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# THE APPLICATION OF SUPPORT VECTOR MACHINES IN FORECASTING INDONESIA'S EXPORT VALUES

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*ABSTRACT*

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Exports play a crucial role in Indonesia's economic growth, but fluctuations in export values can impact national economic stability. While there is existing research on export forecasting, the application of advanced machine learning methods such as Support Vector Machine (SVM) is limited. This study aims to forecast Indonesia's export values using SVM based on monthly data from January 2017 to February 2025. The data were split into 80:20 proportions for training and testing, with input variables optimized using Partial Autocorrelation Function (PACF) analysis. Fifteen input schemes were tested, and the combination of lag 1 and lag 2 produced the lowest Mean Absolute Percentage Error (MAPE) of 5.04% on the test data, indicating very high accuracy. The forecasted results show a declining trend in export values from 21.87 billion USD in March 2025 to 20.66 billion USD in December 2025, driven by external factors such as global economic slowdown and commodity price fluctuations. Despite the decline, Indonesia's export values remain relatively high compared to pre-2021 periods. This research highlights the effectiveness of SVM for export forecasting and suggests that this method could be used to inform policy decisions to mitigate global trade risks. Future research could explore the inclusion of additional external variables and other machine learning techniques to further improve forecast accuracy. The novelty of this study lies in the application of SVM for forecasting Indonesia's export values, filling a gap in the literature on export forecasting models.

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## 1. INTRODUCTION

Export trade plays a crucial role in global economic development as a connector between countries. However, amid global uncertainty and the strengthening wave of anti-globalization, future patterns of global economic development are becoming increasingly unpredictable [1]. International trade arises due to interdependence among nations worldwide. This interdependence stems from the limitations of individual countries in fulfilling domestic needs, both in consumption and industrial sectors [2]. Cross-border trade is universal and requires clear regulations to maintain economic stability, including for Indonesia. As the largest economy in Southeast Asia, Indonesia plays a strategic role in global trade, with export activities serving as a primary driver of economic growth. Through exports, Indonesia earns foreign exchange, which funds' investments and infrastructure development. Key sectors, such as palm oil and coal, contribute significantly to national export value. Additionally, increased exports create employment opportunities and stimulate domestic consumption. However, reliance on specific markets poses risks during price or demand fluctuations, making diversification of export markets and products a critical strategy for sustaining economic stability [3].

Beyond serving as a foreign exchange generator, exports strengthen Indonesia's ties with international markets and support sustainable economic development. As a key factor in economic growth, exports and investments contribute to enhancing national output. Foreign exchange from exports finances imports of raw materials and capital goods, essential components in production processes to generate added value. The added value produced by all production units within an economy accumulates into the Gross Domestic Product (GDP). Economic growth is measured by annual increases in GDP at constant prices [4]. Therefore, accurate export value forecasting is a crucial element in adaptive, data-driven economic policy planning, enabling more effective responses to global market dynamics.

Forecasting time series data, particularly those exhibiting trend and seasonality, requires models capable of capturing such patterns effectively. One of the most widely applied techniques for this purpose is the Autoregressive Integrated Moving Average (ARIMA) model, a generalization of the Autoregressive Moving Average (ARMA) model [5]. ARIMA and its variants, such as SARIMA, are often favored for their simplicity and clear statistical interpretability. However, as technology advances and data complexity grow, machine learning-based methods have emerged as promising alternatives. These approaches align with a paradigm shift in which artificial intelligence, including machine learning and deep learning, is increasingly applied across fields such as finance, healthcare, industry, and networks [6]. Among machine learning algorithms, Support Vector Machine (SVM) is notable for time series forecasting.

