

LSTM BASED STOCK PRICE PREDICTION

Prof. Pritam Ahire¹, Hanikumar Lad², Smit Parekh³, Saurabh Kabrawala⁴

Professor, Computer Engineering, D Y Patil Institute of Engineering and Technology, Pune, India ¹

Student, Computer Engineering, D Y Patil Institute of Engineering and Technology, Pune, India ²

Student, Computer Engineering, D Y Patil Institute of Engineering and Technology, Pune, India ³

Student, Computer Engineering, D Y Patil Institute of Engineering and Technology, Pune, India ⁴

Abstract: Investing in the stock market is one of the most complicated and sophisticated ways to conduct business. The stock market is very uncertain since stock values fluctuate due to a variety of factors, making stock prediction a difficult and exceedingly hard task. Investors nowadays require rapid and reliable information to make efficient judgments, with rapidly expanding technology breakthroughs in stock price prediction. This has attracted their interest in the research area. Understanding the pattern of stock price of a particular company and predicting their future development and financial growth will be highly beneficial. This paper focuses on the usage of a type of RNN (recurrent neural network) based Machine learning which is known as Long Short-Term Memory (LSTM) to predict stock values.

Keywords: Long Short-Term Memory, Recurrent Neural Network, Machine learning, Stock price prediction, Stock market

I. INTRODUCTION

In a stock market, stock price predictions are very important among many business people and the public. People who work in the stock market can make a lot of money or lose a lot of money. Future forecasts based on historical data can be made using algorithmic forecasts and models. Predicting the future has been an overwhelming task, one that many have found difficult to understand. This type of prediction is even more appealing when it involves money and risks such as Stock Market speculation. Researchers are leading research on stock market forecasts from a variety of fields, including computer science and business. Researchers have tried a variety of methods to forecast the stock price, including different strategies and algorithms and the combination of indicators. The attribute that defines a prediction model is determined by characteristics that influence market performance. Short-Term Memory (LSTM) is one of a variety of RNNs structures. LSTM replaces traditional artificial neurons in the hidden network layer into the most useful memory cells. With these memory cells, networks are able to better associate memory with remote input over time, which is why it is worthwhile to understand the formation of strong data over time with great predictive power. A lot of research has been done on stock price forecasts on a daily basis, using different data sources with many built-in models such as news articles, twitter data, google and Wikipedia data. All of these external factors combined with stock prices and stock technology indicators have shown an impact on stock price movements. How to improve the accuracy of stock prices is an open question in today's society. Time series data is a sequence of data from the occasional behavior of certain fields such as social science, finance, engineering, physics and economics. Finance, engineering, physics, and economics. Those types of complexity make it very difficult to predict price trends. The main purpose of predicting a series of time series is to construct future value simulation models given their past values. In many cases, the relationship between past and future recognition is not clear, this is tantamount to exposing the distribution of conditional opportunities as a function of foresight.

II. LITERATURE SURVEY

The first focus of our literature review was to evaluate different algorithms and models to determine whether stock price predictions could be made on real stock prices [2]. However, as we have not been able to detect a possible change in this stock price forecast, we decided to look at existing plans, analyse major issues, and improve ourselves. A brief search of common solutions to the above problem led us to LSTM. After deciding to use the LSTM neural network to make stock forecasts, time series data is collected from stock firm prices of the stock and related macroeconomic variables over a period of 10 years [13][14].

III.METHODOLOGY

In this paper we proposed an algorithm for efficient stock price prediction. The algorithm is LSTM (Long Short-Term Memory) algorithm which is the special type of the Recurrent Neural Network (RNN).

LSTM – an overview

A special type of RNN, which can learn long-term dependence, is called Long-Short Term Memory (LSTM). LSTM enables RNN to remember long-term inputs. Contains information in memory, similar to computer memory. It is able to read, write and delete information in its memory. This memory can be seen as a closed cell, with a closed description, the cell decides to store or delete information. In LSTM, there are three gates: input, forget and exit gate. These gates determine whether new input (input gate) should be allowed, data deleted because it is not important (forget gate), or allow it to affect output at current timeline (output gate) [2].

