Deep neural network for maximizing output power estimation of dual-axis solar tracker

Humairoh Ratu Ayu, Rifki Mohamad Kurniawansyah, Aqua Risma Diansari
Department of Physics, Faculty of Mathematics and Natural Sciences, University of Lampung, Bandar Lampung, Indonesia

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ABSTRACT

The abundance of solar energy sources has encouraged many researchers to maximize solar photovoltaic (PV) output power using dual-axis solar tracking. However, environmental conditions, time of day, and the angle of movement of the solar tracker can affect the resulting power output. This study aims to predict the power output of dual-axis solar tracking in order to maintain the power's stability and quality. Deep neural networks (DNN) with variations of 5 and 6 hidden layers have been proposed. The dataset used in this study was obtained from observation results and then divided into 80% training data and 20% testing data. A series of algorithms are used to recognize relationship patterns between input and hidden layers, between hidden layers, as well as hidden layers and output. Statistical results show that DNN with a variation of 6 hidden layers is better at estimating solar tracking power output with a mean absolute percentage error (MAPE) value of 12.328%, mean square error (MSE) of 0.332, and mean absolute error (MAE) of 0.425. This study can be used as a reference in utilizing artificial intelligence to predict the output power of solar panels as a renewable energy source.

Corresponding Author:

Humairoh Ratu Ayu
Department of Physics, Faculty of Mathematics and Natural Sciences, University of Lampung
Bandar Lampung, Indonesia
Email: humairoh.ratu@fmipa.unila.ac.id

1. INTRODUCTION

Solar resources are a renewable energy source that is abundant, easy to utilize, and environmentally friendly [1]. The availability of solar energy sources is still being determined due to changes in the sun's position, so the solar cells' output power is not optimal. Increasing the output power of solar panels can be done with static systems with fixed angles [2] and single-axis [3]–[5] or dual-axis [6]–[9] solar trackers. The most effective way to increase solar cell energy is to use dual-axis solar tracking by 25.5% while single-axis is only 16.5% compared to a fixed system [10]. Environmental conditions also affect the power output produced, such as the intensity of solar radiation and environmental temperature. When the weather is cloudy, the radiation intensity will decrease, and the temperature will be low, reducing the required electricity supply [11]. The main thing that must be done is to predict the output power of solar cells [12] to maintain the stability and quality of the power produced [1].

Research related to forecasting photovoltaic (PV) output power based on computational intelligence algorithms has been widely carried out; several researchers use the artificial neural network (ANN) method to predict current solar radiation, short-term and long-term predictions [13], ANN with input namely meteorological conditions, climate, and radiometric, including wind speed and relative humidity as well as output in the form of local solar panel energy output [14], input in the form of weather conditions and PV module characteristics [15], input in the form of environmental factors such as irradiance (G), temperature (T), humidity (H), wind speed (W) [11], input based on environmental factors [16]. Feed-forward back propagation neural network (FBANN) [17]. Support vector machine (SVM) [18], long short-term memory (LSTM) [19], support vector machine regression (SVMR) [20], recurrent neural network (RNN) [21], fuzzy regression (FR) [22], particle swarm optimization (PSO-Fuzzy) [1], and PSO-adaptive neuro fuzzy inference system (ANFIS) [23]. Among the computational methodologies used, ANN is a superior method in predicting solar cell power output compared to fuzzy logic [24] and multiple linear regression [25]. Based on this explanation, ANN is considered more effective in predicting the output power of solar panels. However, no research has predicted the power output of dual-axis solar tracking using a deep neural network (DNN) with input parameters of time, tilt angle, solar radiation intensity and environmental temperature. This paper analyses the impact of hidden layers variation in DNN model to reach the best performance based on historical data.

