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A Metaheuristic-Based Approach to Inflation Prediction in Indonesia with Support Vector Regression (SVR)

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ABSTRACT

Inflation prediction plays a vital role in individual, corporate, and government economic decision-making. This study evaluates the performance of the Support Vector Regression (SVR) algorithm in predicting monthly inflation using 251 data points from Bank Indonesia. Two parameter optimization methods, Grid Search Optimization and Particle Swarm Optimization (PSO), are applied to enhance prediction accuracy. Data pre-processing includes normalization using Min-Max Scaler and splitting into training and testing sets with ratios of 85:15 and 90:10. The optimization results indicate that PSO with a 90:10 ratio outperforms other approaches, achieving a Mean Absolute Percentage Error (MAPE) of 20.27% and an R-squared value of 89.76%. These findings highlight the significance of effective parameter optimization methods in improving prediction model performance, especially for non-linear data such as inflation. The results also demonstrate machine learning techniques' potential in analyzing time series data for economic and financial applications. This study provides insights into developing more accurate prediction systems, which can contribute to better economic planning and policy making.

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1. INTRODUCTION

Inflation is a critical indicator of economic performance that directly impacts a country's stability. It reflects the general increase in prices over time and the corresponding decline in purchasing power. Inflation influences individual purchasing power, corporate investment decisions, currency value, and overall economic growth. High and unpredictable inflation often disrupts economic stability, leading to decreased consumer confidence, reduced foreign investment, and impaired economic planning. In developing countries like Indonesia, where economic volatility is more pronounced, the need for accurate inflation prediction is particularly crucial to support effective policy-making and safeguard macroeconomic stability. Inflation instability can harm people's purchasing power, investment, and exchange rate stability, thereby affecting overall economic performance [1]. Understanding inflation trends and making accurate forecasts is essential for enabling governments and financial institutions to formulate appropriate strategies. These forecasts provide critical insights that help mitigate inflation's adverse effects, ensuring sustainable economic growth while maintaining financial stability.

Inflation prediction is inherently complex due to the non-linear relationships between its influencing factors. Traditional statistical models often fall short in capturing these complexities, necessitating the use of advanced computational approaches. Machine learning, particularly Support Vector Regression (SVR), has emerged as a promising tool for time series forecasting. SVR is a regression method from SVM (Support Vector Machine), which is commonly used to overcome overfitting and has good performance for regression cases [2]. It works by finding a hyperplane that best fits the data while minimizing the prediction error. However, the accuracy of SVR models depends heavily on hyperparameter tuning, specifically the penalty parameter (C) and kernel function parameters. Selecting appropriate values for these parameters is vital for achieving high prediction accuracy.

To enhance prediction quality, leveraging advanced optimization techniques is necessary to refine machine learning models. Hyperparameter optimization techniques such as Grid Search Optimization and Particle Swarm Optimization (PSO) provide robust solutions for improving model performance. Grid Search is a systematic hyperparameter search technique where parameters are explored through a predefined grid of values, determined by the lower bound, upper bound, and step size [3]. Grid Search systematically evaluates all possible parameter combinations within a defined range, ensuring a thorough exploration of the parameter space. Meanwhile, Particle Swarm Optimization (PSO), inspired by the social behaviour of bird flocks and fish schools, efficiently searches for optimal solutions by leveraging collective intelligence. PSO has demonstrated strong performance in enhancing machine learning models, including SVR, for inflation prediction in Indonesia [4].

This research aims to integrate SVR with Grid Search and PSO to predict monthly inflation rates in Indonesia using historical data from Bank Indonesia. The study seeks to evaluate and compare the performance of these optimization techniques in improving the accuracy of SVR models. The dataset comprises 251 monthly inflation records, which undergo pre-processing steps including normalization and division into training and testing sets. The models are then optimized using Grid Search and PSO to identify the best-performing configuration.

