

**STOCK MARKET TREND ANALYSIS WITH LONG SHORT-TERM
MEMORY NETWORKS IN MACHINE LEARNING****Sandeep Yadav^{*1}, Samender Singh² and Pushkal Kumar Shukla³**^{1,2,3} Ajay Kumar Garg Engineering College, Ghaziabad, U.P. India.Article Received on
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Ghaziabad, U.P. India.**ABSTRACT**

When someone plan their investment, it is not easy for them to follow the overall daily updates and analysis the complete past records as an investor. They often fall into trap of choosing their known or recommended stocks instead of choosing a stock that has potential for giving them better result and profit based on analysis. Learning to forecast the stock market's investing strategies requires in-depth research of a large amount of data. We believe that the application of AI and machine learning techniques, which are now more prevalent than traditional methodology and approaches, can improve stock market forecasting. A recent breakthrough is the use of machine learning in the field of stock market forecasting. By training from previous values, this system generates projections depending on the stock market's current values indexes. Machine learning itself employs

a variety of models to support and confirm prediction. The study focuses on machine learning using LSTM along with RNN for valuation of stock. Factors include volume, open, close, low, and high. Making it extremely challenging to predict future price changes. To comprehend the long-term dependency of stock prices, deep learning approaches, such as the LSTM approach, are utilised to gather lengthier data reliance and overall stock change patterns.

KEYWORDS: Stock Market, Prediction, LSTM, RNN, unsupervised.**I. INTRODUCTION**

Machine learning-based stock price prediction enables to determine the worth of company stocks and various financial resources that will be sold on a market in future. Making share price predictions is only done for financial gain. It's challenging to forecast how the stock market

will behave. The prediction also takes into consideration biological and psychological elements in addition to rational and illogical behaviours. These elements work together to create a turbulent and dynamic stock market. Therefore, it might be challenging to predict stock prices accurately.

Through the virtual platforms provided by brokers, anyone may buy and sell stocks, currencies, shares, and derivatives in the financial market, which is a dynamic and complicated system. With the stock market, investors may purchase shares of publicly listed corporations by transacting on exchanges or off-exchange markets. Investing in this market offers investors the opportunity to become rich since it entails very minimal risk, as opposed to starting a new firm or requiring high-paying employment. Numerous variables influence the stock market, contributing to its high degree of volatility and unpredictability.

Proposed paper aims to explain a method a different strategy to forecasting share market values. Instead of fitting the records to a particular model, suggested model employing machine learning architectures to detect the latent dynamics present in the data. The model uses machine learning designs like Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and combine approach of LSTM + CNN for price forecasting of NSE listed businesses and differentiating their performance. Long-standing Sling window approach was applied, and root mean square error was used to assess effectiveness. This paper proposes an time series models for forecasting, such as ARIMA or GARCH models, The practical efficacy of several timeseries prediction algorithms has been demonstrated. The bulk of algorithms used today are built upon RNNs, namely A unique type of RNN is Long-Short Term Memory (LSTM), and Gated Recurrent Units (GRU), another special type of RNN. The stock market frequently uses time-series data, and various academics have investigated this area and created numerous models. In proposed research, an LSTM is employed to forecast the share cost.

II. LITERATURE REVIEW

One kind of recurrent neural network called a Long Short-Term Memory (LSTM) is used to learn order dependence in sequence prediction scenarios. Because it can retain previous data, the LSTM is quite useful for stock value predictions. This is because predicting the value of stocks in the future is dependent on their historical pricing.

Massive volumes of price data for the stock market are created and updated instantaneously.^[1] People may either earn money on the stock market or lose all of their life savings in this

difficult and intricate system. An effort is made to anticipate the stock market trend in this research. Two different kinds of models were developed: one for monthly forecasting and the other for daily forecasting. Using supervised machine learning methods, the models are created. The first model, the daily prediction model, takes sentiment and past price into account. Up to 70% accuracy has been seen in a daily prediction model that uses supervised machine learning methods. A monthly prediction model compares the trends of any two months to find patterns. Analysis shows that there is little correlation between a month's trend and another month's trend.

