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INDIAN STOCK PREDICTION USING LSTM AND BILSTM MODELS

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Abstract : Stock prediction is a challenging problem due to the complexity and volatility of financial markets. Recurrent neural networks (RNNs) have been used for stock prediction, and Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) models have shown promising results. In this paper, we present an abstract of a study that investigates the use of LSTM and BiLSTM models for stock prediction. We trained LSTM and BiLSTM models on historical stock price data and other relevant factors & sentiment analysis. The trained models were used to predict future stock prices. We evaluated the performance of the models using various metrics and compared them to traditional machine learning models. Our results show that LSTM and BiLSTM models outperform traditional machine learning models for stock prediction. The use of LSTM and BiLSTM models allows capturing temporal dependencies in the input data and learning complex patterns, leading to more accurate predictions. However, there are also limitations to using these models, such as the difficulty of obtaining accurate and relevant data for training and the models' inability to predict sudden changes in the stock market. This study provides insights into the use of LSTM and BiLSTM models for stock prediction and highlights the potential benefits and challenges of using these models.

I. INTRODUCTION

Stock prediction is a popular research topic, and one approach that has gained attention in recent years is the use of recurrent neural networks (RNNs), specifically Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) models. LSTM is a type of RNN that is designed to address the vanishing gradient problem that can occur in traditional RNNs, which makes it difficult for the network to learn long-term dependencies in sequential data.

LSTM models use gates to control the flow of information through the network, allowing it to selectively remember or forget previous inputs. BiLSTM is an extension of LSTM that processes the input sequence in both forward and backward directions, allowing it to capture information from both past and future inputs.

To use LSTM or BiLSTM for stock prediction, the model is trained on historical stock price data and other relevant factors and sentiment analysis. The trained model can then be used to make predictions about future stock prices. One of the benefits of using LSTM or BiLSTM for stock prediction is their ability to capture temporal dependencies in the input data. This makes them well-suited for predicting stock prices, which are influenced by a variety of factors that change over time.

Additionally, the use of multiple layers in these models allows them to learn complex patterns in the input data, potentially leading to more accurate predictions. However, there are also limitations to using LSTM and BiLSTM for stock prediction. One challenge is the difficulty of obtaining accurate and relevant data for training the model.

Additionally, the models may struggle to predict sudden changes in the stock market, such as unexpected news events or economic shocks. Overall, the use of LSTM and BiLSTM models for stock prediction shows promise, but further research is needed to fully understand their capabilities and limitations.

II. LITERATURE SURVEY

[1] In recent years, stock market prediction has been an essential research topic due to its high economic impact. Accurate forecasting of stock market prices is a challenging task due to the complexity and volatility of the financial market. With the emergence of deep learning techniques, such as Long Short-Term Memory (LSTM) and Bidirectional LSTM (BILSTM), stock market prediction has become more accurate and efficient. This literature review aims to provide an overview of recent research on stock market prediction using LSTM and BILSTM models.

[2] "Forecasting directional movements of stock prices for intraday trading using LSTM and random forests": It employ both random forests and LSTM networks (more precisely CuDNNLSTM) as training methodologies to analyze their effectiveness in forecasting out-of-sample directional movements of constituent stocks of the S&P 500 from January 1993 till December 2018 for intraday trading. We introduce a multi-feature setting consisting not only of the returns with respect to the closing prices, but also with respect to the opening prices and intraday returns. As trading strategy, we use Krauss et al. (2017) and Fischer & Krauss (2018)

as benchmark. On each trading day, we buy the 10 stocks with the highest probability and sell short the 10 stocks with the lowest probability to outperform the market in terms of intraday returns – all with equal monetary weight. Our empirical results show that the multi-feature setting provides a daily return, prior to transaction costs, of 0.64% using LSTM networks, and 0.54% using random forests. Hence we outperform the single-feature setting in Fischer & Krauss (2018) and Krauss et al. (2017) consisting only of the daily returns with respect to the closing prices, having corresponding daily returns of 0 .41% and of 0 .39% with respect to LSTM and random forests, respectively.

