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Monthly Rainfall Prediction Using the Backpropagation Neural Network (BPNN) Algorithm in Maros Regency

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Abstract.
Purpose: This study aims to identify the right combination of network architecture, learning rate, and epoch in making predictions at each rainfall post in Maros Regency. In addition, this study also predicts the monthly rainfall profile in 2021-2025 in Maros Regency.
Methods: The method in this study is the backpropagation neural network algorithm to learn and predict the data. BPNN is one of the most commonly used non-linear methods in making predictions recently. The data used in this study is monthly rainfall data from 2000-2020 as training and testing data at four rainfall stations including BPP Batubassi, Staklim Maros, Stamet Hasanuddin, and BPP Tanralili.
Result: The results showed that the combination of network architecture, learning rate, and epoch obtained at each rainfall post was different. The highest level of prediction accuracy was obtained on 5 layers rather than 3 or 4 layers of network architecture with prediction accuracy at each rainfall post respectively 76.91%, 72.47%, 75.24%, and 76.53%. The predictions of rainfall from 2021-2025 are following the monsoon rain pattern with the highest rainfall in January 2025 of 964.1 mm, while the largest annual rainfall is obtained in 2023 with a total of 3359.6 mm.
Novelty: In this study, various combinations of network architecture parameters consisting of learning rate, epoch, and architecture at each rainfall post obtained different results. Particularly in the Maros Regency, the combination that is most suitable for use in predicting monthly rainfall at the Batubassi BPP post is learning rate 0.7, epoch 50000, and network architecture 11-6-10-7-5, at Staklim Maros post is learning rate 0.5, epoch 50000, and network architecture 11-5-9-10-5, at Stamet Hasanuddin post is learning rate 0.8, epoch 20000, and network architecture 11-5-8-6-5, and at BPP Tanralili post is learning rate 0.5, epoch 10000, and 11-5-9-9-5 network architecture.

Keywords: Backpropagation, Network Architecture, Non-linear Method, Prediction, Rainfall
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INTRODUCTION

Rainfall is a complex atmospheric phenomenon in which water falls in liquid form from clouds to the earth [1]. Increased rainfall or what is commonly referred to as extreme rainfall can result in changes to weather patterns. Extreme increases in rainfall can be caused by unstable atmospheric conditions and the flow of wet air masses. This situation can lead to natural disasters and cause losses and even casualties [2]. To prevent this loss, it is necessary to pay attention to weather parameters, especially rainfall, and how to predict future rainfall. Prediction of rainfall can increase awareness of the consequences that can be caused. It can be done using artificial intelligence technology.

Artificial Intelligence (AI) is a technology with the ability to imitate human intelligence in solving a problem. AI is the same as giving machines the ability to think. AI has been applied in various fields. One that can be used as an example is a smart home. The smart home has various capabilities, such as adjusting room temperature, managing the indoor air quality, turning on music, and much more. Some examples of AI applications are learning, problem solving, pattern recognition, speech recognition, image recognition, decision making, and interlanguage translators. In education, AI is also starting to get more involved. Research related to AI in education has recently increased [3]. One of the AI techniques that attract attention and can be applied to various fields is Machine Learning (ML) [4], [5]. ML is an algorithm development

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that allows to find out patterns by studying the available data so that they can predict based on the data that has been studied [6], [7]. A wide variety of ML algorithms have been used to make predictions [8]–[11].

Artificial Neural Network (ANN) is one of the popular methods for making predictions. In recent years, researchers have begun to use ANN models or artificial neural networks to make non-linear predictions [12]. ANN has more general and flexible functions compared to traditional statistical methods. Each prediction model assumes that there is a relationship (both known and unknown) between the input variable (historical data) and the output variable (prediction data). Often, traditional statistical prediction models have limitations in estimating the underlying function due to the complexity of the actual system. ANN can be a good alternative for identifying these functions [13].

ANN also began to be often used in hydrological forecasting. Several previous studies have used this method in making predictions [7], [14]–[17]. ANN has several algorithms, including Emotional Artificial Neural Network (EANN), Adaptive Ensemble Empirical Mode Decomposition-Artificial Neural Network (AEEMD-ANN), E-SVR-Artificial Neural Network (E-SVR-ANN), Backpropagation Neural Network (BPNN), and the Feed Forward Neural Network (FFNN). The best algorithm for minimizing the error rate in making predictions is Backpropagation Neural Network (BPNN) [18]. Prayoga in [14] shows that the Backpropagation Neural Network Method is a good method for forecasting. It can be seen from the results of the research conducted showing the value of the prediction accuracy rate of 75%. Related research has been carried out by Lesnussa et al [15], which predicts rainfall data in Ambon City using the Backpropagation Neural Network. The results of this study indicate that the level of prediction accuracy obtained is 80%. This shows that the BPNN method can be used to predict rainfall. A few previous researchers focused on predictive results using a small parameter variation. They limit their research to certain parameters. Therefore, in this study, several variations of numbers will be used such as learning rate, epoch, and network architecture. The network architecture used in this study varies from 3-5 layers to see the effect of the number of layers on the prediction results.

