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IMPLEMENTATION GRID SEARCH OF RBF AND POLYNOMIAL ON SUPPORT VECTOR REGRESSON FOR CLOSING STOCK PRICES PREDICTION ON PT INDOFARMA (INAF)

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Abstract: *Stocks represent evidence of ownership of an asset. The highly volatile nature of stock prices makes it difficult for investors to predict stock prices, necessitating the analysis of stock investments. This research aims to forecast for the next 30 days the closing price of PT Indofarma (INAF) stocks using the best model, and the accuracy level of the employed model was analyzed based on the data from the last seven years. The research used the Support Vector Regression (SVR) method, which is known for its capability to handle nonlinear data through kernel functions. The Radial Basis Function (RBF) and polynomial kernels are used in this case. The challenge with SVR lies in determining the optimal hyperparameter, which can be addressed through hyperparameter tuning using grid search. The research results show that the best model is the SVR kernel RBF model with optimal hyperparameter $C=1$, $\gamma=0.01$, and $\varepsilon=0.01$. Based on the performance evaluation results of the best model, the MAPE, MSE, and MAE values are equal to 1.537%,1483.936, and 23.409.*

Keywords: *Kernel, Grid Search, Support Vector Regression (SVR)*

1. INTRODUCTION

One can interpret shares as evidence of a company's ownership [1]. Even though they have high risks, shares are one of investor's favorite products when investing in the capital market because they provide high profits [2]. In a short time, shares allow investors to obtain large returns or capital gains. However, when share prices fluctuate, investors can suffer significant losses if they sell their shares at a lower price than the purchase price.

Indonesia has several stock indices, including the Composite Stock Price Index (IHSG), LQ45 Index, KOMPAS100 Index, IDX-MES BUMN 17, and IDX SMC Composite Index [3]. The price index functions as an indicator to show stock price movements. Stock prices with good liquidity measure the performance of the stock index. Therefore, the IDX creates a stock index that reflects the choice of share type. According to the BEI report, PT INAF is one of the companies listed on the IDX SMC Composite and IDX-MES BUMN 17 indexes, where the BEI index shows the price performance of shares that are considered very good in various aspects.

Stock investments in the capital market are generally challenging to predict because they are very volatile, so investors are faced with high risks. Therefore, in making investment decisions, forecasting is one of the most important factors for investors in preparing strategies to estimate investment patterns in the future. Linear regression is a forecasting method that is commonly used and is synonymous with several assumptions that must be met so that it only sometimes matches the characteristics of the data [4]. Support Vector Regression (SVR) is an application of Support Vector Machine (SVM) in regression cases that does not require assumptions and can overcome nonlinear problems with kernel functions [5]. The SVR method can produce good forecasting values by solving overfitting problems with good accuracy [6].

When forecasting, there are often nonlinear components in the observation data. SVR employs kernel functions to forecast linear and nonlinear data [5]. When the data does not separate linearly, we use the Kernel Radial Basis Function (RBF) and polynomial as kernel functions [7]. Research conducted by Maulana et al. in 2019 regarding forecasting bread sales using the Support Vector Regression (SVR) method produced an RMSE evaluation value for cake bread of 0.00019, white bread of 0.00010, and sweet bread of 0.00176 [6]. Apart from that, the modeling of Islamic stock indices using the grid search method on SVR carried out by Saputra et al. (2019) shows that the linear kernel model is the best [8].

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On the other hand, the problem with SVR is that it is difficult to determine the optimal hyperparameter. Grid search tuning of hyperparameters can overcome this [8]. Therefore, this research employs the SVR method, which combines RBF kernels and polynomials with grid search optimization, to surmount the challenge of identifying optimal hyperparameters and forecasting the closing price of INAF shares. In other words, this research utilizes two kernels to achieve high accuracy in predicting the closing price of INAF shares.

2. METHOD

2.1. Research Data Sources

The type of data used in this research is secondary data obtained from the official website (*www.finance.yahoo.com*), namely historical daily share data for the company PT Indofarma TBK (INAF) in the form of time series data for the period January 1, 2017 to December 31, 2022. The variable used in this research is the daily closing share price of PT Indofarma Tbk (INAF). The data is modified into the $1, \ldots, N-1$ data as the independent variable (X), namely the closing price of INAF shares one period previously, and the $2, \ldots, N$ data as the dependent variable (Y), namely the closing price of INAF shares in the following period. This problem assumes that stock prices influence today's prices in the previous period.

