BAREKENG: Journal of Mathematics and Its Applications
September 2023 Volume 17 Issue 3 Page 1713–1724
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol17iss3pp1713-1724

RAINFALL PREDICTION IN JEMBER REGENCY WITH ADAPTIVE NEURO FUZZY INFERENCE SYSTEM BASED ON GSMaP SATELLITE DATA

Abduh Riski[1*], Wakhidatun Nafi'u Haqqi[2], Ahmad Kamsyakawuni[3]

[1,2,3]Department of Mathematics, Faculty of Mathematics and Natural Sciences, University of Jember
Kalimantan Street No. 37, Jember, 68121, Indonesia

*Corresponding author's e-mail: * **riski.fmipa@unej.ac.id***

ABSTRACT

Article History:

Received: 22nd May 2023
Revised: 15th August 2023
Accepted: 24th August 2023

Keywords:

Prediction;
Rainfall;
Adaptive Neuro Fuzzy Inference System (ANFIS);
GSMaP.

Rainfall is very influential in daily life, including in agriculture. According to the Jember Regency Government, the majority of the economic activities of the Jember people come from the agricultural sector. Significant changes in rainfall conditions will adversely affect the agricultural sphere. The Water Resources Office of Jember Regency measures rainfall directly. Precipitation measurement can also be made indirectly using the Global Satellite Mapping of Precipitation (GSMaP), a project promoted by the Japan Aerospace Exploration Agency (JAXA) to produce rainfall accumulation globally. Rainfall predictions are urgently needed to address rainfall-related issues. The Adaptive Neuro-Fuzzy Inference System (ANFIS) method is an effective method for prediction because its working principle combines adaptive methods of artificial neural networks and fuzzy logic. The RMSE in the ANFIS training and testing process on daily rainfall was 12.7464 and 14.6268. Furthermore, RMSE in ANFIS training and testing on monthly rainfall was 7.6336 and 8.1456. The predicted daily rainfall in Jember Regency on January 1, 2023, is 3.1971 mm. Meanwhile, the predicted monthly rainfall in Jember Regency in January 2023 is 19.9114 mm.

How to cite this article:

A. Riski, W. N. Haqqi and A. Kamsyakawuni., "RAINFALL PREDICTION IN JEMBER REGENCY WITH ADAPTIVE NEURO FUZZY INFERENCE SYSTEM BASED ON GSMaP SATELLITE DATA," *BAREKENG: J. Math. & App.*, vol. 17, iss. 3, pp. 1713-1724, September, 2023.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

Indonesia is located along the equator, with its astronomical position ranging from 6° north to 11° south latitude and 95° east to 141° east longitude. As a result, it falls within the region that has a tropical climate with two alternating seasons every six months dry season and rainy season. The dry and rainy seasons in recent years have occurred under abnormal conditions due to the phenomenon of weather anomalie [1]. Jember Regency is one of the regencies in East Java, where the majority of its economic activities come from the agricultural sector. It has a land area of 2.431 km^2 and agricultural land use covers an area of 329.334 Ha. The agricultural sector requires a good irrigation system to determine the suitability of crops. Due to the unpredictable weather conditions, a farmer in Jember have experienced crop failure and a decline in the quality of their harvests, resulting in significant losses for them [2].

Based on these issues, it is necessary to have information on rainfall conditions over time as a reference for making policies to address problems in the agricultural sector. The rainfall observation center in Jember Regency is not directly managed by the rainfall observation station of BMKG (Indonesian Meteorology, Climatology, and Geophysics Agency), resulting in incomplete and inaccurate rainfall data records. Rainfall data in Jember Regency is manually recorded by the Department of Public Works, Highways, and Water Resources of Jember Regency, East Java. The available rainfall data is still in raw data and difficult to access for the general public. However, rainfall observations can be conducted using the Global Satellite Mapping of Precipitation (GSMaP). GSMaP is capable of providing good estimates of rainy days. The satellite imagery of GSMaP works by measuring precipitation that is still present in the atmosphere [3]. Previous research on validating rainfall using GSMaP satellite data with observation data in the Bali and Nusa Tenggara regions from January 2013 - December 2017 showed similar rainfall patterns and a close correlation value [4]. Besides that, a validation research of rainfall data from the GSMaP satellite with actual rainfall data has also been conducted in Jember Regency using the Backpropagation method. The daily rainfall research resulted in 8,17 for RMSE value and 5,53 for MAE value. As for monthly rainfall, the research resulted in 111,70 for RMSE value and 71,23 MAE value [5].

