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| RESEARCH ARTICLE

Comparative Analysis of Currency Exchange and Stock Markets in BRICS Using Machine Learning to Forecast Optimal Trends for Data-Driven Decision Making

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| ABSTRACT

The BRICS nations' economies show that the countries are global financial powerhouses whose currency exchange rates and stock markets have influence globally. In this paper, the analysis of the forecast trends in both Currency Exchange and Stock Markets using a dual layered machine learning approach exposing models such as Long Short Term Memory (LSTM), Random Forest, Gradient Boosting and Support vector machines (SVM) is conducted. Their performance is tested twice, first on currency exchange and then on stock market data, to compare them on the basis of predictive power to deliver actionable insights. Each model is applied to currency and stock market data, separately, as the study mainly uses extensive historical datasets from BRICS economies. Benchmarking is done using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and R-squared values. For currency exchange, LSTM turned out to be the most effective model as it can handle a sequence of time series data. The best performance for stock market forecasting was achieved by Gradient Boosting, which is adept at finding complex nonlinear relationships. Random Forest proved to be consistent across both Datasets but SVM was found to be challenged on Scalability and Data Complexity, with relatively lower accuracy. The research goes on to repeat the comparative analysis for each of the different models, to illustrate the subtle differences between machine learning techniques in their capacity to effectively process financial datasets of all varieties. Predictive accuracy and reliability is further enhanced to reconcile conflicting trends between currency and stock markets by creating an ensemble model of all algorithms. These findings provide a robust framework for informed decision making for stakeholders to identify the more stable and hence more profitable market in the BRICS context. The results of this study add to the expansion of application of machine learning to global finance by demonstrating how tailored algorithms can offer significant economic planning and investment strategy plans.

| KEYWORDS

BRICS Economies, Machine Learning Forecasting, Currency Exchange Prediction, Stock Market Analysis, Ensemble Modeling, LSTM, Gradient Boosting, Financial Data Analysis, Macroeconomic Indicators, Predictive Accuracy.

| ARTICLE INFORMATION

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1. Introduction

1.1 Background

Brazil, Russia, India, China and South Africa as the BRICS nations are regarded as economic emerging powerhouses (Mottet, 2013). Together these countries make up a great deal of global GDP and trade and affect the stability of the entire international economic system. Their economic, particularly exchange rate of their currency and stock indices, are important factor of global economic trends. Currency exchange rates are a signal of how strong economies are for international trade and investing, whilst stock market performance can tell investors how confident they are, how healthy a corporate is and how likely it is of economic growth (Fraj et al., 2018). As BRICS countries show peculiar patterns of volatility and growth, these financial systems are critical areas to be analyzed and forecasted, due to their dynamic tension between them.

1.2 Importance

Forecasting trends of currency exchange and stock markets is critical for informed investment, political and financial decisions by investors, policy makers, and financial agencies. Fluctuations in these metrics can reverberate across the global economy, and affect not only national economic policies, but cross border investments as well (Siegel, 2021). Accurate prediction of these trends empowers stakeholders to mitigate risk and take advantage of these opportunities, and without financial forecasting, a plan or strategy would be impossible to foresee. Being especially critical for the predictive models applied in the BRICS economies as characterized by pronounced economic disparities and evolving market structures, the uncertainties associated with the emerging markets have to be answered.

1.3 Problem Statement

Although machine learning (ML) has been widely applied in financial forecasting, the use and comparison of many ML models over various financial datasets in the context of BRICS countries has rarely been studied (Ataman & Kahraman, 2022). Most of the existing approaches have focused on one currency exchange rate and at the same time stock market trends but not both jointly. Furthermore, many studies do not address the unique challenges of the modeling of financial data which are nonlinearity, seasonality, and interdependency (Oikonomou et al., 2022). A lack of a strong framework that combines insights from both domains prevents stakeholders from making data driven decisions with a view to the inter-relationship of these financial indicators.

1.4 Objectives

This study attempts to fill the gap by using a dual layered approach of analysis and forecast of currency exchange rates and stock markets in BRICS economies. Specifically, it seeks to:

1. Compare the performance of the advanced ML models, Long Short Term Memory (LSTM), Random Forest, Gradient Boosting and Support Vector Machines (SVM) in both financial contexts.

2. Decide which model to use to deal with large, complex, and structured datasets.

3. The study seeks to create a hybrid model that can reconcile currency and stock market predictions to make more accurate and reliable forecasts.

4. Provide much needed actionable insights for economic planning, investment strategies, and the formulation of policy, contextualized to the BRICS economies.

1.5 Advantages of the Study

This work provides insight into an emerging area of ML in finance, where tailored algorithms improve prediction accuracy and reliability. The research focuses on BRICS economies, where it shows the applicability of these methods in emerging markets which frequently exhibit data irregularities and market volatility. Furthermore, the duality of the approach helps better understand the overall financial trends among the stakeholders and thus identify the more stable and potential profitable opportunities. Ensemble modeling is then integrated to further refine the forecast which provides a novel methodology for reconciling conflicting signals in financial data.

1.6 Challenges

The challenge with doing predictive analysis in the BRICS context is that the heterogeneity of these economies, from China's highly industrialized market to South Africa's resource driven economy, complicates data standardization as well as model applicability (Li et al., 2018). Preprocessing and feature engineering is of critical importance to financial datasets which is often noisy, incomplete or inconsistent. Additionally, while ML models are great at uncovering patterns, scalability, overfitting, interpretability concerns all become stumbling blocks in their effectiveness. To address these challenges, these problems cannot be solved without carefully experimenting, robustly validating techniques, and developing novel modeling strategies to ensure findings are accurate and actionable.

2. Literature Review

2.1. Financial Forecasting in BRICS Economies

2.1.1 Key Studies on Currency Exchange and Stock Market Forecasting

The last few years have observed considerable interest in financial forecasting of BRICS economies, whose economies are inherently dynamic. Both forex and stock prices have been predicted using deep learning models, which Hu, Zhao, and Khushi (2021) have discussed in their paper. One of their points is that these models are good at dealing with non linearities and large datasets, common qualities of BRICS financial markets. Most importantly, the researchers found that the inclusion of macroeconomic indicators increases forecasting accuracy, especially in developing economies where traditional approaches are less well suited to variable environments.

Bustos and Pomares-Quimbaya (2020) make use of this foundation and systematically review stock market movement forecasting. According to their study, the rapid adoption of machine learning techniques over traditional application statistical methods are more effective in grasping the complexities of the market. According to them, machine learning models that can quickly adapt to change are important for BRICS economies, economies with high levels of market volatility.

