International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

Comparative Performance Analysis Of Machine Learning And Deep Learning Models For Nse Stock Market Prediction

Thanki Rajesh Harilal
Research Scholar, Department of Computer Science, Sabarmati University, Ahmedabad.
Email - rajthanki5002@gmail.com
Dr. Krushnadeo T. Belerao
Associate Professor, Department of Computer Science, Sabarmati University, Ahmedabad.
Email - krushnabelerao@gmail.com

ABSTRACT

The ever-changing and unpredictable nature of financial markets makes examination of stock market predictions an attractive topic for research in finance analytics and artificial intelligence. Predicting the NSE stock market using ML/DL methods is the focus of this research. When making predictions, many models were employed, such as decision tree (DT), random forest (RF), Support Vector Machine (SVM), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). The data set included information on the starting and closing prices as well as the highest and lowest prices, as well as the volume of trades. Before being used for modelling, the data in the database underwent cleaning, normalisation, and feature selection. We used Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and prediction accuracy to measure each model's performance. The experiment's findings demonstrate that when it comes to stock market prediction, deep learning (DL) models perform better than machine learning (ML) models. When compared to other models, the Transformer model provided the most accurate predictions and the smallest discrepancy between the actual and anticipated values, making it the clear winner for effective prediction.

Keywords: Stock Market Prediction, Machine Learning, Deep Learning, Transformer Model, NSE Forecasting.

1.INTRODUCTION

The field of stock market prediction has emerged as a significant research interest in financial analytics, AI, and data science. With the development of computational technologies and the availability of huge financial datasets, researchers have been motivated to build intelligent systems for predicting stock market movements. Because of the interplay of societal, political, and economic variables, as well as the inherent volatility and changeability of the market, predicting stock prices is a challenging task. Recently, there has been a lot of buzz around ML and DL because of their promise to reveal previously unseen patterns and produce very accurate predictions. In this

International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

study, authors are interested in comparing different ML and DL models to predict stock prices of the National Stock Exchange of India.

1.1 Background of the Study

The stock market is considered as a critical contributor to economic expansion, with the power to facilitate investment and capital formation. The prediction of stock prices is important for traders and financial institutions because with correct predictions, they can make the right decisions regarding their finances. Predicting the stock market, however, is challenging because the data in the financial markets is quite volatile and not linear.

The National Stock Exchange of India is one of the biggest stock exchanges in the world and it is the exchange generates a lot of data for trading every day. This information can be used to implement predictive analytics and intelligent forecasting methods, minimizing investment risk and boosting returns.

1.2 Using ML and DL to Forecast Stock Market Movements

Moving averages and statistical models, two examples of more conventional methods of predicting, have failed to capture the nuances of the market's recent actions. Hence, ML and DL are gaining popularity in the stock market forecasting domain.

Some examples of ML algorithms in predicting analysis are SVM, DT, Linear Regression (LR), and RF. Because of their ability to understand the dependencies in time series data, DL algorithms such as RNN, LSTM, and GRU have proven to be more suitable for stock market forecasting. Recently, Transformer-based DL architectures have gained significant attention in stock market forecasting because of their ability to process long sequential financial data efficiently. Unlike traditional recurrent models such as RNN and LSTM, Stock market prediction transformers employ attention-based mechanisms to identify long-range dependencies and complicated temporal connections within the dataset. These models improve prediction performance for long-term market trends and large-scale sequential financial data analysis.

1.3 Need and Significance of the Study

Intelligent forecasting systems are necessary due to the increasing complexity and volatility of financial markets. To determine which stock market forecast approach is more accurate, we compare the two models' performance.

A number of predictive models have been analyzed in this research in terms of performance measures including MAE, RMSE, and MAPE. Due to this research, the researchers, investors, and financial organizations would be able to take more informed decisions regarding investments and predictions.

1.4 Research Objectives

The objective of the current research is to assess the efficiency of ML and DL approaches in forecasting the price of the shares traded on NSE. The key objectives of the research are as follows:

- Ability to study the history of the stock market of the NSE-listed companies to find trends and patterns.
- Experiments for prediction using ML and DL for stock market.
- For assessing the performance of forecasting models through comparison of the MAE, RMSE and MAPE measures.
- To find out the most precise model to predict the stock market of NSE and to help in the investment decision.

2. REVIEW OF LITERATURE

DL techniques were compared to more conventional ML methods in a study by Nikou et al. (2019) that looked into stock price prediction. DL models' capabilities in handling complicated financial data and non-linear market dynamics were investigated in the study. Examining how well DL models handled financial data and nonlinear market dynamics was the focus of the research. In comparison to older, more conventional ML methods, DL models produced more accurate predictions, according to the study's authors. The study found that DL methods performed better than other methods in revealing hidden patterns and time-series connections in stock market data.
Mehtab and Sen (2020) investigated models for predicting market values using time-series analysis, ML, and DL. The researchers tested a large number of different approaches to predicting stock market movements in order to determine which strategy would best enable them to do so. Their capacity to manage sequential and historical financial data showed that DL models, especially LSTM networks, much surpassed the conventional ML models. The research showed that in order to make better stock market predictions, cutting-edge AI techniques are required.

