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Prediction Analysis of Jakarta Composite Index Movement Using Support Vector Regression Method

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ABSTRACT

The JCI is an important indicator that reflects the performance of the Indonesian stock market. In recent times, the JCI has faced significant fluctuations due to complex factors, including global economic conditions and market sentiment, which make predicting its movements challenging. Good prediction is needed to support market stability and sustainable economic development as per SDGs point 8. This study applies a modern nonparametric regression method, namely Support Vector Regression (SVR), to predict a dataset in the form of weekly JCI data from the period April 2022 to October 2024 obtained from the investing.com website. The analysis shows that the SVR model with RBF kernel function provides the best performance, with MAPE of 1.43%, RMSE of 121.6196, and MAE of 104.65. The findings also reveal that the fluctuation pattern of the JCI cannot be fully explained based solely on historical data. External variables, such as global economic conditions and market sentiment, have a significant influence on the prediction results. Therefore, the SVR method can be utilized to optimize portfolio allocation based on weekly JCI predictions. In addition, the results of this study provide guidance for policymakers in designing proactive economic policies to mitigate market volatility and increase investor confidence.

INTRODUCTION

Investment is an activity of investing in one or more assets owned with the aim of obtaining future profits (Wijaya & Agustin, 2015). Investment can take the form of physical assets such as land, machinery, gold, buildings, as well as financial assets such as deposits, stocks, or bonds (Vivianti et al., 2015). Investment in the form of shares has become a common thing for many investors, both in Indonesia and abroad. According to Darmadji and Fakhruddin (2012), shares are a sign of ownership of a person or entity in a company or limited liability company. The stock market, which is an important financial instrument in a country's economy, is a meeting place between the demand and supply of investment capital. In Indonesia, the stock market is managed by the Indonesia Stock Exchange (IDX), which is responsible for the management and supervision of listed stock trading. One of the key indicators that reflects the overall performance of the stock market in Indonesia is the Jakarta Composite Index (JCI).

In recent times, the JCI has experienced sharp fluctuations due to various factors, both domestic and global, such as changes in economic policy, political uncertainty, and international market volatility (Handika et al., 2021). In April 2024, the JCI recorded a decline of 1.67% to IDR7036.07, then corrected again until it approached the psychological level of IDR7000 (Dwi, 2024). This decline was caused by simultaneous weakness across all sectors, with the cyclical, healthcare, financial, energy and non-cyclical sectors recording the largest declines of more than 1%. One notable event that showed the vulnerability of the JCI was “Black Monday” on August 5, 2024, when the JCI plummeted by 3.4% in one trading day and almost triggered a trading halt, which is a temporary suspension of stock trading as the index decline reaches a certain limit (Nabila, 2021). This policy aims to handle emergency situations and ensure that securities trading continues to run regularly, fairly and efficiently. However, the JCI began to show recovery, with a gain of 1.16% to IDR7212.13 at the close of trading on August 7, 2024. The industrial sector led the increase by 1.82%, followed by the transportation and property sectors which increased by 1.63% and 1.36% respectively (Muhamad, 2024).

Fluctuations in the JCI pose significant challenges in forecasting its movement, as it is influenced by a variety of complex and dynamic factors, including inflation, interest rates, exchange rates, and GDP growth, all of which are closely tied to capital market stability (Rahman et al., 2009). The inability to accurately predict the JCI's direction may lead to substantial investor losses and a decline in market confidence. Furthermore, suboptimal investment decisions can result in considerable financial setbacks (Patriya, 2020). Thus, the capability to produce precise predictions is essential for assisting investors, companies, and governments in making well-informed decisions, ensuring market stability, and fostering sustainable economic growth.

A nonparametric approach that can be utilized for predicting time series data is Support Vector Regression (SVR). This method relies on the principle of risk minimization, focusing on estimating a function by reducing the upper bound of generalization error. As a result, SVR proves effective in addressing overfitting issues (Yasin et al., 2014). This method has advantages in the form of good generalization ability, producing predictions with high accuracy, and flexibility in modeling linear and nonlinear relationships (Saadah, 2021). Determining the optimal parameters in SVR can be done using the grid search method, which is a technique for testing various combinations of parameters in the SVR model to identify the level of classification error (Purnama & Hendarsin, 2020).

