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EXCHANGE RATE DYNAMICS AND FORECASTING ACCURACY IN EMERGINGECONOMIES: INTEGRATINGENSEMBLELEARNINGMODELS WITH STRUCTURAL TIME SERIES DECOMPOSITION FOR THE USD/ZAR RATE

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Abstract
Thisstudyinvestigatesthepredictiveperformanceofmachinelearningmodelsinforecastingthedailyexchange rate of the South African rand (USD/ZAR) using data from March 5, 2020, to July 19, 2024. Employing statistical diagnostics such as ADF and KPSS tests, the exchange rate series is found to be non-stationary in levels but stationary after first differencing. Descriptive statistics and seasonal-trend decomposition reveal notable structural features, including skewness, excess kurtosis, and strong seasonal effects. Among the models tested, AdaBoost outperformed Random Forest and K-Nearest Neighbors in terms of forecast accuracy, as measured by RMSE and MAE, despite lowexplanatorypower across all models. These findings underscore the potential of ensemble learning methods for improving short-termcurrency forecasts in emerging markets, while alsohighlightingthelimitationsofdata-drivenmodels incapturingtheinherent volatilityandunpredictabilityof exchange rate movements. The study offers relevant policy insights for monetary authorities and financial market participants, and recommends the integration of hybrid modeling frameworks that combine machine learning with structural macroeconomic variables.

Keywords: Exchange Rate Forecasting, South African Rand, Machine Learning, Time Series Analysis, Ensemble Learning, Monetary Policy

1.0 Introduction

Forecasting exchange rates remains a central concern in international finance, particularlyfor emerging economies where currency fluctuations often have significant implications for inflation, trade, and monetary policy (Coulibaly & Kempf, 2019). The USD/ZAR exchange rate,representativeofaresource-rich,politicallycomplex,andfinanciallyopeneconomy,has been a focal point in this literature. In recent years, the development of advanced computational techniques, especially machine learning (ML) models, has opened new avenues for predicting exchange rate movements with greater accuracy. These models offer the potential to capture nonlinear patterns and complex dependencies that traditional econometric approaches often overlook (Abedin et al., 2022; Sharma et al., 2021). The present study evaluates the predictive performance of four machine learning algorithms, including AdaBoost, k-Nearest Neighbors (kNN), Neural Networks (NN), and RandomForest (RF), in forecasting the South African rand (USD/ZAR) exchange rate using high- frequency daily data.

The South African rand, like other emerging market currencies, is subject to pronounced volatility driven by both domestic macroeconomic fundamentals and external shocks such as commodity price swings, interest rate differentials, and global financial uncertainty (Kutu & Ngalawa, 2022). This volatility introduces challenges for policymakers, investors, and firms with cross-border exposure. Accurate forecasting tools are therefore essential for risk management, policy formulation, and investment planning. Given the limitations of traditionaltimeseriesmodelsincapturingabruptshiftsandnonlinearitiesinexchangerate

data, machine learning models offer a promising alternative, especially those capable of ensemble learning and adaptive calibration (Jammazi et al., 2021; Cheung et al., 2021).
This study contributes to the growing body of empirical research that applies machine learning methods to financial forecasting, particularly within the underexplored context of African exchange rate markets. Based on these metrics, AdaBoost outperformed Random Forest and KNN, consistent with recent findings in exchange rate modeling using boosting algorithms (Özkan & Altan, 2020; Mnasri et al., 2023). The paper reinforces the conclusion that boosting-based ensemble methods, such as AdaBoost, can outperform other standard machinelearningmodelswhenappliedtonoisyandnonlinearfinancialtimeseries.However, the generally low R^2 values suggest that further improvements could be achieved by integrating macroeconomic variables, sentiment indicators, or hybrid modeling frameworks. As such, this study offers not only practical insights for monetary authorities and investorsbut also a foundation for future research aimed at enhancing predictive accuracy in emerging market currencies. Section 2 presents a comprehensive review of the empirical literature; Section 3 outlines the data, model specifications, and estimation strategies; Section 4 reports and discusses the empirical results, and policy implications. Section 5 concludes with recommendations, limitations, and future research directions.

