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# CHINESE YUAN EXCHANGE RATE AGAINST THE INDONESIAN RUPIAH PREDICTION USING SUPPORT VECTOR REGRESSION

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*ABSTRACT*

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*Support Vector Regression;*
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*This study aims to forecast the exchange rate between the Chinese Yuan (CNY) and the Indonesian Rupiah (IDR) using Support Vector Regression (SVR), a machine-learning technique that can handle nonlinear and complex data. The authors utilize the monthly selling exchange rate of CNY against IDR from January 2012 to October 2023 sourced from the "investing" platform. The optimal SVR model is obtained by splitting the data into 113 training samples and 28 testing samples and using the Radial Basis Function (RBF) kernel. The model achieves high accuracy, with a Mean Absolute Percentage Error (MAPE) of 1.738%, a Root Mean Squared Error (RMSE) of 50.661 for the training data and a MAPE of 2.516%, and an RMSE of 64.735 for the testing data. The results of this paper can provide valuable insights for policymakers, investors, and traders who are interested in the CNY/IDR exchange rate dynamics and the economic implications of the Belt and Road Initiative (BRI). The study aligns with the Sustainable Development Goals (SDGs), specifically SDG 8, aiming to promote sustained, inclusive, and sustainable economic growth.*



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## 1. INTRODUCTION

The exchange rate between currencies plays a crucial role in international trade and investment. It serves as a measure of commodity value in both domestic and foreign currencies, reflecting the economic conditions of a country [1]. A higher exchange rate of one country's currency against another often indicates stronger economic conditions in that country [2]. This study focuses on the exchange rate between the Chinese Yuan (CNY) and the Indonesian Rupiah (IDR), exploring its significance in the context of China's economic growth and its impact on Indonesia's trade and investment landscape. China's prominent role in global economic growth, as evidenced by a 46.70% increase in the Yuan exchange rate against the Rupiah from 2012 to 2023, underscores the need for a comprehensive understanding of the Rupiah-Yuan exchange rate dynamics. This understanding is crucial not only for policymakers and central banks in formulating monetary and fiscal policies but also for investors and market participants in making informed investment and business decisions. The Chinese government has also allocated $40 billion from its national budget to the Silk Road Economic Belt fund [3].

The study delves into the Belt and Road Initiative (BRI) launched by China in 2012, aiming to enhance international connectivity and cooperation. This policy is not just about inter-country collaboration, but also China's aim to strengthen its cultural, economic, and political influence in countries involved in the BRI projects [4]. This initiative, covering a significant portion of global trade, GDP, and population, involves infrastructure projects across various regions, influencing global economic growth and China's pivotal role. The BRI has led to increased use of the Yuan in international projects, particularly in Eurasian countries, further emphasizing the importance of comprehending the Rupiah-Yuan exchange rate dynamics. Given the rapid economic growth, the BRI's impact on the internationalization of the Yuan, especially in developing countries like those in East and Southeast Asia, is substantial. The research highlights the pivotal role of the BRI in the internationalization of the Yuan and its potential effects on the Yuan-Rupiah exchange rate. As of April 2023, 149 countries, including China itself, have signed Memorandums of Understanding (MoU) with China [5], emphasizing the BRI's crucial role in the Yuan internationalization and its potential effects on the Yuan-Rupiah exchange rate.

This research aligns with the Sustainable Development Goals (SDGs), specifically SDG 8, aiming to promote sustained, inclusive, and sustainable economic growth. It emphasizes the significance of understanding how factors like Foreign Direct Investment (FDI) and Exchange Rates (ER) can influence sustainable economic growth and contribute to achieving SDG 8 targets in developing countries [6]. Considering previous successful applications of Support Vector Regression (SVR) in predicting currency exchange rates where a study conducted by Amanda in 2014 to predict the United States Dollar (USD) price in Indonesia Rupiah (IDR) gave a result of 99.99% coefficient determinant with a Mean Absolute Percentage Error (MAPE) of 0.6131% from linear kernel and 0.6135% from polynomial kernel [7]. Based on the previous study, this study employs SVR to model the Yuan-Rupiah exchange rate dynamics. Originating from Support Vector Machine (SVM), introduced by Vapnik in 1999, SVR is designed to solve regression problems [8]. The potential contributions of this research extend to economic and financial realms, supporting SDG attainment, offering insights to potential investors, and fostering improved collaboration between China and Indonesia for mutual development. This research, therefore, holds not only academic value but also real-world implications, promoting sustainable economic growth and creating significant investment opportunities for both nations.

