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FORECASTING THE NUMBER OF AIRPLANE PASSENGERS USING HOLT WINTER'S EXPONENTIAL SMOOTHING METHOD AND EXTREME LEARNING MACHINE METHOD

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ABSTRACT

Airplanes provide comfort and speed for their users, especially those with limited time. The number of passengers has continued to increase in the last few months at Ahmad Yani International Airport, so a forecast is needed in making decisions to predict the number of passengers in order to maximize existing performance. The data used is secondary data on the number of airplane passengers at Ahmad Yani International Airport from 2012 to 2022 obtained from PT Angkasa Pura 1 (Persero). The Holt Winters Exponential Smoothing method is used because it aligns with the data pattern that includes trends and seasonality in the research, and it has a low level of accuracy. This study also used the Extreme Learning Machine (ELM) method; apart from being a relatively new method, it has a fast learning speed and has low accuracy. This study aims to predict the number of airplane passengers at Ahmad Yani International Airport in Semarang using the Holt Winters Exponential Smoothing and ELM methods. The results of the analysis show that the MAPE value in the Holt Winters Exponential Smoothing method is 8,18% and in the ELM method using 12 input neurons and 43 neurons in the hidden layer, a MAPE of 6,04% is obtained. So, the ELM method is the right method for predicting the number of airplane passengers at Ahmad Yani International Airport in Semarang.

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1. INTRODUCTION

The transportation industry continues to experience growth in sea, land, and air transportation. This occurs because transportation is an essential need for society that cannot be separated; thus, the demand for transportation increases along with the growing population [1]. One of the most popular means of transportation is air transportation. The use of air transportation can provide convenience and speed for users, especially those who have limited time [2]. An airport is a place that accommodates air travel for both domestic and international flights. One of the international airports in Semarang City, Central Java, which is under the auspices of PT Angkasa Pura I (Persero), is Ahmad Yani International Airport. The increase in the number of passengers continues to occur at Ahmad Yani Airport; this is proven by the increase in the number of airplane passengers at Ahmad Yani Airport, namely 65.79% or 1,631,525 passengers in 2022 compared to the previous year, which only amounted to 848,088 people [3].

Forecasting the number of airline passengers is essential to minimize suboptimal operations that affect passengers at Ahmad Yani International Airport and PT Angkasa Pura I (Persero). Forecasting is predicting future events based on past data [4]. Therefore, forecasting is crucial for decision-making to obtain a general understanding of passenger numbers at the time of decision-making. This allows authorities and management to plan and manage resources more effectively. In this research, time series data forecasting is conducted using the Holt Winters Exponential Smoothing method. The advantage of this method is its ability to predict patterns in data that have both seasonal and trend influences simultaneously. It is a relatively simple method with a low error rate [5]. Therefore, this study uses the Holt Winter's Exponential Smoothing method because it aligns with the data patterns being analyzed, namely the presence of trends and seasonality. Additionally, neural network methods are employed in this forecasting. The artificial neural network method with a fast learning speed, commonly known as Single Hidden Layer Feedforward Neural Networks (SLFNs), is the Extreme Learning Machine (ELM) method [6]. ELM's advantages include not requiring assumptions, simple analysis, good accuracy, and its relatively rare use in time series data [7]. Several researchers have conducted forecasts related to the Holt Winters and ELM methods and have achieved good accuracy results for both methods [5][8][9][10]. Based on the results from these two methods, the researcher will search for the best method based on the lowest Mean Absolute Percentage Error (MAPE) to be used for forecasting the number of passengers for the next 12 periods.

Research related to the Holt Winters exponential smoothing and ARIMA methods are as follows. Safitri et al. predicted the number of foreign tourists visiting Bali Ngurah Rai from 2010 to 2015. They obtained a Holt Winters MAPE value of 8.87%[11]. Research conducted by Nurdini et al. used the Holt Winters Additive method to forecast demand for tempeh products in Indonesia. The forecast accuracy obtained was 90.15%, which means very good in predicting future demand for tempeh [8]. Another study conducted by Izati et al. utilized the ELM to predict gold prices and achieved a MAPE of 0.55% using 7 hidden nodes [9]. Research conducted by Triyanna et al. using the ELM method to predict prices of basic food commodities in the eastern region Java Province prediction process basic food commodities are carried out using 3 data features, 7 neurons, and the composition of training and testing data is 80%: 20%. The results showed that the prediction level was average, the accuracy of all basic food commodities is 98.79% which shows the prediction results close to the true value [10]. Based on the background, the researcher intends to compare both methods and determine the best method to be used for forecasting the number of passengers for the next 12 months at Ahmad Yani International Airport.