In Bulut (2018), an alternative exchange rate forecasting approach to that seen in the literature is proposed which is utilizing data gained from Google Trends. The results of this study showed how such unconventional data sources can fill some of the information 'void' around macroeconomic variables, in particular in countries like BRICS where timely data is scarce. The emerging markets addressed with the prediction of exchange rate movements in their prediction task were facilitated by the innovative use of real time data from Google Trends to show the potential for technology driven methods on data limitations in these markets.

2.1.2 Role of Macroeconomic Indicators in Financial Predictions

The financial trends are a function of certain macrometric indicators, such as growth rate of GDP, inflation rate, and interest rate. According to Issah and Antwi (2017), these indicators provide a means of evaluating the actual performance of the firm, and hence its effect on stock market behavior. Firms' financial health were found to be directly linked to these indicators and also found to be directly driven by macroeconomic environment implying that these indicators must be incorporated in forecasting models.

Macroeconomic forecasting using deep neural networks was further explored by Smalter Hall and Cook (2017), who used macroeconomic indicators to see how well the models predicted the market. Their study showed that deep learning models offer greater performance than traditional techniques in modeling of high dimensional variables, when the relations between variables are complex. The insights presented in this paper are especially relevant for BRICS economies where the linkages between macro and financial market variables are intricate and dynamic.

Table 1: Summary of the macroeconomic indicators for BRICS economies

Country	**GDP Growth (%)**	**Inflation Rate (%)**	**Interest Rate (%)**
Brazil	2.3	3.7	4.5
Russia	1.8	4.2	5.0
India	6.1	5.5	6.0
China	6.8	2.4	3.0
South Africa	1.3	4.6	6.5

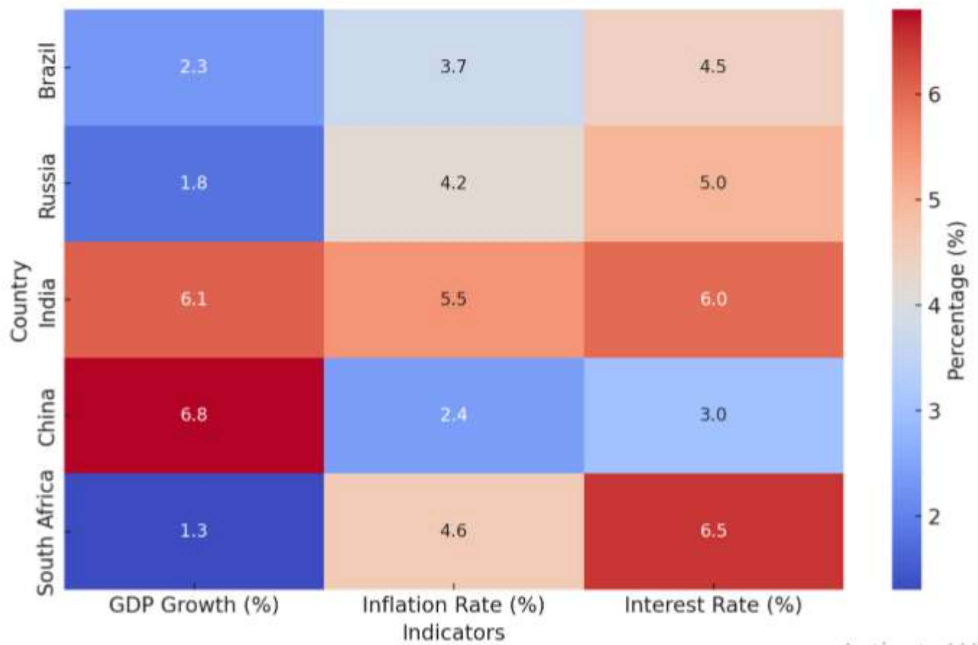

Figure 1: A heatmap comparing key macroeconomic indicators (e.g., GDP growth, inflation rates, interest rates) across BRICS economies, highlighting the variation and trends critical for financial forecasting.

2.2. Machine Learning in Finance

2.2.1 Overview of LSTM, Random Forest, Gradient Boosting, SVM, and Ensemble Methods

Robust models that are applicable to financial data have revolutionized Machine Learning in financial forecasting. In this new study, Mohapatra et al (2023) propose a hybrid ensemble model consisting of a Gradient Boosting machine and LSTM model for stock market prediction. The study of this hybrid approach showed that it achieves better accuracy than standalone models, and is particularly apt for volatile, nonlinear datasets like those of BRICS economies.

In the comprehensive review of machine learning and deep learning model in stock market forecasting, Sonkavde et al. (2023) revealed the previous studies regarding the application of machine learning and deep learning models, and the comparison of predictive performance with other forecasting models. In particular, they emphasized that models such as Random Forest and Gradient Boosting are proficient at finding nonlinear relationships, whilst LSTM performs well in dealing with sequential patterns in time series data. And then the researchers pointed out that model selection based on the characteristics of the dataset is needed, as different models have different strengths and weaknesses.

Additionally, Nabipour et al. (2020) involved the use of deep learning techniques such as LSTM in stock market prediction specifically. According to their findings, deep learning models are more suitable when dealing with high dimensional and noisy datasets, as is the case with BRICS markets.

2.2.2 Limitations of Traditional Statistical Methods vs. Machine Learning Techniques

Although machine learning has had progress in finance, traditional statistical methods continue to dominate in financial forecasting. In his paper Khedr et al. (2021) compare traditional statistical methods with machine learning models in the prediction of the cryptocurrency price. Statistical methods work well in small, structured datasets, but suffer on the complexities of the large, unstructured data that are common to financial markets, they found. In BRICS economies in particular, the reliance on machine learning becomes even more widespread due to the incomplete nature and volatility of the financial data.

Chatzis et al. (2018) applies this comparison, assessing the performance of machine learning model in stock market crisis prediction. Their study found that machine learning techniques are more useful at detecting early warning signs since they can uncover undetected patterns in financial data that conventional models may fail to see. This capability is of prime importance for BRICS economies characterized by sudden market disruptions.

