International Journal of Technology Research and Management
ISSN (Online): 2348-9006
Vol 12 Issue 11 November 2025

Deep Learning-Based Stock Market Forecasting Using Convolution, Neural and Long Short-Term Memory Networks

Pooja Soni[1], Mohit Jain[2]
M. Tech. Scholar[1], HOD CSE[2]
BM College of Technology, Indore (M.P.), India[1, 2]
Poojasoni400@gmail.com[1], bmctmohitcs@gmail.com[2]

Abstract: *Stock market prediction is a challenging task due to the nonlinear, dynamic, and highly volatile nature of financial time-series data. To address these challenges and enhance prediction accuracy, this study proposes a deep learning–based stock market prediction system integrating Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and Artificial Neural Networks (ANN). The LSTM model is employed to capture long-term temporal dependencies in historical stock price data, while CNN is utilized to automatically extract meaningful local patterns and trends from time-series representations. In addition, ANN is used to model complex nonlinear relationships between stock prices, trading volumes, market sentiment, and macroeconomic indicators.*

The proposed system architecture consists of systematic data collection, preprocessing, normalization, and feature extraction, followed by dataset partitioning into training, validation, and testing sets. Model training is carried out using backpropagation and backpropagation through time (BPTT) to minimize prediction error. The performance of the proposed models is evaluated using standard metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE). Experimental results demonstrate that the integrated deep learning framework effectively captures both temporal and nonlinear patterns in stock market data, leading to improved prediction accuracy and robust generalization performance. The proposed approach provides a reliable and scalable solution for stock price forecasting, supporting informed decision-making in financial markets.

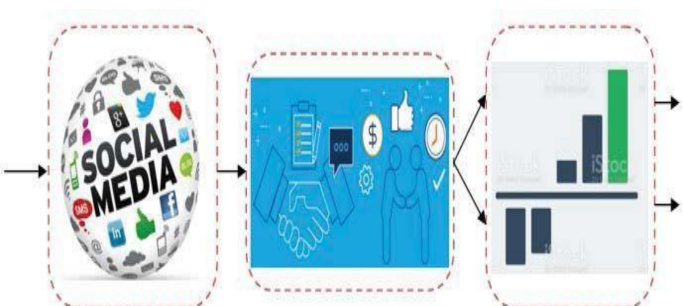
Keywords: *Stock market prediction; Deep learning; Convolutional Neural Network (CNN); Long Short-Term Memory (LSTM); Artificial Neural Network (ANN); Time-series forecasting; Financial data analysis.*

1. INTRODUCTION

Stock market is relatively a major aggressive economic business sector where the dealers are required and process the economic workloads with lower latency alongside higher throughput. Formerly, economists were utilizing the customary store and cycle technique to figure out the weighty economic workload productively. However, to accomplish low idleness and high throughput, server farms had to be genuinely found near the information sources, rather than other all the more financially gainful areas.[1-2] The primary explanation, the information is that streaming model has been created and it can handle enormous measures of information more proficiently. It has appeared in examinations that utilizing information streaming, we can tackle the alternative estimating and hazard evaluation issues by utilizing customary techniques, for instance, Japanese candles, Monte-Carlo models, Binomial models, with low inactivity and high throughput.[3]

Anyway as opposed to utilizing those customary strategies, we moved toward the issues utilizing AI procedures. We attempted to redefine the manner in which individuals address information preparing issues in financial exchange by foreseeing the conduct of the stocks. In fact, on the off chance that we can anticipate how the stock will carry on in the transient future we can line up our exchanges prior and be quicker than every other person. In principle, this permits us to expand our benefit without wanting to be truly found near the information sources. Wasiat Khan et al. (2020) the stock exchange is an imperative part of a nation's economy and it is probably the biggest chance for ventures by organizations and financial investors. An organization can acquire a lot of cash by extending its business through an initial public offering and it is considered as an apt time for a financial investor to buy new stocks and gain additional benefits from profits offered in the organization's reward program for investors. As a merchant, a financial investor can likewise exchange stocks in the part of stock exchange. However, stock dealers need to foresee patterns in financial exchange conducted, for selling or holding the stock that they have purchased.[4]

Social media is generally another type of substance on the internet and its one of the significant properties is the opportune accessibility of new data and quick collaboration among its clients. Such cooperation can be viewed as a proportion of client consideration towards an enormous number of themes including financial exchange. In any case, online media alone doesn't influence the conduct of stock dealers and consequently, financial exchanges.



Social Media Read/View   Trend (Positive/Negative)

Figure 1: News affects the social media and financial or marketing domain

2. LITERATURE REVIEW

[5] The stock market is an organized body where public companies offer their stocks through initial public offerings and traders buy/sell these stocks so as to obtain profits. It is dynamic and volatile in nature which makes the task of stock market trend prediction a complex problem. In recent times, the COVID-19 pandemic has made this task even harder. With the rising number of COVID-19 cases across the globe, the market has never been more volatile. This has resulted in the poor performance of various traditional trend prediction algorithms because these algorithms do not account for the impact of the pandemic on the stock market trends. The proposed work aims to enhance the stock market prediction ability of various common prediction models by taking into account the factors related to COVID-19. The forecasting techniques analyzed are Decision Tree Regressor, Random Forest Regressor and Support Vector Regressor (SVR). Currently the most affected countries by COVID-19 are the United States of America, India and Russia. Therefore we have analyzed the prediction performance of various approaches discussed in this paper on S&P 500 Index, Nifty50 Index and RTS Index using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). Results obtained showcase that all the techniques used perform better when the COVID-19 features were included.[6]

