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Photosynthetic Rate Prediction Model of Golden Melon Plant (*Cucumis melo* L.) at Vegetative Phase in Greenhouse using Artificial Neural Networks

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ABSTRACT

The most critical parameter affecting plant growth is the photosynthetic rate. The parameter can be determined by measuring the rate of CO_2 assimilation that occurs in plants. Developing a photosynthetic rate model can recommend proper cultivation maintenance in melon plants. Hence, the involvement of input parameters in the developed model affects the accuracy of the prediction. This study aims to develop an artificial neural networks (ANNs) prediction model of the photosynthetic rate of melon plants in the vegetative phase in the greenhouse based on seven environmental and growth parameters and find the best model structure. Model development uses artificial neural networks with several stages: data collection and pre-processing, model development with different input variations, model validation, and selection of the best scenario to predict photosynthetic rate. The results showed that five out of seven input parameters, i.e., air temperature, sunlight intensity, CO_2 concentration, air humidity, and plant rows, in the model structure of five inputs, six hidden and one output were the best model scenarios with coefficient of determination (R^2) and root mean square error (RMSE) of 0.986 and 0.420, respectively.

1. Introduction

Indonesia produced 129,147 tons of melons (*Cucumis melo* L.) in 2021, slightly decreasing from its previous production of 138,177 tons in 2020 (BPS 2021). Open field cultivation supplies most of Indonesia's melons but is limited by disease pressure and environmental factors such as high rainfall intensity, heat, and strong winds. A suitable environment for a plant could optimize its growth, while the environment itself could be managed using a greenhouse (Suhardiyanto 2009; Yuwono *et al.* 2014). One of the essential processes in plant growth is photosynthesis during the vegetative and generative phases, as it affects the development of roots, leaves, and stems and the formation and development of flowers, fruits, and seeds (Arbaul Fauziah 2021). Good plant management in the vegetative phase greatly influences the success of growth and productivity in the generative phase so that the quality of fruit is maximized, including melon fruit.

Cultivation of melon in the greenhouse could improve production by providing control of environmental factors, i.e., air temperature, light intensity, carbon dioxide (CO_2) concentration, and relative humidity. Each parameter affects the plant's photosynthetic rate, indicating plant growth (Proklamaningsih *et al.* 2013; Kaiser *et al.* 2017). Photosynthesis is an essential plant metabolic pathway, contributing to growth and biomass production (Calzadilla *et al.* 2022). The photosynthetic rate can be determined by measuring the rate of CO_2 assimilation (Greer 2018). Plant growth is a direct expression of biomass production, driven by photosynthesis, primarily dependent on light, water, and nutrients. Improvements in photosynthetic processes have allowed the development of highly productive agricultural systems (Ribou *et al.* 2013). Photosynthesis is

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influenced by genetic factors, including species, leaf age, and translocation rates, as well as environmental factors, including water availability, CO_2 availability, light, air temperature, and nutrient availability (Trouwborst *et al.* 2011; Ippoliti *et al.* 2016; Fu *et al.* 2017; Zhou *et al.* 2019). Air temperature affects the rate of photosynthesis and other plant physiological parameters (Setyanti *et al.* 2013). Light is the primary energy source for photosynthesis, so light intensity significantly affects the photosynthetic efficiency of plants (Susilawati *et al.* 2016; Yustiningsih 2019). Air humidity is closely related to air temperature and photosynthesis, while an increase in CO_2 partial pressure causes the photosynthetic rate to increase (Kooijmans *et al.* 2019). Another parameter that is not directly related to the model output but can be involved in improving the quality of the prediction model is the plant row position. Setting the appropriate parameter can have an impact on the amount of light that melon plants will receive for photosynthesis needs.

A model estimating the photosynthetic rate in melon plants based on environmental parameters that can be measured directly (i.e., air temperature, light intensity, CO_2 concentration, and relative humidity) would benefit indoor growers by allowing them to adjust these parameters to optimize the photosynthetic rate. Photosynthetic rate models on plant growth cultivated in greenhouses have been carried out by Jung *et al.* and Lenny *et al.* on lettuce plants, and Zhang P *et al.* on cucumber plants, using artificial neural networks (Jung *et al.* 2016; Lenny *et al.* 2020; Zhang *et al.* 2020a). Existing photosynthetic rate models are quite informative for controlling microenvironmental parameters. However, specifically for melon crops, developing a prediction model for the photosynthetic rate of melon crops has yet to be widely done. A good understanding of the factors that affect photosynthetic rates can be used to improve the management of melon plants in the greenhouse.

