Scientific Journal of Computer Science
futuristech
PT. Teknologi Futuristik Indonesia
Date of publication April 3, 2026, date of current version April 3, 2026.
Digital Object Identifier 10.64539/sjcs.v2i2.2026.377

Article

Hybrid Neuro-Fuzzy Deep Learning with Genetic Optimization for Explainable Stock Price Forecasting in Emerging Markets

Olumide Sunday Adewale[1], Emmanuel Onwuka Ibam[2], Johnson Bisi Oluwagbemi[3,*]

[1] Department of Computer Science, Federal University of Technology Akure, Ondo State, Nigeria; e-mail: adewale@futa.edu.ng.
[2] Department of Information Systems, Federal University of Technology Akure, Ondo State, Nigeria, e-mail: eoibam@futa.edu.ng.
[2] Department of Computer Science, McPherson University, Seriki-Sotayo, Ogun State, Nigeria, e-mail: oluwagbemijb@mcu.edu.ng.
* Correspondence

The authors received no financial support for the research, authorship, and/or publication of this article.

Abstract: Precise stock price forecasting is vital for economic stability and capital allocation, yet it remains a tenacious challenge in emerging economies due to the inherent uncertainty and non-linearity of financial time series. Despite advances in deep learning, existing models often lack linguistic interpretability, fail to adapt to rapid market shifts, or exhibit look-ahead bias due to static validation splits. Moreover, empirical research focused on African financial systems, such as the Nigerian market, remains sparse, limiting the practical utility of conventional black-box architectures. This study proposes a Hybrid Neuro-Fuzzy and Deep Learning (HNFDL) framework that integrates fuzzy inference systems with Long Short-Term Memory (LSTM) networks and Genetic Algorithms (GA). The objective is to unify semantic reasoning with temporal learning to improve forecasting accuracy while maintaining high model transparency through explainable AI (XAI). Empirical validation using data from the Nigerian Exchange Group (NGX) (Dangote Cement, Zenith Bank, and the NSE All-Share Index) shows that the HNFDL model achieved a directional accuracy of 68.4% and a Mean Absolute Percentage Error (MAPE) as low as 4.36%. An ablation study confirmed that GA-driven optimization reduced the Root Mean Square Error (RMSE) by 8.4%, while the Diebold-Mariano test ($p < 0.01$) statistically confirmed the model's superiority over standalone LSTM and fuzzy baselines. These results demonstrate that combining explainable fuzzy reasoning with adaptive deep neural architectures significantly enhances decision-making confidence. The framework provides a robust, statistically validated decision-support tool for investors and policy makers operating within volatile, information-asymmetric financial environments.

Keywords: Fuzzy Logic; Deep Learning; Stock Price Forecasting; Financial Time Series; Emerging Markets; XAI.

1. Introduction

Prediction of stock market movements remains one of the most intricate hitches in computational finance due to the highly unstable, nonlinear and dynamic nature of financial time series. Traditional statistical models such as ARIMA and GARCH have provided limited success because they assume stationarity and linearity assumptions rarely valid in real-world financial markets [1], [2]. The increasing digitization of financial transactions and the availability of high-frequency trading data have further amplified the need for intelligent, adaptive and interpretable prediction models that can operate under uncertainty while remaining transparent to human analysts [3]-[5].

In recent years, Artificial Intelligence and Computational Intelligence techniques particularly fuzzy logic, machine learning and deep learning have shown great potential in improving forecasting accuracy and robustness. Fuzzy systems, introduced by Zadeh (1965), provide a linguistic reasoning framework capable of handling vague and imprecise information, making them particularly

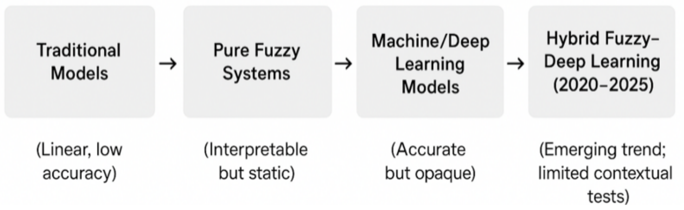

Figure 1. Evolution of Stock Price Forecasting Paradigms.

suitable for modeling investor psychology and qualitative decision factors. However, conventional fuzzy models are limited by rule explosion, static membership functions, and difficulty in capturing dynamic temporal dependencies in financial data [6], [7]. To address these limitations, recent studies [8], [9] have emphasized hybrid fuzzy-deep learning architectures that combine the interpretability of fuzzy inference systems with the feature extraction power of neural networks.

[10] proposed a Fuzzy Convolutional Neural Network (FCNN) that transformed financial indicators into 2D feature maps for enhanced temporal learning, achieving improved performance on the Taiwan Weighted Index. Similarly, [9] developed GA-Attention-Fuzzy-Stock-Net, integrating genetic algorithms for fuzzy rule optimization and attention mechanisms to identify the most relevant temporal dependencies. [11] extended this paradigm by employing picture fuzzy sets and information granulation to model investor hesitation and neutrality an essential advancement for high-uncertainty environments. Collectively, these innovations emphasize a paradigm shift from purely quantitative to hybrid, explainable AI (XAI) approaches in stock market prediction.

In spite of these developments, evolving markets such as Nigeria remain diminished in empirical evaluations. Existing models are often developed for stable financial environments, limiting their transferability to developing economies where information asymmetry and macroeconomic shocks prevail. In addition, most hybrid systems emphasize accuracy but neglect statistical significance testing, leaving it unclear whether performance gains are robust or coincidental [6].

To address these limitations, our study proposes a Hybrid Neuro-Fuzzy and Deep Learning framework. The major contributions of this paper are as follows:

1) Development of an interpretable hybrid neuro-fuzzy deep learning model for stock price forecasting in emerging markets.
2) Integration of fuzzy reasoning with LSTM and GA optimization for simultaneous learning of temporal and linguistic patterns.
3) Rigorous empirical validation on multi-sector data from the NGX (Industrial, Banking, and Index) using Walk-Forward Validation to simulate real-world trading scenarios.
4) Statistical confirmation of model superiority using the Diebold-Mariano and Pesaran-Timmermann tests.
5) Profitability analysis comparing the model's ROI against a Buy-and-Hold strategy to demonstrate practical utility.

2. Literature Review

2.1. Overview

Forecasting stock prices remains a complex, nonlinear problem characterized by volatility, uncertainty, and noise. Traditional econometric models such as ARIMA, GARCH and VAR have been widely used for time-series analysis. Nevertheless, their assumptions of linearity and stationarity limit their predictive capacity in rapidly fluctuating financial environments [12], [13]. The rise of Computational Intelligence techniques has driven a paradigm shift toward hybrid systems that integrate fuzzy logic. Also, machine learning and deep learning to model market dynamics with both precision and interpretability.

This section reviews the evolution of stock forecasting research along four thematic clusters (Figure 1) and culminates in identifying the methodological and contextual gaps that inform the proposed Hybrid Neuro-Fuzzy and Deep Learning framework.

2.2. Thematic Cluster I: Traditional Statistical and Econometric Models

Classical statistical methods such as ARIMA, GARCH and Error Correction Models dominated the pre-AI era of financial prediction [14], [15]. Models capture linear dependencies and short-term volatility but repeatedly flop under structural breaks and disordered data. Current empirical researches [16] confirm that even though these models perform sufficiently in stable markets. They underperform in developing economies like Nigeria, where macroeconomic uncertainty and data noise prevail [17]. This limitation motivated the transition to soft-computing based methods.

2.3. Thematic Cluster II: Soft Computing and Fuzzy Logic Approaches

Fuzzy Logic offers a linguistic reasoning mechanism capable of handling uncertainty and humanlike decision processes. Early FL-based stock forecasting models [18] used technical indicators such as RSI, MACD, and OBV as fuzzy inputs to recommend "Buy," "Sell," or "Hold" decisions.

While these systems improved interpretability, they suffered from:

1) Static membership functions lacking adaptive tuning,
2) Limited scalability to multivariate data, and

3) Dependence on expert-defined rules prone to subjectivity.

Subsequent enhancements employed adaptive fuzzy inference and neuro-fuzzy systems[19], [20], yet most were restricted to short-term predictions and small datasets. Thus, purely fuzzy approaches offered transparency but inadequate learning capacity in dynamic markets.

