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Application of Support Vector Regression in Time Series Analysis of Dior Stock Prices

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ABSTRACT

Christian Dior (Dior) is a multinational company focusing on luxury goods, including fashion products, cosmetics, and accessories. In 2020–2024, Dior's share price will experience significant fluctuations influenced by financial performance, global market trends, etc. These fluctuations require investors to implement appropriate strategies to minimize the risk of losses and support sustainable economic growth. This step aligns with goal 8 of the Sustainable Development Goals (SDGs), emphasizing the importance of sustainable economic growth through investment and infrastructure development for economic prosperity. One of the effective methods for modeling and predicting stock prices is Support Vector Regression (SVR). By applying SVR using the Radial Basis Function (RBF) kernel, this study shows that the model can generate predictions with a MAPE value of 2.5864% on the test data. The SVR method is expected to provide accurate predictions, making it a helpful tool for investors and market analysts to make better investment decisions.

Keyword: Dior's Stock Price; Radial Basis Function; Support Vector Regression

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1. INTRODUCTION

Stock price movements are one of the main indicators reflecting a company's performance as well as the overall market condition. Stock price fluctuations provide an overview of how a company is perceived by investors based on financial performance, future prospects, and responses to global economic dynamics. As a critical benchmark, stock prices also reflect the level of investor confidence in the stability and growth of a company in facing market challenges (Ngui, 2023). In addition, changes in stock prices can serve as a benchmark for investors in terms of making investments to enhance company value (Pratama et al., 2025). Amid increasingly complex market dynamics, observing stock price fluctuations becomes crucial for investors and market analysts to understand market trends and predict changes that might affect asset values. This aligns with the goals of the Sustainable Development Goals (SDGs), particularly Goal 8, which focuses on sustainable economic growth through smart investment (United Nations, 2023).

Christian Dior, or more commonly known as Dior, is a multinational company from France that operates in the luxury goods industry. Founded in 1946, Dior has become one of the most renowned brands in the world, offering a range of products including clothing, cosmetics, perfumes, jewelry, and accessories. The company is known for its elegant and innovative designs, which continue to influence the global fashion industry. As a company in the luxury goods sector, Dior's stock performance is heavily influenced by global trends in luxury consumption, macroeconomic conditions, and market dynamics. During the period 2020–2024, Dior's stock prices showed significant fluctuations due to various factors, including the impact of the COVID-19 pandemic, changes in consumer behavior, and global economic recovery. Sustained demand for luxury goods, especially in Asian markets, has helped support Dior's stock value, with major contributions from the cosmetics and fashion segments (Ningrum & Sukresna, 2024).

Various methods have been developed to analyze and predict stock prices. One popular approach is Support Vector Regression (SVR), which is a modification of Support Vector Machine (SVM) for regression purposes. A previous study on stock price forecasting for ADRO using SVR resulted in a MAPE value of 6.45% (Maghfirah et al., 2025). Additionally, another study predicted gold prices with SVR using a grid search algorithm and achieved a MAPE value of 3.73% (Gunanta et al., 2023). From these studies, most have not specifically applied SVR to luxury goods industry stocks such as Dior using the Radial Basis Function (RBF). RBF is one of the kernel functions commonly used in SVM and SVR methods. This function helps the model handle data with nonlinear patterns by transforming the data so that complex relationships can be better recognized (GeeksforGeeks, 2024). In recent research, more complex machine learning-based methods, such as deep learning, have also been used for stock price prediction. However, these methods tend to require large amounts of data and longer computational times compared to SVR (Faisol et al., 2022). Therefore, SVR remains a relevant and practical method for stock price analysis, especially when available data is limited.

The scientific novelty of this research lies in the development of a Dior stock price prediction model using Support Vector Regression (SVR) with a Radial Basis Function (RBF) kernel designed to capture nonlinear stock price fluctuation patterns during the period 2020–2024. Unlike previous studies that predominantly focused on banking stocks or stock indices such as the IDX Composite (IHSG), this study introduces the context of the luxury goods industry, particularly Dior, which has unique market characteristics and dynamics. The hypothesis of this research is that SVR with an RBF kernel can produce a reliable prediction model with a low error rate measured by the Mean Absolute Percentage Error (MAPE). The aim of this study is to develop an accurate Dior stock price prediction model based on SVR, which can serve as a decision-support tool for investors and market analysts in making better investment decisions. This research is expected to provide significant contributions in the field of stock market analysis, particularly in the luxury goods industry.

