Journal of Global Research in Electronics and Communication
Volume 2, No. 2, February 2026
Available Online at: www.jgrec.info
RESEARCH PAPER

Stock Price Time Series Forecasting: A Comprehensive Analysis of Traditional Machine Learning vs. Deep Learning Approach

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***Abstract*—It is very important to correctly predict BSE Sensex stock prices because of the high market volatility and the increasing monetary value of investment decisions. Conventional forecasting methods have a tendency not to account for complex, non-linear patterns in the market. This paper attempts to forecast stock price movement through machine learning (ML) and deep learning (DL), using BSE Sensex 10- Year Stock Price data available at Kaggle. The data used is the daily data from April 2014 to March 2024 with open, high, low, and close prices of the index. The preprocessing of the data was used to deal with missing data, to transform the data types, and to chronologically order the records. StandardScaler was used to apply feature scaling in order to increase the performance of the model. Two predictive models, Random Forest (RF) and Long Short-Term Memory (LSTM), were implemented for stock price time-series forecasting. The models were compared on the basis of regression measures such as R^2, RMSE and MAE. The experimental findings indicate that the LSTM model outperforms the Random Forest model, with an R^2 of 0.9777, suggesting it is highly predictive. The results provide insight into the usefulness of deep learning (DL) methods for understanding temporal patterns and improving the accuracy of stock market forecasts.**

Keywords—Stock Price Prediction, Time Series Forecasting, Machine Learning, Deep Learning, Financial Data Analysis.

I. INTRODUCTION

The financial industry [1] creates enormous amounts of data, including client data, logs from their financial products [2], and transaction information that might be utilised to aid in decision-making, in addition to outside data, such as information from websites and social media [3]. In addition to disrupting population health and contributing to Earth's depopulation [4], pandemics [5] or widespread outbreaks of infectious illnesses can impede economic expansion and instill fear and uncertainty in the financial sector [6]. Share price fluctuations are a reflection of macroeconomic factors including supply constraints and demand, as well as market expectations for present and future circumstances in a particular industry [7]. Additionally, stock market prices make it easier to analyze the consequences of a crisis, even in its early stages, because they are more accessible than macroeconomic measures like the GDP growth rate and unemployment rate.

The stock market [8], sometimes referred to as the economy's gauge, has long been a focus of academic and business study [9]. On the one hand, the stock market gives businesses access to a favourable funding environment [10]. However, by carrying out investment choices including capital allocation, stock selection, and timing, investors might potentially profit from the stock market [11]. Prospective Stock Researchers are interested in price prediction. Many studies disagree with proponents of the efficient market theory, who claim that it is difficult to accurately predict stock values [12]. Additionally, machine learning (ML) and deep learning (DL) have gained popularity when it comes to forecasting stock values and monitoring their trends [13].

A process known as time series forecasting (TSF) uses sequential historical data to estimate future values. The intrinsic forecasting is challenging due to the variety and complexity of time series data, while the multivariate issues' hidden patterns, irregular values, and channel correlation make the process much more difficult. Predicting stock prices gives traders, investors, and financial organisations vital information [14] need to manage risks, make well-informed decisions, and increase their profitability, it continues to be a major issue for companies in the finance industry [15]. It is especially challenging to create reliable forecasting models because financial systems are inherently complex, dynamic, and non-linear [16] markets [17].

Accurately forecasting stock market movements is one of the persistent problems of contemporary finance. Additionally, it has enormous potential for both individual and institutional investors [18]. Furthermore, there is a well-established link between stock market performance and sustained economic growth. Because of improvements in computation and algorithms, the fields of artificial Intelligence (AI) [19][20] and ML [21] have had a significant impact on financial markets [22]. By improving trade practices and risk management, these technologies are transforming several industries, most notably finance [23] [24]. AI [25][26][27] and Additionally, ML [28] has started to transform the banking industry by improving decision-making procedures, automating operations, and customising services. Further, DL [29] has drastically changed the finance industry [30]. DL [31] Innovations in fields like credit scoring have resulted from the capacity to handle and evaluate enormous amounts of data [32], fraud detection [33], and algorithmic trading. The key contributions of this study are as follows:

- Utilized the BSE Sensex 10-Year Stock Price dataset to analyze and predict stock price movements.

- Conducted some pre-processing of the data, such as filling in of missing values, sorted the data into dates, and the normalization of features by using standard scaling.
- Implemented RF and LSTM models for Stock Price Time Series Forecasting.
- Assessed the model's performance using regression metrics, including R^2, MAE, and RMSE.
- Conducted a comparison of the prediction models to identify the best effective ones for stock market forecasting.

