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Comparison of Adaptive Holt-Winters Exponential Smoothing and Recurrent Neural Network Model for Forecasting Rainfall in Malang City

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***Abstract* -** Rainfall forecast is necessary for many aspects of regional management. Prediction of rainfall is useful for reducing negative impacts caused by the intensity of rainfall, such as landslides, floods, and storms. Hence, a rainfall forecast with good accuracy is needed. Many rainfall forecasting models have been developed, including the adaptive Holt-Winters exponential smoothing method and the Recurrent Neural Network (RNN) method. The research aimed to compare the result of forecasting between the Holt-Winters adaptive exponential smoothing method and the Recurrent Neural Network (RNN) method. The data were monthly rainfall data in Malang City from January 1983 to December 2019 obtained from a website. Then, the data were divided into training data and testing data. Training data consisted of rainfall data in Malang City from January 1983 to December 2017. Meanwhile, the testing data were rainfall data in Malang City from January 2018 to December 2019. The comparison result was assessed based on the values of Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The result reveals that the RNN method has better RMSE and MAPE values, namely RMSE values of 0,377 and MAPE values of 1,596, than the Holt-Winter Adaptive Exponential Smoothing method with RMSE values of 0,500 and MAPE values of 0,620. It can be concluded that the non-linear model has better forecasting than the linear model. Therefore, the RNN model can be used in modeling and forecasting trend and seasonal time series.

Keywords: adaptive Holt-Winters exponential smoothing, Recurrent Neural Network (RNN) model, rainfall forecasting

I. INTRODUCTION

As a result of global warming, climate change has become a serious concern in the world. The agricultural sector is considered to be the most affected sector (Masud et al., 2017; Arora, 2019). One of the climate elements affected by climate change is rainfall. As a result, changes in rainfall patterns affect agricultural production. In light of this situation, rainfall supports the availability of water needed for plants and affects the emergence of pests and plant diseases (Meza-Pale & Yunez-Naude, 2015; Kyei-Mensah, Kyerematen, & Adu-Acheampong, 2019). Thus, mitigation and adaptation efforts are needed to face climate change. One of the adaptation efforts to face climate change is by predicting the rainfall utilizing existing rainfall data. Hence, forecasting is an essential tool in planning effectively and efficiently.

Moreover, an accurate forecast can help the farmer to reduce losses due to crop failure (Yang & Liu, 2020). Various methods can be conducted in forecasting, such as the Kalman filter (Tengger & Ropiudin, 2019), ARIMA (Swain, Nandi, & Patel, 2018; Dimri, Ahmad, & Sharif, 2020), Box Jenkins (Desvina & Anggraini, 2017), and exponential smoothing method (Su, Gao, Guan, & Su, 2018). Exponential smoothing is a forecasting method to predict the future by carrying out a smoothing process by generating forecast data with a smaller error value. In exponential smoothing, one or more smoothing parameters are explicitly defined, and the result of choice determines the weight imposed on the observation value.

In time series forecasting, the data often show different seasonal behavior. Seasonality is defined as a

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trend of time series data that repeats itself every period. Seasonality is a term used to represent a recurring period. Seasonal data have a pattern that repeats itself over time. Seasonal data mean the tendency to reduce behavior patterns over a seasonal period, usually one year. Seasonal time series has characteristics indicated by a strong correlation over time intervals, namely the time that lasts for the number of observations per seasonal period (Hyndman & Athanasopoulos, 2018).

Rainfall data is seasonal data. Thus, it needs a model that can accommodate seasonal patterns in predicting rainfall. One of the exponential smoothing methods that can be used on data with a seasonal pattern is adaptive Holt-Winters exponential smoothing (Liu & Wu, 2022). The method utilizes three parameters to predict the value of data. The Holt-Winters method is an extension of the two Holt parameters. The Holt-Winters method is a time series prediction method that can handle seasonal behavior in data based on past data. The advantage of the Holt-Winters exponential smoothing method is that it is very good at predicting data patterns that have a seasonal effect with trend elements. At the same time, the method is simple, easy to implement, and competitive against more complex forecasting models. For example, Şahinli (2020) compared the double exponential smoothing, multiplicative Holt-Winters, and additive Holt-Winters methods for forecasting the price of lime, chili, and lemongrass in Thailand. The three plants had high economic value in Thailand. It showed that multiplicative Holt-Winters and additive Holt-Winters provide a smaller forecast error value for forecasting lime prices from October 2016 to December 2016.