2. LITERATURE REVIEW

2.1 Dior Stock Price

Christian Dior (Dior) is a multinational company operating in the luxury goods industry, offering products that include fashion, cosmetics, and accessories. Dior's stock is traded on the Paris Stock Exchange. In recent years, Dior's stock price has exhibited significant fluctuations, influenced by various factors such as the company's financial performance, global market trends, and dynamics within the luxury goods industry. According to data from Yahoo Finance, Dior's stock price reached a 52-week high of €832.50 on March 14, 2024, and a 52-week low of €529.50 on November 12, 2024 (Yahoo Finance, 2024). These fluctuations reflect the stock's sensitivity to market conditions and other external factors. Analyzing Dior's stock price is crucial to understanding market behavior and assisting investors in making informed decisions.

2.2 Support Vector Regression (SVR)

Support Vector Regression (SVR) is an application of the Support Vector Machine (SVM) method designed for regression tasks. One of the methods used to model and predict stock prices is Support Vector Regression (SVR). SVR has been applied in various studies to estimate stock price movements and has proven effective in identifying patterns in time series data and solving nonlinear problems (Saadah, 2021). SVR produces outputs in the form of real or continuous values. The main advantage of this method lies in its ability to handle overfitting issues, thus achieving optimal performance. SVR models are often utilized to minimize the Mean Square Error (MSE). The SVR algorithm is an advancement in machine learning theory and possesses strong capabilities in solving prediction accuracy problems (Arfan & Lusiana, 2020). The goal of the SVR algorithm is to determine the optimal hyperplane as the best separating line. Suppose there is a training dataset $\{(x_1, y_1), (x_2, y_2), \dots, (x_i, y_i)\}, i = 1,2, \dots, d$ when $x_i \in \mathbb{R}^d$, with d is a dimension and y_i is a result score (Purwoko et al., 2023). The following is the SVR model equation.

$$f(x) = \boldsymbol{w}^T \varphi(x) + b \tag{1}$$

with
$\boldsymbol{w}$ is an n-dimensional weight vector
$\varphi(x)$ is a function in n-dimensional space that maps x
b is the bias

2.3 Kernel Function in SVR

The performance of the SVR method heavily depends on the choice of kernel function used. The selected kernel function can be applied as a substitute to help overcome issues of data nonlinearity in high-dimensional spaces (Liu et al., 2021). A kernel function is dot product $\varphi(x_i).\varphi(x)$ which can be formulated into the following equation

$$K(x_i, x) = \varphi(x_i).\varphi(x) \tag{2}$$

Thus, the SVR regression function can be explained as follows.

$$y_i = f(x_i) = \sum_{i=1}^{n} (a_i - a_i^*)\, K(\boldsymbol{x}_i, x) + b \tag{3}$$

Parameters and kernel functions in the SVR model need to be properly tuned because they can affect the accuracy level in making predictions. Table 1 presents several kernel functions that are commonly used in SVR modeling.

Table 1. Kernel Functions in SVR

Types of Kernel Functions	Formula
Linier	$K(x_i, x) = x_i^T x$
Polynomial	$K(x_i, x) = (\gamma(x_i^T x) + r)^p, p = 1,2, \dots$
Radial Basis Function (RBF)	$K(x_i, x) = \exp\left(-\gamma\|\|x_i - x\|\|^2\right)$
Sigmoid	$K(x_i, x) = tanh\ (\gamma x_i^T, x + r)$

Source: Isnaeni et al., 2022

with
$tanh$ is a hyperbolic function that produces values between -1 and 1
g is a kernel parameter that determines how sensitive the kernel is to differences in the input.
T is the transpose operator that produces the transpose of a matrix.

2.4 Grid Search Optimization

Grid search optimization is a technique used to find the optimal combination of parameters for a model by systematically evaluating all possible parameter combinations that have been predefined (Fajri & Primajaya, 2023). To search for the optimal parameters, the grid search method divides the range of parameters to be optimized and iterates through each point. The best SVR cross-validation parameters are determined by the grid search algorithm. The main goal is to find the best combination of hyperparameters that can predict the test data with high accuracy.

The grid search method for finding the optimal hyperparameters requires a considerable amount of time. Therefore, the grid-based hyperparameter search process is carried out in two stages: loose grid and finer grid (Purnama & Hendarsin, 2020). The loose grid stage is the initial step where the optimal parameters are selected from integer power values. Next, the finer grid stage is conducted by searching for the optimal parameters around the values obtained in the loose grid stage to achieve more precise results.