2.2. Stages of Research

In this research, there are steps that will be taken to obtain INAF share price forecasting results. The stages carried out in this research are as follows.

1. Collecting daily data on the closing price of INAF shares obtained from Yahoo Finance from January 1, 2017, to December 31, 2022.
2. Carrying out data preprocessing, which includes inputting data that is empty or null using the Last Observation Carried Dorward (LOCF) method, then defining the dependent variable (Y) and independent variable (X).
3. Conduct descriptive analysis and a Ramsey-RESET nonlinearity test.
4. Divide the data into training data and testing data in certain proportions.
5. Determines the kernel function used.
6. Perform Support Vector Regression (SVR) analysis (default) without grid search optimization.
7. Carrying out performance measurements using MAPE, MSE, and MAE.
8. Hyperparameter tuning using grid search on SVR to get the best hyperparameter that will be used to build the best model. The data analysis carried out was as follows:
   a) Determines the hyperparameter limit values to be used.
   b) Perform SVR analysis using grid search with the best hyperparameter.
9. Carry out future forecasts using the best analytical model produced on SVR.

2.3. Support Vector Regression (SVR)

Support Vector Regression (SVR) is an application of Support Vector Machine (SVM) introduced by Vapnik in the case of regression [9] SVR will perform well in forecasting results because it can overcome overfitting problems [6]. SVR aims to find the best-dividing line (hyperplane) as a regression line and minimize the deviation between model predictions and actual values in the training samples by maintaining the maximum possible margin distance [10]. The SVR regression function is formulated as follows.

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

where,

$\boldsymbol{w}^{\boldsymbol{T}}$: transpose the l dimensional weight vector

$\varphi(\boldsymbol{x})$: a function that maps l dimensional space

b : bias

Here is the optimazation of problem solving in Quadratic Programming form [10].

$$min\frac{1}{2}\|\boldsymbol{w}\|^2 \tag{2}$$

with constraint

$$\begin{gathered} y_i - \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) - b \leq \varepsilon, \text{untuk } i = 1, \dots, l \\ \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) + b - y_i \leq \varepsilon, \text{untuk } i = 1, \dots, l \end{gathered} \tag{3}$$

where,

$\varphi(\boldsymbol{x_i})$: a function that maps $\boldsymbol{x_i}$ to a space with l dimensional

y_i : actual value to i

ε : epsilon parameter (insensitivity bound)

Equation (2) assumes that all points are within the range $f \pm \varepsilon$ (feasible). If several points are out of the range $f \pm \varepsilon$ or in an infeasibility condition, then slack variables ξ and ξ^*will be added to overcome the limitation problem, which is infeasible (infeasible constraints) in the optimization problem. The optimization problem can be seen in Equation (4).

$$min\frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_{i=1}^{l}(\xi_i, \xi_i^*) \tag{4}$$

with constraint

$$\begin{gathered} y_i - \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) - b - \xi_i \leq \varepsilon, \text{for } i = 1, \dots, l \\ \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) - y_i + b - \xi_i^* \leq \varepsilon, \text{for } i = 1, \dots, l \\ \xi_i, \xi_i^* \geq 0 \end{gathered} \tag{5}$$

The constant $C > 0$ determines the trade-off between the flatness of function f and the upper limit of deviations of more than ε that can still be tolerated. All deviations greater than ε will be subject to a penalty of C [11]. The loss function can be defined as a function that shows the relationship between errors and how errors are subject to penalties [11]. The simplest loss function is the ε-insensitive loss function. Using the ε-insensitive loss function ($L_\varepsilon(y)$), the formulation is as follows [11].

$$L_\varepsilon(y) = \begin{cases} 0, & \text{for } |f(\boldsymbol{x}) - y| < \varepsilon \\ |f(\boldsymbol{x}) - y| - \varepsilon, & \text{for other} \end{cases} \tag{6}$$

The optimization solution for Equation (4) with the constraint of Inequality (5) will be resolved into the Lagrange formula [11].