The implementation of a rainfall prediction system is crucial in addressing such issues. Research on rainfall prediction has been extensively conducted using various methods. The research on rainfall prediction using the Real Coded Genetic Fuzzy System (RCGFS) method resulted in an RMSE of 8,45 [6]. In addition, research on rainfall prediction has also been conducted in the Tengger region using the Tsukamoto Fuzzy Inference System method, resulting in an RMSE of 8,64 [7]. The research on rainfall prediction using a hybrid combination of Tsukamoto Fuzzy Inference System (FIS) with a genetic algorithm resulted in an RMSE of 6,63 [8]. In the next reasearch, the combination of the ANFIS method with the Genetic Algorithm method resulted in an RMSE of 5,41 [9].

The use of the Adaptive Neuro Fuzzy Inference System (ANFIS) method is considered appropriate for predicting rainfall because it has a lower error rate compared to using the Artificial Neural Network (ANN) method [10]. The ANFIS method is a combination of Artificial Neural Network (ANN) and Fuzzy Logic. Basically, Artificial Neural Networks (ANN) can provide an overview of the complex relationship between inputs and outputs. On the other hand, Fuzzy Logic has the advantage of being highly flexible, as it can adapt to changes and uncertainties in a given scenario [11]. The use of the ANFIS method in rainfall prediction systems is further strengthened by related research that has achieved an RMSE of 1,88 [12]. In the subsequent study, the prediction of confirmed Covid-19 cases in Indonesia was conducted using the ANFIS method, and the results obtained an MAPE (Mean Absolute Percentage Error) of less than 20% [13]. The ANFIS method has also been applied to predict the unemployment rate in Maluku Province, resulting in an error of 4,49% [14]. The subsequent application of ANFIS was conducted to predict rubber tree production, which showed a Mean Absolute Percentage Error (MAPE) of 1,182% [15]. The research related to the forecast of electricity consumption in Medan City also utilized the ANFIS method, yielding a MAPE of 0,0059% [16]. The application of the ANFIS method can also be used to predict the highest stock prices and forecast inflation. The results, respectively, show a MAPE of 97,8% and an RMSE of 1,35E-07 [17], [18]. In this research, the application of the ANFIS method will be conducted to predict daily and monthly rainfall in Jember Regency. The prediction will be performed using rainfall data from the GSMaP satellite to replace the actual data, which is difficult to access.

2. RESEARCH METHODS

2.1 Data Collection

This research used two sets of data as follows:

1. Actual daily and monthly rainfall data of Jember Regency for the years 2018-2022, obtained from the Department of Public Works, Highways, and Water Resources of Jember Regency, East Java.
2. Daily and monthly rainfall data from the GSMaP satellite for Jember Regency for the years 2018-2022, obtained from the official website https://sharaku.eorc.jaxa.jp/GSMaP/.

2.2 Design of ANFIS System

The rainfall prediction system using the ANFIS method is a system that can provide future rainfall prediction results based on time series data. Design of the prediction system using the ANFIS method is divided into three process that is training process, testing process, and the prediction process. The steps for this process are as follow [19]:

1. To determine the output layer-1 in the form of the membership degrees for all input variables using the generalized bell membership function, we can refer to **Equation (1)**.

$$\mu_{A_{kj}}(x_k) = \frac{1}{1 + \left|\frac{x_k - c}{a}\right|^{2b}},\ k = 1,2,\ldots,p \tag{1}$$

   Where a is the half-width of the membership function curve, b controls the slopes at the crossover points, and c determines the center of the corresponding membership function.

2. To determine the output layer 2 in the form of firing strength by multiplying the membership degrees of the input with the rules, we can use **Equation (2)**.

$$w_j = \prod_{k=1}^{p} \mu_{A_{kj}}(Z_{t-k}), j = 1,2,\ldots,m \tag{2}$$

3. Calculate the output in layer 3, which is the value of the normalized firing strength, using **Equation (3)**.

$$\overline{w_j} = \frac{w_j}{\sum_{j=1}^{m} w_j} \tag{3}$$

4. Calculate the output in layer 4 by multiplying the output weights in layer 3 with the consequent parameters, using **Equation (4)**.

$$\overline{w_1} z_t^{(1)} = \overline{w_j}\left(\theta_{j1} Z_{t-1} + \theta_{j2} Z_{t-2} + \cdots + \theta_{jp} Z_{t-p} + \theta_{j0}\right) \tag{4}$$

5. Determine the output in layer 5, which is the rainfall prediction, using **Equation (5)**.

$$Z_t = \sum_{j=1}^{m} \overline{w_j}\left(\theta_{j1} Z_{t-1} + \theta_{j2} Z_{t-2} + \cdots + \theta_{jp} Z_{t-p} + \theta_{j0}\right) \tag{5}$$

6. Determine the level of accuracy of the prediction results with actual data using the Root Mean Squared Error (RMSE) using **Equation (6)**.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - \overline{y_i})^2}{N}} \tag{6}$$

3. RESULTS AND DISCUSSION

3.1 Training Process

The training process involves using data from the years 2018 to 2020. In this process, the appropriate parameters are determined based on the patterns in the training data. These parameters will be used in the testing and prediction process.