2.5 Mean Absolute Persentage Error (MAPE)

One of the criteria for determining the goodness of prediction results from the model is by looking at the Mean Absolute Percentage Error (MAPE). MAPE shows the level of absolute error of the prediction results. The MAPE value can be obtained using the following formula.

$$MAPE = \frac{\sum_{1=1}^{n} \frac{|y_i - \hat{y}_i|}{y_i}}{n} \times 100\% \quad (4)$$

with
y_i is the observed value at time period t
$\hat{y}_i$ is the predicted value at time period t
n is the number of prediction data points

The magnitude of the MAPE value can be interpreted as the level of accuracy of the predictions produced by a model. A model that produces a MAPE value below 10% indicates that the model yields accurate predictions, while a MAPE value above 50% indicates that the model produces inaccurate predictions. The interpretation of the MAPE values can be seen in Table 2.

Table 2. MAPE Value Criteria

MAPE	Accuracy Rate
MAPE < 10%	The prediction results are classified as very accurate
10% ≤ MAPE < 20%	The prediction results are relatively accurate
20% ≤ MAPE < 50%	The prediction results are considered worthy
MAPE ≥ 50%	The predicted results are relatively poor

Source: Moreno et al., 2013

3. METHOD

3.1 Data Source and Variables

This research was conducted using a quantitative approach focusing on time series data analysis. The analyzed data comprises Dior's stock prices obtained from the investing.com website. The study utilizes weekly data covering the period from August 2020 to November 2024. The research data is divided into two parts, namely training data and testing data, with 90% allocated for training and 10% for testing. The training data will be used to build the model, covering data from the first week of August 2020 to the last week of May 2024. Meanwhile, the testing data will be used to assess the model's accuracy, covering data from the first week of June 2024 to the last week of November 2024. The variable in this study is Dior's stock price.

3.2 Stages of Data Analysis

Data analysis is conducted using R software. The following outlines the detailed stages of data analysis applied in this study.

1. Determine the characteristics of Dior's stock price by creating a time series plot and performing descriptive statistical analysis.
2. Split the research data into two parts: training data and testing data, with proportions of 90% and 10%, respectively.
3. Conduct Terasvirta test and White test to examine the assumptions of linearity and heteroscedasticity in the data.
4. Generate a PACF plot to determine the significant lags in Dior's stock price data.
5. Perform initial modeling to determine the best kernel function for predicting Dior's stock price data based on the criteria of minimum RMSE and MAPE values.
6. Tune parameters using the grid search method in two stages: loose grid and finer grid.
7. Model SVR on the training data using the optimal parameters obtained from the grid search tuning process.
8. Predict Dior's stock prices on the testing data based on the best SVR model.
9. Calculate the MAPE value from the predictions on the testing data and draw conclusions.

The series of analytical stages described earlier can be more clearly and systematically illustrated through the following flowchart

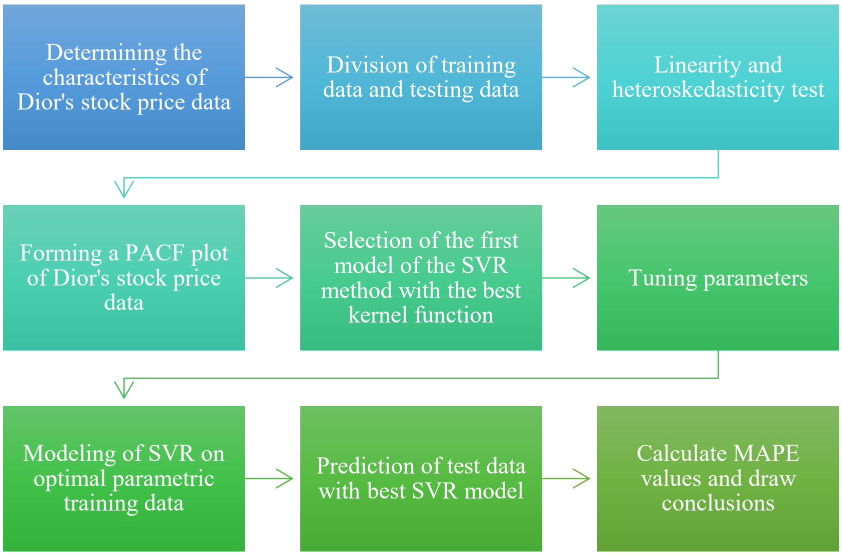

Figure 1. Flowchart of Data Analysis Stages (Source: Analysis, 2024)

4. RESULT AND DISCUSSION

4.1 Characteristics of Dior Share Price Data

In this study, the characteristics of Dior's stock prices are visualized using a time series plot and explained through descriptive statistics, which include the number of observations, mean, minimum, and maximum values. Prior to this, the Dior stock price data is divided into training and testing sets with a respective proportion of 90% and 10%. According to Aisyah et al. (2021), the proportion for splitting training and testing data is subjectively determined by the researcher. The time series plot of Dior stock prices is presented below.

