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Artificial Neural Network Backpropagation for Predicting Rainfall (Case Study in Sultan Muhammad Kaharuddin Meteorological Station)

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Abstract

The climate of a region is strongly influenced and determined by the amount of rainfall in the region. Therefore, knowing the results of rainfall predictions in that area will provide an overview of the climatic conditions that will occur so that anticipatory steps can be taken against unwanted possibilities. This study aims to make predictions of rainfall in Sumbawa Regency for 2023 using a Backpropagation Neural Network. The data used is rainfall data from 2008 to 2022 recorded at the Sultan Muhammad Kaharuddin Meteorological Station. Data Processing is carried out in three stages, namely the data normalization stage, the data training stage, and the data testing stage. The prediction results obtained show that the highest rainfall occurs at the beginning and end of the year, namely January, February, March, and April with rainfall of 343,4 mm/month, 421,3 mm/month, 295,2 mm/month, and 134,1 mm/month. Whereas at the end of the year it takes place in November (178.8 mm/month) and December (223.7 mm/month). The precipitation decline graph (start of dry season) starts from May (24.2mm/month) to September (22.1mm/month) with a dry peak in July (2mm/month). Whereas for the end of the year it takes place in November (302,1 mm/month) and December (308,4 mm/month). The decrease in rainfall (early dry season) begins in May (51,7 mm/month) to October (66 mm/month) with the peak of the dry season in June to August (0 mm/month)..

Keywords: Rainfall Prediction; Artificial Neural Networks; Back Propagation.

INTRODUCTION

Weather and climate are one of the most important natural factors in human life. Knowledge of seasonal patterns, rainfall, and wind movement, for example, can be used in the agricultural, plantation, transportation, and other sectors. Weather and climate greatly affect the pattern of people's lives, so that information about the current weather is needed by the community, both individuals, agencies and companies. Weather conditions are influenced by many things, including air pressure, temperature, wind speed, and rainfall. Rainfall is an attribute that has a great influence on weather conditions and changes. If an area has heavy precipitation, it can be said that the area is in the wet season or the weather is not sunny.

Rainfall has a very important role. Based on rainfall data, climate classification can be carried out according to the comparison between the average number of dry months and the average number of the wettest months. Driest months occur if the monthly rainfall is less than 60 mm/month, while wet months occur if the monthly rainfall is above 100 mm/month. Between the dry and wet months there are humid months, which occur when the monthly rainfall is between 60-100 mm/month (Ritha et al. 2016; Seno et al. 2014). Considering that rainfall has a large influence on weather conditions, it is very important to know the future rainfall conditions. This is the basis for the authors to create a predictive model that can forecast rainfall using past historical data. In the past, rainfall estimates depended on the month, there was a dry season and a rainy season. But nowadays, rainfall is increasingly difficult to predict, so a model or system is needed that can predict rainfall accurately. For this reason, it is necessary to forecast precipitation with a high degree of accuracy based on previous data so that adverse effects can be avoided by preventive measures.

One of the factors that affect the type of climate is rainfall. Accuracy in predicting rainfall is an important factor because it can be used for various purposes (Lee et al, 2018;Nayak et al, 2013; Wu and Chen, 2009; Ammar et al, 2017). Predictions using past data (historical data) can be carried out using the Artificial Neiral Network (ANN) method (Sofian et al. 2018; Abhishek et al. 2012; Narvekar and Fargose, 2015).

ANN is a classification algorithm that mimics the working principle of human neural networks (Siang, 2005). This algorithm maps the input data at the input layer to the target at the output layer via neurons in the hidden layer. The input data is propagated forward, connected by input weights that have previously been initialized randomly. Towards neurons in the hidden layer, input data that has been linked to these weights is then processed using an activation function. Furthermore, the processed data from the hidden layer is connected by hidden weights to the neurons in the output layer. Furthermore, the processed data from the hidden layer is connected by hidden weights to the neurons in the output layer. ANN Is one of the artificial representations of the human brain, which always tries to simulate the learning process in the human brain. The term artificial is used here because this neural network is implemented using a computer program that is capable of completing a number of calculation processes during the learning process (Mastur and Hadi, 2005; Kusumadewi, 2003).

