Development of a model for the estimated maximum compressive force from oil palm frond (OPF) with artificial neural network (ANN) approach

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Abstract. The compressive force is one of the mechanical properties of a material such as oil palm frond (OPF) which is important to know. It is used as a guide for engineers in designing machines to work effectively. However, the availability of a compressive force value and its model for OPF materials have not been studied in depth. Therefore, this study aims to predict the modeling of the compressive force using artificial neural networks (ANN) for OPF materials. In the model, oil palm age, OPF ripening times, and OPF sections were used as input data. Output data in the form of compressive force from the test results using a universal testing machine (UTM). The predictions were obtained for compressive force by [3–10–10–1], [3–10–10–10–1], and [3–10–10–10–10] network architectures with a variations hidden layer, respectively. An impressive performance of the neural network, with experimental data, was achieved with the developed model, the compressive oil palm age, OPF ripening times, and OPF sections. The prediction results showed that the ANN with [3–10–10–1] network architectures were superior in terms of prediction capability compared to other network architectures.

1. Introduction
Data on the physical and mechanical properties of OPF are essential in designing a machine and the processes associated with that material [1]. It is because it is very closely related to the working principle of the device that will be applied in designing the machine [2, 3]. Likewise, an oil palm frond (OPF) must be known for its physical and mechanical properties. Some characteristics of OPF have been studied by several researchers [4, 5]. Bulan et al. [4] reported the results of studies of some physical properties of OPF and mechanical properties of the leaves. It was taken to design a chopper machine. Intara et al. [5] conducted a study of some mechanical properties in the form of physical and mechanical properties of the bunch OPF and stem. This study aims to find out some physical and mechanical characteristics of OPF to develop pruner and harvester machinery design. However, in the two research reports, there was not found a model that could show the relationship between the physical and mechanical characteristics of OPF with things that could influence it.

From this research, it can be concluded that the need for measurement results of the characteristics of OPF is critical to know in designing a machine. On the other hand, providing OPF characteristic data is very difficult to do because of time and cost limitations, especially mechanical properties. One
of the essential mechanical properties of OPF is the compressive force. Therefore, many researchers try to propose a model to be able to predict these mechanical properties by various methods. Researcher Kara et al. [6] conducted a prediction model to determine the cutting force of AISI 316L stainless steel using ANN and multiple regression method. The results indicate that the ANN method is superior in making predictions compared to various regression methods. From the results of several studies, the ANN method is superior in forming a prediction model compared to other methods. Vasudepan and Srinivasan [7] compared the ANN method with response surface methodology (RSM) to predict spring-back and bend force in air bending. The comparison shows that the ANN models provide more accurate prediction than the RSM models. From the two results of the study stated that the ANN method is better at forming prediction models of a particular phenomenon.

There is still no compressive force prediction model for OPF making this very important to do at this time. The literature review results state that the prediction model has the potential to be approached through the ANN method. Therefore, this study aims to develop a predictive model of the mechanical properties of OPF in the form of a compressive force. The results of this study are expected to be useful information for researchers and engineers who carry out design related to OPF.

2. Material and Method

2.1. Experiment Description

This experiment using a universal testing machine (UTM) Instron 3369 type with a maximum force of 50 kN, Maximum speed 500 mm/min (20 in/min), and 1193 mm (47 in) vertical test space. OPF samples were obtained from two ages of oil palm plants namely five years and ten years. The example is then ripened with a duration of 3 days, 5 days, 7 days, 9 days. Each sample is cut into three main parts, namely initial, middle and edge (Figure 1). The sample OPF will be tested using UTM with three replications each time to get a compressive force. The maximum value of the compressive force will be chosen to represent each experiment in making a prediction model. The description of the test is presented in Figure 2.

![Figure 1. Oil palm frond (OPF) and Figure 2. Measurement of compressive force](image)

2.2. Arsitektur ANN

Prediction of compressive force OPF using multi-layered ANN feeds forward with the back-propagation algorithm. The training uses the type of Levenberg-Marquardt. Network architecture consists of three, three types of hidden layers, and one output or can be written like [3-10-10-1], [3-10-10-10-1], and [3-10-10-10-10-10]. Learning is done with the learning rate parameter; the momentum and the gain of each model have the same values, which are 0.1, 0.2, and 0.9. Termination criteria are based on cross-validation between training data and testing data.