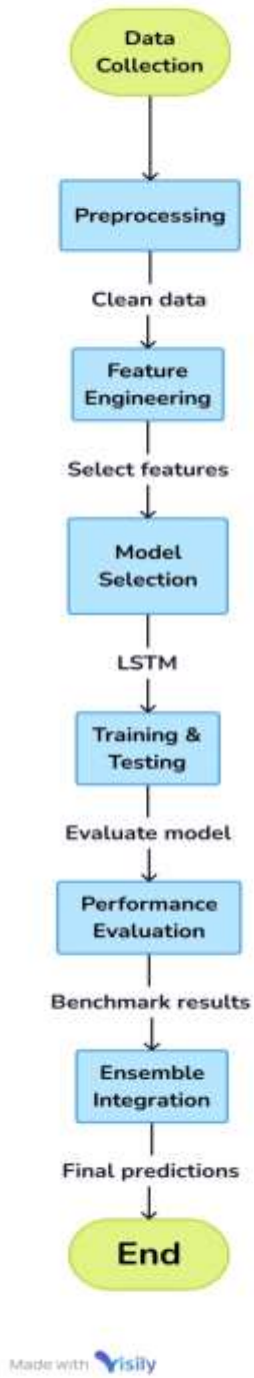

Figure 2: The flowchart above outlines the steps in applying machine learning models to financial forecasting, from data preprocessing to model evaluation and optimization

2.3. Gaps in Existing Research

2.3.1 Lack of Comparative Studies Focusing on BRICS Economies

While machine learning application to finance forecasting has enlarged, there exist few comparative studies on BRICS economies. In Nasir et al. (2018) they follow the study of oil price shocks on BRICS nations with a view of their unique response to global economic events. The study emphasized the necessity of region specific research taking into account the peculiarities of economic relations and structures in BRICS countries.

In Moch (2024), geopolitical and economic importance of BRICS nations in relation to their money system are discussed according to the global perspective they have. The study, however, noted a lack of comparative analyses that combine the various financial indicators, ranging from the exchange rate for a specific currency to stock market indices. As Upadhyaya and Rajasekharan Pillai (2019) also identify, this gap already exists, in that there is often research on individual countries, but rarely on the group as a whole.

2.3.2 Limited Insights into Dual-Layered Forecasting for Currency Exchange and Stock Markets

The final gap that is not covered by current research is the lack of dual layer forecasting which involves currency exchange and stock market outlook and the lack of a model that can identify when and where one trend is taking precedence over the other. To supply more holistic predictions, Deep (2024) introduced a novel framework, that unifies Monte Carlo simulations and ensemble machine learning models. In this way, conflicting trends can be reconciled and the multiple sides of financial market can be cohered.

Based on this, Han et al. (2024) proposed the advanced series decomposition techniques using the combination of gated recurrent units and the graph convolutional neural network. In particular, these methods deal with the non-stationary data patterns found in BRICS economies. Results point to the promise of using advanced machine learning techniques in combination with more routine methods of forecasting to increase accuracy and reliability.

Table 2: Summary of topics discussed in the literature review

Author(s)	**Topic Discussed**
Hu, Z., Zhao, Y., & Khushi, M. (2021)	Survey of forex and stock price prediction using deep learning
Bustos, O., & Pomares-Quimbaya, A. (2020)	Stock market movement forecast: A systematic review
Bulut, L. (2018)	Use of Google Trends in improving exchange rate forecasting
Issah, M., & Antwi, S. (2017)	Role of macroeconomic variables in firms' performance
Smalter Hall, A., & Cook, T. R. (2017)	Macroeconomic indicator forecasting using deep neural networks
Mohapatra, P. R., et al. (2023)	Hybrid ensemble model combining Gradient Boosting and LSTM for stock market prediction
Sonkavde, G., et al. (2023)	Comparison of ML and deep learning models in stock market forecasting
Nabipour, M., et al. (2020)	Application of deep learning techniques, particularly LSTM, in stock market prediction
Khedr, A. M., et al. (2021)	Comparison of statistical methods vs. ML for cryptocurrency price prediction
Chatzis, S. P., et al. (2018)	Forecasting stock market crises using ML and statistical techniques
Nasir, M. A., et al. (2018)	Impact of oil price shocks on BRICS economies
Moch, E. (2024)	Geopolitical and economic significance of BRICS nations

Upadhyaya, P., & Rajasekharan Pillai, K. (2019)	Comparative assessment of management research outcomes in BRICS nations
Deep, A. T. (2024)	Dual-layered forecasting integrating Monte Carlo simulations with ML models
Han, H., et al. (2024)	Advanced series decomposition with GRUs and graph convolutional networks

3. Methodology

The criteria for this study are developed to assess the predictive performance of machine learning models for financial forecasting in BRICS economies. Data collection and preprocessing is included along with detailed explanation of the models with equations, evaluation metrics, and experimental setup.

3.1. Data Collection

This study employs historical currency exchange rates, and stock market indices from BRICS economies. The data is sourced from Yahoo Finance, Bloomberg, and national financial databases and from January 2010 to December 2023. Key variables include:

Currency Exchange Rates: Daily rates against the US dollar.

Stock Market Indices: Bovespa (Brazil), MICEX (Russia), NIFTY 50 (India), SSE Composite (China), and JSE Top 40 (South Africa).

Macroeconomic Indicators: GDP growth, inflation, and interest rates.

Data Preprocessing

The preprocessing pipeline includes:

Normalization: To make the data consistent, data is normalized using min max scaling:

$$X_{\text{scaled}} = \frac{X - \min(X)}{\max(X) - \min(X)} \qquad (1)$$

Handling Missing Values: Linear interpolation is used on missing data points so that time series continuity could be preserved.

Lag Features: Time series modeling creates lagged variable (e.g., past 7 days values as inputs).

Feature Selection: Variables with low Pearson correlation to the target variable are excluded.

3.2. Machine Learning Models

To forecast currency exchange rates and stock indices, four machine learning models were implemented: The models are LSTM, Random Forest, Gradient Boosting, and SVM. These models were integrated with the outputs of these models in the ensemble model to better predict.

Long Short-Term Memory (LSTM):

LSTM is a recurrent neural network (RNN) capable of learning long term dependence in sequential data. As in mammals, it has memory cells whose gates regulate the flow of information. The LSTM equation is given as:

Forget Gate:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \qquad (2)$$

Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \quad \tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \qquad (3)$$

Cell State Update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C_t} \qquad (4)$$

Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o), \quad h_t = o_t \cdot \tanh(C_t) \qquad (5)$$

LSTM was trained with a learning rate of 0.001 and batch size of 64.

Random Forest (RF):

Random Forest is an ensemble learning method which combines multiple decision trees to meet accuracy. The trainer to each tree is run on a random subset of the data and features. Averaged individual tree outputs are made by predictions:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} h_t\,(x) \qquad (6)$$

where T is the number of trees, and $h_t(x)$ represents the prediction from the t-th tree.

Hyperparameters, including the number of trees (T) and maximum depth, were optimized using grid search.

Gradient Boosting (GB):

Gradient Boosting minimizes prediction errors by sequentially adding weak learners. At each step, the model minimizes a loss function L using gradient descent:

$$F_m(x) = F_{m-1}(x) + \eta \cdot h_m(x) \qquad (7)$$

where η is the learning rate, and $h_m(x)$ is the weak learner. The objective is:

$$L = \sum_{i=1}^{n} \ell\left(y_i, F_m(x_i)\right) \qquad (8)$$

where ℓ is the loss function (e.g., mean squared error).