Previous research related to JCI prediction has been conducted by Santoso and Hansun (2019) using the Backpropagation Neural Network (BPNN) method. The study showed that BPNN was able to predict daily JCI data from January 25, 2013 to January 24, 2014 quite well, as indicated by the Mean Squared Error (MSE) value for the testing data of 320.4987. This method uses a learning rate of 0.3 and 3000 epochs. However, this research has limitations, including a relatively short data coverage that is less representative, as well as the lack of in-depth discussion of model parameters and the risk of overfitting. Further development was carried out by Sihombing and Martha (2022) who used the ARIMA-SVR hybrid method to predict JCI. This research produced the best model in the form of ARIMA (3,1,3) combined with SVR parameters C, γ, and ε of $2^{-6,75}$, $2^{-2,25}$, and 0.1, respectively. The accuracy of the model is proven by the very small Mean Absolute Error (MAPE) value, which is 0.971% for training data and 0.733% for testing data. However, this study only uses MAPE as an evaluation measure and does not compare the method used with other prediction models, so the assessment of the effectiveness of the model is limited. These limitations highlight the need for a more comprehensive approach in predicting JCI movements.

This research addresses these gaps by applying the SVR method, a modern nonparametric approach that is more flexible and capable of handling overfitting problems, providing more stable results with larger and more complex datasets. A key innovation of this study is the application of SVR with a well-structured kernel selection process, where hyperparameter tuning is performed to ensure the best kernel is chosen. The effectiveness of the selected kernel is evaluated through commonly used performance metrics such as MAPE, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). This research is driven by the need to improve market stability and support sustainable economic development, specifically SDGs point 8. By providing reliable predictive tools, the study aims to offer valuable insights for market participants and policymakers in managing market volatility. The expected outcomes will enrich the understanding of stock market dynamics and contribute to more informed decision-making for investors and analysts.

RESEARCH METHODS

This study uses JCI weekly secondary data taken from investing.com website for the period of week 1 April 2022 to week 4 October 2024. Based on the criteria proposed by Woschnagg and Cipan (2004), the dataset division is carried out with a proportion of 80%: 20% for training and testing data. Thus, data from week 1 April 2022 to week 3 April 2024, totaling 107 data, were used as training data, while data from week 4 April 2024 to week 4 October 2024, totaling 27 data, were used as testing data. The variables used in this study are presented in Table 1.

Table 1. Study Variables

Variables	Unit
Jakarta Composite Index (y_t)	IDR
Time Period (x_t)	Weekly Period

Based on the objectives of this study, there are five stages of data analysis carried out as follows:

1. Presenting a description of the JCI weekly data.
2. Divide the dataset into two parts, namely training and testing data.
3. Perform modeling using the SVR approach through the following steps:
   a. Nonlinearity Testing
   Using the Terasvirta test to determine whether the data has a linear or nonlinear pattern. This test is included in the Lagrange Multiplier (LM) test category and is known as one of the methods for detecting nonlinearity using neural network models (Purwoko et al., 2023).
   b. Determination of Influential Lags
   Identifying significant lags through PACF plots, then converting the weekly JCI data into time lags as input for the SVR model.
   c. Hyperparameter Optimization
   The optimal parameters C, γ, ε, and coef0 are determined using grid search optimization, which identifies the best parameters within a specified range of values. This process is conducted in two stages: a loose grid and a finer grid (Purnama & Hendarsin, 2020). The loose grid evaluates C and γ using integer powers, while the finer grid focuses on values near the optimal parameters identified in the loose grid, aiming to minimize error (Hendayanti et al., 2019).
4. Selection of the best kernel function. Determining the best SVR kernel based on the MAPE, RMSE, and MAE values of the training data prediction results. According to Moreno et al. (2013), MAPE has the advantage of being easy to interpret, free of units, and clear in its presentation. The MAPE value is used to assess the ability of the model based on a certain range of values, as presented in Table 2 (Moreno et al., 2013).

Table 2. MAPE Value Criteria

MAPE Value	Description
MAPE < 10%	Highly accurate prediction results
10% ≤ MAPE ≤ 20%	Accurate prediction results
20% < MAPE ≤ 50%	Decent prediction results
MAPE > 50%	Bad prediction results

Besides MAPE, another commonly used metric to evaluate model performance and prediction accuracy is RMSE. RMSE quantifies the distribution of prediction errors within the model, making it widely applied in various fields such as climatology, forecasting, and regression analysis to assess the accuracy of experimental outcomes (Subiyanto et al., 2023). Additionally, MAE serves as a straightforward and intuitive measure, as it computes the average of absolute errors without considering the direction of the prediction error (Suryanto & Muqtadir, 2019). The formulas for these three accuracy metrics are provided in Equations (1), (2), and (3).