Artificial Neural Networks can show a number of characteristics possessed by the human brain (Mastur and Hadi, 2005), including:

a. Ability to learn from experience

b. Ability to generalize to new input from existing knowledge.

c. The ability to abstract important characteristics from inputs that contain unimportant data

One of the ANN algorithms that are often used to make predictions is the Backpropagation Algorithm (Mislan et al, 2015). Backpropagation is a neural network model with multiple screens. As with other artificial neural network models, backpropagation trains the network to achieve a balance between the network's ability to recognize the patterns used during training and the network's ability to respond correctly to input patterns that are similar (but not the same) as the patterns used during training (Devi et al. 2012). In general, forecasting problems can be expressed by a number of time series data x1, x2,..., xn. The problem is estimating what xn+1 is based on x1, x2,..., xn. There are several steps to designing a network with the backpropagation algorithm, namely, first, collecting data that will be used as input variables and targets that will be the output. Then divide the data into training data and testing data. Next, determine the network architecture according to the algorithm used. Then, determine the number of cells (neurons) for the hidden layer and the activation feature used by each layer. Additionally, multiple parameters must be configured for training. These parameters are the maximum epoch, learning rate and momentum.

This study aims to forecast rainfall of 2023 in Sumbawa Regency based on rainfall time series data recorded at the Sultan Muhammad Kaharuddin Meteorological Station. The results of this study are expected to provide an overview of the condition of rainfall in Sumbawa Regency in 2023 so that efforts or actions can be taken against potential unexpected events.

RESEARCH METHODS

The forecast of rainfall in this study takes a specific case in the Sumbawa Regency region. The data used in this study is monthly rainfall data from January 2008 to December 2022 recorded by the Sultan Muhammad Kaharuddin Sumbawa Besar Meteorological Station which was downloaded on the www.dataonline.bmkg.go.id page (Table 1).

In the ANN Backpropagation algorithm, the binary sigmoid activation function is used where this function has a value between 0 to 1. However, the binary sigmoid function actually never reaches 0 or 1. Therefore, rainfall data must be normalized first in the range 0.1 up to 0.9 using the following equation:

$$X' = \frac{0.8(X-b)}{(a-b)} + 0.1 \quad (1)$$

where X' is the normalized data, X is the rainfall data, a is the maximum rainfall data, and b is the minimum rainfall data. Normalized rainfall data can be seen in Table 2.

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Table 1. Rainfall Data

Rainfall Data (mm)													
No	Tahun	JAN	FEB	MAR	APR	MEI	JUN	JUL	AGU	SEP	OKT	NOP	DES
1	2008	289	295	113	111	5	8	1	0	1	86	108	183
2	2009	150	301	104	115	36	0	17	0	17	2	168	78
3	2010	492	100	168	62	132	1	91	4	157	94	233	388
4	2011	249	317	172	250	232	0	0	0	0	15	230	174
5	2012	346	157	467	31	70	0	0	0	0	11	46	179
6	2013	446	334,8	189,6	99,7	98,7	139	3	0	0	5	65,8	236,8
7	2014	255,2	89,2	465,5	109	13,1	1,4	19,1	0	0	0	109,1	214,8
8	2015	54,8	181,3	205,5	57,1	0	0	0	0	0	0	48,7	174,9
9	2016	303,7	464,3	156,8	124,2	40,3	107,7	58,6	3,7	43,7	160,7	151,2	331,9
10	2017	430,1	311,6	213,8	202,6	42,9	49,4	6,3	0	0	71	389,1	220,7
11	2018	199,4	265,1	169	16,3	0,2	25	1,1	0	18,9	0	159,5	164,9
12	2019	447,5	288,7	284,8	11,8	86,2	0	0	0	0	0	57,5	121,1
13	2020	303,7	175,1	304,5	25,4	97,7	0,6	0,3	0,9	0	94,8	74,5	294,5
14	2021	234,7	421	147,5	103,3	17,2	28,4	0	0	81,5	100,3	335,8	300,7
15	2022	244,5	185	159,4	102,3	24,2	41,7	2,3	4,5	22,1	126,4	178,8	223,7

