Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2025, 2025:83
https://doi.org/10.28919/cmbn/9343
ISSN: 2052-2541

ENHANCING WATER LEVEL FORECASTING IN THE CILIWUNG RIVER USING MULTIPLE INPUT BiLSTM

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Abstract: Accurate forecasting of river water levels is crucial for flood disaster mitigation, especially in flood-prone areas such as Jakarta, Indonesia. We propose a deep learning model for water level forecasting using a Multiple Input Bidirectional Long Short-Term Memory (MI-BiLSTM) architecture enhanced by an outlier-handling framework based on DeepAnT and linear interpolation techniques. Water level data were collected hourly from three monitoring stations: Katulampa Barrage, Depok Gauge, and Manggarai Gate. Two prediction scenarios were evaluated: the model with raw data and DeepAnt-BiLSTM model based on integrated process. The proposed model showed a significant improvement in the predictive performance, achieving an RMSE of 10.81 cm, MAPE of 1.07%, and NSE of 0.94. In addition, when evaluated based on the flood alert classification, the model accurately detected 130 out of 155 alert-level events (water level > 750 cm) in the testing set, achieving an alert classification accuracy of 83.87%. These results demonstrate the capability of the model to capture extreme hydrological events and its practical suitability for early warning systems. This study highlights the potential of combining outlier handling and BiLSTM-based architectures to enhance the accuracy of water level forecasting. The proposed approach is particularly relevant to improve the performance of prediction models and supporting the development of a more reliable flood early warning system.

Keywords: BiLSTM; water level; time series outlier; hydrological forecasting; early warning system.

2020 AMS Subject Classification: 68T07.

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Received May 07, 2025

1. INTRODUCTION

Forecasting water levels in river systems is crucial for flood disaster mitigation and water resource management, particularly in urban areas with high population densities. One of the main rivers flowing through Jakarta is the Ciliwung river, which frequently experiences flooding due to extreme seasonal rainfall and other hydrological dynamics [1, 2, 3]. This river flows from Katulampa Barrage upstream to several floodgates across Jakarta. Presently, the strategy for flood preparation relies on real-time monitoring at this upstream station to provide preliminary alerts for the downstream regions. The water level observed at the Katulampa Barrage reaches Jakarta in 13 to 14 hours. This estimated time is used as a waiting period to provide flood alert information if there is an increase in extreme water levels at Katulampa Barrage [4]. However, the increasing threat of flooding requires a more effective early warning system, one of which is forecasting river water levels. Better accuracy in predicting TMA can provide significant benefits in early warning systems and flood disaster mitigation in Jakarta. To address this need, recent advances in deep learning have provided promising solutions.

Deep learning-based methods have shown great potential in hydrological time series forecasting due to their ability to capture complex patterns and non-linear relationships in data [5, 6, 7]. One of the models widely used in time series forecasting is Long Short-Term Memory (LSTM), which is designed to handle long-term dependencies in data [8, 9, 10, 11]. Despite its advantages, conventional LSTM models can only process data with unidirectional input, restricting their learning scope to historical inputs that progress forward in time. Therefore, Bidirectional LSTM (BiLSTM) was developed to enhance the capabilities of LSTM by allowing the model to learn in both directions: forward and backward [12]. Several studies have indicated that BiLSTM can make predictions more accurate than LSTM, especially in time series with complex patterns and high variability [13, 14].