A. Problem Statement and Motivation

The stock market is incredibly volatile and complicated, and is subject to a large number of economic, social, and political factors, such that it is difficult to properly predict the price of stock. Conventional statistical methods may not be able to capture nonlinear trends and volatility of financial time-series data and have a restricted predictive ability. As huge financial data becomes widely available, there is a demand of sophisticated analytical methods that are capable of eliciting obscure patterns and tendencies of stock market data of these issues. The present research examines how ML and DL models may increase the accuracy of stock price predictions, enabling financial analysts and investors to make better financial risk management and investing decisions.

This study is justified by the increased significance of correct stock market prediction to an investor and a financial analyst. The stock market is an extremely dynamic process affected by numerous factors, so it is necessary to predict it using reliable methods to make the right decisions. The study utilize ML models like the RF and LSTM to forecast the price of the Sensex stock by using historical data of the BSE Sensex to enhance forecasting accuracy. The methodology is useful in discovering trends in large financial data, and it leads to better investment policies and financial analysis.

B. Organization of the Paper

The following is how the paper is organized: Section II examines current studies, Section III discusses the dataset, methodology, and model implementation, Section IV presents experimental results and analysis, and Section V concludes with future research directions.

II. Literature Review

This section reviews literature on stock-price forecasting, focusing on accuracy and the ability to capture complex patterns. Table I summarizes the available literature, giving the models used, datasets, performance, contributions and gaps.

Y. Nejatbakhsh and M. Aliasgari (2026) simulated a Federated Learning environment, which solves privacy issues in the financial services industry by allowing decentralized model training without disclosing raw financial data. Ten significant tech companies, including Tesla, Apple, Amazon, Microsoft, Google, and others, have conducted experiments demonstrate that the hybrid model produces better short-term forecasting results, with a trend accuracy of 65.36% and an average R^2 variance score of 0.91 across 10 significant technological businesses, demonstrating high forecasting performance for short-term stock forecasting [34].

H. Gadam (2025) proposed a Dynamic Reverse Learning Strategy with Dwarf Mongoose Algorithm in Long Short-Term Memory (DRLS-DMA-LSTM) for more accurate SP prediction. The DRLS-DMA is integrated with LSTM for hyperparameter tuning, which enhances the performance and efficiency of the LSTM model. The performance analysis reveals that the R-squared coefficient (R^2) acquired is 0.137, with a Mean Absolute Error (MAE) of 0.011, outperforming the existing Graph Convolutional Network (GCN) approach [35].

L. Gao (2025) study formalizing financial statements as heterogeneous temporal knowledge graphs and develops specialized algorithms for multi-hop financial reasoning. The multi-hop financial reasoning accuracy increased from 69.2% to 91.7%, particularly for complex queries integrating quantitative and qualitative financial information. Scalability tests confirm near-linear scaling up to 32 nodes with efficiency remaining above 0.85 for data volumes reaching 8TB [36].

Ishica et al. (2024) proposed a Random Forest Classifier; high precision and recall metrics were attained along with an accuracy of 85.97%. The model performs well in forecasting rises in stock price, indicating the influence of market mood on stock behavior. In order to conduct a more thorough contextual analysis, future work involve extending the model to include historical stock data, macroeconomic variables, and sophisticated NLP approaches like BERT [37].

R. Nashir et al. (2023) leveraged the GDELT event dataset; this study uses an organized database of news stories and enhances stock price index predictions by including sentiment variables into the Stacked Bidirectional Unidirectional LSTM (SBU-LSTM) model. The SBU-LSTM used BDLSTM and LSTM layers (256 units each) with RMSprop, learning rate 0.0001, window size 10, batch size 64, 3-day latency, and 25 epochs to obtain an average MAPE of 0.81%. Previous LSTM models achieved MAPE scores of 1.5% to 5%. The study surpassed the SBU-LSTM research article (MAPE 5.67%) with a MAPE score of 0.80% when optimistic sentiment was the only sentiment used [38].

T. N. A. B. T. M. Busu et al. (2022) demonstrated the accuracy of the LSTM model utilizing the RNN technique, and the stock market's anticipated value increased by 1.87% on October 5, 2021. It may be applied to forecast future closing stock prices in the FBM KLCI stock market. An accurate forecast for a higher profit is anticipated from the outcomes. Thus, long-term economic growth or, to put it another way, economic sustainability can be encouraged through stock market prediction [39].