In order to forecast the stock market, Abdullah, Ali, Jassim, and Hussain (2025) compared DL models with ML ones. Different market situations and degrees of volatility were employed to evaluate the effectiveness of different forecasting models. In the end, through testing both DL and ML models, it was discovered that DL models generated better forecasts in terms of error rate. Using DL techniques, the study found that complex financial data and dynamic stock market swings may be better evaluated.

Verma, Sahu, and Sahu (2023) investigated methods for predicting stock market movements utilising DL and ML with a variety of input sources. We looked at how well various prediction models could foretell how the stock market will act. The researchers shared their insights on the contribution of technical indicators, past price data, and market factors to enhancing prediction accuracy. The review revealed that the use of DL methods, particularly those involving LSTM-based models, was more successful in predicting compared to traditional ML methods, as DL methods are capable of recognizing complex and nonlinear associations within financial data.

Khan, Khan, Shafique, Ansar, Imran, Altamish, and Hamza (2025) employed ML approaches in performing a comparative analysis of behaviour of stock market prices. The goal of this study was to investigate the effectiveness of a number of ML approaches in predicting the future dynamics of the stock market. Various algorithms, data processing approaches, and market indicators produced various predictions, as seen by the researchers. Because they helped uncover hidden market trends and decreased forecast mistakes, the study's results showed that sophisticated ML models may improve prediction accuracy, which in turn aided with informed financial decision-making.

Vaswani et al. (2017) introduced the Transformer architecture based on self-attention mechanisms for sequence modelling and natural language processing tasks. Unlike traditional recurrent neural networks, the Transformer model processes sequential data in parallel and captures long-range dependencies more effectively through attention mechanisms. The study demonstrated that Transformer models significantly improved learning efficiency, scalability, and predictive accuracy in handling large sequential datasets. Recent applications of Transformer-based architectures in financial forecasting and stock market prediction have shown their superiority in analysing long-term temporal dependencies, complex nonlinear relationships, and dynamic market fluctuations. Researchers observed that Transformer models outperform conventional recurrent models such as RNN, LSTM, and GRU in handling long financial sequences and improving prediction accuracy with reduced forecasting errors. The study highlighted that self-attention mechanisms enhance the model's capability to identify important financial trends and hidden market patterns for more reliable stock market forecasting.

2.1 Research Gap

Existing studies have compared Machine Learning (ML) and Deep Learning (DL) techniques for stock market prediction using various financial datasets and forecasting approaches. Several researchers reported that Deep Learning models such as LSTM and GRU outperform traditional ML models in handling nonlinear and sequential stock market data. Recent studies have also highlighted the importance of Transformer-based architectures for long-sequence financial forecasting.

However, limited studies provide a comprehensive comparative analysis among traditional ML models, recurrent DL architectures, and Transformer-based models specifically for NSE stock market forecasting using a unified preprocessing framework, identical evaluation metrics, and consistent training-testing procedures. Moreover, many previous studies primarily focused on either ML or DL models individually without evaluating their comparative forecasting reliability under the same experimental environment.

Therefore, the present study addresses this research gap by conducting a comparative evaluation of ML and DL models, including Transformer architecture, to identify the most reliable and accurate prediction framework for NSE stock market forecasting.

3. RESEARCH METHODOLOGY

The researcher has a systematic approach to doing and analysing the research thanks to methodology, which is one of the primary components of the research. Accurate study results can be achieved with its help in selecting suitable techniques of data collecting, data pre-processing, predictive models, and evaluation. The methodology adopted for this research work was explicitly developed to enable an analysis of the efficiency of DL and ML methods in predicting NSE stock prices.

3.1 Research Design

The main objective of this experimental and quantitative study is to predict stock values in NSE through the application of ML and DL methods. The study employed the use of historical stock market data and Comparative Research method to evaluate the efficiency of stock market forecasting models.

3.2 Data Collection and Preprocessing

The research relies heavily on secondary data analysis that draws from financial databases and publicly available information on the stock market. The data collected encompassed crucial market indicators such as opening and closing prices, high and low prices, trading volume, and more.

Prior to utilising the model to enhance prediction accuracy and computational efficiency, the dataset underwent data cleaning, normalisation, and feature selection. In addition, a training set and a test set were made from the data, which would allow validation of the models and analysis for predicting.