DNN have shown remarkable capabilities in various tasks, including perception-related ones such as image and speech recognition [26]. These models can learn increasingly abstract, higher-level representations of the input data, and have been successfully applied to medicine and health care [27]. One of the critical architectural advantages of deep learning is the use of many hidden neurons and layers, typically more than two, which allows for extensive coverage of the raw data at hand [28]. Nevertheless, the determination of the optimal number of hidden layers is a crucial aspect in the design of DNN models, as it directly impacts their performance and generalization capabilities.

2. METHOD

2.1. Architecture of deep neural network

The method applied in this paper to predict the output power of a dual-axis solar tracker is an ANN with many hidden layers, also called a DNN. There is a training process carried out to produce the desired output. The training process uses a series of algorithms to recognize relationship patterns between input and hidden layers as in (1), hidden layer 1 to the next hidden layer as in (2), and hidden layer to output as in (3) [29]. In the final stage, the neuron applies a transfer function to obtain output [14]. Therefore, the performance of DNN depends on the work of neurons [11]. The developed DNN architecture is shown in Figure 1.

$$\bar{h}_1 = \Phi(W_1^T \bar{x}) \quad (1)$$

$$\bar{h}_{p+1} = \Phi\left(W_{p+1}^T \bar{h}_p\right) \forall p \in \{1 \ldots k-1\} \quad (2)$$

$$\bar{y} = \Phi\left(W_{k+1}^T \bar{h}_k\right) \quad (3)$$

Where $\bar{h}_1$ is the first hidden layer, W is the weight, Φ is the activation function, and $\bar{y}$ is the output.

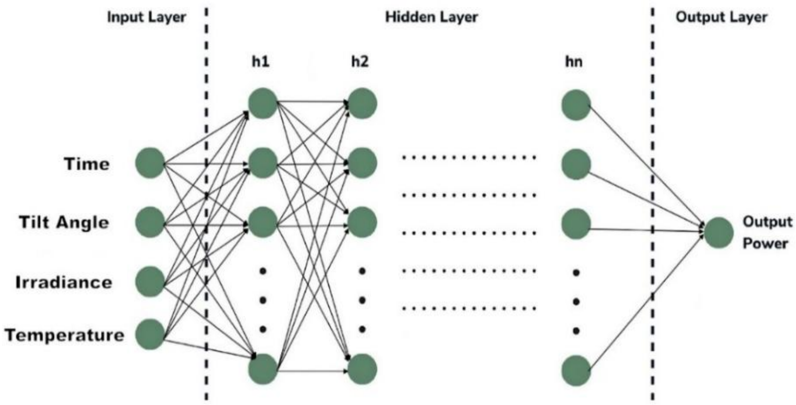


Figure 1. Architecture of DNN

The activation function functions to receive and send signals between layers [15]. Several activation functions are often used, namely Tanh, Linear, and rectified linear unit (ReLu), but the ReLu activation function provides the best results among the two [14]. Determining the number of neurons in the hidden layer is based on trial and error, because there is no mathematical equation that can determine the number of neurons in a layer [15].

2.2. Data collection

The dataset used in this research was obtained from observations made from 08.30 to 16.30. Time parameters are divided into two categories, namely am and pm. Temperature (°C) is the environmental temperature measured during observations as well as the radiation parameter (W/m^2). Meanwhile, the tilt angle (°) is the angle of movement of the solar tracking which is measured at a certain time during the observation [30]. Before the training process, the dataset is divided into 80% training data and 20% testing data. The algorithm will take data periodically from all datasets in the training process using the Adamax optimizer with 100 epochs.

