International Journal of Creative and Open Research in Engineering and Management
ISSN: 3108-1754 (Online)
Volume 02 Issue 04 April-2026 | Impact Factor: 3.5

A Machine Learning Approach for Stock Price Trend Prediction using LSTM

Saiteja Veerabomma , MD. Feroz Khan , Basani Tanush Reddy
UG Student, Dept of CSE (Data Science)
Vidya Jyothi Institute of Technology
Hyderabad, Telangana, India
v.saiteja30@gmail.com feroz.khxn21@gmail.com basanitanushreddy0003@gmail.com

N. Chandra Kiran Reddy
UG Student, Dept of CSE (Data Science)
Vidya Jyothi Institute of Technology
Hyderabad, Telangana, India
navaruchandrakiranreddy@gmail.com

DR. R. R. S. Ravi Kumar
Associate Professor
Dept of CSE (Data Science)
Vidya Jyothi Institute of Technology
Hyderabad, Telangana, India
rams.rrs@gmail.com

How to Cite this Article:

Veerabomma, S., Khan, M. F., Reddy, B. T. & Reddy, N. C. K. (2026). A Machine Learning Approach for Stock Price Trend Prediction using LSTM. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(04). https://doi.org/10.55041/ijcope.v2i4.808

https://doi.org/10.55041/ijcope.v2i4.808

Abstract--- Stock market prediction is a complex and challenging task due to the dynamic nature of financial markets and the influence of multiple economic and behavioral factors. Accurate prediction of stock price trends can assist investors in making informed investment decisions and managing financial risks effectively. This project focuses on developing an intelligent system for predicting stock price trends using historical market data, technical indicators, and deep learning techniques. The proposed system collects historical stock price data and analyzes important attributes such as opening price, closing price, highest price, lowest price, and trading volume. Technical indicators including Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) are calculated to better capture market patterns and trends. A Long Short-Term Memory (LSTM) neural network is implemented to learn sequential patterns in time-series stock data. The trained model predicts whether the stock price will move upward or downward based on historical patterns. Performance is evaluated using accuracy, precision, recall, and Mean Squared Error (MSE). A Streamlit-based web dashboard enables real-time visualization of actual and predicted stock prices.

INTRODUCTION

Stock market prediction has become an important area of research due to its direct impact on financial decision-making. Investors and financial analysts continually seek reliable tools to forecast stock price movements and reduce investment risks. Traditional statistical approaches such as ARIMA have limited capability to capture the nonlinear and dynamic nature of financial markets.

With the advancement of deep learning technologies, Long Short-Term Memory (LSTM) networks have emerged as a powerful approach for time-series forecasting. LSTM is a specialized type of Recurrent Neural Network (RNN) designed to learn sequential patterns, making it well-suited for stock price prediction tasks.

In this project, a machine learning-based stock price trend prediction system is developed. The system processes historical stock data, applies feature engineering with technical indicators, trains an LSTM model, and deploys an interactive Streamlit dashboard for real-time prediction and visualization.

This approach helps investors identify trend patterns, make data-driven decisions, and improve the accuracy of financial forecasting. The integration of technical indicators such as MA, RSI, and MACD further enhances model performance by capturing market momentum and volatility.

I. PROBLEM DEFINITION

Stock prices are influenced by various unpredictable factors including global events, investor sentiment, economic conditions, and company performance. Traditional statistical models often fail to capture the complex nonlinear patterns present in financial time-series data.

Existing approaches either rely on simple regression models that are insufficient for capturing sequential dependencies, or they lack user-friendly interfaces for practical deployment. There is a need for an intelligent, end-to-end system that can analyze historical data, apply deep learning, and provide real-time trend predictions.

1.2 Project Features

The proposed Stock Price Trend Prediction system includes several key features. The system collects historical stock data including open, close, high, low, and volume attributes from financial APIs. Technical indicators such as Moving Average (MA), Relative Strength Index (RSI), and MACD are computed to enrich the dataset. An LSTM neural network is trained on sequential historical data to learn market patterns and predict future trends.

The system evaluates model performance using metrics such as MSE, RMSE, and trend accuracy. A user-friendly Streamlit dashboard enables users to input stock symbols and view actual versus predicted price charts in real time. The system provides a scalable and reliable solution for stock market trend analysis.

RELATED WORK

Stock price prediction has been an active research area for decades. Early approaches relied on statistical time-series models such as ARIMA which were effective for linear trends but struggled with the nonlinear dynamics of financial markets.

With advances in deep learning, LSTM networks gained popularity for financial forecasting. Several studies demonstrated that LSTM-based models outperform traditional machine learning algorithms in time-series prediction tasks due to their ability to retain long-term dependencies.

