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Application of a Levenberg–Marquardt-Based Backpropagation Neural Network for Rainfall Prediction Using a Single Weather Station

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Abstract: This study aims to develop an accurate monthly rainfall prediction model for Sabang City, Indonesia, to support agriculture, disaster mitigation, and water resource management in coastal regions with complex climatic conditions. An Artificial Neural Network (ANN) trained using the Levenberg–Marquardt (LM) algorithm was employed, combining the Gradient Descent and the Gauss–Newton methods to enhance convergence speed and training stability. Meteorological data from 2015–2024, including temperature, humidity, air pressure, sunshine duration, wind direction, wind speed, and rainfall, were obtained from the Maimun Saleh Meteorological Station. Model performance was assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). The optimal architecture consisted of a single hidden layer with 25 neurons, producing an MSE of 955.84 mm^2, an RMSE of 30.91 mm, an MAE of 23.06 mm, a MAPE of 34.8%, and an R^2 of 0.93. These results indicate that the ANN-LM model effectively captures nonlinear climatic relationships and seasonal rainfall variability. The MAPE value falls within the acceptable range reported in forecasting literature, demonstrating practical reliability. Overall, the ANN-LM approach outperformed conventional backpropagation in accuracy and training efficiency, indicating its suitability for rainfall prediction in coastal areas.

Keywords: Artificial neural network; Forecasting; Levenberg-Marquardt; Rainfall prediction

Introduction

Weather information plays a crucial role across various sectors of human life, including agriculture, tourism, marine affairs, and aviation (Saputra et al., 2023; Thakur et al., 2021). Sabang City, located at the westernmost tip of Indonesia, is an archipelagic region entirely surrounded by the ocean. This geographical condition leads to high levels of evaporation and water vapor accumulation, which play an essential role in the rainfall formation process, particularly in coastal and island regions influenced by ocean–atmosphere interactions (Dutta et al., 2020; Yaseen et al., 2019).

Conventional forecasting methods commonly applied in Indonesia, such as Autoregressive Integrated Moving Average (ARIMA), Multiple Linear Regression (MLR), and Seasonal Trend Decomposition, often yield low accuracy when applied to nonlinear meteorological

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data (Permai et al., 2021). Therefore, a more adaptive approach is needed—one capable of capturing the dynamic and nonlinear relationships among meteorological variables such as temperature, humidity, pressure, and wind speed (Doddy et al., 2020).

Based on historical observations, future rainfall cannot be determined deterministically but can be predicted probabilistically by utilizing past data. However, the ability to predict weather accurately at a local scale remains limited, making the improvement of prediction accuracy an urgent necessity to support planning and disaster mitigation efforts (Beddal et al., 2020; Sheikhi et al., 2023).

With advancements in computational technology and data science, artificial intelligence (AI)–based approaches such as Artificial Neural Networks (ANN) have been increasingly adopted in various fields, including mapping (Irwandi et al., 2025) and climate data prediction (Syaharuddin et al., 2022; Rizaldi et al., 2021) ANN, particularly those trained with the Backpropagation algorithm, have proven effective in modeling nonlinear and complex relationships among climate variables (Saputra et al., 2023; Utama & Sidharta, 2022; Zulfiani & Fauzi, 2023; Satria Wibawa, 2017). The Backpropagation algorithm adjusts network weights iteratively based on output errors, making it well suited for modeling dynamic meteorological data (Syaharuddin et al., 2020; S. A. Ramírez-Revilla, 2024; Setiawan et al., 2022; Li et al., 2023; Mzyece et al., 2024; Doddy et al., 2020).

Several previous studies have implemented ANN for rainfall prediction across different regions of Indonesia. A study in North Sumatra reported a Mean Absolute Percentage Error (MAPE) of 35.55% using the Backpropagation algorithm, indicating a reasonably good accuracy level (Nabila et al., 2024). Similarly, a study conducted in Maros Regency demonstrated that ANN models can effectively predict monthly rainfall (Aslim et al., 2023). However, most of these studies relied on conventional Backpropagation, which is known for its slow convergence rate and tendency to become trapped in local minima (Sholahudin et al., 2022).