Table 2. Data Normalization

Data Normalization													
No	Tahun	JAN	FEB	MAR	APR	MEI	JUN	JUL	AGU	SEP	OKT	NOP	DES
1	2008	0,57	0,58	0,284	0,28	0,11	0,113	0,1	0,1	0,1	0,24	0,276	0,398
2	2009	0,344	0,589	0,269	0,287	0,16	0,1	0,13	0,1	0,13	0,103	0,373	0,227
3	2010	0,9	0,263	0,373	0,201	0,31	0,102	0,25	0,11	0,36	0,253	0,479	0,731
4	2011	0,505	0,615	0,38	0,507	0,48	0,1	0,1	0,1	0,1	0,124	0,474	0,383
5	2012	0,663	0,355	0,859	0,15	0,21	0,1	0,1	0,1	0,1	0,118	0,175	0,391
6	2013	0,825	0,644	0,408	0,262	0,26	0,326	0,1	0,1	0,1	0,108	0,207	0,485
7	2014	0,515	0,245	0,857	0,277	0,12	0,102	0,13	0,1	0,1	0,1	0,277	0,449
8	2015	0,189	0,395	0,434	0,193	0,1	0,1	0,1	0,1	0,1	0,1	0,179	0,384
9	2016	0,594	0,855	0,355	0,302	0,17	0,275	0,2	0,11	0,17	0,361	0,346	0,64
10	2017	0,799	0,607	0,448	0,429	0,17	0,18	0,11	0,1	0,1	0,215	0,733	0,459
11	2018	0,424	0,531	0,375	0,127	0,1	0,141	0,1	0,1	0,13	0,1	0,359	0,368
12	2019	0,828	0,569	0,563	0,119	0,24	0,1	0,1	0,1	0,1	0,1	0,193	0,297
13	2020	0,594	0,385	0,595	0,141	0,26	0,101	0,1	0,1	0,1	0,254	0,221	0,579
14	2021	0,482	0,785	0,34	0,268	0,13	0,146	0,1	0,1	0,23	0,263	0,646	0,589
15	2022	0,498	0,401	0,359	0,266	0,14	0,168	0,1	0,11	0,14	0,306	0,391	0,464

The Artificial Neural Network architecture used in this study is 156-10-1, which means it consists of 156 input values (156 month rainfall data), 10 neurons in the hidden layer, and one output value, namely rainfall data for the following month (Figue 1 and Table 3).

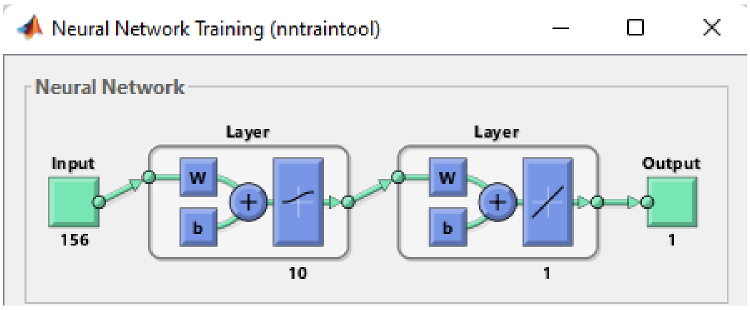

Figure 1. ANN architecture 156-10-1

Table 3. Input data patterns and prediction targets

Patterns	Input	Target
1	1st Month to nth Month	n+1 Month
2	2nd Month to n+1 Month	n+2 Month
3	3rd Month to n+2 Month	n+3 Month
4	4th Month to n+3 Month	n+4 Month
5	5th Month to n+4 Month	n+5 Month
6	6th Month to n+5 Month	n+6 Month
7	7th Month to n+6 Month	n+7 Month
8	8th Month to n+7 Month	n+8 Month
9	9th Month to n+8 Month	n+9 Month
10	10th Month to n+9 Month	n+10 Month
11	etc	etc

The normalized data is then divided into 2 types of data, namely training data and testing data. The data used as training data in this study were rainfall data from 2009 to 2021 with the training target being 2022 rainfall data. Meanwhile, the 2010-2022 rainfall data being used as test data with the test target being 2023 rainfall data. The stages of the research are shown in Figure 2.

