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PREDICTION SYSTEM FOR THE AMOUNT OF SUGAR PRODUCTION USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

Sugar is one of the staple foods most Indonesians use, so sugar production needs to be done optimally to meet people's needs. This research will design a prediction system for the amount of sugar production in PTPN XI PG Prajekan using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method. ANFIS is a combined method of two systems, namely a fuzzy logic system and an artificial neural network system. This research consists of data collection, ANFIS system design, ANFIS training, ANFIS testing, accuracy calculation, and result analysis. The prediction system for the amount of sugar production is designed to predict the variable y_{t+1} which is the amount of sugar production in the year $(t+1)$ using the input variables $x_{1,t}$ (sugarcane harvested area in year t), $x_{2,t}$ (amount of sugarcane in year t), $x_{3,t}$ (average of yield in year t), and $x_{4,t}$ (number of milling days in year t). The experiments in this research used variations of the type of membership function and the number of membership functions. The best model obtained in this research is a model with a difference between two sigmoidal membership functions and a product of two sigmoidal membership functions with a total of 2 membership functions for each input variable. Both models have the same Mean Absolute Percentage Error (MAPE) value, which is 1.79% in the training process and 4.82% in the testing process.

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1. INTRODUCTION

Sugar is one of the staple foods most Indonesians use, so sugar production needs to be done optimally to meet people's needs. Sugar is also a relatively cheap calorie source [1]. The amount of sugar production is influenced by several factors, such as the sugarcane harvested area, the amount of sugarcane, the average yield [2], and the number of milling days [3]. One of the companies in East Java that produces sugar is PTPN XI PG Prajekan. The amount of sugar production in the company fluctuates yearly, so a prediction system is needed to be the basis for decision-making or planning in the future.

One of the effective methods for prediction systems is the Adaptive Neuro Fuzzy Inference System (ANFIS) method, a combined method of fuzzy inference system and artificial neural network system. Fuzzy inference systems have several advantages, such as modeling qualitative aspects of human knowledge. The fuzzy inference system makes decisions by applying rules [4]. Artificial neural networks have several benefits, i.e., they can solve complex problems such as pattern recognition, classification, and prediction using a machine learning approach [5]. ANFIS has all the advantages of fuzzy inference systems and artificial neural networks.

Several previous types of research support the application of the ANFIS method for the prediction process. Siregar et al. [6] have successfully predicted the competency exam results for the doctor professional program with a MAPE value of 0.07%. Harahap and Sukmawati [7] have successfully predicted the rupiah exchange rate with an accuracy rate of more than 99%. Siregar et al. have successfully predicted the competency exam results for the doctor professional program with a MAPE value of 0.07%. Nugraha et al. [8] successfully predicted Aceh's electrical energy consumption with a MAPE error rate of 0.002%. Mutmainah [9] has successfully predicted the consumer price index in Denpasar City-Bali with a MAPE error rate of 0.79%. Matsniya [10] has successfully predicted the number of tobacco products in Jember with a MAPE error rate of 0.00015% in the training process and 0.091% in the testing process.

Based on the description and some of the research that has been given, the prediction process can use the Adaptive Neuro Fuzzy Inference System method. Therefore, the author also wants to prove whether this method can predict well or not on different objects from previous research. This research will indicate the amount of sugar production in PTPN XI PG Prajekan, Bondowoso, based on the variables of sugarcane harvested area, the amount of sugarcane, the average sugarcane yield, and the number of milling days. Researchers hope this research can provide accurate prediction results concerning the amount of sugar production in PTPN XI PG Prajekan, Bondowoso, in the future.

2. RESEARCH METHODS

2.1 Data Collection

This research uses quantitative data, which consists of the amount of sugar produced, sugarcane harvested area, amount of sugarcane, average sugarcane yield, and milling days. The data used is time series data from 2007 - 2022. We collected the data from submitting data requests to PTPN XI PG Prajekan.

2.2 Multicollinearity Test

The multicollinearity test determines whether there is a high correlation between the independent variables. The detection of multicollinearity problems can be seen in the tolerance value and VIF (Variance Inflation Factor). The equation for calculating the tolerance value is as follows:

$$\text{Tolerance} = 1 - R^2 \tag{1}$$

The VIF value can be calculated using the following equation:

$$\text{VIF} = \frac{1}{1-R^2} \tag{2}$$

The R^2 is the coefficient of determination. Multicollinearity problems are indicated by VIF values greater than 5 [11].

2.3 Adaptive Neuro Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) method is a combined method of fuzzy inference system and artificial neural network system. The ANFIS structure uses the Sugeno fuzzy inference system. Suppose that the fuzzy inference system has p inputs $x_1, x_2, \dots, x_p$ and has one output z, then the 0th order Sugeno fuzzy inference system models with m if-then rules are as follows [12]:

$$\text{The j-th Rule: If } \underbrace{x_1 \text{ is } A_{1j} \text{ and } x_2 \text{ is } A_{2j} \dots \text{and } x_p \text{ is } A_{pj}}_{\text{Premise}}, \text{ then } \underbrace{f_j = \theta_{j,0} + \sum_{k=1}^{p} \theta_{j,k} x_k}_{\text{Consequent}} \tag{3}$$

and 1st order Sugeno fuzzy inference system models with m if-then rules is as follows

$$\text{The j-th Rule: If } \underbrace{x_1 \text{ is } A_{1j} \text{ and } x_2 \text{ is } A_{2j} \dots \text{and } x_p \text{ is } A_{pj}}_{\text{Premise}}, \text{ then } \underbrace{f_j = \theta_{j0}}_{\text{Consequent}} \tag{4}$$

The ANFIS structure consists of five layers. The following is an explanation of each layer [13].

a. Layer-1 (Fuzzification)

Layer 1 is used for the fuzzification process. Each node in layer 1 is adaptive with the following node functions:

$$\mu_{A_{kj}}(x_k) \text{ with } k = 1,2,\dots,p \tag{5}$$

which $\mu_{A_{kj}}(x_k)$ is the membership degree of the k-th input and the j-th rule and p is the number of inputs. The degree of membership is obtained from inputting the value of the input variable into the membership function. The membership functions used in this research are as follows [14]:

1. Triangular Membership Function (trimf)

$$\mu[x] = \begin{cases} 0, & x \le a \cup x \ge c \\ \dfrac{(x-a)}{(b-a)}, & a < x \le b \\ \dfrac{(c-x)}{(c-b)}, & b < x < c \end{cases} \tag{6}$$

