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Forecasting Palm Oil Production in North Sumatera Using the Adaptive Neuro Fuzzy Inference System Method

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ABSTRACT

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Indonesia is an agricultural and maritime country because it is the country that has the largest agriculture and plantations in ASEAN. One of them is palm oil production, because palm oil is believed to not only be able to produce various types of butter, cooking oil or soap, but can also be a substitute for fuel oil. In the province of North Sumatra itself, oil palm is a crop that has potential and produces very high profits. Therefore, forecasting is used to determine future palm oil production results using the ANFIS method in order to increase or catalyze palm fruit. The data source used in this research comes from the Badan Pusat Statistik (BPS) of North Sumatra. The aim of this research is to determine the results of forecasting palm oil production in North Sumatra using the ANFIS model. The results of the study show that the ANFIS method can be used to build a prediction model for palm oil production in Sumatra province with the best accuracy and MAPE values obtained being 92% and 12.78%, respectively.

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1. Introduction

Indonesia is an agricultural and maritime country because it is the country that has the largest agriculture and plantations in ASEAN. It cannot ignore its role in the country because apart from being a source of energy for the plantation product processing industry, it can also provide employment because basically what is managed are types of plants that are difficult to plow mechanically, especially annual perennials [1]. One of them is the production of oil palm plants. Palm oil is a promising trade commodity in the future because palm oil is believed to not only be able to produce various types of butter, cooking oil or soap, but can also be a substitute for fuel oil [2]. Where cooking oil itself is one of the staple ingredients in the household.

In the province of North Sumatra itself there are many oil palm farmers, because oil palm is a plant that has great potential and produces very high profits. Apart from that, North Sumatra province is also one of the 5 provinces that produce the most palm oil in Indonesia [3].

According to the data obtained from the Ministry of Agriculture processed by the Central Statistics Agency (BPS), Indonesia's palm oil production volume reached 45.58 million tons and North Sumatra Province produced 6 million tons or 13 percent of the national production volume [4]. However, palm oil production in North Sumatra province experiences fluctuations (up and down), where the highest production was seen in August 2019 at 664,352 while the lowest production was seen in February 2017 at 229,992. Therefore, forecasting is used to find out future palm oil production results before increasing or catalyzing palm fruit.

Forecasting is the basis for the long term for a company [5]. Forecasting palm oil production is important because it can help in making accurate plans for the future, to determine the resources that will be needed in the future. The forecasting method is a way of estimating what will happen in the future systematically on the basis of relevant data in the past, so that the forecasting method is expected to provide greater objectivity [6]. ANFIS is an artificial neural network model that can also be used for forecasting. The ANFIS method has several advantages, namely that it is good for large scale calculations, good for time series forecasting, both short and long term forecasting, able to study patterns well, and able to provide the best solution from unknown data [7].

2. Research Methods

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a combination of fuzzy logic and Artificial Neural Network (ANN) [8]. Fuzzy logic is a way to describe an input into an output [9]. In fuzzy logic theory, fuzzy sets are known. Fuzzy logic has a membership value between 0 and 1. In the Adaptive Neuro-Fuzzy Inference System (ANFIS) analysis, there are steps that must be taken, namely:

1. Data normalization
   To minimize computational calculations that are too large, the data is normalized into a range $0 \leq x \leq 1$.

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

2. Dividing training and test data
   In the Adaptive Neuro-Fuzzy Inference System (ANFIS) method, dividing data into training data and testing data is an important step to ensure the resulting model can generalize well.

3. Training process
   The training process is carried out using MATLAB source code to load input-output data from files, create an initial FIS structure using the 'genfis1' function, train the ANFIS model with training data for the number of epochs, validate the model with test data and calculate MSE, and displays the results of the training process.

4. Testing process
   The testing process involves using test data to evaluate the ANFIS model that has been trained, calculating forecasting errors using MSE, and analyzing the results to assess the generalization ability of the model. Models that show low MSE on test data are considered to have good performance and are reliable for forecasting on new data.

5. Denormalization
   Denormalization is the process of returning normalized data to its original scale. After the model is trained and forecasts are made, these results need to be returned to their original scale so they can be compared with actual data that has not been normalized.

$$Denormalisasi = Y\,(\text{Max} - \text{Min}) + \text{Min} \tag{2}$$

6. Checking actual data and forecasting
   To evaluate model performance, forecasting results are compared with actual data. This evaluation helps in assessing the strengths and weaknesses of the model, and making adjustments if necessary.

$$\text{Error} = \frac{(Average\ of\ forecasting) - (Average\ of\ actual\ data)}{Average\ of\ forecasting} \tag{3}$$

$$\text{Accuracy} = (1 - \text{Error}) \times 100 \tag{4}$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{\sum_{t=1}^{n} \left|\frac{e_t}{X_t}\right| 100\%}{n} \tag{5}$$

