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Alareeni Bahaaeddin
Allam Hamdan *Editors*

Technovate: The Art of Business Transformation through Technology

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Neural Network-Based Volatility Forecasting: A Hybrid GARCH-ANN Model for Nifty 50

Jahnavi M, Pooja R. Takalkar, Purushottam Bung, and N. Nagasubba Reddy

1 Introduction

The area of risk management in finance has prominently evolved with the acceleration of usage of models based on Machine learning (ML) [1]. This change is a paradigm shift in how financial institutions view and manage risk. ML has shown to be a great opportunity for enhancing risk forecasting, particularly in terms of volatility and uncertainty measurement [2, 3].

Volatility refers to changes in the prices of assets over time. One of the most important factor, it forms a significant point of study not just for governments, central banks, and financial analysts but also for the determination of all the economic conditions, formulation of fiscal policies, and making informed investment decisions. In this respect, it would be important to accurately measure market volatility

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for decision-makers. Such decision-makers include policymakers, pension fund managers, portfolio managers, and individual investors who are trying to understand potential risks and opportunities in financial markets.

Since volatility cannot be measured in direct terms, it has to be approximated with the use of different mathematical models. One approximation model of calculating the square of logarithmic returns is achieved. This has become a very important characteristic of volatility: it clusters, meaning that more often than not, periods of high volatility are followed by more high-volatility periods; similarly, low-volatility periods tend to persist. This implies that perhaps individual returns lack a strong mutual correlation, but variance is dependent between periods.

To approximate the volatility, analysts start with simpler models such as the Simple Moving Average (SMA) and the Exponentially Weighted Moving Average (EWMA), which give some basic understanding of how volatility changes over time. Additional predictive precision is achieved through the utilization of more advanced models, such as ARCH and GARCH models. ARCH and GARCH models are very effective in capturing volatility patterns, especially in time-dependent volatility, and are very applicable to the modeling of volatility in financial markets.

While GARCH models are a good approximation of volatility clustering, they still have limitations. They cannot explain the complexity and the nonlinear characteristics often found in financial markets. This gap has driven some researchers to seek alternative means to make forecasting techniques as accurate as possible. One of the promising paths for enhancing volatility forecasts involves combining Machine Learning algorithms with conventional econometric models, such as GARCH. The ML algorithms are more excellent at discovering patterns unknown to common statistical models. The inclusion of ML techniques in finance can help with better risk management, adaptive trading strategies, and the best possible decision-making within financial institutions [4, 5].

Machine learning techniques are applied to analyze key financial market indicators such as interest rates, stock prices, and the level of market indices. These techniques are widely used in most trading platforms, including Bloomberg and Reuters, and also within risk management systems, such as Murex and Calypso. Beyond estimation of important risk metrics such as Value at Risk (VaR), Expected Shortfall (ES), and Greek sensitivities crucial for both regulatory compliance and risk assessment, such algorithms of ML are involved. In recent times, the notion of ANN has suddenly gained force and popularity in the financial forecast due to the excellence of capturing complex, nonlinear relationships in data, an aspect where traditional models, like GARCH, fail to do so. Researchers began combining GARCH models with ANN models for hybrid models, enhancing the accuracy of volatility forecasting.

Mademlis and Dritsakis [6] offered a hybrid model, the application of which provides GARCH with an artificial neuron network (ANN) model for forecasting volatility around the FTSE MIB. Likewise, this hybrid approach included technical analysis-principal component analysis with GARCH and ANN through the forecasting method for the volatile nature of Bitcoin prices proposed in Kristjanpoller

and Minutolo [7]. The output from both, however, happens to be significantly accurate.

According to research conducted by Vidal and Kristjanpoller [8], the network can handle everyday problems of forecasting, including white noise, non-stationarity, and heteroscedasticity, all complicating the time series analysis. Their deep learning approach- a combination of LSTM and CNN- actually improved the predictions regarding volatility in gold price. There are plenty of studies stating that the hybrid models show immense improvement compared to the traditional models in forecasting accuracy, thereby being valid tools for financial risk management and investment decision-making.