This research aimed to build a prediction model of the golden melon plant's photosynthetic rate at a greenhouse's vegetative phase using artificial neural networks (ANNs) involving several environmental parameters related to changes in photosynthetic rate.

2. Materials and Methods

A photosynthetic rate prediction model using ANNs was developed to cultivate melon plants at the vegetative phase. A neural network was used to model the photosynthetic rate because of the ability of ANNs to explain the relationship between these and other parameters inside the greenhouse (Ouyang *et al.* 2020). Some researchers have used prediction model techniques in different aspects of plant management, particularly for predicting total yield (Naroui Rad *et al.* 2015; Ghasemi-Varnamkhasti *et al.* 2018; Niazian *et al.* 2018). The development of the photosynthetic rate prediction model using ANNs follows the stages (Graupe 2019; Malekian and Chitsaz 2021), as shown in Figure 1.

2.1. Data Collection

Plant and environmental data to develop the prediction model were taken on November 23, 2020 (26 days after planting), in an 8 m × 24 m arch-type greenhouse located at the Siswadhi Soepardjo Field Laboratory, Department of Mechanical Engineering and Biosystems, Faculty of Agricultural Technology, IPB University. Figure 2 shows that hydroponic melon cultivation was automatically controlled using an evaporative cooling and drip irrigation system. Drip irrigation, using a pump, delivered water and nutrients from a nutrient tank to the growing media. Nutrient concentrations and pH values were controlled using an automatic control system.

Melon plants were configured on five rows of plants with a distance between rows of plants 50 cm, while in each row, there were two plants with a distance of 30 cm. Plants were cultivated with planting media of cocopeat and rice husks combination at a 3:1 ratio. The melon seeds used in this experiment were Golden Luna (F1). During the experiment, air temperature, relative humidity, and sunlight intensity were observed using a sensor installed inside the greenhouse.

