<u>Predicting Stock Prices Using Long Short-</u> <u>Term Memory (LSTM)</u>

ABSTRACT- Accurate prediction of stock prices is a very challenging task due to volatile and non linear nature of financial stock. Thus to maximize the profit and minimize the losses, technique to predict values of stock in advance by analysing the trend over last few years. This research paper covers a approach for predicting stock prices, aiming to estimate the stock price of a particular stock of the following day based on its past 50,100,200 days of historical stock data that includes it's open price, close price, low, high and volume. This model is trained to read and analyse patterns withing given time series data using layers of Long Short-Term Memory(LSTM) cells. LSTM cells represents the memory of network, storing information over time while discarding the irrelevant information. Dropout layers technique are used in this model to improve the LSTM networks by reducing overfitting. This paper is about to discuss different techniques related to the prediction of stock market.

INTRODUCTION

Stock market is characterized as dynamic, unpredictable and non-linear in nature. Predicting stock prices is a challenging task as it depends on various factors that can influence prices, it can include political conditions, global economy, company's financial reports and performance etc. Thus, to maximize the profit and minimize the losses, techniques to predict values of the stock in advance by analyzing the trend over the last few years, could prove to be highly useful for making prediction about stock market movements. Traditionally, main approach have been proposed for predicting the stock price of an organization. Technical analysis method uses historical price of stocks like closing and opening price, volume traded, adjacent close values etc. of the stock for predicting the future price of the stock.

The model is arranged in layers which contain LSTM cells. These types of cells are a kind of neural network layer that has been engineered to work well with data that comes in series, such as days and the prices of stock on those days. They are termed "Long Short-Term Memory" in that they retain relevant and beneficial data for extended periods of time while discarding irrelevant information. If you want to predict how much the stocks will cost tomorrow, you do not need to bother with knowing every little detail, but you do have to keep in mind about the trends that are relevant within for example the last couple of days or weeks.

In recent years, LSTM network models have become a good topic for researchers. The LSTM neural network is a type of neural network model with selective memory and intra-temporal influence, which is very suitable for the non-stationary series of stock price time series. LSTM network is considered to be one of the most accurate forecasting techniques. A large number of studies is currently active on the subject of LSTM neural network used in finance.

In this paper, I have applied LSTM techniques to train the model, LSTM, by setting the prediction scope and using the historical data of Yahoo finance stock market from 1/1/2014 to 1/10/2024 by default, as the original data for short-term prediction. The prediction performance of the models is evaluated using root mean square error (RMSE) and mean absolute percentage error (MAPE).

The main objective of this paper is to find the prediction accuracy of LSTM neural network models applied to short-term prediction ranges and to see whether the LSTM model shows certain advantages, compared to other machine learning algorithms.

<u>METHODOLOGY</u>

Description of data- The historical data of all the companies listed in stock market has been collected from Yahoo Finance. The dataset includes the last 10 years data of the selected stock from 1/1/2014 to 1/10/2024 that is of user's choice. The data contains information about the stock such as Adjacent close, low, high, close price, open price and volume.

[15]:	Price	Date	Adj Close	Close	High	Low	Open	Volume	
	Ticker		GOOG	GOOG	GOOG	GOOG	GOOG	GOOG	
	0	2014-01-02 00:00:00+00:00	27.656164	27.724083	27.839401	27.603037	27.782366	73129082	

Preview of information of a stock

In this model, the data is divided into a training set and a testing set based on an 80-20 split of the time period from 1/1/2014 to 1/10/2024. In this time interval the data is divided as following.

- Training data: January 2014 to November 2022(approx. 80% of dataset)
- Testing data: November 2022 to October 2024(approx.. 20% of dataset)

Training Model using LTSM:

In this stage of model training, the data is processed through Neural Network and trained for prediction for the remaining 20% of the dataset.

The model is arranged in layers which contain LSTM cells. These types of cells are a kind of neural network layer that has been designed to work well with data that comes in series, such as days and the prices of stock on those days.

The model comprises various levels where each level performs a task and collectively helps in coming up with predictions of the stock.

LSTM Layers: Consider these levels as those that detect and understand the presence of particular pattern. Every LSTM layer processes the price data for 100 days and tries to find some relation, for example, whether pricing tends to go up after a specific order.

