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Prediction of Rainfall Using a Backpropagation Artificial Neural Network Model over Muaro Jambi Regency

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This study aims to predict rainfall in Muaro Jambi Regency using the Backpropagation Artificial Neural Network (ANN) method. The input variables include air humidity, air temperature, air pressure, and wind speed, with data obtained from the BMKG Muaro Jambi Climatology Station. The method is quantitative with a time series approach, involving data collection, normalization, and division into training, validation, and testing, along with the application of Trainlm, Trainrp, and Traindx. The results show that air humidity has the greatest influence on rainfall, while temperature, air pressure, and wind speed show weak negative correlations. Testing variations in the number of neurons in the hidden layer shows that 100 neurons with the Traindx algorithm produce the best performance, with a Mean Square Error (MSE) of 4.95%, categorized as very accurate. The Backpropagation ANN model follows the actual rainfall pattern from BMKG with a conformity level of more than 95% and recognizes seasonal patterns such as peak rainfall in March and a decrease in the middle of the year. Thus, this model is effective for predicting rainfall and supports disaster mitigation planning and water resource management in Muaro Jambi Regency.

Keywords: *artificial neural network, backpropagation, MSE, Muaro Jambi, rainfall*

1. INTRODUCTION

Indonesia is located on the equator, between 6° North Latitude and 11° South Latitude, and between 95° and 141° East Longitude. The dry season and the rainy season are the two main seasons in Indonesia, which significantly affect the lives of living organisms in various regions. One of the factors that determines the seasonal patterns in Indonesia is rainfall. Rainfall itself refers to the amount of water that falls to the earth's surface over a certain period, typically measured in millimeters (mm) on a horizontal plane. Additionally, this term is also used to indicate the height of water accumulated on a flat surface, assuming no evaporation, infiltration, or flow elsewhere (Pebralia, 2022).

In order to predict rainfall, a system capable of estimating based on available data is required (Aminoto et al., 2024). Temperature, humidity, wind speed, and air pressure are used as inputs to develop a rainfall prediction system in this study. Predictions are made using computational methods to calculate the estimated rainfall. The goal of this research is to produce a rainfall prediction system with high accuracy, providing a solution to rainfall forecasting problems. Artificial Neural Networks (ANNs) are used in rainfall prediction due to their ability to identify patterns from historical data, enabling future predictions by utilizing various meteorological variables as inputs (Prasetyo et al., 2024).

The data used to predict rainfall, humidity, temperature, air pressure, and wind speed are obtained from observational instruments at the Meteorology, Climatology, and Geophysics Agency

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(BMKG). BMKG collects climatological parameter data to study weather conditions. After data collection, the next step is data processing for prediction purposes. However, the large amount of data may cause errors in predictions, especially in rainfall prediction analysis. Therefore, an accurate prediction method is needed to forecast monthly rainfall accurately.

Several researchers have conducted studies on rainfall prediction using the Artificial Neural Network method. For instance, Yoranda et al. (2018) utilized rainfall intensity data obtained from the Public Works and Planning Department of Ponorogo Regency in their study. Meanwhile, Muflih et al. (2019) applied a similar method using a single variable, rainfall, based on data collected over three years from the Wanganaji observation station in Wonosobo Regency. Sutawinaya et al. (2017) also used Artificial Neural Networks to predict rainfall.

The backpropagation artificial neural network model will be applied to predict rainfall using wind speed, air pressure, temperature, and humidity. Since each variable contributes significantly to rainfall formation, it is expected that the use of these variables will improve prediction accuracy. It is hoped that this better prediction model will assist many people, especially in agricultural planning and disaster mitigation, and provide deeper insights into atmospheric dynamics in the study area.

2. METHOD

Various studies on rainfall prediction using the Backpropagation Artificial Neural Network (ANN) method have shown significant results in different regions. Netty (2023) found discrepancies between JST predictions and field data in the Rongkong Watershed, with a decrease in rainfall during some months and an increase in September. Fitriyanti (2023) applied JST in Wajo Regency to help farmers determine planting times, achieving high accuracy based on RMSE evaluation. Adnyana et al. (2019) predicted the climate in Mataram City with good accuracy using MSE. Prasetyo et al. (2024) developed a JST-based prediction system beneficial for agriculture, business, and transportation sectors. Leliak (2022) and Rochmawati (2024) also demonstrated the effectiveness of JST in predicting rainfall with accurate and efficient results. All these studies prove that Backpropagation JST can be effectively used to predict rainfall and climate changes with adequate accuracy.

2.1 **Prediction of Rainfall Using Backpropagation Neural Networks**

This research is based on a review of several previous studies and relevant supporting theories, which can be grouped into three main areas: evidence of method application, understanding of variables, and the foundation of the methods used.

2.1.1 Evidence of Application and Effectiveness of the Method

Various studies have demonstrated the reliability of the Backpropagation Artificial Neural Network (ANN) in predicting rainfall and other weather parameters with high accuracy. Research in the Rongkong Watershed (Netty, 2023) and Wajo Regency (Fitriyanti, 2023) successfully predicted rainfall patterns with low error (RMSE 0.024 - 0.150), while a study in Mataram City (Adnyana et al., 2019) predicted various parameters such as temperature, humidity, and rainfall with very high accuracy (MSE for rainfall was 1.00×10^{-3}). The development of a website-based prediction system (Prasetyo et al., 2024) and research in Ambon City (Leliak, 2022) further strengthen the argument that Backpropagation ANN is a reliable solution that can be implemented in real-world systems, with error values (MSE) approaching zero.

2.2 **Meteorological Parameters as Key Variables**

Weather prediction, particularly rainfall, heavily relies on the analysis of key meteorological parameters (Aminoto et al., 2024). This document outlines four key parameters that are most commonly used in prediction models. Weather prediction, particularly rainfall, depends on the analysis of four main meteorological parameters. Rainfall, measured in millimeters (mm), is defined as the amount of water that accumulates in a specific area over a given time, with its intensity categorized by the Meteorology, Climatology, and Geophysics Agency (BMKG) from "Very Light" (≤5 mm) to "Very Heavy" (>100 mm). Air humidity, expressed in Relative Humidity (RH), measures the amount of water vapor in the atmosphere and is influenced by temperature, air pressure, and geographic conditions, with high rainfall areas tending to have high humidity. Air temperature, which is affected by solar radiation, cloud cover, and the type of Earth's surface, is closely related to humidity and influences rainfall patterns. Finally, air pressure and wind speed, measured with barometers and anemometers, play a crucial role in predicting weather systems, including the potential for storms, as pressure differences drive air movement.

