JAISEN: Journal of Advanced Information Systems and Engineering
Vol. 1, 2 (February, 2026), pp 1-11
ISSN: - EISSN: - , DOI: -

Optimization of LSTM and GRU Deep Learning Models for Tidal Sea Level Time Series Prediction to Support Early Warning Systems

Hana Ramadila[1], Susandri Susandri[2], Ahmad Zamsuri[3]

[1] Master of Computer Science, Lancang Kuning University; hanaramadila22@gmail.com
[2] Master of Computer Science, Lancang Kuning University; susandri@unilak.ac.id
[3] Master of Computer Science, Lancang Kuning University; ahmadzamsuri@unilak.ac.id

ARTICLE INFO

Keywords:

Tidal Sea Level Prediction;
Deep Learning;
LSTM;
GRU;
Early Warning Systems.

Article history:

Received 2026-01-20
Revised 2026-02-10
Accepted 2026-02-25

ABSTRACT

Coastal regions are increasingly vulnerable to hazards associated with tidal sea level variability, including recurrent tidal flooding that threatens coastal infrastructure and communities. Accurate tidal prediction is therefore essential to support effective coastal early warning systems, particularly in regions with diverse tidal characteristics such as Indonesia. This study aims to optimize and compare Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) deep learning models for tidal sea level time series prediction. The analysis uses observational tidal data from four stations located in West Sumatra and North Sumatra, covering a continuous period from October to December 2025. The proposed framework includes data preprocessing, time series construction, baseline model development, and systematic hyperparameter tuning using Bayesian Optimization. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and the coefficient of determination (R^2). The results indicate that Bayesian Optimization significantly enhances the predictive accuracy of both models. LSTM achieves the best performance at Bungus, an open-ocean station with more complex tidal dynamics, while GRU outperforms LSTM at Belawan, Kuala Tanjung, and Sibolga, which exhibit more regular tidal patterns. These findings demonstrate that model performance depends strongly on local tidal characteristics rather than on model architecture alone. Overall, the study concludes that optimized LSTM and GRU models provide a reliable and adaptable approach for tidal sea level prediction and offer strong potential to support location-specific coastal early warning systems.

This is an open access article under the CC BY-NC-SA license.

Corresponding Author:
Hana Ramadila
Master of Computer Science, Lancang Kuning University; hanaramadila22@gmail.com

1. INTRODUCTION

Coastal regions are increasingly vulnerable to hazards associated with sea-level variability, including tidal flooding, storm surges, and long-term sea-level rise. These processes pose serious threats to coastal infrastructure, maritime activities, and human settlements, particularly in low-lying and densely populated coastal zones. In Indonesia, an archipelagic country with one of the longest coastlines in the world, tidal dynamics play a central role in shaping daily sea-level fluctuations and amplifying the impacts of coastal hazards such as recurrent tidal flooding (rob) (BMKG, 2025; BNPB, 2005). Consequently, improving the accuracy of tidal sea-level prediction is a critical component in strengthening coastal early warning systems and disaster risk reduction strategies.

Tides are periodic oscillations of sea level primarily driven by the gravitational interactions between the Earth, Moon, and Sun. However, their manifestation at specific coastal locations is strongly influenced by local factors such as coastal morphology, bathymetry, river discharge, atmospheric pressure, and wind forcing (Suci et al., 2023; Wicaksono et al., 2025). As a result, tidal characteristics vary considerably across regions. Indonesian waters exhibit diurnal, semidiurnal, and mixed tidal regimes, making generalized prediction approaches less effective and emphasizing the need for locally adaptive models (Rumapea et al., 2024).

Accurate tidal prediction is essential for operational early warning systems, particularly in mitigating the impacts of tidal flooding and supporting coastal management. Historical events have demonstrated that inadequate anticipation of sea-level extremes can result in severe social and economic losses. While catastrophic events such as tsunamis require rapid-response warning mechanisms, recurrent tidal flooding demands reliable short- to medium-term predictions of high-water levels and their timing (BMKG, 2025; BNPB, 2005). Therefore, predictive models must not only achieve low average errors but also be capable of capturing peak tidal events that are critical for early warning purposes.

