Journal of Computer Networks, Architecture and High Performance Computing
Volume 6, Number 3, July 2024
https://doi.org/10.47709/cnapc.v6i3.4360

Submitted : 22 July 2024
Accepted : 30 July 2024
Published : 31 July 2024

Flood Prediction Using Support Vector Regression (Case Study of Floodgates in Jakarta)

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ABSTRACT

Flood can be interpreted as an event that occurs suddenly and quickly enough where the water discharge in the drainage channel cannot be accommodated, so that the blocked area causes the water discharge in the drainage channel in several surrounding areas to overflow and is one of the natural disasters that occurs at an unexpected time and cannot be prevented, because of this, a prediction must be made to detect floods for the next day. Flood prediction is a crucial aspect of disaster management and mitigation, particularly in flood-prone areas such as Jakarta, Indonesia. This study aims to leverage Support Vector Regression (SVR) to predict flood events by analyzing various environmental and hydrological factors that influence flooding. The primary data sources include historical wheater data, river water levels, floodgate positions in Jakarta. The data preprocessing involved cleaning, handling missing values, and normalizing the datasets to ensure compatibility with the SVR model. Feature selection was conducted to identify the most relevant predictors of flooding, such as wheater data, and river water levels. The dataset was then split into training and testing sets, maintaining an 80-20 ratio to ensure robust model validation. An SVR model with a radial basis function (RBF) kernel was trained on the standardized training data. The model's performance was evaluated using Root Mean Squared Error (RMSE) as the primary metric. The RMSE produced in this study was 0.112 with an R Square accuracy of 0.977. The results indicated that the SVR model could effectively predict flood events with a reasonable degree of accuracy, demonstrating its potential as a valuable tool in flood forecasting.

Keywords: Flood, Forecasting; Prediction; Root Mean Square Error (RMSE); Support Vector Regression (SVR)

1. INTRODUCTION

In Indonesia, flooding is one of the most frequent natural disasters (Sulaksana et al., 2021)Flooding occurs when the Water Level (TMA) exceeds the normal limit so that the overflow of river water causes inundation in areas that have lowlands. Early warning of floods is needed to minimize the impact after flooding, such as casualties and loss of property. The National Disaster Management Agency (BNPB) reported that floods were the most frequent disaster and hit many areas throughout March 2024, with a total of 123 events. [2. Some of the factors that increase the potential risk of flooding include inadequate drainage systems in settlements. (Nugroho & Handayani, 2021), lack of public awareness of the importance of the environment (Hadjar, 2022), lack of water conservation efforts (Ihwan et al., 2023), topography with low land elevation, and high rainfall. In addition, uncontrolled urban development also contributes to the increased potential for flooding (Gunawan, 2020).

Forecasting is a technique for estimating future values with respect to past and present data. Forecasting is an essential tool for effective and efficient planning. Forecasting requires a method, model, or approach whose accuracy must be tested. The more accurate a model is, the better it is for prediction. One of the forecasting methods that can be used is the time series analysis forecasting method.

Commonly used methods for flood classification or forecasting are: Support Vector Machine (Dwiasnati & Devianto, 2021), Backpropagation (Iskandar, 2020) , K-Nearest Network (Cumel, David Zamri, Rahmaddeni,

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2022)(Stanley & Lisangan, 2020), Naïve Bayes (Faldi et al., 2023), Fuzzy(Yuliantika & Kartika, 2022)(Adipraja et al., 2020) and many more. One method that can be used to perform forecasting is SVR.

The SVR (Support Vector Regression) method is the development of SVM for regression cases which aims to find a function as a hyperplane (dividing line) in the form of a regression function which fits all input data with the smallest possible error. (Febriasto et al., 2020). The advantage of SVR is the ability to overcome non-linear data problems by using kernel functions so that it can overcome the problem of overfitting [15]. (Ishlah et al., 2023)Therefore, the concept of SVR algorithm can produce a good prediction value.