The benefits of ML methods in financial forecasting have been emphasized and underlined, especially in stock market volatility. Researchers have used the ML algorithm to enhance volatility predictions as well as to estimate market risk; some of these studies include Donaldson and Kamstra [9], Kim and Won [10], King et al. [11], Kristjanpoller and Minutolo [7], and Vidal and Kristjanpoller [8]. In such studies, it has been emphasized that hybrid models- in other words, models that incorporate econometric and traditional research with ML techniques- would be useful for enhancement.

This research is based on previous research and will develop a hybrid model for forecasting the volatility of the Nifty 50 index by combining GARCH models with Artificial Neural Networks (ANN).

2 Literature Review

The introduction of AI in financial market forecasting has revolutionized new techniques to predict the stock price and volatility along with risk. Researchers in the preliminary stages of their studies were highly interested in the volatility prediction of a market. As such, in 1982, Engle introduced the concept of ARCH, and later, Bollerslev [12] extended that concept with the GARCH model, which considers persistent volatility within financial time series data.

These models were developed and combined over time with traditional techniques such as linear regression and support vector regression to further improve predictions.

Some preliminary works by Yoon and Swales [13] showed neural networks outperforming traditional models regarding the prediction of stock prices for 58 Fortune 500 companies. Further, by providing proof that the more sophisticated feedforward neural networks could effectively improve trading results by increasing the appropriate balance between risk and return, researchers such as Haefke and Helmenstein [14] supported the use of neural networks. Tsaih et al. [15] took this a step further by building a hybrid AI model using a combination of neural networks and rule-based systems to forecast daily price movements of S&P 500 index futures. Donaldson and Kamstra [9] presented a semi-nonparametric nonlinear GARCH

model inspired by neural networks that surpassed other standard models like GARCH, EGARCH, and GJR across leading world markets.

Hybrid models have become more sophisticated. Oh et al. [16] proposed an Early Warning System that applied artificial neural networks and Genetic Algorithms for predicting financial crises using daily indicators of financial condition. Bildirici and Ersin [17] further developed the approach by using ARCH, GARCH, and more machine learning techniques to improve precision. More studies along the lines of Bildirici and Ersin [18], Chen et al. [19], Fan et al. [20], Matías et al. [21], and Wang [22] have used hybrid GARCH and ML methods to explore further improvement in the process.

Hybrid models were lately applied to newly emerging assets such as cryptocurrencies. Mtiraoui et al. [23] predicted Bitcoin returns and volatility by a combination of ARFIMA, empirical wavelet transforms, and local linear wavelet neural networks. Similarly, Tissaoui et al. [24] have proposed Hybrid Particle Swarm Optimization for the forecast of the CBOE volatility index.

Decomposition methods have been widely applied to improve the accuracy of forecasts with decomposition. Shen et al. [25] decomposed realized variance by heterogeneous autoregressive models, and Gao et al. [26] decomposed financial asset volatility into upside and downside components and showed that there exist different predictive patterns for upside and downside volatilities. Combining them with deep learning, Li et al. [27] applied variational mode decomposition and a bidirectional long short-term memory neural network to predict crude oil returns and volatility. This further emphasizes the potential integration of decomposition methods with advanced machine learning methods.

The literature exhibits significant progress and advancements in the usage of AI/ML in forecasting in finance, especially hybrid approaches combining traditional approaches with advanced tools, which ultimately provide better and more reliable solutions, very suitable for financial analytics and decision support.

