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The Application of the Long-Short Term Memory (LSTM) Forecasting Method on the Impact of Tropical Cyclones in Indonesia

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Abstract
Effective disaster mitigation strategies are paramount in the realm of risk management concerning natural calamities, with the primary objective of mitigating potential devastation. A pragmatic and impactful method involves predicting the contributory aspects of such disasters, encompassing variables such as torrential rainfall and formidable wind velocities that tropical cyclones bring. In this study, a comparative analysis of forecasting methodologies is undertaken, precisely the Long Short-Term Memory (LSTM) technique and the Holt Winter approach, both directed toward gauging the impact of tropical cyclones. This investigation focuses on two critical factors: the forecast of precipitation intensity and the estimation of maximum wind speed. The outcomes underscore the superior predictive capabilities of the LSTM method, unequivocally revealing its aptitude for predicting rainfall and wind speed. Impressively, the LSTM method yields remarkable precision levels of 97.433% for rainfall and an even higher accuracy of 99.018% for maximum wind speed forecasting. In essence, this study highlights LSTM's efficacy in disaster prediction with substantial accuracy.

Keywords: risk management, forecasting, rainfall, wind speed, LSTM.

Abstrak
Strategi mitigasi bencana yang efektif merupakan hal yang terpenting dalam bidang manajemen risiko bencana alam, dengan tujuan utama memitigasi potensi kehancuran. Metode yang pragmatis dan berdampak melibatkan prediksi aspek-aspek yang berkontribusi terhadap bencana-bencana tersebut, yang mencakup variabel-variabel seperti curah hujan deras dan kecepatan angin kencang yang ditimbulkan oleh siklon

tropis. Dalam studi ini, dilakukan analisis komparatif metodologi peramalan, yakni teknik Long Short-Term Memory (LSTM) dan pendekatan Holt Winter, yang keduanya ditujukan untuk mengukur dampak siklon tropis. Investigasi ini berfokus pada dua faktor penting: perkiraan intensitas curah hujan dan perkiraan kecepatan angin maksimum. Hasil penelitian ini menunjukkan kemampuan prediksi yang unggul dari metode LSTM, yang secara jelas menunjukkan kemampuannya dalam memprediksi curah hujan dan kecepatan angin. Yang mengesankan, metode LSTM menghasilkan tingkat presisi yang luar biasa sebesar 97,433% untuk curah hujan dan akurasi yang lebih tinggi lagi yaitu 99,018% untuk perkiraan kecepatan angin maksimum. Intinya, penelitian ini menyoroti kemanjuran LSTM dalam prediksi bencana dengan akurasi yang tinggi.

Kata kunci: manajemen risiko, peramalan, curah hujan, kecepatan angin, LSTM.

1. INTRODUCTION AND PRELIMINARIES

Introduction

A natural disaster can be defined as any event that can threaten life and disrupt people's lives caused by natural factors. Based on data compiled by the Badan Nasional Penanggulangan Bencana (BNPB), there have been 1354 natural disasters since the beginning of 2022, of which 504 are caused by extreme weather. Extreme weather can cause several disturbances, including tropical cyclones [1].

Tropical cyclones frequently affect Indonesia due to its equatorial location, making it susceptible to the Coriolis effect. These cyclones, also called tropical storms or typhoons in some areas, bring about destructive consequences that endanger both lives and infrastructure [2]. The Badan Meteorologi, Klimatologi, dan Geofisika (BMKG) has identified 11 Indonesian provinces at risk of tropical cyclones, with heavy rainfall and strong winds being their primary repercussions. East Java, for instance, is among the affected regions. Recent data from the Badan Nasional Penanggulangan Bencana (BNPB) indicates that East Java experienced six tropical cyclone incidents from the beginning of April to April 16, 2022, affecting areas like Sidoarjo, Ponorogo, Pasuruan, and Magetan. These cyclones result in intense rainfall and powerful winds, causing considerable destruction and losses. It is imperative to develop strategies to manage and mitigate these impacts effectively.[3].

