Rajiv Gandhi University of Knowledge Technologies

R K Valley, YSR Kadapa (Dist) – 516330

A
Major Project Report
on

Stock price prediction using LSTM

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This project report has been submitted in fulfilment of the requirement for the Degree of Bachelor of Technology in Software Engineering.

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CERTIFICATE

This is to certify that report entitled "**Stock price prediction using LSTM**" Submitted by J.Chandu (R180634) , T.Guna Sekhar (R180663), C.Anil Kumar (R180093) in partial fulfilment of the requirements of the award of bachelor of technology in computer science engineering is a bona fide work carried by them under the supervision and guidence.

The report has been not submitted previously in part or full to this or any other university or institute for the award of any degree or diploma.

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Mrs. V.Sravani	Mr.N.Satyanandaram
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Submitted for the practical examination on ....

Internal Examiner | **External Examinar**

ACKNOWLEDGEMENT

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DECLARATION

We hereby declare that this report entitled **"Stock Price Prediction Using LSTM"** submitted by me under the guidance and supervision of **Mrs. V.Sravani**, is a bonafied work.We also declare that it has not been of Submitted previously in part or in full to this University or other institution for the award of any degree or diploma.

Date : - 14 – 12 –2023

Place : - RK Valley

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ABSTRACT

Stock price prediction using the LSTM Network on time series forecasting

This project focuses on leveraging Long Short-Term Memory (LSTM) networks for stock price prediction, applying them to the domain of Time Series Forecasting. LSTM networks are a specialized type of Neural Networks renowned for their ability to comprehend and model long-term dependencies, addressing challenges commonly encountered in handling sequential data. This project delves into the intricacies of LSTM architecture, highlighting its unique feature of utilizing gates to selectively add or remove information from the cell state.

The process of LSTM involves several key steps. Initially, the network determines the information to be retained or discarded from the cell. Subsequently, it identifies new information to be incorporated into the cell state. Finally, the LSTM network produces an output based on the state of the cells, offering predictions that take into account both short-term and long-term dependencies.

The project unfolds by applying LSTM to the task of Time Series Forecasting, specifically focusing on predicting stock prices. By understanding the LSTM process within the context of stock price prediction, this project aims to contribute valuable insights and methodologies to the realm of financial forecasting, potentially enhancing the accuracy and reliability of predictions in dynamic and complex markets.

INTRODUCTION

1. **Project Context:**

In the dynamic landscape of financial markets, accurate stock price predictions are imperative for informed decision-making. This project ventures into the realm of Time Series Forecasting using Long Short-Term Memory (LSTM) networks. In the volatile stock market, understanding and modeling long-term dependencies can significantly improve the precision of predictions, offering a valuable tool for investors and financial analysts.

2. **Data and Dataset Description:**

This project revolves around analyzing a dataset tailored for stock price prediction, encompassing historical stock prices, market indicators, and relevant financial metrics. The dataset, curated for its relevance to the financial domain, serves as the foundation for training and evaluating the LSTM network's performance in predicting stock prices.

3. **Objective and Purpose:**

The primary goal of this project is to harness the capabilities of LSTM networks for accurate and reliable stock price predictions. By diving into the intricacies of LSTM architecture and its unique ability to capture both short-term fluctuations and long-term trends, the project aims to advance methodologies in Time Series Forecasting within the financial sector.

4. **Scope and Approach:**

This analysis focuses on deploying LSTM networks to forecast stock prices, utilizing historical data and relevant market indicators. The approach involves training the network to recognize patterns, learn from past trends, and make informed predictions. The scope encompasses understanding the LSTM process in the context of financial forecasting, with an emphasis on unveiling insights that can aid investors in navigating complex and dynamic markets.

5. **Expected Outcomes:**

Anticipated outcomes from this project include enhanced precision in stock price predictions, the identification of significant market trends, and a nuanced understanding of the interplay between short-term fluctuations and long-term market dynamics. By the project's conclusion, readers can expect to glean insights that contribute to refining financial forecasting models and strategies.

6. **Significance:**

The significance of this project lies in its potential to revolutionize financial forecasting practices. The application of LSTM networks to stock price prediction not only addresses the challenges of handling sequential financial data but also opens avenues for more accurate predictions in real-world market scenarios. Stakeholders in the financial sector stand to benefit from improved decision-making, risk management, and strategic planning based on the insights derived from this innovative

PURPOSE

The purpose of this project is to harness the capabilities of Long Short-Term Memory (LSTM) networks in the domain of Time Series Forecasting, with a specific focus on predicting stock prices. LSTM networks, known for their proficiency in capturing and modeling long-term dependencies within sequential data, present a novel approach to address challenges prevalent in handling financial time series data.