Rainfall data modeling that accommodates non-linear data is necessary to obtain the most appropriate model. One non-linear time series forecasting method is the Neural Network (NN) (Gonzalez & Yu, 2018). The NN model is divided into two, namely, Feedforward Neural Network (FFNN) and Recurrent Neural Network (RNN) (Fadilah, Djamal, & Ilyas, 2021). In FFNN, the information process runs forward from the input layer to the output layer. In RNN, the input is processed sequentially, sample per sample. In this sense, it only has at least one feedback connection, so a cyclical process can occur. For example, Yanti, Cynthia, Vitriani, Yusra, and Azmi (2019) applied RNN to forecasting solar radiation. The amount of solar radiation was forecasted by input data for the duration of solar radiation, air temperature, rainfall, and air humidity. The RNN method produced a forecasting accuracy value of 96,33% on training data and an accuracy of 90% on testing data using several training scenarios.

In the research, rainfall forecasting is carried out using two different methods. The first method uses adaptive Holt-Winters exponential smoothing representing a linear model. The second method is RNN as a non-linear model. From these two methods, the best model is sought. The research aims to know the most accurate forecasting results from both methods.

II. METHODS

The data in the research are monthly rainfall data in Malang City (January 1983 to December 2019). The data are obtained from the website (https://chrsdata.eng.uci.edu). Then, the data are divided into training data and testing data. Training data consists of rainfall data in Malang City from January 1983 to December 2017. Meanwhile, the testing data are rainfall data in Malang City from January 2018 to December 2019.

Adaptive Holt-Winters exponential smoothing method is used for seasonal data variations from constant time series data. Moreover, adaptive Holt-Winters exponential smoothing utilizes three parameters to achieve forecasting values: α, β, and γ. At the end of the t-period, the forecast value $(\hat{Y}_{t+k})$ for the period $(\hat{Y}_{t+k})$ obtains Equation (1). Then, it has a smoothing model as follows.

$$\hat{Y}_{t+k} = L_t + kT_t + S_{t+k-c} \tag{1}$$

Level smoothing (level)

$$L_t = \alpha(Y_t - S_{t-c}) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{2}$$

Trend smoothing (trend)

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{3}$$

Seasonal smoothing (seasonal)

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-c} \tag{4}$$

The initial values are required for smoothing the level (L_t), trend (T_t), and seasonal index (S_t) to initiate this forecasting method. The L_t value can be assumed to be the same as the first actual data value, namely Y_1. Meanwhile, the T_t value can be assumed to be 0 (as the trend value obtained from the previous period does not exist). Then, the initial estimation value for the seasonal index (S_t) is assumed to be 1 (eliminating seasonal effects on actual data) (Al Mahkya, Yasin, & Mukid, 2014).

The steps to forecast rainfall using adaptive Holt-Winters exponential smoothing method are to determine the initial values α, β, and γ by trial and error. Then, the researchers input data in the form of training data and the data to be predicted in data testing. Next, the researchers determine the initial level, trend, and early seasonal smoothing values. Similarly, the researchers also determine the value of level smoothing (L_t), trend smoothing (T_t), and seasonal smoothing (S_t). After that, the researchers forecast rainfall for the next period by accumulating the results of level, trend, and seasonal smoothing.

Next, the RNN network accommodates network output to be the input to the network, which is then used to generate new output. RNN is a network with dynamic capabilities because the behavior of the network does not only depend on the current input but on the operations before the network. There are two types of RNN networks: Elman and Hopfield (Patnaik, 2005). In the research, the Elman RNN network is used for forecasting, so that the discussion will investigate specifically the Elman network RNN. The Elman network is included in the simple recurrent network because it has a feedback connection only found in the hidden layer. In the Elman network, there is only one hidden layer. Unfolding Elman RNN is presented in Figure 1.

