

Tesla stock price prediction using LSTM model

```
In [ ]: !pip install yfinance
```

#the dataset we will use here to perform the analysis and build a predictive model is Tesla Stock Price data. We will use OHLC('Open', 'High', 'Low', 'Close') data from 1st January 2020 to 31 december 2022 which is for 2 year for the Tesla stocks.

```
In [4]: import yfinance as yf
# Getting Tesla stock data for a specific date range:
tsla = yf.Ticker("TSLA").history(start="2020-01-01", end="2023-01-01")
print(tsla)
```

	Open	High	Low	Close \
Date				
2020-01-02 00:00:00-05:00	28.299999	28.713333	28.114000	28.684000
2020-01-03 00:00:00-05:00	29.366667	30.266666	29.128000	29.534000
2020-01-06 00:00:00-05:00	29.364668	30.104000	29.333332	30.102667
2020-01-07 00:00:00-05:00	30.760000	31.441999	30.224001	31.270666
2020-01-08 00:00:00-05:00	31.580000	33.232666	31.215334	32.809334
...
2022-12-23 00:00:00-05:00	126.370003	128.619995	121.019997	123.150002
2022-12-27 00:00:00-05:00	117.500000	119.669998	108.760002	109.099998
2022-12-28 00:00:00-05:00	110.349998	116.269997	108.239998	112.709999
2022-12-29 00:00:00-05:00	120.389999	123.570000	117.500000	121.820000
2022-12-30 00:00:00-05:00	119.949997	124.480003	119.750000	123.180000

	Volume	Dividends	Stock Splits
Date			
2020-01-02 00:00:00-05:00	142981500	0.0	0.0
2020-01-03 00:00:00-05:00	266677500	0.0	0.0
2020-01-06 00:00:00-05:00	151995000	0.0	0.0
2020-01-07 00:00:00-05:00	268231500	0.0	0.0
2020-01-08 00:00:00-05:00	467164500	0.0	0.0
...
2022-12-23 00:00:00-05:00	166989700	0.0	0.0
2022-12-27 00:00:00-05:00	208643400	0.0	0.0
2022-12-28 00:00:00-05:00	221070500	0.0	0.0
2022-12-29 00:00:00-05:00	221923300	0.0	0.0
2022-12-30 00:00:00-05:00	157777300	0.0	0.0

[756 rows x 7 columns]

```
In [4]: tsla.shape
```

```
Out[4]: (756, 7)
```

From this, we got to know that there are 756 rows of data available and for each row, we have 7 different features (columns). Before moving further let's check for the null values if any are present in the data frame.

```
In [5]: tsla = yf.Ticker("TSLA").history(start="2020-01-01", end="2023-01-01")
tsla.isnull().sum()
```

```
Out[5]: Open          0
High          0
Low           0
Close         0
Volume        0
Dividends     0
Stock Splits  0
dtype: int64
```

This implies that there are no null values in the data set provided.

