Stock Market Prediction Using Long Short-Term Memory (LSTM) Networks

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Abstract—*Stabilizations of stock market prices vary rapidly, and the market is unpredictable and hard to forecast the prices; therefore, the need for robust time-varying models like the LSTM. To enhance the quality of prediction, this study uses several financial features to feed the model with more information and richer features. It performs the required preprocessing, including data cleaning, data normalization, and the generation of time windows to make sure that the dataset is prepared well to be trained in the LSTM architecture. A stacked LSTM network is then trained to know both the short-term and long-term changes in the price in the market. The model performance is measured by RMSE, MAE, and R² in order to obtain a clear and precise measurement of performance in terms of prediction accuracy. The results indicate that LSTM is better than traditional models like ARIMA and linear regression because it is more appropriate for predicting stocks in a stock market.*

Index Terms—*Stock market prediction, long short-term memory (LSTM), deep learning, financial data analysis, Python programming, and machine learning techniques.*

I. INTRODUCTION

A. Background of the Study

The stock markets are sensitive and subject to economic, political, and social factors. This complexity cannot be handled by traditional forecasting, but deep learning allows making predictions more precisely by using large datasets and revealing the hidden dynamics of past price changes [10].

Time-series LSTM networks are useful in time-series prediction, where long-term dependencies are to be modeled, and vanishing gradients are to be prevented. They do a better job with nonlinear financial data than traditional models and are commonly employed to forecast stock trends and price movements and assist algorithmic trading [7].

B. Problem Statement

The prediction of stock price is not an easy task because of uncertainty and non-linear behaviour. Conventional models such as ARIMA and regression are based on the assumption of steady trends and do not reflect profound patterns and long-term dependencies, which leads to poor and unreliable real-world forecasting [3].

The stock market data are noisy, irregular, and seasonal and thus difficult to analyse. Conventional approaches cannot deal with high-dimensional, time-based, and feature weights, resulting in poor predictions. Therefore, sophisticated models are required to acquire patterns in a dependable way of past price trends [9].

C. Research Objectives

The project will focus on creating an LSTM-based model to forecast stock prices based on historical data. It emphasizes the learning patterns and trends to make correct predictions and eliminate the constraints of the traditional methods in assessing performance under varying market conditions [10].

The paper makes a comparison between the LSTM and conventional forecasting techniques in terms of the measures such as MAE, RMSE, and MSE. It seeks to prove that LSTM is more effective and predictable and is better at forecasting the stock market than older models [1].

D. Scope of the Study

The research aims at the forecast of the stock closing price based on historical data. It trains LSTM on time-series patterns, preprocessing features (such as normalization and data splitting), and assesses its performance with validation and other applicable measures [7].

It does not consider using hybrid methods, only LSTM models, in predicting stocks in the short term. It puts an emphasis on the sequential data learning; it does not target long-term economic forecasting beyond the dataset it has [6].

E. Significance of the Study

The study notes that LSTM is an effective instrument for stock forecasting, which assists investors and analysts to find intricate trends. Better decision-making, less risk, and better returns than the traditional methods are supported by accurate forecasts [9].

II. LITERATURE SURVEY

A. Research Paper 1 — Stock Market Prediction using LSTM

This paper explains how the LSTM networks can be used to predict stock prices. The authors indicate that the traditional statistics cannot address the market dynamics, but LSTM can acquire the long-term patterns of price change. Other required processes, including cleaning and normalization of data and splitting, are also described in the paper. Overall, the experiment demonstrates the relevance of LSTM as a reliable tool of short-term stock forecasting.

B. Research Paper 2 — Stock Market Prediction

The researchers are concerned about the effect of preprocessing processes and sequence lengths on the performance of LSTM models. The authors show that correct feature selection, scaling, and sequence generation are some of the key features that can lead to improved prediction. They also discuss the significance of hyperparameters, such as learning rate and batch size, which may affect model stability. The general conclusion is that LSTM is more effective when the data is cleaned and the model is trained using proper training parameters.

C. Research Paper 3 — Stock Market Prediction

In this paper, a comparison will be made between LSTM and the other traditional models and why LSTM is better than the other models in stock forecasting. The authors state that LSTM helps to overcome the problem. They also demonstrate how the performance of models can be measured through appropriate training, testing, and assessment on the basis of metrics like RMSE. The research highlights that LSTM is an effective model, but the success of it depends greatly on the availability of data.