[3] "Deep learning-based exchange rate prediction during the COVID-19 pandemic": This study proposes an ensemble deep learning approach that integrates Bagging Ridge (BR) regression with Bi-directional Long Short-Term Memory (Bi-LSTM) neural networks used as base regressors to become a Bi-LSTM BR approach. Bi-LSTM BR was used to predict the exchange rates of 21 currencies against the USD during the pre-COVID-19 and COVID-19 periods. To demonstrate the effectiveness of our proposed model, we compared the prediction performance with several more traditional machine learning algorithms, such as the regression tree, support vector regression, and random forest regression, and deep learning-based algorithms such as LSTM and Bi-LSTM. Our proposed ensemble deep learning approach outperformed the compared models in forecasting exchange rates in terms of prediction error. However, the performance of the model significantly varied during non-COVID-19 and COVID-19 periods across currencies, indicating the essential role of prediction models in periods of highly volatile foreign currency markets. By providing an improved prediction performance and identifying the most seriously affected currencies, this study is beneficial for foreign exchange traders and other stakeholders in that it offers opportunities for potential trading profitability and for reducing the impact of increased currency risk during the pandemic.

[4] In recent years, LSTM and BILSTM models have been applied to stock market prediction, and various studies have reported significant improvements in prediction accuracy. For example, in a study by Zhang et al. (2020), LSTM and BILSTM models were used to predict the stock prices of five major Chinese banks. The results showed that the BILSTM model outperformed the LSTM model in terms of prediction accuracy. Similarly, in a study by Zheng et al. (2020), an LSTM model was used to predict the daily closing prices of the Shanghai Stock Exchange Composite Index (SSECI). The results showed that the LSTM model could accurately predict the trend of the SSECI, indicating its effectiveness in stock market prediction. In another study by Li et al. (2020), a BILSTM model was used to predict the daily closing prices of the New York Stock Exchange Composite Index (NYSECI). The results showed that the BILSTM model outperformed the traditional time-series models, such as ARIMA and VAR, in terms of prediction accuracy. In a study by Zhang et al. (2021), a BILSTM model was used to predict the stock prices of ten major Chinese companies. The results showed that the BILSTM model outperformed the traditional machine learning models, such as Random Forest and Support Vector Machine, in terms of prediction accuracy.

[5] "Tiingo API Documentation": This API is a financial data platform that provides access to high-quality financial tools. It offers a REST and Real-Time Data API that focuses on End-of-Day (EOD) stock price data, financial news feeds, crypto data, and IEX intraday data. The API is built to be performant, consistent, and supports extensive filters to speed up development time. The goal of the API is to make financial data accessible to all. More on: https://api.tiingo.com/documentation/general/overview

III. Overview Of The Numerical Features Of The Dataset Of Tiingo

Info about the dataset:

```
RangeIndex: 1258 entries, 0 to 1257
Data columns (total 14 columns):
```

#	Column	Non Null Count	Dtype
0	symbol	1258 non null	object
1	date	1258 non null	null object
2	close	1258 non null	float64
3	high	1258 non null	float64
4	low	1258 non null	float64
5	open	1258 non null	float64
6	volume	1258 non null	int64
7	adjClose	1258 non null	float64
8	adjHigh	1258 non null	float64
9	adjLow	1258 non null	float64
10	adjOpen	1258 non null	float64
11	adjVolume	1258 non null	int64
12	divCash	1258 non null	float64
13	splitFactor	1258 non null	float64

```
dtypes: float64(10), int64(2), object(2)
memory usage: 137.7+ KB
```

