Forecasting Stock Prices Volatility with Information (An ANN-GARCH Hybrid Approach)

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Abstract
This study compares the forecast performance of volatilities between three models for forecasting stock returns: GARCH, hybrid ANN-GARCH with only GARCH output as the ANN input, and a hybrid ANN-GARCH with information. Through the extensive evaluation, the research found out that the hybrid ANN-GARCH model with information outperforms the other two models in terms of forecasting accuracy and predictive power. This study is set to find out the improvement performance of the hybrid ANN-GARCH with information vis a vis the Univariate GARCH
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1. Introduction

Volatility modeling plays a vital role in finance and economics as it provides critical insights for decision making, risk management, and portfolio optimization. However, the GARCH model, in its standalone form, is limited in its ability to consider external information that can influence stock price volatility. To address this limitation, this research aims to develop a hybrid ANN-GARCH model that incorporates additional factors such as interest rates, exchange rates, inflation, and the NSE 20 Share Index. The objective of this study is to investigate the effectiveness of the hybrid ANN-GARCH model in capturing complex relationships by incorporating external factors. By integrating the ANN component, the model aims to leverage the capabilities of artificial neural networks to capture complex nonlinear relationships and patterns between the external variables and stock price volatility.[1] used a hybrid GARCH-ANN model to forecast volatility of the Chinese stock market and found that the hybrid model was more accurate and gives a better prediction than traditional GARCH models. Hybrid ANN-GARCH and GARCH was used by Kristjanpoller et al to determine whether improvements can be achieved in the forecasting of oil price volatility by incorporating financial variables (Euro/Dollar and Yen/Dollar exchange rates, and the DJIA and FTSE stock market indexes) [2]. The study concluded that hybrid model increases the volatility forecasting precision by 30% over previous models as measured by a heteroscedasticity-adjusted mean squared error (HMSE) model.[3] again applied this same GARCH-ANN hybrid approach to the metals markets, specifically prices of gold, silver, and copper. The study concluded again that the hybrid GARCH-ANN model improved forecasting performance when compared to the forecasts of the standalone GARCH models.

2. Methodology

Generalized Autoregressive Conditional Heteroscedasticity (GARCH)

GARCH model is an extension of the autoregressive conditional heteroscedasticity (ARCH).[3] GARCH model was generalized by Bollerslev and is widely used in modelling volatility in financial data because of its ability to capture volatility clustering. GARCH models can account for conditional heteroskedasticity, a common characteristic of many financial time series data. There is a risk of overfitting when using GARCH models, especially when using high-order models with many parameters. GARCH model uses daily closing price to calculate the returns which are given by;

$$Y_t = \log X_t - \log X_{t-1} \quad (1)$$

The general form of GARCH (1,1) is given as;

$$\sigma_t^2 = \alpha_0 + \alpha_1 Y_{t-1}^2 + \beta_1 \delta_{t-1}^2 \quad (2)$$

The assumptions of the GARCH.

The assumptions of the GARCH model include;

1. Stationarity
2. Normality
3. Conditional heteroskedasticity

Testing model assumptions

a. Augmented Dickey-Fuller Test (ADF)

The ADF test was used to test for stationarity.

The hypothesis to be tested in ADF test are;

H_0: The data is non-stationary

H_1: The data is stationary

The ADF equation is given by;

$$\Delta x_t = \alpha_0 + \beta_t + \theta x_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta x_{t-1} + \varepsilon_t \qquad (3)$$

If the ADF test statistic is less than the critical value at the 5% significance level, the null hypothesis is rejected and hence we conclude that the data is stationary.

b. The Jarque-Bera

The Jarque -Bera test will be used to test for normality of the residuals.
The hypothesis to be tested in JB test are;

H_0: The residuals are normally distributed.

H_1: The residuals are not normally distributed.

JB test is shown by the following equation;

$$JB = \frac{n}{6}(\mathrm{S}^2 + \frac{1}{4}(\mathrm{K}-3)^2) \qquad (4)$$

If the Jarque-Bera test statistic is less than the critical value, you fail to reject the null hypothesis and conclude that the residuals are normally distributed.

c. Ljung-Box test

Ljung-Box test was used to test for the ARCH effects. The hypothesis to be tested are;