Conventional tidal prediction methods are predominantly based on harmonic analysis, which decomposes observed sea-level variations into sinusoidal constituents linked to known astronomical frequencies. Harmonic analysis has long been regarded as a robust and interpretable approach and remains widely used in operational tidal forecasting (Wulandari et al., 2021). However, this method assumes stationarity and performs less effectively under non-linear and non-stationary conditions, such as those induced by extreme weather events, river inflow, or long-term sea-level rise associated with climate change (Maulana et al., 2025). These limitations have motivated the exploration of alternative and complementary approaches.

Numerical hydrodynamic models offer a physics-based framework for simulating tidal processes and their interaction with atmospheric and oceanographic forcing. Although such models can provide detailed representations of sea-level dynamics, they require extensive input data, accurate boundary conditions, and high computational resources (Suci et al., 2023). These requirements often limit their applicability in operational early warning systems, especially in regions with limited observational coverage or real-time constraints.

In recent years, advances in artificial intelligence and machine learning have introduced data-driven alternatives for time series prediction. Deep learning, in particular, has shown strong potential in modeling complex, non-linear temporal relationships without explicit physical assumptions (Erlin et al., 2024). Recurrent Neural Networks (RNNs) and their improved variants have become prominent tools for sequential data analysis. Among them, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures are widely used due to their ability to overcome the vanishing gradient problem and capture long-term temporal dependencies (Susandri et al., 2025).

LSTM networks employ memory cells and multiple gating mechanisms input, forget, and output gates to regulate information flow across time steps. This structure enables LSTM models to retain relevant historical information over long sequences, making them suitable for time series with strong periodicity and non-linear behavior, such as tidal data (Ambadar et al., 2025). GRU models, by contrast, adopt a simpler architecture with fewer gates, resulting in reduced computational complexity and faster training while maintaining competitive predictive performance (Sinurat et al., 2024). The relative merits

of LSTM and GRU remain a topic of debate, with empirical studies reporting mixed results depending on data characteristics and model configuration (Kim et al., 2025).

Several studies have demonstrated the effectiveness of deep learning models for sea-level and tidal prediction. Maulana et al. (2025) showed that LSTM models could accurately capture sea-level trends and residual variability in Indonesian coastal waters, particularly after systematic parameter tuning. Sinurat et al. (2024) reported that Bidirectional LSTM slightly outperformed GRU in predicting sea-level variations, although GRU exhibited superior computational efficiency. International studies have similarly found that deep learning models outperform traditional statistical approaches such as ARIMA and SARIMA in modeling complex sea-level dynamics (Jabbar et al., 2025).

Despite these advances, several challenges remain. One major limitation is the suboptimal selection of model hyperparameters, which are often determined through manual trial-and-error rather than systematic optimization. Hyperparameters such as learning rate, number of hidden units, lookback window length, and dropout rate strongly influence model performance and generalization ability (Zamsuri et al., 2024). Inadequate tuning can lead to overfitting or underfitting, particularly when dealing with noisy and incomplete environmental datasets (Ambadar et al., 2025).

Bayesian Optimization has emerged as an efficient and principled approach for hyperparameter tuning in deep learning models. By constructing a probabilistic surrogate model of the objective function, Bayesian Optimization can identify near-optimal configurations with significantly fewer evaluations than grid or random search methods (Simamora et al., 2025). Although this technique has been successfully applied in various machine learning domains, its use in tidal sea-level prediction, especially for comparative studies of LSTM and GRU models, remains limited.