Table 1. Premise Parameter

Membership Degree	Daily			Monthly		
	a	b	c	a	b	c
μ_{A_1}	24,47	0,139	0,004	5,597	0,121	-0,0018
μ_{A_2}	24,78	1,226	48,73	6,468	2,083	10,43
μ_{A_3}	24,51	1,859	97,92	6,289	1,199	21,47

Table 1 contains the premise parameters that will be used to calculate the degree of membership using the Generalized Bell membership function. These parameters are obtained from the Backpropagation Error method with 100 iterations for daily rainfall and 125 iterations for monthly rainfall. Hese parameters are obtained through the use of MATLAB software and the ANFIS Editor.

a. Layer-1

The nodes in first layer are adaptive nodes whose parameters can vary. The function for these adaptive nodes is presented in Equation (1).

Table 2. Membership Degree of Training Process

Daily			Monthly		
μ_{A_1}	μ_{A_2}	μ_{A_3}	μ_{A_1}	μ_{A_2}	μ_{A_3}
0,635	0,185	0,007	0,418	0,082	0,997
0,450	0,999	0,077	0,465	1,000	0,190
0,766	0,162	0,006	0,484	0,957	0,126
0,528	0,341	0,011	0,560	0,255	0,063
⋮	⋮	⋮	⋮	⋮	⋮
0,917	0,160	0,006	0,635	0,147	0,053
0,658	0,177	0,006	0,599	0,177	0,056
0,578	0,227	0,008	0,534	0,386	0,072
0,595	0,210	0,007	0,475	0,993	0,148
0,596	0,209	0,007	0,500	0,767	0,098

Table 2 represents the output of the first layer, which consists of the degree of membership. The premise parameters are used for all input variables using the generalized bell membership function.

b. Layer-2

Table 3. Fuzzy Rules

Rules
If (X is μ_{A_1}) then (*output* is $w_{1,a,b}$)
If (X is μ_{A_2}) then (*output* is $w_{2,a,b}$)
If (X is μ_{A_3}then (*output* is $w_{3,a,b}$)

Table 4. Firing Strength of Training Process

Daily			Monthly		
$w_{1,a}$	$w_{2,a}$	$w_{3,a}$	$w_{1,a}$	$w_{2,a}$	$w_{3,a}$
0,635	0,185	0,007	0,418	0,082	0,997
0,450	0,999	0,077	0,465	1,000	0,190
0,766	0,162	0,006	0,484	0,957	0,126
0,528	0,341	0,011	0,560	0,255	0,063
⋮	⋮	⋮	⋮	⋮	⋮
0,917	0,160	0,006	0,635	0,147	0,053
0,658	0,177	0,006	0,599	0,177	0,056

0,578	0,227	0,008	0,534	0,386	0,072
0,595	0,210	0,007	0,475	0,993	0,148
0,596	0,209	0,007	0,500	0,767	0,098

Table 3 shows the 3 rules that will be used in this study, which are obtained from a combination of the number of input variables. Each rule will produce a firing strength by multiplying the degree of membership with the input that represents the fuzzy rules.

Table 4 represents the output of the second layer, which is the firing strength. The nodes in this layer are non-adaptive nodes, where all parameters remain constant and function to multiply each incoming input signal**.** The function for non-adaptive nodes is presented in **Equation (2)**.

c. Layer-3

The third layer consists of normalized firing strength, which functions to display the normalized activation degree function and is non-adaptive in nature.