Table 1: Dataset Description and Distribution Used for NSE Stock Market Prediction Analysis

Parameter	Value
Source	Yahoo Finance / NSE
Market	National Stock Exchange (NSE)
Companies	Reliance, TCS, Infosys, HDFC Bank, ICICI Bank
Start Date	January 2018
End Date	December 2024
Records	10,000
Features	Open, High, Low, Close, Volume
Training Records	8,000
Testing Records	2,000

The dataset consisted of historical stock market data collected from Yahoo Finance and NSE-listed companies. The selected records included major financial indicators such as opening price, closing price, highest price, lowest price, and trading volume. The dataset was divided into training and testing subsets to ensure proper model learning and performance validation.

3.3 Machine Learning and Deep Learning Models

The objective behind the use of different ML models like DT, SVM, LR, and RF is to predict stock market trends. Besides, linear and non-linear behaviours of the stock market were analysed by using advanced DL models like RNN, LSTM, GRU, and Transformers networks. The reason for including the Transformer architecture is its capability in capturing long dependencies and sequential relationships between variables of stock market time series data using self-attention mechanisms. Forecasting capabilities and forecasting performance are two criteria for evaluating how well the models predict. The models have been developed based on historical stock market data.

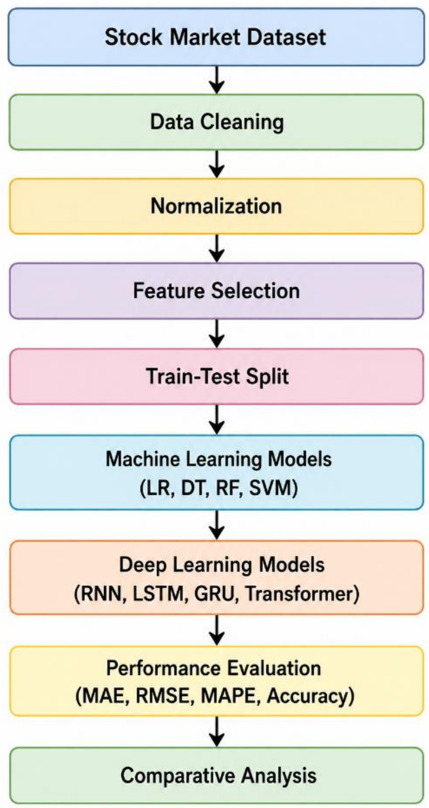

Figure 1: Architecture Flow Diagram of the Proposed ML and DL-Based NSE Stock Market Prediction Framework

3.3.1 Hyperparameter Configuration

Table 2: Hyperparameter Configuration and Training Settings for ML and DL Models

Parameter	**Value**
Epochs	100
Batch Size	32
Optimizer	Adam
Learning Rate	0.001
Activation Function	ReLU
Loss Function	Mean Squared Error (MSE)
Sequence Window	30

The hyperparameters were selected experimentally to achieve stable convergence and improved forecasting accuracy during model training. The Adam optimizer and ReLU activation function were adopted because of their computational efficiency and ability to improve nonlinear learning performance.

3.4 Performance Evaluation

To evaluate the forecasting performance of the implemented Machine Learning (ML) and Deep Learning (DL) models, different statistical evaluation metrics such as Accuracy, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) were used.

Accuracy

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100$$

Root Mean Square Error (RMSE)

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

Mean Absolute Error (MAE)

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

Mean Absolute Percentage Error (MAPE)

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

Where:

- y_i= Actual stock value
- $\hat{y}_i$= Predicted stock value
- n= Total number of observations

These metrics were used to evaluate prediction accuracy and forecasting error of the implemented ML and DL models.

4. RESULTS AND DISCUSSION

In the results and discussion part of this report, we highlight the comparison between all the different DL and ML models employed in predicting the stock market for the NSE. Performance evaluation of these models involved the use of measures like prediction accuracy, RMSE, MAPE, and MAE. The process of identifying the best stock market prediction model from among the three will be easier thanks to the findings.

4.1 Dataset Analysis

Predictive research and forecasting made use of stock market historical data sourced from National Stock Exchange-listed companies. There are the following stock-related attributes included in the

International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

dataset: The trade volume, best and lowest prices, highest and lowest prices, and opening and closing prices. To put the model and its implementation to the test, the data was first partitioned into a training set and a testing set. They were then cleaned and processed separately.

Table 3: Distribution of Dataset Used in the Study

Dataset Category	Number of Records	Percentage
Training Dataset	8,000	80%
Testing Dataset	2,000	20%
Total Dataset	10,000	100%

The distribution of the dataset for the stock market prediction analysis is shown in Table 3. The total of 10,000 stock market records of which 8,000 are used for training the predictive models, and the 2,000 records used for testing and validating represent 20% of the total.

