IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, July 2026
Impact Factor: 8.2

Stock Market Forecasting: A Comparative Analysis of Machine Learning and Deep Learning Methods

Vidushi and Dr. Priyanka Rani
[1]M.Tech Scholar, Ganga Institute of Technology & Management, Jhajjar, India
[2]Assistant Professor, Ganga Institute of Technology & Management, Jhajjar, India

Abstract: *Stock market forecasting is a challenging task due to the highly dynamic, nonlinear, and volatile nature of finan-cial markets. This research presents a comparative analysis of Machine Learning (ML) and Deep Learning (DL) techniques for stock price prediction. The study focuses on data preprocessing, feature engineering, model selection, and performance evaluation using historical market data. Various algorithms are analyzed based on accuracy, robustness, and computational efficiency. The findings highlight the strengths and limitations of each approach, providing insights into selecting appropriate models for real-world financial applications.*

Keywords: Stock Market Prediction, Machine Learning, Deep Learning, Time Series Analysis, LSTM, Regression, Forecasting Accuracy

I. INTRODUCTION

The stock market is a critical component of the global finan-cial ecosystem, significantly influencing economic growth, in-vestment strategies, and capital allocation. Accurate prediction of stock prices is essential for investors, financial institutions, and policymakers to minimize risk and maximize returns. However, stock market forecasting remains a challenging task due to its nonlinear, dynamic, and stochastic nature, where prices are influenced by multiple factors such as economic indicators, investor sentiment, geopolitical events, and market volatility [1]. Traditionally, stock price prediction relied on statistical and econometric models such as regression analysis and Autoregressive Integrated Moving Average (ARIMA). While these models provide a mathematical foundation, they often fail to capture the complex patterns and nonlinear relationships inherent in financial time-series data. This limi-tation has led to the growing adoption of Machine Learning (ML) techniques, which enable systems to learn patterns from historical data and make data-driven predictions without explicit programming [2] . Machine Learning approaches, including Support Vector Machines (SVM), Decision Trees, Random Forest, and Artificial Neural Networks (ANN), have demonstrated improved predictive capabilities over traditional methods. These models are particularly effective in han-dling structured datasets and identifying hidden relationships among financial variables. However, their performance may be limited when dealing with long-term dependencies and highly complex temporal patterns [3]. With advancements in computational power and the availability of large-scale financial data, Deep Learning (DL) techniques have emerged as a powerful alternative. Models such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks are specifically designed for sequential data and have shown superior performance in capturing temporal dependen-cies in stock price movements . Deep Learning models can automatically extract high-level features, reducing the need for manual feature engineering [4]. Despite these advancements, predicting stock markets remains inherently difficult. The Efficient Market Hypothesis (EMH) suggests that stock prices reflect all available information, making consistent prediction and excess returns challenging . Additionally, issues such as data noise, overfitting, model interpretability, and dependency on large datasets continue to limit the effectiveness of both ML and DL approaches [5]. Therefore, a comprehensive comparative analysis of Machine Learning and Deep Learning techniques is necessary to understand their strengths, limita-tions, and real-world applicability. This study aims to evaluate various models based on prediction accuracy, computational efficiency, and robustness, providing insights into selecting suitable approaches for stock market forecasting [6].

II. LITERATURE REVIEW

Stock market forecasting has attracted significant attention from researchers due to its complex, nonlinear, and highly volatile nature. Over the years, various approaches ranging from traditional statistical methods to advanced Machine Learning (ML) and Deep Learning (DL) techniques have been explored [7]. Early research primarily focused on statistical and econometric models such as Autoregressive Integrated Moving Average (ARIMA) and linear regression. However, these models often failed to capture nonlinear relationships and dynamic market behavior. As a result, Machine Learn-ing techniques gained popularity for their ability to model complex patterns using historical data [8]. Several studies have explored the effectiveness of ML algorithms such as Support Vector Machines (SVM), Decision Trees, Random Forest, and Artificial Neural Networks (ANN). These methods demonstrated improved predictive performance compared to traditional models, particularly in structured datasets. Research indicates that neural network-based models, especially Multi-Layer Perceptrons, often outperform other ML techniques in stock prediction tasks due to their capability to model non-linear relationships [9]. With advancements in computational power and data availability, Deep Learning techniques have emerged as powerful tools for financial forecasting. Models such as Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have been widely applied to stock market prediction. Among these, LSTM models are particularly effec-tive in capturing temporal dependencies and long-term patterns in financial time-series data. Studies show that LSTM-based models often outperform traditional ML approaches in terms of prediction accuracy and robustness [10]. Recent literature emphasizes hybrid and ensemble approaches that combine ML and DL techniques to enhance forecasting performance. For instance, models integrating Random Forest, XGBoost, and LSTM have shown improved accuracy and generalization ability compared to standalone models . These hybrid models leverage the strengths of both approaches—ML for feature selection and interpretability, and DL for capturing com-plex temporal patterns. Despite these advancements, several challenges remain. The Efficient Market Hypothesis (EMH) suggests that stock prices reflect all available information, making consistent prediction difficult. Additionally, financial data is often noisy, non-stationary, and influenced by external factors such as news, sentiment, and global events, which limits model performance [11] . Furthermore, issues such as overfitting, lack of interpretability in deep models, and dependency on large datasets continue to pose challenges. While Deep Learning models provide higher accuracy, they require significant computational resources and careful tuning. On the other hand, Machine Learning models offer simplicity and interpretability but may fail to capture deep temporal dependencies [12].

