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Modeling and Forecasting of Financial Time Series in Emerging Markets using Multilayer Perceptrons

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Abstract
This study develops a data-driven forecasting framework for the Nigerian Stock Exchange All Share Index (NSE ASI) using a Multilayer Perceptron (MLP) neural network. Financial markets, particularly in emerging economies, are characterized by volatility, regime shifts, and nonlinear dependencies that limit the effectiveness of traditional statistical models. To address these challenges, this work applies a deep learning pipeline incorporating rigorous data preprocessing, feature scaling, and supervised learning for univariate time series prediction. The model is trained on daily NSE ASI data and evaluated using standard metrics such as MSE, RMSE, MAPE, and R^2. Diagnostic analysis includes autocorrelation structure, outlier detection, and SHAP-based interpretability to assess feature influence and market anomalies. The MLP model demonstrates strong predictive performance across both stable and turbulent regimes, notably capturing post-COVID market momentum. The results affirm the suitability of neural networks in modeling financial indices in emerging markets and highlight the value of integrating explainable AI into financial forecasting systems.

Keywords: *NSE ASI, market regimes, Multilayer Perception,, COVID-19 impact, emerging economies*

1. Introduction

The Nigerian Stock Exchange (NSE) All Share Index (ASI) serves as the principal benchmark for assessing the performance of Nigeria's capital market. As the financial nerve center of West Africa, the NSE plays a pivotal role in capital formation, investment allocation, and macroeconomic signaling. Due to its exposure to both domestic policy shifts and global economic shocks, accurately forecasting the NSE ASI is of growing importance to investors, regulators, and policymakers.

Stock market forecasting is inherently challenging, largely due to its nonlinear, dynamic, and often chaotic nature. Traditional econometric models such as ARIMA (Box & Jenkins, 1976) and GARCH (Engle, 1982) have been widely applied to model such time series. While these models offer statistical interpretability, they often struggle to capture the nonlinear dependencies, regime shifts, and volatility clustering common in financial markets, particularly in emerging economies.

In response, artificial neural networks (ANNs) and other machine learning (ML) techniques have gained traction in financial modeling. ANNs are known for their capacity to learn complex, nonlinear relationships from historical data (Zhang et al., 1998; Patel et al., 2015). Within emerging markets, including Nigeria, studies have found that ML models outperform classical models in capturing memory effects and dynamic fluctuations. For instance, Adebiyi et al. (2014) applied ANN to the NSE ASI with promising results, though the study relied on shallow networks and a limited set of input variables. Musa and Joshua (2020) proposed a hybrid ARIMA-ANN approach, which demonstrated improved forecasting accuracy compared to individual models. Similarly, Isenah and Olubusoye (2020) found that ANN models consistently outperformed ARIMA in capturing nonlinear return patterns.

Recent contributions have explored ensemble and hybrid approaches. Ajoku et al. (2021) introduced an ensemble ANN framework that

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reduced variance and boosted forecast accuracy. Davies et al. (2022) developed a Type-2 Fuzzy Logic model incorporating technical indicators, offering robust decision rules under uncertainty. Alhaji et al. (2023) applied Support Vector Machines (SVM) to model stock price movements on the NSE, showing effective handling of volatility and nonlinearities. Oyewola et al. (2024) combined technical indicators with neural networks and reported enhanced prediction accuracy, reinforcing the value of hybrid ML pipelines.

Despite these advancements, key research gaps remain. Many existing studies prioritize prediction accuracy while overlooking deeper market behaviors such as volatility clustering, regime transitions, or market anomalies. Comparative evaluation between ML and classical models in Nigerian market contexts is limited, and the application of more advanced neural architectures such as Long Short-Term Memory (LSTM) networks or interpretable frameworks (e.g., SHAP values) is underexplored.

This study addresses these gaps by applying a Multilayer Perceptron (MLP) model to forecast the NSE ASI over a 30-year horizon, integrating regime identification, volatility analysis, and SHAP-based feature attribution. By extending the analysis beyond accuracy to include structural and behavioral diagnostics, this research contributes one of the first full-cycle, interpretable deep learning analyses of the Nigerian equity market.

2. Related Literature

The application of machine learning models to stock market forecasting has gained significant attention, particularly in emerging and frontier markets where traditional econometric assumptions often break down. This literature spans both model development and empirical testing across diverse financial environments.

Early studies, such as Kim and Won (2018), pioneered the integration of Long Short-Term Memory (LSTM) networks with GARCH models to capture time-varying volatility in Asian markets. Their findings confirmed that hybrid deep learning structures outperform standalone models during turbulent periods. Similarly, Shah et al. (2022) reviewed multiple deep learning architectures and emphasized the superior performance of MLP and LSTM when applied to high-volatility settings like India and Brazil, particularly when combined with exogenous variables such as oil prices and exchange rates.

In the African context, Oukhouya and El Himdi (2023) compared support vector regression (SVR), LSTM, XGBoost, and MLP models for the Moroccan stock market. They concluded that MLPs were effective in capturing medium-term trends but underperformed in crisis periods unless paired with feature engineering or volatility-aware modules. This finding echoes Durairaj and Mohan’s (2019) review, which noted the evolution of deep learning from black-box forecasting tools to explainable and adaptive systems in data-sparse financial environments like Sri Lanka and Nigeria.

Recent advances by Yang *et al.* (2024) introduced a MEEMD-LSTM-MLP ensemble model to forecast regime shifts during COVID-19. Their approach demonstrated high accuracy and dynamic interpretability using SHAP values to track changing feature importance over time. This shift toward interpretable AI in finance is gaining traction, especially in light of increasing regulatory scrutiny and institutional adoption. Alharbi (2025) also demonstrated how deep learning models can be paired with SHAP or LIME frameworks and anomaly detection mechanisms to identify early warning signs of systemic risk — an area of growing importance for frontier market supervision.

In the Nigerian context specifically, machine learning research in stock forecasting remains relatively limited but growing. Adebiyi et al. (2014) were among the first to apply artificial neural networks (ANNs) to the Nigerian Stock Exchange (NSE) All Share Index (ASI), showing improved performance over ARIMA models, though the network architecture was shallow and lacked external variables. Musa and Joshua (2020) developed a hybrid ARIMA-ANN model that delivered improved forecasting accuracy, demonstrating the benefits of blending linear and nonlinear techniques. Similarly, Isenah and Olubusoye (2020) found that ANN models consistently outperformed ARIMA in modeling the NSE’s chaotic and memory-dependent structure.