By leveraging advanced optimization techniques, this study intends to address the challenges associated with inflation prediction and provide actionable insights for policymakers. Accurate forecasts can enable more effective economic planning, better resource allocation, and improved financial stability. The findings are also expected to contribute to the broader application of machine learning in economic modelling and highlight the potential of metaheuristic algorithms in enhancing predictive analytics.

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2. METHODS

The analytical steps used in this study, starting from preparing the dataset to optimizing the model, are illustrated through the flowchart in **Figure 1.**

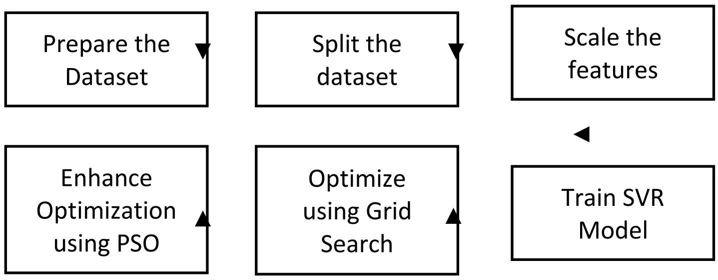

Figure 1. Flowchart the Method

Based on the flowchart, the first step is to prepare the dataset by adjusting the date-time format and data types, as well as defining the input and output features. Next, the data is split with a ratio of 0.85, followed by training the SVR model using default parameters. After obtaining the model evaluation results, predictions are made on the training data to assess whether the SVR with default parameters has a low error rate. The subsequent step involves optimization using grid search by testing splitting ratios of 0.85 and 0.90. The final step is to further enhance the SVR model using a metaheuristic algorithm, specifically Particle Swarm Optimization (PSO).

2.1. Support Vector Regression

SVM is a kernel-based method designed to determine the best hyperplane for separating classes. In contrast, SVR, which is an extension of SVM for regression problems, focuses on identifying a hyperplane that approximates the data while allowing for a permissible margin of error, rather than segmenting it into distinct categories as SVM does [5]. SVR is a method that can overcome overfitting, so it will produce a good performance [6]. The objective of SVR is to determine a regression function *f(x)* that effectively captures the relationship between the input dataset $x = \{x_1, x_2, x_3, ..., x_n\}$ and the target values $y = \{y_1, y_2, y_3, ..., y_n\}$ [7] as follows:

$$f(x) = w\phi(x) + b \tag{1}$$

W is a representation of the function's weight vector, b is the offset factor, and ϕ denotes the nonlinear mapping. To prevent overfitting the calibration data samples, SVR utilizes an objective function (Equation 2) and a loss function (Equation 3) to derive the regression parameters in (Equation 1):

$$\min \frac{1}{2} \| w \|^2 + C \sum_{1}^{n} (\xi_i + \xi_i^*) \tag{2}$$

subject to: $$\xi_i^* \begin{cases} y_i - (w\phi(x) + b) \le \varepsilon + \xi_i \\ (w\phi(x) + b) - y_i \le \varepsilon + \xi_i^* \\ \xi_i \ge 0, \xi_i^* \ge 0, i = 1, ..., n \end{cases} \tag{3}$$

The goal of SVM is to divide the dataset (classification) into 2 zones, while the goal of SVR is the opposite, namely, how to get all the dataset into one zone, while still minimizing the epsilon value (ε)[2]. The steps for using SVR are as follows [8].

a. Preparing training data
b. Selecting the kernel and parameters and their regulation

c. Creating a model to obtain coefficients
d. Using coefficients, then making estimates

The model's prediction accuracy is evaluated using the Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error (MAPE), calculated using the following formulas in Equations (4) and (5) [9].

$$MAPE = \frac{1}{T}\sum_{i=1}^{T}\left|\frac{d_i - \hat{d}_i}{d_i}\right| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(d_i - \hat{d}_i)^2} \tag{5}$$

The description of each index in the formulas is as follows: *T* represents the total number of test samples, *d* denotes the actual sample value, and $\hat{d}$ refers to the predicted value.

