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Leveraging Machine Learning for Exchange Rate Prediction: Fresh Insights from BRICS Economies

Haseen Ahmed*

New Delhi Institute of Management, New Delhi, India. *Email: ahmedhaseen210@gmail.com

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ABSTRACT

In the background of de dollarisation and continuous uncertainty looming around oil prices, this research assesses how well machine learning-based linear regression models predict currency exchange rates for the BRICS nations using oil prices as a predictive factor. The analysis focuses on evaluating the effectiveness of these models in forecasting exchange rates for these five emerging economies. This study shows that oil prices serve as key indicators for all five currencies examined. The models' performance was evaluated using three statistical measures: MSE, RMSE, and R-Squared. The results suggest that, among the currencies studied, the Chinese Yuan demonstrated the most accurate predictions, as evidenced by its lowest MSE and RMSE values. By contrast, the South African Rand displayed the highest R-squared value, indicating that oil prices had a greater explanatory capacity for exchange rate fluctuations. Nevertheless, the models demonstrate limited predictive power, indicating a disconnection among oil prices and forex rates in these nations. The findings suggest that relying solely on oil prices may not provide accurate exchange rate predictions and that considering additional variables could improve the effectiveness of the models.

Keywords: Foreign Exchange, Financial Markets, Forecasting, Machine Learning, Oil Prices
JEL Classifications: F31, E44, C53, C45, Q43

1. INTRODUCTION

Currencies are exchanged in a worldwide decentralized financial marketplace, known as the currency exchange market. The exchange rate is a crucial factor that affects the international trade and investment of a country and has an influence across markets (Liao, 2020). The exchange rate market is a major financial market in a country and is crucial for its macroeconomic stability (Panda et al., 2020). Exchange rates are linked not only to national macroeconomic control, but also to the international economy. Large-scale fluctuations in the exchange rate can be devastating to the macroeconomic structure and financial market of a country (Cao et al., 2021; Hu et al., 2020; Ahmed et al., 2025).

Globally, numerous studies have examined the connection among Brent crude prices and currency rates, making this a widely investigated topic. Researchers worldwide have explored the interplay between these two economic variables. Akram (2009) indicated that an increase in the US dollar value resulted in a decrease in oil prices. Conversely, Amano and Van Norden (1998) discovered that higher oil prices led to real appreciation of the US dollar. Research has identified three primary mechanisms through which oil prices and currencies are interrelated. The first is the trade channel, which refers to the pathway through which goods and services move across national borders, from producers in one country to consumers or businesses in another. The wealth channel reflects the global movement of capital, assets, and investments, contributing to economic growth, wealth accumulation, and inequality dynamics among nations. The portfolio channel is the flow of financial capital across countries through investments in financial assets such as stocks, bonds, and other securities. (Amano and Van Norden, 1995; Habib et al., 2016; Beckmann and Czudaj, 2013; Ji et al., 2019, Coudert et al., 2008, Bénassy-Quéré et al., 2007). Although research exists, and relationships continue to evolve, the connection between currency values and oil prices remains inconclusive.

Crude oil is the largest trade commodity in the world, and global trade in oil is dominated by the dollar. BRICS has also expanded to include six other countries that contain major oil-exporting countries such as Iran, Saudi Arabia, and the UAE. Given the talks around the BRICS currency and de dollarization across the world, this study examines the role of brent crude oil in estimating currency rates. This study examines the currencies of five BRICS members.

Research examining the potential of oil as an exchange rate indicator for BRICS nations is currently insufficient. This research investigates whether an ML-based regression model utilizing oil as a predictive factor can forecast exchange rates in BRICS nations. This study aims to assess the effectiveness of the ML model in accurately predicting currencies. Research proposes that oil prices serve as a key indicator for predicting exchange rates among the BRICS nations. Sections 2 and 3 review the relevant studies and methodology, respectively. Sections 4 and 5 present the results, findings, and conclusions, respectively.

2. LITERATURE REVIEW

The literature on machine learning has increased significantly in recent years. The rise in research can be attributed to the feature of machine learning to capture the complexity of the interconnection among variables, thereby improving the accuracy of forecasting. This section discusses studies that have used machine learning to forecast various time-series variables, along with evaluation metrics. Furthermore, the findings are discussed.

