Plant growth prediction model for lettuce (*Lactuca sativa*.) in plant factories using artificial neural network

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Abstract. One of the applications of precision agriculture is the monitoring of plant growth in a plant factory production to observe the behavior and predict the estimated yield of plant production. Plant growth is unique and is affected by internal and external factors, such as environmental conditions and nutrition supply. The estimation of plant growth considering the environmental conditions as well as initial plant height is necessary for plant management during the production cycle. Therefore, to answer the challenge, the purpose of this study was to develop a model of plant growth prediction using the resilient backpropagation Artificial Neural Network (ANN) method with environmental parameter input at the plant factory and evaluate the model. The ANN model was tested using a different number of nodes at the hidden layer, which are 1 to 7 nodes with the input of daily average temperature, average daily humidity, EC, and light intensity and then produces high lettuce increase output for 45 days. The model was developed and tested using the lettuce (*Lactuca sativa*) in plant factory production. As a result of the evaluation, the best prediction model with ANN is using the network architecture 4-7-1 with the results of the interpretation of $R^2$ on the training data, and testing data are 0.987 and 0.728. From the verification test of the developed model, it can be found that the most affecting way to optimize lettuce growth is the rate of EC in nutrition. The results of the RMSE model validation is 0.032. Accordingly, the developed model can be used to predict the height increase of Lettuce (*Lactuca sativa*) plants in a plant factory.

1. Introduction
Precision agriculture is a technology that combines a sensor, information system, and management information to increase plant production. This technology could be used to determine parameters for plant growth, controlling the growth period and harvest period. These benefits could be used for the agriculture industry on a small, medium, and large scale [1]. The purpose of PA is to meet the needs of the agricultural industry in gathering more comprehensive data on production variability both in space and time [2]. Before the industrial revolution, agriculture was carried out in small fields with farmers who did not have a detailed understanding of how to calculate variability in their production systems.
Since the implementation of agricultural mechanization has increasingly increased the desire to increase profit margins which led to the 20th century being dominated by large-scale agricultural practices so that at the end of the 20th century and the beginning of the 21st century there was progress in technology so that agriculture could return to farming in specific locations which can maintain large economies of scale [3]. The fundamental concept of PA can be adopted by the application of monitoring of crop growth, which can be used to estimate the rate by using a mathematical model to determine the state of the plant during the growth period. Plant growth modeling has become a trend during these two decades due to the growth of computer and science technology [4]. Precision agriculture can be developed to be a monitoring system in a plant factory.

Plant factory works to make a good environment for plant growth and the environment to be easily controlled and regulated. All growth factors such as light, carbon dioxide levels, temperature, humidity, water, and nutrition are regulated by a combination of technology so it is always available for plant growth so, it can produce a high-quality production [5]. Plant monitoring systems can work automatically in controlling growth and development in living plants without requiring the role of humans who must monitor at all times. Plant monitoring in identifying plant growth and development behavior can be done based on the physiological properties of the plant [6]. The plant monitoring system was applied to the assessment of plant physiology, it can be utilized to certain plant parts such as height, width, leaf area, leaf angle, and also leaf color [7]. The use of monitoring equipment to assist the implementation of Precision Agriculture in the tropics leads to an increase in knowledge on conventional agriculture which more generally uses intuition (feeling) or estimates in daily tactical decision making [8]. Monitoring for plant growth is very important to evaluate the field environmental condition and also to know field environmental information and plant growth status, however, the existing monitoring system is very expensive [9], to support this technology it is necessary to predict (forecast) plant growth. So far, the application of predictive models has developed quite a lot, such as Naive Bias and SVM (Support Vector Machine). However, these prediction models have some weaknesses, including a lack of data accuracy due to the correlation between variables, and the limited number of variables measured. These weaknesses need to be minimized or even eliminated with an artificial neural network prediction model (ANN), as has been proven by Taufiq, et al [10] who compared the three methods and the best accuracy results using ANN because it produces the level of accuracy, precision, and the best recall among others.