D. Research Paper 4 — Stock Market Forecasting

In this paper the benefits of LSTM alongside the normal technical indicators are established to increase the accuracy of the forecast. The authors show that the model is able to better predict the way the market operates using the characteristics such as moving averages and volatility measures. They also talk about dropout, extra layers in LSTM, and feature engineering to reduce the error and enhance generalization. The paper concludes that LSTM with carefully selected indicators is more stable and reliable to forecast.

E. Research Paper 5 — Literature Survey and LSTM Applications

In the present paper, an overview of the various machine-learning algorithms used to predict stocks is provided, and it explains why LSTM works better than them. It gives an introduction to the findings of previous research and why LSTM is more likely to be more effective with time-series data. Normalization, proper dataset separation, and the correct choice of evaluation metrics are also highlighted by the authors. The article is an easy way to introduce a novice to the grander scheme of things where LSTM is used in stock forecasting.

F. Research Paper 6 — Stock Market Prediction Model using LSTM

The paper gives a step-by-step description of developing an LSTM model. It entails selection of features, data preprocessing, model design, and evaluation. The authors present visual comparisons between the predicted and actual prices. They also remark on such common issues as data insufficiency and overfitting. The article is also practical and can apply to any individual who is implementing an LSTM model.

G. Research Paper 7 — Stock Market Analysis and Prediction Using LSTM

In this paper a stacked LSTM architecture is employed to predict stock prices of Apple over several years. They state that they perform well in terms of RMSE and R2 values and that stacked LSTM layers are able to learn more about the data. The paper also provides a comparison of LSTM and other forecasting models and demonstrates the benefits of LSTM in long-term dependency learning.

H. Research Paper 8 — Advanced Stock Market Prediction Using LSTM

The present paper is more progressive in that it uses sentiment analysis in conjunction with price data to enhance the quality of predictions. The authors have gone into detailed exploratory data analysis, graphical analysis, and an articulated description of their deep learning framework. Their results show that the LSTM model is more accurate when there are features of sentiment. The paper additionally gives real-life recommendations on how to build hybrid models that make use of both numerical and textual data.

I. Research Paper 9 — Stock Price Prediction Using LSTM

This project focuses on forecasting the values of Indian stock markets with LSTM and compares the performance of the model with other forecasting models, such as ARIMA and linear regression. Proper windowing and scaling and proper training data are also emphasized by the authors in order to achieve the proper predictions. Their results reveal that LSTM is more stable concerning the values of error, and the trend lines are more realistic. The article is helpful in getting insight into the behaviour of LSTMs with respect to datasets of Indian exchanges such as NSE.

J. Research Paper 10 — Stock Market Trends Using Deep LSTM Networks

The paper will explain the deep LSTM architectures in detail and how they can be used to predict the stock trends. The authors describe the process of creating multi-layer LSTM models, dropout, and hyperparameter optimization to achieve good results. They compare various Indian stocks and test the model based on measures of standard errors. The paper also mentions future enhancements, such as incorporating sentiment data or transformer-based models, to further improve prediction accuracy.

TABLE I

COMPARISON OF THE RESEARCH ARTICLES ON THE STOCK MARKET PREDICTION USING LSTM.