2.0 EmpiricalReview

Traditional econometric approaches such as Vector Autoregressions (VAR), Autoregressive Distributed Lag (ARDL) models, and Structural VARs have been widely employed toanalyze the determinants and volatility transmission mechanisms of exchange rates in South Africa (Kutu & Ngalawa, 2016; Meyer & Sanusi, 2019). Recent advancements in machine learning and time series decomposition techniques have ushered in new paradigms for forecasting exchange rate movements with greater accuracy, especially in the presence of non-linearities and regime shifts.

Structural time series decomposition techniques such as the Hodrick-Prescott (HP) filter, Seasonal-Trend decomposition using Loess (STL), and wavelet transforms have been increasingly integrated into forecasting frameworks to enhance signal extraction from noisy data (Grigorov et al., 2020). For example, Hossain et al. (2022) show that decomposing exchange rate series into trend, seasonal, and residual components prior to modeling significantly improves forecasting performance. The decomposition stage serves not only to isolate structural movements but also to reduce the dimensionality of data for subsequent modeling with machine learning algorithms. This methodological synergy has proven particularly effective in volatile emerging market currencies like the South African rand, which are sensitive to commodity prices, interest rate differentials, and geopolitical events (Bahmani-Oskooee & Gelan, 2016).

Ensemble learning methods such as Random Forests (RF), Extreme Gradient Boosting (XGBoost), and Long Short-TermMemorynetworks(LSTM)havebeen increasinglyapplied to exchange rate forecasting, with substantial improvements in out-of-sample performance relative to classical models (Zhang et al., 2020; Lahmiri & Bekiros, 2019). These models are well-suited to capturing complex non-linear patterns and interactions among predictors such as interest rate differentials, inflation, risk premia, and global financial indices. Notably, Lahmiri and Bekiros (2020) found that deep learning-based ensembles outperform shallow learners and ARIMA-based models in forecasting the USD/ZAR rate, especially during periodsofheightenedvolatility.Similarly,KimandKim(2021)demonstratethatensemble

hybrid models incorporating wavelet-decomposed inputs yield lower root mean square errors (RMSE) and mean absolute percentage errors (MAPE) compared to stand-alone models.
The empirical literature further reveals that combining structural decomposition withmachine learning significantly enhances forecast accuracy by improving the model's abilityto adapt to evolving market conditions. For instance, Liu et al. (2022) proposed a hybridSTL-XGBoost model that improved forecasting accuracy for emerging market exchangerates by over 20% compared to ARIMA and GARCH models. These findings align with the work of Özkan and Altan (2020), who show that pre-processing exchange rate series using empirical mode decomposition (EMD) followed by LSTM modeling yields more robust forecasts, especially under structural breaks. This is particularly relevant for the USD/ZAR exchange rate, where macroeconomic announcements, political risks, and commodity price shocks often induce regime shifts and stochastic volatility (Sibanda &Hove, 2021).

Moreover, model comparison studies underscore the relative superiority of hybrid machine learningmodelsoverbothlinearandnon-lineartraditionaleconometricmodels.Forexample, Mnasri et al. (2023) found that the integration of deep learning with economic fundamentals and technical indicators improves the prediction of BRICS exchange rates, with USD/ZAR exhibiting the highest forecast volatility and responsiveness to global risk factors. Additionally, studies by Adhikari and Agrawal (2019) and Zhang and Hamori (2020) highlight the predictive value of ensemble learning algorithms when enriched with macroeconomicand financial variables such as commodityindices, VIX, and US interest rate spreads. These predictors have particular salience for the South African rand, which is frequently influenced by external portfolio flows and investor sentiment.