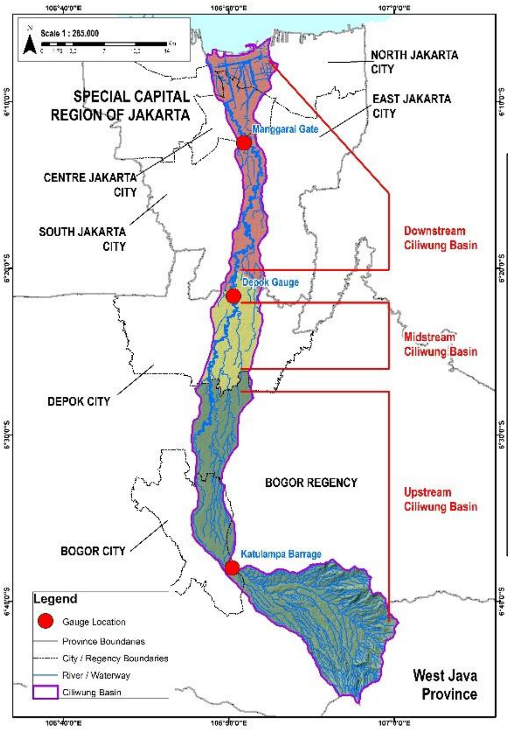
However, one of the main challenges in deep learning-based hydrological forecasting is the presence of outliers in the data. Water level data obtained from sensors often contain outliers due to measurement errors, signal disturbances, or extreme hydrological changes [15, 16]. Outliers in the time series can cause the model to produce biased and less accurate predictions, necessitating a special approach to handle anomalies before modeling. The general approach to handling outliers in time series data includes the removal of anomalous data points, the use of robust methods, or the interpolation of missing values [17]. In hydrological forecasting, linear interpolation is often used because it can maintain the continuity of data patterns without altering the main statistical characteristics. Wahir [17] handled outliers in time series data by treating them as missing values and then performed linear interpolation to replace the outliers with other values. The research concluded that forecasting accuracy improved after handling outliers with linear interpolation, compared to not handling them. Accordingly, this study incorporates a rigorous outlier handling protocol prior to model training.

This study used water level data from three main locations along the Ciliwung river, namely Katulampa Barrage, Depok Gauge, and Manggarai Gate. This study implements a Multiple Input Bidirectional LSTM (MI-BiLSTM) architecture, which allows the model to simultaneously process multiple time series inputs to forecast water levels at the Manggarai Gate more accurately. The integration of outlier detection and linear interpolation into the data preparation pipeline was intended to mitigate noise-induced forecasting errors and strengthen the model robustness. The results of this study aim to advance the application of deep learning in river stage prediction, with particular emphasis on tropical river systems that are susceptible to extreme hydrological events. By improving the accuracy of water level predictions, this study contributes to the development of a more reliable flood early warning system and better flood disaster mitigation planning in flood-prone areas of Jakarta and similar urban catchments.

2. MATERIAL AND METHOD

2.1 Data and Study Area

This study used water level data collected using an Automatic Water Level Recorders (AWLR) sensor. The sensor data were managed and published by the Jakarta Water Resources Department (DSDA Jakarta) via its official website (https://poskobanjirdsda.jakarta.go.id/). Data were gathered from three monitoring stations strategically positioned along the Ciliwung river, namely the Katulampa Barrage located upstream, the Depok Gauge located midstream, and the Manggarai Gate located downstream. These stations were selected to represent the water level dynamics throughout the interconnected upstream-downstream system. Figures 1 and 2 illustrate the spatial mapping of the study area, including the estimated flow travel times between the monitoring stations.



