IRJCS: International Research Journal of Computer Science ISSN: 2393-9842
Volume 13, Issue 03, March 2026 https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1303.47

Stock Market High and Low Analysis

M.Kalaivani
Assistant Professor, Department of Computer Science & Engineering
Sengunthar Engineering College (Autonomous),Tiruchengode, India
mkalaivani.cse@scteng.co.in
https://orcid.org/0009-0008-9122-7206
Naveen.A,GiriPrasath.S,Gowtham K
UG Students, Department of Computer Science & Engineering
Sengunthar Engineering College (Autonomous),Tiruchengode, India
naveenashok5118@gmail.com,giriprasath7567@gmail.com,gowthamcs77766@gmail.com

Publication History
Manuscript Reference: IRJCS/RS/Vol.13/Issue03/CSMR26.MRCS10126
Research Article | Open Access | Double-Blind Peer Reviewed Article ID: IRJCS/RS/Vol.13/Issue03/CSMR26.MRCS10126
Received: 30, January 2026, Revised: 13, February 2026, Accepted: 28 February 2026 Published Online: 25 March 2026
https://www.irjcs.com/volumes/Vol13/iss-03/47.CSMR26.MRCS10126.pdf
Article Citation: Kalaivani,Naveen,GiriPrasath,Gowtham(2026),Stock Market High and Low Analysis, IRJCS: International Research Journal of Computer Science, Volume 13,Issue 03 of 2026 pages 373-375
Doi:> https://doi.org/10.26562/irjcs.2026.v1303.47 **BibTeX Key Kalaivani@2026Stock**
Orcid: https://orcid.org/0009-0004-9398-7488
IRJCS papers should be cited as IRJCS (International Research Journal of Computer Science, AM Publications, India 2026, ISSN 2393-9842, https://doi.org/10.26562/ijrcs.2025.v1303.47 The journal's official abbreviation is IRJCS.

Abstract: The stock market is an important component of the global financial system and plays a crucial role in economic growth. Predicting stock price movements is a challenging problem due to the volatile nature of financial markets. This paper presents a comprehensive analysis of stock market high and low values using time series forecasting and machine learning techniques. Historical stock market data including open price, close price ,high price, low price, and trading volume are analyzed using statistical and deep learning models. The study applies ARIMA, PROPHET, and Long Short-Term Memory (LSTM) algorithms to forecast future stock price trends. Exploratory Data Analysis (EDA) techniques are used to identify patterns, correlations, and seasonal variations in the dataset. Experimental results demonstrate that deep learning models outperform traditional statistical approaches in capturing complex nonlinear relationships within financial time series data.
Keywords: Stock Market, Time Series Forecasting, Machine Learning, ARIMA, LSTM, Financial Analytics.

I. INTRODUCTION

The stock market serves as a platform where investors buy and sell shares of publicly traded companies. Stock prices fluctuate continuously based on supply and demand, company performance, macro economic conditions, and investor sentiment. Understanding and predicting stock price movements has been as significant research topic in financial analytics and data science. Stock price prediction can assist investors in making informed decisions regarding portfolio management and risk mitigation. The identification of the highest and lowest stock prices during trading periods provides insights into market volatility and potential investment opportunities. Time series forecasting methods are widely used for analyzing financial data because stock prices are recorded sequentially overtime. Traditional models such as ARIMA rely on historical patterns to forecast future values. However, these models often struggle to capture nonlinear relationships present in financial markets. With the advancement of machine learning and deep learning techniques, more sophisticated models such as Long Short-Term Memory (LSTM) networks have been introduced for financial forecasting. These models are capable of learning complex patterns and dependencies in time series data, making them suitable for stock market prediction tasks.

LITERATURE REVIEW

Numerous studies have explored stock market prediction using statistical, machine learning, and deep learning approaches. Traditional econometric models such as ARIMA and GARCH have been widely used for modeling financial time series and volatility patterns. Machine learning techniques including Support Vector Machines (SVM), Random Forest, and Gradient Boosting algorithms have also been applied to financial forecasting. These models can capture nonlinear relationships between variables and improve prediction performance compared with classical models. Recent research has focused on deep learning architectures such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks. These models are specifically designed to process sequential data and retain long-term dependencies in time series datasets. Hybrid models that combine statistical techniques with machine learning methods have also been proposed to enhance forecasting accuracy and robustness in volatile financial markets.

EXISTING SYSTEM

The existing systems for stock market high and low price analysis primarily rely on traditional statistical techniques and basic data visualization tools. These systems utilize historical stock data, including open, close, high, and low prices, to identify trends and patterns over time. Common methods include moving averages, regression analysis, and technical indicators such as Relative Strength Index (RSI) and Bollinger Bands.

ISSN: 2393-9842
https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1303.47

Most conventional approaches depend on time series analysis, where past price movements are used to estimate future highs and lows. These systems often employ linear models, which assume a consistent relationship between historical and future values. While such methods are simple and computationally efficient, they fail to capture the complex, nonlinear, and highly volatile nature of stock market behavior. Additionally, many existing platforms provide visual analytics dashboards that allow users to observe historical trends and manually interpret price fluctuations. However, these systems lack advanced predictive capabilities and do not adapt well to sudden market changes caused by external factors such as economic news, political events, or market sentiment. Another limitation of traditional systems is their dependency on limited feature sets. Most models consider only price-based data and ignore other influential factors such as trading volume, macroeconomic indicators, and real-time news data. This results in lower prediction accuracy, especially for short-term high and low price forecasting. Furthermore, existing systems often do not incorporate machine learning or deep learning techniques, which are more effective in handling large-scale, complex datasets. As a result, their ability to provide accurate and reliable predictions remains limited. In summary, while existing systems provide a foundational understanding of stock price movements through statistical and visualization methods, they suffer from several drawbacks, including low prediction accuracy, inability to handle nonlinearity, lack of real-time adaptability, and limited use of advanced analytical techniques.