Another important issue concerns model evaluation for early warning systems. Most existing studies rely primarily on aggregate error metrics such as RMSE, MAE, or MAPE. While these metrics provide a general measure of accuracy, they do not fully reflect a model's ability to detect extreme events that are crucial for early warning applications (Sitepu et al., 2025). Recent studies have emphasized the need to evaluate predictive models based on their performance in capturing peak sea levels and minimizing missed extreme events, even at the expense of slightly higher average errors (Nurcahyo & Sasongko, 2023).

Against this backdrop, the present study aims to optimize and compare LSTM and GRU deep learning models for tidal sea-level time series prediction to support coastal early warning systems. Using observational tidal data from multiple stations in coastal Sumatra, this study applies Bayesian Optimization to systematically tune model hyperparameters and evaluates model performance from both statistical and operational perspectives. The main objective is to identify a predictive framework that balances accuracy, computational efficiency, and reliability in detecting high-tide events relevant to early warning.

The principal findings indicate that hyperparameter optimization significantly enhances the predictive performance of both LSTM and GRU models. While LSTM demonstrates slightly superior accuracy in capturing long-term dependencies and peak tidal events, GRU offers comparable performance with lower computational cost, making it attractive for real-time applications. These results highlight the importance of systematic optimization and context-aware evaluation in advancing deep learning–based tidal prediction and strengthening early warning systems in coastal regions.

2. METHODS

The overall research workflow is illustrated in Figure 1, which presents the sequential stages from data acquisition to early warning system implementation.

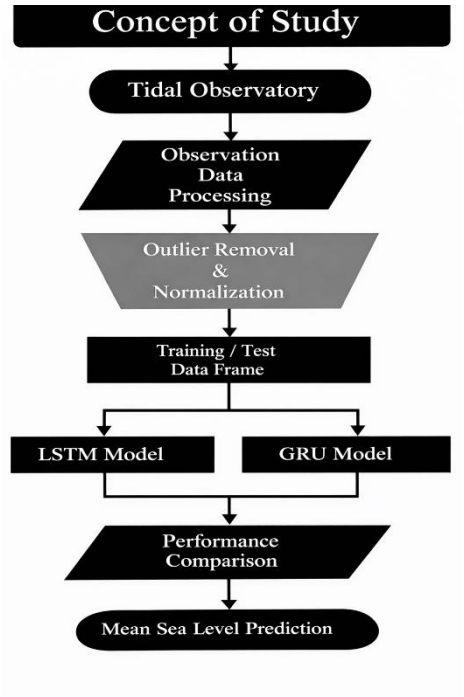

Figure 1. Research framework for tidal sea level time series prediction

The framework begins with tidal sea level data collection, followed by preprocessing and time series construction. Two deep learning models LSTM and GRU are then developed using baseline configurations and subsequently optimized through Bayesian Optimization. Model performance is evaluated using multiple error metrics, after which the best-performing model is selected and implemented within an early warning system context.

2.1 Study Area, Population, and Sample

The study area covers coastal regions of West Sumatra and North Sumatra, Indonesia. The population comprises all official tidal observation stations operating in these provinces. Using purposive sampling, four stations were selected based on data completeness, continuity of records, geographical representativeness, and relevance to coastal flood risk. The selected stations are Bungus (West Sumatra), Belawan and Kuala Tanjung (North Sumatra), and Sibolga (North Sumatra).

The dataset consists of continuous tidal sea level observations recorded from October to December 2025, covering 92 days of measurements. Each station provides more than 13,000 data points. All available records within this period are used without further reduction. The dataset is divided chronologically into 80% training data and 20% testing data to preserve temporal dependency and reflect real forecasting conditions.

2.2 Data Collection Technique

Tidal sea level data were collected using a documentation method, retrieving secondary data from the official maritime portal of the national meteorological authority. The data consist of time-stamped sea level elevations measured by tidal observatories. The collection procedure includes station identification, selection of observation period, data download in digital format, verification of data

consistency, and storage in a local database for further processing. Using data from an official governmental source ensures reliability and reproducibility.