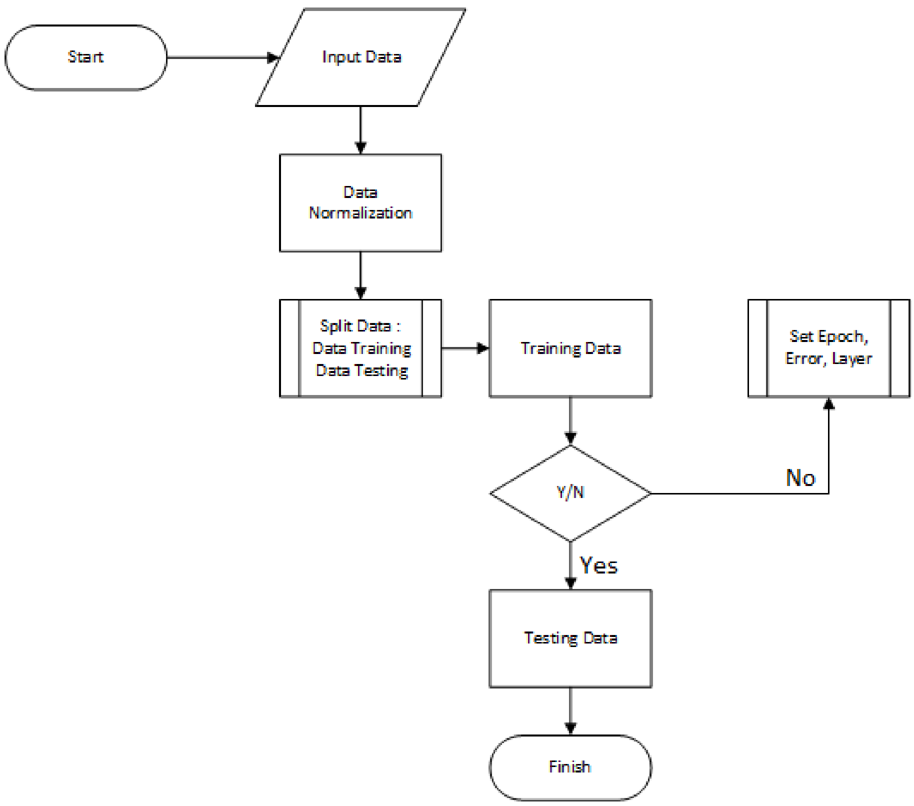

Figure 2. Prediction Flowchart

After obtaining the normalized data, then a training process is carried out on the training data to determine the level of accuracy of the model to be used. The results obtained are then compared with the target data so that the error rate is obtained. If the error rate obtained is smaller than the previously set error rate (target error), then the propagation process will stop. However, if the error rate is still greater than the constant error rate, a backpropagation process is carried out by updating the weights. After the training process, the next stage is the testing stage (data testing) to obtain predictive values.

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RESULT AND DISCUSSION

Result

After data training, the best performance was obtained at the 113th epoch (Figure 3 and Figure 4) with an error goal (MSE) of 0.00009.

