



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71454

www.ijraset.com

Call: © 08813907089 E-mail ID: ijraset@gmail.com



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538

Volume 13 Issue V May 2025- Available at www.ijraset.com

Predicting the Trends in Stock Movement Based on Neural Networks

Yukti Dewangan¹, Priyanka Bande²

¹Research Scholar, ²Assistant Professor, Department of Computer Science and Engineering, Shri Rawatpura Sarkar University, Raipur, Chhattisgarh

Abstract: Forecasting results for stock markets exhibit variabilities in forecasting accuracy as the tenure of prediction is varied. Typically stocks are predicted for long, short as well as mid term tenures based on the tenure of prediction. While longer tenures have relatively much larger data to be trained as training data, divergences are also potentially large as the forecasting period may render higher randomness due to unprecedented events. The short term forecasting is relatively less prone to unprecedented events due to the tenure of forecasting. However, the lesser amount of training data may result in less accurate pattern recognition. A common ground is typically found in terms of mid term forecasting. This paper presents an experimental evaluation of all three formats of forecasting based on the training, testing split. The deep neural network model is used for the forecasting purpose and the forecasting MAPE and accuracy has been tabulated for a multitude of stocks. The comparative values of the MAPE for prediction have been tabulated to estimate prediction performance of the proposed approach.

Keywords: Stock Market Forecasting, Neural Networks, Variable Forecasting Tenures, Forecasting MAPE, Forecasting Accuracy.

I. INTRODUCTION

Stock movement forecasting is a crucial aspect of financial markets and investment decision-making. Several factors contribute to the necessity and importance of predicting stock movements. Typically, financial markets are inherently volatile, influenced by a myriad of factors such as economic indicators, geopolitical events, and market sentiment [1]. Forecasting stock movements helps investors and traders navigate through this uncertainty, allowing them to make informed decisions and mitigate potential risks. Accurate stock movement forecasts are essential for effective risk management. Investors need to anticipate potential price fluctuations to implement strategies that protect their portfolios from adverse market conditions [2].

By understanding the potential risks, investors can make better-informed decisions about portfolio diversification and asset allocation. Investors rely on stock forecasts to make strategic investment decisions [3]. Whether it's choosing when to buy or sell a stock, enter or exit a market, or adjust portfolio holdings, accurate predictions enable investors to capitalize on opportunities and avoid losses. Timely and precise information is critical for optimizing investment strategies [4]. Forecasting stock movements aids in optimizing investment portfolios. By identifying trends and correlations, investors can adjust their portfolio mix to achieve a balance between risk and return.

This optimization process involves considering factors such as asset class performance, sectoral trends, and the overall economic outlook. In today's digital age, algorithmic trading and automated systems heavily rely on stock movement forecasts [5]. These systems use historical data, technical indicators, and machine learning algorithms to predict future price movements. Investors and institutions use these automated tools to execute trades swiftly and efficiently. Typically, stock market forecasting can be categories based on the tenure of training and testing intervals [6]. Typically, the intervals defined are:

- 1) Short
- 2) Mid
- 3) Long

Sometime ultra short and ultra long term forecasts are also analyzed, though they are under the sub domain of short and ling term forecasts [7]

II. INCORPORATING GLOBAL FACTORS

To incorporate global influencing factors, opinion mining and sentiment analysis has been extensively employed. Opinion mining, also known as sentiment analysis, involves analyzing public opinions, attitudes, and emotions expressed in textual data [8].



International Journal for Research in Applied Science & Engineering Technology (IJRASET)

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538

Volume 13 Issue V May 2025- Available at www.ijraset.com

Applying opinion mining to stock market forecasting involves extracting sentiment from financial news, social media, and other sources to gauge investor sentiment and potential market trends. The first step in opinion mining for stock market forecasting is the collection of relevant textual data [9]. This data can include financial news articles, social media posts, analyst reports, and other sources. Text processing techniques, such as natural language processing (NLP), are then applied to preprocess and clean the data for sentiment analysis [10].

