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# Comparison of Arima Method and Artificial Neural Network Method to Predict Productivity Rice In Panti District

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**Abstrak**

Produksi padi merupakan kegiatan masyarakat untuk menghasilkan beras, hal itu dimaksudkan untuk menjaga ketahanan pangan di masa yang akan datang. Tujuan dari penelitian ini adalah mengembangkan model terbaik dalam meramalkan produksi padi berdasarkan pendekatan ARIMA (Autoregressive Integrated Moving Averages) dan ANN (Artificial Neural Network). Hasilnya akan dibandingkan dengan nilai tingkat kesalahan dari metode ARIMA dan ANN tersebut dengan data yang tersedia. Data yang digunakan dalam penelitian ini adalah data produksi padi di Kecamatan Panti Kabupaten jember . Tingkat akurasi peramalan yang dihasilkan oleh setiap metode peramalan diukur dengan kriteria MAPE (Mean Absolute Percentage Error), MSE (Mean Square Error) dan RMSE (Root Mean Square Error). Hasil penelitian menunjukkan bahwa dari metode peramalan yang digunakan dalam penelitian ini, metode ARIMA (1,0,1) (1,0,2)[12] merupakan metode peramalan yang terbaik luas panen padi terbaik di Kecamatan Panti Kabupaten jember dengan rata-rata nilai MAPE sebesar 0.05668374, MSE sebesar 5.587553, dan RMSE sebesar 2.3638. Sedangkan pada peramalan produktivitas padi dengan metode ANN BP (7,(7,3),1) merupakan metode peramalan yang cukup baik dengan rata-rata nilai MAPE sebesar 0.05703856 MSE sebesar 4.828465, dan RMSE sebesar 2.197377. Oleh karena itu, model ARIMA (1,0,1) (1,0,2)[12] cukup efektif untuk memprediksi jumlah produksi padi di Kecamatan Panti Kabupaten Jember Provinsi Jawa Timur untuk beberapa tahun yang akan datang.

**Kata Kunci**: *Produksi Padi, ARIMA, ANN*

**Abstract**

*Rice production is a community activity to produce rice, it is intended to maintain food security in the future. The aim of this research is to develop the best model for forecasting rice production based on ARIMA (Autoregressive Integrated Moving Averages) and ANN (Artificial Neural Network) approaches. The results will be compared with the error rate values of the ARIMA and ANN methods with the available data. The data used in this study is data on rice* *production in Panti District, Jember Regency. The level of forecasting accuracy produced by each forecasting method is measured by the criteria of MAPE (Mean Absolute Percentage Error), MSE (Mean Square Error) and RMSE (Root Mean Square Error). The results showed that from the forecasting method used in this study, the ARIMA (1,0,1) (1,0,2) method is the best forecasting method for the best rice harvest area in Panti District, Jember Regency with an average MAPE value is 0.05668374, MSE is 5.587553, and RMSE is 2.3638. Meanwhile, forecasting rice productivity using the ANN BP method (7,(7,3),1) is a fairly good forecasting method with an average MAPE value of 0.05703856 MSE of 4.828465, and RMSE of 2.197377. Therefore, the ARIMA model (1,0,1) (1,0,2)[12] is quite effective for predicting the amount of rice production in Panti District, Jember Regency, East Java Province for the next few years.*

***Keywords****: Rice Production, ARIMA, ANN*

## Introduction

Indonesia is a rice-producing country that has extensive agricultural land, namely around 10.61 million hectares in 2022. Most of the rice producers are spread across various islands, including the islands of Bali and Nusa Tenggara, Sumatra, Kalimantan, Sulawesi, Maluku and Irian Jaya, as well as the islands Java. The island of Sumatra is estimated to have a rice harvest area of up to 2.21 million ha or 20.88% of the national rice harvest area. On this island, Lampung Province has the largest rice harvest area, namely 23.34% of the harvested area of Sumatra Island. In the next sequence is Sulawesi Island with an estimated rice harvest area of 1.51 million ha 14.27%, followed by Kalimantan Island 680 thousand ha 6.43%, and the Bali and Nusa Tenggara regions 570 thousand ha 5.38%. Meanwhile, the rice harvest area in Maluku and Papua is the least, namely only 80 thousand ha or 0.8% of the national rice harvest area. Java Island is estimated to have a rice harvest area of up to 5.54 million ha or the equivalent of 52.24% of the national rice harvest area. Meanwhile, East Java is recorded as the province with the largest rice harvest area on the island of Java and nationally, which is estimated to reach 1.7 million ha or the equivalent of 31.07% of the rice harvest area of Java Island (BPS, 2022).

East Java Province for rice production from January to September 2022 reached around 8.17 million tons of GKG, or decreased by around 232.72 thousand tons of GKG by 2.77 percent compared to January-September 2021 which amounted to 8.41 million tons of GKG. Meanwhile, based on observations of the rice growing phase from the September 2022 KSA Rice Survey, the potential for rice production during October-December 2022 is 1.51 million tons of GKG (BPS, East Java, 2022).

Jember Regency for paddy production from January to December 2021 reached around 615.70 thousand tons of GKG, or an increase of around 25.43 thousand tons of GKG (4.31 percent) compared to 2020 which amounted to 590.26 thousand tons of GKG. The highest rice production in 2021 occurred in April, which was 196.29 thousand tons of GKG while the lowest production occurred in December, which was 19.50 thousand tons of GKG. Similar to conditions in 2021, the highest rice production in 2020 also occurred in April (BPS, Jember, 2022).