$$\begin{aligned} Q(\boldsymbol{w}, b, \xi, \xi^*, \alpha, \alpha^*, \eta, \eta^*) &= L \\ &= \tfrac{1}{2}\|\boldsymbol{w}\|^2 + C\textstyle\sum_{i=1}^{l}(\xi_i, \xi_i^*) - \sum_{i=1}^{l}\alpha_i(\varepsilon + \xi_i - y_i + \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) + b) \\ &\quad - \sum_{i=1}^{l}\alpha_i^*(\varepsilon + \xi_i^* + y_i - \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) - b) - \sum_{i=1}^{l}(\eta_i\xi_i + \eta_i^*\xi_i^*) \end{aligned} \tag{7}$$

L is called the Lagrangian, $\eta_i, \eta_i^*, \alpha_i, \alpha_i^*$are Lagrange multipliers. To obtain the optimal solution, the partial derivatives of Q concerning $\boldsymbol{w}, b, \xi, \xi^*$ are taken [10]. The value of $\boldsymbol{w}$ can be expressed as [11]

$$\boldsymbol{w} = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\varphi(\boldsymbol{x}_i) \tag{8}$$

Therefore, the optimal hyperplane is written as follows [11]:

$$f(\boldsymbol{x}) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\varphi^T(\boldsymbol{x}_i)\varphi(\boldsymbol{x}) + b \tag{9}$$

For example, beta = $\beta_i = (\alpha_i - \alpha_i^*)$

Then, $f(\boldsymbol{x}) = \sum_{i=1}^{l}\beta_i\,\varphi^T(\boldsymbol{x}_i)\varphi(\boldsymbol{x}) + b$

The optimal solution for b using KKT (Karush-Kuhn-Tucker) conditions is as follows [11].

$$\begin{aligned} b &= y_i - \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) - \varepsilon \text{ for } 0 < \alpha_i < C \\ b &= y_i - \boldsymbol{w}^T\varphi(\boldsymbol{x}_i) + \varepsilon \text{ for } 0 < \alpha_i^* < C \end{aligned} \tag{10}$$

2.4. Kernel Function

Data that can be separated linearly is generally rarely encountered in the real world because most data are nonlinear [12]. The case of nonlinear data can be overcome with a kernel approach in SVR, allowing it to be separated linearly in a new feature space [13]. Data $\boldsymbol{x}$ in the input space is mapped to a feature space with higher dimensions using a function φ in the kernel method, so that $\varphi: \boldsymbol{x} \to \varphi(\boldsymbol{x})$. The kernel trick is able to overcome the unknown and difficult-to-understand function φ, namely by calculating the dot product $\varphi(\boldsymbol{x_i})\varphi(\boldsymbol{x_j})$ in the feature space, which is replaced by the kernel function in the following equation[13].

$$\mathrm{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) = \varphi(\boldsymbol{x_i})\varphi(\boldsymbol{x_j}) = \mathrm{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) \tag{11}$$

The value $\mathrm{K}(\boldsymbol{x_i}, \boldsymbol{x_j})$ is a kernel function that shows a linear mapping in feature space and implicitly defines the transformation φ [13]. The SVR regression function can be written as follows [13].

$$f(\boldsymbol{x}) = \sum_{i,j=1}^{l}(\alpha_i - \alpha_i^*)\mathrm{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) + b \tag{12}$$

SVR kernel parameters are influenced by the type of kernel function used because it can affect regression accuracy [12]. There are two types of kernel functions used in SVR analysis, as follows [14].

1. Kernel Polynomial

$$\mathrm{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) = \left(\gamma \boldsymbol{x_i^T} \boldsymbol{x_j} + 1\right)^d \tag{13}$$

2. Kernel Radial Basis Function (RBF)

$$\mathrm{K}(\boldsymbol{x_i}, \boldsymbol{x_j}) = \exp\left(-\gamma \left\|\boldsymbol{x_i} - \boldsymbol{x_j}\right\|^2\right) \tag{14}$$

In this case $\boldsymbol{x_i}, \boldsymbol{x_j}$ is a pair of two training data sets. The parameter $d, \gamma > 0$ is a constant [15].

2.5. Grid Search

In the SVR model analysis, the grid search method obtains optimal hyperparameter [8]. Grid search is an optimization method that works by trying each combination of hyperparameter values one by one and then comparing the smallest error value of the hyperparameters [8].