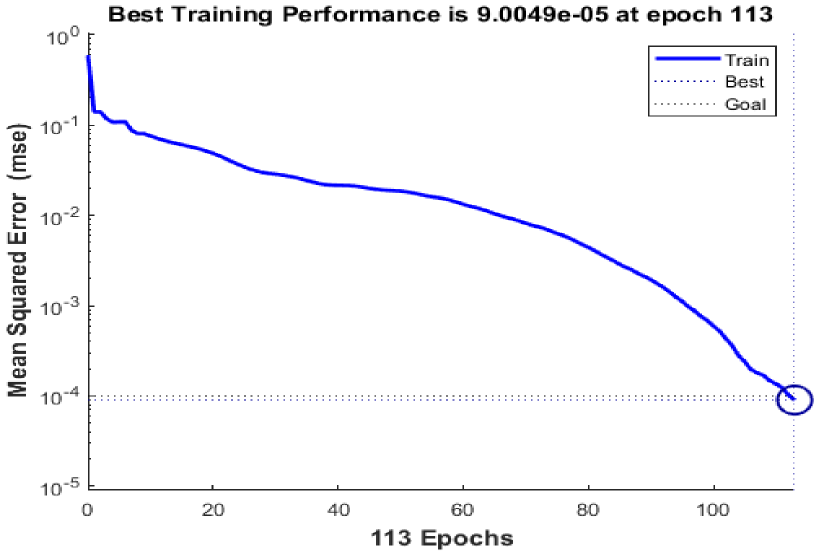

Figure 3. Target error in epoch 113th

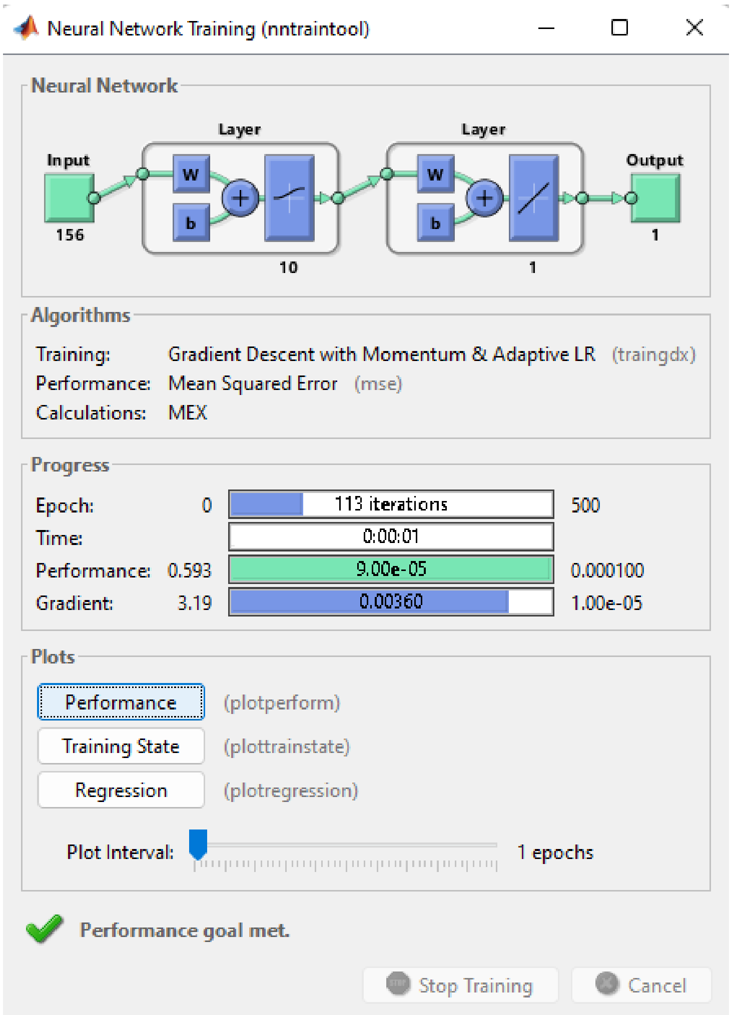

Figure 4. Data Training Process

The Regression process produces a value of 0.9991, meaning that this training algorithm is good enough to be applied to the data testing process (Figure 5).