The project aims to delve into the intricacies of LSTM architecture, emphasizing its distinctive feature of employing gates to selectively include or exclude information from the cell state. By comprehensively understanding the LSTM process, the project seeks to contribute valuable insights and methodologies to the field of financial forecasting.

Through the application of LSTM networks to the task of predicting stock prices, the project endeavors to provide a nuanced understanding of how these networks can effectively handle the complexities of dynamic and intricate financial markets. The overarching purpose is to enhance the accuracy and reliability of stock price predictions by leveraging the unique capabilities of LSTM networks, thereby offering valuable contributions to the advancement of financial forecasting techniques..

OVERALL DESCRIPTION

1.Company Name : Indicates the name of company (e.g., Apple,google,Netflix,amazon) chosen by users.

2.. **Date**: The date of a particular stock market trading day.

3. **Open**: The opening price of a stock on a given trading day.

4. **High**: The highest price reached by a stock during a trading day.

5. **Low**: The lowest price reached by a stock during a trading day.

6. **Close**: The closing price of a stock at the end of a trading day.

7. **Adj Close**: The adjusted closing price, accounting for corporate actions such as dividends and stock splits.

8.**Volume**: The total number of shares traded for a particular stock on a given trading day.

The purpose of this project is to train the LSTM network model and predict the future Stock close values , we aim to achieve the following objectives:

1. Capture Patterns Over Time:

- Leverage LSTM's ability to understand long-term trends in stock data for more accurate predictions over extended periods.

2. Handle Sequential Patterns:

- Effectively process the order and sequence of historical stock prices, recognizing the importance of temporal relationships.

3. Understand Complex Relationships:

- Model non-linear relationships within stock price movements, capturing the intricate nature of market dynamics.

4. Adapt to Relevant Information:

- Selectively use important information while filtering out noise, improving the network's ability to make informed predictions.

5. Consider Short and Long-Term Trends:

- Make predictions that factor in both short-term fluctuations and long-term patterns, providing a comprehensive view of market behavior.

6. Contribute to Financial Forecasting:

- Provide insights and methods to improve financial forecasting practices, offering practical tools for investors and analysts.

7. Improve Prediction Accuracy:

- Enhance the precision and reliability of predicting future stock prices, empowering better decision-making in the dynamic financial landscape.

EXISTING SYSTEM

Existing System: Stock price prediction using LSTM Network

1. Python Programming Language :

- Python is a versatile and widely-used programming language in data analysis and scientific computing.

- It provides a rich ecosystem of libraries (such as Pandas, NumPy, Matplotlib, Seaborn) that are essential for data manipulation, analysis, and visualization.

2. Jupyter Notebook :

- Jupyter Notebook is an open-source web application that allows you to create and share documents containing live code, equations, visualizations, and narrative text.

- It provides an interactive environment where you can write and execute code in a modular and organized manner.

3. Data Loading and Preprocessing :

- Python's Pandas library is used to load, manipulate, and preprocess the dataset. You can read data from various file formats (e.g., CSV, Excel) into Pandas DataFrames for analysis.

- Data cleaning, handling missing values, and performing basic transformations are done using Pandas functions.

4. Data Visualization:

- Matplotlib and Seaborn are Python libraries commonly used for creating a variety of visualizations, including line charts, bar plots, scatter plots, histograms, and more.

- These libraries allow you to visually explore the data, identify patterns, and present insights.

5. Statistical Analysis :

- NumPy provides tools for numerical computations and statistical operations. You can calculate summary statistics, correlations, and other metrics relevant to LSTM.

- Scipy, another library, offers additional statistical functions and hypothesis testing capabilities.

6. ML Libraries:

TensorFlow, Keras, PyTorch, Scikit-learn, Pandas, NumPy, Matplotlib, Seaborn,

Statsmodels.

7. Interactive Exploration :

- Jupyter Notebook's interactive environment enables you to write and execute code cells in a step-by-step manner. This facilitates the iterative nature of LSTM.

- You can include text, explanations, and markdown cells to document your thought process and findings.

