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LONG-SHORT TERM MEMORY (LSTM) FOR PREDICTING VELOCITY AND DIRECTION SEA SURFACE CURRENT ON BALI STRAIT

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Abstract. *The strategic role of the Bali Strait as a connection between the islands of Java and Bali is growing in line with the increase in the economy and tourism of the two islands. Therefore, it is necessary to have a further understanding of the condition of the waters in the Bali strait, one of which is ocean currents. This study aims to predict future ocean currents based on 30-minute data in the Bali Strait in the range of 16 May 2021 to 9 June 2021 obtained from the Perak II Surabaya Maritime Meteorological Station. In this study, the Long Short Term Memory method was used. The parameters used are hidden layer, batch size, and learn rate drop. Based on the parameters used, the results showed that the smallest MAPE value was 18.64% for U ocean current velocity data and 5.29% for V ocean current velocity data.*

Keywords: *Bali Strait, LSTM, prediction, sea current, velocity.*

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1. INTRODUCTION

The Bali Strait is a strait that separates the islands of Java and Bali [1]. The strategic role of the Bali Strait as a liaison between the two islands is growing along with the increase in the economy and tourism [2]. This water area with an area of about 2,500 km2 stores small pelagic fish resources that have high economic value, namely Lemuru fish (*Sardinella lemuru*) [3]. In addition, in the Bali Strait, there are also crossing activities, passenger transportation, loading and unloading of goods. The Bali Strait current is known to be quite strong and the presence of other bad weather often causes disturbances in all activities [4]. Ocean currents are the movement of water masses vertically and horizontally so that they are in balance, or very broad water movements that occur throughout the world's oceans [5]. In general, the characteristics of ocean currents in Indonesian waters are influenced by wind and tides [6]. An accurate prediction of the speed and direction of ocean currents is needed to ensure the safety of passing ships and fishermen. However, until now the process of making predictions of the speed and direction of ocean currents is still limited from modeling data. Where the modeling still has shortcomings such as the use of the number of parameters, mathematical assumptions, and equation formulations that tend to be complicated [7]. Weaknesses can be understood because producing model results that are close to reality, requires a lot of input parameters and fulfilling assumptions which are sometimes very difficult to do.

Therefore, the development of the ability to learn, analyze, and draw conclusions on computers is carried out, known as deep learning. Deep learning itself is part of machine learning in charge of studying the data available through existing algorithms [8]. Several deep learning methods were used for prediction by several researchers, including Dilla Dwi Kartika et al. using the Exponential Smoothing Holt-Winters method with a case study in the Bali Strait which produces a MAPE value of 49.837% for sea flow velocity U and a MAPE value of 60.976% for ocean current velocity V [9]. Other researchers, namely Laily Jumhuriyah et al. using the Backpropagation method, the best MAPE results are obtained from the distribution of 70% of the training data with a learning rate of 0.1 of 7.59%. Meanwhile, with 80% data sharing, the best MAPE training data is located at a learning rate of 0.1, which is 0.57%. Then from the distribution of 90% of the training data, the best MAPE results were obtained at a learning rate of 0.4 of 6.65% [10]. Meanwhile, Dwiyanto [11] with research using the RNN method with 1218 data resulted in an accuracy of 94% for training data and 55% for test data. In some studies, predictions still have a large enough error value so further research is needed to find a smaller error value. Then another study by Novi Yanti with a prediction of solar radiation using the Elman Recurrent Neural Network method produced the best accuracy value of 96.33% in the distribution of training data and test data of 90%:10% with a learning rate parameter set of 0.1 epoch 500 and a minimum error 0.0001 [12].

An example of using deep learning in other time-series data that is widely used is Long-Short Term Memory (LSTM). LSTM itself was created by Hochreiter and Schmidhuber in 1997 [13]. Many other studies are also found in the fields of economy [14]–[17], air quality [18], [19], health [20]–[22] and even e-commerce which is currently growing rapidly [23], [24]. Weather and climate predictions have been carried out by several researchers, including Irkhana Indaka Zulfa by predicting the speed and direction of sea surface currents using the LSTM to obtain the smallest MAPE values for the U component and the V component of 14.15% and 8.43% [25]. Eko [7] with research shows that the RMSE results with all-weather parameter validations are getting better when using LSTM with updates.

Another study that showed a comparison of methods conducted by Efrike [26] showed predictions with the LSTM method had a lower error value than ARIMA in predicting product sales to estimate raw material needs with the results of the average percentage of model error between the smallest daily values using MAPE, the LSTM method is 29.57% and the ARIMA model is 73%. Arfan's research [27] obtained test results, LTSM was able to predict with good performance and a relatively small error rate compared to SVR in predicting stock prices in 2017-2019.