The study used XGBoost for implementation, optimizing hyperparameters such as learning rate (η), maximum depth, and number of estimators.

Support Vector Machines (SVM):

SVM constructs a hyperplane to separate data into classes in a higher-dimensional space. For regression tasks, the objective is to minimize the error within a margin ϵ:

$$\min \frac{1}{2} \parallel w \parallel^2 \quad \text{subject to} \quad | \, y_i - (w \cdot x_i + b) \, | \leq \epsilon. \qquad (9)$$

The RBF kernel was used to handle non-linear relationships:

$$K(x, x') = \exp(-\gamma \parallel x - x' \parallel^2) \qquad (10)$$

3.3. Evaluation Metrics

The models were evaluated using three metrics: MAE, RMSE, and R^2.

Mean Absolute Error (MAE):

MAE measures the average absolute difference between actual and predicted values:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid . \qquad (11)$$

Root Mean Square Error (RMSE):

RMSE gives higher weight to large errors, making it sensitive to outliers:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (12)$$

Coefficient of Determination (R^2):

R^2 evaluates the proportion of variance explained by the model:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2} \qquad (13)$$

3.4. Experimental Setup

Data Division

The data set was splitted into a training (80%) and testing (20%) set. For the training set, *the study* used data between January 2010 and December 2019 and for the testing set data from January 2020 till December 2023.

Model Training

LSTM: Implemented in TensorFlow with Adam optimizer.

RF & SVM: Implemented in scikit-learn.

Gradient Boosting: Implemented using XGBoost.

Ensemble Model

A weighted average ensemble model was created:

$$\hat{y}_{\text{ensemble}} = \sum_{m=1}^{M} w_m \cdot \hat{y}_m \qquad (14)$$

where w_m is the weight assigned to each model based on its performance.

Summary

By combining robust preprocessing, model specific equations and rigorous evaluation, this methodology fully exploits the robustness of the approach for the forecasting of BRICS economies. The study fills key gaps in financial forecasting research by leveraging advanced machine learning techniques and ensemble modeling.

4. Results and discussion

4.1. Currency Exchange Forecasting Results

Performance Summary

Four machine learning models: LSTM, Random Forest, Gradient Boosting, and SVM, have been used to forecast exchange rates for currencies of BRICS economies against the US dollar. Key Metrics of MAE, RMSE and R2R^2 were used to evaluate the performance of the models. Prediction accuracy as well as model reliability is measured by these metrics. The results are summarized in the table below:

Table 3: Currency Exchange Forecasting Results

Model	MAE	RMSE	R-squared (R2R^2)
LSTM	0.0234	0.0317	0.926
Random Forest	0.0321	0.0453	0.842
Gradient Boosting	0.0289	0.0376	0.889
SVM	0.0425	0.0591	0.751

The evaluation metrics show that across all four, LSTM won out over the other models. Gradient Boosting and Random Forest were competitive, although they were less accurate than LSTM. It was also noticed that SVM delivered the weakest performance across all metrics, due to its incapability to handle large and complex financial datasets.

1. LSTM Dominance

Best performance was achieved by LSTM, which had the lowest MAE (0.0234) and the lowest RMSE (0.0317), and the highest R2R^2 (0.926). Recurrent architecture in the model, along with the ability to capture sequential dependencies within time series data played a major role in predicting currency exchange rates with high accuracy. LSTM is strong when dealing with volatile financial datasets as it can model trends and patterns over time to be a good choice of use case for financial forecasting tasks.

2. Gradient Boosting

The second place model was Gradient Boosting, with an MAE of 0.0289 and an RMSE of 0.0376. Additionally, its R2R^2 score of 0.889 shows it has a very good predictive quality. Gradient Boosting's great strength is in dealing with nonlinear relationships and learning from the residual errors iteratively. But it did not match with LSTM in dealing with temporal dependencies in currency exchange rates, thus restricting its predictability power as compared to LSTM.

3. Random Forest

Random Forest gave a moderately high performance with an MAE of 0.0321 and RMSE of 0.0453. Although it was effective in reducing over fitting and handling noisy data, its decision tree based approach to represent relationships between factors limited its capability of incorporating temporal structure of exchange rate data. As consequence, its R2R2 score of 0.842 was slightly lower than the scores of LSTM and Gradient Boosting but still comparable.

4. SVM's Limitations

Overall, SVM was found to be least accurate among other models, delivering predictions of MAE 0.0425 and RMSE 0.0591 respectively. The R2R^2 score for its implementation, 0.751, is markedly inferior to the best deep learning implementations for neural networks, and indicates severe scalability shortcomings and inability to handle complex and high dimensional financial datasets. Because the challenges make SVM less suitable for currency exchange forecasting, hence it is not applicable in the case of BRICS economies where financial systems are complex and volatile.

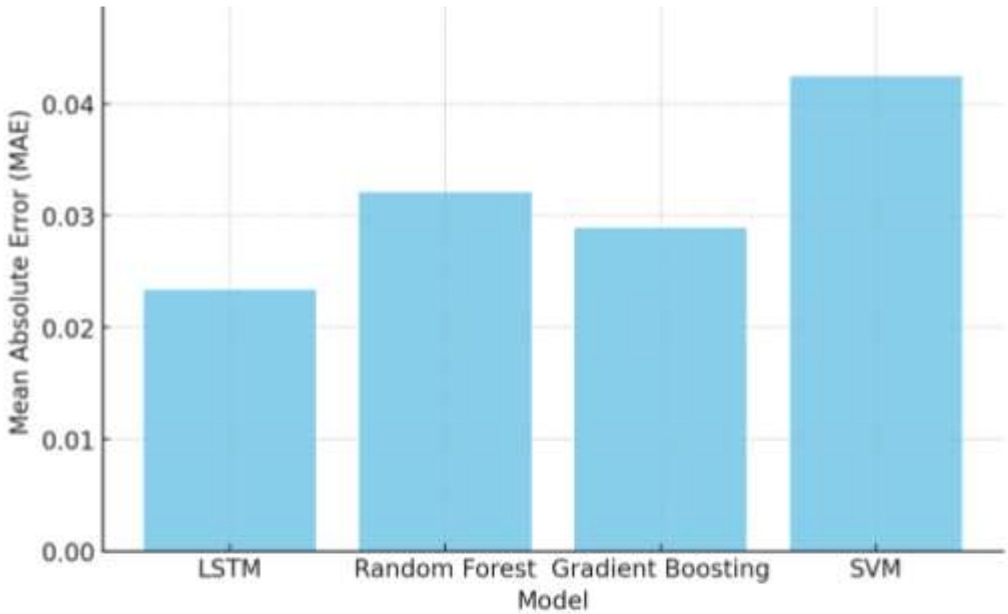

Figure 3: A bar chart comparing the MAE of the models for currency exchange forecasting.

