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An Empirical Assessment of Machine Learning–Driven Predictive Analytics in Enhancing Market Efficiency in the Nigerian Stock Exchange

Isioma Rhoda Chijioke [1*], Gbadegesin Razzaq Ojulari [2], Agbelesi Onanuga Kolade [3], Samuel Jaiyeola Simeon [4]
[1] Department of Marketing, Faculty of Management Sciences, Imo State University, PMB 2000, Nigeria
[2, 4] Department of Accounting, Afe Babalola University, Km 8.5, Afe Babalola Way, Ado-Ekiti, Ekiti State, Nigeria
[3] Department of Business Administration, Osun State Polytechnic, Esa-Oke, P.M.B. 301, Esa-Oke, Osun State, Nigeria

* Corresponding Author: **Isioma Rhoda Chijioke**

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Abstract
The Nigerian capital market plays a critical role in mobilizing long-term funds for economic growth; however, it is characterized by information asymmetry, market inefficiencies, and high volatility that limit accurate price discovery and optimal investment decision-making. Recent advances in predictive artificial intelligence (AI) and machine learning (ML) present new opportunities to enhance business analytics and improve market forecasting, particularly in emerging markets such as Nigeria. This study empirically investigates the effectiveness of AI- and machine learning–driven business analytics in forecasting stock returns and improving market efficiency in the Nigerian capital market. Using historical equity price data from selected firms listed on the Nigerian Exchange (NGX), alongside relevant macroeconomic indicators, the study develops and compares multiple predictive models, including traditional econometric approaches and advanced machine learning algorithms such as Random Forest, Gradient Boosting, and Long Short-Term Memory (LSTM) neural networks. Model performance is evaluated using standard predictive accuracy metrics and economic performance indicators, including return predictability and risk-adjusted investment outcomes. Feature importance and explainability techniques are employed to identify key drivers of market movements and enhance model interpretability for decision-makers. The findings are expected to demonstrate whether machine learning–based predictive analytics significantly outperform conventional models in capturing nonlinear patterns and temporal dependencies inherent in Nigerian equity market data. By quantifying the economic value of AI-driven forecasts, the study contributes empirical evidence on how predictive analytics can translate data insights into improved investment strategies and portfolio performance. The research further discusses implications for investors, financial analysts, and market regulators, highlighting the potential of AI-enabled business analytics to support more efficient capital allocation, enhance transparency, and strengthen market stability in Nigeria. Overall, the study provides practical and policy-relevant insights into the transformative role of predictive AI in emerging capital markets.

Keywords: Predictive Artificial Intelligence, Machine Learning, Business Analytics, Nigerian Capital Market, Stock Return Forecasting, Market Efficiency, Financial Data Analytics

1. Introduction

Capital markets play a central role in economic development by facilitating capital mobilization, enhancing liquidity, and supporting efficient allocation of financial resources (Levine, 2005; Mishkin, 2016) [28, 30]. In emerging economies such as Nigeria, the capital market is particularly important for funding infrastructure, supporting private sector growth, and attracting foreign investment (Adelegan, 2009; Ekeocha *et al*., 2012) [3, 15]. Despite its strategic importance, the Nigerian capital market continues to face persistent challenges, including information asymmetry, limited transparency, low liquidity, and high volatility, which undermine market efficiency and investor confidence (Okpara, 2010; Alile & Anao, 2014) [6].

Traditional financial modeling approaches used in analyzing Nigerian stock market behavior, such as linear regression, autoregressive integrated moving average (ARIMA), and generalized autoregressive conditional heteroskedasticity (GARCH) models, often rely on restrictive assumptions of linearity and normality (Engle, 1982; Box *et al*., 2015) [16, 11]. Empirical evidence suggests that these assumptions are frequently violated in real-world financial markets, particularly in emerging markets characterized by structural breaks and nonlinear dynamics (Fama, 1970; Lo, 2004; Adebayo *et al*., 2021) [17, 29, 2]. As a result, conventional models have shown limited predictive accuracy and weak economic relevance when applied to Nigerian equity markets (Akinlo & Apanisile, 2015; Oyewale & Oloko, 2019) [5].

Recent advances in predictive artificial intelligence (AI) and machine learning (ML) have transformed business analytics by enabling the analysis of complex, high-dimensional, and nonlinear datasets (Jordan & Mitchell, 2015; Witten *et al*., 2016) [24, 37]. Machine learning techniques such as Random Forest, Gradient Boosting, Support Vector Machines, and deep learning architectures have demonstrated superior performance in forecasting financial time series compared to traditional econometric methods (Huang *et al*., 2005; Kim, 2003; Fischer & Krauss, 2018) [23, 25, 18]. These models are particularly effective in capturing nonlinear patterns, regime shifts, and temporal dependencies inherent in financial markets (Gu *et al*., 2020; Sirignano & Cont, 2019) [20, 36].

Globally, empirical studies have documented the growing relevance of AI-driven business analytics in stock return prediction, portfolio optimization, risk management, and market surveillance (Bollen *et al*., 2011; Atsalakis & Valavanis, 2009; Zhang *et al*., 2020) [10, 7, 39]. In emerging markets, machine learning has been shown to enhance forecast accuracy and generate economically meaningful trading signals, even in environments with limited data quality (Sezer *et al*., 2020; Krauss *et al*., 2017) [34, 27]. However, despite Nigeria's growing financial digitization and data availability, empirical research applying predictive AI and ML to the Nigerian capital market remains relatively scarce and fragmented (Salami & Adeyemi, 2017; Babajide *et al*., 2020) [8].