Table 5. Normalized Firing Strength of Training Process

Daily			Monthly		
$\overline{w_j}_{1,a}$	$\overline{w_j}_{2,a}$	$\overline{w_j}_{3,a}$	$\overline{w_j}_{1,a}$	$\overline{w_j}_{2,a}$	$\overline{w_j}_{3,a}$
0,769	0,223	0,008	0,279	0,055	0,666
0,295	0,654	0,051	0,281	0,604	0,115
0,820	0,174	0,006	0,309	0,611	0,080
0,600	0,387	0,013	0,638	0,290	0,072
⋮	⋮	⋮	⋮	⋮	⋮
0,847	0,148	0,005	0,760	0,176	0,064
0,782	0,210	0,007	0,720	0,212	0,068
0,711	0,279	0,010	0,538	0,389	0,073
0,733	0,258	0,009	0,294	0,614	0,092
0,734	0,257	0,009	0,367	0,562	0,072

Table 5 represents the output of the third layer, which is the normalized firing strength. The fixed neurons in this layer are the result of calculating the ratio of the output of the first nodes in the previous layer to the firing strength with respect to all outputs of the previous layer. The functional form is presented in **Equation (3)**.

d. Layer-4

This layer produces an output by multiplying the normalized firing strength with the consequent parameters. The consequent parameters are obtained using the recursive Least Squares Estimation (LSE) calculation with the help of the "*recursively*" function in MATLAB.

Table 6. Consequent Parameter

Parameter	Daily	Monthly
θ_{j1}	−2,1266	-1,5883
θ_{j2}	32,3603	26,7724
θ_{j3}	40,7105	42,7791

Table 6 contains the consequent parameters obtained using recursive least squares (LSE) calculation with the help of the "recursivels" function in MATLAB. These consequent parameters will also be used for testing and prediction purposes in the later stage.

Table 7. Layer-4 Output of Training Process

Daily			Monthly		
-1,635	7,232	0,323	-0,443	1,461	28,501
-0,627	21,179	2,059	-0,446	16,174	4,913
-1,744	5,626	0,255	-0,490	16,355	3,435
-1,276	12,528	0,522	-1,014	7,769	3,062
⋮	⋮	⋮	⋮	⋮	⋮
-1,801	4,782	0,217	-1,207	4,721	2,723
-1,663	6,807	0,305	-1,144	5,686	2,889
-1,513	9,025	0,393	-0,855	10,422	3,103
-1,558	8,358	0,368	-0,467	16,443	3,929

-1,560	8,331	0,367	0,224	5,408	0,001

Table 7 represents the output of the fourth layer. The nodes in this layer are adaptive and specific to an output variable. The consequent parameters obtained through recursive least squares (LSE) calculation are used to determine the results for the calculations in the fourth layer. The function refers to **Equation (4)**.

e. Layer-5

Table 8. Output of Training Process

Daily			Monthly		
Date	**Actual Data**	***Output***	**Date**	**Actual Data**	***Output***
2 February 2021	0	5,92	February 2021	21,99	29,52
3 February 2021	25	22,61	Maret 2021	9,96	20,64
4 February 2021	0	4,14	April 2021	7,35	19,30
5 February 2021	0	11,77	May 2021	2,06	9,82
6 February 2021	10	16,25	June 2021	0,65	6,43
⋮	⋮	⋮	⋮	⋮	⋮
27 December 2022	5	3,20	August 2022	0,57	6,24
28 December 2022	17	5,45	September 2022	1,07	7,43
29 December 2022	40	7,91	October 2022	3,2	12,67
30 December 2022	0	7,17	November 2022	8,44	19,91
31 December 2022	5	7,14	December 2022	5,57	17,52

Table 8 shows the output of the training process, which consists of crisp numbers. In a systematic manner, the fifth layer consists of fixed nodes that function to sum up all the outputs from the previous layer. The output of the ANFIS model refers to Equation 5.

f. Accuracy Calculation

Table 9. RMSE Calculation of Training Process

Daily	Monthly
12,7464	7,6336

Table 9 shows the RMSE (Root Mean Square Error) values during the training process. For daily rainfall using the generalized bell membership function with 100 iterations, the obtained RMSE is 12,7464. On the other hand, for monthly rainfall using the generalized bell membership function with 125 iterations, the RMSE value obtained is 7,6336.

3.2 Testing Process

The testing process is conducted for a dataset that has not undergone the previous training process. Testing process used the daily and monthly rainfall data from the years 2021-2022.

a. Layer-1

Table 10. Membership Degree of Testing Process

Daily			Monthly		
μ_{A_1}	μ_{A_2}	μ_{A_3}	μ_{A_1}	μ_{A_2}	μ_{A_3}
0.625	0.190	0.007	0.459	1.000	0.228
0.600	0.206	0.007	0.455	0.999	0.259
0.540	0.300	0.010	0.486	0.938	0.120
0.568	0.241	0.008	0.537	0.361	0.070
⋮	⋮	⋮	⋮	⋮	⋮
0.582	0.223	0.008	0.699	0.128	0.051
0.624	0.190	0.007	0.679	0.131	0.051
0.428	0.600	0.373	0.614	0.161	0.055
0.614	0.196	0.007	0.479	0.982	0.138
0.697	0.169	0.006	0.455	0.998	0.263