Parameter variations in this study will use the BPNN method which is carried out in Maros Regency. Maros Regency is an area that is prone to flooding. Research related to flooding has been carried out by Barkey who models the level of vulnerability to floods in Maros Regency [19]. Based on the level of rainfall, it shows that the increase in rainfall affects the area affected by flooding. This study shows that there are 42 villages that have a high level of flood vulnerability. The level of vulnerability to flooding is also influenced by the characteristics of the landscape of the river basin. Based on some of the previous points, it is necessary to make predictions about weather parameters, especially the rainfall parameter which is the main cause of disasters in the Maros Regency area as an early warning in flood disaster management and as information on water availability.

METHODS

Materials

The study area in this research was Maros Regency using rainfall data from several rainfall posts. The distribution of the rainfall post can be seen in Figure 1.

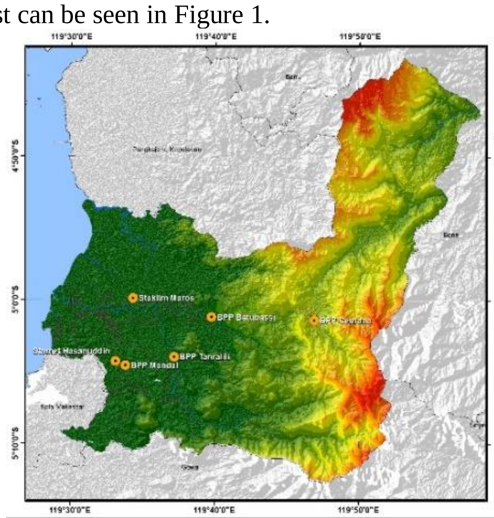

Figure 1. Rainfall post map

As shown in Figure 1, the data used in this study consisted of six rainfall posts. The rainfall post data used are BPP Batubassi, Staklim Maros, Stamet Hasanuddin, BPP Tanralili, BPP Cenrana, and BPP Mandai. The data to be used was monthly rainfall data from January 2000- December 2020. The data was obtained from Sultan Hasanuddin Class I Meteorological Station.

Stage of Research

There are several steps in this study that can be seen in Figure 2.

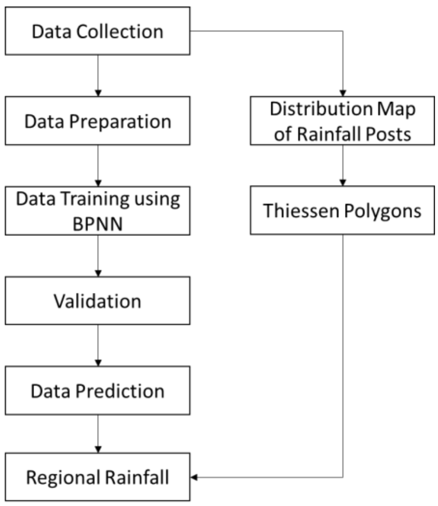

Figure 2. Stage of research

Figure 2 shows that the stage of research in this study namely data collection, data preparation, data training, validation, rainfall prediction, and calculating the regional rainfall based on the predicted data and the weight of Thiessen polygons.

Data Collection

The data used in this study is secondary data on monthly rainfall from January 2000 - December 2020. The data in this study were taken at Sultan Hasanuddin Class I Meteorological Station office in Maros Regency on June 30, 2021. These data contain the name of the rainfall post, the geographic location of the rainfall post, and the monthly rainfall value. Based on the geographic location of rainfall post, the distance between rainfall posts can be obtained using the Google Earth application. Data description can be seen in Table 1 below.