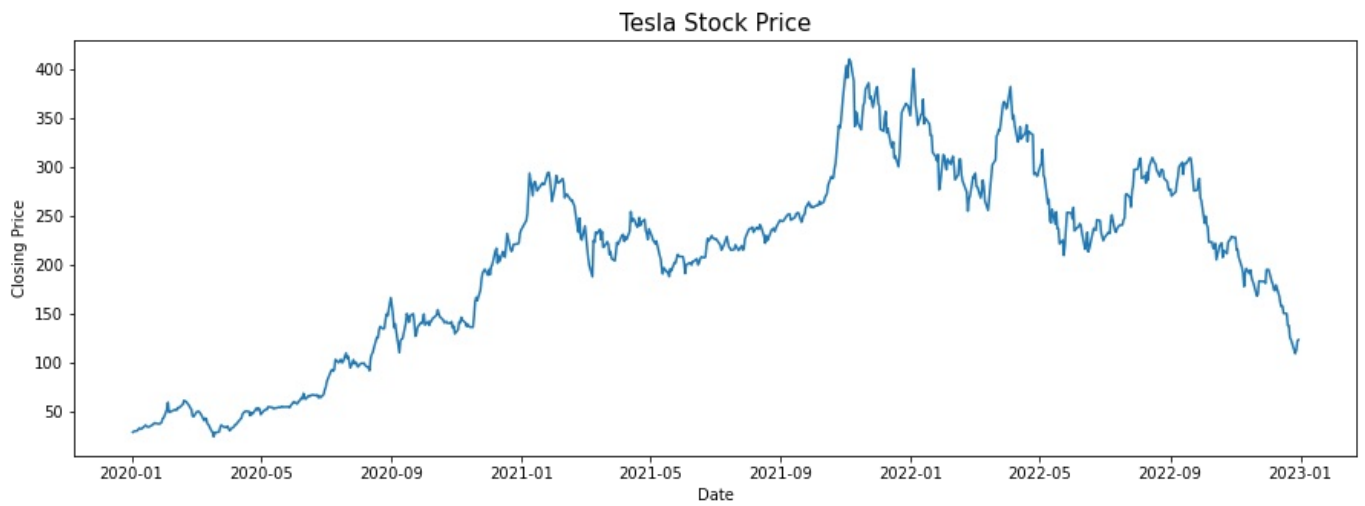
```
In [ ]: #Exploratory Data Analysis      ###      EDA      ###
```

```
In [6]: import matplotlib.pyplot as plt

# Plot the closing prices
plt.figure(figsize=(15,5))
plt.plot(tsla['Close'])

# Add labels and title
plt.xlabel("Date")
plt.ylabel("Closing Price")
plt.title("Tesla Stock Price", fontsize=15)

# Show the plot
plt.show()
```



```
In [ ]: !pip install mplfinance
```

```
In [8]: !pip install plotly
```

Requirement already satisfied: plotly in c:\users\client\anaconda3\lib\site-packages (5.6.0)
 Requirement already satisfied: tenacity>=6.2.0 in c:\users\client\anaconda3\lib\site-packages (from plotly) (8.0.1)
 Requirement already satisfied: six in c:\users\client\anaconda3\lib\site-packages (from plotly) (1.16.0)

```
In [1]: import plotly.graph_objs as go
import yfinance as yf

tsla = yf.Ticker("TSLA").history(start="2020-01-01", end="2023-01-01")

# Create the candlestick chart
fig = go.Figure(data=[go.Candlestick(x=tsla.index,
                                     open=tsla['Open'],
                                     high=tsla['High'],
                                     low=tsla['Low'],
                                     close=tsla['Close'])])

# Add title and axis labels
fig.update_layout(title='Tesla Stock Price',
                  yaxis_title='Stock Price',
                  xaxis_title='Date')

# Show the chart
fig.show()
```



Tesla Stock Price



LSTM

2 steps : 1-train the model -2- test the model

```
In [10]: import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

from matplotlib.pylab import rcParams
rcParams['figure.figsize']=20,10
from keras.models import Sequential
from keras.layers import LSTM,Dropout,Dense
```

```
In [17]: #Sort the dataset on date time and filter "Date" and "Close" columns:
tsla = yf.Ticker("TSLA").history(start="2020-01-01", end="2023-01-01")
data=tsla.sort_index(ascending=True,axis=0)
close_dataset=pd.DataFrame(index=range(0,len(tsla)),columns=['Date','Close'])

for i in range(0,len(data)):

    close_dataset["Date"][i] = data.index[i].strftime('%Y-%m-%d')
    close_dataset["Close"][i] = data["Close"][i]
print(close_dataset)
```

	Date	Close
0	2020-01-02	28.684
1	2020-01-03	29.534
2	2020-01-06	30.102667
3	2020-01-07	31.270666
4	2020-01-08	32.809334
..
751	2022-12-23	123.150002
752	2022-12-27	109.099998
753	2022-12-28	112.709999
754	2022-12-29	121.82
755	2022-12-30	123.18