Panti sub-district is a sub-district located in the northern part of Jember Regency. Most of this sub-district includes plantation areas owned by the local government and the private sector and agriculture. Agriculture in the Panti sub-district for rice productivity throughout 2021 reached 371.91 thousand tons of GKG, while in 2020 rice productivity reached 376.56, experiencing a decrease of 1.2% (Umi, 2022).

Several methods for predicting rice productivity results are using ARIMA (Auto

Regressive Integrate Moving Average) and ANN (Artificial Neural Network). The ARIMA model is also called the Box-Jenkins model which assumes a linear function of several past observations. The assumption of stationarity is something that must be met in the ARIMA model. When the linear model produces a small level of forecasting accuracy and a large forecasting error, it is possible that the nonlinear model (nonlinear) is able to explain and predict better than the linear model. In addition, in the real world there are many data that are nonlinear, so the ARIMA method may be lacking. suitable for describing the data. Artificial Neural network (ANN) is a model capable of explaining complex problems with nonlinear relationships for long-term forecasting. Therefore, this research was conducted by testing several parameters to identify the best parameter values from the linear ARIMA model and the ANN nonlinear model in forecasting rice productivity in Panti Jember District.

## Method

This research is an applied research with a quantitative approach. The data used in this study is the monthly report on rice productivity in the Panti sub-district. Paddy productivity data in Panti sub-district is primary data in a study obtained directly from the source by measuring, self-counting in the form of questionnaires, observations. The data is in the form of monthly rice productivity reports which are packaged in Microsoft Excel files from 2014 to 2022.

ARIMA data processing. The data obtained will be processed in the following steps:

1. Test the stationarity of the data on the amount of rice production which is carried out by displaying the actual data plot, looking at the autocorrelation value and the shape of the ACF and PACF plots from the data. To test the stationarity of more specific data, the Augmented Dickey-Fuller test is used.
2. If the data does not meet the stationarity requirements, a Box-Cox transformation is performed to stationary the data with respect to the variance and differencing to stationary the data with respect to the mean.
3. Identification of data seasonal lag through ACF and PACF plots of data that is already stationary. The identification of the ACF and PACF plots is assisted by the R Studio software.
4. Parameter estimation. Estimating the parameters of the model by means of an iterative algorithm using the Maximum Likelihood (ML) estimation method, namely by testing several different values. The estimation of these parameters is assisted by the R Studio software.
5. Diagnostic Test. Performing a diagnostic check, this stage is used to check whether the estimation model meets the white noise test and the residual normality test
6. Predictions. Performed based on the equation of the selected model

ANN Data Processing. Steps of the Artificial Neural Networks method

1. Determine the input and output layers. The input layer is determined based on trail and error, namely the number of factors of rice productivity in the previous Panti sub-district, while the paddy productivity in the Panti sub-district is the $t$ period. The learning coefficient (learning rate) is 0.01.
2. Normalize the data, so that the input and output data are in the range of values from 0 to 1. Data normalization is done with the following formula:

$$\frac{x_n - x_{min}}{x_{max} - x_{min}}$$

3. The total factor productivity of rice and the total productivity of rice that has been normalized, xt is the total productivity of rice at time t, $xmaks$ is the total productivity of the highest rice, and $xmin$ is the total productivity of the lowest rice.
4. Building an ANN architecture from input and output neurons, by first determining the number of hidden and the number of neurons in the hidden layer. The neurons that have been determined in each layer will be applied the backpropagation algorithm repeatedly until the desired model is obtained.

Models that have met the requirements for the diagnostic characteristics of ARIMA and ANN are evaluated. The measuring tools used to calculate prediction errors are MAPE (Mean Absolute Percentage Error), MSE (Mean Square Error), RMSE (Root Mean Square Error).

## Results and Discussion

### Data Exploration

Based on the results of data collection carried out by Field Agricultural Extension (PPL), the realization of the rice harvest from January to December 2021 was 6072.93 hectares, or obtaining rice productivity of 37,208,290.11 thousand tons, this shows that productivity has decreased by 2,769,934 .30 thousand tons of which in 2020 productivity was 39,978,224.41 thousand tons with an agricultural land area of 6058.93 hectares.

### ARIMA Model Implementation

Determining the data to be modeled in ARIMA form is productivity data which is plotted through the graph below