2.2. Grid Search Optimization

Optimize Parameter Grid is an effective method for determining optimal parameter values in an operator subprocess. This method involves evaluating the performance for each combination of selected parameter values. By communicating the optimal parameter values through the parameter set port, this method can be applied to various types of operators such as Support Vector Classifier, Lasso, Random Forest, and others [10]. The Optimize Parameter Grid has two modes: synchronous and asynchronous. Synchronous mode uses a list of predefined parameter value combinations, while asynchronous mode generates all possible parameter value combinations. By using Optimize Parameter Grid, we can systematically and efficiently find the best parameter values [10].

Grid search has been successfully applied in many inflation forecasting studies. For example, Alfiyatin et al. [11] combined Extreme Learning Machine (ELM) with improved Particle Swarm Optimization to forecast inflation accurately. Isnaeni et al. [12] applied SVR with RBF kernels and optimized parameters using grid search to predict inflation in Indonesia. In addition, non-parametric approaches such as Nadaraya-Watson kernel regression and B-spline have also been compared with parametric models like ARIMA in regional inflation forecasting, as discussed by Wulandari et al. [13].

2.3. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is based on the behaviour of flocks of birds or fish. The PSO algorithm mimics the social behaviour of these organisms. Social behaviour consists of individual actions and the influence of other individuals in a group. The word particle refers, for example, to a bird in a flock of birds. Each individual or particle behaves by using its intelligence and is also influenced by the collective behaviour of the group. Thus, if one particle or a bird finds the right or shortest path to a food source, the rest of the group will also be able to follow the path immediately, even though they are far away in the group. In Particle Swarm Optimization (PSO), the swarm is assumed to have a certain size, with each particle initially located at a random location in a multidimensional space. Each particle is assumed to have two characteristics: position and velocity. Each particle moves in a certain space and remembers the best position it has ever travelled to, or found the food source, or the value of the objective function. Each particle communicates its best position or information to the other particles and adjusts its position and velocity based on the information it receives about the position [4].

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The application of PSO has been widely explored in various forecasting models. Fauziah et al. [14] applied ELM for inflation prediction in Indonesia, showing that optimization methods improve model performance. In Egypt, El-Daly [15] employed neural networks for inflation forecasting, highlighting the effectiveness of machine learning. Ponziani [16] used ARDL models, showing comparative accuracy with newer models. Bandara and De Mel [17] evaluated multiple supervised learning models in Sri Lanka, demonstrating PSO's viability. In Indonesia, Raharja et al. [18] implemented ANFIS for inflation prediction, while Aysun and Ekinci [19] explored various machine learning techniques in Turkey. Notably, Nurjanah and Sumarna [20] applied PSO to train a feedforward neural network for Indonesian inflation prediction, validating the utility of metaheuristics in economic modelling.

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

The analysis will be conducted using monthly inflation rate data obtained from Bank Indonesia (BI). The dataset consists of 251 data points, with the structure of input (inflation rate at n-1 and n-2) and output (inflation rate at n) features for the SVR model in **Table 1**.

Table 1. Inflation Rate

Month (n)	Inflation Rate		
	n	n-1	n-2
March 2004	5,11%	4,60%	4,82%
April 2004	5,92%	5,11%	4,60%
May 2004	6,47%	5,92%	5,11%
June 2004	6,83%	6,47%	5,92%
July 2004	7,20%	6,83%	6,47%
August 2004	6,67%	7,20%	6,83%
November 2024	1,55%	1,71%	1,84%

A descriptive analysis will then be conducted as an initial step to observe the inflation rate trends over time, with the analysis results presented in a time series plot in **Figure 2**.

