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Prediction of Sea Surface Current Velocity and Direction Using LSTM

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Abstrak

Labuan Bajo dianggap memiliki peranan yang penting sebagai jalur transportasi para pedagang dan wisatawan. Karena itu, diperlukan adanya pemahaman lebih lanjut mengenai kondisi perairan di Labuan Bajo, salah satunya adalah arus laut. Tujuan dari penelitian ini adalah untuk memprediksi kecapatan arus permukaan laut beserta arahnya menggunakan LSTM. Terdapat banyak metode prediksi salah satunya adalah Long short-term Memory (LSTM). Prinsip kerja LSTM adalah memproses suatu informasi dari memory sebelumnya dengan melalui tiga gate yaitu forget gate, input gate dan output gate sehingga menghasilkan output yang akan menjadi input pada proses berikutnya. Berdasarkan uji coba dengan beberapa parameter antara lain Hidden Layer, Learning Rate, Batch Size, dan Learning rate drop period diperoleh nilai MAPE terkecil pada komponen U dan komponen V sebesar 14.15% dan 8.43% dengan parameter hidden layers 50, Batch size 32 dan Learn rate drop 150.

Kata kunci*—LSTM, Labuan Bajo, Sea Surface Current Velocity*

Abstract

Labuan Bajo is considered to have an important role as a transportation route for traders and tourists. Therefore, it is necessary to have a further understanding of the condition of the waters in Labuan Bajo, one of them is sea currents. The purpose of this research is to predict sea surface flow velocity and direction using LSTM. There are many prediction methods, one of them is Long short-term memory (LSTM). The fundamental of LSTM is to process information from the previous memory by going through three gates, that is forget gate, input gate, and output gate so the output will be the input in the next process. Based on trials with several parameters namely Hidden Layer, Learning Rate, Batch Size, and Learning rate drop period, it achieved the smallest MAPE values of U and V components of 14.15% and 8.43% with 50 hidden layers, 32 Batch size and 150 Learn rate drop.

Keywords— *LSTM, Labuan Bajo, Sea Surface Current Velocity, Predict*

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1. INTRODUCTION

Labuan Bajo is located on the west coast of Flores Island, Komodo, West Manggarai. Based on its strategic location, Labuan Bajo has become a center of trade, therefore Ferry Pier, PELNI Port, Komodo Airport, and a tourism center were built because Labuan Bajo is one of the closest gateways when tourists want to visit Komodo National Park [1] so tourists wanting to go to Komodo National Park will pass Labuan Bajo first. This makes Labuan Bajo play an important role in the transportation route for traders and tourists. Because of this important role, it is necessary to have a further understanding of the condition of the waters in Labuan Bajo to anticipate bad incidents that will occur, such as the incident which took place on January 21, 2020, a Pinisi ship carrying a group of journalists and staff from the Presidential Palace Press Bureau sank in Labuan Bajo due to bad weather (Source: kompas.com). One of the water conditions which is important for further study is sea currents [2]. Therefore, it is important to discuss sea currents further to produce information in terms of shipping, tourists, and marine resource management.

The discussion to determine the velocity of the sea surface currents in the future can be conducted using predictions. The prediction of sea currents has previously been conducted using the Holt-Winters Exponential Smoothing method in the waters of the Bali Strait. The results obtained showed that the MAPE of U and V components, respectively were 49.837% and 50.98% [3], because MAPE was more than 50% it can be said that the Holt-Winters Exponential Smoothing method was not appropriate for predicting sea current velocity. Another researcher conducted a research on the velocity of sea currents using the Backpropagation method. The results obtained reached MAPE value of 0.57% with 80% training data, 100 hidden layer nodes, and 0.1 learning rate [4].

In other problems, Divit Karmiani conducted a study comparing the Backpropagation method, SVM Kalman Filter with Long Short-Term Memory (LSTM) for stock predictions. The results obtained using the T-test and a combination of the backpropagation-LSTM method was 0.39, LSTM method had a smaller variant than Backpropagation, it can be concluded that LSTM was better than Backpropagation and SVM Kalman Filter [5]. Further research predicted economics and finance using ARIMA and LSTM. The results of the financial data showed that the ARIMA and LSTM methods reached RMSE values of 511.48 and 64.21, and those of the economic data showed the ARIMA and LSTM methods had RMSE values of 5,99 and 0.94. The researcher concluded that the LSTM method was better than the ARIMA method [6].