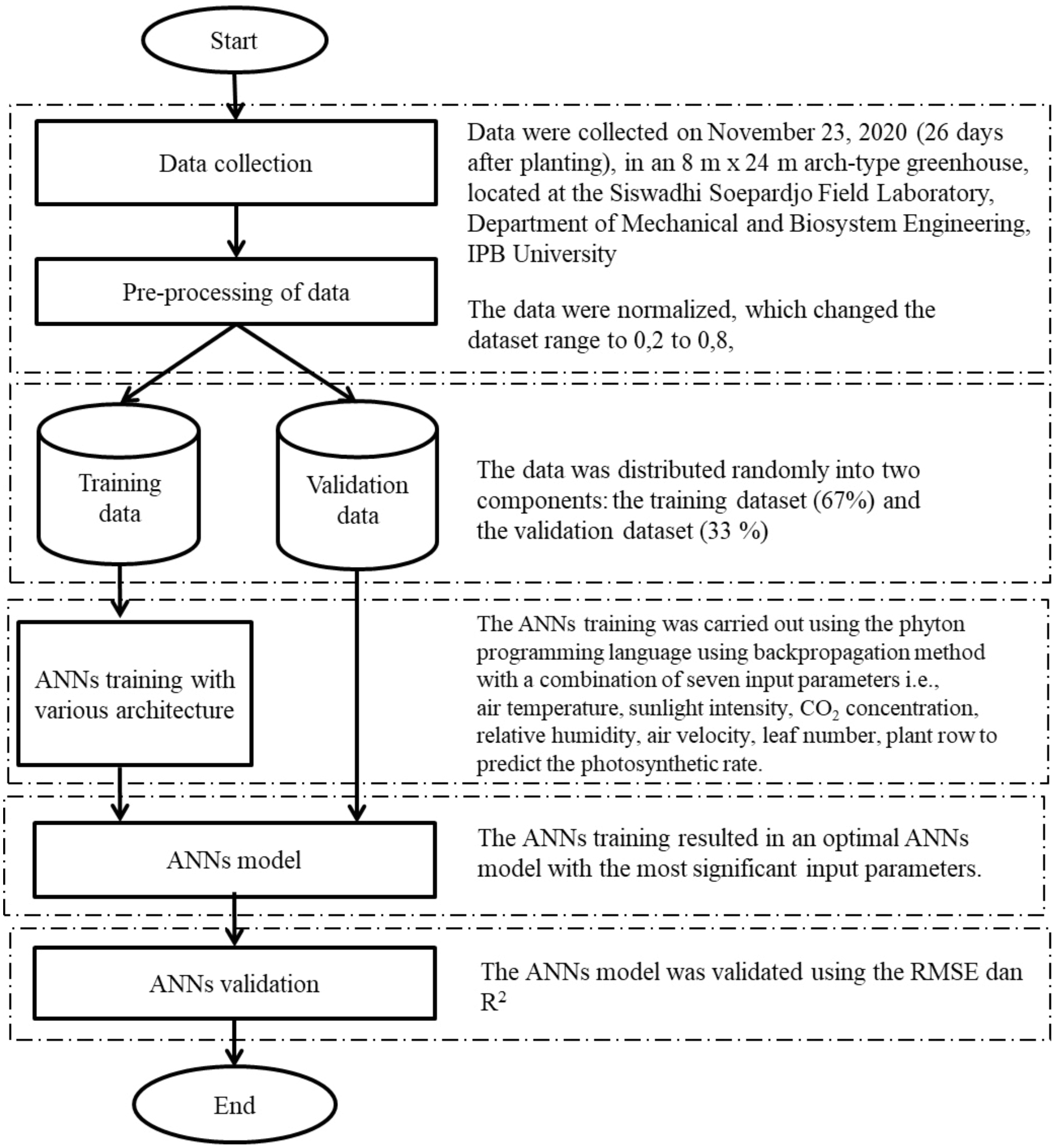


Figure 1. ANNs model development process for the photosynthetic rate prediction of vegetative melon plants in the greenhouse

The plants used to observe the photosynthetic rate were 75, randomly selected from a population of 400 plants cultivated in the greenhouse. The photosynthetic rate (CO_2 assimilation rate) was measured using a portable photosynthetic instrument (LI-COR) with LI-6800 type on selected leaf samples, namely between the 12th leaf to the 15th leaf from the first leaf branch to grow on melon plants. The leaf samples were selected from leaves in the middle, the outermost leaves, and leaves facing upward and not shaded by other leaves on the same stem to have the full photosynthetic ability (Zakiyah *et al.* 2018). Other environmental parameters were measured using a sensor installed inside the greenhouse, i.e., air temperature, air relative humidity, sunlight intensity, air velocity, and CO_2 concentration. Figure 3 shows a photosynthetic rate measurement process with LI-6800 as a measuring instrument.