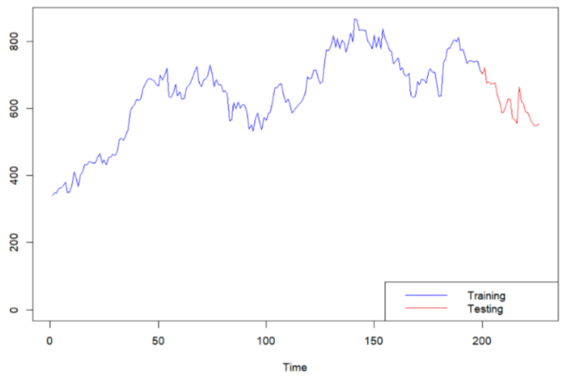

Figure 2. Time Series Plot (Source: Analysis, 2024)

Based on Figure 2, the difference in line colors on the plot is used to distinguish between training and testing data. It can be identified that Dior's stock prices exhibit an upward trend from 2020 to 2024, with weekly fluctuations. The highest stock price appears on the 141st data point, dated April 9, 2023, while the lowest is on the 1st data point, dated August 2, 2020. The results of the descriptive statistical analysis of Dior stock prices are presented in detail in Table 3.

Table 3. Descriptive Statistics of Dior Stock Price Data

Data	Amount of Data	Mean	Minimum	Maksimum
Overall Data	226	641.41	340.4	866
Training Data	199	644.79	340.4	866
Testing Data	27	616.44	548.5	722

Source: Analysis, 2024

Based on Table 3, using the 90% and 10% data split, a total of 199 training data points are obtained with the lowest stock price of 340.4 EUR and the highest of 866 EUR. Additionally, 27 testing data points are identified, with respective minimum and maximum stock prices of 548.5 EUR and 616.44 EUR. A total of 226 observations will be used in the time series analysis using the SVR method.

4.2 Test of Linearity and Heteroscedasticity of Dior Share Price Data

To verify the presence of nonlinearity and heteroskedasticity in Dior stock price data, tests such as the Terasvirta test and White test are employed. The Terasvirta test is used to assess linearity in the data, and the following hypothesis is applied

H_0: The data contains a linear pattern

H_1: The data does not contain a linear pattern

Subsequently, the White test is performed to detect heteroskedasticity in the data, using the following hypothesis.

H_0: Data are not indicated heteroscedasticity

H_1: Data indicated heteroscedasticity

Using the testing criterion to reject H_0 if the $p - value < \alpha = 5\%$, the results of the Terasvirta and White tests are shown in Table 4.

Table 4. Results of Linearity and Heteroscedasticity Test

Test	*P-Value*
Terasvirta Test	0,001143
White Test	0,004557

Source: Analysis, 2024

Based on Table 4, the *p-value* from the Terasvirta and White tests are 0.001143 and 0.004557, respectively. With $\alpha = 5\%$, the decision is to reject H_0 and it can be concluded that the data exhibits nonlinearity and heteroskedasticity. Therefore, the data fulfills the assumptions required for analysis using the SVR method.

4.3 Dior Share Price Time Series Analysis with SVR Method

The SVR method is considered a modern, non-parametric approach. Before model fitting, the data is transformed into time lag format by identifying and removing insignificant lags with the help of a Partial Autocorrelation Function (PACF) plot. Significant lags identified in the PACF plot are used as predictor variables (Bawues et al., 2022). The PACF plot for Dior's stock price is visualized in Figure 3.