Further research on daily river flow analysis to Ermenek hydroelectric dam, Turkey used ANN, simple RNN, Deep RNN, Bi-LSTM, LSTM, and GRU methods. The results showed the three best methods, RNN, ANN, and LSTM with RMSE reached the values of 17.92, 18.71, and 0.87, so it can be concluded that LSTM could work well for prediction [7]. The LSTM method was also used by Ismail Kirbas to predict COVID-19 cases in eight European cities and he conducted an analysis comparing LSTM, ARIMA, and NARNN. The results of the analysis showed that the SMAPE values of the LSTM, ARIMA, and NARNN methods, respectively were 0.16-2.55, 0.34-5.46, 0.27-7.95 [8].

Based on several previous research, the LSTM method produces a better level of accuracy than other methods, so the researcher will use the LSTM method to predict the velocity of sea surface currents in Labuan Bajo. This research is accompanied by a discussion of the direction of sea surface currents, where the current pattern consists of an east to west direction and a north to south direction which has not been explained in previous researches. It is expected that the LSTM method can be used to predict the velocity of sea surface currents so that it can be helpful in trade, tourism, or other aspects.

2. METHODS

2.1 Data Collection

The type of research used in this research was quantitative. The coordinates where the research was taken were -8.368 ° south latitude and 119.755 ° east longitude which shown in Figure 1. The data was obtained from Perak Maritime Meteorology Station II in the form of data on hourly sea surface current velocity on August 2 consisting of 2020 24 data. The sample of sea surface current velocity data in Labuan Bajo shown in Table 1.

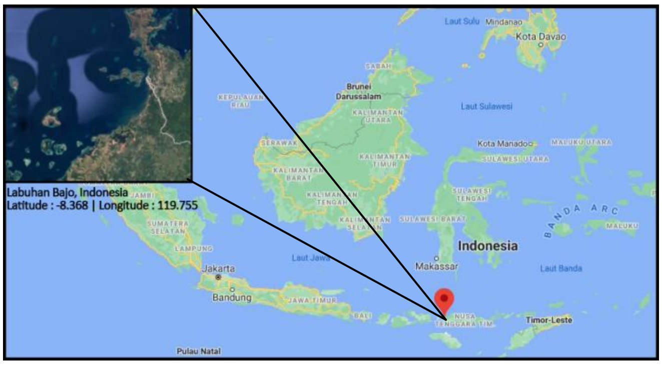


Figure 1 Coordinate Point of Research Place *(Source: Google)*

Table 1 Sea Surface Current Velocity Data Sample

No	Sea currents velocity data	
	U	V
1	-17.41	-23.02
2	-14.14	-15.52
3	-6.81	-1.90
4	-1.15	22.73
5	0.31	24.19

2.2 Technical Research

The first step to predict the velocity of sea surface currents was to collect the velocity of sea surface data, then the data was normalized using the MinMax method which can be seen in Table 3, next a time-series sequence was made on the normalized data which can be seen in Table 4 and 5. After that the time-series pattern was predicted using LSTM with several parameters and finally the optimal model was obtained. The technical research for predicting the velocity of sea surface currents can be seen in Figure 2.