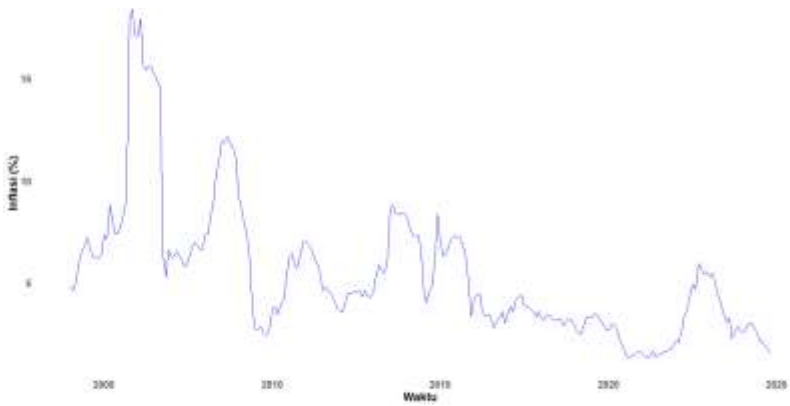

Figure 2. Inflation Rate Time Series Plot

Figure 2 shows a decreasing trend in the inflation rate from January 2004 to November 2024. Additionally, the inflation rate appears to fluctuate each year, with no clear linear pattern, indicating that the data is non-linear. The highest inflation rate occurred in November 2005 at 18.38%, while the lowest was in August 2020. The next step in the analysis is to prepare the data for processing using Support Vector Regression (SVR).

3.2. Support Vector Regression

Analysis using SVR is sensitive to data scale, so a pre-processing step is required. First, the data is split into training and testing sets with a ratio of 0.85, while maintaining the sequence of the data since it is a time series. Then, a min-max scaler is applied to standardize

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the data, resulting in a value range from 0 to 1. The model was built using the ***caret*** package, focusing on two main parameters, c and sigma. By default, the *caret* package uses a value of C = 1. The results of the inflation rate predictions on the training data using C = 1 and Sigma = 0.1 are shown in **Figure 3**.

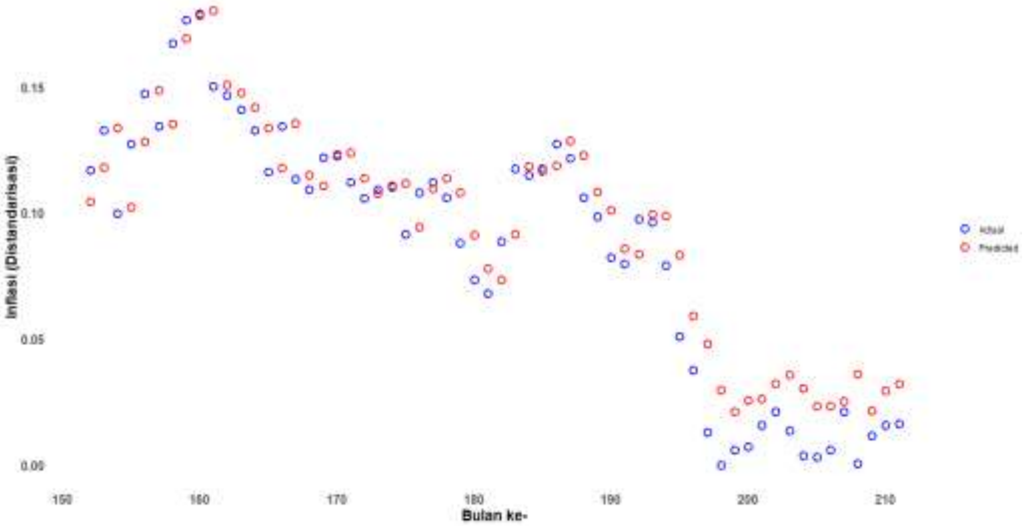

Figure 3. Prediction Results on the Training Data Using the RBF Kernel and Default Parameters

Figure 3 shows the prediction results on the training data, where the blue points represent the actual data and the red points represent the predicted values. The plot is used to assess how well the model captures the underlying pattern and to visually evaluate the magnitude of the error. Based on the figure, it can be observed that some patterns are not captured well. This is further supported by the model evaluation on the testing data using parameters C = 1 and Sigma = 0.1, which resulted in an MAPE of 29% and an accuracy of 89.38%.