2.3. Test performance of model

Mean square error (MSE) is used to measure the average squared error to minimize the error as in (4) [31].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y - \bar{y}_i)^2 \quad (4)$$

With y is actual data and n representing the total number of samples. The mean absolute error (MAE) is the average of the absolute error value of actual data and the predicted value as in (5) [31].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y - \bar{y}_i| \quad (5)$$

Mean absolute percentage error (MAPE) aims to measure the level of model accuracy by calculating the absolute difference between actual data and predicted values, then dividing it by the actual value, then multiplying by 100 to express it as a percentage as in (6) [31].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y-\bar{y}_i}{y}\right| x100 \quad (6)$$

3. RESULTS AND DISCUSSION

The main objective of this research is to develop a DNN model by comparing 5 hidden layers, and 6 hidden layers to predict the output power of a dual-axis solar tracker with the input parameters of time, tilt angle, solar radiation intensity, and environmental temperature. Table 1 shows the performance of the DNN model used with various hidden layers in the training and testing process. Based on Table 1, it can be seen that both predictors track actual data and can be used for estimation, but the DNN model with 6 hidden layers have the best performance compared to 5 hidden layers. The best performance is the DNN model with 5 hidden layers at the 95th epoch with a loss (MSE) of around 0.9626 and 0.3213 for 6 hidden layers at the 89th epoch. This is because each layer builds on the features extracted by the previous layer, allowing the model to understand and represent complex patterns and structures in the data.

Table 1. Performa DNN model with a variety of hidden layer

Hidden layers	Training			Testing		
	MAPE (%)	MSE	MAE	MAPE (%)	MSE	MAE
5	33.228	1.309	0.891	42.553	1.001	0.776
6	19.417	0.595	0.586	12.328	0.332	0.425

The performance of the model developed in the training and testing process is shown in Figure 2, with matrix performance in Figures 2(a) to 2(f). Meanwhile, the comparison of actual data with predicted data for the two models is shown in Figure 3, with 5 hidden layers in Figure 3(a) and 6 hidden layers in Figure 3(b). The results clearly show that the DNN algorithm may be used to estimate the output power of PV modules. The following provides a succinct and understandable summary of the outcomes of trained DNN mapping predictors to continuous responses. It is important to highlight from the above results that testing and validity dates were not conducted on the training dataset.

From the Figure 3, we can see that there is still a significant inaccuracy in predicting the output power of the solar tracker on the 1st, 6th, 7th, 19th, and 21st test data using DNN with 5 hidden layers; the resulting prediction results are lower than the actual data. Otherwise, on the 3rd, 11th, and 14th test data, the

DNN model with 5 hidden layers predicts higher results than the actual data. Meanwhile, the performance of the DNN model with 6 hidden layers can better predict the solar tracker's output power. This is because the more hidden layers can produce higher accuracy [15].