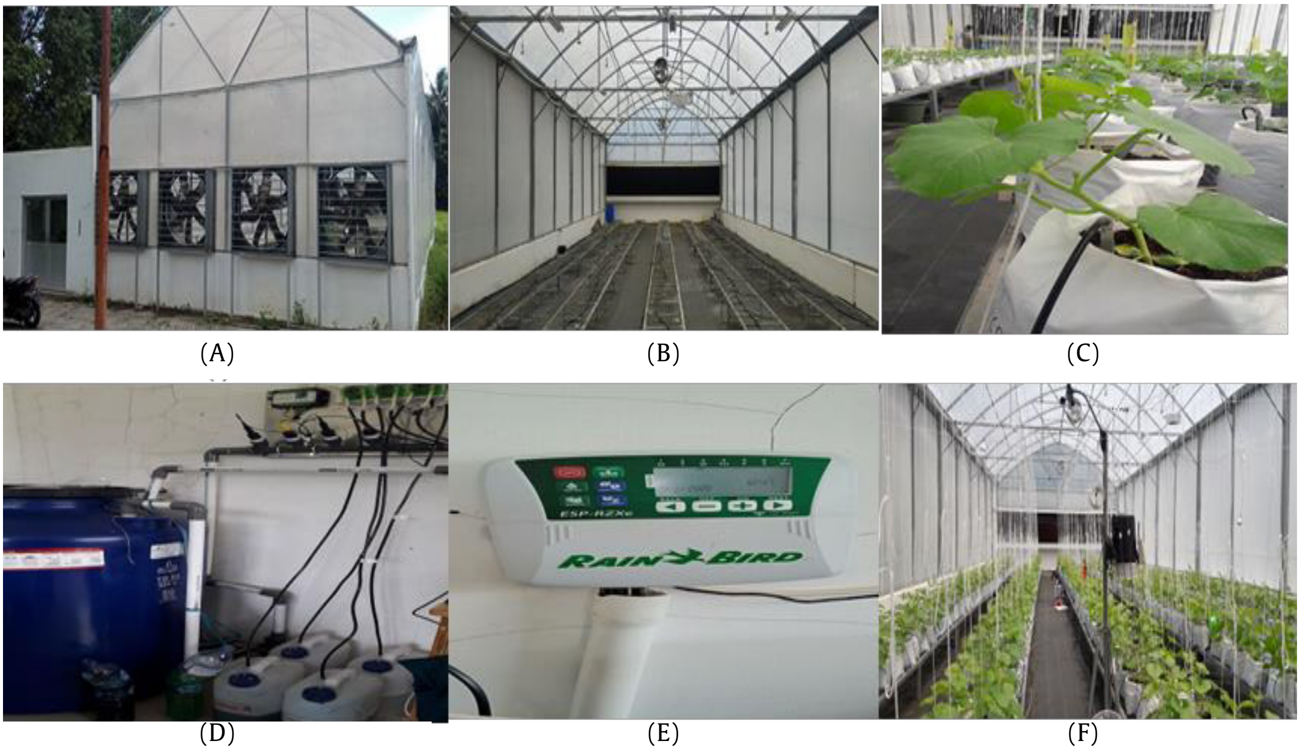


Figure 2. Hydroponic melon cultivation location: (A) Arch type greenhouse 8 m × 24 m, (B) greenhouse environment, (C) drip irrigation system, (D) dosing control system, (E) nutrient solution distribution control, and (F) hydroponic installation

Figure 3. Photosynthetic rate measurement process: (A) LI- 6800 as measuring instrument, (B) chambers LI-6800; (C) melon plant sample leaf

2.2. Pre-processing Data

The collected data were tabulated, cleaned, and normalized to produce a dataset format ready to be trained in the learning process. The pre-processing stage was conducted to prepare the best dataset, allowing the ANNs to learn more efficiently and produce accurate results. The 1108 datasets generated in this stage were divided into two groups, 67% for training and 33% for validation. The data were then normalized to a value range of 0.2 to 0.8. Normalization was done to standardize the input variable values scale and avoid the dominance of variables with a more extensive range of values that can interfere with the learning process. Examples of data pre-processing results of environmental parameters and photosynthetic rates for melon cultivation in the greenhouse are given in Table 1.

2.3. ANNs Development Model with Inputs Variation Scenarios

The photosynthetic rate prediction model was built using the Python programming language using a backpropagation method, and the following ANNs parameters, such as learning rate, momentum, learning rate initial, and iteration, as given in Table 2. Backpropagation-type ANNs are based on the ability of the algorithm to minimize prediction errors by repeatedly repropagating those errors from the output layer to the input layer (Mouloodi *et al.* 2022). ANNs backpropagation starts its training process with a forward propagation (Dragović 2022), then propagates the signals from the seven input parameters to predict the photosynthetic rate. Based on the ANNs parameters, the model is trained by trial and error using the normalized training dataset on the input-hidden-output structure. The iteration process will end when it has found the ANNs structure with the lowest error.

Table 1. Example of normalized environmental parameter data pre-processing results in the range of 0.2 to 0.8

Internal air temperature	Air relative humidity	sunlight intensity	Photosynthetic rate
0.35	0.45	0.30	0.40
0.55	0.35	0.60	0.60
0.75	0.30	0.70	0.65
0.30	0.60	0.35	0.35
0.80	0.25	0.80	0.75
0.20	0.80	0.20	0.25
0.85	0.27	0.85	0.80
0.45	0.50	0.45	0.50
0.60	0.40	0.55	0.55
0.40	0.55	0.40	0.45

Table 2. ANNs parameters used in model development

Parameter	Unit
Hidden Layer	1–10
Activation Function	logistic
Solver Stochastic Gradient	Descent
Momentum	0.1-0.9
Learning Rate	Constant
Learning Rate Initial	0.1–0.9
Maximum Iteration	10,000
Random state	Initial weights and biases