H_0:No ARCH effects

H_1:There exists ARCH effects

Artificial Neural Network

Artificial neural network (ANN) is a parallel connection of a set of nodes called the neurons. There are three types of layers in ANN which are input layers, hidden layers and output layers that are organized hierarchically. The model is able to capture complex nonlinear relationship in financial time series data. There are two types of artificial neural network which are feed forward neural network and feedback neural network. In feed forward neural network, information flows in one direction from input layer to the output layer. Back propagation is an algorithm that is used to train feed forward neural networks. The algorithm uses the gradient descent optimization technique to adjust the weight of the network to minimize the error between the predicted output and actual output. Sigmoid activation function was used in ANN to determine the output of a neuron and also to introduce non-linearity into the model. The ANN equation is given by;

$$\hat{R}V_{t+n} = f\left(\sum_{i=1}^{n}\sum_{j=1}^{m} w_{ij}x_i + \varepsilon_j\right) \qquad (5)$$

Where $\hat{R}V_{t+n}$ is the forecasted realized volatility, f is the sigmoid activation function, x_i represents the inputs, w_{ij} is the weights feature and ε_j is the bias term.

Feature reduction technique

The study used Least Absolute Shrinkage and Selection Operator (LASSO) regression to determine the significant variables that will be used as input in the ANN model. [5] LASSO adds a penalty term to the linear regression objective function. This penalty encourages sparsity by shrinking the coefficients of irrelevant features to zero. Features with non-zero coefficients are considered important. The lasso equation is given by;

$$Ls = \min_{\beta}\left\{\frac{1}{2N}\|y - X\beta\|^2 + \lambda\|\beta\|_1\right\} \qquad (6)$$

Where y represents the dependent variable or target variable, β represents the weights assigned to each feature in the linear regression model, $\|y - X\beta\|^2$ represents the sum of squared errors, N is the number of observations in the dataset, λ is the regularization parameter, which controls the strength of the L1 regularization and $\|\beta\|_1$ represents the L1 norm.

Hybrid ANN-GARCH (1,1) Model

This study used two types of hybrid models, hybrid ANN-GARCH with only GARCH output as the ANN input, and a hybrid ANN-GARCH with information. Hybrid type I is hybrid ANN-GARCH with only GARCH output as the ANN input and hybrid type II is a hybrid ANN-GARCH with information. The independent variables for hybrid type II include, exchange rate (USD/KES, Yen/KES, Euro/KES, Tzshiling/KES, Ugshiling/KES, SA Rand/KES and Pound/KES), interest rates (repos and reverse repos), inflation and NSE20 share index. The hybrid architecture is given by the following figure;

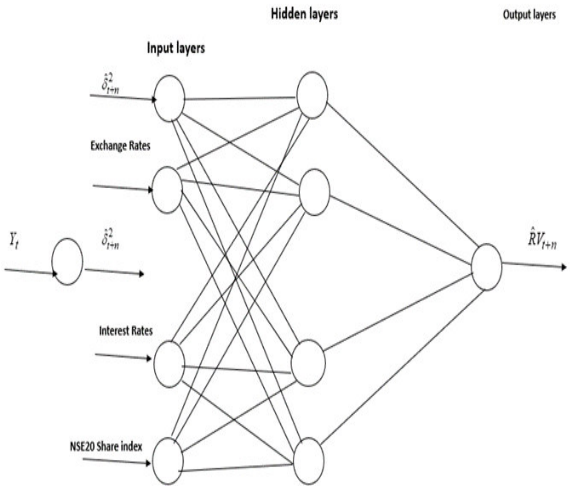

Figure 1: ANN-GARCH (1,1) hybrid Architecture

The hybrid equation is given by;

$$\hat{R}V_{t+n} = f\begin{pmatrix} w_i\hat{\delta}^2_{t+n} + \sum_{i=1}^{7} w_{1i}X_{1i},t + \sum_{i=1}^{2} w_{2i}X_{2i},\mathrm{t} + w_{3i}X_{3i},t \\ +\varepsilon_j,t \end{pmatrix} \quad (7)$$

Where $\hat{R}V_{t+n}$ is the forecasted realized volatility f is the activation function , $\hat{\delta}^2_{t+n}$ denotes the forecasted n-day ahead GARCH volatility, X_{1i},t is the exchange rates, X_{2i},t represents the interest rates , X_{3i},t is the NSE20 share index, ε_t represent the error term and the w_{ij} terms represents the weights.

Performance Evaluation

The performances of modelling and forecasting the two hybrid models and GARCH (1,1) model will be evaluated using mean square error, root mean square error and Heteroskedasticity mean squared error.

$$MSE = \frac{\sum_{i=1}^{n}\left(y_t - \hat{y}_t\right)^2}{n} \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_t - \hat{y}_t\right)^2}{n}} \quad (9)$$

$$HMSE = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{\hat{y}_t}{y_t}\right)^2 \quad (10)$$

Where y_t is the actual values and $\hat{y}_t$ are observed values.

