A Hybrid Expert System for Forecasting Stock Market Volatility with GARCH, Markov Switching, and Deep Convolutional Neural Networks

Peace Ifeoluwa, Ikuforiji
Department of Mathematics,
Kebbi State University of Science and Technology, Aliero, Nigeria

Tolu. O. James
Department of Mathematics,
Kebbi State University of Science and Technology, Aliero, Nigeria.

Wasiu. A. Babayemi
Department of Mathematics,
Kebbi State University of Science and Technology, Aliero, Nigeria.

Yabani Gelwasa Galadima
Department of Elect/Elect Engineering
Kebbi State University of Science and Technology, Aliero, Nigeria.

Sani. F. Abubakar
Department of Mathematics,
Kebbi State University of Science and Technology,Aliero, Nigeri

Abstract
In emerging economies such as Nigeria, predicting stock market volatility is vital for making sound investment and policy decisions. Sudden price swings and shifting market conditions make this task especially challenging. Although established econometric models like ARCH and GARCH are widely used, they often fall short when it comes to capturing nonlinear behaviors and abrupt changes in volatility regimes. To address this gap, we present a hybrid expert system that integrates GARCH-type models, Markov Regime Switching, and Deep Convolutional Neural Networks (CNNs). In our approach, daily stock returns from the Nigerian Stock Exchange between 2012 and 2023 are transformed into Gramian Angular Field (GAF) images, enabling the CNN to detect complex temporal spatial structures. The models are evaluated using RMSE and MAE, and their performance is compared to that of Individual methods. The hybrid system consistently produces more accurate and resilient forecasts, particularly during regime shifts. These findings highlight its value as a decision-support tool for investors, policymakers, and portfolio managers. We recommend the adoption of similar integrated approaches for analyzing volatile markets, particularly in environments with limited or unstable data.

Keywords: Expert System, Stock Market Volatility, Convolutional Neural Networks (CNN), Markov Regime Switching, Financial Forecasting

Introduction

For efficient risk administration, possession cost, and formulating policies, especially in developing nations like Nigeria, it is essential to forecast stock market fluctuation. For many years, the ARCH and GARCH relatives of conventional fluctuation prototypes have been the cornerstones of fiscal time series modeling (Engle, 1982; Bollerslev, 1986). Nevertheless, irregular trends and system alterations found in explosive markets in terms of structure-changing markets are frequently not adequately captured by these models. A portion of this restriction has been overcome by incorporating Markov regime-switching prototypes into fluctuation predicting, which enables prototypes to alternate between minimal and maximal fluctuation systems (Hamilton, 1989). However, even these advancements fall short of accounting for the intricate, irregular dependents present in economic data, especially in situations of elevated regularity and arising markets. New developments in machine studying, especially profound knowledge, present encouraging substitutes. When time series facts are inscribed into configurations that resemble pictures, Convolutional Neural Networks (CNNs), which were initially created for computer perception exercises, have shown significant achievement in monetary time series predicting because of their ability to recognize trends and characteristics of hierarchies (Sezer et al., 2020). Although they take into account impacts of leverage and inequalities, extensions such as EGARCH and TGARCH are still limited by line-based econometric prototypes like GARCH and ARCH continue to be fundamental in benchmarking and estimating fluctuation. Convolutional Neural Networks (CNNs), a type of profound knowledge, have attracted interest in fiscal predicting because of their ability to determine the hierarchical attributes and prototypes' nonlinear dependencies (Sezer et al., 2020).CNNs are particularly good at converting time series facts into configurations that are similar to pictures, which allows them to identify temporal-spatial dependencies that traditional prototypes are unable to.

Convolutional neural networks (CNNs), one type of profound knowledge prototype, have shown great promise in capturing intricate, nonlinear dynamics in monetary time series, particularly for tasks involving fluctuation prediction (Chen et al., 2021; Huang and Li, 2023). Additionally, combining profound knowledge architectures with monetary time series has produced encouraging results in exercises that require prediction (Lee and Chang, 2020). It has been demonstrated that mixed prototypes that combine profound knowledge and econometric techniques can improve forecasting precision.

