Utilization of Big Data in Oil Palm Plantation to Predict Production Using Artificial Neural Network Model

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ABSTRACT
The oil palm plantations in Indonesia are more than 14 million hectares and have been cultivated for more than 100 years in various types of land, climates, and various technical cultural treatments. The cultivation process will produce very large data. However, the utilization of these data has not been optimal and is still being managed partially. In the 4.0 industrial revolution, big data is a key asset in building artificial intelligence to support precision agriculture. One of the uses of big data is to build predictive models. An artificial Neural Network (ANN) is a model that can be used to predict by utilizing big data. On the other hand, production prediction is a very important activity to help planters in making decisions on all plantation activities. This study aims to use big data in oil palm plantations to predict production using ANN. The input data used in this study are components that have an influence on production. Meanwhile, the output to be predicted is annual yield and FFB production. The ANN model used is multilayer perceptron backpropagation with architecture 24-25-35-25-1. This model can accurately predict annual yield and total production based on block, division, estate, palm age, and progeny with MAPE and R are 10.52 % and 0.96 respectively.

***Keywords**: Oil Palm, Precision Agriculture, Big Data, Artificial Neural Network*

1. INTRODUCTION

Oil palm is one of the plantation commodities that contributes to the country's foreign exchange. Based on data compiled by Indonesian Palm Oil Association (IPOA), the total national exports in 2017 were valued at USD 168.7 billion, consisting of oil and gas exports of USD 15.3 billion, and non-oil and gas exports (including palm oil exports) of USD 152.9 billion [1]. The planted area of oil palm plantations in 2011 – 2019 has increased by 5.62 million hectares, whereas in 2019 the planted area in Indonesia has reached 14.72 million hectares [2]. Based on status, private has the largest share of oil palm area at 55% followed by smallholder and state plantations at 41% and 4% respectively [3].

Currently, oil palm production is still very low. The average production for large plantations are 19.5 tons FFB/ha/year, while smallholders are 15 tons FFB/ha/year. In fact, the production that can be achieved by only applying best management practices (BMP) is around 25 - 35 tons FFB/ha/year. There are several factors that cause oil palm not to reach its production potential including climatic (rainfall, solar radiation, CO_2 concentration, and air temperature), soil (soil type, topography, irrigation, and slopes), technical culture (fertilization, pruning, palm spacing, pollination, weeds, pests, and diseases) and the planting material [4]. To

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determine the influence of these factors, it is necessary to good record data from land clearing to production. but unfortunately, the data that should be recorded is not used properly. Data is one of the important components for plantations to make effective and efficient decisions to increase production.

Oil palm in Indonesia has been planted for more than 100 years. Certainly, it has produced a lot of data, but this data is still not well recorded and stored locally so the data tends to be lost. In the revolution era 4.0, with the internet of things (IoT), the data can be stored centrally. The data collected will be very large (big data) and can be used to produce the right decisions for increased oil palm production. In other sectors, other researchers have done a lot of research related to the use of big data, like the utilization of big data for logistics and transportation [5], weather forecasting [6] [7] [8], paddy growth stages detection [9], and digital accounting application in oil palm plantation [10].

One of the uses of big data in oil palm plantations is to make production predictive models. This prediction of oil palm production is very useful for plantations to plan activities, especially those related to more effective and efficient financing. In addition, the plantation can also simulate various conditions such as climatic conditions, fertilization, pruning, and other technical cultural improvements to increase production. Thus, the company can make the right decision.

The models based on data usually can be built on are empirically-based models, but these models tend to have low accuracy compared to mechanistic models [11]. Machine/deep learning-based models especially neural networks have recently been used for big data analysis. Like empirical models, machine/deep learning-based models are built on correlation patterns between input and output variables. The difference is the machine/deep learning model uses an output label to get a fit equation, while the empirical model uses an equation to get the output. Thus, machine/deep learning-based models are more flexible to input changes.

Machine learning is a machine/computer able to emulate human intelligence [12]. Artificial neural network (ANN) is one of the models used in machine learning. The neural network model has existed since 1943, but its development was not so significant until the last decade when the development of computers was so rapid. Now, the researchers are able to develop more complex architectures or known as the deep learning [13].

Table 1. Results of previous research related to ANN in oil palm plantations.