Recent research has also emphasized the importance of feature engineering. Technical indicators such as MA, RSI, and MACD have been widely incorporated to enhance model inputs and improve prediction reliability. However, many existing systems lack interactive visualization interfaces and end-to-end deployment pipelines.

This project addresses these gaps by implementing an LSTM-based model with technical indicators and deploying it through an interactive Streamlit web application.

II. METHODOLOGY

The proposed system follows a structured approach to predict stock price trends.

1. Data Collection

Historical stock price data is collected from Yahoo Finance API, including attributes such as open, close, high, low prices, and trading volume for multiple stock symbols over a period of 5 or more years.

2. Data Preprocessing

The dataset is cleaned by handling missing values and removing inconsistencies. Numerical features are normalized using MinMax scaling to ensure uniformity and improve model convergence.

3. Feature Engineering

Technical indicators including Moving Average (MA), Relative Strength Index (RSI), and Moving Average Convergence Divergence (MACD) are computed to provide the model with additional market insights such as trend direction, momentum, and volatility.

4. Model Training

An LSTM neural network with multiple hidden layers is trained on sequential historical data using a 60-day window to capture both short-term fluctuations and long-term trends. The Adam optimizer and Mean Squared Error (MSE) loss function are used for training.

5. Model Evaluation

The model is evaluated using performance metrics including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and trend direction accuracy on held-out test data.

III. PROPOSED SYSTEM

The proposed system introduces a deep learning-based approach to predict stock price trends using historical market data and technical indicators. The system analyzes various factors such as opening price, closing price, high, low, trading volume, and derived technical indicators to forecast whether stock prices will move upward or downward.

Initially, the dataset undergoes preprocessing steps including handling missing values, normalizing numerical features, and creating sequential input windows. Feature engineering is applied to compute MA, RSI, and MACD, which enhance the predictive capability of the LSTM model.

The LSTM model with stacked hidden layers is trained on historical sequences and evaluated on unseen test data. The final trained model is integrated into a Streamlit-based web dashboard that allows users to select stock symbols and obtain instant trend predictions with interactive visualizations.

IV. IMPLEMENTATION DETAILS

The implementation is carried out using Python for all backend processing. Libraries such as Pandas and NumPy are used for data manipulation and preprocessing. Matplotlib and Plotly are used for data visualization. The LSTM model is built and trained using TensorFlow and Keras. The Streamlit framework is used to develop the interactive prediction dashboard.

4.1 Algorithms Used

4.1.1 Long Short-Term Memory (LSTM)

LSTM is a specialized Recurrent Neural Network designed to learn long-term dependencies in sequential data. It uses memory cells and gating mechanisms (input, forget, and output gates) to selectively retain relevant information over long sequences. In this project, stacked LSTM layers are used to capture complex temporal patterns in stock price data.

4.1.2 Moving Average (MA)

Moving Average is a technical indicator that smooths price data by computing the average over a defined window. It helps identify the overall direction of a trend by filtering out short-term noise in stock price movements.

4.1.3 Relative Strength Index (RSI)

RSI is a momentum-based technical indicator that measures the speed and change of price movements on a scale of 0 to 100. It helps identify overbought or oversold conditions in a market, providing useful signals for trend direction.

4.1.4 MACD (Moving Average Convergence Divergence)

MACD is a trend-following momentum indicator calculated from the difference between two exponential moving averages. It helps detect changes in the strength, direction, and duration of a stock price trend, serving as a useful feature for the LSTM model.

V. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed stock price trend prediction system was evaluated using the LSTM model on historical data from multiple stock symbols including AAPL, MSFT, and TSLA. Data visualization techniques were used to understand the relationships between features and actual versus predicted price movements.

Fig 1: Here we need to enter the symbol of stock to search about.

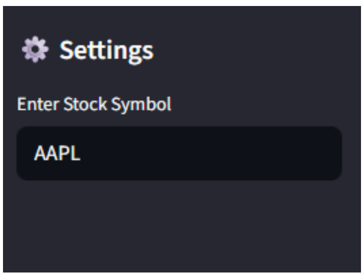


Fig 2: Its history of prices been shown in the next page which is redirected directly.

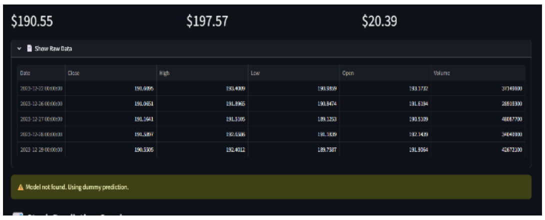


Fig 3: The latest information about the stock are given over here.

