International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 4, 2025

Stock Price Prediction Using LSTM Model

Tasneem Rahath[1], Duluri Harika[2], Nuthalaganti Meenakshi[3], Asfiya Naaz[4]

[1]Assistant Professor, Department Of Information Technology, Bhoj Reddy Engineering College For Women, India.

[2,3,4]B. Tech Students, Department Of Information Technology, Bhoj Reddy Engineering College For Women, India.

meenakshi261104@gmail.com

ABSTRACT

Stock price prediction is a critical yet complex task in the financial sector due to the volatile and dynamic nature of the market. Traditional prediction methods like statistical analysis and basic machine learning often fail to capture long-term dependencies and real-world market influences. To address these limitations, this project proposes a web-based stock price prediction system using Long Short-Term Memory (LSTM) networks—a type of Recurrent Neural Network (RNN) designed to model sequential data effectively.

The system is built to analyze historical stock data and generate accurate future price forecasts. It features a user-friendly web interface developed with React and a backend powered by Flask and TensorFlow/Keras. Key functionalities include data collection, preprocessing, model training, real-time prediction, and graphical visualization using Chart.js or Plotly.js. The model is trained using CSV data and enhanced through feature selection techniques like PCA and RFE.

This solution offers improved prediction accuracy, scalability to multiple stocks, and automated analysis, making it a valuable tool for investors and financial analysts. The project is developed as a mini-project under the Information Technology curriculum and fulfills the partial requirements for the award of the Bachelor of Technology degree.

Keywords*- LSTM (Long Short-Term Memory), Time Series Forecasting, Machine Learning, Historical Data, Stock Prediction, Price.*

1-INTRODUCTION

The stock market is essential to the global economy, providing people and organizations the chance to invest and accumulate wealth. Predicting stock prices remains a challenging task because to the extremely volatile, non-linear, and dynamic characteristics of financial markets. Market mood, economic data, corporate performance, and global events may induce abrupt and unforeseen price fluctuations. Investors, traders, and financial analysts often depend on statistical methodologies or human acumen, which may inadequately address these intricacies and long-term dependencies.

The emergence of machine learning and deep learning technologies has created new prospects for developing prediction models capable of analyzing extensive historical data and uncovering concealed patterns. Long Short-Term Memory (LSTM) networks, a kind of recurrent neural networks (RNN), have shown notable efficacy in simulating time-series data such as stock prices. LSTM networks can preserve and learn from long-term dependencies, making them appropriate for predicting trends in sequential data. This project seeks to create a web-based application that use LSTM models to forecast future stock values using previous data. The system has an easy interface enabling users to enter stock names, get forecasts, and see outcomes via interactive charts. This project aims to provide a realistic and scalable solution for stock price forecasting by integrating deep learning with an intuitive platform, therefore assisting investors in making data-driven choices.

Existing System:

Statistical analysis is the examination of previous market data to identify patterns and trends that may forecast future price movements. Statistical models often presume and simplify the data and relationships among variables. These assumptions may not withstand reality and may lead to erroneous predictions. While ANN is a versatile machine learning algorithm capable of revealing intricate patterns in data, it is susceptible to overfitting and may perform inadequately in a dynamic market context. Convolutional Neural Networks (CNNs) may evaluate historical pricing data to identify patterns and trends; yet, comprehending their underlying mechanisms is difficult owing to their complexity and several layers.

Proposed System:

The suggested project aims to use a Long Short-Term Memory algorithm to predict stock prices. Long Short-Term Memory (LSTM), a kind of recurrent neural network (RNN) architecture, has been used to predict stock prices. LSTM networks have become prevalent in this field owing to their capacity to manage long-term dependencies and effectively represent sequential data. The fundamental concept of using LSTM for stock price prediction involves training a model on a historical dataset of stock prices to then anticipate future values.

2. RELATED WORK

Literature Review

As financial markets grow increasingly complex, precise stock price forecasting has emerged as a vital area of focus. Researchers have employed a range of machine learning (ML) and deep learning (DL) methodologies to examine historical data, identify patterns, and predict future stock market trends. Below is an overview of notable contributions within this field.