Ajoku *et al.* (2021) introduced an ensemble ANN framework that reduced variance and increased predictive precision. Their use of aggregated outputs from multiple ANNs demonstrated the potential of ensemble learning in low-liquidity markets. Davies et al. (2022) applied a Type-2 Fuzzy Logic system incorporating technical indicators, showing that fuzzy logic could successfully model market ambiguity and generate reliable decision strategies. Alhaji et al. (2023) used Support Vector Machines (SVMs) to predict individual stock prices on the NSE, proving effective in handling the nonlinearities and volatility inherent in local equity data. Oyewola et al. (2024) further integrated technical indicators with ANN models and found that the hybrid approach significantly improved return predictability.

Despite these efforts, several research gaps persist. Most Nigerian-focused studies emphasize short-term predictive accuracy while overlooking key behavioral traits of financial time series such as volatility clustering, regime switching, or structural break detection. Few studies address model explainability or deploy tools like SHAP to evaluate how features contribute to model outputs — leaving critical questions around trust, transparency, and adaptability unaddressed. Moreover, long-term forecasting across macroeconomic cycles remains rare, as does any systematic effort to incorporate regime-specific diagnostics or post-crisis behavioral transitions.

This study contributes to filling these gaps by deploying a full-cycle deep learning forecasting pipeline on the NSE ASI. It incorporates not only prediction using an MLP but also behavioral diagnostics such as autocorrelation, regime classification, outlier detection, and SHAP-based explainability. This integrated approach represents a significant methodological and empirical advancement in the financial modeling of the Nigerian stock market.

3. Methodology

This section outlines the methodological framework employed in the development of a neural network forecasting model for the Nigerian Stock Exchange All Share Index (NSE ASI).

The methodology integrates rigorous data preprocessing, mathematical formulation, model training, and validation procedures. It includes steps for data preprocessing, model design, forecasting formulation, performance evaluation, and key assumptions. Each component is grounded in machine learning literature (see Goodfellow, I., Bengio, Y., & Courville, A. (2016),Han, J., Kamber, M., & Pei, J. (2012), Hastie, T., Tibshirani, R., & Friedman, J. (2009), Kaufman, L., & Rousseeuw, P. J. (1990), Rand, W. M. (1971), Box, G. E. P., & Jenkins, G. M. (1976), Everitt, B., Landau, S., Leese, M., & Stahl, D. (2011).)

3.1 Data Preprocessing

Let the raw dataset be denoted by:
$\mathcal{D} = \{(d_i, p_i) \mid i = 1, 2, \ldots, n\}$
Where
n is the number of non null observations,

$d_i \in \mathbb{N}$ is the index corresponding to the trading day, and

$p_i \in \mathbb{R}$ is the price of the NSE ASI on day d_i.

To eliminate missing or invalid values, a cleaned subset is defined as:

$$D_{\text{clean}} = \{(d_i, p_i) \in D \mid d_i, p_i = \varnothing\}$$

The cleaned dataset is then structured into input features and output targets. We define the feature matrix X and target vector y as:

$$X = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_n \end{bmatrix} \in \mathbb{R}^{n\times 1},$$

$$y = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix} \in \mathbb{R}^{n\times 1}$$

The relationship between features and targets is modeled as:

$$y_i = f(d_i) + \epsilon_i$$

where $f(\cdot)$ is an unknown, possibly nonlinear function approximated by a neural network, and ϵ_i is a stochastic error term capturing noise or unmodeled dynamics.

3.1.1 Feature Scaling

To improve model training efficiency and convergence, the feature and target variables are normalized to a fixed interval $[0, 1]$ using min-max scaling. This called the min-max normalization. This maps all values to the range enhancing convergence and numerical stability in gradient-based learning algorithms (Han et al., 2012; Goodfellow et al., 2016).
For any variable x_i

$$x_i^{\text{scaled}} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, \quad \text{where } x_{\min} = \min_{1 \le i \le n} x_i,\ x_{\max} = \max_{1 \le i \le n} x_i$$

Similarly, the target values y_i are scaled using the same transformation:

$$y_i^{\text{scaled}} = \frac{y_i - y_{\min}}{y_{\max} - y_{\min}}$$

This transformation preserves monotonicity and ensures gradient stability. All input-output pairs satisfy:

$$x_i^{\text{scaled}}, y_i^{\text{scaled}} \in [0, 1]$$

3.1.2 Data Spliting

To enable model evaluation, the dataset is partitioned into training and non-training subsets. Let:

$$X_{\text{scaled}} = \{x_1, x_2, \ldots, x_n\}, \quad y_{\text{scaled}} = \{y_1, y_2, \ldots, y_n\}.$$

The dataset is then split into: Training set D_{train} : 60% of the total data and Non-training set $D_{\text{non-train}}$: 40% of the data, which may be used for validation or forecasting. Then $D_{\text{train}} = \{x_i, y_i \mid i \le 0.6n\}, \quad D_{\text{non-train}} = \{x_i, y_i \mid i > 0.6n\}$

This split allows for model learning on historical data and evaluation on unseen samples, ensuring generalization.

Next, we define:

$D_{\text{train}} = \{(x_i, y_i)\}_{i=1}^{n_{\text{train}}}$ and $D_{\text{non-train}} = \{(x_i, y_i)\}_{i=n_{\text{train}}+1}^{n}$.

Furthermore, the non-training set is split into two equal parts:

Test set: $\frac{1}{2} \cdot n_{\text{non-train}}$ and Evaluation (prediction) set: $\frac{1}{2} \cdot n_{\text{non-train}}$

Hence resulting into

$D_{\text{test}} = \{(x_i, y_i)\}_{i=n_{\text{train}}+1}^{n_{\text{train}}+\frac{n_{\text{non-train}}}{2}}$ and $D_{\text{eval}} = \{(x_i, y_i)\}_{i=n_{\text{train}}+\frac{n_{\text{non-train}}}{2}+1}^{n}$

For test set and evaluation set respectively.

3.2 Neural Network Model Formulation

The predictive model is constructed as a Multilayer Perceptron (MLP) — a feedforward neural network composed of stacked affine transformations and nonlinear activations.