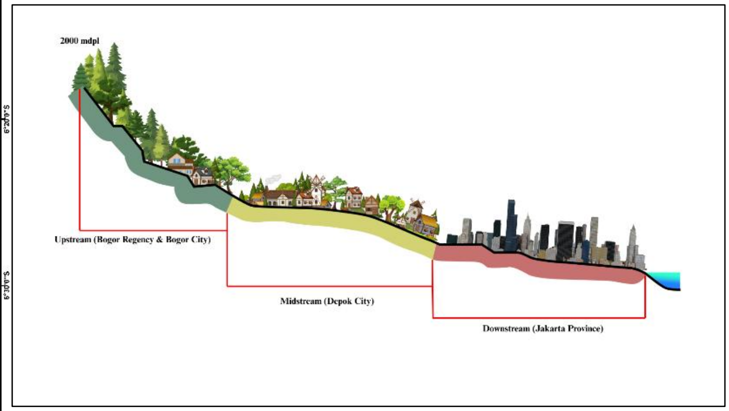


FIGURE 1. Ciliwung river flow map

FIGURE 2. Zonation of the Ciliwung river basin

The Ciliwung river, located in Indonesia, extends for 124 kilometers and has a watershed area of 270 square kilometers [4]. This river originates in Bogor Regency, with the Katulampa Barrage marking the boundaries of the upper Ciliwung river basin. From there, the river flows through several major cities into DKI Jakarta Province, as illustrated in Figure 1. The Ciliwung river is elevated, varying from 0 to 2985 meters, as shown in Figure 2. The Ciliwung river basin categorizes land use into three zones: upstream, midstream, and downstream. Bogor Regency and Bogor City in the upstream zone serve as conservation areas and water sources, while Depok City in the intermediate zone functions as a buffer zone and water catchment region. DKI Jakarta Province in the downstream zone pertains to agricultural lands and coastline defense [1].

The dataset comprises historical hourly water level data from 1, January 2020 to June 30, 2024. We performed data pre-processing prior to modelling. Pre-processing data indicated the presence of missing values across all three monitoring stations. Table 1 summarizes the descriptive statistics, including the minimum and maximum of water level data, mean, standard deviation, and total number of missing values for each station.

Table 1. Descriptive Statistics of Water Level Data

Station	Min (cm)	Max (cm)	Mean (cm)	Std. Dev (cm)	Missing Value (%)
Katulampa	0	240	19.37	13.63	0.06%
Depok	6.67	697	92.27	30.98	1.51%
Manggarai	0.5	967	586.31	115.76	1.48%

2.2 DeepAnT Detection Method

DeepAnT (Deep Learning-based Anomaly Detection in Time Series) is an unsupervised outlier detection method proposed by Munir [18] specifically designed for time series data. It consists of two main modules: the Time Series Predictor and the Anomaly Detector. The Time Series Predictor utilizes a Convolutional Neural Network (CNN) to forecast future data points based on historical observations within a specified sliding window. Subsequently, the Anomaly Detector assessed outliers by calculating the deviation between the actual and predicted data, and flagging substantial deviations as anomalies. DeepAnT does not require labeled data for training and maintains high generalization capabilities even when trained on relatively small datasets, making it highly applicable to real-world streaming scenarios where labeling data is often impractical.

2.3 Bidirectional Long Short-Term Memory (BiLSTM)

Long Short-Term Memory (LSTM) is an improved version of Recurrent Neural Network (RNN) that overcomes the main problem of RNN in remembering information over a long period of time, caused by issues such as vanishing gradients and exploding gradients [8, 19]. The LSTM adds memory cells and three main gate units: input gate, forget gate, and output gate, which control how information moves using sigmoid and tanh activation functions. These gates determine what information should be stored, deleted, or removed from long-term memory, so that the network is able to retain and access important information over long periods of time [20].

With a linear relationship between cell states and internal control mechanisms, LSTM successfully maintains gradient stability during the backpropagation learning process, making it superior in processing sequential data such as time series. The equation for LSTM is as follows:

$$\left.\begin{aligned} f_t &= \sigma(W_f \,.\, [h_{t-1}, x_t] + b_f]) \\ i_t &= \sigma(W_i \,.\, [h_{t-1}, x_t] + b_i]) \\ \tilde{C}_t &= \tanh\,(W_C \,.\, [h_{t-1}, x_t] + b_C]) \\ C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \\ o_t &= \sigma(W_o \,.\, [h_{t-1}, x_t] + b_o]) \\ h_t &= o_t * \tanh\,(C_{t)}) \end{aligned}\right\} \quad (1)$$

However, the limitation of conventional LSTM, which only flows information in one direction (from past to future), is the reason for the development of Bidirectional LSTM (BiLSTM). BiLSTM combines two LSTM layers in parallel: one processes data from start to finish (forward layer), and the other from finish to start (backward layer), and then combines the two to form a more comprehensive representation of the context of sequential data [9, 21, 22]. Thus, each time point in the time series obtains information from two directions, allowing the BiLSTM to understand more intricate temporal dependencies.

$$\left.\begin{array}{c} \overrightarrow{h_t} = \overrightarrow{LSTM}(h_{t-1}, x_t, c_{t-1}), t \in [1, T] \\ \overleftarrow{h_t} = \overleftarrow{LSTM}(h_{t+1}, x_t, c_{t+1}), t \in [1, T] \\ H_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \end{array}\right\} \quad (2)$$

2.4 Evaluation Metrics

The performance of the models was assessed using three metrics including Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Nash-Sutcliffe Efficiency (NSE).

The RMSE was used to measure the difference between the value predicted by the model and the actual observed value. The RMSE score ranges from [0, ∞], where the model prediction was ideal if the RMSE was 0. The smaller the RMSE value, the closer the predicted data is to the original data [16]. RMSE is defined by the following equation:

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{N}(y_t - \widehat{y_t})^2}{N}} \quad (3)$$

MAPE is the average absolute differentiation between the forecast and actual values and is expressed as a percentage of the actual value. The MAPE was used to calculate the percentage of error between the actual and the predicted data. The MAPE is defined using the following equation:

$$\text{MAPE} = \frac{\sum_{t=1}^{n}\left|\frac{\hat{Y}_t - Y_t}{Y_t}\right|}{n} \, 100\% \quad (4)$$

NSE evaluates the accuracy of the hydrological model, with values extending from 1 to negative infinity. A score of 1 indicates an ideal correspondence between the predicted and observed flows, while a negative NSE indicates inadequate model performance. The formula used for these criteria is elaborated below [23, 24].

$$\text{NSE} = 1 - \frac{\sum_{t=1}^{T}(Q_{t,o} - Q_{t,m})^2}{\sum_{t=1}^{T}(Q_{t,o} - \overline{Q_o})^2} \quad (5)$$

2.5 Procedure of Data Analysis

This study aims to evaluate the impact of outlier handling on the accuracy of water level forecasting using the BiLSTM model for the Ciliwung River. Forecasting performance is evaluated in two different scenarios: (1) using raw data containing outliers without prior handling, hereinafter referred to as the BiLSTM model, and (2) using preprocessed data, where outliers have been detected and imputed, hereinafter referred to as the DeepAnT-BiLSTM model.

The data analysis framework employed in this study comprises a sequential process of preprocessing, feature engineering, model development, and evaluation, all of which are tailored to enhance the quality and predictive power of time series inputs. Missing data identified in section 2.1 were subsequently imputed. Outlier detection was then performed using the DeepAnT method. The detected outliers were removed and replaced using linear interpolation. The resulting cleaned dataset form the basis for model training in what is referred to as the DeepAnT-BiLSTM architecture. This section introduces the state-of-the-art contribution of this study, highlighting the integration of outlier detection, outlier handling and deep learning for enhanced hydrological forecasting.

Following the outlier handling process, the dataset was partitioned into two subsets: training data with a ratio of 80% and testing data with a ratio of 20%. Furthermore, these data were normalized with a scale range of 0-1 using the min-max method. The min-max method is obtained by dividing the reduction of the i-th data with the smallest data by the largest data with the smallest data.

The DeepAnT-BiLSTM model was then built using important settings, including the number of neurons, dropout rate, batch size, learning rate, number of epochs and Adaptive Moment Estimation (Adam) optimization algorithm. To optimize model performance, hyperparameter tuning was performed using the RandomizedSearchCV method. This method efficiently explores the hyperparameter space by randomly selecting parameter values, significantly reducing the computational cost compared with an exhaustive grid search while maintaining near-optimal performance. We then trained the model using the obtained optimal parameters that summarized in Table 2. After training, the model was used to predict the test data.