In [1], a single-layer Recurrent Neural Network (RNN) model was introduced to predict both the closing value and the subsequent day's peak price utilizing six fundamental input features: high, low, open, close, volume, and adjusted close prices. This model exploits the temporal characteristics of stock data and demonstrates superior performance compared to more complex architectures such as CNN and LSTM in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The analysis validated that the straightforwardness and effectiveness of the single-layer RNN render it highly appropriate for stock price forecasting, providing investors with valuable insights for informed and profitable decision-making.

Article [2] provided an extensive review of research employing conventional Stock Market Prediction (SMP) models. It analyzed feature selection techniques, dimensionality reduction methods, and data visualization approaches employed in preprocessing. The review identified Support Vector Machines (SVM) as the most frequently employed algorithm, while Artificial Neural Networks (ANN) and Deep Neural Networks (DNN) were acknowledged for delivering more rapid and precise outcomes. Furthermore, integrating financial indicators with external web-based data sources such as news and social media markedly enhanced the accuracy of predictions.

In [3], a multi-value LSTM-based deep recurrent neural network was proposed for the simultaneous prediction of multiple stock values. By comparing it with conventional LSTM and deep RNN models, the study demonstrated that the Associated Net model attains an average accuracy exceeding 95%. This capability to generate multi-stock predictions in a single execution renders it highly efficient, although the authors recognize the potential for further improvements in scalability and robustness.

Study [4] introduced a stock market forecasting model utilizing both LSTM and RNN architectures, trained on historical stock data obtained from Yahoo Finance for two NYSE-listed companies: Google (GOOGL) and Nike (NKE). Approximately 80% of the data was allocated for training, and the model's efficacy was assessed using Mean Squared Error (MSE). The quantity of training epochs and the choice of input intervals markedly affected prediction accuracy, underscoring the significance of meticulous hyperparameter optimization.

In [5], the influence of web news and social media, particularly Twitter, on behavior was integrated into a machine learning-based prediction system. Utilizing sentiment analysis to derive polarity scores from tweets, the study integrated these with real-time market data to enhance short-term forecasting. An RNN was employed because of its proven efficacy in time-series forecasting. The findings indicate that social media exerts a greater influence on short-term predictions, whereas its significance diminishes in the context of long-term forecasts.

The study in [6] concentrated on forecasting the stock prices of Apple Inc. utilizing TensorFlow in conjunction with LSTM networks. The model was developed employing two methodologies: one that relies exclusively on historical closing prices, and another that employs a multivariate approach incorporating opening prices, trading volume, and additional metrics. Mean Absolute Error (MAE) and Mean Squared Error (MSE) were employed to assess the performance. The results verified that multi-feature models enhance forecast accuracy, thereby fulfilling practical forecasting requirements.

A comparative analysis in [7] assessed conventional statistical techniques, including Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Smoothing, and Naive Forecasting, in comparison with machine learning methods such as Linear Regression, K-Nearest Neighbors (KNN), Random Forest, Support Vector Machines, Single-Layer Perceptron (SLP), Multi-Layer Perceptron (MLP), and Long Short-Term Memory (LSTM). The findings demonstrated that MLP and LSTM substantially surpass statistical techniques, particularly regarding MSE and Mean Absolute Percentage Error (MAPE), highlighting the superior effectiveness of deep learning in financial time-series forecasting.

In [8], a Random Forest (RF) model was employed to forecast stock market trends, utilizing preprocessing methods such as data normalization to mitigate noise. Sentiment analysis was employed to generate polarity scores from financial articles, which were subsequently correlated with market outcomes. The model's efficacy was assessed using the variance score, MAE, MSE, and Mean Squared Log Error (MSLE). Random Forest demonstrated greater efficacy compared to logistic regression, particularly in managing sentiment-enhanced data.

Study [9] evaluated the performance of LSTM and regression-based models utilizing structured historical data sourced from Yahoo Finance. Inputs comprised the date, stock symbol, and prices (open, close, low, high, volume). Results demonstrated that LSTM models attained markedly higher accuracy compared to traditional regression methods, especially when utilizing larger training datasets and extended time windows. This enhanced LSTM model's capacity to manage time-dependent financial data.

3.REQUIREMENT ANALYSIS

Functional Requirements:

Functional requirements delineate the precise behaviors, activities, and features that a software system must provide to satisfy user expectations and achieve its intended objectives. These specifications emphasize the functionalities of the system and delineate the interactions between the user and the system components.

In your stock price prediction project, functional requirements are crucial as they guarantee that the system executes all necessary processes, including data input, model training, prediction production, and result display. Every functional component directly enhances the usability, efficiency, and success of the program.