ANN inputs are oil palm age, OPF ripening times, and section OPF. Each hidden layer consists of ten interconnected fruits. ANN output is a compressive force. After the stages of ANN, 30 pieces of compressive force data divided into three categories, 70% of which were used for training, 15% of data were used for validation, and 15% were used for testing. The next step of the model is conducted training, validation, and testing, the model is ready to be tested on the sample data. Sample data is measured directly from measurement compressive force. Differences in prediction results from ANN
models and direct measurement results will be calculated as errors. Errors are calculated using the coefficient of determination \( R^2 \) using Equation 1. The classification of error values that have been used by several researchers [8-10] classify models are presented in Table 1. MSE is calculated by Equation 2.

\[
R^2 = \frac{\sum_{i=1}^{n} (y_{i,p} - y_{i,e})}{\sum_{i=1}^{n} (y_{i,e} - y_{e})^2}
\]

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (y_{i,e} - y_{i,p})^2
\]

Where, \( Y_{i,e} \)-experimental data; \( Y_{i,p} \)-prediction data; \( n \)-amount of experimental data; \( Y_{e} \)-eksperimental average data; \( R^2 \)-coefficient of determination.

Table 1. Typical MSE values for model evaluation

| MSE (%)         | Evaluation                      |
|-----------------|---------------------------------|
| MSE ≤ 10%       | High accuracy forecasting       |
| 11% ≤ MSE ≤ 20% | Good forecasting                |
| 21% ≤ MSE ≤ 50% | Reasonable forecasting          |
| MSE ≥ 51%       | Inaccurate forecasting          |

3. Result and Discussion

3.1. ANN Simulation with Two Hidden Layer

Prediction models using two hidden layers are presented in Figure 3. From these results, it can be seen that the prediction model with ANN has been able to follow measurements directly using UTM for a compressive force. The error using the MSE method from the use of this network architecture is 10.3%. This MSE value is categorized as good forecasting based on standards used by some researchers in assessing an error from the model.

![Figure 3. Compressive force measurement vs. ANN model predictions using network architecture [10-10]](image-url)
3.2. **ANN Simulation with Three Hidden Layer**

Prediction models using three hidden layers are presented in Figure 4. From this result, it can be seen that the maximum compressive force resulting from the prediction model can also follow the direct measurement results using UTM. The error using the MSE method from using this network architecture is 11.8%. This MSE value is categorized as good forecasting based on standards used by some researchers [8-10] in assessing an error from the model. However, the MSE is still higher than using the network architecture of two hidden layers.

![Figure 4. Compressive force measurement vs. ANN model predictions using network architecture [10-10-10]](image)

3.3. **ANN Simulation with Four Hidden Layers**

Prediction models using four hidden layers are presented in Figure 5. From this result, it can be seen that the maximum compressive force resulting from the prediction model can also follow the results of direct measurement of compressive force using UTM. The error using the MSE method from using this network architecture is 12.3%. This MSE value is categorized as good forecasting based on standards used by some researchers in assessing an error from the model. However, the value of this MSE is still higher than using all network architectures tested in this study.

3.4. **ANN Modeling Predictions**

The model of the relationship between the compressive force predictive value and the compressive force measurement for the two, three and four layer architectural networks is presented in Equations 3, 4 and 5, respectively. The most significant coefficient of determination is found in the use of network architecture [3-10-10-1] which is equal to 0.84. Graph modeling for training, validation, and testing for network architecture [3-10-10-1] are presented in Figure 6. It indicates that the use of network architecture [3-10-10-1] is still better compared to the others.

\[
\begin{align*}
Y &= 0.69x + 110 \quad R^2 = 0.84 \\
Y &= 0.53x + 200 \quad R^2 = 0.76 \\
Y &= 0.91x + 81 \quad R^2 = 0.82
\end{align*}
\]
Figure 5. Compressive force measurement vs. ANN model predictions using network architecture [10-10-10-10]

Figure 6. Linear regression analysis between experimental results and ANN predicted values for two hidden layer
4. Conclusions
A compressive force prediction model for OPF using ANN has been developed. Network architecture that uses three data inputs, two hidden layers, ten pieces of each node and one output is the best compared to the other two network architectures. The coefficient of determination and MSE of this network architecture are 0.84, 10.3%, respectively. The future research is to develop big-data physical and mechanical properties of OPF to be able to build predictive models of other OPF mechanical properties so that the accuracy of predictions can be increased.

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