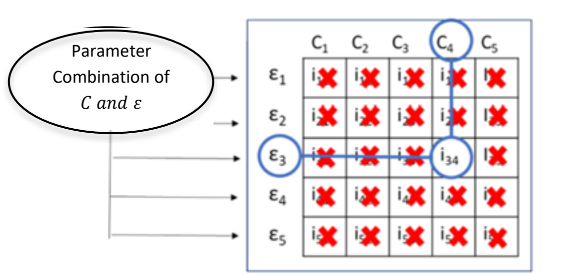

Figure 1. Illustration of the Grid Search Method [8]

Figure 1 illustrates two SVR parameters, combining parameters from the hyperparameter to find the optimal hyperparameter using the grid search method. Next, the smallest error values can be compared from the rows and columns in the grid. In its application, the grid search method must be guided by a performance measure, such as cross-validation of training data. Cross-validation is a standard test to predict error rates [16]. he hyperparameter pair that produces the best accuracy with the smallest error value is the optimal hyperparameter [12].

3. RESULT AND DISCUSSION

3.1. Data Description

In this research, secondary data was obtained from the site www.yahoofinance.com. The data used is daily historical stock data for PT Indofarma Tbk (INAF) from January 1, 2017, to December 31, 2022. PT INAF is a state-owned enterprise (BUMN) that is a stock in the consumer goods sector and operates in the pharmaceutical sector. According to reports from the Indonesia Stock Exchange (BEI), as a provider of capital market transaction facilities, INAF is one of the companies targeted by investors and is listed on the IDX SMC Composite and IDX-MES BUMN 17 indexes, where the BEI index shows the price performance of its shares that are considered very good from various aspects.

In this research, the data used was 1507, with the lowest closing stock price being 344 on December 16, 2019, while the highest closing stock price was recorded at 6975 on January 12, 2021. The range of minimum and maximum values for closing stock prices is quite large, showing fluctuations in the closing stock price during that period.

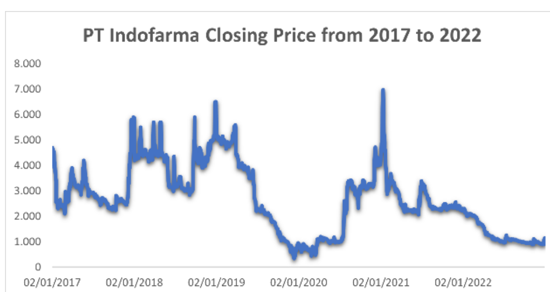

Figure 2. Closing Price of PT INAF

Figure 2 shows the closing price of INAF shares for the last six years, from January 1, 2017, to December 31, 2022. The plot shows a negative or decreasing trend data pattern, showing that when the plot is at its peak, it will decline. This indicates that the closing price of INAF shares decreased after reaching a certain peak.

3.2. Nonlinearitas *Ramsey-RESET* and Data Splitting

A nonlinearity test was carried out using the Ramsey RESET test on INAF closing share price data for the period January 1, 2017, to December 31, 2022. Based on the results of the Ramsey RESET nonlinearity test, it was found that the statistical value of the Ramsey RESET test was greater than $F\ (0.05; 2; 1503)\ =\ 3.0017$ or a *p-value* of 8.588×10^{-9} is smaller than $\alpha = 5\%$, so it can be concluded that H_0 is rejected. This shows that the model is nonlinear.

The division of training data and test data continues with a proportion of 80:20. The dataset is divided into training and testing data with an 80:20 ratio, a standard in machine learning for evaluating models on previously unseen data [17]. The training data used is 80% of the total data, namely 1206, while the testing data is 20%, namely 301. The division results produce data from January 2, 2017, to October 12, 2021, as training data and the remainder, namely, from October 13, 2021, to December 29, 2022, as testing data.