Stock Closing Price Prediction Using Machine Learning Techniques.^[2] Mehar Vijha, Arun Kumar, Deeksha Chandolab, and Vinay Anand Tikkiwal. It is very difficult to get precise projections of market returns because of how volatile and non-linear the stock markets are. Programmable estimate systems have become more good at anticipating fluctuations in stock prices as a result of the rising use of artificial intelligence and computer technologies. In this research, random forest and artificial neural network techniques were used to forecast the closing prices of five companies from different industrial sectors. The stock's open, high, low, and close prices are utilised to create new variables that are then included into the model. The models are assessed using RMSE and MAPE, two popular strategic metrics.

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This problem is addressed in the article was the feasibility of stock market prediction using artificial intelligence for sentiment analysis is studied.^[4], which was proposed by Surbhi Soni¹, Ashok Kumar Shirvastava², and Deepak Motwani. With minimal effort and great efficacy, real-world problems are being resolved utilising AI and ML techniques. Today, investing in the stock market is a profitable choice when the power of ML is applied to sentiment analysis to forecast the moment of the stock. Forecasting the share trading is a

challenging task since it is dependent on a number of factors, including as investor emotion, stock market synchrony, economic fundamentals, likewise social media sentiment. Proposed article presents a summary of different stock price forecasting and sentiment models in addition to AI advancements and applications in the financial industry. Some of the techniques for the stock market forecasting include Long Short Term Memory (LSTM), ARIMA model Recurrent Neural Network (RNN), linear regression, and k- Nearest Neighbours.

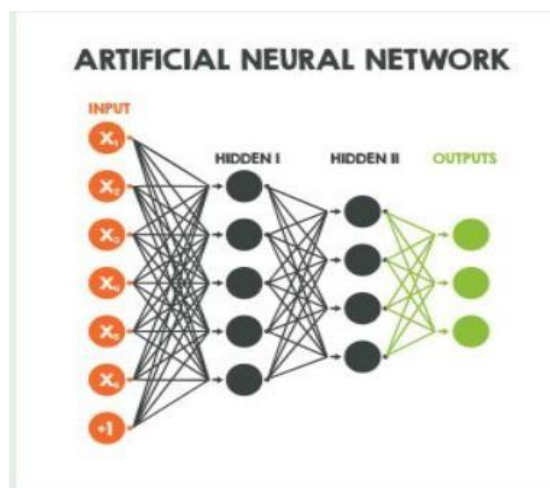


Figure 1: ANN.

A Character-based Neural Language Model for Event- based Trading by Leonardo dos Santos Pinheiro and Mark Dras: Stock Market Prediction using Deep Learning.^[5] With numerous encouraging findings in stock price predictions from financial news, machine learning has recently gained a lot of traction as a tool for analysing financial text data. Efficient Markets Hypothesis (EMH), which is the cornerstone of much economic theory, is affected by this finding. This study investigates For both intraday and interday stock market forecasting, recurrent neural networks with character-level language model pre-training are utilised. This approach is competitive with existing state-of-the-art approaches for forecasting directional changes in the Standard & Poor's 500 index, both for individual companies and the entire index.

I. RELATED TERMINOLOGIES

Before going through the proposed paper, one should have a clear understanding of some related terminologies like LSTM , RNN, CNN, time series analysis, technical analysis, fundamental analysis, etc.

A. RNN: Future input to the same nodes from some nodes may be influenced by their output in

An artificial neural network that can create loops through connections between nodes and is a member of the RNN family. This allows it to exhibit temporal dynamic behaviour. Using their internal state (memory), the RNNs, which descended feeding neural networks forward, can handle sequences of different lengths as input. As a result, they may be used to tasks like speech recognition or connected, unsegmented handwriting recognition. Since recurrent neural networks are Turing complete, they can potentially run any programme to handle any input sequence.