3.3. Optimization

To obtain the best SVR model with the smallest error, parameter optimization will be conducted using two approaches: grid search and metaheuristic algorithms. The model was built using the *caret* package, focusing on two main parameters c and sigma. Optimization was performed through k-fold validation using the *SVM Radial* kernel, also known as the *Radial Basis Function* (RBF). The results of the grid search optimization for various combinations of C and sigma with a splitting ratio of 0.85 and 0.90 are presented in Table 2.

Table 2. Grid Search Optimization

Splitting Ratio	k	c	sigma	RMSE
0.85	2	13.5	0.051	0.059
	3	16.1	0.051	0.057
	4	3.9	0.051	0.056
	5	19.5	0.051	0.054
0.90	2	17.5	0.051	0.056
	3	18.7	0.051	0.057
	4	**9.1**	**0.051**	**0.050**
	5	24.5	0.201	0.052

Table 2 shows that the best model is achieved using a splitting ratio of 0.90, an SVR RBF kernel with 4-fold cross-validation, C = 9.1, and Sigma = 0.051. The best parameters obtained

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through grid search optimization resulted in a MAPE value of 28.437%. A comparison will be made using a metaheuristic algorithm, specifically Particle Swarm Optimization (PSO), to determine if there is a difference in performance. The description of the parameters used in the PSO is shown in Table 3, and the results are presented in **Table 3**.

Table 3. PSO Parameters

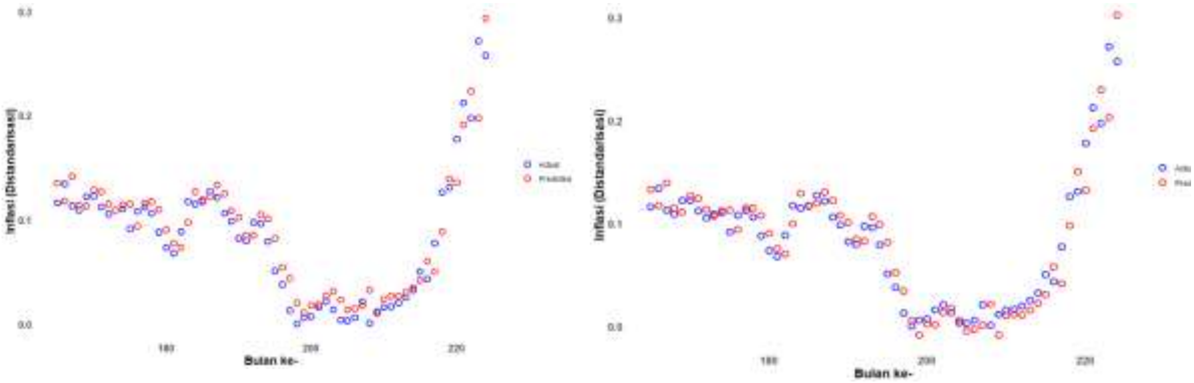
Parameters	Description
par	random from lower and upper
lower	C = 0.1, Sigma = 0.001
upper	C = 20, Sigma = 1
Control max iteration	50, 100

Table 3 presents the parameters used in PSO, while the optimization results with a maximum of 50 and 100 iterations, as well as splitting ratios of 0.85 and 0.90, are shown in **Table 4**.

