

Review of Neural Network-Based Approaches for Stock Market Price and Volatility Prediction

¹Nitish Kumar, ²Dr. Dinesh Sahu

M. Tech. Scholar, Department of Computer Science and Engineering, Madhyanchal
Professional University (MPU), Bhopal, India¹

Professor, Department of Computer Science and Engineering, Madhyanchal Professional
University (MPU), Bhopal, India²

Abstract

Stock market price prediction and volatility forecasting are challenging financial forecasting problems because stock prices are generally characterized by nonlinear, noisy, non-stationary, and rapidly changing patterns. The increasing availability of historical market data, technical indicators, financial information, and alternative data has encouraged the application of neural network and deep learning techniques for extracting complex temporal relationships from financial time series. This review, entitled “Review of Neural Network-Based Approaches for Stock Market Price and Volatility Prediction,” presents a comprehensive overview of neural network methodologies applied to stock price forecasting, market trend prediction, and volatility estimation. The review examines conventional Artificial Neural Networks (ANNs) along with advanced architectures such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNNs), Bidirectional LSTM, hybrid neural networks, attention-based models, and Transformer architectures. Recent literature indicates that neural networks are increasingly being used to model nonlinear temporal dependencies and integrate heterogeneous financial information. Particular attention is given to volatility forecasting because volatility is an important indicator for financial risk assessment and portfolio management. Previous systematic research has identified challenges related to inconsistent datasets, volatility definitions, experimental settings, and difficulties in making meaningful comparisons among neural-network-based models.

Furthermore, the review discusses major challenges such as market non-stationarity, data leakage, overfitting, changing market regimes, limited interpretability, and differences in backtesting practices. Recent reviews also highlight emerging approaches involving Transformers, Graph Neural Networks, multimodal data, and hybrid architectures. The study concludes by identifying future research directions involving explainable artificial intelligence, robust cross-market validation, multimodal financial data, uncertainty-aware forecasting, and standardized evaluation frameworks. Overall, this review provides a structured foundation for researchers seeking to understand the development, advantages, limitations, and future potential of neural network-based approaches for stock price and volatility prediction.

Keywords: - Neural Network, Stock Market, Price Volatility

1. INTRODUCTION

One indicator of a nation's economic success is stock market growth. Because of the potential investment returns, accurate share market prediction is a crucial topic in the fields of commerce, mathematics, engineering, finance, and science [1]. On the other side, it gives shareholders a helping hand in making pertinent, wise decisions. Particularly, those directly involved in the stock market may avoid unpleasant surprises. In order to achieve financial stability in India, proper and acceptable speculative activity may offer significant and valuable information. Due to its greater level of volatility and uncertainty, the stock market is infamously difficult to forecast. Compared to other speculating regions, it is riskier. This is the reason why it is so difficult to get accurate predictions the share prices. To predict the stock market accurately, artificial neural networks, a soft computing technology, can be used. Neural networks offer a variety of capabilities as a tool for data analysis and a comparatively effective implementation approach in relation to computation speed and memory usage. An ANN model reveals non-linear and complex correlations without putting certain assumptions in place about sample distribution, and it is capable of recognizing new samples even though they weren't part of the training set [2, 3]. Because of their distinctive characteristics, artificial neural networks hold great promise for use in prediction problems. Since ANN are general function approximations, they may determine how the inputs and outputs of an arrangement are connected, even if the relationship appears to be exceedingly complicated.

- Multilayered Perceptron Neural Networks have been shown to be able to approximate any complicated continuous function, it enables them to receive training on any intricate relationship between system input and production. This characteristic of ANNs is referred to as generic function approximation.
- Even if fresh samples are not in the training set, ANN can nevertheless recognize them. This is regarded as a neural network's capacity for generalization.

The main uses of ANN also known as artificial neural networks are pattern recognition, classification, and differentiation from the vast amount of available data. Share market forecasting has long been a popular subject of study [4, 5]. The “Efficient Market Hypothesis” and the “Random Walk Hypothesis” are two of the most prevalent ideas. According to the Random Walk Hypothesis, stock prices are determined independently of previous prices. According to the Efficient Market Hypothesis, prices are fully and instantly changed as soon as new information becomes available, and the market accurately reflects all freely available information [6]. If this is the case, then there should be no value in making predictions because the market will respond and make up for any decisions made based on the information available.

