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Forecasting Rupiah Exchange Rate Volatility using a Hybrid ARIMA–SVR Model as an Early Warning System to Address Global Dynamics

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ABSTRACT

Exchange rate volatility of the Indonesian Rupiah against the US Dollar has increased due to global uncertainty. This study addresses the limitation of prior research that predominantly relies on single linear or nonlinear models in emerging markets by developing a Hybrid ARIMA SVR approach, thereby enhancing exchange rate predictability to support macroeconomic stability. This study contributing to the advancement of quantitative forecasting methods aligned with SDG 8 and SDG 16 through enhanced financial predictability. This research uses a univariate time-series dataset of weekly Rupiah US Dollar exchange rates obtained from Bank Indonesia, comprising 150 observations from March 2023 to January 2026. Novelty from this research is ARIMA model selected to capture linear temporal dependencies, while SVR is employed to model nonlinear patterns in residuals justifying the hybrid approach as a complementary integration of statistical and machine learning methods. Data preprocessing includes Box-Cox transformation and second order differencing to ensure stationarity, followed by diagnostic tests (Ljung Box, Kolmogorov Smirnov, and ARCH LM). SVR parameters are optimized using grid search to ensure robust model performance. The analysis included visualization, Box–Cox transformation ($\lambda = -1$), and second-order differencing to achieve stationarity. Diagnostic tests (Ljung Box, Kolmogorov Smirnov, ARCH LM) confirmed that ARIMA (3,2,0) met model assumptions. ARIMA residuals were subsequently model using SVR, with parameters optimized through grid search, forming the Hybrid ARIMA–SVR model. Results show that the Hybrid ARIMA SVR model outperformed the standalone ARIMA, achieving a lower MAPE. The best performance (MAPE = 0.56%) was obtained using the Radial kernel with $\varepsilon = 0.2$, $C = 2^3$, and $\gamma = 2^8$. These findings indicate that integrating linear and nonlinear models improves forecasting accuracy.

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A. INTRODUCTION

The volatility of the Indonesian Rupiah against the US Dollar has increased due to global economic pressures. As a key macroeconomic variable, exchange rates influence trade, investment, and inflation, particularly in emerging markets where external dependencies heighten instability. Global monetary tightening, geopolitical tensions, and trade policy shifts have intensified these fluctuations (Rezki et al., 2025). This underscores the importance of analyzing both exchange rate levels and volatility, as increased instability reflects broader macroeconomic uncertainty and the need for robust analytical approaches (Hoek I., 2022).

Empirical data show that in 2024, the Rupiah depreciated to around Rp16,300 per US Dollar, declining by approximately 5–7% compared to the 2021–2023 average (Bank Indonesia, 2024). During the global interest rate tightening in 2025, volatility increased by more than 8%, indicating strong sensitivity to external shocks. Such fluctuations have significant implications for inflation, trade, and investment.. These conditions emphasize the importance of accurate exchange rate forecasting. Understanding volatility is therefore crucial for maintaining macroeconomic stability.

Forecasting exchange rate movements is crucial for economic stability and effective policymaking, yet most analyses focus on short-term responses rather than predictive modelling (Makore & Chikutuma, 2025). This limits the ability to anticipate future dynamics. Bank Indonesia emphasizes the need for reliable forecasting systems to reduce uncertainty and improve decision-making, highlighting the importance of more advanced and accurate approaches amid growing global uncertainty (Bank Indonesia, 2025).

Previous studies have demonstrated the effectiveness of ARIMA in capturing trend and seasonal patterns in time series data (Simanungkalit, 2024). The strength of ARIMA lies in its ability to model linear dependencies through autoregressive and moving average components, making it widely used in economic and financial forecasting. However, limited research has systematically evaluated ARIMA performance specifically in volatility forecasting using more recent datasets (Gunnarsson et al., 2024). Considering that financial markets are highly dynamic and continuously evolving, the use of updated data becomes crucial to ensure that model performance remains relevant.

In this context, volatility, by nature, exhibits complex and nonlinear characteristics that cannot be fully explained by linear models alone (Xu et al., 2019). Fluctuations in financial time series are often influenced by sudden shocks, structural breaks, and asymmetric responses, which introduce nonlinear patterns in the data. Therefore, hybrid ARIMA–SVR approaches are considered advantageous, as they integrate the strengths of both linear and nonlinear modeling techniques (Zhang & Zhou, 2024). In this hybrid framework, ARIMA is first applied to capture the linear structure of the series, while the remaining residuals containing nonlinear information are further modeled using SVR.

In this context, ARIMA functions as a baseline model to extract trend and linear dynamics, whereas SVR enhances the model by learning complex nonlinear residual patterns (Cihan, 2024). This complementary mechanism allows the hybrid model to better represent the underlying data-generating process. Furthermore, this study employs 150 recent observations, which strengthens the empirical contribution by providing more up-to-date and relevant evidence. The use of recent data not only improves the reliability of parameter estimation but also enhances the external validity of the findings, allowing the results to be more generalizable to current market conditions.

Conceptually, this study aligns with the Sustainable Development Goals (SDGs), particularly Goal 8 and Goal 16, which emphasize economic stability and data-driven governance. A predictive exchange rate system can assist monetary authorities and market participants in anticipating exchange rate fluctuations, thereby reducing risks to investment, trade, and inflation. This study contributes both academically and practically to strengthening Indonesia’s economic resilience amid increasing global uncertainty.

B. METHODS

1. Data Source

This study uses a quantitative approach with a time-series forecasting design. The data consist of secondary univariate financial time-series data, namely weekly nominal Rupiah–US Dollar exchange rates from March 2023 to January 2026, totaling 150 observations, obtained from Bank Indonesia. The dataset is divided into 90% training and 10% testing data, which is appropriate for time-series analysis to preserve temporal order while ensuring sufficient data for model evaluation.