III. PROBLEM STATEMENT

Most people putting money into stocks do not really grasp how the market moves. Because of this gap, picking what to buy or when to sell becomes tricky. Data pulled from Yahoo Finance the base for our approach. Patterns in past prices help reveal where values might head next. A forecast tool then signals whether a stock may rise or fall tomorrow. With that hint, traders adjust choices aiming for better returns. Clarity comes not from guesses but from tracing what numbers have done before. Decisions shift based on direction, not impulse. What worked yesterday does not guarantee success today - yet history offers clues. Seeing those hints early changes how one plays the game. Profits grow not by luck, but through noticing subtle shifts others miss. Python runs the whole setup. So nothing gets spent on licenses These days, investing means keeping an eye on the stock market. A better way to guess where prices are headed would help a lot. Prices jump around all the time, shifting with news, trends, even moods. Because so many things mix together, one clear pattern rarely lasts. That is why a smarter method might make sense right now.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 3, July 2026

Impact Factor: 8.2

IV. METHODOLOGY

This study adopts a comparative approach to evaluate the performance of Machine Learning (ML) and Deep Learning (DL) models for stock market forecasting. Historical stock price data, including open, high, low, close, and trading volume, is used for model training and testing. The method- ology consists of data preprocessing, feature selection, model training, and performance evaluation.

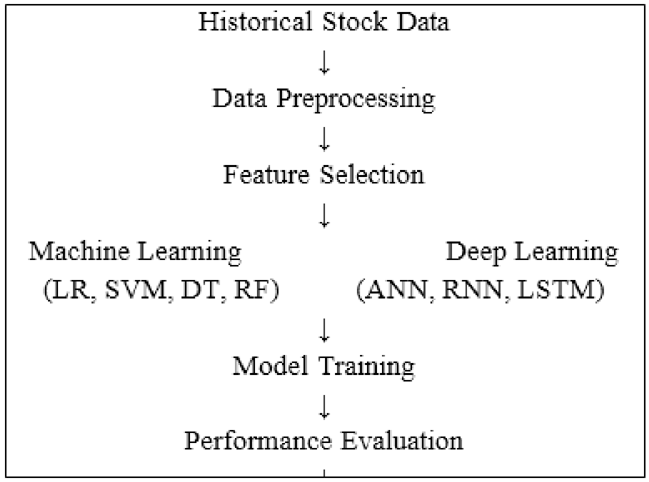

Fig. 1. Overall methodology for stock market forecasting using Machine Learning and Deep Learning models.

A. Machine Learning Models

Machine Learning techniques are widely used for stock prediction because of their simplicity, interpretability, and efficiency when working with structured datasets. The models considered in this study are:

- Linear Regression
- Support Vector Machine (SVM)
- Decision Tree
- Random Forest

These models perform well on smaller datasets and provide faster computation with easier implementation.

Consider predicting the next-day closing price of Reliance Industries using the past 10 days of stock price and trading volume data. A Linear Regression model identifies a linear re-lationship between historical prices and future values, whereas a Random Forest model captures nonlinear interactions be-tween features such as trading volume and price trends [4], [10].

For instance, if the stock shows a consistent upward trend with increasing trading volume, Random Forest can detect this pattern and predict a price increase. However, these models rely heavily on manually engineered features and may struggle when the data exhibits complex temporal dependencies or sudden market fluctuations caused by external events.

