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What Drives the Indonesian Rupiah? Evidence from VECM and Machine Learning

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ABSTRACT

Research Originality: Unlike previous studies that primarily focus on either macroeconomic determinants of exchange rates or forecasting performance separately, this study integrates both perspectives by examining exchange rate determinants and comparing conventional econometric and machine learning approaches within a single framework.

Research Objectives: This study examines the effects of inflation, interest rates, money supply, trade balance, and foreign exchange reserves on the Indonesian Rupiah exchange rate and compares the forecasting performance of VECM and machine learning models.

Research Methods: This study employs a VECM to investigate long-run and short-run relationships and compares its forecasting performance with SVR, Random Forest, and LSTM models using monthly data from 2010 to 2024.

Empirical Results: The results indicate a long-run cointegrating relationship between exchange rates and macroeconomic fundamentals. In the short run, money supply significantly affects exchange rate movements. Among the forecasting models, LSTM achieves the highest predictive accuracy based on MAE, MAPE, and RMSE.

Implications: The findings highlight the importance of macroeconomic fundamentals in maintaining exchange rate stability and demonstrate the potential of machine learning techniques, particularly LSTM, for exchange rate forecasting in Indonesia.

Keywords:
macroeconomic fundamentals; cointegration; forecasting; long short-term memory

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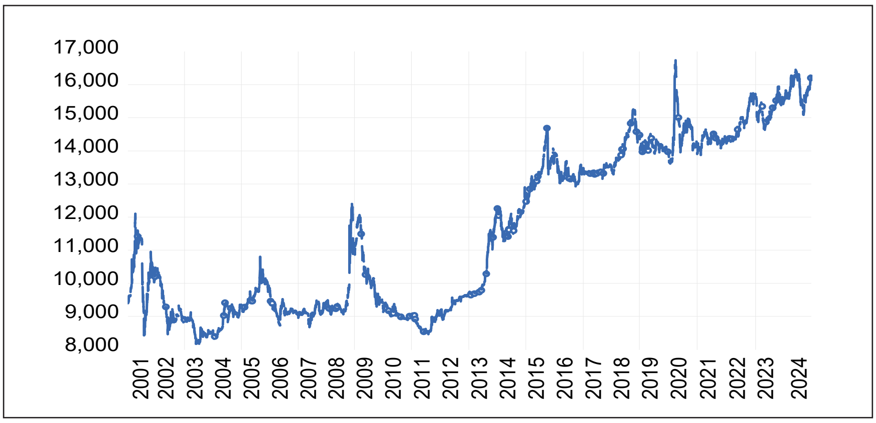
INTRODUCTION

The exchange rate is a significant indicator of a country's economic health, influencing trade competitiveness, inflation, and financial stability (Anwar et al., 2022). For Indonesia, a small open economy highly exposed to global market fluctuations, understanding exchange rate dynamics is especially important. As shown in Figure 1, the Indonesian Rupiah exhibited relative resilience from 2001 to 2010, tending to revert to its long-term level following global or regional disturbances. However, beginning in 2010, the exchange rate experienced a persistent depreciation trend. This structural shift in behavior has been influenced by several global developments, including the United States Federal Reserve's tapering announcement in 2013, the COVID-19 pandemic in 2020, and subsequent geopolitical tensions (Cristanto & Bowo, 2021). These events have triggered capital flow volatility and exposed vulnerabilities in Indonesia's external sector, thereby amplifying pressure on the exchange rate (Bank Indonesia, 2024).