Next, the mathematical model for the Elman network is presented in Equation (5). It has several variables. It shows y_t^* as *the output* variable, Y_{t-i} as *the input* variable, U_j *as the input variable* existing in additional neurons (context neuron) with j = 1, 2, ..., q, b_k as bias weight on the neuron layer k in the hidden layer with = 1, 2, …, q, b_0 as bias weight on the output layer neuron, $W_{ik(a)}$ as the weight from the input layer -i to the neuron -k in the hidden layer, $W_{jk(b)}$ as the weight from the input layer (additional neuron) -j 0-to the neuron k in the hidden layer, v_k as the weight from neuron k in the hidden layer to the output layer k = 1, 2, …, q, and ε as an error.

$$y_t^* = \sum_{k=1}^{q} v_k \frac{1-\exp\left(-\left(\sum_{i=1}^{p} y_{t-i} w_{ik(a)} + \sum_{j=1}^{q} U_j w_{jk(b)} + b_k\right)\right)}{1+\exp\left(-\left(\sum_{i=1}^{p} y_{t-i} w_{ik(a)} + \sum_{j=1}^{q} U_j w_{jk(b)} + b_k\right)\right)} + b_0 + \varepsilon \qquad (5)$$

The backpropagation algorithm is included in the supervised algorithm. This algorithm consists of two stages, namely forward propagation and backward propagation. Forward propagation is conducted to get errors. Then, the error obtained changes the weight values in the backward direction. During forward propagation, the neurons are activated using a differentiable activation function.

The steps of analysis using the RNN method are explained as follows. First, it is data normalization. Second, there are parameter initiation in the form of the learning rate, number of hidden layers, number of hidden layer neurons, target error, and maximum epoch. Third, the researchers carry out forward propagation, calculate the activation function on the hidden layer, and copy the result to the context layer. Fourth, the researchers calculate the activation function at the output layer and compare the error value with the target error. The learning process will stop if the error value is smaller than the target error. If it is not, backward propagation and updating of the weight values in the system will be carried out.

It can use several criteria to determine the best model, including the in-sample and out-of-sample criteria. In-sample criteria are commonly used to select a model based on residuals. The in-sample criteria used in the research are the Root Mean Squared Error (RMSE). RMSE measures the difference between the predicted value of the model and the actual observed value. RMSE value can be calculated using Equation (6). It shows N as many predictions made, $Z_{i(t)}$ as actual data, and $\hat{Z}_{i(t)}$ as data forecast using the model formed.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\sum_{t=1}^{T}\left(Z_{i(t)} - \hat{Z}_{i(t)}\right)^2\right)} \qquad (6)$$

Meanwhile, the out-of-sample criteria used is Mean Absolute Percentage Error (MAPE). It is calculated by using absolute error in each period divided by the actual observed value for that period and the average absolute percentage error. MAPE value can be calculated using Equation (7).