B. Deep Learning Models

Deep Learning models are capable of capturing complex nonlinear relationships and automatically extracting meaning-ful features from raw financial data. The models considered in this study are:

- Artificial Neural Network (ANN)
- Recurrent Neural Network (RNN)
- Long Short-Term Memory (LSTM)

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, July 2026
Impact Factor: 8.2

Among these, LSTM is particularly effective for time-series forecasting because it retains long-term dependencies in sequential data.

Consider the same Reliance Industries dataset containing several years of historical stock prices. Unlike ML models, an LSTM network processes the data as a sequence and learns seasonal trends, momentum, and long-term dependencies [5], [8].

For example, if a stock tends to recover after a continuous five-day decline, LSTM can learn this behavior automatically through its memory cells. This enables it to capture delayed effects such as quarterly earnings announcements or macroe-conomic events.

In practice, ML models generally predict tomorrow's stock price based mainly on recent observations, whereas LSTM considers both recent and long-term historical information, resulting in more accurate predictions in volatile market con-ditions.

Therefore, while ML models provide simplicity, faster com-putation, and better interpretability, Deep Learning models offer superior performance in capturing the dynamic behavior of stock markets.

V. MODEL SELECTION CRITERIA

Choosing the appropriate model depends on: • Dataset size and complexity • Requirement for interpretability • Com-putational resources • Prediction accuracy Simpler models may outperform complex ones when interpretability is cru-cial, while Deep Learning models excel in large-scale data environments.

VI. RESULTS AND DISCUSSION

The performance of Machine Learning (ML) and Deep Learning (DL) models is evaluated using historical stock data (e.g., Reliance Industries daily stock prices). The models are compared based on accuracy, error metrics, computational efficiency, and their ability to capture temporal dependencies.

A. Comparative Analysis

Table I compares the performance of Machine Learning (ML) and Deep Learning (DL) models for stock market predic-tion. Linear Regression performs well only under stable linear trends but fails during sudden market fluctuations. Support Vector Machine (SVM) captures limited nonlinear relation-ships, while Decision Tree improves prediction using rule-based learning but may suffer from over fitting. Random Forest achieves higher accuracy by combining multiple decision trees and reducing over fitting.

TABLE I

COMPARATIVE PERFORMANCE ANALYSIS OF ML AND DL MODELS

Model	Acc.	MAE	RMSE	Time	Pattern	Interp.
Linear Regression	72	Moderate	Moderate	Low	Linear	High
SVM	75	Moderate	Moderate	Medium	Limited NL	Medium
Decision Tree	78	Low	Moderate	Low	Rule-based	High
Random Forest	82	Low	Low	Medium	Strong NL	Medium
ANN	85	Low	Low	High	Moderate NL	Low
RNN	87	Low	Low	High	Sequential	Low
LSTM	92	V. Low	V. Low	High	Long-term	Low

Among the Deep Learning models, Artificial Neural Net-work (ANN) learns hidden nonlinear relationships but can-not retain long-term information. Recurrent Neural Network (RNN) considers sequential data but is affected by the van-ishing gradient problem. Long Short-Term Memory (LSTM) achieves the highest accuracy (92%) because it effectively cap-tures long-term temporal dependencies through memory cells. Although LSTM requires higher computational resources and longer training time, it provides the most reliable predictions for stock market forecasting.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, July 2026
Impact Factor: 8.2

B. Example

Consider predicting the daily closing price of Reliance Industries using six months of historical stock market data. During a stable upward trend, Linear Regression follows the overall trend but fails to respond effectively to sudden price fluctuations caused by events such as quarterly earnings announcements or economic news. Support Vector Machine (SVM) and Decision Tree models improve prediction accuracy by learning nonlinear and rule-based relationships; however, they still struggle to capture long-term dependencies.

Random Forest provides more stable predictions by combin-ing multiple decision trees, thereby reducing overfitting and improving generalization. In contrast, Deep Learning mod-els process stock prices as sequential data. Artificial Neural Networks (ANN) learn complex hidden relationships, while Recurrent Neural Networks (RNN) utilize previous time steps for prediction but may suffer from the vanishing gradient prob-lem. Long Short-Term Memory (LSTM) networks overcome this limitation by retaining long-term historical information through memory cells. Consequently, LSTM can recognize patterns such as a market recovery after several consecutive days of decline, resulting in more accurate and reliable stock price predictions than conventional Machine Learning models.

C. Evaluation Metrics

The performance of Machine Learning (ML) and Deep Learning (DL) models is evaluated using several standard evaluation metrics. These metrics measure prediction accuracy and estimate the error between actual and predicted stock prices.