8. Collaborative Sharing :

- Jupyter Notebook documents can be easily shared with colleagues, stakeholders, or collaborators, allowing them to reproduce your analysis and understand your insights.

9. Python Ecosystem :

- Beyond the libraries mentioned, Python offers a wide range of additional libraries that you can leverage based on the specific needs of your analysis.

The combination of Python and Jupyter Notebook provides a powerful platform for conducting EDA. It allows you to load, manipulate, visualize, and analyze data in an interactive and flexible manner, making it a popular choice among data analysts and scientists.

Drawbacks of Existing System

1. Manual Analysis : Current analysis is manual and time-consuming, prone to errors.

2. Limited Visualization : Lack of interactive visualizations hampers effective data exploration.

3. Handling Large Datasets: Challenges with processing and analyzing large datasets efficiently.

4. Limited Insights : Inadequate tools for advanced insights and patterns discovery.

5. No Automation : Lack of automation for ongoing data updates.

6. Security Risks : Potential security and data privacy concerns.

7. Inefficient Decision-Making : Lack of dynamic visualizations affects decision-making.

8. Collaboration Issues : Difficulty in collaborative analysis and sharing insights.

9. Inconsistent Processes : Absence of standardized analysis methods.

10. Limited Relationship Analysis : Inability to explore complex variable relationships

11. Everytime Training:
Need Continuous training for the predictions .

PROPOSED SYSTEM

System Overview :

The proposed system will be a run time program which runs on the jupyter-notebook[a python interpreter] to facilitate the Stock price prediction on the yahoo finance data. The people who are investing in the particular stocks are gaining the prediction price regarding stocks and make data-driven decisions.

Key Features :

1. Data Import and Preprocessing :

- User is going to download the stocks data on yahoo finance website.

- The system will handle data preprocessing tasks such as handling missing values and outliers.

2. Data Exploration and Visualization:

- Users can select attributes of interest (e.g., open,high,low,close,volume) for analysis.

- The system will generate summary statistics and visualizations (e.g., scatter plots) to provide an initial overview of the data.

3. User Stock Analysis :

- The system will offer to represent how the stocks prices are going up and down in the time series.

4. Geographical Insights :

- The system will display a map visualization to show the Stock prices on year by year.
- Users can zoom in on specific year and view stock prices.

5. Model training And testing:

- Divide the data into Training and testing and train the model using the training data.

6. Calculate mean squared Error:

- By using the testing data calculate the error value and find the error loss then fit the model.

7. Future value prediction :

- Allows users to give the input values and it will predict the the final values.

- **Non-Functional Requirements :**

1. Usability :

-The user interface will be intuitive, with interactive controls to customize visualizations and explore data subsets.

2. Performance :

-The system will be responsive, generating visualizations and summary statistics in real-time for a smooth user experience.

3. Security :

- User authentication and access control will ensure that only authorized users can upload data and perform analysis.

4. Scalability :

- The system will handle moderate-sized datasets and provide efficient analysis even with a large number of concurrent users.

Technology Stack :

The proposed system will be Done using Data analysis libraries (e.g., Pandas, Matplotlib, Plotly) will be utilized for processing and visualization. And machine learning model(LSTM networks) for the future stock price predictions.

Benefits :

The LSTM network project for stock price prediction provides enhanced accuracy by leveraging the network's capacity to capture both short-term fluctuations and long-term dependencies. This adaptability to time series data and non-linear relationships contributes to more reliable forecasts, aiding risk management and informed decision-making in dynamic financial markets. The project's potential for real-time predictions and innovation in financial technology further positions it to offer valuable insights for investors and financial professionals.

SYSTEM REQUIREMENTS

➢ SOFTWARE COMPONENTS

- Windows / Ubuntu
- Jupyter Notebook
- Terminal
- Technologies : Python
- Modules : Numpy, Pandas, Matplotlib, Datetime,Keras,tensorflow,Scikit-learn.

➢ HARDWARE COMPONENTS

- Processor – Core i5
- Hard Disk – 512 GB
- RAM – 8 GB
- Internet Connections

TOOLS AND TECHNOLOGIES USED

1. Python :

- Python is a popular programming language widely used for data analysis, machine learning, and scientific computing.

- It provides a rich ecosystem of libraries and tools for data manipulation, analysis, and visualization.

2. Jupyter Notebook :

- Jupyter Notebook is an interactive web-based environment that allows you to create and share documents containing live code, equations, visualizations, and narrative text.