For example, Guo et al. (2022) showed that mixed ARIMA–LSTM structures, which provide both linear interpretable and nonlinear knowledge capacity, routinely provide good fluctuating forecast results than standalone prototypes like ARIMA and GARCH. Similar to this, recent studies have shown that collective prototypes that use CNNs, particularly when paired with LSTM or GRU layers, generally perform better than individual prototypes in terms of precision and resilience (Huang et al., 2023). To improve predicting precision, collective and mixed structures that combine machine learning and conventional statistical prototypes are being used more and more (Xu et al., 2022; Rahman and Kim, 2023).

In this study, a collective fluctuation predicting structure that combines CNNs, Markov System Altering, and GARCH is developed and applied specifically to the Nigerian Inventory Trade, building on previous research in this area. The purpose of the study is to assess how well a mixed prototype that combines CNN-based profound knowledge strategies, Markov regime-switching, and GARCH prediction works. We use this prototype to analyze everyday information from the Nigerian Inventory Trade (2012–2023), a market with higher fluctuation, liquidity issues, and data asymmetries. Our main participation is the collective structure we propose, which provides a more comprehensive tool for fluctuation forecast by capturing both linear and nonlinear dynamics.

2. Methodology

A thorough explanation of the methodological techniques used in inventory market fluctuation modelling and predicting is given in this segment. Three different prototypes are used: GARCH, Convolutional Neural Networks (CNN), and Markov Regime Switching ARCH (MS-ARCH), which we then combine into a collective structure to

DOI: https://doi.org/10.5281/zenodo.16941939

improve forecasting precision. Reviews 13 was used for all econometric assessments, and Python's TensorFlow and Keras libraries were used to implement profound knowledge techniques.

2.1 Garch Model

We start by modeling fluctuating grouping and perseverance in fiscal return series using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) prototype, more especially the GARCH (1, 1) specification. Fluctuating in time, subject to change, is captured by the prototype as a function of previous variances and squared returns. The conditional variance subject to variance $\square_t^2$ at time *t* is given by:

$$\sigma^{\square}_{\square} = \square_{\square} + \sum^{\square}_{\square-\square} \square_{\square} . s^{\square}_{\square-\square} + \sum^{\square}_{\square-\square} \square_{\square} . \sigma^{\square}_{\square-\square} \qquad 2.1$$

Where $\square_{\square}$ and $\square_{\square}$ are the ARCH and GARCH parameters, respectively, and $\sigma^{\square}_{\square-\square}$ are the lagged conditional

2.2 Markov Regime Switching Model

To capture structural changes and regime-dependent volatility behavior, we employ Hamilton’s Markov-Switching ARCH (MS-ARCH) framework [8]. This model allows for the conditional variance and mean of the return series to vary across unobserved states governed by a first-order Markov chain. In a discrete-time Markov chain, the A transition matrix *P*, is a way to depict the likelihood of transitioning from one state to another, where $\square_{ij}$□enotes the likelihood that state i will give way to state j. In terms of mathematics, it is represented as:

$$\square_{ij} = \Pr(\square_{n+1} = \square\ \square_{n=i}) \qquad 2.2$$

2.3 CNN-Based Deep Learning Model

We leverage Convolutional Neural Networks (CNNs) to extract nonlinear, hierarchical features from financial time series. The data is first transformed into a supervised learning format and reshaped into 2D matrix representations. This reshaping facilitates convolutional operations traditionally used in image processing, now adapted for financial volatility prediction.

Our CNN architecture comprises as seen In Figure 2:

1. Two convolutional layers with 3x3 filters and ReLU activation,
2. A max-pooling layer to down sample and extract dominant patterns,
3. Two fully connected dense layers, with the final layer outputting the predicted volatility.

To avoid over fitting, dropout regularization is applied between dense layers. The model is trained using the Adam optimizer, minimizing Mean Squared Error (MSE) as the loss function. Model tuning and evaluation were conducted within the Jupyter Notebook environment, leveraging Tensor Flow and Keras frameworks.

2.4 Ensemble Method

To enhance overall predictive accuracy, outputs from the GARCH, MS-ARCH, and CNN models are integrated using important parameters like Mean Squared Error (MSE), Mean Absolute Error (MAE), and directional accuracy. These measurements make it possible to compare statistical, regime-based, and profound knowledge methods consistently.