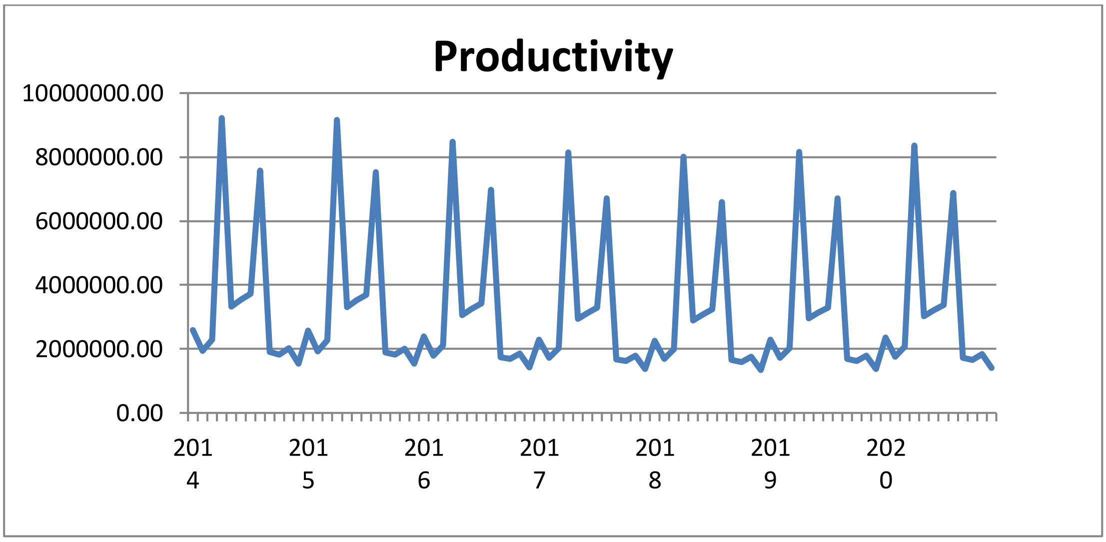



**Figure 1.** Plot of productivity data

### Data Stationarity Test

Stationarity is essential for identifying ARIMA models, so the first step is to test stationarity. The stationarity test using the Augmented Dickey-Fuller (ADF) Stationarity Test is a test performed on time series data to find out whether the time series data is stationary or not. Some time series analyzes require that the data be stationary first before further analysis is carried out. , for example data analysis using ARIMA. Therefore, to fulfill these requirements, the stationarity test needs to be carried out. The stationarity in question is the stationary data with respect to the mean and stationary with respect to the variance.

**Table 1.** Stasioneritas Test

| Augmented Dickey - Fuller Test | | | | | |
|---|---|---|---|---|---|
| Data: | Train | | | | |
| Dickey- Fuller = | -4.9457 | Lag order = | 4 | p-value = | 0.01 |
| Alternative hypothesis : | stationary | | | | |

The results of the Augmented Dickey-Fuller (ADF) test show that the value of ADF = -4.9457 with a lag order of 4 fails to accept the null hypothesis that the time series is stationary with a p-value of 0.01. The productivity time series has a unit root and is stationary and does not require differentiation.

It can be seen from the plot provided above in the figure that the productivity data is stationary in the variance so that the Box-Cox transformation is not carried out. The following is a Box-Cox plot showing the values $-1 \leq \lambda \leq 1$

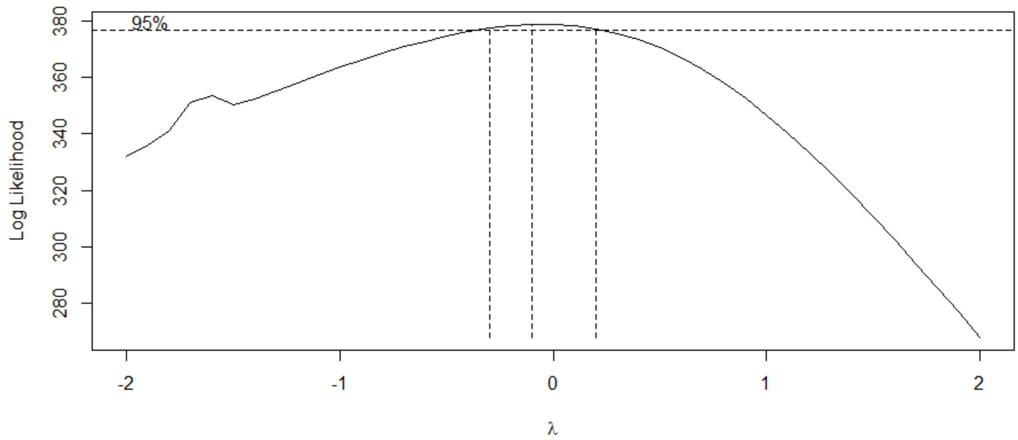



**Figure 2.** Stationary BoxCox Plot

**Identifikasi Model**

In the ACF plot it can be seen that the plot is truncated at lags 1 to 2 and the PACF plot is truncated after lags 1 and 8. The ACF plot is used to form the model (p,d,q) as order q and the PACF plot is used to form the model (p,d,q ) as order p. While order d = 0 is differencing.