Table 1. Data description

Statistical Parameter	***BPP Batubassi***	***BPP Cenrana***	***BPP Mandai***	***Staklim Maros***	***Stamet Hasanuddin***	***BPP Tanrallili***
Number of Data	246	155	183	252	251	216
Mean	298.073	218.136	305.798	279.897	263.833	305.171
Standard Error	18.238	17.162	26.234	17.826	16.775	18.796
Median	248.5	163	179	199.5	181	236
Mode	0	0	0	0	0	0
Standard Deviation	286.057	213.667	354.888	282.975	265.761	276.237
Sample Variance	81828.525	45653.546	125945.843	80074.794	70629.148	76307.036
Kurtosis	1.783	1.840	3.198	0.709	0.374	0.460
Skewness	1.249	1.311	1.713	1.126	1.092	0.930
Range	1532	1105	1910	1308	1066	1360
Minimum	0	0	0	0	0	0
Maximum	1532	1105	1910	1308	1066	1360
Period	January 2000-December 2020	January 2007-December 2020	January 2003-December 2020	January 2000-December 2020	January 2000-December 2020	January 2000-December 2020

Data Preparation

The data preparation includes data interpolation, data selection, data normalization, and dataset split. After collecting the data from Sultan Hasanuddin Class I Meteorological Station, there are some missing rainfall data. The missing data was obtained using the Interpolation Distance Weighted (IDW) method. This method requires rainfall data from other stations and the distance between rainfall posts.

Based on the data selection, Predictions are made at the rainfall post which has 252 available monthly rainfall data from January 2000 – December 2020. Prediction will be made at four rainfall posts station including BPP Batubassi, Staklim Maros, Stamet Hasanuddin, and BPP Tanralili. After being selected, the next step is to normalize the data.

Rainfall data were normalized using the min-max normalization method [20]. The equation of min-max normalization can be written in Equation (1).

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

however, the normalized data used in this study is in the range of [0.1-0.9], so Equation (1) above is transformed into Equation (2) below.

$$x' = 0.8\frac{x - \min(x)}{\max(x) - \min(x)} + 0.1 \tag{2}$$

where: x' = normalized data
x = initial data
max(x) = the largest data value
min (x) = the smallest data value

The last step of data preparation is separating the data. The dataset is split into training data and validation data. The proportions used are 76 % training data and 24 % testing data.

Data Training Using BPNN

Backpropagation is one of the algorithms of artificial neural networks. The learning process using this algorithm is carried out by adjusting the weights of the neural network connections with the direction backward based on the level of error in the learning process. Backpropagation Neural Network is supervised learning. This algorithm is called to be supervised learning because the learning is done by creating a function from the training data to learn the function mapping from input to output. This algorithm has output as the target of input data to estimate the mapping function. Stage preparation for this algorithm is done by creating a data set learning consisting of training and target data. The learning process of backpropagation involves 3 stages, namely, feedforward to data training patterns input, backpropagation based on processing errors, and weight adjustment [21], [22]. The activation function used in this study was the unipolar sigmoid biner [21]. The equation of the unipolar sigmoid biner can be written as in Equation (3).

$$\phi(t) = \frac{1}{1+e^{-t}} \tag{3}$$

The output of unipolar sigmoid biner can be ranged between [0-1] and the derivative function can be written as in Equation (4).

$$\phi'(t) = \phi(t)\big(1 - \phi(t)\big) \tag{4}$$

where, t is the input data.

The total data used at this stage is 192 monthly rainfall data from January 2000 – December 2015. The initial step of this process was to find the learning rate (α) and epoch values that produce the smallest Mean Square Error (MSE) using Equation (5) [23].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_k - y_k)^2 \tag{5}$$

where, n = the amount of data
t_k = observed value
y_k = predicted value

This step using a fixed network architecture with 11 input neurons, 5 hidden neurons, and 5 output neurons which can be seen in Figure 3.

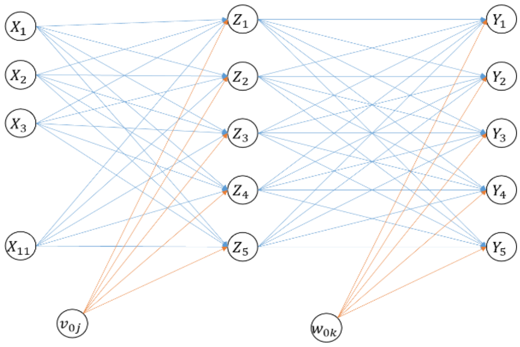

Figure 3. Network architecture on learning rate and epoch

The next step is to find the best architecture that produces the best level of accuracy at the validation (prediction) stage. The network architecture variations used include the number of hidden layers and the number of hidden neurons. At this stage, 3 layers to 5 layers network architecture are used with the number of hidden neurons varying from 5-10 with an increase of 1 neuron.