This study innovatively applies SVR with Grid Search Optimization to model the CNY/IDR exchange rate dynamics. This approach aims to improve prediction accuracy compared to traditional methods. By leveraging this novel methodology, the research seeks to provide valuable insights for stakeholders and contribute to advancements in exchange rate forecasting within international finance.

## 2. RESEARCH METHODS

### 2.1 Data Source

The data utilized in this study comprises monthly interval data tracking the exchange rate of the Indonesian Rupiah (IDR) against the Chinese Yuan (CNY). Historical data spanning from January 2012 to October 2023, totaling 141 months, were sourced from the Investing platform [9].

To ensure robustness in model training and evaluation, the dataset was partitioned into a training set comprising 80% of the total data and a testing set comprising the remaining 20%. Consequently, the training dataset spans from January 2012 to May 2021, encompassing 113 months, while the testing dataset covers June 2021 to October 2023, spanning 28 months. This division was determined to yield the most optimal outcomes in modeling and predicting exchange rate dynamics using the Support Vector Regression (SVR) method.

### 2.2 Support Vector Regression

Support Vector Regression (SVR) is a supervised learning algorithm derived from Support Vector Machine (SVM), introduced by Vapnik in 1999, specifically designed for regression tasks [8]. SVM is a machine learning application for classification cases, producing integer or real values, while SVR is tailored for regression scenarios, generating real-numbered outputs [10].

The fundamental principle of SVR involves minimizing risk by estimating a function, thereby minimizing the upper limit of generalization errors to prevent overfitting. The SVR algorithm aims to find the best hyperplane, optimizing a linear function represented in Equation (1) as follows.

$$f(x) = \langle w \cdot x \rangle + b \tag{1}$$

Where $f(x)$ represent the output of the predicted value, $\langle w \cdot x \rangle$ denotes the inner product (or dot product) between the weight vector $w$ and the input vector $x$, where $w$ contains the coefficients associated with the input features and $x$ represents the feature vector of the data point. The inner product operation calculates the sum of the products of the corresponding components of the two vectors. Additionally, $w$ represents the weight vector in SVR, containing the coefficients associated with the input features. Similarly, $x$ denotes the input vector, which consists of features of the data point for which the output is being predicted. Lastly, $b$ represents the bias or intercept in the linear equation, providing an offset to the regression line.

The cost parameter $(C)$ in SVR controls the trade-off between the model's complexity and the amount of error that is acceptable in the training data. A smaller value of $C$ leads to a softer margin, allowing more training points to be misclassified or falling outside the margin, thus creating a simpler model with higher bias and lower variance. On the other hand, a larger value of $C$ results in a harder margin, forcing the model to classify all training points correctly, which can lead to a more complex model with lower bias and higher variance [11].

The epsilon parameter $(\varepsilon)$ in SVR determines the margin of tolerance where no penalty is given for errors. It specifies the size of the tube within which no penalty is associated with errors. In other words, it controls the width of the margin of tolerance around the predicted value. A smaller value of $\epsilon$ results in a smaller margin and a more sensitive model, while a larger value of $\epsilon$ leads to a wider margin and a less sensitive model [12].

These parameters play crucial roles in determining the trade-off between the model's complexity and its error tolerance, thus contributing to the prevention of overfitting and the minimization of generalization errors in SVR. The margin, i.e., the distance from the hyperplane to the nearest data point, is crucial in SVR, with support vectors being the data points closest to the margin. In SVR, the objective is to minimize the norm of the weight vector $||w||$ while addressing the optimization problem $\frac{1}{2}||w||^2$, constrained by $y_i - \langle w \cdot x \rangle - b \leq \varepsilon$ and $\langle w \cdot x \rangle + b - y_i \leq \varepsilon$. Introducing a soft margin or total slack variable $(\xi_i + \xi_i^*)$ , where $\xi_i$ represents the slack variable associated with the $i$-th data point, while $\xi_i^*$ represents the slack variable associated with the upper bound side of the margin allows for conditions where error values may exceed the $\varepsilon$ threshold. The $\varepsilon$-insensitive loss function is defined in Equation (2) as follows.