2.3 Artificial Neural Network (ANN)

ANN is a machine learning algorithm inspired by the way the human brain works, making it well-suited to handle non-linear and complex problems such as weather prediction. The basic structure of an ANN consists of three layers: Input (receiving data), Hidden (processing data, which can include multiple layers), and Output (producing the final result). ANN learns patterns from historical data to make predictions or classifications. For prediction tasks, the Multi-layer architecture (Multi-layer Network) is most commonly used due to its ability to handle complex relationships.

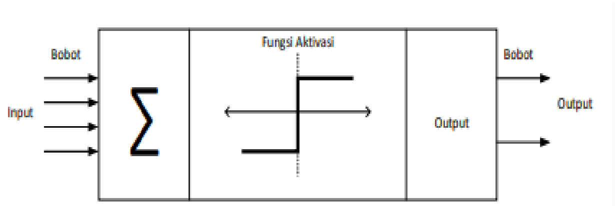

Figure 1 Structure of ANN

Figure 1 shows the basic structure of a neuron in an artificial neural network, which involves an activation function F. Neurons are grouped into layers, with connections between neurons in the input, hidden, and output layers. Data is processed starting from the input, through the hidden layers, and to the output. The Artificial Neural Network (ANN), used for predicting rainfall, is a non-linear model that learns from previous weather data and evolves during the learning process to solve problems. Inspired by biological neural networks, ANN is widely used in data mining for clustering, regression, classification, and forecasting. The basic structure of an ANN includes the input, hidden, and output layers, where the hidden layer may be optional depending on the needs.

2.3.1 Architecture of Artificial Neural Networks

The architecture of an Artificial Neural Network (ANN) is designed to resemble biological neural networks, where neurons are interconnected to receive input from external data and the output of other neurons. Each input has a certain weight, which is processed by neurons with a threshold value, generating activation that is processed through an activation function to produce the output of the neuron (Pangaribuan and Sagala, 2017). According to Herdhyanti et al. (2022), there are three types of ANN architecture: 1) Single-layer networks that only have input and output layers, with input neurons directly connected to the output layer, 2) Multi-layer networks that have input, output, and hidden layers, and can handle more complex problems, and 3) Competitive-layer networks, where neurons compete to be the most active.

2.4 Backpropagation Method

The momentum backpropagation algorithm is an evolution of the conventional backpropagation algorithm that uses momentum during the learning process. The momentum constant value ranges from 0 to 1. While the steps of this algorithm are similar to standard backpropagation, its main difference lies in the backward propagation phase. The Backpropagation Algorithm, also known as the Backward Propagation Algorithm, is a supervised learning technique applied to artificial neural networks. This algorithm uses training data to determine the most suitable weights for each neuron that has the desired target. (Andrian & Putra, 2017). According to Yoranda et al. (2018), the Backpropagation Algorithm has evolved into one of the most commonly used methods in forecasting, consisting of three main training stages that allow artificial neural networks to learn and improve their prediction accuracy:

1. Forward Propagation, in this step, each signal is passed through the hidden layers until it reaches the output layer. A previously defined activation function is used to generate the activation output.
2. Backward Propagation, at this stage, backward propagation is used to process the difference between the produced output and the expected error. The weights are then updated to generate an output that is closer to the target.
3. Weight Adjustment: In this step, the weights are adjusted to reduce the error.

In the artificial neural network learning method using the backpropagation algorithm, these are the main stages:
Step 0: Specify the maximum time, target error, and learning rate for the weights, then start with an initial value of 0.
Step 1: Continue by performing steps 2 to 9 if the epoch is still less than maximum_epoch and the MSE is less than target_error.
Step 2: Follow steps 3 through 8 for each training data.
Step 3: Each input unit receives the input signal and propagates it through the hidden layer above it.
Step 4: Compute the full output result at the hidden layer.

$$z\_in_j = v_{0j} + \sum_{i=i}^{n} x_{iv_{ij}} \tag{1}$$

z_{in_j} as an input signal to hidden layer j, v_{0j} is a bias of the j hidden layer, v_{ij} as an intermediate weight for the i input layer and the j hidden layer, x_i as an input unit to the i layer, and p is the maximum number of units in the hidden layer

Step 5: Calculate all network outputs y_k (with k = 1,2,3,...)

$$y\_in_k = w_{ok} + \sum_{j=1}^{n} z_j\, w_{jk} \tag{3}$$

$$y_k \quad = f(y_{netk}) = \frac{1}{1+e^{-z_{ink}}} \tag{4}$$

y_{in_k} is the signal delivered to -k, w_{ok} is the bias of the k hidden layer (the initial weight value is randomly set between -0.5 and 0.5), w_{jk} is the weight between the j hidden layer and the k output (The initial weight value is randomly set between -0.5 and 0.5), y_k is the value of the k layer's output activated, and n is the highest number of units produced by the output layer.

Step 6: calculate the δ factor for each output unit based on the error of each output unit y_k (k = 1,2,..,m)

$$\delta_k = (t_k - y_k) f'(y_{netk}) \tag{5}$$

$$= (t_k - y_k) y_k (1 - y_k) \tag{6}$$

δ_k is the error factor that will be used to update the weights in the previous layer. Calculate the value of the weight change w_{kj} (which will be used later to update the weights w_{kj}) using the acceleration rate α

$$\Delta w_{jk} = \alpha \delta_k z_j \delta \tag{7}$$

$$k = 1,2, \ldots., m; j = 0,1, \ldots, p \tag{8}$$

Calculate the bias correlation Δw_{k0} which will later be used to update the value used to update the value of w_{k0}.

$$\Delta w_{0k} = \alpha \delta_k \tag{9}$$

Simultaneously send δ_k to the unit in the rightmost layer with δ_k is the weight error correction factor w_{jk}, k is the k-th target output, α is the learning rate, Δw_{jk} is the correction value for weight error w_{jk}, Δw_{0k} is the correction value for bias error w_{0k}, z_j is the activation of the j hidden layer.