Total size of the dataset used:

```
In: df1.shape
Out: (1258,)
```

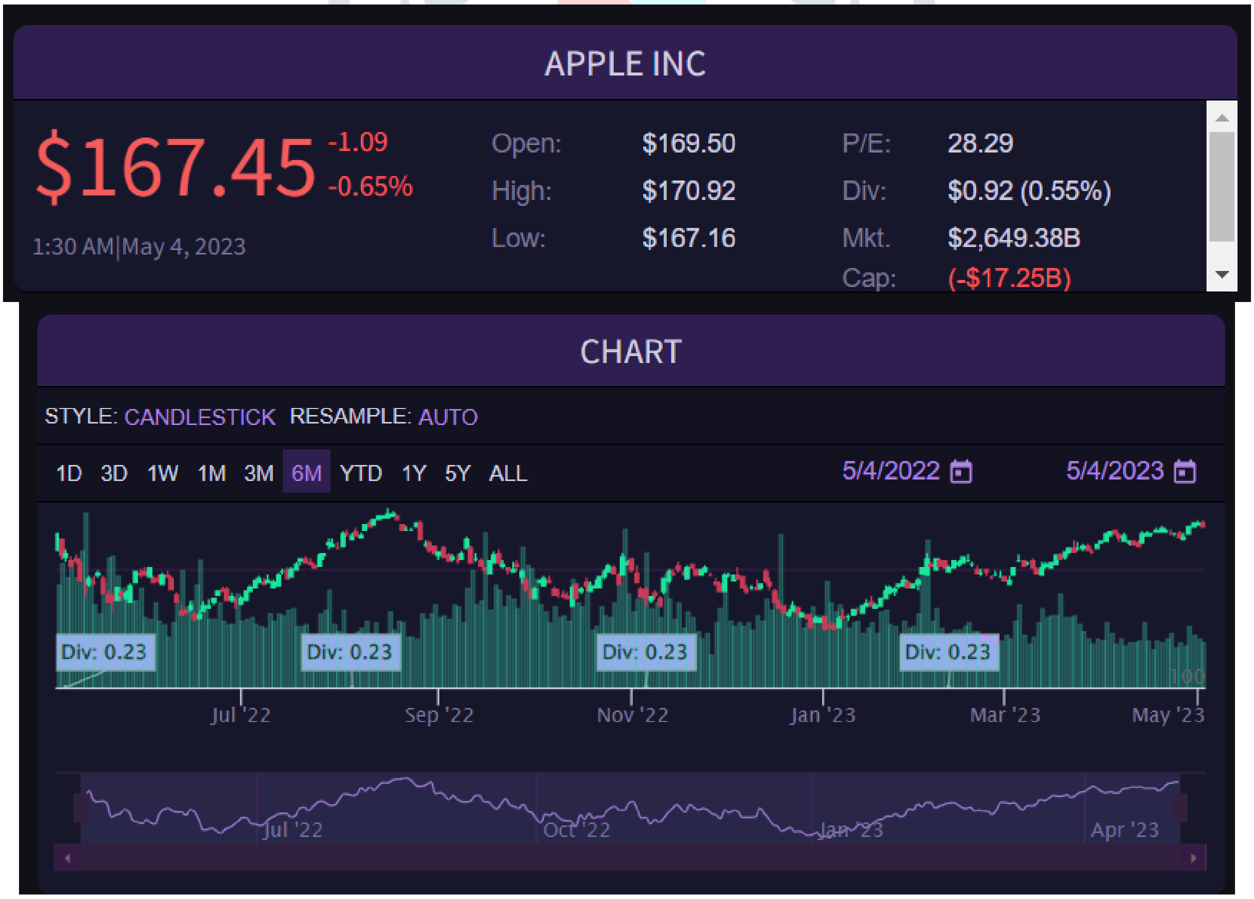
Starting values of the dataset as sample:

