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Forecasting Poverty Ratios in Indonesia: A Time Series Modeling Approach

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Abstract – *Poverty is one of the main problems still faced by Indonesia today. To help find the right solution, an annual prediction of the poverty rate in Indonesia is needed. This study uses data on the 'Ratio of the Number of Poor People in Indonesia per year from 1998 to 2023' obtained from data.worldbank.org. The prediction methods used include Naïve Model, Double Moving Average, Double Exponential Smoothing, ARIMA, Time Series Regression, and Neural Network, with a total of 26 models. Of these, only 19 models passed the model comparison stage. The evaluation using RMSE, MAE, MAPE, and MDAE metrics concluded that the NNETAR Neural Network model, with embedding dimension (p) of 3 and 10 nodes in the hidden layer, showed the best performance. The model performed well in both training and testing stages, ranking second and third smallest in metric values, respectively. The one-year prediction for 2024 showed that the poverty ratio could increase to 4.2% from 1.9% in 2023, highlighting the need for preventive action by the government and community. However, this study is limited by the small dataset, and future research should explore larger datasets and more advanced neural network models like RNN, LSTM, GRU, or Transformers.*

Keywords: *Poverty; Naïve Model; Double Moving Average; Double Exponential Smoothing; ARIMA; Time Series Regression; Neural Network*

I. INTRODUCTION

Poverty is one of the problems that until now still cannot be fully resolved. Poverty is a situation where an individual or group of people do not have the ability to obtain basic needs to achieve economic prosperity (Vania Grace Sianturi et al., 2021). According to the Central Bureau of Statistics, poverty is a person's inability to meet basic needs, both consumption and non-consumption needs (Hafiz & Kurniadi, 2024). Based on data as of March 2023, it has shown that the poverty rate in Indonesia is 25.9 million people (*03 Menanti Pemerintah "Buka-Bukaan" Data Kemiskinan Yang Sebenarnya.Pdf*, n.d.). Where this figure includes a percentage of the poor population of 9.36 percent with a poverty line of IDR 550,458, - / capita / month. This figure is still high when compared to the 2020-2024 National Medium-Term Development Plan (RPJMN) target of 6.5-7.5% (Badan Pusat Statistik Indonesia, 2023).

Therefore, in this study, time series modeling was carried out on the data of the Ratio of the Number of Poor People in Indonesia per Year from 1998 to 2023 obtained from data.worldbank.org. In this study, 5 time series models are used, namely ARIMA (Auto Regressive Integrative Moving Average), DMA (Double Moving Average), DES (Double Exponential Smoothing), Naive, and Regression models. The five models will be evaluated based on their accuracy using the RMSE, MAE, MAPE, and MDAE values.

Previously, there have been several studies that analyzed poverty data using time series models. Kumila, et all (2019) conducted research to find the best model for forecasting poverty data (Kumila et al., 2019). The models used are the Moving Average model (SMA, WMA, and EMA) and the Naive method, in this study it was found that of the two models, the Naive model had the most accurate results compared to the Moving Average model. Aspriyani and Istikaanah (2023) have also conducted research on predicting the number of poor people in Cilacap using moving average, weighted moving average, and exponential smoothing methods (Aspriyani & Istikaanah, 2023). From the research that has been done, the exponential smoothing method is obtained as the best method of the three methods used.

In addition, the five time series methods used in this study are also often used in other studies outside of poverty forecasting. Ningtiyas (2019) used DES and ARIMA methods to forecast voluntary counseling and testing of PLWHA in East Java province. Based on the results of the metric comparison of the two models, it is found that the DES model has better results than the ARIMA model(Ningtiyas et al., 2018). A comparison between the Multiple Linear Regression and ARIMA methods was also carried out by Winnos, Septima, and Gemasih (2022) to predict the shares of PT BSI, Tbk. From the results of the research that has been done, the Multiple Linear Regression method has higher accuracy results than the ARIMA method in predicting the value of PT. BSI shares(Hilman Winnos et al., 2022).