No	Result	Author
1.	Input: Rainfall and d-tapped delayed (rainfall lag) (5 years data) Output: FFB production Architecture: ANN (2-3-4-1, 2-24-5-1, 2-2410-1, and 2-3-5-1) Model evaluation: R = 0.74 – 0.86	[11]
2.	Input: Rainfall, temperature, humidity, light intensity, and wind speed (6 years data) Output: Yield Architecture: ANN (60-5-1) Model evaluation: MAE = 0.53; MSE = 0.47	[14]
3.	Input: Crop (progeny and planting year), Satellite (vegetation index and humidity) (16 years data). Output: Yield Architecture: ANN Model evaluation: MAE = 0.26; RMSE = 0.34; NSE = 0.81, R^2 = 0.81	[15]
4.	Input: Soil type, soil depth, pH, rainfall, temperature, water deficit, humidity, and solar radiation Output: Yield Architecture: ANN (15-3-1) Model evaluation: R^2 = 0.99; RMSE = 0.494	[16]

ANN is a model that imitates the way of human brain works. This model will perform repeated calculations to produce weights and biases with the smallest error in the output. Research on using ANN in oil palm plantations has been carried out in oil palm plantations (Table 1). However, the previous study has not explored many input variables that are always recorded on the plantation, several studies have not considered the time lag factor and long time-series data, and the prediction results are less applicable if replicated on the plantation.

This study aims to predict oil palm production using the ANN model by utilizing data recorded on plantations.

2. MATERIALS AND METHODS

This study uses historical oil palm plantation data for 11 years. The plantation has 4630.60 ha planted area which is divided into 5 division and 112 blocks. The number distribution of datasets for training, validation, and testing can be seen in Table 2.

Table 2. Datasets used in training, validation, and testing

Dataset	Data amount (block)	Year (n year)	Year (n-1 year)
Training	963	2011 – 2020	2010 – 2019
Validation	107	2011 – 2020 (Randomly selected)	2010 – 2019 (Randomly selected)
Test	112	2021	2020
Total	1182	2011 – 2021	2010 – 2020

Data preprocessing starts from the separation of input and output variables. In this study, Block data is used as a data point. Component data Block will be grouped as input and output data. Input data is grouped into two types, namely static and dynamic. Static data is data that does not change every year, while dynamic data is data that changes every year. The dynamic data grouping (n year – 1) is also intended to see patterns that occurred in the past that have the possibility of affecting the current data (n years) including the time-lag of environmental stress factors. Meanwhile, the output data that is the target of prediction is yield. Generally, a more complete distribution of datasets can be seen in Figure 1 and research method stages can be seen in Figure 2.

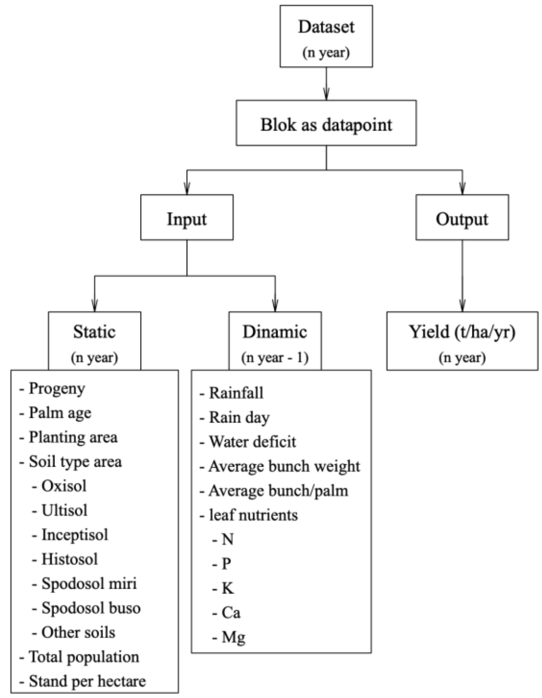

Figure 1 Flowchart of dataset division into input and output components.