2. Trapezoidal Membership Function (trapmf)

$$\mu[x] = \begin{cases} 0, & x \le a \cup x \ge d \\ \dfrac{(x-a)}{(b-a)}, & a < x < b \\ 1, & b \le x \le c \\ \dfrac{(d-x)}{(d-c)}, & c < x < d \end{cases} \tag{7}$$

3. Generalized Bell-Shaped Membership Function (gbellmf)

$$\mu[x] = \frac{1}{1 + \left|\frac{x-c}{a}\right|^{2b}} \tag{8}$$

4. Gaussian Membership Function (gaussmf)

$$\mu[x] = e^{-\frac{(x-c)^2}{2a^2}} \tag{9}$$

5. Gaussian Combination Membership Function (gauss2mf)

$$\mu[x] = \begin{cases} e^{-\frac{(x-c_1)^2}{2{a_1}^2}}, & 0 \le x < c_1 \\ 1, & c_1 \le x \le c_2 \\ e^{-\frac{(x-c_2)^2}{2{a_2}^2}}, & x > c_2 \end{cases} \tag{10}$$

6. Pi Membership Function (pimf)

$$\mu[x] = \begin{cases} 0, & x \le a \cup x \ge d \\ 2\left(\frac{x-a}{b-a}\right)^2, & a < x \le \frac{a+b}{2} \\ 1-2\left(\frac{x-b}{b-a}\right)^2, & \frac{a+b}{2} < x < b \\ 1, & b \le x \le c \\ 1-2\left(\frac{x-c}{d-c}\right)^2, & c < x \le \frac{c+d}{2} \\ 2\left(\frac{x-d}{d-a}\right)^2, & \frac{c+d}{2} < x < d \end{cases} \tag{11}$$

7. Difference Between Two Sigmoidal Membership Function (dsigmf)

$$\mu[x] = \frac{1}{1 + exp\;(-a(x-c))} \tag{12}$$

8. Product of Two Sigmoidal Membership Function (psigmf)

$$\mu[x] = \frac{1}{1 + \exp\;(-a_1(x-c_1))} - \frac{1}{1 + \exp\;(-a_2(x-c_2))} \tag{13}$$

b. Layer-2 (Product)

Layer 2 is used to determine the firing strength. Each node in this layer is non-adaptive and is symbolized by $\prod$. The output of layer 2 is the product of the membership degree of each input. The equation of the product of the membership degree of each input is:

$$w_j = \prod_{k=1}^{p} \mu_{A_{kj}}(x_k) \text{ with } j = 1,2,\dots,m \tag{14}$$

which w_j is the firing strength of the j-th *rule*, p is the number of inputs, and m is the number of rules.

c. Layer-3 (Normalization)

Layer 3 is used to determine the normalized firing strength. Each node in this layer is non-adaptive and is symbolized by N. The equation for calculating normalized firing strength is as follows:

$$\overline{w}_j = \frac{w_j}{w_1 + w_2 + \cdots + w_m} \text{ with } j = 1,2,\dots,m \tag{15}$$

which $\overline{w}_j$ is the normalized firing strength of the j-th rule and m is the number of rules.

d. Layer-4 (Defuzzification)

Layer 4 is used for the defuzzification process. The output of this layer is the product of $\overline{w}_j$ and the consequent parameters of each rule. Each node in layer 4 is adaptive for an output which the following equation can express:

$$\overline{w}_j f_j = \overline{w}_j\left(\theta_{j,1}x_1 + \theta_{j,2}x_2 + \cdots + \theta_{j,p}x_p + \theta_{j,0}\right) \text{ with } j = 1,2,\dots,m \tag{16}$$

which m is the number of rules. In the 0th order Sugeno fuzzy inference system, the value of $\theta_{j,1}, \theta_{j,2}, \dots, \theta_{j,3} = 0$ so that $f_j = \theta_{j,0}$.

e. Layer-5 (Total Output)

Layer 5 of ANFIS is used for the total output calculation process. Each node in this layer is non-adaptive and is symbolized by $\sum$. The output of this layer is a single neuron, which is the sum of all outputs from the fourth layer and can be expressed by the following equation:

$$f = \sum_{j=1}^{m} \overline{w}_j f_j = \frac{\sum_{j=1}^{m} w_j f_j}{\sum_{j=1}^{m} w_j} \text{ with } j = 1,2,\dots,m \tag{17}$$

which m is the number of rules.

2.4 Mean Absolute Percentage Error (MAPE)

MAPE is a calculation that determines the mean of the sum of all percentage errors for a data set taken from its absolute value. The error value is obtained from the difference between the predicted and actual values. The equation for calculating MAPE is as follows [15]:

$$\text{MAPE} = \left(\frac{1}{n}\sum_{i=1}^{n}\frac{|y_i - \hat{y}_i|}{y_i}\right) \times 100\% \tag{18}$$

A lower MAPE value indicates that the prediction results are closer to the actual data. Table 1 categorizes the MAPE values in several ranges.

Table 1. MAPE Value Categories

MAPE	CATEGORIES
$< 10\%$	Very Good
$10\% - 20\%$	Good
$> 20\% - 50\%$	Enough
$> 50\%$	Bad

2.5 Prediction Process Using Adaptive Neuro Fuzzy Inference System Method

The prediction process using the Adaptive Neuro Fuzzy Inference System in this research can be represented in the following flowchart:

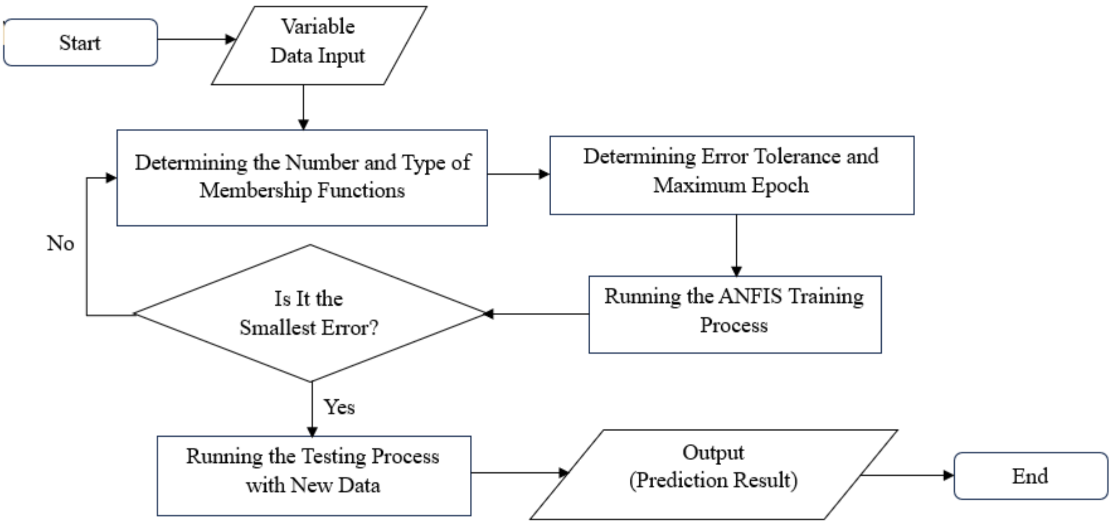


Figure 1. Prediction process using ANFIS method

3. RESULTS AND DISCUSSION

3.1 Multicollinearity Test

The multicollinearity test results of the research data can be seen in Table 2.

