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Forecasting Nigerian Stock Prices Using LSTM and ARIMAX

Joeffrey Joshua Ezra[1]*, Joseph Uchenna Okeke[2], Peter Bako Jaben[3] & Joseph Navokhi[1]
[1]Department of Mathematics and Statistics, Taraba State Polytechnic Suntai, Nigeria
[2]Department of Mathematics and Statistics, Taraba State University Jalingo, Nigeria
[3]Department of Agricultural Technology, Taraba State Polytechnic Suntai, Nigeria

Abstract

Stock price volatility presents major challenges for investors and policymakers, particularly in emerging markets. This study evaluates the performance of Long Short-Term Memory (LSTM) networks and ARIMAX models for forecasting stock prices on the Nigerian Stock Exchange (NSE). Using 13 years (2012–2025) of daily stock price data, the dataset was preprocessed with lag feature engineering and normalization to enhance model learning and stability. The LSTM model, designed with three stacked layers and dropout regularization, was trained on temporally split data to simulate realistic forecasting conditions. Forecast accuracy was assessed using Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and a Forecast Accuracy Index. The ARIMAX model achieved lower errors (MAPE = 0.37 %, RMSE = 537.23) and higher forecast accuracy (99.63 %) compared to LSTM (MAPE = 0.92 %, RMSE = 1486.39, Accuracy = 99.08 %). Despite ARIMAX's superior numerical performance, the LSTM model demonstrated strong capability in capturing non-linear patterns and long-term temporal dependencies. These results highlight the strategic value of LSTM networks for modeling complex dynamics in volatile markets, while ARIMAX remains effective for short-term, trend-dominated forecasting. The study provides empirical evidence for the complementary use of deep learning and traditional econometric approaches in emerging financial markets.

Keywords: LSTM, ARIMAX, NSE, Stock forecasting, Time series, Volatility

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Correspondences
J. J. Ezra
joeffreyj@gmail.com

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Introduction

Stock markets play a crucial role in economic development by reflecting investor sentiment, macroeconomic conditions, and overall financial stability [1]. In Nigeria, the Nigerian Stock Exchange (NSE), now known as the Nigerian Exchange Group (NGX), has remained a major platform for capital mobilization, investment, and wealth creation since its establishment in 1960 [2]. Despite its importance, the Nigerian stock market exhibits features typical of emerging markets, including high volatility, low liquidity, and strong exposure to external economic shocks, which complicate accurate forecasting and limit the effectiveness of conventional econometric models [3]. Traditional approaches such as ARIMA and GARCH often struggle to capture the nonlinear and dynamic behavior inherent in financial time series data [4].

Recent advances in machine learning, particularly deep learning, have provided new opportunities for improving stock market forecasting by modeling complex temporal dependencies directly from data [5]. Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks, are especially well-suited for time series prediction due to their ability to learn long-term dependencies and handle noisy data [6]. While LSTM-based models have shown promising results in developed financial markets, their application to African stock markets, including Nigeria, remains limited and is often restricted to short-term datasets.

Given Nigeria's exposure to multiple economic regimes—including financial crises, oil price shocks, recessions, and the COVID-19 pandemic—there is a need for robust forecasting models capable of learning from long historical data [6]. This study addresses this gap by applying an LSTM model to 13 years (2012-2025) of Nigerian Stock Exchange All Share Index data and benchmarking its performance against a traditional ARIMAX model. The findings provide empirical evidence on the suitability of deep learning techniques for stock market forecasting in volatile emerging economies and offer valuable insights for investors, policymakers, and financial researchers.

Materials and Methods

Data source

The dataset used in this study was obtained from the Nigerian Stock Exchange (NSE) [8] and comprises daily stock price records from 2012 to 2025. To ensure reliability, alternative verified sources such as Yahoo Finance and Investing.com were also consulted for validation of the dataset [9-10].