2. Data Stationarity

Data preprocessing includes Box–Cox transformation to stabilize variance and differencing to achieve stationarity. Stationarity is confirmed using the Augmented Dickey-Fuller (ADF) test, while Ljung–Box and ARCH-LM tests are applied to check autocorrelation and heteroskedasticity, ensuring that model assumptions are satisfied (Dervishi et al., 2025).

$$Z_t = \begin{cases} Z_t^{\lambda}, & \lambda \neq 0 \\ ln(Z_t), & \lambda = 0 \end{cases} \quad (1)$$

where Z_t represents the time series at time t and Zt is the transformed series with parameter λ. If the data were not stationary in the mean, differencing was applied. Differencing is a transformation that computes differences between consecutive observations (Y_t). This process uses the backward shift operator (B). defined as (Zhang et al., 2019):

$$BZ_t = Z_{t-1} \quad (2)$$

$$BBZ_t = B2Z_t = Z_{t-2} \quad (3)$$

$$B^d Z_t = Z_{t-d} \quad (4)$$

Thus, the differencing equation can be written as:

$$Z_t^d = (1-B)^d Z_t, \quad d = 1,2,\ldots \quad (5)$$

where Z_t^d denotes the time series after differencing of order d.

3. Linearity Test

The linearity test was conducted to determine whether the relationship between variables was linear using the Teräsvirta test, which is part of the Lagrange Multiplier (LM) test. The hypotheses are defined as follows:

H_0: residuals do not contain nonlinear patterns

H_1: residuals contain nonlinear patterns

The Teräsvirta test statistic is calculated as:

$$F_{calc} = \frac{\frac{SSR_0 - SSR_1}{m}}{\frac{SSR_1}{(n - p - 1 - m)}} \quad (6)$$

where SSR_0 s the sum of squared residuals from the initial model, SSR_1 is the sum of squared residuals from the Taylor expansion auxiliary regression, n is the number of observations, p is the number of predictor variables, and m is the number of additional predictors from the Taylor expansion. The decision rule is to reject $F_{calc} > F_{(n-p-1-m)}$ or if the p-value is less than the significance level of 0.05 (Massacci, 2017).

4. Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a time series modeling approach that combines the Autoregressive (AR) process of order p, the Moving Average (MA) process of order q, and differencing of order d to achieve stationarity (Bhaumik & Santra, 2020). The AR component expresses the current value as a function of its previous values and a current error term, defined as:

$$Z_t = \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + \varepsilon_t \quad (7)$$

the MA component expresses the current value as a function of past and current error terms, defined as:

$$Z_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (8)$$

in general, the ARIMA (p,d,q) model is expressed as:

$$\phi_p(B)(1 - B)^d Z_t = \theta_q(B)\varepsilon_t \quad (9)$$

where $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ is the AR polynomial, $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ is the MA polynomial. $(1 - B)^d$ represents differencing of order d, B s the backward shift operator, and ε_t is the error term at time (t) (Lee, 2025).

5. Support Vector Regression (SVR)

Support Vector Regression (SVR) is a machine learning method used to identify patterns in time series data for prediction, including nonlinear patterns . The SVR process involves splitting the data into training and testing sets (García-Floriano et al., 2018). The training set is used to build the model by minimizing prediction error relative to actual values, while the testing set is used to evaluate model performance Click or tap here to enter text.. The nonlinear SVR regression function is defined as (Annas et al., 2023):

$$f(x_i) = \sum_{i=1}^{m} (\alpha_i - \alpha_i^*)\, \varphi(x_i)\, \varphi(x) + b \quad (10)$$

where $f(x_i)$ is the SVR function, α_i dan α_i^* are Lagrange multipliers, $\varphi(x_i)$ is the feature mapping function, b is the bias. x_i is the input vector. Since $\varphi(x_i)$ is generally unknown, it is replaced using a kernel function defined as (Wu & Wang, 2023):

$$K(x_i, x) = \varphi(x_i).\varphi(x) \tag{11}$$

The kernel function represents the inner product in feature space. This study uses the Radial Basis Function (RBF) kernel, defined as (Pervez et al., 2023):

$$K(x_i, x) = exp(-\gamma\|x_i - x\|^2), \text{ dengan } \gamma > 0 \tag{12}$$

where $K(x_i, x)$ is the RBF kernel and γ is the gamma parameter. he SVR regression function with the RBF kernel is expressed as (Wei & He, 2023).

$$f(x_i) = \sum_{i=1}^{m}(\alpha_i - \alpha_i^*)\, exp(-\gamma\|x_i - x\|^2) + b \tag{13}$$

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with constraints $0 < \alpha_i \leq , C, 0 < \alpha_i^* \leq C$.

6. Hybrd ARIMA SVR

To capture nonlinear patterns, ARIMA residuals are modeled using Support Vector Regression (SVR). Parameter selection (kernel, ε, C, γ) is optimized using grid search. The Radial Basis Function (RBF) kernel is chosen due to its effectiveness in modeling nonlinear relationships (Saleem et al., 2023). In this hybrid approach, the time series is assumed to consist of two components: a linear component and a nonlinear component (Domingos et al., 2019). The combined model is expressed as (Wei & He, 2023)**:**

$$f(x_i) = \sum_{i=1}^{m}(\alpha_i - \alpha_i^*)\, exp(-\gamma\|x_i - x\|^2) + b \tag{14}$$

where Y_t is the observed value at time t, Z_t is the linear component modeled by ARIMA and N_t is the nonlinear component modeled by SVR. The residual from the ARIMA model is defined as: $\varepsilon_t = Z_t - \widehat{Z_t}$ where $\widehat{Z_t}$ is the estimated linear component from ARIMA (Carista et al., 2025). These residuals are then modeled using SVR to obtain the nonlinear component estimate $\widehat{N_t}$. Thus, the final prediction of the hybrid ARIMA–SVR model is given by (Rubio & Alba, 2022):

$$\widehat{Y_t} = \widehat{Z_t} + \widehat{N_t} \tag{15}$$

where $\hat{Y}_t$ represents the final forecast produced by the hybrid ARIMA–SVR model at time t.

