Ocean Systems Engineering, *Vol. 16, No. 1 (2026) 19-31*
https://doi.org/10.12989/ose.2026.16.1.019

Techno-Press

Ocean current speed prediction model in the sunda strait using Long Short-Term Memory (LSTM)

Anton Daud[1,2], Khomsin*[1], Danar Guruh Pratomo[1], Agie Wandala Putera[2]

[1]Department of Geomatic Engineering, Institute Technology Sepuluh Nopember, Surabaya, Indonesia
[2]Meteorology, Climatology, and Geophysics Agency, Jakarta, Indonesia

(Received June 21, 2025, Revised February 22, 2026, Accepted March 3, 2026)

Abstract. This research focuses on predicting the speed of ocean currents in the Sunda Strait by employing a Long Short-Term Memory (LSTM) model based on historical data. The approach includes data preprocessing, normalization of features using MinMaxScaler, segmentation of the data into training and testing sets, and the development of layered LSTM model architecture. The dataset comprises longitude, latitude, current velocity, and time information from 2022 to 2024. The findings indicate that the LSTM model can predict ocean current speeds with a Root Mean Squared Error (RMSE) of 13.66 cm/s, a mean absolute error (MAE) of 9.06 cm/s, and a determination coefficient (R^2) of 0.87. The demonstration illustrated the typical design of ocean current speed fluctuations; however, forecasting unusual variations remains challenging. In summary, the LSTM model represents a practical approach for predicting ocean currents based on historical data, aiming to enhance prediction accuracy. This model will support navigation efforts and marine resource management in the Sunda Strait region.

Keywords: historical data; LSTM; ocean currents; prediction; Sunda Strait

1. Introduction

Ocean currents refer to the movement of seawater, influenced by multiple elements such as wind, the gravitational pull of the moon and sun, which create tides, variations in temperature, the configuration of the seafloor, changes in pressure, and ocean waves [1]. Ocean currents are crucial for nutrient distribution, the movement of marine species, and regional climate dynamics. Additionally, the presence and nature of ocean currents directly affect the safety of maritime navigation, fishing operations, and the management of coastal resources [2]. Thus, it is essential to have a solid understanding of ocean currents to effectively plan shipping and fishing operations and minimize the likelihood of maritime accidents in Indonesian waters [3].

One region that requires particular focus is the waters of the Sunda Strait. As the primary link between the Indian Ocean and the Java Sea, the Sunda Strait experiences significant maritime traffic and is influenced by intricate oceanographic processes [4]. The current in this region is significantly affected by seasonal changes, tidal variations, and the interactions between water masses from two distinct oceanic bodies [5]. Studies on the Sunda Strait are crucial due to its unique oceanographic features and connection between the Java Sea and the Indian Ocean.

---

*Corresponding author, Ph.D., E-mail: khomsin@its.ac.id

http://www.techno-press.org/ose/5

ISSN: 2093-6702 (Print), 2093-677X (Online)

Numerous studies have been conducted regarding current speed prediction, including one by [6], which utilizes historical data on current velocity every 30 minutes in the Bali Strait to determine beneficial data sequences for prediction. The study's findings indicate that the Deep Learning approach using the Long Short-Term Memory (LSTM) framework can effectively forecast the velocity and direction of ocean currents. In this research, the training data constituted 90%, while the test data comprised 10%, with parameters set to 50 for the Hidden layer, a Batch Size of 32, and a Learn Rate Drop of 150. The MAPE values achieved were 18.64% for the U component and 5.29% for the V component [6].

According to earlier studies, LSTM modeling has demonstrated acceptable effectiveness in specific situations. Consequently, the researcher plans to employ the LSTM approach to forecast the velocity of sea surface currents in the Sunda Strait. Long Short-Term Memory (LSTM) is a practical deep learning approach for forecasting time series data and represents an advancement of the Recurrent Neural Network (RNN) [7]. The primary benefit of LSTM is its capacity to remember information from lengthy data sequences while retaining previous knowledge, a skill that is difficult to achieve with conventional feature methods [8]. As a result, information is not progressively lost during the processing stage. This research utilizes historical information from the Meteorology, Climatology, and Geophysics Agency BMKG Serang Station over a specific time frame and includes field data collection. This research aims to enhance the precision of forecasting ocean current speeds and provide advantages for diverse maritime operations in the Sunda Strait area.

Recent developments in data-driven oceanographic modeling have demonstrated that deep learning approaches can effectively capture the nonlinear behavior of ocean dynamics. According to [9] applied neural network–based inverse modeling techniques to estimate vertical current profiles using FPSO motion data, highlighting the capability of deep learning to reconstruct complex current structures from limited or indirect measurements. Their findings underscore the potential of deep neural networks to enhance current prediction accuracy in regions influenced by variable oceanographic processes, providing a conceptual foundation for the application of LSTM models in this study.