Opinion mining employs various sentiment analysis techniques to determine the sentiment expressed in the collected texts. These techniques may include rule-based methods, machine learning algorithms, and deep learning models [11]. The goal is to classify the sentiment as positive, negative, or neutral, providing insights into how the market participants perceive certain stocks or the overall market. Sentiment analysis generates sentiment scores that quantify the degree of positivity or negativity in the expressed opinions. These scores can be aggregated over time to create sentiment time series data. High positive sentiment may indicate bullish market expectations, while consistently negative sentiment could signal bearish sentiments among investors. However, the authenticity of the opinion mined data from social media can not be authenticated in all cases. Moreover, bias in opinion may also lead to incorrect pattern recognition [12].

III. PROPOSED MODEL

The methodology of the proposed approach can be thought of as an amalgamation of data pre-processing, feature selection and training using deep neural networks. Each of the sections have their own importance. The methodology is presented in each of the following heads which comprise the algorithm. The variation of the tenure of training and testing has been leveraged to forecast long, short and mid term movement [13].

1) Data Pre-Processing: The DWT:

Discrete Wavelet Transform (DWT) based filtering has gained attention in recent years as a powerful tool for signal processing, and it has found applications in stock market forecasting [14]. DWT is a mathematical tool that decomposes a time-series signal into different frequency components or scales. In the context of stock market data, this means breaking down the original time series into various frequency bands or levels. High-frequency components may capture short-term fluctuations, while low-frequency components represent longer-term trends [15]. DWT-based filtering allows for the separation of signal and noise components. By decomposing the stock market time series into different scales, it becomes possible to filter out high-frequency noise, which may be attributed to market volatility or irregularities [16]. This noise reduction helps in extracting meaningful features from the data that are more indicative of underlying market trends. The multi-resolution property of DWT enables the identification of trend and cyclical patterns in stock prices. Improved signal quality allows for more accurate modeling and prediction of future stock prices [17]. DWT-based filtering not only aids in forecasting stock prices but also contributes to risk management strategies. By identifying trends and patterns at different time scales, investors can make more informed decisions about when to enter or exit the market. Understanding the underlying structure of the data helps in managing investment risks effectively [18]. The DWT can be mathematically expressed as [19]:

$$F(x,y) \xrightarrow[DWT2]{} C_{A}, C_{D}, C_{H}, C_{V} \quad (1)$$

Here,

 C_A represents the approximate co-efficient values.

 C_D represents the detailed co-efficient values.

 C_V represents the vertical co-efficient values.

 C_H represents the horizontal co-efficient values.

DWT2represents the discrete wavelet transform on the actual data.

The idea is to keep the C_A values while removing the C_D values so that the data can be filtered. The filtered data is then applied to the deep neural network model.

2) Moving Window:

To sample the recent trends in the data, a two way moving filter based windowing has been employed in this work which captures the recent (l-m) samples of the data. This is fed as an additional sliding input to the training vector [20]:

$$\frac{n}{2} \le k \le n(2)$$

Here.



International Journal for Research in Applied Science & Engineering Technology (IJRASET)

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538

Volume 13 Issue V May 2025- Available at www.ijraset.com

n is the number of samples for forecasting.

k is the length of the sliding window.

We also introduce an additional parameter, r_k , in the range $k \in [\frac{n}{2}, n]$, such that,

$$r_k = \frac{\partial y(n,k)}{\partial n} \ \forall k \in [\frac{n}{2}, n](3)$$

Here

 r_k signifies the rate of change of the target in the sliding interval of $[\frac{n}{2}, n]$.

3) Deep Neural Network Model for Pattern Recognition:

Several approaches have been explored to forecast stock trends accurately but one of the most effective techniques happens to be the deep neural network model [21]. The algorithm proposed in this approach aims to reduce the swing or overshoot of the training algorithm while attaining convergence.