The best-structured model in this study was sought through five scenarios based on the number and type of input parameters. The five scenarios include scenario A with three parameters, i.e., air temperature, sunlight intensity, CO_2 concentration; scenario B with four parameters, i.e., air temperature, sunlight intensity, CO_2 concentration, relative humidity, scenarios C, D, and E, each with five parameters, but one of them is given a difference, i.e., air velocity as the last parameter in C, leaf number as the last parameter in D and plant row as the last parameter in E, respectively. The best ANNs model formed by the best combination of inputs was indicated by the higher R^2 value and the lower RMSE values (Supriyanto *et al.* 2019, Zhang *et al.* 2020b), indicated by the coefficient of determination and Root Mean Square Error as in equations 1 and 2. (Sushmi and Subbulekshmi 2022).

$$R^2 = 1 - \left(\sum_i^n (T_i - Y_i)^2 \Big/ \sum_i^n (T_r - T_i)^2\right) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_i^n (T_i - Y_i)^2} \quad (2)$$

Where:

T_i = measurement result for the i-th dataset
Y_i = prediction result for the i-th dataset
T_r = average measurement results
N = quantity of validation data

2.4. Validation of Model

Validation is the process of evaluating the performance of a model that has been trained using validation data (data that has never been used before) to ensure that the model can generalize well to unknown data. If the model can generalize well, then the performance of the model will also be confirmed. The performance indicators still use equations 1 and 2.

3. Results

3.1. Microenvironmental Data Conditions

Table 3 shows the microenvironmental parameters inside and outside the greenhouse and the growth parameter of melon cultivated in the greenhouse. The sunlight intensity ranged from 118 to 411 Wm^{-2}, with very low air velocity inside the greenhouse (0.0 to 0.9 ms^{-1}). The CO_2 concentration ranged from 370 to 395 ppm, and the photosynthetic rate ranged from 2.45 to 17.39 μmol m^{-2} s^{-1}.

The highest standard deviation to the mean value of the parameters occurred in light intensity at 76.97, while the lowest standard deviation occurred in air velocity at 0.18. The higher the standard deviation value, the more dispersed the light in the plant house is from the mean value or more volatile than the other parameters. Eight environmental and growth parameters were measured, showing that each parameter changed quite volatile except for air velocity and temperature inside the greenhouse.

3.2. Photosynthetic Rate Model

One thousand one hundred and eight collected datasets were used to develop the photosynthetic rate model with many parameters, such as momentum, learning rate, and hidden layers, to identify the model structure model that produced the best prediction output. The model was trained by modifying the weights and biases with 10,000 maximum iterations for each combination. Each combination's applied learning rate and momentum were 0.8 and 0.6, respectively. The modeling phase developed five scenarios for predicting photosynthetic rates to compare with measured photosynthetic rates. The parameters used for photosynthetic rate prediction are based on parameters easily measured with standard devices in the greenhouse. Then, based on previous research, those parameters with a strong relationship with photosynthetic rate were selected. One of the best-performing structures for photosynthetic rate with three inputs is shown in Figure 4.

The best performance of the photosynthetic rate prediction model for three input parameters was obtained at the number of hidden layers 5, with R^2 and RMSE of 0.9881 and 0.464, respectively. The measured photosynthetic rate was strongly correlated with the predicted results, indicating that the developed ANNs can predict the photosynthetic rate of melon crops using measured environmental conditions. The linear equation obtained in the model scenario also shows that the predicted photosynthetic rate is 0.09 mol^{-2} s^{-1} lower than the actual photosynthetic rate. A summary of the performance of the five prediction model development scenarios is presented in Table 4.

Scenario A has three input parameters, i.e., air temperature, sunlight intensity, and CO_2 concentration. The models in scenario A had lower errors in the 3-5-1 ANNs structure (3 input-5 neuron hidden-1 output) with an R^2 value of 0.981 and an RMSE value of 0.464. In the second scenario (scenario B), the relative humidity parameter was added, so the model was developed using four inputs, i.e., air temperature, sunlight intensity, CO_2 concentration, and relative humidity. The models have lower errors in the 4-6-1 ANNs structure with an R^2 value of 0.979 and an RMSE value of 0.492.