Step 7: Count the number of hidden units with their respective errors.

$$z_j = (j = 1,2, \dots, p) \quad (10)$$
$$\delta_{net_j} = \sum_{k=1}^{m} \delta_k w_{kj} \quad (11)$$

Components hidden unit:

$$\delta_{j=\delta\_net_j} f'(z\_net_j) = \delta\_net_j z_j (1 - z_j) \quad (12)$$

Calculate the amount of change in v_{ji}(for a change in v_{ji})

$$\Delta v_{ji=\alpha\delta_{jx_i}} \quad (13)$$
$$j = 1,2, \dots, p; i = 0,1, \dots, n \quad (14)$$

Next, calculate the bias correction, which is shown by the equation.

$$\Delta v_{0j=\alpha\delta_j} \quad (15)$$

Step 8: Calculate all weight and bias modifications, especially those related to the output units.

$$w_{kj(baru)} = w_{kj(lama)} + \Delta w_{kj} \quad (16)$$
$$k = 1,2, \dots., m; j = 0,1, \dots, p \quad (17)$$

To improve the accuracy of the artificial neural network, the latest weight values are used to connect the units in the hidden layer:

$$v_{ji(baru)} = v_{ji(lama)} + \Delta v_{ji} \quad (18)$$
$$j = 1,2, \dots. p; i = 0,1, \dots, n \quad (19)$$

Step 9: Stopping the process. Once data training is complete, the network can be used for pattern recognition. In this case, the network output is determined solely through the forward phase (steps 4 and 5). If the activation function does not use a binary sigmoid, steps 4 and 5 must also be adjusted, and their derivatives, steps 6 and 7, must also be adjusted. (Yoranda et al., 2018).

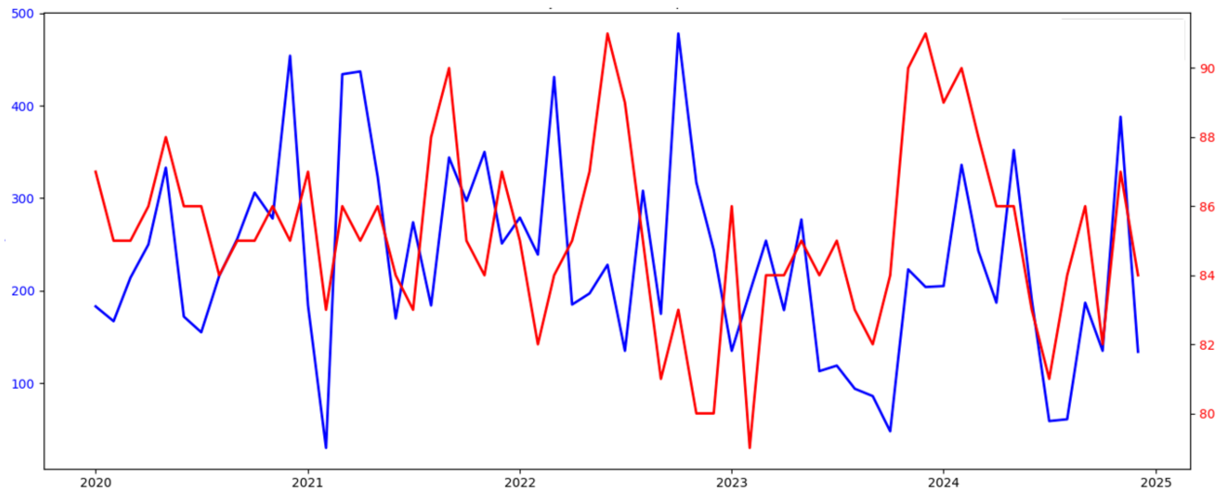

Figure 2 Relationship between Rainfall in mm/day (blue) and Humidity in percent (red).

3. RESULTS AND DISCUSSION

3.1 Relationship between Humidity, Temperature, Pressure, and Wind Speed and Rainfall.

Figure 2 illustrates the temporal variation and relationship between daily rainfall (blue line) and relative humidity (red line) over the study period. In general, both variables exhibit noticeable fluctuations, reflecting the dynamic nature of tropical atmospheric conditions. Periods of increased rainfall tend to coincide with elevated relative humidity, indicating a positive association between the two parameters. This relationship is expected, as higher atmospheric moisture content promotes cloud formation and precipitation processes.

However, the relationship is not perfectly linear, as several instances show high humidity without corresponding rainfall events. This condition suggests that while high relative humidity is a necessary condition for precipitation, it is not sufficient on its own, as other atmospheric factors such as temperature, atmospheric instability, and wind patterns also play significant roles in triggering rainfall (Trenberth et al., 2003).

The variability observed in rainfall is more pronounced compared to humidity, with sharp peaks indicating extreme precipitation events. Such variability is typical in tropical regions influenced by convective rainfall and seasonal climate patterns. Meanwhile, relative humidity shows comparatively smoother fluctuations, generally remaining within a high range (approximately 80–95%), which is characteristic of humid tropical climates (Aldrian & Susanto, 2003).

Humidity and rainfall show a positive correlation, with increasing humidity tending to be followed by increased rainfall, and vice versa. For example, in March 2020, humidity was 87%, and rainfall was 330 mm, while in August 2022, with humidity at 81%, rainfall dropped to 150 mm. This data was consistent from 2020 to 2024, with the highest rainfall recorded in October 2022 (480 mm) when humidity reached 89%, and March 2024, with humidity at 91% and rainfall of 350 mm. According to Wahyuni et al., humid air containing more water vapor facilitates cloud formation and precipitation, increasing the chance of rain. This pattern is also related to air temperature fluctuations, as shown in Figure 3.