Some previous studies that use the SVR method are research (Panahi et al., 2021) This study describes support vector regression (SVR) optimization for flood modeling in the Qazvin Plain, Iran. The geospatial data included nine commonly available geo-environmental flood conditioning factors (i.e., slope, aspect, elevation, plane curvature, profile curvature, proximity to river, land use, lithology and rainfall) with accuracy of RMSE = 0.31 and MSE = 0.098. Research (Mehravar et al., 2023) In this study, a flood vulnerability mapping framework was developed based on the novel integration of nature-inspired algorithms into support vector regression (SVR). For this purpose, various remote sensing (RS) and geographic information system (GIS) data were applied to a hybrid SVR model to map flood vulnerability in Ahwaz city, Iran with an accuracy of 0.77. Research (Saha et al., 2021)Eight flood conditioning variables were selected based on topography and hydro-climatological conditions, and by applying a new ensemble support vector regression (SVR) machine learning (ML) approach with SVR accuracy (AUC = 0.871). Research (Dodangeh et al., 2020) This study proposed several new hybrid intelligence models based on meta-optimization of support vector regression (SVR) & GMDH models. The results showed that the SVR model had superior performance (AUC = 0.70-0.75, RMSE = 0.29-0.36, MSE = 0.08-0.13) compared to the GMDH model (AUC = 0.67-0.74, RMSE = 0.32-0.39, MSE = 0.1-0.15).

Based on several previous studies, the SVR method applied in the above research provides a conclusion that the SVR method is quite good in its prediction results. The resulting error is quite minimal with the help of the kernel and the selection of the right parameters. Based on this, the author took Support Vector Regression research to predict flooding in Jakarta.

2. LITERATURE REVIEW

2.1. Forecasting

Forecasting or can be called forecasting is an activity to predict or predict future conditions through testing in the past. (Ahmad, 2020). Forecasting is the process of predicting future values that include demand in terms of quantity, quality, time and location. (Hamirsa & Rumita, 1927). Some forecasting techniques try to project historical experience in the form of time series into the future.

2.2. Support Vector Regression (SVR)

Support Vector Regression (SVR) is a development of SVM for regression cases. The goal of SVR is tofind a function as a hyperplane in the form of a regression function which fits all input data with an error and make it as small as possible. (Febriasto et al., 2020). If the value is equal to 0 then a perfect regression equation is obtained. SVR has similarities with SVM classifiers, which can maximize margins and kernel tricks to map non-linear data. Suppose there are l training data, (xi,yi), i = 1,...,l with input data x = {x_(1.)...,x_l} ⊆ ℜN and y = {y_1,... ,y_l} ⊆ ℜ and l is the number of training data. The regression function of the SVR method is in Equation 1 (Melati N et al., 2023) :

$$f(x)=w\,\varphi(x)+b \quad (1)$$

where :
w : weight vector
φ(x) : a function that maps x in a dimension
b : bias

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2.3. KERNEL FUNCTION

In reality, not all data is linear so finding a linear separation plane is difficult. Therefore, in non-linear cases, kernel functions are used. This function can mapping the input space from training data to a higher feature space. There are several kernel functions that are often used in SVM literature including Linear kernel, Polynomial kernel, Radial Basic Function (RBF) kernel or commonly called the Gaussian kernel and Sigmoid kernel. (Rais, 2022). The kernel function formula is listed in Table 1

Table 1 Types of Kernels (Rais, 2022)

Kernel Name	Function
Gaussian RBF	$K\ (x_i , x_j) = \exp(\gamma(\ x_i , x\ )\ )_j{}^2$
Linear	□□ $(x_i , x_j) = x_i , x_j$
Polynomial	$(x_i , x_j) = (x_i , x_j + c)d$
Sigmoid	$K\ (x_i , x_j) = \tan(\sigma(x_i , x_j) + c)$

The way SVR works is determined by the type of kernel function to be used and the kernel parameter settings. So in this study researchers will use RBF as the SVR kernel function.