Research Paper	Authors	Methodology Used	Dataset	Key Contributions	Performance / Results
Paper 1	Sidhu, P., Aggarwal, H., & Lal, M. (2021)	LSTM-based stock forecasting with preprocessing, normalization, sequence modelling.	Historical OHLC stock data.	Showed LSTM performs better than classical models for short-term forecasting.	Improved prediction accuracy using MSE/RMSE.
Paper 2	Patil, P.P., Khandare, N., Nadar, K., Gupta, D., & Sahani, D. (2022)	LSTM with optimized windowing, scaling, hyperparameter tuning.	Daily historical stock data.	Highlighted importance of correct preprocessing for stable predictions.	More stable predictions after tuning sequence lengths.
Paper 3	Sharma, R., Jain, S., Singh, S., & Nitin Kumar, M. (2020)	LSTM compared to RNN and regression; time-series evaluation.	Long-term historical stock prices.	Demonstrated LSTM captures long-term dependencies better.	Achieved lower RMSE than RNN and regression.
Paper 4	Li, Z., Yu, H., Xu, J., Liu, J., & Mo, Y. (2023)	LSTM with technical indicators (MA, volatility) + engineered inputs.	Technology stock datasets with indicators.	Proved hybrid LSTM + indicator model improves stability.	Improved validation accuracy vs raw-price-only models.
Paper 5	Gaur, Y. (2023)	Literature survey of ML models and LSTM for time series.	Multiple datasets referenced across studies.	Summarized that LSTM outperforms ARIMA, SVM, RF consistently.	Reports compiled from prior research showing higher accuracy.
Paper 6	Bhanuse, P., Bansode, P., & Pukale, P. (2023)	End-to-end LSTM pipeline; min-max scaling; stacked layers.	OHLCV stock data.	Provided complete workflow with architecture diagrams.	Strong alignment between predicted and actual values.
Paper 7	Chen, Y. (2023)	Stacked LSTM model with normalization, RMSE/R2 evaluation.	Apple stock dataset (2010–2020).	Showed stacked LSTM significantly boosts predictive accuracy.	R2 = 0.93 and low RMSE (high performance).
Paper 8	Chaudhary, R. (2025)	Advanced multi-layer LSTM with sentiment + numerical features.	Stock OHLC data + sentiment from news articles.	Sentiment-enhanced LSTM improved accuracy.	Lower MAE, MSE, RMSE with hybrid model.
Paper 9	Sharma, Y., Kumar, A., Dubey, V., & Rai, V. (2023)	LSTM vs ARIMA and Linear Regression; data scaling + windowing.	NSE stock market OHLC datasets.	Proved LSTM outperforms ARIMA & LR for NSE stocks.	Better trend-fitting and lower error values.
Paper 10	Shelar, A. (2025)	Deep LSTM architecture with multiple layers + Adam optimizer.	Multiple Indian stock datasets.	Provided full development workflow for deep LSTM models.	Strong performance across multiple tickers.

III. METHODOLOGY

A. Data Collection

The information was collected considering the valid and trusted sources of finances to ascertain the accuracy, consistency, and validity of the information utilized in training. Historical stock data of Yahoo Finance (NSE) were used to collect the data. Other characteristics like past close, last traded price, and trading date were also taken to capture detailed market behaviour and trends with time. The data obtained was systematized to enable effective processing and analysis. With trusted financial sources and multi-feature datasets, the pattern learning is accurate, the noise is minimized, and the stability of LSTM-based stock price forecasts can be enhanced.

B. Data Preprocessing

Missing values were processed, the features were normalized with MinMaxScaler in scikit-learn (min-max scaling), and time sequences were processed. The information was also refined to remove inconsistencies and transformed into a numerical format in a structured form to be compatible with deep learning models. To produce time-series sequences, a sliding-window approach was applied so that the inputs are of constant length and the LSTM model can acquire long-term effects on the stock market.

C. LSTM Model Architecture

To avoid overfitting, the model will consist of stacked LSTMs with two layers (50 units each) and dropout (0.2). The LSTM gates (input, forget, output) allow accurate prediction of the financial time series by modelling nonlinear patterns and long-term dependencies.

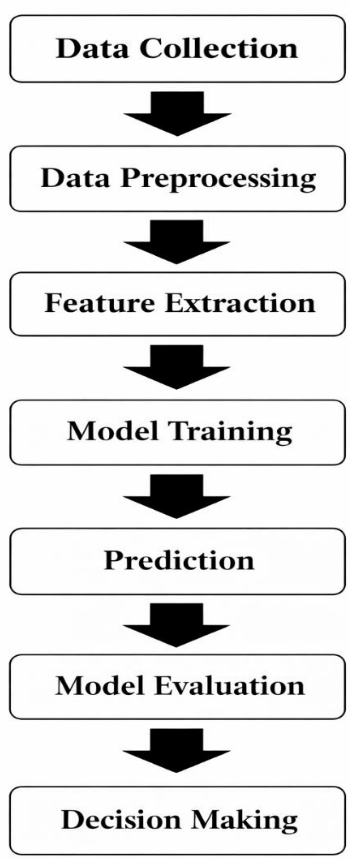
D. Model Training

The Adam optimizer is applied with MSE loss, and the train-test split is 80:20 to train the model. Multi-epoch sequential training and validation tracking enhance accuracy, reduce overfitting, and guarantee predictive accuracy on unknown stock data.

E. Performance Evaluation

The model performance was measured using standard error measures in an attempt to ensure that predictions were effective and reliable. The accuracy of predictions and magnitude of errors in the model performance are gauged using MAE, MSE, and RMSE. These steps provide an idea of the average error and how the deviations of the predicted values are affected. Predicted and actual price-plotted graphs can also be used to analyse the tendency and turning points graphically and the overall generalization capability of the model.