The first layer has the extremely raw data for the past 100 days and starts to hold on simplistic trends.

Following layers are built upon the trends of the former layers and are designed to get more detailed interrelations. The deeper we go in the layers, the more the model can interpret how the price changed with time.

Dropout Layers: These layers are useful to enable the model to perform well by preventing it from learning specific features in the training data. Dropout is like preparing to sit for an examination by not learning everything word for word but knowing terms that can help to answer the questions. Dropout layers prevent the model from overfitting to the training data by taking out portions of the training neural network for each iteration. This is because the model becomes too regular to recognizing specific patterns that may not be present in new data, thus 'dropping out' helps to avoid this.

Dense Layer: A Dense layer is typically added after the LSTM layers to take the processed sequence data and make the final prediction. For example, in this stock prediction, the Dense layer would take the LSTM output and produce a single number (like the next day's predicted price) or multiple outputs (if predicting more than one future time point).

Model Sequential Summary

[51]: model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #	
lstm (LSTM)	(None, 100, 50)	10,400	
dropout (Dropout)	(None, 100, 50)	0	
lstm_1 (LSTM)	(None, 100, 60)	26,640	
dropout_1 (Dropout)	(None, 100, 60)	0	
lstm_2 (LSTM)	(None, 100, 80)	45,120	
dropout_2 (Dropout)	(None, 100, 80)	0	
lstm_3 (LSTM)	(None, 120)	96,480	
dropout_3 (Dropout)	(None, 120)	0	
dense (Dense)	(None, 1)	121	

Total params: 536,285 (2.05 MB)

Trainable params: 178,761 (698.29 KB)

Non-trainable params: 0 (0.00 B)
Optimizer params: 357,524 (1.36 MB)

Feature's:

In the model, it uses three graphs of Moving averages (MA) against closing price to the stock to help users to understand the stock price trends over different time periods. Each graph shows the actual closing price of the stock along with moving averages calculated over different periods (50 days, 100 days, and 200 days). The information about graphs are following:

• **Price vs. 50-Day Moving Average (MA50):** The graph shows 50-day moving average against closing price over a specific time period. It represents the average price of the stock over the last 50 days. Since it's a shorter moving average, it reacts more quickly to recent price changes.

This graph helps users see short-term trends and the recent momentum of the stock price. If the stock price is consistently above the 50-day moving average, it may indicate bullish (upward) momentum and vice versa.

Price vs. 50-Day and 100-Day Moving Averages (MA50 vs. MA100):

This graph represents the 100 days moving average. It is less sensitive to recent fluctuations than the 50-day MA and more responsive to the overall trend over a slightly longer period. By plotting both the 50-day and 100-day moving averages, users can observe the pattern between short-term and medium-term trends. When the 50-day MA crosses above the 100-day MA, it is often seen as a bullish signal, indicating potential upward momentum. When the 50-day MA crosses below the 100-day MA, it could signal a bearish trend.

• Price vs. 100-Day and 200-Day Moving Averages (MA100 vs. MA200):

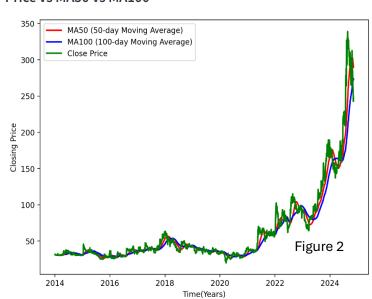
This graph represents the long-term trend movements of 100 and 200 day MA. This graph helps users identify longer-term trends. The 200-day moving average is often used by investors to understand the stock's fundamental strength.

Visual representation of above graphs are given below.