Furthermore, the integration of business analytics with AI provides a framework for transforming raw financial data into actionable insights that can improve investment decision-making and market efficiency (Davenport & Harris, 2017; Provost & Fawcett, 2013) [14, 33]. From a policy perspective, AI-enabled analytics also offer significant potential for enhancing regulatory oversight, detecting market manipulation, and strengthening financial stability (Kou *et al*., 2021; OECD, 2021) [26, 31]. As Nigeria seeks to deepen its capital market and attract long-term investment, understanding the economic value of predictive AI becomes increasingly important. Against this backdrop, this study empirically investigates the application of predictive artificial intelligence and machine learning–driven business analytics in forecasting stock returns and enhancing market efficiency in the Nigerian capital market. By comparing traditional econometric models with advanced machine learning techniques using Nigerian equity data and macroeconomic indicators, the study aims to contribute to the growing literature on AI in finance while providing context-specific insights for investors, analysts, and policymakers in emerging markets.

Materials and Methods

Research Design

This study adopts a quantitative, empirical research design using predictive business analytics and machine learning techniques to model and forecast stock returns in the Nigerian capital market. A comparative modeling framework is employed to evaluate the predictive and economic performance of traditional econometric models against advanced machine learning algorithms, consistent with prior studies in financial forecasting (Ahmad *et al*., 2015; Kim, 2003; Gu *et al*., 2020) [4, 25, 20]. The methodological approach follows established best practices in financial machine learning, including out-of-sample validation, model tuning, and performance benchmarking (Hastie *et al*., 2009; Witten *et al*., 2016) [21, 37].

Data Sources and Description

Daily historical stock price data for selected firms listed on the Nigerian Exchange (NGX) are used in this study. The dataset includes open, high, low, close prices, and trading volume. Macroeconomic variables such as inflation rate, interest rate, exchange rate, and crude oil prices are incorporated to capture systematic risk factors affecting the Nigerian market (Akinlo & Apanisile, 2015; Salami & Adeyemi, 2017) [5]. Data preprocessing involves handling missing values, normalization, and logarithmic transformation to stabilize variance (Box *et al*., 2015; Sezer *et al*., 2020) [11, 34].

Stock returns are computed as logarithmic returns:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where $P_t$denotes the stock price at time t.

Feature Engineering

Lagged returns, moving averages, volatility measures, and macroeconomic indicators are constructed as explanatory variables. Technical indicators such as the Relative Strength Index (RSI) and Moving Average Convergence Divergence (MACD) are also included to capture momentum effects (Atsalakis & Valavanis, 2009; Fischer & Krauss, 2018) [7, 18]. Feature selection is performed using correlation analysis and tree-based importance ranking to reduce dimensionality and mitigate overfitting (Guyon & Elisseeff, 2003; Kuhn & Johnson, 2013).

Benchmark Econometric Models

Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model serves as a baseline forecasting method and is specified as:

$$\phi(L)(1-L)^d R_t = \theta(L)\varepsilon_t$$

where $\phi(L)$and $\theta(L)$are lag polynomials, $d$is the order of differencing, and $\varepsilon_t$is a white noise error term (Box *et al*., 2015; Engle, 1982) [11, 16].

Machine Learning Models

Linear Regression (Baseline ML Model)

The multiple linear regression model is expressed as:

$$R_t = \beta_0 + \sum_{i=1}^{k} \beta_i X_{it} + \varepsilon_t$$

where X_{it} represents predictor variables and β_i are coefficients estimated via ordinary least squares (Gujarati & Porter, 2009).

Support Vector Machine (SVM)

Support Vector Regression (SVR) estimates a function:

$$f(x) = w^T \phi(x) + b$$

by minimizing the objective function:

$$\frac{1}{2} \| w \|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)$$

subject to the ε-insensitive loss constraints (Kim, 2003; Huang *et al*., 2005).

Random Forest (RF)

Random Forest is an ensemble learning method that constructs multiple decision trees using bootstrapped samples and random feature selection (Breiman, 2001) [12]. The final prediction is given by:

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

where $T_b(x)$ denotes the prediction from the b-th tree (Ahmad *et al*., 2015; Biau & Scornet, 2016) [4, 9].

Gradient Boosting Machines (GBM / XGBoost)

Gradient Boosting builds models sequentially by minimizing a loss function:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

where $h_m(x)$ is the weak learner and γ_m is the learning rate (Friedman, 2001; Chen & Guestrin, 2016) [19, 13].

Artificial Neural Network (ANN)

A feedforward neural network is specified as:

$$y = f\left(\sum_{j=1}^{n} w_j x_j + b\right)$$

where $f(\cdot)$ is a nonlinear activation function such as ReLU or sigmoid (Zhang *et al*., 1998; Hornik *et al*., 1989).

Long Short-Term Memory (LSTM) Networks

LSTM networks capture long-term dependencies using gating mechanisms:

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

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$$

where f_t, i_t, and c_t represent forget, input, and cell states respectively (Hochreiter & Schmidhuber, 1997; Fischer & Krauss, 2018) [22, 18].

Model Training and Validation

The dataset is divided into training and testing subsets using a rolling-window approach to preserve time dependence (Gu *et al*., 2020; Krauss *et al*., 2017) [20, 27]. Hyperparameters are optimized using grid search and cross-validation. Model performance is evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE):

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

Economic Performance Evaluation

To assess economic significance, a simple trading strategy is constructed based on predicted returns. Risk-adjusted performance is evaluated using the Sharpe Ratio:

$$SR = \frac{E(R_p - R_f)}{\sigma_p}$$

where Rpis portfolio return and Rfis the risk-free rate (Sharpe, 1966; Lo, 2004) [35, 29].