3. Results And Discussion

3.1. Data Analysis

The data used in this research is palm oil production data in North Sumatra Province for the period January 2017 to December 2022 which can be seen in **Table 1** below:

Table 1. Palm Oil Production

Month	Year (Ton)					
	2017	2018	2019	2020	2021	2022
January	242,755	429,749	475,028	332,010	361,261	295,933
February	229,992	388,100	444,940	343,211	354,044	383,144
March	271,785	421,731	480,645	389,519	467,409	413,875
April	329,171	443,181	530,881	420,047	454,715	437,013
May	349,462	465,064	597,532	391,778	422,648	412,945
June	341,090	435,769	518,167	446,986	474,495	461,369
July	443,583	506,684	613,160	460,311	474,011	428,992
August	444,848	499,408	664,352	487,438	494,422	484,040
September	433,855	494,275	648,406	492,232	492,916	490,084
October	360,023	483,213	629,004	425,553	431,044	455,799
November	363,950	451,258	542,753	379,406	414,987	412,917
December	334,106	427,399	500,672	582,292	422,782	375,429

Data source: *North Sumatra Province Central Statistics Agency*

Based on **Table 1** above, it shows the amount of data per month from 2017 to 2022. Each row represents the amount of data for each month, from January to December, with columns showing the figures for each year. In the table above you can also see the maximum and minimum values. Where the maximum value is 664,352 and the minimum value is 229,992.

3.2. Data Normalization

To minimize excessively large computational calculations, data normalization was carried out into the range $0 \leq x \leq 1$ using MATLAB source code. By using the MATLAB source code, normalized data is obtained as shown in **Table 2** below:

Table 2. Data Normalization

Month	Year					
	2017	2018	2019	2020	2021	2022
January	0.029383	0.459888	0.564131	0.23487	0.302212	0.151812
February	0	0.364002	0.494861	0.260657	0.285597	0.352592
March	0.096217	0.441429	0.577063	0.367269	0.54659	0.423342
April	0.228334	0.490812	0.692718	0.437552	0.517366	0.476612
May	0.275048	0.541192	0.846164	0.37247	0.44354	0.421201
June	0.255774	0.473748	0.663447	0.499572	0.562904	0.532685
July	0.491737	0.637011	0.882144	0.530249	0.56179	0.458145
August	0.49465	0.62026	1	0.592702	0.608781	0.584879
September	0.469341	0.608442	0.963289	0.603739	0.605314	0.598794
October	0.299362	0.582975	0.91862	0.450228	0.46287	0.519861
November	0.308403	0.509407	0.72005	0.343987	0.425902	0.421137
December	0.239695	0.454478	0.62317	0.811078	0.443848	0.334831

3.3. Splitting Training and Test Data

Testing is carried out by dividing training data and test data. Where the training data is taken from the period January 2017 to December 2020, while the test data is taken from the period January 2021 to December 2022. Then, if compared with percent, the comparison between training data and test data (testing) is 67% versus 33%.

3.4. Training Process

The training process (training set) is carried out using MATLAB source code to load input-output data from files, create an initial FIS structure using the 'genfis1' function, train the ANFIS model with training data for the number of epochs, validate the model with test data and calculate MSE, and displays the results of the training process. So that the results obtained from the training data and training targets are as shown in **Table 3** below:

Table 3. Training Data and Training Targets

Data to	Training Data						Training Targets
1	0.029383	0.459888	0.564131	0.23487	0.302212	0.151812	0
2	0.459888	0.564131	0.23487	0.302212	0.151812	0	0.364002
3	0.564131	0.23487	0.302212	0.151812	0	0.364002	0.494861
4	0.23487	0.302212	0.151812	0	0.364002	0.494861	0.260657
5	0.302212	0.151812	0	0.364002	0.494861	0.260657	0.285597
6	0.151812	0	0.364002	0.494861	0.260657	0.285597	0.352592
7	0	0.364002	0.494861	0.260657	0.285597	0.352592	0.096217
8	0.364002	0.494861	0.260657	0.285597	0.352592	0.096217	0.441429
9	0.494861	0.260657	0.285597	0.352592	0.096217	0.441429	0.577063
10	0.260657	0.285597	0.352592	0.096217	0.441429	0.577063	0.367269
11	0.285597	0.352592	0.096217	0.441429	0.577063	0.367269	0.54659
12	0.352592	0.096217	0.441429	0.577063	0.367269	0.54659	0.423342
13	0.096217	0.441429	0.577063	0.367269	0.54659	0.423342	0.228334
14	0.441429	0.577063	0.367269	0.54659	0.423342	0.228334	0.490812
15	0.577063	0.367269	0.54659	0.423342	0.228334	0.490812	0.692718
16	0.367269	0.54659	0.423342	0.228334	0.490812	0.692718	0.437552
17	0.54659	0.423342	0.228334	0.490812	0.692718	0.437552	0.517366
18	0.423342	0.228334	0.490812	0.692718	0.437552	0.517366	0.476612
19	0.228334	0.490812	0.692718	0.437552	0.517366	0.476612	0.275048
20	0.490812	0.692718	0.437552	0.517366	0.476612	0.275048	0.541192
21	0.692718	0.437552	0.517366	0.476612	0.275048	0.541192	0.846164
22	0.437552	0.517366	0.476612	0.275048	0.541192	0.846164	0.37247
23	0.517366	0.476612	0.275048	0.541192	0.846164	0.37247	0.44354
24	0.476612	0.275048	0.541192	0.846164	0.37247	0.44354	0.421201
25	0.275048	0.541192	0.846164	0.37247	0.44354	0.421201	0.255774
26	0.541192	0.846164	0.37247	0.44354	0.421201	0.255774	0.473748
27	0.846164	0.37247	0.44354	0.421201	0.255774	0.473748	0.663447
28	0.37247	0.44354	0.421201	0.255774	0.473748	0.663447	0.499572
29	0.44354	0.421201	0.255774	0.473748	0.663447	0.499572	0.562904
30	0.421201	0.255774	0.473748	0.663447	0.499572	0.562904	0.532685
31	0.255774	0.473748	0.663447	0.499572	0.562904	0.532685	0.491737
32	0.473748	0.663447	0.499572	0.562904	0.532685	0.491737	0.637011
33	0.663447	0.499572	0.562904	0.532685	0.491737	0.637011	0.882144
34	0.499572	0.562904	0.532685	0.491737	0.637011	0.882144	0.530249
35	0.562904	0.532685	0.491737	0.637011	0.882144	0.530249	0.56179
36	0.532685	0.491737	0.637011	0.882144	0.530249	0.56179	0.458145
37	0.491737	0.637011	0.882144	0.530249	0.56179	0.458145	0.49465
38	0.637011	0.882144	0.530249	0.56179	0.458145	0.49465	0.62026
39	0.882144	0.530249	0.56179	0.458145	0.49465	0.62026	1
40	0.530249	0.56179	0.458145	0.49465	0.62026	1	0.592702
41	0.56179	0.458145	0.49465	0.62026	1	0.592702	0.608781
42	0.458145	0.49465	0.62026	1	0.592702	0.608781	0.584879

The ANFIS model which was trained using MATLAB succeeded in achieving good performance, this is shown by the low MSE value and high correlation between the training data and the training target, namely 0.270566 and MAPE of 7.40% with the MAPE <10% criterion. rated 'very good'. Thus, the model can effectively learn and be able to capture non-linear relationships in the data, making it reliable for future forecasting applications.

3.5. Test Process

The testing process (testing set) is carried out using MATLAB source code which involves using test data to evaluate the ANFIS model that has been trained, calculating forecasting errors using MSE, and analyzing the results to assess the generalization ability of the model. Models that show low MSE on test data are considered to have good performance and are reliable for forecasting on new data. So that the results obtained from the test data and test targets are shown in **Table 4**:

Table 4. Test Data and Test Targets

Data to	Test Data						Test Targets
1	0.49465	0.62026	1	0.592702	0.608781	0.584879	0.469341
2	0.62026	1	0.592702	0.608781	0.584879	0.469341	0.608442
3	1	0.592702	0.608781	0.584879	0.469341	0.608442	0.963289
4	0.592702	0.608781	0.584879	0.469341	0.608442	0.963289	0.603739
5	0.608781	0.584879	0.469341	0.608442	0.963289	0.603739	0.605314
6	0.584879	0.469341	0.608442	0.963289	0.603739	0.605314	0.598794
7	0.469341	0.608442	0.963289	0.603739	0.605314	0.598794	0.299362
8	0.608442	0.963289	0.603739	0.605314	0.598794	0.299362	0.582975
9	0.963289	0.603739	0.605314	0.598794	0.299362	0.582975	0.91862
10	0.603739	0.605314	0.598794	0.299362	0.582975	0.91862	0.450228
11	0.605314	0.598794	0.299362	0.582975	0.91862	0.450228	0.46287
12	0.598794	0.299362	0.582975	0.91862	0.450228	0.46287	0.519861
13	0.299362	0.582975	0.91862	0.450228	0.46287	0.519861	0.308403
14	0.582975	0.91862	0.450228	0.46287	0.519861	0.308403	0.509407
15	0.91862	0.450228	0.46287	0.519861	0.308403	0.509407	0.72005
16	0.450228	0.46287	0.519861	0.308403	0.509407	0.72005	0.343987
17	0.46287	0.519861	0.308403	0.509407	0.72005	0.343987	0.425902
18	0.519861	0.308403	0.509407	0.72005	0.343987	0.425902	0.421137
19	0.308403	0.509407	0.72005	0.343987	0.425902	0.421137	0.239695
20	0.509407	0.72005	0.343987	0.425902	0.421137	0.239695	0.454478
21	0.72005	0.343987	0.425902	0.421137	0.239695	0.454478	0.62317
22	0.343987	0.425902	0.421137	0.239695	0.454478	0.62317	0.811078
23	0.425902	0.421137	0.239695	0.454478	0.62317	0.811078	0.443848
24	0.421137	0.239695	0.454478	0.62317	0.811078	0.443848	0.334831