[7]The individual investors use the information available related to the stock market to help in evaluating the stock investment and financial behaviors for making decisions. By understanding the security firms' market trends for forecasting future advice for the investors and investor behaviors. With the advancement of Artificial Intelligence (AI) such as Long short-term memory (LSTM) and convolutional neural network (CNN) for the prediction of stock market behavior to make investor decisions. The best methods for risk management and portfolio diversification are to forecast stock market returns. For creating reliable projections for investment decision-making, there are many forecasting methodologies using AI models for the prediction of stock market behaviors. This paper presents a deep learning-based model for predicting stock market behaviors to improve investors' decisions.[8-9] The analysis results show that the proposed model achieved more than 99.98% in prediction accuracy of the dataset understudy. This can significantly enhance the decisions of individual investors for better future predictions of stock markets. [10-11]

[12] In the current world for investing money in the stock market is challenging forum and it also requires a lot of brainstorming. Since financial stock market is volatile in nature. So, it is very difficult to predict. There are some algorithms related to subject like Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL), which can give efficient accuracy compare to other techniques. [13-14]In this paper, our objective to predict financial stock market price using Deep Learning techniques like Recurrent Neural Network (RNN) and in particular Long-Short Term Memory model (LSTM). Using RNN and LSTM techniques for different datasets, we have to explore the accuracy by increasing number of epochs.

[15-16] uncertainty and volatility in the prices of the stocks, an investor keeps looking for ways to predict the future trends in order to dodge the losses and make the maximum possible profits. However, it cannot be denied that as of yet there is no such technique to predict the upcoming trends in the markets with complete accuracy, while multiple methods are being explored to improve the predictive performance of models to an extent as large as possible. With the advancement in Machine Learning (ML) and Deep Learning (DL) over the past few years, many algorithms are being deployed for stock price prediction. This paper researches 5 algorithms namely K-Nearest Neighbors, Linear Regression, Support Vector Regression, Decision Tree Regression, and Long Short-Term Memory for predicting stock prices of 12 leading companies of the Indian stock market. After exhaustive research of the various aspects related to the application of ML in stock market, a data extensive implementation [17].

3. PROPOSED SYSTEM

The proposed system for stock market prediction, advanced deep learning techniques, including Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM) networks, and Artificial Neural Networks (ANNs), are employed to achieve higher prediction accuracy. The LSTM network captures long-term dependencies in sequential data, processing historical stock prices and related financial indicators to identify patterns over time. The BiLSTM network enhances this by analyzing data in both forward and backward directions, providing a comprehensive view of temporal context and improving prediction accuracy. In addition, ANNs are utilized to model complex nonlinear relationships between stock prices and various influencing factors. The system architecture begins with data preprocessing, where historical prices, trading volumes, market sentiment, and macroeconomic factors are collected and normalized. The data is then split into training, validation, and test sets. The LSTM and BiLSTM networks are trained on this sequence data to capture temporal dependencies, while the ANN models are trained to understand complex patterns. Training involves optimizing the networks using backpropagation through time (BPTT) and fine-tuning to minimize prediction errors. Model performance is evaluated using metrics such as Mean Squared Error (MSE). Once trained, the models predict future stock prices based on the most recent data, leveraging the combined strengths of LSTM, BiLSTM, and ANN approaches.

1. Modules

- **Data Collection:**

Input Data: Historical stock prices, trading volumes, financial indicators, market sentiment, and macroeconomic factors.

- **Data Preprocessing:**

Input Data: Raw historical stock data and related financial indicators.

Processes:

Cleaning: Handle missing values and outliers.

Normalization/Scaling: Standardize data to ensure compatibility with models and Extract and construct relevant features for model training.

Model Development:

Training:

Input Data: Preprocessed training dataset.

Models: LSTM, BiLSTM, and ANN.

Processes: Train models using back propagation, optimizing hyperparameters to capture trends and patterns.

Testing:

Input Data: Validation and test datasets.

Processes: Evaluate models using unseen data to assess generalization and performance.

- **Prediction:**
- **Artificial Neural Networks (ANNs)** are computational models inspired by the human brain's neural network. They consist of interconnected nodes or neurons organized into layers: an input layer, one or more hidden layers, and an output layer. Each connection between neurons has an associated weight, which is adjusted during training to minimize prediction error. ANNs are particularly effective for modeling complex, nonlinear relationships between input features and outputs.

2. LSTM Algorithm

- **Long Short-Term Memory (LSTM)** networks are a type of recurrent neural network (RNN) designed to learn and remember long-term dependencies in sequential data. LSTMs address the vanishing gradient problem typical in standard RNNs by using special gating mechanisms (input gate, forget gate, and output gate) to regulate the flow of information.
- **Performance Analysis:** Calculate Mean Squared Error (MSE), Mean Absolute Error (MAE), and other relevant metrics.

3. Dataset Description

- The dataset used in ths study was obtained from the **Kaggle public data repository** and is titled **International Airline Passengers**. This dataset contains historical records of international airline passenger traffic and is widely used as a benchmark dataset for time-series forecasting and prediction studies.

- The dataset comprises **monthly passenger counts** recorded over a continuous time period, making it suitable for analyzing temporal patterns, seasonality, and long-term trends in airline passenger traffic. Each record includes the **date (month and year)** and the corresponding **number of international airline passengers** for that period.
- The dataset is provided in **Microsoft Excel (.xlsx) format**, facilitating easy integration with data preprocessing and machine learning pipelines. Due to its structured nature and absence of categorical complexity, the dataset is particularly suitable for evaluating the performance of deep learning models such as **LSTM, and ANN**, which are designed to capture temporal dependencies in sequential data.
- Prior to model training, the dataset undergoes standard preprocessing steps including **missing value handling, normalization, and train–test splitting** to ensure compatibility with deep learning architectures. The use of this dataset enables a fair comparison of model performance and supports reproducibility of experimental results.