Validation

The total data used at this stage is 60 monthly rainfall data from 2016-2020. The results of the learning process in the form of weights and biases will be used to predict validation data with a feedforward process. The prediction results are then compared with the validation data to calculate the level of prediction accuracy. The first step is to calculate the Mean Absolute Percentage Error (MAPE) using Equation (6) [23].

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\left(\frac{t_k - y_k}{t_k}\right) \times 100\right| \tag{6}$$

Where t_k is the observed value and y_k is the predicted value. The accuracy of prediction can be calculated using Equation (7).

$$Accuracy = 100\% - MAPE \tag{7}$$

Data Prediction

The network architecture that produces the best level of accuracy at the validation stage will be used to predict monthly rainfall at each rainfall post. At the prediction stage, 132 monthly rainfall data from January 2010 – December 2020 are used to predict 60 monthly rainfall data from January 2021- December 2025.

Calculation of Regional Rainfall

The coordinates of each rainfall post are then inputted into ArcGIS to obtain the weight of the Thiessen polygon for each rainfall post so that the average regional rainfall calculation for Maros Regency can be calculated based on the predicted denormalized data.

RESULT AND DISCUSSION

Leaning Rate and Epoch

The first step is to find a combination of learning rate and epoch that produces the smallest MSE value. The architecture of this step is fixed network architecture with 1 input layer with 11 node, 1 hidden layer with 5 node, and 1 output layer with 5 node. The variation of learning rate used in this study was 0.1 to 0.9 with an interval of 0.1, while the epoch from 10000 to 50000 with an interval of 10000. The result of the combination that produces the smallest MSE at each rainfall post can be seen in Table 2.

Table 2. Combination of learning rate and epoch

Rainfall Post	Learning Rate	Epoch	MSE
BPP Batubassi	0.7	50000	0.000053
Staklim Maros	0.5	50000	0.000169
Stamet Hasanuddin	0.8	20000	0.000429
BPP Tanralili	0.5	10000	0.000370

As shown in Table 2, The best combination of learning rate and epoch in BPP Batubassi is 0,7 for the learning rate and 50000 for the epoch. In Staklim Maros, the best combination is 0,5 for the learning rate and 50000 for the epoch. In Stamet Hasanuddin, the best combination is 0,8 for the learning rate and 20000 for the epoch. In BPP Tanralili, the best combination is 0,5 for the learning rate and 10000 for the epoch. These combinations of learning rate and epoch in every rainfall post produce the smallest value of Mean Square Error (MSE). The combination of these parameters as shown in Table 2 is then used to find the best network architecture that produces the best level of prediction accuracy.

Network Architecture Variations and Data Validation

The data learning phase to identify the target data is carried out on each variation of network architecture with a total of 258 network architectures. Structure of the architecture can be seen in Table 3.

Table 3. Structure of network architecture variation

Characteristic	3 Layers	4 Layers	5 Layers
Architecture	1 input layer, 11 nodes 1 hidden layer, 5-10 nodes 1 hidden layer, 5 nodes	1 input layer, 11 nodes 2 hidden layers, 5-10 nodes 1 hidden layer, 5 nodes	1 input layer, 11 nodes 3 hidden layers, 5-10 nodes 1 hidden layer, 5 nodes
Total of network architecture	6 Architectures	36 Architectures	216 Architectures

After the data learning process, data validation was carried out by predicting the 2016-2020 validation data using the connection weights between layers and the bias in each layer. Figure 4 shows the results that have been obtained at this stage.