B. CNN: Deep Learning teaches robots or computers to perceive, categorise, and learn from experience in a manner comparable to that of the human brain. Deep Learning is shown as an effective method of assessing large amounts of data. Convolutional neural networks, or Often used for object recognition in deep learning, CNNs are a subtype of artificial neural networks. recognition and classification in photos. Deep Learning uses a CNN as a result to identify items in a picture. CNNs are widely utilised for many different jobs and activities, including as speech recognition for natural language processing, video analysis, and challenges with image processing, computer vision, and self- driving vehicle obstacle identification.

C. LSTM: Information persistence is made possible by A deep learning, sequential neural network called Long Short-Term Memory Networks. The vanishing gradient issue that RNNs encounter can only be resolved by a certain type neural network, recurrent. Schmidhuber and Hochreiter created LSTM to address the issue using conventional rnn and machine learning methods. The Keras library in Python may be utilised to implement LSTM.

1. Assume for the moment that when you watch a movie or read a tale, you are able to recall the events of the previous scene or chapter. They retain previous knowledge and apply it to the current input, much like RNNs. RNN has the disadvantage of not being able to recall long-term dependence because of the decreasing gradient.
2. *LSTM Architecture* – LSTM performs at a high level very similarly to an RNN cell. Using the LSTM network is demonstrated here the functions perform inside. As shown in the picture below, the LSTM network design is separated into three parts, each of which serves a particular purpose.

Whether or whether the data from the previous timestamp has to be remembered determined in the first section. This cell attempts to learn new information using the input from the second part. After then, the cell transmits the updated data using the current

timestamp of the third segment to the subsequent timestamp. One LSTM cycle is regarded as one single-time step.

3. *Forget Gate*— A neural network of LSTM cell's first action to choose whether to retain or throw away the data from the previous time step. The gate of forget formula is displayed below.

$$F_t = \sigma (Y_t * v_f + i_{t-1} * x_f)$$

Y_t : input of the current timestamp.

v_f : suitable weight for the input

i_{t-1} : The preceding timestamp's concealed state

x_f : It really consists of the weight matrix related to the hidden state.

It then goes via a sigmoidal function. Consequently, F_t will change as value 1 and 0. This F_t is affected by the succeeding multiplier's cell state.

D. Analysis of Time Series — A series of time is a predetermined group of numerical observations that a system collects over a predetermined period of time, such daily, monthly, or yearly. Specialised models are used to analyse, characterise, and interpret the gathered time-series data, and certain presumptions are based on shifts and anomalies in the data collection. These shifts and probabilities include, but are not limited to, changes in trends, seasonal demand spikes, certain recurring changes, non-systematic changes in usual patterns, etc.

	date	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	02.01.2013	0	59	22154	999.00	1.0
1	03.01.2013	0	25	2552	899.00	1.0
2	05.01.2013	0	25	2552	899.00	-1.0
3	06.01.2013	0	25	2554	1709.05	1.0
4	15.01.2013	0	25	2555	1099.00	1.0

Figure 3: Time Series Dataset.

All of the previously, recently, and presently gathered data is utilised as input for time series forecasting, which uses sophisticated mathematically driven algorithms to generate future trends, seasonal changes, irregularities, and the like. Time series forecasting also becomes faster, more accurate, and more productive over time using machine learning.