Either the ML or the DL models learned the stock market patterns from the larger part of training data. The testing set was employed to test the forecast accuracy and prediction performance. This dataset distribution boosted the reliability of the models, decreased overfitting concerns and increased the total effectiveness of stock market forecast models.

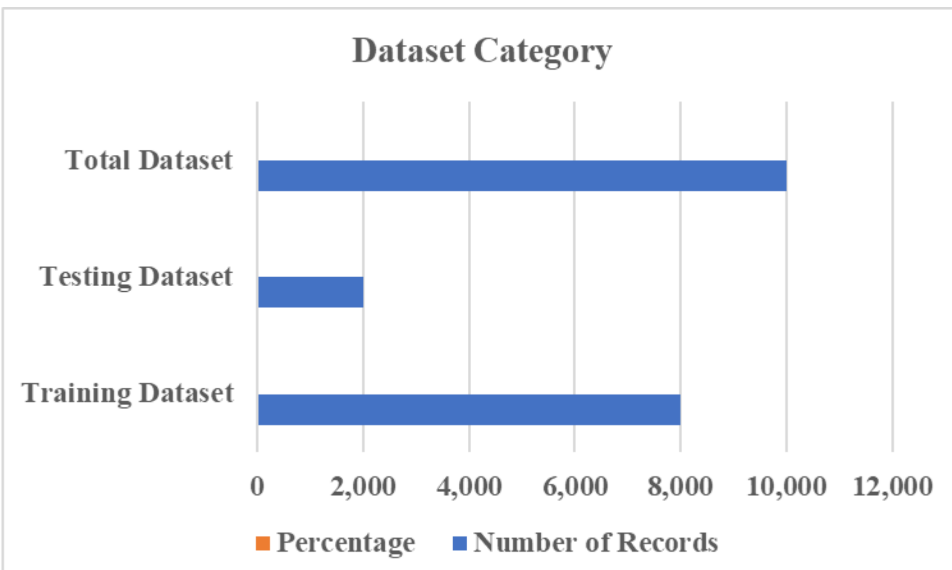

Figure 2: Graphical Representation of Distribution of Dataset Used in the Study

The distribution of the training and testing datasets in the study is graphically presented in Figure 2. As seen in the graphical representation, most of the stock market data was used for the training data set, and a smaller portion was used for the testing and validation data sets.

This approach of balanced distribution of the models ensured effective learning of the models and accurate performance evaluation. The graphical analysis also suggested that the data was adequate for model training and testing as well, which led to the better capability to forecast and prediction reliability.

4.2 Models for Machine Learning and Their Effectiveness

The past records of the stock market in the NSE were entered into different ML models which predicted future values of the stock market. The level of errors made by the models and their accuracy levels were used to measure the models' performances. The four measures used in the evaluation include accuracy, mean absolute error, root mean square error, and mean absolute percentage error.

Table 4: Performance of Machine Learning Models

ML Model	Accuracy (%)	MAE	RMSE	MAPE (%)
LR	71	5.82	7.14	8.6
DT	75	4.95	6.32	7.4
RF	82	3.68	4.91	5.3
SVM	84	3.25	4.45	4.9

The performance of various ML models used to forecast the NSE stock market is compared in Table 4 below. SVM performed the best among the models employed for prediction, with an accuracy of 84% and the lowest values for MAE, RMSE, and MAPE. When it came to predicting stock values and reducing prediction errors, SVM was the clear winner.

RF also proved to be effective in forecasting, with 82% prediction accuracy, which also can handle nonlinear data patterns, and it has the capability of ensemble learning. The prediction accuracy achieved was moderate for DT, and low for LR with comparatively higher error values of 71%. LR is not as effective as other models, mainly due to the dynamic and complex nature of the stock market.