Figure 1. Exchange Rate (IDR/USD) in Indonesia from January 2001–December 2024



Source: Bank Indonesia

A growing body of literature suggests that several macroeconomic variables have significant effects on exchange rate dynamics. In the Indonesian context, Carissa and Khoirudin (2020) found that money supply and trade-related variables are among the most influential factors affecting exchange rate fluctuations, whereas inflation plays a relatively minor role. Setiawan et al. (2021) reported that money supply and interest rates significantly affect the Rupiah exchange rate in the long run, while inflation and export-import variables do not exhibit significant impacts. Anwar et al. (2022) further showed that interest rates, money supply, inflation, and foreign exchange reserves influence exchange rate behavior through monetary policy transmission channels. Dewi and Fauzan (2023) also documented a long-run relationship between exchange rates and macroeconomic fundamentals using a VECM framework. While these studies provide valuable insights into the determinants of exchange rates, most focus primarily on identifying macroeconomic drivers and pay limited attention to the comparative forecasting performance of alternative analytical approaches. Moreover, existing evidence is largely based on conventional econometric

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models, leaving uncertainty regarding whether machine learning techniques can provide more accurate exchange rate forecasts in the Indonesian context.

Among conventional econometric approaches, the Vector Error Correction Model (VECM) has been widely employed to analyze exchange rate dynamics because it can capture both long-run equilibrium relationships and short-run adjustments among cointegrated macroeconomic variables (Dewi & Fauzan, 2023; Setiawan et al., 2021). VECM is particularly useful for analyzing non-stationary variables that exhibit cointegration, allowing researchers to distinguish between temporary fluctuations and long-run equilibrium movements. However, despite its strong theoretical foundation and interpretability, VECM is limited in capturing nonlinear relationships and complex interactions that frequently characterize financial and macroeconomic time series (Lin et al., 2025; Makridakis et al., 2023).

To address the limitations of conventional econometric models, recent studies have increasingly adopted machine learning approaches for exchange rate forecasting. Models such as Support Vector Regression (SVR), Random Forest, and Long Short-Term Memory (LSTM) have demonstrated promising forecasting performance by capturing nonlinear relationships and long-term dependencies in financial time series (Abouzaid & Boussedra, 2025; Ghahremani & Nguyen, 2025). Recent evidence suggests that machine learning models often outperform traditional forecasting methods, particularly during periods of heightened uncertainty and structural change (Yu et al., 2023; Tang & Xie, 2025; Reikard, 2026). Furthermore, hybrid and ensemble approaches that combine economic fundamentals with machine learning algorithms have shown significant improvements in forecasting accuracy, highlighting the growing role of artificial intelligence in financial and macroeconomic prediction (Adesina & Obokoh, 2025; Bai et al., 2026).

Despite the growing literature, several important gaps remain unresolved. First, many previous studies on Indonesia focus either on identifying macroeconomic determinants of exchange rates using conventional econometric approaches or on forecasting exchange rates using machine learning techniques. As a result, evidence that simultaneously examines exchange rate determinants and compares forecasting performance within a single analytical framework remains limited. Second, most existing studies rely on relatively short sample periods and do not fully capture major economic disruptions experienced by Indonesia between 2010 and 2024, including the taper tantrum, the COVID-19 pandemic, and the recent global monetary tightening cycle. Third, direct empirical comparisons between VECM, Support Vector Regression, Random Forest, and Long Short-Term Memory models using recent Indonesian data are still scarce.

This study addresses these gaps by integrating macroeconomic analysis and forecasting evaluation within a unified framework. The novelty of this research lies in simultaneously investigating the long-run and short-run effects of inflation, interest rates, money supply, trade balance, and foreign exchange reserves on the Indonesian Rupiah exchange rate using VECM, while comparing its forecasting performance with SVR, Random Forest, and LSTM models. Using monthly data from January 2010 to December 2024, this study provides updated evidence on exchange rate dynamics during a period characterized by substantial economic and financial disruptions. Therefore, this research contributes not only to the literature on exchange rate determinants but also to the growing literature on machine learning-based exchange rate forecasting, offering insights for policymakers and practitioners seeking to improve exchange rate monitoring and forecasting in Indonesia.