The studies reviewed are devoted to enhancing stock price prediction accuracy using sophisticated ML and DL algorithms such as Federated Learning, LSTM variants, Random Forest, and knowledge graph-based reasoning. Most of the works combine other sources of information such as sentiment analysis, financial statements, and event-based data in order to improve forecasting. Also, the problem of scalability, the utilization of various financial indicators, and the ability to cover all features are not exhaustively covered. Therefore, there is a need for more efficient, scalable, and generalized models that can effectively combine diverse financial data sources to improve stock price time-series forecasting accuracy.

TABLE I. SUMMARY OF EXISTING STUDIES ON STOCK PRICE TIME SERIES FORECASTING

Ref.	Data Source	Model	Features	Results	Contributions	Gaps
Nejatbakhsh & Aliasgari (2026)	Stock information from well-known tech firms (such as Tesla, Apple, Amazon, Microsoft, Google, etc.)	Hybrid Model with Federated Learning	Decentralized training, privacy-preserving model, no raw financial data sharing	Average R^2 score = 0.91, Trend precision = 65.36%	Improved short-term stock forecasting while maintaining data privacy	Focuses mainly on short-term forecasting and limited to selected tech companies
Gadam (2025)	Stock price dataset (not specifically stated)	DRLS-DMA-LSTM	Dynamic Reverse Learning Strategy with Dwarf Mongoose Algorithm for hyperparameter tuning	R^2 = 0.137, MAE = 0.011	Enhances LSTM efficiency through optimized hyperparameter tuning	Lower R^2 value and limited comparison with other advanced deep learning models
Gao (2025)	Financial statements represented as heterogeneous temporal knowledge graphs	Knowledge Graph-based Financial Reasoning Model	Multi-hop financial reasoning, heterogeneous temporal knowledge graphs	Accuracy improved from 69.2% to 91.7%, efficiency >0.85 with scalability up to 32 nodes and 8TB data	Enables complex financial reasoning, integrating quantitative and qualitative data	Focuses more on financial reasoning rather than direct stock price prediction
Ishica et al. (2024)	Market sentiment and stock-related data	Random Forest Classifier	Sentiment-based analysis, classification for stock movement prediction	Accuracy = 85.97% with high precision and recall	Demonstrates how market sentiment influences changes in stock prices.	Does not include macroeconomic factors or advanced NLP models like BERT
Nashir, Gunawan & Palupi et al. (2023)	GDELT event dataset (news and global event data)	Stacked Bidirectional Unidirectional LSTM (SBU-LSTM)	Sentiment variables, BDLSTM + LSTM layers, RMSprop optimizer	Average MAPE = 0.81% (better than previous models with 1.5–5% MAPE)	Improves stock index prediction using news sentiment and deep learning	Requires complex architecture and large event datasets
Busu et al. (2022)	FBM KLCI stock market dataset	LSTM using Recurrent Neural Network (RNN) approach	Time-series forecasting using LSTM architecture	Predicted stock value increase of 1.87%	Demonstrates effectiveness of LSTM for stock price prediction	Limited evaluation metrics and tested on a single stock market

III. RESEARCH METHODOLOGY

The aim of the proposed methodology is to predict stock price trends using the BSE Sensex 10-Year Stock Price dataset sourced from Kaggle. The dataset is preprocessed, that is, the analysis of missing values and the changes to the columns, such as the sorting of the data according to dates to preserve the chronological order. The data thus obtained are further divided into training (80%) and testing (20%) sets. Standard Scaling is used to normalize feature values, making the model more efficient. This is followed by the application of ML models such as Random Forest and Long Short-Term Memory (LSTM) to make predictions. Lastly, regression metrics, such as R^2, MAE, and RMSE, are used to evaluate model performance and assess predictive accuracy. Fig. 1 shows the framework's flow.