Among the earliest works on exchange rate prediction, Zhang and Beradi (2001) compared the neural-network-based ensemble model with the single keep-the-best model. The author found the neural network-based model to be a better performer than classical models. He and Shen (2007) use the bootstrap method to forecast currency rates. Bootstrapping combines the outputs of the various models. The study used the neural network as the base model and predicted six major currency rates: Swiss Francs, Japanese Yen, European Euros, Canadian Dollars, British Pounds, and Australian Dollars.

Neural network-based estimation models are prevalent in the literature, in combination with other ML and traditional models. Various variants of models are neural networks that have been used in prediction analysis (Zheng et al., 2019; Fathian and Kia, 2002; Butt et al., 2019; Sreeram and Sayed, 2020; Islam and Hossain, 2021; Pradeepkumar and Ravi, 2018; Wang and Chen, 2021). Choudhry et al. (2012) explore the role of various market microstructures in predicting exchange rates. Based on Artificial Neural Networks, the study found that bid and ask prices are significant in predicting exchange rates. Majhi et al. (2012) applied the “Wilcoxon artificial and functional link artificial neural network (WA&FLANN).” Empirical results indicate that both models are identical in performance; however, owing to low complexity, a functional link neural network is preferred. Khan et al. (2013) proposed the “Cartesian Genetic Programming Evolved Artificial Neural Network (CGPANN)” for estimating currencies. This study found the CGPANN to be highly accurate and cost-effective. The model can be trained using the least amount of data for the prediction. Yuan (2013) proposed a “Polynomial Smooth Support Vector Machine (PSSVM) and predicted China’s exchange rate. The empirical findings indicate that this model is both powerful and effective. Tu et al. (2024) predicted Vietnamese currency rate by using the ARIMA and various ML models. The authors used a random forest and an ANN. Furthermore, the hybrid ARIMA-ANN was also applied to reduce prediction errors. The Random Forest model was found to have a better performance.

Additionally, Plakandaras et al. (2015) built a model for predicting daily prices across five different exchange rates. Authors selected the variables by using the smoothing technique, and applied the SVM, and Neural Networks. The model’s integrated predictive capabilities outperform alternative forecasting approaches. Bhattacharya et al. (2017) examined the fluctuations in currency rates in the BRICS countries. Based on the GARCH, EGARCH, Maximal Lyapunov Exponent and Correlation Dimension test confirms the volatile nature of the currency rates, except in case of Africa. Furthe, the short-term predictability is found to be accurate in comparison to the long-term predictability. Özorhan et al. (2017) applied to genetic algorithms and support vector machine model for forecasting exchange rates. In a study focused on Malaysia, Butt et al. (2019) probed the interconnection among commodity prices and exchange rate forecasting.The authors compare the three-machine learning based models, Random Forest, SVM, and NNs. Authors found the Random Forest to be better in prediction accuracy as compared to the SVM, and NNs. Further, the crude oil, palm oil, gold and rubber are the significant predictors of the Malasiyan exchange rate.

By Zheng et al. (2019), researchers utilized the deep belief network (DBN) model to estimate the currency rates, and compared the DBN model’s predictions for INR/USD and CNY/USD with those generated by the feedforward neural network (FFNN) model. The study found the DBN model be better predictor of exchange rates. Das et al. (2018) built a Kernel Extreme Learning Machine (KELM) to forecast the model. A study by Sun et al. (2018) evaluated the accuracy of the ANN and LS-SVM models in predicting performance. On the analysis of empirical results, LS-SVM is found to be better in comparison. Pradeepkumar and Ravi (2018) reviewed the computing hybrids methods to estimate forex rates. The study concluded that ANN based models are more prevalent and powerful. Fathian and Kia (2002) predicted the exchange rate of Euro, British Pound, and Yen, by applying the multilayer perceptron neural network. The study used the gold as the predictor. Panda et al. (2020) reviewed the studies forecasting the exchange rate by using the ANN and deep learning. The study found the new proposed models, and also models for forecasting which considered systematic procedure and theoretical support in making new models.