Based on research that has been done before, either to predict poverty or other topics. some researchers say that the Naive Bayes model is a better model, some say that the DES model is better, and some also say that the Multiple Linear Regression model gives the best results, where these results vary based on the dataset used. Therefore, this research aims to:

- Create a Naive model for poverty data.
- Create a DMA model for poverty data.
- Creating a DES model for poverty data.
- Create an ARIMA model for poverty data.
- Creating a Time Series Regression model for poverty data.

II. METHODS

2.1 Data

The data utilized in this study is derived from the World Bank Open Data website and represents the annual ratio of the poor population in Indonesia. This dataset includes the percentage of individuals living on an income of less than $2.15 per day, equivalent to approximately IDR 35,000 per day based on the current exchange rate, with prices adjusted to the 2017 purchasing power. The data spans from 1984 to 2023; however, there are missing entries for the years 1985 to 1997. Consequently, this study will focus exclusively on the data from 1998 to 2023.

2.2 Methods

This research was conducted through several stages to ensure the reliability of the research results. Stages of this research could be seen at Fig. 1 Research Flow

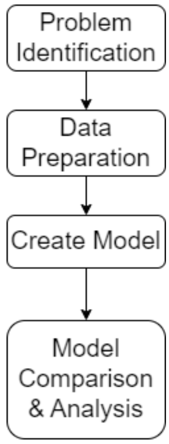

Figure 1. Research Flow

2.2.1 Problem Identification

2.2.2 Data Preparation

- Divide data for training and testing with ratio 7:3. Since the data used is time series data, the data division is done manually and sequentially.
- Changing the format of training and testing data into time series format by using ts() function to perform several modeling methods.
- Analyzing the data pattern to determine the model that will be used to predict the data. After the analysis, there are 6 time series models that can be used, namely Naive Model, DMA, DES, ARIMA, Time Series Regression, and Neural Network.

2.2.3 Create Model

- Naive Model: Naive modeling is performed using 2 existing Naive equations. This modeling is done by forming a for loop function to implement the Naive equations used (Dhakal & Dhakal, 2017)
- Double Moving Average Model (DMA): DMA modeling is done by entering the existing DMA equation. The calculation results are then combined into one table using the cbind function to help analyze the model results. To get the best results, this model To get the best results, this model was run three times using different n parameters of 3, 4, and 5 (Ruspriyanty et al., 2018) (Layakana & Iskandar, 2020)52 diperoleh nilai MSE dan MAPE terkecil yaitu sebesar 18920.9 dan 0,091. ABSTRACT Double Moving Average and Double Exponential Smoothing forecasting method is a periodic data forecast model (Time Series (Najib, 2022) .
- Double Exponential Smoothing Model (DES): This modeling was carried out three times with model type parameters AAN, MAN, and MMN (Ningtiyas et al., 2018) (Najib, 2022) .

2.2.4 ARIMA Model

ARIMA modeling, have 3 stages:

- Stationerity Test: There are 2 stages of the stationarity test that need to be passed, namely the data stationarity test against the variance and against the average. If the results of the stationarity test do not meet the stationarity assumption for the variance, then the data needs to be transformed until the stationarity assumption is met. After the stationarity assumption is met, a stationarity test is carried out on the average on data that meets the stationarity test for variance. If the data does not meet the assumption of stationarity with respect to the mean, then the data needs to be differentiated. The amount of differentiation will then be used as the order d value (Trisnawati & Prastuti, 2022) (Catur Putri & Junaedi, 2022).

- The p and q order Identification: After fulfilling the two stationarity assumption tests, the p and q orders are identified (Fauzi, 2015).
- Modeling: ARIMA modeling is performed 5 times with all combinations order p, d, and q.