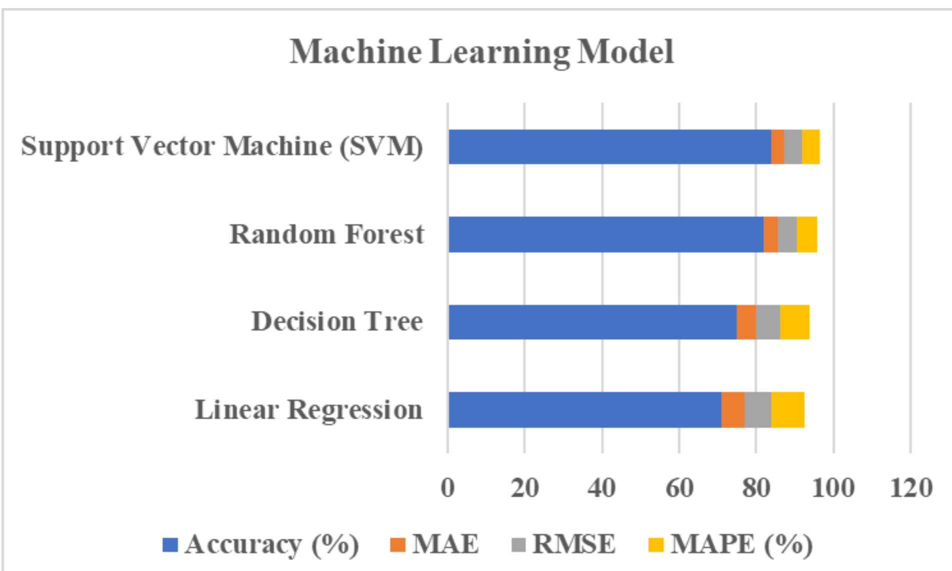

Figure 3: Graphical Representation of Performance of Machine Learning Models

International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

Figure 3 below represents the outcomes of a comparison conducted between the different ML models that have been used during the research process. From the observation made in the graph, it can be concluded that amongst the different ML models, the SVM gives the highest accuracy in its predictions.

In addition, the prediction capability of RF was efficient and LR showed lowest prediction performance. The graph depicts the effectiveness of complex ML techniques in comprehending the dynamics of stock markets and improve the prediction accuracy of the NSE stock market.

4.3 Deep Learning Model Performance

Table 5 illustrates the performance comparison of different DL models which were considered to predict NSE stock market trends. These different DL models have been compared with respect to their performance criteria such as prediction accuracy, MAE, Root Mean Square Error (RMSE), and MAPE. These DL models include RNN, LSTM, GRU, and Transformers.

Table 5: Performance of Deep Learning Models

DL Model	Accuracy (%)	MAE	RMSE	MAPE (%)
RNN	87	2.94	4.12	4.3
LSTM	91	2.15	3.28	3.1
GRU	89	2.41	3.56	3.5
Transformer	93	1.88	2.94	2.7

From the result shown in Table 5 below, it can be clearly stated that the prediction model based on Transformer has been able to predict stock returns with maximum accuracy of 93%, minimum MAE, RMSE, and MAPE values as compared to other DL approaches. This highlights the ability of the Transformer model in dealing with long sequential financial data. The LSTM model also showed strong forecasting performance with 91% accuracy due to its efficient memory-based learning capability for sequential data. GRU performed efficiently with moderate computational complexity and satisfactory prediction accuracy, while RNN showed comparatively lower performance due to its inability to capture long-term dependencies and market fluctuations. Overall, the findings confirm that advanced attention-based DL architectures significantly improve stock market forecasting accuracy and reliability.

Figure 4 graphically illustrates the comparative performance of the DL models employed for NSE stock market prediction. The figure represents the forecasting accuracy and error metrics of RNN, LSTM, GRU, and Transformer models, enabling visual comparison of their predictive effectiveness and forecasting reliability.