Yilmaz and Arabaci (2020) applied the ten machine learning models, and two forecasting models in the prediction of Canadian Dollar, British Pound and Australian Dollar. The study used the model confidence set to examine the forecasting performance of the models, and found the ARIMA-LSTM hybrid Model to be better performer. Sreeram and Sayed (2020) investigated the short-term forecasting ability of hybrid models in BRIC countries. The study employs automatic hybrid model, residual hybrid model, and least square support vector machine. The study found the residual hybrid model framework, ARIMA-ANN model to be higher in accuracy. Further, the higher accuracy was observed in case of China. Higher accuracy was also found in case of Brazil, India and Russia, though less than China. Wang and Chen (2021) proposed the Ada-boost based reinforcement ensemble learning framework combining deep learning models with two-stage feature extraction. To simplify the model, variable selection is done to extract the features, by using the Auto-encoder, and self-organizing map. The combination of Deep Recurrent Neural Network (DRNN) and Ada-boost provide high accuracy in exchange rate prediction.

LSTM, a type of deep learning architecture, has also been employed for exchange rate forecasting. Islam and Hossain (2021) proposed an ensemble model of LSTM and GRU to forecast the currencies. The study used the Euro, British Pound, Canadian Dollar, and Franc. The MAE, MSE, RMSE, and R-square is used to evaluate the model. The author compared the combined model with the standalone simple moving average, LSTM and GRU model. In terms of R-square, the proposed model's performance was found to be better. Abedin et al. (2021) combined the Bagging Ridge (BR) regression and the Bi-Directional LSTM network as regressor to predict the 21 currencies during the COVID-19. The Bi-LSTM BR model worked better in comparison to the other traditional machine learning models. The study found the varied prediction accuracy during pandemic of COVID-19, and normal period across the forex rates. Rabbi et al. (2022) predicts the currency exchange rate of twenty-two countries. The study used SVM, Random Forest, and deep learning model (LSTM) model. Using the evaluation matrix of MAE, MSE, RMSE, and MAPE. Findings indicate the high accuracy of all the models, but the LSTM shows better accuracy than others. Dautel et al. (2020) explored the deep learning techniques in predicting the exchange rate. The authors compared the two deep learning techniques, LSTM network and the GRU architecture. The models were found to be suitable for prediction, however the implementing and tuning is found to be the difficult.

There are various variables which are used as predictor in exchange rate prediction. Choudhry et al. (2012) used the market microstructure variables, whereas Ramakrishnan et al. (2017) used the commodity prices to predict the Malaysian exchange rates. Similarly, Butt et al. (2019) predicted the Malaysian exchange rate, using the commodity prices as predictor. The study applied the ANN, Random Forest, and SVM. The results showed that random forest outperformed both the ANN and SVM in terms of accuracy. Goncu (2019) predicted the average monthly exchange rate of Turkish Lira, by using the linear regression, ridge regression, decision tree, SVM. The predictors used in the study were previous month's average forex rate, federal rates of USA, real interest rate and domestic money supply. The results found the Ridge regression to be most accurate in estimation. Filippou et al. (2020) developed the model for predictability of monthly forex rate on the basis of 70 predictors. The predictors captured the country characteristics, worldwide variables, and interaction among them.

After examining the aforementioned studies, it becomes evident that deep learning algorithms, particularly neural networks and LSTM models, are the predominant methods used for predicting exchange rates. Nevertheless, machine learning techniques are utilized in conjunction with conventional approaches. Additionally, MSE, RMSE, and R-Square are commonly employed evaluation metrics. However, various studies have utilized different variables in predicting exchange rates. Few studies have utilized oil as a predictive variable. Considering the unpredictable, nonlinear, and intricate nature of Brent crude oil prices, this study gains significance in light of several factors. These include the ongoing process of de-dollarization, the potential introduction of a BRICS currency in the future, and the expansion of the BRICS alliance. This research investigates how oil impacts currency exchange rates in BRICS nations, addressing a gap in existing literature. The research's outcomes are groundbreaking and offer valuable insights for both investors and policymakers.