7. Forecast Accuracy

Mean Absolute Percentage Error (MAPE) is a statistical measure used to evaluate the accuracy of a forecasting model by quantifying the average percentage deviation between actual and predicted values. MAPE is defined as (Jierula et al., 2021):

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \widehat{Y}_t}{Y_t}\right| \times 100\% \quad (16)$$

with Y_t is Actual value and $\widehat{Y}_t$ is Predicted value

C. RESULT AND DISCUSSION

1. Descriptive Statistics

The exchange rate data of the Indonesian Rupiah against the US Dollar during March 2023 to January 2026 consist of 150 observations, with a mean of 15,699, a minimum of 14,777, and a maximum of 16,946. For the training data (135 observations), the mean is 15,596, with values ranging from 14,777 to 16,466. For the testing data (15 observations), the mean is 16,627, with values ranging from 16,356 to 16,946. The minimum value reflects the Rupiah's strongest level, while the maximum value indicates significant depreciation. The higher mean and range in the testing period compared to the training period suggest an increasing depreciation trend toward the end of the observation period.

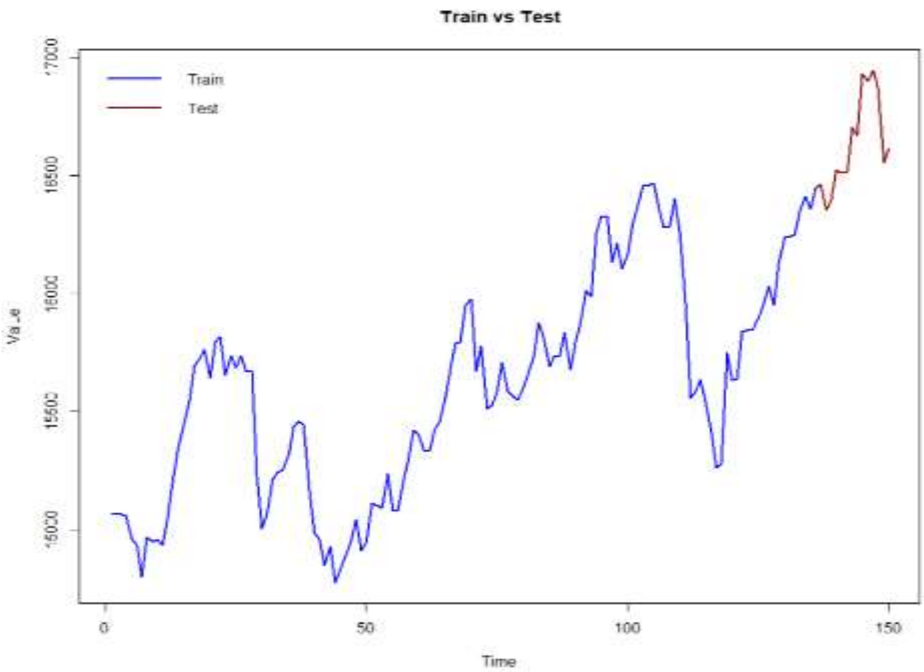


Figure 1. Weekly Exchange Rate Plot of Indonesian Rupiah Against the US Dollar

Based on Figure 1, the training data initially exhibit relatively stable movement with several fluctuations and a downward trend, followed by a consistent upward trend toward the end of the training period, although a sharp correction occurs mid-period. Meanwhile, the testing data at the end of the observation period show higher exchange rate levels compared to most of the previous period, with fluctuations within a relatively narrower range.

2. Autoregressive Integrated Moving Average (ARIMA)

Before ARIMA modeling, stationarity in variance was achieved using a Box–Cox transformation with an estimated λ=-1 as presented in Table 1 indicating that transformation was required.