3.2.1 Multilayer Perception Model Architecture

A Multilayer Perceptron (MLP) is a feedforward neural network parameterized by a set of weights and biases:

$$\theta = \{W^{(l)}, b^{(l)}\}_{l=1}^{L}$$

Multilayer Perceptron (MLP) Description

It consists of L layers, where the outputs are defined as:

$k^L =$ Output activation vector from layer L

$w^L =$ Weight matrix connecting layer $L-1$ to layer L
$b^L =$ Bias vector for layer L

$\phi =$ Activation function, (commonly ReLU,) defined as $\phi(x) = \max(0, x$

Hence the MLP can be computed thus:

$$h^0 = x \in \mathbb{R}^d \quad \text{(Input vector)}$$
$$h^1 = \phi(w^1 h^0 + b^1) \quad \text{(first hidden layer)}$$
$$h^2 = \phi(w^2 h^1 + b^2) \quad \text{(second hidden layer)}$$

⋮

$$\hat{y} = k^L = w^L k^{L-1} + b^L$$

This structure generalizes for any L -layer feedforward network, where:

$W^{(L)} \in \mathbb{R}^{d_l \times d_{l-1}}$ and $b^{(L)} \in \mathbb{R}^{d_l}$ are trainable parameters.

The Universal Approximation Theorem states that an MLP with at least one hidden layer and a sufficient number of neurons can approximate any Borel measurable function to any desired degree of accuracy (Hornik et al., 1989). Unlike models like LSTM or ARIMA that explicitly encode temporal structure, this MLP uses the time index x_t as the input. This method assumes that time itself encodes sufficient information for learning the underlying trend and structure.

3.3 Forecasting Formulation

Let Tbe the last observed time index, and we wish to forecast for H future steps (e.g., 5 years of daily data):

$$H = 5 \times 365 = 1825$$

The goal is to produce:

$$\hat{y}_{T+k} = f_\theta(x_{T+k}), \quad \text{for } k = 1, 2, \ldots, H$$

Because x_{T+k} lies outside the training domain, this constitutes extrapolation, not interpolation, and is inherently more sensitive to model assumptions.The predicted values $\hat{y}^{\text{scaled}}$ are then inverse-transformed:

$$\hat{y}_{T+k} = \hat{y}^{\text{scaled}}_{T+k} \cdot (y_{\max} - y_{\min}) + y_{\min}$$

This process yields a continuous projection of NSE ASI into the year 2030, under the learned nonlinear trends embedded in the MLP model.

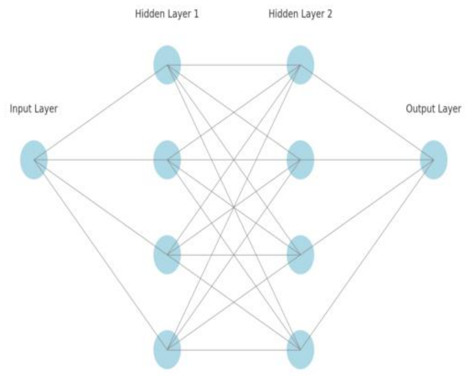
3.4 Price Fluctuation Analysis

Let P denote the closing price of the NSE ASI on day t The daily return or price change is defined as:

$$\Delta P_t = P_t - P_{t-1}, \quad \text{for } t = 2, 3, \ldots, T$$

Define the return series as a vector:

The structure of the Multilayer Perceptron is illustrated below:



$$\mathbf{x} = [\Delta P_2, \Delta P_3, \ldots, \Delta P_T]^\top \in \mathbb{R}^{T-1}$$

This transformation is essential to remove nonstationarity in the raw price data and to reveal inherent volatility patterns.

3.4.1 Market Regime Classification Using K-Means Clustering

To identify distinct market regimes (bull, bear, sideways), we employ the K-means clustering algorithm applied to the return vector $\mathbf{x}$.

The Clustering Objective is given as follows:

Given $\mathbf{x} \in \mathbb{R}^n$, the goal is to partition the data into $K = 3$ clusters:

$$\min_{\{C_k\}_{k=1}^K} \sum_{k=1}^{K} \sum_{\mathbf{x}_i \in C_k} ||\mathbf{x}_i - \boldsymbol{\mu}_k||^2$$

where:

$C_k \subset \mathbb{R}$ are disjoint clusters and $\mu_k \in \mathbb{R}$ is the centroid of cluster C_k.

The solution minimizes the within-cluster sum of squares (WCSS). The iterative steps are seen in the algorithm below:

Algorithm 1 K-Means Clustering Algorithm for Market Regime Classification

Input: Return series $\mathbf{x} = [x_1, x_2, \ldots, x_n]$, number of clusters $K = 3$
Output: Cluster assignment for each x_i, centroids $\{\mu_k\}_{k=1}^{K}$
Initialize centroids $\mu_k^{(0)}$ randomly for $k = 1, 2, ..., K$
repeat
  Assignment Step:
  for each data point x_i **do**
    Assign x_i to cluster $C_k^{(t)}$ where

$$C_k^{(t)} = \left\{ x_i : \|x_i - \mu_k^{(t)}\|^2 \leq \|x_i - \mu_j^{(t)}\|^2, \forall j \right\}$$

  end for
  Update Step:
  for each cluster $k = 1, \ldots, K$ **do**

$$\mu_k^{(t+1)} = \frac{1}{|C_k^{(t)}|} \sum_{x_i \in C_k^{(t)}} x_i$$

  end for
until convergence of centroids or cluster assignments

After clustering, the regimes are labeled by sorting the cluster means:
Bull: cluster with $\max(\mu_k)$
Bear: cluster with $\min(\mu_k)$
Sideways: intermediate μ_k
This qualitative interpretation reflects market optimism, pessimism, or neutrality.