III. RESULTS AND DISCUSSION

3.1 Time Series Plot Formation

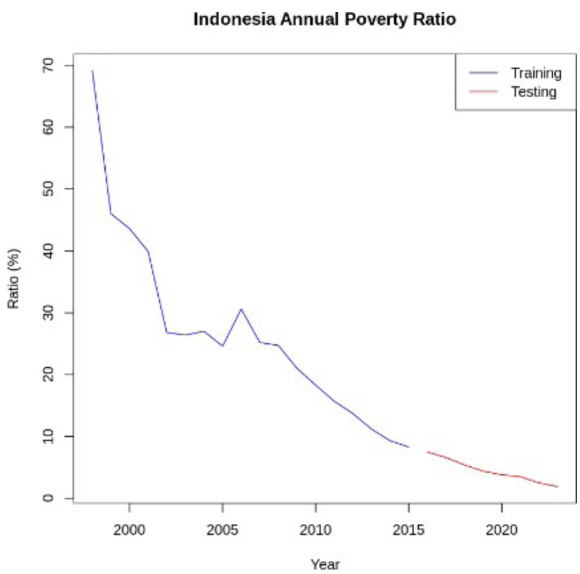

Figure 2. Indonesia Annual Poverty Ration 1998-2023

The first step after dividing the data into two is to plot the time series. Here is the resulting plot:

The resulting plot shows that the data has a downward trend pattern with some fluctuations around 2005 to 2008. Therefore, the method used in this study is the time series prediction method for trend-patterned data.

3.2 Naive Model

There will be 2 models is created based on metric evaluation of training data. Table I shows the result.

Table I. Naive Model Evaluation Metric

	RMSE	MAE	MAPE	MDAE
Naive 1	9.00925	5.71111	0.18890	2.15000
Naive 2	5.79768	3.72947	0.13741	1.20962

And the evaluation metric value of the model prediction results against the testing data. Table II shows the result.

Table II. Evaluation Metric Value of Naive Model Prediction Results

	RMSE	MAE	MAPE	MDAE
Naive 1	0.85440	0.65000	0.23874	0.40000
Naive 2	0.86027	0.71838	0.24925	0.77996

It can be seen in the two tables above that the Naive 2 model has better training results between the two, but the Naive 1 model is better at making predictions.

3.3 Double Moving Average Model

There are 3 models created with model evaluation metric values using training data. Table III shows the result.

Table III. Evaluation Metric Value DMA Model

	RMSE	MAE	MAPE	MDAE
DMA (n = 3)	4.49316	3.42479	0.15064	2.23333
DMA (n = 4)	5.61132	3.75322	0.17821	1.77917
DMA (n = 5)	4.07729	3.32556	0.19318	2.46800

And the metric values for evaluating model prediction results against testing data. Table IV shows the result.

Table IV. Evaluation Metric Value of DMA Model Prediction Results

	RMSE	MAE	MAPE	MDAE
DMA (n = 3)	5.95459	5.36111	1.76471	5.01111
DMA (n = 4)	6.99372	6.32500	2.07308	5.97500
DMA (n = 5)	8.31204	7.57800	2.46442	7.22800

Tabel III shows that there are no consistent evaluation metric results for the three DMA models, where the smallest RMSE and MAE values are owned by the DMA model (n = 5), MAPE by DMA (n = 3), and MDAE by DMA (n = 4). While Fig. 7 shows that the DMA model (n = 3) has the smallest value for the three evaluation metrics indicating that the model is the best DMA model for making predictions.

3.4 Double Exponential Smoothing Model

There are 3 models created with model evaluation metric values using training data. Table V shows the result.

Table V. Model Evaluation Metric Value of DES Model

	RMSE	MAE	MAPE	MDAE
DES (AAN)	4.40948	3.53270	0.14858	2.53691
DES (MAN)	6.10271	3.30228	0.10730	1.46507
DES (MMN)	5.51244	3.27168	0.10311	0.93242

And the metric values for evaluating model prediction results against testing data. Table VI shows the result.

Table VI. Evaluation Metric Value of Model Prediction Result DES

	RMSE	MAE	MAPE	MDAE
DES (AAN)	3.96238	3.64804	1.16933	3.93258
DES (MAN)	5.32001	4.68112	1.57251	4.33112
DES (MMN)	1.03887	0.88120	0.30138	0.98788

Just like DMA, the evaluation results of the three DES models show inconsistencies where the DES model (MMN) has the smallest values for all metrics except the RMSE value. However, the DES model (MMN) is the best DES model for predicting because the values of all its metrics are smaller than other DES models.

3.5 ARIMA Model

The first step in creating an ARIMA model is the stationarity test of the variance and mean. The following are the results of the stationarity test for variance using training data and the power transformation method:

Table VII. Power Transformation Test Results

Rounded Pwr (λ)	pval lamba 0	pval lambda 1
0	0.82985	0.01851

Because λ is 0 and the p-value lambda 1 is smaller than alpha (0.05), a log transformation must be carried out on the training data. Data that has been transformed must be checked again to ensure that the data is stationary regarding variance.