2. Research methods

Quantitative descriptive analysis utilizes a predictive modeling technique based on the LSTM algorithm. This design was chosen to analyze and forecast the velocity pattern of ocean currents using historical data [10]. This research uses time-series data from the BMKG at the Serang Maritime Meteorological Station to create a precise prediction model. The modeling is conducted through computational methods by splitting the data into training and testing sets and evaluating the model's performance using defined metrics.

In Fig. 1, the square markers represent the spatial positions of the observation points included in the ocean current dataset. These points correspond to the geographic coordinates (longitude–latitude pairs) where surface current measurements were recorded by the BMKG Serang Maritime Meteorological Station during the 2022–2024 observation period. Each square indicates a unique location at which ocean current velocity data were obtained.

Because the dataset consists of measurements collected at multiple spatial points across the Sunda Strait—rather than a single fixed location—the squares illustrate the spatial distribution of these measurement stations. This visualization is intended to show that the ocean current data

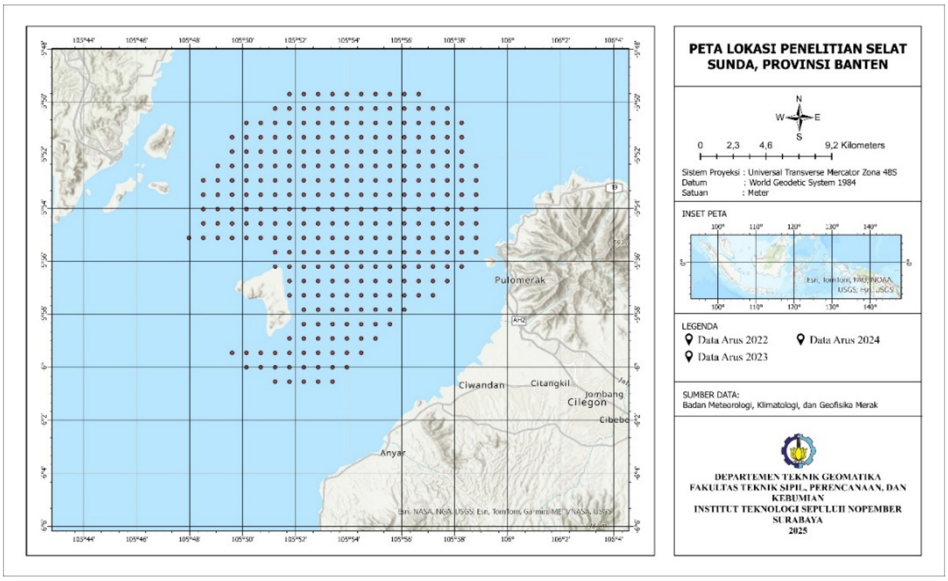

Figure 1. Research Location

originate from several observation points around the Sunda Strait, providing a more representative depiction of regional circulation patterns. The squares do not indicate model grid cells, satellite pixels, or interpolation nodes, but rather the actual observation coordinates available in the historical dataset.

This study focuses on the Sunda Strait, a vital passage linking the Java Sea to the Indian Ocean, between the Sumatra and Java islands. The research concentrates on the Merak port area at 105°53’47.615” E and 5°55’0.089” S. Over three months, this study involved gathering historical sea current speed data from the BMKG at the Serang Maritime Meteorological Station and modeling the prediction of sea current using the LSTM algorithm.

This research employs historical data regarding sea currents in a time series from 2022 to 2024, with information from the BMKG Serang Maritime Meteorological Station. LSTM modeling is utilized to forecast the velocity of ocean currents using historical data. The phases of the research encompass these steps.

2.1 Data collection

This phase gathers the information required to forecast ocean current speed. Data was collected from the BMKG Serang Station as historical records of sea current speeds for 2022 to 2024. This information encompasses various attributes, including time, latitude, longitude, and the speed of ocean currents. Historical data serves as a source of information from the past that will be modeled through deep learning utilizing LSTM architecture.

Ocean current data used in this research were obtained from the BMKG Serang Maritime Meteorological Station, which routinely conducts oceanographic observations in the Sunda Strait region. The measurements represent sea surface current velocity, collected as part of operational maritime monitoring to support navigation safety and weather services.

The ocean current data were measured using a surface current meter integrated with BMKG’s coastal observation system. This instrument records the horizontal current speed in real time at the ocean surface. The sensor measures the motion of surface water masses based on the drift of instrumented buoys and the Doppler shift of returned acoustic signals. The effective measurement depth of the instrument is 0–1 meter below the sea surface, enabling the data to represent pure surface currents influenced by tides, wind stress, and regional circulation.

