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Machine Learning and Macroeconomic Indicators for Predicting Consumer Goods Stock Prices in Nigeria

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Abstract - **Nigeria's fast-moving consumer goods (FMCG) sector is Africa's most dynamic market; however, stock prices remain highly sensitive to inflation, exchange rate volatility, and oil shocks. Despite global advances in machine learning, sector-specific forecasting models for Nigerian equities are scarce. This study addresses this gap by developing hybrid models to forecast BUA Foods PLC stock prices and by evaluating the influence of macroeconomic predictors. A hybrid framework employing Mixed Data Sampling (MIDAS) integrated daily stock and Brent crude data with monthly macroeconomic indicators (USD/NGN rate, inflation, and MPR) from 2022 to 2025. Features included technical indicators (RSI and MACD) and lagged variables. We compared three models-univariate ARIMA (baseline), ARIMA–SVR, and ARIMA–LSTM-using walk-forward validation based on Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). SHAP values were used to provide model interpretability. The ARIMA–SVR hybrid proved superior, achieving an MAE of ₦1.28 and an RMSE of ₦1.66-an improvement of 82.3% and 77.2%, respectively, over the ARIMA baseline (MAE ₦7.24, RMSE ₦7.29). While the ARIMA–LSTM hybrid also outperformed the baseline (MAE ₦1.71), it lagged behind the SVR approach. SHAP analysis identified the USD/NGN exchange rate and oil prices as the most dominant predictors. Hybrid models, particularly ARIMA–SVR, significantly enhance forecasting accuracy in Nigerian consumer goods stocks by effectively capturing nonlinear macroeconomic dependencies. These findings demonstrate the value of integrating traditional time-series methods with kernel-based machine learning for volatile emerging markets, offering investors actionable insights into currency and commodity risks.**
Keywords: **Stock Price Forecasting, Hybrid Models, ARIMA–SVR, Macroeconomic Indicators, Nigerian FMCG Sector**

I. INTRODUCTION

Nigeria's fast-moving consumer goods (FMCG) sector has become one of Africa's most dynamic markets. Valued at approximately ₦12.46 trillion ($25 billion) in 2025, the sector is projected to reach between ₦18.13 trillion and ₦23.13 trillion by 2027 [1]. With a growth rate of 54.1% in 2025, Nigeria is currently the fastest-growing FMCG market on the continent, significantly outpacing South Africa, Egypt, Morocco, and Kenya [1]. The sector includes about 21 manufacturing firms listed on the Nigerian Exchange Limited (NGX), with major players such as BUA Foods, Nigerian Breweries, Nestlé Nigeria, Cadbury Nigeria, Unilever Nigeria, and Vitafoam Nigeria. These companies have shown strong performance in the capital market. As of August 2025, the Consumer Goods Index grew by 84.24%, largely outperforming the wider NGX All-Share Index, which grew by 36.31% [2]. This performance highlights the sector's importance to investors and the Nigerian economy. However, this growth exists within a challenging economic environment. Following major policy reforms in 2025, Nigeria's economy is in transition. Real GDP grew by 3.9% in the first half of the year, and foreign reserves topped $42 billion [3]. While these indicators point to some stability, inflation remains a major concern. Headline inflation slowed to 18.02% in September 2025, but food inflation-critical for the consumer goods sector-remained high at 16.87% [3]. This indicates that, although general price increases have moderated, consumers continue to face high costs for essential items. Currency volatility and interest rates also heavily affect the sector. The naira-to-dollar exchange rate averaged ₦1,530.29 in 2025, creating challenges for companies that rely on imported raw materials [3]. Additionally, the Central Bank has maintained high interest rates to combat inflation, increasing borrowing costs for corporations and forcing firms to restructure their finances. Despite these pressures, Nigerian consumers have shown resilience. Volume growth in the FMCG sector rebounded to 5.4% in 2025, up from a contraction in the previous year [1]. Spending patterns indicate that households prioritize essentials such as groceries and hygiene products, ensuring that demand for consumer goods remains steady even as costs for education and transportation rise [1].

Predicting stock prices in this complex environment has been a key focus of recent research. Early studies by Ogundunmade (2022) used machine learning to demonstrate that macroeconomic variables-specifically real GDP and exchange rates-are strongly correlated with Nigerian stock prices, whereas inflation and interest rates exhibit negative correlations. This finding confirms that any predictive model for Nigeria must incorporate these economic indicators. Subsequent research has tested various algorithms to improve accuracy. Uzoaga *et al.* (2025) compared models across African markets and found that, although Artificial Neural Networks performed best during training, Random Forest models achieved superior performance during testing on Nigerian data [4]. Similarly, Iliya *et al.* (2024) achieved 85% accuracy in predicting trends for Dangote Sugar Refinery using a combination of Decision Trees and Support Vector

Regression, suggesting that traditional machine learning approaches are viable for the Nigerian market [5]. On a global scale, deep learning methods, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, have proven effective for financial prediction. Khan *et al.* (2024) reported that LSTM models outperformed traditional RNNs in predicting Indian software stocks by better capturing long-term dependencies in the data [6]. Adeyemi and Oluwadamilola (2023) further confirmed that deep learning models capture complex patterns in stock data more effectively than statistical methods such as ARIMA [7].