Artificial Neural Networks are techniques in machine learning that can mimic human nerves which are a fundamental part of the brain. ANN consists of an input layer, a hidden layer, an output layer. Each layer consists of one or several node units that have an activation function that determines the output of that unit [11] An Artificial Neural Network (ANN) prediction model in agriculture is useful as a forecasting system in a plant monitoring system. As it has been proven by Barus, et al. [12] that its application can be implemented to predict the growth of stem length, number of flowers, flower diameter, number of leaves, and number of sprouts on a daisy (Asteraceae). The results showed that the accuracy of the ANN results was higher than the previous studies, and the new data tested was following the target, but there was still some data that did not correspond to the reality. This happens because this research is still being carried out on plantations without greenhouses, consequently, the plant environment cannot be regulated then affects the flower growth. Plant growth is unique and is affected by internal and external factors, such as environmental conditions and nutrition supply. The estimation of plant growth considering the environmental conditions as well as initial plant height is necessary for plant management during the production cycle. From previous research, this study was inspired to apply a prediction model of lettuce growth (Lactuca sativa) in plant factories with artificial neural networks (ANN) and the purposes of this study are to design a model of plant growth prediction using the resilient backpropagation artificial neural network method with environmental parameter input at the plant factory and to evaluate the model.

The objective of this study was to develop a model of plant growth prediction using the resilient backpropagation Artificial Neural Network (ANN) method with environmental parameter input at the plant factory and evaluate the model. This study also contributes to the improvement of growth
prediction models by considering environmental change parameters such as temperature, humidity, light intensity, and electrical conductivity. This parameter is used in this study because it is closer to the actual environmental conditions of a plant. As it is known that the development and growth of plants cannot be separated from these parameters.

2. Materials and Methods
This research was conducted in a Plant Factory at Smart Agriculture Research, Laboratory of Agricultural Energy and Machine, Agricultural and Biosystems Engineering, Faculty of Agricultural Technology, Gadjah Mada University. The plant factory was supported by RStudio for the software also the hardware was an LED growth lamp, digital timer, water pump, Wemos D1 mini, Temperature-humidity sensor, ruler, TDS meter, and lux meter. The materials were nine Lettuce (Lactuca sativa) seeds and AB Mix nutrition. The used samples in this study were nine Lettuce (Lactuca sativa) plants with the age of seven days after planting. The measuring parameter consisted of lettuce growth (height changing) and environment condition (air temperature, air relative-humidity, light intensity, and EC). The measurement was for 45 days.

2.1. Artificial neural network development
This phase needed both training data samples and testing data samples. The partition into them intended to develop the ANN model, to evaluate the prediction of the model, to represent of population, and to estimate serial time in the data. This study used 36 training data samples and 9 testing data samples. The designing process consisted of ANN architecture’s determination, determination of activation function, normalization of data, ANN model designing with resilient backpropagation method, and estimation of the weight and the bias. The diagram of the algorithm’s artificial neural network is displayed in Figure 1.

![Figure 1. Algorithm of artificial neural network.](image)

3. Results and Discussion
3.1. Lettuce height
Lettuce height was observed for 45 days and the results increase every day. These results show that lettuces grew. Environmental factors also affect lettuce height [13]. The influential experimental factors are humidity (RH), light intensity, and nutrient concentration [14]. However, plant factories can be used
to regulate the environmental condition according to plant needs so it was expected lettuces grew optimally.

During the observation, the temperature was kept constant at 20ºC. Nevertheless, the data of temperature were not constant because the observation room was not fortified with a heat absorber. Temperature data changes do not affect lettuces growth as is shown in Figure 2. The inconsistent humidity data do not also affect the growth (Fig 3). Furthermore, the light intensity fluctuated because the lux-meter used has an accuracy of ± 4% rdg ± 0.5% f.s (Figure 4). Figure 4 shows that the light intensity may not affect the growth of the lettuce either. The effect of EC nutrition on the Lettuces (Lactuca sativa) growth is shown in Figure 5. According to Binaresa [15], EC nutrition for lettuce was 600-1000 ppm. Every week, the concentration of EC nutrition was added 100 ppm. EC nutrition which was added according to Lettuce (Lactuca sativa) age was the most environmental factor which affects the growth of the lettuce as shown in Figure 2 to Figure 5. Sample S4, S5, and S6 represent the best growth compared to the other samples. This happens because of the effect of light radiated by grow light (Figure 6). Lettuces growth was better in the middle row of the plant factory because LED grows light radiates from both sides and the distance between light to lettuces is closer than the other plant in the right or left rows.
3.2. Prediction lettuce height with artificial neural networks
The number of hidden layers and nodes in the layer was obtained by a trial and error method. In this experiment, one to seven nodes were used. Initially, the lettuce height data were averaged to find training and test data.