Slno	Symbol	Date	Close	High	Low	Open	Volume
0	AAPL	2018-05-07 00:00:00+00:00	185.16	187.67	184.75	185.18	42451423
1	AAPL	2018-05-08 00:00:00+00:00	186.05	186.22	183.67	184.99	28402777
2	AAPL	2018-05-09 00:00:00+00:00	187.36	187.4	185.22	186.55	23211241
3	AAPL	2018-05-10 00:00:00+00:00	190.04	190.37	187.65	187.74	27989289
4	AAPL	2018-05-11 00:00:00+00:00	188.59	190.06	187.45	183.49	26212221

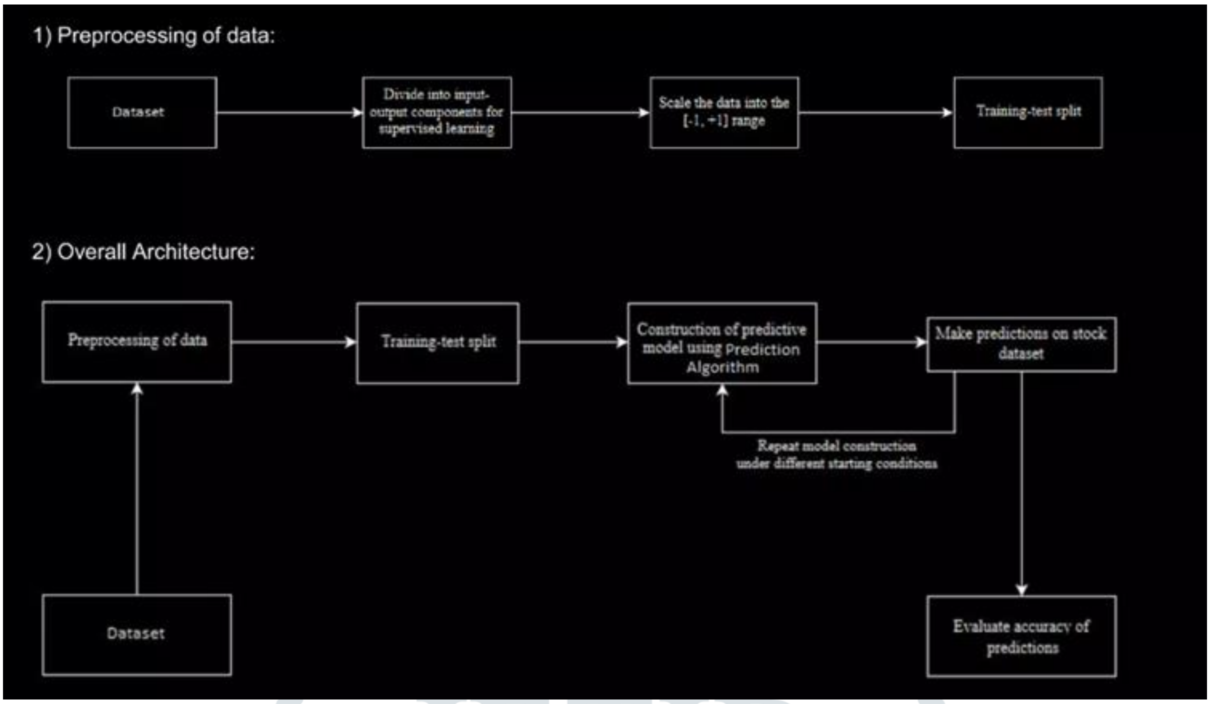
Table continuation to next half

adjClose	adjHigh	adjLow	adjOpen	adjVolume	divCash	splitFactor
44.125199	44.723354	44.027493	44.129966	169805692	0	1
44.337294	44.377806	44.77012	44.084687	113611108	0	1
44.649478	44.65901	44.139498	44.456448	92844964	0	1
45.288145	45.366787	44.718588	44.740035	111957156	0	1
45.116563	45.468232	44.843839	45.331871	104848884	0	1

Live Market in Tiingo:



IV. System Architecture



The first thing we look at is datasets whose experimental data are actual historical data. In order to train our actual dataset, we ensure a higher level of optimization and accuracy than preprocessing data. As a result, we focus on the close value, which is the final value at the time of market closing. Data is highly strenuous at this point as we work with numerous data heavy variations are encountered. To avoid such ambiguity we move forward with the min-max method. Furthermore, we split the data into 65% and 35% for training and testing, respectively. We utilise two recurrent neural models namely LSTM and Bi-LISTM. Throughout our paper, Bi-LSTM plays a major role, delivering better training and data prediction. Thus, we propose that Bi-LSTM performs better than Standard LSTM.