International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

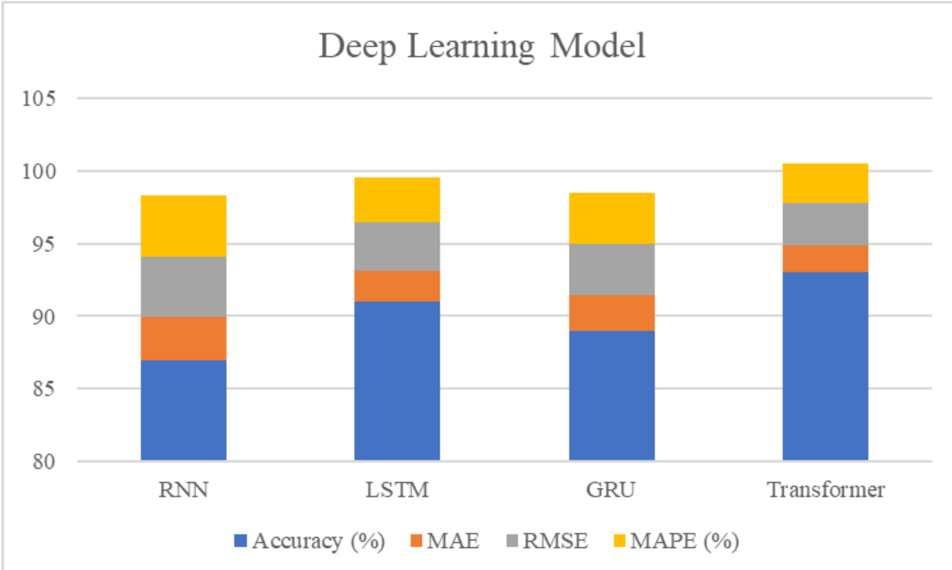

Figure 4: Graphical Representations of Performance of Deep Learning Models

It is evident from the results shown in Figure 3 below that the Transformer model performed better than any other DL model in respect to predicting accuracy and reducing forecasting errors. The figure highlights the effectiveness of the Transformer's self-attention mechanism in analysing long-term sequential dependencies and nonlinear financial market patterns. LSTM also exhibited strong forecasting capability because of its ability to retain historical market information through memory cells. GRU achieved comparatively good prediction performance with reduced computational complexity, whereas RNN displayed lower forecasting efficiency due to difficulties in handling long-range dependencies in stock market sequences. Graphical results show that the DL architecture, especially the Transformer model, offers better accuracy in terms of predicting stock markets due to their dynamism.

4.4 Comparative Analysis of ML and DL Models

Table 6 below shows the comparative analysis between the best ML and DL models that have been applied for forecasting the stock market of NSE. The analysis is done based on accuracy, RMSE, and forecasting performance in general. SVM has been identified as the best ML algorithm while Transformer has been established as the best DL algorithm for stock market forecasting**.**

Table 6: Comparative Evaluation of Deep Learning and Machine Learning Models

Model Type	Best Performing Model	Accuracy (%)	RMSE	Overall Performance
ML	SVM	84	4.45	Very Good
DL	Transformer	93	2.94	Excellent

The outcomes revealed from the data in Table 6 prove that the DL method performed better than the traditional ML method in predicting NSE stock market performance. Among the ML models, SVM achieved an accuracy of 84% with an RMSE value of 4.45, demonstrating effective

International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

prediction capability for nonlinear financial data. However, the Transformer model produced the highest prediction accuracy of 93% with the lowest RMSE value of 2.94, indicating superior forecasting precision and reduced prediction error. The improved performance of the Transformer model is mainly attributed to its self-attention mechanism, which efficiently captures long-term sequential dependencies and complex financial market trends. The findings confirm that advanced DL architectures provide more reliable and accurate stock market forecasting compared to conventional ML models.

Figure 4 depicts the performance comparison between the ML and DL models that were utilized to predict stocks of NSE through graphs. Performance comparison graphically showcases the prediction accuracy and error estimation of the two most efficient models of both methodologies which are SVM and Transformer.

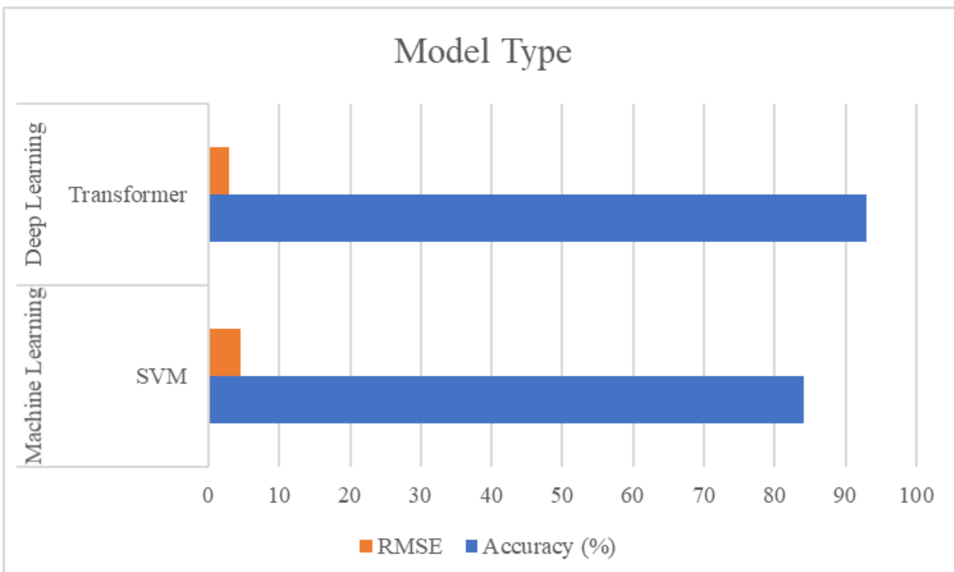

Figure 5: Graphical Representation of Comparative Analysis of Machine Learning and Deep Learning Models

The graphical analysis presented in Figure 5 clearly demonstrates that the DL model achieved better forecasting performance compared to the ML model. The Transformer model exhibited higher prediction accuracy and lower RMSE values than SVM, indicating greater forecasting reliability and prediction stability. The figure also illustrates the effectiveness of Transformer-based architectures in handling long sequential financial datasets and capturing dynamic market behaviour through attention mechanisms. Although SVM showed satisfactory performance in predicting stock market trends, its forecasting capability was comparatively lower than the Transformer model. Overall, the graphical findings emphasize that DL techniques, particularly Transformer architectures, are more suitable for accurate and efficient stock market prediction in highly volatile financial environments.