Table 2. Multicollinearity Test Results

Variable	Collinearity Tolerance	Statistics VIF
Sugarcane Harvested Area	0.491	2.037
Amount of Sugarcane	0.269	3.724
Average of Yield	0.442	2.262
Number of Milling Days	0.219	4.557

a. Dependent Variable: Amount of Sugar Production

Based on Table 2, it can be concluded that there is no multicollinearity problem in each independent variable because, for each independent variable, the VIF statistics value is less than 5.

3.2 ANFIS Prediction System

The prediction system for the amount of sugar production is designed to predict the variable y_{t+1} which is the amount of sugar production in the year $(t+1)$ using the input variables $x_{1,t}$ (sugarcane harvested area in year t), $x_{2,t}$ (amount of sugarcane in year t), $x_{3,t}$ (average of yield in year t), and $x_{4,t}$ (number of milling days in year t). The ANFIS system for predicting the amount of sugar production can be seen in Figure 2.

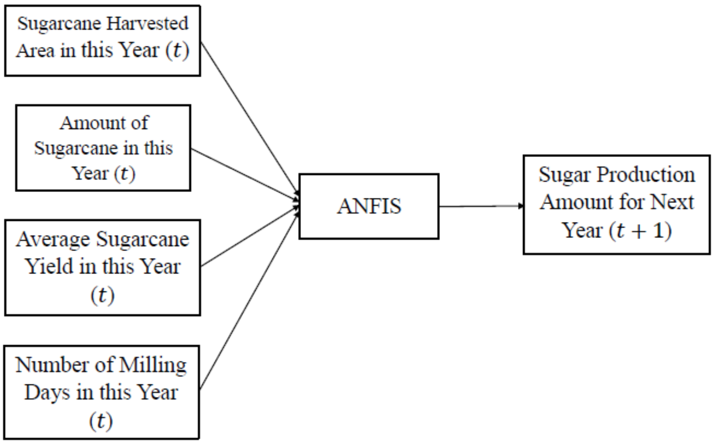


Figure 2. ANFIS structure

The ANFIS system is constructed with the ANFIS Editor, one of the MATLAB software toolboxes. This research consisted of model-building experiments with different types of membership functions, followed by model-building experiments with several combinations of the number of membership functions. Various experiments were made to obtain the best model. Table 3 shows the difference in error values (MAPE) resulting from several experiments with different types of membership functions.

Table 3. Experiment Results of Different Types of Membership Functions

No.	Structure		Output Membership Function	Epoch	MAPE	
	Membership Function Type	Number of Membership Function			Training	Testing
1	trimf	3 3 3 3	Constant	30	0.00085%	21.81%
2	trapmf	3 3 3 3	Constant	30	0.00085%	2.12%
3	gbellmf	3 3 3 3	Constant	30	0.00085%	2.47%
4	gaussmf	3 3 3 3	Constant	30	0.00085%	8.094%
5	gauss2mf	3 3 3 3	Constant	30	0.00085%	4.13%
6	pimf	3 3 3 3	Constant	30	0.001%	2.766%
7	dsigmf	3 3 3 3	Constant	30	0.00085%	0.84%
8	psigmf	3 3 3 3	Constant	30	0.00085%	0.84%

The best models obtained based on Table 3 are models with membership function types dsigmf and psigmf. Both models have the smallest MAPE value in the training and testing process compared to other models.

The following experiment is modeled with the same type of membership function: the difference between two sigmoidal but with a different combination of the number of membership functions. The error value (MAPE) resulting from some of these experiments can be seen in Table 4.

Table 4. Experiment Results of Membership Function Type dsigmf with Combination of Number of Membership Functions

No.	Structure		Output Membership Function	Epoch	MAPE	
	Membership Function Type	Number of Membership Function			Training	Testing
1	dsigmf	3 3 3 3	Constant	30	0.00085%	0.84%
2	dsigmf	2 2 2 2	Constant	30	1.79%	4.82%
3	dsigmf	3 3 2 2	Constant	30	0.0186%	5.85%
4	dsigmf	3 3 2 3	Constant	30	0.00085%	3.51%
5	dsigmf	4 3 3 3	Constant	30	0.00085%	5.28%
6	dsigmf	3 3 3 2	Constant	30	0.00085%	0.91%
7	dsigmf	4 3 3 2	Constant	30	0.00085%	2.57%
8	dsigmf	4 3 2 3	Constant	30	0.00085%	4.34%

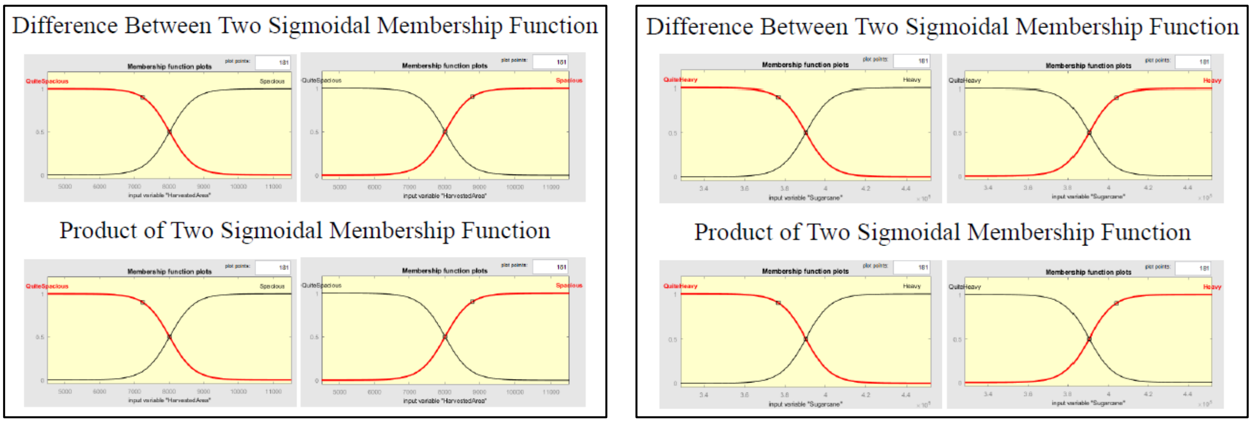
Experiments with combinations of the number of membership functions were also made for the product of two sigmoidal membership function types. The error value (MAPE) resulting from some of these experiments can be seen in Table 5.