3. METHODOLOGY AND DATA

3.1. Linear Regression

In machine learning, linear regression is a cornerstone for continuous prediction tasks. This supervised learning method discovers the connection among a target variable and one or more influencing variables. Linear regression seeks the straight line that most closely aligns with this overall trend. Various studies have applied the machine learning based linear regression in forecasting the oil prices (Guliyev and Mustafayev, 2022; Jahanshahi et al., 2022; Boussatta et al., 2023; Sulaiman et al., 2023).

The model learns from a dataset where the independent variables (inputs) and their corresponding dependent variable values (outputs) are trained. This training helps the model discover the ideal coefficients for the straight-line equation that best captures the trend in the data. After completing the training process, the model becomes capable of generating predictions for entirely new, unseen data points. By feeding the values of the independent variables for a new instance, the model can estimate the corresponding dependent variable value based on the learned relationship between them. The linear regression equation can be written as -

$$y_i = \theta_1 + \theta_2 x_i \tag{1}$$

Where y_i are the predicted values, whereas x_i are the independent input variable which is trained. θ_1 and θ_2 are the intercept and the coefficient of x_i respectively. To find the best fit regression line, the difference between the y_i, and x_i should be minimum.

3.2. Evaluation Metrices

MSE, RMSE, and the R-squared are the common evaluation techniques of model. These metrics provide a valuable toolbox for assessing model performance. The MSE, can be written as

MSE is calculated as –

$$MSE = \frac{1}{n}\sum_{n}^{i}(\hat{y}_i - y_i)^2 \tag{2}$$

J is the loss function, Where, $\hat{y}_i$ is predicted value, and y_i are the actual values. Whereas, the formula for

RMSE can be written as –

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{n}^{i}(\hat{y}_i - y_i)^2} \tag{3}$$

and R-Square formula is

$$\text{R} - \text{squared} = \frac{(\hat{y}_i - \bar{y})^2}{(y_i - \bar{y})^2} \tag{4}$$

Where $\bar{y}$ is the mean value of the actual values.

3.3. Data

The study employs the data of forex rate of 5 BRICS countries and crude oil prices. The data ranges from March 2013 to February 2024. The five currencies are India, China, Brazil, Russia and South Africa, and are denoted by INR, CNY, BLR, RUBLE, and ZAR respectively. The descriptive statistics calculated from the transformed data. The data transformation is done by doing first differentiation and taking log of resultant data.

Table 1 show the descriptive statistics. Mean values represent the average returns of exchange rates over the period considered, which is highest in case of BLR (Brazilian Real). The exchange rates' variability or dispersion is quantified by the standard deviation. BLR has the highest variation, while INR has the lowest. As per Table 1, INR, CNY, RUBLE, ZAR are positively skewed, whereas BLR is negatively skewed. INR, CNY, and BLR show the platykurtic, Ruble is leptokurtic, whereas ZAR mesokurtic. Oil prices are highly leptokurtic.

4. RESULTS AND FINDINGS

Table 2 shows the linear regression coefficients of five BRICS currencies. Beginning with the coefficients for the Indian Rupee, indicates that the y-intercept is 75.020. This means that when the oil variable equals zero, the estimated value of the dependent variable is 75.020. The standard error of 0.2792 is very low, indicating a high level of precision in this estimate. The T value of 268.61 is extremely high, suggesting the intercept is significantly different from zero. The estimate for oil is −0.118423, indicating every unit increase in oil the dependent variable decreases by approximately 0.118423 units. The standard error of 0.0033986 is very low, suggesting a precise estimate of the coefficient. The T value of −29.71 is large in magnitude and negative, indicating that oil is a strong and statistically significant predictor of the dependent variable. The model's explanatory power, as indicated by the multiple R-squared value, accounts for roughly 27.95% of the variation in the dependent variable. This suggests a moderate level of fit, implying that while oil serves as a significant predictor, the model likely omits other crucial variables that could further

Table 1: Descriptive statistics

	Oil	INR	CNY	BLR	RUBLE	ZAR
Mean	0.0619	0.0613	0.2857	0.3428	0.0696	0.1901
Median	0.0615	0.0616	0.2858	0.3492	0.0649	0.1864
Maximum	0.2875	0.0749	0.2978	0.3871	0.0749	0.2533
Minimum	0.0357	0.0530	0.2700	0.2977	0.0339	0.1503
Standard deviation	0.0190	0.0050	0.0070	0.2074	0.0169	0.0225
Skewness	2.1274	0.2243	-0.0888	-0.4224	1.3259	0.5487
Kurtosis	15.023	2.6351	1.8446	1.6892	3.7199	2.7354