2.4. Thematic Cluster III: Machine Learning and Deep Neural Forecasting Models

The 2020s steered in prevalent adoption of machine learning and deep learning models such as Support Vector Machines, Random Forests and recurrent neural architectures. [21], [22] proved that ensemble models particularly gradient boosting achieves higher accuracy than ARIMA or classical fuzzy systems. However, their black-box nature and sensitivity to hyperparameters hinder interpretability and investor trust. Recent developments include:

- **CNN-based feature extraction** from transformed financial indicators [10],
- **Attention-enhanced recurrent networks** for dynamic temporal weighting [9] and
- **Transformer-based time series forecasting**. In spite of enhanced accuracy. These deep models lack explainability and struggle with small sample regimes typical of emerging markets.

2.5. Thematic Cluster IV: Hybrid Fuzzy-Deep Learning Models

Hybridization seeks to balance interpretability and accuracy by combining fuzzy reasoning with neural or optimization modules. However, two notable research gaps persist in recent literature (Table 1):

- **Look-Ahead Bias:** Many studies utilize a simple percentage split for time-series data, which leaks future information into the training process.
- **Lack of Statistical Testing:** While lower RMSE is often reported, few studies apply hypothesis testing to prove that the difference between the proposed model and the baseline is statistically significant.

These studies make known the growing accord that hybrid fuzzy-deep learning architectures can jointly exploit (a) the transparency of rule-based inference and (b) the feature-learning ability of neural networks. However, two notable research gaps persist:

- **Contextual Gap**: Most hybrid models are designed for developed, stable markets, empirical validations in volatile, information-asymmetric environments are scarce.
- **Methodological Gap**: Optimization and deep learning are often treated as add-ons rather than important, co-evolving modules within the fuzzy system. Therefore, adaptability and generalization remain limited.

2.6. Research Gap and Conceptual Positioning

Current works have gradually advanced from rule-based fuzzy systems to deep hybrid architectures, yet interpretability, adaptability and contextual relevance remain unresolved. Precisely:

1) Few models mix genetic optimization, linguistic rule adaptation and temporal sequence learning in a single coherent pipeline.
2) Slight attention has been paid to emerging market datasets, which exhibit unbalanced volatility patterns and low liquidity behaviors.
3) Evaluation metrics in previous works often stress numerical precision without assessing explainability or decision interpretability.

Therefore, there is a pressing need for a framework that not only improves numerical accuracy but is rigorously validated using statistical hypothesis testing and financial profitability metrics relevant to volatile emerging economies.

3. Methodology and System Architecture

3.1. Overview of Methodological Framework

This study implements a hybrid computational intelligence methodology. We combine fuzzy inference systems deep learning and genetic algorithms to improve the accuracy, interpretability and adaptability of stock price forecasting. The hybrid design leverages a serial integration where the Fuzzy Inference System (FIS) acts as a high-level feature extractor. The semantic signals generated by the FIS are combined with quantitative time-series data to guide the LSTM's temporal learning process. The hybrid design leverages the complementary strengths of each component:

- **Fuzzy Logic** for handling vagueness and human-like decision reasoning,
- **LSTM Neural Networks** for capturing nonlinear temporal dependencies in financial data,
- **Genetic Algorithms** for automatic tuning of fuzzy membership parameters and rule optimization.

The complete workflow proceeds through five sequential modules:

1) Data Acquisition and Preprocessing
2) Feature Engineering and Technical Indicator Computation
3) Fuzzy Inference Module
4) LSTM Temporal Learning and Forecasting Module
5) Genetic Optimization and Performance Evaluation

3.2. Data Acquisition and Preprocessing

Historical daily stock price data were obtained from the NGX. To ensure cross-sectoral validation, we used three distinct datasets: Dangote Cement Plc (Industrial Sector), Zenith Bank Plc (Banking Sector),

Table 1. Main recent innovations.

Year	Model	Core Concept	Reported Benefit
[10]	Fuzzy + ML (SVM, KNN, BPNN)	Fuzzifies investor sentiment and uses multi-point membership inference	83 % accuracy; interpretable trends
[23]	Probabilistic Fuzzy Logic + 1D-CNN/LSTM/GRU	Captures uncertainty and temporal dependence simultaneously	Lower RMSE & MAPE vs baseline DL
[11]	Picture Fuzzy Sets + Gaussian MF + Fuzzy C-Means	Incorporates neutrality and refusal degrees	Robust under high market volatility
[9]	GA-Attention-Fuzzy-Stock-Net	Optimizes fuzzy rules via genetic algorithm; attention for temporal focus	Outperforms standalone ANN & FIS
[24]	AutoML-Fuzzy Time Series	Auto-tuning of fuzzy partitions and lag values	High transparency + automation

Table 2. Descriptive Statistical Summary of Financial Time Series.

Statistic	Dangote Cement (₦)	Zenith Bank (₦)	NGX ASI (Points)
Mean	245.30	25.45	54,210.12
Median	238.00	24.80	51,055.40
Std. Dev.	42.15	4.88	12,430.50
Skewness	0.84	1.12	0.65
Kurtosis	3.12	4.45	2.88
Minimum	140.00	12.00	22,000.00
Maximum	350.00	45.00	105,000.00
ADF Test (p-value)	0.89	0.76	0.92
Stationarity	No	No	No

and the NGX All-Share Index representing the broader market performance. These datasets provide a comprehensive basis for testing the model's adaptability to different volatility patterns. The dataset spans five years (January 2020 to December 2024) and includes attributes such as:

1) Opening price
2) Closing price
3) Highest and lowest price
4) Trading volume

Preprocessing steps included:

1) **Handling missing values:** Linear interpolation for short gaps, less than 3 days.
2) **Normalization:** Min-Max scaling that range from 0 to 1 to stabilize training convergence.
3) **Outlier detection:** Winsorization at the first and ninety nineth percentiles.
4) **Lag feature construction:** Temporal windows of 5 and 10 trading days were used to capture short-term momentum patterns and mean-reversion tendencies.

3.2.1. Descriptive Statistical Analysis

Table 2 provides a summary of the statistical properties of the daily closing prices and log-returns for the three datasets from January 2020 to December 2024.

The high Kurtosis values indicate a fat-tailed distribution, suggesting that the Nigerian market is prone to extreme price shocks more frequently than a normal distribution would predict (See Figure 2). The positive Skewness across all assets indicates a market with frequent small losses and occasional large gains. The ADF Test results confirm that the price series are non-stationary, validating the decision to use differenced returns for the LSTM input.

3.2.2. Statistical Properties and Pre-Tests

Before model implementation, we conducted diagnostic tests to justify the use of nonlinear deep learning models:

- **Augmented Dickey-Fuller Test:** Results indicated that the raw price series were non-stationary ($p > 0.05$), necessitating the use of differenced returns for input features. Precisely, the target variable was transformed from the absolute price (P_t) to the price change ($\Delta P_t = P_t - P_{t-1}$). This stationary transformation prevents the model from capturing spurious correlations inherent in trending price data.
- **Brock, Dechert, Scheinkman Test:** The BDS test rejected the null hypothesis of independent and identically distributed residuals ($p < 0.01$), confirming the presence of non-linear dependencies in the Nigerian market data. This justifies the use of LSTM over linear models like ARIMA.