2.3 Data Preprocessing

Preprocessing is conducted to ensure data quality prior to deep learning modeling. The process includes handling missing values, detecting and treating outliers, and ensuring uniform time intervals. Missing values are addressed using interpolation methods that preserve the natural tidal cycle. Outliers are examined carefully to distinguish sensor-related anomalies from genuine extreme tidal events, which are important for early warning purposes. After cleaning, the data are normalized to a common scale to stabilize neural network training and improve convergence. These preprocessing steps ensure that the tidal time series data are consistent, reliable, and suitable for LSTM and GRU modeling.

2.4 Time Series Construction

The cleaned data are transformed into a time series learning format using a sliding window approach. Historical sea level values (time-lag features) are used as inputs to predict future sea level values. Data partitioning is performed sequentially rather than randomly to prevent information leakage. In addition, multistep forecasting is applied to assess the ability of the models to predict multiple future time steps, which is essential for early warning system applications.

2.5 LSTM Model Development

The LSTM model is designed to capture both short-term and long-term temporal dependencies in tidal sea level data. Model development begins with a baseline LSTM configuration, serving as a reference for subsequent optimization. Key hyperparameters including the number of neurons, number of layers, learning rate, and batch size are then optimized using Bayesian Optimization to improve predictive performance. The optimized LSTM model is trained using the training dataset and evaluated on the testing dataset. Its prediction results are retained for comparison with the GRU model.

2.6 GRU Model Development

In parallel, a GRU model is developed as a comparative approach. GRU employs a simpler gating mechanism than LSTM, resulting in fewer parameters and faster training. Similar to the LSTM procedure, a baseline GRU model is first constructed, followed by hyperparameter optimization using Bayesian Optimization within a comparable search space. The optimized GRU model is trained and tested using the same data partitioning scheme to ensure a fair and objective comparison with the LSTM model.

2.7 Model Evaluation and Selection

Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Percentage Error (MPE), and the coefficient of determination (R^2). These metrics provide complementary insights into prediction accuracy, sensitivity to extreme errors, systematic bias, and the ability of the model to explain data variability. The model exhibiting the lowest error values and the most stable performance across stations is selected as the final model.

2.8 Early Warning System Implementation

The final stage involves integrating the selected model into a tidal early warning system. The model is used to generate continuous sea level predictions based on historical data, enabling the identification of potentially hazardous high-tide conditions. This implementation demonstrates that the proposed methodology not only improves predictive accuracy but also provides practical value for coastal risk mitigation and early warning applications.

3. FINDINGS AND DISCUSSION

This section presents and discusses the main findings of the study, addressing the research objectives and hypotheses related to the optimization and comparative performance of LSTM and GRU models for tidal sea level prediction. The results are analyzed based on quantitative evaluation and interpreted in relation to previous studies and their implications for early warning system applications.

3.1 Characteristics of Tidal Sea Level Dataset

The characteristics of the tidal sea level datasets used in this study are summarized in Table 1. Each station provides high-resolution observations with consistent temporal intervals and sufficient data length to support deep learning–based modeling.

Table 1. Summary of tidal sea level dataset

Station	Observation Period	Number of Records	Tidal Setting
Bungus	Oct–Dec 2025	13,249	Open ocean (Indian Ocean)
Belawan	Oct–Dec 2025	13,283	Semi-enclosed (Malacca Strait)
Kuala Tanjung	Oct–Dec 2025	13,283	Semi-enclosed (Malacca Strait)
Sibolga	Oct–Dec 2025	13,231	Open ocean (Indian Ocean)

The characteristics of the tidal sea level dataset play a fundamental role in determining the effectiveness of deep learning–based prediction models. In this study, each tidal station provides more than 13,000 observations recorded at regular intervals over a continuous three-month period. From a time series modeling perspective, this data density is particularly advantageous because recurrent neural networks such as LSTM and GRU rely on long sequential patterns to learn temporal dependencies. The availability of uninterrupted records ensures that the models can capture both short-term tidal oscillations and longer periodic components associated with lunar and solar forcing.