2. RESEARCH METHODS

2.1 Data Source

This research uses monthly airline passenger data at Ahmad Yani International Airport. The data spans from January 2012 to December 2022.

2.2 Research Steps

The research steps taken were as follows:

a. Enter the number of passengers' data into the R Studio software program.

b. Conduct descriptive analysis of data on the number of passengers at Ahmad Yani Airport Semarang.

c. Divide the data into 90% training data and 10% testing data.

d. Holt Winter's Exponential Smoothing Analysis Stages:

1) Determine the values of α, β, γ by trial and error.

2) Determine the initial exponential smoothing value, trend smoothing value, and initial seasonality.

3) Determine the level smoothing value (L_t), trend smoothing value (b_t), and seasonal smoothing value (S_t).

4) Make forecasts for the next 13 months with the best model.

5) Create plotting of actual data and forecasting data.

6) Calculate forecasting accuracy values for passenger number data by looking at MAPE.

e. Stages of ELM Analysis:

1) Carry out the normalization process on all data.

2) Defines input and target.

3) Carry out a training process on the number of passengers data to get the output weight or output weights used to get prediction results.

4) Carry out a testing process on passenger number data based on training results.

5) Carry out the denormalization process to the original value.

6) Determine the accuracy value using MAPE.

f. Compare the MAPE values of the two methods.

g. Determine the best accuracy based on the lowest MAPE.

h. Forecasting the number of airplane passengers using the best method.

i. Drawing conclusion.

2.3 Holt Winters Exponential Smoothing

The Holt Winters method is a combined method of Holt and Winters on data that contains trend and seasonal patterns. The weights are alpha (α) for level, beta (β) for trend, and gamma (γ) for seasonality, which has a range between 0 and 1 for each parameter **[12]**. The Holt Winters method can be used for non-stationary data **[13]**. To obtain the initial values of alpha, beta, and gamma in the Holt-Winters method, it can be done using the trial and error method or optimization methods. Two models of the Holt Winters exponential smoothing method, namely:

a. Multiplicative Holt Winters method

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_t + b_{t-1}) \tag{1}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{2}$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{3}$$

$$F_{t+m} = (L_t + b_t m)S_{t+m-s} \tag{4}$$

b. Holt Winters Additive Method

$$L_t = \alpha(Y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{5}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{6}$$

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-s} \tag{7}$$

$$F_{t+m} = L_t + mb_t + S_{t+m-s} \tag{8}$$

In **Equation (1)**- **Equation (8)**, s denotes the seasonal length, L_t denote level components, b_t denote trend component, S_t denote seasonal components, Y_t denote data to-t, F_{t+m} denote forecast for the next m periods, t denote $1,2,\cdots,t$ and α, β, γ denote smoothing constant.

2.4 Extreme Learning Machine

Extreme learning machine (ELM) is a method of development from artificial neural networks known as single hidden layer feedforward neural networks, first introduced by Huang et al. in 2004. ELM is designed to address several weaknesses in feedforward neural networks, especially those related to learning speed **[14]**. In ELM, there are three main layers: the input layer, the hidden layer, and the output layer. The input layer receives input data, and the hidden layer contains neurons with randomly assigned weights. The activation function in the hidden layer is often a simple non-linear function, such as sigmoid. The ELM architecture emphasizes fast training of the hidden layer with random weights, allowing for efficient learning and quick convergence. ELM calculation stages include:

a. Data normalization

Normalization is a process to transform data so that the data used falls within a specific range, with the aim of obtaining data with a small normalization value.

$$d' = \frac{Y_t - D_{min}}{D_{max} - D_{min}}(D_{maxb} - D_{minb}) + D_{minb} \tag{9}$$

b. Training process

1) Initialize input weights randomly between -1 and 1.
2) Calculate H_{init} by multiplying the normalized input (X_{train}) with the input weight matrix (W) that has been previously transposed.
$$H_{init\ train} = X_{train} \cdot W^T \tag{10}$$
3) Calculate the output of the hidden layer using the binary sigmoid function.
$$H = \frac{1}{1 + exp^{-(H_{init\ train})}} \tag{11}$$
4) Calculate the Moore-Penrose Generalized Inverse.
$$H^+ = (H^T H)^{-1} H^T \tag{12}$$
5) Calculate the value of the output weight (β). Producing weights used to connect the hidden layer to the output.
$$\beta = H^+ T \tag{13}$$
6) Calculate the prediction results for the training data. The value generated by the ELM model for the training data
$$Y_{latih} = H\beta \tag{14}$$

c. Testing process

The purpose of this testing is to evaluate the ELM approach based on the results of the previous training process. In this case, we use the output weights and input weights obtained from the training process **[15]**. The steps of the testing process are almost identical to the training process, with the key difference being that in the testing process, we do not perform weight initialization, and the output weights have already been obtained from the training process.