The next preprocess data is checking for missing values and outliers. Outlier data will be discarded, and missing values will be imputed using the linear interpolation method. After that, this data will be converted into a range of 0 – 1 using Min-Max Normalization. Furthermore, the data is separated into two, 90% for training data and 10% for validation data. Linear interpolation and Min-Max Normalization can be seen in equations (1) and (2).

$$f_1(x) = f(x_0) + \frac{f\,(x_1) - f\,(x_0)}{x_1 - x_0} \qquad .....(1)$$

where:
$f_1(x)$ = Missing value
$f(x_0)$ = The value of the dependent variable from the previous data
$f\,(x_1)$ = The value of the dependent variable from the data afterwards
x_0 = The value of the independent variable from the previous data
x_1 = The value of the independent variable from the data afterwards

$$X_{new} = \frac{(X_{old} - X_{min})\,x\,(X_{newmax} - X_{newmin})}{X_{max} - X_{min}} + X_{newmin} \qquad ....(2)$$

where:
x_{new} = Normalized data
x_{old} = Data before normalization
x_{min} = The smallest data from a single column of data rows
x_{max} = The largest data from a single column of data rows
X_{newmin} = Minimum value limit of normalization
X_{newmax} = Maximum value limit of normalization

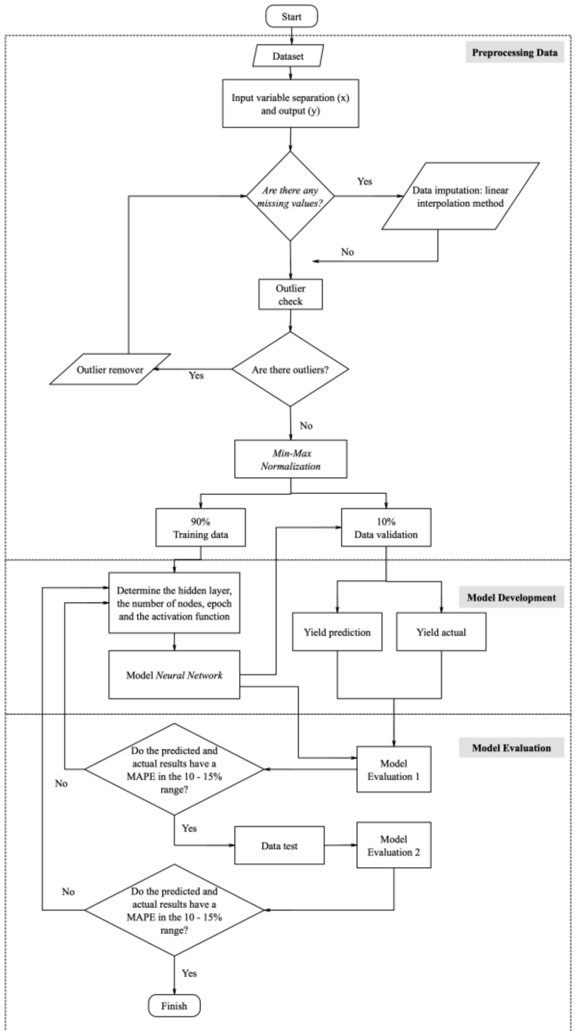

Figure 2 Research method stages

Development of ANN model using python 3.7 with KERAS and TensorFlow libraries. The development of this model begins by determining the nodes in the input layer, the number of hidden layers and its nodes, and the output as a target of the prediction. In this study, the architecture is used 24 – 25 – 35 – 25 – 1 (24 nodes in the input layer, 25 nodes in the hidden layer 1, 35 nodes in the hidden layer 2, 25 nodes in the hidden layer 3, and 1 node in the output layer). The activation function used in the input and hidden layers is RELU, while the output layer is Sigmoid. Backpropagation on the model is compiled with the Adam optimizer and the error/loss function uses Mean Absolute Percentage Error (MAPE).

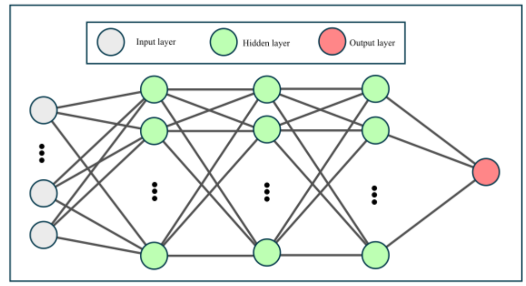

Figure 3 ANN architecture used in research

The model that has been trained is then validated and tested into new data that has not been recognized. Actual and predicted fresh fruit bunch (FFB) production distribution will also be calculated following the following formula (3).

$$\text{FFB Production (t)} = \text{Y.Pa} \qquad .....(3)$$

where:
Y = Yield (t/ha/yr)
Pa = Planted area (ha)

