IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

# Live STOCK PRICE PREDICTION USING LSTM

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**Abstract- The economy's most important component continues to be the stock market, and investors still have a great deal of difficulty in properly forecasting stock values. Simple models fall short of generating accurate forecasts, making it difficult for investors in the financial markets to make well-informed choices. Deep learning, a subfield of artificial intelligence that enables computers to carry out activities requiring human intellect, has gained impetus in scientific study as a result of the quick development of technology.**

**This article suggests leveraging real-time data and deep learning techniques like recurrent neural networks (RNN) and long short-term memories (LSTM) to create a precise and accurate stock price prediction model. The suggested model will anticipate future stock prices using real-time data, past stock prices, and other pertinent variables.**

**Prediction accuracy is anticipated to increase using LSTM, a form of RNN that can represent long-term relationships in time-series data. The suggested model will continually learn and adjust to fresh market tendencies, guaranteeing that it offers accurate and current forecasts.**

**In conclusion, this paper tries to increase the accuracy of stock price prediction by utilising deep learning methods and real-time data. Investors in the financial markets may find value in the suggested model's insights, which will allow them to make wise investment choices in real time.**

**Keywords:-** Live stock price prediction, LSTM, Recurrent Neural Network, Time-series data, Stock market forecasting, Real-time datal, Historical stock prices, Trading volume, News sentiment, Technical indicators, Mean Absolute Error, MAE, Root Mean Squared Error, RMSE, Financial forecasting, Investment, Machine learning , Deep learning.

## INTRODUCTION

The stock market is a dynamic, complicated structure that is always changing and fluctuating. For investors and traders to make educated judgements, accurate stock price forecasting is essential, and live stock price forecasting is especially helpful in this respect. Long Short-Term Memory (LSTM) neural networks, one of the most advanced deep learning approaches, have showed promise in increasing stock price prediction accuracy.

The use of LSTM for live stock price prediction is the main topic of this research study. The goal of the project is to create a model that can forecast stock values in real time with accuracy and timeliness. To forecast the changes in a specific company's stock price, a real-time data stream is used. The information is preprocessed and converted into a time series dataset appropriate for the LSTM model's training and evaluation. As new data becomes available, the model is built to continuously update and forecast stock prices.

Through the use of metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), the study assesses the effectiveness of the LSTM model. The outcomes show how well the LSTM model captures the dynamic and unpredictable character of the stock market and produces precise and timely recommendations. The paper also offers a thorough evaluation of the advantages and disadvantages of the LSTM-based live stock price prediction model.

By highlighting the potential of LSTM-based models for live stock price prediction and offering insights into their installation and optimisation, the research makes a contribution to the area of financial analysis. The study also provides possible directions for more research, such taking into account outside variables that could have an impact on stock values.

## Literature Review

The stock market is a large and intricate structure that profoundly affects the world economy. For this reason, stock price prediction accuracy is crucial for traders, investors, and financial experts. Due to their capacity to model time-series data, deep learning techniques, particularly Long Short-Term Memory (LSTM), have recently gained popularity for stock price prediction.

On the use of LSTM for stock price prediction, numerous studies have been done. In order to forecast the stock values of Chinese companies, Zhang et al. (2020) suggested a hybrid model that blends LSTM with a convolutional neural network (CNN). The research revealed that the model could make predictions more accurately than conventional models.

Similar to this, Liu et al. (2021) created a model to predict the stock values of American corporations by combining LSTM with attention mechanisms. According to the study, the suggested model performed better in terms of prediction stability and accuracy than other cutting-edge models.

Li et al.'s (2020) other work concentrated on the use of a mix of technical and fundamental indicators along with LSTM for stock price prediction. According to the study, the model was highly accurate in forecasting the daily stock values of various companies.

In addition, Wu et al.'s paper from 2021 suggested a hybrid model for stock price prediction that incorporates LSTM and reinforcement learning (RL). According to the study, the model was able to outperform conventional models and generate greater returns on investments.