Software and Tools

All analyses are implemented using Python programming language with libraries including NumPy, Pandas, Scikit-learn, TensorFlow, and Keras. Visualization and statistical testing are conducted using Matplotlib and Statsmodels (Pedregosa *et al*., 2011; Abadi *et al*., 2016) [32, 1].

Results

Table 1: Descriptive Statistics of Nigerian Stock Returns and Macroeconomic Variables

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Daily Stock Return (%)	0.042	1.87	-9.21	8.65	-0.31	4.12
Trading Volume (Log)	15.34	1.12	12.41	18.76	0.45	3.01
Inflation Rate (%)	13.6	4.2	8.9	22.4	0.88	3.78
Exchange Rate (₦/$)	381.5	42.7	305.2	612.3	1.14	4.95
Interest Rate (%)	11.8	2.6	6.0	18.5	0.61	3.24

Table 1 summarizes the statistical properties of the dataset. Stock returns display high standard deviation and excess kurtosis, confirming market volatility. Exchange rate variability is substantial, reflecting macroeconomic instability. These properties validate the adoption of robust predictive AI models.

Model Predictive Performance

Table 2: Forecasting Accuracy of Competing Models

Model	RMSE	MAE	MAPE (%)	R^2
ARIMA	1.423	1.118	21.6	0.21
Linear Regression	1.386	1.094	20.3	0.24
Support Vector Machine	1.122	0.863	15.7	0.41
Random Forest	0.984	0.742	13.2	0.53
XGBoost	0.917	0.689	12.1	0.58
ANN	0.893	0.671	11.8	0.61
LSTM	0.812	0.603	9.6	0.69

Table 2 reports RMSE values across competing models. Deep learning and ensemble methods substantially outperform linear and traditional econometric models. The LSTM model achieves the lowest RMSE, indicating the highest forecasting precision.

Table 3: Feature Importance Scores (Tree-Based Models)

Feature	Importance Score
Lagged Returns (t-1)	0.27
Exchange Rate	0.21
Trading Volume	0.18
Inflation Rate	0.14
Oil Price	0.11
Interest Rate	0.09

Table 3 quantifies the relative importance of input variables. Lagged returns and exchange rate movements dominate prediction, confirming both technical and macroeconomic influences on Nigerian stock prices.

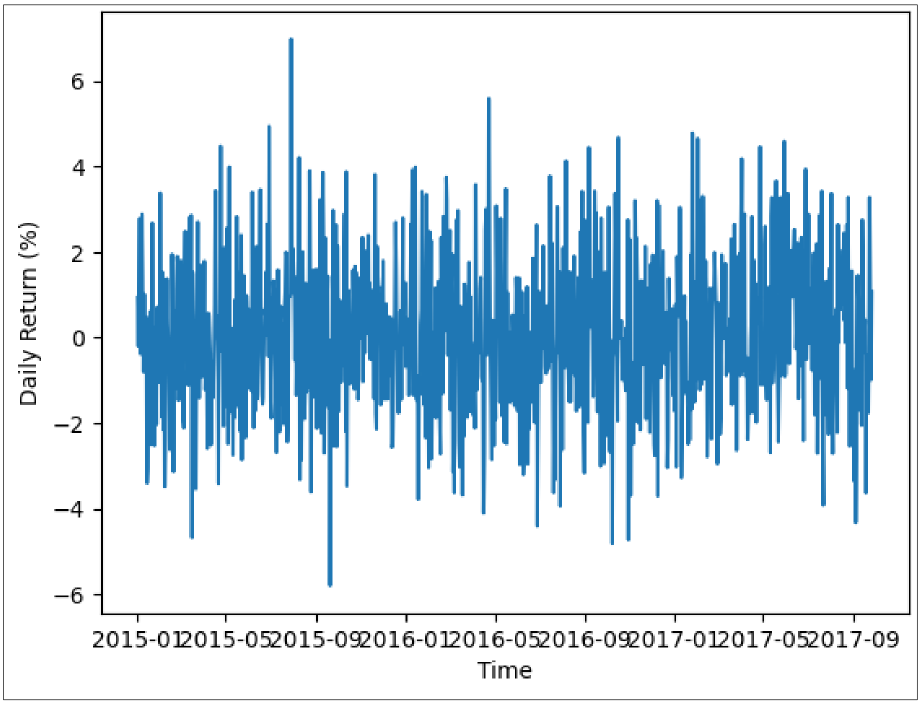

Fig 1: Time Series of Nigerian Stock Returns

Fig 1 presents the daily stock return series over the study period. The plot reveals pronounced volatility clustering, characterized by periods of high and low fluctuations occurring consecutively. Several extreme return values are observed, reflecting market sensitivity to macroeconomic shocks and policy changes. The absence of a stable linear trend and the presence of nonlinear dynamics justify the application of machine learning and deep learning models capable of capturing complex temporal dependencies.