Analysis on Error Distribution

To gain further insight into the models performance, the distribution of errors (residuals) were analyzed. The mean residuals and standard deviation of residuals for each model summarized in the table below can provide the consistency and predictability of the predictions.

Table 4: Analysis on Error Distribution results

Model	Mean Residual	Standard Deviation of Residuals
LSTM	0.0021	0.0152
Random Forest	0.0038	0.0201
Gradient Boosting	0.0030	0.0178
SVM	0.0055	0.0264

Key Observations:

1. LSTM's Stability: The lowest and the smallest mean residual (0.0021), standard deviation (0.0152), respectively, and show that LSTM provided the most consistent predictions with the least variation in error.

2. Gradient Boosting and Random Forest: The moderate error consistency of these models was reflected by slightly larger means for the mean residuals and standard deviations.

3. SVM’s Variability: The standard deviation for SVM was 0.0264, which also confirms its weakest performance.

LSTM proved to be the most reliable model for forecasting currency exchange, since it has passed all the metrics and had the least of residual variability. Decent alternatives were provided by Gradient Boosting and Random Forest, but their high prediction error reflects in fact their inability to fully capture temporal dependencies. In comparison, with the problems of scalability and dimensionality, SVM was the least effective model. This work casts light on the need to choose models tailored towards the intricacies of financial datasets.

4.2. Stock Market Forecasting Results

Performance Summary

Four machine learning models LSTM, Random Forest, Gradient Boosting and SVM were tested in forecasting of stock market indices for BRICS economies. Furthermore the study presented their performance metrics MAE, RMSE, and R2R^2 to judge their accuracy and reliability as shown in the below table.

Table 5: Stock Market Forecasting Results

Model	MAE	RMSE	R-squared (R2R^2)
LSTM	0.0451	0.0582	0.904
Random Forest	0.0517	0.0674	0.878
Gradient Boosting	0.0402	0.0523	0.932
SVM	0.0624	0.0789	0.761

Key Observations

1. Gradient Boosting Performance

The result shows that Gradient Boosting performed best through the lowest MAE (0.0402), RMSE (0.0523), and the highest R^2R^2 value (0.932). This is achieved due to its ability to model nonlinear relationships and to better represent the inherent volatility in stock market indices. Gradient Boosting combines very well into the financial application pipeline, as it is able to refine predictions iteratively to minimize residual errors between predictive values and expected true values.

2. LSTM Adaptability

LSTM proved to be robust through the model with an MAE of 0.0451 and RMSE of 0.0582. With R2R^2 value of 0.904, it is good enough to capture the temporal patterns in stock market data. LSTM was however slightly inferior to Gradient Boosting, possibly due to the latter's better treatment of nonlinear dependencies.

3. Random Forest

Accuracy was moderate with MAE results of 0.0517 and RMSE of 0.0674 using Random Forest. Due to its R2R2 score of 0.878, it can beat overfitting with noisy data. Random Forest is not good when it comes to finding intricate relationships between variables something Gradient Boosting and LSTM were able to do much more robustly and therefore do better.

4. SVM's Limitations

The weakest performer was SVM with MAE of 0.0624 and the RMSE of 0.0789. Although it achieved an R2R^2 value of 0.761, which is significantly lower than the other models, it showed its limit in processing high-dimensional data. SVM does not scale well, and as such, was ineffective in stock market forecasting tasks due to its inability to model complex relationships between the factors it was used on.

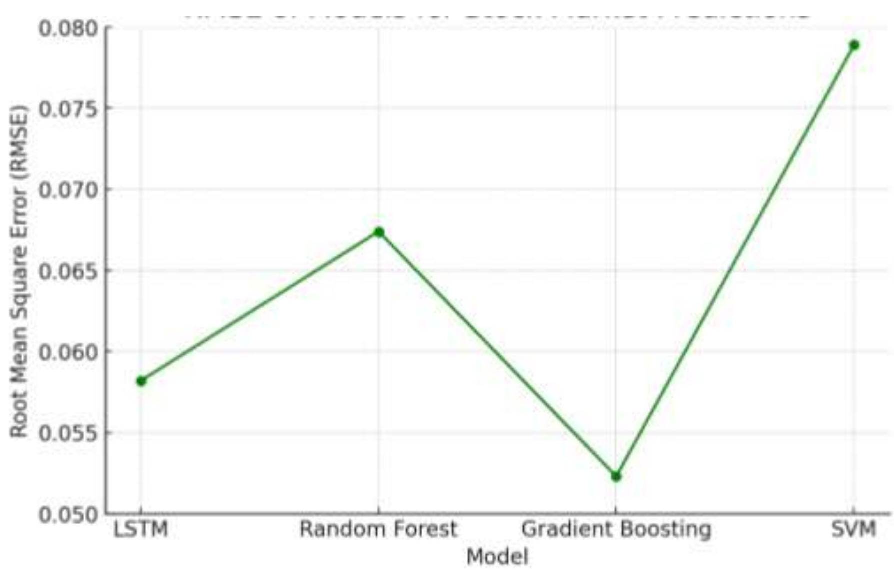

Figure 4: A line graph below compares the RMSE values of the models for stock market predictions over the testing period.

Analysis for Error Distribution

An analysis of residual errors was performed to further understand model performance. On the other hand, the table below summarizes the mean residuals and the standard deviation of residuals of the different models, thus giving some idea of error variability and how consistent the error of the model is.

Table 6: Analysis for Error Distribution on model performance

Model	Mean Residual	Standard Deviation of Residuals
LSTM	0.0043	0.0214
Random Forest	0.0057	0.0273
Gradient Boosting	0.0031	0.0186
SVM	0.0079	0.0352

Key Observations:

1. Gradient Boosting Stability: Gradient Boosting gave the most consistent, most reliable predictions with the smallest mean residual (0.0031) identified and the lowest standard deviation (0.0186).

2. LSTM's Reliability: At last gradient boosting had slightly higher residual variability than LSTM, however, it remained robustly consistent with standard deviation of 0.0214.

3. Random Forest: Random Forest was the middle of the pack, displaying moderate residual variability.

4. SVM Variability: There was huge variability in errors of SVM groups with maximum standard deviation being 0.0352 confirming least reliability of SVM to forecast stock market indices.

