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Research Article

A Comparative Analysis of an Enhanced Hybrid Model for Predicting Dollar Against Naira Exchange Rate Using Deep Learning and Statistical Methods

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Abstract: In today's global economy, accurately predicting foreign exchange rates or estimating their trends correctly is crucial for informed investment decisions. Despite the success of standalone models like ARIMA and deep learning models like LSTM, challenges persist in capturing both linear and nonlinear dynamics in highly volatile exchange rate environments. Motivated by the limitations of these individual models and the need for more robust forecasting tools, this study proposes a hybrid ARIMA-LSTM model that integrates ARIMA's strength in modeling linear trends with LSTM's capability to capture nonlinear dependencies, using historical USD/NGN exchange rate data from the Central Bank of Nigeria (CBN) spanning 2001 to 2024. The research hypothesis posits that the hybrid ARIMA-LSTM model will significantly outperform standalone models in forecasting accuracy. By comparing these models against state-of-the-art approaches, the study highlights the advantages of hybridizing statistical and deep learning methods. The findings demonstrate that the hybrid model achieved the lowest Root Mean Squared Error (RMSE) of 2.216 and the highest R^2 of 0.998, indicating superior forecasting performance. This study fills a critical research gap by demonstrating the effectiveness of hybrid deep learning in financial time series forecasting, providing valuable insights for investors, policymakers, and financial analysts. Future research will extend this work by incorporating the latest dataset and evaluating model robustness during the recent surge in the Naira/Dollar exchange rate from 2023 to 2024.

Keywords: Deep learning; Exchange rate; Forecasting; FOREX; Hybrid machine learning; Statistical method.

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1. Introduction

The Foreign Exchange (FOREX) market has evolved significantly over time, becoming crucial to global economic stability and growth. Historically, currency values were tied to physical commodities, limiting opportunities for speculative trading[1]. However, in today's dynamic financial landscape, exchange rates influence trade balances, inflation, interest rates, and international investments [2], [3]. As economies worldwide increasingly rely on exchange rates to shape monetary policies, forecasting these rates has become essential for businesses and policymakers[4], [5]. Uncertainty in monetary policy can cause fluctuations in exchange rates, affecting economic variables such as interest rates, wages, and economic growth [6], [7].

Exchange rate forecasting is critical for risk management, investment strategies, and policymaking, yet it remains a complex challenge due to market volatility [8]–[10]. The introduction of floating exchange rates in the 1970s shifted exchange rate determination to private market forces, making accurate prediction more difficult[11]. This is particularly relevant for economies like Nigeria, where foreign exchange rates significantly impact trade, investment, and economic stability.

Traditional forecasting methods, like the Autoregressive Integrated Moving Average (ARIMA), have been extensively applied in exchange rate forecasting. However, they often struggle with capturing the nonlinear and dynamic patterns of financial time series data [12]. As a result, modern forecasting techniques increasingly integrate Artificial Intelligence (AI) and machine learning models to improve prediction accuracy[13]. Additionally, researchers have explored the potential of online user queries, such as Google Trends, to reflect public expectations and improve forecasting models [14], [15].

Machine learning methods, especially deep learning architectures such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have demonstrated significant potential in time-series forecasting by capturing complex temporal dependencies and extracting features from high-dimensional data[16], [17]. Hybrid models that combine statistical methods with AI techniques have emerged as a promising solution to address the limitations of traditional approaches, resulting in improved forecasting accuracy[18].

This paper compares the effectiveness of ARIMA, LSTM, and a hybrid ARIMA-LSTM model against state-of-the-art models in forecasting the Naira/Dollar exchange rate. Utilizing a dataset from the Central Bank of Nigeria (CBN) spanning 2001 to 2023, the research evaluates model accuracy using various performance metrics. The motivation for proposing the hybrid model stems from the limitations of standalone models in capturing both the linear and nonlinear components of highly volatile financial time series. ARIMA excels in modeling linear trends, while LSTM captures complex nonlinear dependencies. The hybrid ARIMA-LSTM model is expected to deliver superior predictive performance by integrating both. The research hypothesis posits that the proposed hybrid model will significantly outperform standalone and existing state-of-the-art models in forecasting accuracy. Also, to our knowledge, no prior documented study has employed or validated the hybrid ARI-MA-LSTM model for foreign exchange rate forecasting. The comparative analysis highlights the strengths and limitations of each approach, demonstrating how hybrid deep learning and statistical methods can outperform existing models. The findings provide valuable insights for investors, policymakers, and financial analysts seeking to enhance exchange rate forecasting accuracy and improve economic decision-making.