$$|\xi_i|_\varepsilon = \begin{cases} 0, & |\xi_i| \leq \varepsilon \\ |\xi_i| - \varepsilon, & otherwise \end{cases} \tag{2}$$

For non-linear problems, SVR transforms values using the feature space with a kernel function $K(x_i, x_j)$. The final equation for non-linear problems is presented in **Equation (3)** as follows.

$$f(x) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x_i, x_j) + b \tag{3}$$

The function in **Equation (3)** encompasses several critical components fundamental to SVR where $l$ represents the number of support vectors in the SVR model, indicating the size of the training dataset subset that significantly influences the decision boundary. $\alpha_i$ denotes the Lagrange multiplier associated with the $i$-th support vector, and $\alpha_i^*$ represents the dual variable linked to the $i$-th support vector. Additionally, $K(x_i, x_j)$ denotes the kernel function applied to the input vectors $x_i$ and $x_j$, facilitating the transformation of input data into a higher-dimensional space, which aids in capturing complex relationships between data points. Lastly, $b$ signifies the bias term in the regression equation, serving as an offset to the regression line.

## 2.3 Kernel Function

To address non-linear problems in high dimensions, the inner product ($x_i$ and $x_j$) is replaced with a kernel function **[13]**. The performance of the SVR method is determined by the type of kernel function and the parameters used **[14]**. **Table 1** below shows kernel functions that can be used in the SVR method.

**Table 1. Kernel Function in Support Vector Regression**

| Kernel Type | Formula |
|---|---|
| Linear | $K(x_i, x_j) = (x_i^T x)$ |
| Polynomial | $K(x_i, x_j) = \left(\gamma(x_i^T x)\right)^p$ |
| Radial Basis Function | $K(x_i, x_j) = \exp\left(-\gamma(x_i - x_j)^2\right)$ |

Where $p$: degree of polynomial and $\gamma$: gamma parameter. Each kernel has its own function, and the choice of kernel should be appropriate for the data conditions. The linear kernel facilitates modeling linear relationships between input and target variables, suitable for data with linear or nearly linear structures. The polynomial kernel allows the learning of non-linear models through polynomial representations of original variables, while caution is needed to avoid overfitting at higher orders. The RBF kernel, also known as the Gaussian kernel, measures the similarity between inputs based on their distance in a high-dimensional space. The parameter $\gamma$ in the RBF kernel controls the width of the bell curve, influencing the extent of a single data point's impact. Although the RBF kernel projects into an infinite-dimensional space, SVR can express only a subset of these functions.

## 2.4 Grid Search Optimization

Grid Search Optimization (GSO) systematically explores a predefined grid of hyperparameters to optimize machine learning models. In the context of SVR, this involves defining ranges for parameters like kernel type, regularization parameter, and kernel coefficient, then evaluating multiple model combinations to find the optimal configuration **[15]**.

Grid Search employs cross-validation on training data to measure model performance. By dividing the data into parts and calculating error rates, it assesses the effectiveness of different parameter pairs **[16]**. This iterative process selects models with the lowest error rates, ensuring robust performance. The algorithm of Grid Search Optimization to obtain the best solution is as follows **[17]**.

1. Define ranges for SVR hyperparameters such as kernel type, regularization parameter, and kernel coefficient.
2. Initialize candidate SVR models with different parameter combinations.

3. Evaluate model performance using a chosen metric.
4. Select models with the best performance.
5. Enhance exploration by adjusting hyperparameters iteratively.
6. Accelerate convergence using this method.
7. Promote diversity in the model population for robustness.
8. Repeat steps 3-7 until the stopping criterion is met.
9. Choose the best-performing model as the optimal solution.

Moreover, Grid Search Optimization often complements other optimization techniques like line search and surrogate model-based algorithms, enhancing efficiency, especially when the hyperparameter space is manageable [18].