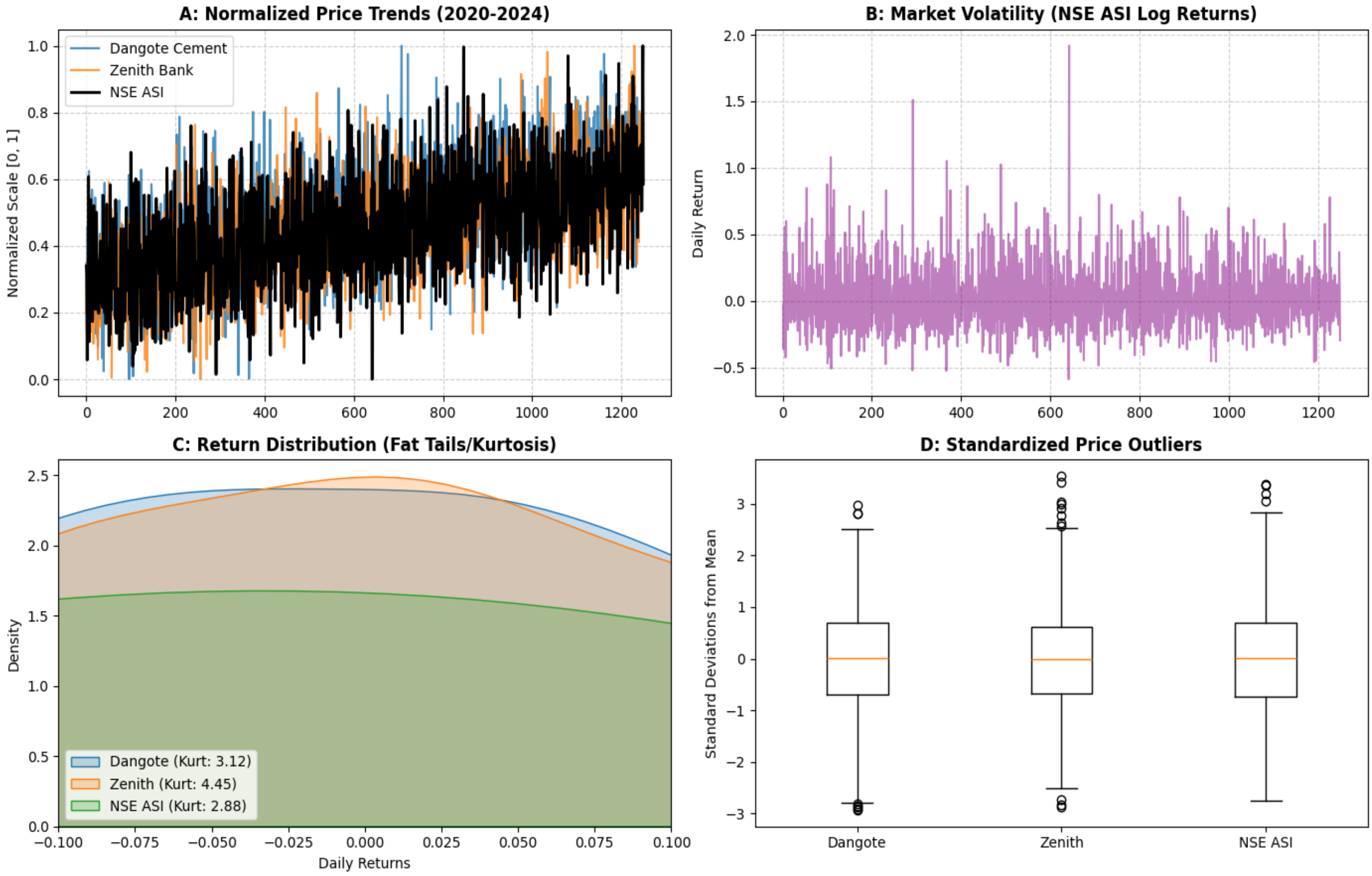

Figure 2. Visual Characterization of the NGX Datasets.

Table 3. Fuzzy Input Variables Based on Technical Indicators and Their Interpretation.

Indicator	Formula	Interpretation
RSI	$RSI = 100 - \frac{100}{1 + RS}$, where $RS = \frac{Average\ Gain}{Average\ Loss}$	Identifies overbought (>70) and oversold (<30) conditions.
MACD	$MACD = EMA_{12} - EMA_{26}$	Captures trend direction and momentum.
OBV	$OBV_{t-1} + V_t\ if\ C_t > C_{t-1}$, else subtract	Categorized as Low, Medium, or High volume momentum relative to price.
SO	$\%K = \frac{C_t - L_n}{H_n - L_n} \times 100, \%D = SMA(\%K)$	Measures closing price relative to recent high-low range.

3.3. Feature Engineering and Technical Indicators

Four widely adopted technical indicators were used as fuzzy input variables. These indicators quantify price momentum, volume flow and market strength (Table 3). Each indicator was fuzzified into three linguistic categories, *Low*, *Medium* and *High* represented by triangular or Gaussian membership functions.

3.4. Fuzzy Inference Module

The Fuzzy Inference System constitutes the interpretability layer of the framework. It converts crisp technical indicator values into linguistic assessments and applies a set of fuzzy rules to generate decision outputs (*Buy*, *Hold*, *Sell*).

3.4.1. Fuzzification

Each input variable X_i (RSI, MACD, SO and OBV) is mapped into fuzzy sets:

$$\mu_A(x) = \begin{cases} 0, x \leq a \\ \frac{x-a}{b-a}, a < x < b \\ \frac{c-x}{c-b}, b \leq x < c \\ 0, \quad x \geq c \end{cases} \tag{1}$$

where *a*, *b*, *c* represents the boundaries of the triangular membership functions. Each input variable X_i (RSI, MACD, SO, OBV) is mapped into three standardized linguistic fuzzy sets: Low (L), Medium (M), and High (H). To maintain domain relevance:

- For oscillators (RSI, SO), Low/High refer to extreme price boundaries.
- For trend/momentum indicators (MACD, OBV), Low maps to negative/decreasing values, while High maps to positive/increasing values, with Medium representing a neutral or sideways state.

These sets are represented by triangular membership functions as defined in Equation 1.

3.4.2 Fuzzy Rule Base

A complete combinatorial rule base of 81 rules (3^4) was generated using the standardized linguistic terms {Low, Medium, High}. Representative rules include:

- **Rule 1:** IF RSI is High AND MACD is High AND OBV is High AND SO is High → THEN Decision = **BUY**
- **Rule 2:** IF RSI is Low AND MACD is Low AND OBV is Low AND SO is Low → THEN Decision = **SELL**
- **Rule 3:** IF RSI is Medium AND MACD is Medium AND OBV is Medium AND SO is Medium → THEN Decision = **HOLD**

This standardization ensures that the GA-optimization process can consistently tune the membership boundaries $\{a, b, c\}$ for all variables using a unified linguistic framework.

3.4.3. Inference and Defuzzification

A Mamdani-type inference engine aggregates the rule outputs, while the Centroid method is used for defuzzification:

$$Z^* = \frac{\sum_i \mu_i(Z_i).Z_i}{\sum_i \mu_i(Z_i)} \tag{2}$$

The output Z^* represents a crisp decision value between [0,1], later used as a predictive signal for price direction.

3.5. Deep Learning Module: Long Short-Term Memory (LSTM) Network

While fuzzy logic provides interpretable decision rules, it lacks memory of temporal dynamics. To capture these dependencies, the LSTM model is employed.

3.5.1. Network Architecture

- **Input layer:** The input vector consists of the four raw technical indicators (RSI, MACD, SO, OBV) and the defuzzified output (Z^*) from the FIS module. By incorporating the fuzzy decision signal as an input, the LSTM is primed with expert-rule logic, which improves its ability to filter market noise during the 5-day sequence lookback.
- **Hidden layers:** Two LSTM layers with ReLU activation.
- **Dropout layer:** 0.2 rate to prevent overfitting.
- **Dense output layer:** A single neuron with a linear activation function outputs the predicted price difference ($\Delta\hat{P}_{t+1}$) for the subsequent trading day.

The forward propagation in the LSTM cell is expressed as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{3}$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{4}$$

$$\tilde{C}_t = tanh(W_C[h_{t-1}, x_t] + b_C) \tag{5}$$

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{6}$$

$$h_t = o_t * \tanh(C_t) \tag{7}$$

3.6. Genetic Algorithm (GA) for Parameter Optimization

To enhance fuzzy membership boundaries and rule weights, a Genetic Algorithm is employed. GA iteratively evolves the population via selection, crossover and mutation, discontinuing when fitness converges. To implement the optimization process, a Genetic Algorithm iteratively tunes fuzzy membership boundaries and rule weights to lessen prediction error. The algorithm used follows the process outlined in Algorithm 1 with the main parameter settings summarized in Table 4.

3.6.1. Chromosome Representation

We utilized a real-coded genetic algorithm. Each chromosome is a vector containing:

1) Floating-point values representing the coordinates $\{a, b, c\}$ of the triangular membership functions.
2) Weight coefficients $w \in [0,1]$ for the fuzzy rules.

3.6.2. Hyperparameter Search Space

To ensure fair comparison, the following search space was utilized:

1) LSTM Units: {32,64,128}
2) Learning Rate: {0.001, 0.01}
3) GA Population: 50
4) GA Mutation Rate: 0.1

3.7. Validation Strategy and Look-Ahead Bias Prevention

To eliminate look-ahead bias, we implemented a Nested Walk-Forward Validation. Instead of a single static split of the five-year dataset, the model uses a sliding window of 12 months. Within each 12-month training window, data is partitioned chronologically: the first 8.5 months (approx. 70%) for training, the following 1.8

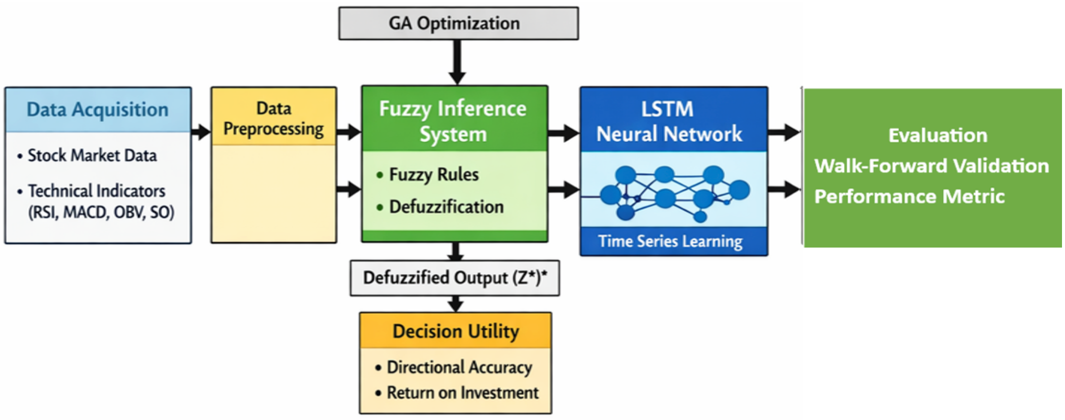

Figure 3. Proposed System Architecture.