The distinction between open-ocean stations (Bungus and Sibolga) and semi-enclosed strait stations (Belawan and Kuala Tanjung) introduces meaningful variability in the dataset. Open-ocean environments are generally influenced by a combination of astronomical tides, regional circulation, and wave-induced effects, which can lead to more complex and less regular tidal patterns. In contrast, semi-enclosed waters such as the Malacca Strait tend to exhibit more predictable tidal oscillations due to constrained geometry and reduced exposure to ocean swell. These differences are reflected in the subsequent modeling results and highlight why a multi-station dataset is essential for evaluating model robustness.

From a scientific standpoint, the dataset characteristics directly address the study's initial objective of assessing whether tidal observation data are suitable for deep learning–based forecasting. The high temporal resolution and continuity observed here align with findings from previous studies, which emphasize that deep learning models outperform traditional statistical methods when trained on dense, high-quality time series data (Maulana et al., 2025; Sinurat et al., 2024). Moreover, the use of in-situ observations from official tidal observatories enhances the ecological validity of the findings, ensuring that the models learn from real-world conditions rather than idealized or synthetic data.

Importantly, these dataset characteristics also have practical implications for early warning systems. Early warning applications require models that can operate reliably under varying local

conditions. By incorporating stations with different hydrodynamic settings, this study demonstrates that the proposed modeling framework is not limited to a single tidal regime. Instead, it is capable of adapting to diverse coastal environments, thereby strengthening its applicability for broader coastal risk mitigation efforts.

3.2 Performance of Optimized LSTM Models

The predictive performance of the optimized LSTM model is presented in Table 2, which summarizes the quantitative evaluation results obtained for each tidal observation station using multiple performance metrics.

Table 2. Performance metrics of optimized LSTM models

Stasiun	MAE	RMSE	R^2
Bungus	0.002152	0.002577	0.999817
Belawan	0.002693	0.003259	0.999629
Kuala Tanjung	0.003532	0.004173	0.999507
Sibolga	0.003686	0.004441	0.999279

The optimized LSTM models exhibit consistently high predictive accuracy across all stations, with MAE and RMSE values remaining below 0.004 and R^2 values exceeding 0.999. These results provide strong empirical support for the hypothesis that LSTM, when combined with systematic hyperparameter optimization, is highly effective for tidal sea level prediction. The improvement observed after Bayesian Optimization highlights the importance of model tuning in extracting the full predictive potential of deep learning architectures.

The superior performance of LSTM at the Bungus station deserves particular attention. Bungus, located in an open-ocean setting, is subject to more complex tidal dynamics and longer-term dependencies. LSTM's memory cell structure, which explicitly preserves information over extended time horizons, enables it to capture such dependencies more effectively than simpler architectures. This finding is consistent with theoretical expectations and aligns with prior studies reporting that LSTM excels in environments characterized by complex and non-stationary temporal patterns (Kim et al., 2025).

From a methodological perspective, the station-specific optimal configurations identified through Bayesian Optimization suggest that a one-size-fits-all model design is suboptimal. Instead, tailoring the number of neurons, learning rate, and batch size to local data characteristics leads to measurable performance gains. This observation reinforces the argument that hyperparameter optimization should be considered an integral part of deep learning–based environmental modeling, rather than an optional refinement.

In comparison with earlier approaches such as ARIMA or SVR, the magnitude of error reduction achieved by the optimized LSTM models is substantial. Traditional statistical models often struggle to represent non-linear relationships and long-term dependencies inherent in tidal data. The results of this study confirm that LSTM offers a significant methodological advancement, particularly when accuracy requirements are stringent, as in early warning systems. Accurate prediction of peak tidal levels is crucial, and the low RMSE values observed here indicate that LSTM is capable of meeting this operational demand.