Table VIII. Power Transformation Test Results Transformation Data

Rounded Pwr (λ)	pval lamba 0	pval lambda 1
1	0.32911	0.88246

Because the power transformation test has produced a value of λ of 1 and a p-value of lambda 1 greater than alpha (0.05), the data can be declared to have passed the stationary test on variance. Then a stationarity test was carried out on the mean using the transformed data and the Augmented Dickey-Fuller test with the following results:

Table IX. ADF Test Result of Transformed Data

Dickey-Fuller	p-value
-1.2763	0.8481

Because the resulting p-value is greater than alpha (0.05), the data is not stationary to the mean and must be differencing until it passes the stationary test to the mean. The following are the results of the ADF test using data that has been differencing four times until it produces a p-value smaller than alpha (0.05) so that the data is stationary to the mean and the order d is 4.

Table X. ADF Test Results of Transformed-Differencing Data

Ordo d	Dickey-Fuller	p-value
1	-1.238	0.8627
2	-2.3205	0.4503
3	-3.1986	0.1158
4	-7.4702	>0.01

The next step is to determine the orders of p and q using the ACF and PACF plots.

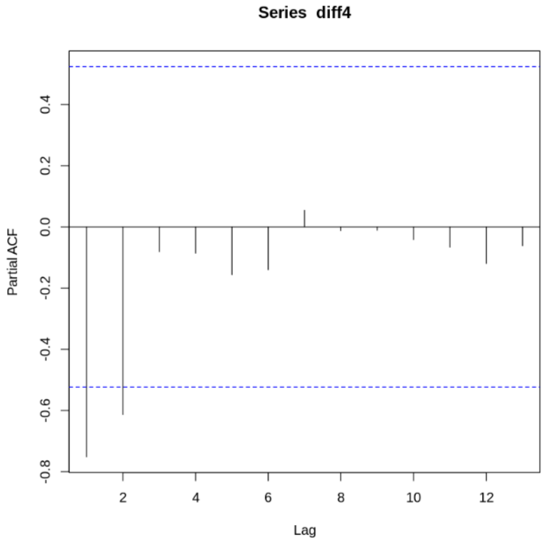

Figure 3. PACF Plot

The PACF plot in Fig. 3 shows that the data is significant only up to the second lag where the bars at the first and second lags cross the significant boundary line. Thus, the maximum order of p is 2.

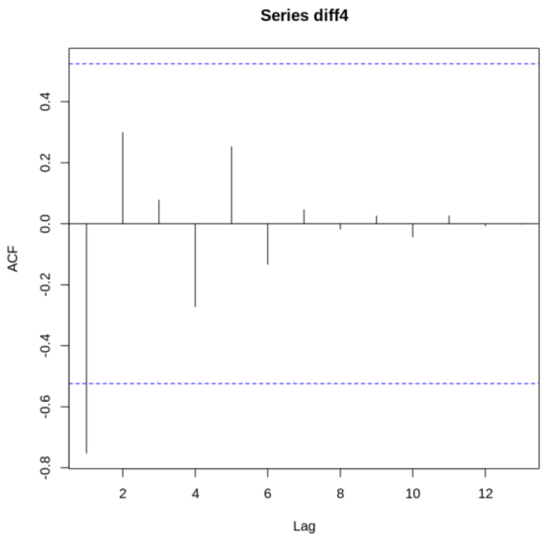

Figure 4. ACF plot graph using data that has been stationary

Figure 4. ACF plot above shows that the data is significant until the first lag where the bar at the first lag crosses the significant boundary line. Therefore, the maximum order of q is 1.

After obtaining information about the candidate values of each order, model building and significance testing can be carried out. By considering all combinations of orders, 5 models are obtained as follows:

3.3.1 ARIMA (1, 4, 0)

Table XI. Arima Model Coefficient (1, 4, 0)

	Estimate	p-value
AR (1)	-0.70818	1.579e-05

The table above shows that the p-value for all coefficients in the ARIMA model (1, 4, 0) is smaller than the alpha value (0.05), so the null hypothesis is rejected, indicating that all coefficients are significant.