Current measurements are recorded at fixed observation intervals following standard BMKG operational procedures. Each record consists of a timestamp, geographic coordinate (longitude and latitude), and the measured ocean current velocity in centimeters per second (cm/s). All observations undergo internal BMKG quality control procedures to ensure validity, including removal of inconsistent readings and verification of instrument performance calibration.

The use of surface current data is relevant to the objectives of this study, as surface circulation plays a dominant role in shipping operations, oil spill drift estimation, fisheries activities, and short-term oceanographic forecasting in the Sunda Strait.

2.2 Pre-processing data

Pre-processing is a crucial step to ensure that the input dataset is suitable for modeling and to improve prediction accuracy. The raw data used in this study were obtained from BMKG sensors, consisting of time-series records of longitude, latitude, and ocean current velocity. Since sensor data often contains noise, missing values, or inconsistent formats, several pre-processing steps were applied.

First, the time variable was standardized to a consistent datetime format, enabling the extraction of temporal features such as year, month, day, and hour. Sensor signals were checked for duplication and irregularities. Missing or invalid values (NaN or infinite) were handled through linear interpolation, while extreme outliers were filtered using statistical thresholds to reduce noise effects. To further enhance signal quality, a moving average smoothing filter was applied, allowing the model to capture underlying patterns without being excessively influenced by short-term fluctuations.

Finally, all features (longitude, latitude, and temporal variables) and the target variable (ocean current velocity) were normalized to a range of 0–1 using the MinMaxScaler method. This normalization ensures that no single feature dominates due to scale differences and accelerates model convergence during training [11].

Ocean currents are inherently vector quantities, consisting of both magnitude and direction. In oceanographic observations, current vectors are typically represented by two horizontal components.

- **U component** → zonal (east–west) current velocity
- **V component** → meridional (north–south) current velocity

These components describe the horizontal transport of water masses in orthogonal directions. When U and V components are available, the **absolute current velocity (speed)** can be computed using the Euclidean norm:

$$V = tan\sqrt{U^2 + V^2}, \tag{1}$$

Meanwhile, the **current direction (θ)** can be calculated from the inverse tangent of the vector ratio

$$\theta = tan^{-1}(\frac{V}{U}), \tag{2}$$

This representation is widely used in ocean dynamics analysis because it allows the reconstruction of both magnitude and direction of ocean flow from its orthogonal components.

However, the dataset used in this research—sourced from the BMKG Serang Maritime Meteorological Station—provides direct measurements of the absolute surface current speed, without separating the U and V components. As a result, the predictive modeling in this study focuses solely on forecasting the scalar magnitude of ocean current speed rather than the full vector field. This limitation is addressed in the Discussion Section as a key point for potential model improvement by incorporating U–V components in future work.

2.3 Data sharing

This arrangement involves separating the information into training data and test data. Training data assesses model designs, whereas testing evaluates model quality. According to [12] the preparation and testing of the data will influence the model's accuracy. The training data consists of more than the test data [13]. Generally, test data only accounts for 10% to 30% of the total data. This study divided the data with the proportion of test data at 10% and training data at 90%.

Fig. 2 shows a visualization of the distribution of training and testing data for ocean current speeds in the Sunda Strait. The data are displayed as a continuous line graph with the X-axis representing the data index and the Y-axis showing the normalized current speed values (scale between 0 and 1). In this study, the data were divided with a proportion of 90% for training and 10% for testing because the amount of ocean current observation data is relatively limited, so a large training portion is required for the model to optimally capture temporal patterns. Meanwhile, 10% of the test data is considered sufficient to evaluate model performance objectively without reducing generalization ability. The blue color depicts the training data that covers most of the data range, while orange shows the portion of the test data located at the end of the time series. This separation aims to maintain the temporal order of the data, which is an important characteristic in time series modeling with LSTM, so the model can learn from historical patterns of current speed and test its ability to predict future conditions based on realistic data sequences.

2.4 LSTM modeling

The modeling was implemented on the Google Colaboratory platform using the Long Short-Term Memory (LSTM) algorithm to forecast ocean current speed. The inputs consisted of time, latitude, and longitude, while the output was the corresponding ocean current velocity [14]. A sliding window approach (lookback window) was applied to transform sequential data into supervised learning form. After testing different configurations, the optimal lookback window was set to 24-time steps, representing one day of hourly data. This allowed the model to effectively capture daily current speed variations [15].

The final LSTM architecture consisted of multiple stacked layers: an initial LSTM layer with 256 units, followed by a dropout layer (0.2) to mitigate overfitting, two additional LSTM layers with 128 units each, and a final dense layer for regression output. The model was trained using the Adam optimizer with a learning rate of 0.0001 and Mean Squared Error (MSE) as the loss function. Early stopping and ModelCheckpoint callbacks were employed to avoid overfitting and retain the best-performing model.