### 2.5 Terasvirta for Non-linearity Test

The non-linearity test is conducted to detect nonlinear relationships in data, employing both parametric and nonparametric tests. Parametric tests include the Terasvirta test, RESET test, Tsay test, Lagrange Multiplier test, and Likelihood Ratio test. Nonparametric tests involve the Ljung-Box chi-square residual test and Bispectral test [19]. In this study, the non-linearity test used is the Terasvirta test. The Terasvirta test is a non-linearity detection test developed from a neural network model and falls under the category of Lagrange Multiplier (LM) tests. This test is an LM-type test developed with a Taylor expansion. In the Terasvirta test, $m$ additional predictors, represented by quadratic and cubic terms, are used, stemming from the Taylor expansion approach. Linearity test with Terasvirta can be done using one of the statistical tests, namely the $\chi^2$ test. The procedure to obtain the $\chi^2$ test is as follows:

1. Regressing $y_t$ on $1, y_{t-1}, \dots, y_{t-p}$ and calculating the residual values $\hat{a}_t = y_t - \hat{y}_t$
2. Regressing $\hat{a}_t$ on $1, y_{t-1}, \dots, y_{t-p}$ and $m$ additional predictors, then calculating the coefficient of determination from this regression, namely $R^2$. In this test, $m$ additional predictors are quadratic and cubic terms resulting from the Taylor expansion approach.
3. Calculating $\chi^2 = qR^2$, with $q$ being the number of observations used.

The formulated hypothesis for this test is as follows:

$H_0$: The model of the data follows a linear pattern.
$H_1$: The model of the data does not follow a linear pattern.

Hence, the criteria for rejecting $H_0$ are if the $\chi^2$ value is greater than or equal to $\chi^2_{\alpha,q}$ or if the $p$-value obtained from the probability value of $\chi^2$ is less than the significance level $\alpha$.

### 2.6 Model Evaluation

In the context of evaluating the Support Vector Regression (SVR) model, two key metrics are employed: Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). RMSE, as defined by [20], serves as a measure of the difference between predicted values from a statistical model and the actual values. Mathematically, RMSE represents the standard deviation of residuals, which are the distances between the regression line and data points. The calculation of RMSE, expressed in Equation (4) is as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \tag{4}$$

Equation (4) involves the actual data at the time $t$ ($y_t$), the predicted data at the time $t$ ($\hat{y}_t$), and the total number of data points ($n$). A lower RMSE value indicates better predictive accuracy, with values approaching 0 being rare in practical applications.

Complementing RMSE, Mean Absolute Percentage Error (MAPE), outlined by [21], measures the accuracy of a forecasting method in statistics. This metric is expressed in Equation (5) as follows.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|y_t - \hat{y}_t|}{y_t} \quad (5)$$

where $y_t$ represents actual data at the time $t$, $\hat{y}_t$ denotes predicted data at the time $t$, and $n$ is the total number of data points. MAPE gauges accuracy in percentage form, offering an intuitive interpretation of relative errors. It is frequently utilized in various loss functions in model analysis.

In model evaluation, these metrics provide insights into the accuracy and reliability of SVR predictions, guiding the selection of optimal parameters and kernel functions through techniques like Grid Search Optimization.

## 3. RESULTS AND DISCUSSION

The dataset, spanning from January 2012 to October 2023 with 141 months, provides a comprehensive overview of the Chinese Yuan (CNY) to Indonesian Rupiah (IDR) exchange rates. Descriptive statistics indicate an average exchange rate of Rp2,008.3, with a minimum of Rp1,423.1 and a maximum of Rp2,303.2. The time series plot reveals an increasing trend until September 2015, followed by fluctuating data until September 2023. The time series plot in **Figure 1** visually represents the exchange rate trend over the period, illustrating an increasing trend from 2012 to September 2015. Subsequently, the data exhibits fluctuations in each period until September 2023. The dataset is divided into training (80%) and testing (20%) sets, covering the periods from 2012 to May 2021 and June 2021 to October 2023, respectively. This division sets the stage for further analysis and modeling of the exchange rate dynamics.

