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RAINFALL FORECASTING WITH AN INTERMITTENT APPROACH USING HYBRID EXPONENTIAL SMOOTHING NEURAL NETWORK

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ABSTRACT

Rainfall forecasting is crucial in agriculture, water resource management, urban planning, and disaster preparation. Traditional approaches fail to capture complicated and intermittent rainfall patterns. The "Hybrid Exponential Smoothing Neural Network" is introduced in this study to handle intermittent rainfall forecasting issues. Exponential Smoothing, an established approach for discovering underlying patterns and seasonal fluctuations in time series data, is combined with Neural Networks, which are good at capturing complex linkages and nonlinearities. Using these two methods, this model hopes to deliver a complete rainfall forecasting solution that accounts for short-term changes and long-term patterns. This research uses residuals from the exponential smoothing model and is modeled using a Neural Network. The residual input is transformed using rolling mean. The results show that the hybrid model is able to capture patterns well, but there still exists patterns that experience time lag. Experimental results obtained reveal that the hybrid methodology performs better than the model exponential smoothing, implying that the proposed model hybrid synergy approach can be used as an alternative solution to the rainfall time series forecasting. The results show that the Hybrid method can form patterns better than individual exponential smoothing models or neural networks. The RMSSE values for all areas are 1.0185, 1.55092, 1.0872.

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1. INTRODUCTION

These days, the climate is very unpredictable, especially in tropical regions like Indonesia. By the empirical data, rain can even occur in the dry season. Thus, this can be very difficult to predict and harmful to farmers. Many ways can be done to predict the rainfall year by year. We can use artificial intelligence or innovative hardware like the Internet of Things in this era. The rainfall data can be collected using a machine called a rainfall recorder. That machine works by measuring the water from the rain on the same day, then the data is reported and stored on the website as an archive. Data is recorded as zero if there is a dry season. Thus, it makes the data sparse or contain many zero values in some periods. This problem also makes rainfall challenging to predict using an artificial model like Autoregressive Integrated Moving Average (ARIMA). Because the training data contain many zero values, the predicted value from ARIMA can be a negative number, which makes no sense. The rainfall predicted should be zero or more than zero [1].

Recently, machine learning methods have shown a potential to enhance the precision of weather predictions. In order to enhance rainfall forecasting, several research have looked at combining conventional time series approaches with machine learning strategies. Research on the use of Recurrent Neural Networks (RNNs) for predicting data on fluctuating demands traditional forecasting approaches, which presume continuous and steady patterns, might struggle to account for scenarios with intermittent demand data [2]. The research looks at combining Holt's Exponential Smoothing with Neural Network models to predict interval-valued time series data with the end goal of improving the precision with which uncertainty and variability may be captured across different application domains [3]. To further improve time series forecasting accuracy, another research provides a novel strategy [4] that blends Exponential Smoothing approaches with Recurrent Neural Networks.

The Neural Networks method is often used to create a forecasting model. We can calculate its predicted value using the lag data as an input neuron. Then, we can keep the data as a non-negative value with a specific activating function, such as the sigmoid function or ReLu function. Moreover, the Neural Network result is combined with The Exponential Smoothing method. We use the average for the ensemble and the error as the weighted value for the ensemble result. As long as the data contain many zero values, the evaluation score used in this study is Root Mean Squared Scaled Error (RMSSE). RMSSE (Root Mean Squared Scaled Error) and MSE (Mean Squared Error) tests are carried out to see the error value prediction, and a suitable error value is close to 0. Using Mean Absolute Error (MAE) or Mean Absolute Percentage Error (MAPE) will produce an undefined score because the formula is not robust for many zero data [1]. Moreover, we treat the rainfall data like intermittent data, using a rolling mean as an input neuron to the model. It will make the model more robust than only using lag data.