Table 2. BiLSTM and DeepAnT-BiLSTM configuration

Hyperparameter	**Optimal Values**
Neurons	48
Dropout	0.1
Batch size	48
Learning rate	0.0001
Epochs	100
Optimizer	Adam

For comparison, a BiLSTM model was also built using the same procedure but using the original data without outlier handling. Thus, the difference in performance between the two models reflects the contribution of the outlier detection and imputation stages to prediction accuracy. The performances of the two models, BiLSTM and DeepAnT-BiLSTM, were compared directly based on the RMSE, MAPE, and NSE values. The model with the lower prediction error rate was determined as the best model in the context of water level prediction in the Ciliwung River.

3. RESULTS AND DISCUSSION

3.1 Pre-processing and Outlier Detection

Data pre-processing was conducted prior to model training. The water level data from the three locations have missing values, as listed in Table 1. Missing values from the three locations were imputed using the kNN with k=5. Next, we detect outliers in the entire dataset using the DeepAnT method. As explained in the previous section, Time Series Predictor DeepAnT uses the CNN approach, with the architecture shown in Table 3.

Table 3. Time Series Predictor configuration

Hyperparameter	Value
Time window	10
CNN filter	64
Epoch	50
Optimizer	Adam

Figures 3, 4, and 5 show the visualization of the outlier detection results on the high-water level time series data at Katulampa Barrage, Depok Gauge, and Manggarai Gate. The detected outliers are marked with red dots in the peaks of the significant deviations in the data. In percentage terms, the number of identified outliers is relatively small, namely Katulampa Barrage at 0.02%, Depok Gauge at 0.02%, and Manggarai Gate at 0.025%. Although the proportion was low, the existence of these outliers can have a major impact on the performance of the model.

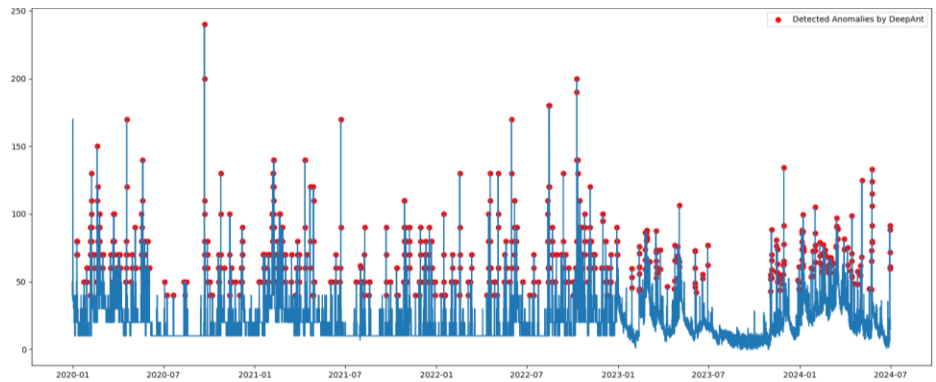


FIGURE 3. Result of outlier detection at the Katulampa Barrage, red dots indicate the existence of outliers

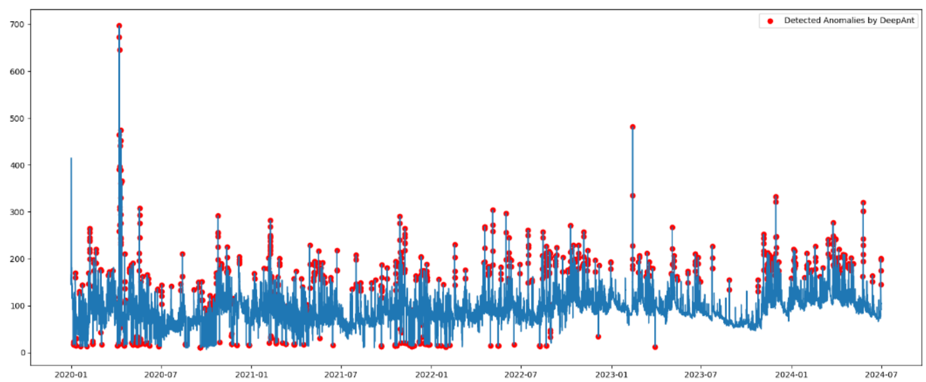


FIGURE 4. Result of outlier detection at the Depok Gauge, red dots indicate the existence of outliers