Hyperparameter tuning was conducted experimentally by adjusting the number of epochs (50–150), batch sizes (16–64), and lookback windows (12, 24, 48). The best configuration was

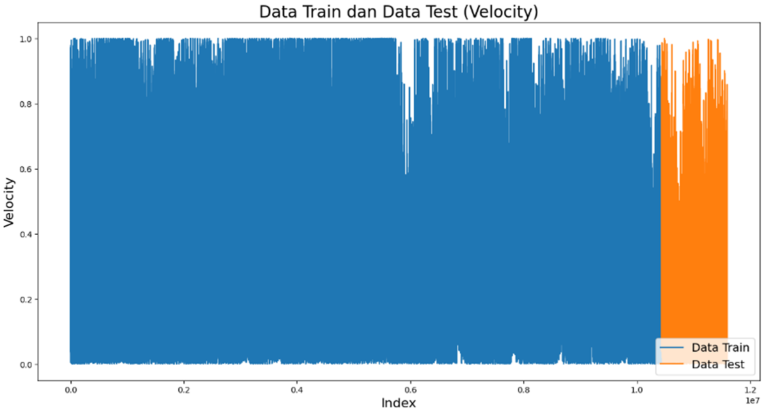

Figure 2. Data Sharing

identified based on validation loss minimization. Model evaluation metrics included Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which provided insights into both average prediction errors and sensitivity to large deviations [16].

This setup demonstrated that incorporating temporal dependencies through LSTM, together with optimized hyperparameters, significantly improved the model's predictive performance for ocean current speed forecasting [17].

2.5 Model evaluation

This arrangement was carried out for modeling using the Google Collaboratory platform's Long Short-Term Memory (LSTM) algorithm. LSTM predicts the speed of sea currents based on historical information such as time, scope, longitude, and sea current speed [10]. The properties of time, scope, and longitude will be independent factors (input), while the speed of sea currents will be a dependent factor (output). The execution of the LSTM incorporates several critical components, such as the LSTM layer, the number of epochs, the batch size, and the choice of the appropriate optimizer [18]. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) will be metrics to measure model forecast errors. According to [14], using LSTM on historical data allows the model to make more accurate predictions using temporal data.

2.5.1 Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is an evaluation method based on the average of absolute errors between predicted and actual values. According to [19], MAE is an evaluation technique that calculates absolute error values to analyze model errors [19]. This metric is intended to measure the accuracy of a prediction model [20]. A smaller MAE value indicates better model performance when making predictions. The formula for calculating MAE can be expressed as follows.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \bar{y}_i|, \tag{3}$$

where:

n = total amount of data

y_i = actual value

$\check{y}_i$ = predicted value
$|y_i - \check{y}_i|$ = absolute difference between the two values

2.5.2 Root Mean Squared Error (RMSE)

Root Mean Square Error (RMSE) is an evaluation metric used to measure a model's average error of predicted values. According to [20], RMSE is a method to measure the error of a prediction model. The smaller the RMSE value, the better the model captures data patterns. The RMSE calculation formula can be written as follows

$$RMSE = \sqrt{\frac{1}{n}\sum_{i-1}^{n}(y_i - \check{y}_1)^2}. \tag{4}$$

where:

n = total amount of data
y_i = actual value
$\check{y}_i$ = predicted value
$(y_i - \check{y}_1)^2$ = absolute difference between the two values

These two metrics differ in how they measure error rates. MAE measures absolute error averages without accounting for significant errors, while RMSE gives greater weight to large errors, making it more sensitive to outliers.

3. Results and discussion

This study utilizes the Long Short-Term Memory (LSTM) model to predict the speed of ocean currents in the waters of the Sunda Strait based on historical data collected. The choice of the LSTM model is based on its capability to recognize temporal patterns in time series data, enabling the capture of the dynamics of changes in ocean current velocity influenced by various oceanographic and geographical factors. The dataset includes information about time, longitude, latitude, and current velocity during the observation period (see Table 1).

Table 1 presents a sample (head) of the dataset used in this study. The index values shown in the first column (0–4) are dataframe row numbers generated for illustration purposes and do not represent observation stations or fixed measurement points. Each row corresponds to an individual ocean current observation at a unique longitude–latitude location and time. The dataset does not contain station identifiers; instead, it represents spatially distributed measurement points across the Sunda Strait.

Table 1. Part of the Dataset Content

Time	Longitude $(^0)$	Latitude $(^0)$	Velocity (cm/s)
0 2022-11-27 08:00:00	105.853733	-6.009025	112.90
1 2022-11-27 08:00:00	105.817612	-5.873383	204.26
2 2022-11-27 08:00:00	105.980159	-5.882413	130.13
3 2022-11-27 08:00:00	105.971128	-5.882415	127.49
4 2022-11-27 08:00:00	105.962098	-5.882416	136.24

3.1 Data preprocessing

The initial stage is to ensure the quality of the data set used. Data collected from 2022 to 2024 through multiple sources is consolidated into a single dataset. In this stage, the data is checked to avoid duplication and to ensure consistency in the time format, which is converted to a datetime type to facilitate the extraction of additional information such as year, month, day, and hour. In addition, checks are conducted for missing and outlier data to maintain the validity of the dataset. Data with an empty value (NaN) or an invalid value, such as infinite (inf), is cleaned through deletion or interpolation.