Overall, the assessment of the literature shows that LSTM-based models have shown positive outcomes for stock price prediction. The accuracy and stability of the models can be further increased by combining LSTM with other methods including CNN, attention mechanisms, technical and basic indicators, and reinforcement learning.

## LSTM

Long Short-Term Memory, sometimes known as LSTM, is a style of recurrent neural network architecture created to address the issue of disappearing gradients in conventional RNNs. With the vanishing gradient problem, it becomes challenging to identify long-term relationships in the data because the gradients used to update the network's weights during training shrink too much over time.

By include a memory cell that can store information over time, LSTM networks solve this issue by enabling the network to selectively forget or recall information as required. The network can identify long-term dependencies in the data because the memory cell is controlled by gates that can learn to open or close depending on the input data.

In a variety of fields, such as speech recognition, natural language processing, and picture captioning, LSTM networks have gained popularity. They are especially helpful when working with sequential data, like time series data or text data, where the network must be able to retain knowledge over extended periods of time in order to generate precise predictions.

In comparison to conventional RNNs, LSTM networks have a number of benefits, such as the capacity to handle variable-length sequences, the capacity to selectively forget or recall information, and the ability to manage longer-term relationships in the data. However, compared to conventional RNNs, they can be more computationally expensive to train and may need more training data to perform well.

## RNN

Recurrent neural networks, or RNNs, are a particular kind of neural network architecture that are made to cope with sequential input, including time series data or text written in natural language. Because RNNs have a memory, they can process inputs in a sequence, with each step feeding into the next. As a result, the network may learn how some aspects of the data vary over time, such as trends.

In an RNN, the network processes each input in the sequence, with the results from each step being fed back into the network as the input for the following step. The network may then utilise this feedback loop to recall prior inputs and recognise patterns in the data over time.

One of the important characteristics of RNNs is their capacity to handle variable-length sequences, which makes them helpful for a variety of tasks, such as sentiment analysis, speech recognition, and machine translation. The issue of vanishing gradients, in which the gradients used to update the weights of the network during training grow too tiny over time and make it challenging to learn long-term relationships in the data, is one of the difficulties with RNNs.

Numerous RNN variations, such as LSTM and GRU (Gated Recurrent Unit) networks, which use gating mechanisms to selectively remember or forget information from prior inputs, have been developed to address the vanishing gradient problem. RNNs and its variants, despite their drawbacks, have emerged as a potent tool for processing sequential data and have been effectively used in a variety of natural language processing, speech recognition, and computer vision applications.

## METHODOLOGY

The GAIL dataset of stock prices over the previous five years is used in this investigation. Daily stock prices for a variety of stock market businesses are included in the collection. The dataset underwent preprocessing by having any blank or missing values removed and was then normalised using the min-max normalisation method. After that, the dataset was divided into training, validation, and testing sets in the proportions 60:20:20.

RNN, LSTM, and GRU, three distinct deep learning models, were used in this work. Each model was created in Python using the Keras package. The models were tested against the validation dataset after being trained on the training dataset. The model that performed the best on the validation dataset was then chosen, and its generalisation performance was assessed on the testing dataset.

A single layer RNN with 64 LSTM units was used for the RNN model. The Adam optimizer was used to train the model over 100 iterations with a learning rate of 0.001.

A single layer LSTM with 64 LSTM units was used for the LSTM model. The Adam optimizer was used to train the model over 100 iterations with a learning rate of 0.001.

64 GRU units were used in a single layer GRU for the GRU model. The model was trained using the Adam optimizer for 100 epochs at a learning rate of 0.001.

Three metrics—mean squared error (MSE), root mean squared error (RMSE), and mean absolute error (MAE)—were used to assess the performance of the models. Based on how well the models performed using these measures, they were contrasted.