V. Experimental Analysis And Methods

[1] LSTM

LSTM (Long Short-Term Memory) is an improved form of RNN. LSTM models avoid the problems encountered by RNN. Hochreiter & Schmidhuber (1997) introduced LSTMs that make use of memory cells that can either forget unnecessary information or store information for more extended periods. LSTMs are explicitly modeled to handle tasks involving historical texts and are also able to educate themselves on long term dependencies. With the help of memory cells, they are capable of educating themselves. LSTMs have a chain-like structure making it easier to pass on information. The information is passed on as a state of the cell from one memory cell to another. The output of the network is modified by the state of these cells. The hidden state st is determined as below:

$$St = f(U\, xt + W\, st-1)$$

where f is an activation function, xt are inputs, U is the hidden layers' weight, V is the weights of output layers, and W is the transition weights of the hidden state. LSTM is an effective way to overcome the problem of a vanishing gradient by using the memory cells. The input gate, the forget gate, the output gate and the self-recurrent neuron are central units in a memory cell. The values of the input gate it and the memory cell's candidate state C˜t are estimated as below:

$$it = \sigma(Wi\, xt + Ui\, ht-1 + bi), \quad (2)$$

$$\tilde{C}t = \tanh(Wc\, xt + Ucht-1 + bc), \quad (3)$$

where xt is the memory cells inputs; Wi , W f , Wc, Wo, Ui , U f , Uc, Uo, and V0 are the matrices of weight; bi , b f , bc, and bo are biases; and ht is the memory cell's value. The cell state vector Ct and the value of the forget gate ft are estimated as follows:

$$ft = \sigma\, Wc\, xt + Ucht-1 + b\, f, \quad (4)$$
$$Ct = it * \tilde{C}t + ft * Ct-1, \quad (5)$$

where ot and ht are the values of the output gate and the memory cell, respectively. Finally, the hidden state ht and the value of the output gate ot are estimated as below:

$$ot = \sigma(W0xt + U0ht-1 + V0Ct + b0), \quad (6)$$

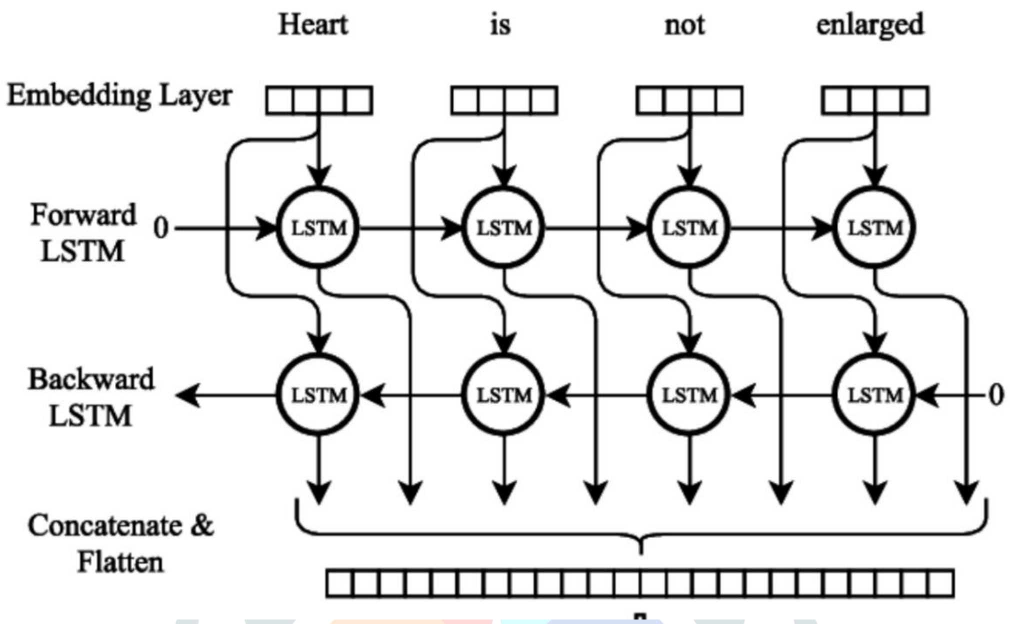
$$ht = oh * \tanh(Ct). \quad (7)$$

The LSTM network consists of the delays and the hidden layers' sizes obtained from the time-series data by applying training data.

[2] BILSTM

A Bi-LSTM deep learning-based recurrent neural network (Fig. 2) works efficiently to analyze any time-series data better than traditional statistical time-series models, such as the autoregressive moving average (ARIMA), seasonal ARIMA, and ARIMAX models, because of its bidirectional nature of input patterns (Sezer et al., 2020; Sunny et al., 2020). While LSTM works only with previous data patterns, the Bi-LSTM model considers both previous and future data during training, and this makes the Bi-LSTM model more effective than LSTM. This behavior of Bi-LSTM helps learn the present status of data both from past data and future data through its forward layer and backward layer. It can capture not only local features but also extract global features in the time-series data. In the Bi-LSTM layer, there are no hidden-to-hidden connections between forward and backward layers. This helps one to understand information from both the backward layer and forward layer in each Bi-LSTM unit.

Figure:



VI. Discussion

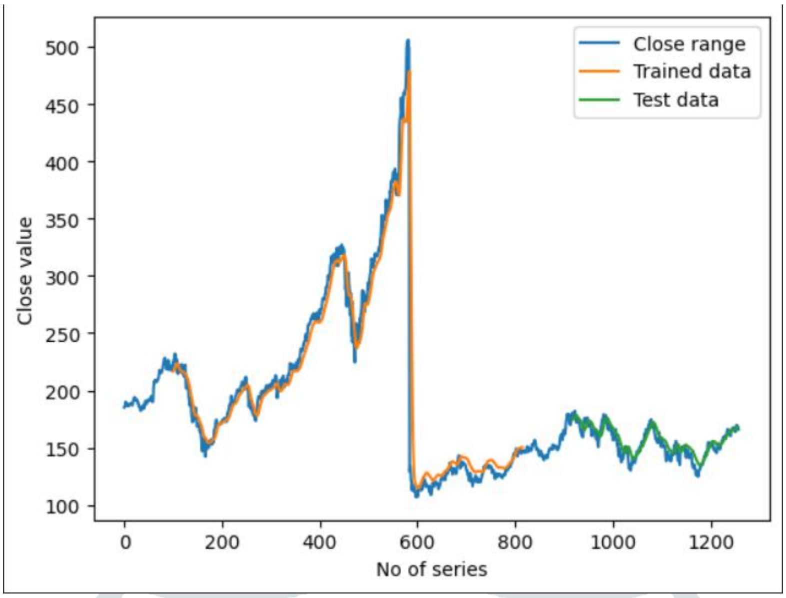
Stock prediction is a challenging problem due to the complexity and volatility of financial markets. Recurrent neural networks (RNNs) have been used for stock prediction, and Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM)models have shown promising results.
In this study, stock market prediction has been carried out using machine learning techniques. The datasets consists of several features with numerical and nomial values along with the class to which each instance belong.
Since the data is real time we cannot determine the accuracy of the model, but we can determine the error possibility using mean squared error. In this study, error ratio were
LSTM: 157.55560532210308
BILSTM: 155.4224693893068