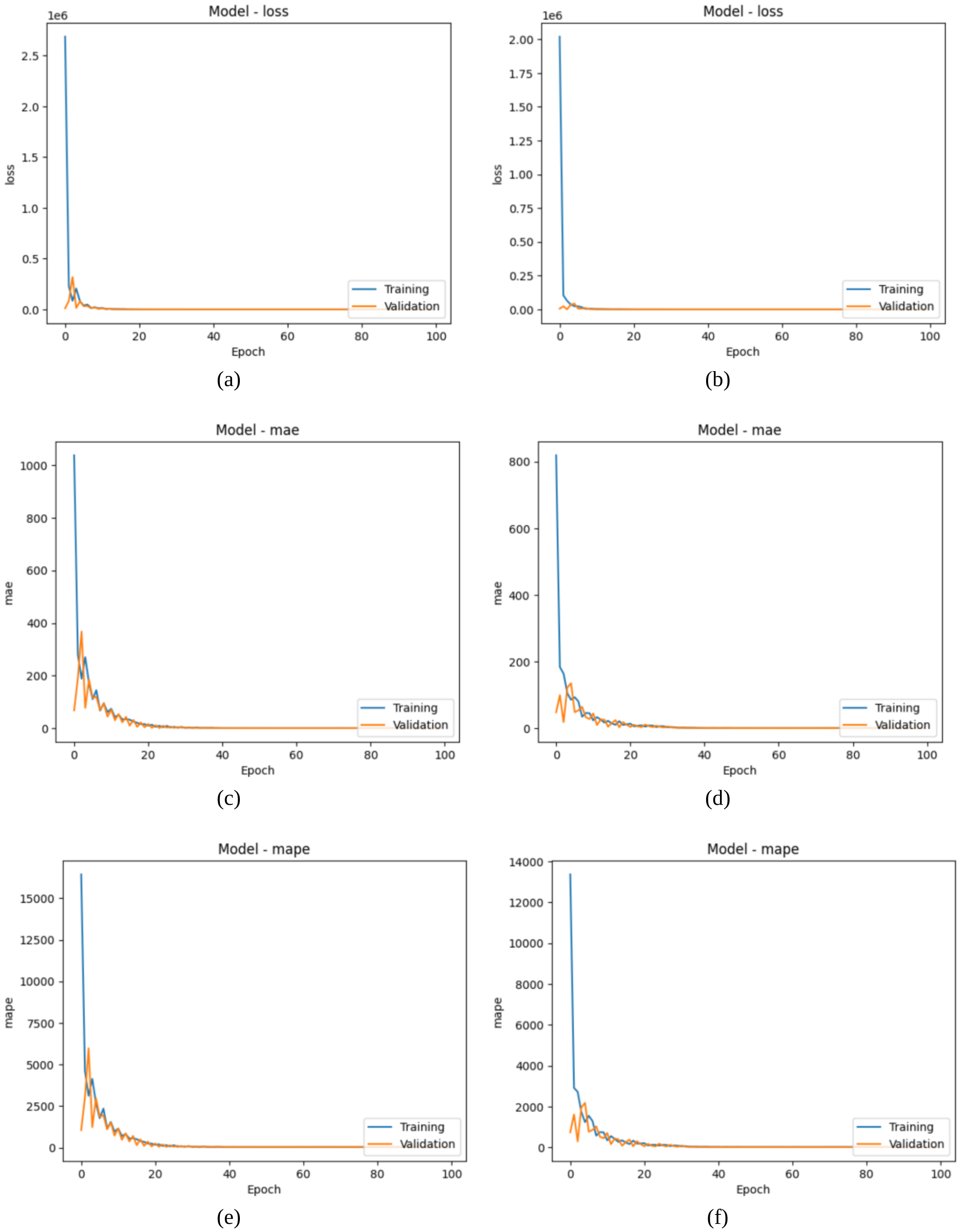
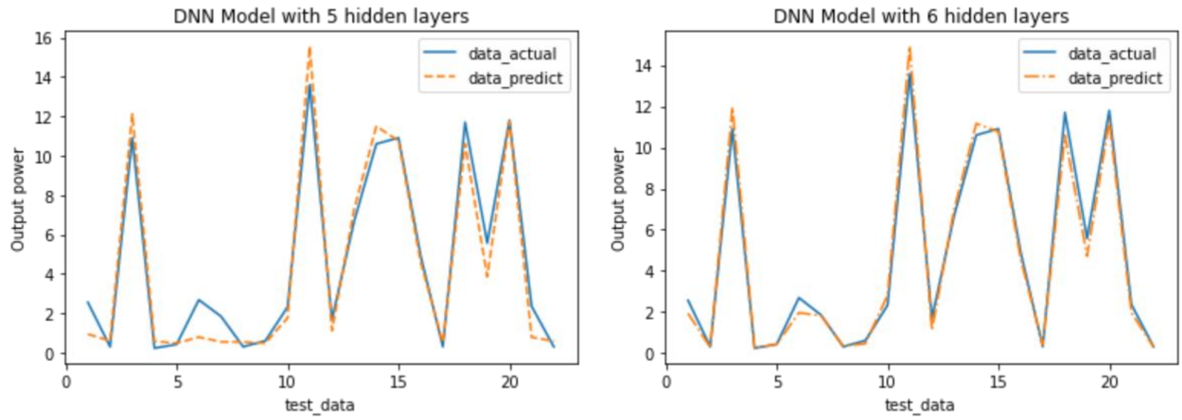