3.Data analysis

The assumptions of GARCH model were tested using ADF test, Jacque bera test and Ljung-Box test as shown in the table below;

Table 1: Diagnostic test

Test	P-Value
ADF test	0.01
Jacque bera	0.4902
Ljung-Box test	2.2e-16

From Table 1, ADF test indicates that the residuals are stationary, Jacque bera test indicates they are normally and Ljung-Box test indicates that there is arch effect.

The hybrid model feature selection using lasso was done to select the significant variables to be included in the hybrid model. The results of the lasso were as follows;

Table 2: Lasso output

Variables	Lasso coefficient
GARCH output	0.006287
Ug/KES	0.005793
Pound/KES	0.003443
Repos	0.001182
USD/KES	0.000962
YEN/KES	0.000457
N days	0.000168
Tzsh/KES	-0.006651
Euro/KES	-0.004452
Rand/KES	-0.002596
Reverse repos	-0.001524
NSE20 share index	-0.000102
Inflation	0

From the Table 2 an increase in Ugsh/KES, Pound/KES, Repos, USD/KES, Garch output, YEN/KES, and ndays is associated with an increase volatility. On the other hand, an increase in Tzsh/KES, Euro/KES, Rand/KES, Reverse repos and NSE20 share index leads to a decrease in volatility. Inflation has a coefficient of 0 indicating that it does not have a significant impact on volatility. A hybrid model was fitted the variables that were considered significant and the results were compared as shown in the tables below;

Table 3: Comparing GARCH and hybrid ANN-GARCH

Evaluation creteria	GARCH	Hybrid ANN-GARCH
MSE	0.000491	0.000154
RMSE	0.022146	0.012445
HMSE	0.009512	0.005576

Table 3 shows that hybrid ANN-GARCH has lower MSE RMSE and RMSE. This indicates that hybrid ANN-GARCH improves the forecasting accuracy.

Another hybrid ANN-GARCH with more information was fitted and the results were compared with hybrid ANN-GARCH with Garch output only as ANN input as shown in the table below;

Table 4: Comparing performance of Hybrid ANN-GARCH and Hybrid ANN-GARCH with information

Evaluation criteria	Hybrid ANN-GARCH	Hybrid ANN-GARCH with covariates
MSE	0.000163	0.000154
RMSE	0.012798	0.012445
HMSE	0.005897	0.005576

Table 5: Improvement performance of ANN-GARCH with covariates in percentage

Model	MSE	RMSE	HMSE
GARCH (1,1)	68.6%	34.2%	41.4%
Hybrid ANN-GARCH without covariate	5.52%	2.27%	5.44%

shows that hybrid ANN-GARCH with information improves the forecasting accuracy by 5.52% when comparing the MSE,2.79% for RMSE and 5.44% for the HMSE.

4. Discussion

Volatility serves as the predominant force influencing stocks and the broader stock market. The result of this study shows that hybrid ANN- GARCH with GARCH output as ANN input performs better that the standalone GARCH model. The finding was in line with a study conducted by Liu and So forecasted stock price volatility using hybrid ANN-GARCH and GARCH model. The finding showed that that a hybrid model performs better than standalone GARCH type models [6]. Tseng et al also develop a new hybrid asymmetric volatility framework into an ANN option-pricing model in order to enhance the forecasting ability of the Taiwan stock index option prices. Results showed that the hybrid model provides greater predictability compared to traditional volatility models [6].[7] used GARCH-type models and enhanced them with Neural Networks to examine the volatility of daily returns in the Istanbul stock market. Their hybrid models showed improved forecast as compared to GARCH-type model alone. Guresen et al used hybrid GARCH-ANN models to forecast daily stock exchange rates of NASDAQ, the results obtained show improvements for the hybrid model in comparison to the traditional models [8]. The results of the study also shows that hybrid ANN-GARCH with covariates performs better compared to hybrid ANN-GARCH with GARCH output as ANN input. Hybrid ANN-GARCH covariates improves the forecasting accuracy compare to the GARCH model by 5.52% when comparing the MSE,2.79% for RMSE and 5.44% for the HMSE**.**The study was in line with studies done by [2],[9] and [10].

5. Conclusion

The research conducted a comparative analysis of three models for forecasting stock returns: GARCH, hybrid ANN-GARCH with only GARCH output as the ANN input, and a hybrid ANN-GARCH with additional information including exchange rates, interest rates, and NSE20 share index. Through the extensive evaluation, the research found out that the hybrid ANN-GARCH model with additional information outperforms the other two models in terms of forecasting accuracy and predictive power.

6. References

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