Based on several previous studies, the LSTM method produces a better level of accuracy than other methods, so researchers will use the LSTM method to predict the speed and direction of sea surface currents in the Bali Strait. By knowing the results of this study, it is hoped that it can anticipate bad events and reduce the rate of accidents that occur in the Bali Strait.

2. RESEARCH METHODS

2.1 Research Data

This study uses current velocity data per 30 minutes in the Bali Strait with coordinates of 114,43383 east longitude – 115,11576 east longitude and (-8.77491) south latitude – (- 8.35426) south longitude. The data was taken from May 15, 2021, at 00.30 to June 9, 202,1 at 23.30, which was obtained from the Surabaya II Perak Metrology Station. The data is 1,152 records with the column arrangement of the U component and the V component as shown in Table 1.

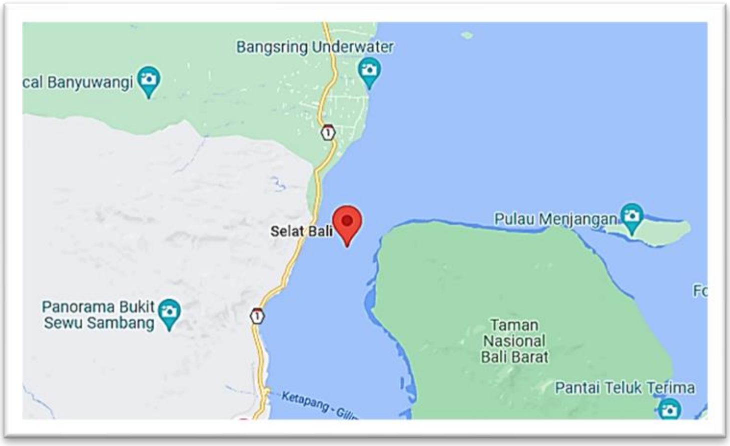

Figure 1. Coordinate Point of Bali Strait

Table 1. Samples of Sea Surface Current Velocity Data

No	U	V
1	14,743	-110,143
2	13,226	-89,888
3	17,567	-65,982
…	…	…
1.152	-61,621	-62,323

2.2 Technical Research

The following steps will be used in this study using the equations described in the previous chapter.

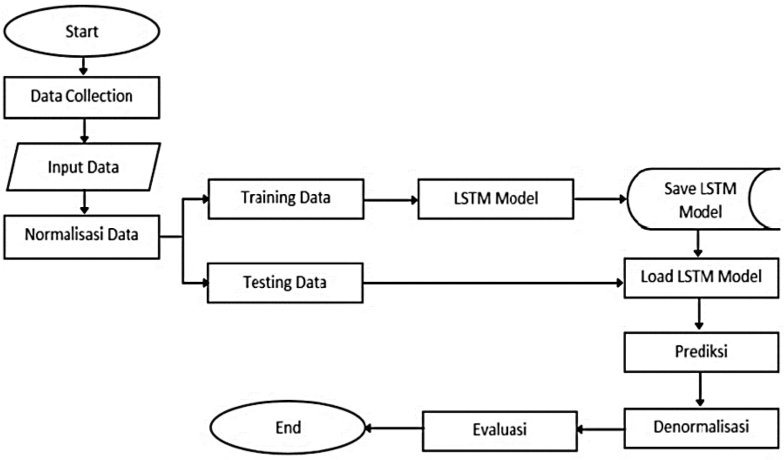

Figure 2. Flowchart

The first step in the research begins with data collection. The data obtained is then inputted and data normalization is carried out. After that, the data is divided into training data and data testing. In the training data, the LSTM model is obtained, which will be stored. Then load the LSTM model for data testing. After that, predictions are made. Then the prediction results will be denormalized and evaluated.

2.3 Sea Currents

Sea currents is a process of mass movement of water towards an equilibrium which causes mass transfer of water horizontally and vertically [28]. The movement of currents has direction and speed so that the currents form a pattern of movement in a water area [29]. In shallow waters (coastal areas), ocean currents can be generated by ocean waves, ocean tides, or to some extent wind. In narrow and semi-enclosed waters such as straits and bays, the tide is the main driving force for the circulation of the water mass [6]. Current as the movement of the flow of a mass of water can be caused by wind, differences in seawater density and water pressure [5]. 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 [30]. The ocean current formula is shown in equation (1).