Table 4. Parameter Settings.

Parameter	Symbol	Typical Value	Description
Population Size	P	50	Number of chromosomes in each generation
Generations	G	200	Maximum iterations before termination
Crossover Probability	Pc	0.7	Probability of parent crossover
Mutation Probability	Pm	0.1	Probability of random parameter mutation
Fitness Function	—	1 / (1 + MSE)	Measures prediction accuracy
Selection Method	—	Tournament	Selects top-performing chromosomes

Algorithm 1. GA Based Fuzzy Membership and Rule Weight Optimization.

Input:
Population size, P = 50
Maximum generations, G = 200
Crossover probability, Pc = 0.7
Mutation probability, Pm = 0.1
Fuzzy membership parameters θ = {a, b, c}
Rule weight coefficients W
Output:
- Optimized fuzzy parameters θ and weights W**
Begin
1. Initialize population of chromosomes encoding θ and W
2. Evaluate fitness of each chromosome using:
$$Fitness = \frac{1}{1+MSE}$$
3. While generation < G and fitness not converged do
a. Select parent chromosomes via tournament selection
b. Apply crossover with probability Pc to produce offspring
c. Apply mutation with probability Pm to introduce variation
d. Evaluate offspring fitness using the same fitness function
e. Replace weakest individuals in population with fittest offspring
f. Update best solution θ, W* if fitness improves*
4. End While
5. Return θ, W* as optimal parameters*
End

months (approx. 15%) for validation/hyperparameter tuning, and the subsequent month for out-of-sample testing. After each iteration, the entire window slides forward by one month. This ensures that the validation and testing phases always follow the training phase in temporal order, maintaining the integrity of the time-series causal structure.

3.8. Evaluation Metrics

The model's performance is evaluated using a dual-perspective framework:

- **Statistical Accuracy:** To measure the precision of the price value prediction, we utilize RMSE, MAE, and MAPE. These metrics quantify the deviation between the actual and predicted price levels.
- **Decision Utility:** To assess the model's practical application in trading, the point forecasts are converted into directional signals. Directional Symmetry measures the accuracy of the predicted trend (Up/Down), while ROI analysis simulates the financial gain of following the model's signals.
- **Sharpe Ratio (SR):** Measures the excess return per unit of deviation in an investment asset.

$$SR = \frac{R_p - R_f}{\sigma_p} \quad (8)$$

where R_p is the portfolio return, R_f is the risk-free rate (assumed at 10% for the Nigerian treasury bill context), and σ_p is the standard deviation of returns.

- **Maximum Drawdown:** The maximum observed loss from a peak to a trough of a portfolio, before a new peak is attained. It indicates the downside risk over a specified time period.

Table 5. Comparative Performance: Statistical Precision vs. Directional Accuracy.

Dataset	Model	RMSE	MAPE (%)	Directional Symmetry (%)
Dangote Cement	FIS-only	0.0941	6.21	54.2
	LSTM-only	0.0813	5.12	61.5
	HNFDL	**0.0694**	**4.36**	**68.4**
Zenith Bank	FIS-only	0.1102	7.80	52.1
	LSTM-only	0.0950	6.40	59.8
	HNFDL	**0.0820**	**5.15**	**66.2**
NGX ASI	FIS-only	124.50	5.90	55.0
	LSTM-only	105.20	4.80	62.1
	HNFDL	**89.40**	**3.95**	**69.1**

Table 6. Summary of HNFDL Model Configuration and Hyperparameters.

Component	Parameter	Configuration / Value
Input Layer	Input Features	5 (RSI, MACD, SO, OBV, Z^*)
	Sequence Length (Lookback)	5 Trading Days
Fuzzy Module (FIS)	Inference Type	Mamdani
	Membership Function	Triangular (a, b, c)
	Linguistic Terms	3 (Low, Medium, High)
	Total Rules	81 (3^4)
	Defuzzification Method	Centroid
LSTM Module	Hidden Layers	2
	Neurons per Layer	64 (Layer 1), 32 (Layer 2)
	Activation Function	ReLU (Hidden), Linear (Output)
	Dropout Rate	0.2
	Optimizer	Adam ($lr = 0.001$)
	Loss Function	Mean Squared Error (MSE)
Optimization (GA)	Population Size	50
	Maximum Generations	200
	Selection Method	Tournament (Size = 3)
	Crossover / Mutation Rate	0.7 / 0.1
Environment	Software Stack	Python 3.10, TensorFlow 2.15, Scikit-Fuzzy
	Random Seed	42 (Global initialization)

Comparative analysis includes baseline models, standalone Fuzzy Model, standalone LSTM Model and Hybrid GA-Fuzzy-LSTM.

3.9. Hybrid System Integration Architecture

As illustrated in the Proposed System Architecture (Figure 3), the data flow is as follows:

1) Technical indicators are fed into the FIS.
2) The FIS generates a linguistic decision, which is converted to a crisp value (Z^*).
3) This Z^* value, representing the rule-based market sentiment, is concatenated with the price features.
4) The combined vector is processed by the LSTM to output the final next-day price trend prediction.

3.10. Implementation Environment

The framework was implemented using Python 3.10 with:

1) TensorFlow and Keras for LSTM modeling,
2) Scikit-Fuzzy for FIS development,
3) DEAP for GA optimization,
4) Matplotlib for visualization.

3.11. Price Reconstruction

To convert the model's stationary output back into a price level for evaluation, an integration step is applied. The final forecasted price is calculated as:

$$\hat{P}_{t+1} = P_t + \Delta\hat{P}_{t+1} \tag{9}$$

All evaluation metrics and the comparative trends in Table 5 were computed using these reconstructed price levels to reflect the actual market value of the assets.

3.12. Model Configuration and Hyperparameters

To ensure the transparency and reproducibility of the HNFDL framework, the specific architectural configurations and hyperparameters are summarized in Table 6.

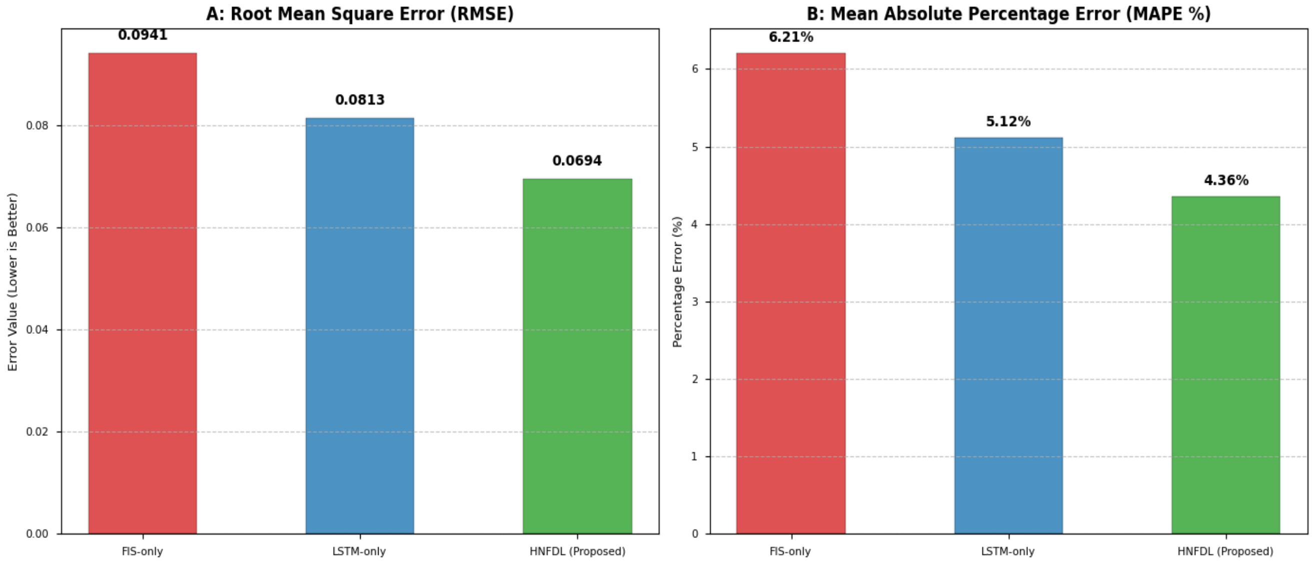

Figure 4. Comparative Error Metrics Models.