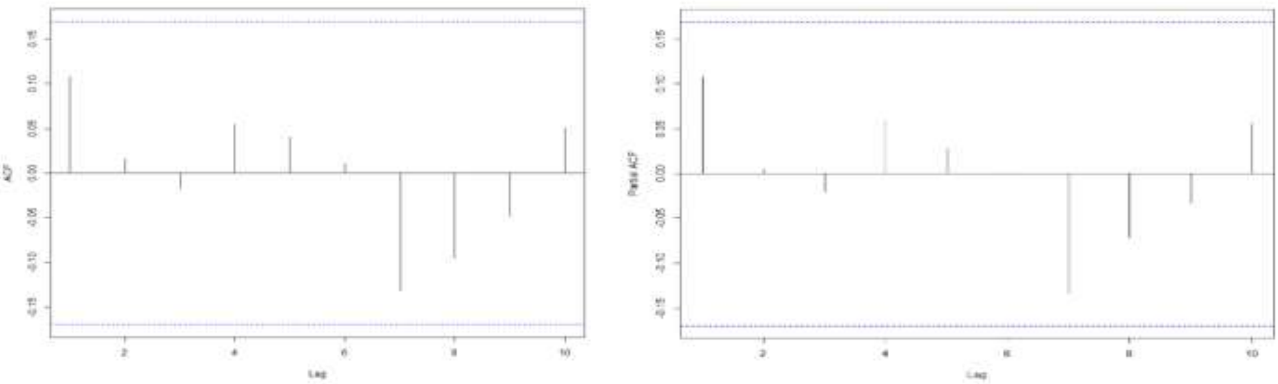
Table 1. Box–Cox transformation

Box–Cox transformation	
Rounded Value	λ=-1

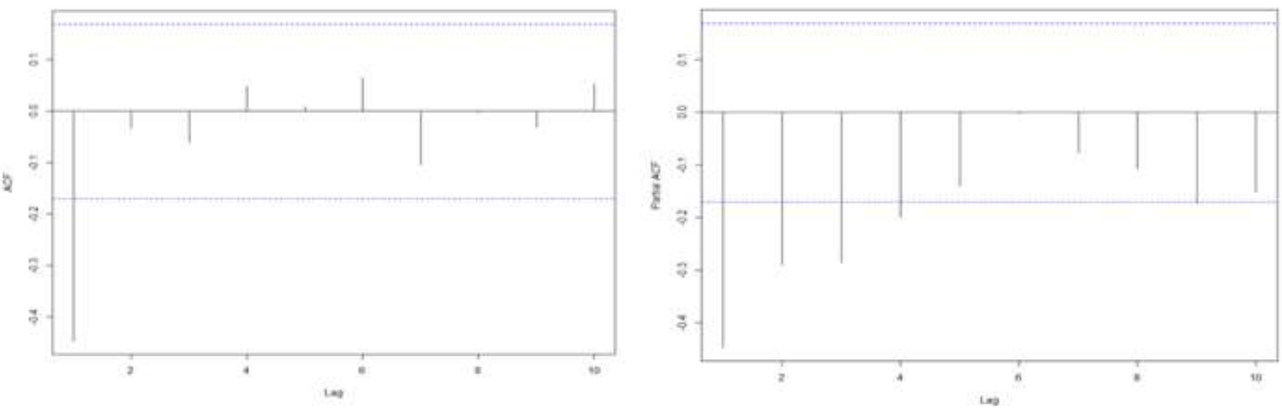
The transformed data were then tested for stationarity in the mean using the Augmented Dickey–Fuller (ADF) test. The results are presented in Table 2.

Table 2. Results of the Augmented Dickey–Fuller (ADF) Test

Test Statistics	**Result**		
	Before Differencing	**Differencing 1**	**Differencing 2**
Dickey-Fuller	-2.98	-4.23	-6.62
P-value	0.17	0.01	0.01



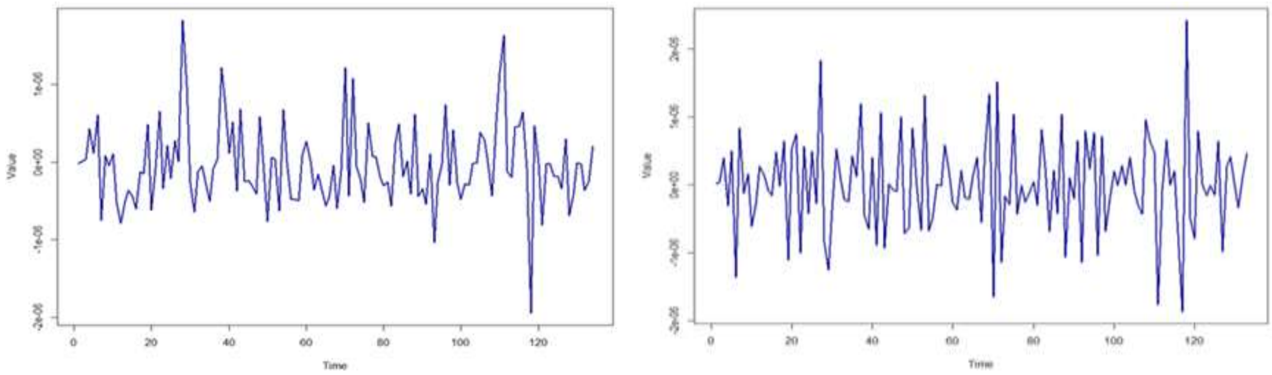
(a)



(b)

Figure 2. ACF and PACF Plot (a) Differencing 1 dan (b) Differencing 2

Based on Table 2 and Figure 2, before differencing, the Dickey–Fuller statistic was −2.98 with a p-value of 0.17 (> 0.05), indicating that the series was non-stationary in the mean. After first differencing, the statistic decreased to −4.23 with a p-value of 0.01 (< 0.05), indicating stationarity. However, the ACF and PACF plots in Figure 2(a) still showed significant autocorrelation at certain lags, suggesting the need for further differencing. After second differencing, the Dickey–Fuller statistic decreased to −6.62 with a p-value of 0.01 (< 0.05), confirming stationarity in the mean. Figure 2(b) shows that most ACF and PACF values fall within the significance bounds without clear autocorrelation patterns. This indicates that the data have achieved stationarity in both mean and variance, with weakened autocorrelation, satisfying the assumptions required for ARIMA model identification. The transformed and differenced data are presented in Figure 3.



(a) (b)

Figure 3. Plot (b) *Differencing* 1(c) *Differencing* 2

Based on the stationary data in mean and variance, ARIMA model identification was performed. The candidate ARIMA models derived from the ACF and PACF plots after second differencing in Figure 2(b) are presented in Table 3, along with their probability values (Pr>|z|) for parameter significance testing.