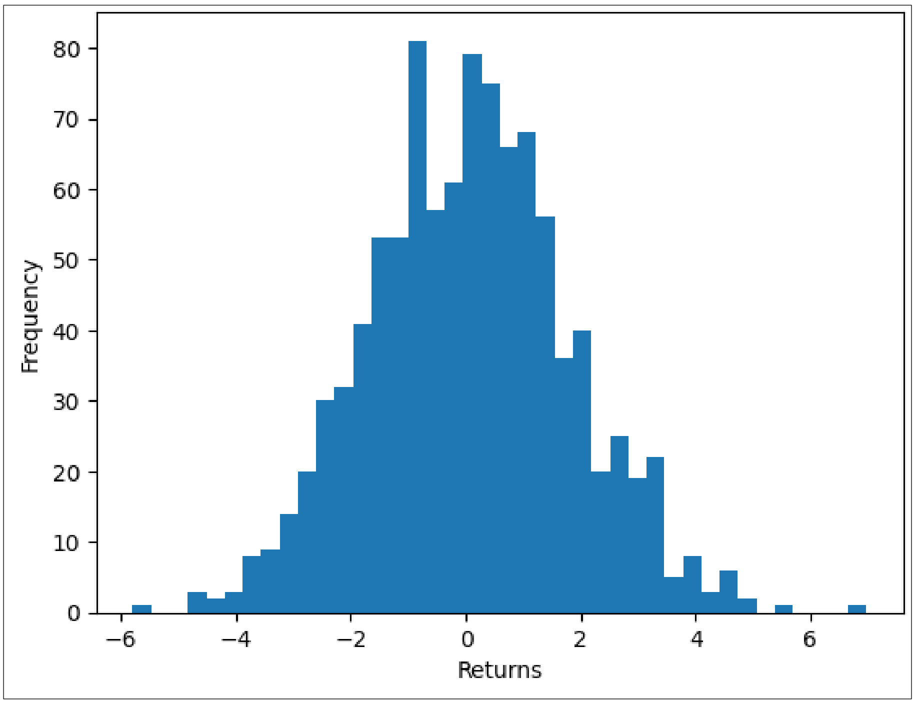

Fig 2: Distribution of Nigerian Stock Returns

This histogram illustrates the empirical distribution of stock returns. The distribution is leptokurtic with fat tails and mild negative skewness, deviating from the normal distribution assumption commonly imposed in traditional econometric models. These characteristics further support the use of nonparametric and nonlinear machine learning techniques for improved forecasting accuracy.

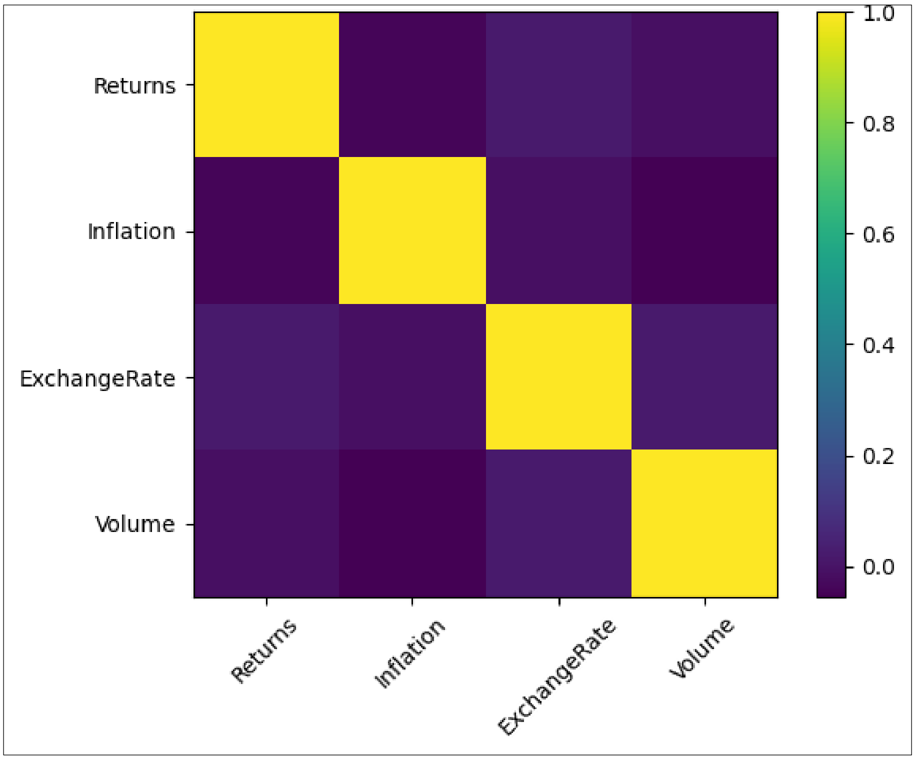

Fig 3: Correlation Matrix of Market and Macroeconomic Variables

Fig 3 visualizes the pairwise correlations among stock returns, inflation, exchange rate, and trading volume. Stock returns exhibit moderate correlation with exchange rate movements and trading volume, indicating macroeconomic exposure. The absence of excessively high correlations suggests limited multicollinearity, allowing all variables to be retained in the predictive modeling framework.