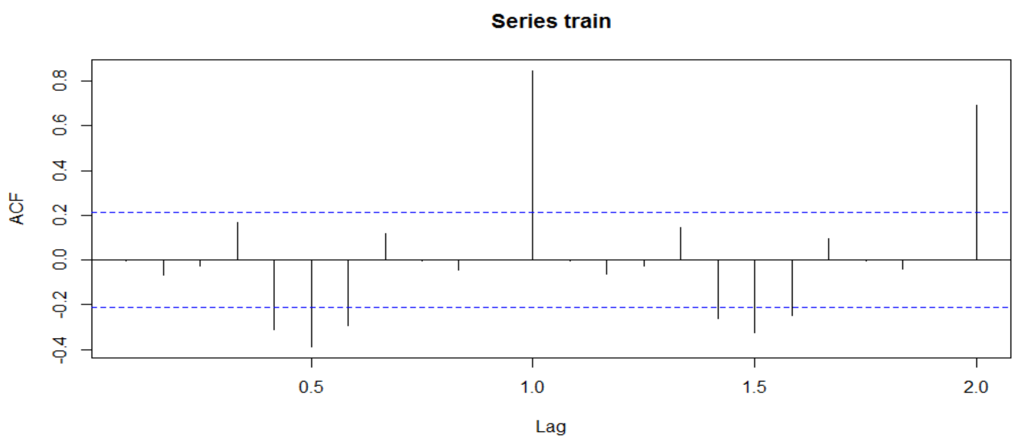



**Figure 3.** Plot ACF Stasioner

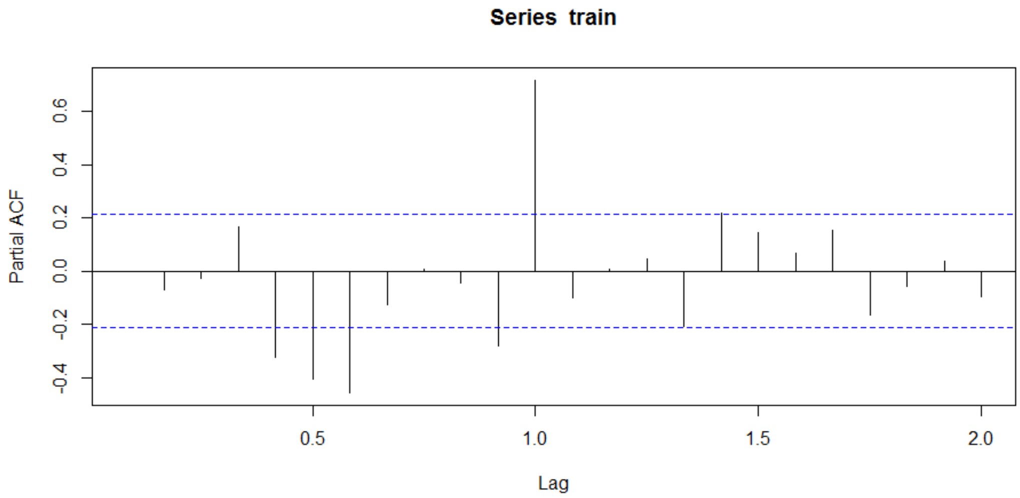



**Figure 4.** Plot PACF Stasioner

Because, both components have been stationary. Identification of the tentative model seasonal component obtained from the ACF and PACF plots, there are several models formed, including ARIMA(0,0,3)x(0,0,2)[12], ARIMA(1,0,1),x (1,0,1)[12], and ARIMA(1,0,1)x(1,0,2)[12].

**Tabel 2.** coefficient ARIMA (1,0,1)x(1,0,2)[12].

| Coefficients ***ARIMA*(1,0,1)x(1,0,2)[12].** | | | | | | |
|---|---|---|---|---|---|---|
| | ar1 | ma1 | sar1 | sma1 | sma2 | Mean |
| | 0.8845 | -0.4842 | 0.9976 | 0.5611 | 0.5807 | 3254113 |
| | 0.0534 | 0.1007 | 0.0012 | 0.1287 | 0.2895 | 2409422 |
| Sigma^2 = 6.904e+09: | | Log likelihood = -1115.17 | | | | |
| AIC = 2244.33 | | AICC =2245.81 | | BIC =2261.35 | | |

**Tabel 3.** Coefficient ARIMA (0,0,3)x(0,0,2)[12].

| Coefficients ***ARIMA*(0,0,3)x(0,0,2)[12].** | | | | | | |
|---|---|---|---|---|---|---|
| | ma1 | ma2 | ma3 | sma1 | sma2 | Mean |
| | -0.0324 | -0.2723 | -0.3232 | 1.7329 | 1.000 | 3210065.29 |
| | 0.1123 | 0.0941 | 0.0996 | 0.1432 | 0.137 | 89730.95 |
| Sigma^2 = 4.367e+11: | | Log likelihood = -1268 | | | | |
| AIC = 2550 | | AICC =2551.48 | | BIC =2567.02 | | |

**Tabel 4.** Coefficient ARIMA (1,0,1)x(1,0,1)[12].

| Coefficients ***ARIMA*(1,0,1)x(1,0,1)[12].** | | | | | |
|---|---|---|---|---|---|
| | ar1 | ma1 | sar1 | sma1 | Mean |
| | 0.8872 - | 0.4929 | -0.9986 | 0.4713 | 3264237 |
| | 0.0531 | 0.1017 | 0.0006 | 0.1152 | 3998813 |
| Sigma^2 = 8.224e+09: | | Log likelihood = -1117.77 | | | |
| AIC = 2247.54 | | AICC =2248.63 | | BIC =2262.13 | |

The best model is obtained based on the smallest AIC and AICc values of the model candidates. Therefore, the best model obtained is ARIMA(1,0,1)x(1,0,2)[12]. which model is the best model (with the smallest AIC value) of the models based on ACF, PACF.