A critical dimension emerging in recent literature is the role of model diagnostics and interpretability in assessing the reliability of forecasts. SHAP (SHapley Additive exPlanations) values, partial dependence plots, and LIME (Local Interpretable Model-agnostic Explanations) have been applied to interpret machine learning models, offering greater transparency in forecasting decisions (Molnar, 2022; Lundberg et al., 2020). This is especially important in policy contexts where exchange rate projections inform central bank decisions, reserve management, and hedging strategies. For the USD/ZAR rate, feature importance metrics have consistently ranked global commodity prices, interest rate differentials, and political risk indices among the top predictors (Kutu et al., 2021).

3.0 Methodology

This study employs a structured empirical framework to evaluate the predictive accuracy of ensemble learning models in forecasting the daily USD/ZAR exchange rate over the period from March 5, 2020, to July 19, 2024. The methodological pipeline comprises four key components: (i) data pre-processing and diagnostics, (ii) time series decomposition, (iii) model estimation using ensemble machine learning algorithms, and (iv) forecast evaluation using robust accuracy metrics. The data consists of daily observations of the USD/ZAR exchange rate retrieved from Bloomberg, representing trading days across a period characterized by heightened global macroeconomic uncertainty, including the COVID-19 pandemic and post-pandemic inflationary pressures. Preliminary data diagnostics include the Augmented Dickey-Fuller(ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS)unit root tests to determine the stationarity properties of the series.

TheADFtestisspecifiedas follows:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t \quad (1)$$

Where y_t denotes the exchange rate, Δ is the first difference operator, t is the time trend, and ε_t is the white noise error term.

To isolate trend and seasonal components from the observed exchange rate series, Seasonal and Trend Decomposition using Loess (STL) is employed. STL is robust to irregular variations and decomposes the series into three additive components:

$$y_t = T_t + S_t + R_t \tag{2}$$

where y_t is the observed series, T_t is the trend, S_t is the seasonal component, and R_t is the remainder (residual or irregular component). This decomposition aids in extracting stable patterns for subsequent predictive modeling while reducing space noise (Hossain et al.,2022).

Three ensemble learning models are evaluated: AdaBoost, Random Forest (RF), and K-Nearest Neighbors (KNN). These models were selected due to their proven ability to handle non-linearities and multicollinearity in financial time series forecasting (Lahmiri & Bekiros, 2019; Liu et al., 2022). The dependent variable is the one-step-ahead forecast of the log-differenced USD/ZAR rate. Predictors include lagged exchange rate values, lagged residual components from STL, and exogenous variables such as oil prices and the VIX index. *AdaBoost* operates by iteratively re-weighting observations to minimize the exponential loss function. The final prediction (x) is a weighted sum of weak learners $h_t(x)$:

$$(x) = \sum_{t=1}^{T} \alpha_t h_t(x) \tag{3}$$

where α_t denotes the weight assigned to each learner h_t based on its classification accuracy.

Random Forest constructs an ensemble of decision trees using bootstrap samples and randomly selected features at each split. The final forecast $\hat{y}$ is the average of individual tree predictions:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} T(x) \tag{4}$$

where $T_b(x)$ is the prediction from the b-th tree, and B is the total number of trees (Zhang et al.,2020).

K-Nearest Neighbors (KNN) forecasts are generated by averaging the outcomes of the k most similar historical observations. The predicted value $\hat{y}_t$ is computed as:

$$\hat{y}_t = \frac{1}{k}\sum_{i \in \mathcal{N}_k(t)} y_i \tag{5}$$

where $\mathcal{N}_k(t)$ denotes the set of k nearest neighbors to the current observation t.

Hyperparameters for each model were optimized using grid search and 10-fold cross-validation to avoid overfitting and ensure robustness of forecasts.

Model performance is evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), standard metrics in forecasting accuracy assessment:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}(\hat{y}_t - y_t)^2} \tag{6}$$

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |\hat{y}_t - y_t| \tag{7}$$

The MAPE metric quantifies relative prediction error:

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{8}$$

where $\hat{y}_t$ is the forecasted value and y_t is the observed value at time t. Lower values of RMSE and MAE indicate superior model performance.