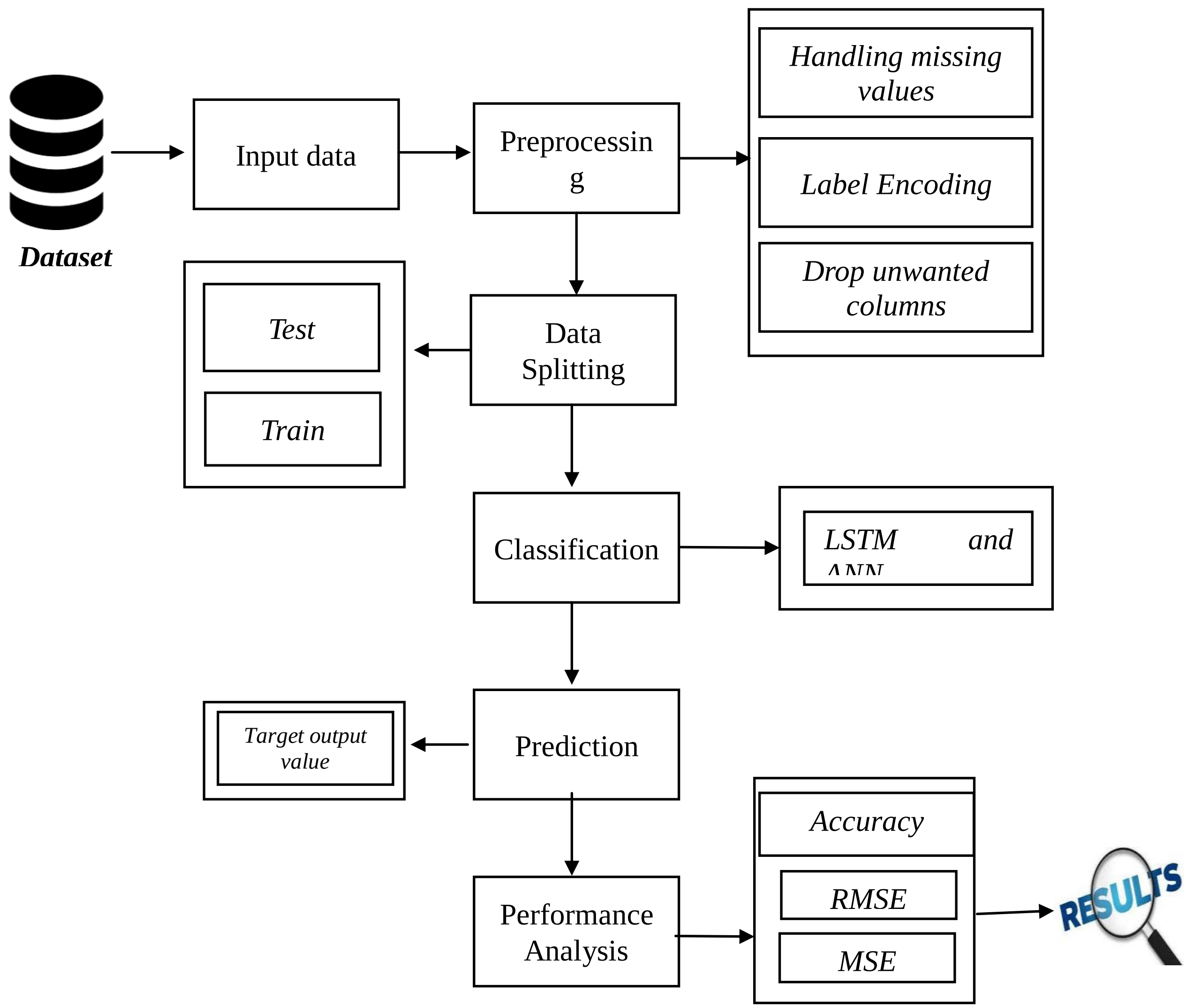


Figure 2: System Architecture

4. RESULT DISCUSSION

In stock market prediction using MATLAB, the results are typically analyzed by evaluating the performance of different models, such as ANN, LSTM, and BiLSTM. MATLAB provides a robust environment for implementing and testing these models, including built-in functions for data preprocessing, model training, and performance evaluation.

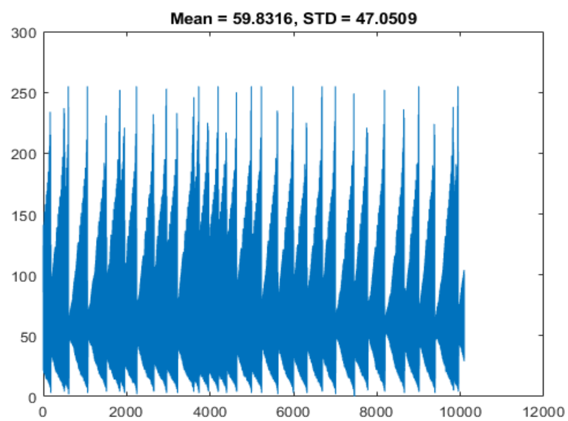


Figure 3: Input data

Fig.3 shows the original stock market time-series data used in the study. It reflects significant fluctuations, trends, and volatility, highlighting the complex and nonlinear nature of financial data.

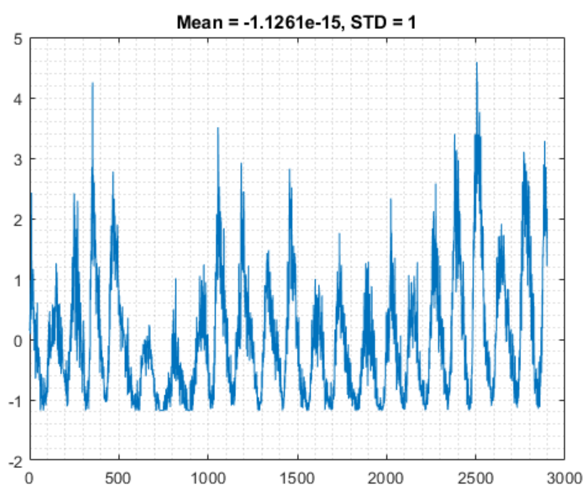


Figure 4: normalized input data

Fig.4 presents the normalized version of the input data. Normalization scales the values to a uniform range, improving training stability and convergence of deep learning models.