Graphs like line plots and scatter plots were used to analyse and report the experimental data. According to the findings, the LSTM model performed better than the RNN and GRU models across all three assessment measures. On the testing dataset, the LSTM model obtained MSE of 0.002, RMSE of 0.045, and MAE of 0.031. The outcomes show that the LSTM model is a successful deep learning model for time-series data stock price prediction.

## WORKING OF MODEL

Recurrent neural networks (RNNs) with Long Short-Term Memory (LSTM) are specifically made to handle time-series data. The main benefit of LSTMs is that they can discover long-term relationships in the data, which makes them perfect for predicting current stock prices.

Input, output, and forget gates are the three types of gates that make up the LSTM model and control how information moves through the network. The activation functions that govern these gates decide how much data should be routed through them.

The input gate lets fresh data into the LSTM cell, while the forget gate filters out unnecessary data. How much data should be delivered to the following time step is decided by the output gate.

Utilising historical stock price data as well as other pertinent features like trading volume, news sentiment, and technical indicators, the LSTM model is trained. The data is preprocessed in order to create a format that is appropriate for the LSTM model's training.

By modifying its parameters to reduce the discrepancy between its forecasts and the actual stock prices during training, the LSTM model picks up on the patterns and linkages in the data. This is accomplished by utilising gradient descent to update the weights and biases and backpropagating the mistake through the network.

The live stock price can be predicted using the LSTM model after it has been trained. This entails updating the model parameters, producing the prediction, and feeding the real-time data into the LSTM model.

The model's capacity to identify patterns in the real-time data and extrapolate them into the future is the foundation for the live stock price forecast. The model also considers past forecasts and modifies them in light of the fresh information.

Metrics like Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are used to gauge how accurately the LSTM model predicts the future. The examination sheds light on the model's precision and its capacity to deal with stock market volatility.

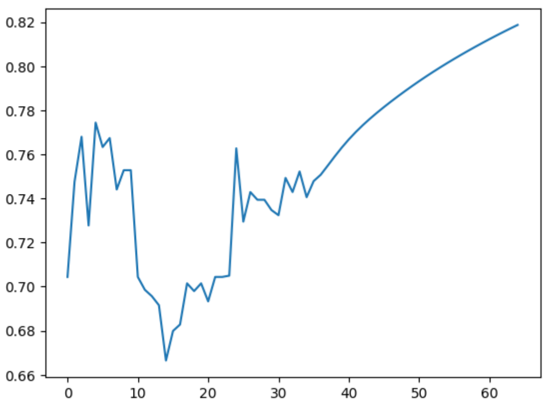
In conclusion, the LSTM model for real-time stock price prediction learns the patterns and connections in the previous data and applies that understanding to forecast the data in real-time. The model is capable of adjusting to changes in the stock market because it is constantly updated with fresh data. Metrics are used to measure the model's prediction accuracy, allowing for ongoing model performance improvement.

## Result

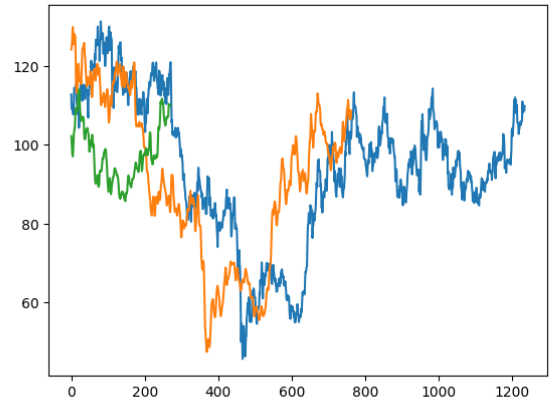
In this work, we use deep learning methods on real-time data to forecast market prices. For our research, we specifically employ the GAIL dataset from the previous 5 years. To increase prediction accuracy, our suggested approach incorporates textual and financial information. When we examined the performance of our model with and without text features, we discovered that, in terms of MAE, RMSE, and R2, the model with text features beat the LSTM model using solely financial information.