4) Algorithm

The algorithm of the proposed approach is presented subsequently:

Step. 1 Divide the data for training and testing

Step.2 Apply DWT to filter data by keeping the C_A values while removing the C_D values

Step.3 Apply dual averaging window of (l-m) and samples and $\frac{\partial y(n,k)}{\partial n} \forall k \in$.

Step.4 To train the network, employ the following training rule:

$$v_a \partial w = m v_a \partial w + (1 - m) \partial w \tag{4}$$

Here

 v_a represents the learning velocity along 'a'.

m represents the momentum factor

w represents the weights.

 ∂w represents the differential weights

Step.5If (MSE is stable for multiple iterations)

Stop training process

else if (exhausted max. iterations)

Stop training process

else

Feedback the errors of prediction and adjust weights accordingly.

Step.6: Vary the training testing tenure for prediction to estimate variable period prediction.

Step.8 Compute performance metrics.

The experimental results are presented subsequently.

IV. EXPERIMENTAL RESULTS

The data collected is from Yahoo Finance for Tesla stocks. The experimental results have been presented in this section with variations in the forecasting samples so as to incorporate long, mid and short term forecasting. The Tesla stocks over a ten year period has been used for evaluating the performance of the proposed algorithm. A similar approach can be employed for all the other stocks.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538

Volume 13 Issue V May 2025- Available at www.ijraset.com

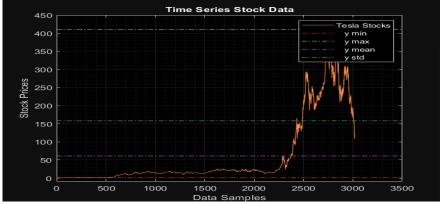


Fig.1Statistical Features of Raw Data

Figure 1 depicts the variability of the raw data.

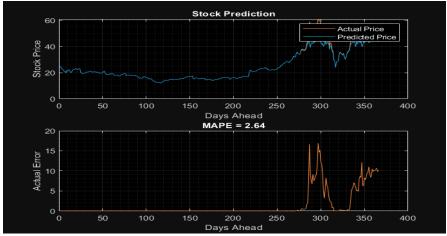


Fig.2 Long Term Forecast

Figure 2 presents the MAPE results for the Tesla stocks over a period of 1 year. It can be observed that the MAPE is 2.64%.

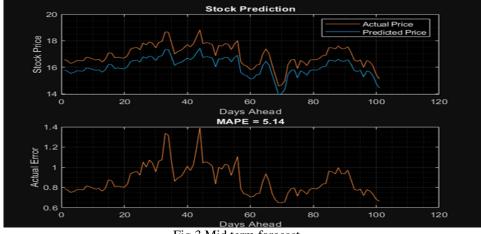


Fig.3 Mid term forecast

Figure 3 presents a similar prediction for a tenure of 100 days renders the perdition MAPE of 5.14%

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

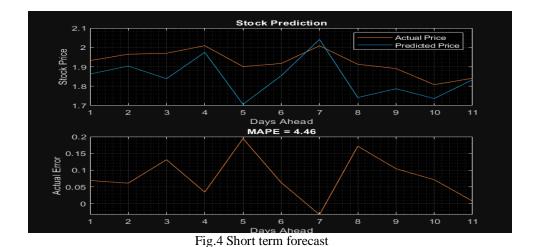


Figure 4 presents the prediction for a tenure of 10 days (short term) renders the perdition MAPE of 4.46%

Table I. Perdition MAPE values obtained.

S.No.	Duration	Days Ahead	MAPE	Accuracy%
1	Long Term	365	264 %	97.36%
2	Mid Term	100	5.14 %	94.86%
3	Short Term	10	4.46 %	95.54%
4.	Mean MAPE		3%	97%

The comparative analysis of the MAPE for all the 3 forecasting models indicate the following:

- 1) The long term forecast yields the minimum MAPE thereby rendering maximum accuracy of forecasting, for the Tesla stocks.
- 2) The mid term forecast attains the maximum MAPE thereby rendering the minimum accuracy for the Tesla stocks.
- 3) Short term forecasting attains slightly lower MAPE than mid-term forecasting for the Tesla stocks.