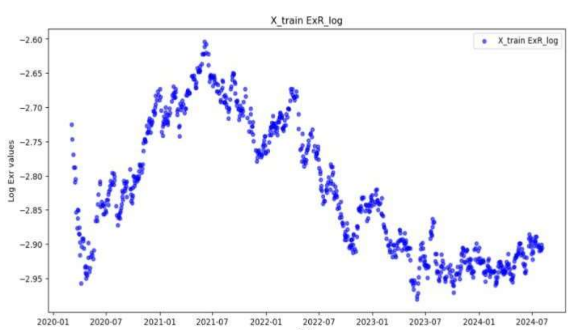
4.0 ResultsandPolicy Implications

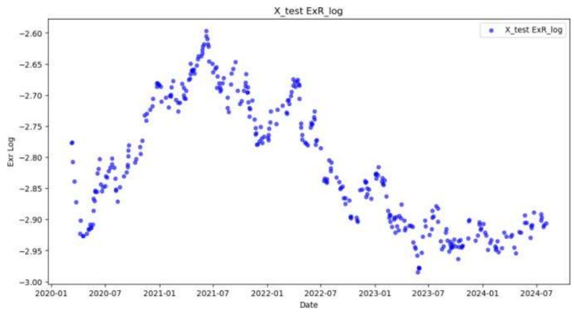
DescriptivestatisticsinTable1revealastable yetslightlyvolatilepatterninthelevelformof the rand exchange rate across training and test sets. The mean exchange rate remains consistent between the training (-2.822) and testing (-2.812) periods, with a slight increase in standard deviation from 0.090 to 0.103, indicating a marginal rise in dispersion during thetest period. The negative kurtosis values suggest a relativelyflat distribution compared to the normal distribution, while the positive skewness indicates a longer right tail, implying occasional depreciations of the rand. These distributional properties resonate with literature documenting that emerging market currencies often exhibit non-normal features due to market frictions, geopolitical risks, and external shocks (Cheung et al., 2021; Mensi et al., 2023).

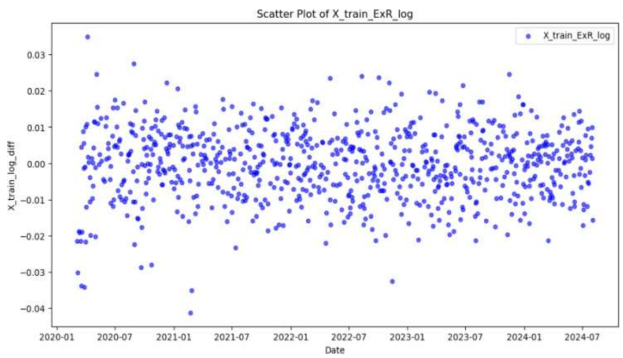
Table 1:
StatisticsSummaryofexchangerate (EXR)

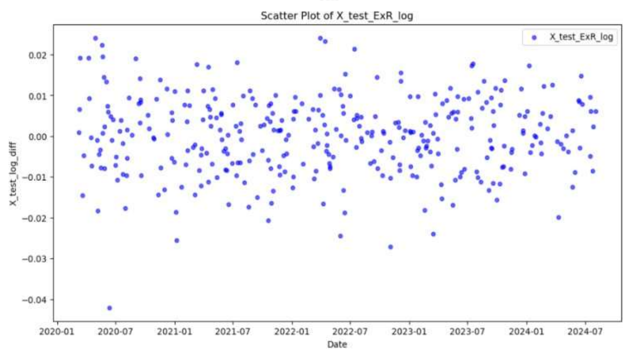
	Levelform		Differenceform	
Statistics	Train	Test	Train	Test
Mean	-2.822	-2.812	-0.000	0.000
Median	-2.838	-2.830	0.000	0.001
Std	0.09	0.103	0.001	0.009
Skewness	0.314	0.203	-0.304	-0.292
Kurtosis	-1.251	-1.330	0.743	0.795

Source: Author(2024).