2. Related Work

Ibekwe and Ajijola [3] conducted a comparative analysis of three modeling techniques for predicting the Naira/U.S. Dollar exchange rate, utilizing monthly data from 2008 to 2021 sourced from the CBN database. They evaluated Ordinary Least Squares (OLS), Decision Trees (DTs), and Random Forest (RF) algorithms based on model fit and prediction accuracy. The study revealed that RF consistently outperformed OLS and Decision Trees in model fit and prediction accuracy. While OLS provided reasonable results, Decision Trees suffered from overfitting issues. The authors concluded that Random Forest is the preferred choice for future research in this area, although OLS could also be considered a viable option.

Kabari et al. [11] investigate using machine learning algorithms to forecast the Nigerian Naira exchange rate against the British Pound, US Dollar, and Euro. They evaluated the performance of various algorithms using performance metrics such as MSE, RMSE, MAE, and R^2 scores. Their findings revealed that Recurrent Neural Networks (RNNs) were particularly effective for time series analysis and exchange rate forecasting. The study also utilized MATLAB's polyfit/polyval function to project the GBP and EUR to NGN exchange rates for 2020 and 2022.

Abimbola et al. [19] examined the use of machine learning techniques in predicting the Dollar/Naira (DOL/NGN) exchange rate trend, focusing on the effectiveness of Linear Regression and Support Vector Machine models. The study built upon the established success of these algorithms in predicting stock exchange-traded funds and index exchange-traded funds, aiming to extend their applicability to currency exchange-traded funds. Using a dataset of DOL/NGN exchange rate values spanning five years (2016-2021) sourced from Oanda, a U.S. based foreign exchange and market analysis company, they conducted predictions and assessed the performance of both models. Their findings revealed that while both LR and SVM effectively predicted the exchange rate trend, the SVM model based on the performance metrics outperformed the LR model, demonstrating superior accuracy.

Ugoh et al. [20] examined the predictive performance of various time series forecasting methods for the Nigerian Naira against U.S. Dollar and Gambian Dalasi against U.S. Dollar exchange rates. They compared ARIMA, SES, Holt's Linear Trend, and Damped Holt models using annual data from 1960 to 2020. The study evaluated the models' accuracy using RMSE, MAE, MAPE, and MASE. The findings revealed that ARIMA (0,2,2) was the most suitable model for exchange rates. The authors projected future exchange rate trends, indicating a continued depreciation of both currencies against the U.S. Dollar. The study highlights the need for Nigeria and The Gambia to implement stronger economic policies to stabilize their exchange rates.

Mbato and Kabari-Ledisi [21] investigated machine learning techniques to forecast foreign exchange rates for five currencies: USD, Swiss Franc, Yen, Euro, and British Pounds, using data from the CBN spanning 2001 to 2020. They developed a hybrid model that combined ARIMA and Artificial Neural Network (ANN) algorithms. The study found that the hybrid model achieved high accuracy and efficiency with minimal training time and errors. The model completed training on the data in just 26 seconds., outperforming other models that required longer training and testing periods. Furthermore, it recorded a minimum training error, with an RMSE of 0.7, and the predictions closely matched the actual prices, demonstrating its effectiveness in providing accurate foreign exchange rate forecasts.

Ukabuiro and Stella [22] focused on predicting foreign exchange (FX) rates in the Nigerian market, particularly the USD/NGN pair, using machine learning algorithms. Their study addressed non-linearity challenges in the FX market and the difficulty in generating accurate predictions, particularly in a developing economy like Nigeria. They applied several machine learning models, including Gated Recurrent Unit (GRU), ANN, and Long Short-Term Memory (LSTM), to forecast exchange rates, evaluating their performance using RMSE, MAE, MSE, and R^2 metrics. The results demonstrated that the GRU model outperformed the others, with the lowest RMSE (0.112), MAE (0.075), MSE (0.013), and the highest R^2 (0.969), indicating its effectiveness in predicting exchange rates over the 19 years of data from 2003 to 2023.

Mahmud et al. [23] explored the application of predictive modeling for time series analysis in the context of Foreign Exchange trading, focusing on the USD, EUR, and GBP currency pairs against BDT. The study employed a 15-year dataset spanning from September 2008 to September 2023 and applied different machine learning and deep learning algorithms, such as Support Vector Regression, Random Forest Regressor, Decision Tree Regressor, K-neighbors Regressor, SGD Regressor, XGBRegressor, Convolutional Neural Network, Long Short-Term Memory, and Bidirectional LSTM. The results indicated that the Random Forest Regressor and Bidirectional LSTM models outperformed others, demonstrating high accuracy in predicting exchange rates. The Bi-LSTM model achieved an impressive performance with an R^2-score of 0.999340, and hybrid models like CNN+BiLSTM showed excellent results with an R^2-score of 0.997543.