Animas conducted research on rainfall forecasting in 2022. This study presents a comparative analysis of machine learning algorithms for forecasting rainfall in five major British cities. The results showed that the Bidirectional-LSTM method could be used as a rainfall forecasting model that has comparable performance to the Stacked-LSTM. Among all tested models, Stacked-LSTM with two hidden layers and Bidirectional-LSTM had the best performance. This shows that the LSTM with a small number of hidden layers can be used to forecast rainfall. Meanwhile, the Holt-Winter (HW) method, as one of the simple forecasting methods, is often used for forecasting data that has seasonal trends. Sinay et al., in 2019, conducted a study to predict rainfall in Ambon city using the HW method. The results show that the HW method can predict rainfall well, which is indicated by the small RMSE value [4].

Based on the background of the problems described, this study discusses forecasting rainfall and wind speed, which is the main impact of the tropical cyclone disaster in East Java, using the Long-Short Term Memory (LSTM) and Holt-Winters (HW). The results of this study are expected to be the basis for determining the management of hurricane disaster due to extreme weather changes and can provide an overview of the situation in the future.

Literature Review

Tropical Cyclones in Indonesia

Weather in Indonesia is influenced by several factors, including local influences, monsoonal winds, trade winds, the Inter Tropical Convergence Zone (ITCZ), El Nino and La Nina phenomena, dipole mode phenomena, and finally, tropical depressions and cyclones. Tropical cyclones are one of the regional-scale phenomena that occur in tropical oceans, causing significant impacts due to their large size, strong winds, and dense cloud clusters. These impacts include high winds, continuous heavy rainfall, and prolonged flooding, as well as high waves and storm surges. An example of the direct impact of a tropical cyclone in Indonesia was observed during the rare event of Tropical Cyclone Kirrily passing over the Kai Islands, Banda Sea, on April 27, 2009, which resulted in heavy rainfall and storm surge, damaging dozens of houses, flooding others, causing road damage, and generating high waves from April 26 to 29, with recorded 24-hour rainfall of 20 mm, 92 mm, and 193 mm on April 27, 28, and 29, 2009, respectively [5].

Long-Short Term Memory

Long-Short Term Memory (LSTM) is a deep machine learning method developed by Hochreiter and Schmidhuber in 1997. This development is applied to overcome the vanishing gradient problem found in the Recurrent Neural Network (RNN) architecture [6]. The LSTM architecture studies long-term dependencies and allows the network to handle and normalize an unlimited number of states [7]. The basic architecture of the LSTM used in this study is shown in Figure 1.1

LSTM mathematical formula can be shown as follows.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i x_i + U_i h_{t-1} + b_i) \tag{2}$$

$$\widetilde{c_t} = tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{3}$$

$$c_t = f_t \times C_{t-1} + i_t \times \widetilde{c_t} \tag{4}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{5}$$

$$h_t = o_t \times \, tanh(c_t) \tag{6}$$

The LSTM mechanism revolves around the cell state c_t, which is written on equation (4) and (6). In the cell state, information is added or deleted through three gates: forget gate f_t, input gate i_t, and output gate o_t. Gates evaluates whether sequential data on the input is stored and passed to the last stage. After that, based on equation (1), the forget gate decides to add or remove information. Information will be stored if the value of f_t is close to one and will be removed if f_t is close to zero. Input gates are calculated to update the cell state. Through this update, an evaluation of the importance of the input sent into the next cell is carried out. Next, the output gate is used to calculate the output in the hidden state based on equation (5). The respective activation and repetitive activation functions used in the LSTM are hyperbolic tangent functions (denoted as $tanh$) and sigmoid functions (denoted as σ) [8].