Table 5. Experiment Results of Membership Function Type psigmf with Combination of Number of Membership Functions

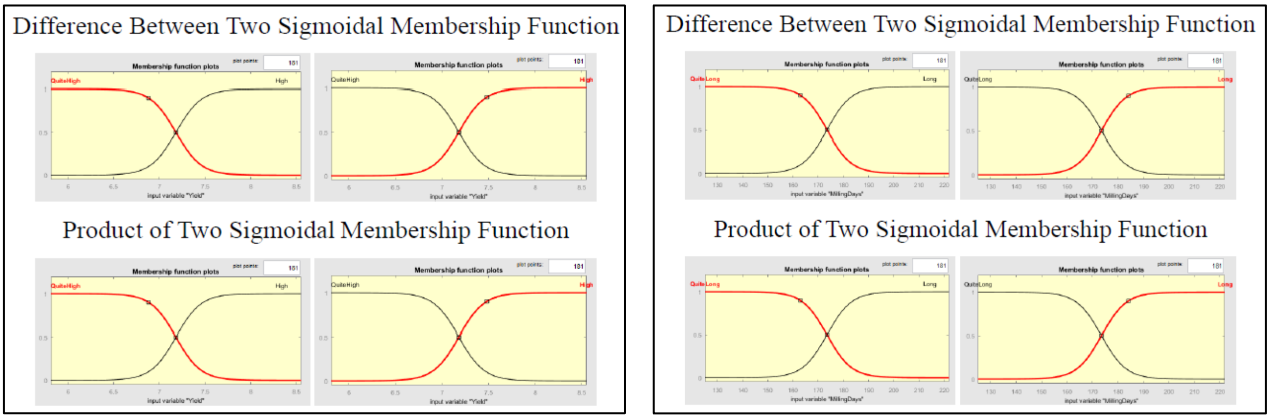
No.	Structure		Output Membership Function	Epoch	MAPE	
	Membership Function Type	Number of Membership Function			Training	Testing
1	psigmf	3 3 3 3	Constant	30	0.00085%	0.84%
2	psigmf	2 2 2 2	Constant	30	1.79%	4.82%
3	psigmf	3 3 2 2	Constant	30	0.01901%	4.384%
4	psigmf	3 3 2 3	Constant	30	0.00085%	3.51%
5	psigmf	4 3 3 3	Constant	30	0.00085%	5.28%
6	psigmf	3 3 3 2	Constant	30	0.00085%	0.91%
7	psigmf	4 3 3 2	Constant	30	0.00085%	2.57%
8	psigmf	4 3 2 3	Constant	30	0.00085%	4.34%

The best model obtained based on Table 4 and Table 5 is a model with membership function types dsigmf and psigmf with a combination of 2 2 2 2 membership functions. The meaning of the number of membership functions 2 2 2 2 is that the number of membership functions in the first, second, third, and fourth input variables are two each. The model was selected because although the number of membership functions 2 2 2 2 has a higher MAPE value than other combinations of membership functions, the MAPE value in the training process and the testing process in this model is still relatively small and not significantly different so it can avoid overfitting problems.

Figure 3 is a plot of the membership function for each input variable with the difference between two sigmoidal membership functions and the product of two sigmoidal membership functions with two membership functions for each input.



(a) (b)



(b) (d)

Figure 3. Membership function plots
(a) Sugarcane Harvested Area; (b) Amount of Sugarcane; (c) Average of Yield; (d) Amount of Milling Days

Figure 3 (a) shows the membership function plot of the sugarcane harvested area variable. **Figure 3 (b)** shows the membership function plot of the amount of sugarcane variable. **Figure 3 (c)** shows the membership function plot of the average yield variable. **Figure 3 (d)** shows the membership function plot of the amount of milling days variable.

The number of rules is obtained from a combination of the number of membership functions for each input variable. The number of rules in the best model that has been obtained is 16 rules. The rules used can be seen in **Figure 4**.

1. If (HarvestedArea is QuiteSpacious) and (Sugarcane is QuiteHeavy) and (Yield is QuiteHigh) and (MillingDays is QuiteLong) then (Sugar is out1mf1) (1)
2. If (HarvestedArea is QuiteSpacious) and (Sugarcane is QuiteHeavy) and (Yield is QuiteHigh) and (MillingDays is Long) then (Sugar is out1mf2) (1)
3. If (HarvestedArea is QuiteSpacious) and (Sugarcane is QuiteHeavy) and (Yield is High) and (MillingDays is QuiteLong) then (Sugar is out1mf3) (1)
4. If (HarvestedArea is QuiteSpacious) and (Sugarcane is QuiteHeavy) and (Yield is High) and (MillingDays is Long) then (Sugar is out1mf4) (1)
5. If (HarvestedArea is QuiteSpacious) and (Sugarcane is Heavy) and (Yield is QuiteHigh) and (MillingDays is QuiteLong) then (Sugar is out1mf5) (1)
6. If (HarvestedArea is QuiteSpacious) and (Sugarcane is Heavy) and (Yield is QuiteHigh) and (MillingDays is Long) then (Sugar is out1mf6) (1)
7. If (HarvestedArea is QuiteSpacious) and (Sugarcane is Heavy) and (Yield is High) and (MillingDays is QuiteLong) then (Sugar is out1mf7) (1)
8. If (HarvestedArea is QuiteSpacious) and (Sugarcane is Heavy) and (Yield is High) and (MillingDays is Long) then (Sugar is out1mf8) (1)
9. If (HarvestedArea is Spacious) and (Sugarcane is QuiteHeavy) and (Yield is QuiteHigh) and (MillingDays is QuiteLong) then (Sugar is out1mf9) (1)
10. If (HarvestedArea is Spacious) and (Sugarcane is QuiteHeavy) and (Yield is QuiteHigh) and (MillingDays is Long) then (Sugar is out1mf10) (1)
11. If (HarvestedArea is Spacious) and (Sugarcane is QuiteHeavy) and (Yield is High) and (MillingDays is QuiteLong) then (Sugar is out1mf11) (1)
12. If (HarvestedArea is Spacious) and (Sugarcane is QuiteHeavy) and (Yield is High) and (MillingDays is Long) then (Sugar is out1mf12) (1)
13. If (HarvestedArea is Spacious) and (Sugarcane is Heavy) and (Yield is QuiteHigh) and (MillingDays is QuiteLong) then (Sugar is out1mf13) (1)
14. If (HarvestedArea is Spacious) and (Sugarcane is Heavy) and (Yield is QuiteHigh) and (MillingDays is Long) then (Sugar is out1mf14) (1)
15. If (HarvestedArea is Spacious) and (Sugarcane is Heavy) and (Yield is High) and (MillingDays is QuiteLong) then (Sugar is out1mf15) (1)
16. If (HarvestedArea is Spacious) and (Sugarcane is Heavy) and (Yield is High) and (MillingDays is Long) then (Sugar is out1mf16) (1)