The ANN model architecture typically consists of an input layer, one or more hidden layers, and an output layer. The hidden layer plays a crucial role in capturing the complex relationships within the data, while the network architecture and the number of neurons significantly influence prediction accuracy. The ANN ability to learn adaptively from data makes it particularly advantageous for predicting climate parameters that are difficult to model explicitly (Heng et al., 2022).

In addition to the network architecture—such as the number of hidden layers and neurons—the training algorithm also plays a critical role in determining model performance. An optimal number of hidden neurons enhances the network's capability to identify complex data patterns, whereas an excessive number can lead to overfitting (Ritha & Wardoyo, 2016). Hence, sensitivity analysis of hidden neuron configuration is essential to obtain the most effective model for rainfall prediction.

To overcome the limitations of conventional Backpropagation, several optimization algorithms have been developed. One of the most widely used is the Levenberg–Marquardt (LM) algorithm, which combines the advantages of the Gradient Descent and Gauss–Newton methods to accelerate convergence without compromising training stability (Ritha & Wardoyo, 2016). A related study Rudrappa et al. (2025) reported a significant improvement in the coefficient of determination (R^2) up to 0.87 using an LM-based ANN model, compared to only 0.57 with linear regression, demonstrating the LM algorithm's superior ability to handle nonlinear weather data.

However, to date, no studies have applied the Levenberg–Marquardt algorithm for rainfall prediction in Sabang City. Previous research in this area employed the Adaptive Neuro-Fuzzy Inference System (ANFIS) (Ardana et al., 2025), but the resulting accuracy was still suboptimal. Given the complex and dynamic climatic characteristics of coastal regions, an ANN-based approach using the LM algorithm is expected to provide more accurate and stable predictions.

Based on this background, this study aims to develop a rainfall prediction model for Sabang City using an Artificial Neural Network (ANN) trained with the Levenberg–Marquardt (LM) algorithm. This approach was chosen for its proven ability to capture complex nonlinear relationships among climatic variables while offering faster convergence than conventional training methods. Through testing various neuron configurations and hidden layer architectures, this study seeks to identify the optimal model configuration for minimizing prediction errors. The results are expected to contribute significantly to improving the accuracy of rainfall forecasting systems, thereby supporting decision-making in agriculture, regional planning, and hydrometeorological disaster mitigation in coastal regions such as Sabang City.

Method

The research procedures carried out are shown in Figure 1, starting from the data collection stage until the research results are obtained. The data used in this study are monthly average meteorological data obtained from the Maimun Saleh Meteorological Station in Sabang City from January 2015 to December 2024. The data variables monthly average used are average temperature, maximum temperature, minimum temperature, humidity, sunshine, air pressure, wind direction and speed, and rainfall.