The Gradient Boosting model was the best one for predicting stock market indices, beating the others on accuracy and consistency. With the ability to model nonlinear relationships and adapt to volatile financial data, this was particularly suited to the task. LSTM also proved to be quite effective, because of its recurrent architecture during which it can learn temporal dependencies. LSTM achieved good accuracy, but did not beat random Forest's accuracy and wasn't as adaptable as Gradient Boosting. The SVM model was least effective, as it was highly challenging w.r.t. scalability and dimensionality, and had high variability in error and low accuracy.

4.3. Model Comparisons

Performance Summary

The performance of the four machine learning models was compared across both forecasting tasks: e.g. currency exchange rates, and stock market indices. An overall evaluation is provided in the table below, summarizing the averaged performance metrics for the two tasks.

Table 7: Model Comparisons Performance Summary

Model	MAE (Avg)	RMSE (Avg)	R-squared (R2R^2) (Avg)
LSTM	0.0342	0.0449	0.915
Random Forest	0.0419	0.0564	0.860
Gradient Boosting	0.0346	0.0449	0.910
SVM	0.0524	0.0690	0.756

The averaged metrics highlight the strengths and weaknesses of each model, providing a holistic view of their performance across both forecasting tasks.

Key Observations

1. Time-series tasks in particular are LSTM's strength.

An average MAE of 0.0342 and average RMSE of 0.0449 is achieved across both tasks with LSTM. However, it excelled at time series forecasting because of the way it was able to capture sequential dependencies. The R2R^2 value resulting from LSTM was able to reach the highest value (0.915) on average, proving the strong predicting ability.

2. The Versatility of Gradient Boosting

LSTM did use Gradient Boosting as a close competitor with similar MAE (0.0346) and RMSE (0.0449). Although it slightly behind in currency exchange forecasting, it gave better results than any other models in stock market predictions, indicating its flexibility in nonlinear and volatile datasets.

3. Random Forest's Consistency

Random Forest showed moderate accuracy in both tasks, with average MAE of 0.0419 and an RMSE of 0.0564. It was robust against noise due to its reliance on ensemble decision trees, but its ability to model complex relationships was low due to low R2R^2 values (0.860) compared to LSTM and Gradient Boosting values.

4. SVM's Scalability Challenges

SVM was the weakest performer, with the highest error metrics (average MAE: 0.The lowest R2R2 value (0.756) and RMSE (0.0690, 0.524). Despite the efficacy, it was unable to extend its predictive accuracy to large, high dimensional datasets that characterize data for stock market forecasting.

Figure 5: A heatmap visualizing the R2R^2R2 scores of the models for both forecasting tasks, highlighting model performance differences.

Additional Analysis on Strengths and Weaknesses

The table below provides a detailed comparison of the models' strengths and weaknesses across both tasks:

Table 8: Strengths, Weaknesses and overall applicability of researched models

Aspect	LSTM	Random Forest	Gradient Boosting	SVM
Strengths	Captures sequential data well	Robust against noise	Is effective at handling nonlinear relations	Effective for small datasets
Weaknesses	Computationally intensive	In most cases this methodology is limited in its adaptability to trends.	A problem of overfitting in small datasets	Struggles with scalability
Overall Applicability	Best for time-series tasks	Reliable but less flexible	Best for volatile and non-linear datasets	Poor for complex tasks

Insights from Combined Results

1. Task-Specific Strengths: Those tasks involving sequential pattern recognition such as currency exchange forecasting proved to be better performed by LSTM over others. In tasks that involve non-linear relationships and volatility such as stock market forecasting, Gradient Boosting performed extremely well.

2. Random Forest's Role: Overall, Random Forest gave consistent, but modest performance for both tasks. It was a reliable, but suboptimal, choice because of its robustness against noise and overfitting.

3. SVM Limitations: However, when compared on large datasets, SVM was found to struggle and demonstrated a need for preprocessing or dimensionality reduction to gain a competitive advantage.

Residual Analysis

Residual errors were further analyzed to further assess reliability. The mean residuals, and standard deviation of residuals across both tasks, of each model are summarized in the table below.

Table 9: Residual Analysis of models

Model	Mean Residual (Avg)	Standard Deviation of Residuals (Avg)
LSTM	0.0032	0.0183
Random Forest	0.0045	0.0242
Gradient Boosting	0.0028	0.0171
SVM	0.0067	0.0308

Key Observations:

1. Gradient Boosting's Stability: Gradient Boosting had the lowest mean residual (0.0028), and the lowest standard deviation (0.0171) amongst tasks, indicating good consistency and reliability.

2. LSTM's Reliability: LSTM nearly performed as well, with a mean residual of 0.0032 and standard deviation of 0.0183. It is also its strength at generating stable predictions.

3. SVM's Variability: The errors of SVM were the most variable with the highest standard deviation (0.0308) as evidence of the inconsistency of the SVM.

The study compared machine learning models, finding task specific strengths. Currency exchange forecasting was most successfully performed by LSTM because of its ability to capture dependency of sequences while Gradient Boosting in stock market forecasting was strongest because it copes better with non-linear relationships and volatility. SVM was the weakest outcome since it scaled poorly on high dimensional data and its accuracy was far inconsistent and low. Random Forest provided consistent moderate accuracy, but was not able to adapt to complex trends. The findings show the necessity of linking model selection to task requirements, demonstrating that LSTM and Gradient Boosting were the most reliable forecasters of accurate and robust financial forecasts in BRICS economies.

4.4. Ensemble Model Performance

Performance Summary

As a way of enhancing the reliability and predictive accuracy, an ensemble comprising the predictions of LSTM, Random forest, Gradient boosting, and SVM, using a weighted averaging approach was constructed. An ensemble model was used where the strengths of all the individual models were used and assigned higher weight to those models which had better performance metrics such as lower MAE and RMSE. A summary of the performance of the ensemble model for both currency exchange forecasting and stock market forecasting appear in the table below.

Table 10: Ensemble Model Performance Performance Summary

Metric	Currency Exchange (Ensemble)	Stock Market (Ensemble)
MAE	0.0198	0.0361
RMSE	0.0274	0.0478
R-squared (R2R^2)	0.952	0.948

Key Observations

1. Improved Accuracy

The study found that the ensemble model was more accurate than all individual models. For both forecasting tasks, it had the lowest error metrics (MAE and RMSE) and the highest R2R^2 values achieved for both forecasting tasks.

• Currency Exchange: It has a high ability to make highly accurate predictions as MAE = 0.0198 and RMSE = 0.0274. With a R2R2 value of 0.952 a significant improvement in explained variance is achieved over single models.