3 Research Methodology

This paper makes use of the hybrid approach by combining GARCH models with ANN to improve the efficiency in forecasting daily volatility. The dataset used for this purpose is the daily closing prices of the Nifty 50 index derived from the NSE database from January 2013 to December 2024. Log returns are calculated from the price series to achieve stationarity. In the presence of volatility clustering, a set of different orders of GARCH models are estimated. Then, with information criteria, including AIC and BIC, the optimal model is chosen in conjunction with residual diagnostics for further validation of model performance. Estimated conditional variances from the best-fitting GARCH model become the input features to machine learning models. Four different Neural Network models were constructed with different combinations of hidden layers, and the best model was chosen for further analysis to forecast the average volatility of 2025 for the Nifty 50 index. The hybrid

GARCH-ANN framework, therefore, combines econometric modeling with machine learning techniques, offering a more adaptive and data-driven approach to volatility forecasting. This increases the accuracy of the prediction and captures the complex market dynamics more effectively than traditional models. The entire analysis is carried out using R-Studio.

4 Data Analysis & Methods

A hybrid model is proposed in this study to enhance volatility forecasting as estimated using traditional volatility estimation techniques GARCH integrated with neural networks (NN). This enables the neural network to learn from the patterns and relationships of the data and improves the accuracy of volatility prediction. Further, to develop the model by improving the forecast performance, we incorporated multiple hidden layers so the model could become deeper with a better ability to recognize complex patterns.

There are many practical benefits in this hybrid approach. It is capable of identifying major market behaviours like volatility clustering—a phenomenon that describes the persistence of high volatility over time and asymmetric market reactions to positive and negative shocks. Also, it takes into account factors such as macroeconomic conditions, geopolitical events, and others that influence the behavior of markets.

Such an approach generates insights useful for various levels of investors. Investors and portfolio managers can use the model in better forecasting market risks, optimization of asset allocation, and devising hedging strategies. Policymakers and regulators can apply its predication ability toward monitoring systemic risk, designing particular interferences, and improving stability in markets. Such a hybrid model in translating complicated, high-frequency financial data into meaningful patterns translates into more informed decisions within financial markets.

Daily returns of the Nifty 50 index have been calculated using the function dailyReturn(), which calculates the percentage change in price from 1 day to the next. It has been highlighted in returns plot that large price movements are followed by further large movements and that smaller movements tend to persist, as shown in Fig. 1. Such behavior is indeed consistent with the financial market phenomenon, where the volatility tends to be time-dependent rather than distributed randomly.

The above calculation of the daily returns for the Nifty 50 index from 2013 to 2024 yields crucial insights into the behavior of the market. The daily returns, reflect the rise and fall of the market performances, and the existence of volatility clusters affirms that financial markets are ones where high volatilities during a period mostly lead to future instability. Analysis of the volatility data shows that the distribution is not uniform but, rather, takes place in bursts, corresponding to major economic events and market shocks. For example, the huge spikes in 2020 can be attributed to the uncertainty generated by the pandemic, while the relatively stable periods, such as 2017 and 2023, are indicative of less market fluctuation. These patterns help