3.3 Performance of Optimized GRU Models

The performance of optimized GRU models is summarized in Table 3, which presents the evaluation results obtained for each tidal observation station using several quantitative performance metrics.

Table. 3 Performance metrics of optimized GRU models

Stasiun	MAE	RMSE	R^2
Bungus	0.002885	0.003558	0.999650
Belawan	0.001423	0.002156	0.999838
Kuala Tanjung	0.002056	0.002551	0.999816
Sibolga	0.002241	0.002696	0.999734

The optimized GRU models demonstrate predictive accuracy comparable to, and in some cases exceeding, that of LSTM. Notably, GRU achieves the lowest MAE and highest R^2 values at Belawan, Kuala Tanjung, and Sibolga. These findings underscore GRU's effectiveness in modeling tidal sea level time series, particularly in environments where tidal patterns are relatively regular and exhibit moderate complexity.

The strong performance of GRU can be explained by its simplified gating mechanism, which reduces model complexity while retaining the ability to capture essential temporal dependencies. By employing fewer parameters than LSTM, GRU reduces the risk of overfitting and accelerates the training process. This efficiency becomes especially valuable in operational contexts, where computational resources and response times are constrained. The observed computation times of 6–13 milliseconds per step suggest that GRU models are well suited for near-real-time prediction tasks.

From a theoretical standpoint, these results support the growing body of literature suggesting that GRU offers an effective trade-off between learning capacity and computational efficiency (Akmal et al., 2025). While LSTM may provide advantages in highly complex temporal environments, GRU's streamlined architecture allows it to generalize well across a wide range of conditions without sacrificing accuracy. This characteristic is particularly advantageous for early warning systems that must operate continuously and reliably.

The consistency of GRU's performance across three of the four stations also highlights its robustness. In semi-enclosed waters such as the Malacca Strait, where tidal oscillations are more uniform, GRU appears to capture dominant periodic patterns with minimal error. This observation aligns with previous marine forecasting studies that report GRU's suitability for regular and moderately complex time series (Kim & Huang, 2023).

3.4 Comparative Analysis of LSTM and GRU Models

The selection of the best-performing model for each station is shown in Table 4, which summarizes the comparative results of the optimized LSTM and GRU models based on the evaluation metrics used in this study.

Table. 4. Best-performing model by station

Station	Best Model
Bungus	LSTM
Belawan	GRU
Kuala Tanjung	GRU
Sibolga	GRU

The comparative analysis reveals that no single model dominates across all stations, a finding that directly addresses the central research question of this study. Instead, model performance is strongly influenced by local tidal characteristics. LSTM performs best in Bungus, while GRU outperforms LSTM at Belawan, Kuala Tanjung, and Sibolga. This outcome emphasizes the importance of data-driven model selection in environmental applications.

Scientifically, this result challenges the notion that more complex models are always superior. While LSTM's advanced memory structure is beneficial in certain contexts, it may introduce

unnecessary complexity in environments with simpler temporal dynamics. GRU's success at multiple stations demonstrates that simpler architectures can achieve equal or superior performance when matched appropriately to data characteristics.

This finding is consistent with comparative studies in oceanographic forecasting that report mixed results depending on location, temporal scale, and data structure (Jabbar et al., 2025). It also highlights the risk of relying on a single architecture without considering local conditions. For early warning systems, adopting a flexible framework that allows different models to be deployed at different locations may be more effective than enforcing uniformity.

3.5 Implications for Early Warning Systems

The integration of optimized deep learning models into an early warning system represents a significant practical contribution of this study. The consistently low prediction errors observed across stations indicate that both LSTM and GRU can reliably forecast mean sea level variations, including high-tide events that are critical for coastal flood warnings.

From an operational perspective, the ability to select the best-performing model for each station enhances system reliability. Underestimating peak tides can lead to delayed warnings, while overestimation may reduce public trust. The balanced error characteristics demonstrated by the optimized models suggest that they can support more accurate and timely decision-making.