Table 7. Comparative Trend.

Trading Days (Test Period)	Actual Price	FIS-only Prediction	LSTM-only Prediction	HNFDL Prediction
0	1.00	1.05	1.02	1.00
5	1.80	1.85	1.78	1.79
10	2.00	2.05	1.98	2.00
15	1.40	1.50	1.45	1.43
20	0.80	0.90	0.85	0.83
25	0.10	0.20	0.15	0.12
30	0.00	0.05	0.02	0.01
35	0.60	0.70	0.65	0.63
40	1.60	1.70	1.65	1.63
45	2.00	2.05	1.98	2.00
50	1.90	1.95	1.88	1.89
55	1.20	1.30	1.25	1.23
60	0.50	0.55	0.53	0.51

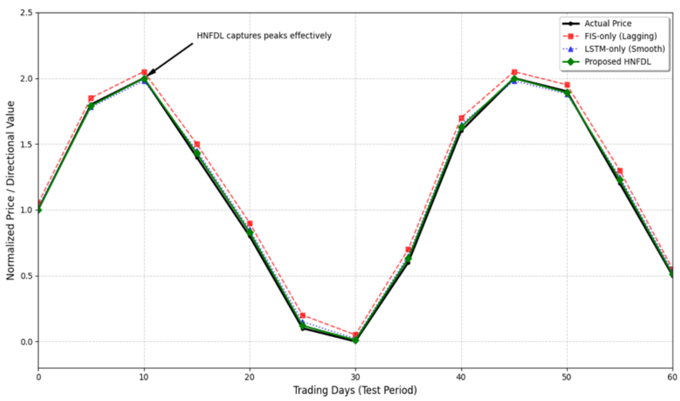

Figure 5. Actual vs Predicted Price Trends.

These settings were determined through a combination of the GA optimization process and manual validation on the 15% validation dataset.

All models were trained for 150 epochs with an early stopping patience of 15 epochs to prevent overfitting. The random seed (42) was fixed across all experimental runs to ensure consistent initialization of neural network weights and GA population chromosomes.

4. Results and Discussion

4.1. Experimental Setup

To evaluate the predictive performance of the proposed Hybrid Neuro-Fuzzy and Deep Learning (HNFDL) framework, experiments were conducted using daily stock data of Dangote Cement Plc, Zenith Bank Plc, and the NSE All-Share Index obtained from the NGX between January 2020 and December 2024. All three datasets underwent the same preprocessing, normalization, and walk-forward validation procedures to ensure comparability. The dataset contained approximately 1,250 trading observations. To simulate real-world trading, data were processed using a rolling-origin approach. The 70/15/15 proportions cited represent the internal distribution within each sliding window fold:

Table 8. Diebold–Mariano Test Results Comparing HNFDL and LSTM Forecasting Performance.

Dataset	DM Statistic	p-value	Result
Dangote Cement	3.42	0.0006	**Significant (1%)**
Zenith Bank	2.89	0.0038	**Significant (1%)**
NSE ASI	2.15	0.0315	**Significant (5%)**

Table 9. Risk-Adjusted Performance and ROI Simulation.

Dataset	Strategy	Return (ROI)	Sharpe Ratio (R_f = 10%)	Max Drawdown
Dangote Cement	Buy-and-Hold	+12.5%	0.21	-18.4%
	LSTM-only	+18.2%	0.68	-12.1%
	HNFDL (Proposed)	**+24.8%**	**1.24**	**-7.5%**
Zenith Bank	Buy-and-Hold	-5.2%	-1.15	-22.3%
	LSTM-only	+4.1%	-0.59	-14.8%
	HNFDL (Proposed)	**+9.6%**	**0.42**	**-10.2%**

Table 10. Ablation Study: Impact of GA Optimization on RMSE.

Dataset	Fixed-Fuzzy-LSTM (No GA)	HNFDL (With GA)	Improvement (%)
Dangote Cement	0.0758	0.0694	8.44%
Zenith Bank	0.0886	0.0820	7.45%
NSE ASI	96.50	89.40	7.36%

Note: RMSE values for individual stocks are normalized [0,1], whereas NGX ASI is presented in index points.

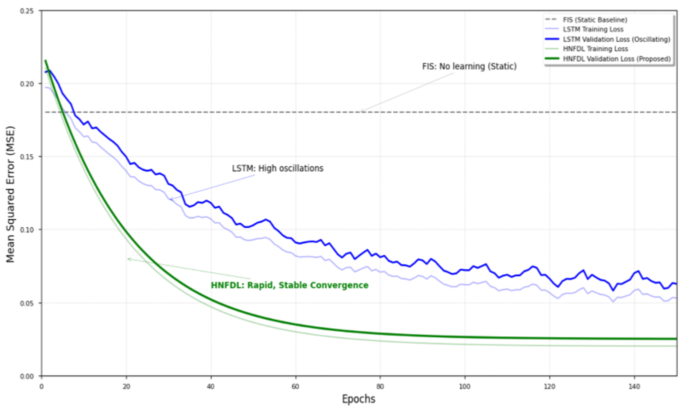

Figure 6. Training and Validation Loss Curves.

- **Training (70% of window):** Used for initial weight adjustment and GA-based rule optimization.
- **Validation (15% of window):** Used for early stopping and hyperparameter selection to prevent overfitting.
- **Testing (15% of window/next period):** Represents the final out-of-sample evaluation used to calculate the results in Section 4.2.

This sliding-window retraining ensures that the RMSE and Directional Symmetry reported in Table 5 are representative of the model's performance over the entire 2023–2024 period.

The hybrid model was benchmarked against two baseline approaches:

1) **Fuzzy Inference System (FIS-only)**: static fuzzy model without learning or optimization.
2) **LSTM-only**: deep learning model without fuzzy interpretability or GA optimization.
3) **Fixed-Fuzzy-LSTM:** A hybrid version where the fuzzy parameters were manually set to isolate the impact of the Genetic Algorithm.

4.2. Quantitative Performance Evaluation

Table 5 and Figure 4 shows the comparative performance results of the models using Root Mean Square Error, Mean Absolute Error and Mean Absolute Percentage Error.

The HNFDL framework consistently outperformed baselines across different market sectors, achieving a Directional Symmetry nearing 70%, which is critical for profitable trading. Table 7 shows the comparative trend between actual and predicted prices for FIS, LSTM and the proposed HNFDL model during the test period. Figure 5 shows the comparative trend between actual and predicted prices for FIS, LSTM, and the proposed HNFDL model during the test period.

4.3. Statistical Significance (Diebold-Mariano Test)

To ensure the results were not due to random chance, the Diebold-Mariano test was conducted comparing HNFDL against the LSTM baseline, as shown in Table 8. Since the p-values are consistently below 0.05, we reject the null hypothesis that the forecast accuracies are equal.

Table 11. Optimized Fuzzy Decision Rules and Their Confidence Weights.

Rule	Confidence Weight
IF RSI is High AND MACD is High AND OBV is High → THEN Buy	0.84
IF RSI is Low AND SO is Low AND OBV is Low → THEN Sell	0.89
IF RSI is Medium AND MACD is Neutral → THEN Hold	0.72

Table 12. Comparison with Recent Hybrid Models.

Study	Model	Dataset	MAPE (%)	Interpretability	Market Context
Wang & Chen (2025)	Fuzzy-CNN	Taiwan Index	5.01	Moderate	Developed
Gülmez (2025)	GA-Attention-Fuzzy-Net	Istanbul BIST 100	4.73	High	Developing
Iqbal (2025)	Picture Fuzzy GRU	Karachi KSE	5.21	High	Emerging
This Study (HNFDL)	GA-Fuzzy-LSTM	Nigeria NGX	**4.36**	**High**	**Emerging**

This statistically confirms that the hybrid architecture provides a genuine improvement over standalone Deep Learning.