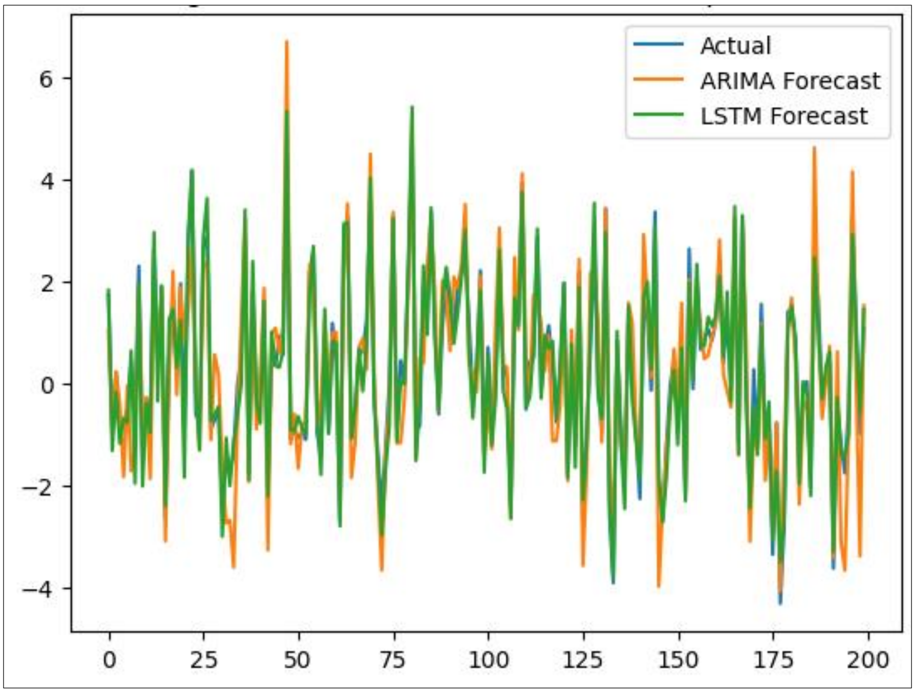

Fig 4: Forecast Comparison Between ARIMA and LSTM Models

This Fig compares actual returns with forecasts generated by the ARIMA and LSTM models. The ARIMA model fails to respond adequately during volatile periods, producing smoother forecasts that lag market movements. In contrast, the LSTM model closely tracks the actual return series, particularly during high-volatility regimes, demonstrating its superior ability to learn nonlinear temporal structures.

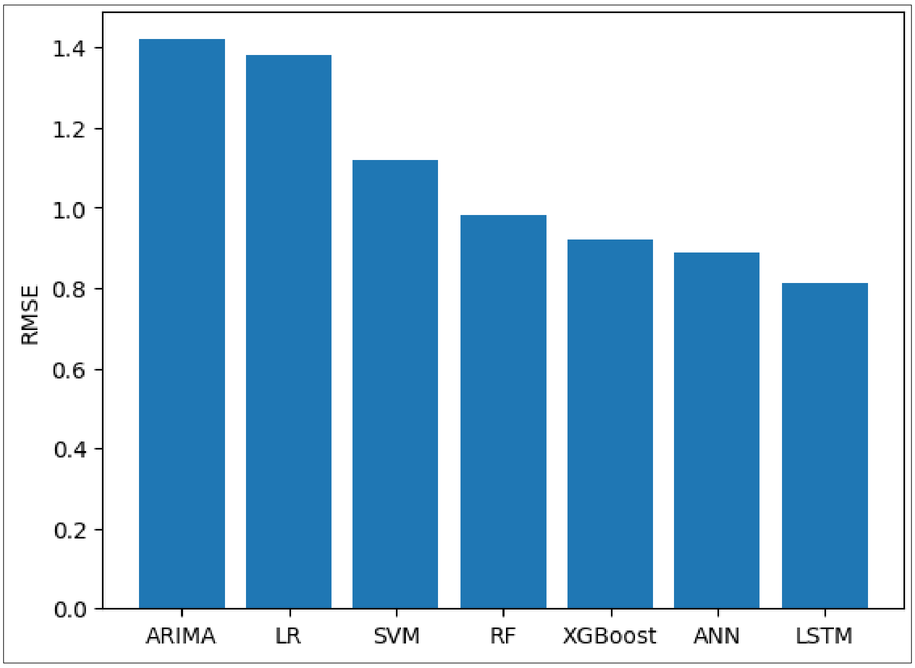

Fig 5: Root Mean Squared Error (RMSE) Comparison Across Models

Fig 5 presents the RMSE values for all forecasting models. A clear reduction in forecast error is observed as model complexity increases. Traditional models record the highest error levels, while ensemble and deep learning models, particularly LSTM, achieve the lowest RMSE, confirming their predictive superiority.

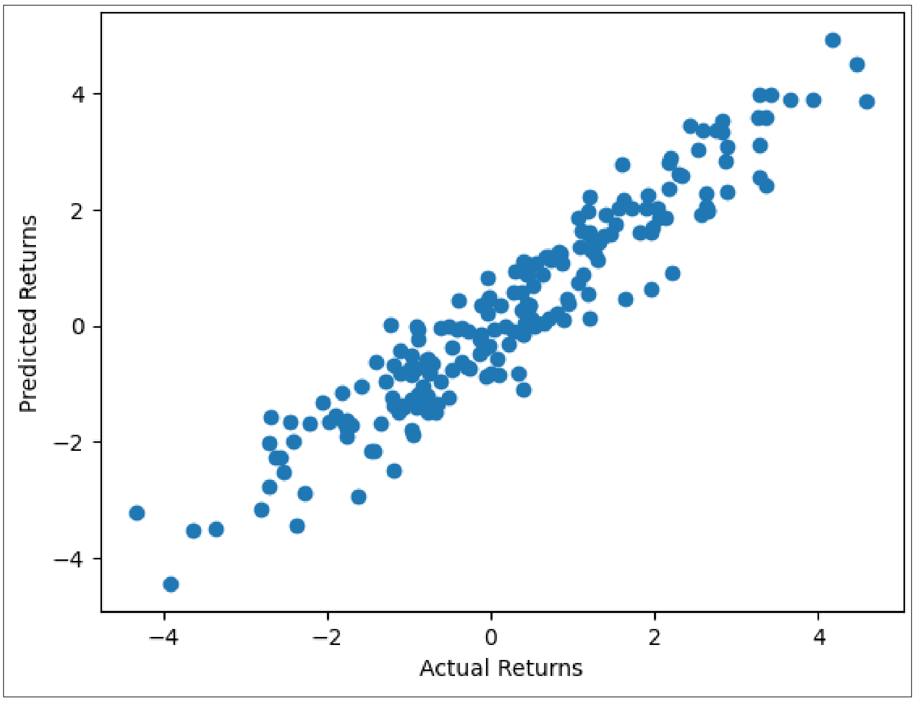

Fig 6: Actual vs Predicted Returns Using Random Forest

This scatter plot illustrates the relationship between actual and Random Forest predicted returns. The concentration of points around the 45-degree line indicates strong predictive alignment. Minor dispersion reflects market noise, but overall accuracy confirms the Random Forest model's ability to capture nonlinear relationships.