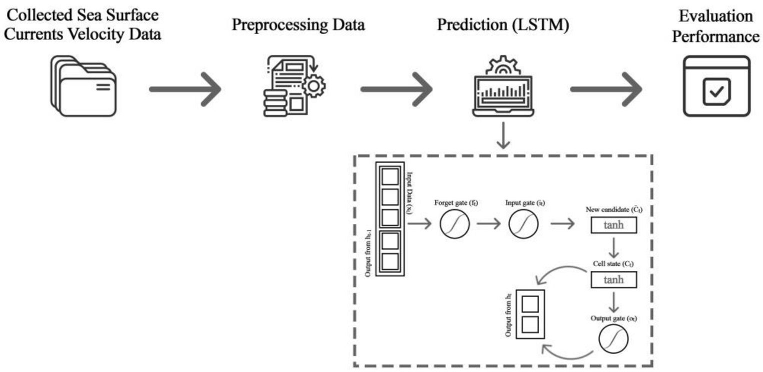


Figure 2 The Technical Research for Predicting the Velocity of Sea Surface Currents using LSTM

2.3 Sea Currents

Sea currents are vertical and horizontal movements of water towards balance [9]. There are several types of sea currents grouped based on the process of occurrence, depth level, temperature, and location. Based on the depth level, the sea currents are divided into surface currents and deep currents. Surface currents are currents that occur due to wind distribution patterns and occur at the surface [10]. The current pattern consists of speed and direction, the current velocity in the east to west direction is called the U component while the current velocity in the north-south direction is called the V component [11]. According to BMKG [12], to determine the direction of sea currents, a formula such as equation (1) can be used. Where π is 3.1416 and atan2 is the arc tangent of u and v.

$$\theta = \frac{180}{\pi} atan2(u,v) \tag{1}$$

2.4 Long Short-Term Memory (LSTM)

The LSTM method is a modification of the RNN method [13]. The LSTM method was first explained by Horcher and Schmidhuber in 1997 [14]. LSTM can overcome the long-term dependencies [15] that occur in the RNN by using a "memory cell" [16]. In LSTM there are three gates namely forget gate, input gate, and output gate [17] which shown in Figure 3.

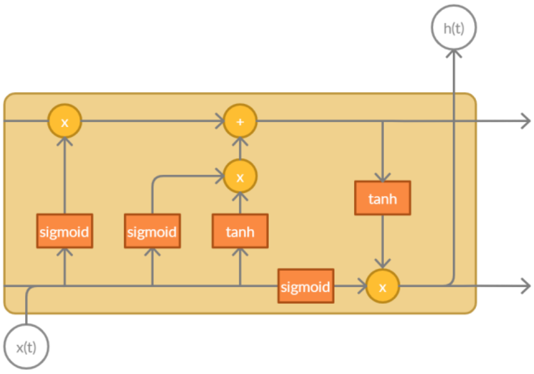


Figure 3 Architecture of LSTM

According to Li Wei [17], the steps for forming an LSTM model are shown in equations (2) to (7). The first step to determine what information will be removed from the previous cell [18] can be seen in equation (3). Where f_t is the forger gate, σ is the sigmoid function, W_f is the forget gate weight, x_t is the t-sequence input, h_{t-1} is the output in the previous step, and b_f is the forget gate bias.

$$f_t = \sigma\left(W_f \cdot [x_t, h_{t-1}] + b_f\right) \tag{2}$$

The next step is to determine what new information will be stored in the cell state by adding a new candidate value ($\tilde{C}_t$) and updating the information at the input gate (i_t). Next, update the cell state value (C_t). Finally, determine the hidden state output (h_t).

$$\tilde{C}_t = \sigma\left(W_c \cdot [x_t, h_{t-1}] + b_c\right) \tag{3}$$

$$i_t = \sigma\left(W_i \cdot [x_t, h_{t-1}] + b_i\right) \tag{4}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{5}$$

$$o_t = \sigma\left(W_o \cdot [x_t, h_{t-1}] + b_o\right) \tag{6}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{7}$$

2.5 Adaptive Moment Estimation Optimization (Adam)

There are a number of optimization methods such as SGD, Adagrad, Adadelta, RMSprop, Adam, AdaMax, and Nadam [19]. This research uses the Adam optimization method. Adam optimization method is a gradient optimization algorithm for training deep neural networks [20]. Adam optimization method works well in prediction problems [21] and is able to work faster than other optimization methods [22].