Source: Author's work

Table 2: Predictor coefficients of currencies

	Indian Rupee			
	Estimate	**Standard Error**	**T-value**	**Pr(>|t|)**
Intercept	75.020	0.2792	268.61	<2e-16***
Oil	−0.118423	0.0033986	−29.71	<2e-16***
R-squared	0.2795			
Adjusted R-Squared	0.2791			
F Statistics	882.8			
P-value	<2.2e-16			
	Chinese Yuan			
Intercept	**7.128714**	**0.015988**	**445.87**	**<2e-16*** **
Oil	−0.008720	0.0007695	−38.33	<2e-16***
R-squared	0.3909			
Adjusted R-Squared	0.3906			
F Statistics	1461			
P-value	<2.2e-16			
	Brazilian Real			
	Estimate	**Standard Error**	**T-value**	**Pr(>|t|)**
Intercept	7.128714	0.015988	445.87	<2e-16***
Oil	−0.008720	0.0007695	−38.33	<2e-16***
R-squared	0.3909			
Adjusted R-Squared	0.3906			
F Statistics	1461			
P-value	<2.2e-16			
	Russian Ruble			
	Estimate	**Standard Error**	**T-value**	**Pr(>|t|)**
Intercept	91.38386	0.539199	169.48	<2e-16***
Oil	−0.482408	0.0007695	−62.69	<2e-16***
R-squared	0.6333			
Adjusted R-Squared	0.6331			
F Statistics	3930			
P-value	<2.2e-16			
	S. African Rand			
	Estimate	**Standard Error**	**T-value**	**Pr(>|t|)**
Intercept	18.00734	0.085319	211.06	<2e-16***
Oil	−0.069127	0.001218	−56.77	<2e-16***
R-squared	0.5861			
Adjusted R-Squared	0.5859			
F Statistics	3223			
P-value	<2.2e-16			

Source: Author's Compilation

explain the dependent variable. The F statistic tests the overall significance of the model. A value of 882.8 indicates that the model is statistically significant overall. Further, the low P-values of oil estimate, indicate that oil is significant predictor of BRICS currencies.

It can be seen in the Figure 1 that observed and predicted value of INR is closer in the initial period of test data. The early period corresponds to the gradual opening of the global economy after the prolonged lockdown due to COVID-19. This duration is also marked by the Russian-Ukraine conflict. Though the observed and forecasted values follow the similar trends, the distance is high, and increasing continuously. The predictiveness of Indian rupee is not impacted by the Israel – Hamas conflict. However, as shown in the Figure 2, the Brazilian real shows the opposite trend, the actual and forecasted values move closer over the time. The observed and forecasted values are volatile during the Russia-Ukraine conflict, but follow the similar trend nonetheless. There is decline in the distance between the forecasted and observed values during the conflict between the Israel and Hamas.

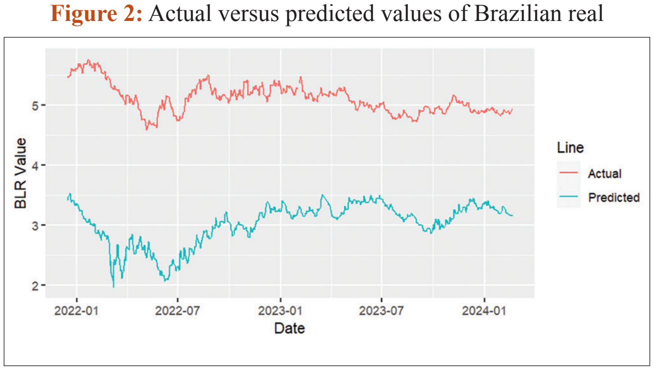
As shown in the Figure 3, the actual and predicted values of Brazilian Real intersect with each other in the early period of test data. The values intersect with each other. The trend between the actual and forecasted values not similar. The values come closer during the beginning of Israel-Hamas conflict, but the distance widens among the actual and predicted.