2. RELATED WORK

Y. Huang et al. [1], “Enhancing stock price forecasting with a modular deep learning framework incorporating plug-and-play transformer variants,”. The study proposes a modular RevIN-CNN-Transformer-BiLSTM framework for stock-price forecasting. The architecture combines local feature extraction with long-range temporal modeling and is designed to

accommodate different Transformer variants. The authors report improvements in forecasting error across several stocks, including AAPL, MSFT, 600519, and HSBC.

P. K. Sahu et al. [2], “A novel hybrid deep learning framework with volatility-weighted loss for high-fidelity stock price prediction,”. The work develops a Hybrid Temporal Feature Integration Network (HTFIN) that combines positional encoding, Transformer blocks, CNN, LSTM, and GRU architectures. The study uses stock-market data and technical indicators such as opening price, closing price, volume, and volatility measures to model complex short- and long-term dependencies in financial time series.

S. Agal et al. [3], “A hybrid deep learning framework for volatility prediction in financial markets,”. The study introduces FinAnalyzeNet, which integrates Temporal Convolutional Networks (TCN), Bidirectional LSTM, and multi-head attention mechanisms for financial volatility prediction. The framework was evaluated over 23 years of data across multiple asset classes, including equity indices, individual stocks, currencies, and commodities. The study reports improved RMSE and directional accuracy compared with several benchmark models, particularly during high-volatility and transitional market periods.

G. Taneva-Angelova et al. [4], “Deep Learning and Transformer Architectures for Volatility Forecasting: Evidence from U.S. Equity Indices,”. The authors compare LSTM, CNN-LSTM, PatchTST-lite, and Vanilla Transformer models with traditional HAR-RV, ARIMA, and GARCH approaches for forecasting realized volatility of the S&P 500, NASDAQ 100, and Dow Jones Industrial Average. The study evaluates different forecasting horizons using QLIKE, RMSE, MAE, and Diebold–Mariano tests.

M. Vo et al. [5], “Stock Market Volatility Forecasting: Exploring the Power of Deep Learning,”. This study compares TiDE, LSTM, DeepAR, TCN, and Transformer architectures with an extended HAR model using more than 22 years of high-frequency data from the S&P 500, DJIA, and Nasdaq. The research also investigates macroeconomic variables such as DXY, VIX, US10Y, and US1M. The findings indicate that the effectiveness of deep learning models depends on the availability of exogenous variables and forecasting horizon.

Shravan Raviraj et al. [6], stock exchanges essentially constitute the major stock exchanges in India through two stock exchanges, the BSE and the NSE. Experts and financial investors analyze various factors and try to predict the stock price models of these exchanges. Valuing stocks is undoubtedly an extremely complex task as it is unconventional in nature. Despite being deluged with data, studies often fail to make accurate predictions with optimal accuracy. Recent advances in the development of critical learning have demonstrated its value as a tool to evaluate the accuracy of hypotheses. The proposed critical learning-based hypothesis calculation uses intermittent brain tissue, long-term instantaneous memory, and gated repeated units of online data over a long period of time. As a result of the calculation, the model is now able to predict up to 5 days in advance. To select the critical experience, the impact of the introduction on the inventory of various companies is investigated.

J. J. Duarte et al. [7], Market participants use a wide range of information strategies before deciding to invest in stocks or other venture funds. Financial investors constantly follow the news to gather information that can help them choose their strategy. In this review, we

examine how public messages and recorded prices can be combined to predict and prevent financial misfortunes on the Brazilian Stock Exchange. For our analysis, we study a wide range of 64 securities covering different sectors of the Brazilian economy. Our analysis explores traditional buy-and-hold and standard move strategies down to a few starters organized using 11 computer-based data algorithms. We look at average, daily and monthly time periods for both diversification and maturity periods. This approach allowed us to analyze the evolution of data that is important for investor decision-making and to determine how long the data will remain relevant to the market. We found significant strength between news movements and stock price changes in Brazil, also suggesting an overlap in short-term trading. This study shows that it is possible to predict price drops considering a large amount of data in Portuguese and that text mining-based methods can outperform traditional methods in problem selection.