d. Denormalization

Denormalization is a process to transform the prediction results back into the original data **[10]**.

$$d = d'(D_{max} - D_{min}) + D_{min} \tag{15}$$

In **Equation (9)** - **Equation (15)**, d' denotes normalized data result, Y_t denotes actual data, D_{min} denotes minimum value of actual data, D_{max} denotes maximum value of actual data, D_{minb} denotes latest minimum value, D_{maxb} denotes latest maximum value, $H_{init\ train}$ denotes training hidden layer output matrix, X_{train} denotes normalized input matrix, W^{T} denotes transpose input weight, H denotes binary sigmoid activation function, exp denotes exponential, H^{+} denotes Moore Penrose Generalized Inverse, $(H^T H)^{-1}$ denotes inverse of the multiplication of matrices H^{+} and H, H^{T} denotes transpose matrix, β denotes output weight matrix, T denotes target matrix, $\mathrm{Y}_{\mathrm{latih}}$ denotes training data predictions, d denotes denormalized actual value, and d' denotes prediction results before denormalized.

2.5 Evaluation of Forecasting Results

One reference for evaluating the accuracy of a model is by using MAPE **[16]**. The formula for MAPE is as follows:

Table 1. Criteria for MAPE Values

MAPE	Interpretation
<10%	Very good
10%-20%	Good
21%-50%	Adequate
>50%	Not accurate

$$\mathrm{MAPE} = \frac{1}{\mathrm{N}} \sum_{\mathrm{t}=1}^{\mathrm{N}} \frac{|\mathrm{Y_t} - \hat{\mathrm{Y}}_{\mathrm{t}}|}{\mathrm{Y_t}} \times 100\% \tag{16}$$

In **Equation (16)**, Y_t denotes actual value, $\hat{\mathrm{Y}}_{\mathrm{t}}$ denotes predicted value, and N denotes number of data periods.

3. RESULTS AND DISCUSSION

Descriptive analysis was carried out to provide a general description of the characteristics of the data. The data used is data on the number of airplane passengers at Ahmad Yani International Airport, Semarang. The data analyzed covers the period January 2012 to December 2022 with a total of 132 data, which can be seen in **Table 2** and **Figure 1**.

Table 2. Descriptive Analysis of the Number of Airplane Passengers

N	Mean	Minimum	Maximum	Standard deviation
132	262.945	2.185	512.397	114.473,2

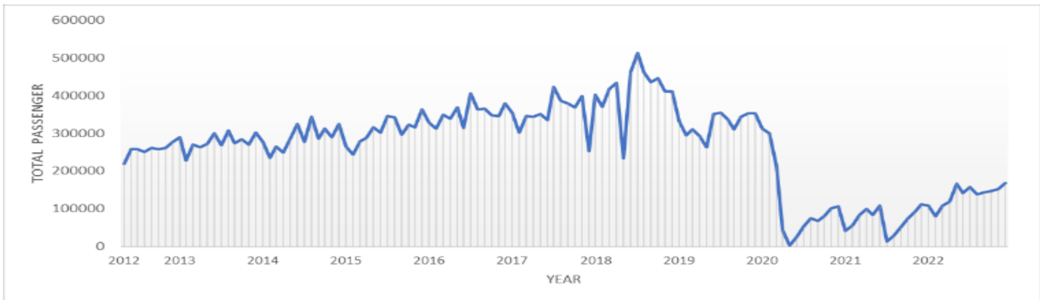

Figure 1. Plot of the Number of Airplane Passengers

Based on **Table 2** and **Figure 1**, it is observed that the number of airline passengers at Ahmad Yani Airport in Semarang experienced fluctuations that tended to increase from 2012 to 2018. However, from 2019 to 2021, there were fluctuations that tended to decrease, with variations in the number of passengers during certain seasons, such as holidays. The highest number of passengers occurred in 2018, reaching a total of 4,996,920 passengers, while the lowest occurred in 2021, with 848,088 passengers. The decline in the number of passengers is partly attributed to the COVID-19 pandemic that affected Indonesia and the world.