After the model is trained, test data is used to test the model's ability to forecast values that have never been seen before. This test data is used to evaluate the extent to which the model can generalize the patterns that have been learned during the training process. Thus, the ANFIS model trained using MATLAB managed to maintain good performance when tested with data that had never been seen before, this can be seen based on the testing process with an MSE value of 0.314078 and a MAPE value of 12.78% with a MAPE criterion of 10% - 20% rated 'Good'.

3.6. Denormalization

Denormalization is the process of returning normalized data to its original scale. In the ANFIS method, normalization is often used to facilitate training the model and speed up convergence. After the model is trained and forecasts are made, these results need to be returned to their original scale so they can be compared with actual data that has not been normalized. By using MATLAB source code, the following denormalization results are obtained:

Table 5. Data Denormalization

Forecasting Results	
In 2023	**In 2024**
531,669	422,147
503,711	385,183
589,740	488,610
459,968	513,860
495,594	411,526
428,327	386,830
559,795	336,033
485,052	414,998
575,112	493,772
414,379	428,742
507,144	497,337
505,751	339,348

Overall, denormalization ensures that the forecasting results from the ANFIS model can be interpreted correctly in the context of the original problem. This process is an important step to ensure that the model results can be used practically and compared with real data on a scale that is easy to understand.

3.7. Checking Actual and Forecasting Data

Checking of actual and forecasting data is carried out to increase accuracy in forecasting. To evaluate model performance, forecasting results are compared with actual data. This evaluation helps in assessing the strengths and weaknesses of the model, as well as making adjustments if necessary. So, based on checking the actual data and forecasting results using formula (3) and (4), the accuracy of the forecasting results is 92% and MAPE is 12.78%.

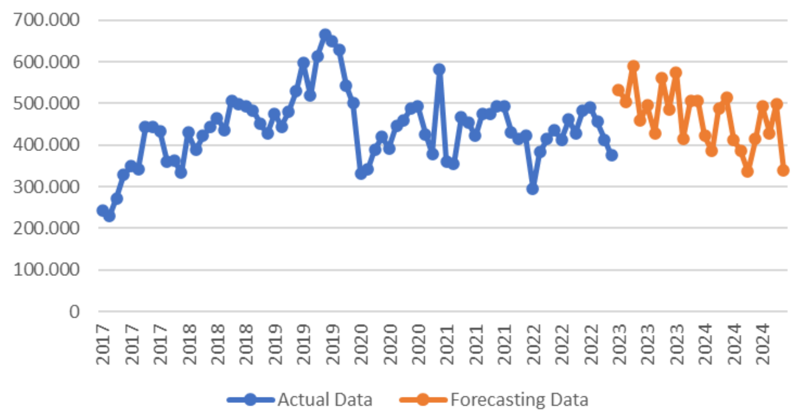

Figure 1. Graphs between actual data and forecasting data using ANFIS

Figure 1 shows the plot the results between the actual data and forecasting data using ANFIS. Thus, it can be seen in the graph above that palm oil production results in North Sumatra Province will experience fluctuations in the future. Therefore, data from forecasting can be used to support the agricultural sector in ensuring production stability.

4. Conclusions

Based on the results and discussion, the author can draw conclusions, namely, the results of forecasting palm oil production in North Sumatra province using the ANFIS (Adaptive Neuro-Fuzzy Inference System) method for the period January 2023 to December 2024 (tons) respectively, namely, 531,669; 503,711; 589,740; 459,968; 495,594; 428,327; 559,795; 485,052; 575,112; 414,397; 507,144; 505,751; 422,147; 385,183; 488,610; 513,860; 411,526; 386,830; 336,033; 414,998; 493,772; 428,742; 497,337; and 339,348 with the best obtained Accuracy and MAPE values of 92% and 12.78% respectively.

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