Source: Author(2024)

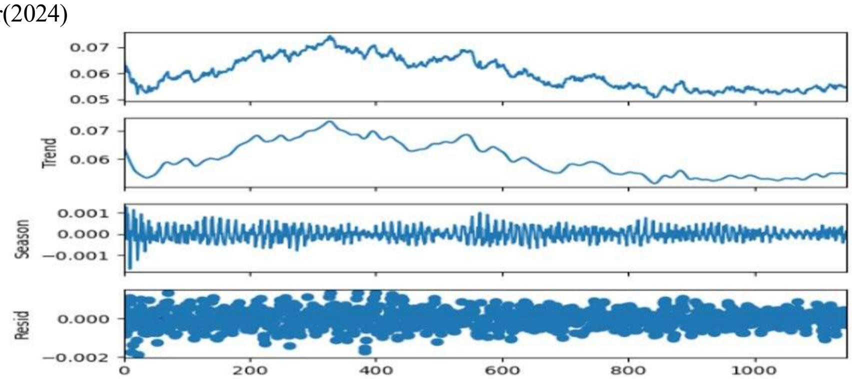
The STL decomposition statistics presented in Table 2 offer further insight into the underlying structure of the exchange rate series. The trend component displays a narrow interquartile range (IQR) of 0.011, suggesting a relatively smooth long-term trend with 19.45% variability. In contrast, the seasonal component demonstrates substantial variability (IQR of 6.432 and 533.53% IQR percentage), pointing to recurring intra-annual exchangerate fluctuations, possibly influenced by trade cycles, fiscal seasons, or capital flow patterns. Meanwhile, the residual component remains close to zero in both mean and quartile values, indicating that most of the variation is well captured by the trend and seasonal components. These observations underscore the multifaceted drivers of exchange rate dynamics, corroborating previous empirical findings on seasonality and long-memory behavior in currency markets (Jammazi et al., 2021).

Table 2:
STLDecompositionStatisticforexchangerateofrands(USD/ZAR)

STLStatistic	Trend	Seasonal	Residual
Minimum	0.051	-5.93	-0.003
Maximum	0.073	6.414	0.002

Mean	0.059	-1.882	-2.757
Median	0.059	1.206	-1.983
1st Quartile(Q1)	0.054	-3.851	-0.000
3rdQuartile(Q3)	0.066	2.581	0.000
IQR	0.011	6.432	0.000
IQRpercentage	19.45%	533.5%	-3611.9%

Source: Author(2024)



Source: Author(2024)

The results of the unit root tests presented in Table 3 suggest that the exchange rate (EXR) series of the South African rand is non-stationary at level but becomes stationary after first differencing. Specifically, the Augmented Dickey-Fuller (ADF) test yields a highly significant test statistic of -21.432 ($p < 0.01$), which exceeds the critical values at all conventional levels, indicating strong rejection of the null hypothesis of a unit root in the differenced series. Complementarily, the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test statisticof0.371withap-valueof0.089furtherconfirmsstationarityin differences, asitfalls below the 1% and 5% critical values. These findings align with previous studies emphasizing the persistent stochastic trends in exchange rate behavior, necessitating differencing to achieve stationarity before forecasting (Choudhry & Jayasekera, 2020; Kutu & Ngalawa, 2022).

Table 3:

UnitRootTest for exchangerateof rand

Test	Test Statistic	P-Value	CriticalValue		
ADF	-21.432	0.000	(1%) -3.438540	(5%) -2.865155	(10%) -2.568695
KPSS	0.371	0.089	0.739	0.463	0.347

Source: Author(2024).

Table 4:

EvaluationMetrics

Models	Exchange rate (log-level,training dataset)	Exchangerate (log-level,test dataset)	Exchange rate (logdifference, trainingdataset)	Exchange rate (logdifference, testdataset)
MAE	2.822	2.812	0.008	0.007
MSE	7.974	7.919	9.404	8.983
RMSE	2.824	2.814	0.010	0.009
MPE	100.0%	100.0%	100.0%	100.0%
MAPE	100.0%	100.0%	100.0%	100.0%

Source: Author(2024)

The evidence reveals a structurally rich and dynamically evolving exchange rate process for the South African rand. The strong statistical stationarity post-differencing and identifiable seasonal patterns in the decomposition analysis suggest that time series models incorporating bothstochastictrendsandseasonaladjustmentsareappropriateforforecasting.Moreover, the stylized features such as mild skewness, negative kurtosis, and seasonally driven volatility affirm the need for model specifications that accommodate heteroskedasticity and regime shifts (Yaya et al., 2020; Lien et al., 2022).