Figure 4. Rules determination result

Figure 5 shows the structure of the best ANFIS model

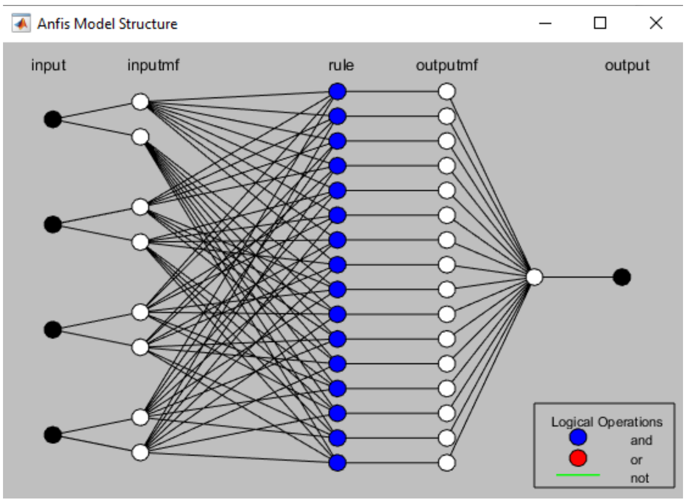


Figure 5. ANFIS network structure of sugar production amount prediction system

Based on Figure 5, we can see that the best ANFIS model consists of four variables (layer-1), each of which has two membership functions (layer-2), with the types of membership functions used as differences between two sigmoidal and product of two sigmoidal. There are 16 rules in the structure (layer-3 and layer-4). There is one output variable (layer-5) with a constant output type.

3.3 Manual Calculation ANFIS Prediction

This manual calculation is used to determine the process and output of each ANFIS layer. Manual calculations are performed for the best model obtained, namely the model with membership functions dsigmf and psigmf. The following is the output of each ANFIS layer.

3.3.1 Training Process

The training uses input variables from 2007 – 2019 and output variables from 2008 – 2020. The training process is used to determine the parameters in the ANFIS model, namely the premise parameters in layer 1 and the consequent parameters in layer 4 based on the training data pattern.

a. Layer-1

Layer-1 is used for the fuzzification process. The output of the training process at layer-1 is the premise parameter, which is the parameter in the membership function. There are four parameters in the dsigmf and psigmf membership functions, namely $a_1, c_1, a_2,$ and c_2, based on Equation 12 and Equation 13. The parameters for the dsigmf membership function can be seen in Table 6 and the parameters for the psigmf membership function can be seen in Table 7.

Table 6. Parameters in Difference Between Two Sigmoidal Membership Function (dsigmf)

Variable	Linguistic Variable	Parameter			
		a_1	c_1	a_2	c_2
Harvested Area	Quite Spacious	0.002844	982.1	0.002844	8,014
	Spacious	0.002844	8,014	0.002844	15,050
Sugarcane	Quite Heavy	0.0001614	266,300	0.0001614	390,300
	Heavy	0.0001614	390,300	0.0001614	514,200
Yield	Quite High	7.299	4.44	7.299	7.18
	High	7.299	7.18	7.299	9.92
Milling Days	Quite Long	0.2062	76.5	0.2062	173.5
	Long	0.2062	173.5	0.2062	270.5

Table 7. Parameters in Product of Two Sigmoidal Membership Function (psigmf)

Variable	Linguistic Variable	Parameter			
		a_1	c_1	a_2	c_2
Harvested Area	Quite Spacious	0.002844	982.1	-0.002844	8,014
	Spacious	0.002844	8,014	-0.002844	15,050
Sugarcane	Quite Heavy	0.0001614	266,300	-0.0001614	390,300
	Heavy	0.0001614	390,300	-0.0001614	514,200
Yield	Quite High	7.299	4.44	-7.299	7.18
	High	7.299	7.18	-7.299	9.92
Milling Days	Quite Long	0.2062	76.5	-0.2062	173.5
	Long	0.2062	173.5	-0.2062	270.5

The output of layer-1 is the degree of membership that is obtained by substituting the value of each input variable into the membership function. The result of substituting the input value into the dsigmf membership function has the same value as the result of substituting the input value into the psigmf membership function. Based on Figure 3, the dsigmf membership function plot has the same shape as the psigmf membership function plot. The following is the membership degree of each input variable as output in layer-1.

Table 8. Membership Degree of Each Input Variable for Training Data

Harvested Area		Sugarcane		Yield		Milling Days	
Quite Spacious	Spacious	Quite Heavy	Heavy	Quite High	High	Quite Long	Long
0.841	0.159	0.00005	0.9999	0.906	0.094	0.00005	0.9999
0.867	0.133	0.002	0.998	0.763	0.237	0.001	0.999
0.987	0.013	0.9997	0.0002	0.852	0.148	0.968	0.032

Harvested Area		Sugarcane		Yield		Milling Days	
Quite Spacious	Spacious	Quite Heavy	Heavy	Quite High	High	Quite Long	Long
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0.999	0.001	0.126	0.874	0.788	0.212	0.986	0.014
0.9997	0.0002	0.102	0.898	0.051	0.949	0.996	0.004
0.997	0.003	0.206	0.794	0.00005	0.9999	0.988	0.012
0.9999	0.00005	0.9999	0.00005	0.0002	0.998	0.9999	0.00005

b. Layer-2

Layer-2 is used to determine the firing strength of each rule, which is obtained by multiplying the membership degree on each input according to **Equation 14**. The results of the firing strength calculation for each rule as output in layer-2 can be seen in **Table 9**.