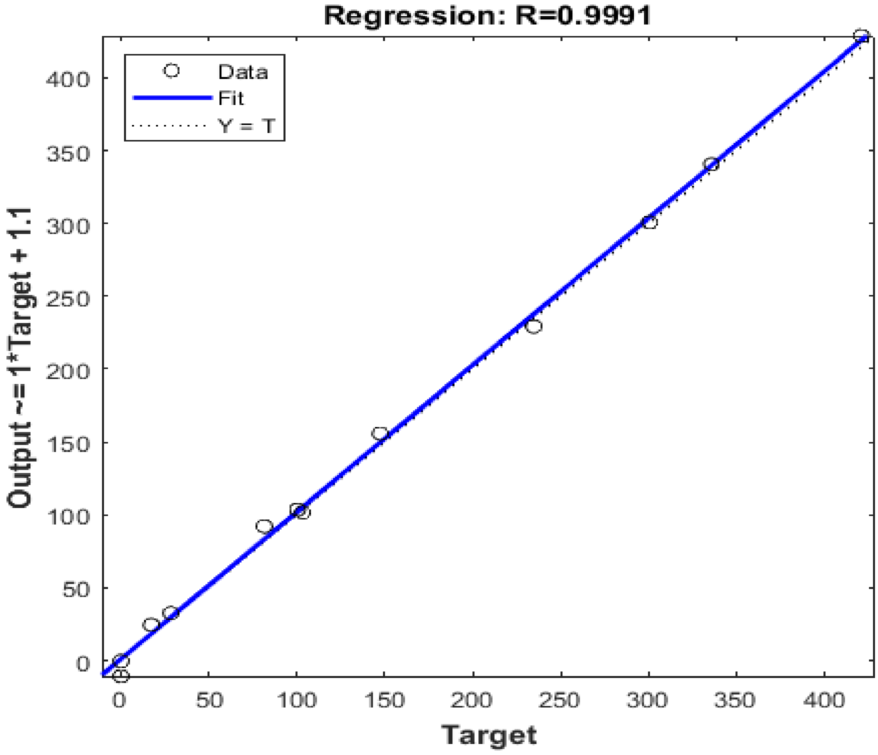

Figure 5. Data training regression outcomes

While the comparison graph between the ANN output and the actual value is as follows (Figure 6).

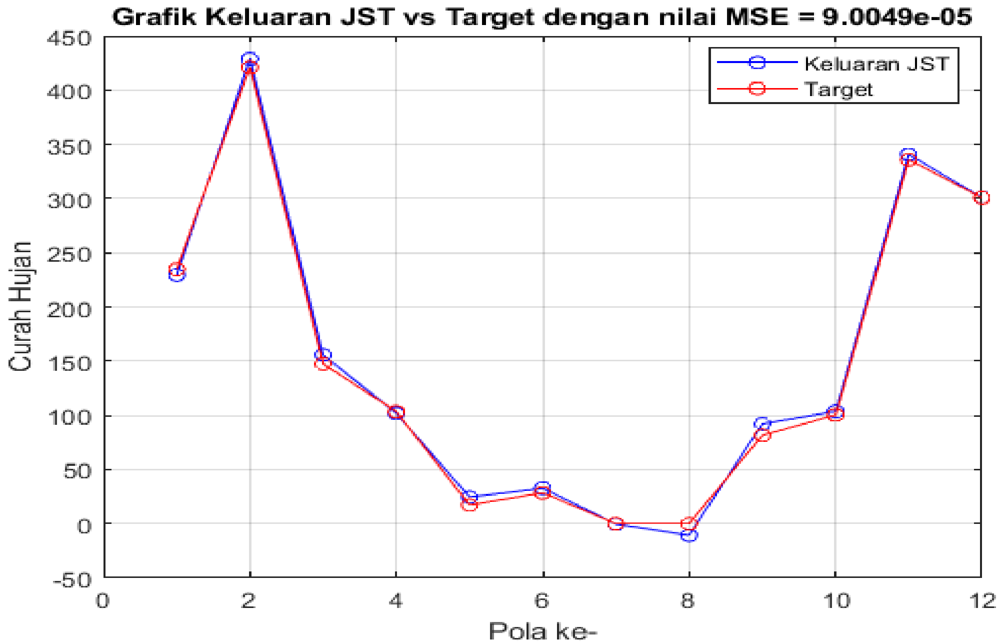

Figure 6. Comparison graph of ANN output training results with actual values

Based on the value of the correlation coefficient and the value of MSE (Mean Square Error) obtained in the training process, it shows that ANN Backpropagation can forecast precipitation very well. After the data testing process, a graph for predicting rainfall in 2023 is obtained (Figure 7) and the estimated amount of rainfall is shown in table 4.