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{y_t}}{n} \times 100\% \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \quad (2)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \quad (3)$$

with

y_t : the actual value at time t;

$\hat{y}_t$: the predicted value at time t;

n : the total number of predictions.

5. Build an SVR model using the best kernel based on the optimal parameters that have been determined.
6. Predict the weekly JCI data using the SVR model with the best kernel that contains optimal parameters.

The stages of this research are further summarized in the flow chart shown in Figure 1.

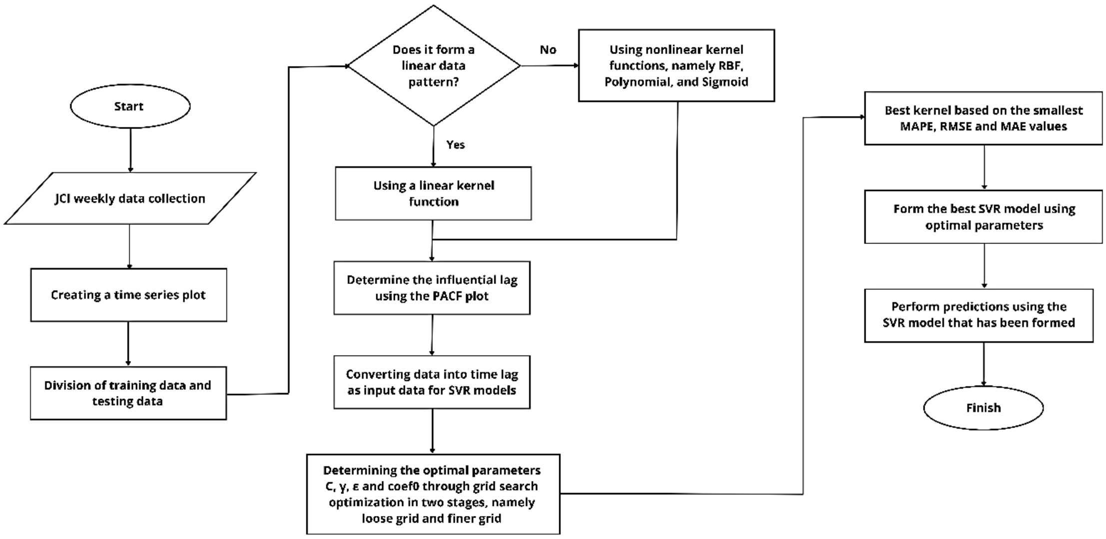

Figure 1. Research Flowchart

RESULTS AND DISCUSSION

JCI Weekly Data Description

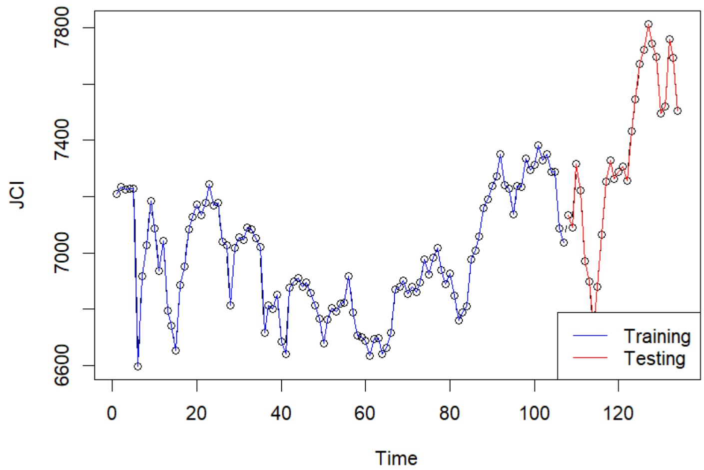

Figure 2. Time Series Plot of JCI Weekly Data

Based on Figure 2, it can be seen that the JCI in the period March 2022 to October 2024 showed significant fluctuations, with the highest point of the JCI recorded in the second week of September 2024 at Rp7812.13. From 134 weekly JCI data, an average of Rp7052.63 and a standard deviation of Rp273.2 were obtained. This standard deviation value illustrates the extent to which the JCI data spreads or varies from its mean value. In this case, the standard deviation indicates that the weekly JCI data variation is at a moderate level around the average.