- It's commonly used for data analysis and exploration due to its ability to combine code execution with explanatory text.

3. NumPy :

- NumPy is a fundamental library for numerical computations in Python.

- It provides support for large, multi-dimensional arrays and matrices, along with a variety of mathematical functions to operate on these arrays efficiently.

4. Pandas :

- Pandas is a powerful library for data manipulation and analysis.

- It offers data structures like Series and DataFrame, which simplify handling and analyzing structured data, such as CSV files, SQL tables, and Excel spreadsheets.

-

5. Matplotlib :

- Matplotlib is a widely used 2D plotting library in Python.

- It provides various types of plots and charts for visualizing data, making it suitable for creating static, interactive, and animated visualizations.

6. Keras:

- An open-source high-level neural networks API written in Python. Keras serves as a user-friendly interface to TensorFlow and other deep learning libraries, making it convenient for constructing LSTM models.

7. Scikit-learn:

- A machine learning library for classical machine learning algorithms, including preprocessing, model selection, and evaluation. While Scikit-learn doesn't directly support LSTMs, it can be useful for data preprocessing and post-processing tasks.

8.TensorFlow:

- An open-source machine learning library developed by the Google Brain team. TensorFlow provides comprehensive support for building and training deep neural networks, including LSTM networks.

DATA COLLECTING

Collecting the data from the Stocks(Eg:APPL{apple})

In [9]:
```
import pandas as pd
import yfinance as yf
import datetime
from datetime import date, timedelta
today = date.today()

d1 = today.strftime("%Y-%m-%d")
end_date = d1
d2 = date.today() - timedelta(days=5000)
d2 = d2.strftime("%Y-%m-%d")
start_date = d2

data = yf.download('AAPL',
                      start=start_date,
                      end=end_date,
                      progress=False)
data["Date"] = data.index
data = data[["Date", "Open", "High", "Low", "Close",
             "Adj Close", "Volume"]]
data.reset_index(drop=True, inplace=True)
data.tail(15)
```

Out[9]:

	Date	Open	High	Low	Close	Adj Close	Volume
3433	2023-11-22	191.490005	192.929993	190.830002	191.309998	191.309998	39617700
3434	2023-11-24	190.869995	190.899994	189.250000	189.970001	189.970001	24048300
3435	2023-11-27	189.919998	190.669998	188.899994	189.789993	189.789993	40552600
3436	2023-11-28	189.779999	191.080002	189.399994	190.399994	190.399994	38415400
3437	2023-11-29	190.899994	192.089996	188.970001	189.369995	189.369995	43014200
3438	2023-11-30	189.839996	190.320007	188.190002	189.949997	189.949997	48794400
3439	2023-12-01	190.330002	191.559998	189.229996	191.240005	191.240005	45679300
3440	2023-12-04	189.979996	190.050003	187.449997	189.429993	189.429993	43389500
3441	2023-12-05	190.210007	194.399994	190.179993	193.419998	193.419998	66628400
3442	2023-12-06	194.449997	194.759995	192.110001	192.320007	192.320007	41089700
3443	2023-12-07	193.630005	195.000000	193.589996	194.270004	194.270004	47477700
3444	2023-12-08	194.199997	195.990005	193.669998	195.710007	195.710007	53377300
3445	2023-12-11	193.110001	193.490005	191.419998	193.179993	193.179993	60943700
3446	2023-12-12	193.080002	194.720001	191.720001	194.710007	194.710007	52696900
3447	2023-12-13	195.089996	198.000000	194.850006	197.960007	197.960007	69726500