Table 10 represents the output of the first layer, which consists of the degree of membership calculated using the Generalized Bell membership function. The premise parameters used are the parameters obtained during the training process.

b. Layer-2

Table 11. Firing Strength of Testing Process

Daily			Monthly		
$w_{1,a}$	$w_{2,a}$	$w_{3,a}$	$w_{1,a}$	$w_{2,a}$	$w_{3,a}$
0.625	0.190	0.007	0.459	1.000	0.228
0.600	0.206	0.007	0.455	0.999	0.259
0.540	0.300	0.010	0.486	0.938	0.120
0.568	0.241	0.008	0.537	0.361	0.070
⋮	⋮	⋮	⋮	⋮	⋮
0.582	0.223	0.008	0.699	0.128	0.051
0.624	0.190	0.007	0.679	0.131	0.051
0.428	0.600	0.373	0.614	0.161	0.055
0.614	0.196	0.007	0.479	0.982	0.138
0.697	0.169	0.006	0.455	0.998	0.263

Table 11 represents the output of the second layer, which is the firing strength. There are 3 rules being used, and for each rule, the firing strength is obtained by multiplying the degree of membership with the input that represents the fuzzy rules.

c. Layer-3

Table 12. Normalized Firing Strength of Testing Process

Daily			Monthly		
$\overline{w_J}_{1,a}$	$\overline{w_J}_{2,a}$	$\overline{w_J}_{3,a}$	$\overline{w_J}_{1,a}$	$\overline{w_J}_{2,a}$	$\overline{w_J}_{3,a}$
0.761	0.231	0.008	0.272	0.593	0.135
0.738	0.253	0.009	0.266	0.583	0.151
0.635	0.353	0.012	0.315	0.607	0.078
0.695	0.295	0.010	0.555	0.373	0.073
⋮	⋮	⋮	⋮	⋮	⋮
0.716	0.275	0.010	0.797	0.145	0.058
0.760	0.232	0.008	0.788	0.152	0.060
0.305	0.428	0.266	0.740	0.194	0.066
0.752	0.240	0.008	0.299	0.614	0.086
0.800	0.193	0.007	0.265	0.582	0.153

Table 12 represents the output of the third layer, which is the normalized firing strength. The fixed neurons in this layer are the result of calculating the ratio of the output of the first nodes in the previous layer to the firing strength with respect to all outputs of the previous layer.

d. Layer-4

Table 13. Layer-4 Output of Testing Process

Daily			Monthly		
-1,618	7,473	0,333	-0,432	15,872	5,771
-1,570	8,190	0,361	-0,422	15,605	6,477
-1,350	11,430	0,482	-0,500	16,260	3,336
-1,477	9,557	0,414	-0,881	9,973	3,105
⋮	⋮	⋮	⋮	⋮	⋮
-1,523	8,883	0,388	-1,265	3,893	2,482
-1,616	7,497	0,334	-1,252	4,078	2,549
-0,649	13,858	10,846	-1,175	5,200	2,816
-1,599	7,753	0,344	-0,476	16,448	3,688
-1,701	6,254	0,282	-0,421	15,571	6,560

Table 13 represents the output of the fourth layer. The nodes in this layer are adaptive and specific to an output variable. The parameters used for the calculation in the fourth layer are the consequent parameters obtained during the training process.

e. Layer-5

Table 14. Output of Testing Process

Daily			Monthly		
Date	**Actual Data**	***Output***	**Date**	**Actual Data**	***Output***
2 February 2021	22	6,19	February 2021	11	21,21
3 February 2021	9	6,98	Maret 2021	11,73	21,66
4 February 2021	38	10,56	April 2021	7,06	19,10
5 February 2021	31	8,49	May 2021	3,01	12,20
6 February 2021	4	17,38	June 2021	0,63	6,38
⋮	⋮	⋮	⋮	⋮	⋮
27 December 2022	0	7,75	August 2022	0,17	5,11
28 December 2022	2	6,21	September 2022	0,25	5,38
29 December 2022	110	24,05	October 2022	0,82	6,84
30 December 2022	0	6,50	November 2022	7,96	19,6
31 December 2022	0	4,84	December 2022	11,81	21,7

Table 14 shows the output of the training process, which consists of crisp numbers. In a systematic manner, the fifth layer consists of fixed nodes that function to sum up all the outputs from the previous layer.

f. Accuracy Calculation

Table 15. RMSE Calculation of Training Process

Daily	Monthly
14,6268	8,1456

Table 15 shows the RMSE (Root Mean Square Error) values during the training process. For daily rainfall using the generalized bell membership function with 100 iterations, the obtained RMSE is 14,6268. On the other hand, for monthly rainfall using the generalized bell membership function with 125 iterations, the RMSE value obtained is 8,1456.