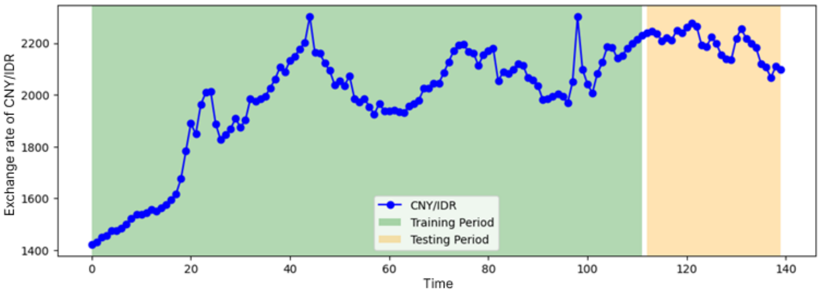


**Figure 1. Time Series Plot for CNY to IDR Exchange Rate**

A non-linearity test was conducted to ascertain whether the data follows any specific pattern. The chosen method for testing non-linearity in this research is the Terasvirta test based on a Neural Network model. The hypothesis for the Terasvirta non-linearity test is as follows.

$H_0$: The model of the CNY/IDR rate follows a linear pattern.

$H_1$: The model of the CNY/IDR rate does not follow a linear pattern.

The results of the Terasvirta test are presented in **Table 2**.

**Table 2. Terasvirta Test Results**

| $\chi^2$ | Degrees of Freedom | P-Value | Conclusion |
|---|---|---|---|
| 8.262 | 2 | 0.01607 | Non-linear Model |

From **Table 2**, the obtained $p$-value for the Terasvirta test is 0.01607. Using a significance level $\alpha$ of 5%, it is determined that the null hypothesis ($H_0$) is rejected. Therefore, it can be concluded that the CNY/IDR data for the period from January 2012 to August 2023, monthly, does not exhibit any discernible pattern and is non-linear. Consequently, Polynomial and Radial Basis Function (RBF) kernels are chosen for the SVR modeling.

The selection of autoregressive lag is aimed at determining the lags that significantly influence the actual data. By identifying significant lags, the values from those lags can be utilized to model the data with high accuracy. Lag selection in this study involves plotting the Partial Autocorrelation Function (PACF) as shown in Figure 2.

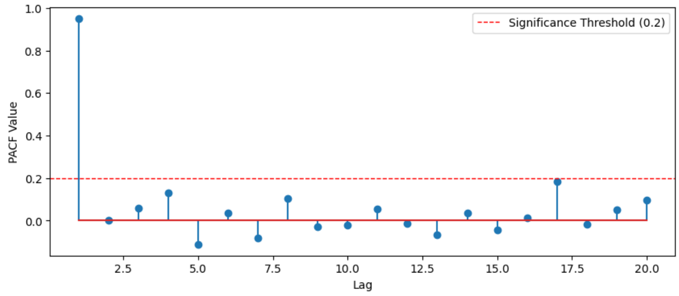


**Figure 2. Partial Autocorrelation Function for Yuan Exchange Rate Against Indonesian Rupiah**

Based on Figure 2, it is evident that the lag considered significant is lag 1. Therefore, the data exhibits dependence on the data from the previous period. This implies that the data can be effectively modeled with this significant lag. The Support Vector Regression (SVR) modeling involves several stages, starting with hyperparameter tuning using Grid Search Optimization to estimate the best parameters based on data. The parameter grid utilized for obtaining the best parameters is presented in Table 3.

**Table 3. Parameter Grid**

| Parameter | Range |
|---|---|
| $C$ | $2^0, 2^1, 2^2, \dots, 2^9$ |
| $\gamma$ | $0.1, 0.2, 0.3, \dots, 1.0$ |
| $\varepsilon$ | $0.1, 0.2, 0.3, \dots, 1.0$ |
| $p$ | $2, 3, 4, 5$ |

The selection of the best parameters relies on the Mean Squared Error (MSE) as the evaluation metric, and negative MSE is used for comparison. The negative MSE concept is applied in machine learning model evaluation, where higher return values are considered better than lower ones. The hyperparameter tuning with the specified grid aims to obtain the best parameter combination for the SVR model. Subsequently, hyperparameter tuning for the polynomial kernel is illustrated in Figure 3, while the formal results are presented in Table 4.