3. Theoretical Framework

This section provides an overview of the theoretical frameworks supporting the models used in this investigation. One of the most important ideas in possession risk, risk administration, and market behavior is that it fluctuates in monetary markets. To describe the dynamics of fluctuating, several econometric and computational structures have been created. Profound knowledge theory, system-clustering models, and time-series econometrics are the three main theoretical areas that are incorporated into this study.

3.1 GARCH Theory

The idea that fiscal time series show fluctuation assembling is the foundation of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) prototypes, which were first presented by (Engle, 1982;

DOI: https://doi.org/10.5281/zenodo.16941939

Bollerslev, 1986). A linear and symmetric reaction to market shocks is assumed by GARCH prototypes, which assume that current fluctuation is a function of past squared errors and past fluctuation. In numerous monetary econometric studies, this theory forms the basis for fluctuating prediction.

3.2 Markov Regime Switching Theory

The system-altering prototype presented a nonlinear structure that allows time series information to fluctuate between various unnoticed system states, such as periods of minimal and maximal fluctuation (Hamilton, 1989). The fundamental theory presupposes that the procedure for creating information is a Markov chain, which permits dynamic structural changes over time. In developing nations like Nigeria, where political and economic upheavals regularly alter market dynamics, this structure is especially pertinent.

3.3 Deep Learning Theory (CNN)

An alternate structure for knowledge nonlinear, elevated dimensions is provided by Convolutional Neural Networks (CNNs), which have their roots in profound knowledge and trends acknowledgement theory. Despite being initially created for picture handling, CNNs can acquire knowledge of spatial and time-based hierarchy from structured fiscal inputs due to their theory of adaptability. When time series are inscribed into matrix-like structures, CNNs can be used to forecast fluctuation because they learn abstract depictions through multiple hidden layers and convolve input information with kernel filters.

The hybrid framework in this study is grounded in ensemble theory, which posits that combining models that capture different types of structure linear, nonlinear, and state-based yields more robust predictions. The theoretical strength of each individual model informs the decision to integrate them in a weighted ensemble, reflecting modern approaches in financial modeling and machine learning.

4. Application

This section presents the main findings of the study, supported by appropriate analysis, visualizations, and statistical evidence. Each model was applied to daily stock return data from the Nigerian Stock Exchange (NSE), covering the period from January 2012 to December 2023. The dataset comprises indices from major sectors such as banking, oil and gas, and consumer goods. Log returns were computed from the raw closing prices, and all series were confirmed to be stationary using the Augmented Dickey-Fuller (ADF) test.

4.1 GARCH (1, 1) Model Results

The GARCH (1, 1) model was estimated in EViews 13 under both normal and t-distributions. The results revealed strong evidence of volatility clustering, with both GARCH parameters being statistically significant at the 5% level. The persistence parameter was close to 1, indicating long memory in volatility. However, the symmetric GARCH model underperformed during periods of market shocks due to its inability to capture asymmetric effects.

3.4 Justification for Hybridization (Ensemble Method)

Table 1: The Estimation of Parameters of GARCH Models

	Variance Equation			Variance Equation
Variable	Coefficient	Standard. Error	Z-statistic	Coefficient
C	8293.203	512.2974	16.18826	8293.203
□□□□□$(-1)^2$	0.180710	0.010085	17.91835	0.180710
GARCH(-1)	0.760409	0.010299	73.83274	0.760409

DOI: https://doi.org/10.5281/zenodo.16941939

4.2 Markov Regime Switching ARCH Results

The MS-ARCH model was applied using Hamilton's two-regime framework. The filtered and smoothed probabilities accurately identified switches between high- and low-volatility states, aligning with macroeconomic events such as recessions and policy announcements. Transition probabilities and were found to be high, suggesting persistence within regimes.