3.3 Prediction Process

The prediction is performed for the rainfall output data in the year 2023. The steps in the prediction process are the same as the steps in the testing process.

a. Layer-1

Table 16. Membership Degree of Prediction Process

Daily			Monthly		
μ_{A_1}	μ_{A_2}	μ_{A_3}	μ_{A_1}	μ_{A_2}	μ_{A_3}
0,917	0,160	0,005	0,475	0,992	0,148

Table 16 represents the degree of membership in the prediction process. The parameters used are the same as those obtained during the training process.

b. Layer-2

Table 17. Firing Strength of Prediction Process

Daily			Monthly		
$w_{1,a}$	$w_{2,a}$	$w_{3,a}$	$w_{1,a}$	$w_{2,a}$	$w_{3,a}$
0,917	0,160	0,005	0,475	0,992	0,148

Table 17 represents the output of the second layer, which is the firing strength. There are 3 rules being used, and for each rule, the firing strength is obtained by multiplying the degree of membership with the input data prediction that represents the fuzzy rules.

c. Layer-3

Table 18. Normalized Firing Strength of Prediction Process

Daily			Monthly		
$\overline{w_J}_{1,a}$	$\overline{w_J}_{2,a}$	$\overline{w_J}_{3,a}$	$\overline{w_J}_{1,a}$	$\overline{w_J}_{2,a}$	$\overline{w_J}_{3,a}$
0,846	0,147	0,005	0,293	0,614	0,092

Table 18 represents the output of the third layer, which is the normalized firing strength. The fixed neurons in this layer are the result of calculating the ratio of the output of the first nodes in the previous layer to the firing strength with respect to all outputs of the previous layer.

d. Layer-4

Table 19. Layer-4 Output of Prediction Process

Daily			Monthly		
-1,799	4,7569	0,203	-0,465	16,438	3,935

Table 19 represents the output of the fourth layer. The nodes in this layer are adaptive and specific to an output variable. The parameters used for the calculation in the fourth layer are the consequent parameters obtained during the training process.

e. Layer-5

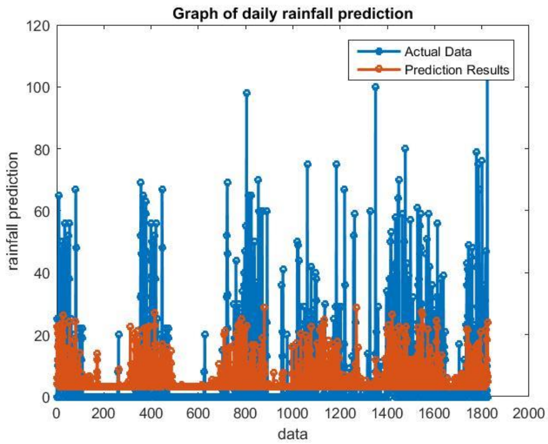
Table 20. *Output* of Prediction Process

Daily		Monthly	
Date	**Prediction**	**Date**	**Prediction**
1 January 2023	3,1971	January 2023	19,9114

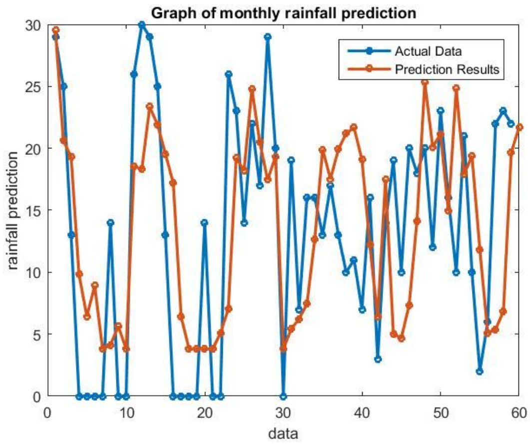
Table 20 shows that the ANFIS prediction for daily rainfall in Jember regency on January 1, 2023 is 3,1971 mm. For monthly rainfall in Jember regency in January 2023, the prediction is 19,9114 mm. This indicates an increase in rainfall from the previous day, which was 3,1971 mm on December 31, 2022. However, for monthly rainfall, there is a decrease of 2,886 mm from the previous month, which was December 2022.