1) Mean Absolute Error (MAE): Mean Absolute Error (MAE) calculates the average absolute difference between the predicted and actual stock prices. A lower MAE indicates better prediction performance.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (1)$$

where yi represents the actual stock price, yˆi represents the predicted stock price, and n is the total number of observations.

2) Root Mean Square Error (RMSE): Root Mean Square Error (RMSE) measures the square root of the average squared prediction error. It gives more weight to larger prediction errors.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad (2)$$

3) Prediction Accuracy: Prediction Accuracy represents the percentage of correctly predicted stock market trends.

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100 \quad (3)$$

These evaluation metrics provide a comprehensive assess-ment of forecasting performance. MAE and RMSE quantify prediction errors, while Accuracy measures the effectiveness of the prediction model in identifying correct market trends. Lower values of MAE and RMSE, together with higher Accuracy, indicate better model performance.

D. Dataset Description

The experiments are performed using historical stock market data collected from publicly available financial sources such as Yahoo Finance. The dataset contains daily stock prices of Reliance Industries Limited, including Open, High, Low, Close, Adjusted Close, and Trading Volume.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, July 2026
Impact Factor: 8.2

Before model training, the dataset undergoes preprocess-ing to improve prediction performance. Missing values are removed, duplicate records are eliminated, and numerical fea-tures are normalized using Min-Max Scaling. The processed dataset is divided into training and testing sets with an 80:20 ratio. The training dataset is used to build the prediction models, while the testing dataset evaluates their performance on unseen data.

The selected features provide sufficient information for learning market behavior and enable both Machine Learning and Deep Learning algorithms to identify historical trends and forecast future stock prices effectively.

E. Advantages and Limitations

Table II presents a comparison between Machine Learn-ing (ML) and Deep Learning (DL) models used for stock market forecasting. The comparison highlights their strengths and limitations in terms of implementation, computational requirements, prediction capability, and suitability for different datasets.

Machine Learning models are computationally efficient and well suited for small- to medium-sized datasets. They provide faster training, lower computational cost, and better inter-pretability, making them appropriate for applications where model transparency is important. However, their ability to cap-ture complex nonlinear relationships and long-term temporal dependencies is limited.

In contrast, Deep Learning models, particularly Long Short-Term Memory (LSTM) networks, are capable of learning complex sequential patterns from historical stock market data.

TABLE II

COMPARISON OF MACHINE LEARNING AND DEEP LEARNING MODELS

Machine Learning	Deep Learning
Simple to implement	Learns complex nonlinear relationships
Faster training	Higher prediction accuracy
Requires less computational power	Requires powerful hardware
Easy to interpret	Difficult to interpret
Suitable for small datasets	Performs well on large datasets
Limited in capturing long-term dependencies	Excellent for sequential time-series data

These models generally achieve higher prediction accuracy and better generalization for time-series forecasting. Never-theless, they require larger datasets, greater computational resources, and longer training time. Therefore, the choice between Machine Learning and Deep Learning depends on the availability of data, computational resources, and the desired prediction accuracy.

VII. CONCLUSION

The proposed research article uses a comprehensive compar-ative analysis of Machine Learning (ML) and Deep Learning (DL) approaches for stock market forecasting. The results demonstrate that while traditional Machine Learning models such as Linear Regression, Support Vector Machines, Decision Trees, and Random Forest provide efficient and interpretable solutions, their performance is limited when dealing with complex, nonlinear, and time-dependent financial data. On the other hand, Deep Learning models, particularly Long Short-Term Memory (LSTM) networks, show superior performance in capturing sequential patterns and long-term dependencies inherent in stock price movements. The ability of LSTM to retain past information enables it to model market trends more effectively, resulting in higher prediction accuracy and lower error rates. However, this improved performance comes at the cost of increased computational complexity, longer training time, and reduced interpretability. Therefore, the selection of an appropriate model depends on the specific application requirements, such as dataset size, need for accuracy, and computational resources.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 3, July 2026
Impact Factor: 8.2

VIII. FUTURE SCOPE

Stock market forecasting continues to evolve with rapid ad-vancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL). Future research can improve prediction accuracy by integrating additional data sources such as financial news, social media sentiment, macroeconomic indicators, and global market trends with historical stock price data. The incorporation of Natural Language Processing (NLP) techniques can enable forecasting models to capture investor sentiment and market psychology more effectively.