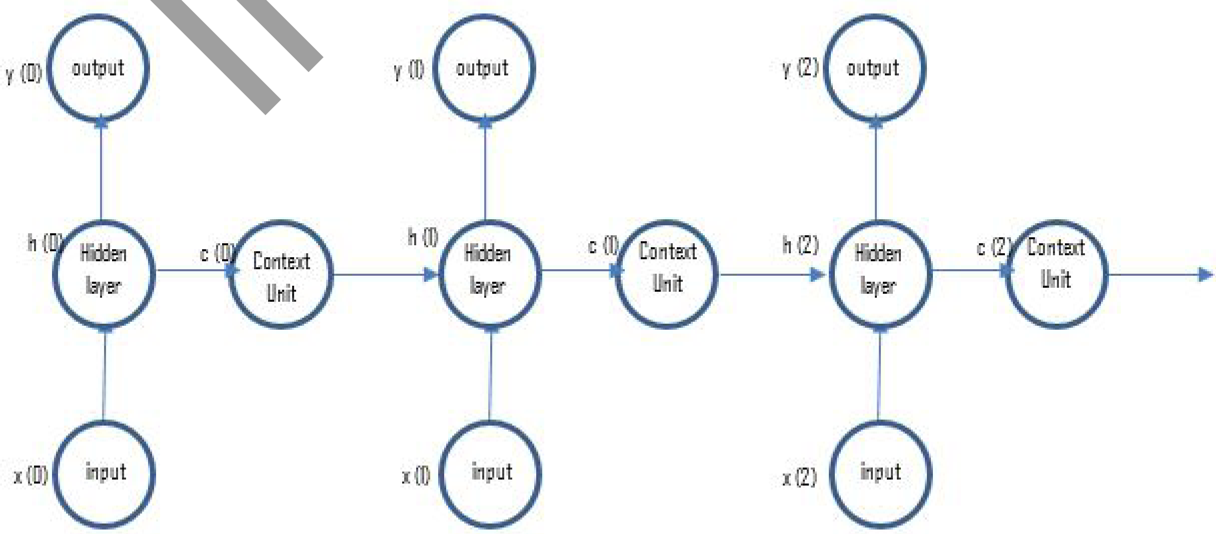

Figure 1 Unfolding Elman RNN

$$MAPE = \frac{1}{N}\left(\sum_{t=1}^{T}\left|\frac{z_{i(t)}-\hat{z}_{i(t)}}{z_{i(t)}}\right| x\ 100\right) \quad (7)$$

III. RESULTS AND DISCUSSIONS

The data analyzed in the research are quantitative data regarding rainfall in Malang City from January 1983 to December 2019. The average rainfall in Malang City every year is shown in Table 1. In Table 1, rainfall is presented in millimeters (mm). It presents information about the minimum, maximum, and average rainfall that occurs every year in Malang City. For example, the highest average rainfall occurred in 1984 at 280,1913 mm, and the lowest average was in 1991 with an average of 139,134 mm. A rainfall value of 0 mm indicates no rain during the day. The peak of the rainy season fluctuates every year

Table 1 Annual Rainfall Data in Malang City

Year	Mean	Minimum	Maximum
1983	232,8083	8,344	463,125
1984	280,1913	40,965	582,708
1985	208,5908	30,725	446,12
1986	225,0988	59,507	442,912
1987	190,5905	0	516,471
1988	172,3408	28,829	390,451
1989	196,4674	29,37	405,712
1990	150,8193	7,665	375,773
1991	139,1134	0	386,247
1992	176,241	37,935	458,203
1993	145,0493	5,264	354,648
1994	142,2463	0	410,679
1995	206,6078	6,234	438,367
1996	156,4341	22,062	336,883
1997	143,0531	23,844	379,181
1998	213,7152	15,382	373,749
1999	178,2214	4,73	345,409
2000	201,2313	10,389	377,463
2001	198,0779	22,249	382,859
2002	166,394	5,868	404,813
2003	177,8425	14,907	416,336
2004	180,3259	13,987	438,856
2005	186,6338	12,617	366,709
2006	165,3199	0	345,122
2007	153,5914	11,552	344,716
2008	161,0954	18,514	375,137
2009	150,1258	0	365,595
2010	277,7098	66,581	528,312
2011	167,5799	7,608	330,507
2012	152,8964	0	363,809
2013	221,8502	10,759	412,975
2014	162,3378	4,434	380,99
2015	159,7839	8,252	366,812
2016	222,9918	33,904	459,074
2017	180,8534	11,875	397,086
2018	179,8331	2,644	646,085
2019	161,3624	5,085	382,719

between December to March. During these months, the highest rainfall occurs every year. The peak of the rainy season every year is between July to September. It shows that the highest seasonal rainfall occurred in February 2018, which amounted to 646,085 mm.

Figure 2 shows monthly rainfall data in Malang City from January 1983 to December 2019. It can be seen that the rainfall data pattern has decreased and increased repeatedly in certain months, where the data pattern is seasonal from December to March. In 1996 and 2008, the highest rainfall fluctuations occurred in December. In 1988, 1990-1994, 1999, 2002, 2013, 2017, and 2019, seasonality occurred in January. Meanwhile, seasonality occurs in February in 1984, 1985, 1987, 1989, 1995, 1997, 1998, 2000, 2003, 2005, 2009, 2010, 2014, 2016, and 2018. Then, seasonality also happened in March 1983, 1986, 2001, 2004, 2006, 2007, 2011, 2012, and 2015. These seasonal fluctuations continued to repeat until 2019. Thus, it identifies that rainfall data in Malang City contain seasonal elements. The graph shows the high and low changes in rainfall data for each period and the same pattern every year. The highest rainfall is 646,09 mm and the lowest rainfall is 0,00 mm.