Evaluation between the predicted and actual values using MAPE and R which is calculated through the following (4) and (5).

$$\text{MAPE (\%)} = \frac{100\%}{n}\sum_{t=1}^{n}\frac{Y-\hat{Y}}{\hat{Y}} \qquad ....(4)$$

where:
n = Amount of data
Y = Yield actual (t/ha/yr)
$\hat{Y}$ = Yield prediction (t/ha/yr)

$$R = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2} \qquad ....(5)$$

where:
x_i = Actual data sample-i
y_i = Prediction data sample-i
$\bar{x}$ = Average of actual data
$\bar{y}$ = Average of prediction data
n = Amount of data

3. RESULTS AND DISCUSSION

1.1. Dataset characteristic

The data generated from oil palm plantations has unique characteristics because the data produced (e.g.the incidence of drought stress) at this time has a relationship with production for the next 2 years [17]. Therefore, more extreme stress in this phase will affect the oil palm production [4]. In this modeling, 24 data are used which are used as inputs to predict oil palm production. However, factors related to rainfall such as water deficit have a significant impact on decreasing palm oil production [18].

Figure 4 shows a graph showing the pattern of oil palm production compared to water deficit in 2010 -

2021. In the plantation, there is no clear pattern of the effect of the water deficit in the 1st or 2nd year after. However, the effect of the water deficit is more likely to affect production in 1st year afterward. Therefore, the rainfall data used in the dataset is 1st year lag.

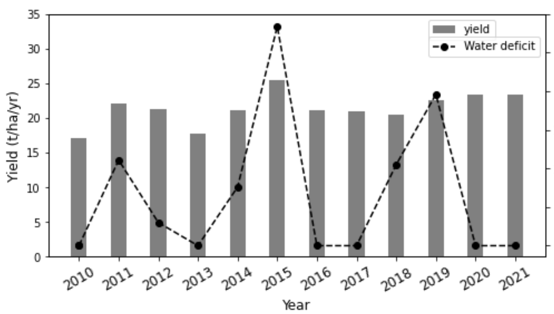

Figure 4 Distribution pattern of production and rainfall from 2010 – 2021.

Palm age and progeny also affect oil palm production. With increasing palm age, production will increase until it reaches peak production at the age of 13 – 14 years. Meanwhile, each progeny has characteristics in flower and fruit formation which will be one of the limiting factors in determining production potential. Some varieties are also susceptible to environmental stress.

The number of blocks as data points that make up variations in training also determines how much the model can predict oil palm production accurately. Figure 5. shows the number of blocks used during the training process based on palm age and progeny. Palm age has a representative sample of training data blocks from the age of 2 – 16 years. Palm ages 2 – 5 and 16 years have a smaller sample representation (<50 samples). Meanwhile, for progeny, the dominant progeny for the sample in the training data is FELDA (> 500 samples) followed by LONSUM, PPKS, and GH. Meanwhile, for the progeny, the dominant progeny for the sample in the training data was FELDA (> 500 samples) followed by LONSUM, PPKS, and GH. This data variation is very interesting to see how the performance of the ANN model in predicting production, especially data that has a small sample and has never been trained.

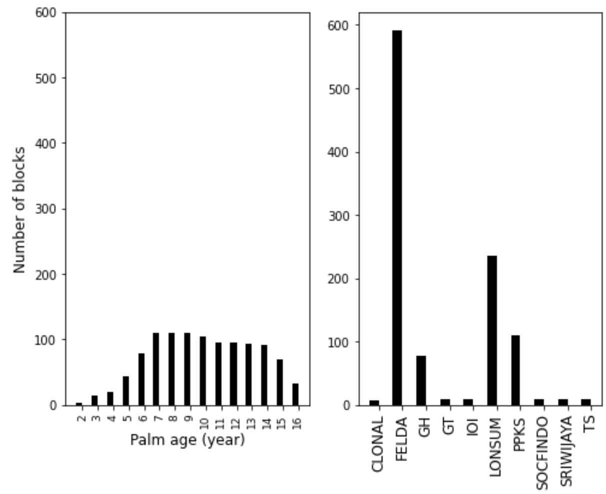

Figure 5 The number of blocks used during the training process is based on palm age and progeny.

1.2. Model training

The ANN architecture used is 24 – 25 – 35 – 25 – 1. This architecture is obtained by using a try and error procedure to get a small error [19]. After that determine the optimal number of epochs. This study uses 1000 epochs to produce production predictions with the lowest error. The number of iterations of all epochs is presented in Figure 6.