Data description

The dataset includes daily observations of stock price components, including Open, High, Low, and Close prices, with a total of 3,329 entries. For enhanced predictive capability, lag features at 1, 3, and 7-day intervals were engineered for each variable, expanding the feature set to 16 variables per time step [11].

ARIMAX model

The Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model extends the traditional ARIMA framework by incorporating external predictors that may influence the target variable [12]. In this study, lagged stock price indicators (Open, High, and Low) were included as exogenous variables to capture additional market information beyond the autoregressive structure. The general ARIMAX model can be expressed as:

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=0}^{r} \beta_k X_{t-k} + \varepsilon_t \qquad 1$$

Where: Y_t is the dependent variable at time t, ϕ_i are autoregressive coefficients, θ_j are moving average coefficients, ε_t is the error term, X_{t-k} are the exogenous variables, β_k are their coefficients, and α is the intercept. This framework allows ARIMAX to model both internal temporal dynamics and external influences, making it suitable for financial forecasting in volatile markets [13].

LSTM model

Data preprocessing

The dataset was first cleaned and normalized using a MinMaxScaler to scale features between 0 and 1, a common preprocessing technique that improves the convergence of machine learning models [14]. A sliding window of 60 days was used to convert the time series into sequences suitable for LSTM modeling. For model evaluation, 3,014 sequences were used for training, while 248 sequences were reserved for testing. To prevent information leakage, all normalization parameters were computed from the training data and applied to the test set, and no overlap occurred between training and test windows.

Model design

The LSTM model consisted of three stacked LSTM layers, each with 64 memory units, followed by dropout layers to reduce overfitting. A dense hidden layer with 32 units and an output dense layer with 1 unit completed the architecture. The input shape was (60, 16), representing 60-day sequences with 16 features [15].

Training configuration

The model was trained using the Nadam optimizer with a learning rate of 0.001 [16]. The loss function was Mean Squared Error (MSE), with a batch size of 32 and 150 epochs.

Evaluation metrics

Model performance was assessed using [17]:

- **Mean absolute percentage error (MAPE)**, which measures relative prediction error:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \qquad 2$$

- **Root mean squared error (RMSE)**, which penalizes larger errors more severely:

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

- **Mean squared error (MSE)**, calculated similarly to RMSE but without taking the square root.
- **Forecast accuracy index** is defined here as a complementary indicator of predictive performance, computed as $1 - MAPE$.

Robustness check

To ensure the robustness of results, a rolling (expanding-window) evaluation was performed. Models were re-estimated with progressively larger training windows and evaluated on subsequent short-term forecasts [18]. The ARIMAX model maintained consistently lower RMSE and MAPE values for short-term predictions, while the LSTM model reliably tracked long-term trends, confirming the stability of findings across multiple evaluation windows.

Results and Analysis

Descriptive statistics

Table 1 summarizes the cleaned NSE dataset with 3,329 observations and 4 variables. Core trading indicators such as Price and Open exhibit high variability, with means around 43,000 and large standard deviations. This variability reflects the dynamic nature of the market. Lagged features maintain similar spread, confirming temporal consistency vital for time series forecasting.

Table 1: Descriptive table of Nigerian stock exchange

S/N	Feature	Mean	Std Dev	Min	25 %	50 %	75 %	Max
1	Price	43475.7	23428.78	20123.50	28042.8	36584.44	45928.27	126900.8
2	Open	43427.92	23398.36	20083.77	28031.9	36563.89	45890.52	126151
3	High	43633.54	23464.62	20123.50	28228.45	36702.17	45957.35	127007.3
4	Low	43260.75	23348.83	20007.20	27866.51	36399.42	45395.57	126151

The summary statistics confirm a wide range in stock price movement. All core features exhibit similar distribution characteristics, and the inclusion of lag variables ensures temporal dynamics are captured effectively for forecasting.