Table 2 shows that the average rainfall in Malang City is 183,389 mm/month. The highest frequency of rainfall is 646,085 mm/month, which means that the total monthly rainfall in Malang City has the highest range of 646,085 mm. Meanwhile, the lowest rainfall in Malang City is 0 mm/month. It indicates that there are several months without rain for one month. Next, the standard deviation value is 139,927. The value means that the distribution of rainfall from the average is 139,927 mm. The kurtosis value of -0,90806 means that the distribution of values is sloping. It indicates that the rainfall data in Malang City have a fairly large diversity. Next, the skewness value of 0,3755 indicates that the data distribution is skewed to the left of the normal distribution. In this sense, there is a high-frequency value to the left of the midpoint of the normal distribution.

Before conducting the modeling rainfall data, the data should be divided into two: training data and testing data. The training data consists of rainfall data of Malang City for 35 years, from January 1983 to December 2017. Meanwhile, testing data consists of rainfall data from Malang City from January 2018 to December 2019.

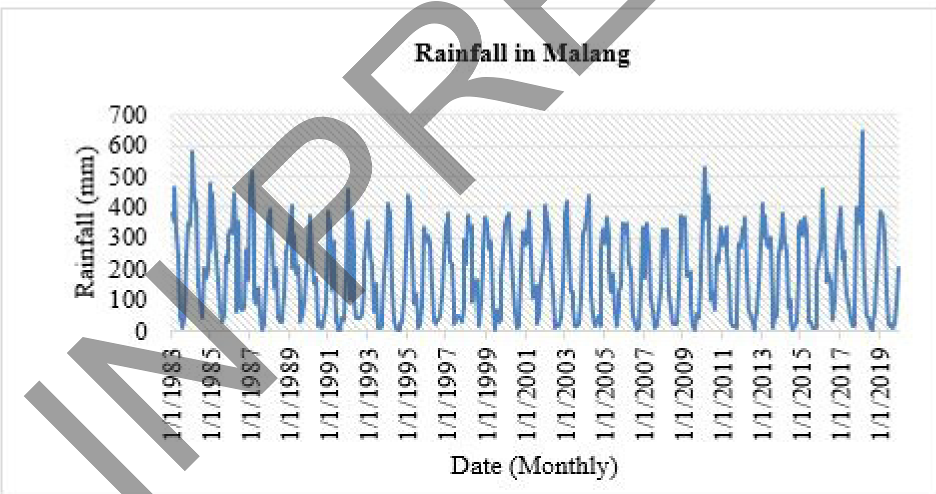

Figure 2 Rainfall Graphs in Malang City

Table 2 Descriptive Statistics of Rainfall Data

Characteristics	**Value**
Mean	183,3899
Standard Deviation	139,9271
Kurtosis	-0,90806
Skewness	0,375594
Range	646,085
Minimum	0
Maximum	646,085

An initial value is set for each parameter to perform parameter estimation. The value of L_t can be assumed to be the same as the value of the first actual data, namely Y_1. Meanwhile, the value of T_t can be assumed to be 0, and the initial estimated value for the seasonal index (S_t) is 1. From the modeling results, the values for each parameter in the arrow obtain α=0,1185, β=0,0141, γ=0,2111. The adaptive Holt-Winters exponential smoothing model for forecasting rainfall data in Malang City is presented as follows.

Level smoothing (level):

$$L_t = 0{,}1185(Y_t - S_{t-c}) + (1 - 0{,}1185)(L_{t-1} + T_{t-1})$$

Trend smoothing (trend):

$$T_t = 0{,}0141(L_t - L_{t-1}) + (1 - 0{,}0141)T_{t-1}$$

Seasonal smoothing (seasonal):

$$S_t = 0{,}0141(Y_t - L_t) + (1 - 0{,}0141)S_{t-c}$$

Forecasting results using the Holt-Winters Adaptive Exponential Smoothing method are shown in Figure 3. It displays training data and a comparison between prediction data and testing data. Figure 3 also portrays that the predicted value of the adaptive Holt-Winters exponential smoothing model is close to the actual value. The benefit of this model is calculated using the RMSE and MAPE values. From this model, the RMSE value is 0,500, and the MAPE value is 2,62049. The results of forecasting with this method are presented in Table 3.