Support Vector Machine (SVM) is a machine learning method that employs a hypothesis space of linear functions in high-dimensional feature spaces. The model is trained via optimization to identify the optimal separation between data classes. Furthermore, kernel functions enable SVM's application in time series analysis [7]. Unlike conventional linear approaches, SVM mitigates overfitting risks by implementing structural risk minimization. This method balances model complexity and prediction accuracy through margin error optimization, ensuring the model retains classification accuracy [8]. The Support Vector Machine algorithm offers benefits such as a comprehensive theoretical foundation, global optimization, high adaptability, and strong generalization capabilities, all derived from Statistical Learning Theory (SLT) [9].

In scholarly literature on time series forecasting, SVM and ARIMA are frequently compared across diverse datasets. In economics, a study by Makala and Li [10] compared classical ARIMA and SVM in predicting daily gold prices. Results demonstrated SVM's superiority over ARIMA based on root mean square error (RMSE) and mean absolute percentage error (MAPE) metrics, with SVM yielding RMSE = 0.0275 and MAPE = 2.49, while ARIMA produced RMSE = 36.179 and MAPE = 2897.59. These findings reinforce SVM's potential as an accurate predictive tool, particularly for commodity or product prices, bolstering its popularity in economic applications. Such advantages support SVM's use in diverse time series forecasting and classification contexts, including economics and trade. However, its application to forecast Indonesian exports remains underexplored. Thus, this study aims to analyze Indonesian export time series data from 2017 to 2024 to develop an SVM model for predicting export values from January to June 2025.

This research contributes significantly through an input variable selection scheme based on correlation analysis and model performance evaluation using Mean Absolute Percentage Error (MAPE). The findings are expected to expand insights into machine learning applications in Indonesia's economic domain. Consequently, the study not only addresses the practical need for accurate export projections but also strengthens data-driven economic planning foundations.

## 2. METHODS

### Material and Data

This study is quantitative research that utilizes secondary data in the form of Indonesia's total monthly export values, measured in thousand USD, for the period from January 2017 to February 2025. The data were obtained from the official website of Bank Indonesia (https://bi.go.id/).

### Research Method

Support Vector Machine (SVM) was first introduced by Vapnik in 1992 as a machine learning method based on the principle of Structural Risk Minimization (SRM). This principle aims to identify the optimal hyperplane that can separate two classes within the input space. SVM employs a hypothesis in the form of a linear function within a high-dimensional feature space, applying a learning bias derived from statistical learning theory. The model's accuracy heavily depends on the choice of kernel function and the parameters used, which play a critical role in determining the effectiveness of the classification process [11].

SVM is a supervised learning-based classification and regression method that integrates various computational theories developed over decades. One of its fundamental concepts is the margin hyperplane, initially introduced by Aronszajn in 1950, along with other supporting concepts. In practice, SVM requires a training set comprising both positive and negative data to determine the optimal separating boundary. The main process in SVM involves identifying and optimizing the hyperplane that separates the two classes with the maximum margin in an n-dimensional space, thereby enhancing the model's generalization ability [8]. Prediction using SVM is formulated through the following equation:

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

where $x$ represents the input feature vector, $b$ is the bias term, and $w$ is the weight vector optimized during the model training process [12]. The principle behind using the SVM model for load forecasting is to identify an optimal classification boundary that minimizes the error across all training samples relative to this boundary [13].

MAPE quantifies the error as a percentage of the actual values, offering a direct measure of the model's predictive accuracy [14]. MAPE computes the difference between actual and forecasted values, using actual values derived from testing data. One of MAPE's key advantages is that its output is expressed as a percentage, facilitating comparison across different forecasting models [15]. The formula for calculating MAPE is expressed as follows:

$$MAPE = \left( \frac{1}{N} \sum_{t=1}^{N} \frac{|A_t - F_t|}{A_t} \right) \times 100 \tag{2}$$

The interpretation of MAPE values in forecasting results can be categorized based on the percentage of error obtained. If the MAPE value is less than or equal to 10%, the forecast is considered highly accurate. A value between 10% and 20% is categorized as good. MAPE in the range of 20% to 50% indicates a fairly accurate or acceptable forecast. However, if the MAPE exceeds 50%, the forecast is deemed inaccurate and unreliable [15]. The analytical stages of this study consist of the following steps:

1. Conduct descriptive analysis to identify patterns in Indonesia's export values.

2. Perform lag significance testing using the Partial Autocorrelation Function (PACF) plot to determine input variables.
3. Construct variable input schemes using different lag combinations based on PACF results.
4. Divide the data into training and testing sets using an 80:20 ratio, where the training data is used to build the model and the testing data is used to evaluate model performance.
5. Apply the prediction model on the training data using the SVM algorithm.
6. Evaluate the forecast by comparing the predicted results to the testing data using MAPE.
7. Compare the MAPE values of each input variable scheme to identify the best-performing model with the lowest prediction error.
8. Use the best model obtained to forecast Indonesia's export values for the next ten periods.

## 3. RESULTS

### Descriptive Analysis

The descriptive analysis in this study was conducted using line charts to identify patterns in the movement of Indonesia's export values in Figure 1. Through this visual representation, the dynamics of export value fluctuations can be more clearly observed, including the upward and downward trends in Indonesia's export values during the research period under investigation.

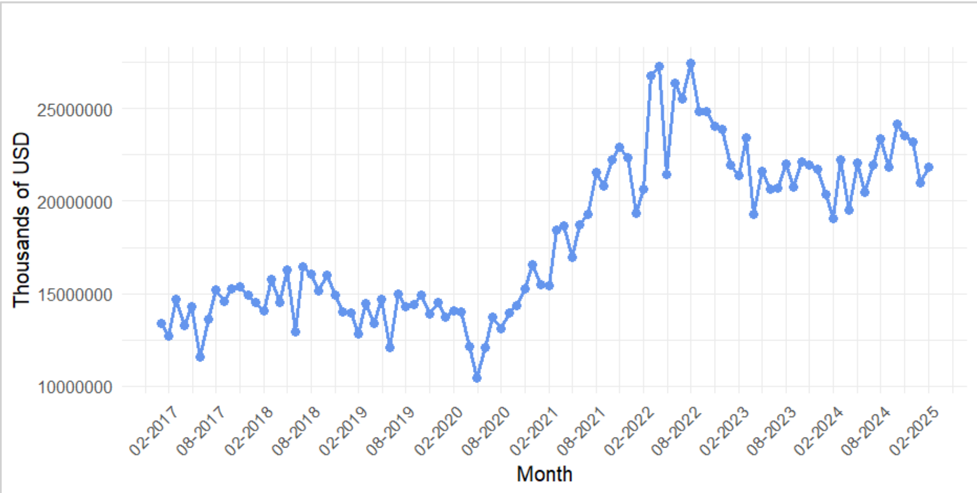


**Figure 1. Indonesia's Export Values**

### Partial Autocorrelation Function Analysis

Identifying influential lags is a critical step in modeling using the Support Vector Machine (SVM) method. This process aims to determine the input variables to be incorporated into the model based on temporal relationships within the data. One method used to identify influential lags is the Partial Autocorrelation Function (PACF) analysis in Figure 2.