**Model Parameter Testing**

The best model is the ARIMA(1,0,1)x(1,0,2)[12] model because all estimated model parameters have a significant effect. Parameter estimator $\varphi$=0.8845, $\theta$=-0.4842, $\Phi$=0.9976, $\Theta$= 0.5611, $\Theta$= 0.5807 with sigma^2 = 6.904e+09

**Table 5.** Z test of coefficients:

| **Z test of coefficients:** | | | | |
|---|---|---|---|---|
| | Estimate | Std.Error | Z Value | Pr(>\|Z\|) |
| ar1 | 8.8454e-01 | 5.3431e-02 | 16.5547 | < 2.2e-16*** |
| ma1 | -4.8420e-01 | 1.0066e-01 | -4.8103 | 1.507e-06*** |
| sar1 | 9.9763e-01 | 1.1690e-03 | 853.4293 | < 2.2e-16*** |
| sma1 | 5.6113e-01 | 1.2817e-01 | 4.3780 | 1.198e-05*** |
| sma2 | 5.8074e-01 | 2.8954e-01 | 2.0057 | 0.04489* |
| intercept | 3.2541e+06 | 2.4094e+06 | 1.3506 | 0.17683 |

**Model Diagnostics**

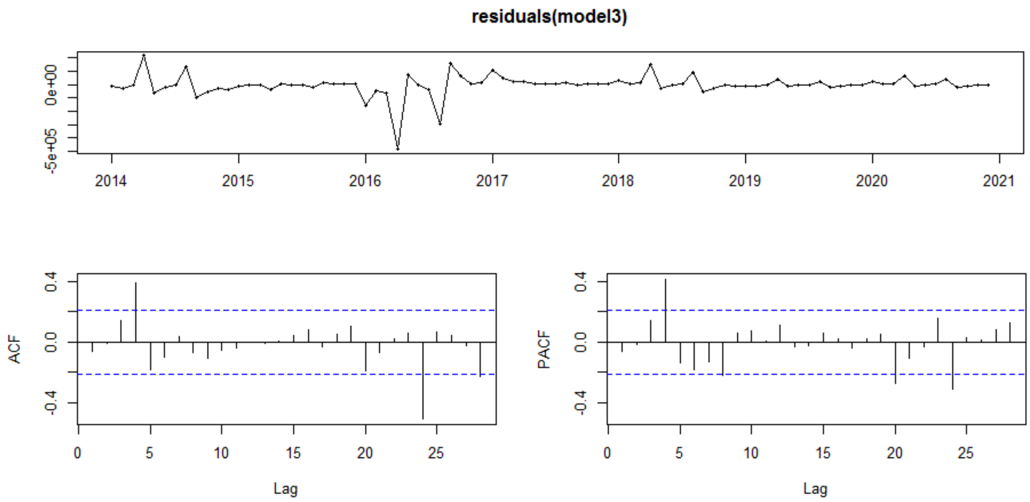



**Figure 5.** Diagnostics

Based on the plot above, it can be seen that the residuals do not follow a normal distribution. Furthermore, from the ACF and PACF plots, it can be seen that there is a significant lag. This indicates that there may be autocorrelation symptoms in the residuals. Furthermore, to make sure again, a formal assumption test will be carried out:

**Table 6.** Box-Ljung test

| **Box-Ljung test** | | |
|---|---|---|
| data: ARIMA$residuals | | |
| X-squared = 0.30268 | df = 1 | p-value = 0.5822 |

Based on the results of the Ljung-Box test above, there is an autocorrelation of the residuals, because the p−value has an insignificant lag or p − value > α = 0.05. Furthermore, a formal assumption test was carried out on the normality of the residuals using the Kolmogorov-Smirnov test. Test results, Data Normality: Result: p – value = 2.2e-16<α=0.05. The residue does not spread normally.

**Table 7.** Kolmogorov-Smirnov

| **Exact one-sample Kolmogorov-Smirnov test** | |
|---|---|
| data: sisaan | |
| D = 0.5119, | p-value < 2.2e-16 |
| alternative hypothesis: | two-sided |

So, based on the assumption test formally the ARIMA(1,0,1)×(1,0,2)[12] model will be used for further analysis. Prediction (forecasting).

**Predictions**

ARIMA prediction results (1,0,1)×(1,0,2)[12] are shown in the following table:

**Table 8.** Predictions *ARIMA*(1,0,1)×(1,0,2)[12]

| | Point Forecast | Lo 80 | Hi 80 | Lo 95 | Hi 95 |
|---|---|---|---|---|---|
| **Jan-21** | 23.8752 | 22.8023 | 24.9481 | 22.2343 | 25.5161 |
| **Feb-21** | 17.9054 | 16.7508 | 19.0599 | 16.1396 | 19.6711 |
| **Mar-21** | 21.083 | 19.8684 | 22.2976 | 19.2254 | 22.9406 |
| **Apr-21** | 84.3377 | 83.0781 | 85.5973 | 82.4113 | 86.2641 |
| **May 2021** | 30.5639 | 29.2702 | 31.8576 | 28.5853 | 32.5425 |
| **Jun-21** | 32.4581 | 31.1383 | 33.7779 | 30.4397 | 34.4765 |
| **Jul-21** | 34.1281 | 32.7883 | 35.4679 | 32.0791 | 36.1772 |
| **Aug 2021** | 69.3604 | 68.0051 | 70.7157 | 67.2877 | 71.4331 |
| **Sep-21** | 17.4444 | 16.0772 | 18.8117 | 15.3534 | 19.5354 |
| **Oct 2021** | 16.7952 | 15.4187 | 18.1717 | 14.69 | 18.9004 |
| **Nov 2021** | 18.5551 | 17.1714 | 19.9389 | 16.4389 | 20.6714 |
| **Dec 2021** | 14.1911 | 12.8017 | 15.5804 | 12.0663 | 16.3159 |
| **Jan-22** | 24.1544 | 21.8943 | 26.4145 | 20.6979 | 27.6109 |
| **Feb-22** | 18.1513 | 15.7664 | 20.5362 | 14.5039 | 21.7987 |
| **Mar-22** | 21.3279 | 18.8497 | 23.8061 | 17.5379 | 25.1179 |
| **Apr-22** | 84.782 | 82.2332 | 87.3307 | 80.884 | 88.6799 |
| **May 2022** | 30.8224 | 28.2198 | 33.425 | 26.842 | 34.8027 |
| **Jun-22** | 32.7163 | 30.0724 | 35.3603 | 28.6727 | 36.7599 |
| **Jul-22** | 34.3868 | 31.711 | 37.0627 | 30.2945 | 38.4792 |
| **Aug 2022** | 69.732 | 67.0315 | 72.4324 | 65.602 | 73.8619 |
| **Sep-22** | 17.642 | 14.9225 | 20.3615 | 13.4828 | 21.8011 |