METHODS

This study uses monthly data from January 2010 to December 2024, yielding 180 observations for each variable. The period was selected because it captures several major economic events affecting exchange rate dynamics in Indonesia, including the 2013 taper tantrum, the COVID-19 pandemic, and the post-pandemic global monetary tightening cycle. The data were obtained from Bank Indonesia (BI) and Statistics Indonesia (BPS). The dependent variable is the Indonesian Rupiah exchange rate against the United States Dollar (IDR/USD). The independent variables consist of inflation, interest rate, money supply, trade balance, and foreign exchange reserves. These variables were selected based on their theoretical relevance and empirical evidence from previous studies examining exchange rate determinants in Indonesia. Table 1 presents the operational variables used in this study.

Table 1. Operational Variables

Variables	Definitions	Measurements	Sources	References
Exchange Rate	Value of one country's currency compared to another	IDR/USD	BI	(Mankiw, 2022)
Inflation	An increase in the price level of goods and services	Percentage (%)	BPS	(Mankiw, 2022)
Interest Rate	The cost of borrowing money or the return on savings	Percentage (%)	BI	(Mankiw, 2022)
Money Supply	The total amount of money that is circulating in an economy at any point in time	Billion Rupiah (M2)	BI	(Mankiw, 2022)
Trade Balance	The difference between a nation's exports and imports	Million USD	BPS	(Mankiw, 2022)
Foreign Exchange Reserves	The foreign-currency equivalents of the central banks of nations	Million USD	BI	(Ibrahim & Sukmana, 2023)

To examine the relationship between macroeconomic variables and exchange rate dynamics, this study employs a Vector Error Correction Model (VECM). VECM is appropriate when variables are integrated of order one (I(1)) and cointegrated, allowing both long-run equilibrium relationships and short-run adjustments to be estimated simultaneously (Dewi & Fauzan, 2023; Ibrahim & Sukmana, 2023). The empirical model is specified as follows:

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$$\Delta ER_t = \alpha_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta ER_{t-i} + \sum_{i=1}^{p-1} \beta_{2i} \Delta INF_{t-i} + \sum_{i=1}^{p-1} \beta_{3i} \Delta IR_{t-i} + \sum_{i=1}^{p-1} \beta_{4i} \Delta MS_{t-i} + \sum_{i=1}^{p-1} \beta_{5i} \Delta TB_{t-i} + \sum_{i=1}^{p-1} \beta_{6i} \Delta FER_{t-i} + \gamma ECT_{t-1} + \epsilon_t \quad (1)$$

where ER denotes the exchange rate, INF represents inflation, IR denotes the interest rate, MS refers to money supply, TB represents the trade balance, FER denotes foreign exchange reserves, and ECT is the error correction term representing deviations from long-run equilibrium. The empirical analysis follows four stages. First, the Augmented Dickey-Fuller (ADF) test is employed to examine stationarity. Second, the optimal lag length is determined using information criteria. Third, the Johansen cointegration test is conducted to identify long-run relationships among the variables. Finally, the VECM is estimated to evaluate both long-run and short-run effects.

In addition to the econometric analysis, this study applies three machine learning models, namely Support Vector Regression (SVR), Random Forest, and Long Short-Term Memory (LSTM), to forecast exchange rate movements. These models are selected because they can capture nonlinear relationships and complex interactions that may not be adequately represented by conventional econometric approaches. SVR constructs a regression function by minimizing prediction errors within a predefined margin while maintaining model simplicity. Random Forest is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and reduce overfitting. Meanwhile, LSTM, a type of recurrent neural network, is particularly suitable for time-series forecasting because it can capture long-term dependencies and nonlinear patterns in sequential data.

The forecasting performance of VECM, SVR, Random Forest, and LSTM is evaluated using Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Lower values of these indicators imply better forecasting performance. The measures are defined as follows:

$$MAE = \frac{1}{n} \sum_{t=1}^{n} |y_t - \hat{y}_t| \quad (2)$$

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \quad (3)$$

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

where y_t denotes the actual value and $\hat{y}_t$ denotes the predicted value.