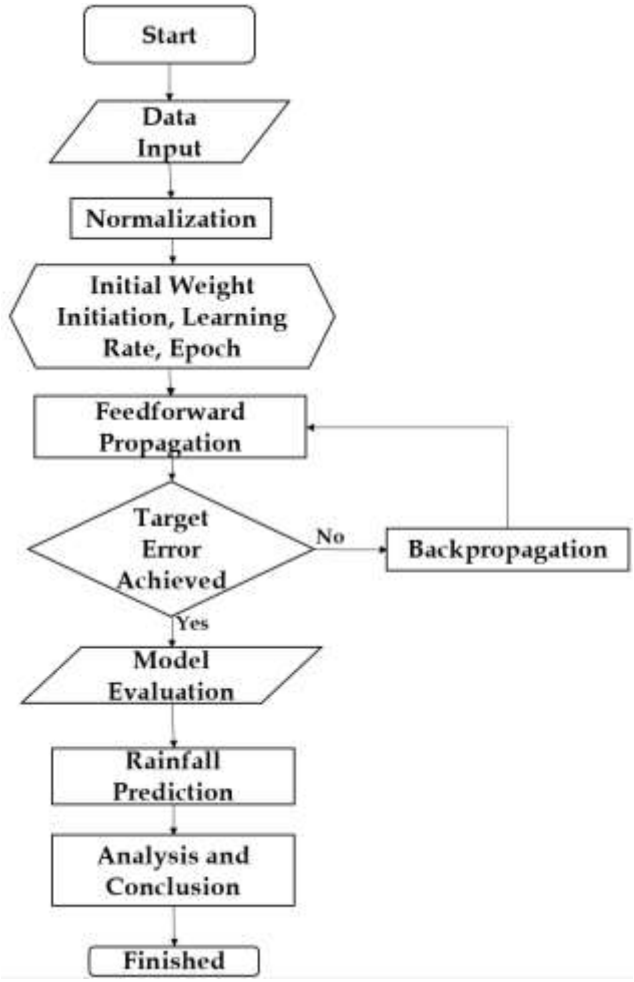

Figure 1. Research flow diagram

The dataset used in this study contains variables with different measurement units and ranges; therefore, a normalization process was applied to ensure all features operate on a comparable scale. This step is essential to prevent variables with larger numeric ranges from dominating the learning process of the neural network. In this study, the Min–Max normalization technique was adopted, which performs a linear transformation of the original data into a predefined range of (0,1).

The Min–Max method was selected because it is simple, computationally efficient, and well-suited for datasets without significant outliers, ensuring balanced feature scaling and faster convergence during neural network training (Patro & Sahu, 2015). Moreover, compared to z-score normalization, the Min–Max approach is more compatible with Artificial Neural Network (ANN) models employing sigmoid activation functions, as these functions perform optimally within a bounded input range. Therefore, the choice of Min–Max normalization in this study is justified by its alignment with the data characteristics and its ability to enhance model stability and convergence efficiency during ANN training (Deepa & Ramesh, 2022).

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where:
X' : Normalized data results
X : Original data
X_{min} : Minimum value of the data
X_{max} : Maximum value of the data

According to Setiyaris et al. (2023), the Levenberg-Marquardt algorithm is one of the Backpropagation Artificial Neural Network (ANN) training methods that uses two calculation methods, namely forward calculation and backward calculation. Several parameters used in the training process include the Levenberg-Marquardt parameter with a value greater than zero (η > 0), the tau factor parameter (Ʈ), the target error, and the maximum epoch. The updating of weights and biases is done using the Hessian matrix method (H) which can be calculated using the equation (Satria Wibawa, 2017).

$$H = J^T J \quad (2)$$

The gradient calculation is used:

$$g = J^T e \quad (3)$$

Where J is a Jacobian matrix, namely a matrix composed of the first derivative of the error function with respect to each weight and network bias. The weight changes are calculated using equation.

$$\Delta w = (J^T J + \eta I)^{-J^T e} \quad (4)$$

The next step is to reduce the old weight from the weight change results that have been obtained to calculate the new weight. Next, check whether the error obtained is smaller than the specified target error. If not, return to the previous step and check again whether the error obtained is smaller than the previous error. If it is smaller, then the value of η is divided by the tau factor (Ʈ). After that, perform the forward propagation process and recalculate the weight changes. Repeat this process continuously until the error value is smaller than the specified target error, so that the MSE value and the optimal weight value are obtained.

The activation functions used in this study are the binary sigmoid and bipolar sigmoid functions, which play a crucial role in mapping nonlinear inputs and regulating the transmission of signals between neurons in the network. The selection of these activation functions is directly related to the characteristics of the data being modeled. Specifically, the binary sigmoid function is employed in the hidden layer to transform the input variables into non-linear representations within the (0,1) range, facilitating the extraction of complex patterns. Meanwhile, the bipolar sigmoid function is applied in the output layer because the target data represent continuous values that have been normalized to the (-1,1) range, ensuring that the network outputs remain consistent with the scale of the prediction task (Satria Wibawa, 2017).

The next step is to design the artificial neural network architecture and implement the parameters used in this research. The input network consists of eight weather parameters, with one hidden layer, and the output is rainfall. The architecture is shown in Figure 2.

The next stage is the network implementation phase using MATLAB, where coding is performed to produce output in the form of rainfall predictions based on the predetermined architecture. The complete training parameters used for the network process are presented in Table 1.