Compared with earlier early warning systems based on statistical or hybrid models, the proposed approach offers improved adaptability and scalability. By leveraging deep learning and hyperparameter optimization, the system can be updated as new data become available, ensuring long-term relevance. These advantages position the proposed framework as a robust foundation for future coastal early warning applications.

4. CONCLUSION

This study set out to optimize and compare LSTM and GRU deep learning models for tidal sea level time series prediction with the explicit objective of supporting coastal early warning systems. The findings demonstrate that both models, when systematically optimized using Bayesian Optimization, are capable of producing highly accurate and stable tidal predictions across different coastal environments in West Sumatra and North Sumatra. This confirms the main research objective that deep learning–based approaches can serve as reliable alternatives to conventional tidal prediction methods, particularly under non-linear and non-stationary conditions.

The results further reveal that model performance is strongly influenced by local tidal characteristics rather than by model architecture alone. LSTM exhibits superior performance at Bungus, an open-ocean station characterized by more complex temporal dependencies, highlighting its strength in capturing long-term patterns. In contrast, GRU outperforms LSTM at Belawan, Kuala Tanjung, and Sibolga, demonstrating that simpler architectures can achieve equal or better performance in environments with more regular tidal dynamics. This finding represents an important research discovery, as it emphasizes that data-driven and location-specific model selection is more effective than relying on a single universally applied model.

From a methodological perspective, the study confirms that Bayesian Optimization plays a critical role in enhancing predictive performance by identifying optimal hyperparameter configurations tailored to local data characteristics. This addresses a key limitation identified in previous studies, where suboptimal manual tuning often constrained model generalization. The consistently low error values and high coefficients of determination obtained in this study indicate that optimized deep learning models are not only accurate but also sufficiently robust for operational use.

In terms of practical implications, the integration of the optimized models into a tidal early warning system framework demonstrates that the proposed approach has direct applicability for coastal risk mitigation. The ability to accurately predict tidal variations, including high-tide conditions, supports more timely and reliable decision-making for coastal management and disaster preparedness.

Nevertheless, this study is limited to univariate tidal data and a three-month observation period. Future research should extend the temporal coverage to assess long-term model stability and seasonal variability. Incorporating meteorological and hydrological variables, such as wind speed, atmospheric pressure, and river discharge, is also recommended to improve prediction performance during extreme events. Ongoing work is directed toward developing multivariate and spatiotemporal deep learning models, as well as exploring hybrid architectures that combine recurrent networks with attention mechanisms to further enhance early warning capabilities.

REFERENCES

Akmal, M. F., Susrama, I. G., Diyasa, M., & Junaidi, A. (2025). *Penerapan Gated Recurrent Unit dengan Bayesian Optimization dalam Prediksi Harga Saham Sektor FMCG*. *09*, 36–41.

Ambadar, P. R., Novitasari, D. C. R., Farida, Y., Hafiyusholeh, M., & Setiawan, F. (2025). Implementation of LSTM Method on Tidal Prediction in Semarang Region. *Journal of Applied Informatics and Computing*, *9*(2), 398–304. https://doi.org/10.30871/jaic.v9i2.8932

Badan Meteorologi, Klimatologi, dan G. (2025). *Peringatan dini banjir pesisir (rob) wilayah pesisir utara Pulau Jawa*. Jakarta.

Erlin; Arda Yunianta; Lili Ayu Wulandhari; Yenny Desnelita; Nurliana Nasution; Junadhi. (2024). Enhancing Rice Production Prediction in Indonesia Using Advanced Machine Learning Models. *IEEE Access*, *12*(September), 151161–151177. https://doi.org/10.1109/ACCESS.2024.3478738

Jabbar, A., Alhallaf, B., Vilcáez, J., Rudra, P., & Lafta, A. A. (2025). Predicting sea level variations for early warning using SARIMA model and deep learning techniques in the northwest Arabian Gulf. *Discover Geoscience*, *3*(158), 1–20.