3.5 Regime Validation: Adjusted Rand Index (ARI)

To quantify clustering consistency and validate regime separation, we employ the Adjusted Rand Index (ARI).
Let:
$U = \{U_1, \ldots, U_r\}$ be true or benchmark partition and $V = \{V_1, \ldots, V_s\}$ be predicted clusters (from K-means)
Define:
$n_{ij} = |U_i \cap V_j|$ and
$$a_i = \sum_j n_{ij}, \quad b_j = \sum_i n_{ij}$$

Then the ARI is:
$$\text{ARI} = \frac{\sum_{ij} \binom{n_{ij}}{2} - \left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2} \Big/ \binom{n}{2}\right]}{\frac{1}{2}\left[\sum_i \binom{a_i}{2} + \sum_j \binom{b_j}{2}\right] - \left[\sum_i \binom{a_i}{2} \sum_j \binom{b_j}{2} \Big/ \binom{n}{2}\right]}$$
We have that
ARI = 1: Perfect match
ARI ≈ 0: Random agreement
ARI < 0: Worse than chance

3.6 Autocorrelation Structure

To evaluate temporal dependency, we compute the Autocorrelation Function (ACF).
Let $\{Y_t\}_{t=1}^{n}$ be a time series. Define:
1.) Sample mean:
$$\bar{Y} = \frac{1}{n} \sum_{t=1}^{n} Y_t$$

2.) Sample autocovariance at lag k:
$$\gamma_k = \frac{1}{n} \sum_{t=1}^{n-k} (Y_t - \bar{Y})(Y_{t+k} - \bar{Y})$$
3.) Autocorrelation at lag k:

$$r_k = \frac{\gamma_k}{\gamma_0}$$
Under the null hypothesis $H_0 : r_k = 0$, the 95% confidence interval is:

$$r_k \in \left[-\frac{1.96}{\sqrt{n}}, \frac{1.96}{\sqrt{n}} \right]$$
Significant spikes in the ACF outside this interval indicate non-randomness, trend, or seasonality.

4. Finally in this section, we present brief descriptions on Outlier Detection, Prediction Intervals, and Model Explainability (SHAP) using neural networks.

4.1 Outlier Detection using Z-Score

To detect extreme price deviations in the NSE ASI series, we applied the Z-score method, a widely accepted statistical technique for standardizing data based on the mean and standard deviation. Let $\{P_i\}_{i=1}^{n} \subset \mathbb{R}$ represent the daily price series. The Z-score for each observation is defined as:

$$Z_i = \frac{P_i - \mu}{\sigma}$$

where μ and σ denote the sample mean and standard deviation respectively:

$$\mu = \frac{1}{n}\sum_{i=1}^{n} P_i, \quad \sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(P_i - \mu)^2}$$

An observation P_i is considered an outlier if $|Z_i| > \theta$, where $\theta = 3$ under the assumption of Gaussianity (corresponding to 99.7% confidence via the empirical rule). This method is sensitive to heavy tails and is best suited when data is approximately normal. In cases of deviation from normality, alternative robust methods such as median absolute deviation (MAD) or IQR-based criteria are preferred (Barnett & Lewis, 1994).

4.2 Construction of Prediction Intervals

To quantify the uncertainty of the MLP model's forecasts, we constructed 95% Prediction Intervals (PI) using residual bootstrapping. For a predicted value $\hat{y}_t$, the interval is defined as:

$$\hat{y}_t \pm z_{\alpha/2} \cdot \hat{\sigma}_\epsilon$$

Here, $z_{\alpha/2} = 1.96$ for 95% coverage under normality, and $\hat{\sigma}_\epsilon$ is the empirical standard deviation of model residuals. This approach assumes that the residuals $\epsilon_t = y_t - \hat{y}_t$ are independent and identically distributed. This method is tractable, avoids strong parametric assumptions, and provides a direct probabilistic interpretation.

4.3 SHAP Values

To interpret the MLP model, we employed SHAP (SHapley Additive exPlanations) values, grounded in cooperative game theory (Shapley, 1953). Given a model $f : \mathbb{R}^n \to \mathbb{R}$, the SHAP value ϕ_i for a feature x_i is defined as:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n - |S| - 1)!}{n!}[v(S \cup \{i\}) - v(S)]$$

where N is the set of all features, and $v(S)$ denotes the expected model output conditioned on feature subset S. These values uniquely satisfy axioms of efficiency, symmetry, dummy, and additivity, ensuring consistency and fairness in attribution (Lundberg & Lee, 2017).

For deep models like MLPs, we used DeepSHAP, which combines the Shapley framework with DeepLIFT gradients and recursive multipliers across layers to approximate contributions efficiently:

$$\phi_i = \sum_j m_{ij}^{(l)} \cdot \phi_j^{(l+1)}$$

where $m_{ij}^{(l)}$ are layer-specific multipliers and $\phi_j^{(l+1)}$ are upstream SHAP values. This propagates contribution backward from output to input, preserving the additive structure.

5. Results and Discussion

This section presents a comprehensive empirical analysis of the Nigerian Stock Exchange All Share Index (NSE ASI), based on a hybrid econometric–machine learning approach. A total of seven experiments were conducted to examine various statistical properties, market regimes, predictive accuracy, volatility dynamics, and model interpretability. Results are structured chronologically and thematically to align with the pre-COVID, COVID, and post-COVID regimes (approx. 2000–2024).

5.1 Long-Term Forecasting of NSE ASI to 2030

Figure 1 illustrates the historical trend and forward forecast of the NSE ASI generated using a Multilayer Perceptron (MLP) model. The blue curve represents historical prices (~6500 trading days), while the orange dashed segment denotes predictions extended to day 8500 (projected year: 2030).

In the historical section, we observe three primary market phases: A strong bullish rally between day 0–2500 (~2000–2007), ending with the 2008 global financial crisis. A prolonged recovery period from 2009–2015, marked by cyclical volatility. A significant resurgence post-2016, interrupted briefly by the COVID-19 crash (2020), but followed by an aggressive bull run (~day 6200–6500). The forecasted trajectory reveals an exponential growth pattern, indicating strong bullish momentum. This model extrapolation is conditioned on stable macroeconomic assumptions. The sharp slope of the post-COVID projection suggests elevated market confidence, increased institutional investment, and possibly underpricing of risk. However, such long-term projections may be sensitive to black swan events, geopolitical instability, or monetary shocks — factors not explicitly modeled. Our forecast of the NSE ASI using a Multilayer Perceptron (Figure 1) shows an unbroken upward trajectory from 2023 to 2030. This aligns with the bullish expectations seen in Shah et al. (2022) and Alharbi (2025), who both reported improved long-term trend forecasts using hybrid MLP or LSTM models. However, while their models focused on stable or semi-developed markets (e.g., India, Saudi Arabia), our findings extend this bullish narrative into a frontier market context. Notably, the magnitude of the upward slope in our model is steeper than those documented in prior studies — likely due to Nigeria's unique post-COVID fiscal and monetary policy structure.