Figure 2. Training and testing process of (a) loss (MSE) value for 5 hidden layers, (b) loss (MSE) value for 6 hidden layers, (c) MAE for 5 hidden layers, (d) MAE for 6 hidden layers, (e) MAPE for 5 hidden layers, and (f) MAPE for 6 hidden layers



(a) (b)

Figure 3. Comparison between actual data with predicted data for both models of (a) 5 hidden layers and (b) 6 hidden layers

4. CONCLUSION

The main goal of the current study was to optimize the power output of a dual-axis solar tracker. These experiments confirmed that a DNN model was successfully trained with hidden layer variations. The current data highlight the importance of the number of hidden layers. The accuracy of DNN with 6 hidden layers have better model performance in the testing process with a MAPE value of 12.328%, MSE of 0.332, and MAE 0.425 compared to DNN with 5 hidden layers. This work contributes to the existing solar tracker power output forecasting knowledge by providing a predictive model that leverages historical data. By optimizing power output predictions, this research could support the development of more efficient and cost-effective solar tracking systems. This, in turn, can encourage wider adoption of solar energy as a more reliable energy source. The model’s performance may vary based on geographical location, sun path, and environmental factors not included in the training data. Testing the model in diverse locations could reveal limitations in generalizability.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Humairoh Ratu Ayu	✓	✓	✓	✓	✓			✓	✓	✓		✓	✓	✓
Rifki Mohamad Kurniawansyah		✓				✓	✓	✓		✓	✓			
Aqua Risma Diansari			✓	✓	✓		✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [H. R. A.], upon reasonable request.

REFERENCES

[1] D. M. Teferra, L. M. H. Ngoo, and G. N. Nyakoe, "Fuzzy-based prediction of solar PV and wind power generation for microgrid modeling using particle swarm optimization," *Heliyon*, vol. 9, no. 1, 2023, doi: 10.1016/j.heliyon.2023.e12802.

[2] I. B. K. Sugirianta, I. G. A. M. Sunaya, and I. G. N. A. D Saputra, "Optimization of tilt angle on-grid 300 Wp PV plant model at Bukit Jimbaran Bali," *Journal of Physics: Conference Series*, vol. 1450, no. 1, 2020, doi: 10.1088/1742-6596/1450/1/012135.

[3] A. Barbón, V. Carreira-Fontao, L. Bayón, and C. A. Silva, "Optimal design and cost analysis of single-axis tracking photovoltaic power plants," *Renewable Energy*, vol. 211, pp. 626–646, 2023, doi: 10.1016/j.renene.2023.04.110.

[4] M. Ghassoul, "Single axis automatic tracking system based on PILOT scheme to control the solar panel to optimize solar energy extraction," *Energy Reports*, vol. 4, pp. 520–527, 2018, doi: 10.1016/j.egyr.2018.07.001.

[5] N. Naval and J. M. Yusta, "Comparative assessment of different solar tracking systems in the optimal management of PV-operated pumping stations," *Renewable Energy*, vol. 200, pp. 931–941, 2022, doi: 10.1016/j.renene.2022.10.007.

[6] C. Jamroen, P. Komkum, S. Kohsri, W. Himananto, S. Panupintu, and S. Unkat, "A low-cost dual-axis solar tracking system based on digital logic design: design and implementation," *Sustainable Energy Technologies and Assessments*, vol. 37, 2020, doi: 10.1016/j.seta.2019.100618.

[7] A. Mansouri, F. Krim, and Z. Khouni, "Design of a prototypical dual-axis tracker solar panel controlled by geared DC servomotors," *Scientia Iranica*, vol. 25, no. 6D, pp. 3542–3558, 2018, doi: 10.24200/sci.2018.20045.

[8] P. Muthukumar, S. Manikandan, R. Muniraj, T. Jarin, and A. Sebi, "Energy efficient dual axis solar tracking system using IoT," *Measurement: Sensors*, vol. 28, 2023, doi: 10.1016/j.measen.2023.100825.