In a gated cell, LSTMs store information outside of the regular flow of the recurrent network. Similar to data in a computer's memory, information can be stored in the cell and also write and read from a cell. The cell makes decisions about, when to allow reads, writes and erasures, and what to store via gates that close and open. Unlike the digital storage on computers, however, these gates are analog, implemented with element-wise multiplication by sigmoid, which are all in the range of 0-1. Analog has the benefit over digital of being differentiable, and therefore suitable for backpropagation.

Those gates act on the signals they receive, blocking or passing information according on its strength and import, which they filter with their own sets of weights, much like the nodes in a neural network. The learning process for recurrent networks adjusts such weights, as well as the weights that control input and hidden states.

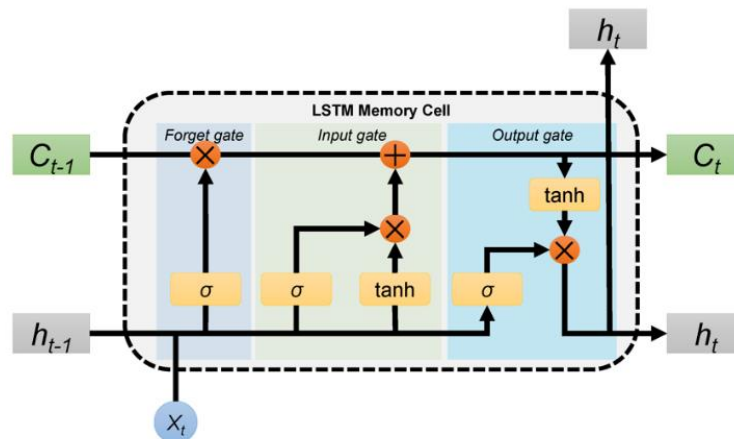


Figure 1. LSTM Memory Cell

- (i) **Forget gate:** The forget gate determines when certain parts of the cell will be inserted with information that is more recent. It subtracts almost 1 parts of the cell state to be kept, and zero in values to be ignored.
- (ii) **Input gate:** Based on the input (e.g., previous output $o(t-1)$, input $x(t)$, and the previous state of cell $c(t-1)$), this network category reads the conditions under which any information should be stored (or updated) in the state cell.
- (iii) **Output gate:** Depending on the input mode and the cell, this component determines which information is forwarded in the next location in the network.

Flask:

Flask is a WSGI web application framework that is lightweight. It's built to make getting started simple and quick, with the flexibility to scale up to more sophisticated projects. It started off as a basic wrapper for Werkzeug and Jinja and has since grown into one of the most popular Python web application frameworks. Flask makes recommendations but does not impose any dependencies or project structure. The developer is free to use whatever tools and libraries they wish. The community has created a number of extensions that make adding additional functionality simple.

Advantages of LSTM:

One of the main advantages of LSTM is its capacity to read intermediary context. Each unit remembers details for a long or short period without unambiguously utilizing the activation function within the recurring components. An important fact is that any cell state is repeated only with the release of the forget gate, which varies between range of 0 to 1. That's to say, the gateway for forgetting in the LSTM cell is responsible for both the hardware and the function of the cell state activation. Thus, the data from the previous cell can pass through the unchanged cell instead of explicitly increasing or decreasing in each step or layer, and the instruments can convert to their appropriate values over a limited time. This allows LSTM to solve a vanishing gradient problem - because the amount stored in the memory cell is not converted in a recurring manner, the gradient does not end when trained to distribute backwards [2].

Algorithm:

Algorithm: LSTM stock price prediction algorithm

Input: Historical stock price data

Output: Prediction for stock prices

Step 1: Collect the data.