Table 4. Result of PSO

Splitting Ratio	Max Iteration	Best C	Best Sigma	MAPE	RMSE	R-sq
0.85	50	2.959	0.592	21.71%	0.027	87.89%
	100	2.903	0.600	21.69%	0.027	87.90%
0.90	**50**	**18.274**	**1**	**20.27%**	**0.027**	**87.89%**
	100	18.717	0.999	20.28%	0.023	89.76%

Table 4 shows that the best SVR performance is achieved with a splitting ratio of 0.90, a maximum iteration of 50, C = 18.274, and Sigma = 1. A comparison of training data predictions using grid search optimization and metaheuristics is presented in **Figure 4**.



(a) Grid Search Optimization **(b)** Particle Swarm Optimization

Figure 4. Prediction Using Grid Search and PSO

Figure 4 shows that, visually, the error produced is not significantly large for both the grid search and PSO methods. However, based on the evaluation metric, namely the MAPE value, the model chosen to predict the inflation rate for the next 12 months is SVR-PSO with a splitting ratio of 0.90, maximum iteration = 50, C = 18.274, and Sigma = 1.

3.4. Prediction Result

The predicted inflation rate for the next 12 months using the best model from SVR-PSO is presented in **Table 5**.

Table 5. Prediction Result for 12 Months

Month	Inflation Rate
December 2024	3.74%
January 2025	3.98%
February 2025	4.31%

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March 2025	4.67%
April 2025	5.00%
May 2025	5.24%
June 2025	5.36%
July 2025	5.41%
August 2025	5.39%
September 2025	5.35%
October 2025	5.31%
November 2025	5.28%

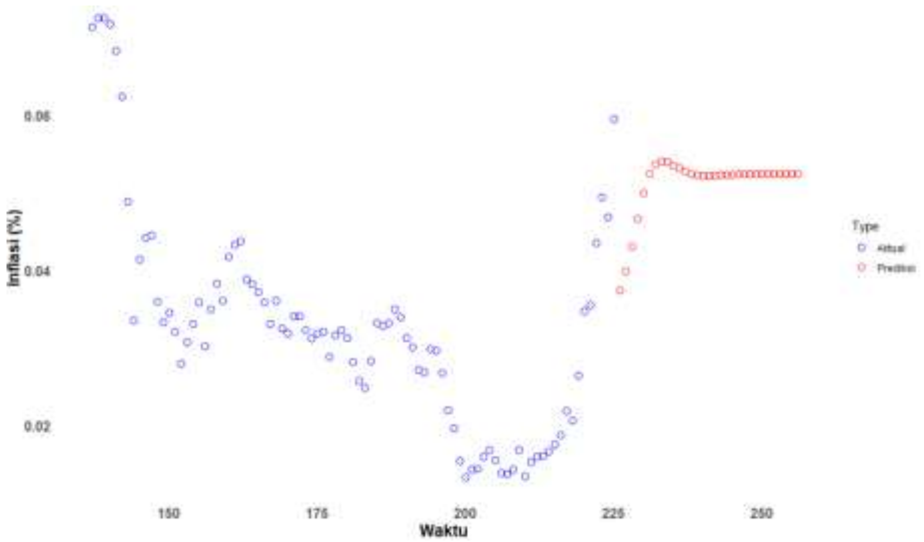

Figure 5. Inflation Rate Prediction

Figure 5 shows that the prediction results exhibit an upward trend at the beginning, which resembles the pattern observed in the previous months, characterized by significant fluctuations.

4. CONCLUSION

The results highlight that SVR performance is highly influenced by the choice of parameters, necessitating pre-processing and parameter optimization. Grid Search and Particle Swarm Optimization (PSO) were applied to determine the optimal parameters, with PSO yielding the best performance. The final model, SVR-PSO with a splitting ratio of 0.90, maximum iterations of 50, C = 18.274, and sigma = 1, achieved the lowest MAPE value and produced predictions closely aligned with the actual data. These findings suggest that the SVR-PSO approach can serve as a reliable method for inflation rate forecasting, supporting more accurate economic decision-making.

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