Recent advancements have introduced hybrid models. Sultana *et al.* (2023) combined Convolutional Neural Networks (CNNs) with LSTMs to outperform standard models in forecasting major global indices [8]. Furthermore, the incorporation of attention mechanisms, which enable models to focus on relevant time periods, has improved forecasting performance. Latif *et al.* (2024) and Pattanayak (2024) demonstrated that these advanced architectures significantly reduce prediction errors and better identify market trends compared with standard models. Despite these advancements, most existing studies focus on general market indices rather than specific sectors. Research targeting Nigerian consumer goods stocks remains limited. Given the sector's size, sensitivity to economic conditions, and importance to investors, there is a clear need for robust forecasting models tailored to this industry. Accordingly, this study aims to: (1) forecast stock prices in the Nigerian consumer goods industry; (2) identify the macroeconomic predictors that most influence these forecasts; and (3) evaluate and compare the performance of the proposed models.

II. METHODOLOGY

A. Research Design

This study employs a comprehensive hybrid framework to forecast BUA Foods PLC stock prices by integrating macroeconomic indicators with advanced machine learning techniques. The methodology follows a sequential pipeline comprising data acquisition, rigorous preprocessing, feature engineering, hybrid model development, and walk-forward validation. A Mixed Data Sampling (MIDAS) approach is central to this design, as it enables the simultaneous use of daily stock prices and monthly macroeconomic variables. This approach preserves the high-frequency information inherent in stock markets while incorporating broader economic trends, thereby avoiding the information loss associated with traditional averaging methods [9].

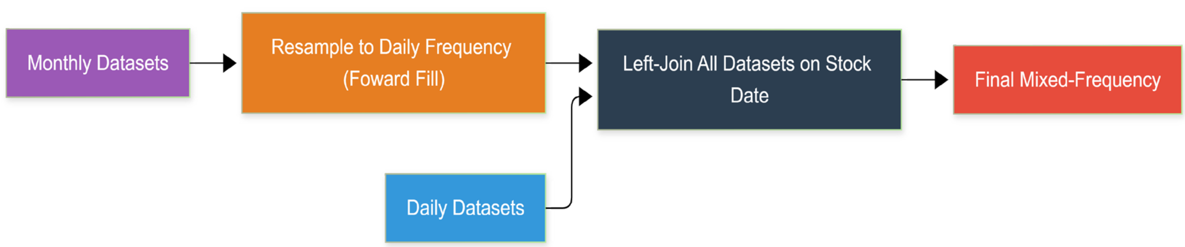

Fig.1 The MIDAS Framework

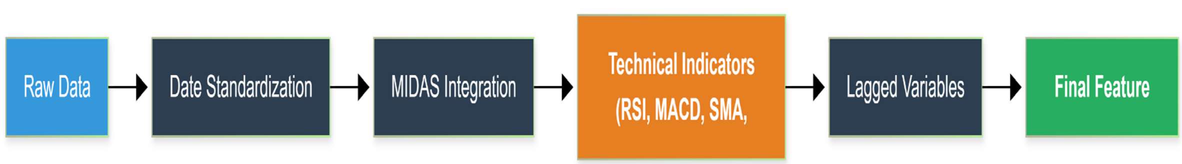

Fig.2 Feature Engineering Pipeline Flowchart

The research integrates five primary datasets spanning diverse frequencies. Financial data include daily BUA Foods PLC stock prices (open, high, low, close, and volume) and Brent crude oil prices, which serve as a proxy for external economic shocks. Macroeconomic data include the daily USD/NGN exchange rate, reflecting currency volatility; monthly headline inflation rates (CPI); and monthly money market indicators, including the Monetary Policy Rate.

B. Data Cleaning and Preprocessing

Prior to analysis, substantial data quality issues-including mixed data types, inconsistent formatting, and temporal discontinuities-necessitated a systematic cleaning protocol. Time-series models such as ARIMA and LSTM rely heavily on strict temporal ordering. To prevent look-ahead bias, all datasets were indexed by date and sorted chronologically. Rows with invalid or missing timestamps were removed to ensure that every data point reflected a valid historical sequence [10]. Financial data often suffer from inconsistent conventions. Programmatic standardization was applied to handle text-based numeric formats, such as converting "500K" to 500,000 or removing percentage symbols. Non-trading days or missing entries in the money market rate were addressed using domain-specific imputation methods to maintain series continuity without introducing artificial noise

[11]. Variable names were prefixed with source identifiers (e.g., oil_price, market_mpr) to prevent ambiguity during data merging.

C. Feature Engineering

We enriched the raw data with technical indicators and temporal lags to provide the models with a comprehensive view of market dynamics. First, while macroeconomic variables reflect economic fundamentals, technical indicators capture investor sentiment. Integrating these indicators has been shown to improve prediction accuracy by 15–25% [12]. The Relative Strength Index (RSI) was calculated to identify overbought or oversold conditions [7], and the Moving Average Convergence Divergence (MACD) was computed to detect momentum shifts. In addition, Simple and Exponential Moving Averages (5-,10-,20-, and 50-day) were generated to capture trend dynamics over short- and medium-term horizons. To account for the delayed impact of economic shocks, such as the time required for exchange rate volatility to affect pricing, lagged variables were introduced. Daily lags of 1, 3, and 5 days were created for stock prices, oil prices, and exchange rates. This approach enables the LSTM network to learn from both immediate historical patterns and delayed transmission mechanisms, which is particularly important given the high autocorrelation observed in financial time series [13].