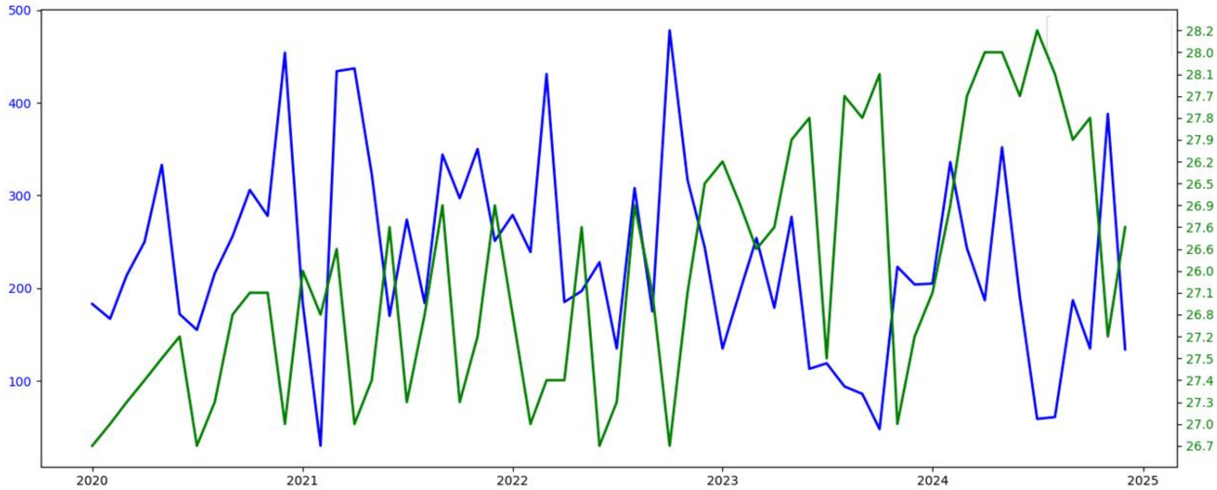

Figure 3 Relationship between rainfall (blue, mm/day) and temperature (green, ºC).

Based on Figure 3, rainfall in Muaro Jambi Regency varied between January 2020 and December 2024, with peak rainfall exceeding 400 mm occurring in February to March 2021 and September 2022, while drier months, such as July to August 2022 and August 2023, recorded rainfall below 100 mm. Air temperatures remained stable at around 26.7 °C to 28.2 °C, but tended to increase annually, peaking in mid-2024. This temperature pattern indicates that when rainfall is high, temperatures tend to decrease, while when rainfall is low, temperatures increase, consistent with Muaro Jambi's tropical climate. According to Suhadi et al. (2023), this long-term climate change affects temperature, precipitation, and extreme weather phenomena such as very high or low rainfall. Recent studies also indicate that Indonesia has experienced increasing trends in extreme rainfall indices over recent decades, suggesting a growing intensity and frequency of heavy precipitation events (Aminoto et al., 2026).

Apart from air temperature, air pressure also shows different patterns of change. The graph shows fluctuations in rainfall (blue line) and air pressure (yellow line) between 2020 and 2024. Rainfall showed significant variations, particularly in 2021 and 2022, with values that could increase by up to

500 mm, but also decrease drastically in certain months, reflecting the influence of seasons and atmospheric dynamics. Air pressure was relatively stable, ranging between 1006 and 1012 hPa, with an inverse pattern between rainfall and air pressure. As rainfall increased, air pressure tended to decrease, in accordance with the meteorological principle that low pressure favors cloud formation and rain, while high pressure indicates stable and dry atmospheric conditions. This confirms that air pressure variability is closely related to rainfall patterns in the region.

From January 2020 to December 2024, the rainfall and wind speed graphs show sharp fluctuations, with rainfall varying significantly across months, while wind speeds gradually increase. In 2020, rainfall ranged from 160–330 mm, peaking in April–May, while wind speeds were low (20–100 m/s). In 2021, rainfall jumped from around 30 mm in January to over 400 mm, while wind speeds remained high. In 2023, rainfall varied significantly, peaking at nearly 480 mm in February, but dropping sharply in July–September, although wind speeds remained high. In 2024, rainfall was initially low (70–200 mm) but increased mid-year (300–350 mm) as wind speeds increased. The relationship between rainfall and wind speed is inconsistent; sometimes increasing wind speeds correlate with high rainfall, while in other periods, rainfall decreases even though winds remain strong. The analysis shows that meteorological variables such as air pressure, air humidity, temperature, and wind speed influence rainfall in the region, with low air pressure favoring cloud formation and rain, high humidity correlating with more rain, high temperature encouraging evaporation, and wind speed influencing water vapor distribution and rainfall intensity.

3.2 Correlation between Humidity, Temperature, Pressure, and Wind Speed and Rainfall

Correlation analysis is a statistical technique used to determine the magnitude of the relationship between two variables. It shows the degree of dependence of one variable on another variable. Guilford (1956) stated that correlation not only makes it easier to analyze the linear relationship that exists between certain variables, but can also help in determining the strength and direction of the relationship. Pearson's correlation ranges between -1 and 1. Positive values indicate a unidirectional relationship that is growing and growing, while negative values indicate a unidirectional relationship that is growing and will decrease. (Nugroho, S. 2008). Table 1 shows the interpretation or criteria for the closeness of the relationship based on the correlation coefficient value.

Table 1 Correlation coefficient interval and its interpretation.

Correlation Interval	Interpretation
0,00-0,20	Very Weak
0,21-0,40	Weak
0,41-0,70	Moderate
0,71-0,90	Strong
0,91-0,99	Very Strong
1	Perfect Correlation

Table 2 Correlation among variables under study

Variable	Humidity	Temperature	Pressure	Wind Speed
Rainfall	0.17	-0.31	-0.10	-0.18

The results of the correlation coefficient (r) analysis (Table 2) show that the relationship between rainfall and humidity has a value of 0.17, which falls into the very weak positive category, meaning that an increase in humidity is only slightly related to an increase in rainfall. The relationship between rainfall and temperature has a value of -0.31, which is considered weakly negative, indicating that higher temperatures tend to decrease rainfall, although the effect is not large. Meanwhile, the correlation between rainfall and air pressure is -0.10, and between rainfall and wind speed is -0.18, both showing very weak negative relationships, meaning these two variables have almost no effect on rainfall. The relationship between humidity, temperature, and pressure also shows very weak to weak negative correlations (-0.18 and -0.28). On the other hand, the correlation between temperature and wind speed is -0.52, which is considered moderately negative, suggesting that temperature tends to decrease as wind speed increases.

3.3 Measuring the Accuracy Level of ANN Models in Estimating Rainfall

The testing was conducted on three training algorithms (Table 3), namely trainlm, trainrp, and traindx, with variations in the number of neurons (50, 100, and 150), to evaluate the accuracy of the artificial neural network (ANN) model in predicting rainfall in Muaro Jambi Regency using the variables of air humidity, temperature, air pressure, and wind speed. According to Nailah et al. (2024), test data that had never been used in the training process were used to assess the system's ability to recognize the trained samples. During the testing phase, the correlation coefficient and mean square error (MSE) values showed that the backpropagation artificial neural network model with these variations in the number of neurons was quite effective in predicting rainfall, as shown in Table 3.