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

Description:

ϕ = direction of sea surface current

$(atan2)$ = arc tangen

v = v component

u = u component

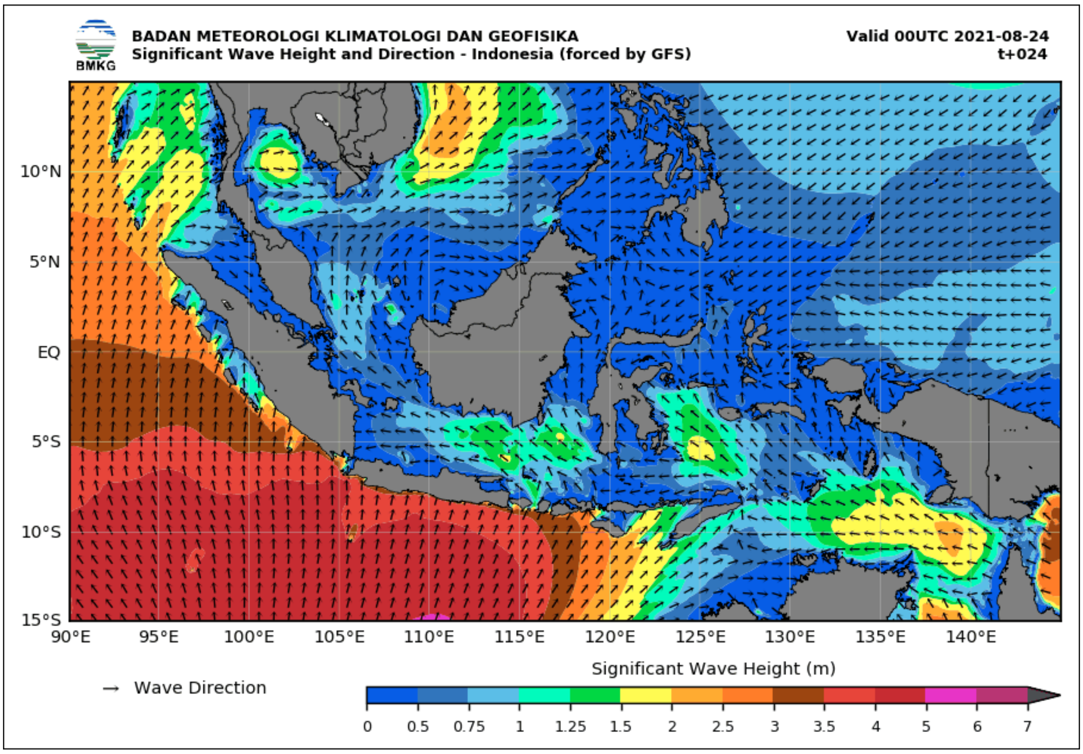

Figure 3. Ocean Currents [Source: BMKG 2021]

2.4 Data Normalization

The data in the dataset sometimes has a value with an unequal range. Of course this can affect the measurement results of data analysis, so the need for a data normalization method. Data normalization is the process of scaling the attribute values into a smaller range with the same weight [31]. The new data attribute value scale can help classification performance because it can remove features with high noise and low relevance [32]. This study uses the MinMaxScaler normalization method with a range of [0, 1]. MinMaxScaler can be calculated using the following formula:

$$\hat{x} = \frac{Xi - Xmin}{Xmax - Xmin} \tag{2}$$

Description:

$\hat{x}$ = normalized value

Xi = the actual data value to be normalized

X_{min} = the minimum value of the actual data

X_{max} = maximum value of actual data

2.5 Long-Short Term Memory

Long Short Term Memory (LSTM) is a neural network development that can be used for time series data modeling [33]. LSTM stores information on patterns in the data. LSTM can learn which data will be stored and which data will be discarded, because each LSTM neuron has several gates that regulate the memory of each neuron itself [14]. LSTM cells are able to connect previous information with subsequent information, and the effectiveness of storing this long information is very necessary in processing time series data [15].

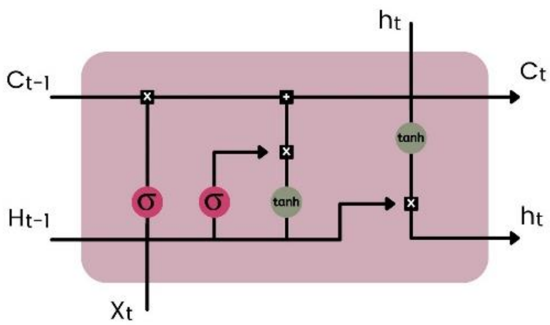

Figure 4. Architecture of LSTM

In the LSTM there are three gates namely ft, it, and ot as shown in Figure 4. Gate ft is forget gate, it is input gate, and ot is output gate. The equation for each gate is given by equation (3)-(8) [14].