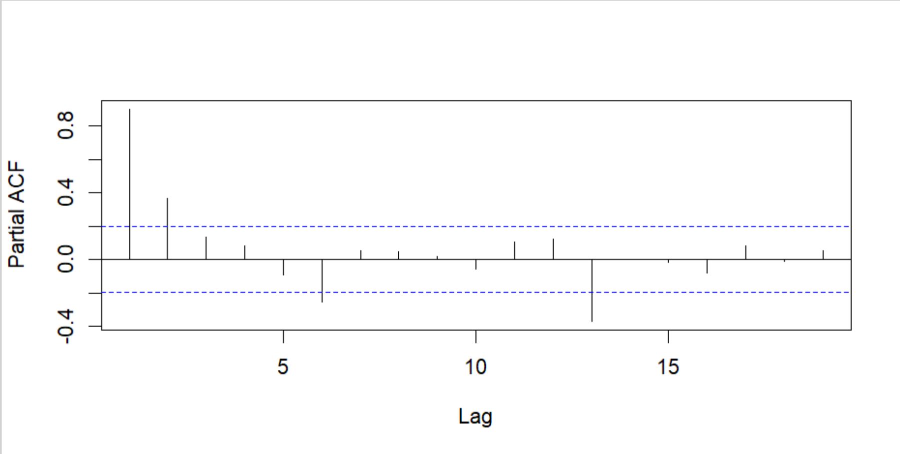


**Figure 2. PACF Plot of Indonesia's Export Values**

Lags indicating a strong correlation with the current data are marked by lines crossing the blue boundary in the PACF plot. Based on Figure 2, the significant lags in this study are lag 1, lag 2, lag 6, and lag 13. Therefore, this combination of lags will be used as input variables in the SVM model.

**Table 1. Input Variable Schemes**

| Scheme | Input Variables |
|---|---|
| 1 | Lag 1 |
| 2 | Lag 2 |
| 3 | Lag 6 |
| 4 | Lag 13 |
| 5 | Lag 1, Lag 2 |
| 6 | Lag 1, Lag 6 |
| 7 | Lag 1, Lag 13 |
| 8 | Lag 2, Lag 6 |
| 9 | Lag 2, Lag 13 |
| 10 | Lag 6, Lag 13 |
| 11 | Lag 1, Lag 2, Lag 6 |
| 12 | Lag 1, Lag 2, Lag 13 |
| 13 | Lag 1, Lag 6, Lag 13 |
| 14 | Lag 2, Lag 6, Lag 13 |
| 15 | Lag 1, Lag 2, Lag 6, Lag 13 |

In this study, fifteen schemes with different input variables were employed, as presented in Table 1. Each scheme divides Indonesia's export values data into two main components: training data and test data. The training data were used to construct the SVM model, while the test data served as the basis for evaluating the model's accuracy and predictive performance on previously unseen data. A linear kernel was used in the SVM model, making C (cost) the only tuning parameter involved. The optimal function was estimated by minimizing the regularized error, where C controls the trade-off between model complexity and the tolerance to deviations within the specified margin of error. As the model was built without specifying a tuning grid or explicitly setting the value of the regularization parameter C, a default value of $C = 1$ was applied.

**Evaluate The Forecast**

According to Table 2, Scheme 5 demonstrated the lowest prediction error with a MAPE value of 5.04%, while Scheme 10 showed the highest prediction error with a test data MAPE of 9.95%. Based on forecasting accuracy evaluation criteria, Scheme 5 falls into the 'highly accurate' category. These results indicate that the Support Vector Machine (SVM) method generally produces reasonably good predictions for estimating Indonesia's export values.

**Table 2. Forecasting Accuracy (MAPE) of Input Variable Schemes**

| Scheme | MAPE (%) |
|---|---|
| 1 | 6.44539 |
| 2 | 5.794284 |
| 3 | 8.503969 |
| 4 | 8.775836 |
| 5 | 5.043717* |
| 6 | 6.48068 |
| 7 | 6.574192 |
| 8 | 5.842329 |
| 9 | 6.385956 |
| 10 | 9.952893 |
| 11 | 5.076951 |
| 12 | 5.110951 |
| 13 | 6.985109 |
| 14 | 6.299202 |
| 15 | 5.198745 |

*) Smallest MAPE value

**Future Forecasting**

Considering these evaluation results, subsequent modeling will employ Scheme 5, as it yields the lowest prediction error on test data. This model will be used to forecast Indonesia's export values from March 2025 through December 2025.