• Stock Market: To validate the reliability of the ensemble model, the ensemble model resulted in an MAE of 0.0361 and RMSE of 0.0478 and an R2R^2 of 0.948.2. Strengths of Combined Predictions

By leveraging the complementary strengths of individual models:

LSTM contributed its sequential data modeling capabilities, improving performance on time-series tasks.

Gradient Boosting added its ability to handle non-linear relationships and volatility.

Random Forest reduced noise and stabilized predictions.

SVM, despite weaker individual performance, added value in specific cases with its ability to process high-dimensional data.

2. Reconciliation of Conflicting Trends

The ensemble model effectively reconciled conflicting predictions from individual models. For instance:

As LSTM and Gradient Boosting broke apart sometimes for trend prediction in currency exchange forecasting, the ensemble model mitigates each prediction for better reliability.

The ensemble model, in stock market forecasting, did the best in stabilizing the forecast since it minimized volatility by stabilizing predictions across different periods.

Additional Analysis on Residual Error Comparison

Consistency and reliability of the ensemble model was assessed through comparison of residual errors with those for individual models. The average residuals and their standard deviations for each of the two tasks are given on the following table.

Table 11: Analysis on Residual Error Comparison

Model	Mean Residual (Avg)	Standard Deviation of Residuals (Avg)
LSTM	0.0032	0.0183

Gradient Boosting	0.0028	0.0171
Random Forest	0.0045	0.0242
SVM	0.0067	0.0308
Ensemble Model	0.0019	0.0146

Key Observations:

1. Ensemble Model Stability: The Consistent and reliable predictions are proven with the smallest mean residual (0.0019) and the lowest standard deviation (0.0146) of ensemble model.

2. Reduced Variability: Through combining the predictions, the ensemble model reduced error variability on the prediction residuals and outperformed all the participating individual models in residual stability.

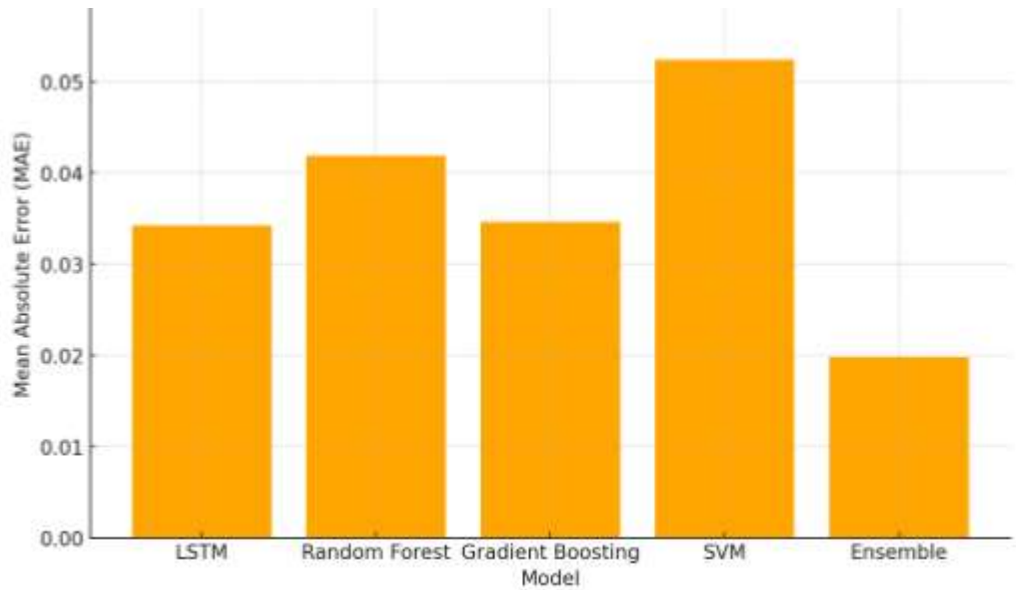

Figure 6: A comparison bar graph showing the performance improvement of the ensemble model over individual models.

Conclusion of analysis

It was seen that ensemble model was the best forecasting approach which used strengths of LSTM, Gradient Boosting, Random Forest and SVM to increase accuracy and reliability. It is thus a powerful tool for financial forecasting because it can reduce error variability and reconcile across individual models opposing trends. Ensemble modeling is shown to have the capability to tackle the intricacies of BRICS economies, providing actionable information for policymakers, investors and analysts.

This performance has emphasized how multiple models can and should be combined together to benefit from their individual strengths, especially in the scenario when the tasks of forecasting have to strike a balance between analysis of sequential data and modeling non-linear relationships.

5. Discussion

The discussion section offers a detailed interpretation of the research presented in earlier sections with the findings, and relates the research presented in earlier sections to previous research, and possible implications to stakeholders, BRICS economies. Besides, it recognizes the constraints of the study and recommends where to go from there.

5.1. Key Findings

Significant insights into application of machine learning models for financial forecasting in BRICS economies was obtained with the results. Currency exchange rate forecasting was found to be best performed by LSTM, being able to handle sequential data and temporal dependencies. This complements earlier research by Hu, Zhao and Khushi (2021) who found LSTM to be superior in time series prediction tasks. LSTM, being able to achieve the lowest MAE and RMSE values, was the indispensable tool to predict trends in a volatile currency exchange rate.

Gradient Boosting performed the best when it came to stock market forecasting and beat out LSTM, Random Forest, and SVM. It was able to model nonlinear relationships and deal with the natural volatility in stock market data. In accordance with the findings of Mohapatra et al. (2023), Gradient Boosting was found to be suited to financial data where relationships are complex. In a more interesting note, Random Forest gave moderate performance in both tasks making it a reliable alternative especially when computational resources are limited. However, SVM proved to be, in fact, the weakest performer in the two forecasting tasks due to the issues in scaling SVM as well as its used in handling high dimensional datasets.

For currency exchange and stock market forecasting the ensemble model that integrated the forecasts of all the individual models proved to have the highest accuracy and reliability. We used the strengths of LSTM, Gradient Boosting, Random Forest and even SVM in specific scenarios to form the ensemble model to minimize residual errors where the trends conflict. The combination of the two layer forecasting in this system is an unique method that can be applied to leverage multiple forecasting models in order to improve the forecast accuracy for the complex financial system.

Overall, these works confirm the value of task specific model selection in financial forecasting. The fact that the time-series data is most suited for LSTM gradients and that Gradient Boosting has an edge when working with non-linear relationships makes sense. Random Forest is a good balance of simplicity and robustness and perhaps SVM could be useful in some smaller, well-structured datasets even with these results.