Further, a comparison with existing work for multiple datasets has been presented next:

Table II.
Comparison with Previous Work

S. No.	Stock	MAPE (%)	
1.	Amazon	1.11	
2.	Apple	0.98	
3.	Google	1.08	
4.	Microsoft	0.91	
5.	Tesla	1.24	
Average MAPE (Proposed Approach)		1.064 (average)	
MAPE Subakkar et al.), [22]		14	
MAPE (Li et al.) [23]		0.6462, 1.4805 and 1.3851 for different datasets	
		respectively.	

It can be observed that the proposed work attains lesser prediction error compared to exiting research in the domain.

V. CONCLUSION

This paper presents a DWT-Neural Network based approach for forecasting stock trends over a varied interval period. The categorization of the forecasting has been done based on the number of samples ahead in forecasting. A 365, 100 and 10 day split has been chosen for the long, mid and short term forecasts respectively.



International Journal for Research in Applied Science & Engineering Technology (IJRASET)

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538

Volume 13 Issue V May 2025- Available at www.ijraset.com

An illustration analysis has been made for the Tesla stocks over the variable forecasting period. The prediction MAPE analysis shows that the accuracy achieved is 97.36%, 94.86% and 95.54% for long, mid and short term forecasts respectively, with a mean MAPE of 3% across all intervals of forecast. The model also attains an MAPE of around 3% across various stocks for benchmark S&P 500 dataset obtained from Yahoo Finance. Low values of the MAPE ascertains accurate prediction of the stock trends.