Table 3 MSE calculation with number of neurons and JST training

Number of neurons	Training	*Mean square error* (MSE) %
50	Trainlm	5.79 %
	Trainrp	5.13 %
	Traindx	5.75 %
100	Trainlm	5.61 %
	Trainrp	5.70 %
	Traindx	4.95 %
150	Trainlm	5.64 %
	Trainrp	6.42 %
	Traindx	6.16 %

The results of the Mean Squared Error (MSE) calculations show that the training algorithms used have different accuracy levels. With 50 neurons, the trainlm algorithm produced an MSE of 5.79%, trainrp produced 5.13%, and traindx produced 5.75%. This difference indicates that a certain number of neurons can affect the model's ability to identify climate data patterns. With 100 neurons, the MSE for trainlm was 5.61%, trainrp was 5.70%, and traindx was 4.95%, showing that adding more neurons does not always improve accuracy but is greatly influenced by how well the algorithm fits the data characteristics. Testing with 150 neurons showed that trainlm had the best performance with an MSE of 5.64%, followed by trainrp (6.42%) and traindx (6.16%). Based on these results, the ANN model with the trainlm algorithm and 100 neurons performed the best in predicting rainfall in Muaro Jambi Regency. According to Zahara et al. (2025), increasing the number of hidden layers can improve the model's accuracy, as reflected in the decrease in MSE values. Overall, the Backpropagation ANN model proved to be very accurate in predicting rainfall in the region, with results consistent with BMKG data, showing that this model can be relied upon for weather prediction in Muaro Jambi.

3.4 The Effect of the Number of Neurons on the Performance of the ANN Model

The research on the comparison of the number of neurons in the hidden layer was conducted during the testing phase to obtain the best pattern with optimal parameters, as the number of neurons can affect prediction accuracy. According to Nailah et al. (2024), there is no definite formula to determine the ideal number of neurons in the hidden layer. This study uses data from 5 years (2020–2024), with training data from 2020–2023 and test data from 2024. The number of neurons was adjusted to the appropriate training function, which was used to predict rainfall based on the variables of humidity, temperature, air pressure, and wind speed. The calculation of the average error percentage was used to assess the accuracy of the prediction results.

3.4.1 Number of Neurons: 50

This section presents the comparison between the actual rainfall data and the prediction results from the ANN using three different training algorithms: Trainlm, Trainrp, and Traindx, with 50 hidden neurons. This analysis uses normalized rainfall data for the period from January to December 2024. The actual data shows significant fluctuations throughout the year, with rainfall increasing from 0.39 in

January to 0.68 in February, then sharply dropping to 0.09 in July (dry period), and rising again to peak at 0.80 in November before falling again to 0.32 in December. Predictions using the Trainlm algorithm show more stable results, with values ranging from 0.46 to 0.49 throughout the year, not capturing the extreme fluctuations seen in the actual data. Although the MSE of 5.79% indicates that Trainlm is fairly good at predicting the overall trend, this algorithm struggles to capture sharp spikes in certain months, such as June and November. According to Oktaviani & Afdal (2013), Trainlm is effective in improving weights and biases through momentum and adaptive learning rate techniques, making the learning process more optimal. On the other hand, the Trainrp algorithm produces rainfall predictions with values ranging from 0.50 to 0.55, slightly higher than Trainlm, and while stable, it does not fully capture the extreme fluctuations. Trainrp shows the best performance with the lowest MSE of 5.13%, indicating that this algorithm is more effective at adjusting the network weights and providing results that are closer to the actual data.

The Traindx algorithm produces rainfall predictions with values ranging from 0.51 to 0.56, which is similar to Trainlm, but with slightly lower performance, recording an MSE of 5.79%. This indicates that although Traindx provides reasonably good predictions, this algorithm has limitations in capturing seasonal variations in rainfall. According to Wibowo et al. (2019), the Trainrp algorithm reduces the influence of the magnitude of partial derivatives in the training process by only using the sign of the derivative, thus determining the direction of weight adjustment based on the sign without considering the value of the derivative. In addition, predictions using the Trainlm algorithm result in higher values compared to Traindx and Trainrp, while Traindx has flatter results with the smallest variation, and Trainrp shows more noticeable variation. Although all three algorithms provide predictions that are fairly close to the average rainfall, they cannot capture the extreme patterns in the actual data, particularly in June (0.71), July (0.09), and November (0.80) of 2024. The Trainrp algorithm proved to be the most efficient with the smallest error value of 5.13%, followed by Trainlm and Traindx with error values of 5.79% and 5.75%, respectively. Overall, the graph shows that Trainrp is the most aligned with the actual data with 50 neurons, followed by Trainlm, while Traindx is the least aligned, confirming that the chosen training algorithm significantly affects the accuracy of the ANN prediction results.

3.4.2 Number of Neurons: 100

The actual rainfall data shows large variations, with peaks in May and November and a sharp decline in July. The other three lines represent the ANN predictions: the blue line for Trainlm, the red for Trainrp, and the green for Traindx. These predictions are more stable and flat compared to the actual data. During training, the average percentage error for Trainlm was 5.61%, Trainrp 5.70%, and Traindx 4.95%. The training results with Traindx have the closest pattern to the BMKG data, with a relatively small error, indicating an optimal combination of training function and number of neurons. According to Oktaviani & Afdal (2013), these optimal results are achieved due to the suitability of the network architecture and its ability to recognize data patterns. With 100 neurons, Trainrp outperforms Trainlm, although this number of neurons is not optimal, and the error increases. Training with the Resilient Backpropagation (Trainrp) method eliminates the large effects of partial derivatives, which increase the weights and bias. (Silvia Ningsih, 2025).