After the pre-processing is completed, the features are selected, considering factors affecting the speed of ocean currents. The features used include longitude, latitude, velocity, and temporal attributes (year, month, day, and hour). Data from the three years were combined, and unique observation points were used to avoid bias in the training model.

3.2 Data sharing

Furthermore, the dataset was normalized using the MinMaxScaler method. This normalization is important to equalize the range of values of each feature so that no feature dominates model training due to scale differences [21]. All input features are normalized to the range of 0 – 1, including the output target in ocean current speed. This normalization has been proven to accelerate model convergence and improve stability during the training process.

The dataset is divided into training data (90%) and test data (10%). This division measures the model's ability to generalize to new, unseen data. The distribution is performed randomly to ensure fair evaluation.

3.3 LSTM model

The model begins with a 256-unit LSTM layer that takes a SEQ_LENGTH x feature-dimensional sequence input, followed by a 0.2 dropout layer to mitigate overfitting. Next, I added a second LSTM layer with 256 units and dropouts. Subsequently, two LSTM layers with 128 units each were implemented to capture deeper patterns, concluding with one final LSTM layer and dropout, along with a linear Dense output layer to produce predictions of ocean current velocity.

The model training process used the Adam optimizer with a learning rate of 0.0001 and the Mean Squared Error (MSE) loss function. The Model Checkpoint mechanism stores the best model based on the smallest validation loss value to maintain model performance. Early stopping is used to stop training if there is no improvement in five consecutive epochs. Training is conducted for 100 epochs with large batch sizes adapted to the computational distribution strategy.

Predictive results are visualized by comparing actual and predicted values in the graph (Fig. 3). The blue line on the graph represents the actual speed of the ocean current, while the dotted red line indicates the predicted outcome. In general, model predictions follow the main pattern of actual ocean current velocity, although there are still some deviations, especially at very sharp fluctuations. This shows that the model can capture general trends but faces challenges in responding appropriately to extreme changes in ocean current speeds.

After the training, the model is stored and tested with test data. The model's ocean current velocity prediction is compared to the actual value to evaluate its performance. The evaluation was carried out

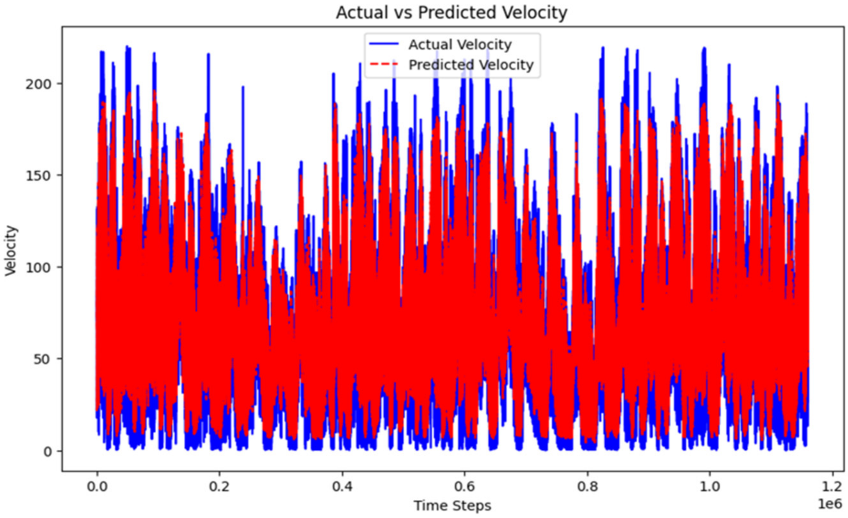

Figure 3. Visualization of Prediction Results Ocean Currents (cm/s)

using three main metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2). The model shows an MSE value of 186.71, an MAE of 9.06, and an R^2 of 0.868. This R^2 value indicates that the model can explain approximately 86.86% of the variation in the actual data, demonstrating a strong performance in the prediction.

Further analysis of the prediction results shows that the model's predictions are very close to the actual value in many cases. For example (Fig. 3), at one observation point, the actual velocity was recorded at 89.34 cm/s, while the model's prediction result was 87.57 cm/s, resulting in a slight difference. However, there are also some cases where the model's prediction has a larger deviation, such as the case with an actual value of 107.06 cm/s and a prediction of 96.39 cm/s. This discrepancy may be due to limited input data that does not fully capture external factors such as local winds, complex tidal conditions, or irregular data collection.