As shown in Figure 4, the observed and forecasted values between of the Russian Ruble shows an irregular pattern. The distance

Figure 1: Actual versus predicted values of Indian rupee

Source: Author's compilation

Figure 2: Actual versus predicted values of Brazilian real



Source: Author's compilation

among the observed and forecasted values is high at the time of onset of Russian Invasion of Ukraine. But the actual and forecasted values are significantly closer to each other, and remained close to each other for more than half year. The trained values are significantly closer to each other. However, both moves apart from each other. The gap between the values widens during the conflict of Israel and Hamas. Further, as shown in the Figure 5, the predicted and actual values follow a similar trend, though there is distance between the actual and the predicted values. No impact of any crisis is observed on the predictability of the Rand of South Africa.

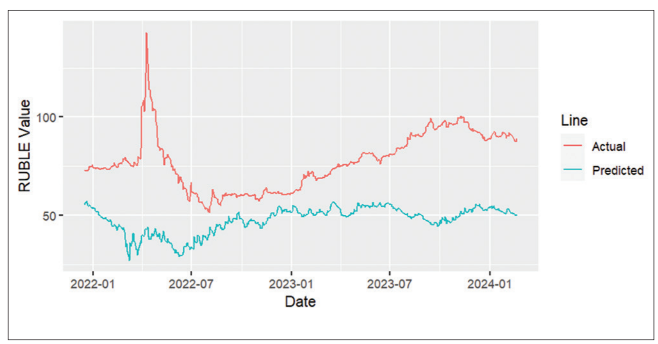
4.1. Evaluation Metrices

The evaluation metrics (Table 3) for the linear regression-based machine learning model reveal distinct differences in how effectively the model predicts the values of various currencies,

Figure 3: Actual versus predicted values of Chinese yuan

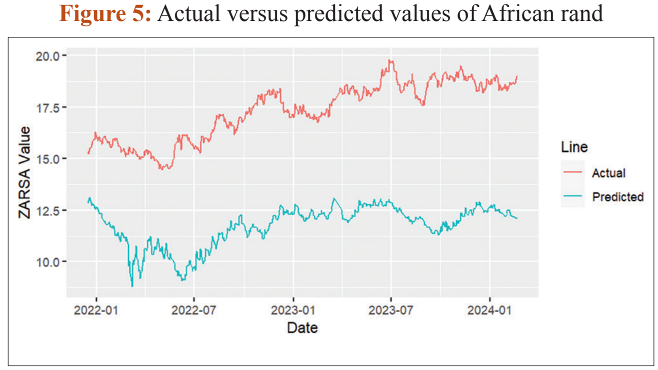
Source: Author's compilation

Figure 4: Actual versus predicted values of Russian ruble



Source: Author's compilation

Figure 5: Actual versus predicted values of African rand



Source: Author's compilation

Table 3: Evaluation metrix

Metrics	INR	CNY	BLR	RUBLE	ZAR
MSE	261.5153	0.3709039	40.31978	1100.661	32.33721
RMSE	16.17143	0.6090188	4.763488	33.17621	5.686582
R-Squared	0.4117973	0.2725725	0.408134	0.02408107	0.4586906

Source: Author's work

as measured by key performance indicators such as R-squared (R^2) MSE, and RMSE.

In case of South African Rand (ZAR), the model achieves the highest R^2 value among all the currencies analyzed. The R^2 suggest that the model explains 45.87% of the variance in the ZAR's value, suggesting that the model captures nearly half of the factors influencing this currency's fluctuations. This relatively high R^2 value is a sign of a good fit, meaning the model can reasonably predict changes in the ZAR. However, while the fit is strong, the prediction errors—reflected in the MSE of 32.34 and RMSE of 5.69—are moderate. These values suggest that while the model performs well in capturing the trends in the ZAR, there is still a notable level of error in the predictions, which could be due to factors not included in the model or inherent volatility in the currency.