Actual data also shows significant fluctuations from December 2023 to December 2024, with increased rainfall in February, May, and November, and a sharp decrease in July and August. According to Rahayu & Mustafidah (2022), neural networks can adapt outputs to inputs thanks to hidden layers. The number of neurons in the hidden layer influences the prediction results, and changes in the number of neurons can affect the error. Predictions using Trainlm (blue) are stable between 0.46 and 0.48, although they do not follow the extreme spikes in the actual data. Trainrp (red) produces a slightly different pattern, but still fails to capture the large spikes in May and November. Meanwhile, Traindx (green) produces lower predictions (0.31–0.35), although they follow the time pattern, but deviate further from the actual data. Overall, Trainlm with 100 neurons shows the best stability despite being less adaptive to fluctuations, while Trainrp is closer to the data variations but still fails to capture large changes. Traindx has the disadvantage of underpredicting the actual data.

3.4.3 Number of Neurons: 150

A comparison analysis of the performance of the Artificial Neural Network (ANN) model was conducted through the evaluation of the architecture with 150 neurons in the hidden layer. From the comparison plot between the actual rainfall data and the prediction results from three training algorithms—Levenberg-Marquardt (Trainlm), Resilient Propagation (Trainrp), and Adaptive Gradient Descent with Momentum and Learning Rate (Traindx), it shows that these algorithms are used for ANN modeling in forecasting complex time series data, such as rainfall. The goal of this evaluation is to identify the best training algorithm for capturing non-linear patterns in the data. Based on the calculation of the average percentage error values, trainlm produces an error of 5.64%, trainrp 6.42%, and traindx 6.16%. Trainlm has a smaller average percentage error, indicating that the number of neurons used is more optimal. Meanwhile, the weight and bias adjustments in trainrp and traindx are nearly identical, even though the number of neurons in traindx is more optimal. Nailah et al. (2024) explain that the number of weights is influenced by the number of neurons in the hidden layer— the more neurons that are trained, the more weights are created, meaning the percentage error value decreases.

The prediction with trainlm closely matches the actual data, while traindx shows a more consistent pattern, despite some deviation, especially in the high rainfall data. Trainrp fails to capture the variation in rainfall patterns and produces relatively constant predictions. Overall, these results indicate that trainrp is closer to the actual conditions compared to trainlm and traindx, although there are still discrepancies during extreme periods. From this study, it can be concluded that the choice of training algorithm is crucial in determining the accuracy of the ANN in predicting rainfall, with Trainrp being the best option. Additionally, the use of 100 neurons in the hidden layer proves to be the most optimal for rainfall prediction, which indicates that all three training functions approach the actual data with this number of neurons. Nailah et al. (2024) also mention that the learning rate is adaptive, can change over time, and stops when the iteration reaches the maximum limit or the target error is achieved.

3.5 Rainfall Prediction Results Using JST Backpropagation with BMKG Data for 2025.

This study compares the results of rainfall predictions for 2025 between actual data from the Meteorology, Climatology, and Geophysical Agency (BMKG) and predictions using Backpropagation ANN. The actual BMKG data used only covers up to July 2025. The Backpropagation ANN prediction uses the best test results, namely, with the traindx training function and 100 neurons in the hidden layer for rainfall. We can see this in Figure 4 in the rainfall prediction graph below.

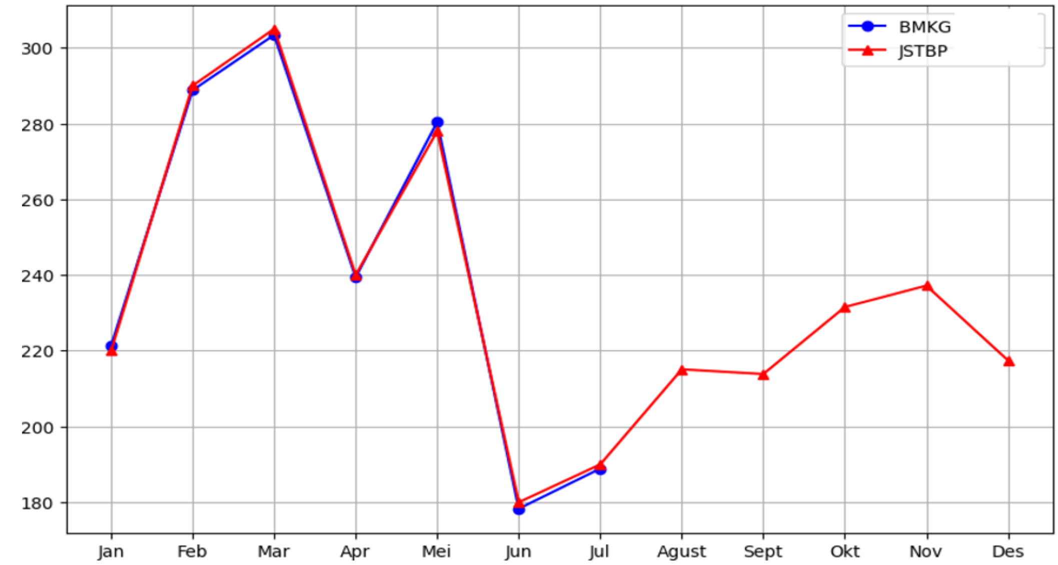

Figure 4 Rainfall prediction results for 2025

Figure 4 shows a comparison between the prediction results of the Artificial Neural Network Backpropagation (ANN) model for 2025 and the actual rainfall data from the Meteorology, Climatology, and Geophysics Agency (BMKG). The horizontal axis represents the months from January to December, while the vertical axis shows the rainfall amount in millimeters (mm). The blue line shows the actual BMKG data, while the red line shows the prediction results of the ANN model. Overall, the graphs show a very similar pattern of rainfall changes, with a Mean Square Error (MSE) value of 2.27, which falls into the "very accurate" category according to the BMKG classification, indicating a small difference between the prediction and the observed data.

From January to March, rainfall increased sharply, peaking in March at around 305 mm, demonstrating the JSTBP model's ability to identify the peak of the Muaro Jambi rainy season. From April to June, rainfall decreased from 240 mm in April to 180 mm in June, reflecting the transition to the dry season. Although there were slight differences between predictions and actual data in May and June, the JSTBP model followed this trend accurately. Furthermore, from July to September, rainfall fluctuations were relatively low and stable between 180 and 215 mm, with JSTBP predictions slightly exceeding actual data, likely due to other atmospheric factors not captured by the model, such as variations in ocean temperature or local winds.