Table 9. Firing Strength Calculation Result for Training Data

w_1	w_2	w_3	w_4	⋯	w_{14}	w_{15}	w_{16}
1.6×10^{-9}	3.5×10^{-5}	1.6×10^{-10}	3.6×10^{-6}	⋯	1.4×10^{-1}	6.8×10^{-7}	1.5×10^{-2}
1.2×10^{-6}	1.4×10^{-3}	3.6×10^{-7}	4.4×10^{-4}	⋯	1.0×10^{-1}	2.6×10^{-5}	3.2×10^{-2}
8.1×10^{-1}	2.7×10^{-2}	1.4×10^{-1}	4.7×10^{-3}	⋯	8.6×10^{-8}	4.5×10^{-7}	1.5×10^{-8}
⋮	⋮	⋮	⋮	⋰	⋮	⋮	⋮
9.8×10^{-2}	1.4×10^{-3}	2.6×10^{-2}	3.8×10^{-4}	⋯	1.3×10^{-5}	2.4×10^{-4}	3.6×10^{-6}
5.2×10^{-3}	2.2×10^{-5}	9.7×10^{-2}	4.1×10^{-4}	⋯	4.6×10^{-8}	2.0×10^{-4}	8.6×10^{-7}
9.2×10^{-6}	1.1×10^{-7}	2.0×10^{-1}	2.4×10^{-3}	⋯	1.3×10^{-9}	2.5×10^{-3}	3.0×10^{-5}
1.8×10^{-4}	8.2×10^{-9}	10×10^{-1}	4.5×10^{-5}	⋯	2×10^{-17}	2.1×10^{-9}	9×10^{-14}

c. Layer-3

Layer-3 is used to determine the normalized firing strength of each rule using **Equation 15**. The calculation results of normalized firing strength for each rule as output in layer-3 can be seen in **Table 10**.

Table 10. Normalized Firing Strength Calculation Result for Training Data

$\overline{w}_1$	$\overline{w}_2$	$\overline{w}_3$	$\overline{w}_4$	⋯	$\overline{w}_{14}$	$\overline{w}_{15}$	$\overline{w}_{16}$
1.6×10^{-9}	3.5×10^{-5}	2×10^{-10}	3.6×10^{-6}	⋯	1.4×10^{-1}	6.8×10^{-7}	1.5×10^{-2}
1.2×10^{-6}	1.4×10^{-3}	3.6×10^{-7}	4.4×10^{-4}	⋯	1.0×10^{-1}	2.6×10^{-5}	3.2×10^{-2}
8.1×10^{-1}	2.7×10^{-2}	1.4×10^{-1}	4.7×10^{-3}	⋯	8.6×10^{-8}	4.5×10^{-7}	1.5×10^{-8}
⋮	⋮	⋮	⋮	⋰	⋮	⋮	⋮
9.8×10^{-2}	1.4×10^{-3}	2.6×10^{-2}	3.8×10^{-4}	⋯	1.3×10^{-5}	2.4×10^{-4}	3.6×10^{-6}
5.2×10^{-3}	2.2×10^{-5}	9.7×10^{-2}	4.1×10^{-4}	⋯	4.6×10^{-8}	2.3×10^{-4}	8.6×10^{-7}
9.2×10^{-6}	1.1×10^{-7}	2.0×10^{-1}	2.4×10^{-3}	⋯	1.3×10^{-9}	2.5×10^{-3}	3.0×10^{-5}
1.8×10^{-4}	8.2×10^{-9}	10×10^{-1}	4.5×10^{-5}	⋯	2×10^{-17}	2.1×10^{-9}	9×10^{-14}

d. Layer-4

Layer-4 is the defuzzification layer. The output of this layer is the product of the normalized firing strength ($\overline{w}_j$) with the consequent parameters of each rule. The consequent parameters are obtained using Least Square Estimation (LSE) which is helped by "recursivels" function in MATLAB and obtained as follows:

Table 11. Consequent Parameters of 0th Sugeno Fuzzy Inference System

Parameter	Value
$\theta_{1,0}$	33,308.60428
$\theta_{2,0}$	99,504.19002
$\theta_{3,0}$	25,939.14504
⋮	⋮
$\theta_{13,0}$	702,876.3062
$\theta_{14,0}$	761,151.5101
$\theta_{15,0}$	−55,361.48164
$\theta_{16,0}$	536,598.0475

The output calculation of layer-4 uses **Equation 16** and obtained the results as in **Table 12**.

Table 12. Layer-4 Output for Training Data

$\bar{w}_1\theta_{1,0}$	$\bar{w}_2\theta_{2,0}$	$\bar{w}_3\theta_{3,0}$	$\bar{w}_4\theta_{4,0}$	$\cdots$	$\bar{w}_{14}\theta_{14,0}$	$\bar{w}_{15}\theta_{15,0}$	$\bar{w}_{16}\theta_{16,0}$
5.3×10^{-5}	3.45	4.2×10^{-6}	1.9×10^{-2}	$\cdots$	1.1×10^{5}	-4×10^{-2}	8×10^{3}
3.9×10^{-2}	1.4×10^{2}	9.4×10^{-3}	2.39	$\cdots$	7.7×10^{4}	-1.42	2×10^{4}
2.7×10^{4}	2.7×10^{3}	3.7×10^{3}	2.5×10^{1}	$\cdots$	6.5×10^{-2}	-3×10^{-2}	8×10^{-3}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$	$\vdots$
3.3×10^{3}	1.4×10^{2}	6.8×10^{2}	2.1	$\cdots$	1.0×10^{1}	-1×10^{1}	1.91
1.7×10^{2}	2.19	2.5×10^{3}	2.2	$\cdots$	3.5×10^{-2}	-1×10^{1}	5×10^{-1}
3.1×10^{-1}	1.1×10^{-2}	5.3×10^{3}	1.3×10^{1}	$\cdots$	1.0×10^{-3}	-1×10^{2}	2×10^{1}
6.05	8.2×10^{-4}	2.6×10^{4}	2.4×10^{-1}	$\cdots$	1.3×10^{-11}	-1×10^{-4}	5×10^{-8}

e. Layer-5

Layer-5 is used for the total output calculation process using Equation 17. The following is the output of layer-5.