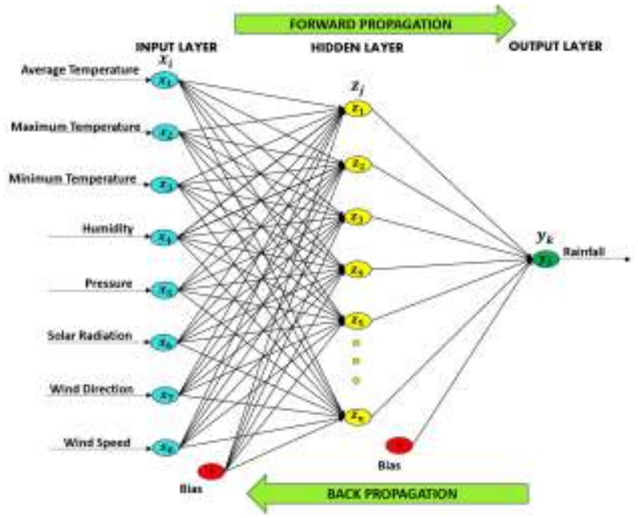

Figure 2. Backpropagation artificial neural network architecture one hidden layer used in this research

The rainfall dataset used in this study was divided into three subsets: 80% for training, 10% for validation, and 10% for testing. This data split follows common practice in Artificial Neural Network (ANN) training to ensure that the model learns effectively while maintaining generalization capability.

Table 1. Backpropagation Neural Network Parameters

Network Type	Backpropagation Artificial Neural Network
Training Function	Trainlm
Activation Function	Input to Hidden – logsig Hidden to Output – tansig
Input Layer	8 Input
Hidden Layer :	
1 Hidden Layer Neuron	5, 10, 25, 50 Neurons
2 Hidden Layer Neuron	5 5, 5 10, 5 25, 5 50 Neuron
3 Hidden Layer Neuron	5 5 5, 5 5 10, 5 5 25, 5 5 50 Neuron
Output Layer	1 Output Layer
Data Composition	Training 80% : Validation 10% : Testing 10%
Learning Rate	0.01
Goal Error	0.0001
Model Evaluation	RMSE, MSE, MAE, MAPE and R^2

A hold-out validation approach was adopted instead of full cross-validation, primarily because the dataset represents a time series where the temporal order of observations carries important information. Applying standard k-fold cross-validation could violate the temporal dependencies among samples, potentially leading to data leakage and overly optimistic performance estimates. Therefore, a separate 10% validation set was employed to monitor model performance during training and to prevent overfitting.

This partitioning strategy is consistent with previous studies that have demonstrated the effectiveness of the 80–10–10 data split for climatic and meteorological datasets, as it provides a good balance between training and evaluation data without introducing temporal bias (Setiyaris et al., 2023).

In this study, the training process of the Artificial Neural Network (ANN) involved identifying the optimal random seed value within the range of 1 to 10,000. This procedure was implemented to ensure model stability and accuracy, since the initialization of weights in neural networks is inherently stochastic and may influence both convergence behavior and overall model performance (Wong et al., 2024).

By testing multiple seed values, this study aimed to determine the initialization configuration that yields the best performance, particularly in minimizing training error and avoiding convergence to local minima (Desai, 2024; Jesus et al., 2021). A similar approach was adopted by Setiyaris et al. (2023) in rainfall prediction using the Levenberg–Marquardt algorithm, where careful selection of random seeds improved the consistency and robustness of the training outcomes.

The seed search was conducted for each training function and for every predefined number of hidden neurons to guarantee consistent and reproducible results, following best practices for neural network model training (Skorski et al., 2021). The output results of rainfall prediction will be evaluated using validation of Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and R-Squared (R^2) values which will be validated against the actual values (X. Li & Zhang, 2023).

Mean Squared Error (MSE): Measures the average squared difference between actual and predicted values. A smaller MSE value indicates a more accurate prediction.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (5)$$

Root Mean Square Error (RMSE): Used to measure the magnitude of the error between the model's predicted value and the actual value. The smaller the RMSE, the better the model's performance. The RMSE formula is as follows:

$$RSME = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (6)$$

Mean Absolute Error (MAE): Measures the average of the absolute errors between the predicted and actual values. MAE calculates how far the model's predicted values are from the actual values and then averages all these absolute differences. The smaller the MAE, the better the model's predictions.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} y_i - \hat{y}_i \vee \quad (7)$$

Coefficient of determination (R^2): Is a statistical measure used to evaluate how well a regression model explains variation in the dependent data (dependent variable). The R^2 value ranges from 0 to 1, with the following interpretations:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \quad (8)$$