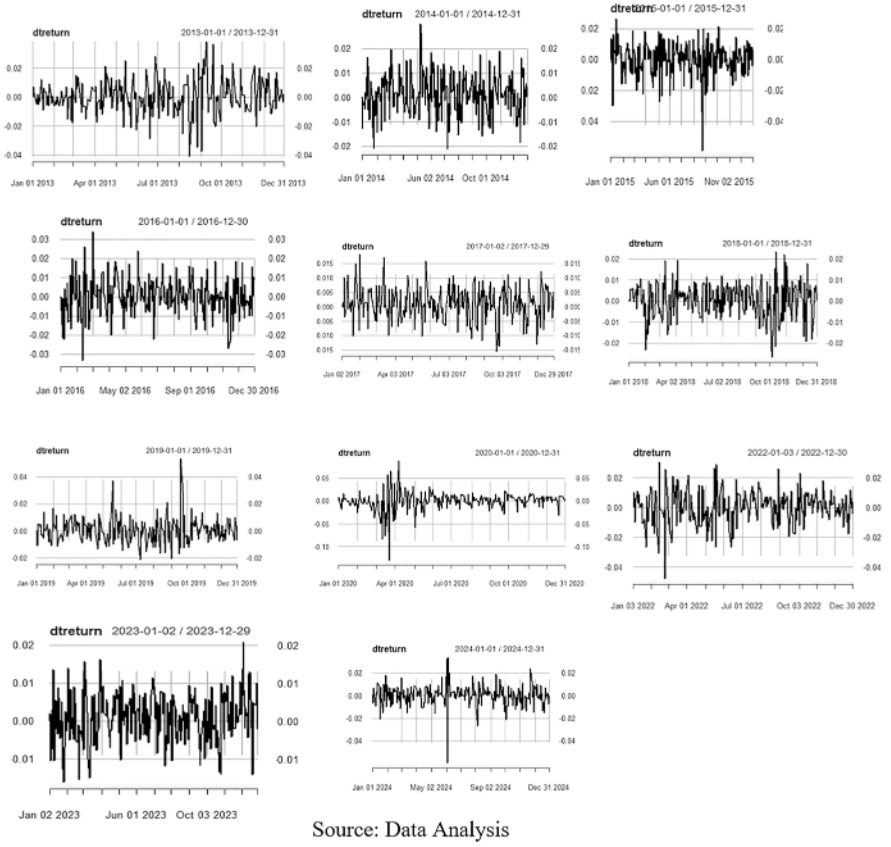


Fig. 1 Calculation of daily returns and identification of volatility clusters of Nifty 50 for the period of 2013–2024. (Source: Data Analysis)

investors and policymakers assess risk, diversify their portfolios, and develop strategies for reducing financial instability. The findings thus buttress the applicability of GARCH models in describing time-varying volatility and emphasize the importance of using efficient forecasting techniques for the proper management of financial risks.

The Box-Ljung Test and the ADF Test were performed on the returns of the Nifty 50 index from the years 2013 to 2024, as shown in Table 1, revealed the statistical behavior of market returns. The outcome of the ADF test supported the stationarity of the return series across each year. The Box-Ljung Test measures the autocorrelation in residuals. It can be found that for most of the years, the test is insignificant at a p-value >0.05; therefore, there seems to exist no strong relation in past returns, and the market follows a random pattern. However, during 2020, $p = 0.003$, and for the year 2021, $p = 0.01995$, which is significant at test levels due to the COVID-19 pandemic. This suggests that the significant influence of past movements on future returns was considerable during the period of economic disruption. Overall, the

Table 1 Results of Box Ljung test & ADF test of Nifty 50 for the period 2013–2024

	Box-Ljung test			ADF test			
Year	x-squared	p-value	Result	Dickey fuller	Lag order	P-value	Result
2013	15.782	0.2014	Insignificant	−5.4589	6	0.01	Stationary
2014	7.883	0.5755	Insignificant	−6.0454	6	0.01	Stationary
2015	8.58	0.73	Insignificant	−5.87	6	0.01	Stationary
2016	6.488	0.1699	Insignificant	−6.4867	6	0.01	Stationary
2017	6.8434	0.8678	Insignificant	−6.5933	6	0.01	Stationary
2018	25.13	0.1357	Insignificant	−6.69	6	0.01	Stationary
2019	17.42	0.134	Insignificant	−6.566	6	0.01	Stationary
2020	48.094	0.003	Significant	−4.9297	6	0.01	Stationary
2021	24.061	0.01995	Significant	−4.9297	6	0.01	Stationary
2022	3.495	0.9909	Insignificant	−4.9297	6	0.01	Stationary
2023	13.849	0.3104	Insignificant	−4.9297	6	0.01	Stationary
2024	6.5048	0.8885	Insignificant	−4.9297	6	0.01	Stationary