RESULT AND DISCUSSION

This study examines the effects of macroeconomic fundamentals on the Indonesian Rupiah exchange rate and compares the forecasting performance of conventional econometric and machine learning approaches. The empirical results reveal three main findings. First, the exchange rate and macroeconomic variables exhibit a long-run cointegrating relationship, confirming the importance of macroeconomic fundamentals in explaining exchange rate dynamics. Second, money supply is identified as the only variable with a significant short-run effect on exchange rate movements, while money supply, trade balance, and foreign exchange reserves significantly influence exchange rate equilibrium in the long run. Third, among the forecasting models evaluated, Long Short-Term Memory (LSTM) achieves the highest predictive accuracy, outperforming VECM, Support Vector Regression (SVR), and Random Forest. These findings highlight the continued relevance of macroeconomic fundamentals while demonstrating the potential of machine learning techniques for exchange rate forecasting in Indonesia.

Table 2. Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Exchange Rate	180	12887.48	2324.421	8508	16421
Inflation	180	4.127	1.844	1.32	8.79
Interest Rate	180	5.692	1.251	3.5	7.75
Money Supply	180	5328838	2080837	2066481	9210816
Trade Balance	180	1307.594	1828.662	-2331.1	7558.8
Foreign Exchange Reserves	180	119610.3	17875.19	69562	155719

To provide an overview of the data characteristics, Table 2 presents the summary statistics of the variables used in this study. The average exchange rate during the observation period was IDR12,887.48 per USD, with a standard deviation of IDR2,324.42, indicating considerable fluctuations in the value of the Indonesian Rupiah. The minimum exchange rate was IDR8,508 per USD, while the maximum reached IDR16,421 per USD, reflecting substantial exchange rate movements between 2010 and 2024. Inflation averaged 4.13 percent with a standard deviation of 1.84, suggesting relatively moderate price fluctuations over the study period. Inflation ranged from 1.32 percent to 8.79 percent, reflecting periods of both low and high inflationary pressure. The average interest rate was 5.69 percent, with a standard deviation of 1.25. The minimum interest rate was 3.50 percent, while the maximum reached 7.75 percent, indicating adjustments in monetary policy in response to changing macroeconomic conditions. The money supply averaged IDR5.33 quadrillion, with a standard deviation of IDR2.08 quadrillion. The minimum value was IDR2.07 quadrillion, while the maximum reached IDR9.21 quadrillion, reflecting the continuous expansion of liquidity in the Indonesian economy throughout the observation period. Trade balance exhibited substantial variability, with an average surplus of USD1.31 billion and a standard deviation of USD1.83 billion. The minimum value of negative USD2.33 billion indicates periods of trade deficit, whereas the maximum value of USD7.56 billion reflects periods of strong export performance. Foreign exchange reserves averaged USD119.61 billion, with a standard deviation of USD17.88 billion. The lowest reserve level was USD69.56 billion, while the highest reached USD155.72 billion, indicating a steady accumulation of reserves and strengthening external sector resilience.

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Table 3. Stationary Test Results using ADF Test

Variables	Prob. Level	Prob. 1st Difference
Exchange Rate	0.7419	0.0000
Inflation	0.1819	0.0000
Interest Rate	0.3293	0.0000
Money Supply	0.9973	0.0000
Trade Balance	0.1253	0.0000
Foreign Exchange Reserves	0.2849	0.0000

Table 3 reports the results of the Augmented Dickey-Fuller (ADF) test. The findings indicate that all variables are non-stationary at level, as their probability values exceed the 5% significance level. However, after first differencing, all variables become stationary with probability values below 0.05. These results suggest that all variables are integrated of order one, I(1), satisfying the prerequisite for cointegration analysis and VECM estimation.