This parameter helps identify the extent to which the model can provide reliable and accurate predictions based on the analyzed data. Mean Absolute Percentage Error (MAPE), where the MAPE value indicates the magnitude of the forecast error compared to the actual value. The lower the MAPE, the better the forecasting model's performance.

$$MAPE = \sum_{i=1}^{n} y_i - \hat{y}_i \vee \frac{}{y_i \vee} x100\% \quad (9)$$

Results and Discussion

The results of the evaluation of the Backpropagation artificial neural network model with the Levenberg-Marquardt training function (trainlm) in 2024 are shown in Table 2.

Table 2. Evaluation of the Backpropagation Network Model in 2024

Algorithm	Number of Neurons	MSE (mm^2)	RMSE (mm)	MAE (mm)	R^2
LM (1 hidden layer)	5	1,581.46	39.76	32.80	0.87
	10	1,182.28	34.38	31.08	0.89
	25	955.84	30.91	23.06	0.93
	50	1,650.77	40.63	34.29	0.86
LM (2 hidden layer)	5 5	2,052.39	45.30	40.46	0.82
	5 10	1,076.09	32.80	26.04	0.91
	5 25	1,719.08	41.46	36.06	0.82
	5 50	1,452.83	38.11	32.45	0.90
LM (3 hidden layer)	5 5 5	1,609.62	40.12	32.95	0.87
	5 5 10	1,725.97	41.54	36.08	0.85
	5 5 25	1,573.07	39.66	31.98	0.89
	5 5 50	2,233.85	47.26	35.05	0.83

The testing results indicate that the Artificial Neural Network (ANN) model trained using the Levenberg–Marquardt (LM) algorithm with a single hidden layer containing 25 neurons achieved the best overall performance. The model produced an MSE of 955.84 mm^2, an RMSE of 30.91 mm, an MAE of 23.06 mm, and a coefficient of determination (R^2) of 0.93. These results indicate a high level of predictive accuracy, demonstrating that the ANN–LM model is capable of explaining most of the variability in actual rainfall observations. Similar levels of accuracy have been reported in international studies employing ANN–LM for rainfall forecasting, where high R^2 values and low prediction errors were consistently obtained (Mishra et al., 2018; Rudrappa et al., 2025).

The experimental results further show that increasing the number of neurons from 5 to 25 significantly improved model performance. This improvement suggests that a larger number of neurons enhances the network's ability to capture complex nonlinear rainfall patterns. Comparable findings were reported by Setiyaris et al. (2023) and Mishra et al. (2018), who demonstrated that ANN models trained using the Levenberg–Marquardt algorithm achieved optimal performance when a moderate number of neurons was employed in a single hidden layer. However, when the number of neurons was increased to 50, the model performance declined, indicating the occurrence of overfitting. In this condition, the network becomes overly adapted to the training data, resulting in reduced generalization capability when applied to unseen data.

In addition, models with two and three hidden layers did not provide significant performance improvements. In several configurations, deeper network architectures even resulted in lower accuracy compared to simpler structures. This finding suggests that increasing architectural complexity does not necessarily enhance prediction accuracy, particularly when working with limited datasets such as monthly rainfall records. This observation is consistent with previous studies, which reported that simpler ANN architectures trained using the LM algorithm tend to be more stable, computationally efficient, and less prone to overfitting (Setiyaris et al., 2023).

Overall, the results confirm that the Levenberg–Marquardt algorithm offers notable advantages in terms of training stability, rapid convergence, and prediction accuracy compared to conventional Backpropagation and Quasi-Newton methods. Similar conclusions were drawn by Rudrappa et al. (2025), who demonstrated that ANN–LM models outperform traditional statistical and machine learning approaches in rainfall prediction tasks, particularly in regions with complex climate dynamics. The high coefficient of determination (R^2 = 0.93) achieved in this study further supports the suitability of the ANN–LM approach for rainfall prediction in coastal regions characterized by strong ocean atmosphere interactions (Kumar et al., 2023). Therefore, the proposed ANN–LM model with a single hidden layer and an optimal number of neurons can be considered a robust and reliable approach for rainfall prediction using data from a single weather station, particularly in coastal environments such as Sabang City.