Source: Data Analysis

Table 2 AIC table of different orders of GARCH model—Nifty 50 index

Year	1,1	2,2	3,3	2,3	4,4	3,2
2013	−6.189889	**−6.2069**	−6.1888	−6.1956	−6.1720	−6.1966
2014	**−6.7940**	−6.7777	−6.7613	−6.77	−6.7550	−6.7695
2015	−6.3051	**−6.3382**	−6.274	−6.3321	−6.3309	−6.3294
2016	**−6.4696**	−6.4547	−6.43825	−6.4463	−6.4236	−6.44659
2017	**−7.4732**	−7.4572	−7.4411	−7.4492	−7.4258	−7.4492
2018	**−6.8824**	−6.8652	−6.8643	−6.8725	−6.8533	−6.8590
2019	**−6.7142**	−6.7026	−6.6870	−6.695	−6.6724	−6.6955
2020	−5.645590	**−5.652216**	−5.634892	−5.642829	−5.66078	−5.640586
2021	**−6.51719**	−6.501506	−6.489938	−6.49800	−6.479121	−6.49348
2022	**−6.2468**	−6.2352	−6.2207	−6.2288	−6.2061	−6.227137
2023	**−7.31197**	−7.30269	−7.2944	−7.302539	−7.2906	−7.295640
2024	**−6.7839**	−6.77195	−6.75578	−6.763817	−6.73972	−6.763817

Source: Data Analysis

empirical results support that the autocorrelation of returns of the Nifty 50 is generally weak, and thus, the time series remains stationary, which justifies the use of ARCH and GARCH models in volatility estimation.

The Akaike Information Criterion (AIC) values for the various GARCH model orders between 2013 and 2024 are shown in Table 2, which are used in finding the best model. For example, GARCH(2, 2) has consistently appeared with the lowest AIC for several years, including 2013 and 2015, suggesting that a more complex structure was required to pick up the volatility during these periods. However, in most years, the AIC of the GARCH(1, 1) model is the lowest, indicating that market volatility can generally be explained by past returns and past volatility with a simple structure. The highest AIC values across all models are shown for the year 2020,

which indicates that the uncertainty during the COVID-19 pandemic made the patterns of volatility harder to predict. The years 2017 and 2023 have the lowest AIC, suggesting a period of more stable market behavior. The best model for forecasting volatility is the GARCH(1, 1), while more complex models, such as GARCH(2, 2) and GARCH(3, 3), might be required for years of high uncertainty.

Figure 2 represents the estimated average daily volatility of the Nifty 50 index from 2013 to 2024. Taking into consideration the best GARCH model chosen based on the minimum AIC, it provides valuable information related to time-varying risk in the market and various forms of fluctuations. Results indicate that market volatility is not time-invariant but varies substantially from 1 year to another and is influenced by economic events and financial market circumstances. High-volatility periods would include 2019 and 2020 due to the COVID-19 pandemic. The periods of lower volatility would be marked by the years 2017 and 2023 as they reflect stable market conditions with minimal price shocks. Annual selection of the best-fitting GARCH model implies that in each year, a more accurate description of volatility is obtained, which indicates the use of dynamic models since changing behavior in the market is best captured thereby. This points out the importance of volatility forecasting, the need for such from investors and policymakers, and the continuous integration of the practice into the decision-making process in finance because it now provides a key component of risk management and stands as a critical input for asset allocation in financial stability planning (Table 3).