Research in rainfall forecasting is often done. Ref [5] uses machine learning to forecast rainfall data. The methodology comes from Multiple Linear Regression. Moreover, Ref [6] use some interesting approach in forecasting rainfall data. They used the fusion method to forecast the rainfall. Instead of forecasting the rainfall volume, they classified the original rainfall data into some classes. Then they create the model to predict the class from those data. This approach is interesting we just need to predict the class, and each class describes the volume of the rainfall. The proposed method uses an intermittent approach and combines two distinct methods, namely exponential smoothing and neural networks. Both of these methods are complementary to one another. Exponential smoothing techniques are particularly good in identifying underlying patterns in time series data as well as seasonal changes [7].

In this study, we explore an innovative approach for rainfall forecasting using the Hybrid Exponential Smoothing Neural Network model. The method we have developed combines the strengths of Exponential Smoothing in capturing intermittent patterns in rainfall data with the neural network's ability to understand complex relationships within the data. This research aims to enhance the accuracy of rainfall predictions, particularly in intermittent scenarios that are often challenging for traditional methods. The outcomes of this study are expected to make a significant contribution to our understanding of rainfall forecasting and can be applied in various domains, including water resource management, agriculture, and disaster mitigation. Modeling residuals using a neural network with rolling mean as an input is a common approach in outcome research involving time series data. In this context, rolling mean can be used as a feature input for your neural network.

2. RESEARCH METHODS

The research method for rainfall forecasting with an intermittent approach using a Hybrid Exponential Smoothing Neural Network typically involves several methodologies.

2.1 Exponential Smoothing

In the application of the exponential smoothing model, there are three types of models that are widely used in different time series. Simple exponential smoothing is used when the time series has no trend. Double exponential smoothing is an exponential smoothing method for handling a time series that displays a slowly changing linear trend. The third is Winters' method, which is an exponential smoothing approach to predicting seasonal data. Exponential smoothing is often used as a preferred technique for short-term demand forecasting, owing to its straightforwardness and precision, which outperforms more intricate approaches such as multiple regression and Box-Jenkins. The term "Jenkins" refers to a popular open-source automation server that is used for References [8], [9] that are cited in support of the preceding statement. Triple exponential smoothing is an extension of double exponential smoothing that is used to model and forecast seasonal time data. The Holt-Winters technique derives its name from the individuals who developed it. The approach developed by Holt was further improved by Winters with the use of a third parameter that accounts for the influence of seasonality. Hence, the proposed methodology effectively mitigates the impact of fluctuations in time series data, including diverse magnitudes, patterns, and periodicity. The Triple Exponential model has two fundamental variations that are contingent upon the kind of seasonality present. There are two types of seasonality models: additive and multiplicative. If the seasonality is multiplicative, which implies a non-linear relationship, the three smoothing equations for p-period cycles are as follows:

$$L_t = \alpha\left(\frac{X_t}{I_{t-p}}\right) + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{1}$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1} \tag{2}$$

$$I_t = \delta\left(\frac{X_t}{L_t}\right) + (1-\delta)I_{t-p} \tag{3}$$

The level (L_t) is estimated by the smoothed data value at the end of each period. The trend (T_t) is estimated by the smoothed average increase at the end of the period. I_t is seasonality adjusting equation, p is the number of periods in seasonal cycle and δ is its smoothing parameter such that $0 \leq \delta \leq 1$. Where α $(0 < \alpha < 1)$ and γ $(0 < \gamma < 1)$ are smoothing parameters for level and trend respectively.

2.2 Deep Learning Neural Network

Deep Learning Neural Networks (DLNN) is a Feed Forward Neural Networks (FFNN) with the number of hidden layers more than one. In the time series model, the relationship between outputs $\widehat{\boldsymbol{Y_t}}$ and inputs $(\boldsymbol{Y_{t-1}}, \boldsymbol{Y_{t-2}}, \dots, \boldsymbol{Y_{t-p}})$ in the DLNN model with two hidden layers is given as follows.

$$\hat{Y}_{(t)} = f^o\left[\sum_{i=1}^{s}\alpha_i f_i^{h_2}\left[\sum_{j=1}^{r}\beta_{ij} f_j^{h_1}\left(\sum_{t=1}^{p}\gamma_{it}X_{i(t)} + b_j^{h_1}\right) + b_i^{h_2}\right] + b^o\right] + \varepsilon_t \tag{4}$$

Where $\boldsymbol{\alpha_i}$ weight of neuron from second hidden layers to output layer, $\boldsymbol{b_i^{h_2}}$ are biases from neuron second hidden layer. The following is an overview of a deep learning neural network with 2 hidden layers presented in the Figure 1.