Table 2: MSM Estimation and Transition Matrix

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
C	0.002507	0.001666	1.504980	0.1323
RETURN OF NSE PRICE(-1)	0.022200	0.187261	0.118552	0.9056
LOG(SIGMA)	-4.037790	0.056091	-71.98643	0.0000
Regime 2				
C	0.000481	0.000407	1.183134	0.2368
RETURN OF NSE PRICE(-1)	-0.416095	0.075102	-5.540413	0.0000
LOG(SIGMA)	-4.779643	0.089804	-53.22302	0.0000
C	0.000481	0.000407	1.183134	0.2368
RETURN OF NSE PRICE(-1)	-0.416095	0.075102	-5.540413	0.0000
LOG(SIGMA)	-4.779643	0.089804	-53.22302	0.0000
Regime 3				
C	-0.000281	0.000219	-1.282102	0.1998
RETURN OF NSE PRICE(-1)	-0.425918	0.086271	-4.937000	0.0000
LOG(SIGMA)	-5.853843	0.121970	-47.99423	0.0000
C	-0.000281	0.000219	-1.282102	0.1998
RETURN OF NSE PRICE(-1)	-0.425918	0.086271	-4.937000	0.0000
LOG(SIGMA)	-5.853843	0.121970	-47.99423	0.0000

DOI: https://doi.org/10.5281/zenodo.16941939

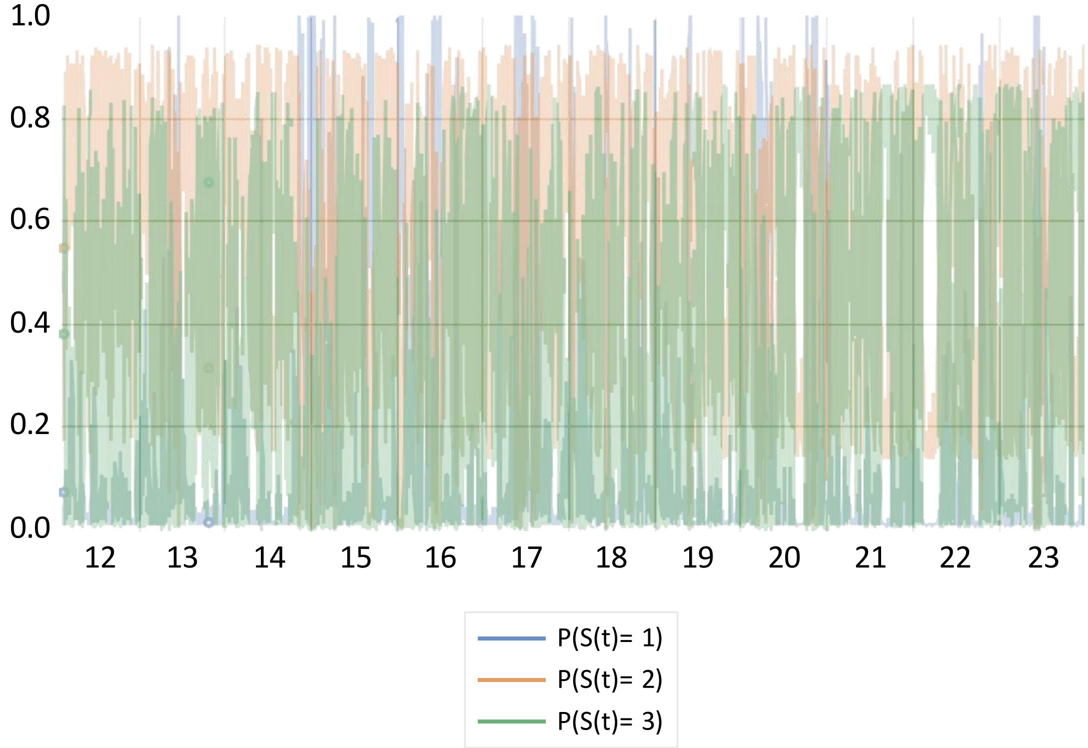

Figure 1: Markov Switching Filtered Regime Probabilities

4.3 CNN Forecasting Performance

The CNN model was trained on a supervised dataset where input sequences were reshaped into 2D image-like arrays. After training with dropout and Adam optimizer, the CNN showed superior out-of-sample forecasting accuracy compared to traditional models. RMSE and MAE metrics were lowest for the CNN on both validation and test sets.