Based on the calculations from the first layer to the fifth layer, the ANFIS system is unable to produce a prediction output of 0. From the degree of membership, firing strength, normalized firing strength, and recursive LSE calculations in each formula, it can be observed that the overall calculations cannot result in an output of 0. Based on the information provided, it appears that the ANFIS prediction system for daily and monthly rainfall cannot detect days without rainfall.

A comparison graph between actual data and ANFIS rainfall output in Jember Regency using the ANFIS method can be seen in **Figure 1(a)** and **Figure 1(b)**.



(a)



(b)

Figure 1. Graph of the comparison between prediction results and actual data (a) Daily precipitation graph, (b) Monthly precipitation graph

Figure 1 (a) and **Figure 1 (b)** show the comparison graph between actual data and ANFIS output for daily and monthly rainfall in Jember Regency using the ANFIS method. Based on the graph, the prediction results for rainfall are able to follow the pattern of actual rainfall data. However, it is unable to predict the actual lowest rainfall, which is 0.

4. CONCLUSIONS

Based on the results and discussion, the following conclusions can be drawn:

1. The best model for the ANFIS method in predicting daily rainfall in Jember Regency using the generalized bell membership function with 100 iterations, resulting in accuracy levels measured by RMSE in the training and testing process. Specifically, for daily rainfall, the RMSE values achieved were 12.7464 in the training process and 14.6268 in the testing process. The predicted daily rainfall in Jember Regency on January 1, 2023, is 3.1971 mm.
2. The best model for the ANFIS method in predicting monthly rainfall in Jember Regency using the generalized bell membership function with 125 iterations, resulting in accuracy levels in terms of RMSE for training and testing process. Specifically, for monthly rainfall, the RMSE values achieved were 7,6336 in the training process and 8,1456 in the testing process. The predicted monthly rainfall in Jember Regency on January 1, 2023, is 19,9114 mm.
3. The ANFIS method has the advantage of being able to capture extreme rainfall patterns, but it may not be able to detect days without rainfall. Indeed, while the ANFIS method may have limitations in detecting days without rainfall, it can still detect rainfall amounts as low as 3 mm. This sensitivity to low rainfall values can be beneficial in capturing even minor precipitation events.

ACKNOWLEDGMENT

This research was supported by the Institute for Research and Community Service (LP2M) University of Jember. Research funding by Grant No. 3287/UN25.3.1/LT/2023. For the preparation of this paper, we thanks to all member of Mathematical Optimization and Computation (MOCo) Research Group.

REFERENCES

[1] Badan Meteorologi Klimatologi dan Geofisika, *Climate Outlook 2023*. Jakarta: Badan Meteorologi Klimatologi dan Geofisika, 2022.
[2] Dinas Komunikasi dan Informatika Kabupaten Jember, “Geografis dan Topografi,” 2021. https://www.jemberkab.go.id/selayang-pandang/geografis-dan-topografi/ (accessed Jan. 23, 2023).

[3] T. Kubota *et al.*, “Global Satellite Mapping of Precipitation (GSMaP) Products in the GPM Era,” 2020, pp. 355–373. doi: 10.1007/978-3-030-24568-9_20.

[4] I. G. A. M. Duwanda and I. K. Sukarasa, “Validation of Daily Rainfall Based on Global Satellite Mapping Of Precipitation (Gsmap) Data with Observation Data in The Bali Region,” *BULETIN FISIKA*, vol. 23, no. 2, p. 106, Aug. 2021, doi: 10.24843/BF.2022.v23.i02.p05.

[5] Sumila, “Validasi Curah Hujan Satelit GSMaP Pada Data Curah Hujan Aktual Kabupaten Jember,” University of Jember, Jember, 2022.

[6] T. Fatyanosa and W. Mahmudy, “Implementation of Real Coded Genetic Fuzzy System for Rainfall Forecasting,” in *International Conference on Sustainable Information Engineering and Technology (SIET)*, International Conference on Sustainable Information Engineering and Technology (SIET), Oct. 2016, pp. 24–33.

[7] I. Wahyuni, W. F. Mahmudy, and A. Iriany, “Rainfall prediction in Tengger region Indonesia using Tsukamoto fuzzy inference system,” in *1st International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, IEEE, Aug. 2016, pp. 130–135. doi: 10.1109/ICITISEE.2016.7803061.