REFERENCES

- [1] Y. Soun, J. Yoo, M. Cho, J. Jeon and U. Kang, "Accurate Stock Movement Prediction with Self-supervised Learning from Sparse Noisy Tweets," 2022 IEEE International Conference on Big Data (Big Data), Osaka, Japan, 2022, pp. 1691-1700.
- [2] F. Juairiah, M. Mahatabe, H. B. Jamal, A. Shiddika, T. Rouf Shawon and N. Chandra Mandal, "Stock Price Prediction: A Time Series Analysis," 2022 25th International Conference on Computer and Information Technology (ICCIT), IEEE, 2022, pp. 153-158
- [3] Jithin Eapen; Doina Bein; Abhishek Verma, "Novel Deep Learning Model with CNN and Bi-Directional LSTM for Improved Stock Market Index Prediction", 2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC), IEEE 2019 pp. 0264-0270.
- [4] Min Wen; Ping Li; Lingfei Zhang; Yan Chen, "Stock Market Trend Prediction Using High-Order Information of Time Series", IEEE Access 2019, Volume 7, pp: 28299 28308.
- [5] Y Guo, S Han, C Shen, Y Li, X Yin, Y Bai, "An adaptive SVR for high-frequency stock price forecasting", Volume-6, IEEE Access 2018, pp. 11397 11404.
- [6] MS Raimundo, J Okamoto, "SVR-wavelet adaptive model for forecasting financial time series", 2018 International Conference on Information and Computer Technologies (ICICT), IEEE 2018, pp. 111-114.
- [7] Y Baek, HY Kim, "ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module" Journal of Expert System and Applications, Elsevier 2018, Volule-113, pp: 457-480.
- [8] S Selvin, R Vinayakumar, E. A Gopalakrishnan; Vijay Krishna Menon; K. P. Soman, "Stock price prediction using LSTM, RNN and CNN-sliding window model", 2017 International Conference on Advances in Computing Communications and Informatics (ICACCI), IEEE 2017, pp. 1643-1647.
- [9] Z Zhao, R Rao, S Tu, J Shi, "Time-weighted LSTM model with redefined labeling for stock trend prediction", 2017 IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI), pp. 1210-1217.
- [10] DMQ Nelson, ACM Pereira, Renato A. de Oliveira, "Stock market's price movement prediction with LSTM neural networks", 2017 International Joint Conference on Neural Networks (IJCNN), IEEE 2017, pp. 1419-1426
- [11] M Billah, S Waheed, A Hanifa, "Stock market prediction using an improved training algorithm of neural network", 2016 2nd International Conference on Electrical, Computer & Telecommunication Engineering (ICECTE), IEEE 2016, pp. 1-4,
- [12] HJ Sadaei, R Enayatifar, MH Lee, M Mahmud, "A hybrid model based on differential fuzzy logic relationships and imperialist competitive algorithm for stock market forecasting", Journal of Applied Soft Computing, Elsevier 2016, Volume 40, pp. 132-149.
- [13] GRM Lincy, CJ John, "A multiple fuzzy inference systems framework for daily stock trading with application to NASDAQ stock exchange", Journal of Expert Systems with Applications, Volume-44, Issue-C, ACM 2016.
- [14] YE Cakra, BD Trisedya, "Stock price prediction using linear regression based on sentiment analysis", 2015 International Conference on Advanced Computer Science and Information Systems (ICACSIS), IEEE 2015, pp. 147-154.
- [15] GV Attigeri, MP MM, RM Pai, "Stock market prediction: A big data approach", TENCON 2015 2015 IEEE Region 10 Conference", pp. 1-5.
- [16] J Patel, S Shah, P Thakkar, K Kotecha, "Predicting stock market index using fusion of machine learning techniques", Journal of Expert Systems with Applications, Elsevier 2015, Volume 42, Issue 4, pp. 2162-2172.
- [17] M Xu, Y Lan, D Jiang, "Unsupervised Learning Part-Based Representation for Stocks Market Prediction", 2015 8th International Symposium on Computational Intelligence and Design (ISCID)", IEEE 2015, pp. 63-66,
- [18] KN Devi, VM Bhaskaran, "Cuckoo optimized SVM for stock market prediction", 2015 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS), IEEE 2015, , pp: 1-5
- [19] A Yoshihara, K Fujikawa, K Seki, K Uehara, "Predicting stock market trends by recurrent deep neural networks", Pacific Rim International Conference on Artificial Intelligence PRICAI 2014: PRICAI 2014: Trends in Artificial Intelligence, Lecture Notes in Computer Science, Volume-8862, Springer 2014, pp 750-760
- [20] Alexander Porshnev; Ilya Redkin; Alexey Shevchenko, "Machine Learning in Prediction of Stock Market Indicators Based on Historical Data and Data from Twitter Sentiment Analysis", 13th International Conference on Data Mining Workshops, IEEE 2013, pp. 440-444.
- [21] Chang Sim Vui; Gan Kim Soon; Chin Kim On; Rayner Alfred; Patricia Anthony, "A review of stock market prediction with Artificial neural network (ANN)", 2013 IEEE International Conference on Control System, Computing and Engineering, IEEE 2013, pp. 477-482.
- [22] Y. Li, L. Chen, C. Sun, G. Liu, C. Chen and Y. Zhang, "Accurate Stock Price Forecasting Based on Deep Learning and Hierarchical Frequency Decomposition," in IEEE Access, vol. 12, pp. 49878-49894, 2024.
- [23] A Subakkar, S Graceline Jasmine, L Jani Anbarasi, J Ganesh, CM Yuktha, "An Analysis on Tesla's Stock Price Forecasting Using ARIMA Model", Proceedings of the International Conference on Cognitive and Intelligent Computing, Springer, 2023, pp 83–89.









45.98



IMPACT FACTOR: 7.129



IMPACT FACTOR: 7.429



INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call: 08813907089 🕓 (24*7 Support on Whatsapp)