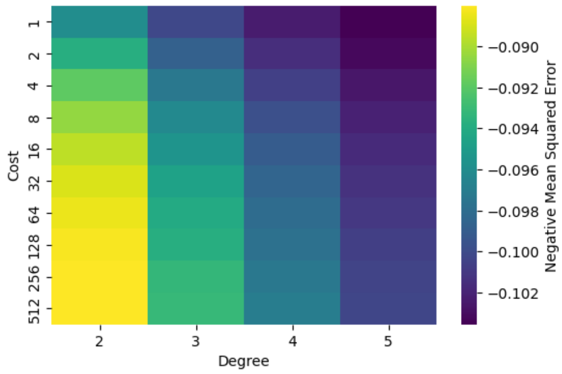


**Figure 3. Grid Search Optimization Results for Polynomial Kernel**

**Table 4. Grid Search Optimization Results for Polynomial Kernel**

| $C$ | $\varepsilon$ | $\gamma$ | $p$ | Score |
|---|---|---|---|---|
| 4 | 0.1 | 0.6 | 2 | -0.023053137 |
| 16 | 0.1 | 0.3 | 2 | -0.023053137 |
| 64 | 0.1 | 0.5 | 2 | -0.023053137 |
| 256 | 0.1 | 0.8 | 2 | -0.023053137 |
| 4 | 0.1 | 0.4 | 2 | -0.023053137 |
| 8 | 0.1 | 0.2 | 2 | -0.023053155 |
| 32 | 0.1 | 0.1 | 2 | -0.023053155 |
| 16 | 0.1 | 1.0 | 2 | -0.023154618 |

| $C$ | $\varepsilon$ | $\gamma$ | $p$ | Score |
|---|---|---|---|---|
| 64 | 0.1 | 0.5 | 2 | -0.023157322 |
| 256 | 0.1 | 0.8 | 2 | -0.023157322 |

The process is repeated for the radial basis function (RBF) kernel, as shown in **Figure 4,** and formalized in **Table 5**.

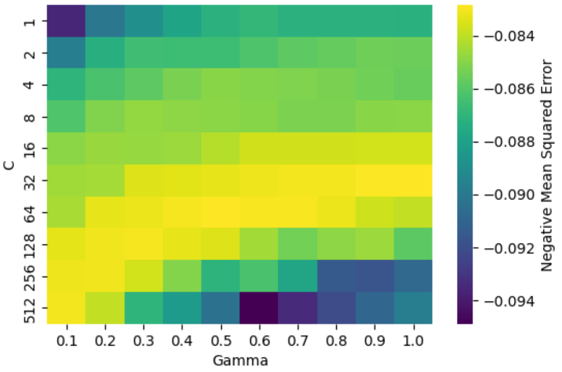


**Figure 4. Grid Search Optimization Results for Radial Basis Function Kernel**

Based on **Figure 4**, which uses a radial basis function kernel, the optimal combination of parameters can be identified in the brightest area. This area corresponds to a higher negative mean squared error value. The optimal parameters seem to vary diagonally from the bottom left to the top right. For improved results, the top 10 combinations are presented in **Table 5**.

**Table 5. Grid Search Optimization Results for Radial Basis Function Kernel**

| $C$ | $\varepsilon$ | $\gamma$ | Score |
|---|---|---|---|
| 32 | 0.1 | 0.4 | -0.003574233 |
| 32 | 0.1 | 0.5 | -0.003627554 |
| 32 | 0.1 | 0.6 | -0.003636616 |
| 32 | 0.1 | 0.3 | -0.003651547 |
| 16 | 0.1 | 0.6 | -0.0036528 |
| 64 | 0.1 | 0.2 | -0.003663258 |
| 256 | 0.1 | 0.1 | -0.003707638 |
| 16 | 0.1 | 0.7 | -0.003732414 |
| 32 | 0.1 | 0.7 | -0.003795851 |
| 16 | 0.1 | 0.4 | -0.003922918 |

According to **Table 5**, the optimal configuration for Support Vector Regression (SVR) utilizing the radial basis function kernel is achieved with parameters set at $C = 32$, $\varepsilon = 0.1$, and $\gamma = 0.4$. This specific combination yields the most favorable performance, evidenced by the highest negative mean squared error value of negative 0.00357.