Non-Functional Requirements:

Non-functional requirements define the quality attributes of a system — how the system performs rather than what it does. While functional requirements describe specific features and behaviors, non-functional requirements focus on system performance, reliability, usability, scalability, maintainability, and security. For your LSTM-based stock prediction project, non-functional requirements ensure the application is not just functional, but also efficient, user-friendly, secure, and adaptable to real-world conditions.

Performance

The system should generate stock price predictions within 2 seconds after input is submitted. Data loading, preprocessing, and visualization should be completed with minimal delay.

Accuracy

The LSTM model should deliver predictions with minimal error (e.g., low RMSE or MAPE). Feature extraction methods like PCA and RFE should be used to improve model precision.

Usability

The web interface should be intuitive, clean, and easy to navigate for all users. The system should be responsive and usable on desktops, laptops, tablets, and smartphones.

Software Requirements:

- Programming Language / Platform : Python, JavaScript
- Framework : React.js, Flask
- IDE : VS Code, Jupyter, Notebook, Pycharm
- Operating System : Windows 10, macOS, or Linux

Hardware Requirements

- Processor : Intel i5 or higher
- RAM : 4GB and higher
- Hard Disk : 100Gb minimun

4.DESIGN

System Architecture:

System architecture is the conceptual framework that delineates the structure, behavior, and components of a system. It delineates the interaction between software, hardware, data, and users inside the system to fulfill its functioning. System architecture pertains to the design and arrangement of software components and their intercommunication. It encompasses layers including the frontend (user interface), backend (application logic), database or data storage, and interaction points (e.g., APIs, machine learning models).

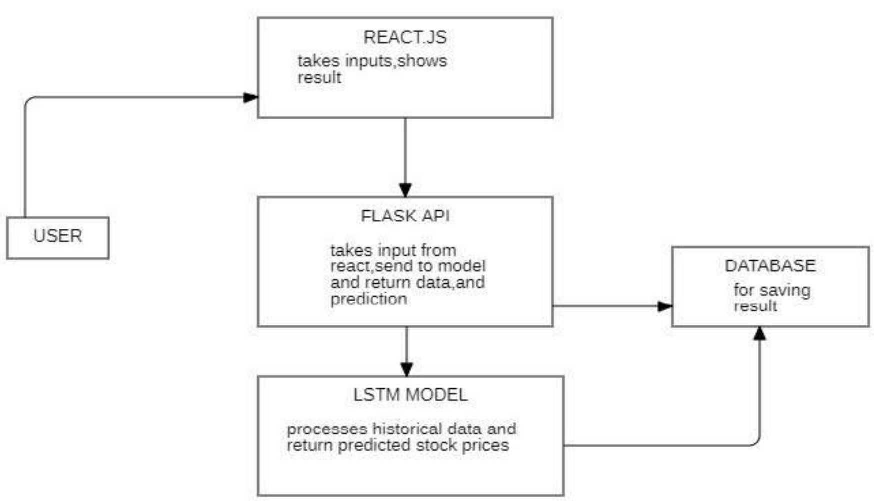


Fig. 1 System Architecture

International Journal of
Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 4, 2025

Technical Architecture:

Technical architecture denotes the comprehensive design and framework of the technologies, tools, frameworks, and systems used to build, operate, and maintain an application. It delineates the interaction of diverse software and hardware components to satisfy the system's functional and non-functional criteria.

The technical architecture of your stock price prediction system delineates the integration of the frontend, backend, machine learning model, and data sources to construct a comprehensive predictive online application.