Table 3. Parameter Significance Testing

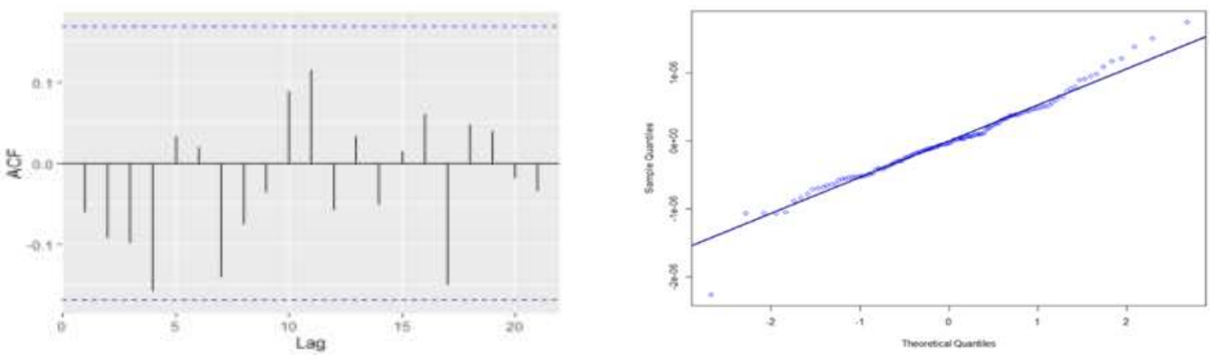
Model	Parameter	Estimation	P-Values	Result	AIC	BIC
ARIMA (1,2,0)	ϕ_1	-0.45	0.00	Significant	-3422.64	-3414.86
ARIMA (2,2,0)	ϕ_1	-0.58	0.00	Significant	-3432.37	-3421.70
	ϕ_2	-0.29	0.00	Significant		
ARIMA (3,2,0)	ϕ_1	-0.66	0.00	Significant	-3472.63	-3465.07
	ϕ_2	-0.45	0.00	Significant		
	ϕ_3	-0.28	0.00	Significant		
ARIMA (0,2,1)	θ_1	-1.00	0.00	Significant	-3465.07	-3457.29
ARIMA (1,2,1)	ϕ_1	0.12	0.18	Not Significant	-3464.85	-3454.18
	θ_1	-1.00	0.00	Significant		
ARIMA (2,2,1)	ϕ_1	0.11	0.19	Not Significant	-3462.87	-3449.31
	ϕ_2	0.01	0.90	Not Significant		

Model	Parameter	Estimation	P-Values	Result	AIC	BIC
	θ_1	-1.00	0.00	Significant		
ARIMA (3,2,1)	ϕ_1	0.11	0.19	Not Significant	-3460.89	-3444.44
	ϕ_2	0.01	0.88	Not Significant		
	ϕ_3	-0.01	0.88	Not Significant		
	θ_1	-1.00	0.00	Significant		

Table 3 presents the parameter estimation and significance test results for several candidate ARIMA models. The results show that in the ARIMA (1,2,0), ARIMA (2,2,0), ARIMA (3,2,0), and ARIMA (0,2,1) models, all parameters are statistically significant at the 5% significance level (p-value < 0.05). Model selection was further evaluated using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Among the candidate models, ARIMA (3,2,0) produced the smallest AIC (−3472.63) and BIC (−3465.07) values compared to the other models, indicating superior model performance. Therefore, the ARIMA (3,2,0) model was selected as the best model and further evaluated through residual diagnostic testing to verify the white noise assumption, as presented in Figure 5 and Table 4.

Table 4. Residual Normality Test Results

Tes Statistik	P value
Ljung-Box test	0.47
Kolmogorov-Smirnov test	0.45
ARCH-LM	0.98



(a) (b)

Figure 5. Diagnostic Test of the ARIMA (3,2,0) Model: (a) Residual ACF and (b) Residual Normality Test

Figure 5(a) shows that the residual ACF of the ARIMA (3,2,0) model lies within the significance bounds, indicating no residual autocorrelation. Figure 5(b) shows that the residuals follow the diagonal line, indicating an approximately normal distribution. This is supported by the Kolmogorov–Smirnov test with a p-value of 0.45 (> 0.05), confirming residual normality. Furthermore, the Ljung–Box test produced a p-value of 0.47 (> 0.05), indicating that the residuals are white noise. The ARCH–LM test resulted in a p-value of 0.98, indicating no heteroscedasticity. Therefore, the ARIMA (3,2,0) model satisfies all diagnostic assumptions and is considered adequate.

Based on the parameter estimates in Table 6, the ARIMA (3,2,0) model is expressed as:

$$\widehat{Z_t^*} = 2Z_{t-1} - Z_{t-2} - 0.66(Z_{t-1} - 2Z_{t-2} + Z_{t-3}) - 0.45(Z_{t-2} - 2Z_{t-3} + Z_{t-4}) \\ - 0.28\,(Z_{t-3} - 2Z_{t-4} + Z_{t-5}) + \varepsilon_t \tag{17}$$

with:
Z_t^* = the predicted value at time t from the transformed data
Z_t = time series data
ε_t = residual or error

Since the Box–Cox transformation parameter is λ=-1, the inverse transformation is $Z_t^* = \frac{1}{Z_t}$ Thus, the ARIMA (3,2,0) model in the original scale is expressed as.

$$\widehat{Z_t} = \left[\frac{2}{Z_{t-1}} - \frac{1}{Z_{t-2}} - 0.66\left(\frac{1}{Z_{t-1}} - \frac{2}{Z_{t-2}} + \frac{1}{Z_{t-3}}\right) - 0.45\left(\frac{1}{Z_{t-2}} - \frac{2}{Z_{t-3}} + \frac{1}{Z_{t-4}}\right) \\ - 0.28\left(\frac{1}{Z_{t-3}} - \frac{2}{Z_{t-4}} + \frac{1}{Z_{t-5}}\right)\right]^{-1} \tag{18}$$

The residuals of the ARIMA (3,2,0) model are calculated as: $\varepsilon_t = Z_t - \widehat{Z_t}$.

3. HYBRID ARIMA-SVR

To assess the linearity of the ARIMA residuals, Table 5 presents the results of the residual linearity test.

Table 5. ARIMA Residual Linearity Test

Data	Test Statistics χ^2	P-Value
ARIMA (3,2,0) Residuals	1.49	0.48

The linearity of the residuals from the best ARIMA (3,2,0) model was evaluated using the Teräsvirta test, as presented in Table 5. The results show a test statistic of 1.49 with a *p*-value of 0.48. Since the *p*-value exceeds the significance level of 0.05, the null hypothesis cannot be rejected, indicating no evidence of nonlinear patterns in the residuals. Therefore, the residuals of the ARIMA (3,2,0) model are linear, and the modeling process can proceed to the SVR stage.