At the beginning of the iteration, the resulting MAPE is very large. However, in the 55 epochs, the change in MAPE value was not too significant. In the 335 epochs, the MAPE value shows < 20%. This indicates that the results of changes in weights and biases that occur between the actual and predicted values during the iteration process are sufficient. This indicates that the results of changes in weights and biases that occur between the actual and predicted values during the iteration process are quite good. Furthermore, the iteration continues until the 1000 epochs. However, the resulting change in the MAPE value is 10-20%. Based on iterations in the study, the lowest MAPE value was produced at the 992 epochs with a MAPE value of 11.83%. Meanwhile, in the 1000 epochs, the MAPE value increased by around 12%. The MAPE value will reach saturation at a certain point. In addition, the smaller the epoch value generated in the training process, this does not mean the weight and bias values generated will be better than the error values generated during validation and testing.

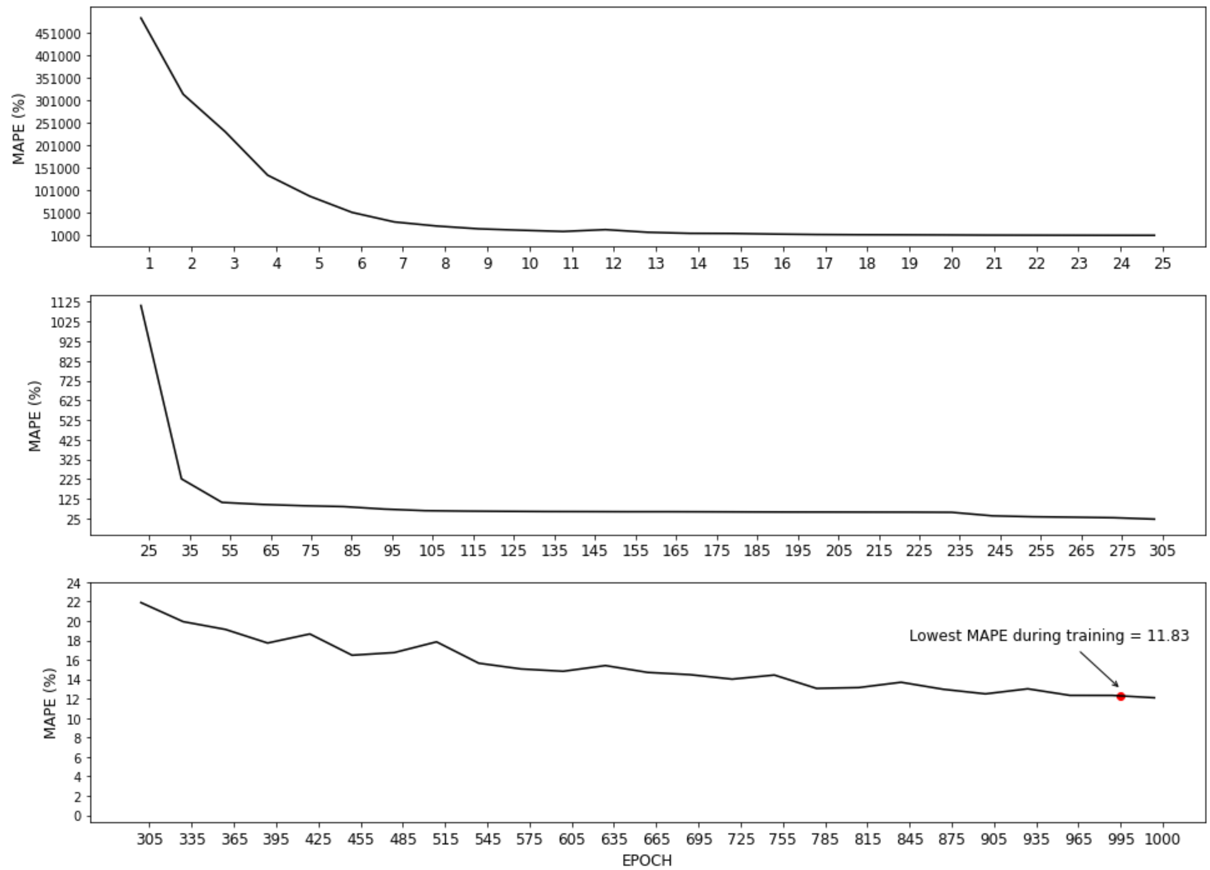

Figure 6 The number of iterations of all epochs in training process.