Data Normalization

Data normalization is carried out so that the data is in the same range so that the complexity of the calculation is reduced. Then data normalization aims to reduce the level of error in computation. Normalization is the process of scaling the attribute values of certain data into values within a certain range. Normalization is done to reduce errors in the data mining process. In general, this normalization technique can be divided into 5 types, namely: 1) Min-Max, 2) Z-Score, 3) Decimal Scaling, 4) Sigmoidal, 5) Softmax. (Mayori & Tresnawati, 2024)

The Min-Max method is the simplest method by performing a linear transformation of the original data, the advantage of this method is the balance of the comparison value between the value before passing the normalization process and the value after passing the normalization process. In this study using min-max data normalization with a min-max range of 0.1 to 1,. The following is the formulation of data normalization calculations found in Equation 2 (Mayori & Tresnawati, 2024):

$$N = \frac{y\text{-}\min(y)}{\max(y)\text{-}\min(y)} \quad (2)$$

Description:
N = Normalization result value
y = Value
min(y) = Minimum value
max(y) = Maximum value

2.4. Time Series Data

Time series data is data that is organized and collected, over time in sequence. The time period can be yearly, quarterly, monthly, weekly and daily or hourly. Time series models attempt to predict the future using historical data, in other words, time series models try to see what happened in a certain period of time and use past data to predict the future. If the observations in time series data can be predicted with certainty and do not require further investigation, it is called a deterministic time series and if the observations can only show the structure of a probabilistic state, then it is called stochastic. In modeling time series analysis it is assumed that

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the data is stationary. Stationary data is said if there is no trend change in average and variance change. (Faris Nasirudin & Abdullah Ahmad dzikrullah, 2023)

2.5. Root Mean Square Error (RMSE)

One method to calculate the evaluation results of a model we can use the calculation of Root Mean Squared Error RMSE is used to measure the error rate of a model in predicting a set of values, where the smaller (closer to zero) the RMSE value, the more accurate the prediction results will be. (Yudanegara et al., 2021). The error value (error) is used to determine the magnitude of the deviation of the estimated value from the actual value. Error calculation using Root Mean Square Error (RMSE) is formulated in Equation 3 (Yudanegara et al., 2021):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \qquad (3)$$

Description:
Yi = initial data (actual data)
Ŷi = final data (estimated data)
n = number of data

3. METHOD

3.1 Data Source

The data used in this study is data https://pantaubanjir.jakarta.go.id/ In this study the data used is daily data with the amount of data for 1 month is 13593.

Types and Characteristics of Data such as Temporal Granularity Monthly Data: Data collected on a monthly basis may summarize more granular data and could be used to identify seasonal patterns. **Example**: Monthly average rainfall, average river levels. Daily Data: More detailed data collected daily would provide a finer resolution and allow the model to capture short-term variations and trends. Example : daily river water levels, daily floodgate positions. Hourly Data: High-resolution data that can capture rapid changes in environmental conditions and flood events.. Example: Hourly rainfall intensity, hourly river levels, hourly floodgate status.

Types of Features Hydrological Data: River Water Levels: Measured at various points along the river, typically daily or hourly. Operational Data: Floodgate Positions: Status of floodgates (open or closed) and their adjustments, recorded at specified intervals.

Example Data Structures
Daily Data Example:
Date: 2023-01-01, 2023-01-02, ...
River Level (m): 2.3, 2.1, ...
Monthly Data Example: Month-Year: 2023-01, 2023-02, .

Understanding these types and characteristics will help in effectively preparing and analyzing the data for SVR modeling, ultimately improving the flood prediction accuracy for floodgates in Jakarta.

3.2 Data Analysis Technique

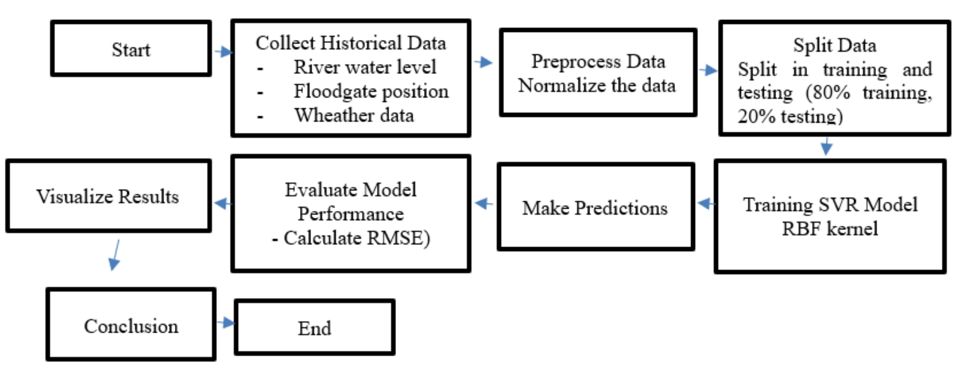

Fig.1 Flowchart Flood Prediction Using Support Vector Regression

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The steps of the analysis technique that will be carried out in this study are:

1. Secondary data collection, namely data https://pantaubanjir.jakarta.go.id/ Access the website and download the required datasets.Ensure data includes all relevant features and covers a sufficient time span for accurate model training.
2. Normalize the data Normalize or standardize the data to ensure that all features contribute equally to the model training and to improve the convergence and performance of SVR. Apply normalization or standardization to both training and testing datasets.Verify that all features are scaled appropriately to facilitate effective model training.
3. Determining training data and testing data. In this study, the amount of training data and testing data 80% - 20% respectively. Train the model on the training data and evaluate its performance on the testing data to ensure generalizability.
4. Determination of the best model by looking at the accuracy of the prediction accuracy results with the calculation of RMSE. Use RMSE (Root Mean Squared Error) to measure prediction accuracy.
5. Make predictions for the next five days. Use the selected SVR model to predict flood levels for the next five days.
6. Visualize Results create visual representations of the model's predictions and actual flood levels to facilitate interpretation and analysis.
7. Conclusions Discuss the effectiveness of SVR in predicting flood levels. Comment on the accuracy and reliability of predictions based on RMSE and other metrics.
8. Suggest improvements for future studies or implementations.

4. RESULTS AND DISCUSSION

4.1 Descriptive Analysis

Support Vector Regression (SVR) is a powerful technique in machine learning, typically not directly supported in Excel without using additional tools or programming languages. However, you can approximate it using Excel's built-in functions for a simpler form of regression analysis.

Here's a step-by-step guide to implement a basic linear regression, which can be seen as a simple case of SVR, in Excel. Assume your data is in cells A2 and B2:B10

Mean of X:	=AVERAGE(A2:A10)
Mean of Y:	=AVERAGE(B2:B10)
Standard Deviation of X :	=STDEV.P(A2:A10)
Standard Deviation of Y:	=STDEV.P(B2:B10)
Correlation Coefficient:	=CORREL(A2:A10, B2:B10)
Slope (m):	=CORREL(A2:A10, B2:B10) * (STDEV.P(B2:B10) / STDEV.P(A2:A10))
Intercept (b):	=AVERAGE(B2:B10) - (m * AVERAGE(A2:A10))

Regression Equation for predicted Y: =m * A2 + b

Assume X = 'river_level' Y = 'level_status'. Based on the provided statistical metrics, let's break down and interpret the results. It seems that you have performed a simple linear regression analysis where

Mean of X	:	173,8669904
Mean of Y	:	1,150445082
Standard Deviation of X	:	155,4499816
Standard Deviation of Y	:	0,488169448
Correlation Coefficient	:	0,035155977
Slope (m)	:	0,000110403
Intercept (b)	:	1,131249723
Regression Equation for predicted Y	:	1,142621186

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Can use Python with scikit-learn to train the SVR model. Below is a Python example code for training an SVR model :

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error

# Load the data
data = pd.read_csv('jakarta_flood_data.csv')

# Feature selection (example features)
features = [ 'river_level',]
X = data[features]
y = data['level_status']

# Splitting the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize the data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train the SVR model
svr = SVR(kernel='rbf')
svr.fit(X_train_scaled, y_train)