[9] E. K. Mpodi, Z. Tjiparuro, and O. Matsebe, "Review of dual axis solar tracking and development of its functional model," *Procedia Manufacturing*, vol. 35, pp. 580–588, 2019, doi: 10.1016/j.promfg.2019.05.082.

[10] O. R. Alomar, O. M. Ali, B. M. Ali, V. S. Qader, and O. M. Ali, "Energy, exergy, economical and environmental analysis of photovoltaic solar panel for fixed, single and dual axis tracking systems: an experimental and theoretical study," *Case Studies in Thermal Engineering*, vol. 51, 2023, doi: 10.1016/j.csite.2023.103635.

[11] M. A. Khan *et al.*, "Output power prediction of a photovoltaic module through artificial neural network," *IEEE Access*, vol. 10, pp. 116160–116166, 2022, doi: 10.1109/ACCESS.2022.3216384.

[12] M. R. Hossain, A. M. T. Oo, and A. B. M. S. Ali, "Hybrid prediction method of solar power using different computational intelligence algorithms," *2012 22nd Australasian Universities Power Engineering Conference: "Green Smart Grid Systems", AUPEC 2012*, 2012, doi: 10.4236/sgre.2013.41011.

[13] M. Bou-Rabee, S. A. Sulaiman, M. S. Saleh, and S. Marafi, "Using artificial neural networks to estimate solar radiation in Kuwait," *Renewable and Sustainable Energy Reviews*, vol. 72, pp. 434–438, 2017, doi: 10.1016/j.rser.2017.01.013.

[14] W. Zeng, "Artificial neural network modeling of solar photovoltaic panel energy output," *Journal of Future Sustainability*, vol. 4, no. 3, pp. 149–158, 2024, doi: 10.5267/j.jfs.2024.8.001.

[15] A. T. Mohammad, H. M. Hussen, and H. J. Akeiber, "Prediction of the output power of photovoltaic module using artificial neural networks model with optimizing the neurons number," *International Journal of Renewable Energy Development*, vol. 12, no. 3, pp. 478–487, 2023, doi: 10.14710/ijred.2023.49972.

[16] S. A. Jumaat, F. Crocker, M. H. A. Wahab, N. H. M. Radzi, and M. F. Othman, "Prediction of photovoltaic (PV) output using artificial neutral network (ANN) based on ambient factors," *Journal of Physics: Conference Series*, vol. 1049, no. 1, 2018, doi: 10.1088/1742-6596/1049/1/012088.

[17] B. Shboul *et al.*, "A new ANN model for hourly solar radiation and wind speed prediction: a case study over the north & south of the Arabian Peninsula," *Sustainable Energy Technologies and Assessments*, vol. 46, 2021, doi: 10.1016/j.seta.2021.101248.

[18] D. Nurwaha, "Using artificial intelligence techniques for prediction and estimation of photovoltaic system output power," *Journal of Modeling and Simulation of Materials*, vol. 3, no. 1, pp. 15–21, 2020, doi: 10.21467/jmsm.3.1.15-21.

[19] S. U. Sabareesh, K. S. N. Aravind, K. B. Chowdary, S. Syama, and V. S. K. Devi, "LSTM based 24 hours ahead forecasting of solar PV system for standalone household system," *Procedia Computer Science*, vol. 218, pp. 1304–1313, 2022, doi: 10.1016/j.procs.2023.01.109.

[20] A. K. Tripathi *et al.*, "Advancing solar PV panel power prediction: a comparative machine learning approach in fluctuating environmental conditions," *Case Studies in Thermal Engineering*, vol. 59, 2024, doi: 10.1016/j.csite.2024.104459.

[21] L. Fang and B. He, "A deep learning framework using multi-feature fusion recurrent neural networks for energy consumption forecasting," *Applied Energy*, vol. 348, 2023, doi: 10.1016/j.apenergy.2023.121563.