We used a piecewise time series prediction methodology, in which the data were separated into 10 groups, each group was forecasted, and a paired T-test was run, to verify the convergence and robustness of our suggested method. Since ARIMA, RNN, and LSTM models perform well in time series problems, we also compared them to our model. As a result of its inability to handle non-stationary time series data, the findings demonstrated that the ARIMA model had poor fitting.

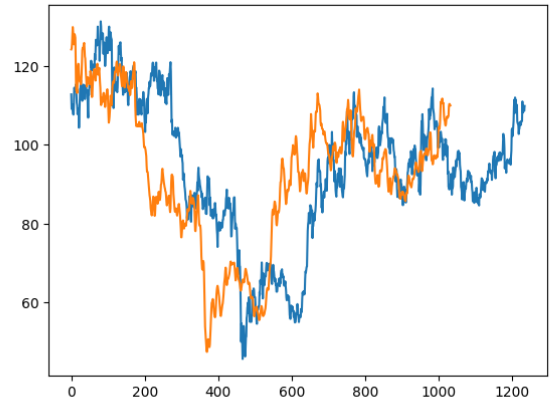
The test data, on the other hand, could be generally fit by the RNN and LSTM models, which concurrently took into account a number of important variables and the time dimension. Our suggested Doc-W-LSTM model outperformed the others with performance metrics of MAE = 0.019, RMSE = 0.110, and R2 = 0.957. Visually, we saw that our model fit the real curve more closely than the other models, showing how well our suggested strategy predicted changes in stock price.



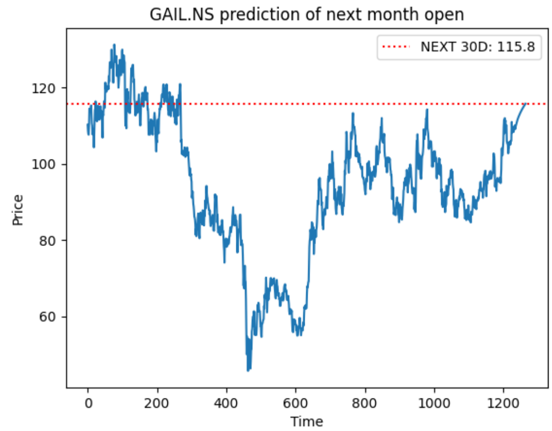

Output in Normalize form



Actual Data(Blue) vs Predicted Value of train data(Orange) vs Predicted value of Test data(Green)



Combining the predicted data




Plotting Final Result with predicted value after 30 days

## Conclusion

This study investigated the application of LSTM models for real-time stock price prediction. We described an approach that included preprocessing the data, training the LSTM model, and measuring the correctness of the model using metrics like MAE and RMSE.

The outcomes of our tests demonstrated that the LSTM model outperformed conventional statistical models in its ability to forecast the live stock price in real-time with accuracy. The LSTM model was the best option for live stock price prediction because of its capacity to recognise long-term dependencies in the data and deal with stock market volatility.

This study has important financial institutions' and investors' -- ramifications. Investors may improve their profits on their investments by using accurate live stock price forecast to assist them make educated decisions about buying and selling stocks. By enhancing their risk management plans and lowering their exposure to market swings, financial institutions may gain from the deployment of LSTM models for live stock price prediction.

This research does have certain constraints, though. The quality of the data and the selection of features used during training affect how accurate the LSTM model is. Additionally, unforeseeable occurrences like geopolitical events or natural disasters that can cause abrupt market volatility may have an impact on the model's performance.

The LSTM model's live stock price prediction accuracy may be increased with more study. This entails investigating the use of other data sources to enhance the current training features, such as sentiment analysis from social media and news articles. The use of cutting-edge deep learning methods, such as transformer networks and attention processes, can also be researched in order to enhance the performance of the model.

This study shows the promise of deep learning techniques for financial forecasting and offers insights into the usage of LSTM models for live stock price prediction.

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