Table 4. Optimal Lag Selection Results

Lag	LR	FPE	AIC	HQ
0	NA	9.76×10^{25}	76.87045	76.91518
1	153.1078*	5.85×10^{25}*	76.35792*	76.67101*
2	49.44919	6.53×10^{25}	76.46600	77.04746
3	26.11442	8.41×10^{25}	76.71525	77.56508
4	34.84927	1.02×10^{26}	76.89760	78.01581
5	46.01288	1.13×10^{26}	76.98999	78.37657

The optimal lag length was determined using the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), and Hannan-Quinn Criterion (HQ). As shown in Table 4, lag 1 is selected as the optimal lag because it maximizes LR and minimizes the FPE, AIC, and HQ criteria. Therefore, lag 1 is used in the subsequent VECM estimation.

Table 5. Johansen Cointegration Test Results using Trace Statistic

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None*	0.231797	108.0584	95.75366	0.0054
At most 1	0.131842	61.11946	69.81889	0.2026
At most 2	0.110548	35.95361	47.85613	0.3987
At most 3	0.044720	15.10093	29.79707	0.7735
At most 4	0.035963	6.957213	15.49471	0.5826
At most 5	0.002457	0.437936	3.841465	0.5081

The Johansen cointegration test confirms the existence of a long-run equilibrium relationship among the variables. Both the Trace Statistic and Max-Eigen Statistic reject the null hypothesis of no cointegration at the 5% significance level. The results indicate the presence of one cointegrating equation, suggesting that exchange rates and macroeconomic fundamentals move together in the long run. Therefore, the use of VECM is appropriate for capturing both long-run equilibrium and short-run adjustments.

Table 6. Johansen Cointegration Test Results using Max-Eigen Statistic

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.
None*	0.231797	46.93893	40.07757	0.0073
At most 1	0.131842	25.16585	33.87687	0.3739
At most 2	0.110548	20.85268	27.58434	0.2852
At most 3	0.044720	8.143716	21.13162	0.8947
At most 4	0.035963	6.519277	14.26460	0.5475
At most 5	0.002457	0.437936	3.841465	0.5081

Table 7 presents the short-run VECM estimation results. Money supply is the only macroeconomic variable that significantly affects exchange rate movements. The coefficient of money supply is negative and statistically significant, indicating that increases in liquidity are associated with Rupiah appreciation, although the magnitude of the effect remains relatively small. This finding highlights the importance of monetary conditions in influencing short-term exchange rate dynamics and is consistent with previous studies that identified money supply as a key determinant of exchange rate movements in Indonesia (Setiawan et al., 2021; Anwar et al., 2022). Similar evidence has also been documented in emerging economies, where changes in domestic liquidity conditions influence exchange rates through portfolio adjustments, inflation expectations, and capital flow responses (Ibrahim & Sukmana, 2023).

Table 7. VECM Estimation Results (Short-Run)

	Coefficient	Std. Error
ΔER_{t-1}	-0.332*	0.082
ΔINF_{t-1}	27.624	49.924
ΔIR_{t-1}	-20.370	166.214
ΔMS_{t-1}	-0.001*	0.000
ΔTB_{t-1}	-0.040	0.025
ΔFER_{t-1}	0.015	0.001
ECT_{t-1}	-0.233*	0.064
F-Statistic	10.9062	
R-Square	0.31117	

Note:* significant at 5%

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The lagged exchange rate variable exhibits a significant negative coefficient, suggesting a self-correcting mechanism in which exchange rate shocks gradually dissipate over time. Furthermore, the error correction term is negative and statistically significant, indicating that approximately 23.3 percent of any deviation from long-run equilibrium is corrected within one period. This result confirms the stability of the long-run relationship among the variables and supports the suitability of the VECM framework for analyzing exchange rate dynamics. Inflation, interest rates, trade balance, and foreign exchange reserves do not exhibit statistically significant short-run effects. Although their estimated coefficients generally conform to theoretical expectations, the findings suggest that short-term exchange rate fluctuations are driven primarily by liquidity conditions rather than by inflationary pressures or external sector variables. This result is broadly consistent with Carissa and Khoirudin (2020), who reported that monetary variables tend to exert stronger short-run influences on exchange rates than external sector indicators.