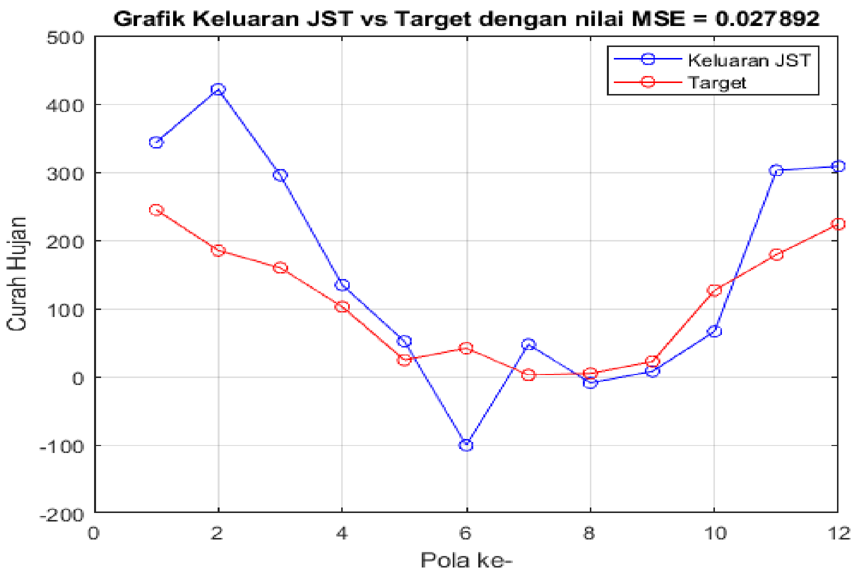

Figure 7. Forecast rainfall graphic for 2023.

Table 4. Rainfall prediction value

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Des
Rainfal Prediction	343.4	421.3	295.2	134.1	51.7	0	47	0	7.6	66	302.1	308.4

The results of data testing (Figure 7 and Table 4) show that for 2023, the quantity of rainfall in Sumbawa Regency is not as much as in previous years, there is even a tendency that in 2023 there will be a long dry season. The prediction results obtained show that the highest rainfall occurs at the beginning of the year, namely January, February, March and April with rainfall of 343.4 mm/month, 421.3 mm/month, 295.2 and 134.1 respectively. Mm/month. The decrease in rainfall (early dry season) began in May (51.7 mm/month) to October (66 mm/month) with a dry peak from June to August (0 mm/month). The rainy season is expected to resume starting in November (302.1 mm/month).

Discussion

Based on the rainfall data recorded at the Sultan Muhammad Kaharuddin Meteorological Station and the prediction results using the Backpropagation Neural Network, it is known that the rainy season in Sumbawa tends to start at the end of the year, namely October to April the following year.

The BMKG divides rainfall based on the amount of rainfall per month into 4 categories, namely low (0-100 mm/month), moderate (100-300 mm/month), high (300-500 mm/month), and very high (> 500 mm/month) (Supriyati et al., 2018). Based on these categories, the rain that will occur in Sumbawa in 2023 will include rain with high intensity, especially at the beginning of the year (January and February). Then there was a decrease to moderate intensity in March and April. In May to October, it is estimated that the rain intensity will be very low. At the end of the year (November and December), high-intensity rains occur again.

This high intensity of rain is very concerning because of the decreasing forest area that becomes a water catchment area in Sumbawa. The Independent Forest Monitoring Fund in 2021 made a release on the condition of Sumbawa's forests which showed that at the end of 2020 critical forest was estimated to have reached 72.06%, while forest which was severely damaged was around 81,499.18 ha (21%).

The loss of water catchment areas means that the flow of high-intensity rainwater cannot be absorbed into the ground and goes straight into rivers and low-lying areas. The large volume of water will be accommodated in the lowlands and has the potential to become a flood disaster.

CONCLUSION

Based on the results obtained, it can be predicted that the highest rainfall in 2023 in Sumbawa Regency will take place at the beginning of the year, namely January, February and March with rainfall of 343.4 mm/month, 421.3 mm/month and 295.2 mm/month respectively. Decreased rainfall (early dry season) began in May (51.7 mm/month) to October (66 mm/month) with a dry peak from June to August (0 mm/month). The rainy season is expected to start again in November (302.1 mm/month). Rainfall in Sumbawa is in the high category during the rainy season so it has the potential for flooding. During the dry season, rainfall is in the low category, so it has the potential for a dry season with high temperatures..

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