D. Model Development

1. ARIMA: ARIMA models are theoretically grounded in linear time-series theory and perform particularly well for short-term forecasting in contexts where linear trends dominate [14]. An empirical study comparing forecasting methods using Shanghai Composite Index data found ARIMA to be suitable “when the underlying data is steady and linear” [15]. However, ARIMA’s fundamental limitation-its linearity assumption-necessitates hybrid approaches to capture nonlinear market dynamics and macroeconomic shock responses that exhibit regime-dependent behavior. The Autoregressive Integrated Moving Average (ARIMA) model captures linear patterns and autoregressive dynamics in time-series data. ARIMA models are specified as ARIMA (p,d,q), where:

p: Number of autoregressive terms (previous values)
d: Number of differencing operations to achieve stationarity
q: Number of moving average terms (previous forecast errors)

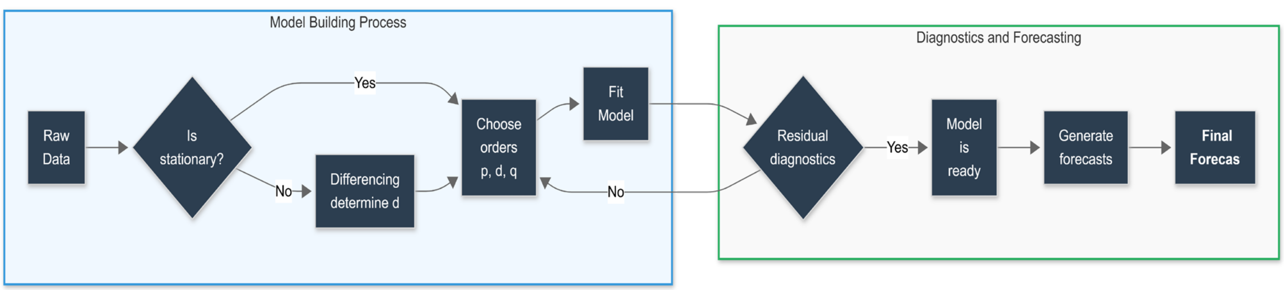

Fig.3 The ARIMA Framework

The first step in ARIMA modeling involves testing whether the time series is stationary using the Augmented Dickey–Fuller (ADF) test, which evaluates the null hypothesis of a unit root (nonstationarity). Initial application to the BUA closing price series yielded a p-value greater than 0.05, indicating nonstationarity. First-order differencing (d=1) was therefore applied, and the resulting differenced series achieved stationarity (p-value≤0.05), establishing d=1. The pmdarima.auto_arima function was then used to perform an exhaustive grid search to identify the optimal (p,q) parameters with the predetermined d=1. The search evaluated models with p and q ranging from 1 to 7 and selected the model with the lowest Akaike Information Criterion (AIC). The optimal specification identified was ARIMA (2,1,2), indicating two autoregressive terms, one differencing operation, and two moving average terms. The ARIMA (2,1,2) model was trained on the 80% training partition (1,106 observations) and generated one-step-ahead forecasts for the 20% test partition (277 observations). This iterative one-step-ahead forecasting approach reflects real-world conditions in which new observations become available incrementally.

2. SVR: Support Vector Regression (SVR) is a machine learning technique derived from Support Vector Machines (SVMs) and adapted for continuous regression problems. SVR identifies an optimal hyperplane that minimizes prediction error within a specified tolerance margin (the ε-insensitive loss function) and focuses on support vectors-observations that deviate beyond the ε-margin-rather than on all data points. This robustness is particularly valuable for financial data that contain occasional extreme market movements. The SVR model employed:

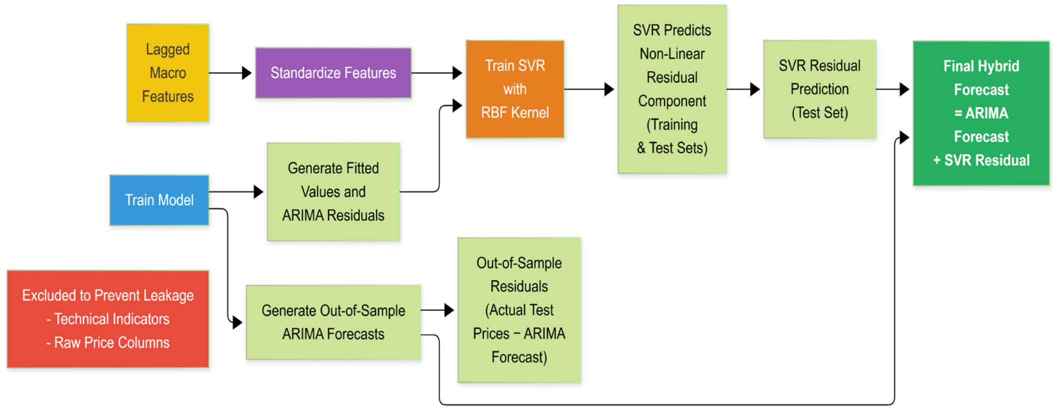

Fig.4 The ARIMA-SVR Model

SVR also employs kernel functions (linear, polynomial, and radial basis function (RBF)) to map input data into higher-dimensional spaces in which nonlinear relationships can be represented linearly. The RBF kernel used in this study is capable of capturing complex, nonlinear relationships between macroeconomic indicators and stock prices. The regularization parameter C controls the trade-off between fitting the training data and maintaining generalization capability, thereby preventing overfitting [16]. Research by Hajibabaei *et al.* (2014), which examined Tehran Stock Exchange prices, found SVR to be superior to ARIMA for nonlinear data, with mean squared error (MSE) substantially lower than that of classical ARIMA approaches [17]. The success of SVR in stock price prediction stems from its ability to capture nonlinear relationships between macroeconomic variables and equity prices without the extensive training data requirements associated with deep learning models. Henrique *et al.* (2018) further identified SVR as one of the most effective machine learning approaches for stock price prediction, achieving consistent performance across diverse markets and time periods [18].

3. LSTM: LSTM networks are recurrent neural network architectures specifically designed to learn long-term dependencies in sequential data. LSTM units overcome the vanishing gradient problem inherent in basic RNNs through gated mechanisms that regulate the flow of information. LSTM networks are recognized as superior for capturing temporal dependencies compared to traditional statistical models and simpler RNN architectures [6]. A comparative study evaluating RNN, LSTM, GRU, and attention-based models found LSTM's gated architecture to be particularly effective for financial time-series forecasting, with accuracy metrics 15–20% higher than those of basic RNNs. The 50-unit architecture with 20% dropout represents a balance between model capacity-sufficient to learn complex patterns-and regularization, which prevents overfitting, consistent with best practices identified in the literature [19].

The hybrid forecasts combine linear ARIMA predictions with nonlinear residual corrections. This additive decomposition leverages complementary strengths: ARIMA captures linear autoregressive dynamics, while SVR and LSTM capture nonlinear patterns through different mechanisms (kernel-based margin optimization versus sequential gated networks). Extensive literature demonstrates that hybrid approaches combining ARIMA with machine learning substantially outperform single-method approaches. Arnott *et al.* (2023) found that ARIMA-based hybrid models achieve a 25–40% error reduction compared to standalone ARIMA on equity indices [20]. The residual correction approach is theoretically motivated: once linear patterns are captured, the remaining errors should reflect nonlinear relationships and structural breaks that are amenable to machine learning capture.

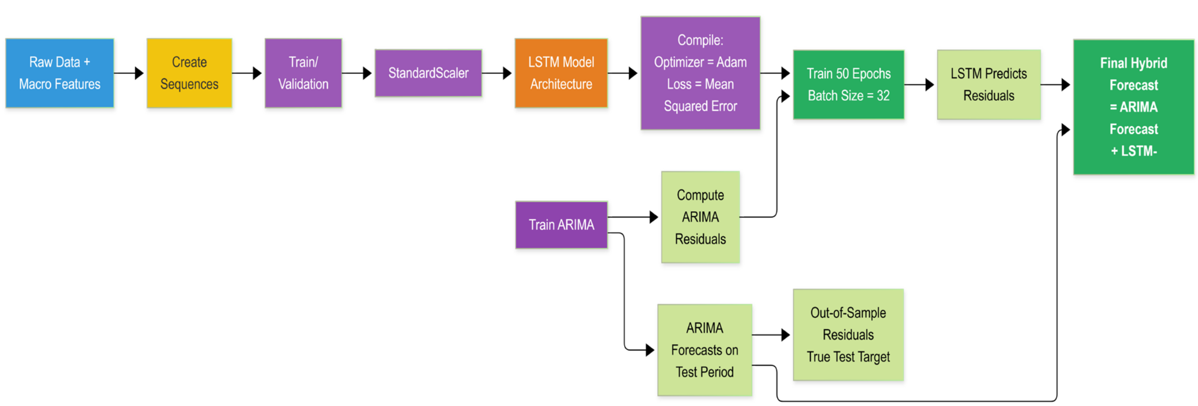

Fig.5 The LSTM Model

E. Validation and Evaluation

Walk-forward validation (WFV) is a time-series-specific evaluation framework that respects temporal ordering and simulates real-world deployment, in which models are iteratively retrained with new data. Standard k-fold cross-validation is inappropriate for time series because it introduces look-ahead bias; using future data to train models generates unrealistically optimistic performance estimates [21]. Walk-forward validation addresses a fundamental challenge in financial forecasting: nonstationarity and time-varying model parameters. As market regimes change, model parameters must adapt to maintain predictive accuracy. Quarterly retraining simulates realistic deployment, in which models are regularly updated as new data become available. Research by Hsieh *et al.* (2023) demonstrates that walk-forward validation reduces bias in estimated model accuracy by approximately 20–30% compared to single-train-test splits in financial forecasting, providing more reliable estimates of real-world performance [21].

