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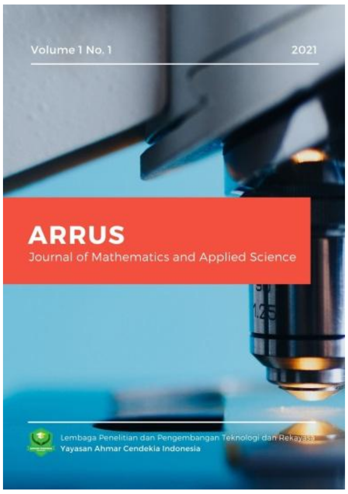

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RESEARCH ARTICLE

Implementation of Support Vector Regression (SVR) and Double Exponential Smoothing (DES) for Forecasting BRI Stock Prices

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Abstract: This study aims to forecast the closing stock prices of BRI using Support Vector Regression (SVR) and Double Exponential Smoothing (DES) methods. The data used in this research is secondary data obtained from the Yahoo Finance website, covering the period from January 2020 to November 2023. The analytical steps using the SVR method involve selecting the optimal model by applying Grid Search Optimization to various kernels (linear, polynomial, radial, and sigmoid). The best-performing model was found to be the radial kernel with parameters $\varepsilon = 0.1$, $C = 100$, and $\gamma = 10$, yielding a Mean Absolute Percentage Error (MAPE) of 0.2431%, which was then used for forecasting. For the DES method, the steps involved parameter determination and minimizing the MAPE value, followed by smoothing calculations and forecasting. The optimal parameters obtained were $\alpha = 0.89$ and $\beta = 0.01$, resulting in a MAPE value of 1.4832%. Based on the comparison of MAPE values, it can be concluded that the SVR method with a radial kernel ($\varepsilon = 0.1$, $C = 100$, $\gamma = 10$) provides the most accurate forecasts for BRI closing stock prices, with the lowest MAPE of 0.2431%.

Keywords: Stock Price, Support Vector Regression (SVR), Double Exponential Smoothing (DES), Mean Absolute Percentage Error (MAPE)

1. Introduction

The stock market is one of the sectors that plays an important role in a country's economy as it reflects both corporate performance and overall economic conditions. The fluctuating movement of stock prices presents a challenge for investors in making the right investment decisions. Therefore, stock price forecasting becomes a crucial aspect of capital market analysis to reduce risks and increase profit potential.

Bank Rakyat Indonesia (BRI) is one of the largest banks in Indonesia, with a high market capitalization and significant stock price movements. Since the COVID-19 pandemic, BRI's stock price has experienced sharp fluctuations, indicating uncertainty in the capital market. Based on historical data, BRI's stock price experienced a significant decline in 2020 due to the pandemic, followed by a gradual recovery in the following years. This phenomenon highlights the importance of stock price forecasting to help investors make more informed decisions.

In recent years, various methods have been developed for stock price forecasting. Traditional methods such as Autoregressive Integrated Moving Average (ARIMA) are often used, but they have limitations in capturing nonlinear patterns in time series data. Therefore, more

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advanced approaches such as Support Vector Regression (SVR) and Double Exponential Smoothing (DES) have begun to be applied in stock price forecasting analysis. SVR, as a machine learning technique, can handle complex data patterns by detecting nonlinear relationships within the dataset. Meanwhile, the DES method is known for its double-smoothing approach that considers trends in historical data to improve forecasting accuracy.

Several previous studies have discussed the application of SVR and DES in stock price forecasting. For example, Rais et al. (2022) demonstrated that SVR with a radial basis function (RBF) kernel outperformed conventional regression methods in forecasting inflation. In addition, a study by Syahfitri et al. (2024) revealed that the use of SVR with Grid Search optimization improved accuracy in predicting gold prices. On the other hand, research by Indriyani et al. (2023) showed that the DES method produced good forecasting results on Bank Tabungan Negara (BTN) stock data, with a low MAPE value.