# Make predictions
y_pred = svr.predict(X_test_scaled)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print(f'Root Mean Squared Error: {rmse}')
```

Descriptive analysis is used to see an overview of the research data. The data used in this study is data sourced from https://pantaubanjir.jakarta.go.id/ in realtime.

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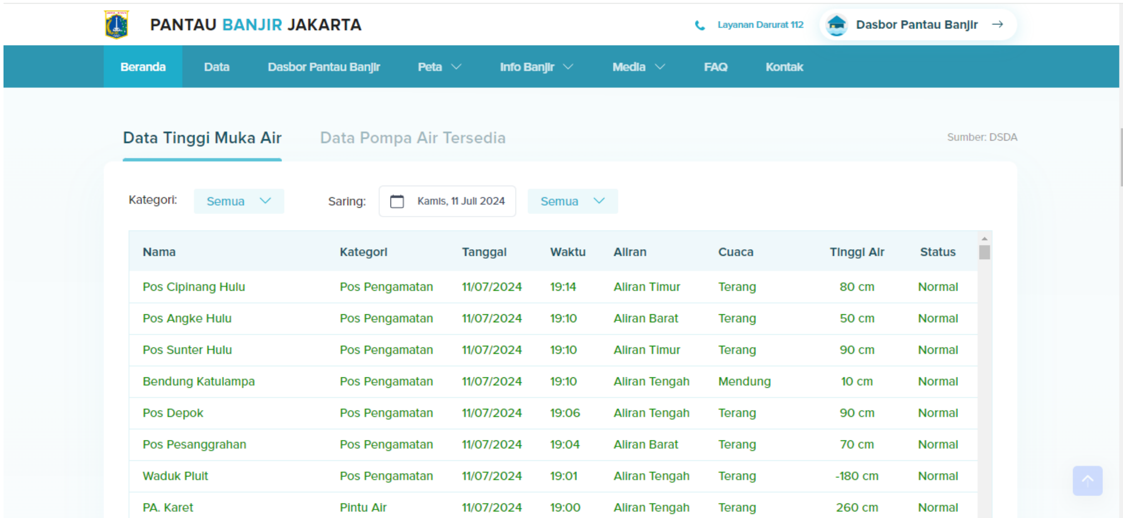

Fig.2 Jakarta Flood Monitoring Website. (*PANTAU BANJIR JAKARTA*, 2020)

Table 2
Example of Water Level Data for Each Sluice Gate (*PANTAU BANJIR JAKARTA*, 2020)

No.	Name	Catagory	Date	Time	Flow	Weather	Water Level	Status
0	Pos Cipinang Hulu	Pos Pengamatan	23/06/2024	14:17	Aliran Timur	Terang	75 cm	Normal
1	Pos Sunter Hulu	Pos Pengamatan	23/06/2024	14:17	Aliran Timur	Terang	90 cm	Normal
2	Bendung Katulampa	Pos Pengamatan	23/06/2024	14:17	Aliran Tengah	Terang	10 cm	Normal
3	Waduk Pluit	Pos Pengamatan	23/06/2024	14:17	Aliran Tengah	Terang	-180 cm	Normal
4	Pos Depok	Pos Pengamatan	23/06/2024	14:16	Aliran Tengah	Terang	75 cm	Normal
s.d								
13593.	Ancol Flushing	Pintu Air	26/05/2024	00:00	Aliran Timur	Mendung Tipis	191 cm	Waspada

4.2 DAT6A NORMALIZATION

Data normalization is the process of forming a database structure so that most ambiguities can be removed. Min-Max normalization is a normalization method by performing a linear transformation of the original data so as to produce a balance of comparison values between data before and after the process.(Mayori & Tresnawati, 2024).

```
# Pra-pemrosesan data
# Mengubah data kategorikal menjadi data numerik menggunakan LabelEncoder
label_encoder_nama = LabelEncoder()
label_encoder_kategori = LabelEncoder()
label_encoder_aliran = LabelEncoder()
label_encoder_cuaca = LabelEncoder()
label_encoder_status = LabelEncoder()

# Melakukan fit pada label encoder dengan semua label yang mungkin
label_encoder_nama.fit(df['Nama'])
```

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```
label_encoder_kategori.fit(df['Kategori'])
label_encoder_aliran.fit(df['Aliran'])
label_encoder_cuaca.fit(df['Cuaca'])
label_encoder_status.fit(df['Status'])

# Mengubah kolom kategorikal menjadi data numerik
df['Nama'] = label_encoder_nama.transform(df['Nama'])
df['Kategori'] = label_encoder_kategori.transform(df['Kategori'])
df['Aliran'] = label_encoder_aliran.transform(df['Aliran'])
df['Cuaca'] = label_encoder_cuaca.transform(df['Cuaca'])
df['Status'] = label_encoder_status.transform(df['Status'])
```

Table 3
Example of Data Normalization into Numeric data (*Data Tinggi Muka Air Jakarta 30 Hari Terakhir*, 2023)