Magaji and Garba [24] explored the hybridization of the ARIMA and GARCH models for forecasting exchange rates, specifically the Nigerian Naira against the U.S. Dollar, using monthly data from January 2002 to February 2020. Their study began with examining the stationarity of the exchange rate series using root tests, which revealed non-stationarity. To address this, they first applied differencing to make the series stationary and estimated ARIMA models using the Box-Jenkins approach. The authors found that the ARIMA(0,1,1) and ARIMA(0,1,2) models, selected based on the Akaike Information Criterion (AIC), exhibited serial correlation and heteroscedasticity in the residuals. Consequently, they hybridized these ARIMA models with GARCH(1,1) to form ARIMA-GARCH models, which improved model fitting and volatility capture. The results showed that the ARIMA(0,1,1)-GARCH(1,1) model provided the best performance, with the lowest RMSE and MAE, effectively addressing volatility in the exchange rate series.

Olawale and Adashu [25] investigated using time series models for forecasting the Nigerian exchange rate, specifically focusing on the Naira-Dollar, Naira-Euro, and Nai-ra-Pound exchange rates. They employed three models: ARIMA, ANN, and a hybrid ARIMA-ANN model. Using secondary data from the CBN spanning from December 2001 to April 2023, their study demonstrated that the ARIMA-ANN model significantly outperformed the individual ARIMA and ANN models. The ARIMA-ANN model achieved the lowest MAE, RMSE, and MAPE for all three exchange rates, making it the most accurate predictor. The authors recommend that further research could be done using alternative models to improve predictive accuracy.

Despite advancements by Olawale and Adashu [25] in forecasting the Nigerian exchange rate using ARIMA, ANN, and a hybrid ARIMA-ANN model, a research gap remains in exploring alternative hybrid models. Specifically, the combination of ARIMA and LSTM for exchange rate prediction has not been documented despite their complementary strengths in capturing linear and temporal dependencies. Additionally, no study has applied a hybridized ARIMA-LSTM model using the CBN Naira-to-Dollar exchange rate dataset from 2001 to 2023. This study addresses this gap by evaluating ARIMA, LSTM, and hybrid ARIMA-LSTM models using key performance metrics to determine the most accurate forecasting method and compare results with this work.

3. Proposed Method

This section presents the dataset, data preprocessing, feature selection, and models used. Figure 1 gives a clear diagrammatic description of the proposed model, and the steps involved are discussed in subsequent sections.