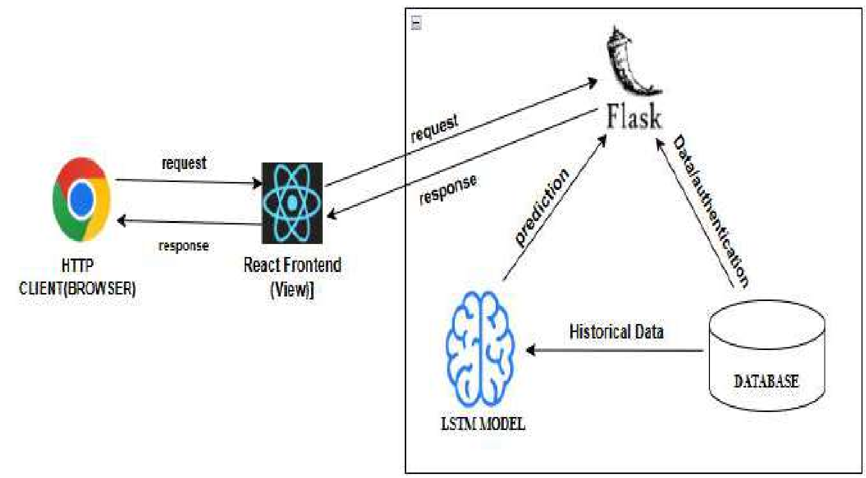


Fig. 2 Technical Architecture

5. IMPLEMENTATION

Numpy

The NumPy library is essential for the effective management of numerical data. It is mostly used in the data preparation step, when historical stock price data, first imported via pandas, is transformed into NumPy arrays for enhanced manipulation efficiency. This facilitates the efficient execution of procedures like normalization, whereby data is scaled to a range appropriate for training deep learning models. A fundamental prerequisite of LSTM networks is the input of sequential data, and NumPy facilitates the generation of time-step-based sequences via sliding windows, enabling the model to discern temporal patterns. Furthermore, NumPy is used to transform the data into the requisite 3D configuration for LSTM models: (samples, timesteps, features). The library's capacity for executing vectorized operations considerably accelerates these procedures in comparison to conventional Python loops. NumPy serves as the cornerstone for fast data translation and preparation, crucial for precise and high-performance stock price prediction using deep learning.

Pandas

The Pandas library is crucial for data management and manipulation. It is mostly used to import and analyze historical stock market data from CSV files, which include variables like date, open, close, high, low, and volume. Pandas offers robust data structures, such as DataFrames, that provide efficient cleaning, filtering, and analysis of tabular data. For instance, superfluous columns may be eliminated, missing values may be addressed, and the dataset might be organized or indexed chronologically. Pandas also enables the computation of moving averages, percentage changes, or other derived indicators as needed for feature development. Prior to inputting the data into the LSTM model, Pandas is used to extract pertinent features and arrange the data for translation into NumPy arrays. Its smooth connection with libraries such as NumPy and Matplotlib renders it an essential instrument in the data pretreatment pipeline, guaranteeing clean and well-structured input for the training of precise stock price prediction models.

Flask

Flask serves as the backend framework to integrate the frontend with the LSTM model. It manages user input, processes requests, executes predictions using the learned model, and transmits the results in JSON format. Flask's simplicity and its support for REST APIs render it optimal for deploying machine

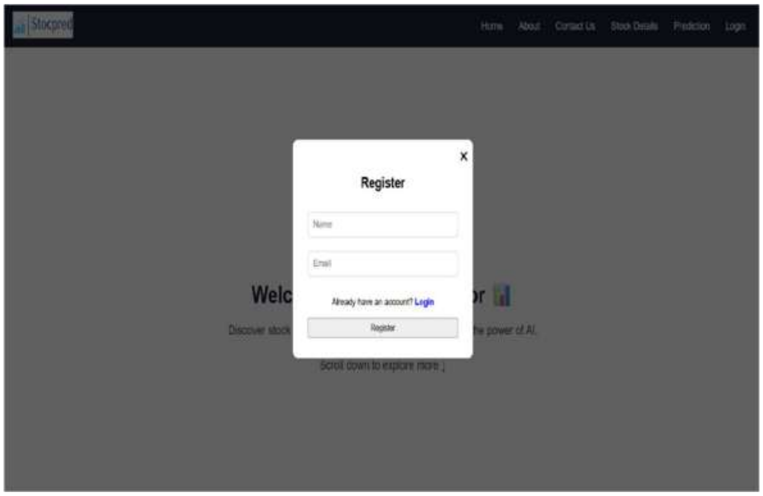
International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