Although these studies show promising results, there is a research gap regarding the comparison of SVR and DES effectiveness in forecasting the stock prices of banking companies in Indonesia, particularly BRI. Most studies only examine one method without conducting a direct comparison. Therefore, this study aims to fill this gap by comparing the forecasting accuracy of BRI's stock prices using both methods and determining which method is superior based on the Mean Absolute Percentage Error (MAPE) value.

Based on the background and gap analysis described above, the main objectives of this research are: To forecast BRI stock prices using the Support Vector Regression (SVR) method with Grid Search optimization to determine the best parameters; To forecast BRI stock prices using the Double Exponential Smoothing (DES) method with smoothing parameter optimization; To compare the forecasting accuracy of the two methods based on MAPE values and determine the more optimal method for forecasting BRI stock prices.

The importance of stocks as an investment instrument lies in their potential to generate income, reduce high costs, enhance investment capacity, and improve overall welfare. Stocks serve as an investment tool that helps investors mitigate financial risks, which may occur if the stock price falls below its purchase price. In this regard, forecasting stock price movements is essential to assist investors in determining the right timing for transactions. To forecast stock prices, statistical methods are required. Hence, this study employs SVR and DES methods to forecast stock prices.

2. Literature Review

2.1. *Stock Price Forecasting*

Stock price forecasting is a process of predicting future price movements based on historical data. Forecasting approaches can be categorized into classical statistical methods, such as ARIMA, and machine learning-based methods, such as SVR. While ARIMA has been widely applied in time series analysis, it has limitations in capturing complex and nonlinear patterns (Hyndman & Athanasopoulos, 2018). Consequently, machine learning approaches have gained increasing attention to overcome these shortcomings.

2.2. *Support Vector Regression (SVR)*

Support Vector Regression (SVR) is a machine learning technique derived from Support Vector Machines (SVM), designed for regression tasks. SVR aims to construct an optimal hyperplane that predicts target values within a specified error tolerance (Smola & Schölkopf, 2004). Previous studies have demonstrated its effectiveness; Rais et al. (2022) found that SVR with a radial basis function (RBF) kernel achieved higher accuracy than linear regression in predicting stock prices, while Syahfitri et al. (2024) highlighted the benefits of Grid Search optimization in enhancing SVR performance.

The general regression function of SVR can be expressed as:

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$$f(x) = w^T\varphi(x) + b \tag{2.1}$$

where w denotes the weight vector, $\varphi(x)$ the feature mapping, b the bias, and $f(x)$ the regression function. The optimization process introduces slack variables ξ and $\xi*$ to allow deviations, with a penalty parameter C controlling the trade-off between margin maximization and prediction error (Smola & Schölkopf, 2004). Kernel functions commonly employed in SVR include linear, polynomial, sigmoid, and RBF (Yu et al., 2006).

2.3. *Grid Search Optimization*

Grid Search is a parameter optimization technique that systematically evaluates predefined parameter combinations to identify the most accurate model. Cross-validation, particularly k-fold cross-validation, is often used in conjunction with Grid Search to reduce overfitting and provide reliable error estimation (Santosa, 2007; Han et al., 2012).

2.4. *Double Exponential Smoothing (DES)*

Double Exponential Smoothing (DES), introduced by Holt in 1958, is a forecasting method that applies double smoothing to account for level and trend components (Hudiyanti et al., 2019). Unlike seasonal models, DES focuses on trend-based forecasting by incorporating two parameters: α (level smoothing) and β (trend smoothing). The model is defined as follows (Rosadi, 2012):

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + T_{t-1}) \tag{2.2}$$
$$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1} \tag{2.3}$$
$$F_{t+m} = S_t + mT_t \tag{2.4}$$

where $X_t$is the actual observation, $S_t$the level, T_t the trend, and F_{t+m} the forecast for m future periods.