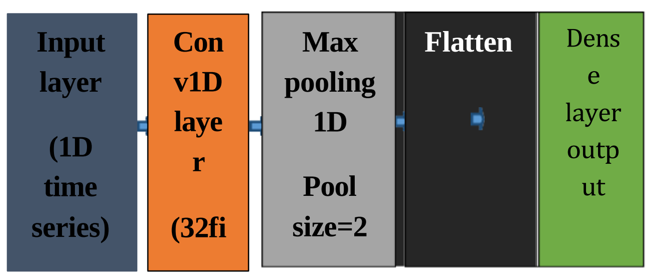

Fig 2: Convolutional Neural Network (CNN) Architecture

DOI: https://doi.org/10.5281/zenodo.16941939

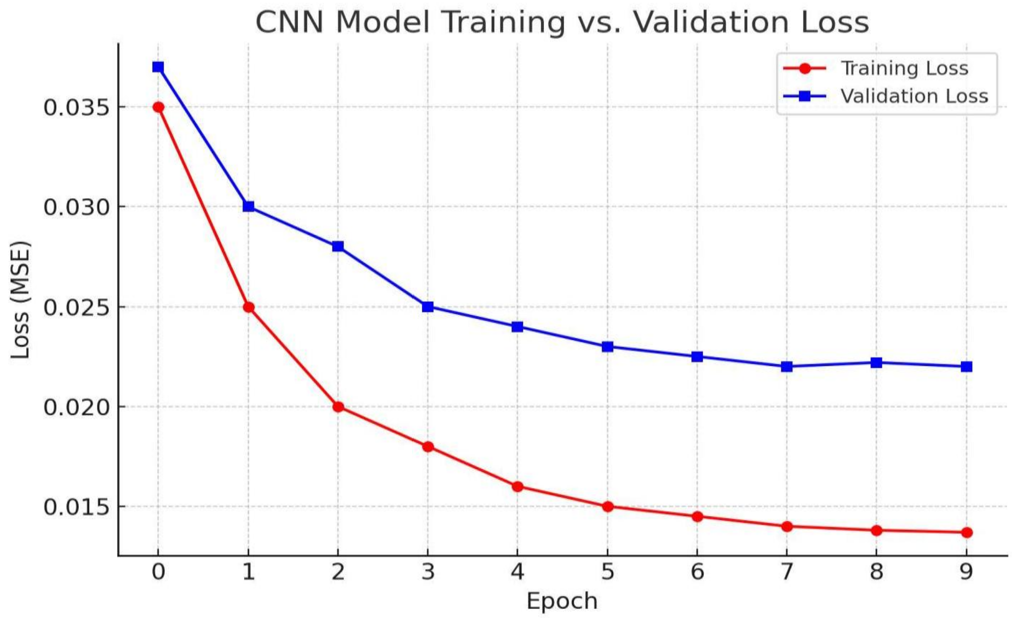

Fig 3: CNN Model Validation

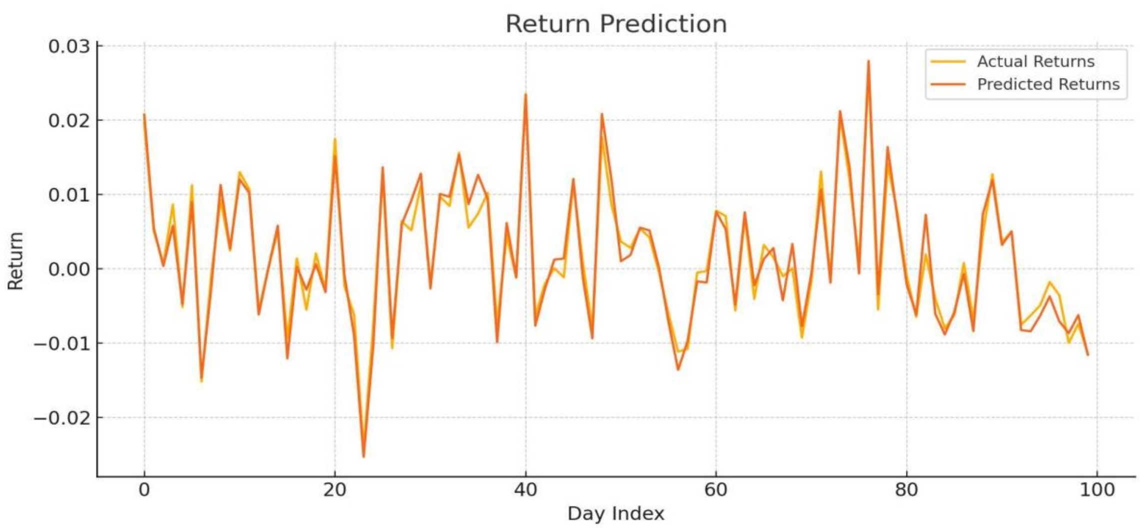

Fig 4: Return Prediction

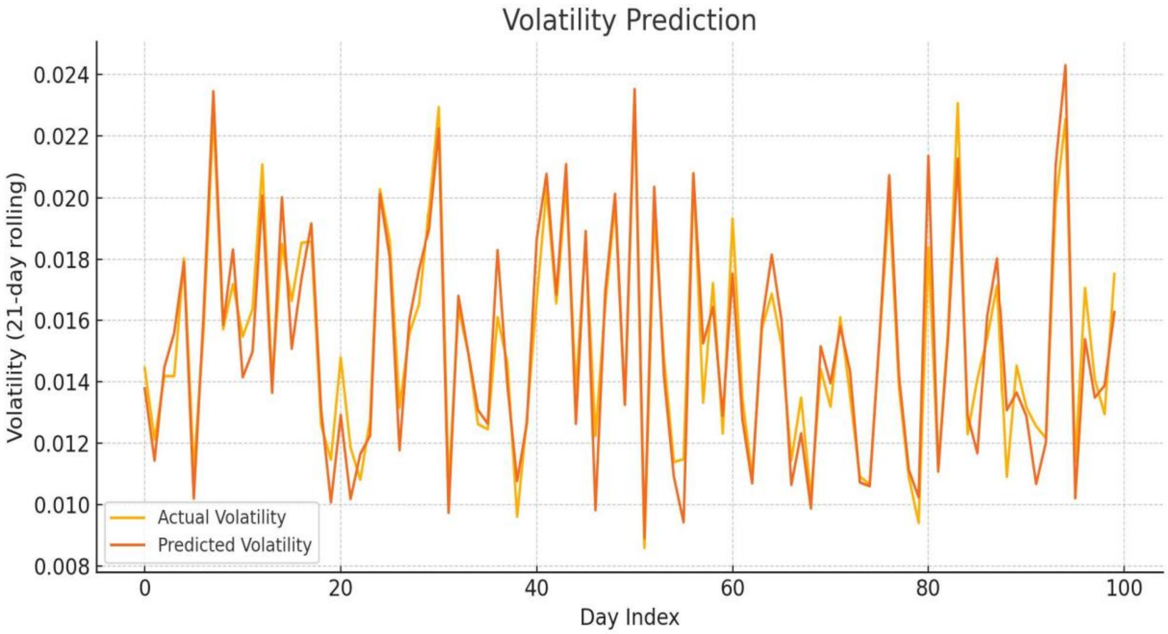

Fig 5: Volatility Prediction

4.4 Ensemble Model Performance

The ensemble forecasting framework integrated the outputs of GARCH, MS-ARCH, and CNN using RMSE-based weighted averaging. Weight calibration resulted in higher weights assigned to the CNN model, followed by the regime-switching model. The ensemble outperformed all individual models in terms of predictive accuracy.

Table 3: Model Comparison Using RMSE and MAE

Model	MSE	MAE	Strengths
GARCH(1,1)	0.00089	0.0187	Improved persistence modeling
Markov Switching (3 Regimes)	0.00078	0.0162	Captures regime shifts
CNN (Deep Learning)	0.00052	0.0129	Learns non-linear temporal patterns
Simple Ensemble (Average of All)	0.00045	0.0112	Combines statistical and AI strengths