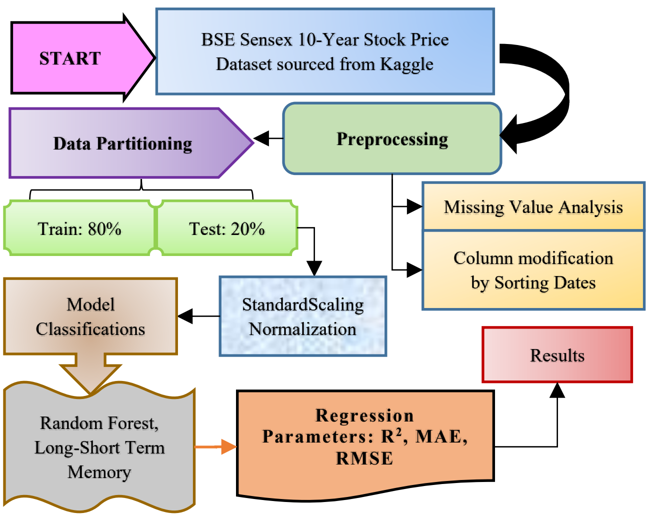


Fig. 1. Flowchart of the Methodology

The proposed methodology steps and implementation strategy are elaborate below:

A. Data Collection and Visualization

The data in this research is the BSE Sensex 10-Year Stock Price dataset on Kaggle which consists of past daily data of the S&P BSE Sensex index between April 1, 2014 and March 31, 2024. The data has 2469 records and 5 variables (shape: 2469: 5), with the move being Date, Open, High, Low and Close prices, indicating index movements on a daily basis. It is appropriate to analyze time-series and predict stock prices using machine learning models.

Fig. 2. Sensex Closing Price Over Time

Fig. 2 shows the historical closing price movement of BSE Sensex 2014-2024. It shows a long-term trend of upward movement with significant volatility with a steep fall in 2020 and a robust recovery. All in all, the trend indicates a long-term Indian stock market growth going back a decade.

Fig. 3 shows the Relative Strength Index (RSI) of the BSE Sensex over time to measure momentum. Overbought is indicated by a number above 70, while oversold is indicated by a value below 30. The crossing and re-crossing of these levels is an indication of repetitive short-term momentum changes in the market.

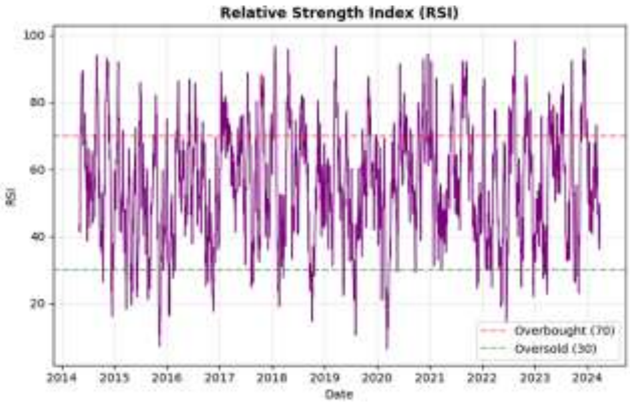


Fig. 3. Relative Strength Index (RSI)

B. Data Preprocessing

The data preprocessing of the BSE Sensex stock price Dataset is emphasized due to inherent noise and inconsistencies. Managing missing values and changing columns are important tasks. The stages for pre-processing are shown below:

- **Missing Value Analysis:** The preprocessing has taken into consideration the missing values in the dataset, and the rows in the dataset that contain null values were identified and deleted. This resulted in a clean dataset, which was further analyzed and modelled.
- **Column Modifying:** The datatype of the format of the date column was changed from object to datetime, and the dates were sorted in ascending order (2014-2024).

C. Data Splitting

The dataset is divided into 80:20 training and testing groups. The division is performed in a sequential rather than random way to maintain time dependency.

D. StandardSclaer Normalization

The data is processed with a scaling technique, namely StandardScaler. Scaling, also known as data normalization, helps the model to adapt more quickly in the training process and also reduces the possibility of overfitting. Based on several studies, normalization has been shown to improve accuracy/minimize error in DL-based prediction models. Data normalization is used in order to minimize variability and expedite the convergence of models in the course of training, which has been proven to enhance prediction in past research. In order to compute Standard Scaling, make use of the following Equation (1):

$$X_{scaled} = \frac{X-\mu}{\sigma} \tag{1}$$

Where, X_{scaled}: the value of the data after scaling; μ: the mean value of the data; σ: the standard deviation of the data; X: the original data value to be scaled.

E. Model Classifications

This section discusses the implemented models in Stochastic Price Time Series Forecasting.