Nonlinearity Testing

The first step in the SVR approach is to identify data patterns that will determine the type of kernel function used in the SVR model. The identification of data patterns is done through the Terasvirta test to determine whether the weekly JCI data pattern is linear or nonlinear. The results of the Terasvirta test can be seen in Table 3 below.

Table 3. Terasvirta Test Result

Variable	Test Statistic Value	P-Value
Jakarta Composite Index (y_t)	10.186	0.00614

Table 3 indicates that the Terasvirta test statistic, valued at 10.186, exceeds $\mathcal{X}^2_{(0,05;2)}$=5.992. Furthermore, the p-value of 0.00614 is less than the significance level α=0.05, leading to the rejection of the null hypothesis (H_0) in this nonlinearity test. Therefore, it can be concluded that the weekly JCI data exhibits a nonlinear pattern, justifying the use of Radial Basis Function (RBF), Sigmoid, and Polynomial kernel functions in the SVR method analysis.

Determination of Influential Lags

After testing the data pattern with the Terasvirta test, the next step is to determine the lag that affects the tth time variable as input data. This lag determination is done based on the Partial Autocorrelation Function (PACF) plot. In the context of SVR, the PACF plot is used to see the dependency pattern between the input and output variables in the time series. The results of determining the influential lag based on the PACF plot can be seen in Figure 3 below.

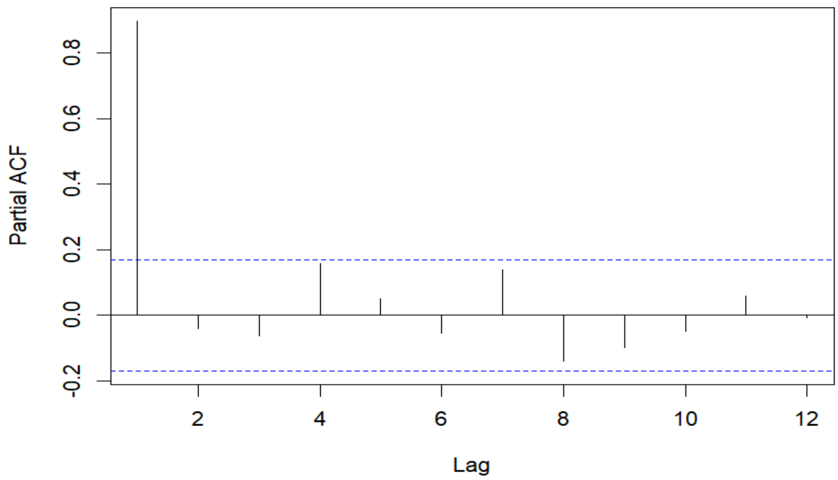

Figure 3. PACF Plot of JCI Weekly Data

Based on Figure 3, it can be seen that the lag that has a significant effect is only the first lag (y_{t-1}) so that the data in the first time period is not used. Therefore, the distribution of y_t data in SVR modeling for training data starts from period $t = 2$ to $t = 108$, while for testing data starts from $t = 109$ to $t = 134$.

Parameter Tuning with Grid Search Optimization

To achieve high prediction accuracy in SVR model development, identifying the optimal parameters is essential. This is accomplished through grid search optimization, which involves tuning C, γ, ε, and coef0. The process is conducted in two stages: a loose grid and a finer grid. In the loose grid stage, integer power values are used for $C, \gamma,$ and coef0, while ε is varied within the range of 0 to 1. The parameter ranges applied during the loose grid stage are presented in Table 4 below.

Table 4. Value Range of Parameters in the Loose Grid Stage

Parameter	Value Range
C	$2^{-6}, 2^{-5}, 2^{-4}, \dots, 2^{3}, 2^{4}, 2^{5}$
γ	$2^{-6}, 2^{-5}, 2^{-4}, \dots, 2^{3}, 2^{4}, 2^{5}$
ε	$0.1, 0.2, 0.3, \dots, 0.8, 0.9, 1$
coef0	$2^{-2}, 2^{-1}, \dots, 2^{1}, 2^{2}$

Following the parameter tuning process in the loose grid stage, the optimal parameters for each kernel function were identified. The results of these optimal parameters for each nonlinear kernel function are summarized in Table 5 below.