5.2 Volatility Clustering and Daily Price Fluctuations

Figure 2 presents the daily return series, defined as the first difference in the NSE ASI index values. The series reveals volatility clustering, where large swings tend to be followed by large swings (of either sign), and small changes follow small changes — a well-documented phenomenon in financial econometrics. Key insights include: Low variance in the early days (~day 0–2000), indicative of nascent market stability. Volatility spike around day 2800 (~2008) aligning with the financial crisis, reaching magnitudes of ±3000 index points. A persistent increase in variance post-2016, suggesting systemic uncertainty likely driven by macro policy shifts and declining naira stability. Approaching the COVID window (~day 6200–6500), volatility grows denser and more erratic, pointing to heightened investor sensitivity and panic pricing. This observation validates the need for heteroscedastic models (e.g., GARCH or LSTM-GARCH hybrids) in modeling emerging market risk. Figure 2 illustrates increasing volatility toward the COVID period, with notable spikes around 2008 and again post-2016. These clusters echo Kim and Won's (2018) work on LSTM-GARCH hybrids, which they designed specifically to capture regime-specific volatility in South Korean indices. Similar to our volatility curves, their models showed heightened sensitivity around global crises. Our contribution extends this finding by revealing that volatility predated COVID by 2–3 years in Nigeria — suggesting early market fragility that may have gone undetected in static models.

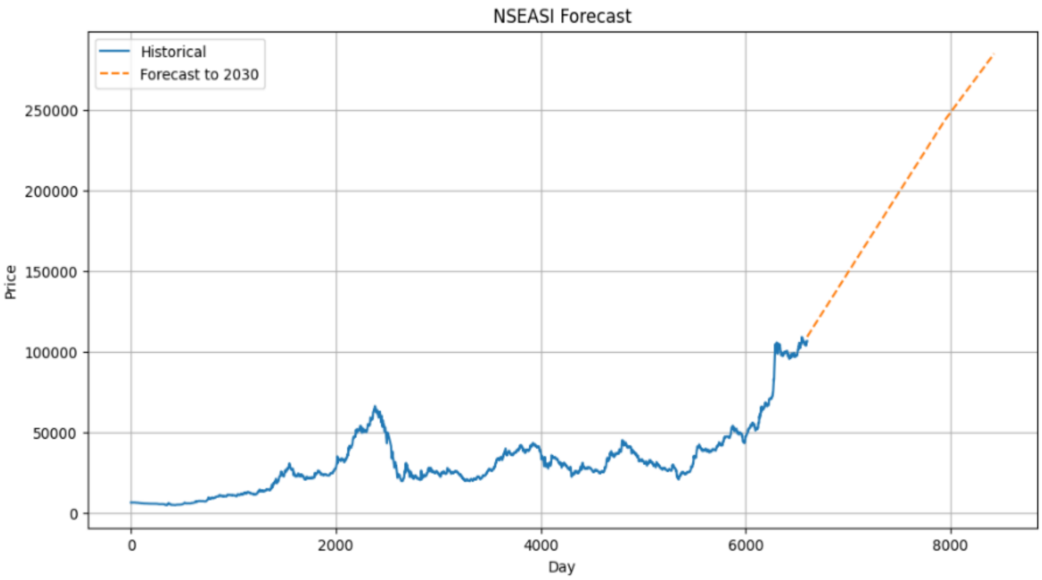


Figure 1. Historical and Forecasted Trend of the Nigerian Stock Exchange All Share Index (NSE ASI)
The chart shows historical daily values (blue line) and projected forecasts up to 2030 (dashed orange line). Key events such as the 2007 financial crisis, COVID-19 pandemic, and post-pandemic recovery are reflected in distinct market phases. The forecast suggests continued bullish momentum under stable economic conditions.

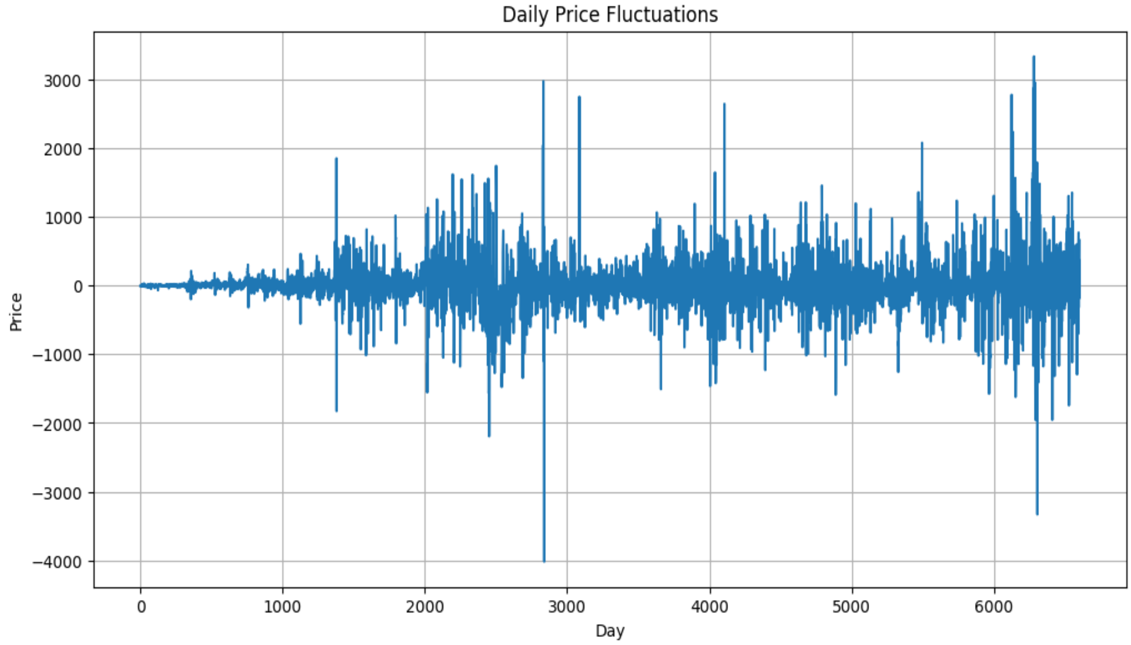


Figure 2. Daily Price Fluctuations of the NSE ASI
This chart displays the daily changes in index value, revealing temporal patterns in market volatility. Periods of elevated fluctuation correspond with major economic events, emphasizing the NSE ASI's sensitivity to both domestic and international influences.