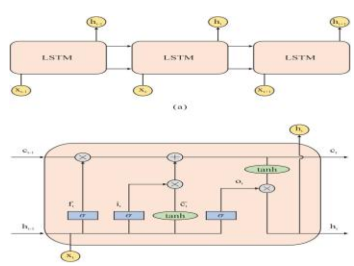


Figure 1.1 Long-Short Term Memory Architecture (a) Basic structure, (b) Detailed structure

Holt-Winter Model

The Exponential Smoothing forecasting method on the time series is used when the data shows trends and seasonal patterns [9]. This method produces predictions as a weighted average of past observations with weights that decrease exponentially with increasing observation time. The Triple Exponential Smoothing method is also known as the Holt-Winter model. This method helps capture the trend and seasonal components. Based on the type of seasonality, there are two variations of the Holt-Winter model, namely additive and multiplicative. The additive method can be applied if the seasonal component is constant. In contrast, the multiplicative method is used if the size of the seasonal component changes in proportion to the trend level [10].

The multiplicative Holt-Winter model can be written mathematically in the following equation.

$$L_t = \alpha\left(\frac{y_t}{S_{t-s}}\right) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{7}$$

$$b_t = \beta\,(L_t - L_{t-1}) + (1-\beta)\,b_{t-1} \tag{8}$$

$$S_t = \gamma\left(\frac{y_t}{L_t}\right) + (1-\gamma)\,S_{t-s} \tag{9}$$

$$F_{t+k} = (L_t + kb_t\,)S_{t+k-s} \tag{10}$$

The following is the basic additive Holt-Winter equation.

$$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{11}$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)\,b_{t-1} \tag{12}$$

$$s_t = \gamma(y_t - L_t) + (1-\gamma)\,S_{t-s} \tag{13}$$

$$F_{t+k} = L_t + kb_t + S_{t+k-s} \tag{14}$$

where L_t is the level in period t, y_t data at time t, b_t trend in period t, S_t is the seasonal component of period t, F_{t+k} is the reuslt of forecasting in period $t+k$, and s is seasonal length. Meanwhile, α, β, γ show the smoothing parameters with values of 0 and 1 [11].

3. METHODOLOGY

Data

The data used in this study is monthly rainfall and wind speed in East Java (Pos Juanda) from 2007 to 2021. Data for these variables will be obtained from the website of the Central Statistics Agency (BPS) of East Java Province, BMKG, and NOOA National Centers. For Environmental Information (NCEI) (https://www.ngdc.noaa.gov). Rainfall data used are in millimeters (mm).

Methods

The framework and stages of analysis in this study include, first, problem identification. From the results of the problem identification, it was found that there two main effects of tropical cyclones: rainfall and wind speed. Furthermore, a literature study is carried out to understand better the theoretical basis that supports or relates to the problem to be solved. Then data collection is carried out. The collected data were analyzed using the Long-Short Term Memory (LSTM) and Holt-Winter (HW) methods. The proportion of training and testing data is 80:20. Modeling using LSTM is carried out with a trial-error process on selecting the number of layers, neurons, and dropout parameters to get maximum accuracy. Meanwhile, the selection parameter is made automatically using HW to get the maximum accuracy value. Then, the two models are compared for their accuracy values , and the best model is chosen with the greatest accuracy value. The best model is used to forecast rainfall and wind speed in 2022. The analysis was carried out using Python and R Studio software.

4. MAIN RESULTS

In this section, rainfall and wind speed values are modeled using Long-Short Term Memory and Holt-Winter. The results of the analysis are described as follows:

Modeling Rainfall and Wind Speed Using Long-Short-Term Memory

Forecasting using the Long-Short Term Memory (LSTM) method requires several parameters that must be defined and determined first. Parameters are determined by selecting value variations based on previous research and a trial-error process to get the best model. The following table describes the parameters used in this study and their accuracy values.