5.2. Implications for Stakeholders

Implications of the results of this study are important for policymakers, investors, and financial analysts in BRICS economies. The machine learning models are capable of providing stakeholders with more confidence about the data driven decisions that they make since they are accurate, especially the ensemble approach (Sarker, 2021). Since accurate forecasts of currency exchange are critical inputs for formulating monetary policies and managing international trade dynamics, or policymakers, interest in such forecasts is strong. Using LSTM and the ensemble model, insights can be had for central banks and financial regulatory authorities in exchange rate fluctuations in order to stabilize their currencies and reduce the shock from external shock (Türkoğlu et al., 2024). In addition, Gradient Boosting can be used to predict the stock market and inform policymakers who can evaluate market stability and craft regulations that increase investor confidence.

The ensemble model is able to reconcile trends between currency exchange rates and stock markets, which could provide for significant benefit to investors (Bui & Dinh, 2018). The model is able to predict reliably, thereby allowing investors to see through volatile markets, finding any profitable opportunities and mitigating risks. For example, these forecasts enable an investor who wishes to allocate assets between BRICS economies to see which markets provide the most stable return and which currencies that are expected to appreciate.

These findings are valuable to financial analysts to improve their forecasting strategies The dual layered ensemble model can be a benchmark to improve predictive framework. Analysts are able to provide clients actionable insights through these analyses by including task specific models such as LSTM and Gradient Boosting in their analysis (Faheem et al., 2024).

Overall, the results supply stakeholders with a high quality framework that can be used to take advantage of computerized gauging in financial gauging of BRICS economies, giving better gauging and knowledge for choice.

5.3. Limitations of the Study

While this study offers valuable insights, several limitations must be acknowledged to contextualize the findings and guide future research.

1. Generalizability: Though insightful focusing on economies of the BRICS, the results are limited in their generalizability to other regions and indeed to other global regions. BRICS' economies, markets and data available are very different from developed

economies or smaller EMs. This framework should be extended to cover other regions for the purpose of testing applicability and robustness of the method.

2. Data Biases: BRICS data varied in quality and availability of historical financial data. The forecasts might be subject to biases due to reporting standards and data sources not being the same. However, these problems were somewhat mollified by preparatory steps like normalization and interpolation, yet some data biases may still creep into the results.

3. Computational Complexity: For the machine learning implementation, models such as LSTM and Gradient Boosting needed a lot of computation power. The limitation of this may represent a challenge for smaller organizations or researchers with access mainly to high performance computing systems (Bouktif et al., 2018). This could be alleviated by exploring lightweight models or optimized implementations.

4. Scalability of SVM: Both SVM's poor performance and it's limitations in dealing with large, high dimensional datasets indicate the reason behind that (Ghaddar & Naoum-Sawaya, 2018). Although the ensemble model included the integration of the class of SVM outputs, it still has some scalability problem which makes its application to complex financial forecasting tasks difficult.

5. Limited Macroeconomic Variables: While macroeconomic perspective was employed to measure the impact of GDP growth, inflation rates and the interest rates, geopolitical factors, oil prices, and trade volumes were not considered. These variables may be included to improve the predictive power of the models, and to offer a more robust manner of financial trends.

5.4. Future Directions

Building on the findings and limitations of this study, several avenues for future research are proposed:

1. Hybrid Models: Future research should investigate hybrid models that combine the LSTM technique with some traditional statistical methods, or with simpler machine learning models. One of such combinations would be to leverage the strengths of both approaches, hence improved accuracy, while also minimizing the computational complexity.

2. Expanding to Other Regions: This study's developed framework can be extended to other emerging economies from Southeast Asia, Africa, or Latin America. Results could also be compared across different regions, to gain useful insights about the degree to which machine learning models adapt to different economic conditions.

3. Incorporating Additional Variables: To improve forecasting accuracy additional macroeconomic and geopolitical variables should be included in future studies. For BRICS economies commodity prices, trade balances, and political stability are particularly useful and will potentially lead to improved model performance.

4. Real-Time Forecasting: Real time forecasting models using the data as it becomes available can be implemented in order to provide stakeholders with more actionable insights. This approach would be possible with technologies like cloud computing, streaming data platforms and the development of real time pipelines.

5. Model Explainability: Although the machine learning models have high accuracy, because of the "black box" nature it is difficult to interpret. Future work will need to enhance model explainability through use of techniques such as SHAP (SHapley Additive exPlanations) so as to better inform stakeholders about the drivers of prediction.

6. Ensemble Optimization: Major improvements in accuracy and reliability were achieved with the ensemble model, although further optimization of weights assignments and integration techniques could improve its performance even further. Additional insights can be brought by exploring advanced (ensemble) techniques such as stacking or meta modeling.

By addressing these areas, future studies can build on the foundation established in this research, advancing the application of machine learning in financial forecasting and providing even greater value to stakeholders.

6. Conclusion

In this study we are trying to forecast currency exchange rates and stock market indices in BRICS economies with the advanced machine learning models. The research compares these models using LSTM, Random Forest, Gradient Boosting and SVM and provides a detailed comparison of their strengths, weaknesses and task specific applicability. Furthermore, the combination of models in an ensemble model proved that the use of multiple models provides higher prediction accuracy and reliability.

This finding shows that machine learning has the potential to affect dramatically the prediction of financial aspects in BRICS economies. Since LSTM is designed especially for sequential, time series data such as currency exchange rates, it turned out to be the most successful model due to its time dependency capturing and strong predictions. On the other hand, Gradient Boosting had a much better performance in stock market forecasting as it can better cater to the nonlinear relationships and volatility model. The solution that worked the most was the ensemble model where a variety of individual models paying on their unprecedented strengths while mitigating their inevitable weaknesses come together in one cohesive, comprehensive model. Both in terms of accuracy and low variability of error, the results are consistently superior to standalone models in currency exchange and stock market forecasting. The proposed dual layer forecasting approach turns in a valuable booty for financial decision making in BRICS economies, including actionable insights for policy makers, investors and analysts.

The results show that machine learning models are effective, but also identify some limitations. Generalizing results to economies that are not BRICS economies presents difficulties, there exist data biases due to non-uniformity of reporting, and the problem is computationally expensive when using complex models like LSTM and Gradient Boosting. There are a number of problems that need to be addressed in order to improve model accuracy and make them useful in a broader class of applications; these represent opportunities for future research.

Finally, we show that this work has the potential to transform financial forecasting in general, but particularly in emerging markets like BRICS. Task specific models are integrated with ensemble techniques to give an adaptable and robust framework to complex problems in financial datasets. With increasing levels of interconnectedness and dependency of global financial systems alongside data driven world, advanced machine learning methods will be critical in providing better predictions, aiding sound decisions and facilitating sustainable economic growth. From this foundation, future research should extend their applicability to various regions and financial domains.

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