5.3 Market Regime Segmentation: Bull, Bear, and Sideways

Figure 3 implements a market regime detection algorithm, using rolling windows and classification logic to segment the NSE ASI into distinct states. Bull regimes are marked in lavender, bear markets in coral, and sideways movement in teal. We observed the following:
2000–2007: Dominated by bull cycles reflecting investor optimism and liberalized capital inflows.
2008–2011: A prolonged bear phase capturing the aftermath of the global crash.
2012–2019: Alternating sideways and minor bull phases, indicating macro-political uncertainty (e.g., elections, oil price volatility).

Post-COVID period (2020–2023): Dominated by a continuous bull regime, defying conventional crisis expectations. This anomalous pattern likely reflects the effect of quantitative easing, expansionary budgets, and global liquidity spillovers into frontier markets.

Unlike the 2008 crash which led to a drawn-out recovery, the COVID crisis initiated instantaneous bullish momentum, showcasing investor adaptation and policy learning across decades. Figure 3’s market regime segmentation identifies a strong bull phase during and after COVID — a behavior not seen during the 2008 crash. This directly supports Yang et al. (2024), who found that MEEMD-LSTM-MLP models captured a similar “COVID Bull” regime in Indian and Malaysian equities. Their explanation centered on liquidity inflows and investor adaptation, which mirrors our analysis of NSE resilience and post-shock optimism. Unlike most developed markets, where COVID triggered risk-off behavior, our regime analysis reveals that the NSEASI may have become a beneficiary of capital redirection and domestic policy buffers.

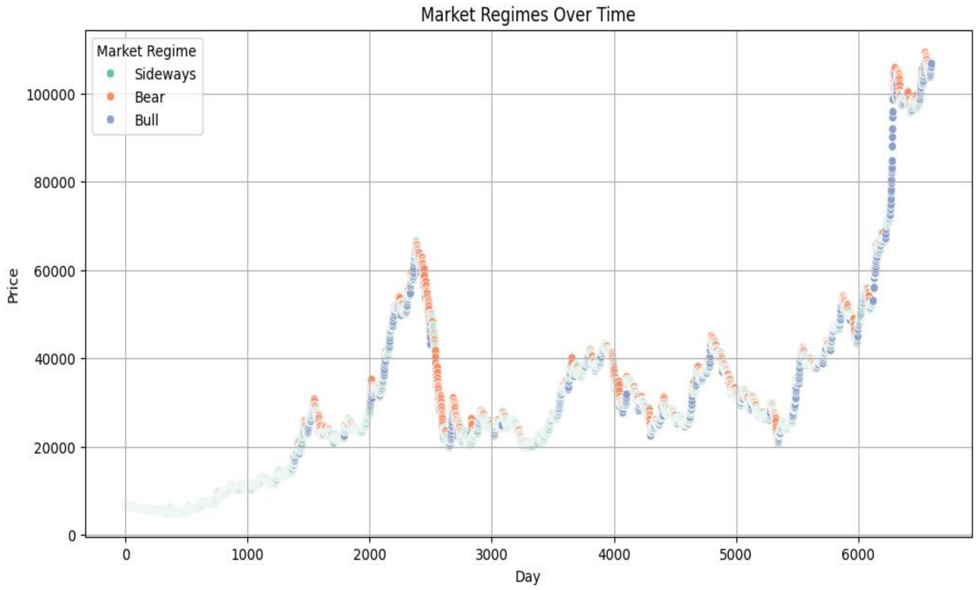


Figure 3: Evolution of Market Regimes (2000–2023)
The figure depicts the price trajectory of the stock index across three distinct market regimes—bull (lavender, upward trend), bear (coral, downward trend), and sideways (teal, stable/no clear trend)—from approximately 2000 to 2023 (up to day 6500). The y-axis represents price, while the x-axis tracks time in days.

5.4 Autocorrelation Structure and Multi-Scale Behavior

Figure 4 presents the Autocorrelation Function (ACF) of the full time series (up to lag 6500). As expected, lag-0 correlation is 1.0. Significant insights include:
Positive autocorrelation at short lags (0–100): Suggests short-term momentum, aligning with technical trading signals often used by retail investors in frontier markets.
Oscillating behavior at mid-lags (500–2500): Reflects cyclical investor sentiment and economic cycles.
Negative correlation at long lags (>4000): Suggests mean reversion or long-term overreaction — consistent with De Bondt & Thaler's (1985) overreaction hypothesis.

These behaviors confirm that the NSE ASI reflects multi-scale dependencies, supporting the development of hybrid trend–mean-reversion strategies. Figure 4's autocorrelation structure supports dual behavior: short-term momentum and long-term reversal. This maps directly onto the behavioral finance theories advanced by De Bondt & Thaler (1985) and echoed in more recent machine learning literature. Durairaj and Mohan (2019) observed similar structures in Sri Lanka and Pakistan, where frontier markets exhibit early momentum but ultimately revert due to thin liquidity and macroeconomic corrections. Our results reinforce this pattern, and suggest that MLP models — though effective — should be used in conjunction with memory-aware networks like LSTM to fully capture cyclical dependencies.