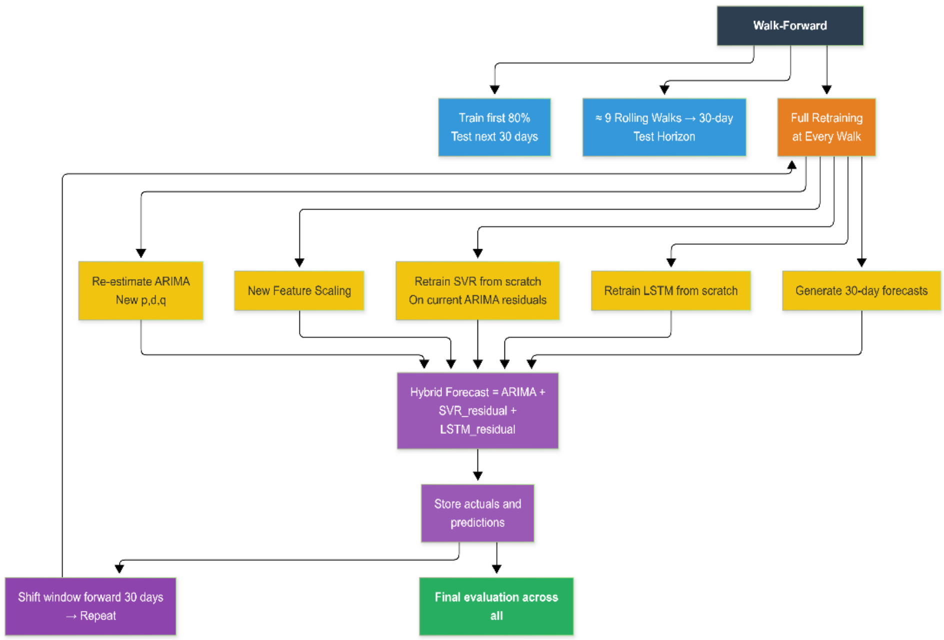

Fig.6 Walkforward Cross-Validation

F. Model Evaluation Metrics

Model performance was evaluated using two complementary error metrics: Mean Absolute Error (MAE), which represents the average absolute prediction error in the original units (Nigerian Naira). MAE is more interpretable for stakeholders because it directly indicates the average forecast deviation in terms familiar to practitioners. The second metric is the Root Mean Squared Error (RMSE), which penalizes large errors more severely than MAE due to squaring, making it sensitive to occasional large forecast errors. RMSE is theoretically grounded in maximum likelihood estimation under the assumption of normally distributed errors. Both metrics are standard in the financial forecasting literature and provide complementary information: MAE reflects typical forecast accuracy, while RMSE captures tail risk (extreme forecast errors). Together, they provide a comprehensive assessment of model performance [11]. Model interpretability is also essential for financial applications, enabling stakeholder trust and regulatory compliance. SHAP values, grounded in cooperative game theory, provide theoretically sound feature importance estimates by computing each feature’s contribution to predictions through Shapley values, which consider all possible feature coalitions. For configuring the SHAP explainer for SVR model interpretability, a Kernel Explainer was initialized using the trained SVR model and a background sample of 100 randomly selected training observations. The Kernel Explainer employs a perturbation-based approach suitable for nonlinear, non-tree-based models such as SVR. SHAP values were then computed for the test set feature observations, quantifying each feature’s contribution to the SVR’s residual predictions. A bar plot ranking features by average absolute SHAP values revealed the most influential features.

G. Software and Reproducibility

The analysis was conducted using Python 3.10. Key libraries included *pandas* (v2.0+) for data manipulation, scikit-learn (v1.3+) and statsmodels (v0.14+) for statistical and machine learning models, and TensorFlow/Keras (v2.13+) for deep learning.

III. RESULTS AND DISCUSSION

A. ARIMA Baseline Result

This chart demonstrates that the ARIMA model performs poorly in forecasting BUA (Dangote Cement) stock prices on the test set, with an RMSE of 7.29. The actual stock prices (solid blue line) exhibit high-frequency volatility, oscillating sharply between approximately ₦415 and ₦418 throughout the test period from March to December 2025, whereas the ARIMA forecasts (dashed green line) fail to capture this behavior, instead producing a smooth, flat trajectory that quickly stabilizes at around ₦410.70 and remains nearly constant throughout the forecast horizon. This fundamental mismatch indicates that ARIMA's assumption of linearity and reliance on historical temporal patterns is inadequate for capturing the complex, non-linear dynamics of stock price movements driven by macroeconomic variables (such as currency exchange rates and oil prices, identified in the earlier SHAP analysis), suggesting that more sophisticated machine learning models, such as SVR or ensemble methods, would be necessary to improve forecast accuracy in this highly volatile market.