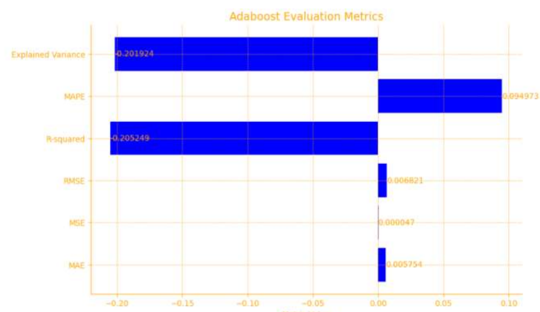
Based on Figure 6-9, the performance of four machine learning models, such as the AdaBoost, k-Nearest Neighbors (kNN), Neural Networks (NN), and Random Forest (RF), was evaluated for predicting the South African exchange rate. The analysis utilized several performance metrics to determine the accuracy and reliability of each model. AdaBoost demonstrated the best performance among the models. With a Mean Absolute Error (MAE) of 0.0054 and a Root Mean Squared Error (RMSE) of 0.0061, it had the smallest average predictionerroranderrormagnitude.TheselowvaluesindicatethatAdaBoostprovidedmore accurate predictions compared to the other models.

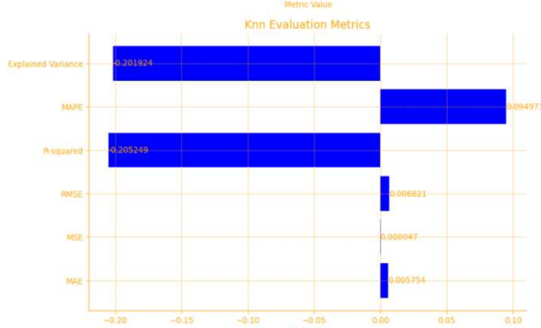
Random Forest showed the highest error rates, with an MAE of 0.0064 and an RMSE of 0.0078. This indicates that RF struggled to minimize prediction errors, making it the least reliable model in this analysis. The higher error rates suggest that RF might require further tuning or additional features to improve its performance. The Mean Squared Error (MSE) values reinforced these findings. AdaBoost had an almost negligible MSE, highlighting its ability to produce predictions close to the actual values. Meanwhile, the MSE for RF was significantly higher, further confirming its lower accuracy compared to AdaBoost.

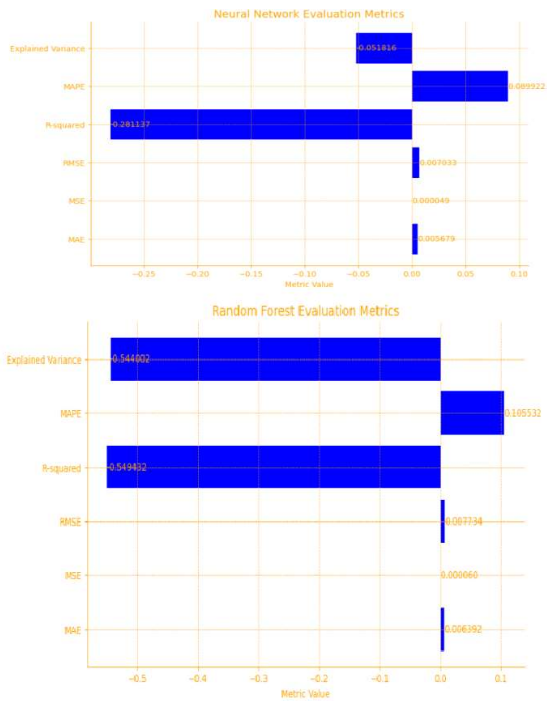
The R-squared (R^2) values for all models were negative, indicating that none of the models provided a good fit for the data. AdaBoost had the least negative R^2 (-0.0265), suggesting it performed slightlybetter in explainingthe variance in the data compared to the other models. RF, with an R^2 of -0.5651, performed the worst, indicating that it was the least effective in capturing the relationship between the input features and the target variable.