In [8]:
```
data.dtypes
```

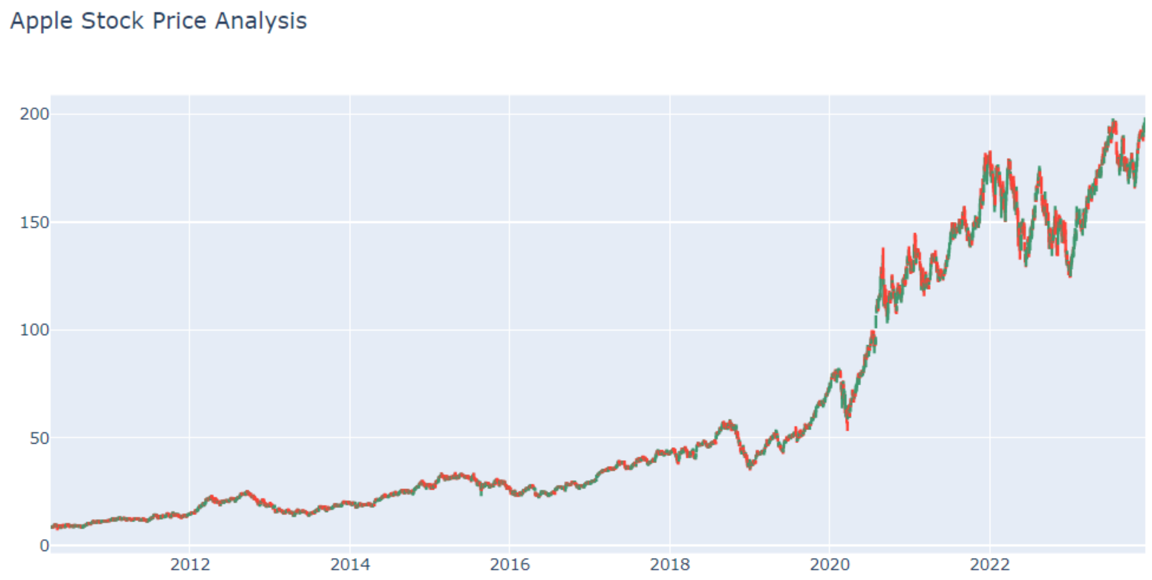
Out[8]:
```
Date         datetime64[ns]
Open                float64
High                float64
Low                 float64
Close               float64
Adj Close           float64
Volume                int64
dtype: object
```

In [11]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3448 entries, 0 to 3447
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       3448 non-null   datetime64[ns]
 1   Open       3448 non-null   float64
 2   High       3448 non-null   float64
 3   Low        3448 non-null   float64
 4   Close      3448 non-null   float64
 5   Adj Close  3448 non-null   float64
 6   Volume     3448 non-null   int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 188.7 KB
```

2) Data Visualization

In [6]:
```
import plotly.graph_objects as go
figure = go.Figure(data=[go.Candlestick(x=data["Date"],
                                        open=data["Open"],
                                        high=data["High"],
                                        low=data["Low"],
                                        close=data["Close"])])
figure.update_layout(title = "Apple Stock Price Analysis",
                     xaxis_rangeslider_visible=False)
figure.show()
```



3) Finding Correlation coefficient:

```
In [7]: correlation = data.corr()
        print(correlation["Close"].sort_values(ascending=False))
```

```
Close        1.000000
Adj Close    0.999953
Low          0.999890
High         0.999884
Open         0.999760
Volume      -0.525386
Name: Close, dtype: float64
```

4) Dividing data Into training and testing sets:

```
In [8]: x = data[["Open", "High", "Low", "Volume"]]
        y = data["Close"]
        x = x.to_numpy()
        y = y.to_numpy()
        y = y.reshape(-1, 1)

        from sklearn.model_selection import train_test_split
        xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size=0.2, random_state=42)
```

5) Choosing model :

```
In [9]: from keras.models import Sequential
        from keras.layers import Dense, LSTM
        model = Sequential()
        model.add(LSTM(128, return_sequences=True, input_shape= (xtrain.shape[1], 1)))
        model.add(LSTM(64, return_sequences=False))
        model.add(Dense(25))
        model.add(Dense(1))
        model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 4, 128)            66560

 lstm_1 (LSTM)               (None, 64)                49408

 dense (Dense)               (None, 25)                1625

 dense_1 (Dense)             (None, 1)                 26

=================================================================
Total params: 117619 (459.45 KB)
Trainable params: 117619 (459.45 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