3.1 Data Determination and Data Testing Training

The data in this study consists of 132 data points divided into two groups: training data and testing data. The training data amounts to 90%, which is 119 data points from January 2012 to November 2021. The testing data amounts to 10%, which is 13 data points from December 2021 to December 2022.

3.2. Holt Winter's Exponential Smoothing

The Holt Winters Exponential Smoothing method is used to forecast data with both trend and seasonality. The Holt Winters method is divided into two models: the multiplicative model and the additive model. Based on **Figure 2**, it is evident that the number of airline passengers exhibits an annual seasonal pattern, as indicated by consistent fluctuations with the same pattern. Therefore, the model to be used is the additive model.

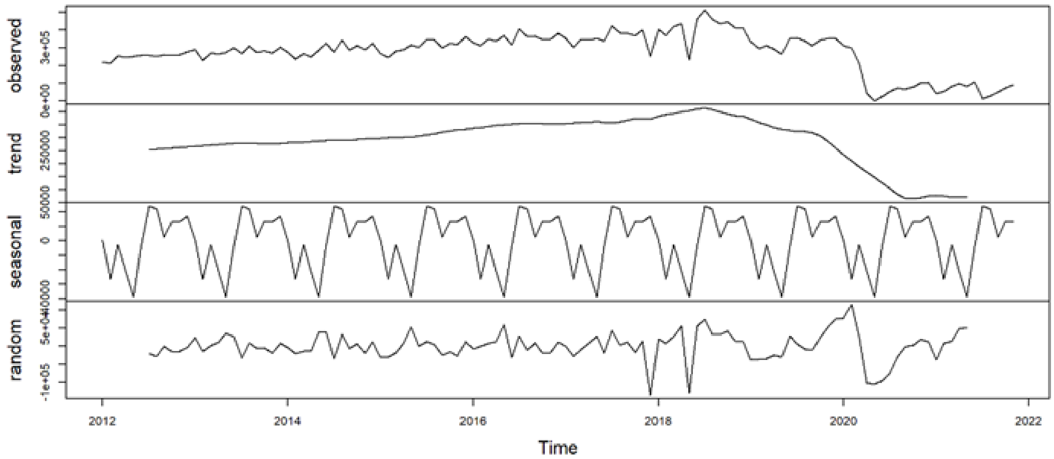

Figure 2. Additive Model

The determination of smoothing parameter values for level (α), trend (β), and seasonality (γ) is done through trial and error to minimize forecast accuracy errors. The estimation results of the smoothing parameters for the Holt-Winters method are presented in **Table 3** for the international Ahmad Yani Airport passenger count data.

Table 3. Smoothing Parameter Values for the Additive Model

α	β	γ	MAPE
1	0.1	0.9	36.55%
1	0.2	0.9	29.92%
0.9	0.2	0.8	29.89%
0.9	**0.2**	**0.7**	**29.85%**
0.8	0.3	0.1	35.37%
⋮	⋮	⋮	⋮
0.3	0.1	0.1	113.75%
0.2	0.2	0.1	124.69%
0.1	0.1	1.1	149.11%

Based on **Table 3**, the optimum values for the smoothing parameters are as follows: alpha (α) is 0.9, beta (β) is 0.2, and gamma (γ) is 0.7. Based on the additive Holt-Winters model parameters, the prediction for the number of airline passengers at Ahmad Yani International Airport for the next 13 months is presented in **Figure 3**.