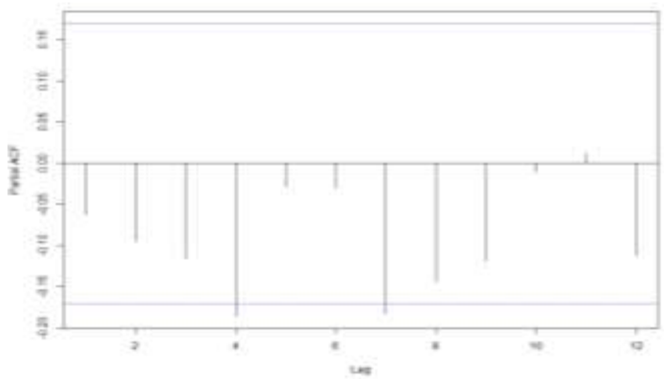


Figure 6. PACF Plot of ARIMA Residuals

Based on the PACF plot of the ARIMA residuals in Figure 6, most spikes lie within the significance bounds; however, significant spikes are observed at lag 4 and lag 7. This indicates that these lags still have a significant influence on the current residual values, suggesting temporal dependence. Therefore, two time lags, lag 4 and lag 7, were selected as input variables for the subsequent SVR modeling stage. Optimal parameter tuning for the SVR model was performed using the grid search method with parameter ranges defined by minimum and maximum values. Four kernel functions linear, radial basis function (RBF), sigmoid, and polynomial were evaluated. The tuning results and kernel performance evaluation are presented in Table 6.

Table 6. Fine Grid Results and Kernel Function Evaluation in SVR Residual Modeling

Kernel	Parameter	RMSE		MAPE	
		Training	Testing	Training	Testing
Linear	$\varepsilon = 0.8$	148.07	162.72	0.76	0.87
	$C = 2^{-11}$				
Radial	$\varepsilon = 0.2$	**148.09**	**140.33**	**0.77**	**0.56**
	$C = 23$				
	$\gamma = 28$				
Sigmoid	$\varepsilon = 0.8$	437.99	159.55	2.13	0.92
	$C = 2^{-9}$				
	$\gamma = 2^{-9}$				
	$coef.0 = 0.1$				
Polynomial	$\varepsilon = 0.1$	145.90	171.00	0.73	0.73
	$C = 2^{-7}$				
	$\gamma = 2^{-4}$				
	$coef.0 = 0.1$				
	$degree = 3$				

Based on the finer grid search results, the optimal SVR parameters were obtained using the RBF kernel with $\varepsilon = 0.2$, $C = 2^3$, dan $\gamma = 2^8$. This configuration produced the lowest RMSE and MAPE values for both training and testing datasets, indicating superior predictive performance compared to other kernel functions. Thus, the SVR model for ARIMA residuals is expressed as:

$$\widehat{N}_t = \sum_{i=1}^{m}(a_t - a_t^*)\ exp(-\gamma\ ||x_t - x||^2) + b, \text{dengan } 0 < a_t \le C, 0 < a_t^* \le C \quad (19)$$

$$\widehat{N}_t = \sum_{i=10}^{126}(a_t - a_t^*)\ exp(-0.5\ ||x_t - x||^2) + 0.05 \quad (20)$$

with:

x_t = input vector (features) of the observation at time t

a_t, a_t^* = Lagrange coefficients obtained from the optimization

b = bias

a_t = 0,11

After determining the optimal ARIMA and SVR models, both components were combined to form the hybrid ARIMA–SVR model. The hybrid model is expressed as:

$$\widehat{Y_t} = \widehat{Z_t} + \widehat{N_t} \tag{21}$$

$$\widehat{Y_t} = \left[\frac{2}{Z_{t-1}} - \frac{1}{Z_{t-2}} - 0.66\left(\frac{1}{Z_{t-1}} - \frac{2}{Z_{t-2}} + \frac{1}{Z_{t-3}}\right) - 0.45\left(\frac{1}{Z_{t-2}} - \frac{2}{Z_{t-3}} + \frac{1}{Z_{t-4}}\right) - 0.28\left(\frac{1}{Z_{t-3}} - \frac{2}{Z_{t-4}} + \frac{1}{Z_{t-5}}\right)\right]^{-1} + \sum_{i=10}^{126} (a_t - a_t^*)\ exp(-0.5\ ||x_t - x||^2) + 0.05 \tag{22}$$

with $a_t = 0{,}11$. Based on this formulation, the linear component of the hybrid ARIMA–SVR model is represented by the ARIMA (3,2,0) model, which captures linear relationships between the current exchange rate and previous observations up to lag 5 through second-order differencing and autoregressive parameters. This component reflects the historical linear structure of the time series. The nonlinear component is modeled using SVR with the RBF kernel, which captures nonlinear residual patterns not explained by the ARIMA model. These nonlinear patterns represent exchange rate fluctuations influenced by complex factors beyond linear dependence. By combining both components, the hybrid ARIMA–SVR model effectively captures linear and nonlinear dynamics, resulting in improved forecasting accuracy and a more comprehensive representation of the Rupiah–US Dollar exchange rate behavior.