Next is the determination of the number of neurons in the input layer, hidden layer, and output layer to perform modeling with the RNN method. Based on the analysis of the number of neurons in the input layer, hidden layer, and output layer, it is found that the optimal number of neurons is (16-6-1). After obtaining the number of neurons used in the network architecture, training is carried out on the training data. The results of training on testing data and testing on training data are presented in Figure 4.

Figure 4 displays training data and a comparison between prediction and testing data. It also reveals that the predicted value of the RNN method is close to the actual value. The benefit of this model is calculated using the RMSE and MAPE values. From this model, the RMSE value is 0,3771, and the MAPE value is 1,5961. The results of forecasting with this method are presented in Table 4.

RNN architecture obtained RNN (16-6-1). The activation function used is the sigmoid activation function in the hidden layer and the linear activation function in the output layer. The rainfall forecasting model is formed in Equation (8).

$$\hat{Y}_k = w_{oj} + \sum_{j=1}^{6} w_{jk}\left(\frac{1}{1+e^{-(v_{oi}+\sum_{i=1}^{16} v_{ij}X_i)}}\right) \quad (8)$$

The last step in the analysis is to compare the forecasting results from adaptive Holt-Winters exponential smoothing and RNN methods. The quality of these models is seen based on the RMSE and MAPE values.

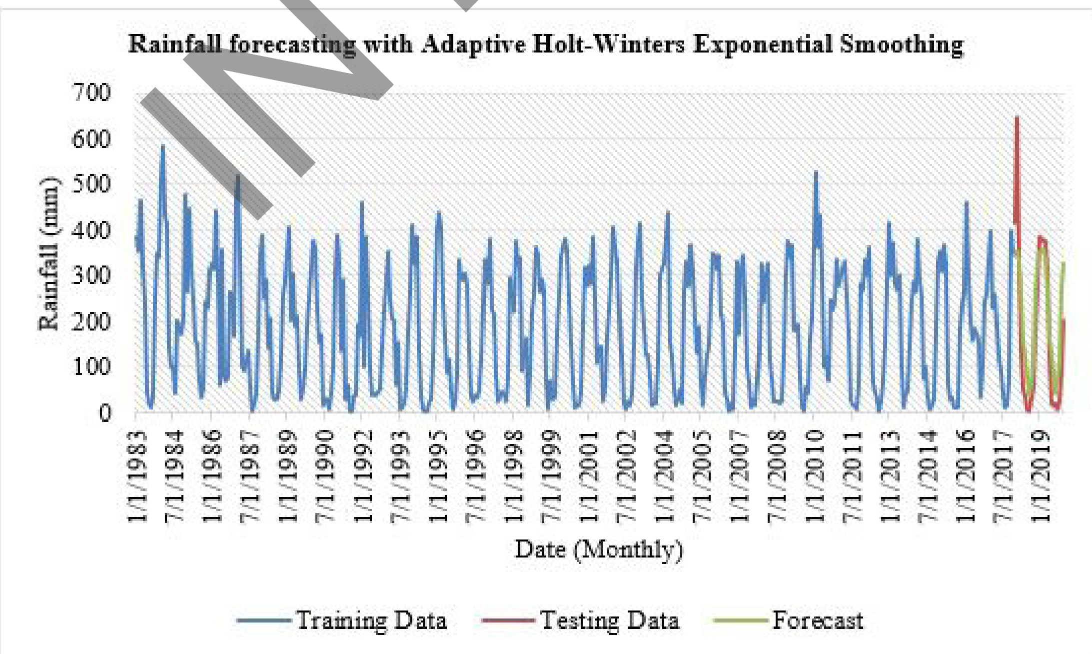

Figure 3 Forecasting Result Using Adaptive Holt-Winters Exponential Smoothing Method