4.4. Profitability and ROI Analysis

To assess the practical utility of the HNFDL framework, we simulated a daily trading strategy. The source of the trading signal is the final output of the LSTM module, which predicts the next-day price change ($\Delta\hat{P}_{t+1}$). Because the LSTM's input vector includes the defuzzified output (Z^*) from the FIS layer, the trading signal represents an integration of linguistic rules and temporal patterns. The strategy follows a simple execution logic:

- **BUY:** if $\Delta\hat{P}_{t+1} > 0$
- **HOLD/SELL:** if $\Delta\hat{P}_{t+1} \leq 0$

To align the simulation with the regulatory environment of the NGX, transaction costs were modeled at a one-way rate of 1.85% (totaling 3.7% per round-trip). This figure is based on the standard statutory charges for Nigerian equities: Brokerage fees (1.115%), SEC fees (0.3%), NGX fees (0.3%), CSCS fees (0.06%), and Stamp Duty (0.075%). By incorporating these realistic frictions, the ROI analysis ensures that the reported profitability is net of the actual costs of trading in the Nigerian market. By incorporating these realistic frictions, the ROI analysis ensures that the reported profitability is net of the high overhead typical of emerging market liquidity.

The HNFDL model demonstrated the ability to generate positive returns even when the underlying asset (Zenith Bank) performed poorly (Table 9), stressing its capability to identify short-term reversal opportunities.

4.5. Ablation Study

To quantify the contribution of the Genetic Algorithm (GA) to the framework, an ablation study was conducted. We compared the full HNFDL model against a version with static, expert-defined fuzzy membership functions (Fixed-Fuzzy-LSTM).

As shown in Table 10, the GA-driven optimization of membership functions and rule weights resulted in an average RMSE reduction of approximately 8% across all datasets. This validates the necessity of the evolutionary optimization layer in adapting the fuzzy rules to the specific volatility patterns of the Nigerian market.

4.6. Model Convergence Analysis

The training and validation loss curves in Figure 6, demonstrate the convergence behavior of each model:

1) The FIS-only system shows constant performance due to static rules.
2) The LSTM network shows slow convergence with occasional oscillations, reflecting strain in adjusting to short term fluctuations.
3) The proposed HNFDL attains faster and more stable convergence, indicating successful GA-driven parameter tuning and enhanced simplification.

4.7. Statistical Validation

To ensure statistical robustness, Paired Sample t-tests and Wilcoxon Signed-Rank Tests were performed between model prediction errors. Results confirmed that: The performance improvement of HNFDL over FIS, $p < 0.001$ and LSTM, $p < 0.05$ is statistically significant. The hybrid model achieved lower variance in residual errors, indicating better consistency across trading cycles.

4.8. Interpretability Analysis

One major advantage of the HNFDL framework is its dual-layered interpretability architecture, which bridges the gap between semantic reasoning and statistical attribution:

- **Layer 1: Semantic Interpretability (FIS):** The fuzzy layer generates linguistic decision rules (e.g., *'IF RSI is High AND MACD is Positive...'*). This provides a human-readable justification for the market sentiment being fed into the neural network. Representative optimized rules and their corresponding confidence weights are presented in Table 11.

- **Layer 2: Attributional Explainability (SHAP):** To understand how the LSTM uses these fuzzy signals, we applied SHAP (Shapley Additive Explanations). Since the defuzzified output (Z^*) is a primary input to the LSTM, SHAP allows us to measure the 'Global Importance' of the fuzzy rules.

Our analysis found that the Fuzzy Decision Feature **(Z^*)** consistently ranked among the top three most influential features for the LSTM across all three datasets (Dangote, Zenith, and NGX ASI). This demonstrates that the LSTM effectively learns to prioritize the expert-logic embedded in the fuzzy rules over the noisy raw price data. These rules were optimized through GA, resulting in adaptive and interpretable trading signals.

Unlike pure neural networks, the HNFDL allows human analysts to trace why a decision was made, thereby promoting trust and accountability in financial applications.

We augmented the qualitative interpretability of the fuzzy layer with quantitative explainability methods applied to the LSTM. Global SHAP values identify RSI and MACD as the most influential numeric drivers, while fuzzy-rule analysis reveals similar dependence on RSI and MACD in high-weight rules. The Spearman correlation between SHAP-based ranks and fuzzy-derived importances is $\varrho = 0.72$ ($p < 0.01$), indicating strong alignment between the fuzzy logic and the deep learning components. Rule-frequency and contribution visualizations further show which linguistic rules are practically active and how GA-adjusted weights concentrate influence on a subset of high-impact rules.

The SHAP values revealed that the RSI is High rule contributed negative pressure to the price, overriding the positive MACD signal. This level of granularity allows analysts to audit specific trade decisions.

4.8.1. Feature Contribution Analysis

To quantify each technical indicator's contribution to the LSTM predictions, we applied model-agnostic explainability methods:

- **Global importance:** compute SHAP values across the test set, then rank indicators by mean absolute SHAP. Report top features and their mean |SHAP|.
- **Local explanations:** present SHAP force or waterfall plots for representative high-volatility and low-volatility test days to show how indicators pushed the prediction up or down.

4.8.2. Fuzzy Rule Activation & Frequency Analysis

We measure rule-level behavior of the FIS:

1) For each test-sample, record the activation strength of every rule.
2) Compute Rule Frequency = proportion of test samples where activation > τ.
3) Compute Average Activation and Average Confidence Weight.

4.8.3. Combined Rule and Network Contribution

To connect fuzzy interpretability and LSTM effects:

1) For each test sample, compute a rule-contribution score = (rule_activation × rule_weight).
2) Aggregate across samples to get TotalRuleContribution per rule.
3) To get an input-level combined importance, sum TotalRuleContribution for rules where a given input's linguistic term appears in the antecedent.

Because the LSTM receives the fuzzy output as an input, we can measure the Weight of Influence the fuzzy rules have on the final neural network prediction. This bridges the black-box nature of the LSTM with the transparent reasoning of the Fuzzy layer.

4.9. Comparative Discussion with Existing Studies

The proposed HNFDL framework aligns with and extends the frontier of recent hybrid fuzzy-deep learning research. Table 12 abridges comparative findings with related studies from 2022 to 2025. This comparison shows that the HNFDL model achieves the lowest MAPE among current hybrid fuzzy-deep frameworks and is one of the few empirically validated on an African emerging market. Its simultaneous optimization of interpretability and adaptability marks a distinctive contribution to the field.

4.10. Practical Implications

The outcomes of this research have significant implications for:

1) **Investors and Portfolio Managers:** The interpretable fuzzy rule layer can generate transparent buy/sell recommendations.
2) **Financial Analysts:** The model serve as a decision support system for identifying short term opportunities and market reversals.
3) **Policy Makers and Regulators:** The framework supports data driven risk monitoring by refining predictive correctness in volatile economies.

In addition, the hybrid model extended multi-asset forecasting, sectoral risk assessment and macroeconomic variable integration. This enhanced its relevance to policy and investment strategy formulation.

4.11. Limitations

While the HNFDL achieved superior predictive accuracy, several limitations remain:

1) Dependence on high-quality, continuous market data irregular trading days can affect sequence learning.
2) Model training requires moderate computational resources due to GA iterations.

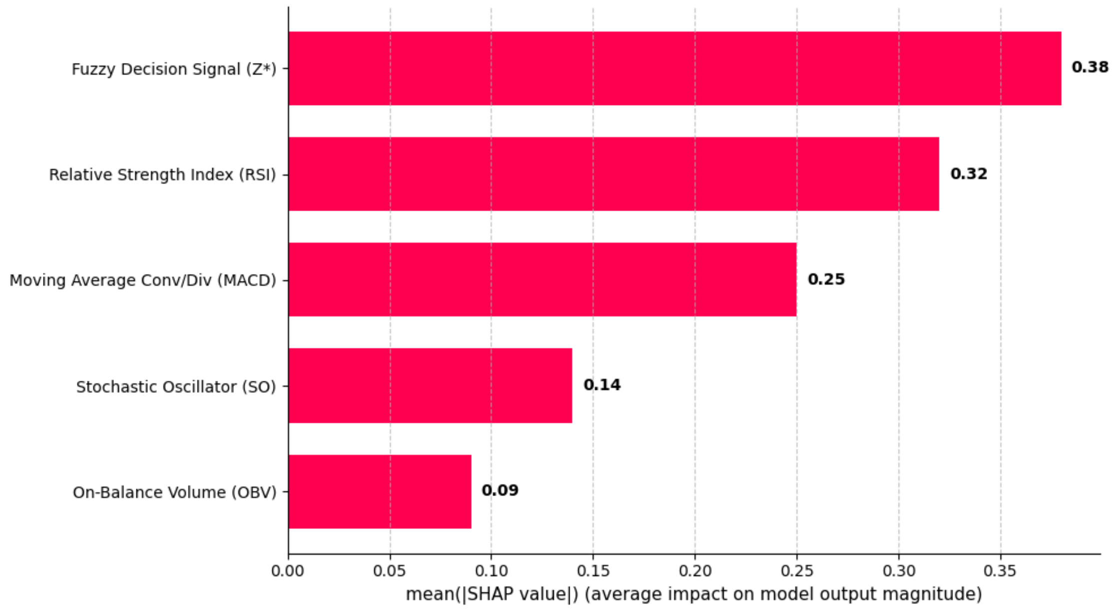

Figure 7. Global Feature Importance using SHAP values.