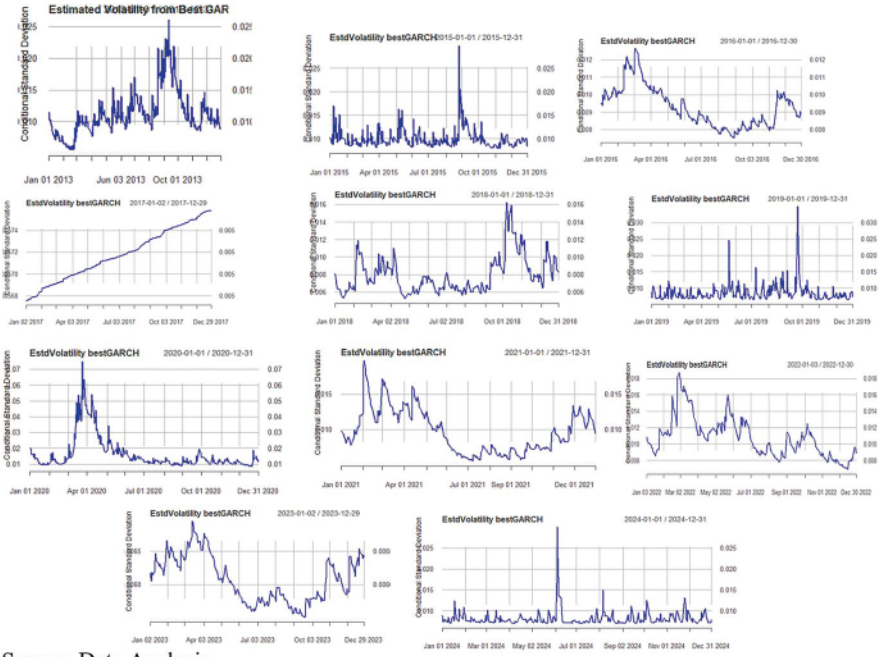


Fig. 2 Estimated volatility of Nifty 50 for best GARCH models for the period 2013–2024. (Source: Data Analysis)

Table 3 Mean estimated volatility of Nifty 50 for best GARCH models for the period 2013–2024

GARCH	Year	Average estimated volatility
Best model – 2,2	2013	0.01124
Best: model – 1,1	2014	0.0079
Best model – 2,2	2015	01008
Best model – 1,1	2016	0.00928
Best model – 1,1	2017	0.005717
Best model – 1,1	2018	0.0079
Best model – 1,1	2019	0.0859
Best model – 2,2	2020	0.01597
Best model – 1,1	2021	0.009643
Best model – 1,1	2022	0.01076
Best model – 1,1	2023	0.0060
Best model – 1,1	2024	0.008189

Source: Data Analysis

The best-fitting GARCH models of the estimated volatility of the Nifty 50 index from 2013 to 2024 indicate some volatility in market risk over the years. For most of the years, the best-fitting model was GARCH(1, 1), indicating that short-term volatility is dominated by past returns and past volatility. However, in 2013, 2015, and 2020, the GARCH(2, 2) model fits better, indicating that during those periods, market volatility was more persistent and needed a more complex model to capture its dynamics. The highest estimated volatility was found in 2019 (0.0859), which indicated high market uncertainty, while 2017 (0.0057) and 2023 (0.0060) had the lowest volatility, suggesting relatively stable market conditions. This accounts for the significance of increased volatility in 2020 as 0.0159, as the global economic disruptions caused by the COVID-19 pandemic introduced greater uncertainty to financial markets. Overall, it tends to represent that volatility levels change based on the state of macroeconomic conditions and that there are years where risk is more pronounced because of external shocks. This outcome highlights the importance of volatility forecasting and risk management for investors and policymakers since understanding market fluctuations can help make informed investment decisions and develop proper financial regulations to stabilize markets during periods of uncertainty.

The analysis of Nifty 50 daily returns from 2013 to 2024 brings out the essence of market volatility and its underlying dynamics. The augmented Dickey-Fuller test confirms that the returns series is stationary across all years, which makes it appropriate for time-series modeling. The overall results of the Box-Ljung test indicate mostly insignificant autocorrelation, mainly in the 2020 and 2021 periods, when markets were more disturbed by external events like pandemics. Based on the Akaike Information Criterion used for the selection of the best ARCH/GARCH models, the respective results show that the GARCH(1, 1) model captured more volatility in most of the years, while during periods of heightened uncertainty in the market and which were evident during 2013, 2015, and 2019, GARCH(2, 2) provided better fit. Estimated mean volatility values indicate times when the market stabilizes and times when there is increased uncertainty during such periods as in