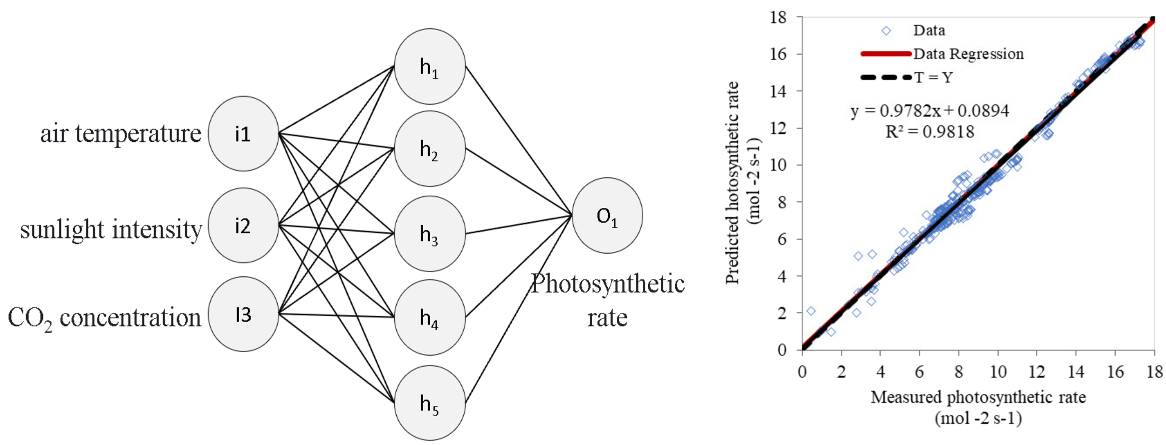
In the third scenario (scenario C), the air velocity parameter is added to form five input parameters, i.e., air temperature, sunlight intensity, CO_2 concentration, relative humidity, and air velocity. The models in these scenarios had a lower error in the 5-6-1 ANNs structure with R^2 and RMSE values of 0.983 and 0.459, respectively. In the fourth scenario (scenario D), with one parameter added, there are five input parameters, i.e., air temperature, sunlight intensity, CO_2 concentration, relative humidity, and leaf number. The models in these scenarios had a lower error in the 5-6-1 ANNs structure with R^2 values of 0.982 and RMSE values of 0.488, respectively. In the fifth scenario (scenario E), with one parameter added, there are five input parameters, i.e., air temperature, sunlight intensity, CO_2 concentration, relative humidity, and plant row. The models in these scenarios had a lower error in the 5-6-1 ANNs structure with R^2 values of 0.986 and RMSE values of 0.420, respectively. Scenario E is the best model, indicated by the largest R^2 value and the smallest RMSE. The structure model and relationship between the predicted photosynthetic rate and the actual value are given in Figure 5.

4. Discussion

Scenario E is the best scenario to predict the photosynthetic rate in melon plants in the vegetative phase using five existing parameters, i.e., air temperature, sunlight intensity, CO_2 concentration,

Table 3. Descriptive statistical analysis of greenhouse environmental parameters

	Parameters	Unit	Min	Max	Mean	SD
Input	Air temperature	°C	25.4	27.8	26.66	0.64
	Sunlight intensity	Wm^{-2}	118.0	411.0	213.48	76.97
	CO_2 concentration	ppm	370.0	395.0	381.77	5.11
	Relative humidity	%	88.0	95.0	91.07	1.95
	Air velocity	$m\ s^{-1}$	0.0	0.9	0.06	0.18
	Leaf number		10.0	18.0	14.00	1.62
	Plant row		1.0	5.0	3.00	1.38
Output	Photosynthetic rate	$\mu mol\ m^{-2}\ s^{-1}$	2.45	17.39	9.23	3.52