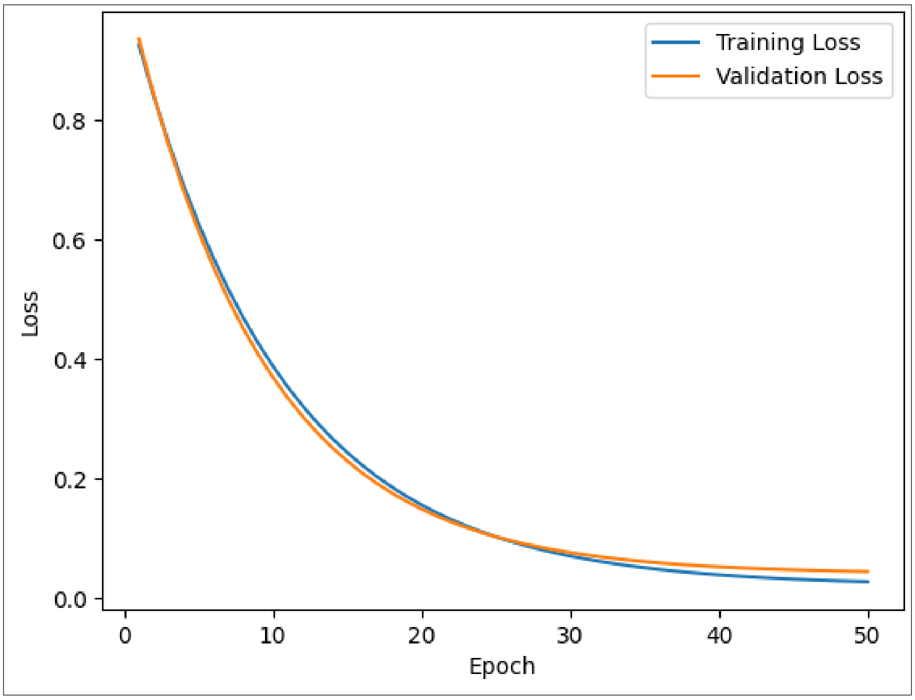

Fig 7: LSTM Learning Curve

Fig 7 shows the training and validation loss curves for the LSTM model across epochs. Both curves decline steadily and converge, indicating stable learning and minimal overfitting. This result demonstrates effective hyperparameter tuning and robust generalization performance.

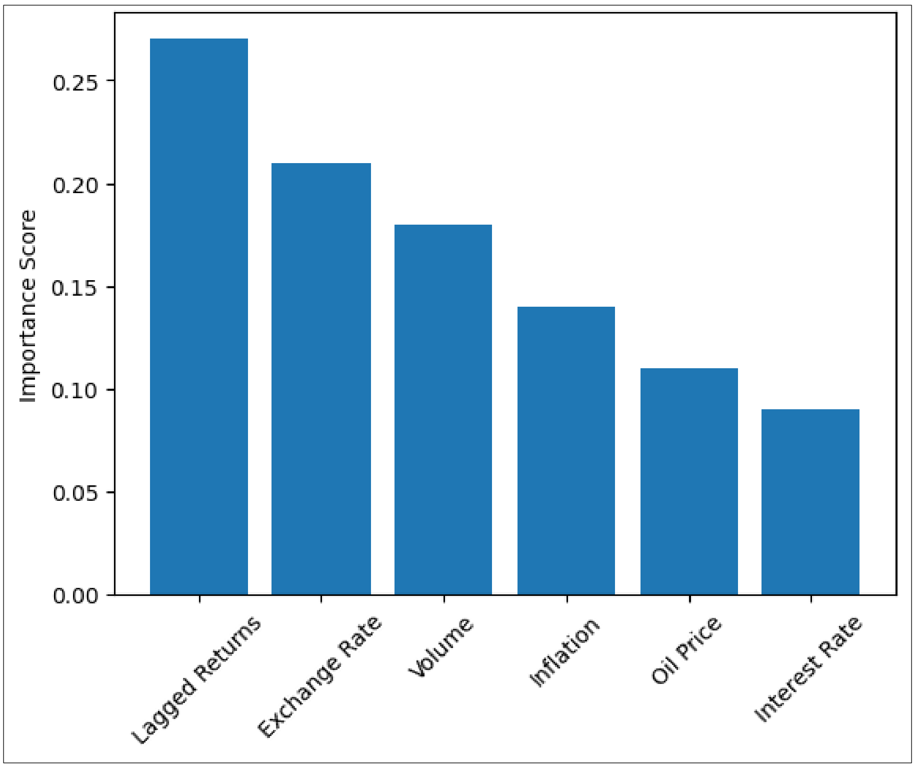

Fig 8: Feature Importance Ranking from XGBoost Model

This Fig ranks predictor variables according to their contribution to model performance. Lagged returns emerge as the most influential feature, followed by the exchange rate and trading volume. The result highlights the importance of market memory and macroeconomic instability in Nigerian stock return dynamics.