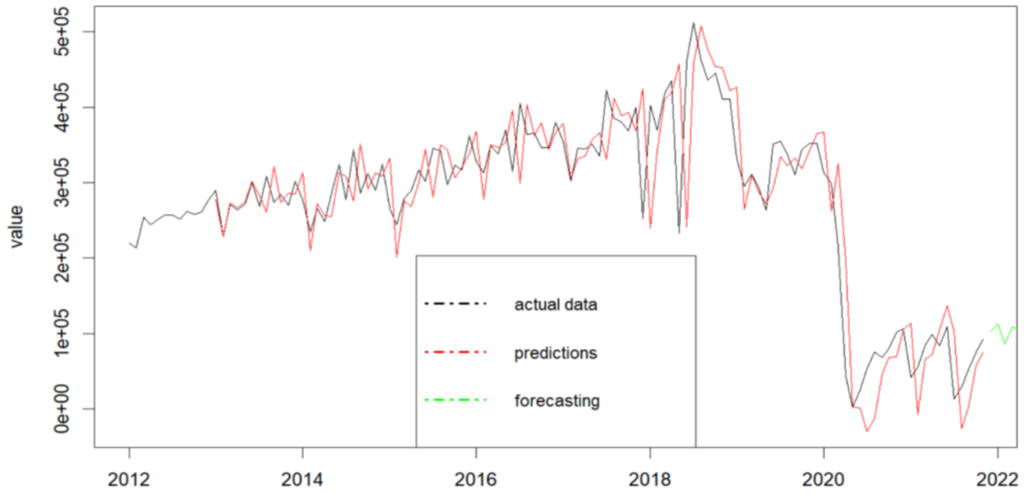

Figure 3. Comparison of Actual Data and Predicted Data from the Additive Model

After obtaining predictions using the additive model, the next step is to test the model's performance by comparing the predicted values with the actual values in the testing data using MAPE:

$$\text{MAPE} = \frac{1}{13}\sum_{t=1}^{13}\left(\frac{|111.408 - 102.654{,}14|}{111408} + \cdots + \frac{|167.279 - 170.694{,}34|}{167.279}\right) \times 100\%$$

MAPE=8.18%

A forecasting capability is considered very good if the MAPE value is less than 10%. Based on the result obtained, a MAPE of 8.18% can be said to have excellent forecasting capability.

3.3. Extreme learning Machine

The initial step of the ELM is to divide the data into two parts, which are the training data and the testing data. In this research, the data is divided with a ratio of 90% for training data and 10% for testing data. The input values used in this study are X_1, X_2up to X_{12}, representing monthly data for one year, totaling 12 inputs. Meanwhile, Y represents the target or output data, which is the data for the next month (the 13th input), as presented in **Table 4**.

Table 4. Pattern of Training Data Inputs

Data To	Input Data				Target
	X_1	X_2	...	X_{12}	Y
1	0.4412	0.4314	...	0.5318	0.5515
2	0.4314	0.4950	...	0.5515	0.4539
3	0.4950	0.4788	...	0.4539	0.5216
4	0.4788	0.4913	...	0.5216	0.5096
⋮	⋮	⋮		⋮	⋮
107	0.2563	0.2630	...	0.2142	0.2418

In this study, the researcher conducted several trials of neurons with the aim of determining the optimal number of neurons based on the smallest MAPE value. Based on the analysis, it was found that the optimal number of neurons is 43, as seen in **Table 5**.

Table 5. Selection of the Best Neuron

Neuron	MAPE Value
1	199.3%
2	162.9%
3	126.3%
4	122.2%
5	121.4%
6	121.4%
⋮	⋮
41	45.8 %
42	42.8%
43	**40.6%**
44	43.1%
45	43.3%
46	44.6 %

The MAPE evaluation result from the training process is 40.6%, which is below 50%. Therefore, it can be concluded that the forecasting accuracy in the training process is considered acceptable or adequate. To compare the actual data with the predictions in the training process, one can refer to **Figure 4**. This figure provides a visualization showing how closely the ELM model predictions approach the actual data during the training process. It is evident that the training process has provided reasonably accurate predictions, as indicated by the proximity between the actual and predicted values, demonstrating that the forecasting model used can capture and describe the data patterns quite well. **Figure 5** illustrates the network architecture visually.