V. PROPOSED METHODOLOGY

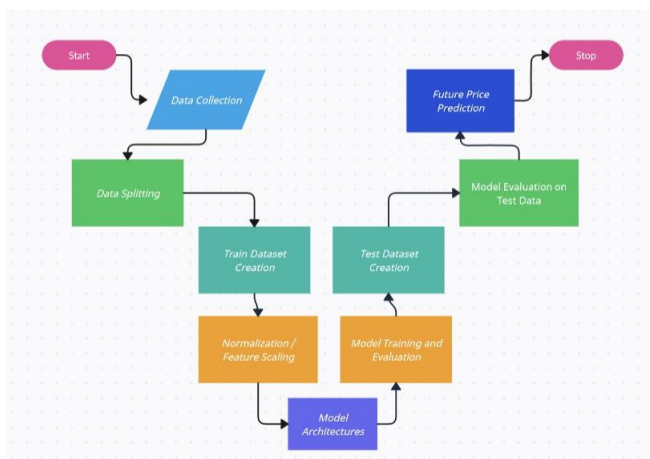
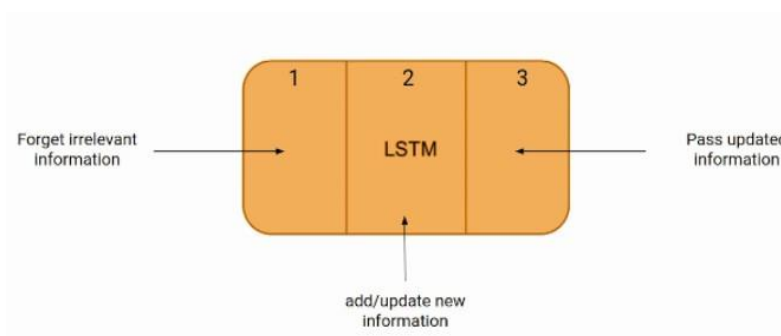


Figure 5: Flowchart.

A. System Model

In this subsection, outline the high-level process this proposed model followed to predict the open price of Tesla stock using Simple RNN and LSTM models.



Data Loading and Preprocessing: Proposed model loaded the Tesla stock price data using pandas. The data includes columns such as Date and Open price. Suggested model ensured that the Date column was in a datetime format for time-based analysis.

Data Splitting: With a split ratio of 70% for training and 30% for validation, this model separated the training and validation datasets. Data Splitting step is essential to evaluate model's performance effectively.

Feature Scaling: Proposed model normalized the Open price values using Min-Max scaling, which scales the values between 0 and 1. This normalization is crucial for training neural network models.

B. Architecture

Detail the architecture of both the Simple RNN and LSTM models suggested model employed for open price prediction:

Simple RNN Model

1. Architecture Overview: Proposed model constructed a Simple RNN model for predicting open prices. The model comprises multiple layers of Simple RNN cells with dropout regularization.
2. Layer Configuration: Proposed model used four layers of Simple RNN cells with tanh activation functions. Each layer has a layer that experiences dropouts at a rate of 0.2.
3. Output Layer: The model concludes with a single Dense output layer.
4. Model Compilation: The suggested model was developed using the "adam" optimizer and the meansquared error (MSE) loss function.
5. Training: The model was trained for 50 epochs with a 32-piece batch size. Suggested model monitored the training loss and accuracy over epochs.

LSTM Model

1. Architecture Overview: Suggested model also implemented an LSTM model for open price prediction, which is known for handling long-term dependencies more effectively than Simple RNN.
2. Layer Configuration: The LSTM model consists of two LSTM layers followed by Dense layers for prediction. Each LSTM layer has 64 units, and the second LSTM layer returns sequences only for the final prediction step.
3. Model Compilation: The model was compiled similarly to the Simple RNN model, using the Optimizer "adam" and MSE loss.

Training: With as much as a 10, the LSTM model was trained for 10 epochs.

VI. EXPERIMENTATION AND ANALYSIS

A. Experimental Setup

This subsection, describe the setup of your experiments, including the hardware, software, and tools used to conduct the experiments.

Hardware and Software Environment

For the successful implementation of employing LSTM RNN machine learning models, predict the stock market, a suitable hardware and software environment was established to facilitate

the model development, training, and evaluation processes. The following components were utilized.

Hardware Environment

The predictive modeling tasks were conducted on a computing system equipped with the necessary computational resources to handle the complex nature of deep learning algorithms.

The hardware specifications used for this research include.

RAM: 32 GB, 16 GB

Processor: Core i7, AMD Ryzen 9

GPU (Graphics Processing Unit): NVIDIA GeForce RTX3080 with 10 GB VRAM

The utilization of a powerful GPU can significantly expedite the training process of deep learning models like LSTM RNN.

Software Environment

The development and execution of the predictive models were facilitated by a comprehensive software environment encompassing programming languages, libraries, and tools.