3.3. Establishment of SVR without Grid Search (Default)

To create an SVR model, an additional package is needed in the RStudio software to create an SVR model, namely e1071. The kernel function is used to overcome the problem of data non-linearity in forming the SVR model. The RBF kernel and polynomial kernel will be used as kernel functions. The SVR model was created based on prepared training data. The SVR model used in forming the SVR model without going through the hyperparameter tuning process or grid search optimization is the default model that the system has provided without changing the existing hyperparameter. The available default SVR values are: the RBF kernel produces cost (C)= 1, gamma(γ)= 1, and epsilon(ε)= 0.1, and the polynomial kernel produces cost (C) = 1, degree(d) = 3, gamma(γ) = 1, and epsilon(ε) = 0.1.

Table 1. Evaluation of the Default SVR Model using The RBF Kernel and Polynomial Kernel

SVR Model	MAPE		MSE		MAE	
	Training	Testing	Training	Testing	Training	Testing
SVR kernel RBF	3.786	3.235	29052.990	3157.887	95.738	45.182
SVR kernel Polynomial	22.655	28.463	661496.400	262184.000	523.079	443.446

Table 1 shows that the MAPE value in the RBF kernel SVR model is in the very good category, while in the polynomial SVR model, the MAPE value is in the quite good category. On the other hand, the smallest values for MSE and MAE are in the SVR kernel RBF model. Therefore, because the default SVR model polynomial kernel still has quite high MAPE, MSE, and MAE values, tuning the hyperparameter to improve the model's performance is necessary.

3.4. Establishment of SVR with Grid Search

Analysis of the SVR model without grid search or hyperparameter tuning does not provide optimal results, so it is necessary to carry out the hyperparameter tuning process with grid search optimization. This process is carried out to obtain optimal hyperparameters to obtain the best model that can be selected for prediction. The hyperparameter tuning process focuses on kernel hyperparameter values such as gamma, degree, cost, and epsilon. Determining the correct hyperparameter values needs to be done repeatedly. The RBF kernel and polynomial kernel will be used as kernel functions. This research conducted experiments on the data four times, with trial and error for each hyperparameter combination.

Table 2 displays the hyperparameter values tested on each model and the best hyperparameter values selected.

Table 2. SVR Model Hyperparameter Values

Kernel	Nilai-Nilai *Hyperparameter*				Best Hyperparameter
	Cost (C)	**Epsilon (ε)**	**Gamma (γ)**	**Degree (d)**	
RBF	1,10, and 100	0.01; 0.02; 0.03; 0.04; 0.05; 0.06; 0.07; 0.08; 0.09; 0.1; 0.2; and 0.3	0.001; 0.01; 0.1; 1; 10; and 100	-	$C = 1, \gamma = 0.01$, and $\varepsilon = 0.01$
Polynomial	1, 100, and 100	0.01; 0.02; 0.03; 0.04; 0.05; 0.06; 0.07; 0.08; 0.09; 0.1; 0.2; and 0.3	0.001; 0.01; 0.1; 1; 10; and 100	1 and 2	$C = 100, d = 1$, $\gamma = 0.1$, and $\varepsilon = 0.06$

We chose the hyperparameter values based on the results of our experiments. A small epsilon (ε) value makes the error tolerance limit small, resulting in a smaller prediction error. On the other hand, if the epsilon (ε) value is large, the prediction error will be greater.

Table 3. Model Evaluation of SVR with RBF Kernel and Polynomial Kernel

Model SVR	MAPE		MSE		MAE	
	Training	Testing	Training	Testing	Training	Testing
SVR kernel RBF	3.181	1.537	28509.500	1483.936	88.134	23.409
SVR kernel Polynomial	3.268	1.981	29080.600	1622.293	89.120	27.603

Table 3 shows that the MAPE values in the SVR kernel RBF and SVR kernel polynomial models tuned for hyperparameters using grid search are in the very good category because they have MAPE values < 10%. On the other hand, the smallest values for MSE and MAE are in the SVR kernel RBF model. This means that hyperparameter tuning using grid search improves model performance, and the forecasting error produced by the model is very small. Based on the results obtained, it was found that the SVR kernel RBF model was better and more accurate in forecasting the closing price of INAF shares because it had a lower value based on the three values, namely the MAPE, MSE, and MAE values. Based on the accuracy calculations that have been carried out, the MAPE, MSE, and MAE values are used as the basis for selecting the best model. The best model can be seen based on low MAPE, MSE, and MAE values. The best model was found to be the SVR kernel RBF model, which had hyperparameter tuning done. Therefore, hyperparameter tuning can improve the model's performance and make it more accurate in forecasting the closing price of INAF shares.