	Name	Catagory	Time	Flow	Weather	Water Level	Status	Day	Month	Year
0	13	1	14	2	4	75.0	1	23	6	2024
1	17	1	14	2	4	90.0	1	23	6	2024
2	1	1	14	1	4	10.0	1	23	6	2024
3	20	1	14	1	4	180.0	1	23	6	2024
4	14	1	14	1	4	75.0	1	23	6	2024

4.3 Division of Training Data and Testing Data

In this study the data used is data sourced from https://pantaubanjir.jakarta.go.id/ in realtime. Before the data is analyzed using the SVR method, the data is first divided into training data and testing data. Training data is data used to build models with the SVR method. Meanwhile, testing data is data used to predict with the SVR method based on the model that has been obtained previously. The results of the division of training data and testing data can be seen in Table. For this study, a division of 80% - 20% was used.(Arfan & ETP, 2020).

Table 4
Division of Training Data and Testing Data (*Data Tinggi Muka Air Jakarta 30 Hari Terakhir*, 2023)

Shape	Data	
X_train	10874	9
X_test	2719	9
y_train	10874	1
y_test	2719	1

5. DISCUSSION

5.1. Training Data Accuracy Results

One method that can be used to calculate the evaluation results of a model is to use the Root Mean Square Error (RMSE) method, where the smaller (closer to zero) the RMSE value, the more accurate the prediction results will be. The RMSE results can be seen in Table 4.

Table 4. **Training Data Accuracy Results** (*Data Tinggi Muka Air Jakarta 30 Hari Terakhir*, 2023).

Data accuracy	Results
Mean Squared Error	0.012652160256533089

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Root Mean Square Error	0.11248182189373129
R Square	0.9773189499119925

5.2 Prediction Result

The prediction results can be viewed on the website http://ds.fewhold.xyz/ on July 12, 2024.

ds.fewhold.xyz

Data Tinggi Muka Air Jakarta 30 Hari Terakhir

Show 10 entries Search:

Nama	Kategori	Tanggal	Waktu	Aliran	Cuaca	Tinggi Air	Status
Pos Depok	Pos Pengamatan	Thu, 11 Jul 2024 00:00:00 GMT	21:08:00	Aliran Tengah	Terang	90	Normal
Pos Cipinang Hulu	Pos Pengamatan	Thu, 11 Jul 2024 00:00:00 GMT	21:05:00	Aliran Timur	Terang	80	Normal
Waduk Pluit	Pos Pengamatan	Thu, 11 Jul 2024 00:00:00 GMT	21:04:00	Aliran Tengah	Terang	-185	Normal
Pos Krukut Hulu	Pos Pengamatan	Thu, 11 Jul 2024 00:00:00 GMT	21:01:00	Aliran Tengah	Mendung Tipis	40	Normal
Pasar Ikan - Laut	Pintu Air	Thu, 11 Jul 2024 00:00:00 GMT	21:00:00	Aliran Tengah	Terang	212	Siaga
PA. Karet	Pintu Air	Thu, 11 Jul 2024 00:00:00 GMT	21:00:00	Aliran Tengah	Terang	260	Normal
HEK PGC	Pintu Air	Thu, 11 Jul 2024 00:00:00 GMT	21:00:00	Aliran Timur	Terang	210	Siaga

Fig.4 Jakarta Water Level Data for the Last 30 Days.(*Data Tinggi Muka Air Jakarta 30 Hari Terakhir*, 2023)

Prediksi Tinggi Air di PA. Karet

2024-07-13: 207.18405384993795 cm - Aman tidak banjir

2024-07-14: 206.69542348575098 cm - Aman tidak banjir

2024-07-15: 205.8711182695693 cm - Aman tidak banjir

2024-07-16: 204.7359600935324 cm - Aman tidak banjir

2024-07-17: 203.3167485528432 cm - Aman tidak banjir

Fig.5 Predicted water level in Jakarta for the next 5 days (*Data Tinggi Muka Air Jakarta 30 Hari Terakhir*, 2023)