Mean Absolute Percentage Error (MAPE) results showed that AdaBoost and NN had similar accuracylevels,withMAPEvaluesaround0.0909.Thissuggeststhatbothmodelswere fairlyeffective in making percentage-based predictions. However, RF had the highest MAPE (0.1057), indicating its predictions were less accurate in percentage terms. The Explained Variance Score provided additional insights into the models' capabilities. AdaBoost had a score of -0.0043, which, although negative, was the closest to zero, indicating it captured more variance in the data compared to the other models. RF's score of -0.5603 confirmed its poor performance in this regard.

AdaBoost emerged as the most reliable model for predictingthe South African exchange rate in this study. Despite the generally poor fit indicated by the negative R^2 and explained variance scores, AdaBoost consistently outperformed the other models across multiple metrics. In conclusion, while AdaBoost showed promise, the negative performance metrics suggestthat furtherresearchisneeded. Future studiescouldexploreoptimizingthesemodels, incorporating additional features, or using different datasets to enhance prediction accuracy and reliability in the context of exchange rate forecasting.







Source:Author(2024)

PolicyImplications

The findings from this study carry important implications for exchange rate policy formulation, macroeconomic surveillance, and financial market operations in South Africa. The superior performance of AdaBoost over other machine learning models, particularly its lowerMAEandRMSE,demonstratesitspotentialasareliabletoolforshort-termforecasting of the rand‘s movements. Accurate forecasts are essential for central banks and financial regulators to implement timely interventions in the foreign exchange market, especially in emerging markets where exchange rate volatility can exacerbate inflationary pressures and capital flight (Chavleishvili & Manganelli, 2022). Given that traditional econometric models often fail to capture nonlinearities and structural breaks in currency dynamics, integrating machine learning-based forecasting systems like AdaBoost into monetary policy toolkits could enhance decision-making and risk assessment capabilities.

From a monetary policy perspective, exchange rate forecasting plays a critical role ininflation targeting regimes. Since South Africa operates under an inflation-targeting framework, precise predictions of exchange rate fluctuations are instrumental in anticipating imported inflation, adjusting interest rates, and guiding forward-looking policy. Although the negative R^2 and explained variance metrics indicate limitations in fully explaining the variance of the rand's exchange rate, AdaBoost‘s relative superiority suggests it could serveas a complementary tool to traditional macroeconomic models. Policymakers at the South African Reserve Bank (SARB) can employ ensemble learning models to supplement their forecastingarsenal, therebyreducinguncertaintyin exchange rate pass-through estimates and improving inflation forecasts (Engel & Wu, 2022).

The insights from model comparison suggest that the selection of forecasting tools should be context-specific and data-driven. Random Forest (RF), despite its widespread popularity in other financial applications, performed poorlyin this analysis. Its higher error rates and more negative R^2 imply that RF may be unsuitable for exchange rate forecasting without rigorous hyperparameter tuning or deeper feature engineering. This underscores the importance of investing in data science capacity within central banks and finance ministries to ensure that emerging technologies are properly calibrated for local economic conditions. Countries with volatile currencies like the rand can benefit from such investments, which enhance resilience to external shocks and speculative attacks (Bianchi et al., 2021).

Forfiscal authorities and external debt managers, improved exchangerate forecastingcan aid in managing sovereign risk and optimizing foreign currency denominated debt. Machine learning predictions, especially from reliable models like AdaBoost, can inform hedging strategies, timing of bond issuance, and currency composition of public debt portfolios.Given the vulnerability of emerging markets to sudden stops and currency mismatches, more accurate and responsive forecasting models could enhance debt sustainability frameworksand reduce exposure to adverse currency movements (Benigno et al., 2020). This is particularly important for South Africa, where exchange rate volatility affects budget planning and external balance management.