Overall, this study's results show that the LSTM-based approach is reasonably practical in predicting the speed of ocean currents in the waters of the Sunda Strait. The model can identify key patterns in historical data, but there is room for improvement in capturing extreme changes. These findings open opportunities for further development by enriching the data inputs using additional oceanographic variables and optimizing the model architecture to improve future predictions' accuracy.

The time series graph (Fig. 4) shows the comparison between the actual values (blue line with circle markers) and the predicted values (red dashed line with square markers) over a 20-day period from January 1-20, 2024. The LSTM model demonstrates good ability to follow the temporal pattern of the actual data with consistent fluctuations. The graph identifies four different operational conditions: (1) Normal Case at the beginning of the period with predictions that accurately follow the actual pattern, (2) Weak Current in the middle of the period where the model successfully detects a decrease in current velocity to ~52 cm/s, (3) Strong Current in the period of January 12-14 with predictions reaching a peak of ~73 cm/s, and (4) Steady State at the end of the period with minimal variations. The strong visual correlation between the two curves indicates that the model has successfully learned the dynamic characteristics of the ocean current system.

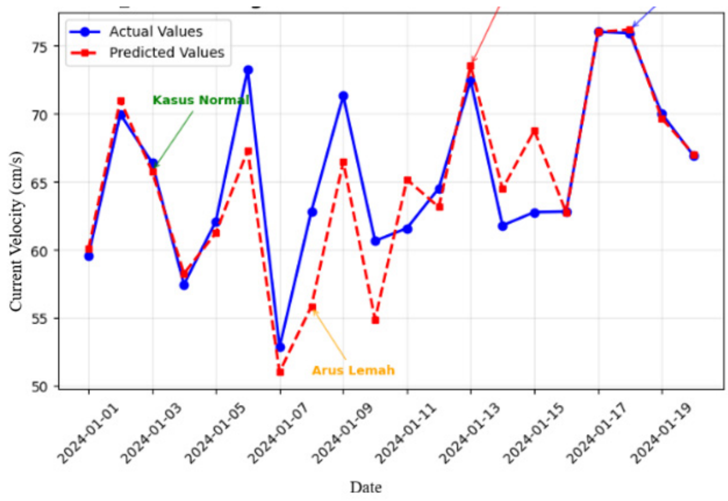

Figure 4. Comparison of Actual Values (blue line) vs. Predicted (red line) Ocean Currents

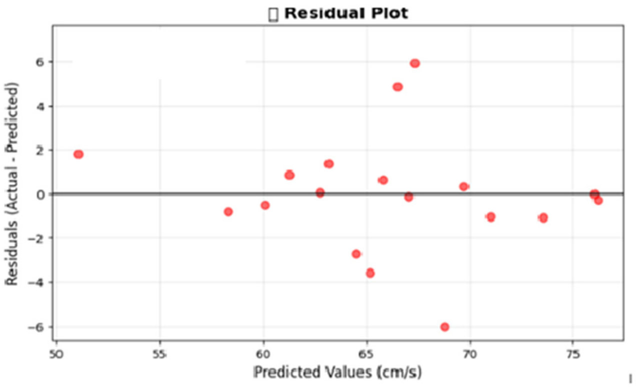

Figure 5. Residual Plot: Error Distribution Analysis

The residual plot, Fig. 5 shows the distribution of prediction errors (the difference between actual and predicted values) against the predicted values. The relatively random distribution of residuals around the zero-horizontal line (y=0) indicates that the model has no significant systematic bias. The residual mean of 0.63 cm/s is close to zero, indicating that the model has minimal bias. The residual standard deviation of 3.15 cm/s indicates an acceptable level of error variability for ocean current prediction applications. The distribution pattern that does not show a particular trend (heteroscedasticity) confirms that the assumption of homogeneity of variance is met, which is an important indicator of the validity of the regression model.

3.4 LSTM comparison before vs after tuning

The metrics comparison bar chart (Fig. 6) displays five key performance indicators of the LSTM model before (red bars) and after (green bars) hyperparameter tuning. Validation Loss