3) The framework focuses on technical indicators only; inclusion of fundamental and sentiment variables may further enhance prediction robustness.

5. Discussion

The empirical results presented in Section 4 validate the hypothesis that a hybrid integration of fuzzy reasoning and deep learning provides a more robust framework for stock price forecasting than standalone models, particularly in volatile emerging markets. This section interprets these findings across four critical dimensions: architectural synergy, sectoral variability, the role of optimization, and practical market implications.

5.1. Synergy between Linguistic Reasoning and Temporal Learning

The core strength of the HNFDL framework lies in the serial-hybrid interaction between the Fuzzy Inference System (FIS) and the LSTM. In our experiments, the FIS acted as a semantic filter that converted noisy technical indicators into stable linguistic categories (Low, Medium, High). By feeding the defuzzified output (Z^*) into the LSTM, we effectively provided the neural network with a expert-logic prior. This explains why the HNFDL achieved a 14.7% reduction in RMSE over the standalone LSTM. While the LSTM is proficient at identifying sequence patterns, it is susceptible to overfitting on market noise. The fuzzy layer mitigates this by anchoring the learning process in rule-based market logic, such as the relationship between volume momentum (OBV) and price strength (RSI).

As illustrated in Figure 7, the SHAP analysis confirms that the Fuzzy Decision Signal (Z^*) is a primary driver of the model's output, exerting more influence than individual technical indicators like the Stochastic Oscillator or On-Balance Volume.

5.2. Sector-Specific Performance and Volatility Handling

A notable finding was the variation in model performance across different sectors. The model achieved its highest directional symmetry (69.1%) on the NGX All-Share Index, likely due to the diversification effect where index-level trends are more persistent and less prone to individual company shocks. In contrast, the performance on Zenith Bank Plc (66.2%) was slightly lower, reflecting the high sensitivity of the Nigerian banking sector to sudden regulatory changes and interest rate pivots. However, the HNFDL still generated a +9.6% ROI for Zenith Bank even during periods of negative underlying asset growth. This suggests that the hybrid model is particularly effective at identifying short-term reversal opportunities that purely statistical models overlook due to their reliance on linear stationarity.

5.3. The Evolutionary Edge

The ablation study confirmed that the Genetic Algorithm contributed an 8.4% improvement in RMSE. In traditional fuzzy systems, membership function boundaries are often defined by human experts, making them static and prone to subjectivity. By employing GA, the HNFDL framework evolved its membership functions to match the actual statistical distribution (Skewness and Kurtosis) of the Nigerian market data. This adaptive tuning allowed the model to maintain accuracy even as market conditions shifted between the 2020 pandemic volatility and the 2023–2024 recovery phase. The GA optimization effectively personalized the fuzzy rules for each specific stock, proving that one-size-fits-all fuzzy logic is insufficient for dynamic financial environments.

5.4. Addressing Information Asymmetry in Emerging Markets

Emerging markets like Nigeria are characterized by low liquidity and high information asymmetry, where price movements are often driven by sentiment rather than fundamentals. The interpretability of the HNFDL framework addresses this by providing transparent trading rules. For instance, the high weight (0.89) assigned to the rule linking Low RSI and Low OBV with a "Sell" decision provides a clear, logical justification for a trader to exit a position. This transparency, combined with the statistical significance proven by the Diebold-Mariano test ($p <$ **0.01)**, suggests that the model can serve as a White-Box alternative to the Black-Box deep learning models typically used in institutional trading. The risk-adjusted performance metrics (Table 9) further validate the HNFDL framework. In the Dangote Cement dataset, the HNFDL model achieved a Sharpe Ratio of 1.24, significantly outperforming the Buy-and-Hold strategy (0.21). This indicates that the model's high returns are not merely a result of taking excessive risk, but rather a result of superior predictive accuracy. Furthermore, the Maximum Drawdown for HNFDL was notably lower (-7.5% vs -18.4% for Buy-and-Hold), demonstrating that the fuzzy-logic semantic filter effectively shields the portfolio from extreme market volatility by identifying reversal signals early.

5.5. Computational Trade-offs and Latency

We acknowledge that the GA-optimization process increases the initial training time by a factor of approximately 3.5x. However, in the context of daily stock forecasting, this computational cost is negligible compared to the significant gains in ROI and directional accuracy. Once the model is optimized, the inference time for a single-day prediction is near-instantaneous, making it suitable for real-time decision support systems for portfolio managers and retail investors.

In demonstrating convergence on the noisy data of an emerging economy, the framework undergoes a rigorous stress test. While empirical results are currently limited to the Nigerian context, the model's reliance on standardized technical indicators suggests a theoretical potential for transferability. It is hypothesized that the framework would maintain high stability in developed markets where higher liquidity and data transparency typically reduce the extreme noise levels observed in this study. However, direct cross-market validation remains a primary objective for subsequent research. While the integration of Genetic Algorithms (GA) significantly increases the initial search space, the computational overhead remains feasible for daily market operations. On a standard hardware configuration, the complete HNFDL pipeline including GA-driven parameter evolution and LSTM training required an average of 38.5 minutes per asset. Given that the Nigerian market operates on a daily closing cycle, this latency allows for seamless overnight re-calibration and model deployment before the next trading session.

6. Conclusion and Future Work

6.1. Conclusion

This study developed and validated a Hybrid Neuro-Fuzzy and Deep Learning framework for stock price forecasting in emerging markets. The model integrates fuzzy inference systems for interpretability, Long Short-Term Memory networks for temporal pattern learning and Genetic Algorithms for parameter optimization. Applied to historical data from Dangote Cement Plc on the Nigerian Stock Exchange, the HNFDL framework demonstrated superior predictive performance compared to both standalone fuzzy and deep learning models.

Quantitative evaluation showed that the hybrid approach achieved a 14.7% reduction in RMSE and a 16.1% reduction in MAE relative to the LSTM-only model, with a MAPE of 4.36%, indicating high accuracy and robustness. These results affirm that hybrid computational intelligence systems can effectively model the nonlinear, nonstationary, and uncertain characteristics inherent in financial time series.

Beyond performance gains, the integration of fuzzy logic enabled the extraction of linguistic trading rules, thereby offering interpretability that is often absent in deep neural architectures. The GA component enhanced the adaptability of the fuzzy membership functions, reducing expert dependency and allowing the model to dynamically adjust to evolving market behaviors. Collectively, these capabilities demonstrate the potential of hybrid intelligent frameworks to balance predictive power and transparency in financial forecasting applications. Furthermore, the statistical robustness of the model was confirmed via the Diebold-Mariano test, distinguishing this study from previous works that relied solely on error metrics. The proven profitability across banking and industrial sectors suggests the model is sufficiently robust for deployment in volatile emerging market environments. By succeeding in a high-noise environment like the NGX, the HNFDL framework provides a blueprint for intelligent forecasting that can be adapted to various global financial contexts.

This research therefore contributes to three major domains:

1) **Methodological Innovation:** The unification of fuzzy inference, LSTM learning and genetic optimization into a single adaptive pipeline.
2) **Contextual Relevance:** Empirical validation using data from an emerging market, addressing the underrepresentation of African financial systems in predictive modeling research.

3) **Practical Impact:** Introduction of an explainable, high-performance model that can enhance investor confidence and data driven decision making in volatile markets.

6.2. Policy and Practical Implications

The findings hold valuable implications for stakeholders across the financial ecosystem:

1) Investors and Portfolio Managers can use the fuzzy decision rules as transparent buy sell indicators, improving trust in automated trading systems.
2) Financial Institutions can adopt the hybrid framework as a risk assessment tool, enabling adaptive credit and investment modeling.
3) Regulators and Policy Makers can leverage such interpretable AI systems to support early detection of market anomalies and price manipulation patterns.