International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

Table 7: Statistical Validation and Prediction Stability Analysis of ML and DL Models

Model	Accuracy (%)	Standard Deviation
SVM	84	±1.2
LSTM	91	±0.8
Transformer	93	±0.5

The statistical validation results indicate that the Transformer model achieved not only the highest prediction accuracy but also the lowest standard deviation, demonstrating improved forecasting stability and consistency compared to other predictive models.

Table 7 presents the computational comparison of the implemented ML and DL models based on training time and computational complexity. Although the Transformer model achieved superior forecasting accuracy, it required higher computational resources and longer training time compared to traditional ML models. Simpler ML models such as LR and RF demonstrated lower computational complexity and faster training performance but comparatively lower forecasting accuracy. The findings indicate that advanced DL architectures provide better prediction capability at the cost of increased computational requirements.

Table 8: Computational Complexity and Training Time Comparison of ML and DL Models

Model	Training Time	Computational Complexity
LR	Low	Low
RF	Medium	Medium
LSTM	High	High
Transformer	Very High	Very High

4.5 Discussion of Findings

The outcomes from the current research compared with the results obtained from using traditional ML techniques have demonstrated that DL approaches deliver more reliable forecasts for the NSE stock market. When compared to previous methods, DL produced more accurate evaluations of financial market behaviour, leading to more precise forecasts with fewer errors. The stock market is a very dynamic, nonlinear, and unpredictable place, making it very difficult to forecast using traditional statistical and ML approaches. We found that DL models were more effective at revealing the market's latent trends, sequential relationships, and temporal variations.

In comparison to the other models, the Transformer model reduced MAE, RMSE, and MAPE values and produced the highest forecasting accuracy. Because of its memory-based nature, LSTM is able to remember past information and manage data with long-term dependencies, which is why it outperforms other models. Its ability to reliably predict was found to be similar to that of the GRU model, which learned the sequence quickly and with little computing cost. According to the research, memory mechanisms and sequential learning greatly enhance the performance of stock market prediction.

International of Advanced Research and Multidisciplinary Journal Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 7.2 Website: https://ijarmt.com ISSN No.: 3048-9458

However, researchers found that ML models such as RF and SVM could generate sufficiently accurate predictions using low computational complexity. The best ML method was SVM since it was able to handle high-dimensional and nonlinear data patterns with ease. Using its ensemble learning structure, RF significantly improved prediction skills by reducing the overfitting problem and boosting prediction stability. Due to their dependence on the market and the inherent volatility of the stock market, ML models outperformed DL in the long term.

One additional significant finding of the study is that metrics like MAE, RMSE, and MAPE can be helpful for assessing the precision of the calculations. Based on these evaluation criteria, we have a good idea of how reliable the model is and how accurate the forecast is. The projected performance of DL models was confirmed by reduced error values, which implies an improvement in the accuracy of forecasts and predictions. The results show that metrics need to be carefully evaluated in order to obtain the optimal predictive model to employ for stock market prediction.

Financial analysis and investment decisions can greatly benefit from AI-based prediction systems, according to the study. By enhancing financial strategy and decreasing investment risks, effective stock market prediction models can be of great advantage to traders, investors, and financial institutions. Forecasting models powered by artificial intelligence can quickly sift through enormous amounts of financial data, allowing for more accurate predictions of future market patterns and behaviour.

DL methods, such as LSTM and GRU models, outperform their more traditional ML counterparts when it comes to predicting NSE stock market data, according to the research. The findings demonstrate the promise of state-of-the-art models for financial trend forecasting and show how AI systems like DL may enhance investment analysis, financial decision-making, and market forecasting.

4.6 Limitations of the Study

The present research is limited to historical stock market data collected from selected NSE-listed companies. External factors such as news sentiment, geopolitical events, macroeconomic indicators, investor psychology, and real-time streaming market data were not included in the forecasting framework. Additionally, computational resource limitations restricted the implementation of more complex hybrid deep learning architectures and large-scale real-time experimentation.

5. CONCLUSION AND FUTURE SCOPE

This research analyzed the forecasting performance of Machine Learning (ML) and Deep Learning (DL) models for NSE stock market prediction using historical financial data. Various predictive models, including LR, DT, RF, SVM, RNN, LSTM, GRU, and Transformer architectures, were evaluated using performance metrics such as Accuracy, RMSE, MAE, and MAPE. The findings revealed that DL models outperformed traditional ML models in forecasting stock market behavior because of their ability to capture sequential dependencies and nonlinear financial patterns. Among all the implemented models, the Transformer model achieved the highest forecasting accuracy and the lowest prediction error values, demonstrating superior capability in handling long sequential financial datasets through self-attention mechanisms. LSTM also showed strong prediction performance because of its efficient memory-based learning structure. Although ML models such as SVM and RF produced satisfactory forecasting results, their performance was comparatively lower in handling highly dynamic and volatile market conditions.