2.5. *Double Exponential Smoothing (DES)*

The Mean Absolute Percentage Error (MAPE) is a widely used metric for evaluating forecasting accuracy, defined as (Gurianto et al., 2016):

$$MAPE = \frac{\sum_{t=1}^{n} \frac{|X_t - F_t|}{X_t}}{n} \times 100\% \tag{2.5}$$

where X_t is the actual value, F_t the forecast value, and n the number of observations. A lower MAPE indicates higher accuracy. Forecasting performance is categorized as very good if MAPE ≤ 10%, good if 10% < MAPE ≤ 20%, acceptable if 20% < MAPE ≤ 50%, and poor if MAPE > 50% (Ferima Talia et al., 2019).

3. Research Method

The data used in this study consist of historical daily closing prices of BRI stocks from January 2020 to November 2023. The variable employed is the daily closing stock price, which represents the final price or benchmark price of a stock in a single trading day. Stock closing prices are measured in rupiah per share.

The data analysis techniques applied in this study are as follows:

(1). Data collection: Secondary data on daily closing stock prices from January 2020 to November 2023, obtained from Yahoo Finance.

(2). Plotting time series data.

(3). Steps of analysis using Support Vector Regression (SVR):

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(a). Determining the values of parameters C (cost), ε (epsilon), and γ (gamma) using Grid Search Optimization.
(b). Identifying the best model by evaluating the smallest parameter values across different kernels.
(c). Conducting forecasting using the best-selected model.
(d). Evaluating the forecasting accuracy using the Mean Absolute Percentage Error (MAPE).

(4). Steps of analysis using Double Exponential Smoothing (DES):

(a). Determining the optimal values of α (alpha) and β (beta) using the trial-and-error method.
(b). Selecting the smoothing parameters based on the smallest MAPE value.
(c). Conducting forecasting using the best smoothing parameters.

(5). Selecting the best method by comparing the MAPE values of both models.

(6). Drawing conclusions based on the results of the analysis.

4. Results and Discussion

4.1. *Descriptive Analysis*

The descriptive analysis of the daily closing prices of BRI stocks from January 2020 to November 2023 is presented in Table 1.

Table 1: Descriptive Analysis of BRI Stock Closing Prices (IDR)

Mean	Minimum	Maximum
3,683	1,655	5,410

As shown in Table 1, the average closing price of BRI stocks during the period from January 1, 2020, to November 30, 2023, was IDR 3,683 per share. The lowest closing price was IDR 1,655 per share, recorded on May 18, 2020, while the highest closing price was IDR 5,410 per share, recorded on August 10, 2023.

The plot of BRI's daily closing stock prices over the period January 2020 to November 2023 is presented in Figure 1.

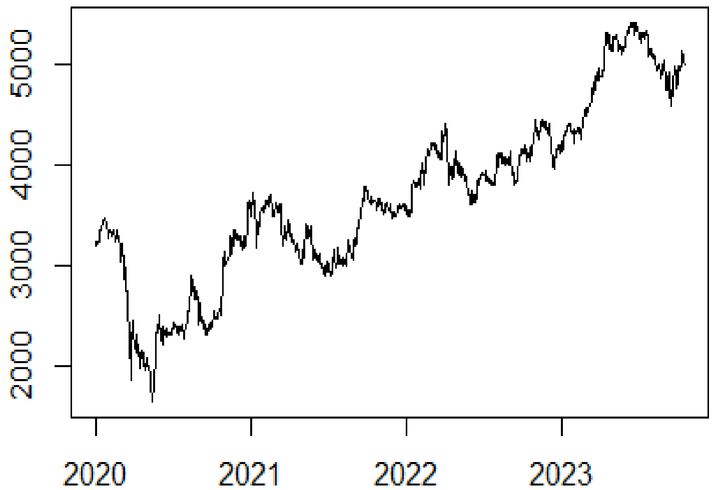

Figure 1: Plot of Daily Closing Stock Prices, January 2020 – November 2023

Based on Figure 1, the daily closing prices of BRI stocks from 2020 to 2023 exhibit a **trend pattern**. It is categorized as a trend because the stock prices experienced upward and downward movements that occurred recurrently. During the first half of 2020, the prices

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showed a declining trend, whereas from 2021 to 2023, they demonstrated an upward trend. Therefore, the use of Support Vector Regression (SVR) and Double Exponential Smoothing (DES) methods is considered appropriate for forecasting BRI's daily closing stock prices.