Step 2: Store the data.

Step 3: Network structure built with dimensions.

Step 4: Train the constructed network on the data.

Step 5: Use the output of the last layer as a prediction of next time-step.

Step 6: Repeat step 4 and 5 until optimal convergence is reached.

Step 7: Obtain predictions by providing test data as input.

Step 8: Evaluate accuracy by comparing predictions made with actual data.

Step 9: Stop

IV. SYSTEM ARCHITECTURE

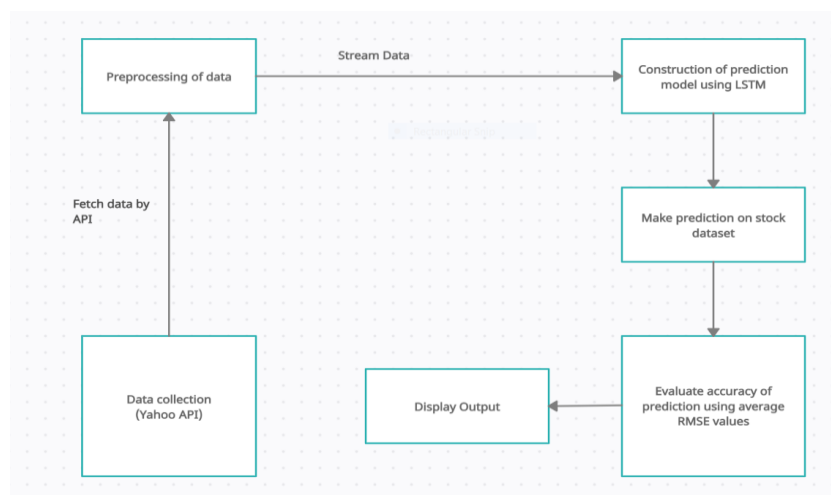


Figure 2. System Architecture

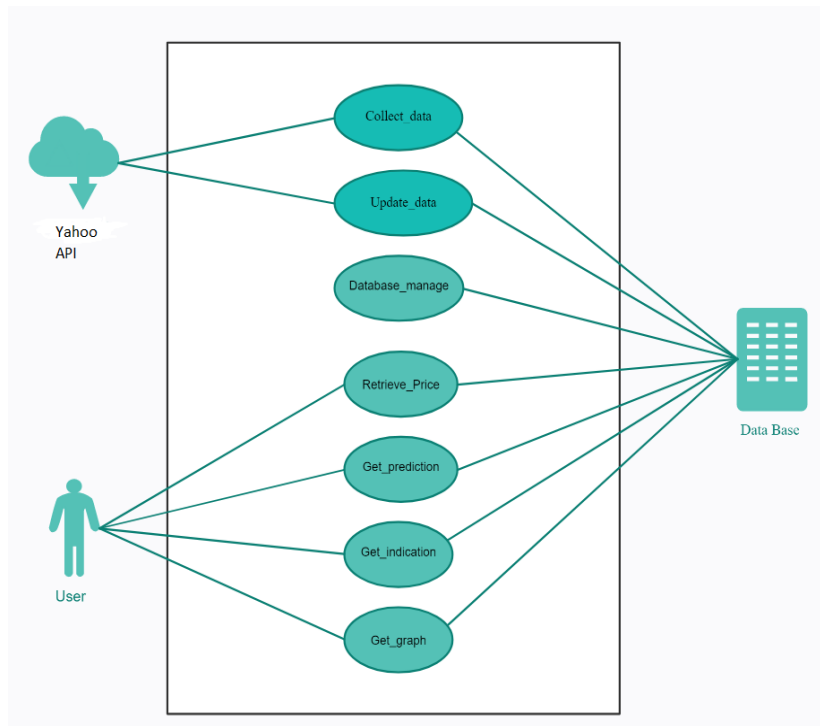


Figure 3. UML Diagram

Obtaining dataset and pre-processing:

The obtained data contained five features:

1. **Date:** Date of stock price.
2. **Opening price:** When trading begins each day this is opening price of stock.
3. **High:** The highest price at which the stock was traded during a period (day).
4. **Low:** The Lowest price at which the stock was traded during a period (day).
5. **Volume:** How much of a given financial asset has traded in a period of time.