After obtaining the best parameters through grid search optimization, a comparison of the two best SVR models is conducted on the training data, evaluating them with MAPE and RMSE. The results are summarized in **Table 6**.

**Table 6. Comparison of Best SVR Models**

| Kernel | $C$ | $\varepsilon$ | $\gamma$ | $p$ | MAPE | RMSE |
|---|---|---|---|---|---|---|
| Polynomial | 4 | 0.1 | 0.6 | 2 | 2.985% | 76.210 |
| Radial Basis Function | 32 | 0.1 | 0.4 | - | 1.738% | 50.661 |

Based on the comparison in **Table 6**, the Radial Basis Function (RBF) kernel with parameters $C = 32$, $\varepsilon = 0.1$, and $\gamma = 0.4$ is identified as the best SVR model, achieving a MAPE of 1.738% and an RMSE of 50.661. **Figure 5** illustrates the prediction results of the CNY/IDR exchange rate based on the best SVR model using the radial basis function kernel.

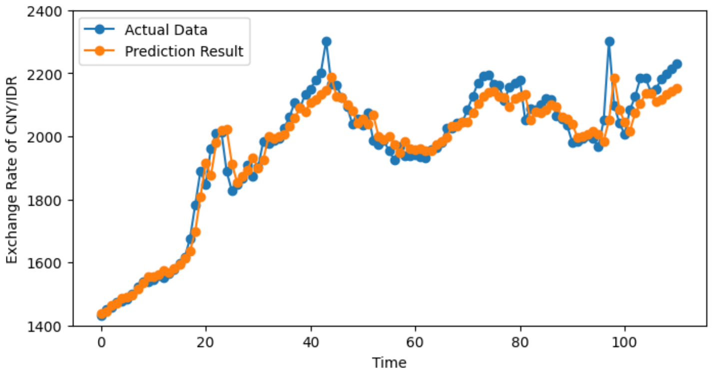


**Figure 5. Plot of Actual Data with Prediction Results on Training Data**

After obtaining the best SVR model (RBF kernel with $C = 32$, $\varepsilon = 0.1$, and $\gamma = 0.4$), the model is tested on the testing data, and predictions are made based on the results of the testing. The performance of the selected SVR model on the testing data is presented in **Table 7**.

**Table 7. Testing the Best SVR Model on Testing Data**

| Kernel | $C$ | $\varepsilon$ | $\gamma$ | MAPE | RMSE |
|---|---|---|---|---|---|
| Radial Basis Function | 32 | 0.1 | 0.4 | 2.516% | 64.735 |

The comparison between the predictions on the testing data and the actual data in Table 8 was done to test the validity and robustness of the clustering method. The results showed that the predicted clusters matched the actual clusters in most cases, and that the method was able to handle noise and outliers in the data.