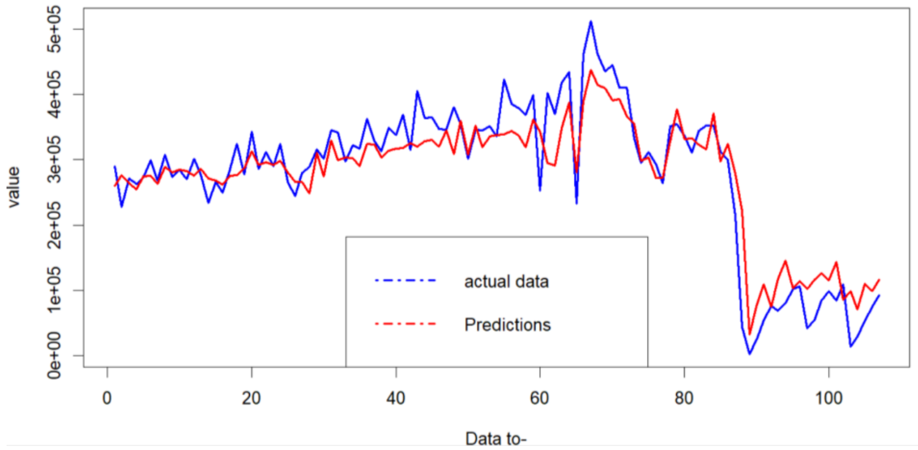

Figure 4. Comparison of Output and Target in the Training Process

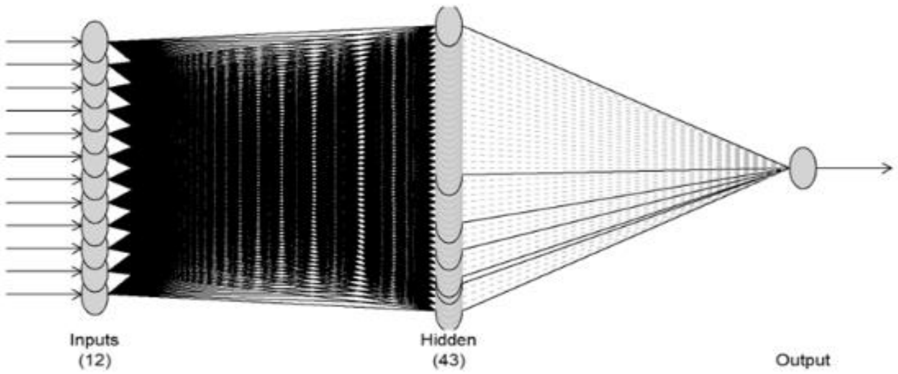

Figure 5. Architecture of the Best ELM Network Model

After completing the training phase, the testing process is then conducted with the aim of measuring the performance of the network model that has been constructed during the training process.

$$\text{MAPE} = \frac{1}{1}\sum_{t=1}^{1}\frac{|167.279 - 157.182{,}165|}{167.279} \times 100\%$$

$$\text{MAPE} = 6{,}04\%$$

Based on the calculations above, this testing was conducted with 119 training data, 13 testing data, 12 input neurons, and 43 neurons. The testing results indicate that the lowest MAPE obtained is 6.04%, indicating very good forecasting capability.

3.4. Evaluation of the Best Method

The validity test of the forecasting results used in this research is the MAPE value for each method, which is presented in **Table 6**.

Table 6. Comparison of MAPE Values between the Holt-Winters and ELM Methods

Method	MAPE
Holt Winters Exponential Smoothing	8.18%
Extreme Learning Machine	6.04 %

Based on the presented **Table 6**, the MAPE value for forecasting the number of airline passengers at Ahmad Yani Airport in Semarang using the Holt Winters Exponential Smoothing method is 8.18%. Meanwhile, using the ELM method, a value of 6.04% is obtained. Therefore, the most suitable method for forecasting the number of airline passengers at Ahmad Yani Airport in Semarang for the next 12 months is the ELM method.

3.5. Forecasting with the Best Method

Below are the forecasting results for the number of airline passengers for the next 12 periods (January 2023 - December 2023) at Ahmad Yani International Airport, as presented in **Table 7**.

Table 7. Forecast of Passenger Count for the Next 12 Periods

Month	Forecasting
Januari 2023	141,063
February 2023	161,627
Maret 2023	142,076
April 2023	151,836
Mei 2023	170,642
Juni 2023	139,964
Juli 2023	176,307
Agustus 2023	130,715
September 2023	190,270
October 2023	157,081
November 2023	165,238
December 2023	180,766

Based on **Table 7**, it can be concluded that the forecasted number of airline passengers at Ahmad Yani International Airport for the period from January to December 2023 shows the highest passenger count occurring in September, with 190,270 passengers. Meanwhile, the lowest passenger count is recorded in August, with a total of 130,715 passengers.

4. CONCLUSIONS

a. A comparison of the Holt Winters Exponential Smoothing and ELM methods for forecasting the number of airplane passengers at Ahmad Yani Airport in Semarang obtained a comparison of MAPE values, namely: Holt Winters Exponential Smoothing of 8.18% and ELM of 6.04%. So, the ELM method is the best method for analyzing forecasting the number of airplane passengers at Ahmad Yani Airport in Semarang.

b. The results of forecasting the number of airplane passengers at Ahmad Yani Airport in Semarang using the best method (ELM), from January to December 2023, indicate that the highest number of passengers occurred in September with 190,270 passengers, while the lowest occurred in August with 130,715 passengers.

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