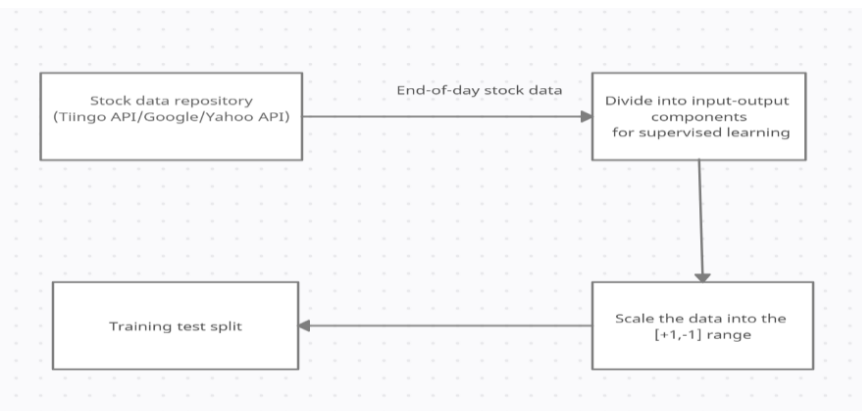


Figure 4. Data Preprocessing

Stock market information is available from key sources: Tiingo API/ Yahoo Finance. These websites give APIs from which stock dataset can be obtained from various companies by simply specifying parameters.

The data is processed into a format suitable to use with prediction model by performing the following steps:

- Transformation of time-series data into input-output components for supervised learning.
- Scaling the data to the [-1, +1] range.