3.5. Prediction of The Stock Price

After determining the best model, it is used to forecast the future closing price of INAF shares. For the next 30 days, the closing price forecast for INAF shares will be carried out. The following are the results of the closing price forecast for INAF shares for the next 30 days using the SVR kernel RBF model with the best hyperparameter obtained after the grid search process, namely with $C = 1,\ \gamma = 0.01,$ and $\varepsilon = 0.01$. The estimated closing price for INAF shares for the next 30 days can be seen in Figure 3 and Table 4 below.

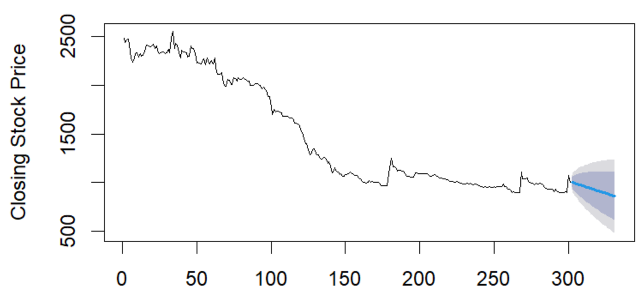

Figure 3. Forecasting the Closing Stock Price of INAF for The Next 30 Day

Based on Figure 3, the black line shows historical data on the estimated closing price of INAF shares, while the blue line represents the estimated closing price of INAF shares for the next 30 days. The plot shows that the forecast results follow the previous historical data pattern, where the plot reaches a peak and then declines. Table 4 provides a detailed view of the closing price of shares.

Table 4. INAF Share Closing Price Forecast Results for the Next 30 Days

Period	Forecasting	Period	Forecasting
01/01/2023	1004.310	16/01/2023	929.377
02/01/2023	999.312	17/01/2023	924.381
03/01/2023	994.316	18/01/2023	919.386
04/01/2023	989.321	19/01/2023	914.391
05/01/2023	984.326	20/01/2023	909.395
06/01/2023	979.330	21/01/2023	904.400
07/01/2023	974.335	22/01/2023	899.405
08/01/2023	969.340	23/01/2023	894.409

Period	Forecasting	Period	Forecasting
09/01/2023	964.344	24/01/2023	889.414
10/01/2023	959.349	25/01/2023	884.418
11/01/2023	954.354	26/01/2023	879.423
12/01/2023	949.358	27/01/2023	874.428
13/01/2023	944.363	28/01/2023	869.432
14/01/2023	939.367	29/01/2023	864.437
15/01/2023	934.372	30/01/2023	859.442

Table 4 shows the results of forecasting the closing price of INAF shares for the next 30 days. The forecasting results revealed a daily decrease in the closing price of INAF shares for the next 30 days.

4. CONLUSIONS

Based on the results of the analysis and discussion that have been carried out, the conclusions obtained from this research are as follows.

1. The RBF kernel SVR and polynomial kernel SVR models have almost the same pattern as the actual data. In other words, the RBF kernel and polynomial kernel SVR models can overcome the overfitting problem in predicting INAF daily closing stock prices. With hyperparameter $C = 1, \gamma = 0.01$, and $\varepsilon = 0.01$, the RBF kernel SVR model gives us 3.181% for MAPE, 28509.500 for MSE, and 88.134 for MAE based on the training data. Meanwhile, the MAPE, MSE, and MAE values obtained in the testing data were 1.537%, 1483.936, and 23.409. On the other hand, the polynomial kernel SVR model with the best hyperparameter =100, $d = 1, \gamma = 0.1$, and $\varepsilon = 0.06$ gets MAPE, MSE, and MAE values of 3.268%, 29080.600, and 89.120 on training data. Meanwhile, the accuracy of MAPE, MSE, and MAE on testing data was 1.981%, 1622.293, and 27.603.
2. The best model that can be used to estimate the daily closing price of INAF shares for the next 30 days is the SVR model with an RBF kernel that has been hyperparameter tuned using grid search with hyperparameter $C = 1, \gamma = 0.01,$ dan $\varepsilon = 0.01$ because it has the lowest MAPE, MSE, and MAE values.

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