PROPOSED SYSTEM

The proposed system introduces an advanced machine learning–based approach for accurate prediction of stock market high and low prices. Unlike traditional statistical models, this system leverages deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, to capture complex patterns and temporal dependencies in stock price data. The system utilizes a comprehensive dataset that includes historical stock prices (open, close, high, low), trading volume, and optionally external factors such as market indices and news sentiment. Data preprocessing techniques such as normalization, handling missing values, and feature scaling are applied to improve model performance. The core component of the proposed system is the LSTM model, a type of Recurrent Neural Network (RNN) specifically designed for time series forecasting. LSTM effectively learns long-term dependencies and nonlinear relationships in sequential data, making it highly suitable for stock market prediction. The model is trained using historical data to predict future high and low prices with improved accuracy.

The architecture of the proposed system consists of the following stages:

1. Data Collection Module: Gathers historical and real-time stock market data from reliable financial sources or APIs.
2. Data Preprocessing Module: Cleans and transforms raw data through normalization, feature selection, and sequence generation.
3. Feature Engineering Module: Extracts meaningful features such as moving averages, volatility indicators, and momentum indicators to enhance prediction capability.
4. Model Training Module: Implements LSTM-based deep learning algorithms to train on time series data and optimize prediction accuracy.
5. Prediction Module: Generates future high and low price predictions based on trained models.
6. Visualization Module: Displays predicted results alongside historical data using graphs and dashboards for better interpretation.

SYSTEM ARCHITECTURE

The proposed system follows the CRISP-DM methodology which consists of six major phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. Stock market data is collected using financial APIs such as Yahoo Finance and Alpha Vantage. The dataset contains features including opening price, closing price, highest price, lowest price, and trading volume. The system architecture consists of the following modules:

1. Data Collection Module – Collects historical stock price data.
2. Data Processing Module – Performs cleaning, normalization, and transformation.
3. Prediction Module – Applies forecasting models such as ARIMA, PROPHET, and LSTM.
4. Visualization Module – Displays graphs and analytics results for users.
5. Decision Support Module – Provides recommendations based on predicted price trends.

Data Analysis and Preprocessing Exploratory Data Analysis (EDA) is performed to understand the characteristics of the dataset. Visualization techniques such as line charts and trend plots are used to identify patterns in stock price movements. Stock market data often contains non-stationary patterns where statistical properties such as mean and variance change over time. To address this issue, differencing techniques are applied to convert the dataset into stationary time series. Data preprocessing steps include handling missing values, removing outliers, scaling features, and transforming data into suitable formats for machine learning algorithms.

Forecasting Models

Three forecasting models are implemented in this study.

ARIMA Model: The Autoregressive Integrated Moving Average model is widely used for time series forecasting. It analyzes historical patterns to predict future values.

PROPHET Model: Developed by Facebook, PROPHET is designed to handle seasonal patterns and trend changes in time series datasets.

LSTM Model: Long Short-Term Memory networks are a type of recurrent neural network capable of learning long-term dependencies in sequential data. LSTM models are particularly effective for financial time series forecasting because they capture non linear relationships between variables.

ISSN: 2393-9842
https://www.irjcs.com/archives
https://doi.org/10.26562/irjcs.2025.v1303.47

EXPERIMENTAL RESULTS

The performance of the models is evaluated using Root Mean Square Error (RMSE)and Mean Absolute Error (MAE). Lower RMSE values indicate better prediction accuracy. Experimental results show that the ARIMA model performs well for simple linear trends but struggles to capture complex nonlinear relationships. The PROPHET model effectively identifies seasonal patterns in stock market data. The LSTM model demonstrates superior performance in forecasting stock price movements because it can learn hidden patterns and temporal dependencies within the dataset.

DISCUSSION

The experimental findings highlight the advantages of deep learning techniques for financial forecasting. LSTM networks outperform traditional statistical models because they capture complex relationships between variables. However, deep learning models require large datasets and higher computational resources. Additionally, model interpretability remains a challenge since neural networks operate as black-box systems. Despite these challenges, integrating machine learning with financial analytics offers significant potential for improving stock market prediction systems.

CONCLUSION

This paper presented a comprehensive analysis of stock market highs and lows using time series forecasting techniques. The study compared ARIMA, PROPHET, and LSTM models for predicting stock price movements. Experimental results indicate that LSTM provides better accuracy for short-term forecasting compared with traditional statistical models. The proposed system can assist investors, traders, and financial analysts in making data-driven investment decisions.

REFERENCES

1. S.Aich et al., 'Stock Market Prediction Using Machine Learning Techniques: A Survey,' Journal of Risk and Financial Management, 2025.
2. H.Chung et al., 'COVID-19 and persistence in the stock market,' Financial Innovation, 2024.
3. R.Engle and T. Bollerslev, 'Modeling volatility in financial markets,' Journal of Econometrics, 2020.
4. M.Kumbure and N.Rouf, 'Machine Learning-Based Prediction of Stock Market Highs and Lows,' IEEE Access, 2022.
5. L.Mozaffari and H.Chen, 'Deep Learning Models for Stock Market Turning Point Detection,' IEEE Transactions on Neural Networks, 2024.
6. J.Brown, 'Financial Time Series Forecasting Using Deep Learning,' IEEE Transactions on Finance, 2023.
7. P.Singh and R. Sharma, 'Machine Learning for Stock Market Prediction,' International Journal of Data Science, 2022.
8. A.Gupta, 'Hybrid Models for Financial Forecasting,' IEEE Conference on Artificial Intelligence, 2021.