V. IMPLEMENTATION

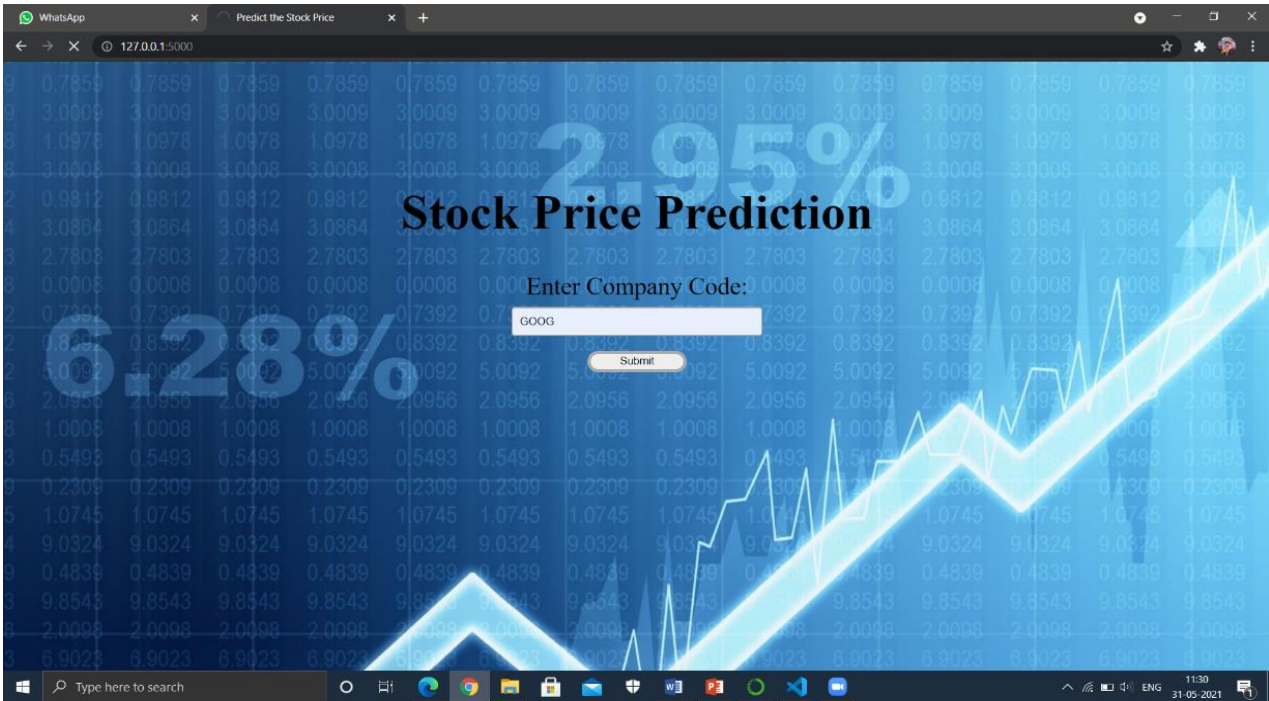


Figure 5 Main Page

```
In [12]: #Train the model
model.fit(x_train, y_train, batch_size=5, epochs=15)
#model.fit(x_train, y_train, batch_size=10, epochs=20)

Epoch 1/15
292/292 [=====] - 15s 52ms/step - loss: 1.4234e-04
Epoch 2/15
292/292 [=====] - 15s 52ms/step - loss: 5.3867e-05
Epoch 3/15
292/292 [=====] - 16s 54ms/step - loss: 4.5260e-05
Epoch 4/15
292/292 [=====] - 18s 60ms/step - loss: 4.0062e-05
Epoch 5/15
292/292 [=====] - 18s 61ms/step - loss: 3.6750e-05 0s - loss: 3.703
Epoch 6/15
292/292 [=====] - 18s 60ms/step - loss: 3.5226e-05
Epoch 7/15
292/292 [=====] - 19s 65ms/step - loss: 2.9855e-05
Epoch 8/15
292/292 [=====] - 18s 63ms/step - loss: 3.3842e-05
Epoch 9/15
292/292 [=====] - 18s 62ms/step - loss: 2.1809e-05 0s - loss: 2.
Epoch 10/15
292/292 [=====] - 19s 63ms/step - loss: 2.5388e-05
Epoch 11/15
292/292 [=====] - 20s 70ms/step - loss: 2.0406e-05
Epoch 12/15
292/292 [=====] - 18s 63ms/step - loss: 1.7375e-05
Epoch 13/15
292/292 [=====] - 18s 62ms/step - loss: 1.9953e-05
Epoch 14/15
292/292 [=====] - 22s 75ms/step - loss: 1.9593e-05
Epoch 15/15
292/292 [=====] - 19s 64ms/step - loss: 1.9669e-05

Out[12]: <tensorflow.python.keras.callbacks.History at 0x21f54ccb88>
```

Figure 6 Model Training

VI. RESULT ANALYSIS

Google:

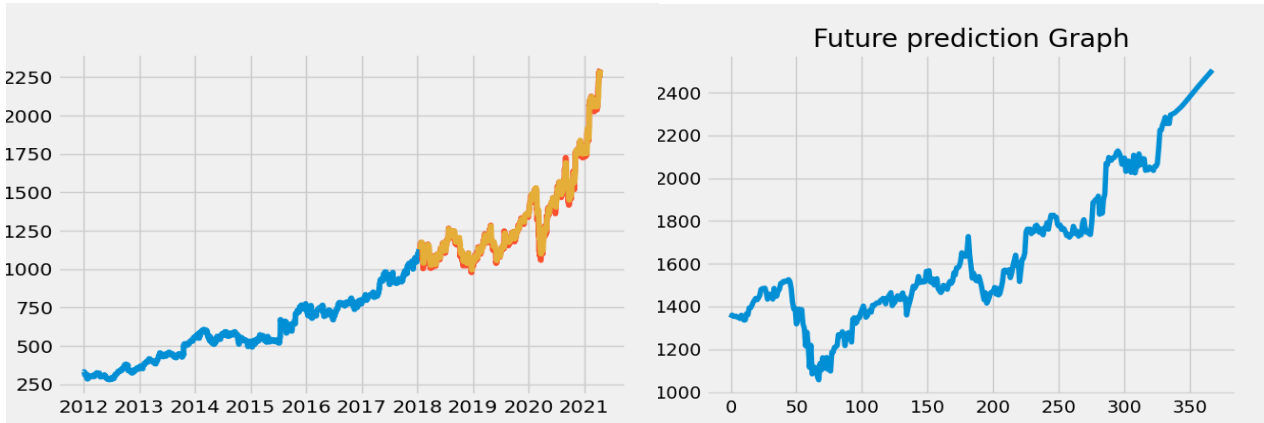


Figure 7. Google Actual and Future prediction Graph

APPLE:

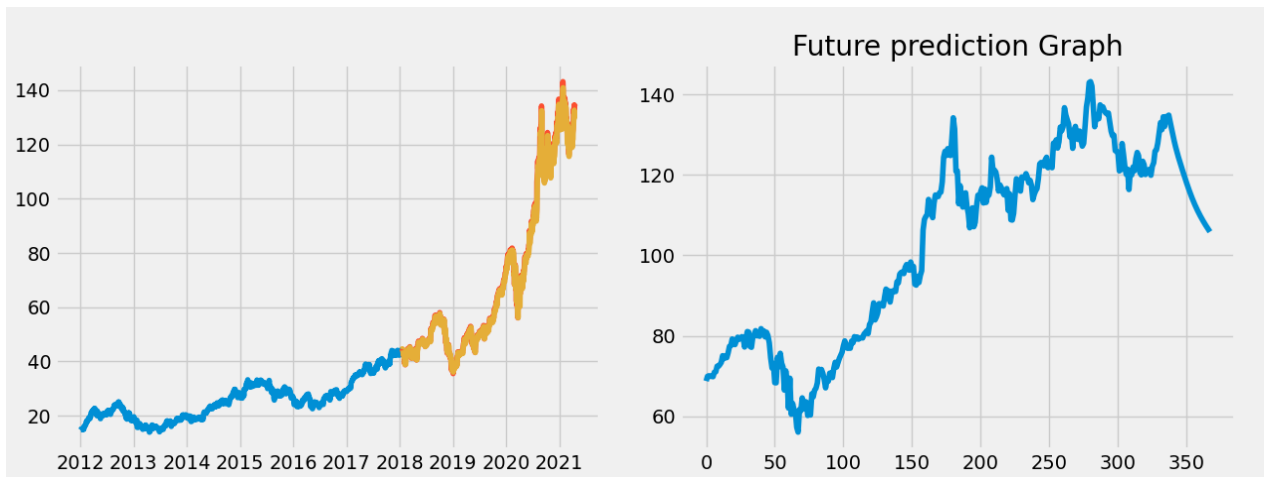


Figure 8. Apple Actual and Future prediction Graph

VII. CONCLUSION

Many individuals all over the world have become interested in stock investment. Making a decision, on the other hand, is tough because there are so many factors to consider. Investors are keen to forecast the stock market's future after making profitable investments. Even a small increase in performance can have a huge impact. By providing supporting information such as future stock price guidance, a competent forecasting system can assist investors in making more accurate and profitable decisions. Other factors, such as politics, economic growth, financial concerns, and the atmosphere on social media, could influence pricing in addition to past pricing. Numerous studies have proven that emotional analysis has a significant impact on future prices. Therefore, the combination of technical and basic analysis can produce very good predictions.

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