Andrea Bucci et al. [8], accurately determining multivariate volatility plays a key role for the financial industry. The Cholesky geometric brain network presented here offers a double advantage in this respect: on the one hand, the use of Cholesky damping guarantees a positive unique number. On the other hand, running an artificial brain network can determine nonlinear relationships without specific distribution assumptions. Tests outside the field have shown that the artificial brain network cannot clearly win against competing models. However, compared to existing econometric models, long-term memory-based cognitive networks such as nonlinear autoregressive model processes with exogenous inputs and long short-term memory show improved prediction accuracy.

Sarat Chandra Nayak et al. [9], extreme Learning Machine (ELM) considers faster learning and preferential speculative execution than traditional bias-based learning. However, irregular selection and the need for additional secret neurons can lead to non-ideal weights and slopes being considered, negatively impacting the usability of the network. Moreover, determining the ideal number of hidden nodes in the network typically requires extensive human intervention, which can lead to suboptimal situations. In this unique case, Composite Response Optimization (CRO) is a metaheuristic worldview that has achieved scalable results in a vast number of application fields. This is explained by its faster assembly capabilities, which require fewer customizable bounds. This work advances a learning structure that combines the advantages of ELM and CRO, called Extreme Learning with Composite Response Optimization (ELCRO). ELCRO simultaneously improves the weights and predisposition vectors, as well as the number of stored neurons in a single-layer feedforward brain network, without compromising the prediction accuracy. We evaluate its performance by predicting daily volatility and closing cost for the BSE dataset. Furthermore, its performance is compared with three other similarly developed models (ELM based on molecular swarm evolution, genetic algorithm, and gradient descent), and we find that the proposed algorithm outperforms. We then perform Wilcoxon labeling and Diebold-Mariano test to confirm the statistical significance of the proposed model. Therefore, this model can be used as a promising financial evaluation tool.

Andres Vidal et al. [10], forecasting the volatility of different types of funds is one of the more mathematically complex tasks in time series forecasting, mainly due to their noisy, non-stationary and heteroscedastic structure. On the other hand, gold is a particularly important commodity to support and enhance investment portfolios, so forecasting the future volatility of this asset is crucial. By combining two deep learning approaches, the goal of this paper is to significantly improve gold volatility forecasting. A LSTM is added to a convolutional brain system (specifically, a pre-built VGG16 system). It is important to note that these hybrid architectures have never been used for time series forecasting, so they are a completely new way to solve such problems. The CNN-LSTM mixture model is able to incorporate images as data, providing a wide range of data related to both static and dynamic characteristics of the series. In parallel, different lags in the productivity of the series are given as input, allowing it to learn from the time structure. When comparing this mixture model with GARCH and LSTM models, the results show significant improvements: the MSE is reduced by 37% compared to the traditional GARCH model and 18% compared to the LSTM model. Finally, the model certainty model (MCS) shows a significant improvement in the predictions of the mixture model. The central importance of this study is the use of different types of designs suitable for handling different data sources in any time series forecasting task.

3. NEURAL NETWORK

The MP model, a mathematical representation of the neural network, was developed in 1943 by W. Pitts and W. S. McCulloch. A mathematical model called an artificial neural network that replicates how the human brain learns and makes decisions. Networks of synthetic neurons called ANNs work together to solve certain problems. A neuron is the essential unit of a neurological system like the brain. Any neuron operates by receiving impulses from other neurons during these connections, known as synapses. An arrangement pertaining to such signals will take effect when the neuron fires, which implies transfer a signal to other neurons associated to it, when an ensured threshold or activation degree is exceptionally high. Every neuron has a soma, which is its physical structure. The cell nucleus, a number of biochemical components and other elements that support current motion are all included in this soma. Dendrites encircle the soma, and different neurons are linked to one another by these dendrites. The purpose of these dendrites is to receive messages from other neurons. Every time a neuron fires, it produces an electrical pulse. The aforementioned pulse begins at the base, or hillock, of an extensive cellular growth known as an axon. An axon eventually splits into a number of button-like stubs.