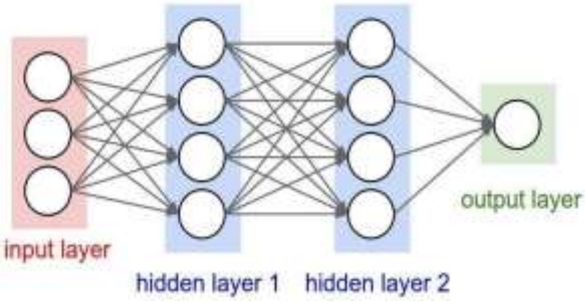


Figure 1. Illustration of Deep Learning Neural Network

The study uses two types of activation functions, namely Rectified Linear Unit (ReLU) and Adaptive Moment Estimation (ADAM). According to a study, the model using the ReLu activation function with 4 hidden layers and 50 neurons in each hidden layer had the highest accuracy score [10]. This shows that ReLu is able to do a good job as an activation function.

The ReLu (Rectified Liner Unit) function is an example of a non-linear operation in which activation of individual neurons does not occur simultaneously but rather only when the linear transform's output is a non-zero value. When used, the functions of ReLu are written on Equation (5)[11].

$$f(x) = \max(0, x) \tag{5}$$

The following of ReLu functions is shown in Figure 2.

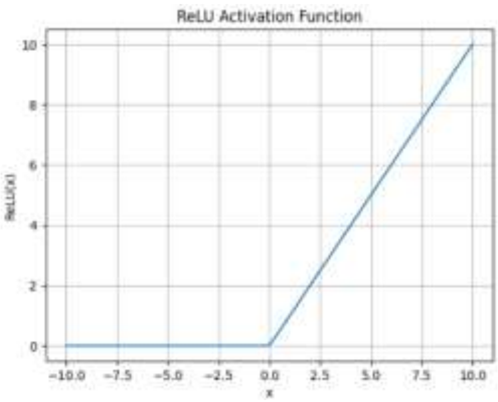


Figure 2. ReLu Activation

2.3 Hybrid Model

The hybrid forecasting approach is used to identify various trends in data. A mix of linear and nonlinear patterns, in particular, since each approach has a limited capacity to capture patterns based on the properties of the data [12]. The hybrid technique improves accuracy and detects the residual patterns of the original model. We integrate the Exponential smoothing with Neural Network. In general, the hybrid model is written as follows.

$$Y_t = L_t + N_t \tag{6}$$

Where L_t is a linear component and N_t denotes a residual. This hybrid model is estimated in two phases. The first step is to model the linear component to produce the residual Exponential Smoothing, which is then applied to by a Neural Network.

$$e_t = Y_t - \hat{L}_t \tag{7}$$

$$\begin{aligned} e_t &= f(e_{t-1}, e_{t-2}, \dots, e_{t-k}) + \varepsilon_t \\ &= \hat{N}_t + \varepsilon_t, \end{aligned} \tag{8}$$

Another research about hybrid method, The final forecast is made by merging ETS and ANN predictions. Performance study of the proposed technique is compared to ARIMA, ETS, MLP, and hybrid ARIMA-ANN models using 16 time series datasets. Experimental findings indicate the hybrid model's statistically promising performance for the datasets [13].