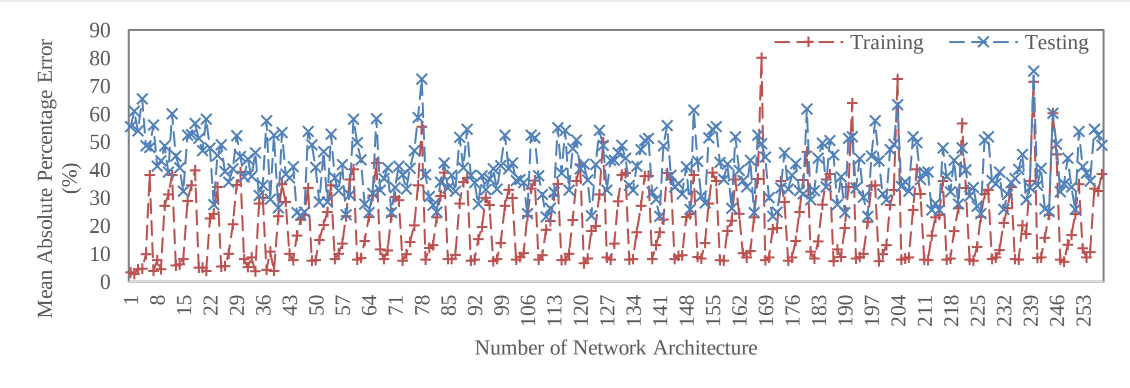

Figure 4. Mean absolute percentage error of network architecture variation

Figure 4 shows the Mean Absolute Percentage Error (MAPE) from the training and testing phase of monthly rainfall data at the BPP Batubassi post. The figure shows that the lowest error rate at the training phase is obtained in the 2nd network architecture or 11-6-5 with an error rate of 2.66 % and produces an error rate at the testing phase of 60.92 %. The network architecture that produces the lowest error rate at the testing phase is obtained at the 111th network architecture or 11-6-10-7-5 with an error rate of 23.09 %. Figure 5 shows the result of the training phase using the 11-6-10-7-5 network architecture.

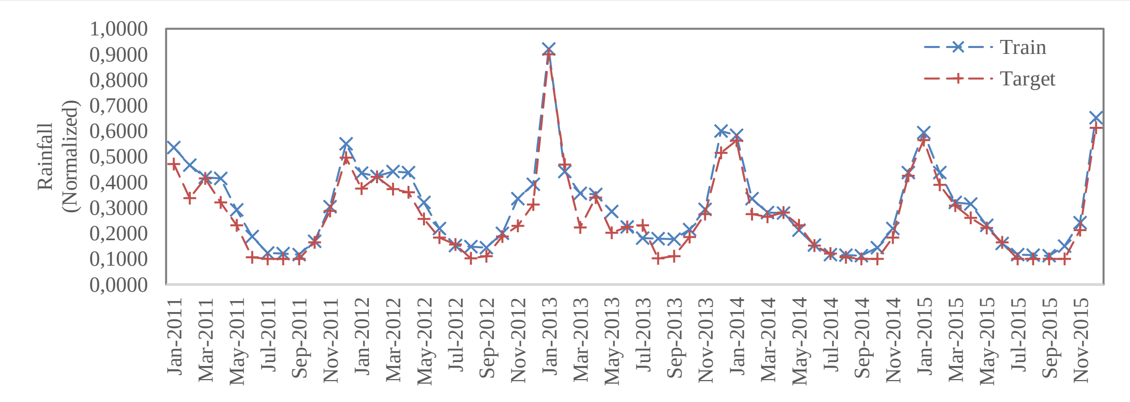

Figure 5. Rainfall chart target and train of the BPP Batubassi

It can be seen from Figure 5 above that there is no significant difference between the train and the target. The MSE calculation obtained was 0.0025 with the MAPE of 18.64 %, so the pattern recognition accuracy was 81.36 %. The connection weights and biases obtained were then used to predict the validation data (testing phase). Figure 6 shows the prediction result that has been obtained.

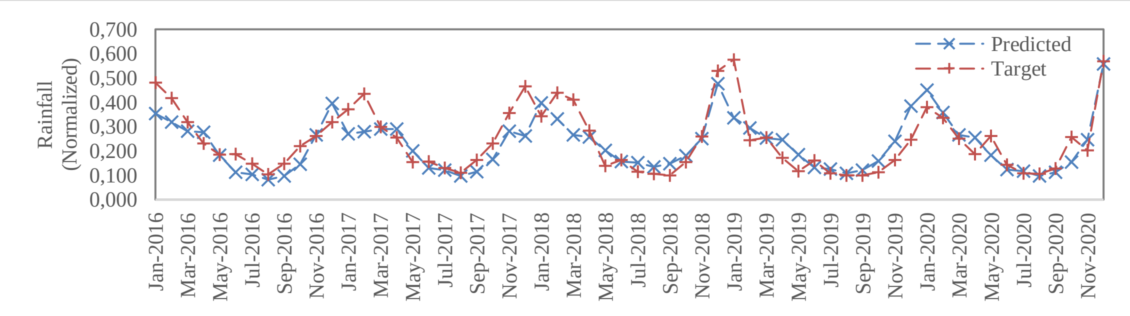

Figure 6. Validation of rainfall prediction result for 2016-2020 of BPP Batubassi

Figure 6 above shows that the validation result with a MAPE value obtained was 23.03 and the MSE value was 0.0054. Based on the MAPE value, the accuracy of prediction obtained was 76.91 %. Prediction using the network architecture of 11-6-5-10-7-5 has the highest level of accuracy at the testing phase. The result that has been obtained at each rainfall post can be seen in Table 4.