| | | | | | |
|---|---|---|---|---|---|
| **Oct 2022** | 16.9896 | 14.2553 | 19.7238 | 12.8079 | 21.1713 |

Based on the prediction results that have been listed, the accuracy value compared to actual data, namely productivity data from January 2021 to October 2022, is as follows:

**Table 9**. Accuracy

| **Productivity Data and** | **MSE** | **RMSE** | **MAPE** |
|---|---|---|---|
| **ARIMA Data (1,0,1)X(1,0,2)** | 5.587553 | 2.3638 | 0.05668374 |

**Implementation of ANN Models**

Artificial Neural Network or commonly referred to as artificial neural networks with backpropagation algorithms is the method used by researchers in this study. The formulation of the problem raised by the researcher is related to predicting rice productivity and knowing the accuracy of the network that has been produced.

Based on the formulation of the problem, researchers used rice productivity data in Panti District, Jember Regency, East Java. This time it will be explained in detail regarding the descriptive analysis of the data obtained and analyzed using the ANN method with the backpropagation algorithm including data preparation, simulation of backpropagation work steps, network training, and network testing accompanied by the accuracy of the network obtained.

**Data Transformation**

Use the formula in the following equation $xnew = \frac{xold - \min(x))}{\max(x) - \min(x)}$, data obtained from the transformation of data with a scale of 0 to 1 as presented in the appendix. After obtaining the results of the transformation, it can be continued in the next step, namely data distribution

The graphic image shown is a descriptive analysis showing the results of rice productivity from 2002 to 2021 and the data has been normalized

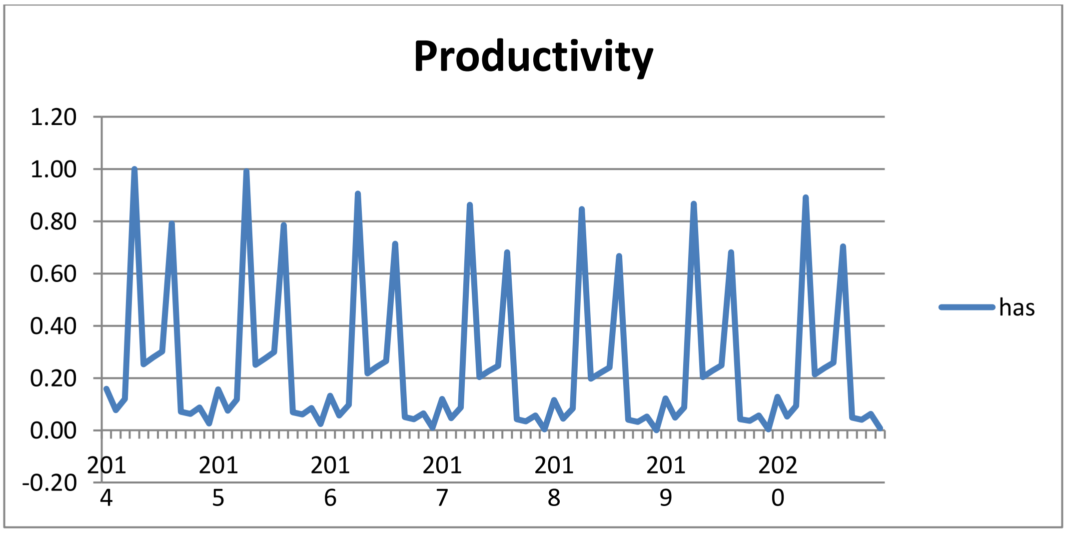



**Figure 6.** Normalized Data Graph

**Defining Input and Output Patterns**

Before entering into the process that will be carried out on the data, the variables used are first defined and the input and output are also determined. The variables used are in accordance with the previous chapter, namely in the research methodology chapter. The following table relates to the determination of input and output patterns.

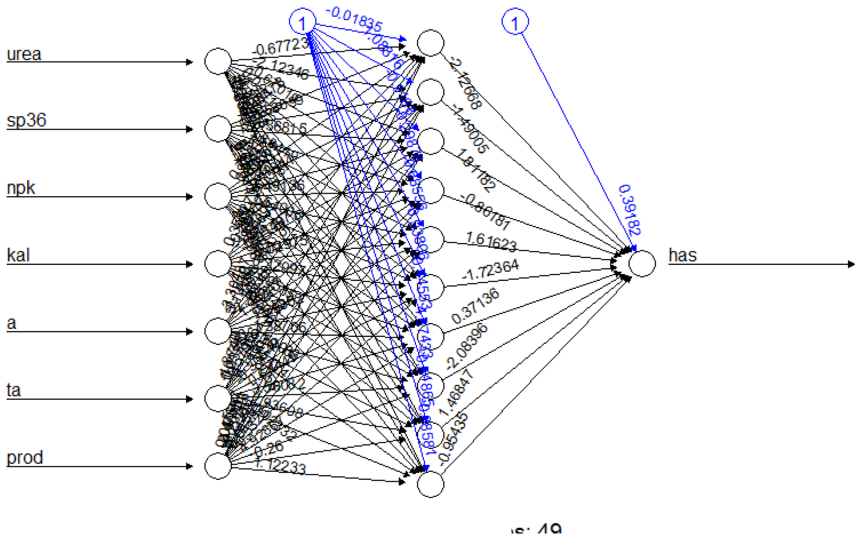
**Table 10. Input and Output Variables**