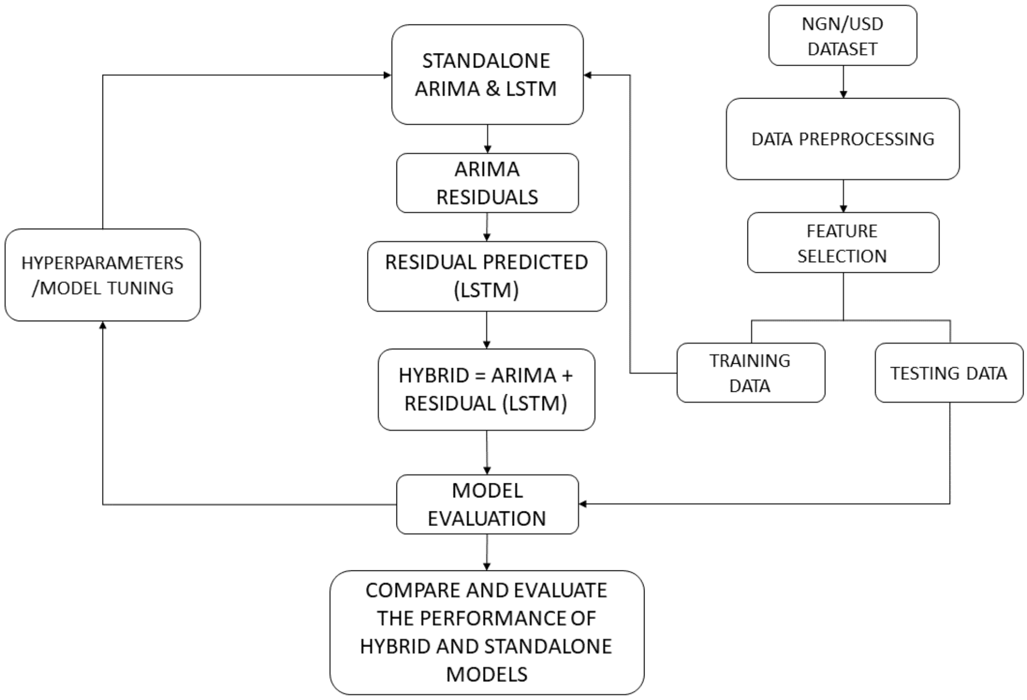

Figure 1. Proposed framework

3.1. Dataset

The NGN/USD historical dataset used in this study was obtained from the Central Bank of Nigeria (CBN) website in Excel, covering the period from 2001 to 2023. The dataset is publicly accessible and available for download on the official CBN website[26]. It consists of rows and five columns: Currency, Date, Buying Rate, Central Rate, and Selling Rate. The Buying Rate, also known as the bid price, represents the rate at which a financial institution or forex dealer buys U.S. dollars from customers. The Central Rate, or the official rate, is the midpoint between the buying and selling rates, often set by central banks as a reference. The Selling Rate, also known as the asking price, represents the rate at which a financial institution or forex dealer sells U.S. dollars to customers, as shown in Figure 2.

3.2. Data Preprocessing

The data is first loaded from a CSV file and cleaned by removing missing values and resetting the index. The 'Date' column is converted to DateTime objects, and only the 'Date' and 'Buying Rate' columns are selected and renamed. The 'Date' column is then set as the DataFrame index. After removing redundant NaN values, the 'Buying Rate' column is extracted as the target variable. Figure 3 depicts the historical trend of the USD/NGN exchange rate over the years.

Currency	Date	Buying Rate	Central Rate	Selling Rate
US DOLLAR	10/12/2001	111.85	112.35	112.85
US DOLLAR	11/12/2001	111.85	112.35	112.85
US DOLLAR	12/12/2001	111.85	112.35	112.85
US DOLLAR	13/12/2001	111.85	112.35	112.85
US DOLLAR	14/12/2001	112.1	112.6	113.1
US DOLLAR	18/12/2001	112.1	112.6	113.1
US DOLLAR	19/12/2001	112.1	112.6	113.1
US DOLLAR	20/12/2001	112.1	112.6	113.1
US DOLLAR	21/12/2001	112.1	112.6	113.1

Figure 2. An overview (screenshot) of the Naira against Dollar Dataset [25]

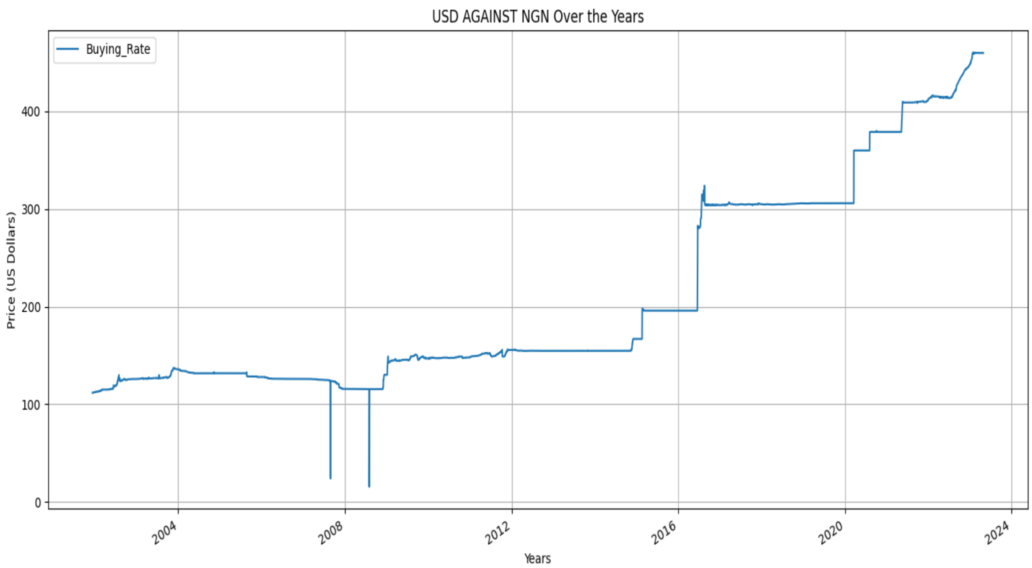

Figure 3. Plot for USD/NGN Dataset from 2001 to 2023

3.3. Splitting Data into Training, Validation and Test Sets

For the LSTM model, the data is normalized using MinMaxScaler to a range of 0 to 1, and the dataset is divided into training and testing sets, with 80% used for training. However, instead of following a general splitting ratio, the optimal split was determined by observing changes in MAE, MSE, RMSE, MAPE, and R^2 values for different percentage splits. To generate input sequences for the LSTM model, a lookback window of 60 days is used, after which the input sequences and corresponding output values are converted into NumPy arrays and reshaped appropriately. Similar initial preprocessing is performed for the ARIMA model to ensure consistency, but unlike the LSTM, ARIMA utilizes the original, unscaled 'Buying Rate' values. The same train-test split is applied, and the training data is stored as a list to facilitate ARIMA's iterative fitting and forecasting process. No separate preprocessing steps are required for the hybrid model, as it relies on the preprocessed data from the LSTM and ARIMA models. The final hybrid forecast was produced by combining ARIMA and LSTM into a hybrid model by utilizing both strengths; ARIMA modeled and captured the linear trends in the time series, while LSTM modeled the nonlinear residuals (errors) that ARIMA couldn't explain.