Furthermore, hybrid forecasting approaches that combine Machine Learning and Deep Learning techniques, such as Random Forest with Long Short-Term Memory (LSTM) net-works or XGBoost with Gated Recurrent Units (GRU), have the potential to improve prediction accuracy and model robust-ness. Recently developed Transformer-based architectures and attention mechanisms may also provide better performance by capturing long-term temporal dependencies in financial time-series data.

Future work may also focus on developing real-time stock market prediction systems using cloud computing and edge computing platforms. Such systems can continuously collect, process, and analyze live market data to generate timely investment recommendations. These intelligent forecasting frameworks can assist investors, financial institutions, and policymakers in making informed decisions while minimizing financial risk and improving portfolio management.

REFERENCES

1. A. W. Lo, ”The Adaptive Markets Hypothesis,” Journal of Portfolio Management, vol. 30, no. 5, pp. 15–29, 2004.
2. G. E. P. Box, G. M. Jenkins, and G. C. Reinsel, Time Series Analysis: Forecasting and Control, 4th ed. Wiley, 2008.
3. T. M. Mitchell, Machine Learning. McGraw-Hill, 1997.
4. L. Breiman, ”Random Forests,” Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
5. S. Hochreiter and J. Schmidhuber, ”Long Short-Term Memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
6. E. F. Fama, ”Efficient Capital Markets: A Review of Theory and Empirical Work,” Journal of Finance, vol. 25, no. 2, pp. 383–417, 1970.
7. K. J. Kim, ”Financial Time Series Forecasting Using Support Vector Machines,” Neurocomputing, vol. 55, pp. 307–319, 2003.
8. S. Fischer and C. Krauss, ”Deep Learning with Long Short-Term Memory Networks for Financial Market Predictions,” European Journal of Operational Research, vol. 270, no. 2, pp. 654–669, 2018.
9. H. M. Nguyen, B. H. Nguyen, and T. T. Nguyen, ”Stock Price Prediction Using Hybrid Deep Learning Model Combining LSTM and XGBoost,” Applied Sciences, vol. 11, no. 3, 2021.
10. J. Patel, S. Shah, P. Thakkar, and K. Kotecha, ”Predicting Stock and Stock Price Index Movement Using Trend Deterministic Data Preparation and Machine Learning Techniques,” Expert Systems with Applications, vol. 42, no. 1, pp. 259–268, 2015.
11. R. S. Tsay, Analysis of Financial Time Series, 3rd ed. Wiley, 2010.
12. J. J. Murphy, Technical Analysis of the Financial Markets. New York: New York Institute of Finance, 1999.
13. I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. MIT Press, 2016.
14. C. M. Bishop, Pattern Recognition and Machine Learning. Springer, 2006.
15. V. N. Vapnik, Statistical Learning Theory. Wiley, 1998.
16. Y. LeCun, Y. Bengio, and G. Hinton, ”Deep Learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015.
17. B. M. Henrique, V. A. Sobreiro, and H. Kimura, ”Stock Price Prediction Using Support Vector Regression on Daily and Up to the Minute Prices,” Journal of Finance and Data Science, vol. 4, no. 3, pp. 183–201, 2018.
18. S. Li, Y. Wang, and X. Zhang, ”Stock Market Prediction Based on LSTM and Attention Mechanism,” IEEE Access, vol. 10, pp. 45621–45634, 2022.

DOI: 10.48175/IJARSCT-37837

19. A. Vaswani et al., ”Attention Is All You Need,” in Proc. Advances in Neural Information Processing Systems (NeurIPS), 2017, pp. 5998–6008.
20. D. P. Kingma and J. Ba, ”Adam: A Method for Stochastic Optimization,” in Proc. International Conference on Learning Representations (ICLR), 2015.
21. F. Chollet, Deep Learning with Python, 2nd ed. Shelter Island, NY, USA: Manning Publications, 2021.
22. J. Brownlee, Deep Learning for Time Series Forecasting. Machine Learning Mastery, 2018.
23. Y. Zhang, X. Liu, and H. Wang, ”A Hybrid Deep Learning Framework for Stock Market Prediction,” Expert Systems with Applications, vol. 213, Art. no. 118956, 2023.
24. K. A. Althelaya, E. M. El-Alfy, and S. Mohammed, ”Evaluation of Bidi-rectional LSTM for Short- and Long-Term Stock Market Prediction,” in Proc. IEEE International Conference on Big Data (Big Data), 2018, pp. 3484–3492