the hidden layer using the activation function softmax.

Model Testing

Tests are carried out to evaluate the model generated by CNN. The Testing stage is the model testing stage that has been carried out at the training stage. The number of test data in this study was 80 image data, with the number of images per class as many as 26 images. At this stage the model is tested with different images with the aim of testing whether the model has produced good performance in classifying an image. The evaluation of this model is carried out using a feature from Tensorflow, namely model.evaluate and also using the confusion matrix technique to see in more detail the evaluation of the model. Table 2 is the confusion matrix design of this research.

Table 2. Confusion Matrics

Matrix		**Class Prediction**		
		Raw	Ripe	Rotten
Real Class	Raw			
	Ripe			
	Rotten			

Images Testing

This process is carried out to implement the model on the image data. In this process, several stages are carried out to produce the accuracy value of the image being tested, the first stage is to input parameters for image data, then define a label that will see the results, after that do a preprocessed definition of the data in which the data before seeing the test results will be analyzed. preprocess first so that the data is more structured, then load the previously created model, then input the image to be tested and the last is to predict the image or the results of the image testing process, the prediction results will come out according to the label that has been previously defined.

RESULT

In this study, data preprocessing was carried out with augmentation techniques so that the computer would detect that the changed image was a different image. The augmentation process carried out is in the form of rotation range to 15, rescaling to 1/255, shearing with a scale of 0.2, doing a horizontal flip then doing width and height shift with a range of 0.1. After the process is done, the variables that have been created previously will then be called again for the implementation process for the dataset, the train_generator section as well as for other data. As well as for the results of the preprocessing can be seen in Figure 3.

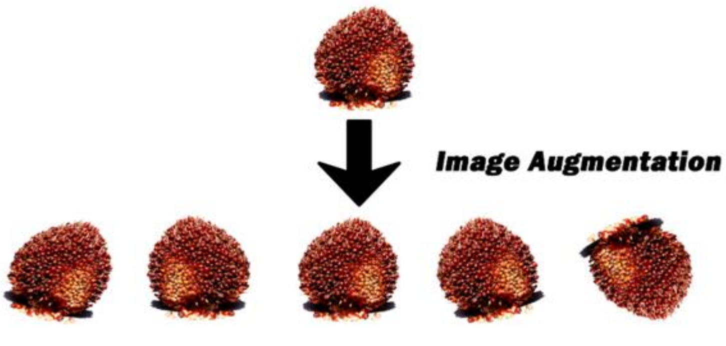

Fig 3. Augmentation Process Results

Based on the training results, the model of the CNN network architecture that was formed is obtained, which is shown in Table 3 below.

Table 3. CNN Model Result

Parameter	**Size**	**Value**
Input	128*128*3	0
Conv2d_2	3*3*3+1*128	896

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Batch_normalization_1	256+256	512
MaxPool_1	63*63*128	0
dropout_1	63*63*128	0
conv2d_2	3*3*128+1*64	73792
batch_normalization_2	128+128	256
MaxPool_2	30*30*64	0
dropout_2	61*61*64	0
conv2d_3	3*3*64+1*32	18464
MaxPool_3	14*14*32	0
dropout_3	14*14*32	0
flatten	6272	0
dense	6272*512+512	3211776
Dense output	512+1*3	1539
TOTAL		3.312.099

Table 3 above is a model formed from the results of the training. To calculate the input into the convo, the formula "input_size + 2*padding - (filter_size -1)" is used. The total parameters formed from the model are 3,312,099 neurons.

After going through several processes in the Convolutional Neural Network (CNN) algorithm, the results of training and validation are obtained. The train process will produce a model that will be used in the testing process, the stored model contains the results of the training carried out by the system. Broadly speaking, the contents of the train model process are shown in Table 5. This process uses a total of 10 epochs. The following is a graph of the training results using tensorflow. Keras.

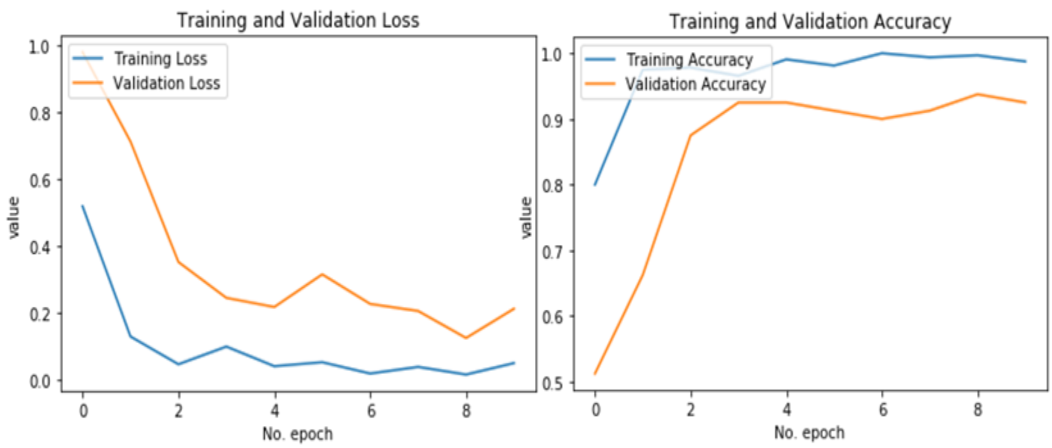

Fig 4. Training Result

Based on Figure 4 there are 4 indicators, namely Training Loss and Accuracy as well as Validation Loss and Validation Accuracy. Training Loss is the result of a train whose data is not legible, the smaller the loss value, the better, while Training Accuracy is the accuracy value obtained from the training process, the higher the accuracy value, the better the model that has been made. Validation Loss is a comparison value from the train process, the lower the validation loss value, the better the model, while Validation Accuracy is a comparison value obtained from the train model process, the higher the validation accuracy value, the better the model that has been made. In this train process, the accuracy of the training model reached 0.98 with a loss value of 0.04. The training process here uses a learning rate of 0.001 with an image input of 64 x 64 pixels. The training time required for 10 epochs in running this training model is 30 minutes. The more epochs, the longer the time needed for model training. Then the accuracy of data validation reaches 0.92 with a loss value of 0.21.