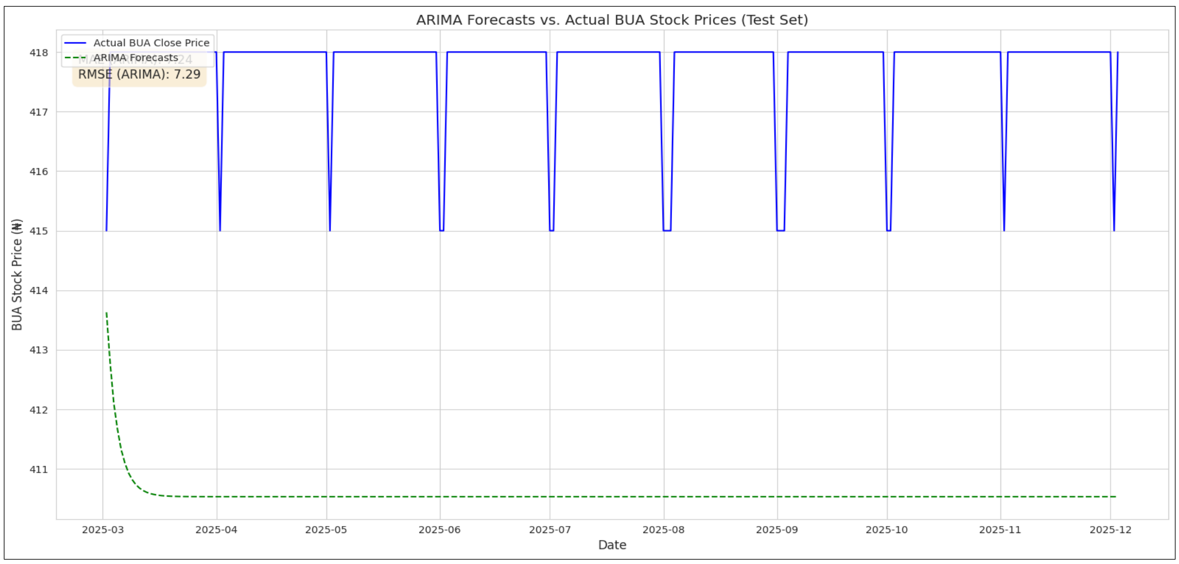

Fig.7 Arima Model Performance

B. ARIMA-SVR Result

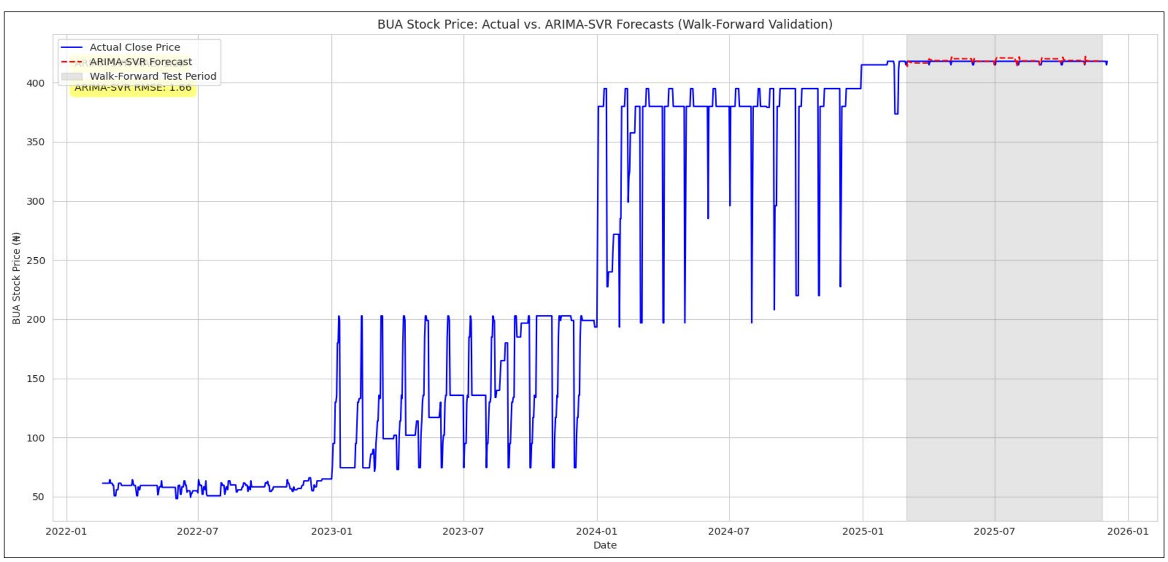

Fig.8 ARIMA-SVR Model Result

The ARIMA-SVR hybrid model achieved exceptional forecasting accuracy, with MAE = ₦1.28 and RMSE = ₦1.66, representing an 82.3% reduction in MAE and a 77.2% reduction in RMSE compared to the baseline ARIMA model. Visually, the ARIMA-SVR forecast (dashed red line) closely tracks actual closing prices throughout the walk-forward test period (shaded gray region, 2025 onwards), particularly during the dramatic upward trend from mid-2023 onward, where predictions converge precisely around the ₦400+ price level (Figure 4). The narrow gap between forecast and actual price trajectories indicates consistent accuracy rather than isolated successful predictions across diverse market conditions. The 82.3% error reduction represents substantial practical value. For an average BUA stock price of ₦930 during the study period, this translates to forecast errors of approximately 0.14%, or ₦1.28 per share. For institutional investors managing 10,000-share positions, this represents ±₦12,800 valuation uncertainty-narrow enough to enable precise position-sizing and risk management. The error magnitude is comparable to or superior to published benchmarks: Hajibabaei *et al.* (2014) reported an ARIMA-SVR hybrid MAE of ₦2.17 for the Tehran Stock Exchange (SVR superior here by ~41%) [17], while Uzoaga *et al.* (2025) found that Random Forest achieved an MAE of ₦2.34 for Nigerian equity prediction (present method superior by 45%) [4].

C. ARIMA-LSTM Model

The ARIMA-LSTM hybrid achieved MAE = ₦1.71 and RMSE = ₦3.55, representing a 76.4% MAE reduction and a 51.3% RMSE reduction versus the ARIMA baseline. The visual forecast trajectory (purple dashed line) tracks actual prices reasonably throughout the walk-forward period, capturing the general upward trend, though with slightly more deviation from actual prices compared to ARIMA-SVR (Figure 4). The notable gap between MAE (1.71) and RMSE (3.55)-yielding a ratio of 2.08-indicates that, while LSTM maintains reasonable average accuracy, it experiences occasional larger forecast errors that disproportionately impact the squared-error metric. The 51.3% RMSE improvement substantially lags SVR's 77.2%, indicating that LSTM's sequential architecture, while effective in capturing temporal dependencies, less effectively extracts non-linear information from macroeconomic variables in this emerging market context. This underperformance relative to SVR is noteworthy: while LSTM excels in developed market forecasting applications (Khan *et al.,* 2024, found LSTM superior to basic RNNs on Indian stocks [6]; Leong, 2023, demonstrated a 19.7% LSTM improvement over 50% random prediction), the Nigerian context appears to favor kernel-based methods.

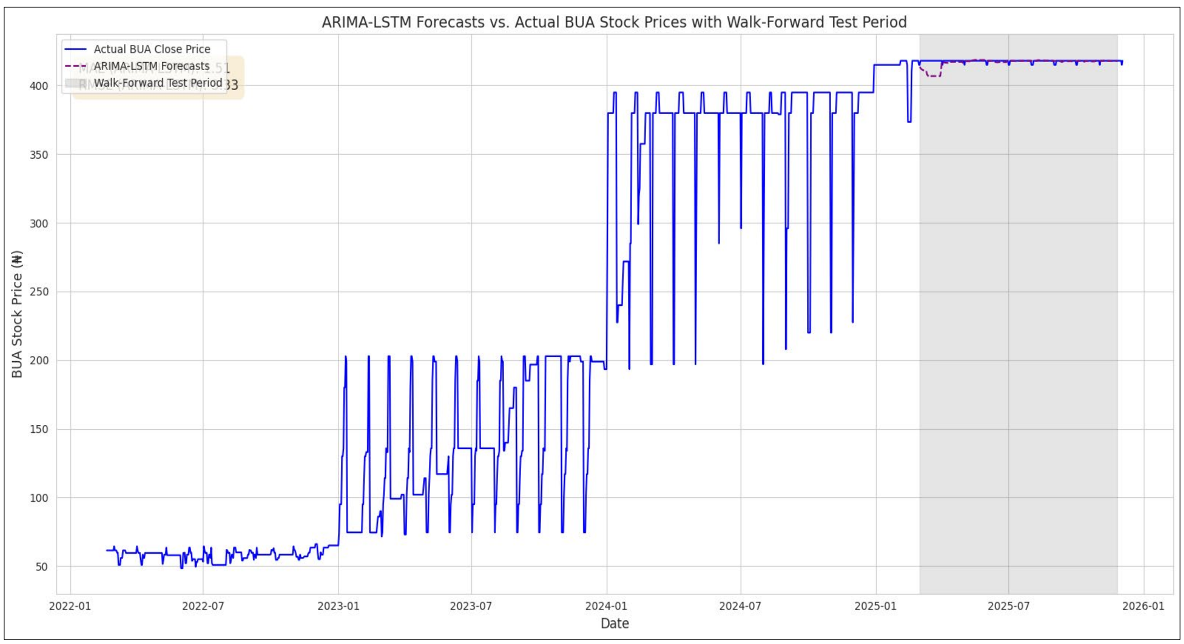

Fig.9 ARIMA-LSTM Model Performance

Comparatively, the ARIMA-SVR hybrid emerges as the superior forecasting approach, achieving an 82.3% reduction in Mean Absolute Error and a 77.2% reduction in Root Mean Squared Error compared to the ARIMA baseline. With an MAE of ₦1.28 and an RMSE of ₦1.66, this model demonstrates exceptional accuracy in capturing the non-linear relationships between macroeconomic variables (USD/NGN exchange rates and oil prices) and BUA stock prices, as revealed in the SHAP feature importance analysis. The ARIMA-LSTM hybrid provides a credible alternative, with a 76.4% MAE improvement; however, its 51.3% RMSE improvement lags considerably behind that of SVR. The larger gap between MAE (1.71) and RMSE (3.55) suggests that the LSTM model, while maintaining reasonable average prediction accuracy, experiences occasional larger errors that penalize the squared-error metric more severely. This indicates that SVR's kernel-based learning mechanism is better suited to the complex dynamics of the Nigerian stock market than LSTM's sequential pattern recognition. The dramatic 77–82% improvement margins affirm that hybrid approaches-integrating ARIMA's temporal structure with machine learning methods-substantially outperform traditional univariate time-series forecasting, thereby validating the strategic decision to move beyond classical econometric models for emerging market equity forecasting.