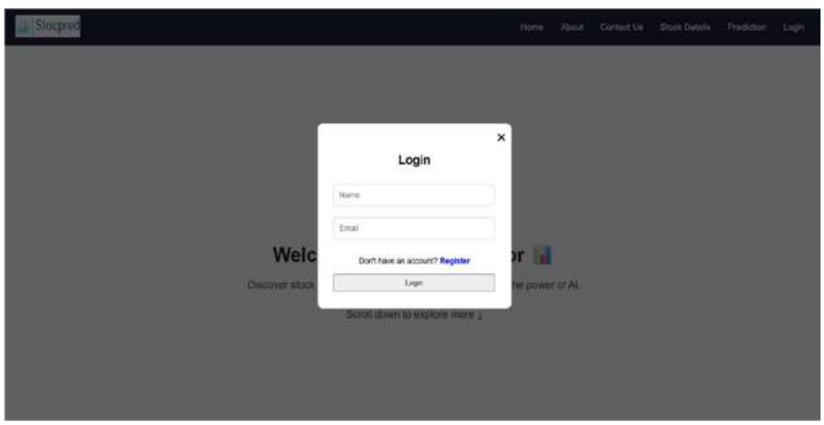
Volume 13, Issue 4, 2025

learning models in real-time web applications. It also integrates with Flask-CORS to provide seamless communication between the React frontend and the Python backend.