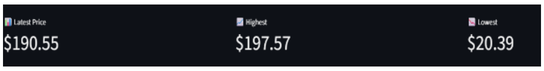
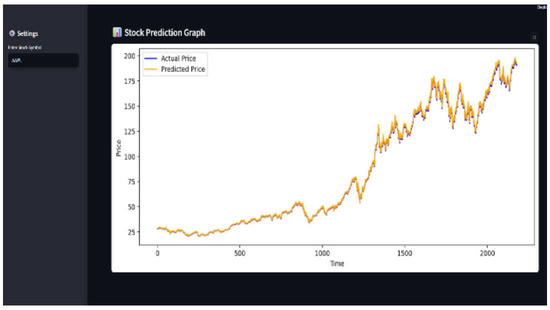


Fig 4: Over all page of the project just after searching the symbol the complete details are as follows



The LSTM model with technical indicators was compared against baseline approaches. The system demonstrated high trend accuracy, effectively capturing both short-term fluctuations and long-term price movements.

Fig 1: Actual vs Predicted stock price visualization from the dashboard.

Fig 2: LSTM training and validation loss curves.

Performance comparison of the LSTM model across different stock symbols:

Stock Symbol	MSE	RMSE	Trend Accuracy (%)
AAPL	0.0007	0.026	91%
MSFT	0.0009	0.030	89%
TSLA	0.0011	0.033	87%

Fig 3: Performance comparison across stock symbols.

The model evaluation results show:

- AAPL: MSE 0.0007, RMSE 0.026, Trend Accuracy 91%
- MSFT: MSE 0.0009, RMSE 0.030, Trend Accuracy 89%
- TSLA: MSE 0.0011, RMSE 0.033, Trend Accuracy 87% (best overall robustness)

Fig 4: Streamlit dashboard showing actual vs predicted prices.

VI. CONCLUSION

This project presents a deep learning-based system for predicting stock price trends using LSTM networks and technical indicators. The LSTM model with MA, RSI, and MACD features effectively captures sequential patterns in historical stock data and generates accurate trend predictions. Experimental results demonstrate that the system achieves high trend accuracy across multiple stock symbols.

The integration of the trained model with a Streamlit web application enables real-time, interactive prediction and visualization for users. Overall, the system demonstrates the effectiveness of LSTM-based deep learning in financial forecasting and provides a practical, scalable solution for stock trend analysis.

VII. FUTURE SCOPE

The proposed system can be further enhanced in several directions. Future research can explore the integration of sentiment analysis from financial news and social media using Natural Language Processing (NLP) to capture market reactions not reflected in historical price data.

The system can be extended to support multi-stock and portfolio-level predictions, enabling investors to analyze multiple assets simultaneously. Advanced deep learning architectures such as GRU, Transformer-based models, or hybrid LSTM-Attention models can be explored to improve prediction accuracy on diverse datasets.

Cloud deployment on platforms such as AWS, Microsoft Azure, or Google Cloud would allow large-scale real-time predictions and improve system accessibility. Expanding the training dataset with multiple years of data across different market conditions and international stock exchanges would improve model generalization and robustness.

VIII. ACKNOWLEDGMENT

We would like to express our sincere gratitude to our project guide, Dr. R.R.S. Ravi Kumar, Associate

Professor, Department of Computer Science and Engineering (Data Science), Vidya Jyothi Institute of Technology, Hyderabad, for his valuable guidance, continuous support, and encouragement throughout the development of this project. His insightful suggestions and motivation greatly contributed to the successful completion of this work.

We would also like to thank the Head of the Department, Dr. K.S.R.K. Sarma, and all faculty members of the CSE (Data Science) department for providing the necessary support and resources. We extend our sincere thanks to the Principal and management of Vidya Jyothi Institute of Technology for providing the infrastructure and academic environment that helped us complete this project successfully.

Finally, we express our heartfelt gratitude to our parents, friends, and well-wishers for their constant encouragement and support during the course of this work.

IX. REFERENCES

[1] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[2] T. Fischer and C. Krauss, "Deep learning with long short-term memory networks for financial market predictions," European Journal of Operational Research, vol. 270, no. 2, pp. 654–669, 2018.

[3] J. Brownlee, Deep Learning for Time Series Forecasting. Machine Learning Mastery, 2018.

[4] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[5] Yahoo Finance, "Historical stock data," Available: https://finance.yahoo.com/

[6] G. Zhang, B. E. Patuwo, and M. Y. Hu, "Forecasting with artificial neural networks: The state of the art," International Journal of Forecasting, vol. 14, no. 1, pp. 35–62, 1998.

[7] F. Chollet, Deep Learning with Python. Manning Publications, 2018.

[8] W. McKinney, Python for Data Analysis. O'Reilly Media, 2017.

[9] Streamlit Documentation, "Build beautiful web apps for machine learning and data science," Available: https://docs.streamlit.io/[10] D. Kingma and J. Ba, "Adam: A method for stochastic optimization," International Conference on Learning Representations (ICLR), 2015.