Table 13. Layer-5 Output for Training Data

Year	ANFIS Output
2008	29,838.70
2009	23,474.37
2010	22,501.22
$\vdots$	$\vdots$
2017	30,835.42
2018	31,300.52
2019	30,545.55
2020	25,943.79

3.3.2 Testing Process

The testing process uses input variables from 2020 – 2021 and output variables from 2021 – 2022. The testing process is a process to test the model that has been obtained using new data that has never been trained before. The following is the output of each ANFIS layer in the testing process.

a. Layer-1

The following is the output of layer-1 in the testing process, which consists of the membership degree of each variable. The calculation of the membership degree uses the dsigmf and psigmf functions with the premise parameters that were obtained during the training process.

Table 14. Membership Degree of Each Input Variable for Testing Data

Harvested Area		Sugarcane		Yield		Milling Days	
Quite Spacious	Spacious	Quite Heavy	Heavy	Quite Spacious	Spacious	Quite Long	Long
0.9999	0.00004	0.9999	0.00002	0.001	0.998	0.998	0.000001
0.9998	0.0002	0.9997	0.0002	0.002	0.998	0.9996	0.000006

b. Layer-2

The following is the output of layer-2 in the testing process, which consists of firing strength. The calculation of firing strength in the testing process is the same as the calculation of firing strength in the training process, which is multiplying the membership degree of each input variable according to the rules that have been formed.

Table 15. Firing Strength Calculation Result for Testing Data

w_1	w_2	w_3	w_4	$\cdots$	w_{14}	w_{15}	w_{16}
1.1×10^{-3}	1.5×10^{-9}	10.0×10^{-1}	1.4×10^{-6}	$\cdots$	1.6×10^{-18}	1.0×10^{-9}	1.4×10^{-15}
1.9×10^{-3}	1.1×10^{-8}	10.0×10^{-1}	5.8×10^{-6}	$\cdots$	5.6×10^{-16}	5.1×10^{-8}	3.0×10^{-13}

c. Layer-3

The following is the output of layer-3 in the testing process, which consist of normalized firing strength.

Table 16. Normalized Firing Strength Calculation Result for Testing Data

$\bar{w}_1$	$\bar{w}_2$	$\bar{w}_3$	$\bar{w}_4$	⋯	$\bar{w}_{14}$	$\bar{w}_{15}$	$\bar{w}_{16}$
1.1×10^{-3}	1.5×10^{-9}	10×10^{-1}	1.4×10^{-6}	⋯	1.6×10^{-18}	1.0×10^{-9}	1.4×10^{-15}
1.9×10^{-3}	1.1×10^{-8}	10×10^{-1}	5.8×10^{-6}	⋯	5.6×10^{-16}	5.1×10^{-8}	3.0×10^{-13}

d. Layer-4

The following is the output of layer-4 in the testing process. This output's calculation uses consequent parameters obtained during the training process.

Table 17. Layer-4 Output for Testing Data

$\bar{w}_1\theta_{1,0}$	$\bar{w}_2\theta_{2,0}$	$\bar{w}_3\theta_{3,0}$	$\bar{w}_4\theta_{4,0}$	⋯	$\bar{w}_{14}\theta_{14,0}$	$\bar{w}_{15}\theta_{15,0}$	$\bar{w}_{16}\theta_{16,0}$
3.7×10^{1}	1.5×10^{-4}	2.6×10^{4}	7.4×10^{-3}	⋯	1.2×10^{-12}	-5.7×10^{-5}	7.5×10^{-10}
6.2×10^{1}	1.1×10^{-3}	2.6×10^{4}	3.1×10^{-2}	⋯	4.2×10^{-10}	-2.8×10^{-3}	1.6×10^{-7}

e. Layer-5

The following is the output of layer-5 in the testing process, which consists of the amount of sugar production in 2021 and 2022 using the ANFIS system.

Table 18. Layer-5 Output for Testing Data

Year	ANFIS Output
2021	25,951.20
2022	25,971.35

3.3.3 Predicting Process

The prediction process is a process that determines the amount of sugar produced in the future. In this research, a predicting process is conducted to determine the amount of sugar production for 2023. The following is the output of each ANFIS layer used to predict the process.

a. Layer-1

The following is the output of layer-1 in the predicting process, which consists of the membership degree of each variable. The calculation in this predicting process is the same as in the testing process, which also uses the premise parameters obtained in the training process.

Table 19. Membership Degree of Each Input Variable for Predicting Data

Harvested Area		Sugarcane		Yield		Milling Days	
Quite Spacious	Spacious	Quite Heavy	Heavy	Quite Spacious	Spacious	Quite Long	Long
0.9999	0.00003	0.806	0.194	0.536	0.464	0.9998	0.0002

b. Layer-2

The following is the output layer-2 in the predicting process, which consists of firing strength.

Table 20. Firing Strength Calculation Result for Predicting Data

w_1	w_2	w_3	w_4	⋯	w_{14}	w_{15}	w_{16}
4.3×10^{-1}	8.3×10^{-5}	3.7×10^{-1}	7.2×10^{-5}	⋯	5.5×10^{-10}	2.5×10^{-6}	4.8×10^{-10}

c. Layer-3

The following is the output of layer-3 in the testing process, which consist of normalized firing strength.

Table 21. Normalized Firing Strength Calculation Result for Predicting Data

$\bar{w}_1$	$\bar{w}_2$	$\bar{w}_3$	$\bar{w}_4$	⋯	$\bar{w}_{14}$	$\bar{w}_{15}$	$\bar{w}_{16}$
4.3×10^{-1}	8.3×10^{-5}	3.7×10^{-1}	7.2×10^{-5}	⋯	5.5×10^{-10}	2.5×10^{-6}	4.8×10^{-10}

d. Layer-4

The following is the output of layer-4 in the predicting process. The calculation in this predicting process is the same as the calculation in the testing process, which also uses the consequent parameters that have been obtained in the training process.

Table 22. Layer-4 Output for Predicting Data

$\bar{w}_1\theta_{1,0}$	$\bar{w}_2\theta_{2,0}$	$\bar{w}_3\theta_{3,0}$	$\bar{w}_4\theta_{4,0}$	$\cdots$	$\bar{w}_{14}\theta_{14,0}$	$\bar{w}_{15}\theta_{15,0}$	$\bar{w}_{16}\theta_{16,0}$
1.4×10^4	8.26	9.7×10^3	3.9×10^{-1}	$\cdots$	4.2×10^{-4}	-1.4×10^{-1}	-2.5×10^{-4}

e. Layer-5

The following is the output layer-5 in the predicting process, which consists of the amount of sugar production in 2023 using the ANFIS system. The prediction of the amount of sugar production in PTPN XI PG Prajekan using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method is 30,256 tons.