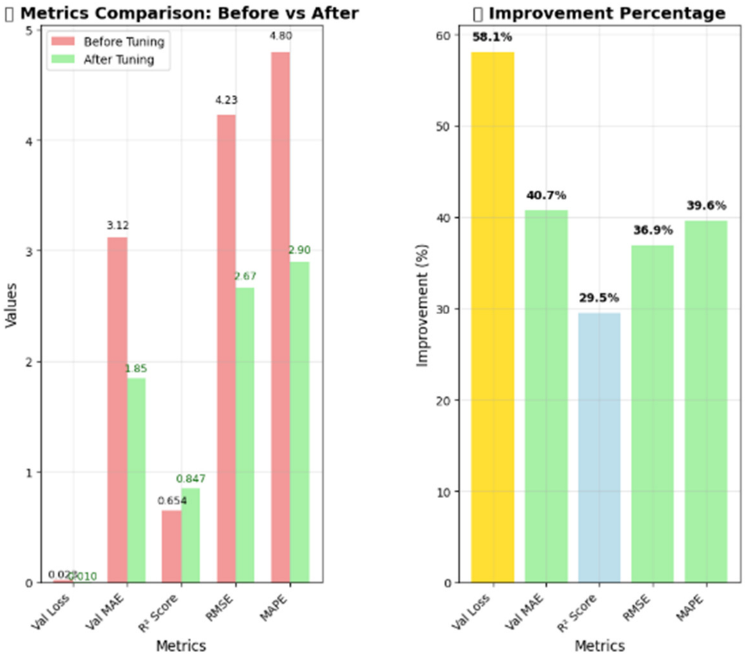

Figure 6. Metrics Comparison and Improvement Percentage

shows a dramatic decrease from 0.0234 to 0.0098, reflecting a significant improvement in the model's generalization ability. Validation MAE saw a substantial reduction from 3.12 cm/s to 1.85 cm/s, indicating a 40.7% increase in prediction accuracy. The R^2 Score increased from 0.654 to 0.847, indicating that the model's ability to explain data variation increased from 65.4% to 84.7%. RMSE decreased from 4.23 cm/s to 2.67 cm/s, reflecting an overall reduction in error magnitude. MAPE improved from 4.80% to 2.90%, indicating a consistent increase in relative accuracy across different magnitude values.

The percentage improvement chart shows the magnitude of improvement for each metric, color-coding it based on the degree of improvement. Validation Loss showed the highest improvement of 58.1% (yellow-gold bar), indicating a fundamental transformation in the model's ability to minimize errors on the validation data. Validation MAE and MAPE showed substantial improvements of 40.7% and 39.6%, respectively (green bar), reflecting consistent improvements across accuracy measures.

RMSE saw a 36.9% increase, indicating a significant reduction in outlier predictions. The R^2 Score improvement of 29.5% (light blue bar) indicates a substantial increase in the model's explanatory power. All metrics showed improvements above 25%, confirming the comprehensive effectiveness of the hyperparameter tuning process.

4. Conclusions

This study aims to model the prediction of ocean current speeds in the waters of the Sunda Strait using the Long Short-Term Memory (LSTM) method based on historical data. The results obtained show that the LSTM model can predict ocean current speeds with considerable accuracy, as indicated by a Root Mean Squared Error (RMSE) of 13.67 cm/s, a Mean Absolute Error (MAE) of 9.06 cm/s, and a determination coefficient (R^2) of 0.868. This R^2 value suggests that the model can explain approximately 86.86% of the variation in actual ocean current velocity, demonstrating an adequate level of accuracy for practical applications such as navigation planning and maritime resource management.

Overall, this study has successfully demonstrated that LSTM is a promising method for predicting the speed of ocean currents in strategic waters such as the Sunda Strait. This finding also fulfills the study's objective of building a predictive model based on historical data to estimate ocean current speed patterns with reasonable accuracy. However, the study also has several shortcomings, potentially due to the limitation of input variables that only include basic spatial and temporal information, without considering other oceanographic factors such as wind direction, tides, or sea surface temperature.

Acknowledgments

We thank the Meteorology, Climatology, and Geophysics Agency (BMKG) for providing data for this research. The authors also gratefully acknowledge financial support from the Institut Teknologi Sepuluh Nopember for this work under the project scheme of the Publication Writing and IPR Incentive Program (PPHKI) 2025.