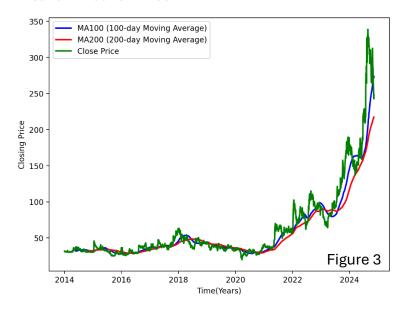
Price vs MA50

MA50 (50-day Moving Average) Close Price 300 250 Closing Price 200 120 150 100 50 Figure1 2014 2016 2022 2024 2018 2020 Time(Years)

Price vs MA50 vs MA100



Price vs MA100 vs MA200



RESULT

Once the model is trained, the input data is fed to the model and tested. The data is used from the remaining 20% of the dataset which is new and unseen data for model. On the basis of training of model on the dataset of stock selected by user, it will predict the closing price of the stock. We have trained the model from a time range of January 1,2014 to November 2022, now from that time series till now the model will predict the closing price of the stock on the basis of training.

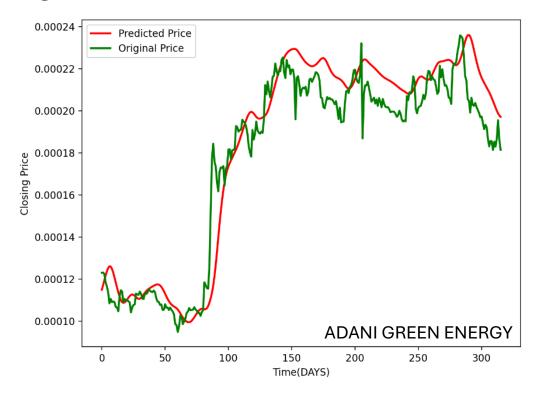
For example: If today is January 1, 2025, we give the model input prices from September to December 2024. The model uses these prices to predict what might happen on January 2, 2025. After training, we can test the model by comparing its predictions to actual prices and plot the results between Original Price and Predicted Price of the stock.

Mean Absolute Percentage Error (MAPE) and Mean Squared Error (MSE) are used as metrics to evaluate prediction accuracy. Lower MAPE and MSE values indicate higher prediction accuracy. The closer these values are to zero, the better the model has observed and learned stock price patterns.

We have plotted a graph between Original Price and Predicted Price by the model, which shows the model accuracy with the help of graph. More the line of Original Closing Price of stock is closed to the line of Predicted Closing Price, the more accurate will be the model.

Few examples has been shown below of few company with accuracy.

Original Price vs Predicted Price



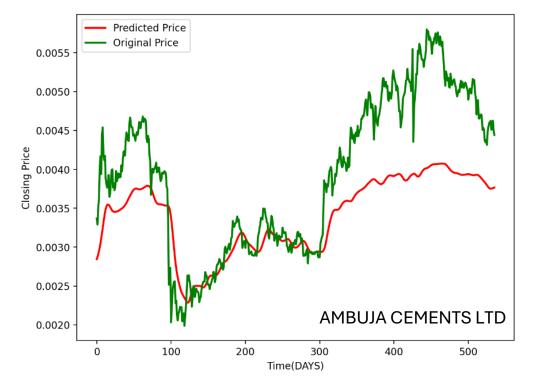
Model Accuracy

Mean Absolute Percentage Error (MAPE): 0.06

Mean Squared Error (MSE): 0.00

Prediction Accuracy: 94.13%

Original Price vs Predicted Price



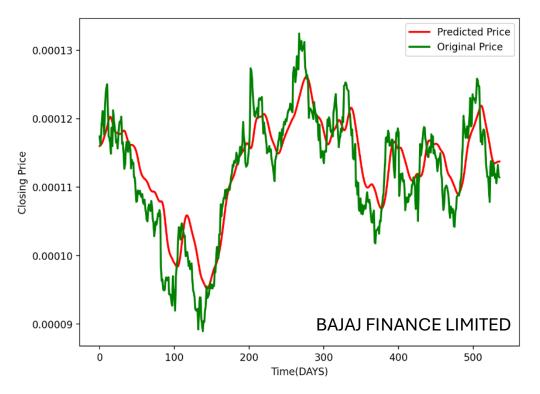
Model Accuracy

Mean Absolute Percentage Error (MAPE): 0.14

Mean Squared Error (MSE): 0.00

Prediction Accuracy: 86.39%

Original Price vs Predicted Price



Model Accuracy

Mean Absolute Percentage Error (MAPE): 0.03

Mean Squared Error (MSE): 0.00

Prediction Accuracy: 96.91%

REFERENCES: