Long Short-Term Memory Optimization Using Hybrid Sparrow Search Algorithm and Particle Swarm Optimization in Prediction of Water Level at Sluice Gates

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| Submitted: February 19, 2024 | Revised: February 22, 2024 | Accepted: April 03, 2024 |

| Published: May 22, 2024 |

ABSTRACT

During the period from 2014 to 2020, approximately 24 out of 44 districts in Jakarta experienced flooding disasters. Notably, at the beginning of January 2020, the Manggarai floodgate recorded a water height of 962 cm, categorized under Alert Level 1, indicating a critical and hazardous situation that required the evacuation of residents to safe places. This circumstance prompted the local government to enhance the monitoring and prediction system for water levels across all floodgates in the DKI Jakarta region. By utilizing improved water height predictions, the government can prepare more effective mitigation measures, such as reinforcing embankments, improving water channels, and implementing preventive actions prior to the occurrence of flooding disasters. The forecasting technique employing Long Short-Term Memory (LSTM) has been widely employed in previous research to predict water heights. Unfortunately, the accuracy of LSTM heavily depends on the manual selection of hyperparameters. The optimization of hyperparameters in LSTM is essential to find the optimal combination of values that influence the performance of the LSTM network. The objective is to maximize the model's performance, such as accuracy or lower error rates on previously unseen data. This optimization process plays a crucial role in achieving good results from the LSTM model, as the right choice of hyperparameters can yield a model that better understands complex patterns in the data. This research aims to determine the optimal hyperparameters using a hybrid optimization method. The hyperparameter optimization involves a combined approach of Sparrow Search Algorithm (SSA) and Particle Swarm Optimization (PSO) known as Hybrid SSA-PSO. This hybrid method is employed to reduce the error rate in predictions. The research outcomes, utilizing the Hybrid SSA-PSO optimization, revealed the smallest Root Mean Square Error (RMSE) evaluation at the Pulo Gadung water gate, measuring 9,553.

Keywords: water levels; hyperparameter; long short-term memory; particle swarm optimization; sparrow search algorithm; RMSE.

INTRODUCTION

Flooding is a natural disaster that often occurs in various regions in Indonesia and many countries (Akbar & Pratiwi, 2020), including Jakarta. Floods can cause several losses such as infrastructure damage, loss of valuables and environmental damage (Taryana et al, 2022). According to the DKI Jakarta Regional Disaster Management Agency (BPBD), from 2014 to 2020 on average there were around 24 sub-districts out of 44 in Jakarta affected by flooding. It was recorded in the disaster that the highest water level was 400 cm and the highest rainfall was 377 mm as shown in Figure 1.

pISSN 2302-4240
eISSN 2655-2086

Volume 13, Issue 2, June 2024, pp.614-626
DOI: http://dx.doi.org/10.32832/astonjadro.v13i12 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

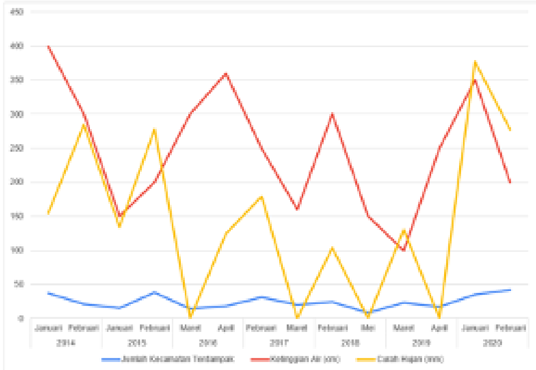

Figure 1. DKI Jakarta Flood Data from 2014 to 2020

At the beginning of January 2020, the water level at the Manggarai sluice gate reached 962 cm. This height is included in Alert 1 status, which is a critical or dangerous status that requires the surrounding community to evacuate to a safe place. Conditions like this mean that the local government needs to improve a system that can monitor and predict water levels at all floodgates in the DKI Jakarta area. By knowing the predicted water levels, the government can prepare more effective mitigation measures, such as strengthening embankments, building better water channels and preventing floods before they occur. Forecasting techniques can be used to predict water levels based on previous data.

Figure 2. Water Level Chart at Manggarai Gate January 2020

Previous research on predicting water level using forecasting techniques using the Long Short-Term Memory algorithm was carried out by (Baek et al., 2020; Shuofeng et al., 2021; Kardhana et al, 2022; Kusudo et al, 2022; Noor et al, 2022). Other research uses the Artificial Neural Network algorithm (Kartini et al., 2021; Mohammed et al, 2022; Jayathilake et al, 2023). Apart from that, there are also those that use the GRA-NARX Neural Network algorithm (Liu et al, 2022), Multilayer Perceptron Neural Network, Elman Neural Network (Deng et al, 2022) and Transformer Neural Network (Xu et al, 2023).

Long Short-Term Memory (LSTM) is a deep learning method that is usually widely used to predict patterns in time series data (Akbar et al, 2023). This method has the ability to remember information over a long period of time (Jaelani, 2022). The disadvantage of the LSTM algorithm is that it is very dependent on the selection of hyperparameters which usually have to be chosen manually (Sun et al, 2023). The shortcomings of LSTM can be overcome by adding hyperparameter optimization methods such as Sparrow Search Algorithm (SSA), Particle Swarm Optimization (PSO), Genetic Algorithm (GA) and Firework Algorithm (FA).

Previous research on hyperparameter optimization in LSTM includes using Particle Swarm Optimization (Wang et al., 2020; Tang et al, 2021; Teng et al, 2023; Gao et al., 2023; Pei & Yang, 2023; Yang, 2023; Zheng & Li, 2023; Jia et al, 2023; Dong et al., 2023; Chen & Long, 2023; Geng et al., 2023). Other research uses algorithms such as the Genetic Algorithm (Dai et al, 2021; Kim & Choi, 2021; Liu and Liu, 2021; Alhussan et al, 2023; Kumar Pandey et al, 2023; Liu et al, 2023) and the Sparrow Search Algorithm (Madiniyeti et al, 2023; PengJun and GuiLin, 2023; Zhang et al, 2023).

Based on previous research, the RMSE results using SSA and PSO optimization are relatively small compared to GA and FA optimization (Teng et al, 2023; PengJun and GuiLin, 2023). In research to predict the water surface height at the DKI Jakarta sluice gate, two hybrid optimization methods were used. This method combines SSA and PSO optimization in order to reduce the error rate in predictions.

The use of clean water is a basic need that is essential for human life, both in housing and around drainage channels. Clean water is needed for various daily activities that support health, cleanliness and comfortable living. In a residential context, clean water is used for drinking, cooking, bathing, washing and various other domestic activities. The availability of sufficient, high-quality clean water is very important to ensure the health and well-being of household residents (Satriadi I, 2021; Ginanjar B, Hariati F, 2015).

In the household, clean water is first used for drinking and cooking needs. The water consumed must be free from contamination and safe for health, because contaminated water can cause various diseases such as diarrhea, cholera and other diseases caused by pathogens. Therefore, a good and reliable clean water supply system is very necessary to ensure that the water reaching households meets health standards (Barid B, Afanda BO, 2022; Imamuddin M, Cahyanto D, 2020).

Apart from drinking and cooking, clean water is also used for bathing and maintaining personal hygiene. This activity is important to prevent skin diseases and other infections. Bathing with clean water helps maintain body cleanliness, removing dirt, sweat and microorganisms that stick to the skin. Good personal hygiene has a big impact on individual health and prevents the transmission of disease among family members (Aminda RS, 2024; Arsana IGNK, Astiti SPC, 2023)

Clean water is also used to wash clothes, dishes and other household utensils. This washing activity is very important to prevent the spread of germs and bacteria. Clean clothing and sterile eating utensils are essential to prevent infection and disease. The water used for washing must be clean enough to effectively remove dirt and microorganisms. Apart from household needs, clean water also plays an important role in the sanitation of the residential environment. A good drainage system is needed to manage wastewater and rainwater so that it does not create puddles that can become nests for disease. Effective drainage helps prevent flooding, reduces the risk of waterborne diseases, and maintains environmental quality (Hasibuan AF, Hariati F, 2020; Alam MP, Lutfi M, 2016).

Clean water management in housing must include a good supply, distribution and disposal system. Clean water supply systems usually include water sources such as wells, springs, or public water networks, which are then distributed through pipes to homes. The system must be designed to prevent contamination during the distribution process, and water storage facilities such as water tanks must be kept clean (Pradyani IAE et.al, 2024).

Apart from the supply system, waste water management is also important to maintain clean water quality. Waste water must be treated before being discharged into the environment to avoid pollution. Wastewater treatment systems, such as septic tanks or wastewater treatment plants, must be implemented in every residence to ensure that water released into the environment does not damage the ecosystem or other water sources (Imamuddin MI, Laraswati L, 2021; Jatmika B et.al, 2023).

Public education and awareness about the importance of using clean water is also very necessary. People must be taught how to save water, keep water sources clean, and understand the importance of good sanitation. Awareness campaigns and education programs can help increase public knowledge about how to maintain and use clean water wisely (Fathar FI et.al, 2023).

pISSN 2302-4240
eISSN 2655-2086
Volume 13, Issue 2, June 2024, pp.614-626
DOI: http://dx.doi.org/10.32832/astonjadro.v13i12 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

Overall, the use of clean water for basic human needs in housing and around drainage channels is very important to support health, cleanliness and comfort. A good clean water supply and management system, together with high public awareness about the importance of clean water, will ensure the availability of safe and sufficient water for all needs. Collaborative efforts between government, society and other related parties are very necessary to achieve this goal (Rabbani MG, Marsoyo A, 2023; Nurul HS, Kendimansyah M, 2023).

RESEARCH METHODS

The research methodology used in this research is the CRISP-DM methodology. The first step in this research is to gain an understanding of the water level at the sluice gates of the DKI Jakarta area. After that, a literature study was carried out to look for references related to methods and solutions that had been carried out in previous research. The result of this stage is the definition of the problem formulation and research objectives. In an effort to increase resilience to changes in river water levels, it is necessary to collect data related to water levels at the flood gates of the DKI Jakarta area. This data covers a certain time period and takes several supporting variables such as rainfall. After the data has been collected, it is necessary to predict water levels for the coming period as a means of early warning and prevention of potential flood disasters. The prediction method used is LSTM, because LSTM can predict long time series data by determining several required hyperparameters. Determining hyperparameters in the LSTM prediction method is very important. This determination will affect the prediction results. Therefore, a hyperparameter optimization method is needed to reduce the prediction error rate. The dataset used in this research was sourced from the DKI Jakarta flood information system from January 2020 to December 2020. There were six sluice gates observed, namely the Manggarai, Karet, Marina Ancol, Pulo Gadung, Hek and Tank sluice gates. Retrieving this data requires web scraping techniques.

In the preparation stage, the data preparation stage is carried out first, namely by separating several required records. For the water level dataset, records were taken including records of the name of the water gate, date and water level. Meanwhile, the rainfall dataset includes records of the name of the water gate, date and amount of rainfall intensity. Then the dataset is transformed from a JSON file to a CSV file. After transformation, the feature scaling process is carried out using the Standard Scaler. The final stage in data preparation is to first divide it into two categories, namely training data and test data with a comparison ratio of 90%:10%. Training data will be used to build the model, while test data will be used as measurement or validation of the model that has been created.

Then the modeling stage, at this stage research is carried out by implementing the LSTM algorithm to create a model from the training data that has been prepared. To build the LSTM model, water level and rainfall parameters are used as input in the training process to produce an LSTM model. After that, we enter the evaluation stage, at this stage testing is carried out using Root Mean Square Error (RMSE) in the testing data. The evaluation was carried out by measuring the Root Mean Square Error (RMSE) value between the Long Short-Term Memory (LSTM), LSTM with Sparrow Search Algorithm (LSTM-SSA), LSTM with Particle Swarm Optimization (LSTM-PSO) and LSTM with Hybrid SSA- PSO. The results of this evaluation will be used as a basis for comparison to determine which method shows the most optimal performance in producing predictions. After that, the deployment stage, at this stage, results are obtained in the form of an LSTM model that has gone through a previous testing process. This model can be used as an early warning and prevention tool before a flood occurs by implementing it in the form of a web-based application to carry out tests on the Manggarai, Karet, Marina Ancol, Pulo Gadung, Hek and Tank Sluice Gates.

RESULT AND DISCUSSION

Business Understanding

According to information provided by the DKI Jakarta Regional Disaster Management Agency (BPBD), during the period 2014 to 2020, around 24 sub-districts out of a total of 44 sub-districts in Jakarta experienced the impact of flooding. The disaster data recorded that the highest water level reached 400 cm and the highest rainfall reached 377 mm. Then at the beginning of January 2020, it was also recorded that the water level at the Manggarai sluice gate reached 962 cm, resulting in an increase in status to alert one, indicating a critical or dangerous situation that required the evacuation of surrounding communities to a safe location.

One way to anticipate the water level from the safe limit at the flood gates in the DKI Jakarta area is to predict water level data using past data. Several researchers previously carried out prediction techniques using various forecasting algorithms. This algorithm is also accompanied by an optimization method to adjust hyperparameters so that the model error rate is reduced.

Based on the results of previous research, the researchers used various time periods for the data collected. The variables used also vary but generally use water level and rainfall variables. These variables are processed in a forecasting algorithm, namely Long Short Term Memory (LSTM) by determining optimal hyperparameters. Next, an evaluation process is carried out using Root Mean Square Error (RMSE) to see the error level of the model created. Determining optimal hyperparameters requires a special method without doing it manually. Therefore, research is needed to optimize hyperparameters in LSTM in order to obtain optimal values so as to reduce the error rate of the resulting model.

Data Understanding

In this research the author used a dataset taken from the Jakarta flood information system. From this dataset, one year's data sample will be taken from January 2022 to December 2022. The data that will be taken is water level data at the Manggarai Sluice Gate (Central), Karet (Central), Marina Ancol (North), Pulo Gadung (East), Hek (East) and Tank (West). These floodgates represent each region in DKI Jakarta. The variables used are water level and rainfall. The data is then processed using the Long Short-term Memory (LSTM) algorithm with the hybrid Sparrow Search Algorithm (SSA) and Partcile Swarm Optimization (PSO) methods. The first dataset is water level, while the second dataset is rainfall. The dataset is in the form of a Javascript Object Notation (JSON) file with a time span of one year from January 2022 to December 2022. The first dataset has records including ID, altitude, alert status, date, time, weather and floodgates. The second dataset has records including ID, intensity, period, date, time, username and measurement post.

Data Preparation

In the initial stage, data was withdrawn from the Jakarta flood information system in the form of a JSON file. Data retrieval is carried out using web scraping techniques with the Java programming language using the built-in library, namely HttpUrlConnection. The flood information system is divided into two URLs, including:

1. https://sisteminformasibanjir.jakarta.go.id/map_report/pintu_air
2. https://sisteminformasibanjir.jakarta.go.id/map_report/hujan

The two URLs above represent data for getting water level and rainfall. From this URL, data will be taken by adding a parameter, namely date and time. After adding the URL parameters, it is run with the HttpUrlConnection library and then the results will be saved in the form of a JSON file. The results of the data collection are in the form of a JSON file which will then be converted into a dataset in the form of a CSV file using the Pandas library in Python. The dataset contains record name, height, date, date time and intensity.

Modeling

At this stage, a model is designed using LSTM in the Python programming language with several supporting libraries such as Pandas, Numpy, TensorFlow and Sklearn. The hyperparameter value configuration of this model will be optimized using the hybrid SSA-PSO method. Here are the modeling steps:

1. The first stage is to determine the length of the sequence that will be used as training data in LSTM. Sequence length is the previous time span that is used to predict the next time. The length of the sequence used is the past seven days. Determining the length of the sequence was previously carried out by carrying out several experiments. The trials started from one day, two days, three days, four days, five days, six days and seven days. Then determine the initial value

pISSN 2302-4240
eISSN 2655-2086
Volume 13, Issue 2, June 2024, pp.614-626
DOI: http://dx.doi.org/10.32832/astonjadro.v13i12 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

as the parameter needed for the hybrid SSA-PSO method to carry out hyperparameter optimization.

2. The second stage is to enter the initial parameter values into SSA optimization according to Equation 2.13. The data training process was carried out using SSA optimization by making four iterations. Each iteration has a value between the best global, the best global RMSE, the best current, the best current RMSE and the final hyperparameter value. The best global in the first iteration is filled with 30 random values, one of which is taken. The best global RMSE in the first iteration is calculated using equation (2.9) in the LSTM algorithm. The best current is calculated using equation (2.13), then the final value is obtained by comparing the best global RMSE value with the best current RMSE. If the best current RMSE is smaller, then the global best value is replaced with the best current value.
3. The third stage is to enter the initial parameter values and optimization results from SSA into PSO optimization according to Equations 2.11 and 2.12. Incorporating SSA values into optimization is called hybrid optimization. The following is the process for obtaining hyperparameter values using PSO optimization. The data training process was carried out using Hybrid SSA-PSO optimization by making four iterations. Each iteration has a value between the best global, the best global RMSE, the best current, the best current RMSE and the final hyperparameter value. The best global in the first iteration is filled with the final hyperparameter results in the previous SSA optimization. The best global RMSE in the first iteration is calculated using equation (2.9) in the LSTM algorithm. The best current is calculated using equations (2.11) and (2.12), then the final value is obtained by comparing the best global RMSE value with the best current RMSE. If the best current RMSE is smaller, then the global best value is replaced with the best current value.
4. Next, data processing is carried out using the LSTM algorithm with hyperparameter values resulting from SSA-PSO hybrid optimization, then saving the model into an h5 file. Then also save the scaler in the joblib file. Scaler files must be created separately for each dataset, especially for water level and rainfall variables. The main reason is the use of the Standard Scaler, which has the potential to influence scaling results on test data. If the scaler is applied simultaneously to both datasets, there will most likely be a mismatch in the scaling results between the training and testing data. After creating a model with training data, the next step is to test it with RMSE. RMSE provides an illustration of the extent to which the model can reproduce the target value well. The lower the RMSE value, the better the model can generalize patterns from training data to data it has never seen before.

Evaluation

At this stage, an evaluation of the results of training data processing in the previous step is carried out. Evaluation was carried out using RMSE with testing data on a dataset of 10% of the total existing data. Then the results of the evaluation are compared between the predicted values and the actual values. For comparison, evaluation was also carried out using LSTM without optimization, LSTM-SSA and LSTM-PSO.

Table 1. RMSE Watergate

Sluice	RMSE LSTM	RMSE LSTM-SSA	RMSE LSTM-PSO	RMSE LSTM Hybrid
Manggarai	14,712	13,251	12,340	12,294
Rubber	9,905	10,615	10,024	9,644
Marina Ancol	5,387	6,266	4,032	4,325
Gadung Island	9,737	13,027	9,626	9,553
Heck	10,965	18,098	8,121	7,935

Tank	32,938	226,374	20,655	20,566

Based on this table, there are RMSE values according to the water gate. The smallest RMSE value is at the Ancol Marina sluice gate, namely 4.325; Meanwhile, the largest value is at the tank sluice gate, namely 20,566. The minimum water level at the Ancol Marina sluice gate is 99, the maximum value is 370 and the average value is 146.7. Meanwhile, for rainfall at the Marina Ancol sluice gate, the minimum value was 0, the maximum value was 76 and the average value was 2.6.

After testing, it was found that the RMSE value decreased in almost all sluice gates using LSTM Hybrid SSA-PSO except for the Marina Ancol sluice gate. At the Ancol Marina sluice gate, the smallest RMSE value was obtained with a value of 4.032 using the LSTM-PSO algorithm.

Deployment

Based on the evaluation results in the previous stage, implementation will be carried out using the hybrid ssa-pso method with optimal hyperparameter values using an independently developed application. The application at this stage uses the Streamlit framework and several Python libraries such as Pandas, Numpy and Matplotlib. Following are the deployment steps:

Install the required framework and libraries

1. After successful installation, it's time to create code to do:
    a. Reading csv files
    b. Read model files

c. Reads scaler files (water level and rainfall)

2. After reading the CSV file, the next step is to transform the dataset using the scaler file that was read previously.
3. The transformed dataset will be combined into one dataset, then divide the data into two parts, namely training data and testing data
4. After sharing, the testing data is then predicted using the model file that has been read previously and displayed in the application.

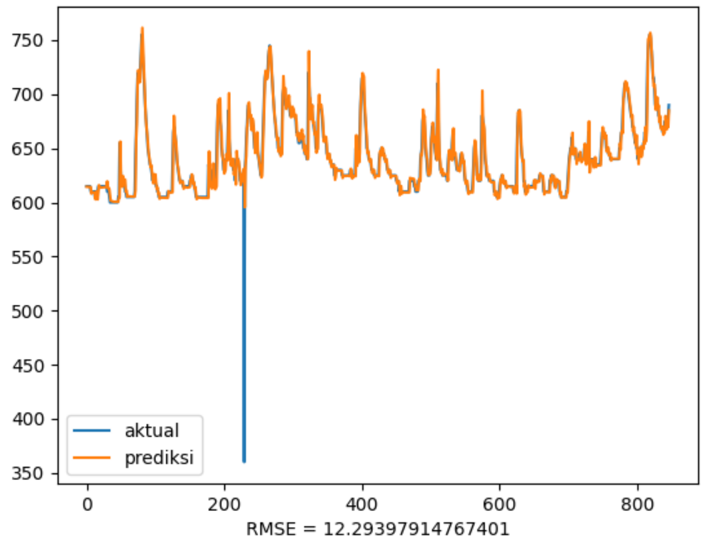

Figure 3. Manggarai Sluice Gate Prediction Results in the Application

pISSN 2302-4240
eISSN 2655-2086

Volume 13, Issue 2, June 2024, pp.614-626
DOI: http://dx.doi.org/10.32832/astonjadro.v13i12 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

Based on the image above, there are evaluation results using RMSE in the application of 12.29397914767401 or if rounded up it becomes 12.294. These results are the same as the evaluation results at the evaluation stage.

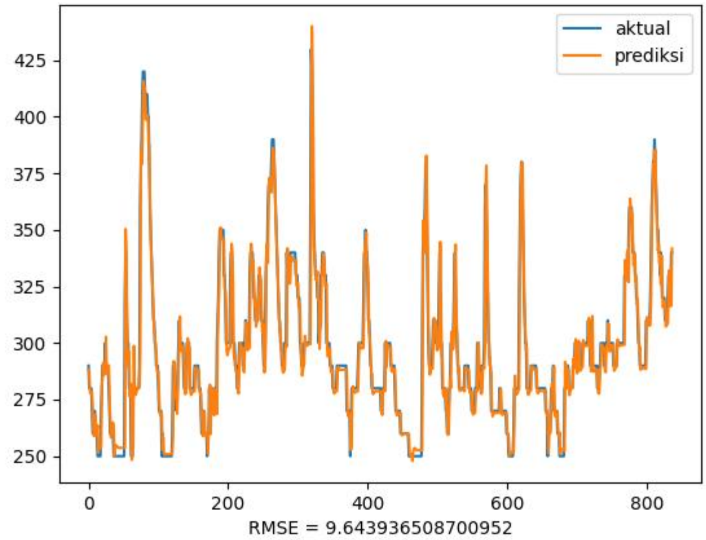

Figure 4. Rubber Sluice Gate Prediction Results in the Application

Based on Figure 4, there are evaluation results using RMSE in the application of 9.643936508700952 or if rounded up it becomes 9.644. These results are the same as the evaluation results at the evaluation stage.

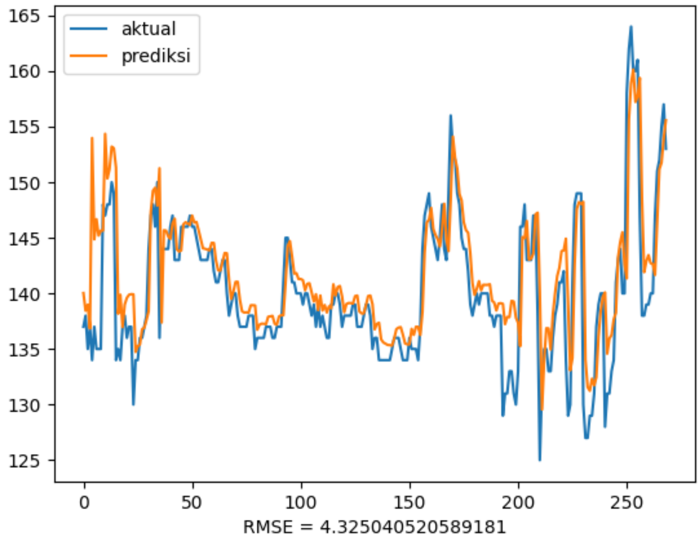

Figure 5. Ancol Marina Sluice Gate Prediction Results in the Application

Based on Figure 5, there are evaluation results using RMSE in the application of 4.325040520589181 or if rounded up it becomes 4.325. These results are the same as the evaluation results at the evaluation stage.

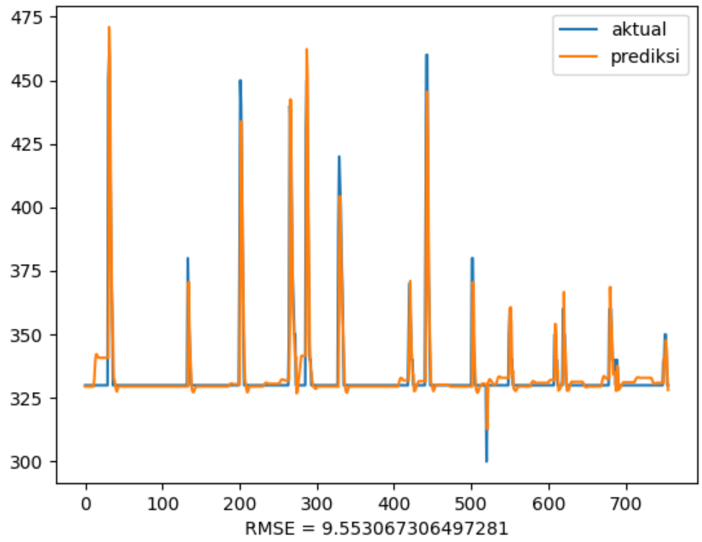

Figure 6. Pulo Gadung Sluice Gate Prediction Results in the Application

Based on Figure 6, there are evaluation results using RMSE in the application of 9.553067306497281 or if rounded up it becomes 9.553. These results are the same as the evaluation results at the evaluation stage.