2.4 Intermittent Approach

The intermittent pattern of rainfall, defined by sporadic and irregular occurrences, poses particular obstacles for reliable forecasting. To overcome these issues, researchers have investigated a variety of intermittent techniques for rainfall forecasting that take into consideration the intermittency and irregularity of rainfall episodes. These methods often need the use of specialised techniques in order to successfully manage data gaps and identify underlying trends. In Neural Network, we apply an intermittent technique in input residual variables [14]. As input variables, we generate a rolling mean. Because it may lower the amount of zero values in the dataset, making the model more resilient and accurate. The rolling mean, often known as the moving average, is a widely used approach for smoothing out differences in time series data. The rolling mean equation can be written as in Equation (8)[15]:

$$Rolling\ mean(t) = \frac{1}{n}\sum_{i=t-w+1}^{t} x_i \qquad (9)$$

Where rolling mean (t) is the rolling mean value at time t, n is the rolling window size (number of data points), and w is its width. Figure 3 shows the rolling mean.

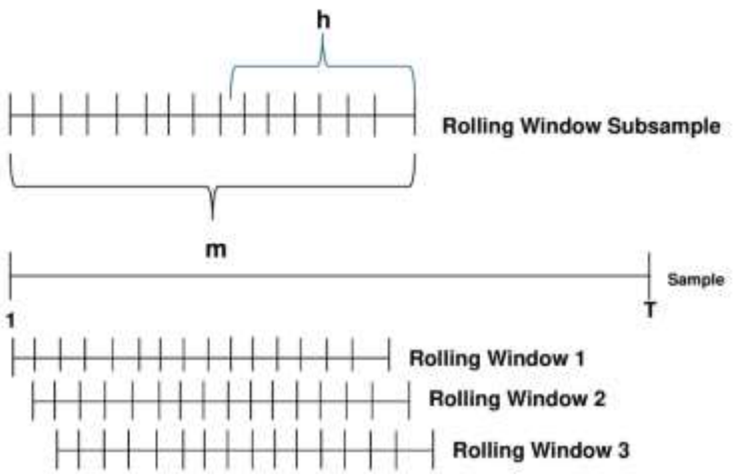


Figure 3. Rolling Mean Illustration

2.5 Metric Evaluation

The RMSSE (Root Mean Squared Scaled Error) is a metric used for evaluating the accuracy of forecasting models, especially in the context of time series forecasting. It is commonly used in research methods involving forecasting, including those related to rainfall forecasting. The RMSSE is a scaled version of the RMSE (Root Mean Squared Error) that takes into account the seasonality and the actual variability in the data, the equation of RMSSE can be written as in Equation (9) [16]:

$$RMSSE = \sqrt{\frac{\frac{1}{h}\sum_{t=n+1}^{n+h}(y_t-\hat{y}_t)^2}{\frac{1}{n-1}\sum_{t=2}^{n}(y_t-y_{t-1})^2}}, \qquad (10)$$

Where y_t is the actual future value of the examined time series at point t, $\hat{y}_t$ is the forecast by the method under evaluation, n is the length of the training sample (number of historical observation), and h is the forecasting horizon.

2.6 Model Training

The method used in this study is known as:

1. Data Preparation: Gather rainfall data for the chosen timeframe. Data was obtained from PSAWS Buntung Peketingan Surabaya, Department of public Works. Table 1 lists study variables.
2. Data Processing: Split train set: from 1 Janauary 2009 to 30 November 2018 of 3621 data. Test Data: from 1 December 2018 to 31 Desember 2018 of 31 Data.
3. Exponential Smoothing Model: Identify the parameters in your chosen exponential smoothing model that need tuning. Common parameters include smoothing level (alpha), smoothing sslope (gamma) , and smoothing seasonality (delta ref on equation (1,2,3)
4. Hybrid Neural Network: Uses 2 hidden layers, where the input is in the form of residual from the Exponential Smoothing model. Optimization using relu and Adam.
5. Model Evaluation: Validate the Neural Network's performance using validation data. Use appropriate evaluation metrics use RMSSE.
6. Result and discussion.
7. Conclusion.

The research steps are illustrated with a flowchart in **Figure 4**.