| Variables | Definition |
|---|---|
| **Urea/Kw** | Input |
| **sp36/Kw** | Input |
| **NPK15an** | Input |
| **Kalium/Kw** | Input |
| **Luas/Ha** | Input |
| **Tanam** | Input |
| **Produksi Ton/ha** | Input |
| **Productivity** | Outputt |

In the table above, the determination of input and output patterns is based on the formulation of this research problem. So that there are 7 variables as input which are considered to have an effect on the target (output).

**Define Network Architecture and Parameters**

ANN Backpropagation is one of the learning algorithms in artificial neural networks (Amrin, 2016). The backpropagation learning process is carried out by adjusting the weights of the artificial neural network in a backward direction based on the error value in the learning process (Windarto, Lubis and Solikhun, 2018). The characteristics of backpropagation involve three main layers: (1) the input layer functions as a network link to the outside world (data source), (2) the hidden layer where the network can have more than one hidden layer or even may not have it at all. So that the network architecture designed for this research there are several models that are formed including 1. ANN BP (7,10,1) , 2. ANN BP (7,(6,4),1) , 3. ANN BP (7, (7,3),1). Where each model has different forecasting accuracy in terms of the epohs or iterations and errors produced by each model. The following is the network architecture model chosen by the researcher.




**Gambar 3.7** Arsitektur Backpropagation (7,10,1)

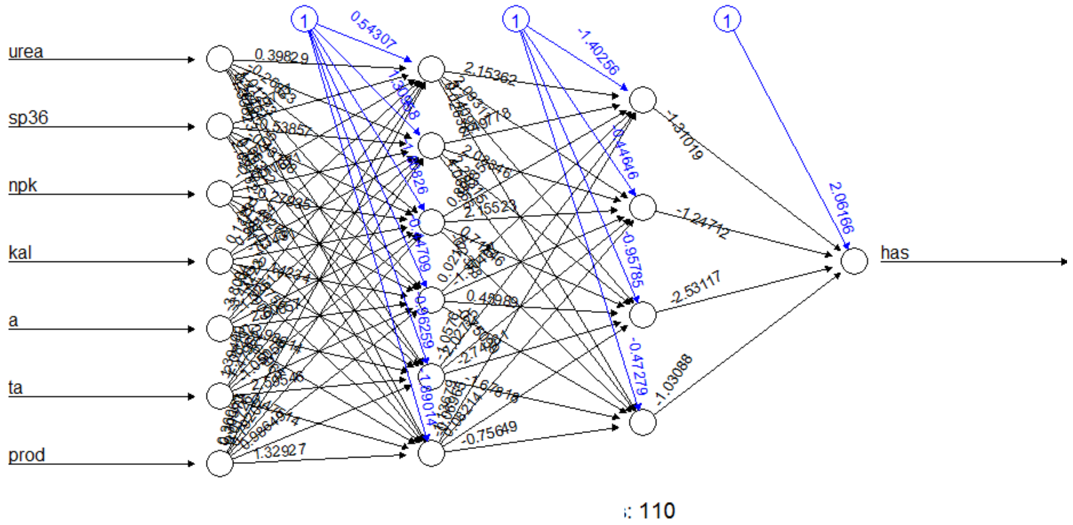



**Figure 8.** Backpropagation Architecture (7,(6,4),1)

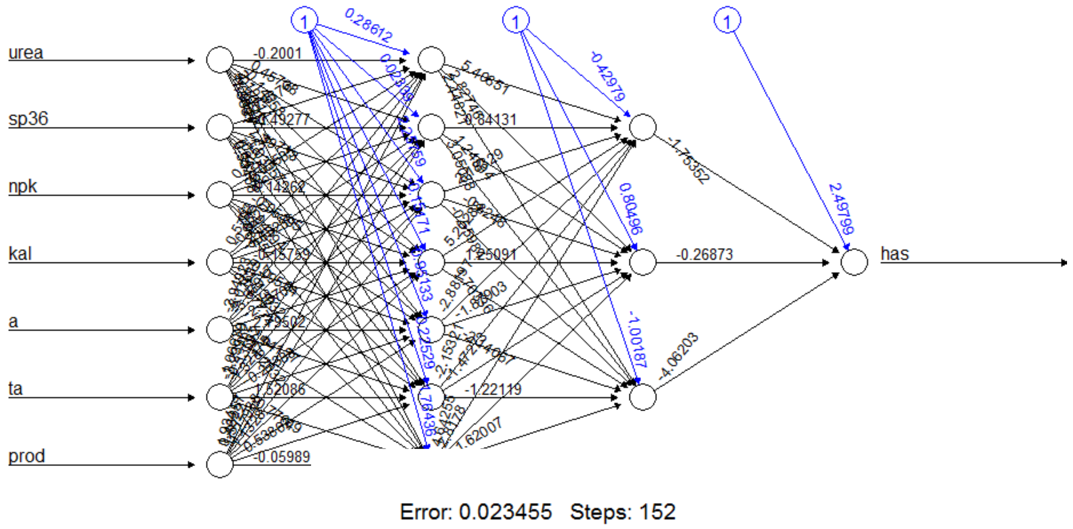



**Figure 9.** Backpropagation Architecture (7,(7,3),1)

To determine the parameters used in this study include the learning rate and activation function. The determination of these parameters will affect the performance of the algorithm on a designed network. The learning rate used in this study is 0.01, while the binary sigmoid function is selected for the activation function because the expected output value is in the range of 0 to 1.