3.4. Feature Selection

The provided codes primarily utilize two features, "Date" and "Buying Rate," for time series forecasting across all models: LSTM, ARIMA, and Hybrid. Therefore, explicit feature selection techniques are not employed. The models rely solely on the historical values of this single time series to predict future values. The lookback window in the LSTM model can be considered an implicit form of feature engineering, as it determines the number of past data points used as input. Similarly, the ARIMA model operates on the same single time series, utilizing its inherent autocorrelation structure to make predictions without external features. A key limitation of this study is that it focuses exclusively on two features: Date and Buying Rate. This constraint is consistent with most related studies, including the referenced state-of-the-art models, which also employ only the historical exchange rate series for forecasting. The Hybrid model, a combination of LSTM and ARIMA predictions, also inherently relies on single features, combining the outputs of the two individual models.

3.5. Proposed Models

This section briefly explains ARIMA, LSTM and hybridized LSTM-ARIMA models.

3.5.1. ARIMA

The ARIMA model is a linear regression-based forecasting method that leverages temporal structures in time series data for prediction. ARIMA (p, d, q) combines the Autoregressive (AR), Integrated (I), and Moving Average (MA) components, where p represents the order of the autoregressive model, d denotes the degree of differencing, and q signifies the order of the moving average. The AR model of order p is defined as a linear process, represented by Equation (1).

$$z_t = \alpha + \phi_1 z_{t-1} + \phi_2 z_{t-2} + \cdots + \phi_p z_{t-p} + w_t \tag{1}$$

where $z_{t-1}, z_{t-2}, z_{t-p}$ are the lagged values; ϕ_1, ϕ_2, ϕ_p are the AR coefficients; w_t is the white noise error term; and α is defined by Equation (2).

$$\alpha = \left(1 - \sum_{i=1}^{p} \phi_i\right)\mu \tag{2}$$

where μ is the mean of the process.

The MA model of order q is expressed by Equation (3).

$$z_t = \alpha + w_t + \theta_1 w_{t-1} + \theta_2 w_{t-2} + \cdots + \theta_q w_{t-q} \tag{3}$$

where $w_t, w_{t-1}, \ldots, w_{t-q}$ are the lagged error terms, and $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients.

ARIMA can only be applied if the data is stationary, meaning the mean and standard deviation remain constant over time. The differencing parameter d indicates the number of times the data needs to be differenced to achieve stationarity. A second-order differencing is computed as:

$$z_t = (Z_t - Z_{t-1}) - (Z_{t-1} - Z_{t-2}) = Z_t - 2Z_{t-1} + Z_{t-2} \tag{4}$$

The general ARIMA (p, d, q) model is given by:

$$z_t = \alpha + \sum_{i=1}^{p} \phi_i z_{t-i} + w_t + \sum_{j=1}^{q} \theta_j w_{t-j} \tag{5}$$

In this study, the NGN/USD exchange rate was used as input to the algorithm to generate forecasts along with error estimates. The dataset was split into training and testing sets in a 90:10 ratio. The ARIMA model was initialized with an order of (4, 1, 0) for forecasting.

This configuration was selected manually based on diagnostic analysis using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. A significant spike at lag 4 in the ACF indicated short-term autocorrelation, supporting the choice of an autoregressive order of 4. Although the PACF showed a notable spike at lag 1, the overall pattern in both plots supported an extended AR structure without an MA term. First-order differencing ($d = 1$) was applied to achieve stationarity, as the original series exhibited non-stationary behavior.

3.5.2. LSTM

The LSTM model, short for Long Short-Term Memory, is an advanced Recurrent Neural Network (RNN) variant. LSTM networks are specifically designed to overcome long-term dependency issues while addressing the vanishing gradient problem through specialized gating mechanisms that regulate the flow of information, allowing relevant information to be retained over extended periods [27].

The LSTM architecture consists of multiple memory blocks, each functioning as a recurrently connected sub-network[28]. These blocks are responsible for preserving the network's internal state across time steps and controlling the flow of information into and out of the cell. Figure 4 illustrates the internal structure of a standard LSTM unit, which includes an input x_t, previous hidden state h_{t-1}, previous cell state c_{t-1}, and produces the updated hidden state h_t and cell state c_t.