Figure 7. shows the testing of the ANN model that has been trained on the validation data. This validation data is new data that are randomly selected from 2010 - 2020 data, with data do not recognize at the time of training. Based on these tests, the ANN model is quite good at predicting the production of 107 sample block with an overall MAPE value of 14.68%.

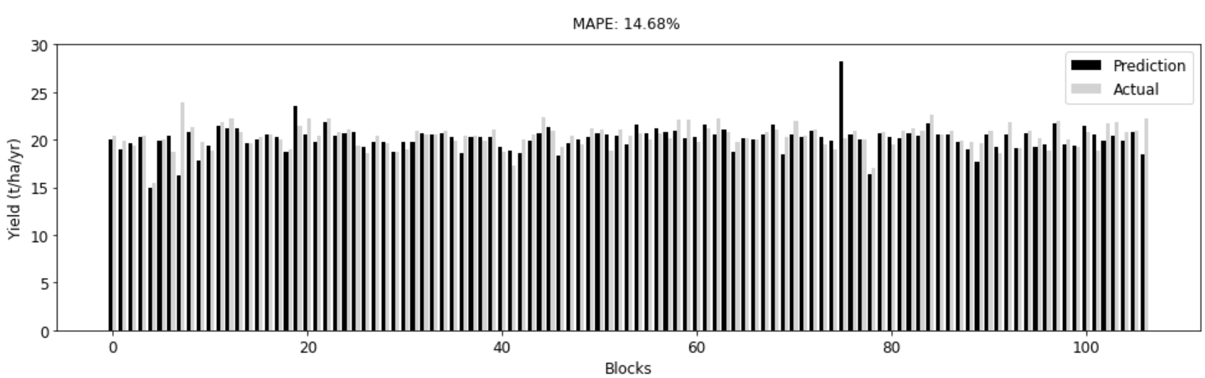

Figure 7 The testing of the ANN model that has been trained on the validation data.

1.3. Model testing and evaluation

Model testing is carried out on the 2021 data. The test is to see how much accuracy the model in predicting production from the block, division, and estate level. In

Figure 8 Actual and predicted yield and FFB production on Block level.

addition, the model will also be evaluated to see its accuracy based on palm age and progeny.

1.3.1. model testing and evaluation by block, division and estate

Table 3. shows the MAPE value generated based on actual and predicted production based on division and estate. Various values are obtained with the smallest MAPE value in Div. 2 while the largest value in Div. 5 is 6.89% and 17.55%, respectively. Overall, the MAPE generated from 112 block is 10.52%. This MAPE value is the smallest MAPE compared to during training and validation.

Table 3. MAPE at the division and estate level

Division	Number of blocks	Planted Area (ha)	MAPE (%)
Div. 1	22	817.40	9.37
Div. 2	20	1044.87	6.89
Div. 3	14	757.14	7.45
Div. 4	27	989.09	8.18
Div. 5	29	1022.10	17.55
Estate	112	4630.60	10.52

Figures 8 and 9 are bar charts that visualize the actual and predicted yield and FFB production values at the block and division levels. The figure shows the performance of the model in each block in predicting from block level to division. In some blocks, the level of accuracy is poor which is indicated by a large gap between the prediction and the actual. However, at the division level, the actual and predicted gaps are not very different. Overall, for estates, the difference in yield and production of FFB is 1622.14 t and 0.35 t/ha/yr, respectively.

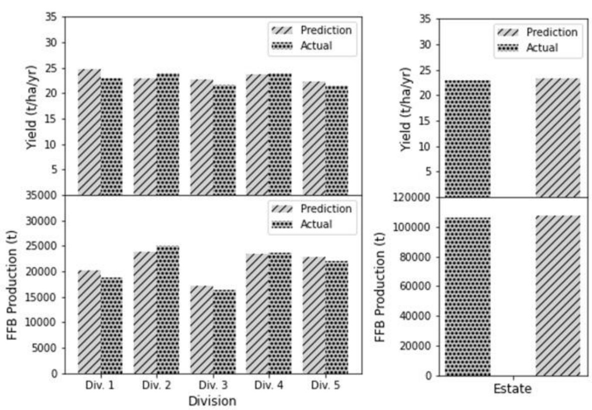

Figure 9 Actual and predicted yield and FFB production on Division and Estate level.