Table 23. Layer-5 Output for Testing Data

Year	ANFIS Output
2023	30,256.05

3.4 Calculation of Error Rate with Mean Absolute Percentage Error (MAPE)

The error rate in this research is measured using Mean Absolute Percentage Error (MAPE) using **Equation 18**. This research obtained a MAPE value of 1.79% in the training process and 4.82% in the testing process. **Figure 6** shows the difference between the actual and ANFIS-predicted values.

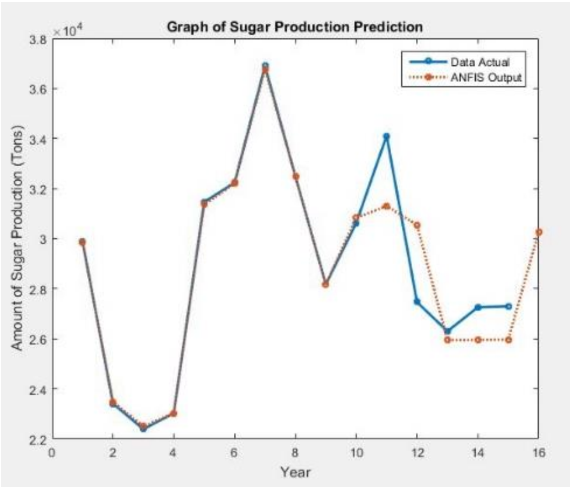


Figure 6. Plot of the difference between actual data and ANFIS prediction data

The plot for the actual data is shown with the blue line, and the plot for the ANFIS output (prediction result) is shown with the orange line. The closer the two lines are, the smaller the value of the error. Conversely, the farther the distance between the two lines, the greater the value of the error.

4. CONCLUSIONS

The Adaptive Neuro-Fuzzy Inference System (ANFIS) method can be used to predict the amount of sugar production at PTPN XI PG Prajekan. The best ANFIS model obtained is one with membership function types dsigmf and psigmf, with 2 membership functions for each input variable. The output membership function type used is constant. The MAPE value of the two models is 1.79% in the training process and 4.82% in the testing process. The resulting MAPE value is relatively small, but the model fits well. Therefore, the prediction model for the amount of sugar production can be said to be accurate based on **Table 1**.

REFERENCES

[1] B. P. Statistik, *Statistik Tebu Indonesia 2019*, vol. 13, no. 1. Jakarta: BPS RI, 2019.
[2] C. N. Aliza, “Faktor-Faktor Yang Mempengaruhi Produksi Gula Di Indonesia,” Universitas Muhammadiyah Surakarta, 2019.
[3] A. Syafri and I. S. Sudrajat, “Faktor-Faktor Yang Mempengaruhi Produksi Gula Di PT. Madubaru (Madukismo) Yogyakarta,” *J. Ilm. Agritas*, vol. 2, no. 2, pp. 13–26, 2018.

[4] A. Setiawan, B. Yanto, and K. Yasdomi, *Logika Fuzzy Dengan Matlab*. Bali: Jayapangus Press, 2018.
[5] D. R. Rochmawati, “Prediksi Cuaca dengan Jaringan Syaraf Tiruan menggunakan Python,” vol. 2, no. 2, 2024.
[6] F. M. Siregar, G. W. Nurcahyo, and S. Defit, “Prediksi Hasil Ujian Kompetensi Mahasiswa Program Profesi Dokter (UKMPPD) dengan Pendekatan ANFIS,” *J. RESTI (Rekayasa Sist. dan Teknol. Informasi)*, vol. 2, no. 2, pp. 554–559, 2018, doi: 10.29207/resti.v2i2.388.
[7] S. A. Harahap and S. N. Endah, “Penerapan Adaptive Neuro-Fuzzy Inference System untuk Prediksi Nilai Tukar Rupiah,” *J. Masy. Inform.*, vol. 10, no. 1, pp. 37–47, 2019, doi: 10.14710/jmasif.10.1.31488.
[8] Y. Tri Nugraha, M. F. Zambak, and A. Hasibuan, “Perkiraan Konsumsi Energi Listrik Di Aceh Pada Tahun 2028 Menggunakan Metode Adaptive Neuro Fuzzy Inference System,” *CESS (Journal Comput. Eng. Syst. Sci.*, vol. 5, no. 1, p. 104, 2020, doi: 10.24114/cess.v5i1.15624.
[9] Mutmainah, “Prediksi Indeks Harga Konsumen di Kota Denpasar-Bali Menggunakan Metode Adaptive Neuro-Fuzzy Inference System (ANFIS),” UIN Syarif Hidayatullah Jakarta, 2021. [Online]. Available: https://repository.uinjkt.ac.id/dspace/handle/123456789/56947%0Ahttps://repository.uinjkt.ac.id/dspace/bitstream/123456789/56947/1/MUTMAINAH-FST.pdf
[10] A. Matsniya, “Penerapan Metode Adaptive Neuro Fuzzy Inference System dalam Prediksi Produksi Tembakau di Kabupaten Jember,” Universitas Jember, 2022.
[11] A. D. Mulyanto, “mVIF Package: A Tool for Detecting Multicollinearity without Dependent Variables,” *MATICS J. Ilmu Komput. dan Teknol. Inf. (Journal Comput. Sci. Inf. Technol.*, vol. 14, no. 2, pp. 70–73, 2022, doi: 10.18860/mat.v14i2.20948.
[12] A. J. Rindengan and Y. A. R. Langi, *Sistem Fuzzy*. Bandung: CV. Patra Media Grafindo, 2019.
[13] 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, pp. 1–8, 2019, doi: 10.1088/1742-6596/1217/1/012083.
[14] B. Santoso, A. I. . Azis, and Zohrahayaty, *Machine Learning & Reasoning Fuzzy Logic Algoritm, Manual, & Rapid Miner*. Yogyakarta: Deepublish, 2020.
[15] S. A. F. Pramesti, U. A. S. Sadikin, I. Nurfitri, and F. Maulida, “Prediksi Indeks Harga Konsumen Kota Pontianak Menggunakan Metode Double Exponential Smoothing dan Analysis Trend,” *Equator J. Math. Stat. Sci.*, vol. 2, no. 2, pp. 37–47, 2023, [Online]. Available: https://jurnal.untan.ac.id/index.php/EMSS/article/view/73302