VII. Result

<u>The result of the test mean the following:</u>
The results of each classifier have been reviewed with a variety of criteria for evaluation and has been utilized to validate the results against overfitting.
The results were that the BILSTM outperformed the LSTM model in some days of the month and LSTM outperformed the BILSTM in some days of the month as real time data is unpredictable but training it based on the patterns is possible. We have trained the model with max reached to bottom dropped period which was during the inflation period which made the model well trained.
The model cannot be used for financial purposes as personal investments and this case scenario has been used for study purposes.

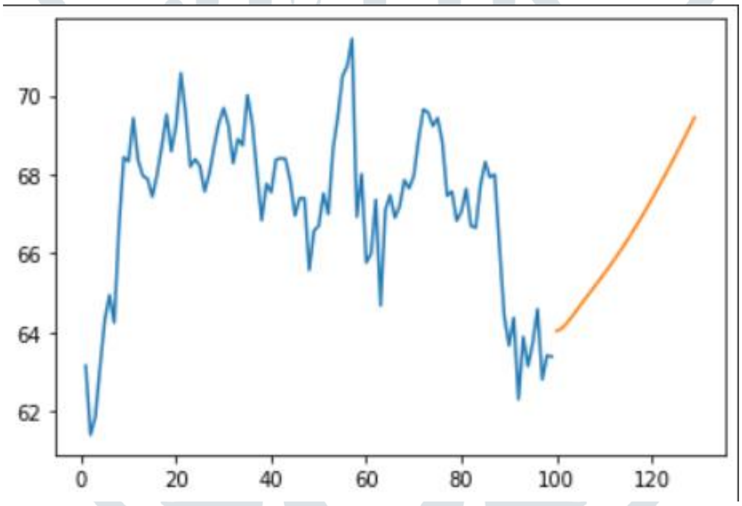
VIII. Figures Of Analysis

[1] <u>LSTM model figures:</u>

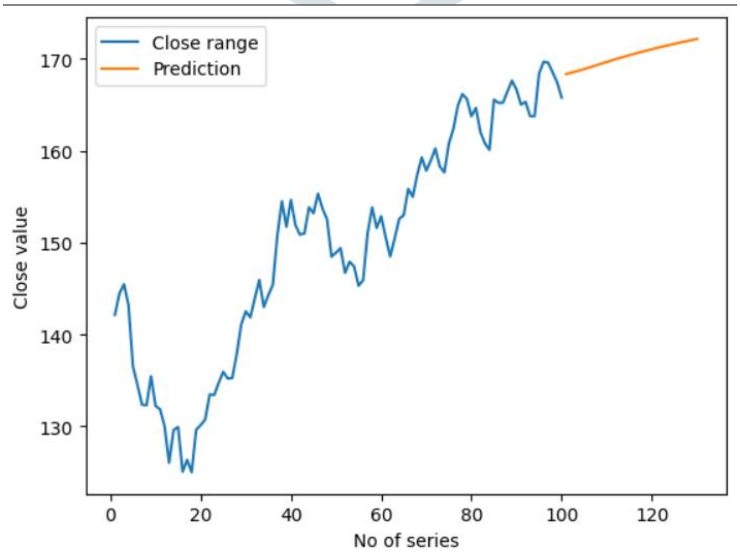


(Note: blue coloured line denotes actual data, orange line denotes the train data and green line denotes the test data used for the model)