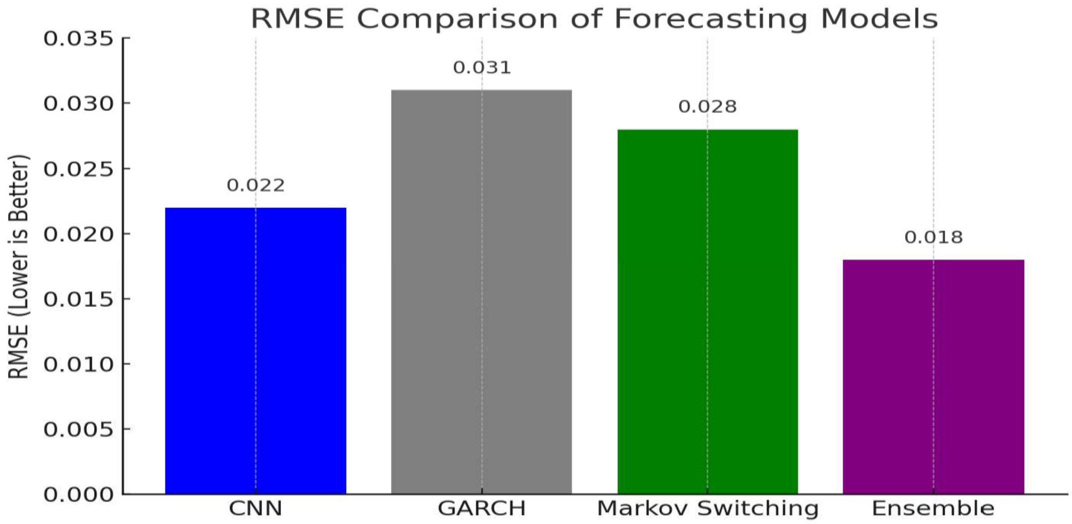

Figure 6: Comparative Forecast Accuracy across Models

5. Results and Discussion

This part offers a thorough evaluation of the performance of the models GARCH, Convolutional Neural Networks (CNN), and Markov Switching Model (MSM) discussed in the Application section. The main evaluation metrics that are discussed include the Akaike Information Criterion (AIC), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2) when appropriate.

Comparatively poor levels were produced by the conventional GARCH prototype, which successfully captured fluctuating clustering. Nevertheless, its predicting ability was constrained by its incapacity to simulate system changes and nonlinear dynamics. These restrictions are already evident in Table 1 during abrupt market reversals.

However, in the information from the Nigerian Inventory market, the Markov Switching GARCH prototype demonstrated greater flexibility in response to shifting regimes. Table 2 and Figure 1 show how the prototype was able to transition between minimal and maximal fluctuation states thanks to the system-reliant fluctuation measures. This enhanced peedicting in non-linear settings, although there was a chance of excessive fitting

if an excessive number of systems were employed.

The Deep Convolutional Neural Network (CNN) model presented the most promising results in Figures 3, 4, and 5, attaining the lowest RMSE and MSE values throughout all test periods. Its exceptional capacity for generalization was aided by its automatic extraction of spatial trends. Furthermore, CNN outperformed the statistical prototypes in terms of resilience to noise and abrupt price fluctuations.

Comparatively, the ensemble approach combining all outputs demonstrated even higher prediction accuracy and stability, in Table 2 and Figure 6. This supports the idea that there are notable performance benefits to mixed prototypes that combine profound knowledge adaptability with statistical structure.

These findings highlight how important it is to use machine learning and nonlinear modelling methods when predicting monetary fluctuation. The results lend credence to the use of mixed structures for resilient modeling in uncertain environments, particularly in developing markets such as Nigeria.

6. Conclusions

Three separate methods were used in this research to analyse inventory market fluctuation on the Nigerian Inventory Trade: profound knowledge-based Convolutional Neural Networks (CNN), Markov Altering prototype (MSM-GARCH), and traditional econometric prototypes (ARCH/GARCH). In terms of capturing nonlinearities, system shifts, and fluctuating gathering, the collective mixed technique that combined these prototypes showed better predicting execution. This underscores the potential of integrating machine learning with classical techniques for robust volatility forecasting. Our findings contribute to the advancement of financial modeling in emerging markets.