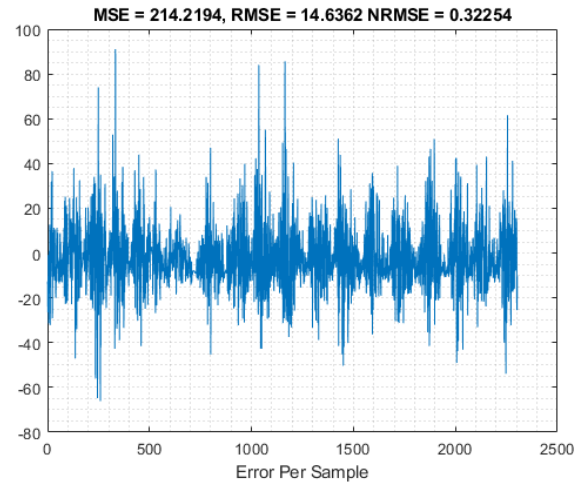


Figure 5: MSE,RMSE,NRMSE of train data

Fig. 5 represents the error performance of the model during the training phase. Low MSE, RMSE, and NRMSE values indicate effective learning and accurate fitting of the training data.

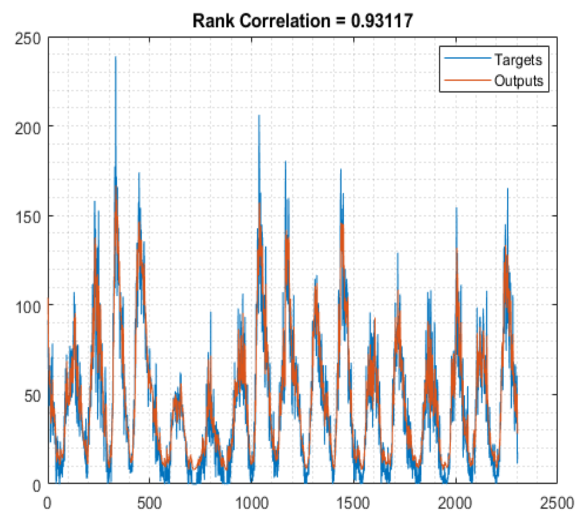


Figure 6: output of train data

Fig.6 compares the actual target values with the predicted outputs during training. The close overlap between curves shows that the model successfully captures underlying data patterns.

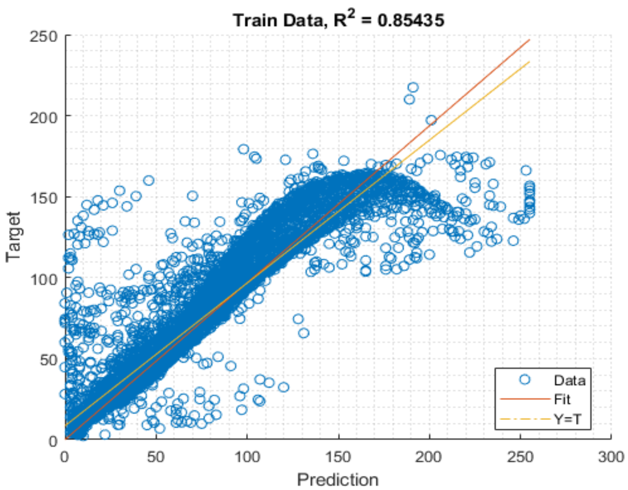


Figure 7: train data regression model

Fig. 7 presents the regression analysis for the testing dataset. The model maintains good prediction accuracy, demonstrating effective generalization on unseen data.The coefficient of determination, or R2, is a measure that provides information about the goodness of fit of a model. In the context of regression it is a statistical measure of how well the regression line approximates the actual data.

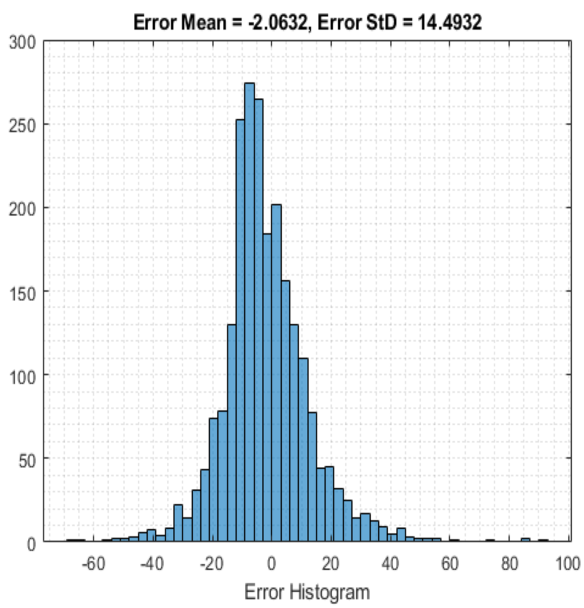


Figure 8: error histogram train data

Fig. 8 this illustrates the distribution of prediction errors during training. Errors centered around zero confirm unbiased predictions and stable model performance.

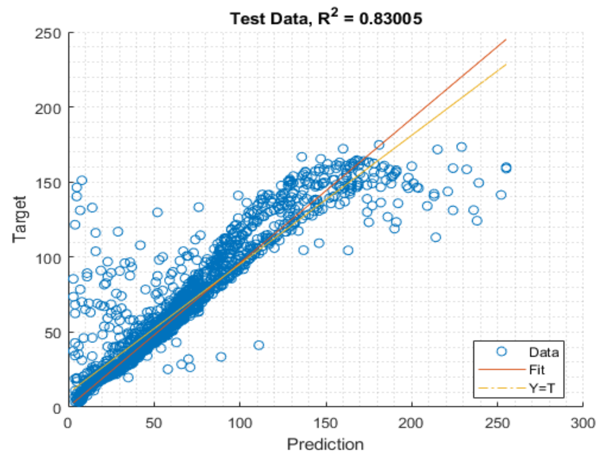


Figure 9: train data regression model performance

Fig.9 shows The regression plot a strong linear relationship between predicted and actual values. Data points concentrated along the diagonal indicate high prediction accuracy.