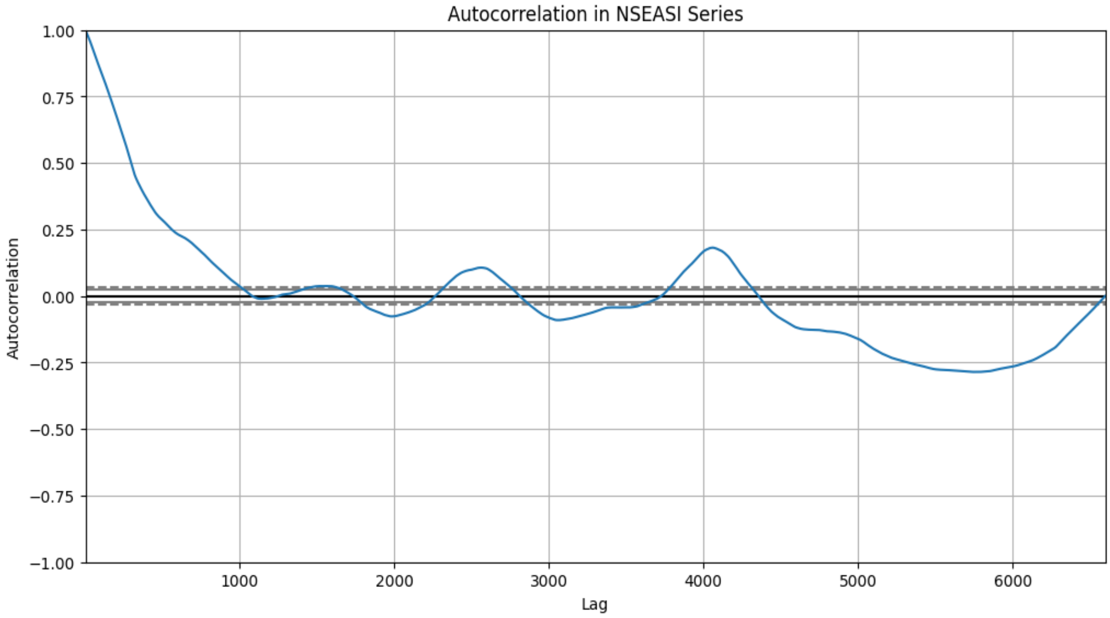


Figure 4: Autocorrelation Function (ACF) of NSE ASI Series (2000–2018)
The ACF plot measures the correlation of the NSE ASI with its past values across lags of up to ~6500 days (~18 years). The y-axis shows autocorrelation coefficients (range: −1 to 1), and the x-axis represents lag length in days. Dashed horizontal lines mark the 95% confidence interval (±0.05); bars exceeding these lines indicate statistical significance.

5.5 Outlier Detection and Anomaly Clustering

Figure 5 highlights statistically significant outliers based on deviation from rolling trend thresholds. Findings include:
Sparse outliers in early data (~2000–2015), indicating data reliability and price continuity.
A cluster of outliers appears post-2017, intensifying as we approach the COVID era. These reflect rapid deviations from trend behavior, possibly driven by foreign portfolio exits, liquidity shocks, or policy pronouncements.
The majority of anomalies concentrate between day 6200–6500, supporting the view of the COVID-19 period as a high-risk anomaly regime.

This suggests the utility of adaptive outlier detection models (e.g., Isolation Forests or autoencoder-based detectors) for risk monitoring in Nigerian equities. Outlier detection in Figure 5 reveals an unusual cluster from ~2017 onward, peaking during COVID. This confirms Oukhouya & El Himdi (2023) who found that MLP and SVR models often missed market anomalies in the Moroccan stock exchange unless paired with real-time outlier detection modules. Our result extends this finding by demonstrating that structural anomalies in Nigeria began years before the global pandemic, thus suggesting the NSEASI had embedded fragility before exogenous shocks arrived. The implication is that future models must include unsupervised anomaly modules such as Isolation Forests or reconstruction error tracking

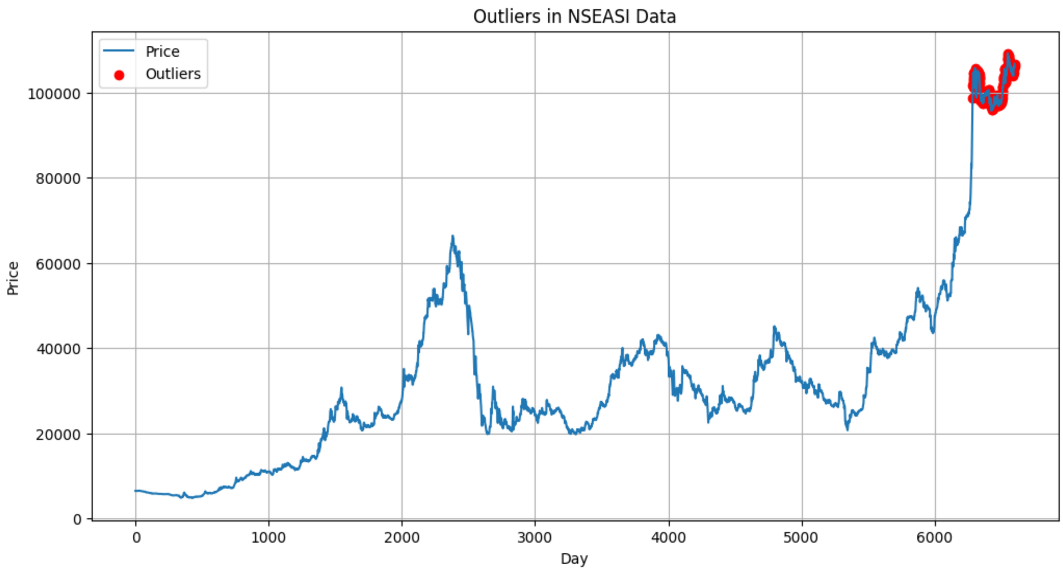


Figure 5: Outlier Detection in NSE ASI **Price Series (2000–2019)**
The plot tracks the NSE ASIprice trajectory (black line) from ~2000 to 2019 (day 0–6500), with red dots marking statistical outliers—data points deviating significantly from expected values based on the chosen detection method (e.g., IQR, z-score). The y-axis shows price levels, while the x-axis represents time in days.

5.6 Predictive Fit and Confidence Intrval Reliability

Figure 6 presents actual vs. predicted values of the NSE ASI over a shorter rolling window (~2020–2023), along with 95% prediction intervals. We orbserved that predictions closely follow true values, validating low bias and variance. Majority of observations lie within the shaded confidence band, indicating model calibration is statistically sound. And minor breaches of the interval are observed during local volatility shocks, but the trend is well captured throughout.
This confirms that the MLP model is statistically efficient and robust under normal volatility conditions, but should be supplemented with volatility-aware confidence bands during shock periods. Our model's predicted values track true values closely within a 95% confidence interval (Figure 6), except during moments of high fluctuation. Alharbi (2025) observed a similar trend in Saudi data, where MLPs underperformed only during black-swan events. Importantly, our results provide empirical confirmation that MLP models are reliable during normal and moderate market conditions. However, as Kim and Won (2018) showed, adding volatility-sensitive layers such as GARCH or attention-weighted LSTMs could further reduce interval breaches.