1.3.2. model testing and evaluation based on palm age and progeny

Evaluation based on age and progeny is very important because conventional models always consider this as a correction factor. Table 4 shows the MAPE values between predicted and actual for various palm ages. The number of test datasets is dominated by 15, 16, and 17 years. The resulting MAPE value also varies between 2.28 – 41.98%. The highest MAPE value is in 6-year-old, while the lowest is in 12-year-old. Meanwhile, for palms aged 15, 16, and 17 years which dominate 91% of the total planted area, the MAPE is classified as good, which is between 7.33 – 10.72%. Moreover, for 17-year-old, there is no dataset at the time of training, but the neural network model can predict very good accuracy values.

Table 4. The MAPE values between predicted and actual for various palm ages

Palm Age	Number of blocks	Planted area (ha)	MAPE (%)
6	2	11.35	41.98
10	5	119.76	17.57
11	9	149.97	20.10
12	1	13.05	2.28
13	2	92.14	19.42
14	1	51.11	11.50
15	23	1070.09	10.72
16	37	1695.02	7.88
17	32	1428.11	7.33

The difference between the predicted and actual values between yield and FFB production can be seen clearly in Figure 10. Palm aged 6 and 13 years have a large yield difference (4 – 6 t/ha/yr), but the actual and predicted FFB does not show much difference. Palm aged 15, 16, and 17 years generally dominated the overall FFB production with the actual and predicted values does not showing much difference.

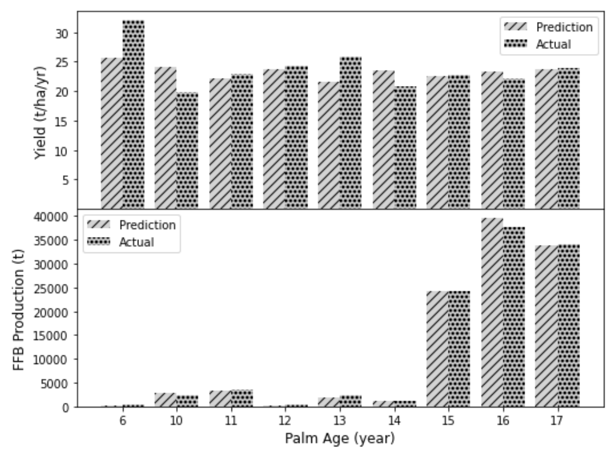

Figure 10 Actual and predicted yield and FFB production based on palm age

Another testing is also carried out based on progeny. Table 4 shows the MAPE values between the predicted and actual several progenies. The resulting MAPE values varied between 2.28 – 41.98% where the lowest is in the TS and the highest is in the CLONAL progeny. The resulting MAPE value is still relatively good, i.e. 8.99% for FELDA and 12.99% for LONSUM.

Table 5. The MAPE values between the predicted and actual several progenies.

Progeny	Number of blocks	Planted area (ha)	MAPE (%)
CLONAL	2	11.35	41.98
FELDA	60	2543.72	8.99
GH	8	288.12	8.85
GT	1	60.94	9.32
IOI	1	42.31	11.76
LONSUM	26	987.00	12.69
PPKS	11	592.94	9.04
SOCFINDO	1	40.06	19.63
SRIWIJAYA	1	51.11	11.50
TS	1	13.05	2.28

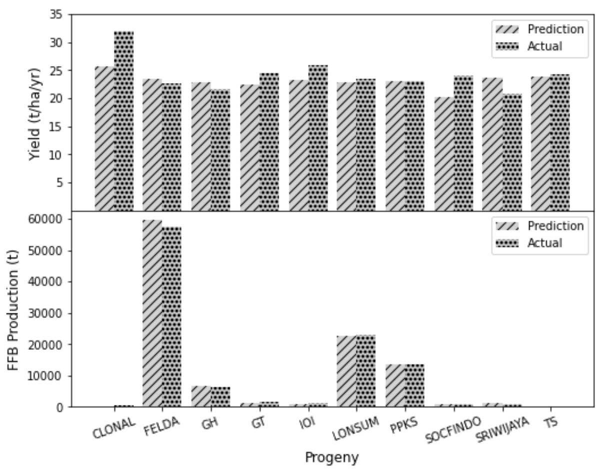

Figure 11 Actual and predicted yield and FFB production several progenies.