6)Train the Model

In [10]:
```
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(xtrain, ytrain, batch_size=1, epochs=30)
```

```
Epoch 1/30
WARNING:tensorflow:From C:\Users\91944\AppData\Roaming\Python\Python310\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

2758/2758 [==============================] - 32s 9ms/step - loss: 405.8429
Epoch 2/30
2758/2758 [==============================] - 22s 8ms/step - loss: 16.1012
Epoch 3/30
2758/2758 [==============================] - 24s 9ms/step - loss: 13.5963
Epoch 4/30
2758/2758 [==============================] - 20s 7ms/step - loss: 10.7523
Epoch 5/30
2758/2758 [==============================] - 18s 7ms/step - loss: 11.8444
Epoch 6/30
2758/2758 [==============================] - 19s 7ms/step - loss: 7.5441
Epoch 7/30
2758/2758 [==============================] - 19s 7ms/step - loss: 9.9108
Epoch 8/30
2758/2758 [==============================] - 19s 7ms/step - loss: 6.9675
Epoch 9/30
2758/2758 [==============================] - 18s 7ms/step - loss: 8.2223
Epoch 10/30
2758/2758 [==============================] - 18s 7ms/step - loss: 8.3694
Epoch 11/30
2758/2758 [==============================] - 18s 6ms/step - loss: 5.8218
Epoch 12/30
2758/2758 [==============================] - 18s 7ms/step - loss: 6.9706
Epoch 13/30
2758/2758 [==============================] - 18s 7ms/step - loss: 6.3067
Epoch 14/30
2758/2758 [==============================] - 18s 6ms/step - loss: 7.1384
Epoch 15/30
2758/2758 [==============================] - 19s 7ms/step - loss: 4.5627
Epoch 16/30
2758/2758 [==============================] - 18s 6ms/step - loss: 5.9180
Epoch 17/30
2758/2758 [==============================] - 17s 6ms/step - loss: 5.1856
Epoch 18/30
2758/2758 [==============================] - 18s 6ms/step - loss: 7.4485
Epoch 19/30
2758/2758 [==============================] - 17s 6ms/step - loss: 5.5078
Epoch 20/30
2758/2758 [==============================] - 18s 7ms/step - loss: 7.9913
Epoch 21/30
2758/2758 [==============================] - 18s 7ms/step - loss: 4.4081
Epoch 22/30
2758/2758 [==============================] - 19s 7ms/step - loss: 4.9682
Epoch 23/30
2758/2758 [==============================] - 19s 7ms/step - loss: 4.9961
Epoch 24/30
2758/2758 [==============================] - 19s 7ms/step - loss: 5.1487
Epoch 25/30
2758/2758 [==============================] - 18s 7ms/step - loss: 4.0021
Epoch 26/30
2758/2758 [==============================] - 18s 6ms/step - loss: 4.7548
Epoch 27/30
2758/2758 [==============================] - 18s 7ms/step - loss: 5.5437
Epoch 28/30
2758/2758 [==============================] - 18s 6ms/step - loss: 4.3672
Epoch 29/30
2758/2758 [==============================] - 17s 6ms/step - loss: 4.8707
Epoch 30/30
2758/2758 [==============================] - 19s 7ms/step - loss: 3.6017
```

Out[10]:
```
<keras.src.callbacks.History at 0x25405b26230>
```

7)Prediction in real life

```
In [15]: import numpy as np
         features = np.array([[177.089996, 180.419998, 177.070007, 74919600]])
         res=model.predict(features)[0][0]
         print("Todays close value = ",res)

         1/1 [==============================] - 0s 31ms/step
         Todays close value =  192.46582
```

```
In [18]: features1 = np.array([[179.0309996, 182.679998, 179.04607, 81919600]])
         res=model.predict(features1)[0][0]
         print("Todays close value = ",res)

         1/1 [==============================] - 0s 48ms/step
         Todays close value =  194.00844
```

```
In [19]: features1 = np.array([[178.0309996, 181.679998, 178.94607, 80819600]])
         res=model.predict(features1)[0][0]
         print("Todays close value = ",res)

         1/1 [==============================] - 0s 47ms/step
         Todays close value =  193.61873
```

This's how it predict the Close values of Stocks based on the high , low , and Volume of the Stocks….

CONCLUSION

In conclusion, this project demonstrates the effective application of Long Short-Term Memory (LSTM) networks in the domain of Time Series Forecasting, with a specific emphasis on predicting stock prices. By delving into the intricacies of LSTM architecture and highlighting its unique features, the project establishes a foundation for understanding how LSTM networks can comprehend and model both short-term and long-term dependencies in sequential data. The outlined process of LSTM, involving the selective retention and incorporation of information through gated mechanisms, showcases the network's ability to handle complex data patterns.

Through the practical implementation of LSTM in stock price prediction, this project contributes valuable insights and methodologies to the field of financial forecasting. The utilization of LSTM networks opens avenues for enhancing the accuracy and reliability of predictions in dynamic and complex markets, providing a promising approach to addressing challenges inherent in Time Series Forecasting. Ultimately, the project underscores the potential of LSTM networks as a powerful tool for improving predictive