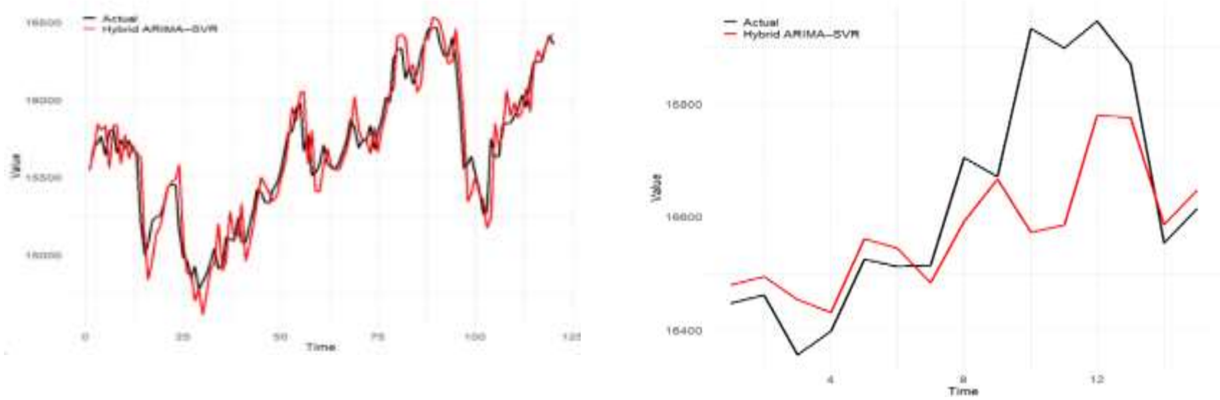
4. Comparison of MAPE, RMSE, and MAE between ARIMA and Hybrid ARIMA–SVR

To compare the best predictive performance of the models, Table 7 summarizes the MAPE, RMSE, and MAE values for ARIMA and Hybrid ARIMA–SVR.

Table 7. Comparison of MAPE Values for the ARIMA and Hybrid ARIMA–SVR

Model	MAPE		RMSE		MAE	
	Training	Testing	Training	Testing	Training	Testing
ARIMA	0.67%	0.93%	137.17	211.47	103.64	156.17
Hybrid ARIMA-SVR	0.77%	0.56%	148.00	140.33	114.88	94.20

Table 7 presents the comparison of ARIMA and hybrid ARIMA–SVR models based on MAPE, RMSE, and MAE using weekly exchange rate data from March 2023 to January 2026. The results show that the hybrid ARIMA–SVR model achieved superior performance compared to the ARIMA model. Specifically, the hybrid ARIMA–SVR model produced a lower testing MAPE of 0.56% compared to the ARIMA model (0.93). Similarly, the testing RMSE and MAE values of the hybrid ARIMA–SVR model (140.33 and 94.20) were substantially lower than those of the ARIMA model (211.47 and 156.17). Although the ARIMA model showed slightly lower training error, the hybrid ARIMA–SVR model demonstrated better generalization performance on testing data. This indicates that the hybrid model more effectively captures both linear and nonlinear patterns, resulting in improved forecasting accuracy for the Rupiah–US Dollar exchange rate, as shown in Figure 7.



(a) (b)

Figure 7. Comparison of Data Plots: (a) Training Data and (b) Testing/Forecasting Data

Figure 7 presents the comparison of predicted and actual values for both training and testing datasets. Figure 7(a) shows that the hybrid ARIMA–SVR model closely follows the actual data pattern in the training set, indicating strong predictive capability and high model accuracy. Figure 7(b) shows that the hybrid ARIMA–SVR model with the RBF kernel more accurately captures the actual data pattern in the testing period compared to the ARIMA model. In contrast, the ARIMA model demonstrates lower predictive accuracy, as its predicted values deviate more from the actual observations. These results confirm that the hybrid ARIMA–SVR model provides better predictive performance in both training and testing periods. Additionally, from outside this research differences may be driven by macroeconomic factors, policy changes, and market sentiment beyond the model's scope.

D. CONCLUSION AND SUGGESTIONS

This study finds that the Hybrid ARIMA–SVR model outperforms standalone ARIMA and SVR models, confirming that integrating linear and nonlinear approaches improves forecasting accuracy in capturing complex exchange rate dynamics. The Support Vector Regression (SVR) model produced a MAPE value of 0.56, and the best kernel function was the Radial kernel with optimal parameter values $\varepsilon = 0.2$, $C = 2^3$, and $\gamma = 2^8$. Based on these results, the Hybrid ARIMA–SVR model is recommended as an effective approach for improving the accuracy of exchange rate volatility forecasting. Furthermore, this model can be utilized as a reliable early warning system to support timely decision-making in response to global economic dynamics. However, the study is limited by a relatively small dataset (150 observations) and the use of univariate data, which may restrict its ability to account for broader macroeconomic factors and limit generalizability. Future research should incorporate longer datasets, include multivariate variables such as inflation and interest rates, and explore alternative hybrid or deep learning approaches to enhance robustness. Differences may be driven by macroeconomic factors, policy changes, and market sentiment. When depreciation occurs, strengthen stabilization and hedge risk and when appreciation occurs, support exports and optimize imports or foreign debt.

REFERENCES

Annas, S., Rais, Z., Aswi, A., Indrayasaro, & Nurfajriani. (2023). *Implementation of Support Vector Regression (SVR) Analysis in Predicting Gold Prices in Indonesia* (Vol. 2023, Number Icsmtr). Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-332-0_12

Bank Indonesia. (2024). *Investor relations: Republic of Indonesia*. Bank Indonesia. 13–84. https://doi.org/10.46883/onc.2024.3811

Bank Indonesia. (2025). Tinjauan Kebijakan Moneter Bank Indonesia (Maret-April 2025). *Departemen Kebijakan Ekonomi Dan Moneter*, 1–3. https://www.bi.go.id/id/publikasi/laporan/Pages/TKM-Maret-2025.aspx?