[22] S. F. Rafique, Z. Jianhua, R. Rafique, J. Guo, and I. Jamil, "Renewable generation (wind/solar) and load modeling through modified fuzzy prediction interval," *International Journal of Photoenergy*, vol. 2018, 2018, doi: 10.1155/2018/4178286.

[23] Y. K. Semero, D. Zheng, and J. Zhang, "A PSO-ANFIS based hybrid approach for short term PV power prediction in microgrids," *Electric Power Components and Systems*, vol. 46, no. 1, pp. 95–103, 2018, doi: 10.1080/15325008.2018.1433733.

[24] M. B. A. Shuvho, M. A. Chowdhury, S. Ahmed, and M. A. Kashem, "Prediction of solar irradiation and performance evaluation of grid connected solar 80 KWp PV plant in Bangladesh," *Energy Reports*, vol. 5, pp. 714–722, 2019, doi: 10.1016/j.egyr.2019.06.011.

[25] G. Sahin, G. Isik, and W. G. J. H. M. V. Sark, "Predictive modeling of PV solar power plant efficiency considering weather conditions: a comparative analysis of artificial neural networks and multiple linear regression," *Energy Reports*, vol. 10, pp. 2837–2849, 2023, doi: 10.1016/j.egyr.2023.09.097.

[26] A. Chowanda, I. A. Iswanto, and E. W. Andangsari, "Exploring deep learning algorithm to model emotions recognition from speech," *Procedia Computer Science*, vol. 216, pp. 706–713, 2022, doi: 10.1016/j.procs.2022.12.187.

[27] C. Chakraborty, M. Bhattacharya, S. Pal, and S. S. Lee, "From machine learning to deep learning: advances of the recent data-driven paradigm shift in medicine and healthcare," *Current Research in Biotechnology*, vol. 7, 2024, doi: 10.1016/j.crbiot.2023.100164.

[28] D. Ravi *et al.*, "Deep learning for health informatics," *IEEE Journal of Biomedical and Health Informatics*, vol. 21, no. 1, pp. 4–21, 2017, doi: 10.1109/JBHI.2016.2636665.

[29] C. C. Aggarwal, *Neural networks and deep learning*, Cham: Springer, 2018, doi: 10.1007/978-3-031-29642-0.

[30] H. R. Ayu, R. M. Kurniawansyah, A. Supriyanto, and Junaidi, "Dual-axis solar tracker system utilizing Fresnel lens for web-based monitoring," *International Journal of Power Electronics and Drive Systems*, vol. 15, no. 3, pp. 1799–1809, 2024, doi: 10.11591/ijpeds.v15.i3.pp1799-1809.
[31] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *PeerJ Computer Science*, vol. 7, pp. 1–24, 2021, doi: 10.7717/PEERJ-CS.623.

BIOGRAPHIES OF AUTHORS

Humairoh Ratu Ayu is a lecturer in Department of Physics, Faculty of Mathematics and Natural Sciences at the University of Lampung, Bandar Lampung, Indonesia. She received her bachelor and magister degrees from University of Lampung and Universitas Diponegoro in 2012 and 2016, respectively. She is currently managing editor of the JTAF and JEMIT, she also joins instrumentation peer group. Her research interests include the field of embedded system, artificial intelligence, intelligent control, renewable energy, and internet of things. She can be contacted at email: humairoh.ratu@fmipa.unila.ac.id.

Rifki Mohamad Kurniawansyah is a physics graduate in 2023 at the University of Lampung, Bandar Lampung, Indonesia. He is also a member of the robotic club. His research interests include the field of mechatronics and intelligent control. He can be contacted at email: rifki.mohamad191011@students.unila.ac.id.

Aqua Risma Diansari is a physics student since 2020 at the University of Lampung, Bandar Lampung, Indonesia. She is also joining instrumentation peer group. Her research interests include the field of data trasnmitions and internet of things. She can be contacted at email: aqua.rismadiansari2052@students.unila.ac.id.