1) Random Forest

Decision trees are useful in many machine learning applications. However, deep trees are more likely to overfit the training sets when they are trained to recognize very irregular patterns. A small amount of noise in the data might lead to a totally different growth pattern for the tree. DT huge variance and extremely low bias are the reasons behind this [40]. In essence, this is a collection of DT, each constructed from an alternative random subset of the training set. The predictions made by RF are calculated by averaging the predictions made by each tree. The main advantages of RF are its low sensitivity to hyperparameters and capacity to generalize. The model was implemented to forecast stock prices using multiple input features. This model has been set with 200 decision trees, with a maximum depth of 20 and optimize node-splitting parameters to be more stable and reduce overfitting. The trees in the ensemble fit varied subsets of the data and features to enable the model to fit nonlinear relationships and intricate market trends.

2) Long Short-Term Memory

The vanishing gradient problem is resolved by LSTM, an improved RNN with an additional method for controlling information [41], enabling it to be kept for extended periods of time, and are specifically made to avoid long-term reliance issues [42]. A DL model based on LSTMs was created to learn temporal relationships in BSE Sensex stock price data. A fixed 60-day sequence window was employed to produce input sequences so that the model can learn long-term trends in price movements. The network architecture was a series of stacked LSTM layers that were dropout-regularized to avoid overfitting, as well as dense layers at the end used to make the final predictions. The Adam optimizer was used to train this model, while mean squared error loss served as an early stopping mechanism. After training, predictions were generated and evaluated using RMSE, MAE, and R^2 to assess the precision of the model and its capacity to generalize to new data, as shown in Equation (2):

$$\hat{y_t} = W_y h_t + b_y \tag{2}$$

Where, $\hat{y_t}$: predicted output at time step t; h_t : Hidden state vector at time step t, which includes knowledge gained from earlier time steps in the series; W_y: weight matrix that transforms the hidden state into the output space and b_y: bias term added to improve model flexibility.

F. Model Evaluation

To assess the predictive performance of the models on the Stock Price Time Series Forecasting, regression-based evaluation metrics are used. These metrics quantify model accuracy, error magnitude, and overall predictive reliability. The metrics employed are described below.

- **R^2 Score:** R^2 score quantifies the degree to which the dependent variable's volatility may be explained by several causes. It represents the percentage of variability that the model accounts for in relation to overall market fluctuations. Higher R^2 values indicate stronger predictive capability.
- **Root Mean Squared Error (RMSE):** RMSE values were used to gauge the appropriateness of the values predicted by models. RMSE is used to calculate the square root of the average squared difference between forecast and actual stock values. It penalizes larger deviations more heavily. Lower RMSE indicates more stable and accurate predictions.
- **Mean Absolute Error (MAE):** MAE using assessment metrics, which shows how the actual and

anticipated values differ (value which is expected through a Model where actual values (target variable). Lower MAE signifies better precision and reliability. These are calculate as Equations (3) to (5):

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \quad (4)$$

$$MAE = \frac{1}{n}\sum|y_i - \hat{y}_i| \quad (5)$$

These metrics collectively evaluate the RF and LSTM models' comparative performance, making it possible to determine which strategy produces better stock price prediction accuracy and lower error.

IV. Result Analysis and Discussion

The experiment results of ML and DL models that are utilized for Stock Price Time Series Forecasting are provided in this section.

A. Experimental Setup

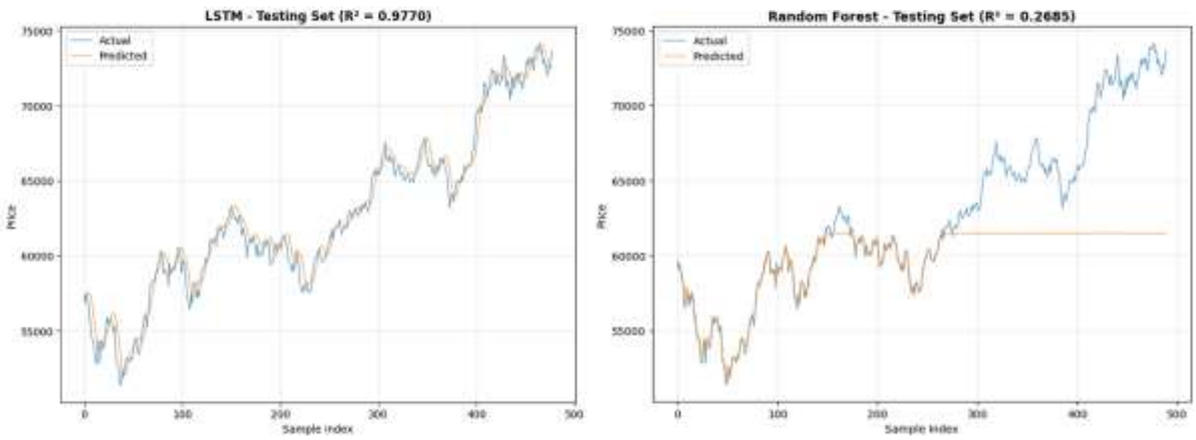
The machine used for this study's testing has an Intel Core i5 quad-core CPU, 8 GB of RAM, and Windows 11. This computing environment provided sufficient processing power and memory to perform data preprocessing, model training, and evaluation efficiently.