4.2. *Analysis of the SVR Method*

4.2.1. Selection of the Best Model Using Grid Search Optimization

Grid Search is employed to identify the optimal parameters for a model so that the selected model can accurately predict the data. The optimization of the SVR model using Grid Search requires parameters that are adjusted to the type of kernel applied. Grid Search Optimization is performed using the k-fold cross-validation technique.

The Grid Search process is adjusted according to the kernel used in the modeling. For the linear kernel, Grid Search is used to determine the most optimal values of C and ε. A very large C value neglects the maximum margin variations, leading to constant errors. Conversely, a very small C value places too much emphasis on penalties in SVR. Meanwhile, a smaller ε restricts the tolerance for errors, while a larger ε increases the allowable error tolerance.

For polynomial, sigmoid, and radial kernels, Grid Search is used to determine the optimal values of C, ε, and γ. The γ parameter specifies the influence of each data point when mapping the input space to higher dimensions.

Table 2: Results of Grid Search Parameters

Kernel	k	Best ε	Best C	Best γ	Smallest Error
Linear	**2**	**0.1**	**0.05**	**-**	**0.00983148**
	4	0.1	0.05	-	0.00992626
	6	0.1	0.05	-	0.00988451
	8	0.1	0.05	-	0.00989179
Polynomial	2	0.1	0.05	1	0.02123879
	4	0.1	0.05	1	0.02115019
	6	0.1	0.05	1	0.02101355
	8	**0.1**	**0.05**	**3**	**0.02057196**
Radial	**3**	**0.1**	**100**	**10**	**0.00096087**
	5	0.1	100	10	0.00099989
	7	0.1	100	10	0.00096414
	9	0.1	100	10	0.00096357
Sigmoid	**2**	**0.1**	**0.05**	**1**	**0.06809274**
	4	0.1	0.05	1	0.12462940
	6	0.1	0.05	1	0.14813030
	8	0.1	0.05	1	0.16040560

From Table 2, it can be observed that for the linear kernel, the smallest error (0.00983148) was obtained when k = 2 with parameters ε = 0.1 and C = 0.05. For the polynomial kernel, the best parameters were ε = 0.1, C = 100, and γ = 3, producing an error of 0.02057196 at k = 8. Meanwhile, the radial kernel yielded the smallest error of 0.00096087 with parameters ε = 0.1, C = 100, and γ = 10 at k = 3. Finally, the sigmoid kernel resulted in an error of 0.06809274 at k = 2 with parameters ε = 0.1, C = 0.05, and γ = 1.

Based on these results, the radial kernel was selected as the most suitable kernel, with parameters ε = 0.1, C = 100, and γ = 10 at k = 3, as it provided the lowest error compared to other kernels.

4.2.2 Stock Price Forecasting

The optimal parameters obtained in the previous step were used to conduct stock price forecasting. The forecasting results are presented in Figure 2.

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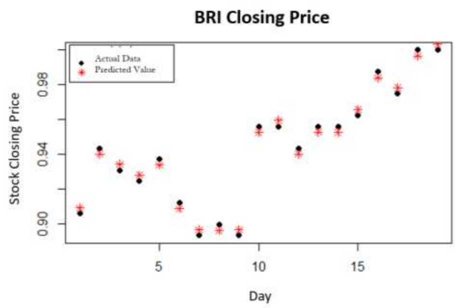

Figure 2: Plot of Predicted Values Against Actual Data

As shown in Figure 2, the red points represent the predicted values, while the black points represent the actual data. The figure indicates that the forecasting results closely follow the actual data. A comparison between the predicted and actual values of the stock closing price is presented in Table 3.