**Table 8. Prediction Results with the Best SVR Model**

| Time | Actual Data | Predicted Data | Time | Actual Data | Predicted Data |
|---|---|---|---|---|---|
| Jul 2021 | Rp2,240.59 | Rp2,158.66 | Sep 2022 | Rp2,198.63 | Rp2,155.26 |
| Aug 2021 | Rp2,244.57 | Rp2,163.10 | Oct 2022 | Rp2,153.28 | Rp2,143.52 |
| Sep 2021 | Rp2,237.70 | Rp2,164.80 | Nov 2022 | Rp2,138.79 | Rp2,118.93 |
| Oct 2021 | Rp2,207.86 | Rp2,161.85 | Dec 2022 | Rp2,135.04 | Rp2,110.34 |
| Nov 2021 | Rp2,219.26 | Rp2,148.10 | Jan 2023 | Rp2,216.43 | Rp2,108.06 |
| Dec 2021 | Rp2,211.04 | Rp2,153.54 | Feb 2023 | Rp2,255.80 | Rp2,152.21 |
| Jan 2022 | Rp2,249.95 | Rp2,149.64 | Mar 2023 | Rp2,218.26 | Rp2,169.43 |
| Feb 2022 | Rp2,240.53 | Rp2,167.04 | Apr 2023 | Rp2,198.49 | Rp2,153.07 |
| Mar 2022 | Rp2,260.47 | Rp2,163.08 | May 2023 | Rp2,181.82 | Rp2,143.45 |
| Apr 2022 | Rp2,276.51 | Rp2,171.28 | Jun 2023 | Rp2,121.30 | Rp2,134.82 |
| May 2022 | Rp2,266.00 | Rp2,177.37 | Jul 2023 | Rp2,106.88 | Rp2,099.51 |
| Jun 2022 | Rp2,193.22 | Rp2,173.43 | Aug 2023 | Rp2,066.65 | Rp2,090.21 |
| Jul 2022 | Rp2,185.09 | Rp2,140.78 | Sep 2023 | Rp2,110.46 | Rp2,062.55 |
| Aug 2022 | Rp2,222.97 | Rp2,136.55 | Oct 2023 | Rp2,097.25 | Rp2,092.55 |

The visual representation of the actual data compared to the predicted data on the testing data is shown in **Figure 6**.

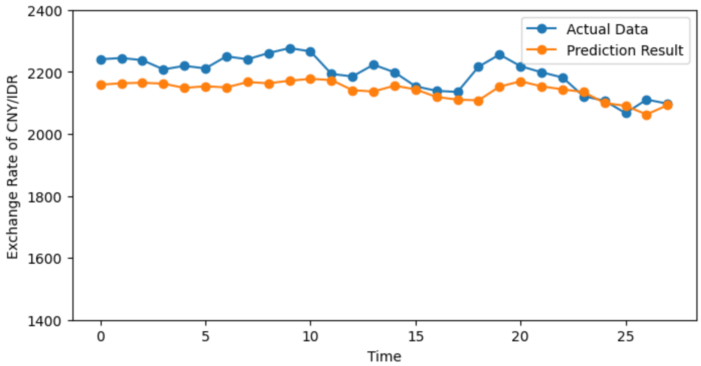


**Figure 6. Plot of Actual Data with Prediction Results on Testing Data**

In conclusion, the SVR model with the radial basis function kernel ($C = 32$, $\varepsilon = 0.1$, and $\gamma = 0.4$) exhibits excellent accuracy in modeling the CNY/IDR exchange rate, with a MAPE of 2.516% and an RMSE of 64.735. This indicates an average error of around 2.516% in predicting the CNY/IDR exchange rate, while the RMSE reflects an average deviation of 64.735 units from the actual values.

## 4. CONCLUSIONS

During the period from January 2012 to October 2023, the average monthly exchange rate of the Chinese Yuan to the Indonesian Rupiah was Rp2,008.3, with the lowest and highest monthly rates recorded at Rp1,423.1 and Rp2,303.2, respectively. Employing the Support Vector Regression (SVR) method with 113 training data points resulted in the best SVR model utilizing the Radial Basis Function (RBF) kernel, achieving a Mean Absolute Percentage Error (MAPE) of 1.738% and a Root Mean Squared Error (RMSE) of 50.661. Subsequent testing on 28 data points using the RBF kernel with parameters $C = 32$, $\varepsilon = 0.1$, and $\gamma = 0.4$ demonstrated excellent accuracy, yielding a MAPE of 2.516% and an RMSE of 64.735. On average, the model exhibited an error of approximately 2.516% in predicting the CNY to IDR exchange rate, with predictions deviating by around 64.735 units from actual values. The results of this research demonstrate that the SVR model accurately follows the actual exchange rate data, indicating its efficacy in predicting future exchange rate movements between CNY to IDR.

In conclusion, this study demonstrates the effectiveness of an SVR model with a MAPE of 2.516% in predicting the CNY to IDR exchange rate. This level of accuracy provides valuable insights for policymakers, investors, and market participants, enabling them to make informed decisions regarding trade and investment activities, ultimately contributing to economic stability and growth. Future research could explore incorporating additional factors or utilizing different machine learning techniques to potentially improve prediction accuracy.

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