References

1. Danilov, V.I. (2021). Ocean currents and tidal movements : the real causes. Progress in Physics, 17(2), 194-197.
2. Havis, M.I., Yunita, N.F. (2017). Surface currents in Indonesian Sea based on ocean surface currents near–realtime (OSCAR) data. Marine Technology for Sustainable Development, 27-31.
3. Dwiputri, D.A., Bainus, A., Widianingsih, I. (2024). Networking that not working: challenges in Indonesia's maritime policy network. Sosiohumaniora, 26(2), 259-270. https://doi.org/10.24198/sosiohumaniora.v26i2.55555.
4. Mayer, B., Siegel, H., Gerth, M., Pohlmann, T., Stottmeister, I., Putri, M., Setiawan, A. (2022). Physical environment of the Indonesian seas with focus on the Western region. In Science for the Protection of Indonesian Coastal Ecosystems (SPICE), 13-43.
5. Fernandez, L., Zavala-Hidalgo, J., Olvera-Prado, E.R. (2019). Seasonal variations of river and tidal flow interactions in a tropical estuarine system. Continental Shelf Research, 188, 103965. https://doi.org/10.1016/j.csr.2019.103965.
6. Pramesti, D.D., Novitasari, D.C.R., Setiawan, F., Khaulasari, H. (2022). Long-short term memory (Lstm) for predicting velocity and direction sea surface current on Bali strait. BAREKENG: Jurnal Ilmu Matematika Dan Terapan, 16(2), 451-462. https://doi.org/10.30598/barekengvol16iss2pp451-462.
7. Cortez, B., Carrera, B., Kim, Y.J., Jung, J.Y. (2018). An architecture for emergency event prediction using LSTM recurrent neural networks. Expert Systems with Applications, 97, 315-324. https://doi.org/10.1016/j.eswa.2017.12.037.
8. Houdt, V.G., Mosquera, C., Nápoles, G. (2020). A review on the long short-term memory model. Artificial Intelligence Review, 53(8), 5929-5955. https://doi.org/10.1007/s10462-020-09838-1.
9. Kwon, D.S., Kim, S.J., Jin, C., Kim, M., Guha, A., Esenkov, O.E., Ryu, S. (2023). Inverse estimation of a vertical current velocity profile using motions of an FPSO and artificial neural network. Ocean

Engineering, 285, 115343. https://doi.org/10.1016/j.oceaneng.2023.115343.

10. Zulfa, I.I., Novitasari, D.C.R., Setiawan, F., Fanani, A., Hafiyusholeh, M. (2021). Prediction of sea surface current velocity and direction using LSTM. IJEIS (Indonesian Journal of Electronics and Instrumentation Systems), 11(1), 93. https://doi.org/10.22146/ijeis.63669.
11. Wang, C., Du, W., Zhu, Z., Yue, Z. (2020). The real-time big data processing method based on LSTM or GRU for the smart job shop production process. Journal of Algorithms & Computational Technology, 14, https://doi.org/10.1177/1748302620962390.
12. Sunardi, A., Rusli, S., Juliane, C. (2022). The effect of amount of data on results of accuracy value of C4.5 algorithm on student achievement index data. Journal Riset Informatika, 4, 191-198. https://doi.org/10.34288/jri.v4i2.374.
13. Rosita, Y.D., Moonlight, L.S. (2024). Comparative analysis of LSTM neural network and SVM for USD exchange rate prediction: a study on different training data scenarios. Scientific Journal of Informatics, 11(1), 195-206. https://doi.org/10.15294/sji.v11i1.49975.
14. Musu, W., Ibrahim, A., Heriadi, H. (2021). Pengaruh Komposisi data training dan testing terhadap Akurasi algoritma C4. 5. *SISITI:* Seminar Ilmiah Sistem Informasi Dan Teknologi Informasi, 10(1), 186-195.
15. Al-Selwi, S.M., Hassan, M.F., Abdulkadir, S.J., Muneer, A., Sumiea, E.H., Alqushaibi, A., Ragab, M.G. (2024). RNN-LSTM: from applications to modeling techniques and beyond—systematic review. Journal of King Saud University - Computer and Information Sciences, 36(5), 102068. https://doi.org/10.1016/j.jksuci.2024.102068.
16. Wang, W., Lu, Y. (2018). Analysis of the mean absolute error (MAE) and the root mean square error (RMSE) in assessing rounding model. IOP Conference Series: Materials Science and Engineering, 324, 12049. https://doi.org/10.1088/1757-899X/324/1/012049.
17. O'Donncha, F., Hu, Y., Palmes, P., Burke, M., Filgueira, R., Grant, J. (2022). A spatio-temporal LSTM model to forecast across multiple temporal and spatial scales. Ecological Informatics, 69, 101687. https://doi.org/10.1016/j.ecoinf.2022.101687.
18. Bouktif, S., Fiaz, A., Ouni, A., Serhani, M.A. (2018). Optimal deep learning lstm model for electric load forecasting using feature selection and genetic algorithm: comparison with machine learning approaches. Energies, 11(7), 1636. https://doi.org/10.3390/en11071636.
19. Sari, S.N., Pratama, B.G., Prastowo, R. (2024). Pemodelan Artificial Neural Network (ANN) untuk identifikasi bangunan daerah rawan Longsor. Device, 14(1), 8-18. https://doi.org/10.32699/device.v14i1.6701.
20. Hodson, T.O. (2022). Root-mean-square error (RMSE) or mean absolute error (MAE): when to use them or not. Geoscientific Model Development, 15(14), 5481-5487. https://doi.org/10.5194/gmd-15-5481-2022.
21. Putra, O.V., Harmini, T., Saroji, A. (2021). Outlier detection on graduation data of darussalam gontor university using one-class support vector machine: deteksi outlier pada data Kelulusan Mahasiswa universitas darussalam gontor menggunakan one-class support vector machine. Procedia of Engineering and Life Scienc*e*, 2.