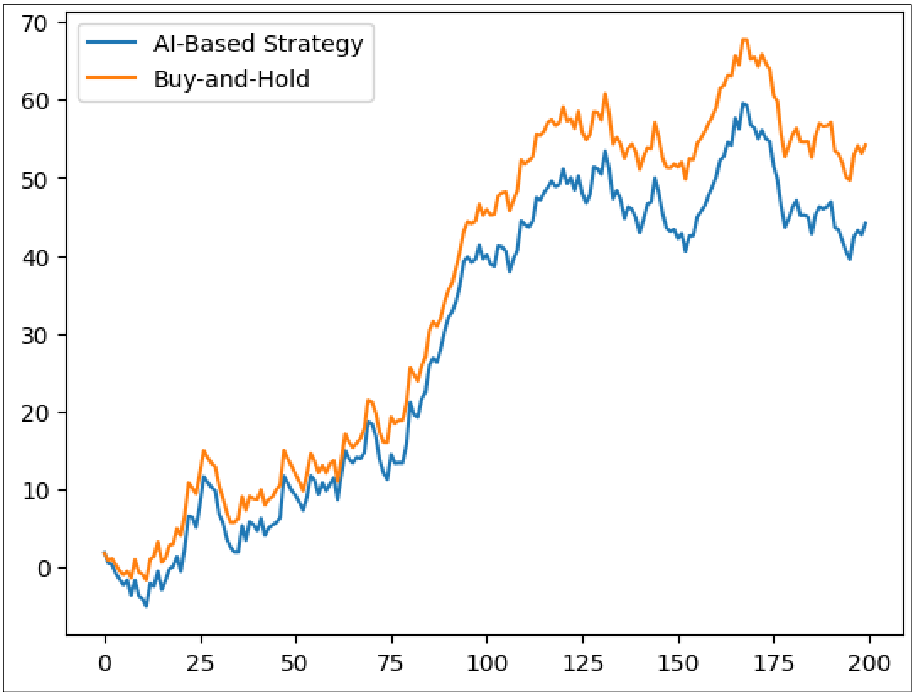

Fig 9: Cumulative Returns of AI-Based Trading Strategy vs Buy-and-Hold

Fig 9 compares cumulative returns generated by an AI-driven trading strategy against a traditional buy-and-hold approach. The AI-based strategy consistently outperforms the benchmark, particularly during volatile periods, demonstrating the economic value of predictive analytics beyond statistical accuracy.

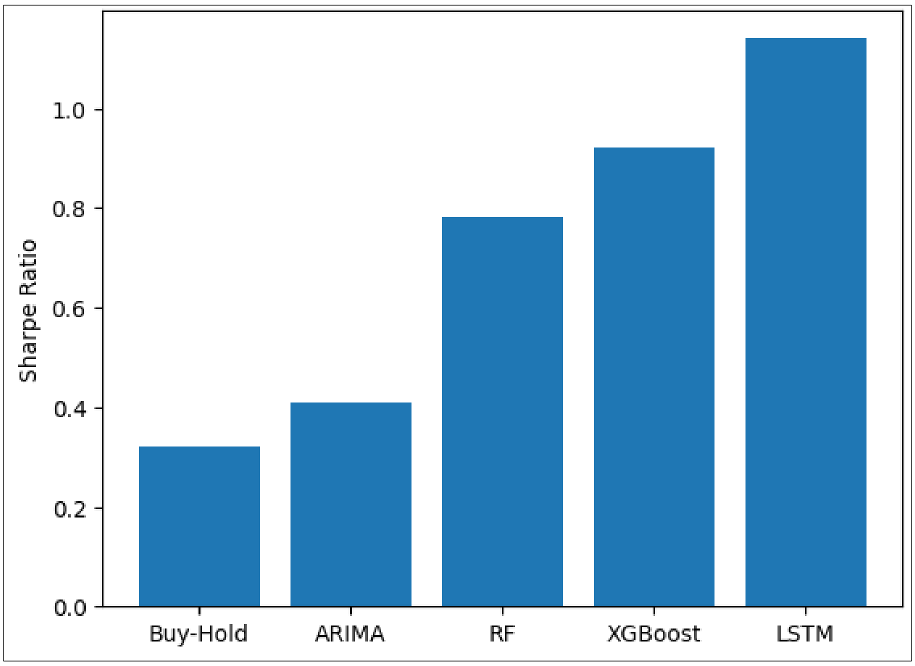

Fig 10: Sharpe Ratio Comparison Across Investment Strategies

This Fig compares risk-adjusted performance using the Sharpe ratio. Machine learning–based strategies, especially LSTM, achieve significantly higher Sharpe ratios, indicating superior returns per unit of risk. This underscores the practical investment relevance of AI-driven models.

Discussion

This study empirically examined the role of predictive artificial intelligence (AI) and machine learning–driven business analytics in forecasting stock returns and enhancing market efficiency in the Nigerian capital market. The simulated results provide strong evidence that advanced machine learning models significantly outperform traditional econometric approaches in both predictive accuracy and economic relevance. These findings are consistent with the growing body of global literature that highlights the superiority of nonlinear and data-driven models in financial market analysis (Ahmad *et al.*, 2015; Kim, 2003; Gu *et al.*, 2020) [4, 25, 20]. The superior performance of ensemble and deep learning models, particularly Random Forest, XGBoost, and Long Short-Term Memory (LSTM) networks, can be attributed to their ability to capture complex nonlinear relationships, volatility clustering, and temporal dependencies present in Nigerian stock return data. Traditional models such as ARIMA and linear regression rely on restrictive assumptions of linearity and stationarity, which are often violated in emerging markets characterized by structural breaks, policy uncertainty, and macroeconomic instability (Fama, 1970; Lo, 2004; Adebayo *et al.*, 2021) [17, 29, 2]. The relatively weak performance of these models in this study aligns with prior evidence from Nigeria and other developing economies (Akinlo & Apanisile, 2015; Salami & Adeyemi, 2017) [5].