In the long run, money supply, trade balance, and foreign exchange reserves are found to significantly influence exchange rate equilibrium. The significance of money supply indicates that monetary conditions play an important role in shaping exchange rate dynamics over time. This finding supports previous evidence that expansion in domestic liquidity can affect exchange rate behavior through inflation expectations, capital flows, and monetary transmission mechanisms (Setiawan et al., 2021; Anwar et al., 2022).

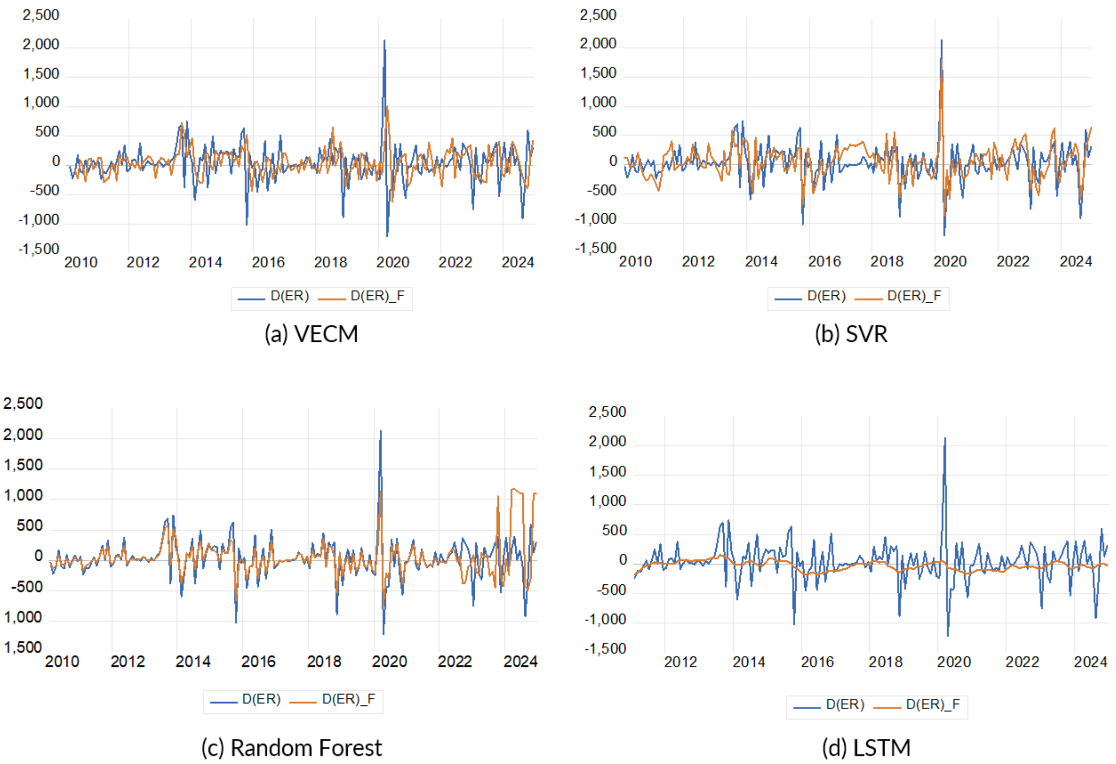
Table 8. VECM Estimation Results (Long-Run)

	Coefficient	Std. Error
INF	29.139	82.296
IR	-373.460	213.202
MS	-0.002*	0.001
TB	-0.645*	0.047
FER	0.061*	0.014

Note:* significant at 5%

The significance of trade balance highlights the importance of export performance and external sector strength in supporting exchange rate stability. A stronger trade balance increases foreign currency earnings and contributes to a more stable exchange rate environment. Similarly, foreign exchange reserves play an important role in maintaining market confidence and reducing vulnerability to external shocks. These findings are consistent with Carissa and Khoirudin (2020), Dewi and Fauzan (2023), and Ibrahim and Sukmana (2023), who also identified external sector fundamentals as important determinants of exchange rate movements in Indonesia and other emerging economies. The long-run significance of money supply, trade balance, and foreign exchange reserves suggests that both monetary and external sector fundamentals continue to play a central role in determining the value of the Indonesian Rupiah. This finding underscores the importance of policy coordination between monetary authorities and external sector management in preserving exchange rate stability amid changing global economic conditions.