Table 4. Mean absolute percentage error of network architecture for each post rainfall

Parameter	Rainfall Post	Architecture	MAPE Training	MAPE Testing
Best Architecture by MAPE Training	BPP Batubassi	11-6-5	2.66	60.92
	Staklim Maros	11-9-7-5	3.81	44.96
	Stamet Hasanuddin	11-5-5	5.73	42.61
	BPP Tanralili	11-10-5	5.88	51.14
Best Architecture by MAPE Testing	BPP Batubassi	11-6-10-7-5	18.64	23.09
	Staklim Maros	11-5-9-10-5	14.63	27.53
	Stamet Hasanuddin	11-5-8-6-5	16.62	24.76
	BPP Tanralili	11-5-9-9-5	23.47	25.95

Table 4 shows that the result obtained at each rainfall post has different network architecture and Table 2 shows that each rainfall post has a different learning rate and epoch. This is in accordance with the research conducted by Widodo and Sarwoko [24], which states that the combination of training parameters that produces the lowest MSE is not always the same. This shows that in making a prediction using the BPNN algorithm, it is necessary to find the right combination of training parameters with the best accuracy of prediction.

The results showed that architectural variations consisting of 3 layers to 5 layers gave the result that the use of network architecture with 5 layers would give a very good prediction in Maros Regency compared to using a network architecture with a total of 3 or 4 layers. It can be seen from the results that the use of a 3-4 layers network architecture provides a very good level of accuracy at the training phase but has a fairly low level of accuracy when predicting validation data. Increasing the number of layers can improve prediction accuracy, as was done by Karsoliya [25]. Adding up to 3 hidden layers will improve better prediction results. However, adding hidden layers will also affect learning time. Other studies also say that the number of hidden neurons should not be too few or too many because it can cause overfitting which can improve accuracy in the training phase but provide poor accuracy in the testing phase. The same thing also happened to the value of MSE training [26].

The accuracy level of the testing phase can also be affected by the amount of data used in the training phase. Previous research has been conducted by Oktaviani and Afdal [27], which predicts one year of rainfall in 2012 with a difference in the amount of training data of 5 years and 10 years. The result of that study indicates that the use of 10 years of data provides a better level of accuracy than the use of 5 years of data. Therefore, it can be concluded that to predict 5 years of rainfall data, the largest amount of data is needed to be used in the training phase.

Rainfall Prediction at Each Rainfall Post in Maros Regency

Based on the learning results in the form of connection weights and biases along with the best network architecture, a monthly rainfall prediction is made from 2021-2025. Figure 7 shows the result of rainfall prediction at each post.

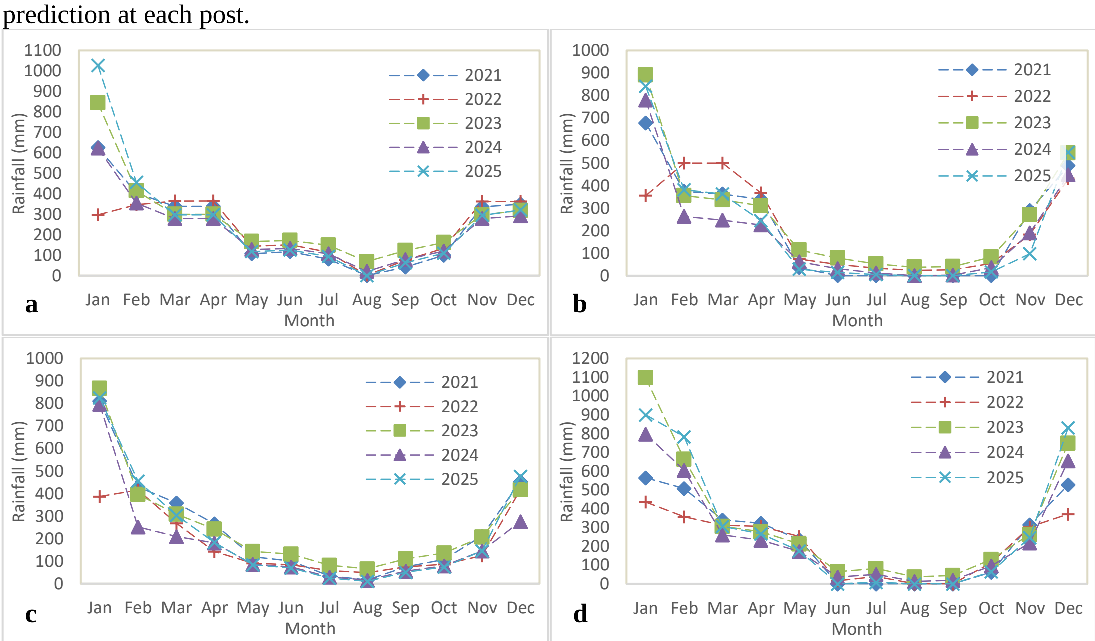

Figure 7. Monthly rainfall prediction results from 2021-2025 (a) BPP Batubassi, (b) Staklim Maros, (c) Stamet Hasanuddin, (d) BPP Tanralili)