2.6 Analytical Steps

The steps to predict the velocity of sea surface currents using the LSTM algorithm are as follows:

2.6.1 Data Normalization

In a dataset, there is a high data range. This range will affect the prediction results [23]. Data can be normalized before the training process. There are many methods for normalizing data. The frequently used normalization methods are Min-Max scaler and standard scaler [24], in this research, the Min-Max scaler method was used as seen in equation (8)

$$\hat{x} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{8}$$

Where, $\hat{x}$ is the normalized value, x is the actual data, x_{min} is the minimum value of actual data, while x_{max} is the maximum value of the actual data.

2.6.2 Data Denormalization

Denormalization is the process of returning a normalized value [25]. Data denormalization aims to get the actual output value [26]. The denormalization formula can be seen in equation (9).

$$x_i = \hat{x}\left(x_{\max} - x_{\min}\right) + x_{\min} \tag{9}$$

Where, x_i is the denormalized value, $\hat{x}$ is the normalized value, x_{min} is the minimum value of the actual data, while x_{max} is the maximum value of the actual data.

2.6.3 Performance Evaluation

After the training and testing process is done, the accuracy is tested by comparing the forecast results with actual data [8]. In this research, MAPE is used because MAPE is the most widely used measurement of forecasting accuracy [27]. The MAPE formula can be seen in equation (10).

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|}{n} \times 100\% \tag{10}$$

Where y_i and $\hat{y}_i$ are the actual and predicted values, while n is the number of predicted values. The smaller MAPE value it has, the better for forecast it will be [28]. The significance of MAPE values can be seen in Table 2.

Table 2 Significance of MAPE Values [29]

MAPE	Significance
<100%	Highly accurate forecasting
10-20%	Good forecasting
20-50%	Reasonable forecasting
>50%	Inaccurate forecasting

3. RESULTS AND DISCUSSION

In this research, 24 data of sea surface current velocity collected from Perak Maritime Meteorology Station II, then each of sea surface current velocity data is normalized by Eq. (8). The results are shown in Table 3.

Prediction use LSTM algorithm is trained by input data and output data. In this research, 8 inputs and 1 output were used, the data was divided into 80% training data and 20% testing data. The input data an the target are shown in Table 4 dan Table 5.

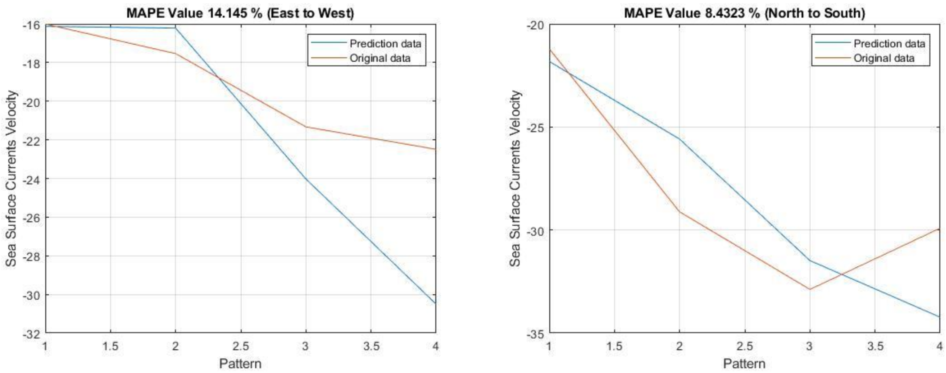
Table 4 Input Pattern of U Component Data

U Components	Target
U1, U2, U3, U4, U5, U6, U7, U8	U9
U2, U3, U4, U5, U6, U7, U8, U9	U10
⋮	⋮
U16, U17, U18, U19, U20, U21, U22, U23	U24

Table 5 Input Pattern of V Component Data

V Components	Target
V1, V2, V3, V4, V5, V6, V7, V8	V9
V2, V3, V4, V5, V6, V7, V8, V9	V10
⋮	⋮
V16, V17, V18, V19, V20, V21, V22, V23	V24

The LSTM method has several parameters that can affect the results of a prediction such as the number of hidden layers, batch size, and learning rate drop period. The hidden layer is the number of calculations in the training process. The batch size is one of the parameyers that need to be set [30], where the number of samples from the time-series patterns included in the model for each iteration. If the batch size is to large it may take the network too long to reach convergence, but if the batch size is too small the network will bounce back and forth without getting acceptable performance [31]. Meanwhile, the learning rate drop period is the number of iterations that must be determined by the learning rate [23]. This research calculates the sea surface current velocity of U and V components. Based on the experiments conducted, the smallest MAPE values obtained shown in Figure 4 and Table 6.