Figure 12. clearly shows the difference in yield and FFB production between actual and predicted. The difference is mainly in the predicted and actual yields of CLONAL, although these differences do not affect the overall production of FFB. The progenies that dominate the total FFB production such as FELDA, LONSUM, and PPKS have an accuracy that does not differ between the prediction and actual.

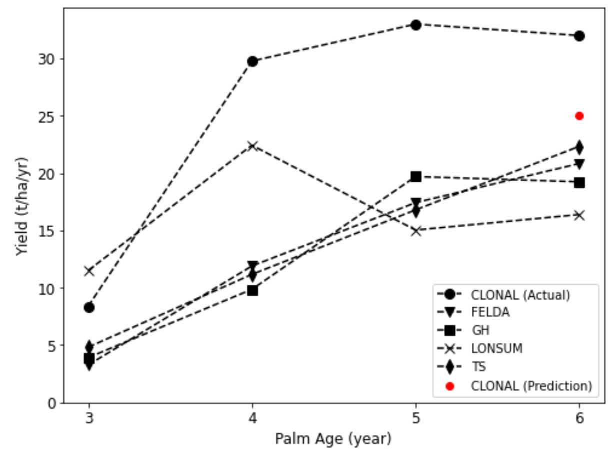

Figure 12 Production of several progenies at 3, 4, 5, and 6 years old.

Several reasons why CLONAL progeny has a high error between prediction and actual because CLONAL progeny was first planted in 2015 and planted in 2 blocks with a total area of 11.35 ha. Compared to the other progeny area, the planted area of the CLONAL is smaller. In addition, the production of CLONAL is unique because compared to the same age, the CLONAL progeny has a higher production (Figure 12). This causes the error to occur which is quite high. During training, the model tends to learn patterns that occur based on the input process of existing progeny.

1.3.3. correlation of predicted and actual FFB production

Correlation tests are also carried out between the actual and prediction for each division and estate. The R-value is in the range of 0.92 – 0.97 for division (Table 6). for the estate R-value is 0.96 (Figure 13). This is a very good correlation which explains that the ANN model can be used in predicting oil palm production.

Table 6. Correlation (R-value) between actual and prediction FFB Production

Division	R^2	R
Div. 1	0.90	0.95
Div. 2	0.95	0.97
Div. 3	0.86	0.93
Div. 4	0.98	0.99
Div. 5	0.84	0.92
Estate	0.92	0.96

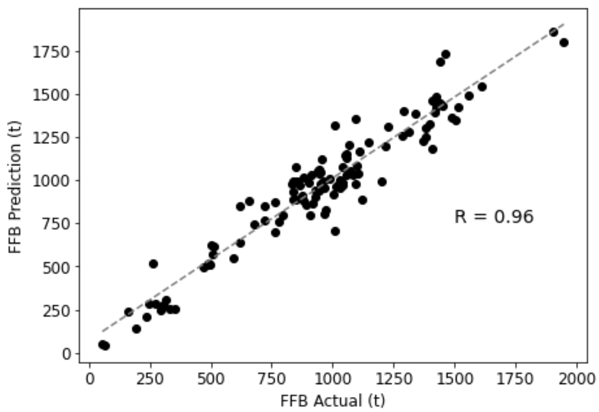

Figure 13 Correlation test between prediction and actual of FFB production

In this study, the ANN model can be used to predict production with the best accuracy. However, in building this model, it is necessary to vary the training data with inputs that represent the predicted output conditions. This can be seen in predicting the production of CLONAL progeny which has a very high error (>40%). However, because the CLONAL progeny planted area only covers 0.27% of the total planted area, the error does not affect the overall prediction. However, even though the dataset does not have patterns of palm age 17-year-old. The model can still predict production accurately.

4. CONCLUSION

The artificial neural network model can effectively predict oil palm production per year starting from the level of block, division, estate, palm age, and progeny level with input data that is always recorded by the plantation. The accuracy of the model will be better if the data (input and output) used during training represent the overall condition of the plantation production. However, this study only predicts the target output yield and FFB production per year. Further research is needed on the target output yield and FFB production per month. Thus, the yield can be used by plantations in predicting monthly production fluctuations as a basis for plantations to make more precise decisions.

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