Table 5. Optimal Parameter Value of Loose Grid Stage

Kernel Function	Parameter	Optimal Parameter Value
RBF	C	2
	γ	2
	ε	0.3
Polynomial	C	16
	γ	0.0625
	ε	0.6
	coef0	0.25
Sigmoid	C	32
	γ	0.0625
	ε	0.6
	coef0	0.25

Once the optimal parameters of the SVR model are determined in the loose grid stage, the next step is to fine-tune the parameters in the finer grid stage. This stage aims to identify the optimal values of C and γ within the range established during the loose grid stage. The range of parameter values used in the finer grid stage to find the optimal C and γ is shown in Table 6 below.

Table 6. Value Range of Parameters in the Finer Grid Stage

Kernel Function	Parameter	Value Range
RBF	C	$2^{-1}, 2^{-0.75}, 2^{-0.5}, \dots, 2^{1.5}, 2^{1.75}, 2^{2}$
	γ	$2^{-1}, 2^{-0.75}, 2^{-0.5}, \dots, 2^{1.5}, 2^{1.75}, 2^{2}$
Polynomial	C	$2^{3}, 2^{2.75}, 2^{2.5}, \dots, 2^{4.5}, 2^{4.75}, 2^{5}$
	γ	$2^{-5}, 2^{-4.75}, 2^{-4.5}, \dots, 2^{-0.5}, 2^{-0.75}, 2^{-1}$
Sigmoid	C	$2^{4}, 2^{3.75}, 2^{3.5}, \dots, 2^{5.5}, 2^{5.75}, 2^{6}$
	γ	$2^{-5}, 2^{-4.75}, 2^{-4.5}, \dots, 2^{-0.5}, 2^{-0.75}, 2^{-1}$

The results of parameter tuning at the finer grid stage using the grid search method resulted in optimal parameters applied to the SVR model for each nonlinear kernel function. The optimal parameters can be seen in Table 7.

Table 7. Optimal Parameter Value of Finer Grid Stage

Kernel Function	Parameter	Optimal Parameter Value
RBF	C	3.75
	γ	1.05
	ε	0.3
Polynomial	C	15
	γ	0.40625
	ε	0.6
	coef0	0.25
Sigmoid	C	23.25
	γ	0.03125
	ε	0.6
	coef0	0.25

Selection of the Best SVR Kernel Function

The best kernel function in the SVR method is determined based on the accuracy value of the SVR model on training data measured using MAPE, RMSE, and MAE. After calculating using the formulas in Equations (1), (2), and (3), the results of SVR model accuracy on training data for RBF, Polynomial, and Sigmoid kernels are presented in Table 8 below.

Table 8. SVR Model Accuracy Results on Training Data

Kernel Function	MAPE	RMSE	MAE
RBF	1.02%	104.3994	70.4166
Polynomial	1.10%	106.4302	76.4756
Sigmoid	1.15%	110.8709	79.8435

The accuracy of the SVR model on training data with the RBF kernel function listed in Table 8 shows very satisfactory results. Thus, it can be concluded that the best SVR model uses RBF kernel function with *Cost* (C) parameter of 3.75, *Gamma* (γ) of 1.05, and *Epsilon* (ε) of 0.3. Based on calculations using R software, the value of ω is 3.1682 and the value of b is -0.3464. The general equation for the SVR model with a nonlinear kernel is as follows.

$$f(\boldsymbol{x}_i) = \sum_{i=1}^{n}(a_i - a_i^*)K\langle \boldsymbol{x}_i, \boldsymbol{x}\rangle + b \qquad (4)$$

with $K\langle \boldsymbol{x}_i, \boldsymbol{x}\rangle = \varphi(\boldsymbol{x}_i).\varphi(\boldsymbol{x})$ and $\omega = \sum_{i=1}^{n}(a_i - a_i^*)$ then Equation (4) can be written into Equation (5) as follows.

$$f(\boldsymbol{x}_i) = \omega\ \varphi(\boldsymbol{x}_i).\varphi(\boldsymbol{x}) + b \qquad (5)$$

with $\varphi(\boldsymbol{x}_i).\varphi(\boldsymbol{x}) = exp(-\gamma(\boldsymbol{x}_i - \boldsymbol{x})^2)$, Equation (5) can be rewritten into Equation (6) as follows.