Forget Gate is a gate (replace gate) that decides whether input and output will be forwarded to the cell state.

$$f_t = \sigma(W_f . [X_t, h_{t-1}] + b_f) \tag{3}$$

Input Gate is an input gate with two activation functions (sigmoid and tanh), to select the part to be updated.

$$i_t = \sigma(W_i . [X_t, h_{t-1}] + b_i) \tag{4}$$

$$\tilde{C}_t = \sigma(W_c . [X_t, h_{t-1}] + b_c) \tag{5}$$

Cell State Gate to update the old value of Ct-1 to the new value of Ct.

$$C_t = f_i . C_{t-1} + i_t . \tilde{C}_t \tag{6}$$

The first output gate is a gate that combines the old value and the new value, i.e

$$O_t = \sigma(W_o . [X_t, h_{t-1}] + b_o) \qquad (5)$$

The first output gate is a gate that combines the old value and the new value, i.e

$$h_t = O_t . \tanh (C_{t)} \tag{6}$$

2.6 Adaptive Moment Estimation optimization (Adam)

Adaptive Moment Estimation (Adam) [34] is a method for efficient stochastic optimization that requires only first-order gradients with minimal memory requirements. Adam is a combination of RMSprop and momentum. Adam is the result of the derivation of the SGD method which is based on the adaptive estimation of the first and second order moments. Optimization algorithm that calculates the learning rate adaptively for each parameter. Adam keeps the mean of the gradient of the previous process exponentially the same as RMSprop. The standard learning rate for Adam is 0.001 [35]. Adam's optimization calculation formula is shown in equation (9).

$$\theta_{t+1} = \theta_t - \frac{\partial}{\sqrt{\hat{v}_t + \varepsilon}} . \hat{m}_t \tag{7}$$

Where θ_{t+1} is the parameter of the result of the update, θ_t is the parameter of the result of the previous update, η is the learning rate, $\hat{m}_t$ is the gradient of the first-order moment square, $\hat{v}_t$ the gradient of the square of the second-order moment, and ε is a small scalar to prevent division by zero.

2.7 Data Denormalization

After getting the prediction results from the prediction process, before calculating the accuracy of the prediction results, denormalization must be carried out, namely the data is converted into real values again [36]. Because the predicted data is still in the form of data in the form of a range interval which is carried out on data normalization. The purpose of denormalization is to make the output easy to understand. Below is the formula for denormalization [33].

$$X_i = \hat{X} (X_{max} - X_{min}) + X_{min} \tag{8}$$

Where $\hat{x}$ is the normalized value, Xi is the the actual data value to be normalized, X_{min} is the minimum value of the actual data, and X_{max} is the maximum value of actual data.

2.8 MAPE

Mean Absolute Percentage Error (MAPE) is the average absolute difference between the predicted and actual values, expressed as a percentage of the actual values. MAPE is used to calculate the percentage error between the actual value and the predicted value [26].

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

Description:

$\hat{y}_i$ = prediction data

y_i = actual data

n = predicted amount of data.

Table 2. Significance of MAPE Values

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

3. RESULTS AND DISCUSSION

The data shown in Table 2 are normalized to obtain a scale of [0,1] using equation (1), where x is the data to be normalized so that data that is too large will not affect the modeling process. The distribution of training and testing data for prediction is 80% training data on 16 May-5 June 2021 and 20% testing data on 6-9 June 2021. Input and target data are shown in Table 3 and Table 4.

Table 3. Input U Component

Komponen U	Target
$U_1, U_2, U_3, U_4, U_5, U_6, U_7$	U_8
$U_2, U_3, U_4, U_5, U_6, U_7, U_8$	U_9
..	..
$U_{1145}, U_{1146}, U_{1147}, U_{1148}, U_{1149}, U_{1150}, U_{1151}$	U_{1152}

Table 4. Input V Component

Komponen V	Target
$V_1, V_2, V_3, V_4, V_5, V_6, V_7$	V_8
$V_2, V_3, V_4, V_5, V_6, V_7, V_8$	V_9
..	..
$V_{1145}, V_{1146}, V_{1147}, V_{1148}, V_{1149}, V_{1150}, V_{1151}$	V_{1152}

In this study, the training data uses three hyperparameters, namely the hidden layer 50,100,150, batch size 32, 64, 128, 256, and the learn rate drop 50,100,150. LSTM has several parameters that affect the prediction results such as hidden layer, batch size, and learn rate drop. The hidden layer is the number of calculations in the training process, the batch size is used to control how often the weights on the network will be updated, and the learn rate drop is the number of repetitions that must be determined by the learning speed [37]. After training the data using the LSTM model, the next step is testing the data to predict the speed of ocean currents per 30 minutes. Prediction results can be seen in Figure 5 and Figure 6.