Figure 7 shows the prediction of monthly rainfall at BPP Batubassi post with the highest rainfall occur in January 2025 at 1027.7 mm and the lowest in August 2021 at 0 mm. The highest rainfall at Staklim Maros post will occur in January 2023 at 891.3 mm and the lowest in June-October 2021, August 2024, August and September 2025 at 0 mm. The highest rainfall at Stamet Hasanuddin post occur in January 2023 at 867 mm and the lowest in August 2025 at 10.2 mm. The highest rainfall at BPP Tanralili pos occur in January 2023 at 1097.7 mm and the lowest occur in June-September 2021; August and September 2022; June, August, and September 2025 at 0 mm. The comparison with the data available in 2021 from January until September can be seen in Figure 8.

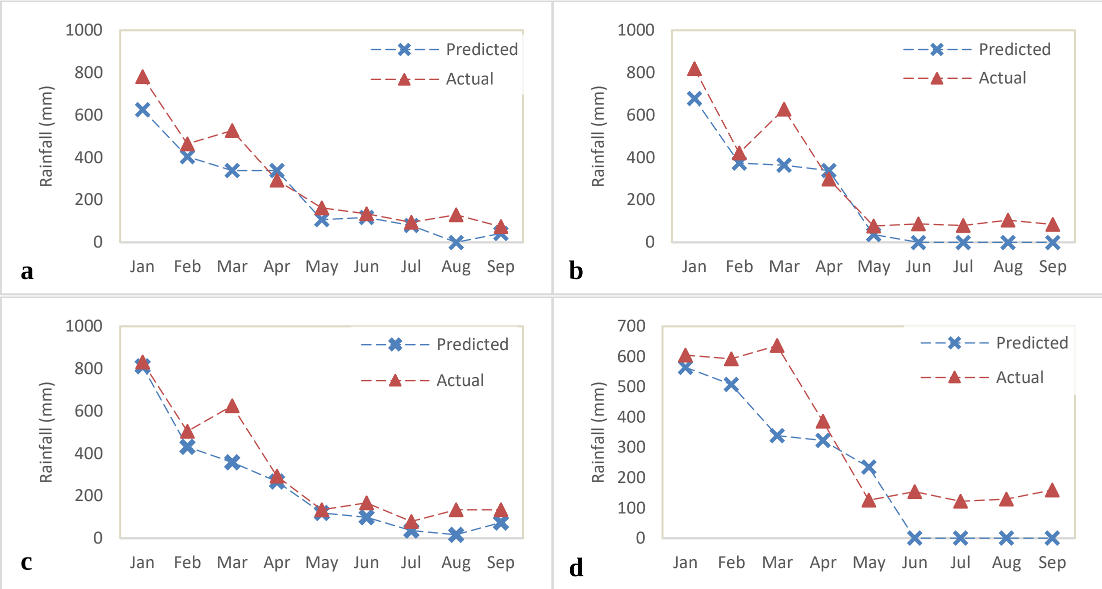

Figure 8. Comparison of predicted results and actual data in 2021 (a) BPP Batubassi, (b) Staklim Maros, (c) Stamet Hasanuddin, (d) BPP Tanralili)

Based on Figure 8, the average difference in data at the BPP Batubassi post is 77.8 mm, at the Staklim Maros post is 98.8 mm, at the Stamet Hasanuddin post is 76.2 mm, and at the BPP Tanralili post is 128.4 mm. It can be seen that the prediction for 2021 from January to September, the overall prediction results follow the pattern of the actual data graph. The biggest difference occurs in March. Based on the BMKG press release [28] which explains that the transition from the Asian monsoon to the Australian monsoon will occur at the end of March 2021 and the South Celebes region in late March to early April has the potential to be dominated by heavy rain. Some areas of South Celebes enter the dry season from May to June 2021.

Rainfall Area in Maros Regency

Based on the result of data processing using ArcGis and Excel to calculate the average rainfall area for the Maros Regency using the predicted data at each rainfall post, Table 5 shows the result.