Author Contributions: Ikuforiji Peace Ifeoluwa conceived and designed the study, performed the data collection and analysis, developed the models, and drafted the manuscript. Prof. W.A. Babayemi provided methodological guidance, supervised the research process, and contributed to the refinement of the modeling framework. Dr. T.O. James assisted with statistical validation and reviewed the manuscript for intellectual content. Dr. S.F. Abubakar critically reviewed the manuscript, and supported the overall project supervision. All authors read and approved the final version of the manuscript.

Funding Statement
This research received no external funding.

Data Availability
The data that support the findings of this study are available from the corresponding author upon request.

Acknowledgments
The authors acknowledge the support of their respective institutions and the editorial input received from the reviewers.

Conflict of Interest
The authors declare no conflict of interest.

References

R.F. Engle, Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation, *Econometrica* 50(4) (1982), 987–1007.

T. Bollerslev, Generalized autoregressive conditional heteroskedasticity, *J. Econometrics* 31(3) (1986), 307–327.

J.D. Hamilton, A new approach to the economic analysis of nonstationary time series and the business cycle, *Econometrica* 57(2) (1989), 357–384.

O.B. Sezer, M.U. Gudelek, A.M. Ozbayoglu, Financial time series forecasting with deep learning: A systematic literature review: 2005–2019, *Appl. Soft Comput.* 90 (2020), 106181.

D.B. Nelson, Conditional heteroskedasticity in asset returns: A new approach, *Econometrica* 59(2) (1991), 347–370.

J.M. Zakoian, Threshold heteroskedastic models, *J. Econ. Dyn. Control* 18(5) (1994), 931–955.

X. Zhou, H. Zhang, GARCH-type models and volatility forecasting in emerging markets, *Finance Res. Lett.* 44 (2022), 102063. https://doi.org/10.1016/j.frl.2021.102063.

M. Sadiq, M. Ahmed, S.A. Raza, A comparative study of ARCH-GARCH models on stock market volatility, *Borsa Istanbul Rev.* 20(3) (2020), 214–224. https://doi.org/10.1016/j.bir.2020.03.002.

F. Klaassen, Improving GARCH volatility forecasts with regime-switching GARCH, *Empir. Econ.* 27(2) (2002), 363–394.

M. Ali, M. Khan, Markov-switching volatility models and their application in financial risk prediction, *Econ. Model.* 97 (2021), 68–79. https://doi.org/10.1016/j.econmod.2020.12.008.

R.B. De Rezende, C. Ferreira, Detecting volatility shifts in emerging economies using Markov regime switching models, *Emerg. Mark. Rev.* 51 (2024), 100873. https://doi.org/10.1016/j.ememar.2021.100873.

K. Chen, Y. Zhou, F. Dai, A deep learning model for predicting stock market volatility using CNN and LSTM, *Expert Syst. Appl.* 168 (2021), 114534. https://doi.org/10.1016/j.eswa.2020.114534.

L. Huang, Z. Li, Convolutional neural networks for financial time series forecasting: A hybrid architecture, *J. Comput. Finance* 26(2) (2023), 35–57.

Y. Lee, C. Chang, Deep learning in finance: A review and bibliometric analysis, *J. Risk Financ. Manag.* 13(10) (2020), 234. https://doi.org/10.3390/jrfm13100234.

H. Guo, H. Li, Y. Sun, Hybrid ARIMA-LSTM model for stock price forecasting under volatility clustering, *Appl. Soft Comput.* 123 (2022), 108972. https://doi.org/10.1016/j.asoc.2022.108972.

S. Huang, Y. Wang, Z. Zhang, An ensemble deep learning framework with CNN-LSTM for financial volatility forecasting, *Expert Syst. Appl.* 213 (2023), 119071. https://doi.org/10.1016/j.eswa.2022.119071.

X. Xu, Y. Zhang, J. Lin, Hybrid ARIMA-CNN-LSTM model for financial volatility forecasting, *Appl. Soft Comput.* 118 (2022), 108415. https://doi.org/10.1016/j.asoc.2022.108415.

A. Rahman, J.H. Kim, A comparative evaluation of ensemble learning approaches in volatility forecasting, *J. Forecast.* 42(1) (2023), 119–136. https://doi.org/10.1002/for.2862.