(a) (b)

Figure 4 (a) Prediction Results of U Component (b) Prediction Results of V Component

Table 6 MAPE Values based on Several Parameters

Parameter			U Component		V Component	
Hidden Layer	Batch Size	Learn Rate Drop	MAPE(%)	Average	MAPE(%)	Average
50	32	50	38.76	26.899	16.80	15.380
		100	22.21		16.00	
		150	14.15		8.43	
	64	50	31.23		21.85	
		100	23.19		17.26	
		150	15.29		13.07	
	128	50	37.11		16.19	
		100	28.54		16.06	
		150	19.61		9.72	
	256	50	40.79		20.49	
		100	33.79		15.89	
		150	18.12		12.80	
100	32	50	35.10	25.425	17.01	14.297
		100	20.72		13.37	
		150	20.12		10.11	
	64	50	38.52		16.86	
		100	16.59		14.37	
		150	18.21		11.49	
	128	50	38.85		17.05	
		100	25.92		14.85	
		150	17.58		8.93	
	256	50	36.72		18.62	
		100	17.76		16.42	
		150	19.01		12.49	
150	32	50	36.73	26.602	17.85	13.437
		100	18.56		12.78	
		150	23.66		10.49	
	64	50	39.52		16.72	
		100	20.03		15.49	
		150	23.66		8.94	
	128	50	36.77		16.55	
		100	14.78		12.09	
		150	27.54		10.49	
	256	50	37.32		16.26	
		100	16.57		14.13	
		150	24.08		9.45	

Table 7 The Direction of Sea Surface Current Velocity

U	V	Direction (°)
-16.13	-21.82	216.47
-16.22	-25.59	212.37
-24.03	-31.48	213.74
-30.51	-34.23	221.71

Based on Table 6, the smallest MAPE values on sea surface current velocity of U and V components were obtained at 14.15% and 8.43% with 50 hidden layers, 32 Batch size and 150 Learn rate drop. After obtaining the MAPE results, a calculation of the sea current direction of U and V components can be done. The results on the calculation of sea surface current direction in degrees can be seen in Table 7. This research used short-term data because the sea current velocity data was not appropriate for long-term prediction. This is in line with previous research where the researcher used 1344 data [3] which had a larger error than using 744 data [4] and

304 data [32]. Meanwhile, the LSTM method is a deep learning algorithm that requires long-term data [33] as described in previous researches [23] and [34]. Therefore, the researchers hope that further research will implement methods that can use short term data, for example, the backpropagation method [4].

Masumbuko Semba stated that the bottom topography of the sea basin and the land where the research was conducted affected the surface of the sea currents [35]. Besides, another research stated that the velocity of sea surface currents was also influenced by seasonal current patterns [36]. Therefore, the researchers hope that further research will analyze sea currents based on seasonal flow patterns.

The velocity of sea currents is also affected by tides, where at high tide the speed of the sea currents will be higher than at low tide [37]. This is related to the tide, at high tide the sea water will be higher, so the velocity of sea currents become faster, but at low tide the sea water will be lower, so the velocity of sea currents become slower. This statement is in line with Simatupang, which states that the maximum speed occurs when the sea water is high and the minimum speed occurs at low tide [38]. Therefore, the researchers hope that further research will analyze sea currents based on tides.

4. CONCLUSIONS

Based on the results of the research on the prediction of sea current velocity in Labuan Bajo using the LSTM method, it produced the smallest MAPE of U and V components, respectively 14.15% and 8.43% with 50 hidden layers, 32 Batch size and 150 Learn rate drop. Sea Surface current velocity data is not appropriate for long-term data, so it can be concluded that the LSTM method is not appropriate for sea surface current velocity data because LSTM is a deep learning algorithm.

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