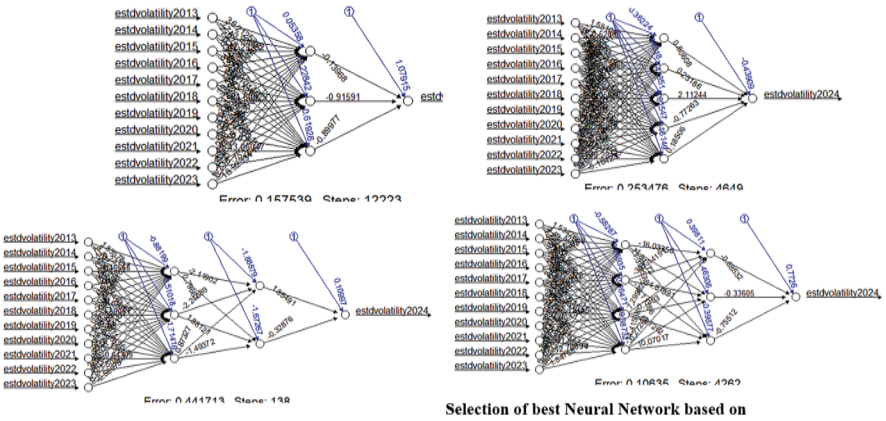


Fig. 3 Neural network model with different hidden layers for predicting Nifty 50 volatility

2017 at 0.0057 and in 2023 at 0.0060, and more so in 2019 at 0.0859 and in 2020 at 0.0159. These volatility fluctuations correlate with key economic events and, hence, enhance the clustering effect typical in financial markets.

Historical GARCH-predicted volatility for the years 2013–2024 is used in predicting the Nifty 50 for the year 2025 using neural network is analysed and the model outputs with different hidden layers as shown in Fig. 3. Four different models with distinct configurations of the hidden layer have been developed to estimate their MSE performance.

Selection of Best Neural Network Based on MSE

```
print(paste("MSE for Model 1 (Hidden: 3) =", mse1))
[1] "MSE for Model 1 (Hidden: 3) = 0.0270829342334353"
> print(paste("MSE for Model 2 (Hidden: 5) =", mse2))
[1] "MSE for Model 2 (Hidden: 5) = 0.0242232915814891"
> print(paste("MSE for Model 3 (Hidden: 3,2) =", mse3))
Source: Data Analysis
[1] "MSE for Model 3 (Hidden: 3,2) = 0.0266028615436445"
> print(paste("MSE for Model 4 (Hidden: 4,3) =", mse4))
[1] "MSE for Model 4 (Hidden: 4,3) = 0.0240782120447728"
bestmodel
[[1]]
neuralnet(formula = formula, data = traindata, hidden = c(4,
    3) linear.output = TRUE)
```

The Model Evaluation is as Follows

- **Model 1 (Hidden: 3)** → MSE = **0.02708**
- **Model 2 (Hidden: 5)** → MSE = **0.02422**
- **Model 3 (Hidden: 3,2)** → MSE = **0.02660**
- **Model 4 (Hidden: 4,3)** → MSE = **0.02408**

Of the four models, model 4(hidden:4,3) has the minimum MSE 0.02408. Hence this the best model for the volatility forecast. As a result, this model was used to predict the estimated volatility of Nifty 50 for the year 2025. The results strongly suggest than an appropriately sized multi-layer neural network improves the predictive performance.