Table 4. Confusion Matrix Results

Matrix		**Class Prediction**		
		Raw	Ripe	Rotten
Real Class	Raw	20	2	6
	Ripe	2	23	2

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	Rotten	6	1	19

Based on Table 4, the prediction results from the model for testing data showed good results, namely predictions for rotten palm fruit were classified as correct as many as 20 and missing data from rotten palm input was classified as mature palm as much as 2 data and rotten palm fruit was classified as crude palm as many as 6 data. The second prediction on ripe palm fruit is classified as correct as many as 23 and missing data from input ripe palm oil is classified as rotten oil as much as 2 data and mature palm oil is classified as crude palm as much as 2 data. Then the last one is predictions on crude palm fruit being correctly classified as crude palm as much as 19 and missing data from input crude palm classified as rotten palm oil as much as 6 data and raw palm oil classified as ripe palm as much as 1 data.

The accuracy generated by the model with the number of samples testing 81 images obtained an accuracy value of 76%. The precision referred to here is the level of accuracy between the requested information and the system's answer, then recall which is the success rate of the system in retrieving an information, the result of recall accuracy is 0.76, while accuracy/f1-score is the level of closeness between the predicted value and the value. actual and the result of the f1-score accuracy is 0.76.

Table 5. Test Result

Images	**Accuracy**	**Class**
	0.9372	Ripe
	0.9916	Raw
	0.4481	Rotten
	0.7787	Ripe
	0.9576	Raw
	0.9752	Rotten

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It can be seen in Table 5 that the first testing process was carried out by testing crude oil palm fruit with a background getting an accuracy of 0.9916 and raw oil palm fruit without a background getting an accuracy of 0.9576, meaning that there is not too much difference in testing raw oil palm fruit. The second test was carried out with the image of ripe palm fruit with a background obtaining an accuracy of 0.9372 and ripe palm fruit without a background obtaining an accuracy of 0.7787, meaning that in the second test the difference is not too much. The third test was carried out by testing rotten oil palm fruit with a background obtaining an accuracy of 0.4481 and rotting oil palm fruit without a background obtaining an accuracy of 0.9752, meaning that in the third test there is a considerable difference, this is because the background color in the rotten palm fruit image has a different color. almost the same as the palm fruit. Based on the testing in this study, it turns out that the color and shape of the background can affect the level of accuracy of the test. In the test there is no missing data from the 6 images tested. However, there are several tests that get quite low accuracy, namely the rotten fruit image test with an accuracy of 0.4481. The process of calculating accuracy is the final process in this research. Accuracy in this study is a variable that represents performance that is used to assess the benchmark for the success of the CNN model in identifying the maturity level of oil palm fruit.

DISCUSSIONS

Convolution is the process of combining two series of numbers to produce a third series of numbers. If implemented, the numbers in this convolution are in the form of an array matrix. The input image has a pixel size of 128x128x3, this shows that the pixel height and width of the image are 128 and the image has 3 channels, namely red, green, and blue or commonly referred to as RGB. Each pixel channel has a different matrix value. The input will be convoluted with the specified filter value. A filter is another block or cube with a smaller height and width but the same depth that is swept over the base image or original image. Filters are used to determine what pattern will be detected which is then convoluted or multiplied by the value in the input matrix, the value in each column and row in the matrix depends on the type of pattern to be detected. The number of filters in this convolution is 128 pixels with a kernel size (3x3), this means that the resulting image from the convolution will consist of 128 map features. In this study, a matrix sample was used in the input image to make it easier to understand the convolution process. Because the input image has a pixel size of 128x128, in this study only a portion of the matrix values were taken as samples in the convolution process.

Testing is done by using test data as many as 6 different images. Images are divided into three classes, namely: raw, ripe and rotten. Before testing, make sure the position of the oil palm fruit image is in the middle and in a clear state (not too far away). Testing is done using the website. The test is carried out using a website which aims to facilitate the process of identifying the maturity level of oil palm fruit. The website was built using the python programming language with the help of the streamlit library, which is one of the new web frameworks from python but is quite popular among data science because it is simple and easy to learn. The accuracy obtained from the testing process using 6 test data shows an accuracy value of 100%.

CONCLUSION

From the results of the study, it was found that the detection of maturity of oil palm fresh fruit bunches using the Deep Learning method got a high accuracy value of 98% in the training process and 76% in the model testing process. This study has used new randomized data to test the model that was created and resulted in a good accuracy value in identifying oil palm fresh fruit bunches. So it can be concluded that the model that has been created by implementing the deep learning method using the Convolutional Neural Network (CNN) algorithm is able to detect oil palm fresh fruit bunches.

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