Figure 2. Forecasting Values of Exchange Rate (*Difference*) for All Models



Source: author's calculation

As a complement to the econometric analysis, this study evaluates the forecasting performance of selected machine learning techniques. Figure 2 and Table 9 compare the forecasting performance of VECM, Support Vector Regression (SVR), Random Forest, and Long Short-Term Memory (LSTM). The results indicate that LSTM achieves the highest forecasting accuracy, recording the lowest MAE (254.44), MAPE (322.29), and RMSE (174.27) among all models. These findings suggest that deep learning approaches are more effective in capturing the complex and nonlinear behavior of exchange rate movements than conventional econometric models. Among the remaining models, VECM ranks second and performs substantially better than both Random Forest and SVR. This result indicates that macroeconomic fundamentals continue to provide valuable information for exchange rate forecasting, particularly when long-run equilibrium relationships exist among variables.

Random Forest exhibits moderate forecasting performance, while SVR produces the largest forecasting errors and ranks last among the evaluated models. The relatively weaker performance of SVR may indicate that exchange rate dynamics during the sample period were characterized by structural changes and nonlinear interactions that the selected model specification could not adequately capture. In contrast, LSTM can learn complex

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temporal dependencies and adapt to changing data patterns, which may explain its superior forecasting performance.

Table 9. Forecasting Performance Comparison Across Models

Model	MAE	MAPE	RMSE
VECM	273.77	424.04	403.37
SVR	1,769.92	4,137.00	1,912.77
Random Forest	445.92	1,050.11	572.13
LSTM	254.44	322.29	174.27

The strong performance of LSTM may be particularly relevant in the Indonesian context, where exchange rate movements are frequently influenced by external shocks, policy adjustments, and changing global financial conditions. Such circumstances generate nonlinear dynamics that are often difficult to capture using conventional linear econometric approaches. These findings are consistent with recent studies highlighting the advantages of deep learning techniques in financial and macroeconomic forecasting (Yu et al., 2024; Tang & Xie, 2025; Li et al., 2026). At the same time, the relatively strong performance of VECM suggests that economically interpretable models remain valuable for policy analysis and for understanding the transmission mechanisms linking macroeconomic fundamentals and exchange rate movements (Ibrahim & Sukmana, 2023).

CONCLUSION

This study examines the effects of inflation, interest rates, money supply, trade balance, and foreign exchange reserves on the Indonesian Rupiah exchange rate and evaluates the forecasting performance of conventional econometric and machine learning approaches using monthly data from 2010 to 2024. The results confirm the existence of a long-run equilibrium relationship between exchange rates and macroeconomic fundamentals. In the short run, money supply is the only variable that significantly influences exchange rate movements, whereas money supply, trade balance, and foreign exchange reserves are significant determinants of exchange rate equilibrium in the long run. The forecasting analysis further reveals that Long Short-Term Memory (LSTM) achieves the highest predictive accuracy among the evaluated models, outperforming VECM, Support Vector Regression (SVR), and Random Forest. These findings indicate that macroeconomic fundamentals remain important in explaining exchange rate dynamics while machine learning techniques offer substantial improvements in forecasting performance.

The findings imply that maintaining sound monetary conditions and a strong external sector is essential for supporting exchange rate stability in Indonesia. In particular, appropriate liquidity management, sustainable trade performance, and adequate foreign exchange reserve accumulation can strengthen resilience against external shocks and exchange rate volatility. In addition, policymakers may benefit from incorporating machine learning techniques, particularly LSTM, into forecasting frameworks to complement conventional econometric approaches and improve the accuracy of exchange rate projections. Future policy formulation may therefore benefit from combining economic fundamentals with data-driven forecasting tools to support more effective macroeconomic decision-making.

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