At the end of the year, from October to December, rainfall intensity increased again, reflecting the second rainy season, with the JSTBP predictions closely following the actual pattern. Overall, the JSTBP model successfully described the fluctuations in monthly rainfall patterns, demonstrating its effectiveness in learning the relationship between input variables such as humidity, temperature, air pressure, and wind speed with rainfall. The Traindx algorithm also proved sensitive to the training ratio, but the prediction results demonstrated that the artificial neural network can model rainfall very well.

4. CONCLUSION

The conclusion of this study shows that air humidity has the greatest influence on rainfall compared to other weather variables, while the correlation between air temperature and rainfall is still weak ($r = 0.17$), and the correlation with air pressure ($r = -0.10$) and wind speed ($r = -0.18$) is very weakly negative. This means that increasing humidity tends to increase rainfall, while temperature, pressure, and wind speed tend to slightly decrease rainfall. In addition, the results of the Backpropagation Artificial Neural Network (ANN) model test show variations in the Mean Square Error (MSE) value depending on the number of neurons and the training algorithm used, with the lowest MSE value of 4.95% in the Traindx algorithm with 100 neurons, which is classified as very accurate. At 50 neurons, the MSE is 5.79% (Trainlm), 5.13% (Trainrp), and 5.75% (Traindx), while at 100 neurons, the MSE becomes 5.61% (Trainlm), 5.70% (Trainrp), and 4.95% (Traindx). The results of the 2025 rainfall prediction using the Backpropagation ANN model show almost the same pattern as the actual BMKG data, with an average MSE of 2.27%, which indicates a very small error rate, and the agreement of the prediction results with the actual data is more than 95%.

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Further research should be conducted to determine the number of neurons in the hidden layer. This is due to the significant improvement in network quality in data pattern recognition, so that further research on this matter will be more effective. Furthermore, the training process can be further optimized by using training functions in data processing. Furthermore, the amount of data used for prediction should be increased to improve the resulting data pattern recognition.

REFERENCES

Adnyana, I. N. T., Wijaya, I. G. P. S., & Albar, M. A. (2019). Jaringan Syaraf Tiruan Model Backpropagation untuk Peramalan Suhu Minimum dan Maksimum, Kelembaban, Tekanan Udara, Jumlah Hari Hujan, dan Curah Hujan Bulanan di Kota Mataram. *Journal of Computer Science and Informatics Engineering (J-Cosine)*, *3*(2), 127–136.

Afsari dewi, K. nonik, Bahri, S., & Irwansyah, I. (2019). Model Prediksi Curah Hujan Harian Menggunakan Jaringan Syaraf Tiruan Backpropagation. *Indonesian Physical Review*, *2*(1), 9.

Aldrian, E., & Susanto, R. D. (2003). Identification of three dominant rainfall regions within Indonesia and their relationship to sea surface temperature. *International Journal of Climatology, 23*(12), 1435–1452. https://doi.org/10.1002/joc.950

Aminoto, T., Susanti, N., Dani, R., & Faqih, A. (2026). Extreme Rainfall Indices Trends in Indonesia During 1971-2020. *Jurnal Penelitian Pendidikan IPA*, *12*(3), 456-467.

Aminoto, T., Faqih, A., Koesmaryono, Y., & Dasanto, B. D. (2024a). A Comparison of the Performance of the Weighted Ensembles Means in CORDEX-SEA Precipitation Simulations. Agromet, 38(1), 19-35.

Aminoto, T. (2024). Performa Model Hujan CORDEX-SEA pada Aspek Spatial-Temporal dan Implementasi Faktor Bobot pada Rata-rata Ansambel. IPB Repository (Dissertation).

Aminoto, T., & Faqih, A. (2024). Tren curah hujan di asia tenggara berdasarkan model cordex-sea dan data era5. Journal online of physics, 10(1), 7-13.

Aminuddin, J., Kecepatan Angin Terhadap Evapotranspirasi Berdasarkan Metode Penman Di Kebun Stroberi Purbalingga, P., Fakultas Sains dan Teknologi, N., Ar-Raniry Banda Aceh, U., Aminuddin Prodi Fisika, J., & Purwokerto, U. (2016). Pengaruh Kecepatan Angin Terhadap Evapotranspirasi Berdasarkan Metode Penman Di Kebun Stroberi Purbalingga. *Elkawnie: Journal of Islamic Science and Technology*, *2*(1), 21–28.

Andrian, Y., & Putra, P. H. (2017). Analisis Penambahan Momentum Pada Proses Prediksi Curah Hujan Kota Medan Menggunakan Metode. *Seminar Nasional Informatika*, *2014*(September), 165–172.

Aprilia, B., Marzuki, M., & Taufiq, I. (2021). Prediksi El Nino Southern Oscillation (ENSO) Menggunakan Jaringan Saraf Tiruan (JST)-Backpropagation. *Jurnal Fisika Unand*, *9*(4), 421–427.

Cipta, R., & Trastaronny Pastika Nugraha, T. R. (2020). Evaluasi Prediksi Curah Hujan dengan Algoritma Backpropogation di BMKG Cilacap. *ZONAsi: Jurnal Sistem Informasi*, *2*(2), 97–109.

Fany Achmalia, A., Walid, S., Artikel, I., & Artikel, S. (2020). Peramalan Penjualan Semen Menggunakan Backpropagation Neural Network Dan Recurrent Neural Network. *UNNES Journal of Mathematics*, *9*(1), 6–21.

Fitriyanti, F. (2023). Aplikasi Jaringan Syaraf Tiruan Backpropagation dalam Prediksi Curah Hujan Bulanan di Kabupaten Wajo Sulawesi Selatan. *JPF (Jurnal Pendidikan Fisika) Universitas Islam Negeri Alauddin Makassar*, *11*(1), 44–55.

Hasibuan, A. Z., Asih, M. S., & Faisal, I. (2020). Sistem Monitoring Suhu Udara Dan Kelembaban Udara Di Ruangan Menggunakan Smartphone. *Jurnal Ilmu Komputer Dan Sistem Komputer Terapan (JIKSTRA)*, *1*(2), 1–9.

Hayati, Z., & Tanjung, D. (2023). Pengaruh kelembapan udara terhadap efektivitas pelaksanaan rukyatul hilal awal bulan qamariyah. *Jurnal EDUCATIO: Jurnal Pendidikan Indonesia*, *9*(2), 754.