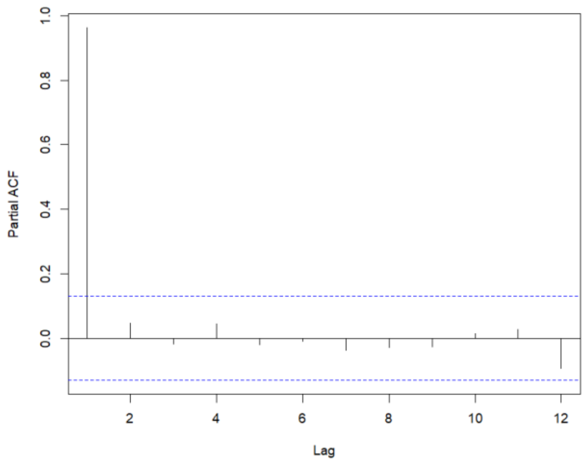

Figure 3. PACF Plot Dior Share Price Data (Source: Analysis, 2024)

Based on Figure 3, lag 1 is identified as a significant lag because it exceeds the upper and lower bounds of the PACF plot. Thus, lag 1 is used as the time lag input for SVR modeling. Next, a comparison of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) values is performed on the initial SVR models using three kernel functions: Radial Basis Function (RBF), sigmoid, and polynomial. The results of the initial SVR modeling on the training data are presented in Table 5.

Table 5. Comparison of Kernel Data Training Functions

Kernel	RMSE	MAPE
RBF	24.29531	2.8485%
Sigmoid	65.23159	9.1944%
Polynomial	1118.558	158.7915%

Source: Analysis, 2024

Based on Table 5, the RBF kernel yields the best performance with an RMSE value of 24.29531 and a MAPE value of 2.8485%. These values indicate relatively low and stable prediction errors. In contrast, the sigmoid kernel produces nearly three times the error of RBF, and the polynomial kernel demonstrates very poor performance with an RMSE exceeding 1000 and a MAPE above 150%, indicating a total mismatch between the polynomial kernel and the data characteristics. This finding supports the selection of the RBF kernel as the basis for parameter tuning due to its effectiveness in capturing nonlinear patterns.

Following the initial modeling using the best-performing kernel, the SVR model's performance is enhanced through parameter tuning. The tuning process uses a grid search method, consisting of two stages: loose grid and finer grid search. Each kernel function has different parameters for tuning. For the RBF kernel, three parameters are tuned: *cost* (C), *gamma* (γ), and *epsilon* (ε). The parameter value ranges used in the tuning process are presented in Table 6.

Table 6. Grid Search Method Parameter Value Range

Grid Search Method	Parameter	Value Range
Loose Grid	*Cost* (C)	$2^{-5}; 2^{-4}; 2^{-3}; \dots; 2^{5}; 2^{6}$
	Gamma (γ)	$0; 0{,}1; 0{,}2; \dots; 0{,}9; 1$
	Epsilon (ε)	$2^{-6}; 2^{-5}; 2^{-4}; \dots; 2^{4}; 2^{5}$
Finer Grid	*Cost* (C)	$2^{-1}; 2^{-0.85}; 2^{-0.70}; \dots; 2^{2.85}; 2^{3}$
	Gamma (γ)	$2^{-1}; 2^{-0.85}; 2^{-0.70}; \dots; 2^{1.85}; 2^{2}$
	Epsilon (ε)	0

Source: Analysis, 2024

From the parameter ranges listed in Table 6, various combinations are tested to find the optimal parameter set. The optimal parameters from each grid search stage are summarized in Table 7.

Table 7. Optimal Parameters of the Grid Search Method

Grid Search Method	Optimal Parameter Combination		
	Cost **(C)**	***Gamma*** **(γ)**	***Epsilon*** **(ε)**
Loose Grid	2	44	0
Finer Grid	1.85	3.8	0

Source: Analysis, 2024

According to Table 7, the optimal parameters obtained from the finer grid method are *cost* (C) = 1.85, *gamma* (γ) = 3.8, and *epsilon* (ε) = 0. This tuning process results in an RMSE value of 23.49748 and a MAPE value of 2.7184% on the training data. Comparing the MAPE values before and after parameter tuning shows that the tuned SVR model achieves the lowest MAPE, indicating improved prediction performance. Therefore, it can be concluded that the tuning process enhances the SVR model's accuracy in forecasting Dior's stock prices. With the initial modeling completed, optimal parameters obtained, and model tuning performed, prediction of Dior's stock prices on the testing data using the SVR method can be conducted.

4.4 Calculation of MAPE Value

The next step involves calculating the Mean Absolute Percentage Error (MAPE) to measure the prediction error. The calculation is carried out using the predicted stock prices of Dior during the 2020–2024 period against the testing dataset. The MAPE calculation results are presented in Table 8.