This further underlines the importance of hidden layer tuning in neural network application for financial time series forecasting. The chosen model can be useful for risk management and investment decision-making purposes. Future research can follow hybrid approaches to combining the neural network paradigm with econometric modelling for further improved predictive performances.

```
head(dt$estdvolatility2025)
            [,1]
[1,] 0.05081245
[2,] 0.05405705
[3,] 0.03629164
[4,] 0.05401919
[5,] 0.03588979
[6,] 0.01379046
> averagevolatility2025<-mean(dt$estdvolatility2025)
> averagevolatility2025
[1] 0.05372732
```

The estimated volatility for Nifty 50 in 2025, based on the selected neural network model, is computed and shown in Fig. 4. The average predicted volatility for 2025 is 0.0537, which suggests moderate market fluctuation.

A neural network approach was adopted to forecast the estimated volatility of Nifty 50 for the year 2025. The data used was from GARCH-predicted volatility from the years 2013 to 2024. The following are the four models designed using the hidden layer configuration:

Model 1: One hidden layer with 3 neurons.
Model 2: One hidden layer with 5 neurons.
Model 3: Two hidden layers with 3 and 2 neurons.
Model 4: Two hidden layers with 4 and 3 neurons.

To assess model performance, Mean Squared Error (MSE) was measured for each of the models. The results reflected that Model 4 (Hidden Layers: 4, 3) had the lowest MSE with a value of 0.024078; therefore, this model was best suited for

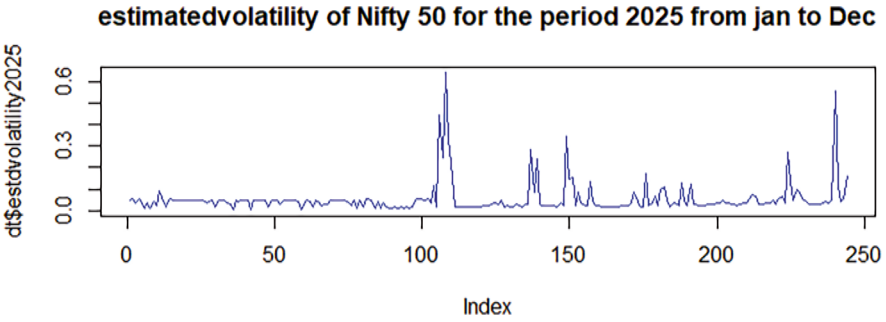


Fig. 4 Estimated volatility of Nifty 50 for the year 2025. (Source: Data Analysis)

predicting volatility. Accordingly, this model was used for forecasting the estimated volatility of Nifty 50 in 2025.

Using the best model, average volatility in 2025 was estimated to be about 0.0537. This will inform the potential market swings and assist traders, analysts, and policymakers to make informed risk management and investment decisions.

This indicates that neural networks may provide successful models for financial time series and reliable volatility forecast if well optimized. Further study on hybrid models that combine neural networks with econometric techniques might be achieved in the future to improve predictability.

5 Conclusion

The current study is based on a hybrid approach by combining GARCH models and neural networks in estimating the volatility of the Nifty 50 index for the period 2025. From the analysis of Garch, it is evident that there is a presence of volatility clusters and periods of heightened instability, particularly during economic shocks like the COVID-19 pandemic. Multiple GARCH models with various orders were constructed, and the selection of the best GARCH model in each year is based on AIC values. Building on this, the next analysis is carried out in building four different neural network models with a variation in several neurons and several hidden layers for predicting Nifty 50 volatility for 2025 by considering GARCH-predicted daily volatility as input. Among the four constructed models of ANN, the best model is ANN with two hidden layers of 4, 3 neurons with a mean squared error of 0.024078; this model is considered the most suitable prediction model. Based on this, the forecast average volatility of the Nifty 50 for 2025 is 0.0537, indicating a moderate market fluctuation. The integration of GARCH models for volatility estimation and neural networks for forecasting demonstrates the effectiveness of combining econometric and machine learning techniques in financial time series analysis. This approach enhances predictive accuracy and provides valuable insights for investors, policymakers, and risk managers. Future research could explore

hybrid models that further refine volatility predictions by incorporating additional macroeconomic and market sentiment variables.

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