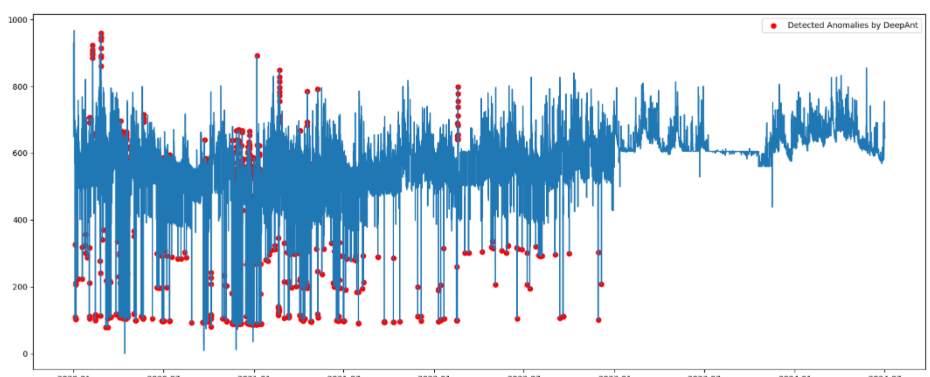


FIGURE 5. Result of outlier detection at the Manggarai Gate, red dots indicate the existence of outliers

After we detected the outliers, all detected outlier points were removed from the dataset and then imputed using the linear interpolation method. This imputation process is performed by estimating the outlier value based on the closest data before and after that point. This step aims to smooth the time series and avoid biases that can be caused by extreme values so that the prediction model that is built can produce more stable, accurate, and representative estimates of the actual pattern of the Ciliwung river flow system.

3.2 Prediction Performance

To evaluate the impact of outlier handling on the accuracy of the prediction model, the performance of the two models, BiLSTM and DeepAnT-BiLSTM, is compared. We evaluated the model performance using RMSE, MAPE, and NSE, as presented in Table 4.

Table 4. Performance metrics between BiLSTM and DeepAnT-BiLSTM

Evaluation Metrics	BiLSTM	DeepAnT-BiLSTM
RMSE	13.83	10.81
MAPE	1.57%	1.07%
NSE	0.91	0.94

Table 4 demonstrates that the DeepAnT-BiLSTM model performed better than the BiLSTM model. The RMSE value decreased from 13.83 to 10.81, indicating a reduction in the mean square error in the prediction. Similarly, the MAPE value decreased from 1.57% to 1.07%, indicating an increase in the accuracy relative to the actual data. The decrease in these two metrics confirms that outlier removal and imputation can improve the accuracy of the results for predicting the water level. In addition, the NSE value also shows an increase from 0.91 in the raw data to 0.94 after outlier handling. This increase indicated that the model is more efficient in representing the variation of actual data, such that the resulting prediction is more representative of real conditions.

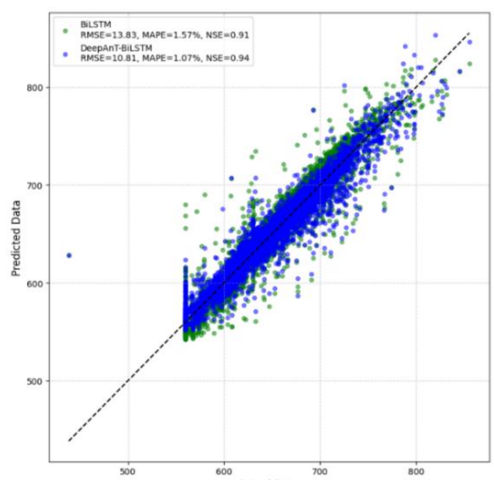


FIGURE 6. Scatter plots illustrate the comparison prediction between BiLSTM and DeepAnT-BiLSTM