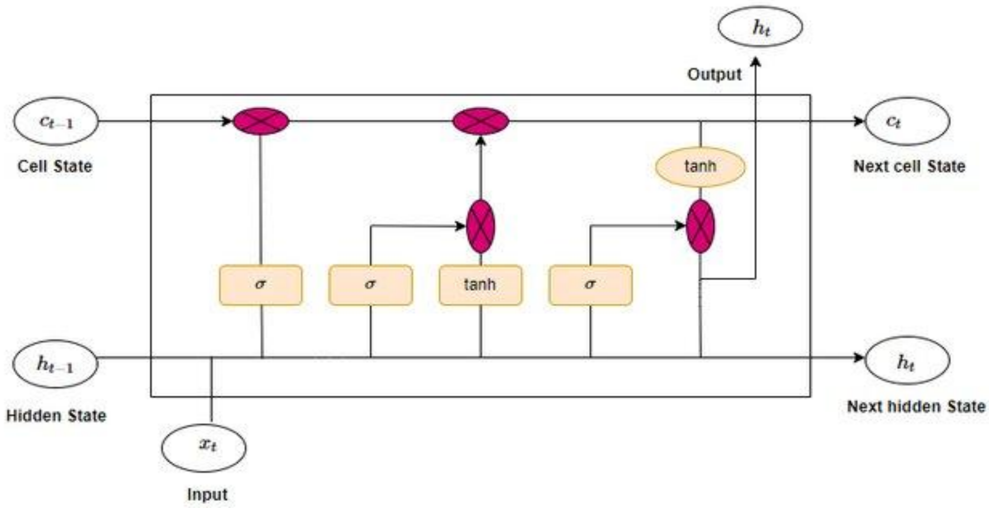

Figure 4. The architecture of a Long Short-Term Memory (LSTM) algorithm [27].

The gates within the LSTM unit are defined as follows:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{6}$$

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{7}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c[h_{t-1}, x_t] + b_c) \tag{8}$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{9}$$

$$h_t = o_t \odot \tanh(c_t) \tag{10}$$

where x_t is input at time step t; h_{t-1}, h_t are previous and current hidden states; c_{t-1}, c_t are previous and current cell states; i_t, f_t, o_t are input, forget, and output gates; W and b are weight matrices and bias vectors for each gate; σ is the sigmoid activation function; $\tanh$ is hyperbolic tangent activation function; and $\odot$ is element-wise multiplication. These equations describe how LSTM updates its internal memory and outputs based on the current input and previous states.

In this study, the LSTM model was implemented using TensorFlow/Keras. The model consists of two LSTM layers followed by two Dense layers. The training used the Adam optimizer and the Mean Squared Error (MSE) loss function. The training settings were defined with a batch size of 32 and 100 epochs. Table 1 shows the configuration parameters of ARIMA and LSTM.

Table 1. Configuration of Arima and LSTM.

Model	Component	Configuration	Parameter Count
ARIMA	ARIMA Order	(4, 1, 0)	-
	Selection Method	Manual (ACF & PACF)	-
	Framework	Statsmodels	-
LSTM	Framework	TensorFlow/Keras	-
	Lookback Window	60	-
	Layer 1	LSTM (50 units, return_sequences=True)	10,400
	Layer 2	LSTM (50 units)	20,200
	Dense Layer 1	25 neurons	1,275
	Output Layer	1 neuron	26
	Optimizer	Adam	63,804
	Loss Function	MSE	-
	Batch Size	32	-
	Epochs	100	-
	Total Trainable Parameters	31,901	-
	Total Parameters (with optimizer)	95,705	-

3.5.3. Hybrid

This research proposes a hybrid model that integrates classical and deep learning approaches for financial time series forecasting. These two models are chosen because they combine a time series into linear and nonlinear trends. The hybrid model can be expressed using Equation (11).

$$x_t = L_t + N_t \tag{10}$$

Here, L_t represents the linear component predicted by the ARIMA model at time step t, N_t represents the nonlinear component predicted by the LSTM model trained on the ARIMA residuals. This hybrid formulation assumes that the time series can be effectively modeled as a combination of its linear and nonlinear components, where residuals are computed as $r_t = x_t - L_t$. The LSTM is trained on the sequence of residuals rt to predict N_t. This residual-based hybrid approach explicitly targets the nonlinear dependencies not captured by ARIMA, thereby improving overall forecasting performance. According to the study, hybrid models enhance forecasting accuracy compared to individual models. Inspired by research on these techniques, we apply this combined model to evaluate the forecasting performance of the Naira against the Dollar exchange rate.