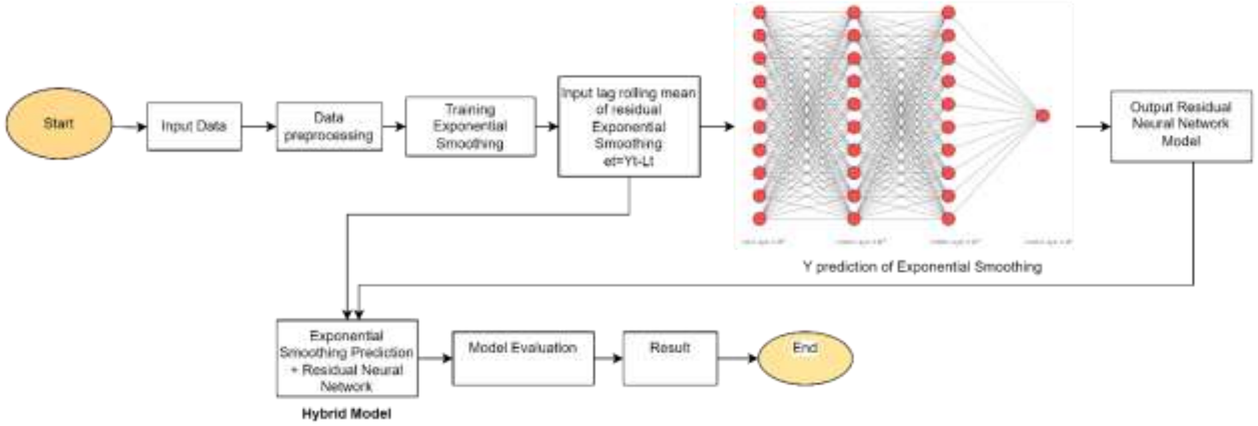


Figure 4. Flowchart of Research

Algorithm Hybrid: The proposed Methodology
1. Given a time series $y_t = [y_1, y_2, \ldots, y_n]^T$
2. Split Split train set: from 1 January 2009 to 30 November 2018 of 3621 data. Test Data: from 1 December 2018 to 31 December 2018 of 31 data.
3. Determine the best Exponential Smoothing using tuning parameter α, γ, δ (as ES parameter). Smoothing_level: [0.1,0.2,0.3,0.4,0.5,0.6] Smoothing_trend: [0.1,0.2,0.3,0.4,0.5,0.6] Seasonal: [3,6]
4. Obtain predictions using selected model $\hat{y}_t = [\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n]^T$
5. Obtain the residual series by subtracting Exponential Smoothing predictions from the original series which represents the second component $e_t = Y_t - \hat{L}_t$
6. Create trend effect and dummy effect of rainfall event. Trend Effect: $t = 1,2,3, \ldots, n$ Rainfall Event: 1, if there is rainfall; 0, if there is no rain.
7. Perfom rolling mean from residual series Exponential Smoothing model. This research use range of rolling mean are 7,8,9,10,11,12,13, and 14.
8. Obtain predictions using Neural Network. Input: 10 input layers 2 hidden layers Using ReLu Activation and ADAM optimization.
9. Final Predictions are obtained by combining.

3. RESULTS AND DISCUSSION

The exponential smoothing approach and neural networks are both considered trustworthy techniques in time series forecasting models. By integrating both methods, it is anticipated that this approach will provide a greater degree of acccuarcy in comparison to using each technique alone. The rationale for the integration of these two models stems from the underlying notion that a single model alone is incapable of fully capturing all the properties shown bu time series data.