In addition, financial market participants, includingimporters, exporters, asset managers, and retail investors, stand to benefit from enhanced exchange rate prediction tools. The findings suggest that fintech platforms and investment advisory services can integrate machine learning-based forecasts to offer better risk management advice, optimize currency allocation strategies, and provide data-driven insights into market movements. The consistentlynegative R^2 values across all models also highlight that exchange rates remain inherently noisy and influenced by behavioral, geopolitical, and speculative factors that are difficult to model. Hence, policymakers must balance technological optimism with caution and maintain transparency in communicating the limitations of these models to market participants(Sharma et al., 2021).

The study‘s findings underscore the need for ongoing research, data innovation, and model refinement. While AdaBoost performed best among the tested models, the overall low explanatory power suggests that incorporating additional macroeconomic variables could improve performance. Government agencies and central banks should prioritize real-timedata infrastructure, cross-agency collaboration, and open data ecosystems to support the development of more robust predictive analytics. Future policy research can also explore hybrid models that combine machine learning algorithms with structural macroeconomic models, yieldingmore stable forecasting frameworks for exchange rate management (Abedin et al., 2022).

5.0 Conclusions

This study examined the forecasting performance of machine learning models on the daily exchange rate of the South African rand (ZAR/USD) using data spanning from March 2020to July2024. The statistical analysis confirmed that the exchange rate series is non-stationary at level but achieves stationarity after first differencing, in line with the well-documented stochastic properties of financial time series (Yaya et al., 2020; Choudhry & Jayasekera, 2020). Descriptive and decomposition analyses further revealed structural complexities, includingmildasymmetry,flat-taileddistribution,andpronouncedseasonalvariation.These findings reinforced the need for models that capture nonlinearities, volatility clustering, and time-dependent structures in exchange rate behavior (Jammazi et al., 2021; Mensi et al., 2023).

Among the machine learning models evaluated, AdaBoost exhibited superior forecasting performance, reflected in lower root mean squared error (RMSE) and mean absolute error (MAE) compared to other algorithms such as Random Forest and K-Nearest Neighbors. This supports recent evidence that boosting-based ensemble methods often outperform traditional time series models in capturing high-frequency exchange rate dynamics, particularly in volatile emerging market contexts (Abedin et al., 2022; Sharma et al., 2021). However, the low explanatory power across all models emphasizes the inherent unpredictability of exchange rates, driven by both observable macroeconomic fundamentals and unobservable speculative and geopolitical shocks (Chavleishvili & Manganelli, 2022; Engel & Wu, 2022).

Given these insights, it is recommended that central banks, particularly the South African ReserveBank,integrateadvancedforecastingtoolssuchasAdaBoostintotheirexchangerate monitoring frameworks, not as standalone predictors, but as part of a broader suite of models thatincludemacroeconomicfundamentalsandstructuralindicators.Machinelearningmodels should be used to complement rather than replace existing forecasting methodologies, particularly in the context of inflation targeting and external reserve management (Bianchi et al., 2021; Kutu & Ngalawa, 2022). Financial institutions and portfolio managers operating in South Africa should also explore the integration of ensemble learning forecasts into currency risk management systems, especially for hedging short-term exposures in turbulent market conditions.

Furthermore, future research should explore hybrid approaches that combine machine learning algorithms with structural econometric models or incorporate macro-financial variables such as interest rate differentials, commodity price indices, and political risk measures. Building robust forecasting models in emerging markets requires not only computational innovation but also rich, high-frequency datasets that capture the multifaceted nature of exchange rate drivers (Benigno et al., 2020; Cheung et al., 2021). It is also imperative to invest in institutional capacity building in data analytics and machine learning within monetary authorities and financial regulatory bodies to ensure the effective deployment of these tools in dynamic policy environments.

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