Kim, D., & Huang, T. (2023). Learning Rate Optimization for GRU Networks in Marine Forecasting. *Journal of Marine AI Systems*, *22*(3).

Kim, T., Yun, H., Yoon, H., & Lee, S. (2025). Comparative Analysis and Validation of LSTM and GRU Models for Predicting Annual Mean Sea Level in the East Sea : A Case Study of Ulleungdo Island. *Applied Sciences*, *15*, 1–19.

Maulana, R. R., Rochaddi, B., & Wijaya, Y. J. (2025). Analisis Prediksi Kenaikan Permukaan Laut Menggunakan Data Satelit Altimetri dengan LSTM di Perairan Jepara dan Sekitarnya. *Buletin Oseanografi Marina*, *14*(2), 322–334. https://doi.org/10.14710/buloma.v14i2.67069

Nurcahyo, J. A., & Sasongko, T. B. (2023). Hyperparameter Tuning Algoritma Supervised Learning untuk Klasifikasi Keluarga Penerima Bantuan Pangan Beras. *Indonesian Journal of Computer Science*, *12*(1), 1351–1365.

Rumapea, M. A., Suhana, M. P., & Putra, R. D. (2024). Tipe dan Pola Pasang Surut pada Perairan di Sekitar Kawasan Reklamasi Kota Tanjungpinang. *Jurnal Kelautan: Indonesian Journal of Marine Science and Technology*, *17*(2), 178–186. https://doi.org/10.21107/jk.v17i2.18218

Simamora, F. P., Purba, R., Pasha, F., Simamora, F. P., Purba, R., & Pasha, F. (2025). Optimisasi Hyperparameter BiLSTM Menggunakan Bayesian Optimization untuk Prediksi Harga Saham Optimisasi Hyperparameter BiLSTM Menggunakan Bayesian Optimization untuk Prediksi Harga Saham. *Jambura Journal of Mathematics*, *7*(1), 8–13.

Sinurat, A. B. N., Arifin, W. A., & Larasati, W. A. (2024). Prediksi Tinggi Muka Air Laut Menggunakan Metode Gated Recurrent Unit Dan Bidirectional Long Short-Term Memory. *Jurnal Inovtek Polbeng - Seri Informatika*, *9*(2), 753–764.

Sitepu, J. P., Mongi, C. E., Widiana, S. A., & Ketaren, E. (2025). PREDIKSI BANJIR DI KOTA MANADO MENGGUNAKAN METODE. *Jurnal TIMES*, *XIV*(1), 70–75.

Suci, D. R., Atmodjo, W., & Setiyono, H. (2023). Analisis pasang surut dalam rangka penentuan tinggi dermaga di Timbulsloko, Demak, Jawa Tengah. *Indonesian Journal of Oceanography (IJOCE)*, *05*(03), 131–137. https://doi.org/10.14710/ijoce.v5i3.16469

Susandri Susandri, N. Feldiansyah Bakri , Fajrizal Fajrizal, S. (2025). Spatial-Temporal Analysis of Earthquakes in Indonesia with Deep Learning Models: Performance Evaluation of CNN, LSTM, and Hybrid CNN-GRU. *Jurnal Resti*, *9*(5), 1020–1029.

Wulandari, S. S., Sufri, & Yurinanda, S. (2021). Penerapan Metode ARIMA Dalam Memprediksi Fluktuasi Harga Saham PT Bank Central Asia Tbk. *BUANA Matematika: Jurnal Ilmiah Matematika Dan Pendidikan Matematika*, *11*(1), 53–68.

Zamsuri, A., Defit, S., & Nurcahyo, G. W. (2024). Development and Comparison of Multiple Emotion Classification Models in Indonesia Text Using Machine Learning. *Journal of Advances in Information Technology*, *15*(4), 519–531. https://doi.org/10.12720/jait.15.4.519-531