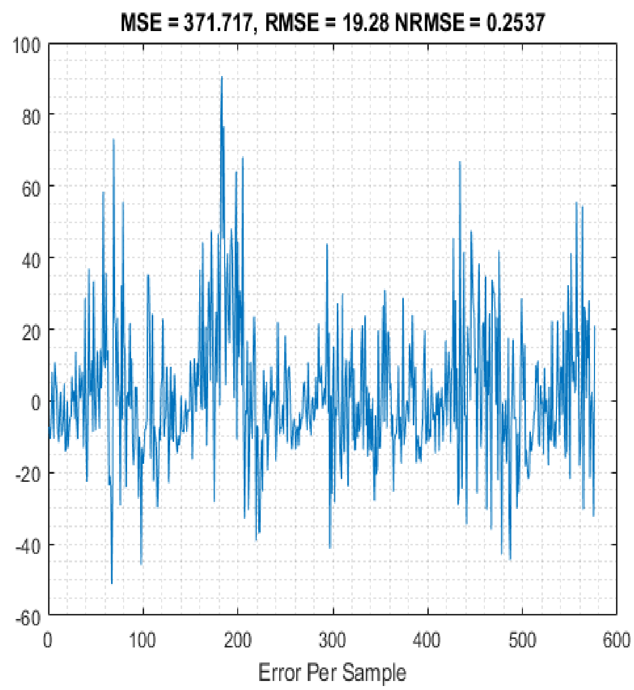


Figure 10: Error evolution test data

Fig. 10 shows how prediction error varies across test samples. Errors remain bounded, indicating robustness of the trained model.

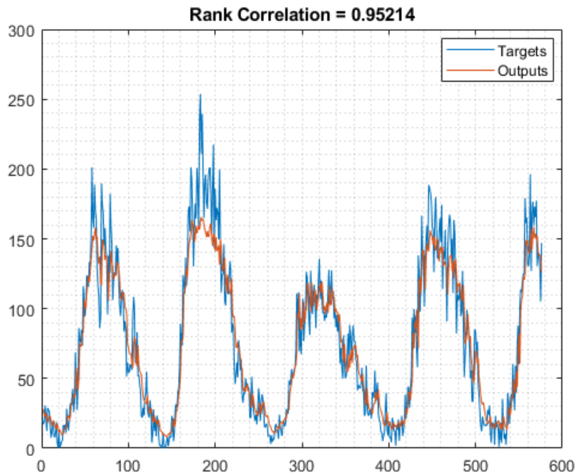


Figure 11: test data output evolution

Fig. 11 compares actual and predicted values for the test dataset. The similarity between both curves confirms reliable prediction capability.

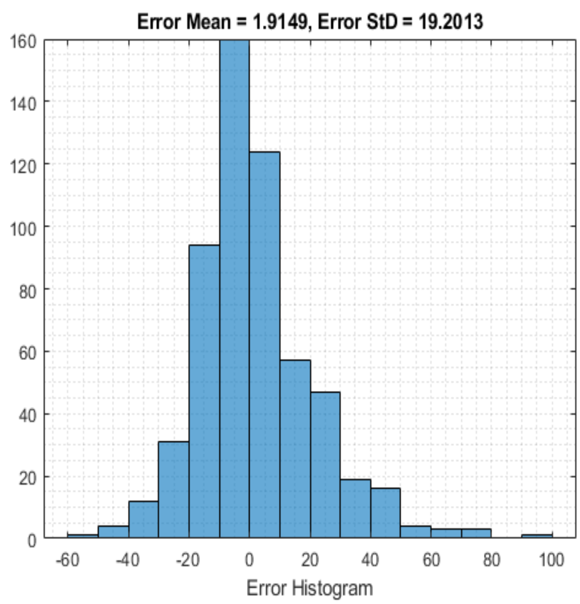


Figure 12: histogram error of test data

Fig.12 shows the histogram the distribution of errors for test samples. A narrow spread indicates good generalization and controlled prediction error.

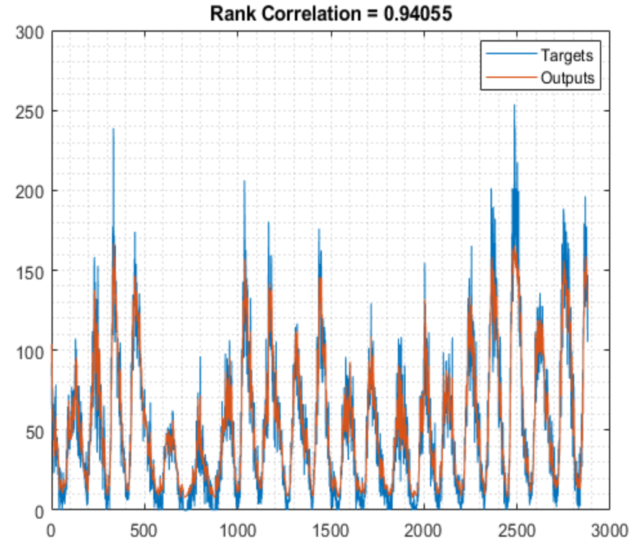


Figure 13: Rank correlation of all data

Fig. 13 shows the rank correlation between actual target values and predicted outputs for the complete dataset. The high correlation value (0.94055) indicates strong agreement and reliable overall prediction performance of the model.