3.3.2 ARIMA (0, 4, 1)

Table XII. Arima Model Coefficient (0, 4, 1)

	Estimate	p-value
MA (1)	-0.98194	3.039e-07

The results table above shows that all p-values for the ARIMA (0, 4, 1) model are smaller than alpha (0.05), which proves that all coefficients in the model are significant.

3.3.3 ARIMA (2, 4, 0)

Table XIII. Arima Model Coefficient (2, 4, 0)

	Estimate	p-value
AR (1)	-1.37760	< 2.2e-16
AR (2)	-0.83221	1.405e-09

Just like the two previous ARIMA models in this ARIMA (2, 4, 0) model, all coefficients have p-values smaller than alpha (0.05). So the null hypothesis is rejected and the model passes the significance test.

3.3.4 ARIMA (1, 4, 1)

Table XIV. Arima Model Coefficient (1, 4, 1)

	Estimate	p-value
AR (1)	-0.63220	0.001165
MA (1)	-0.97521	1.143e-05

The table above shows that the p-value for all coefficients in the ARIMA model (1, 4, 1) is smaller than the alpha value (0.05), so the null hypothesis is rejected, indicating that all coefficients are significant.

3.3.5 ARIMA (2, 4, 1)

Table XV. Arima Model Coefficient (1, 4, 1)

	Estimate	p-value
AR (1)	-1.27864	3.865e-13
AR (2)	-0.79137	3.812e-07
MA (1)	-0.97148	4.493e-05

Just like all previous ARIMA models, the p-value of all coefficients in the ARIMA model (2, 4, 1) is smaller than alpha (0.05). So this model also passes the significance test.

Of the five ARIMA models formed, all models pass the significance test and can proceed to the assumption test stage. The following are the results of the assumption test, namely the white noise test using the Ljung-Box Q test and the normality test using the Kolmogorov-Smirnov test:

Table XVI. Ljung-Box Test Result Q

	X-squared	p-value
ARIMA (1, 4, 0)	52.228	0.02229
ARIMA (0, 4, 1)	86.363	0.003295
ARIMA (2, 4, 0)	0.78257	0.3764
ARIMA (1, 4, 1)	18.155	0.1778
ARIMA (2, 4, 1)	0.15837	0.6907

The white noise test results on the last three ARIMA models returned a p-value greater than alpha (0.05). So the three models are stated to have residual white noise or constant variance, while the first two models do not have residual white noise.

Table XVII. Kolmogorov-Smirnov Test Results

	D	p-value
ARIMA (1, 4, 0)	0.2421	0.006515
ARIMA (0, 4, 1)	0.22288	0.01843
ARIMA (2, 4, 0)	0.12642	0.627
ARIMA (1, 4, 1)	0.23546	0.009444
ARIMA (2, 4, 1)	0.21165	0.03218

The results of the normality test above show that only the ARIMA (2, 4, 0) model has a p-value greater than alpha (0.05). So only this model passes the normality test by failing to reject the null hypothesis and has normally distributed residuals.

Since it has been found that only the ARIMA (2, 4, 0) model passes the assumption test, the evaluation metric calculation can be carried out. The following are the values of the model evaluation metrics using the training data as follows:

Table XVIII. ARIMA Model Prediction Metric Value

	RMSE	MAE	MAPE	MDAE
ARIMA (2, 4, 0)	1.10370	1.07097	5.36476	1.00320

And the evaluation metric value of the model prediction results against the testing data as follows:

Table XIX. Evaluation Metric Value of ARIMA Model Prediction Results

	RMSE	MAE	MAPE	MDAE
ARIMA (2, 4, 0)	186,989	90,3414	42,8426	14,0932

3.4 Time Series Regression Model

There are 5 time series regression models created as follows:

3.4.1 Linear Trend Model

Table XX. Summary Linear Trend Regression Model

Coefficient	Estimate	p-value
Intercept	51.1092	6.00e-11
t	-2.5647	3.54e-07

Table XXI. The table contains a summary of the linear trend regression model

F-statistics	p-value
68.55	3.54e-07

Overall the model has a p-value of 3.54e-07 and is smaller than the alpha value (0.05). This indicates that there is at least one significant variable. To ensure that each variable is individually significant, the p-value of each variable must be seen; Intercept has a p-value of 6.00e-11 and t has a p-value of 3.54e-07. It can be seen that both p-values are smaller than alpha (0.05), so both variables have been proven to be significant.