Bhaumik, H., & Santra, S. B. (2020). Critical properties of deterministic and stochastic sandpile models on two-dimensional percolation backbone. *Physica A: Statistical Mechanics and Its Applications*, *548*(2), 124318. https://doi.org/10.1016/j.physa.2020.124318

Carista, N., Mahadesyawardani, A., Dwiyanto, A. S., & Pusporani, E. (2025). Forecasting Nickel Prices in Indonesia Using ARIMA, SVR, and Hybrid ARIMA-SVR Approach. *Jurnal Matematika, Statistika Dan Komputasi*, *21*(3), 627–645. https://doi.org/10.20956/j.v21i3.42558

Cihan, P. (2024). Comparative Performance Analysis of Deep Learning, Classical, and Hybrid Time Series Models in Ecological Footprint Forecasting. *Applied Sciences (Switzerland)*, *14*(4), 1-18. https://doi.org/10.3390/app14041479

Dervishi, L., Raptakis, A., & Bieber, G. (2025). Forecasting techniques for univariate time series data: Analysis and practical applications by category. *Computer Sciences & Mathematics Forum*, 21(4), 1021. https://doi.org/10.3390/cmsf2025011021

Domingos, D. S., de Oliveira, J. F. L., & de Mattos Neto, P. S. G. (2019). An intelligent hybridization of ARIMA with machine learning models for time series forecasting. *Knowledge-Based Systems*, *175*(2), 72–86. https://doi.org/10.1016/j.knosys.2019.03.011

García-Floriano, A., López-Martín, C., Yáñez-Márquez, C., & Abran, A. (2018). Support vector regression for predicting software enhancement effort. *Information and Software Technology*, *97*(1), 99–109. https://doi.org/10.1016/j.infsof.2018.01.003

Gunnarsson, E. S., Isern, H. R., Kaloudis, A., Risstad, M., Vigdel, B., & Westgaard, S. (2024). Prediction of realized volatility and implied volatility indices using AI and machine learning: A review. *International Review of Financial Analysis*, *93*(4), 103221. https://doi.org/10.1016/j.irfa.2024.103221

Hoek, J., Kamin, S., & Yoldas, E. (2022). Are higher U.S. interest rates always bad news for emerging markets? *Journal of International Economics*, *137*(3), 103585. https://doi.org/10.1016/j.jinteco.2022.103585

Jierula, A., Wang, S., Oh, T. M., & Wang, P. (2021). Study on accuracy metrics for evaluating the predictions of damage locations in deep piles using artificial neural networks with acoustic emission data. *Applied Sciences (Switzerland)*, *11*(5), 1–21. https://doi.org/10.3390/app11052314

Lee, Y.-J. (2025). Data-driven decision analysis for weather observation technology in Japan: Integrating patent forecasting, network analytics, and economic valuation. *Decision Making and Analysis*, *3*(1), 86–100. https://doi.org/10.55976/dma.32025145386-100

Makore, I., & Chikutuma, C. N. (2025). Exchange Rate Volatility and Its Impact on International Trade: Evidence from Zimbabwe. *Journal of Risk and Financial Management*, *18*(7), 1–16. https://doi.org/10.3390/jrfm18070376

Massacci, D. (2017). Least squares estimation of large dimensional threshold factor models. *Journal of Econometrics*, *197*(1), 101–129. https://doi.org/10.1016/j.jeconom.2016.11.001

Pervez, M. N., Yeo, W. S., Mishu, M. M. R., Talukder, M. E., Roy, H., Islam, M. S., Zhao, Y., Cai, Y., Stylios, G. K., & Naddeo, V. (2023). Electrospun nanofiber membrane diameter prediction using a combined response surface methodology and machine learning approach. *Scientific Reports*, *13*(1), 111975. https://doi.org/10.1038/s41598-023-36431-7

Rezki, J. F., Riefky, T., Maizar, F. A., Fitriani, D., Hamonangan, M. G., & Salim, H. (2025). *Macroeconomic Analysis Series: Indonesia Economic Outlook Q2-2025-Entering the Sub-Five Territory (No. 202502).* LPEM, Faculty of Economics and Business, University of Indonesia.

Rubio, L., & Alba, K. (2022). Forecasting Selected Colombian Shares Using a Hybrid ARIMA-SVR Model. *Mathematics*, *10*(13), 1-15. https://doi.org/10.3390/math10132181

Saleem, N., Ali, M., & Mohammed, A. (2023). The use of ARIMA, LSTM and GRU models in time series hybridization with practical application. *Int. J. Nonlinear Anal. Appl*, *14*(2022), 2008–6822. http://dx.doi.org/10.22075/ijnaa.2022.7110

Simanungkalit, E. (2024). Evaluation of ARIMA model performance in projecting future sales: case study on electronic products. *Jurnal Teknik Informatika*, *7*(4), 309–317. https://doi.org/10.35335/idss.v7i4.274

Wei, J., & He, X. (2023). Support vector regression model with variant tolerance. *Measurement and Control (United Kingdom)*, *56*(9–10), 1705–1719. https://doi.org/10.1177/00202940231180620

Wu, J., & Wang, Y. G. (2023). A working likelihood approach to support vector regression with a data-driven insensitivity parameter. *International Journal of Machine Learning and Cybernetics*, *14*(3), 929–945. https://doi.org/10.1007/s13042-022-01672-x

Xu, S., Chan, H. K., & Zhang, T. (2019). Forecasting the demand of the aviation industry using hybrid time series SARIMA-SVR approach. *Transportation Research Part E: Logistics and Transportation Review*, *122*, 169–180. https://doi.org/10.1016/J.TRE.2018.12.005

Zhang, C., & Zhou, X. (2024). Forecasting value-at-risk of crude oil futures using a hybrid ARIMA-SVR-POT model. *Heliyon*, *10*(1), e23358. https://doi.org/10.1016/j.heliyon.2023.e23358

Zhang, X., Xie, S., Vilela, A. L. M., & Stanley, H. E. (2019). Inter-event time interval analysis of organizational-level activity: Venture capital market case. *Physica A: Statistical Mechanics and Its Applications*, *516*(1), 346–355. https://doi.org/10.1016/j.physa.2018.09.050