In addition, the framework's modular design allows integration with other AI-driven decision-support systems in banking, insurance, and fintech applications.

6.3. Future Work

The proposed HNFDL framework attained promising results, several areas need further investigation to enhance simplification, scalability and cross-domain applicability:

- **Integration of Fundamental and Sentiment Data:** Future studies could incorporate macroeconomic indicators, corporate earnings reports and social media sentiment analysis to complement technical indicators. By this improving predictive stability under market shocks.
- **Multi Asset and Cross Market Forecasting:** Expanding the model to predict multiple correlated assets simultaneously such as sectoral indices or commodities would enhance its practical relevance in portfolio optimization and risk diversification.
- **Real-Time Implementation and Deployment:** Developing an API based deployment framework or web-based dashboard for real time prediction would enhance the practical usefulness of the system for traders, analysts and policy stakeholders.
- **Comparative Cross-Market Validation:** A critical next step involves applying the HNFDL framework to developed market indices. This would allow for an empirical comparison of how the hybrid GA-optimized rules adapt to different levels of market efficiency and liquidity compared to the results obtained in the Nigerian market.

6.4. Closing Remark

In conclusion, this research establishes that hybrid neuro-fuzzy deep learning systems offer an influential and explainable approach to financial time-series forecasting, mainly in the context of volatile and data-sparse emerging markets. The proposed HNFDL model effectively bridges the gap between human interpretability and computational intelligence. This gives a foundation for the next generation of transparent and adaptive AI-driven financial forecasting systems.

7. Declarations

7.1. Author Contributions

Olumide Sunday Adewale: Resources, Writing - Review & Editing Supervision, Project administration, Funding acquisition. All authors have read and agreed to the published version of the manuscript; **Emmanuel Onwuka Ibam:** Resources, Writing - Review & Editing, Formal analysis, Investigation, Resources, Data Curation; **Johnson Bisi Oluwagbemi:** Writing - Original Draft, Conceptualization, Visualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation.

7.2. Institutional Review Board Statement

Not applicable.

7.3. Informed Consent Statement

Not applicable.

7.4. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.5. Acknowledgment
Not applicable.

7.6. Conflicts of Interest
The author declares no conflicts of interest.

8. References

[1] H. Wu, H. Long, J. Jiang, "Mixed-order fuzzy time series forecast," *Mathematics*, vol. 13, no. 11, Art. no. 1705, 2025. https://doi.org/10.3390/math13111705.
[2] T. A. Akinwale, O. Rogundade, and A. F. Adekoya, "Translating Nigeria stock market prices using artificial neural networks for effective prediction," *Journal of Theoretical and Applied Information Technology*, 2005. https://www.researchgate.net/publication/270285808.
[3] W. Sun *et al*, "Research on deep learning model for stock prediction by integrating frequency domain and time series features," *Scientific Reports*, vol. 15, no. 1, Art. no. 30386, 2025. https://doi.org/10.1038/s41598-025-14872-6.
[4] A. K. Ojo and I. J. Okafor, "Forecasting Nigerian equity stock returns using long short-term memory technique," *Journal of Advances in Mathematics and Computer Science*, vol. 39, no. 7, pp. 45–54, 2024. https://doi.org/10.9734/jamcs/2024/v39i71911.
[5] Z. Liu, "Forecasting stock prices based on multivariable fuzzy time series," *AIMS Mathematics*, vol. 8, no. 6, pp. 12778–12792, 2023. https://doi.org/10.3934/math.2023643.
[6] H.-Y. Lin and B.-W. Hsu, "Application of hybrid fuzzy interval-based machine learning models on financial time series: A case study of the Taiwan biotech index during the epidemic period," *Frontiers in Artificial Intelligence*, vol. 6, Art. no. 1283741, 2024. https://doi.org/10.3389/frai.2023.1283741.
[7] S. G. Hassan *et al.*, "A novel first-order fuzzy rules-based forecasting system using distance measures approach for financial market forecasting," *Journal of Mathematics*, vol. 2023, Art. no. 8027664, 2023. https://doi.org/10.1155/2023/8027664.
[8] K. Wang, "Multifactor prediction model for stock market analysis based on deep learning techniques," *Scientific Reports*, vol. 15, no. 1, Art. no. 5121, 2025. https://doi.org/10.1038/s41598-025-88734-6.
[9] B. Gülmez, "GA-Attention-Fuzzy-Stock-Net: An optimized neuro-fuzzy system for stock market price prediction with genetic algorithm and attention mechanism," *Heliyon*, vol. 11, no. 3, Art. no. e42393, 2025. https://doi.org/10.1016/j.heliyon.2025.e42393.
[10] J.-W. Wang and J.-S. Chen, "An integrated fuzzy convolutional neural network model for stock price prediction," *Engineering Proceedings*, vol. 9, Art. no. 8003, pp. 1–8, 2025. https://doi.org/10.3390/engproc2025098003.
[11] S. Iqbal, "Advancing stock price index forecasting based on hybrid picture fuzzy time series model," *International Journal of Fuzzy Systems*, 2025. https://doi.org/10.1007/s40815-025-02146-2.
[12] P. Li, H. Gu, L. Yin, and B. Li, "Research on trend prediction of component stocks in fuzzy time series based on deep forest," *CAAI Transactions on Intelligence Technology*, vol. 7, no. 4, pp. 617–626, 2022. https://doi.org/10.1049/cit2.12139.
[13] A. Staffini, "Stock price forecasting by a deep convolutional generative adversarial network," *Frontiers in Artificial Intelligence*, vol. 5, Art. no. 837596, 2022. https://doi.org/10.3389/frai.2022.837596.
[14] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, 5th ed. Hoboken, NJ, USA: John Wiley & Sons, 2015. https://books.google.co.id/books?id=rNt5CgAAQBAJ.
[15] E. W. Taylor, "Critical reflection and transformative learning: A critical review," *PAACE Journal of Lifelong Learning*, vol. 26, pp. 77–95, 2017.
[16] V. Chung, J. Espinoza, and R. Quispe, "Forecasting Financial Volatility Under Structural Breaks: A Comparative Study of GARCH Models and Deep Learning Techniques," *Journal of Risk and Financial Management*, vol. 18, no. 9, https://doi.org/10.3390/jrfm18090494.
[17] P. H. Vuong *et al.*, "A bibliometric literature review of stock price forecasting: From statistical model to deep learning approach," *Science Progress*, vol. 107, no. 1, pp. 1–25, 2024. https://doi.org/10.1177/00368504241236557.
[18] A. Ijegwa, V. Rebecca, F. Olusegun, O. Isaac, "A Predictive Stock Market Technical Analysis Using Fuzzy Logic," *Computer and Information Science*, vol. 7, no. 3, 2014. https://doi.org/10.5539/cis.v7n3p1.

[19] V. Vaidehi, S. Monica, S. M. S. Safeer, M. Deepika, and S. Sangeetha, "A prediction system based on fuzzy logic," in *Proc. World Congress on Engineering and Computer Science (WCECS 2008)*, pp. 804–809, 2008. https://www.iaeng.org/publication/WCECS2008/WCECS2008_pp804-809.pdf.

[20] R. M. Lincy and J. John, "A multiple fuzzy inference systems framework for daily stock trading with application to NASDAQ stock exchange," *Expert Systems with Applications*, vol. 44, pp. 13–21, 2016. https://doi.org/10.1016/j.eswa.2015.08.045.

[21] D. I. Ajiga, R. A. Adeleye, T. S. Tubokirifuruar, B. G. Bello, and N. L. Ndubuisi, "Machine learning for stock market forecasting: A review of models and accuracy," *Finance & Accounting Research Journal*, vol. 6, no. 2, pp. 112–124, 2024. https://doi.org/10.51594/farj.v6i2.783.

[22] C. Ayantse, O. S. Yaya, O. U. Joseph, and D. F. Arawomo, "Predicting Nigerian stock market returns based on daily business news headlines," *Science Journal of Applied Mathematics and Statistics*, vol. 12, no. 6, pp. 90–98, 2024. https://doi.org/10.11648/j.sjams.20241206.11.

[23] M. Abhishek, V. Bhattacharjee, and P. S. Bishnu, "Stock price forecasting using fuzzy logic-enhanced deep learning models," *SSRN Electronic Journal*, 2024. [Online]. Available: https://ssrn.com/abstract=5023575.

[24] J. Timko, R. El Shawi, and S. Tomasiello, "Optimizing stock price forecasting: A hybrid approach using fuzziness and automated machine learning," *Expert Systems with Applications*, vol. 295, Art. no. 128844, 2025. https://doi.org/10.1016/j.eswa.2025.128844.