Figure 6 illustrates a scatterplot comparing the DeepAnT-BiLSTM model and BiLSTM model. The predictions from DeepAnt-BiLSTM (indicated by blue dots) exhibit a tighter distribution around the ideal line compared to the BiLSTM (green dots), suggesting that outlier handling of data contributes to improved model accuracy. As shown, DeepAnT-BiLSTM showed better performance, with an RMSE of 10.81, MAPE of 1.07%, and NSE of 0.94. The lower RMSE indicates reduced average prediction error, while the lower MAPE indicates a smaller relative error. In addition, a higher NSE value close to 1 indicates that the model effectively predicts the water level data. Hence, these results show that DeepAnT-BiLSTM has a significant positive impact on the predictive performance of water level forecasting.

This prediction model was designed as part of a water level forecasting system that supports the implementation of a flood Early Warning System (EWS) downstream of the Ciliwung River (Manggarai Gate). Given the crucial function of EWS in providing timely and accurate early warnings, it is important to assess how well this model can reliably identify flood alert conditions. In this study, the performance of the EWS model was evaluated by comparing the predicted alert status with actual data on a test data subset consisting of 7,861 time points. Based on the classification of the Jakarta Water Resources Agency (DSDA), the alert status is defined as a condition when the water level exceeds 750 cm.

Based on the test data, there were 155 actual data points with alert status. Based on the prediction results, the DeepAnT-BiLSTM model successfully predicted 130 points with alert status accurately (83.87% of 155 data points). This indicates that the model can identify the majority of alert events consistently and reliably. The high prediction accuracy indicates that the approach used in this study (combining DeepAnT-based outlier detection and a multivariate BiLSTM architecture) effectively captures the high temporal dynamics of water levels.

Therefore, it can be concluded that the DeepAnT-BiLSTM model is suitable as a core component in an early warning system (EWS) for floods in Jakarta. The model not only generates accurate numerical predictions but is also sufficiently sensitive in classifying critical conditions directly related to flood mitigation decision-making.

4. CONCLUSION

This study demonstrates the effectiveness of integrating outlier detection and imputation methods to enhance the performance of deep learning-based water level prediction models. By utilizing the DeepAnT method for outlier detection and linear interpolation for data improvement, the multiple input BiLSTM model obtained more accurate and representative predictions. The evaluation results show that handling outliers reduces the RMSE from 13.83 to 10.81, MAPE from 1.57% to 1.07%, and increase NSE from 0.91 to 0.94. In addition to improving numerical accuracy, the model's ability to detect flood alert conditions was also assessed to evaluate its relevance for Early Warning System (EWS) applications. The DeepAnT-BiLSTM model correctly identified 130 of alert conditions, resulting in an accuracy of 83.87% in predicting flood alert conditions. These results indicate that the model not only performs well in forecasting, but also demonstrates strong capability in recognizing critical threshold events. This suggests that the model is suitable for use as a core component in an EWS. Therefore, the integration of robust outlier handling into the modeling workflow is important for supporting the development of more effective flood early warning systems. This study is expected to contribute to the development of deep learning-based hydrological modeling and offer practical implications for the government to provide prepared information in dealing with flood risks. For future development, it is possible to add additional input data such as rainfall, climate, or geospatial effects in the form of river cross-sections. More sophisticated deep learning implementations can also be used to improve prediction accuracy.

ACKNOWLEDGMENT

We acknowledge everyone who helped with this study, including the Jakarta Water Resources Department (DSDA Jakarta), for providing datasets, and the Indonesia Endowment Fund for Education Agency (LPDP), for funding the first author’s study.

CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interests.

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