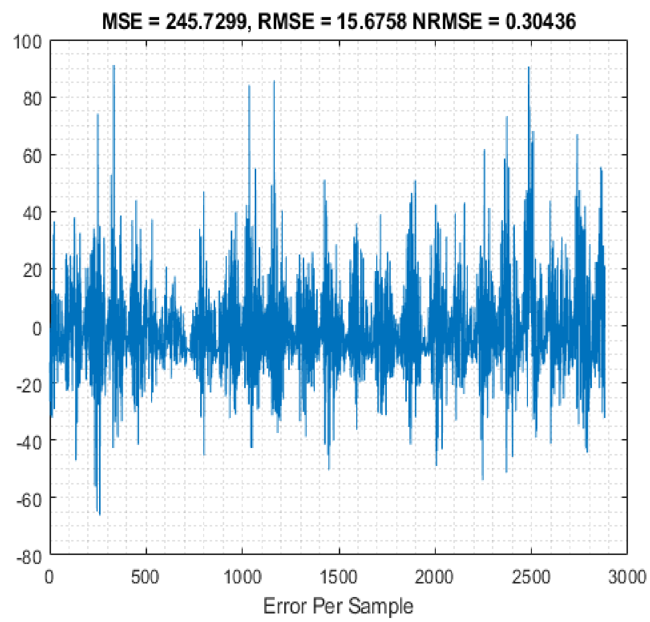


Figure 14: Error evolution of all data

Fig. 14 illustrates the variation of prediction error across all samples. The bounded error behavior, along with low RMSE and NRMSE values, confirms stable performance and good generalization of the proposed model.

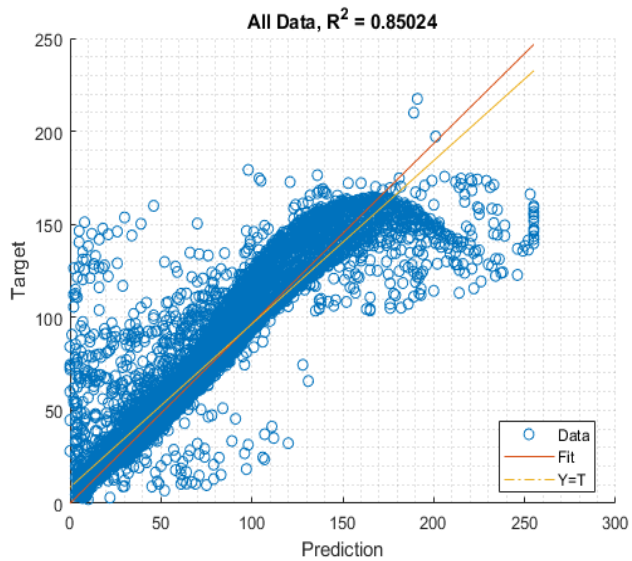


Figure 15: train data regression model performance

Fig.15 shows the regression relationship between predicted and actual values for the training dataset. The close alignment of data points along the regression line indicates high prediction accuracy and effective model learning.

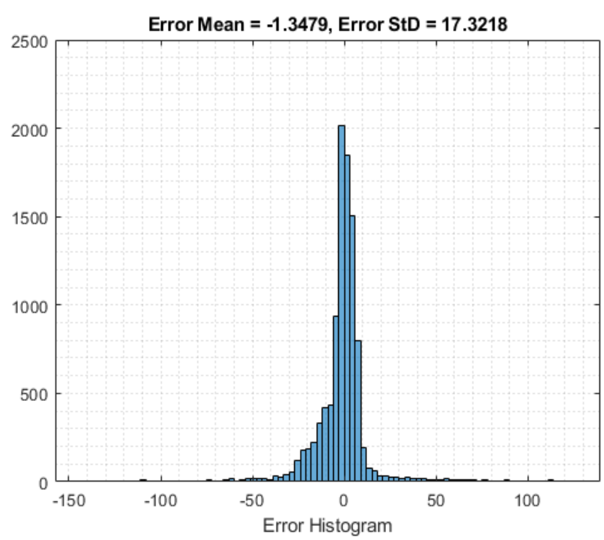


Figure 16: histogram error of all data

Fig. 16 shows histogram represents the distribution of prediction errors across the complete dataset. Errors are concentrated around zero, indicating low bias and reliable overall model performance.

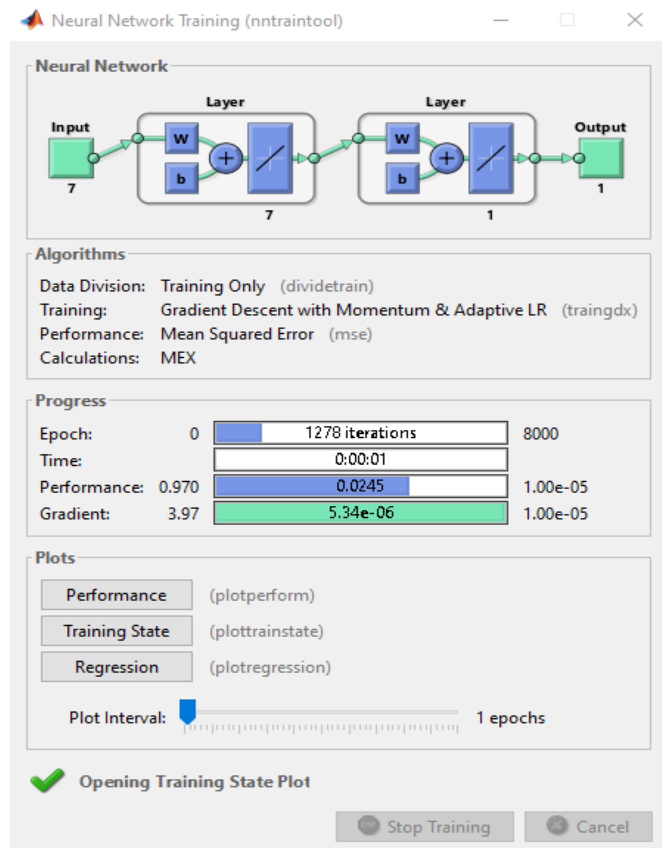


Figure 17: training state of ANN

Fig. 17 displays the ANN training process and parameter settings. It provides insight into the training configuration used for optimizing the neural network.