Table 3 Forecasting Results with Holt-Winters Method

Period	Forecasting	Real value
Jan-18	345,2597	415,391
Feb-18	354,0832	646,085
Mar-18	333,3764	329,926
Apr-18	258,9343	142,132
May-18	157,3876	48,458
Jun-18	126,796	37,779
Jul-18	81,80796	7,178
Aug-18	35,98797	2,644
Sep-18	62,47146	27,175
Oct-18	110,8244	53,435
Nov-18	266,7231	172,99
Dec-18	323,7011	274,804
Jan-19	348,449	382,719
Feb-19	357,2726	374,508
Mar-19	336,5658	373,399
Apr-19	262,1237	312,03
May-19	160,5769	123,148
Jun-19	129,9853	20,936
Jul-19	84,99731	14,545
Aug-19	39,17732	19,858
Sep-19	65,66081	5,085
Oct-19	114,0137	21,198
Nov-19	269,9124	87,08
Dec-19	326,8905	201,843

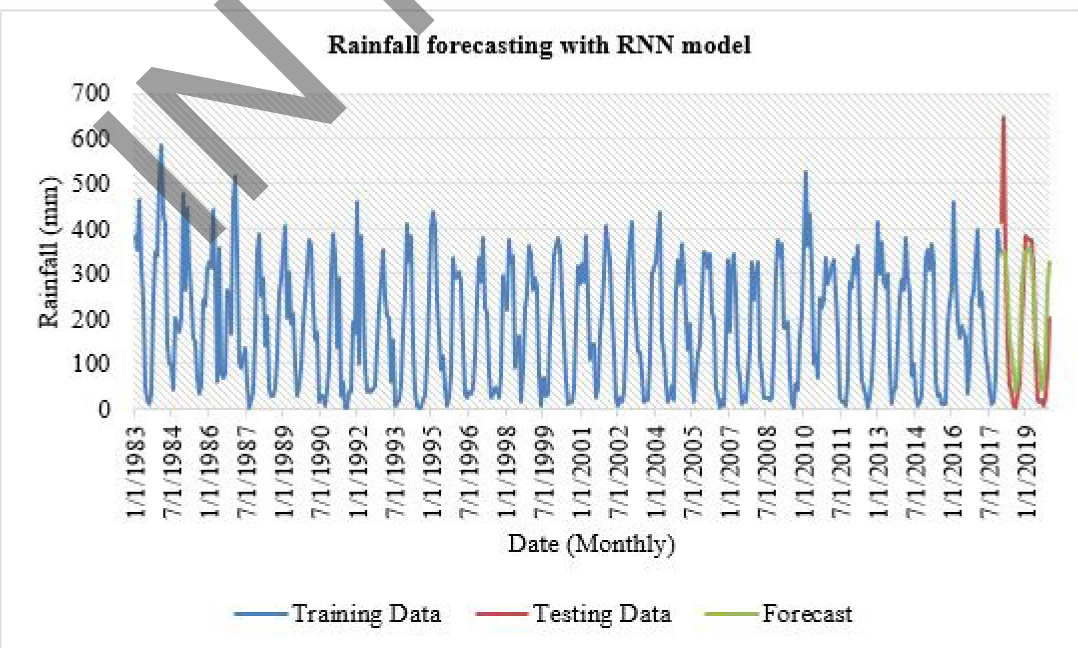

Figure 4 Forecasting Result Using Recurrent Neural Network (RNN) Method

Table 4 Forecasting Results with RNN Method

Period	Forecasting	Real value
Jan-18	368,6735	415,391
Feb-18	372,9232	646,085
Mar-18	403,2766	329,926
Apr-18	231,843	142,132
May-18	103,8684	48,458
Jun-18	68,23579	37,779
Jul-18	44,41058	7,178
Aug-18	36,16043	2,644
Sep-18	48,08866	27,175
Oct-18	136,2545	53,435
Nov-18	221,0298	172,99
Dec-18	276,7855	274,804
Jan-19	317,6795	382,719
Feb-19	354,1999	374,508
Mar-19	346,4235	373,399
Apr-19	280,2337	312,03
May-19	187,7113	123,148
Jun-19	90,72999	20,936
Jul-19	43,28327	14,545
Aug-19	26,61869	19,858
Sep-19	29,19619	5,085
Oct-19	67,8712	21,198
Nov-19	155,76	87,08
Dec-19	241,3827	201,843