**Table 3. Forecasted Indonesia's Export Values (in Thousands of USD)**

| Period | Export Value |
|---|---|
| March 2025 | 21,873,308 |
| April 2025 | 21,274,624 |
| May 2025 | 21,394,010 |
| June 2025 | 21,175,772 |
| July 2025 | 21,126,841 |
| August 2025 | 21,003,327 |
| September 2025 | 20,922,120 |
| October 2025 | 20,826,770 |
| November 2025 | 20,744,129 |
| December 2025 | 20,661,035 |


**Figure 3. Actual vs. Forecasted Export Values of Indonesia**

## 4. DISCUSSIONS

Figure 1 illustrates the trend of Indonesia's export values from 2017 to early 2025. During the period from 2017 to 2019, export values remained relatively stable with minor fluctuations, reflecting both global and domestic economic conditions that proceeded normally without significant disruptions. A sharp decline was observed in early 2020 due to the impact of the COVID-19 pandemic, which impeded global demand and disrupted supply chains. From mid-2020 to 2022, exports experienced a rapid recovery, reaching a peak in 2022. This growth was driven by increased demand for key export commodities to China, supported by the government's optimization of digital platforms [16]. Additionally, the trade balance recorded its highest surplus in over a decade, signaling a revival in the manufacturing sector and significant contributions from small and medium-sized enterprises (SMEs) [17]. Furthermore, commodity downstreaming programs and efforts to enhance the added value of processed industries contributed to the strong export-import performance in the first quarter of 2022 [18]. Between 2023 and the end of 2024, export values exhibited fluctuations due to the normalization of post-pandemic commodity prices and a slowdown in the economies of major trading partners [19]. By early 2025, exports continued to increase, although with some volatility, reflecting the ongoing global economic recovery and improvements in Indonesia's export competitiveness. However, performance remains exposed to geopolitical risks and rising global logistics costs [20].

The appropriate selection of lags plays a crucial role in enhancing the accuracy of the Support Vector Machine (SVM) model for forecasting Indonesia's export values. Based on the evaluation of fifteen input variable schemes, Scheme 5 (Lag 1 and Lag 2) yielded the lowest MAPE value of 5.04%, which falls into the "highly accurate" category. This finding suggests that short-term lag combinations have the most significant influence on current export values. The SVM method demonstrates a generally strong predictive capability, with the majority of input schemes producing MAPE values below 7%.

The forecasted export values presented in Table 3 and Figure 3 demonstrate a declining trend during the first half of 2025. As shown in the table, export values are projected to decrease from USD 21.87 billion in March 2025 to USD 20.06 billion by December 2025. This downward trajectory suggests potential short-term export weakening, likely attributable to external factors such as global economic slowdown, commodity price fluctuations, or shifts in international trade policies. Nevertheless, the overall trend remains within a relatively high export value range compared to pre-2021 levels.

## 5. CONCLUSION

The analytical results demonstrate that the implementation of Support Vector Machine (SVM) using the combined lag 1 and lag 2 scheme proves optimal for predicting Indonesia's export values, as evidenced by the lowest Mean Absolute Percentage Error (MAPE) of 5.04% on test data. The forecast results for March-December 2025 reveal a gradual declining trend, decreasing from USD 21.87 billion in March 2025 to USD 20.66 billion by December 2025. This downward trend may be influenced by external factors, including global economic slowdown, commodity price fluctuations, or international trade policies. Nevertheless, Indonesia's export values remain at relatively high levels compared to pre-2021 periods, indicating the resilience of Indonesia's export sector in the post-COVID-19 pandemic recovery. These findings suggest that SVM serves as an effective predictive tool for export values and can provide a foundation for policy-making to mitigate global trade risks.

Based on the modeling results, the SVM method has several advantages. These include high prediction accuracy, consistent results across different combinations of input variables, and good performance even with a small number of features. However, there are some limitations to note. SVM is not specifically designed for time series data, so it does not directly account for seasonality or trend changes. In this study, the regularization parameter C was not specifically tuned (the default value was used), which may limit the model’s optimal performance. In addition, the forecasted values appeared quite smooth and lacked sharp fluctuations from month to month. While this reflects model stability, it is important to consider whether such a pattern truly represents the real-world behavior of Indonesia’s exports, which may be affected by sudden external shocks.

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