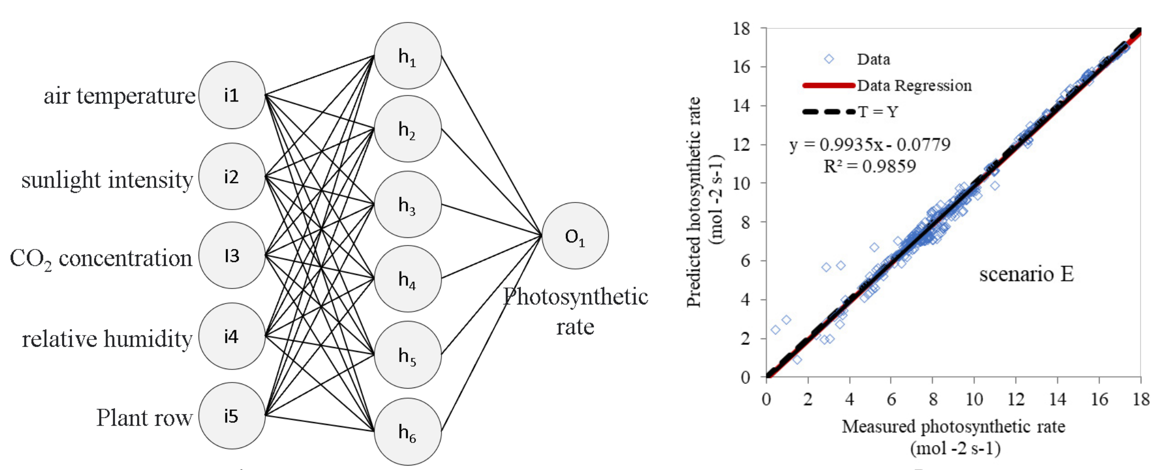


A B

Figure 4. One of the ANNs model structures with three input parameters (A) model structure, (B) model performance

Table 4. Summary of model performance for each scenario in the ANNs backpropagation model

Scenario	Input parameter	ANNs structure	R^2	RMSE
A	air temperature, sunlight intensity, CO_2 concentration	3-5-1	0.981	0.464
B	air temperature, sunlight intensity, CO_2 concentration, relative humidity	4-6-1	0.979	0.492
C	air temperature, sunlight intensity, CO_2 concentration, relative humidity, air velocity	5-6-1	0.983	0.459
D	air temperature, sunlight intensity, CO_2 concentration, relative humidity, leaf number	5-6-1	0.982	0.488
E	air temperature, sunlight intensity, CO_2 concentration, relative humidity, plant row	5-6-1	0.985	0.420



A B

Figure 5. Comparison between measured and predicted melon photosynthetic rates using five input parameters, i.e., air temperature, sunlight intensity, CO_2 concentration, relative humidity, and plant row

relative humidity, and plant rows. Compared to the previous scenario, adding the plant row parameter has a more performance-enhancing effect than adding the number of leaves and air velocity parameters. With the addition of plant rows, the four input parameters have a more substantial influence on photosynthetic rate activity. Therefore, these five parameters may be considered in melon cultivation because they strongly affect the quality of the photosynthetic rate and the growth of melon plants.

The model obtained an R^2 value above 0.9, so the ANNs model can predict the photosynthetic rate of melon plants well. Photosynthesis is one of the most important metabolic processes closely related to plant physiological changes (Sudjatha and Wisaniyasa 2017). Accordingly, photosynthesis is a plant metabolic process to form carbohydrates that affect plant growth factors. It was noted that the model with a 5-6-1 structure can support the best metabolic processes in melon plants, which affect growth-promoting hormones and growth-inhibiting hormones (Khairuna 2019). In scenario E, the parameters that strongly influence the prediction of photosynthetic rate are air temperature, sunlight intensity, CO_2 concentration, relative humidity, and plant row. Air temperature affects enzyme activity and reaction rates in photosynthesis, where the optimal air temperature for melon vegetative growth is 20 to 30°C, while in the generative period, it is around 25°C (Prajnanta 1997). Lack of sunlight will affect the photosynthetic rate of a plant (Samadi 2007); as a C3 plant, melon plants have low photosynthetic efficiency, so they need sunlight that ranges from 10 to 12 hours per day. Higher CO_2 concentrations in the air around melon plants can increase the rate of photosynthesis, while relative humidity affects the rate of transpiration and gas exchange in the leaves.

The recommendation given is the value range of each parameter strongly influencing the photosynthetic rate, for example, air temperature ranging from 25.4 to 27.8°C and other parameters, as in Table 1. Adjustment of these value ranges during the cultivation process was able to predict the photosynthesis rate well, resulting in energy for improved growth and better productivity. The development of the photosynthetic rate model is expected to provide implications for melon cultivators to understand the effects of environmental parameters on plant photosynthetic rates. By understanding the parameters of photosynthetic rate, cultivators can predict how changes in environmental parameters will affect the productivity of melon plants.

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