3.4.2 Exponential Trend Model

Table XXII. Summary Exponential Trend Regression Model

Koefisien	Estimate	p-value
Intercept	4.103545	< 2e-16
t	-0.101395	3.87e-10

Table XXIII. The table contains a Summary Exponential Trend Regression Model

F-statistics	p-value
181	3.868e-10

Simultaneously, the p-value of the model is 3.868e-10, which is less than the alpha value (0.05). This indicates that at least one variable is significant. To ensure that each variable is significant, the p-value of each variable should be checked; the p-value for Intercept is < 2e-16 and for t is 3.87e- 10. It appears that both p-values are less than alpha (0.05) indicating that both variables are significant.

3.4.3 First Lag Model

Table XXIV. Summary First Lag Model Regresssion

Coefficient	Estimate	p-value
Intercept	29.2329	0.000705
t	-1.3261	0.002264
Lag 1	0.2976	0.026856

Table XXV. The table contains a summary of First Lag Model Regresssion

F-statistics	p-value
89.1	**1.088e-08**

The overall p-value of the first lag model shown above is 1.088e-08, which is smaller than the alpha value (0.05); meaning that at least one variable in the model is significant. The p-value of each variable must be checked to ensure that all variables are significant. The p-value is 0.000705 for Intercept, 0.002264 for t, and 0.026856 for Lag 1. Since all three p-values are smaller than alpha (0.05), all variables pass the partial significance test.

3.4.4 Second Lag Model

Table XXVI. Summary Second Lag Model Regresssion

Coefficient	Estimate	p-value
Intercept	21.8574	0.0759
t	-0.9912	0.0861
Lag 1	0.3112	0.2803
Lag 2	0.1237	0.4228

Table XXVII. The table contains a summary of Second Lag Model Regresssion

F-statistics	p-value
41.46	1.308e-06

From the summary table above, it can be seen that the overall model p-value is 1.308e-06, smaller than the alpha value (0.05), and means that there is at least one significant variable. However, if we look at the p-value of each variable, namely Intercept of 0.0759, t of 0.0861, Lag 1 of 0.2803, and Lag 2 of 0.4228, none of them have a value smaller than the specified alpha value. So the model does not pass the partial significance test and cannot proceed to the assumption test stage that will be carried out next.

3.4.5 Quadratic Trend Model

Table XXVIII. Summary Quadratic Trend Model Regresssion

Koefisien	Estimate	p-value
Intercept	60.39142	1.6e-09
t	-5.34939	0.000276
t^2	0.14656	0.023265

Table XXIX. The table contains a summary of Quadratic Trend Model Regresssion

F-statistics	p-value
49	2.648e-07

The p-value of the above quadratic trend model as a whole is 2.648e-07 which is smaller than the predetermined alpha value. This means that at least one variable in the model is significant. To find out which variables are significant, the p-value of each variable individually must be seen; Intercept is 1.6e-09, t is 0.000276, and t2 is 0.023265. All three values are smaller than alpha (0.05), so it is certain that all variables are significant.

Based on the results of the significance test above, all models except the second lag model will proceed to the assumption test stage. The following are the results of the autocorrelation test using the Durbin-Watson test, the homoscedasticity test using the Breusch-Pagan test, and the normality test using the Kolmogorov-Smirnov test:

Table XXX. Durbin-Watson Test Result

	DW	p-value
Tren Linear	0.85894	0.002268
Tren Eksponensial	0.79524	0.001147
Tren Kuadrat	1.0498	0.003975
Lag 1	1.9643	0.5689

The Durbin-Watson test results table above shows that only the first lag model has a p-value greater than alpha (0.05), which is 0.5689. Which means that only this model fails to reject the null hypothesis and its residuals are not autocorrelated.