Table 8. Calculation of MAPE Value Prediction Data Testing Results (EUR) Using the RBF Kernel

Period	Testing Data	Training Data	Difference	APE	MAPE
26/05/2024	702	702.015	0.015	0.002	2.586%
02/06/2024	722	703.080	18.92	2.62	
09/06/2024	675.5	693.647	18.147	2.686	
16/06/2024	678.5	676.255	2.245	0.331	
23/06/2024	671.5	680.819	9.319	1.388	
30/06/2024	675	669.858	5.142	0.762	
07/07/2024	675.5	675.472	0.028	0.004	
14/07/2024	639	676.255	37.255	5.83	
21/07/2024	619.5	619.515	0.015	0.002	
28/07/2024	586	600.106	14.106	2.407	
04/08/2024	589.5	577.156	12.344	2.094	
11/08/2024	609	579.645	29.355	4.82	
18/08/2024	629.5	592.563	36.937	5.868	
25/08/2024	625	608.937	16.063	2.57	
01/09/2024	571.5	604.705	33.205	5.81	
08/09/2024	566	565.984	0.016	0.003	
15/09/2024	556.5	561.539	5.039	0.905	
22/09/2024	662.5	554.077	108.423	16.366	
29/09/2024	619	654.837	35.837	5.79	
06/10/2024	615.5	599.715	15.786	2.565	
13/10/2024	590	597.080	7.08	1.2	
20/10/2024	588	579.994	8.006	1.362	
27/10/2024	570	578.589	8.589	1.507	
03/11/2024	559	564.774	5.774	1.033	
10/11/2024	548.5	555.982	7.482	1.364	
17/11/2024	548.5	548.500	0	0	
24/11/2024	551.5	548.500	3	0.544	

Source: Analysis, 2024

As shown in Table 8, the MAPE value obtained from the predicted Dior stock price data using the SVR method with the Radial Basis Function (RBF) kernel is 2.586%. Thus, it can be concluded that the SVR method is highly effective and accurate in forecasting Dior's stock price over the 2020–2024 period, as the resulting MAPE value is below 10%. This finding is in line with the study conducted by Muhammad et al. (2021), which states that a MAPE value of less than 10% indicates a highly accurate prediction. The predicted results on the testing dataset are visualized in the chart shown in Figure 4.

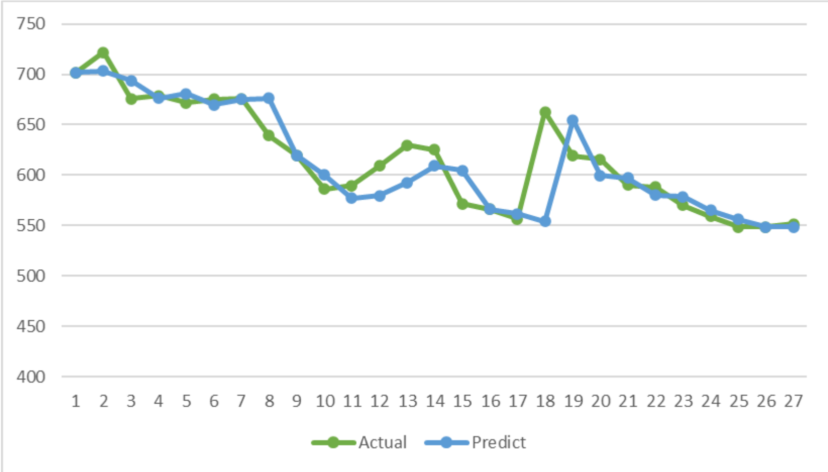

Figure 4. SVR Method Data Testing Prediction Results (Source: Analysis, 2024)

5. CONCLUSION

Based on the results of this study, it can be observed that the stock price of Dior fluctuated on a weekly basis during the 2020 - 2024 period, as shown by the time series plot. Using the SVR approach, the general model form applied to predict Dior's stock price is the one using the RBF kernel. This model produced a MAPE value of 2.586% on the testing dataset. Further research is recommended to evaluate the prediction of Dior's stock price using alternative forecasting methods, such as machine learning or deep learning, which may offer a more accurate approach in analyzing stock price patterns. Understanding and applying appropriate forecasting methods can provide investors with better insights in managing their investments. It is also important to note that stock price prediction cannot fully eliminate risk. By acknowledging limitations and updating analyses regularly, economic actors can make more informed and adaptive decisions when managing their investments in Dior's stock.

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