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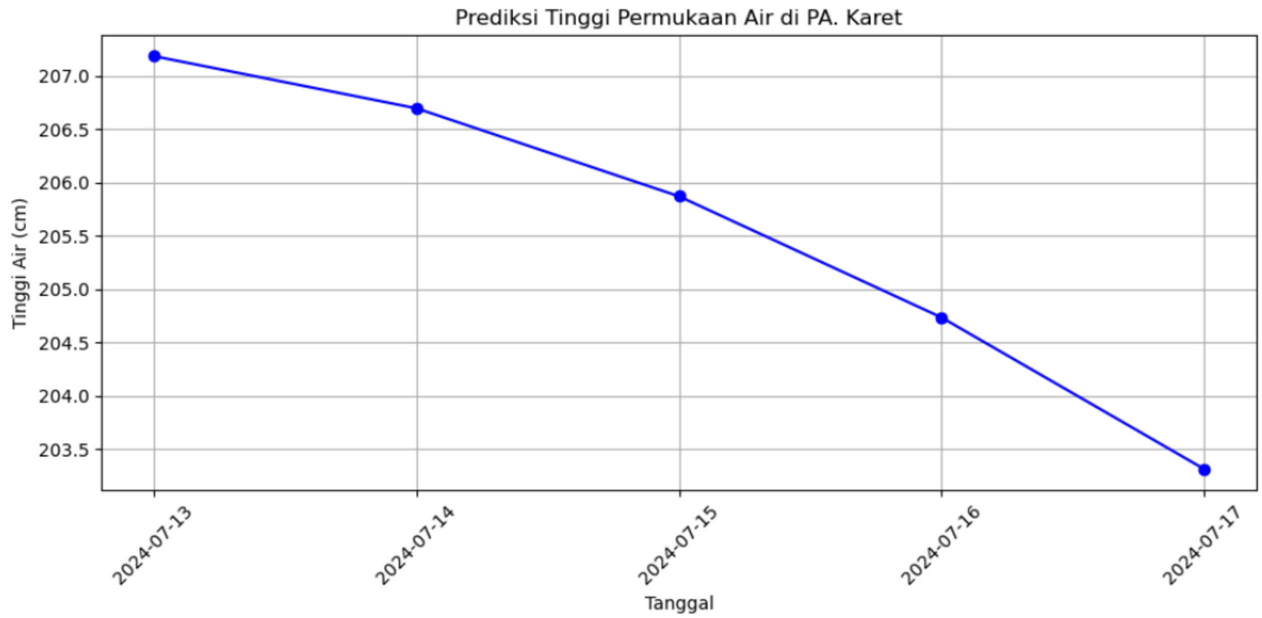

Fig.6 Predicted water level in Jakarta for the next 5 days.(*Data Tinggi Muka Air Jakarta 30 Hari Terakhir*, 2023)

The 5-day prediction data (July 13-17, 2024) from the 30-day data shows a decrease but not too far and is in a safe status, no flooding because it is still within the normal limits of the Karet floodgate. The data shows that the flood level for July 13-17, 2024 tends to decrease, although the decrease is not too significant. This can be interpreted as meaning that the environmental or weather conditions that affect the water level are starting to improve, but with a slow decrease.

Karet Floodgate Status: Based on the prediction, the Karet floodgate status is declared "Safe" for the period. This means that the water level is estimated to still be within safe limits and does not threaten flooding. Although the current prediction shows a safe status, it is important to continue to monitor conditions in real time. Unexpected factors such as sudden rain or changes in weather conditions can quickly affect the flood level.

The prediction results for July 13-17, 2024 show that the flood level is estimated to decrease but not significantly, with a safe status at the Karet floodgate. Although there is currently no threat of flooding, continuous monitoring and effective communication remain essential for better flood risk preparedness and management.

6. CONCLUSION

Based on the research and discussion that has been done to predict flood status with the SVR method, several conclusions are obtained. Flood prediction with the Support Vector Regression method uses the Radial Basic Function (RBF) kernel or commonly called the Gaussian kernel. This kernel will be used to predict river water levels and flood status for the next five days. The accuracy of the prediction results is done by looking at the Root Mean Square Error value. It can be seen that the RMSE value generated in this study is 0.112, which means that the model's ability to follow the data pattern well. Further research is needed to continue and refine the research on the application of the Support Vector Regression method in predicting flood disasters in real time. Further research needs to be conducted and compared with other methods to further select and determine the most appropriate method for real-time flood prediction research.

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Submitted : 22 July 2024
Accepted : 30 July 2024
Published : 31 July 2024

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