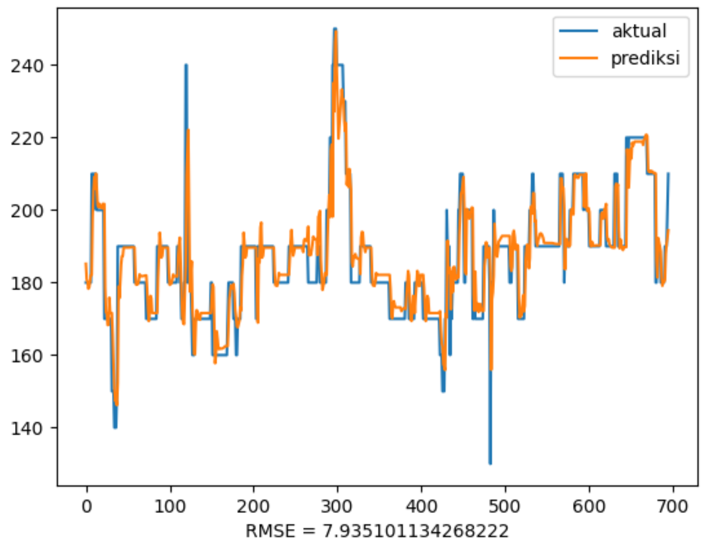

Figure 7. Hek Sluice Gate Prediction Results in the Application

Based on Figure 7, there are evaluation results using RMSE in the application of 7.935101134268222 or if rounded up it becomes 7.935. These results are the same as the evaluation results at the evaluation stage.

pISSN 2302-4240
eISSN 2655-2086
Volume 13, Issue 2, June 2024, pp.614-626
DOI: http://dx.doi.org/10.32832/astonjadro.v13i12 http://ejournal.uika-bogor.ac.id/index.php/ASTONJADRO

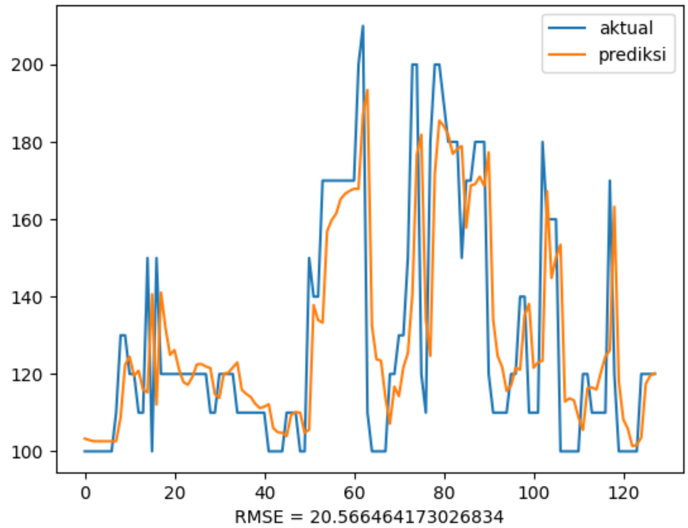

Figure 8. Tank Sluice Gate Prediction Results in the Application

Based on Figure 8, there are evaluation results using RMSE in the application of 20.566464173026834 or if rounded up it becomes 20.566. These results are the same as the evaluation results at the evaluation stage.

CONCLUSION

Based on the descriptions outlined in the previous chapter, the conclusion of the research regarding water level prediction at DKI Jakarta sluice gates is that the LSTM model built with hyperparameter optimization using the hybrid SSA-PSO method can reduce the error rate at several sluice gates. The SSA-PSO hybrid method with the smallest RMSE values is at the Manggarai, Rubber, Pulo Gadung, Hek and Tank sluice gates. Each of these sluice gates reduces the RMSE value for the Manggarai sluice gate from 12,340 to 12,294; rubber from 10.024 to 9.644; Pulo Gadung from 9,626 to 9,553; hectare from 8,121 to 7,935 and tank from 20,655 to 20,566. Meanwhile, the PSO RMSE with the smallest value is at the Ancol Marina sluice gate which reduces the RMSE value from 4.325 to 4.032. From the RMSE testing carried out, it was found that the best Hype parameters of the hybrid SSA-PSO method were the number of lstm units of 45 units, the learning rate was 0.001818 and the epoch value was 123.

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eISSN 2655-2086
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