### Initialize Weights and Bias

Initialization of weights and biases is given before carrying out the training process of a network system that is in ANN. Initialization of this initial weight is given to each interconnected neuron. This weight factor defines the relationship between one neuron and another neuron where the greater the weight value of a connection between the neurons, the more important the relationship between the two neurons is. The results of the ANN BP model (7,10,1) error 0.03876 and epoch 49, for ANN BP (7,(6,4),1) error 0.069505 and epoh 110, while for ANN BP (7,(7,3) ,1) error 0.023455 epoch 153.

### Prediction Stage Analysis

The next stage in predicting rice productivity in Panti District, Jember Regency, East Java Province. Data testing also serves to validate whether the forecasting results from the built model give good results by getting a small error.

The factors that influence the test data are learning rate, error, and iteration. Based on the results of testing these factors have a large influence on data training so that they are able to carry out network training properly. The model selected in the test uses the backpropagation network architecture with adaptive learning, namely the ANN BP model (7,(7,3),1).

**Table 11.** ANN Forecasting

| Month year | ANN BP (7,10,1) | ANN BP (7,(6,4),1) | ANN BP (7,(7,3),1) |
|---|---|---|---|
| Jan-21 | 22.2020191 | 22.15036665 | 21.86481264 |
| Feb-21 | 19.21203604 | 18.09486131 | 17.6833668 |
| Mar-21 | 20.36924688 | 19.91957684 | 19.47820216 |
| Apr-21 | 78.46670634 | 78.08699117 | 79.74554892 |
| Mei-21 | 25.76841222 | 28.25600701 | 28.88786314 |
| Jun-21 | 29.29031474 | 31.22942454 | 33.04262139 |
| Jul-21 | 32.49887289 | 32.94674302 | 35.26627535 |
| Agust-21 | 72.54708506 | 70.11542392 | 66.19780942 |
| Sep-21 | 18.49877648 | 18.07180507 | 17.50720197 |
| Okt-21 | 19.41430793 | 18.73689937 | 17.73208819 |
| Nop-21 | 19.2235878 | 19.27507168 | 18.29722378 |
| Des-21 | 18.11550008 | 17.15388686 | 16.62484883 |
| Jan-22 | 20.74831298 | 19.85070271 | 20.86548313 |
| Feb-22 | 18.15056574 | 17.43131722 | 17.47939898 |
| Mar-22 | 20.08516511 | 18.50164611 | 19.13270665 |
| Apr-22 | 80.7230455 | 75.47749682 | 81.34380359 |
| Mei-22 | 26.87987448 | 25.59938245 | 29.75660624 |
| Jun-22 | 28.98638822 | 28.32325058 | 31.65997688 |
| Jul-22 | 29.80843277 | 28.42075479 | 32.3365867 |
| Agust-22 | 72.27785397 | 76.85876757 | 71.41822781 |
| Sep-22 | 17.17656816 | 17.56199501 | 17.37219414 |
| Okt-22 | 17.72220716 | 16.97026321 | 17.24602914 |

**Table 12.** P ANN Accuracy

| | MSE | RMSE | MAPE |
|---|---|---|---|
| **ANN BP (7,10,1)** | 8.458195 | 2.908298 | 0.0785432 |
| **ANN BP (7,(6,4),1)** | 11.16621 | 3.341588 | 0.07559268 |
| **ANN BP (7,(7,3),1)** | 4.828465 | 2.197377 | 0.05703856 |

## Conclusion

Based on the results of the testing and discussion that has been described in the previous section, it can be concluded that in response to the formulation of the problem in this study, namely the model used is the ANN model with 7 input variables 2 hidden layers totaling 7 hidden layer 1 neurons and 3 hidden layer 3 neurons and 1 output and ARIMA model (1,0,1) (1,0,2)[12] with forecasting results that have an up and down trend, where the deviation results for each model use MAPE (Mean Absolute Percentage Error) , MSE (Mean Square Error), RMSE (Root Mean

Square Error) in the results of forecasting rice production from 2021 to 2022 ANN for MAPE 0.05703856, MSE 4.828465, and RMSE 2.197377, while for ARIMA (1,0,1) (1,0 ,2)[12] MAPE 0.05668374, MSE 5.587553, and RMSE 2.3638 where both models have good forecasting abilities. Therefore, the ARIMA (1,0,1) (1,0,2)[12] model is quite effective for predicting the amount of rice production in Panti District, Jember Regency, East Java Province for the next few years.

For further research, you can use and compare with other methods such as VAR (Vector Autoregressive) and ANN (Artificial Neural Network) perhaps to get the minimum possible deviation values and more accurate forecasting results.

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