Table. 4.1 Long-Short Term Memory Parameters

Parameter	Rainfall	Wind Speed
Optimizer	Adam	
Learning Rate	0.0001	
Epoch	10,000	
Batch Size	32	
Hidden Layer	3	
Dropout	0.2	
Neuron	100, 50, 256	100, 50, 50
Accuracy	97.433%	99.018%

Based on Table 4.1, it can be seen that rainfall can be modeled very well with the LSTM, which has three hidden layers with 100 neurons in the first layer, 50 in the second, and 256 in the third. The accuracy value obtained is 97.433%. In comparison, the best wind speed model has an accuracy value of 99.018%, received in the model with three layers, with 100 neurons in the first layer, 50 in the second, and 50 in the third.

Modeling Rainfall and Wind Speed using Holt-Winter

The Holt-Winter method is used to model data that has seasonal and trend properties. In this study, the seasonal rainfall and wind speed data length are assumed to be twelve because the data used are monthly. Suppose α, β, γ represent smoothing parameters to update the average, trend, and seasonal indices, smoothing the estimation results parameters for the Holt-Winter model are presented in Table 4.2.

Table 4.2 Estimation Results of Smoothing Parameters Using Holt-Winter Model

Predictor Variable	Rainfall	Wind Speed
α	0.0003	0.0003
β	0.0001	0.0001
γ	0.002	0.002
Seasonal Effect	Additive	Additive
Accuracy	58.807%	39.707%

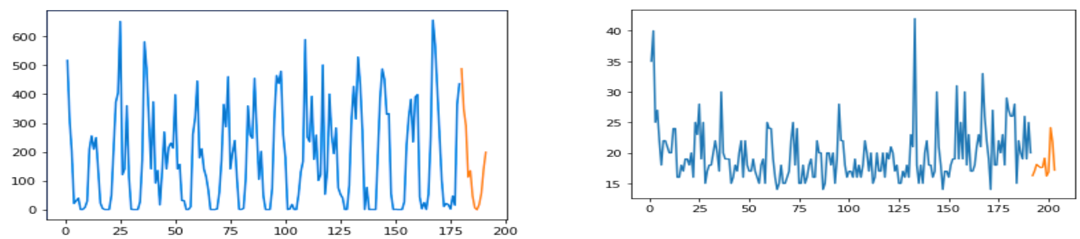
Based on the results in Table 4.2, the mathematical equation of the Holt-Winter model on rainfall and wind speed can be written as in the form of equation (11) to (14), as follows.

$$L_t = 0.0003(y_t - S_{t-s}) + 0.9997(L_{t-1} + b_{t-1})$$
$$b_t = 0.0001(L_t - L_{t-1}) + 0.999\ b_{t-1}$$
$$s_t = 0.002(y_t - L_t) + 0.998\ S_{t-s}$$

$$F_{t+k} = L_t + kb_t + S_{t+k-s}$$

Forecasting Using the Best Model

Based on the level of accuracy produced by the two models, as shown in Tables 4.1 and 4.2, it can be concluded that the LSTM method has the best level of accuracy for the two data studied, namely rainfall data and wind speed data. Hence, the forecasting on both data is conducted by using stacked LSTM. Figure 4.1 is the forecasting result for monthly Maximum Rainfall and Wind Speed Data for the next 12 months or in 2022. In Figure 4.1, the blue line shows the actual historical data used in this study, while the orange line shows the forecasting results.



(a) (b)

Figure 4.1 Forecasting results using Stacked-LSTM, on: (a) Rainfall and (b) Maximum Wind Speed

Based on Figure 4.1, the rainfall forecasting results show the same trend for the next 12 months, namely rainfall decreases at the beginning of the year to June and continues to increase at the end of the year. However, the maximum wind speed forecasting results show that the maximum wind speed can only reach 25 m/s next year.

5. CONCLUSION

The research detailed in this paper underscores a compelling revelation: the LSTM method distinctly outperforms the Holt Winter method in accuracy. This superiority is evident not just within wind speed data but also in the intricate realm of rainfall patterns, even when confronting pronounced seasonal fluctuations. This outcome carries substantial implications. The application of the LSTM method as a forecasting tool empowers us to predict the ramifications of tropical cyclones with remarkable precision. This predictive capability holds profound promise in bolstering disaster preparedness and management strategies.

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