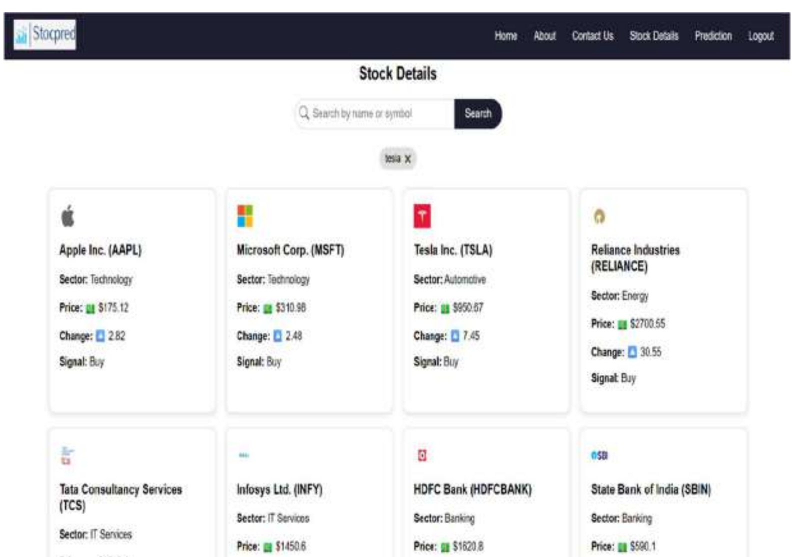
6. SCREENSHOTS



Screenshot 6.1: Register/sign up Image

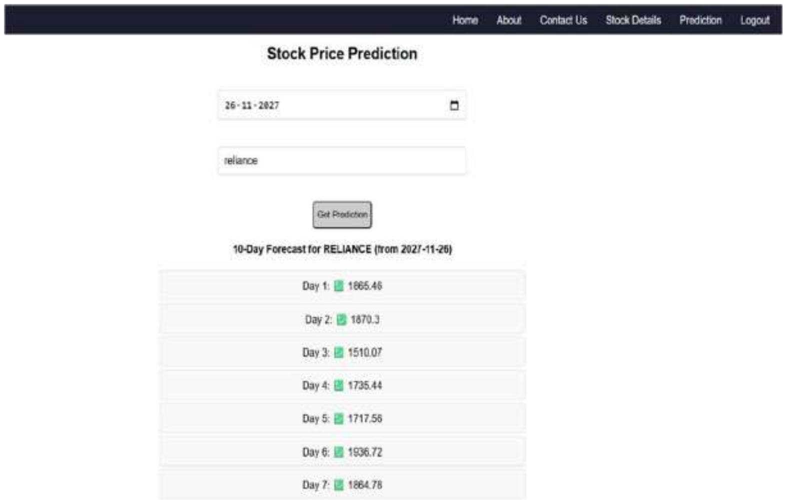


Screenshot 6.2: Login Image



International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 4, 2025

Screenshot 6.3: Stock Details



Screenshot 6.4: Stock Price Prediction

Screenshot 6.5: Graph showing Prediction

7
. CONCLUSION

This study illustrates the efficacy of LSTM-based deep learning models in predicting stock values via historical data analysis. The technology facilitates educated investment choices with a user-friendly online interface and real-time predictive capabilities. It provides a robust basis for further improvements such as real-time data integration and sophisticated financial analysis. Predicting stock prices is a formidable challenge owing to the intrinsic volatility, non-linearity, and dynamic characteristics of financial markets. Conventional statistical models and rudimentary machine learning algorithms often inadequately address long-term interdependence and intricate temporal patterns essential for accurate forecasting. This effort addresses these restrictions by using LSTM networks, which can learn from historical stock price sequences and discern significant patterns over time. The system is structured as a comprehensive online application enabling users to enter stock data and get forecasts via an interactive, user-friendly interface developed using React. The backend, constructed using Flask, acts as the conduit between the user interface and the trained machine learning model, facilitating seamless and efficient data transmission. The LSTM model is executed using TensorFlow and trained on preprocessed historical data that has been cleaned, standardized, and organized using libraries such as Pandas, NumPy, and Scikit-learn. Advanced feature extraction techniques like as PCA (Principal Component Analysis) and RFE (Recursive Feature Elimination) are used to diminish dimensionality and augment the quality of input features, hence enhancing model performance and mitigating overfitting. The system utilizes Chart.js or Plotly.js for visualizations, enabling users to effectively analyze past patterns and future forecasts. Moreover, the program has been designed for scalability and adaptability, rendering it appropriate for the future incorporation of live data sources, supplementary stock symbols, sentiment analysis from news or social media, and portfolio-level forecasts. By automating data processing, prediction, and display, the system minimizes the need for human analysis and enables users—both technical and non-technical—to make better educated investment choices. This study illustrates the practical application of contemporary deep learning methodologies to real-world financial challenges and provides a robust basis for future improvements that may boost its impact, usefulness, and commercial significance.

REFERENCES

[1] Shahzad Zaheer, Nadeem Anjum, Saddam Hussain, Abeer D. Algarni, Jawaid Iqbal Sami Bourouis, and Syed Sajid Ullah, A Multi-Parameter Forecasting for Stock Time Series Data Using LSTM and Deep Learning Model", Mathematics 2023. Forecasting for Stock Time Series Data Using LSTM and Deep Learning Model", Mathematics 2023.

[2] Nusrat Rouf, Majid Bashir Malik, Tasleem Arif, Sparsh Sharma, Saurabh Singh, Satyabrata Aich and Hee-Cheol Kim, "Stock Market Prediction Using Machine Learning Techniques: A Decade Survey on Methodolo gies, Recent Developments, and Future Directions". Electronics 2021.

[3] Guangyu Ding, Liangxi Qin, International Journal of Machine Learning and Cybernetics (2020) 11:1307–1317, Springer.

[4] ADIL MOGHARA, MOHAMED HAMICHEB "Stock Market Predic tion Using LSTM Recurrent Neural Network", in International Work shop on Statistical Methods and Artificial Intelligence. Elsevier 2020.

[5] Naadun Sirimevan; I.G. U. H. Mamalgaha; Chandira Jayasekara; Y. S. Mayuran; Chandimal Jayawardena," Stock Market Prediction Using Machine Learning Techniques ", in International Conference on Ad vancements in Computing. IEEE 2019.

[6] Jingyi Du, Qingli Liu, Kang Chen, Jiacheng Wang, "Forecasting stock prices in two ways based on LSTM neural network", 3rd Information Technology, Networking, Electronic, and Automation Control Confer ence. IEEE 2019.

[7] Indrani Bhattacharjee, Pryonti Bhattacharja," Stock Price Prediction: A Comparative Study between Traditional Statistical Approach and Ma chine Learning Approach" in 4th International Conference on Electrical Information and Communication Technology (ICEICT). IEEE 2019

[8] Subhadra Kompella, Kalyana Chakravarthy Chilukuri, " STOCK MAR KET PREDICTION USING MACHINE LEARNING METHODS", in International Journal of Computer Engineering and Technology (IJCET). IJCET, 2019.

[9] Ishita Parma, Navanshu Agarwal, Sheirsh Saxena, Ridam Arora, Shikhin Gupta, Himanshu Dhiman, Lokesh Chouhan, "Stock Market Prediction Using Machine Learning,"First International Conference on Secure Cyber Computing and Communication(ICSCCC). IEEE 2018.

[10] Sreelekshmy Selvin, Vinaya Kumar R, Gopalakrishnan E.A, Vijay Krishna Menon, Soman K.P, "STOCK PRICE PREDICTION USING LSTM, RNN, AND CNN-SLIDING WINDOW MODEL". IEEE 2017.