Table XXXI. Breusch-Pagan Test Result

	DW	p-value
Linear Trend	4.2903	0.03833
Exponential Trend	0.90616	0.3411
Quadratic Trend	6.0992	0.04738
Lag 1	4.1118	0.128

The Breusch-Pagan test results table above shows that only the exponential trend and first lag models have a p-value greater than alpha (0.05), amounting to 0.3411 and 0.128. This means that only these two models fail to reject the null hypothesis and pass the residual test for homoscedasticity or having constant variance.

Table XXXII. Kolmogorov-Smirnov Test Result

	D	p-value
Tren Linear	0.25042	0.004015
Tren Eksponensial	0.10814	0.8357
Tren Kuadrat	0.13574	0.5124
Lag 1	0.22144	0.0263

Meanwhile, in the Kolmogorov-Smirnov test results table, only the exponential trend and quadratic trend models can reject the null hypothesis and pass the normality test. Because both have a p-value greater than alpha (0.05) of 0.8357 and 0.5124. Because of the three test results above, none of the models passed all the tests, it can be concluded that the time series regression method is not suitable for predicting poor population ratio data in Indonesia.

3.5 Neural Network Model

To build the NN model, 2 methods were used, namely single layer using nnetar with parameters p and size; and multilayer using mlp with parameters hd. There are 5 models created using nnetar and 3 models with 2 layers using mlp. The following are the values of model evaluation metrics using training data

Table XXXIII. NN Model Evaluation Metric Value

	RMSE	MAE	MAPE	MDAE
nnetar (1, 5)	1.80949	0.94611	0,04067	0,20205
nnetar (2, 5)	1,36392	0,77141	0,03362	0,32899
nnetar (1, 8)	1,79237	0,95979	0,04176	0,25452
nnetar (3, 10)	0,19392	0,13968	0,00832	0,10504
nnetar (5, 10)	0,01067	0,00668	0,00056	0,00281
mlp (c(2, 5))	2,26380	1,68810	0,07679	1,35091
mlp (c(3, 1))	2,11993	1,67645	0,07765	1,51274
mlp (c(5, 2))	2,15292	1,69358	0,07837	1,52888

And the evaluation metric values of the model prediction results against the testing data as follows:

Table XXXIV. Evaluation Metric Value of NN Model Prediction Result

	RMSE	MAE	MAPE	MDAE
nnetar (1, 5)	3.51071	3,07669	1.03173	3.35724
nnetar (2, 5)	1.99202	1.63252	0.58069	1.70922
nnetar (1, 8)	2.30508	1.91399	0.67215	2.06933
nnetar (3, 10)	1.52947	1.28231	0.44492	1.09086
nnetar (5, 10)	6.61485	5.58273	1.92600	5.94531
mlp (c(2, 5))	5.01918	4.37326	1.48082	4.05700
mlp (c(3, 1))	5.90336	5.16390	1.74166	4.89656
mlp (c(5, 2))	5.37902	4.69357	1.58693	4.39481

It can be seen in the two tables above that the results of the model evaluation and prediction are similar to the naïve model, where the best NN model is different from the model that can predict the best. The nnetar model with a p parameter of 5 and a size of 10 is the best model, because its four evaluation metrics have the smallest value among the other NN models. Meanwhile, the nnetar model with a p parameter of 3 and a size of 8 is the best model for predicting because it produces the smallest evaluation metric value for testing data.

3.6 Result Comparison

To facilitate the process of determining the best model, all the results of the model evaluation metrics above, both the model and the prediction results, will be combined into one table specifically for the model and another table specifically for the prediction.