3.6 Software Used

The implementation of the proposed LSTM, ARIMA, and Hybrid ARIMA-LSTM models was conducted using Python in a Google Colab environment, utilizing libraries such as TensorFlow, Keras, statsmodels, and matplotlib for data processing, modeling, and visualization. Regarding model validation, cross-validation techniques were employed with consideration of the temporal nature of the dataset. For the ARIMA model, a time-aware validation strategy was applied through a fixed train-test split that respects the chronological order of the data, aligning with the principles of walk-forward validation (a commonly used cross-validation technique for time series models). Similarly, the LSTM model has a similar splitting rate to the ARIMA model with a lookback window, effectively incorporating recent historical data as features, which acts as an implicit form of feature engineering. In the Hybrid ARIMA-LSTM model, cross-validation was conducted in two phases: ARIMA was first trained to capture linear trends and generate residuals, followed by training the LSTM on these residuals using the same fixed split strategy.

4. Results and Discussion

4.1. Results

This section presents the experimental results of the three forecasting models: ARIMA, LSTM, and the proposed Hybrid ARIMA-LSTM. The evaluation is based on a comparison between actual and predicted NGN/USD exchange rates over time. The aim is to assess each model's predictive accuracy and robustness under real-world conditions.

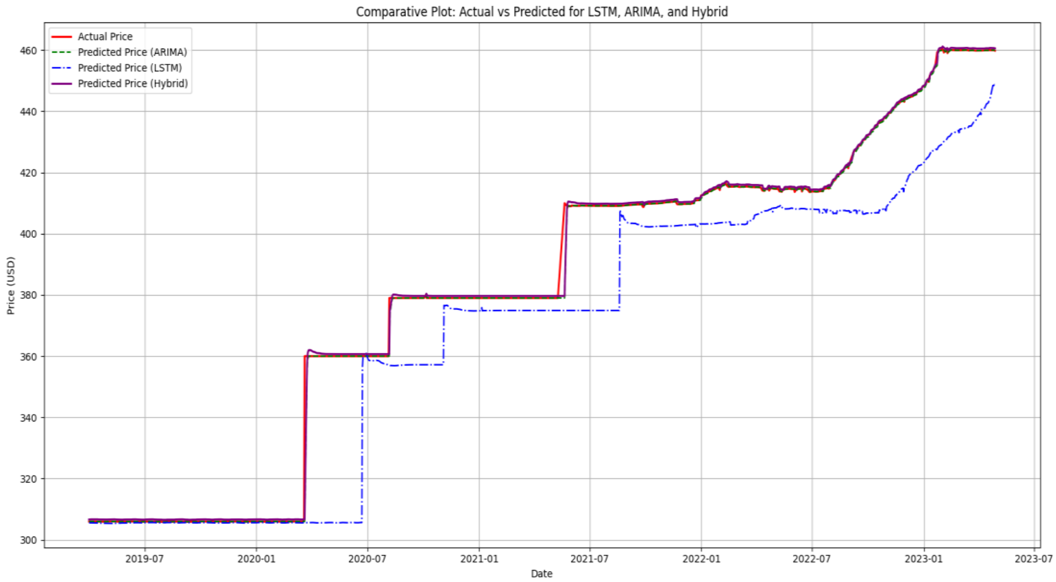

Figure 2. Comparative Analysis of LSTM, ARIMA and Hybrid.

Figure 5 compares the predictions of ARIMA, LSTM, and the Hybrid ARIMA-LSTM model against the actual values. Visually, the hybrid model provides the most accurate and stable forecast, outperforming the standalone ARIMA and LSTM models in tracking fluctuations in the exchange rate.

Table 2 presents a sample comparison of actual vs. predicted values from April 1, 2019, to April 28, 2023, covering a total of 473 daily data points. The LSTM model is slightly underestimated in the early periods, while ARIMA tends to overshoot but maintains a consistent directional trend. In contrast, the hybrid model effectively balances both behaviors, resulting in predictions that closely align with actual values throughout the entire period.

Table 2. Overview of comparative results of actual vs. predicted models of the proposed models.

DATE	ACTUAL	LSTM Predicted	ARIMA Predicted	Hybrid Predicted
2019-04-01	305.95	305.582397	459.856592	306.623503
2019-04-02	306.00	305.536011	374.337631	306.623536
2019-04-03	306.00	305.531799	325.956876	306.659959
2019-04-04	306.00	305.530670	311.149310	306.670284
2019-04-05	306.00	305.530029	307.110840	306.673376
..	..	..	..	..
2023-04-20	459.97	444.175262	454.902079	460.698918
2023-04-25	459.97	448.938873	458.161372	460.659809
2023-04-26	459.97	448.414276	459.126765	460.649221
2023-04-27	459.87	448.735321	459.615041	460.646039
2023-04-28	459.81	448.666260	459.776715	460.570228

Table 3 reports the evaluation metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2).