3.1 Hybrid Forecasting

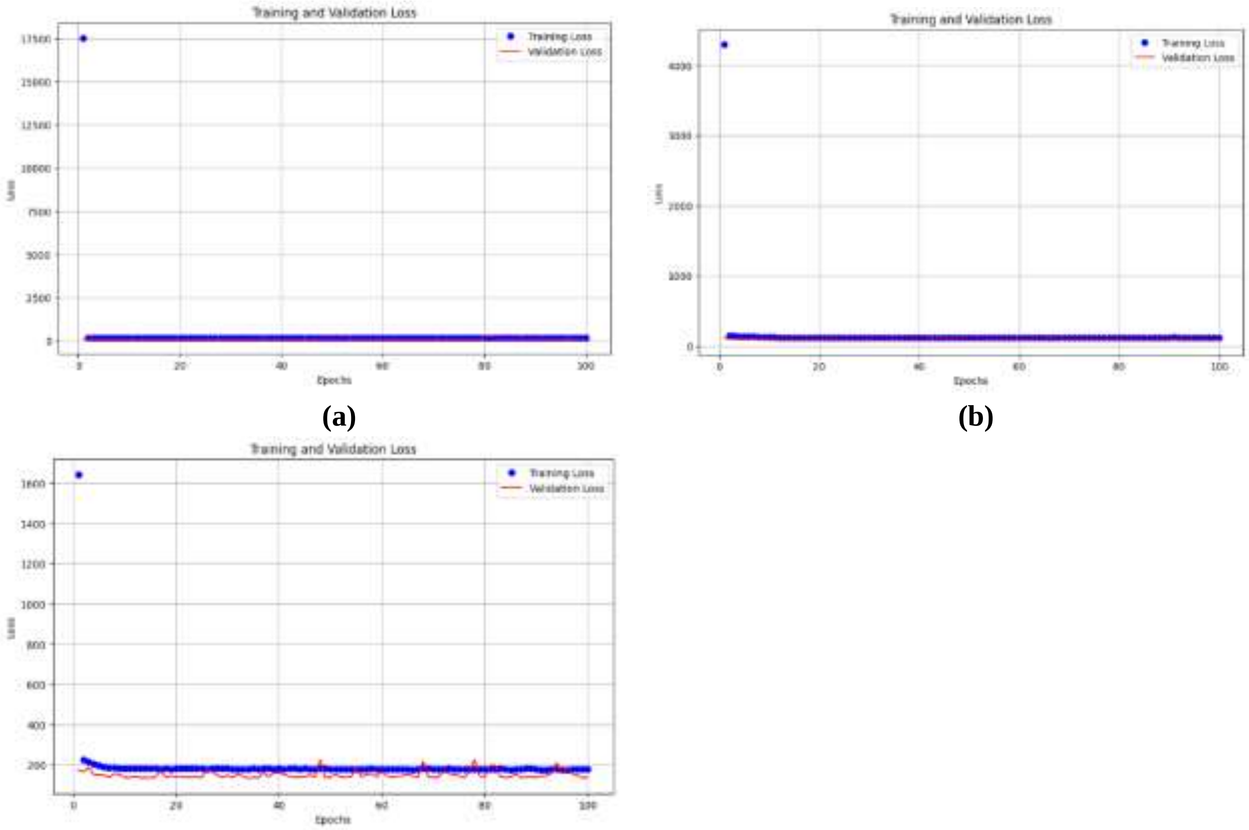
Hybrid Modelling between Exponential Smoothing and Neural Networks. Before doing a hybrid with a Neural Network, we have to do Exponential Smoothing modeling at three locations. Parameters that need to be optimized in exponential smoothing are smoothing level (alpha), smoothing slope (gamma), and smoothing seasonality (delta) presented in **Table 2**.

Table 2. Optimum Parameter of Exponential Smoothing

Located	SmoothingLevel	Smoothing Trend	Seasonal periods
Keputih	0.4	0.6	6
Kedung Cowek	0.1	0.1	6
Gubeng	0.1	0.1	3

The proposed hybrid algorithm is illustrated according to **Figure 4**, which models the residuals using the rolling mean as the NN input. The rolling mean used is 7 to 14.

The results of training loss and validation loss are shown in **Figure 5**.