Table XXXV. Comparison of Evaluation Metric Values Across Models

	RMSE	MAE	MAPE	MDAE
Naïve 1	9.00925	5.71111	0.18890	2.15000
Naïve 2	5.79768	3.72947	0.13741	1.20962
DMA (n = 3)	4.49316	3.42479	0.15064	2.23333
DMA (n = 4)	5.61132	3.75322	0.17821	1.77917
DMA (n = 5)	4.07729	3.32556	0.19318	2.46800
DES (AAN)	4.40948	3.53270	0.14858	2.53691
DES (MAN)	6.10271	3.30228	0.10730	1.46507
DES (MMN)	5.51244	3.27168	0.10311	0.93242
ARIMA (2, 4, 0)	1.10370	1.07097	5.36476	1.00320
nnetar (1, 5)	1.80949	0.94611	0.04067	0.20205
nnetar (2, 5)	1.36392	0.77141	0.03362	0.32899
nnetar (1, 8)	1.79237	0.95979	0.04176	0.25452
nnetar (3, 10)	0.19392	0.13968	0.00832	0.10504
nnetar (5, 10)	0.01067	0.00668	0.00056	0.00281
mlp (c(2, 5))	2.26380	1.68810	0.07679	1.35091
mlp (c(3, 1))	2.11993	1.67645	0.07765	1.51274
mlp (c(5, 2))	2.15292	1.69358	0.07837	1.52888

And the evaluation metric values of the model prediction results against the testing data as follows:

XXXVI. Comparison of Evaluation Metric Values of Prediction Results of All Models

	RMSE	MAE	MAPE	MDAE
Naïve 1	0.85440	0.65000	0.23874	0.40000
Naïve 2	0.86027	0.71838	0.24925	0.77996
DMA (n = 3)	595.459	536.111	176.471	501.111
DMA (n = 4)	699.372	632.500	207.308	597.500
DMA (n = 5)	831.204	757.800	246.442	722.800
DES (AAN)	396.238	364.804	116.933	393.258
DES (MAN)	532.001	468.112	157.251	433.112
DES (MMN)	103.887	0.88120	0.30138	0.98788
ARIMA (2, 4, 0)	186.989	903.414	428.426	140.932
nnetar (1, 5)	351.071	307.669	103.173	335.724
nnetar (2, 5)	199.202	163.252	0.58069	170.922
nnetar (1, 8)	230.508	191.399	0.67215	206.933
nnetar (3, 10)	152.947	128.231	0.44492	109.086
nnetar (5, 10)	661.485	558.273	192.600	594.531
mlp (c(2, 5))	501.918	437.326	148.082	405.700
mlp (c(3, 1))	590.336	516.390	174.166	489.656
mlp (c(5, 2))	537.902	469.357	158.693	439.481

It can be seen in the comparison table of model evaluation metric values that the nnetar model with p parameters of 5 and size of 10 is the first best model, followed by the nnetar model with p parameters of 3 and size of 10. Meanwhile, there is inconsistency for the third and fourth best models where no model has all the third and fourth smallest evaluation metric values.

However, the comparison table of model prediction evaluation metric values shows consistency that the best model for predicting the first data is the first naïve model, the second is the second naïve model, the third is the nnetar model with p parameters of 3 and size of 10, and the fourth is the DES model (MMN). Because only the nnetar model (p = 3, size = 10) produces evaluation metric values that are in line both during training as the second best model and during testing as the third best model, this model is declared the best model among the 26 models created or 17 models that passed the model comparison stage. By using this model to make predictions one year ahead, it was found that the ratio of poor people in Indonesia in 2024 was 4.2%.

IV. CONCLUSION

In this study, predictive modeling for the ratio of poor people in Indonesia per year was carried out using six methods, namely: Naive, Double Moving Average, Double Exponential Smoothing, ARIMA, Time Series Regression, and Neural Network, with a total of 26 models formed. Of the 26 models, only 19 passed to the final model comparison stage. It was found that the Neural Network model with the nnetar function and embedding dimension parameter (p) of 3 and the number of nodes in the hidden layer (size) of 10 was the best model; With the training metric value ranked second smallest, the testing metric value ranked third smallest, and the only model that performed well in training and testing. The results of the one-year prediction using the model stated that the ratio of poor people in Indonesia in 2024 is 4.2% which means there will be an increase of 2.3% from the ratio in 2023 of 1.9%. Therefore, to prevent this increase from happening, preventive measures must be taken by both the government and the community itself.

This study is not without its shortcomings where the data used can be said to be small with only 26 observations from 1998 to 2023. So it would be better for subsequent studies to look for more previous data. In addition, because it has been proven that neural networks have good performance for predicting, modeling can also be added using various variations of neural networks, such as Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) Network, Gated Recurrent Units (GRU), or Transformers.

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