Table 5. Average rainfall area in Maros Regency in 2021-2025

Month	Average rainfall area				
	2021	2022	2023	2024	2025
January	640.6	333.5	890.5	687.1	964.1
February	417.1	376.6	441.6	369.2	493.7
March	343.9	367.5	307.1	265.9	308.1
April	329.6	336.6	292.9	255.8	274.2
May	117.3	144.3	164.3	120.2	110.4
June	80.7	110.3	139.0	98.5	85.2
July	52.6	86.6	119.1	77.8	62.4
August	1.4	8.4	59.0	15.7	1.0
September	32.4	57.1	98.4	56.3	43.4
October	80.1	115.2	143.3	100.9	87.1
November	314.9	306.9	280.5	244.7	245.3
December	404.9	377.8	423.8	366.8	443.2

Table 5 shows that the highest rainfall occur in January 2025 at 964.1 mm and the lowest rainfall occur in August 2025 at 1.0 mm. Figure 9 shows the predicted rainfall pattern for 2021-2025.

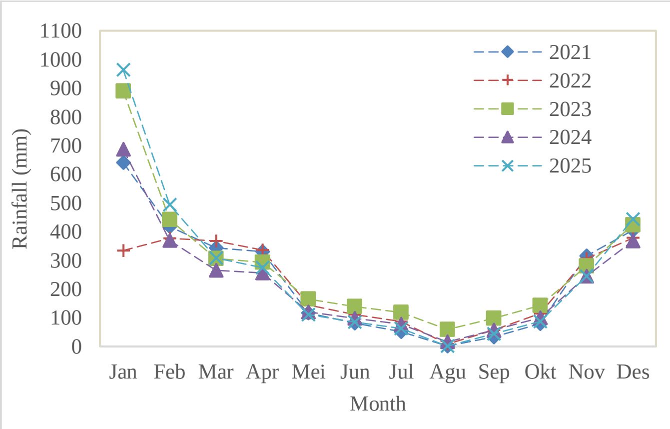

Figure 9. Maros regency monthly rainfall pattern in 2021-2025

Figure 9 shows the rainfall in Maros Regency from 2021-2025 has 2 peaks in January and December, while the lowest rainfall is in August. The figure shows that the general pattern of rainfall has a peak at the beginning of the year in January then begins to decline with the lowest point in August and then rises again until December. This pattern corresponds to the monsoon rainfall pattern. It can be said that the predicted rainfall pattern is following the type of monsoon rainfall.

The result of the prediction of rainfall in 2021-2025 shows that the annual rainfall in Maros Regency is in the range of 2620.7 – 3359.8 mm with the largest amount of annual rainfall occurring in 2023 with a total rainfall of 3359.6 mm while the lowest is in 2021 with a total rainfall of 2620.7 mm. This is in accordance with research conducted by Badwi et al [29], which states that in the Maros watershed area, the annual rainfall ranges from 2000-4000 mm/year which is said to be quite high.

Based on the rainfall prediction results, in 2023 the availability of water is the largest compared to other years. The high the rainfall, the greater potential for water availability. On the other hand, the lower the rainfall, the higher the water deficit [30]. However, this can also show that in 2023, the level of vulnerability to flooding will be even greater.

CONCLUSION

Based on the results of the study, it can be concluded that to predict monthly rainfall in Maros Regency, 5 layers of network architecture are needed to obtain the best accuracy of prediction. The combination of network architecture that produces the best prediction accuracy level at BPP Batubassi post is network architecture 11-6-10-7-5, learning rate 0.7, and epoch 50000 with pattern recognition accuracy rate of 81.36 % and prediction accuracy rate of 76.91 %. At Staklim Maros post, the network architecture is 11-5-9-10-5, learning rate of 0.5, and epoch 50000 with pattern recognition accuracy rate of 85.37 % and prediction accuracy of 72.47 %. At Stamet Hasanuddin post, the network architecture is 11-5-8-6-5, learning rate of 0.8, and epoch 20000 with pattern recognition accuracy rate of 83.38 % and prediction accuracy of 75.24 %. At BPP Tanralili post, the network architecture is 11-5-9-9-5, learning rate of 0.5, and epoch 10000 with pattern recognition accuracy rate of 76.53 % and prediction accuracy rate of 74.05 %. The rainfall prediction from 2021 until 2025 in Maros Regency is according to the monsoon rainfall pattern. The result shows that the highest rainfall occur in January 2025 at 964.1 mm and the lowest in August 2025 at 1.0 mm. The largest annual rainfall is obtained in 2023 with a total of 3359.6 mm.

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