(a) (b)

(c)

Figure 5. Training loss and Validation Loss of Deep Learning Neural Network (a) Training and Validation Loss Keputih, (b) Training and Validation Loss Kedungcowok, (c) Training and Validation Loss Gubeng

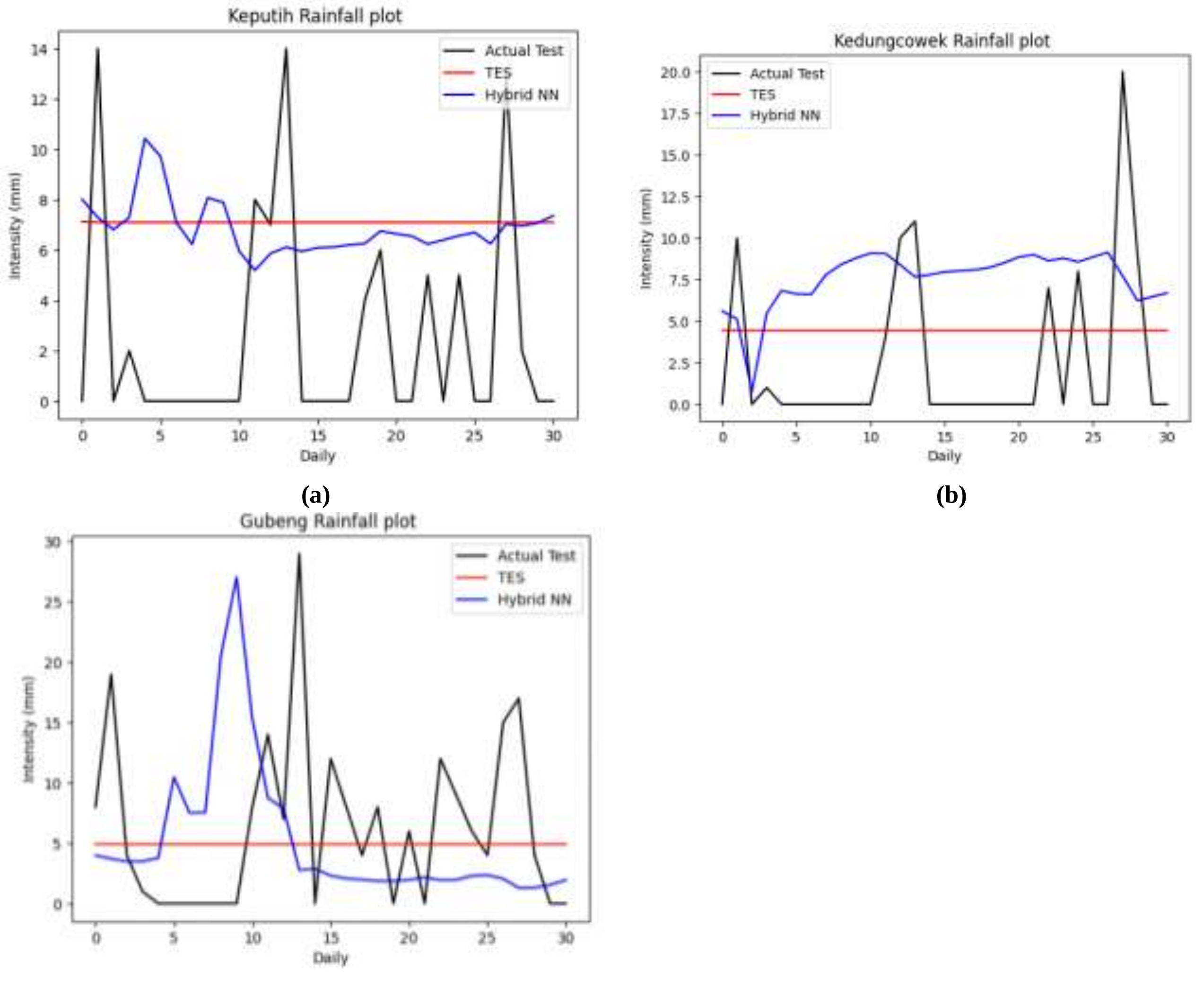
The training loss metric quantifies the effectiveness of the model in learning from the training data. The validation loss metric measures the extent to which your model is capable of generalizing to unseen data during training. Under ideal conditions, it is expected that these two loss values have a low level and decrease as the number of epochs increases. However, keep in mind that attention must also be paid to the possibility of overfitting if there is an increase in the validation loss value.