Herdhyanti, A., Muflikhah, L., & Cholissodin, I. (2022). Prediksi Curah Hujan dengan Empat Parameter menggunakan Backpropagation (Studi Kasus: Stasiun Meteorologi Ahmad Yani). *Jurnal Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *6*(12), 2548–2964.

Irnanda, K. F., Windarto, A. P., & Damanik, I. S. (2022). Optimasi Particle Swarm Optimization Pada Peningkatan Prediksi dengan Metode Backpropagation Menggunakan Software RapidMiner. *JURIKOM (Jurnal Riset Komputer)*, *9*(1), 122.

Leliak, G. (2022). Prediksi Curah Hujan di Kota Ambon Menggunakan Metode Backpropagation. *JATISI (Jurnal Teknik Informatika Dan Sistem Informasi)*, *9*(4), 3310–3318.

Manalu, M. T. (2016). Jaringan Syaraf Tiruan untuk Memprediksi Curah Hujan Sumatera Utara dengan Metode Back Propagation (Studi Kasus : BMKG Medan). *Jurnal Riset Komputer*, *3*(1), 35–40.

Muflih, G. Z., Sunardi, S., & Yudhana, A. (2019). Jaringan Saraf Tiruan Backpropagation untuk Prediksi Curah Hujan di Wilayah Kabupaten Wonosobo. *MUST: Journal of Mathematics Education, Science and Technology*, *4*(1), 45.

Nailah, F., Larasati, D. I., Siswanto, S., & Kalondeng, A. (2024). Optimasi Metode Jaringan Saraf Tiruan Backpropagation Untuk Peramalan Curah Hujan Bulanan Di Kota Denpasar. *MATHunesa: Jurnal Ilmiah Matematika*, *12*(1), 134–140.

Netty. (2023). Prediksi Curah Hujan Wilayah Menggunakan Metode Jaringan Saraf Tiruan (Jst) Backpropagation Di Das Rongkong. *Bandar: Journal of Civil Enginering*, *5*(2), 17–22.

Oktaviani, C., & Afdal. (2013). Prediksi Curah Hujan Bulanan menggunakan Jaringan Syaraf Tiruan dengan Beberapa Fungsi Pelatihan Backpropagation (Studi Kasus: Stasiun Meteorologi Tabing Padang, Tahun 2001-2012). *Jurnal Fisika Unand*, *Vol. 2*, *No*(4), 228–237.

Pangaribuan, Y., & Sagala, M. (2017). Menerapkan Jaringan Saraf Tiruan untuk Mengenali Pola Huruf Menggunakan Metode Perceptron. *Jurnal Teknik Informatika Unika St. Thomas (JTIUST)*, *2*(2), 53–59.

Pebralia, J. (2022). Analisis Curah Hujan Menggunakan Machine Learning Metode Regresi Linier Berganda Berbasis Python dan Jupyter Notebook. *Jurnal Ilmu Fisika Dan Pembelajarannya (JIFP)*, *6*(2), 23–30.

Prasetyo, S. F., Efendi, T. F., & Muqorobin. (2024). Implementasi Sistem Prediksi Curah Hujan Dengan Penerapan Jaringan Syaraf Tiruan Berbasis Website. *Jurtikom*, *1*(2), 80–96.

Rahayu, N., & Mustafidah, H. (2022). Perbandingan Ketepatan Pola Data pada Jaringan Backpropagation Berdasarkan Metode Pembobotan Random dan Nguyen Widrow. *Sainteks*, *19*(1), 27.

Rochmawati, D. R. (2024). Prediksi Cuaca Dengan Jaringan Syaraf Tiruan Menggunakan Python. *Jurnal Teknologi Komputer Dan Informatika*, *2*(2), 162–171.

Setiyaris, S., Hariyadi, M. A., & Crysdian, C. (2023). Prediksi Curah Hujan Bulanan Berdasrkan Parameter Cuaca Menggunakan Jaringan Saraf Tiruan Levenberg Marquardt. *Jurnal Media Informatika Budidarma*, *7*(3), 1125. https://doi.org/10.30865/mib.v7i3.6328

Silvia Ningsih. (2025). Implementasi Jaringan Syaraf Tiruan dalam Memprediksi Hujan. *Elkom: Jurnal Elektronika Dan Komputer*, *18*(1), 413–425.

Suhadi, S., Mabruroh, F., Wiyanto, A., & Ikra, I. (2023). Analisis Fenomena Perubahan Iklim Terhadap Curah Hujan Ekstrim. *OPTIKA: Jurnal Pendidikan Fisika*, *7*(1), 94–100. https://doi.org/10.37478/optika.v7i1.2738

Sutawinaya, I. P., Gede, I. N., Astawa, A., Kadek, N., & Hariyanti, D. (2017). Perbandingan metode jaringan saraf tiruan pada peramalan curah hujan. *Jurnal Logic*, *17*(2), 92–97.

Tamaji, T., Utama, Y. A. K., & Sidharta, J. (2022). Jaringan Saraf Tiruan Menggunakan Metode Backpropagation untuk Prediksi Curah Hujan. *Telekontran : Jurnal Ilmiah Telekomunikasi, Kendali Dan Elektronika Terapan*, *10*(1), 30–37.

Trenberth, K. E., Dai, A., Rasmussen, R. M., & Parsons, D. B. (2003). The changing character of precipitation. *Bulletin of the American Meteorological Society, 84*(9), 1205–1217. https://doi.org/10.1175/BAMS-84-9-1205

Wibowo, F., Sugiyanto, S., & Mustafidah, H. (2019). Tingkat Ketelitian Pengenalan Pola Data pada Algoritma Pelatihan Perbaikan Metode Batch Mode dalam Jaringan Syaraf Tiruan. *Juita*, *II*(4), 259–264.

Yoranda, D. H., Furqon, M. T., & Data, M. (2018). Prediksi Intensitas Curah Hujan Menggunakan Metode Jaringan Saraf Tiruan Backpropagation. *Pengembangan Teknologi Informasi Dan Ilmu Komputer*, *2*(10), 3793–3801.

Zahara, S., Sukmaningtyas, Y. N., Akbar, R. M., & Abidin, M. Z. (2025). Pengaruh Jumlah Hidden Layer dan Neuron pada Model Multilayer Perceptron untuk Prediksi Emas. *Jurnal Ilmiah ILKOMINFO - Ilmu Komputer & Informatika*, *8*(2), 269–275.