Table 3: Forecasting Results of BRI Stock Closing Prices Using SVR

Date	Predicted Value	Actual Value
1 Dec 2023	5068,983	5077,939
4 Dec 2023	5185,228	5220,311
5 Dec 2023	5163,271	5172,854
6 Dec 2023	5139,612	5149,125
7 Dec 2023	5161,662	5196,583
8 Dec 2023	5067,308	5101,668
11 Dec 2023	5021,792	5030,482
12 Dec 2023	5232,328	5054,210
13 Dec 2023	5257,600	5030,482
14 Dec 2023	5185,181	5267,769
15 Dec 2023	5253,418	5267,769
18 Dec 2023	5232,331	5220,311
19 Dec 2023	5281,175	5267,769
20 Dec 2023	5350,242	5267,769
21 Dec 2023	5328,305	5291,497
22 Dec 2023	5350,242	5386,412
27 Dec 2023	5328,305	5338,955
28 Dec 2023	5397,346	5433,869
29 Dec 2023	5422,518	5433,869

From Table 6, it can be observed that the predicted values are very close to the actual values, indicating that the selected parameters are well-suited for the dataset. To further assess forecasting accuracy, the Mean Absolute Percentage Error (MAPE) was calculated using RStudio software. The resulting MAPE value was 0.3561446% ≈ 0.35%, which falls well below 10%, thereby confirming that the forecasting accuracy is excellent.

4.3. *Analysis of the DES Method*

4.3.1. Parameters of the DES Method

In the Double Exponential Smoothing (DES) method, past data are weighted exponentially using two smoothing parameters, namely α and β. A trial-and-error process was conducted by combining different values of α and β to obtain the most optimal parameter combination, with the computation performed using RStudio software. After testing various parameter combinations, the next step was to select the best forecasting model based on the smallest Mean Absolute Percentage Error (MAPE). The results of the parameter testing are presented in Table 4.

Table 3: Forecasting Results of BRI Stock Closing Prices Using DES

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Alpha	Beta	MAPE (%)
0.51	0.01	7.3313
0.51	0.02	6.8787
0.69	0.04	5.5631
0.69	0.05	5.5311
0.79	0.04	5.1762
0.79	0.05	5.1358
0.89	0.04	4.8806
0.89	0.05	4.8406
0.99	0.04	4.6717
0.99	0.05	4.6333

As shown in Table 3, the smallest MAPE value was obtained at $\alpha = 0.99$ and $\beta = 0.05$, yielding a MAPE of 4.6333%. Therefore, the best forecasting model was achieved with parameters $\alpha = 0.99$ and $\beta = 0.05$.

4.3.2. Parameters of the DES Method

Subsequently, the smoothing values for level and trend were calculated using the optimal parameters obtained previously, namely $\alpha = 0.99$ and $\beta = 0.05$. The results of the level smoothing, trend smoothing, and forecasts are presented in Table 4

Table 4: Smoothing Values for Level, Trend, and Forecasts

Period	Level Smoothing (S_t)	Trend Smoothing (T_t)	Forecast
3	0.42053500	0.00194200	0.42247700
4	0.41094053	0.00136518	0.41230571
5	0.41660755	0.00158027	0.41818782
6	0.41282121	0.00131194	0.41413315
7	0.41662582	0.00143657	0.41806239
…	…	…	…
951	0.90563716	0.00202265	0.90765981
952	0.91826686	0.00255301	0.92081987
953	0.90596604	0.00181032	0.90777635
954	0.90583560	0.00171328	0.90754888
955	0.89340091	0.00100588	0.89440679

As illustrated in Table 4, the smoothing process captures both the level and trend components of the BRI stock closing price series. These values provide the foundation for generating accurate forecasts in subsequent periods.