**Table 1. Training results of artificial neural network.**

| Architecture | RMSE Training | Iteration | Total Parameter |
|--------------|---------------|-----------|-----------------|
| 4-1-1        | 0.046         | 2648      | 7               |
| 4-2-1        | 0.029         | 3409      | 13              |
| 4-3-1        | 0.032         | 4086      | 19              |
| 4-4-1        | 0.023         | 1888      | 25              |
| 4-5-1        | 0.012         | 2955      | 33              |
| 4-6-1        | 0.016         | 2090      | 37              |
| 4-7-1        | 0.007         | 1754      | 43              |
Table 2. Prediction results from the training set.

| Day | Actual | Prediction | Day | Actual | Prediction |
|-----|--------|------------|-----|--------|------------|
| 7   | 0.194  | 0.201      | 30  | 0.280  | 0.285      |
| 8   | 0.212  | 0.201      | 31  | 0.294  | 0.294      |
| 9   | 0.239  | 0.239      | 32  | 0.311  | 0.313      |
| 10  | 0.323  | 0.320      | 35  | 0.361  | 0.360      |
| 11  | 0.406  | 0.386      | 36  | 0.380  | 0.382      |
| 12  | 0.416  | 0.417      | 37  | 0.394  | 0.396      |
| 13  | 0.494  | 0.489      | 38  | 0.379  | 0.371      |
| 15  | 0.317  | 0.334      | 39  | 0.361  | 0.367      |
| 16  | 0.289  | 0.295      | 40  | 0.336  | 0.326      |
| 17  | 0.183  | 0.190      | 41  | 0.311  | 0.325      |
| 18  | 0.267  | 0.263      | 42  | 0.347  | 0.355      |
| 19  | 0.350  | 0.356      | 43  | 0.378  | 0.370      |
| 20  | 0.316  | 0.319      | 44  | 0.396  | 0.397      |
| 21  | 0.268  | 0.259      | 46  | 0.366  | 0.365      |
| 23  | 0.250  | 0.249      | 48  | 0.332  | 0.333      |
| 24  | 0.301  | 0.300      | 49  | 0.344  | 0.339      |
| 25  | 0.350  | 0.333      | 50  | 0.404  | 0.402      |
| 26  | 0.333  | 0.347      | 51  | 0.454  | 0.452      |

Table 3. Prediction results from the testing set.

| Day | Actual | Prediction |
|-----|--------|------------|
| 14  | 0.408  | 0.389      |
| 21  | 0.283  | 0.288      |
| 27  | 0.317  | 0.354      |
| 28  | 0.289  | 0.328      |
| 29  | 0.261  | 0.329      |
| 33  | 0.328  | 0.329      |
| 34  | 0.346  | 0.350      |
| 45  | 0.411  | 0.385      |
| 47  | 0.322  | 0.352      |

The first number in the architecture shows the total input, the second number shows the total nodes used, and the third number shows the total output. Based on Table 1, the minimum value of RMSE was chosen to find the predicted results of the models that have been trained showed and the result of prediction from the training set shows in Table 2. The prediction showed that almost approaching the actual result and the prediction result of the testing set can be seen in Table 3. The coefficient of determination of the training prediction is 0.987. The number shows a very strong interpretation. The test data used to evaluate the performance of the model is 4-7-1 network architecture. The R² value of the model evaluation was 0.728. The result shows a strong interpretation. It shows that the prediction performance of lettuces height is quite good.

3.3. Model validation of artificial neural networks

The validation process is used to determine the performance from the weight of the training result on new data and to find the accuracy from predicted results. RMSE results in 4-7-1 network architecture from the testing stage is 0.032. The result was classified as a very good category. RMSE results are
influenced by total nodes used in the hidden layers. Adding the number of nodes in the hidden layers can increase the convergence effect and reduce tissue errors. However, the over nodes addition can make the speed of convergence become slower and the network training time increases.

4. Conclusions
The developed model of the artificial neural networks with resilient backpropagation method using the 4-7-1 network architecture generated the best model. This network architecture showed coefficient determination $R^2$ prediction and actual training data is 0.987 and $R^2$ test data is 0.728. Besides, the most critical environmental factor that affected lettuce growth was nutrient. The validation results with the RMSE method show that the 4-7-1 network architecture was capable of estimating the lettuces height.

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