The software components utilized in this research include.

B. Experimental Parameters

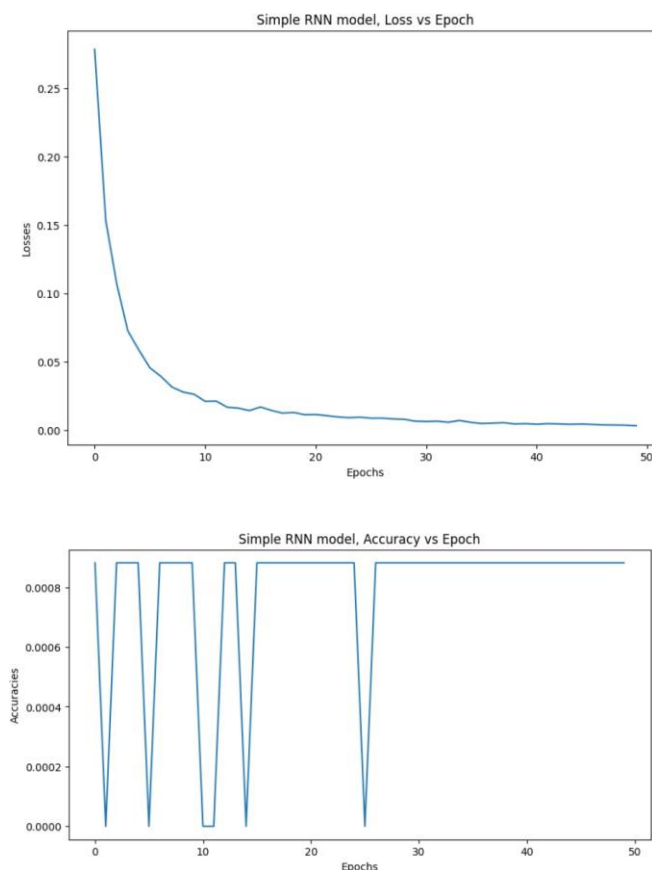
This subsection, provide detailed information about the parameters and configurations used when training and evaluating your models.

1. **Date:** The day the stock market information was compiled. This chronological information is essential for time-series analysis and sequential data processing.
2. **Open:** The price at which Tesla shares trade on a certain trading day. This column serves as the primary target variable for the prediction task, as model aim to forecast the future open price based on historical data.
3. **High:** The stock's highest price throughout the trading day. This information provides insights into the price volatility and potential price trends.
4. **Low:** The stock's lowest price throughout the trading day. Similar to the "High" column, the "Low" column indicates the price range and potential fluctuations.

C. Performance Evaluation

1. Model Evaluation

Loss and Accuracy Plotting: Model evaluated the training process of both the Simple RNN and LSTM models. A graph plotted the training loss and accuracy over epochs, providing insights into the model's convergence and performance.



1. Future Price Prediction

Next Day Prediction: Suggested model demonstrated how to use the trained models to predict the open price for a future date, specifically March 18, 2017. Suggested model prepared the necessary input data by selecting the last 50 days' open prices and scaling them for model input.

Days	Anticipated closing price on the next day	True closing cost
1	3049.85	3111.75
2	2848.77	3153.7
3	2934.06	3195.1
4	2683.15	3117.85
5	3086.26	3174.6

V. CONCLUSION AND FUTURE SCOPE

This study explored the effectiveness of LSTM RNN-based machine learning models in predicting stock market trends, specifically focusing on open price prediction for Tesla stock. By implementing both the Simple RNN and LSTM models, this model gained insights into their capabilities for capturing temporal dependencies within time-series financial data. The results obtained from this experiments demonstrate the potential of LSTM-based models for stock market prediction tasks. The LSTM model outperformed the Simple RNN model, highlighting the significance of capturing long-term dependencies and complex patterns that influence stock prices. A concrete comprehension of the model's performance on both the training and validation datasets is provided by the visualisations of anticipated open prices in comparison to actual prices.

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