4.3.3. Parameters of the DES Method

After the data smoothing process, the next step is to perform forecasting for the upcoming period using the parameters α=0.89 and β=0.01. The forecasting results are presented in Figure 3.

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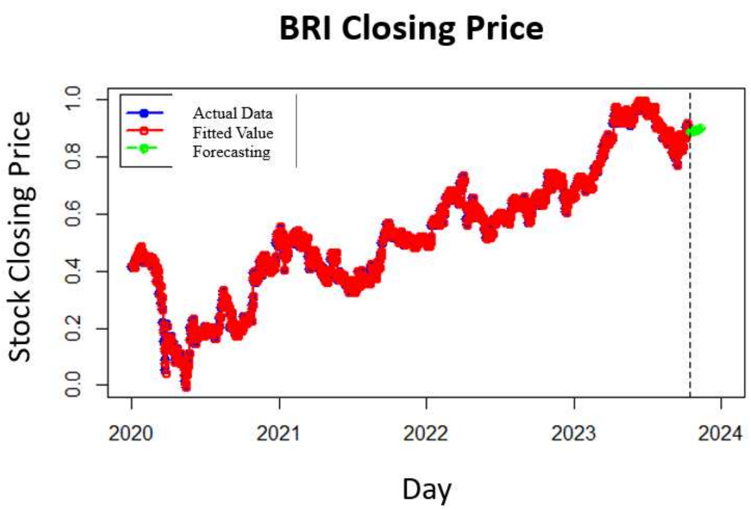

Figure 3: Forecasting Result of BRI Closing Stock Prices

Based on Figure 3, the blue line represents the actual data or the closing stock price data from January 2020 to November 2023. The red line indicates the fitted values, which follow the trend of the actual data quite well, while the green line represents the forecasted data for the upcoming month. From the forecast plot, it can be observed that within the next month, the plot exhibits a relatively stable upward movement, indicating that BRI's stock price is expected to gradually increase. The detailed forecasting results are shown in Table 5

Table 5: Forecasting Results Using the DES Method

Date	Forecast
1 Dec 2023	4988.2815
4 Dec 2023	4990.6780
5 Dec 2023	4993.0744
6 Dec 2023	4993.0744
7 Dec 2023	4997.8673
8 Dec 2023	5000.2638
11 Dec 2023	5002.6602
12 Dec 2023	5005.0567
13 Dec 2023	5007.4532
14 Dec 2023	5009.8496
15 Dec 2023	5012.2461
18 Dec 2023	5014.6425
19 Dec 2023	5017.0390
20 Dec 2023	5019.4354
21 Dec 2023	5021.8319
22 Dec 2023	5024.2283
27 Dec 2023	5026.6248
28 Dec 2023	5029.0213
29 Dec 2023	5031.4177

From Table 5, it can be seen that the forecasted closing stock prices of BRI demonstrate a consistent upward trend throughout December 2023. Starting from IDR 4,988.28 on December 1, 2023, the price is projected to gradually increase and reach IDR 5,031.42 by December 29, 2023. This steady upward trajectory suggests that the DES method successfully captures the positive momentum in the stock's movement. The relatively small incremental increases also imply stability, indicating that BRI's stock price is unlikely to experience abrupt fluctuations in the short term. Such information may provide useful insights for investors and policymakers in anticipating short-term market dynamics.

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4.4. *Selection of The Best Method*

The selection of the best method between SVR and DES is carried out by comparing the MAPE values. Based on both methods, the best model is determined by the smallest MAPE value from each model. The comparison results of the MAPE values from the two methods are presented in Table 6

Table 6: Comparison of MAPE Values

Method	MAPE Value (%)
Support Vector Regression	0.3561
Double Exponential Smoothing	4.6333

Based on Table 10, it is shown that the Support Vector Regression method produces a MAPE value of 0.3561%, while the Double Exponential Smoothing method produces a MAPE value of 4.6333%. Thus, it can be concluded that Support Vector Regression has the smallest MAPE value, which means that this method is the best in forecasting BRI's closing stock prices.