$$f(\boldsymbol{x}_i) = \omega\ exp(-\gamma(\boldsymbol{x}_i - \boldsymbol{x})^2) + b \qquad (6)$$

by entering the values of ω and b from the calculation results in the R software into Equation (6), the SVR model displayed in Equation (7) is obtained as follows.

$$f(\boldsymbol{x}_i) = 3.1682\ exp(-1.05(\boldsymbol{x}_i - \boldsymbol{x})^2) - 0{,}3464 \qquad (7)$$

Furthermore, the comparison between the prediction results of the SVR model with the RBF kernel function on training data and actual data is visualized in Figure 4 below.

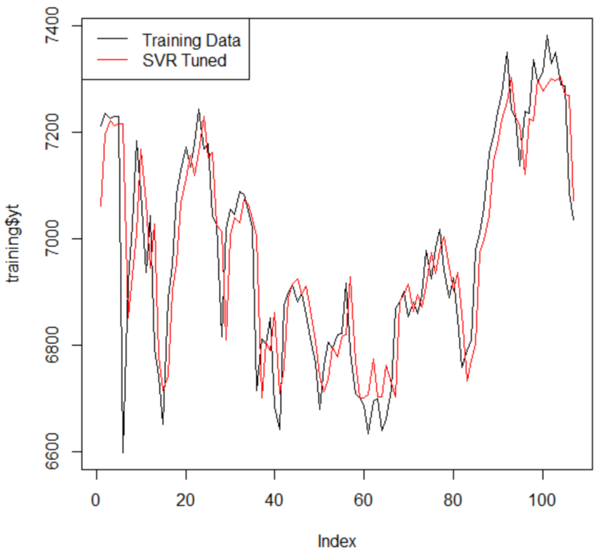

Figure 4. Comparison Plot of SVR Tuning Results with RBF Kernel on Training Data

As shown in Figure 4, the prediction of the SVR model with the RBF kernel on the training data closely follows the data pattern. This suggests that the predictions made by the SVR model with the RBF kernel on the training data are consistent with the actual values. Subsequently, the

SVR model was used to predict the weekly JCI testing data using the optimal parameters. The prediction results for the testing data from the SVR model are displayed in Figure 5.

Figure 5. Comparison Plot of SVR Tuning Results with RBF Kernel on Testing Data

After making predictions, the calculation of MAPE, RMSE, and MAE values is used to evaluate the accuracy of the SVR model. The test results on the testing data show that the SVR model with RBF kernel has excellent prediction performance, with a MAPE value of 1.43%, RMSE of 121.6196, and MAE of 104.65. The best SVR model, which uses the RBF kernel with parameters *Cost* (C) 3.75, *Gamma* (γ) 1.05, and *Epsilon* (ε) 0.3 shows a very high level of accuracy because the MAPE value is below 10%. These results show that the SVR method with RBF kernel proved to be very accurate in predicting the weekly JCI data.

CONCLUSION

The weekly JCI data of 134 observations from the first week of April 2022 to the fourth week of October 2024 showed a fairly volatile pattern and showed nonlinear characteristics, based on the results of the Terasvirta test. From the analysis conducted, the best SVR kernel for modeling JCI is the RBF kernel function with optimal parameters, namely *Cost* (C) of 3.75, *Gamma* (γ) of 1.05, and *Epsilon* (ε) of 0.3 as well as the value of ω 3.1682 and b -0.3464 which is reflected in Equation (7). The prediction results on the testing data for this model show a very good level of accuracy, with a MAPE value of 1.43%, RMSE of 121.6196, and MAE of 104.65.

This research contributes to the literature by demonstrating the effectiveness of the SVR method, particularly with the RBF kernel, in predicting stock market indices like the JCI. The findings provide valuable insights for both investors and policymakers seeking reliable tools for market prediction. To enhance prediction accuracy, future research should consider using longer data periods and further explore the SVR method. For stock investors, the SVR model with the RBF kernel offers a promising tool for short-term investment decisions. However, investors should still account for external factors such as global economic conditions, government policies, and market sentiment, which are not included in the model. Furthermore, adopting portfolio diversification strategies is crucial to mitigating risks amid market volatility.

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