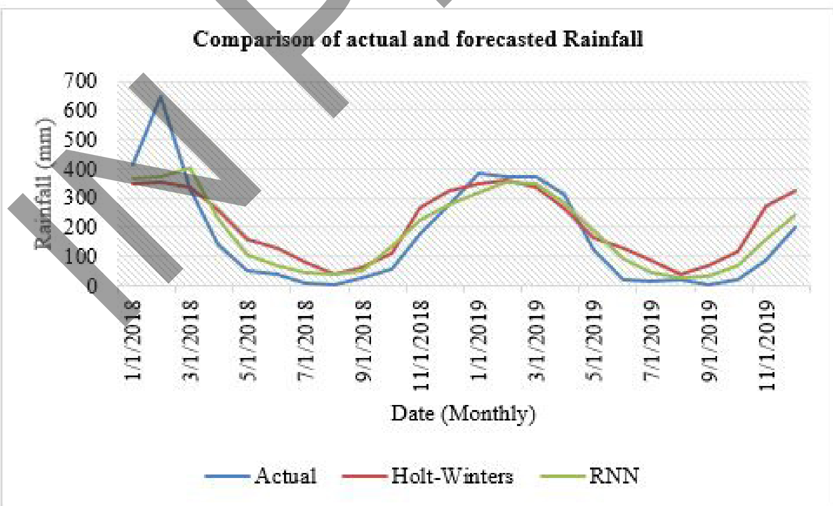

Figure 5 The Comparison between Actual Data and the Forecasting Results

Table 5 The Comparison Between RMSE and MAPE Values

Method	RMSE	MAPE
Adaptive Holt-Winters Exponential Smoothing	0,500	0,620
RNN	0,377	1,596

The result of the prediction of rainfall in Malang City using the adaptive Holt-Winters exponential smoothing and RNN methods has been analyzed, and the result is shown in Figure 5. Forecasting values from both methods are close to the actual data values. The RNN method produces forecasting values that are closer to the actual data. Then, RMSE and MAPE values from both methods are used to find out the best method.

Table 5 describes the performance of adaptive Holt-Winters exponential smoothing and RNN methods. adaptive Holt-Winters exponential smoothing method reveals the RMSE value of 0,500 and the MAPE value of 0,620. Meanwhile, the RNN method has an RMSE value of 0,3771 and a MAPE value of 1,596.

Adaptive Holt-Winters exponential smoothing method is a linear model that produces an error size in a larger sample than the RNN model. In addition, this model also produces a poor measure of the error in sample testing. Meanwhile, the results of the RNN model show better results in training data. This model also produces a better error measure in sample testing. From Table 5, it is evident that the RMSE and MAPE values for the RNN method provide a smaller value than adaptive Holt-Winters exponential smoothing method. The results contradict the research conducted by Suhartono and Subanar (2005) comparing the complex model and the simple model. The research shows that a more complex model does not always provide a better model. It can be caused by differences in the network architecture formed. For rainfall data in Malang City, the RNN model provides a better model than adaptive Holts-Winters exponential smoothing model. On the other hand, these results are in line with Krichene, Masmoudi, Alimi, Abraham, and Chabchoub (2017) and Dada, Yakubu, and Oyewola (2021) showing that the RNN method outperforms other models.

IV. CONCLUSIONS

Based on the results, it can be concluded that the non-linear model has better forecasting than the linear model. The results show that the RNN model provides better predictive results in training and testing data. Therefore, the RNN model can be used in modeling and forecasting trend and seasonal time series. In addition, forecasting using RNN will produce less accurate results when using a more complex model. However, in the research, rainfall forecasting only uses data from the previous time. It is observed that the accuracy of rainfall forecasting using the RNN method can be improved by considering other climatic parameters, such as evaporation, temperature, sunlight intensity, air pressure, and humidity as inputs.

Moreover, the RNN method provides good forecasting results but requires a long computational time. The computational process can be further improved by using more optimal methods such as a combination of RNNs and other machine learning techniques. Examining the validity of network parameters allows the RNN to obtain more accurate results for proper configuration. The performance of neural network models depends primarily on the problem domain and its dataset. The results provide an opportunity to conduct further research on trend forecasting and seasonal time series by combining several forecasting methods, mainly artificial neural network methods.

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