4.5. *Discussion*

Based on BRI's daily closing stock price data from January 2020 to November 2023 obtained from the Yahoo Finance website, both the Support Vector Regression (SVR) and Double Exponential Smoothing (DES) methods were applied. The descriptive analysis results show that the average daily closing stock price during the period was IDR 3,683 per share, with the lowest closing price of IDR 1,655 per share on May 18, 2020, and the highest closing price of IDR 5,410 per share in August 2023. According to Figure 4.1, which displays the plot of BRI's closing stock prices, at the beginning of 2020 the stock price experienced a significant decline, largely due to the impact of the COVID-19 pandemic (Febrianty Lautania et al., 2021). However, after reaching its lowest point, the stock price gradually recovered and continued to rise until the end of 2020. In 2021 and 2022, the upward trend persisted despite some fluctuations. Furthermore, in 2023, BRI's stock price showed a consistent increase throughout the period.

In the Support Vector Regression method, the best model for each kernel was obtained as follows: for the linear kernel, $\varepsilon=0.1$ and $C=0.05$ with an error of 0.00983148; for the polynomial kernel, $\varepsilon=0.1$, $C=100$, and $\gamma=3$ with an error of 0.02057196; for the radial kernel, $\varepsilon=0.1$, $C=100$, and $\gamma=10$ with an error of 0.00096087; and for the sigmoid kernel, $\varepsilon=0.1$, $C=0.05$, and $\gamma=1$ with an error of 0.06809274. Based on these results, it can be concluded that the most appropriate kernel for forecasting is the radial kernel. This conclusion is consistent with studies conducted by Hermawan et al. (2022) and Purnama & Hendarsin (2020), which also found that the RBF kernel provides the best accuracy compared to linear or polynomial kernels.

The testing results of the best model applied to the actual data yielded an accuracy level of 0.3561446, which effectively followed the actual data patterns, as also illustrated in Figure 4.5 where the forecast values closely approximated the actual data. Thus, the forecasting results of BRI's daily closing stock prices for December 2023 indicated unstable changes over the upcoming month.

Meanwhile, the Double Exponential Smoothing method applied the best parameter combination obtained through trial and error across all α and β values, with the optimal combination being $\alpha=0.99$ and $\beta=0.05$. The forecasting results indicate that during December 2023, the stock prices are expected to increase gradually, reflecting a slow upward trend in BRI's closing stock prices.

By comparing the forecasting accuracy based on the MAPE values of both methods, it was found that the Support Vector Regression method achieved a MAPE of 0.3561%, while the Double Exponential Smoothing method achieved a MAPE of 4.6333%. Therefore, it can be

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concluded that the Support Vector Regression method outperforms the Double Exponential Smoothing method in forecasting BRI's daily closing stock prices.

5. Conclusion

Based on the results and discussion of forecasting BRI's daily closing stock prices, the following conclusions can be drawn:

(1). Forecasting using the Support Vector Regression (SVR) method produced the best model with the radial kernel, using the parameters ε=0.1, C=100, and γ=10. Based on the forecasting results with the best model, it was found that the forecasted BRI closing stock prices for December 2023 indicated unstable changes.

(2). Forecasting using the Double Exponential Smoothing (DES) method produced the best parameter combination of α=0.99 and β=0.05. Based on the forecasting results, it was found that BRI's daily closing stock prices in December 2023 are expected to gradually increase.

(3). Forecasting with the Support Vector Regression method resulted in an accuracy level with a MAPE of 0.3561%, whereas the Double Exponential Smoothing method produced an accuracy level with a MAPE of 4.6333%. This means that the best method for forecasting BRI's daily closing stock prices is the Support Vector Regression method.

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