B. Performance Evaluation

The performance is assessed using the following metrics: R^2, MA& RMSE. Table II provides the Random Forest and LSTM model performance for BSE Sensex enhancing forecasting.

TABLE II. Performance of Proposed Models for Stock Price Time Series Forecasting

Parameters	LSTM	RF
R^2	0.9777	0.2685
MAE	647.17	2833.28
RMSE	838.22	4706.77



6(a)

6(b)

Fig. 4. Actual vs. Predicted R^2 Scores of LSTM and RF Models

Fig. 4 illustrates the predicted and actual BSE Sensex closing prices on the testing dataset using two models. The LSTM model is very close to the real price trend and the R^2 value is high at 0.9770 which means that it is very accurate in prediction. Conversely, the Random Forest model is relatively poor in performance with an R^2 value of 0.2685 since its predictions are not so effective in representing the variation of the actual data.

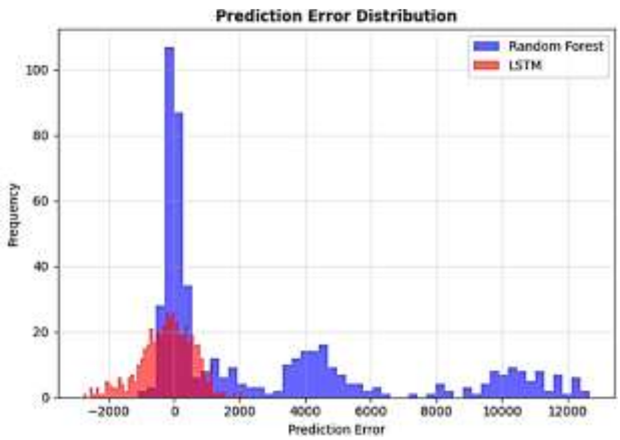


Fig. 5. Error Distribution of LSTM and RF Models

The prediction error distribution for the RF and LSTM models is displayed in Fig. 5. The errors of LSTM are centred around zero which means those are more accurate whereas the errors of the random forest are more distributed meaning that it has poorer prediction performance.

C. Comparative Analysis

The comparative analysis for Stock Price Time Series Forecasting is provided in this section. The comparison of benchmarking models is shown in Table III based on the R^2 Score.

TABLE III. Comparative Analysis of Existing Models in Stock Price Time Series Forecasting

Models	R^2
GRU [43]	0.55
CNN+GRU [44]	0.876
AdaBoost [45]	0.843
ARIMAs [46]	-0.0764
LSTM	0.97

The results indicate that in stock price time-series forecasting, Compared to RF and other benchmark models, the LSTM model performs better. The capability of identifying temporal patterns and sequential dependencies allow it to make more accurate predictions, as well as reduce errors, which makes it more appropriate in the process of stock market trend modeling.

V. Conclusion and Future Scope

In the world of stock investing, changes in stock prices, or their ups and downs, are common. Many inexperienced investors are scared to trade stocks because of these swings. Based on the BSE Sensex 10-Year data, the authors of this study investigated the efficacy of ML and DL techniques in stock price time-series prediction. The findings of the experiments prove that, in comparison to conventional ML-based methods of analyzing financial data, DL models are more adept at identifying intricate temporal trends in financial data. The random forest model had a comparatively lesser predictive capacity, while the Long Short-Term Memory (LSTM) model performed the best among the evaluated models, with the maximum R^2 value of 0.9777, which is extremely high in terms of forecasting stock price movement. The results point to the potential of the LSTM networks in modelling sequential and nonlinear relationships seen in stock market data and enhancing the accuracy of the forecasts, thus guiding more informed decisions made by investors and financial analysts.

This study can be continued in the future through the addition of more financial indicators, macroeconomic features, and news or social media sentiment data to enhance the accuracy of prediction. GRU, Transformers, or ensemble DL models could also be considered as one of the possible ways to improve the forecasting performance and capture the intricate market dynamics in a better manner.

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