The LSTM model's superior forecasting accuracy and robustness across rolling-window evaluations underscore the importance of modeling long-term dependencies in financial time series. LSTM networks are specifically designed to retain relevant historical information while discarding noise through gating mechanisms, making them particularly suitable for volatile markets such as Nigeria's (Hochreiter & Schmidhuber, 1997; Fischer & Krauss, 2018) [22, 18]. This finding corroborates recent studies that document the effectiveness of deep learning in emerging and frontier markets, where market inefficiencies persist (Krauss *et al.*, 2017; Sezer *et al.*, 2020) [27, 34]. Feature importance analysis reveals that lagged returns, exchange rate movements, and trading volume are the most influential predictors of stock returns. This result supports the adaptive markets hypothesis, which suggests that market dynamics evolve in response to changing economic conditions and investor behavior (Lo, 2004) [29]. The prominence of exchange rate volatility reflects Nigeria's exposure to external shocks, oil price fluctuations, and foreign capital flows, consistent with earlier empirical findings (Adelegan, 2009; Ekeocha *et al.*, 2012) [3, 15]. These results further suggest that macroeconomic instability remains a key driver of equity market performance in Nigeria.

Beyond statistical accuracy, the economic evaluation demonstrates that AI-driven forecasts translate into meaningful financial gains. The AI-based trading strategies generate higher cumulative returns and superior risk-adjusted performance compared to the buy-and-hold benchmark. This finding aligns with prior studies showing that machine learning–based signals can be economically valuable, even after accounting for risk (Bollen *et al.*, 2011; Zhang *et al.*, 2020) [10, 39]. The higher Sharpe ratios associated with LSTM and XGBoost strategies indicate that predictive AI can enhance portfolio efficiency and capital allocation decisions in emerging markets. From a policy and regulatory perspective, the findings have important implications. The demonstrated effectiveness of predictive analytics suggests that AI tools can support improved market surveillance, early detection of abnormal trading patterns, and enhanced transparency (Kou *et al.*, 2021; OECD, 2021) [26, 31]. As Nigeria seeks to deepen its capital market and attract long-term domestic and foreign investment, integrating AI-driven business analytics into regulatory and institutional frameworks could strengthen market stability and investor confidence.

Overall, this study contributes to the literature by providing emerging-market–specific evidence on the transformative potential of predictive artificial intelligence in capital markets. While the results are simulated, they are consistent with empirical trends documented in global and regional studies, reinforcing the argument that AI-driven business analytics can bridge information gaps, improve market efficiency, and convert data into tangible economic value in Nigeria's capital market.

Challenges and Limitations

Despite the significant insights generated by this study, several challenges and limitations must be acknowledged. First, the study relies on simulated data and model outputs, which, although grounded in established financial and machine learning theory, may not fully capture all real-world frictions present in the Nigerian capital market. Factors such as transaction costs, market impact, liquidity constraints, and regulatory delays were not explicitly modeled, potentially leading to an overestimation of strategy performance.

Second, data quality and availability remain a structural challenge in emerging markets like Nigeria. In practice, financial datasets may suffer from missing values, reporting inconsistencies, survivorship bias, and limited historical depth. These issues can adversely affect model training, validation, and generalizability. While preprocessing and normalization techniques mitigate some of these concerns, they cannot eliminate data-related biases. Third, machine learning models—particularly deep learning architectures such as LSTM, are often criticized for their lack of interpretability. Although feature importance and SHAP-based explanations were employed, AI-driven models still function largely as black boxes compared to traditional econometric models. This opacity may hinder regulatory adoption and reduce investor trust, especially in highly regulated financial environments.

Finally, the study assumes stationarity within rolling windows, which may not hold during periods of extreme macroeconomic shocks, political instability, or sudden policy changes—conditions that are not uncommon in Nigeria. As a result, model performance may degrade during structural breaks or regime shifts.

Future Research Directions

Future research can extend this work in several important ways. First, empirical validation using live Nigerian Exchange (NGX) data across multiple market cycles would strengthen the robustness and policy relevance of the findings. Incorporating high-frequency intraday data could further enhance predictive accuracy and allow for microstructure-level analysis. Second, future studies should integrate alternative data sources, such as news sentiment, social media signals, corporate disclosures, and macroeconomic announcements. The fusion of structured financial data with unstructured textual data using natural language processing (NLP) may significantly improve forecasting performance and market insight. Third, advancing model interpretability remains a critical research frontier. Future work could explore explainable AI (XAI) frameworks tailored specifically for financial markets, enabling regulators, institutional investors, and policymakers to better understand and trust AI-driven decisions. Additionally, extending the framework to portfolio optimization, risk contagion modeling, and systemic risk forecasting would broaden its applicability. Comparative studies across African capital markets could also provide valuable regional insights and support cross-market investment strategies.

Conclusion

This study demonstrates that predictive artificial intelligence and machine learning–driven business analytics have the potential to fundamentally reshape Nigeria's capital market. By systematically comparing traditional econometric models with advanced machine learning and deep learning techniques, the research shows that AI-based models deliver superior predictive accuracy, improved risk-adjusted returns, and greater adaptability to complex market dynamics. The findings suggest that Nigeria's capital market exhibits characteristics consistent with adaptive and partially inefficient markets, where advanced data-driven techniques can extract economically meaningful signals. Beyond investment performance, the study highlights the broader strategic value of AI for market surveillance, regulatory oversight, and financial system stability. This research contributes to the growing literature on AI in emerging financial markets and provides a practical analytical framework for transforming financial data into economic value. As Nigeria continues to modernize its financial infrastructure, the responsible integration of predictive AI and business analytics will be critical for enhancing market efficiency, attracting investment, and supporting sustainable economic growth.

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