Table 3. Evaluation metrics.

ALGORITHM	MAE	MSE	RMSE	MAPE	R^2
ARIMA	0.3157	5.3752	2.3185	0.0008	0.9979
LSTM	4.823	39.868	6.314	0.012	0.985
HYBRID	0.783	4.910	2.216	0.002	0.998

The ARIMA model records the lowest MAE and MAPE, indicating high precision in absolute and percentage terms. However, its MSE and RMSE are higher than the hybrid model, implying a greater accumulation of squared errors. Meanwhile, the LSTM model exhibits the highest errors across all metrics except R^2, reflecting its strength in capturing general trends but weakness in precise forecasting. The Hybrid ARIMA-LSTM model achieves the best overall performance, with the lowest RMSE and MSE and the highest R^2 value (0.998). This demonstrates its superior ability to model the linear trends captured by ARIMA and the nonlinear dependencies captured by LSTM.

4.2. Discussion

The findings confirm the effectiveness of integrating ARIMA and LSTM models for exchange rate forecasting. While ARIMA excels in short-term predictions and precision (lowest MAE: 0.3157; MAPE: 0.0008), its squared error metrics (MSE and RMSE) are inferior to the hybrid model. This suggests that ARIMA alone struggles to handle the volatility in long-term predictions. The LSTM model, designed to capture complex nonlinear patterns, recorded the highest error metrics (MAE: 4.823; RMSE: 6.314; MAPE: 0.012), maintaining a respectable R^2 of 0.985. Its performance confirms that deep learning models, though powerful, require careful tuning and are sensitive to input scaling and data volume.

In contrast, the Hybrid ARIMA-LSTM model demonstrates a strong balance, recording the lowest RMSE (2.216) and MSE (4.910), along with the highest R^2 (0.998). Although its MAE (0.783) and MAPE (0.002) are marginally higher than ARIMA's, it compensates with improved overall consistency and adaptability across varied temporal patterns. This confirms the hypothesis that is combining ARIMA's linear modeling capabilities with LSTM's nonlinear learning capacity results in a more robust forecasting framework. To benchmark our model further, we compared its performance with previously reported state-of-the-art models, as shown in Table 4.

Table 4. Comparison with other methods.

ALGORITHM	MAE	RMSE	MAPE
ANN [25]	0.57	4.52	0.26
ARIMA [25]	0.42	4.92	0.18
HYBRID [25]	0.41	4.34	0.17
OUR HYBRID	0.783	2.216	0.002

Although the Hybrid ARIMA-ANN model [25] previously achieved the best performance among earlier methods, our proposed Hybrid ARIMA-LSTM model significantly outperformed it in terms of RMSE (2.216 vs. 4.34) and MAPE (0.002 vs. 0.17). This highlights LSTM's advantage in capturing long-term dependencies and reducing cumulative errors in financial time series.

These results validate the effectiveness of hybrid deep learning models in financial forecasting and provide valuable insights for investors, analysts, and policymakers seeking more reliable and precise prediction tools.

5. Conclusions

The study demonstrates that the Hybrid ARIMA-LSTM model outperforms standalone ARIMA and LSTM models and the state-of-the-art Hybrid ARIMA-ANN model in forecasting the USD/NGN exchange rate. By leveraging the complementary strengths of ARIMA's linear trend-capturing ability and LSTM's proficiency in modeling nonlinear and long-term dependencies, the proposed hybrid model achieves a lower RMSE of 2.216 and a higher R^2

of 0.998, indicating superior predictive accuracy and model fit. Compared to the Hybrid ARIMA-ANN model, which recorded an RMSE of 4.34 and a MAPE of 0.17, the Hybrid ARIMA-LSTM model achieves a significantly lower RMSE and a remarkably reduced MAPE of 0.002. This substantial improvement highlights the advantage of incorporating LSTM into the hybrid approach, showcasing its effectiveness in capturing complex temporal patterns in financial time series data. The results affirm that the Hybrid ARIMA-LSTM model is a more robust and precise solution for forecasting the USD/NGN exchange rate. These findings address a crucial research gap by demonstrating the effectiveness of hybrid deep learning approaches in exchange rate forecasting, providing valuable insights for investors, policymakers, and financial analysts seeking more reliable and precise predictive models.

In the future, we intend to extend this research by evaluating the latest dataset spanning 2001-2024, considering the recent surge in the Naira/Dollar exchange rate from 2023 to 2024, to further assess the robustness and adaptability of the proposed model in capturing the evolving dynamics of the foreign exchange market. Also, future expansions may include incorporating external features such as interest rates, inflation, oil prices, and external factors to enhance the model's predictive capability and provide a more comprehensive understanding of the factors influencing exchange rate movements.

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