The study concludes that advanced DL architectures provide more reliable and accurate stock market forecasting for NSE data and can significantly support investment analysis and financial decision-making processes.

Future Scope

Future research can focus on integrating real-time stock market data, financial news sentiment analysis, and macroeconomic indicators to further improve forecasting accuracy. The implementation of Explainable Artificial Intelligence (XAI), reinforcement learning, attention-based hybrid models, and multi-market prediction frameworks can also enhance the reliability and practical applicability of AI-driven stock market forecasting systems.

REFERENCES

1. Chowdhury, M. S., Nabi, N., Rana, M. N. U., Shaima, M., Esa, H., Mitra, A., ... & Naznin, R. (2024). Deep learning models for stock market forecasting: A comprehensive comparative analysis. Journal of Business and Management Studies, 6(2), 95-99.
2. Ghosh, B. P., Bhuiyan, M. S., Das, D., Nguyen, T. N., Jewel, R. M., Mia, M. T., ... & Shahid, R. (2024). Deep learning in stock market forecasting: Comparative analysis of neural network architectures across NSE and NYSE. Journal of Computer Science and Technology Studies, 6(1), 68-75.
3. Barua, M., Kumar, T., Raj, K., & Roy, A. M. (2024). Comparative analysis of deep learning models for stock price prediction in the Indian market. FinTech, 3(4), 551-568.
4. Raturi, A., Mula, K. G., Joshi, K., Sidhu, K. S., Chauhan, S. S., & Singh, V. (2025, April). Comparative Analysis of Stock Price Prediction with Multiple Machine Learning Model. In 2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI) (Vol. 3, pp. 1428-1433). IEEE.
5. Hiransha, M. E. A. G., Gopalakrishnan, E. A., & Soman, K. P. (2018). NSE stock market prediction using deep-learning models. Procedia computer science, 132, 1351-1362.
6. Jain, S. (2024). A Comparative Study of Stock Market Prediction Models: Deep Learning Approach and Machine Learning Approach. Deep Learning Tools for Predicting Stock Market Movements, 249-269.
7. Kakde, A. K., & Dale, M. P. (2024, July). Comparative analysis of deep learning approaches used for stock price prediction. In 2024 2nd World Conference on Communication & Computing (WCONF) (pp. 1-6). IEEE.

8. Khan, A. H., Shah, A., Ali, A., Shahid, R., Zahid, Z. U., Sharif, M. U., ... & Zafar, M. H. (2023). A performance comparison of machine learning models for stock market prediction with novel investment strategy. Plos one, 18(9), e0286362.
9. Barai, A. K., Jain, P., & Kumar, T. (2020). NSE Stock prediction: the deep learning way. In Soft Computing: Theories and Applications: Proceedings of SoCTA 2019 (pp. 783-791). Singapore: Springer Singapore.
10. Fathali, Z., Kodia, Z., & Ben Said, L. (2022). Stock market prediction of Nifty 50 index applying machine learning techniques. Applied Artificial Intelligence, 36(1), 2111134.
11. Nikou, M., Mansourfar, G., & Bagherzadeh, J. (2019). Stock price prediction using DEEP learning algorithm and its comparison with machine learning algorithms. Intelligent Systems in Accounting, Finance and Management, 26(4), 164-174.
12. Mehtab, S., & Sen, J. (2020). A time series analysis-based stock price prediction using machine learning and deep learning models. International journal of business forecasting and marketing intelligence, 6(4), 272-335.
13. Abdullah, H. S., Ali, N. H., Jassim, A. H., & Hussain, S. H. (2025). An analytical comparison of the behavior of machine learning and deep learning in stock market prediction. Baghdad Science Journal, 22(1), 297-309.
14. Verma, S., Sahu, S. P., & Sahu, T. P. (2023). Stock Market Forecasting with Different Input Indicators using Machine Learning and Deep Learning Techniques: A Review. Engineering Letters, 31(1).
15. KHAN, S. N., KHAN, S. U., SHAFIQUE, O., ANSAR, Z., IMRAN, P., ALTAMISH, M. H., & HAMZA, A. (2025). COMPARATIVE ANALYSIS OF STOCK MARKET PRICE BEHAVIOR THROUGH MACHINE LEARNING APPROACHES. Quantum Journal of Social Sciences and Humanities, 6(2), 29-41.
16. Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention Is All You Need. Advances in Neural Information Processing Systems (NeurIPS), 30.