[Fig. 1. Flowchart of the Proposed LSTM-Based Stock Prediction Model]



IV. RESULTS

This project uses a stacked LSTM (long short-term memory) to predict the closing price of stock of NSE-listed corporations. The LSTM model did an excellent task of determining stock prices by analysing historical data. It was able to predict prices that were really close to what happened in the market. LSTM model was highly effective in learning patterns that occurred sequentially and thus the predictions made by the model were consistent and accurate.

[Fig. 2. Stock Close Price Prediction (Actual vs Predicted)]

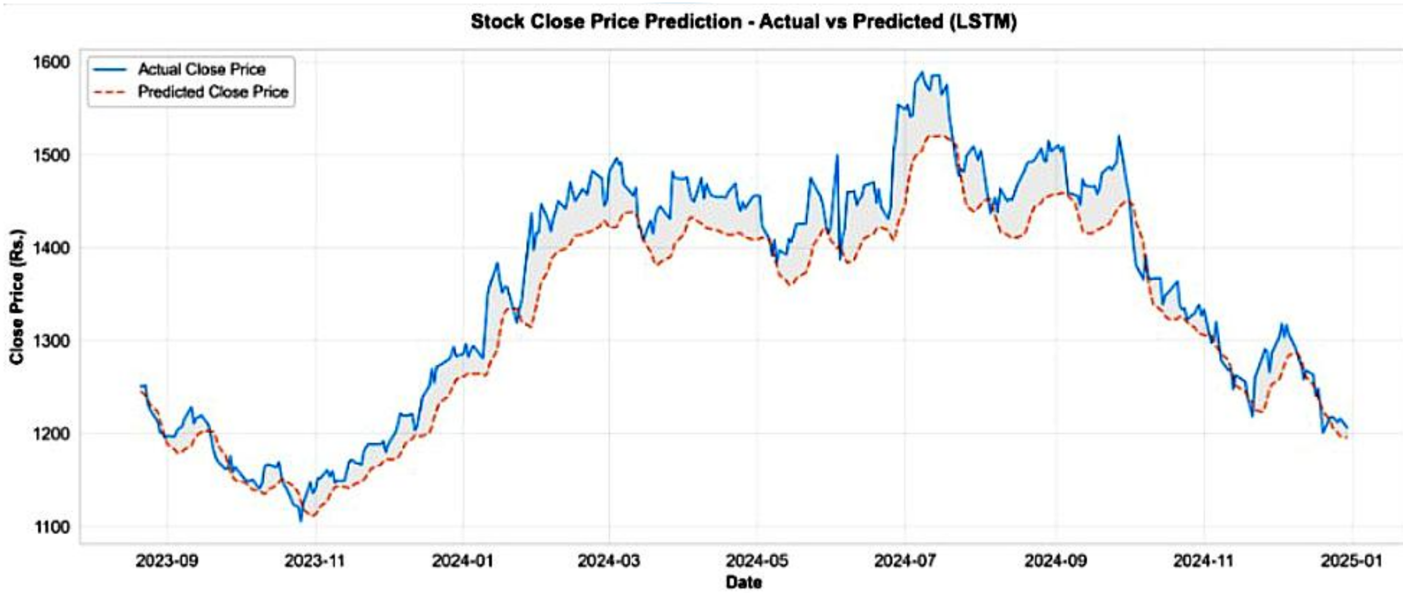


TABLE II
MODEL PERFORMANCE METRICS

Metric	Value
MAE	34.18
RMSE	41.49
R2 Score	0.8928
Accuracy (%)	89.28%

The performance of the proposed LSTM-based stock prediction model is evaluated using MAE, RMSE, and R^2 score, as shown in Table II. The MAE value of 34.18 and RMSE value of 41.49 indicate that the model produces predictions with low error and good consistency. The R^2 score of 0.8928 shows that approximately 89.28% of the variance in stock prices is captured by the model.

V. CONCLUSION

The article concludes that LSTM model is a good predictor of stock prices because it can gain complex time-series features to offer accurate predictions. The model is well-structured in the acquisition of knowledge based on organized financial information and the detection of market trends and can thus help in the process of decision making. Nevertheless, it might not work very well during volatile market environment since it depends on past data. Overall, the article shows that deep learning techniques are significant in financial data prediction, and that it could be enhanced with additional features and more advanced models.

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