Artificial neural networks are based on the biological neural network seen in the human brain. While a non-natural neuron disperses information or data over a network and retains it as weighted interconnections, a biological neuron retains knowledge in a memory bank.

4. METHODOLOGY

There are several advantages to artificial neural networks. The first is the "capability of learning," which refers to the system's ability to learn from examples and the potential for generalization—that is, to produce an output that is adequate for previously hidden input data, which is essential for forecasting tasks like currency exchange rates, weather, stock

prices, and medical research findings, among other things. The input sequence contains missing or low-quality data, which causes the network to continuously sustain [122]. The non-linear property of neural networks is another valuable attribute. Since neural networks are currently a very useful tool in many fields of science and industry, understanding their architecture, methods of use, and functioning is unquestionably beneficial. Neural networks also have the capacity to extract definition from complicated or ambiguous data. This may be used to detect directions and infer patterns that are extremely difficult for computers and people to discover. Additionally, ANNs are capable of processing large amounts of data at once. Fault tolerance is one more benefit of neural networks.

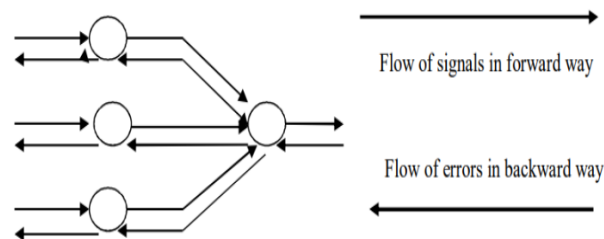


Fig. 1: ML ANN

The main advantage of a neural network is that it may be adjusted to compensate for abnormalities in the input variables and their latent learning potential. An ANN's parallel structure, which is advantageous for fast calculation and response times, makes it suitable for real-time systems.

Stock Market Price

Stock market price refers to the current or historical value at which shares of a publicly traded company are bought and sold in the financial market. The price changes continuously during market trading hours based on demand and supply, company performance, economic conditions, investor sentiment, market trends, and domestic and global events.

For machine-learning-based stock price forecasting, commonly used historical variables include:

- **Open Price** – price at the beginning of the trading session.
- **High Price** – highest price reached during the session.
- **Low Price** – lowest price reached during the session.
- **Close Price** – final trading price of the session.
- **Trading Volume** – number of shares traded.
- **Adjusted Close** – closing price adjusted for events such as dividends and stock splits.

In your research on “Review of Neural Network-Based Approaches for Stock Market Price and Volatility Prediction,” the Closing Price can be selected as the primary prediction target, while Open, High, Low, Volume, technical indicators, and historical prices can be used as input features. Neural-network models such as ANN, RNN, LSTM, GRU, Bi-LSTM, CNN-LSTM, and Transformer can then be investigated for forecasting future stock prices.

5. CONCLUSION

The review of Neural Network-Based Approaches for Stock Market Price and Volatility Prediction shows that artificial intelligence and deep learning techniques have become important tools for analyzing complex financial time-series data. Stock market prices are

influenced by nonlinear and rapidly changing factors, making accurate forecasting a challenging task for conventional statistical models. Neural network approaches can learn complex temporal relationships from historical market data and therefore provide a useful framework for stock price and volatility forecasting.

The reviewed studies indicate that different neural architectures have different capabilities. ANN models are useful for learning nonlinear relationships, while RNN, LSTM, and GRU models are particularly suitable for sequential stock-market data. Hybrid approaches such as CNN-LSTM and CNN-BiLSTM can combine local feature extraction with temporal learning, whereas Attention and Transformer-based models provide mechanisms for capturing long-range dependencies in financial time series. Recent research also demonstrates the use of hybrid architectures involving TCN, Transformer, GRU, and attention mechanisms for volatility forecasting.

The performance of these models is generally evaluated using measures such as MAE, MSE, RMSE, MAPE, R^2 , and directional accuracy. However, direct comparison among published studies remains difficult because researchers use different datasets, prediction horizons, input variables, preprocessing techniques, and evaluation procedures. In addition, challenges such as market non-stationarity, overfitting, data leakage, changing market regimes, and model interpretability remain important issues.

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