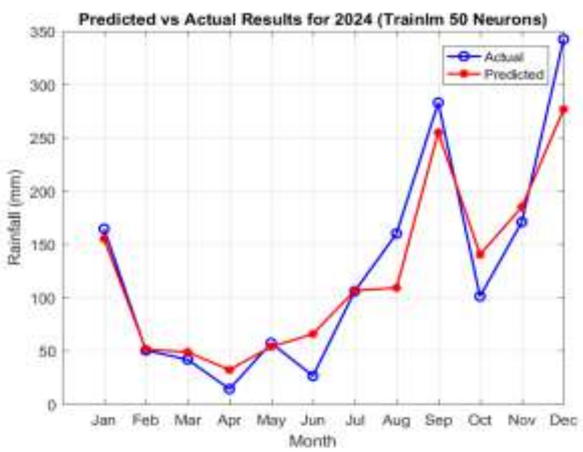

Figure 3. Comparison of predicted and actual rainfall results for 2024 one hidden layer in this study

Figure 3 presents a comparison between observed and predicted monthly rainfall in Sabang City for 2024 generated by the Artificial Neural Network (ANN) model trained using the Levenberg–Marquardt (LM) algorithm. The close agreement between predicted and observed values for most months indicates that the proposed ANN–LM model successfully captured seasonal rainfall variation patterns. This result demonstrates the model's effectiveness in representing monthly rainfall dynamics from historical climatological data, which is consistent with earlier findings in the literature showing that ANN models can accurately reproduce temporal rainfall trends when properly trained (Lee et al., 2018; Mishra et al., 2018).

During the early months of the year (January–March), the prediction results closely matched the actual rainfall observations. For example, in January, the difference between predicted and observed rainfall was only 9.36 mm, indicating excellent model performance during relatively stable rainfall conditions. Comparable performance during climatologically stable periods has also been reported in recent studies, where ANN approaches exhibited high accuracy under consistent seasonal patterns (Aïzansi et al., 2024; Lee et al., 2018).

However, during the dry season (April–June), the ANN–LM model showed a tendency to overestimate rainfall, particularly in April and June. This overestimation can be attributed to very low observed rainfall values in those months, where even small absolute errors lead to large percentage deviations. Such limitations have been documented in ANN-based rainfall prediction studies using monthly aggregated data, in which models are generally more effective at learning recurring patterns than capturing abrupt anomalies or extremely low-rainfall events (Aïzansi et al., 2024; Mishra et al., 2018).

In the second half of the year (July–December), the model's performance stabilized again. Predicted rainfall values from July to November closely matched the observed data, while a slight underestimation occurred in December, which corresponds to the peak of the rainy season. Nevertheless, the ANN–LM model successfully captured the increasing rainfall trend, demonstrating the capability of the Levenberg–Marquardt algorithm to efficiently model nonlinear relationships among climatic variables while maintaining rapid convergence and stable learning behavior. Similar robustness of neural network models for rainfall prediction in coastal and monsoon-influenced regions has been reported in recent research (Esteves et al., 2019; Rudrappa et al., 2025).

Overall, the ANN–LM model with 25 hidden neurons effectively represented the dominant seasonal rainfall patterns in Sabang City, particularly during transitional and rainy seasons. Some performance limitations were observed during the dry months, likely associated with the use of aggregated monthly rainfall data that may obscure short-term variability. Comparable conclusions were drawn in previous studies, which highlighted that higher temporal resolution datasets (e.g., daily data) and inclusion of additional atmospheric variables can improve model sensitivity to extreme rainfall fluctuations (Lee et al., 2018; Mishra et al., 2018). Therefore, future work is encouraged to employ higher-resolution rainfall data and to incorporate additional climatic predictors—such as humidity, wind speed, and sea surface temperature—to further improve model robustness and predictive capability.