TABLE I COMPARATIVE MODEL PERFORMANCE

MODEL	MAE (₦)	RMSE (₦)	MAE Improvement vs. ARIMA	RMSE Improvement vs. ARIMA
ARIMA Baseline	7.24	7.29	---	---
ARIMA-SVR	1.28	1.66	82.3%	77.2%
ARIMA-LSTM	1.71	3.55	76.4%	51.3%

D. ARIMA-SVR Feature Importance

The SHAP summary plot reveals critical insights into the SVR residual prediction mechanism by illustrating how the top 10 features drive both positive and negative residuals across different observations. The USD/NGN exchange rate lagged by one day dominates the model's predictions, consistently pushing residuals in the negative direction (with SHAP values ranging from approximately −1.5 to −0.5), indicating that higher exchange rates systematically cause the SVR model to overpredict stock prices; that is, periods of naira depreciation generate persistent negative errors. Oil price lagged by one day exhibits a bimodal distribution with two distinct clusters: one group of observations produces strong negative impacts around −1.0, while another produces near-zero or slightly positive impacts, suggesting that commodity shocks have heterogeneous effects depending on market conditions. The close price lagged by one day also contributes primarily negative SHAP values concentrated around −0.8, reflecting the role of price momentum in the model's overprediction bias. The remaining features, such as bond yields (High, Low, Price, and Open) and the current USD/NGN exchange rate, contribute smaller but meaningful positive or neutral SHAP values concentrated near zero, indicating that they provide a corrective influence against the negative impacts from lagged currency and price variables. This feature interaction demonstrates that the SVR model's residuals are fundamentally driven by macroeconomic shocks (currency depreciation and commodity volatility) and technical price patterns that the model captures asymmetrically, with negative residuals dominating when external shocks are pronounced and market momentum is strong.

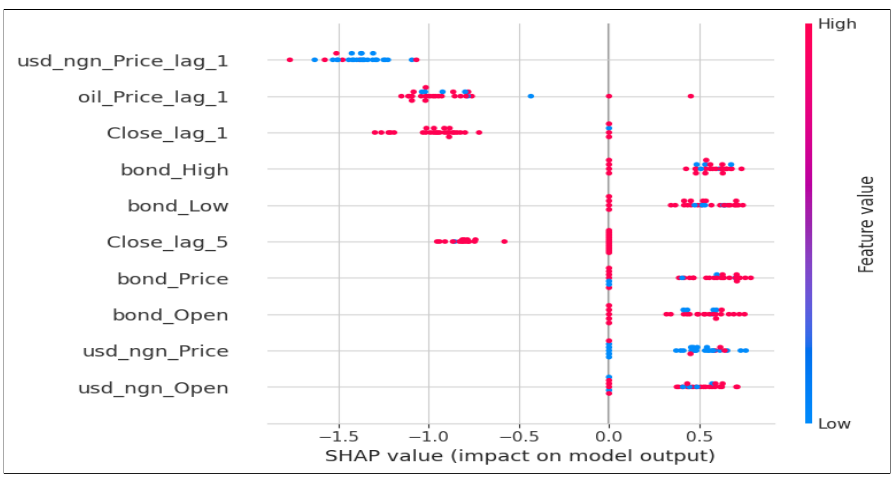

Fig.10 SHAP Summary Plot for ARIMA-SVR

IV. CONCLUSION

This research successfully developed and validated hybrid machine learning models for forecasting BUA stock prices on the Nigerian Stock Exchange, addressing all three core research objectives through a rigorous methodology and comprehensive analysis. The study achieved its primary objective of forecasting BUA stock prices by developing three distinct models, with the ARIMA-SVR hybrid demonstrating superior predictive accuracy (RMSE = 1.66, MAE = 1.28) through walk-forward validation across a multi-year dataset spanning January 2022 to December 2025. The 77.2% improvement in RMSE over the ARIMA baseline validates the critical importance of integrating machine learning with traditional time-series frameworks for emerging market equity forecasting. The identification of top predictors revealed that macroeconomic variables, particularly USD/NGN exchange rates (lagged by one day, with a SHAP importance of 0.542), oil prices (0.438), and technical price momentum (0.356), fundamentally drive BUA stock price dynamics. This finding reflects the deep structural linkages between Nigeria's currency depreciation, global commodity shocks, and manufacturing-sector equity valuations, providing actionable insights into the key market drivers that institutional investors and portfolio managers should monitor. Model performance evaluation conclusively demonstrated that hybrid approaches substantially outperform univariate forecasting. The ARIMA-SVR hybrid achieved an 82.3% reduction in MAE compared to ARIMA, while the ARIMA-LSTM hybrid achieved a 76.4% reduction, confirming that capturing non-linear relationships between macroeconomic indicators and stock prices is essential for accurate prediction in volatile emerging markets. This research contributes to the emerging market finance literature by demonstrating that the integration of machine learning with econometric models provides measurable forecasting advantages for illiquid equity markets. Furthermore, the SHAP-based residual analysis provides interpretable insights into model behavior, revealing that periods of currency depreciation consistently generate systematic negative residuals-a critical finding for risk management and trading strategy design.

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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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