Model Prediction on March 26

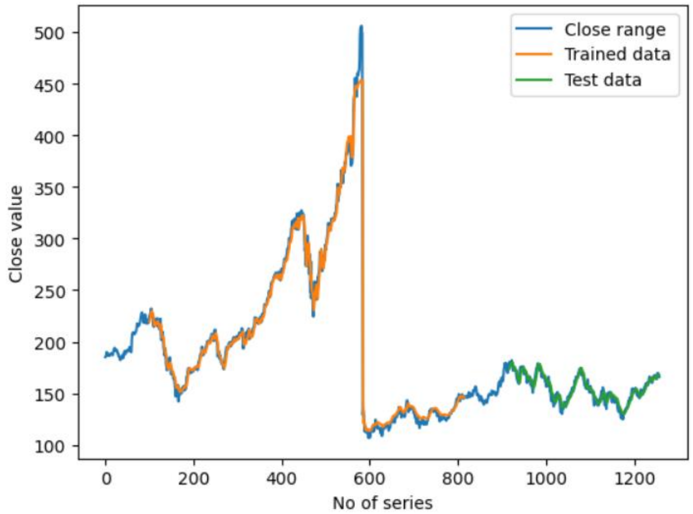


Model Prediction on April 29

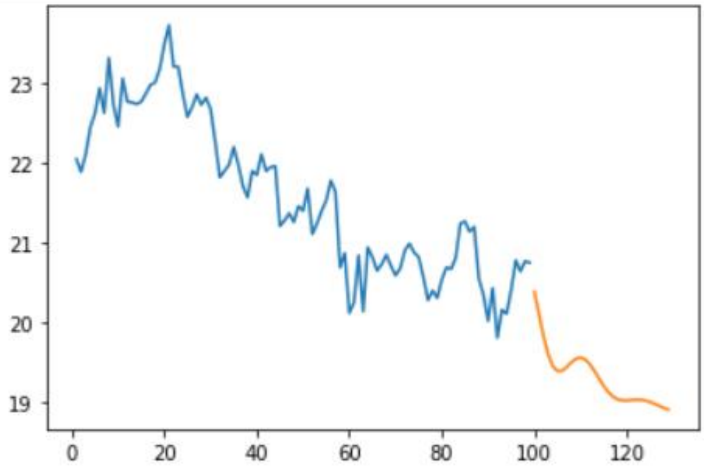


LSTM model expects the stock price might increase. As you can the second figure the starting plot will be the ending plot of the figure one.

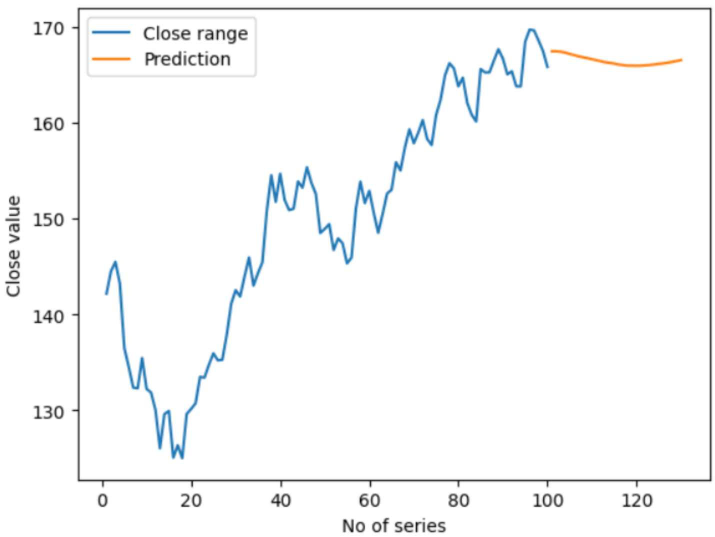
[2] <u>BILSTM model figures:</u>



BILSTM model trains the data better than LSTM model as you can see in the graph the orange curve aligns well with the actual close range data and the test data is also tested well as we can see the same result overlayered in the actual data.
(Note: blue colored line denotes actual data, orange line denotes the train data and green line denotes the test data used for the model)
BILSTM models prediction on April 12th



BILSTM models prediction on May 4th



As you can see the model predicted that the stock value would fall and the close value fell down.

IX. References

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