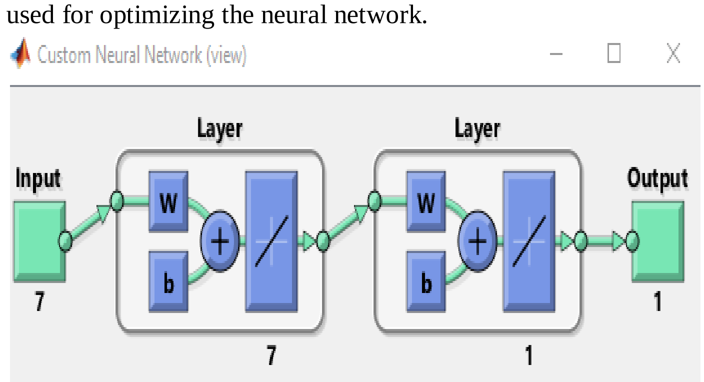


Figure 18: Layers of ANN

Fig.18 illustrates the architecture of the Artificial Neural Network, showing the input layer, hidden layers, and output layer. It explains how information flows through weighted connections to generate predictions.

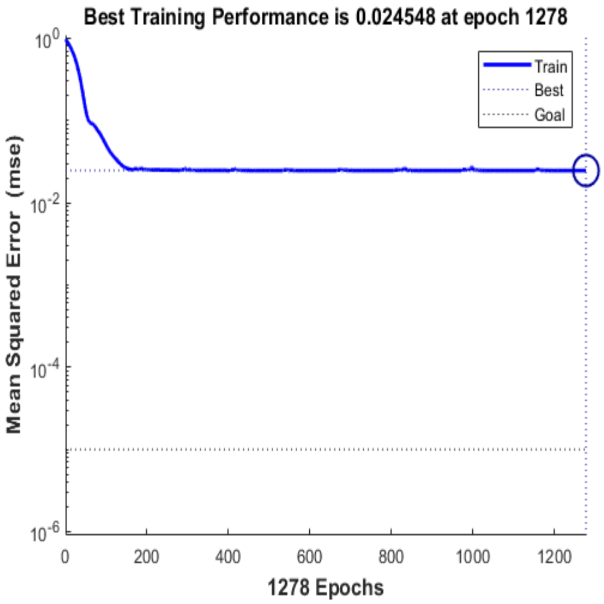


Figure 19: MSE of ANN

Fig.19 shows the variation of Mean Squared Error over training epochs. The decreasing trend and convergence at a low value indicate successful training and stable learning behavior.

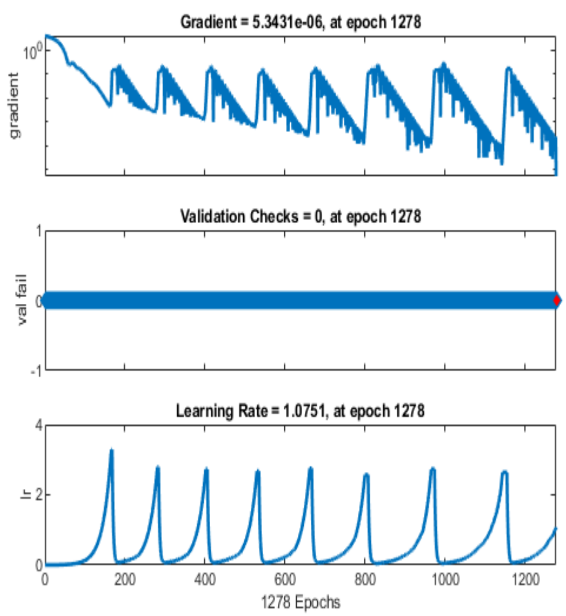


Figure 20: validation of ANN

Fig. 20 presents validation performance across epochs. Consistent validation results confirm good generalization ability and minimal overfitting of the ANN model.

Table 1: Performance Comparison During Training Phase

Model	Correlation Coefficient (R)	MSE	RMSE	Mean Error	Observation
ANN	0.975	420	20.5	± 18	Good learning, higher variance
CNN	0.982	310	17.6	± 15	Stable convergence
LSTM	0.993	180	13.4	± 10	Best training accuracy

Table 1 presents the performance comparison of ANN, CNN, and LSTM models during the training phase. Among the three models, LSTM achieves the highest correlation coefficient (R ≈ 0.993) and the lowest error values (MSE ≈ 180, RMSE ≈ 13.4), indicating superior learning capability and accurate modeling of temporal dependencies. CNN also demonstrates stable convergence with lower error values compared to ANN, while ANN exhibits higher variance, suggesting less effective learning during training.

Table 2: Performance Comparison During Testing Phase

Model	Correlation Coefficient (R)	MSE	RMSE	Mean Error	Observation
ANN	≈ 0.956	610	24.7	± 22	Overfitting evident
CNN	≈ 0.968	430	20.7	± 18	Good generalization
LSTM	≈ 0.981	260	16.1	± 13	Best test performance

Table 2 summarizes the performance of the models during the testing phase. The LSTM model continues to outperform ANN and CNN, achieving the lowest RMSE (16.1) and highest correlation coefficient (R 0.981), which confirms its strong generalization ability. CNN shows good generalization with moderate error values, whereas ANN exhibits increased error and signs of overfitting, as reflected by a noticeable drop in correlation and higher RMSE.