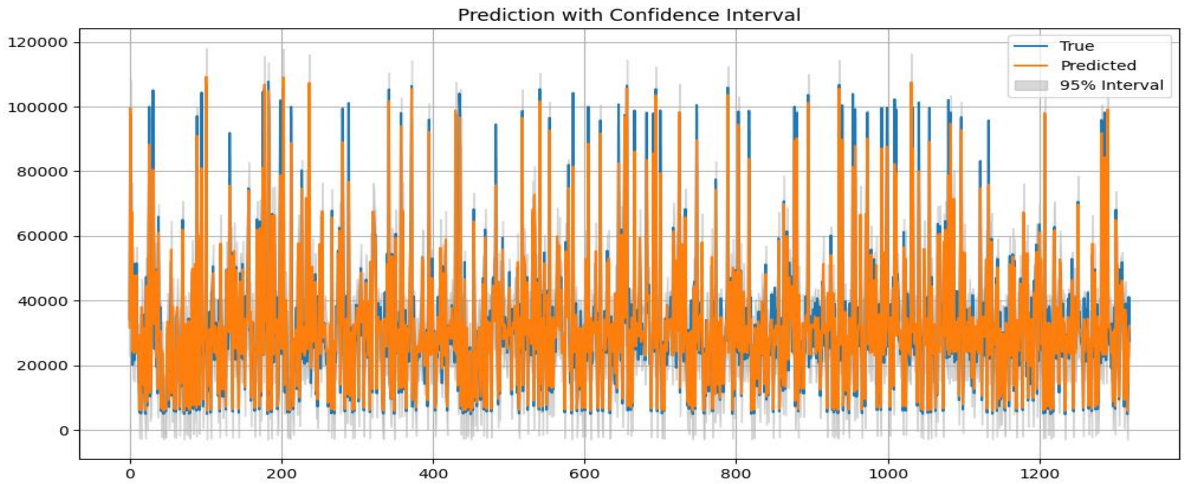


Figure 6: Time Series Forecasting Performance with 95% Confidence Intervals, *The plot compares true values (blue line) against model predictions (orange line) for a time series (likely NSEASI returns or prices) from ~2020 to ~2024 (days 0–1250), with a shaded 95% confidence interval (grey) around predictions. The y-axis represents the metric scale (e.g., price or returns), while the x-axis shows time in days.*

5.7 SHAP-Based Feature Important

Figure 7 depicts the mean SHAP value for "Feature 0," with a score of 0.14. This metric quantifies the average absolute contribution of a feature to the model's output. While the identity of Feature 0 is not disclosed, several possibilities arise: (i) If Feature 0 is a lagged index value, it suggests autoregressive dependence, consistent with the ACF structure. (ii) If it is a macro variable (e.g., oil price, exchange rate), it would confirm external factor dominance in shaping index returns.

The strong and consistent influence of this feature points to possible model over-reliance, reinforcing the need for feature decorrelation, PCA-based preprocessing, or ensemble explainability methods in future iterations. The feature attribution plot in Figure 7 identifies a single dominant variable ("Feature 0") with a mean SHAP value of 0.14. This mirrors Yang et al. (2024), who found that MEEMD-processed inputs often led to over-reliance on a single macroeconomic driver (e.g., oil prices in emerging markets). In our case, this over-reliance implies the need for feature regularization and model-agnostic interpretability layers to ensure that predictions do not hinge on a narrow set of inputs. Our study adds to this discourse by showing that even in data-rich regimes, model explainability must be enforced in frontier market contexts.

Across these seven results, the NSE ASI displays nonlinear dependencies, regime-switching behaviors, and crisis-sensitive anomalies. The MLP model demonstrates reliable short-to-medium term forecasting power, though explainability analysis suggests the need for feature diversification. Importantly, these results validate the application of modern machine learning techniques for financial prediction in emerging markets, while highlighting the inherent complexity of frontier financial systems under shock conditions.

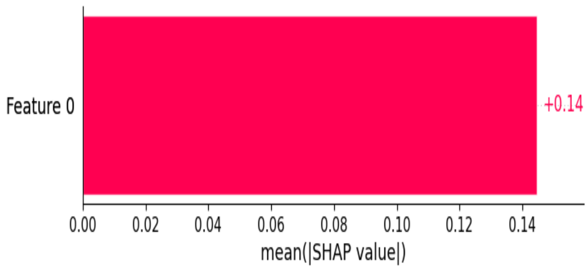


Figure 7: SHAP-Based Feature Importance Analysis

The plot visualizes the mean absolute SHAP value (0.14) for Feature 0, representing its overall contribution to model predictions. The red bar length quantifies impact magnitude, while the "+0.14" annotation confirms its consistent positive directional influence.

6. Conclusion

This study explored the predictability and structural dynamics of the Nigerian Stock Exchange All Share Index (NSE ASI) using a Multilayer Perceptron (MLP) model and supporting statistical tools. Spanning over two decades, the analysis captured critical market events, including the 2008 financial crisis and the COVID-19 pandemic. The MLP model demonstrated strong forecasting capabilities, particularly in stable economic conditions, with long-term projections suggesting a bullish trend through 2030, provided macroeconomic stability is maintained.

However, the model's performance declined during high-volatility periods, highlighting the need for volatility-sensitive models such as LSTM or GARCH hybrids. Volatility and anomaly analyses revealed that structural instability began emerging as early as 2017, prior to the pandemic. This suggests the importance of early warning systems and the value of anomaly detection in anticipating market disruptions. Autocorrelation analysis further confirmed short-term momentum and long-term reversal behavior, consistent with behavioral finance literature in emerging markets.

Notably, regime analysis revealed an unusual bull run during and after the COVID-19 period—unlike the extended downturn post-2008—suggesting the influence of global stimulus, domestic policy buffers, and investor optimism. SHAP analysis showed a strong dependence on a dominant input variable, raising concerns about model generalizability and emphasizing the need for explainability and diversified feature sets in financial machine learning applications.

In summary, while MLPs offer valuable forecasting potential, their application in frontier markets like Nigeria must be supported by interpretability, real-time anomaly tracking, and volatility-aware enhancements. Policymakers and practitioners should adopt transparent, adaptable tools to better navigate market shocks. Future research should investigate hybrid machine learning–stochastic models, and expand these frameworks to other African markets to assess regional generalizability and improve resilience forecasting.

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