In contrast, the Russian Ruble (RUBLE) presents the most significant challenge for the model. The R^2 value for the Ruble is extremely low at just 0.02, which means that the model only accounts for about 2.4% of the variance in the Ruble's value. This near-zero R^2 suggests that the model is almost entirely ineffective at capturing the factors driving changes in the Ruble, indicating a poor fit. The prediction errors further illustrate this issue, with an MSE of 1100.66 and an RMSE of 33.18—both of which are the highest among the currencies evaluated. Such high error metrics suggest that the model's predictions for the Ruble are far off from the actual values, highlighting the Ruble's unpredictability or the inadequacy of the model's structure for this particular currency.

In Chinese Yuan (CNY, different scenario can be observed. The CNY has the lowest MSE (0.37) and RMSE (0.61) of all the currencies, indicating that the model's predictions are very close to the actual values. These low error values suggest that the model is highly accurate in forecasting the Yuan, with only minimal deviations between predicted and actual values. However, despite this accuracy, the R^2 value for CNY is relatively low at 0.27, indicating that while the model's predictions are close to reality, it does not explain a large portion of the variance in the Yuan's value. This could imply that the model is good at short-term predictions but misses out on capturing some underlying factors that influence the currency's broader trends.

The Brazilian Real (BLR) and the Indian Rupee (INR) both fall into a middle ground between the ZAR and RUBLE. For the BLR, the model has an R^2 of 0.41, indicating a moderate fit, with about 40.81% of the variance explained by the model. The prediction errors, with an MSE of 40.32 and an RMSE of 4.76, suggest that while the model captures some of the factors influencing the BLR, there is still a significant margin of error. Similarly, for the INR, the model explains 41.18% of the variance, as reflected by its R^2 value of 0.41, with prediction errors marked by an MSE of 261.52 and an RMSE of 16.17. These metrics indicate a moderate fit and prediction accuracy, suggesting that the model can reasonably forecast the INR but not with high precision.

The model's performance varies significantly across the five currencies, showcasing its strengths and weaknesses in different contexts. The South African Rand (ZAR) represents the best overall fit, with the highest R^2 indicating a strong understanding of the factors influencing this currency, though with moderate prediction errors. The Chinese Yuan (CNY) shows the highest predictive accuracy with the lowest errors, even though its R^2 suggests that the model does not capture all the underlying variance. The Russian Ruble (RUBLE), on the other hand, represents the model's most significant challenge, with very high prediction errors and a low R^2, indicating poor predictive power. The Brazilian Real (BLR) and Indian Rupee (INR) show moderate performance, with a reasonable balance between fit and accuracy but still leaving room for improvement. This analysis highlights the importance of understanding the unique characteristics of each currency and the need for possibly refining or adapting the model to better predict those with more complex or volatile patterns.

5. CONCLUSION

This study investigates and assesses various machine learning-based linear regression models for predicting exchange rates using brent crude prices as a predictor across the five BRICS. The research aims to understand how crude oil influence the exchange rates of these nations, given their diverse economic structures and dependency on oil. The analysis reveals that oil prices are indeed a significant predictor for the exchange rates of all five BRICS currencies. However, the strength of this relationship and the predictive power of the models vary across different countries. The evaluation metrics used to measure the performance of these models include MSE, RMSE, and the R-squared value. The findings reveal that, among the five currencies, the prediction accuracy for the Chinese Yuan is the highest. This is indicated by the lowest MSE and RMSE values, suggesting that the model is better at predicting exchange rate movements for China than for the other BRICS countries. A lower MSE and RMSE imply that the model's estimated values are closer to the observed values, hence more accurate. The MSE and RMSE values suggest that the model function best for the Chinese Yuan, the R-squared value is highest for the South African Rand. The R-squared value quantifies the portion of the variance in the exchange rate that is accounted for by changes in oil prices. The high R-squared value for the Rand suggests that brent oil prices explain a larger portion of the forex rate fluctuations in South Africa than in the other countries. Despite oil prices being a significant predictor for exchange rates in all five countries, the overall predictive accuracy and explanatory power of the models are not particularly strong. This outcome suggests that the interlinkages among brent crude prices and forex rates is complex and possibly weakening, indicating a decoupling between oil and studied currencies. Such decoupling could be due to various factors, including the diversification of economies, different levels of dependency on oil, and the influence of other macroeconomic variables. As a result, while oil prices remain an important factor, they do not cover the dynamics of currency movements in the BRICS countries.

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