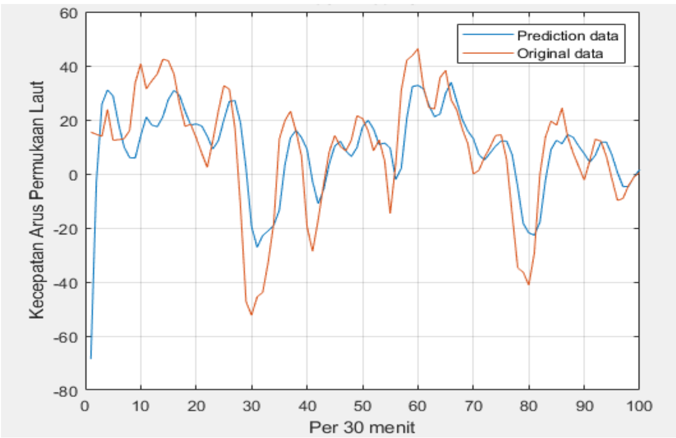

Figure 5. Plot of component U prediction

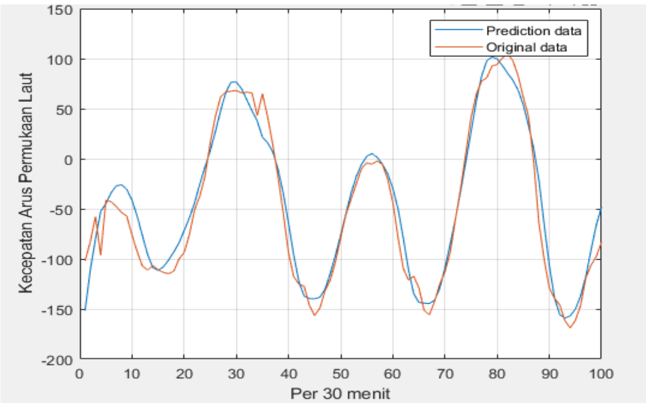

Figure 6. Plot of component V prediction

Table 5. 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	41.32	29.58	19.83	14.20
		100	24.71		14.76	
		150	18.64		5.29	
	64	50	39.87		28.22	
		100	26.35		18.56	
		150	22.15		11.99	
	128	50	38.13		24.56	
		100	25.33		18.81	
		150	21.47		10.87	
	256	50	40.55		25.76	
		100	39.42		15.72	
		150	27.13		9.15	
100	32	50	37.34	31.83	21.63	19,78
		100	31.92		16.34	
		150	19.46		9.33	
	64	50	44.26		23.58	
		100	38.72		14.17	
		150	24.77		6.27	
	128	50	42.39		28.56	
		100	34.75		17.19	
		150	23.86		10.67	
	256	50	36.67		24.98	
		100	26.86		14.16	
		150	20.99		9.29	
150	32	50	39.45	31.59	26.09	18.98
		100	33.72		17.55	
		150	27.87		14.12	
	64	50	43.76		25.24	
		100	38.34		16.77	
		150	27.67		6.87	
	128	50	35.98		26.18	
		100	25.46		18.35	
		150	19.02		10.87	
	256	50	35.55		29.27	
		100	29.83		11.44	
		150	22.45		15.10	

Table 6. The Direction of Sea Surface Current Velocity

u	v	Prediction (°)	Direction
14.743	-110.143	173.4680°	East to South
13.226	-89.888	169.4976°	East to South
17.567	-65.982	166.8069°	East to South
19.697	-44.918	159.8909°	East to South

The results in Table 5, show that the U component has fewer hidden layers, the smaller the batch size, and the greater the learn rate drop, the smaller the resulting MAPE value is 18.64%. The V component shows that the fewer hidden layers, the smaller the batch size, and the greater the learn rate drop, the smaller the MAPE value produced is 5.29%. The smallest MAPE value is found in hidden layer 50, batch size 32 and learn rate drop 150. The results on the calculation of sea surface current direction in degrees can be seen in Table 6.

4. CONCLUSIONS

After conducting research on the prediction of ocean currents velocity in the Bali Strait using the Long Short Term Memory (LSTM) method, it shows that with the composition of training data of 90% and test data of 10% the prediction results obtained are quite good. With the parameters of hidden layer 50, batch size 32 and learn rate drop 150, the smallest MAPE value in the U component is 18.64% while the V component is 5.29%. So it can be concluded that in the final project research Deep Learning with Long Short Term Memory (LSTM) architecture can work quite optimally.

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