The primary objective is to monitor the validity loss throughout training. Ideally, it is expected that validation loss will decrease along with training loss, which indicates that the model is not only able to study the training data well, but also has the ability to make good generalizations. If the validation loss starts to increase while the training loss continues to decrease, it might be indicative of overfitting. In this context, it is advisable to consider the option of stopping training early or applying regularization or dropout techniques as a solution to the problem at hand.

Table 3. Training of Deep Learning Neural Network

Located	Input Layer	Hidden layer	Training Loss & Validation Loss
Keputih	10	2 (15,15)	loss: 159.8032 - val_loss: 106.0436
Kedung Cowek	10	2(10,15)	loss: 117.9217 - val_loss: 92.4553
Gubeng	10	2(10,10)	loss: 186.9310 - val_loss: 159.9060

This study does not use the optimum number of hidden layers, because the number of hidden layers does not affect accuracy, so we use the same [9].



(a) **(b)**

(c)

Figure 6. Actual and Predict Test of Hybrid Neural Network (a) Keputih Rainfall plot, (b) Kedungcowek Rainfall plot, and (c) Gubeng Rainfall plot

Table 4. Metrics Evaluation

Located	RMSSE Model *Exponential Smoothing*	RMSSE Model *Hybrid Exponential Smoothing Neural Network*
Keputih	4.88	1.0185
Kedung Cowek	5.45	1.55092
Gubeng	6.99	1.0872

From the RMSSE (Root Mean Squared Scaled Error) results for three different locations (Located). The RMSSE value at the Keputih location is more than 1.0, which indicates that the model has a significant error rate in predicting rainfall data at this location.

The model tends to perform less well in predicting rainfall in Keputih. The RMSSE at the Kedung Cowek location is more than 1.0, which also indicates a significant error rate in rainfall prediction. The model has similar performance to Keputih, with a fairly high level of inaccuracy. Gubeng has a lower RMSSE of 1.0, indicating that the model may be better at predicting rainfall at this location compared to Keputih and Kedung Cowek. Even though the RMSSE is still high, the model performance in Gubeng seems to be better compared to other locations.

Thus, the results of inaccuracies due to intermittent effects on the testing data indicate a challenge that needs to be overcome in rainfall modeling. With the right approach, deep understanding of the data, and continued effort, it is likely that the model can be scaled up to provide more accurate predictions of rainfall.

4. CONCLUSIONS

The analysis highlights the importance of monitoring training loss and validation loss metrics in rainfall modeling using Deep Learning Neural Networks. Ideally, these two losses should be low and decrease as the number of epochs increases. However, keep in mind that an increase in the validation loss value may indicate overfitting. The study also notes that using the optimal number of hidden layers is not always necessary, especially if the number of layers does not affect the accuracy of the model.The results of the hybrid model evaluation show that rainfall predictions in several locations have a significant level of inaccuracy, especially in Keputih and Kedung Cowek. Gubeng shows a lower level of inaccuracy compared to other locations.

The final conclusion is that the intermittent effect on the test data is a challenge that needs to be overcome in rainfall modeling. However, with the right approach, model improvements, and a deep understanding of the data, there is potential to improve the accuracy of rainfall predictions at various locations.This conclusion emphasizes the importance of continuing research and development in rainfall modeling to provide more accurate and useful results in various applications. Based on the RMSSE comparison results for the two methods in the table above, it can be seen that the hybrid exponential smoothing neural network model is more accurate than the exponential smoothing model because the RMSSE value is smaller at each of the Gubeng, Keputih, and Kedung Cowek observation posts. Experimental results obtained reveal that the hybrid methodology performs better than the model exponential smoothing, implying that the proposed model hybrid synergy approach can be used as an alternative solution to the rainfall time series forecasting.

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