[8] I. Wahyuni and W. F. Mahmudy, “Rainfall Prediction in Tengger, Indonesia Using Hybrid Tsukamoto FIS and Genetic Algorithm Method,” *Journal of ICT Research and Applications*, vol. 11, no. 1, pp. 38–55, Apr. 2017, doi: 10.5614/itbj.ict.res.appl.2017.11.1.3.

[9] I. Wahyuni, W. F. Mahmudy, and A. Iriany, “Rainfall Prediction Using Hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) and Genetic Algorithm,” *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 9, no. 2–8, pp. 51–56, Sep. 2017, [Online]. Available: https://jtec.utem.edu.my/jtec/article/view/2627

[10] N. Triana, “Sistem Pakar Diagnosa Penyakit Pada Tanaman Seledri Menggunakan Metode ANFIS ,” *TIN: Terapan Informatika Nusantara*, vol. 1, no. 8, pp. 418–423, 2021.

[11] R. Janarthanan, R. Balamurali, A. Annapoorani, and V. Vimala, “Prediction of rainfall using fuzzy logic,” *Mater Today Proc*, vol. 37, pp. 959–963, 2021, doi: 10.1016/j.matpr.2020.06.179.

[12] M. I. Azhar and W. F. Mahmudy, “Prediksi Curah Hujan Menggunakan Metode Adaptive Neuro Fuzzy Inference System (ANFIS),” *Jurnal Pengembangan Teknologi Informasi dan Ilmu Komputer*, vol. 2, no. 11, pp. 4932–4939, Jul. 2018, [Online]. Available: https://j-ptiik.ub.ac.id/index.php/j-ptiik/article/view/3139

[13] S. A. Hardiyanti and Q. Shofiyah, “Prediksi Kasus COVID-19 Di Indonesia Menggunakan Metode Adaptive Neuro Fuzzy Inference System (ANFIS),” *Prosiding Seminar Nasional Terapan Riset Inovatif (SENTRINOV)*, vol. 6, no. 1, pp. 974–981, Nov. 2020, [Online]. Available: https://proceeding.isas.or.id/index.php/sentrinov/article/view/569

[14] D. Rahakbauw, Muh. Tanassy, and B. Tomasouw, “Sistem Prediksi Tingkat Pengangguran Di Provinsi Maluku Menggunakan ANFIS (Adaptive Neuro Fuzzy Inference System),” *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, vol. 12, no. 2, pp. 99–106, Dec. 2018, doi: 10.30598/vol12iss2pp099-106ar621.

[15] R. F. Rahmat, Nurmawan, S. Sembiring, M. F. Syahputra, and Fadli, “Adaptive neuro-fuzzy inference system for forecasting rubber milk production,” *IOP Conf Ser Mater Sci Eng*, vol. 308, p. 012014, Feb. 2018, doi: 10.1088/1757-899X/308/1/012014.

[16] Y. T. Nugraha, K. Ghabriel, and I. F. Dharmawan, “Implementasi ANFIS Dalam Prakiraan Konsumsi Energi Listrik Di Kota Medan Pada Tahun 2030,” *RELE (Rekayasa Elektrikal Dan Energi) : Jurnal Teknik Elektro*, vol. 4, no. 1, pp. 55–59, 2021.

[17] M. A. Raharja, I. D. M. B. A. Darmawan, D. P. E. Nilakusumawati, and I. W. Supriana, “Analysis of membership function in implementation of adaptive neuro fuzzy inference system (ANFIS) method for inflation prediction,” *J Phys Conf Ser*, vol. 1722, no. 1, p. 012005, Jan. 2021, doi: 10.1088/1742-6596/1722/1/012005.

[18] I. P. Sedana Wijaya, M. Agung Raharja, L. A. Ayu Rahning Putri, I. P. G. Hendra Suputra, I. B. M. Mahendra, and I. G. Santi Astawa, “Penerapan Metode Adaptive Neuro Fuzzy Inference System (ANFIS) Dengan Membership function Tipe Gaussian dan Generalized Bell Dalam Prediksi Harga Tertinggi Saham,” *JELIKU (Jurnal Elektronik Ilmu Komputer Udayana)*, vol. 11, no. 1, p. 111, Jul. 2022, doi: 10.24843/JLK.2022.v11.i01.p12.

[19] Tarno, A. Rusgiyono, and Sugito, “Adaptive Neuro Fuzzy Inference System (ANFIS) approach for modeling paddy production data in Central Java,” *J Phys Conf Ser*, vol. 1217, no. 1, p. 12083, May 2019, doi: 10.1088/1742-6596/1217/1/012083.