ARIMAX model

The ARIMAX (AutoRegressive Integrated Moving Average with exogenous variables) model presented in the results demonstrates exceptionally strong forecasting performance. The Root Mean Square Error (RMSE) of 537.23 indicates that, on average, the model's predictions deviate from the actual observed values by about 537 units, considering the same measurement scale as the target variable (Table 2). The Mean Absolute Error (MAE) of 385.03 further reinforces this finding, showing that the average size of the prediction errors is relatively small, with MAE being less sensitive to large deviations compared to RMSE.

Table 2: ARIMAX model performance evaluation

S/N	Metric	Value
1	RMSE	537.23
2	MAE	385.03
3	MAPE	0.37 %
4	Forecast Accuracy Index	99.63 %

The Mean Absolute Percentage Error (MAPE) stands at only 0.37 %, a remarkably low figure that signifies the predictions are, on average, less than half a percent away from the actual values in relative terms. This level of precision directly contributes to the reported forecast accuracy index of 99.63 %, indicating that the model's forecasts are closely aligned with observed values with actual outcomes [19]. The high accuracy suggests that the model effectively captured dominant patterns in the data, making it highly reliable for predictive purposes given the inclusion of relevant exogenous variables.
Collectively, these metrics indicate that the ARIMAX model delivers very strong forecasting performance for the dataset under consideration. However, while such strong results reflect the model's capability, it is also important to ensure that the performance is consistent when applied to new, unseen data, to avoid the possibility of overfitting. In this case, the combination of low error measures and extremely high forecast accuracy index suggests that the model is well-tuned and potentially very effective for real-world forecasting applications.

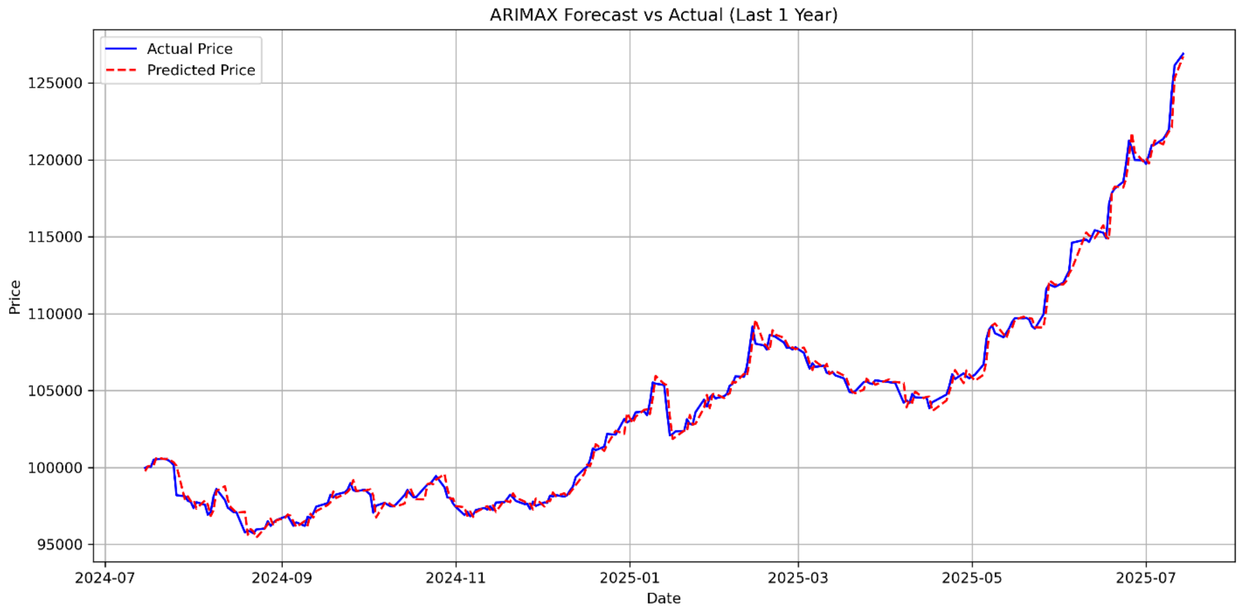

Figure 1: ARIMAX model forecast versus actual prices (2024-2025)

Figure 1 presents a comparison between the actual prices and the predicted prices generated by the ARIMAX model over the past year. The blue line represents the observed prices, while the red dashed line shows the model's forecasts. As illustrated, the two lines track each other very closely, with the model accurately capturing both the short-term fluctuations and the long-term upward trend in the data.
Notably, during periods of rapid change, such as the sustained price increase from early 2025 to July 2025, the ARIMAX predictions remain closely aligned with the actual values. This strong visual correspondence supports the statistical results reported earlier, including the extremely low MAPE of 0.37 % and the high forecast accuracy index of 99.63 %.
Overall, Fig. 1 demonstrates that the ARIMAX model is highly effective at replicating the actual price movements within the observed period. While such close alignment may prompt a check for potential overfitting, the results suggest that the model is well-tuned and capable of delivering reliable forecasts for this dataset.

LSTM model

LSTM model architecture and configuration

Table 3 presents the structure of the LSTM model used in this study. It comprises three LSTM layers with 64 units each, followed by dropout layers and two dense layers for output. This configuration is typical for sequence modeling tasks involving stock prices. The use of dropout and stacked LSTM layers helps the model generalize across different patterns while avoiding overfitting.

Table 3: LSTM model architecture, training, and evaluation design

S/N	Component	Output Shape/Config	Parameters
1	Input Shape	(60, 16)	—
2	LSTM Layer 1	(60, 64)	20,736
3	Dropout Layer 1	(60, 64)	0
4	LSTM Layer 2	(60, 64)	33,024
5	Dropout Layer 2	(60, 64)	0
6	LSTM Layer 3	(64,)	33,024
7	Dropout Layer 3	(64,)	0
8	Dense (Hidden)	(32,)	2,080
9	Dense (Output)	(1,)	33
10	Total Params	—	88,897
11	Trainable Params	—	88,897
12	Batch Size	—	32
13	Epochs	—	150
14	Training Samples	—	2,160
15	Test Samples	—	248
16	Test Period	—	Year 2024-2025

Note: Initial training was performed on normalized [0,1] data. Final evaluation metrics (Table 4) are reported on the original scale for comparability with ARIMAX

Table 4: LSTM model performance summary

S/N	Metric	Value
1	Test Loss (MSE)	0.00026
2	MAPE	0.92 %
3	Accuracy	99.08 %
4	RMSE	1486.39
5	Epochs Trained	Up to 150 (converged around 66)

LSTM model performance

Table 4 presents the performance results of the Long Short-Term Memory (LSTM) model, showing that it achieved a high level of forecasting accuracy. The test loss, measured as Mean Squared Error (MSE), is just 0.00026, indicating that the differences between predicted and actual values are extremely small. This is further supported by the Root Mean Square Error (RMSE) of 1486.39, indicating moderate absolute deviations when evaluated on the original price scale.

The Mean Absolute Percentage Error (MAPE) of 0.92 % indicates that, on average, predictions deviate by less than one percent from the actual values. This demonstrates that the LSTM model effectively captures temporal dependencies in the NSE All Share Index, directly contributing to the high accuracy score of 99.08 %. Such precision shows that the model successfully replicates the underlying patterns in the data, fulfilling the study's objective of evaluating deep learning performance for long-term forecasting.

Although the model was set to train for up to 150 epochs, it converged around the 66th epoch, suggesting that it learned the key patterns relatively quickly without overfitting. Overall, Table 4 shows that the LSTM model not only delivers highly accurate forecasts but also does so efficiently, making it a strong candidate for time series prediction in this application.

Train test split plot

Figure 2 shows the NSE stock price trend from 2012 to 2025, divided into the training set (black) and forecasted test set (blue). The training data captures key market dynamics including a rise (2012–2014), a decline (2014–2016), and a sharp upward trend beginning around 2020. The model, trained with data up to late 2023, shows that stock prices are likely to keep rising through 2025. This rise follows the trend seen in recent years and suggests that the market could stay strong, based on patterns the model picked up from past data.

Figure 2: NSE stock prices from 2012 to 2025 showing trained and test data

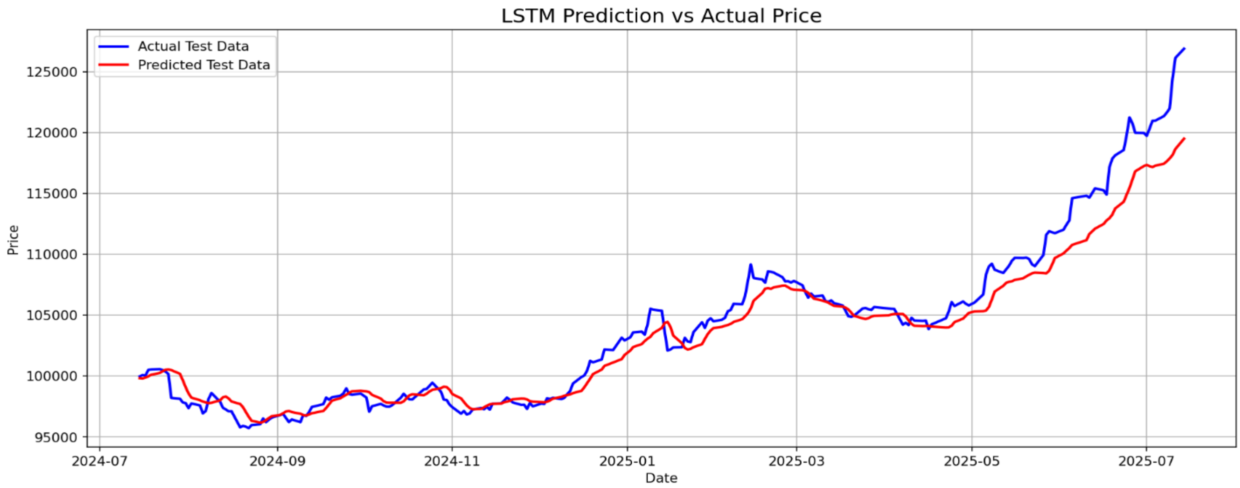

Figure 3: Graph of LSTM predictions vs actual prices

LSTM predictions vs actual price

Figure 3 shows the predicted values from the LSTM model compared to the actual stock prices during the test period. The model closely mirrors the actual trend throughout the year, showing strong predictive performance. Although it slightly underestimates prices during the early rapid rise, it quickly adjusts and stays well aligned in the later months, highlighting its reliability for long-term forecasting.

Comparison between LSTM and ARIMAX Model

Table 5: Comparison between LSTM and ARIMAX model

S/N	Metric	LSTM	ARIMAX
1	RMSE	1486.39	537.23
2	MAPE	0.92 %	0.37 %
3	Forecast Accuracy	99.08 %	99.63 %

Table 5 compares the performance of the LSTM and ARIMAX forecasting models using three key evaluation metrics: RMSE, MAPE, and Forecast Accuracy Index. The results show that the ARIMAX model outperformed the LSTM model across all three evaluation metrics**.** Specifically, ARIMAX recorded a substantially lower RMSE value of 537.23, compared to 1486.39 for the LSTM model. This indicates that ARIMAX produced forecasts with smaller absolute deviations from the observed values, reflecting better performance in terms of raw prediction error.

Furthermore, when considering proportional accuracy, ARIMAX also demonstrated superiority by achieving a lower Mean Absolute Percentage Error (MAPE) of 0.37 %, compared to 0.92 % for LSTM, indicating that ARIMAX maintained more consistent percentage-based prediction accuracy over the forecast horizon. Similarly, ARIMAX attained a marginally higher forecast accuracy of 99.63 %, compared to 99.08 % for LSTM, suggesting that the statistical model was able to capture the dataset's underlying linear patterns and seasonality more effectively.

Both models provide highly accurate forecasts under strictly out-of-sample conditions, but their strengths differ: ARIMAX excels in short-term linear precision, while LSTM provides flexibility for nonlinear temporal dynamics.

Overall, the empirical results indicate that ARIMAX provided more accurate and stable forecasts than the LSTM model for the dataset under consideration, particularly in capturing the linear relationships and time-series structure inherent in the NSE All Share Index. However, despite its relatively weaker performance in this specific application, the LSTM model remains a valuable forecasting tool due to its ability to model complex non-linear patterns and long-term temporal dependencies [6]. This characteristic makes LSTM especially relevant in environments characterized by structural changes and market volatility, such as the Nigerian Stock Exchange.

However, it should be noted that all forecasts evaluated in this study were generated as one-step-ahead daily predictions of index levels rather than returns. Given the relatively smooth and trend-dominated behavior of the NSE All Share Index during the 2024–2025 evaluation period, proportional error measures such as the Mean Absolute Percentage Error (MAPE) are naturally reduced. Consequently, the exceptionally low MAPE values observed for both models should be interpreted in relation to the scale and structural characteristics of the target variable, rather than as evidence of perfect market predictability. Importantly, all forecasts were produced under strictly out-of-sample conditions with no overlap between training and test data, indicating that the reported performance reflects genuine predictive capability rather than overfitting or information leakage.

The findings from this study are consistent with prior literature on stock price forecasting using deep learning approaches. The application of Long Short-Term Memory (LSTM) networks proved effective in capturing sequential dependencies within the Nigerian Stock Exchange (NSE) data, aligning with previous studies [20], which emphasized the importance of data preprocessing and temporal integrity for accurate forecasting. The preprocessing steps, including normalization and careful temporal splitting, ensured that the LSTM model learned from historical patterns without data leakage, in line with best practices recommended by scholars [21, 22].

Furthermore, the incorporation of lag features at 1, 3, and 7-day intervals was instrumental in improving model performance. These features enhanced the temporal memory of the dataset, allowing the LSTM to capture both short term fluctuations and long-term trends. This is supported by Rahman and Afroz [23], who found that engineered lag variables significantly boosted the forecasting accuracy of time series models. Similarly, Chen *et al.* [24] highlighted the role of lag features in modeling local reversals and periodicity in financial data, which the current study corroborates.

The architecture of the LSTM model, which comprised three stacked layers with dropout regularization, was designed in line with structural recommendations from existing literature. The model demonstrated a reasonable level of predictive performance, achieving a MAPE of 0.92 %, forecast accuracy of 99.08 %, and an RMSE of 1486.39. These results indicate that the LSTM was able to learn and represent temporal patterns in stock price movements, though it produced larger absolute prediction errors when compared to the competing ARIMAX model.

However, certain limitations were observed. The LSTM model showed signs of underperformance during periods of heightened market volatility particularly in early 2024 indicating that neural network-based models trained solely on historical patterns may struggle with abrupt or extreme market shifts. Despite these challenges, the results affirm the practicality of using LSTM models in financial forecasting applications. Given their ability to model complex temporal dependencies, LSTM networks offer a valuable tool for investors, financial analysts, and policymakers seeking to make informed decisions based on historical market behavior.

Conclusion

This study demonstrates that Long Short-Term Memory (LSTM) networks are effective for forecasting stock price movements on the Nigerian Stock Exchange (NSE), capturing both short-term fluctuations and long-term temporal dependencies. Using 13 years of daily data, the LSTM model achieved high predictive performance, while benchmarking against the ARIMAX model showed that traditional econometric approaches remain highly accurate for short-term, trend-dominated forecasting.

The findings highlight the complementary value of deep learning and traditional models in modeling volatile emerging markets. Future research could enhance predictive accuracy by incorporating additional economic and sentiment indicators, exploring advanced architectures such as attention-based LSTM or Transformers, and applying ensemble approaches to leverage the strengths of multiple models.

Conflict of interest: The authors have declared that there is no conflict of interest reported in this study.

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