Table 3. Prediction accuracy with actual data for 2024

Month	Actual (mm)	Prediction (mm)	MAPE (%)
January	164.5	155.14	5.69
February	50.3	51.20	1.78
March	41.8	48.81	16.78
April	14	32.01	128.68
May	57.3	53.77	6.17
June	26.3	65.80	150.20
July	105.9	106.38	0.46
August	159.9	109.06	31.80
September	282.9	255.01	9.86
October	101	140.29	38.90
November	170.8	184.91	8.26
December	342.4	276.61	19.22

The performance evaluation of the Artificial Neural Network (ANN) model trained using the Levenberg–Marquardt (LM) algorithm with 25 hidden neurons on actual rainfall data for 2024 yielded very satisfactory results, as presented in Table 3. The model achieved an average Mean Absolute Percentage Error (MAPE) of 34.8%, indicating a good level of predictive accuracy for monthly rainfall forecasting. Recent forecasting studies have shown that MAPE remains a widely used and practical performance metric for evaluating nonlinear prediction models, particularly in hydrological and climatological applications involving complex rainfall dynamics (Aïzansi et al., 2024; Makridakis et al., 2020). These results suggest that the ANN–LM model effectively captures nonlinear relationships among climatic variables, especially in coastal regions such as Sabang City.

On a monthly scale, the model demonstrated very high prediction accuracy in February (1.78%), July (0.46%), and September (9.86%), during which rainfall patterns tend to be relatively stable. In contrast, the highest prediction errors occurred in April (128.68%) and June (150.20%), primarily due to extremely low observed rainfall values. Under such conditions, small absolute prediction errors can produce disproportionately large percentage errors, which is a well-known limitation of percentage-based accuracy metrics when applied to low-magnitude rainfall data. Similar behavior has been reported in recent ANN-based rainfall prediction studies using monthly datasets (Aïzansi et al., 2024; Setiyaris et al., 2023).

The ANN–LM model showed a tendency to slightly overestimate rainfall during dry periods and underestimate rainfall during peak rainy months. Despite this limitation, the model successfully followed the dominant seasonal rainfall patterns throughout the year, demonstrating its robustness in learning recurring precipitation trends. Comparable seasonal performance characteristics have been observed in recent studies, which reported that ANN models trained using the Levenberg–Marquardt algorithm are particularly effective in capturing general rainfall behavior but exhibit reduced sensitivity to extreme low or high rainfall events (Rudrappa et al., 2025; Setiyaris et al., 2023).

Overall, these findings confirm that the Levenberg–Marquardt algorithm is highly effective for monthly rainfall prediction, offering strong capability in optimizing network weights and achieving rapid convergence during training. The high coefficient of determination (R^2 = 0.93) further indicates that the model can explain most of the variability in the observed rainfall data. Nevertheless, future improvements in prediction accuracy may be achieved by incorporating additional atmospheric predictors—such as sea surface temperature (SST), humidity, and wind speed—and by employing higher temporal resolution datasets (e.g., daily rainfall) to better capture extreme rainfall fluctuations, as recommended in recent ANN-based rainfall prediction literature (Aïzansi et al., 2024; Rudrappa et al., 2025).

Conclusion

This study demonstrates that the Artificial Neural Network (ANN) model trained with the Levenberg–Marquardt (LM) algorithm is effective for predicting monthly rainfall in Sabang City. The optimal network architecture, consisting of one hidden layer with 25 neurons, achieved strong performance with an R^2 value of 0.93 and a MAPE of 34.8%, indicating acceptable forecasting accuracy. The model successfully captured seasonal rainfall patterns, particularly during transitional and rainy periods, although minor deviations occurred during dry months with very low precipitation. To further improve prediction accuracy and robustness, future research should employ higher-resolution (daily) data, incorporate additional atmospheric variables, and explore hybrid modeling approaches such as ANN-Fuzzy or ANN-ARIMA to enhance sensitivity to extreme weather anomalies.

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Author Contributions
Wahyu Sukmananda conducted the research and prepared the initial manuscript. Irwandi provided supervision for the research activities and refined the manuscript. Edwar Iswardy reviewed and improved the English language of the paper. Kadarsah contributed to the interpretation of the findings. Yopi Ilhamsyah provided insights into the key parameters influencing weather prediction. Yuwaldi Away offered suggestions regarding the AI algorithms employed in the study. Chakrit Chotamonsak provided additional recommendations for enhancing the rainfall prediction algorithm. Dedy Ardana contributed input related to the processing of data recorded by the BMKG stations.

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Conflicts of Interest
The authors declare no conflict of interest.

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