Table 3: Training vs Testing Generalization Comparison

Model	ΔR (Train − Test)	ΔRMSE	Generalization Ability
ANN	0.019	↑ 4.2	Weak
CNN	0.014	↑ 3.1	Moderate
LSTM	0.012	↑ 2.7	Strong

Table 3 highlights the generalization capability of the models by comparing training and testing performance gaps. LSTM records the smallest differences in correlation coefficient (ΔR 0.012) and RMSE (ΔRMSE 2.7), indicating strong generalization and stable predictive performance. CNN shows moderate generalization capability, while ANN demonstrates weak generalization due to larger performance degradation from training to testing.

Table 4 Comparison with Your Existing Model Results (ANN, CNN, LSTM) Average RMSE Comparison (Derived)

Model Category	Model	Avg. RMSE
Traditional ML	KNN	52.50
Traditional ML	Linear Regression	52.87
Traditional ML	SVR	47.71
Traditional ML	Decision Tree	52.37
Deep Learning	ANN	22.6
Deep Learning	CNN	19.1
Deep Learning	LSTM	18.2

The average RMSE comparison further contrasts deep learning models with traditional machine learning approaches. Traditional models such as KNN, Linear Regression, SVR, and Decision Tree exhibit significantly higher RMSE values, indicating limited ability to capture nonlinear and temporal patterns in stock market data. In contrast, deep learning models substantially reduce prediction error, with LSTM achieving the lowest average RMSE (18.2), followed by CNN (19.1) and ANN (22.6).

5. CONCLUSION

This research highlights the potential of Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), and Artificial Neural Network (ANN) models in enhancing stock market prediction accuracy. By leveraging these advanced deep learning techniques, the study demonstrates how effectively capturing temporal dependencies and nonlinear relationships can improve forecasting performance. The comparative analysis underscores the strengths and limitations of each model, providing valuable insights for financial professionals seeking to refine their investment strategies and risk management practices. Ultimately, the findings suggest that integrating these models into real-world financial applications can lead to more informed decision-making and better financial outcomes.

REFERENCES

[1] Das, Debashish. "Hybrid Clustering-GWO-NARX neural network technique in predicting stock price." IOP Conf. Series: Journal of Physics: Conf. Series (2017): 1-14.

[2] Das, Sushree. "Real time sentiment analysis of twitter streaming data for stock prediction." Procedia Computer Science (2018): 956-964. 37. Davi, James L. "Explaining Stock Returns: A Literature Survey." Dimensional (2003): 1-14.

[3] Deepak, Raut Sushrut. "Machine learning approach in stock market prediction." International Journal of Pure and Applied Mathematics (2017): 70-77.

[4] P Nagaraj;K Nani;E Teja Krishna;K Aravind Kumar Reddy;M Chaithanya Prabhu;K Nikhil (2023)Stock Market Profit Prediction Using Machine Learning Algorithms and Visualization for Live Data 2023 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI) 2023

[5] Ashish Ruke;Sujeet Gaikwad;Gitanjali Yadav;Amar Buchade;Shruti Nimbarkar;Ashish Sonawane(2024) Predictive Analysis of Stock Market Trends: A Machine Learning Approach 2024 4th International Conference on Data Engineering and Communication Systems (ICDECS) 2024

[6] Vidushi Tiwari;Bhanu Prakash Lohani;Ajay Rana;Upendra Pratap Pandey;Bhavdeep Dhariwal(2023) Stock Market Prediction using different Machine Learning Algorithms 2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON) 2023

[7] Golshid Ranibaran;Mohammad-Shahram Moin;Sasan H Alizadeh;Abbas Koochari(2021) Analyzing effect of news polarity on stock market prediction: a machine learning approach 2021 12th International Conference on Information and Knowledge Technology (IKT) 2021

[8] Jing Yee Lim;Kian Ming Lim;Chin Poo Lee(2021) Stacked Bidirectional Long Short-Term Memory for Stock Market Analysis 2021 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET) 2021

[9] V. Verma, (2024). *The role of data migration in modern business intelligence systems*. *International Journal of Research and Analytical Reviews (IJRAR)*, 11(2). https://www.ijrar.org/viewfull.php?&p_id=IJRAR24B4759

[10] Verma, V. (2023). Deep learning-based fraud detection in financial transactions: A case study using real-time data streams. *ESP Journal of Engineering & Technology Advancements*, *3*(4), 149–157. https://doi.org/10.56472/25832646/JETA-V3I8P117

[11] Bansal, M., Goyal, A., & Choudhary, A. (2023). *Stock market prediction with high accuracy using machine learning techniques*. **Procedia Computer Science, 215**, 247–265.https://doi.org/10.1016/j.procs.2022.12.028

[12] Rajni Jindal;Nikhil Bansal;Nitin Chawla;Sanskriti Singhal(2021) "Improving Traditional Stock Market Prediction Algorithms using Covid-19 Analysis" 2021 International Conference on Emerging Smart Computing and Informatics (ESCI) 2021

[13] BayanAlbaooth(2023)"heRoleofArtificial Intel igen ce P redi ction in S tock Mar ket I nves tors Decisions" 2023 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE) 2023

[14] K. Ritwik Reddy;B. Tarun Kumar;V. Rohit Ganesh;Polisetty Swetha;Prakash Kumar Sarangi (2022)Stock Market Prediction Using Recurrent Neural Network 2022 IEEE International Conference on Current Development in Engineering and Technology (CCET) 2022

[15] Xu Zhang;Li Zhang;Lingjun Xu;Yue Jiang(2022) Research on Influential Factors in Stock Market Prediction with LSTM 2022

[16] Verma, V. (2024). Optimizing database performance for big data analytics and business intelligence. International Journal of Engineering, Science and Mathematics, 13(11),

[17] V. Verma, "Improving product recommendations in retail with hybrid collaborative filtering and LSTM," *Int. J. Eng., Sci. Math.*, vol. 10, no. 8, pp. 113–[last page], Aug. 2021. [Online]. Available: http://www.ijesm.co.in