[756 rows x 2 columns]

```
In [18]: close_dataset.drop("Date",axis=1,inplace=True)
print(close_dataset)
```

	Close
0	28.684
1	29.534
2	30.102667
3	31.270666
4	32.809334
..	...
751	123.150002
752	109.099998
753	112.709999
754	121.82
755	123.18

[756 rows x 1 columns]

normalize the new filtered data set: ## LSTM are sensitive to the scale of the data so we apply MinMax scaler: ###transform the values to an array:

```
In [19]: from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
close_dataset= scaler.fit_transform(np.array(close_dataset).reshape(-1,1))
```

```
In [20]: #splitting dataset into train and test split:
training_size= int(len(close_dataset)*0.65) # 65%
test_size=len(close_dataset)- training_size
train=close_dataset[0:training_size,:]
test= close_dataset[training_size:len(close_dataset),:1]
len(train),len(test)
```

Out[20]: (491, 265)

```
In [21]: #convert an array of values into a dataset matrix:
import numpy as np
def create_dataset(dataset, time_step=1):
    x, y = [], []
    for i in range(len(dataset)-time_step-1):
        a = dataset[i:(i+time_step), 0]
        x.append(a)
        y.append(dataset[i + time_step, 0])
    return np.array(x), np.array(y)
```

```
In [22]: #reshape into x=t, t+1,t+2,t+3 and y=t+4
time_step = 100
```

```
x_train, y_train = create_dataset(train, time_step)
x_test, y_test = create_dataset(test, time_step)

[[0.01192745 0.01413016 0.01560381 ... 0.08057246 0.07872046 0.07906425]
 [0.01413016 0.01560381 0.01863059 ... 0.07872046 0.07906425 0.07929921]
 [0.01560381 0.01863059 0.02261792 ... 0.07906425 0.07929921 0.076808 ]
 ...
 [0.49407689 0.49580448 0.50813967 ... 0.87448018 0.81433332 0.80918504]
 [0.49580448 0.50813967 0.5036392 ... 0.81433332 0.80918504 0.84610417]
 [0.50813967 0.5036392 0.49843046 ... 0.80918504 0.84610417 0.86097028]]
```

```
In [24]: #reshape
x_train=x_train.reshape(x_train.shape[0],x_train.shape[1],1)
x_test=x_test.reshape(x_test.shape[0],x_test.shape[1],1)
```

```
In [25]: #build LSTM
from keras.models import Sequential
from keras.layers import LSTM, Dense

lstm_model = Sequential()
lstm_model.add(LSTM(50, return_sequences=True, input_shape=(time_step, 1)))
lstm_model.add(LSTM(50, return_sequences=True))
lstm_model.add(LSTM(50))
lstm_model.add(Dense(1))
lstm_model.compile(loss='mean_squared_error', optimizer='adam')
```

```
In [18]: lstm_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 100, 50)	10400
lstm_1 (LSTM)	(None, 100, 50)	20200
lstm_2 (LSTM)	(None, 50)	20200
dense (Dense)	(None, 1)	51

```
=====
Total params: 50,851
Trainable params: 50,851
Non-trainable params: 0
=====
```

```
In [ ]:
```

```
In [ ]: x_train=x_train.reshape(x_train.shape[0],x_train.shape[1],1)
x_test=x_test.reshape(x_test.shape[0],x_test.shape[1],1)
lstm_model.fit(x_train, y_train, validation_data=(x_test, y_test), epochs=100, batch_size=64, verbose=1)
```

```
In [20]: #the prediction
train_predict = lstm_model.predict(x_train)
test_predict = lstm_model.predict(x_test)

#transform back to the original form:
train_predict = scaler.inverse_transform(train_predict)

test_predict = scaler.inverse_transform(test_predict)
```

```
13/13 [=====] - 2s 26ms/step
6/6 [=====] - 0s 25ms/step
```

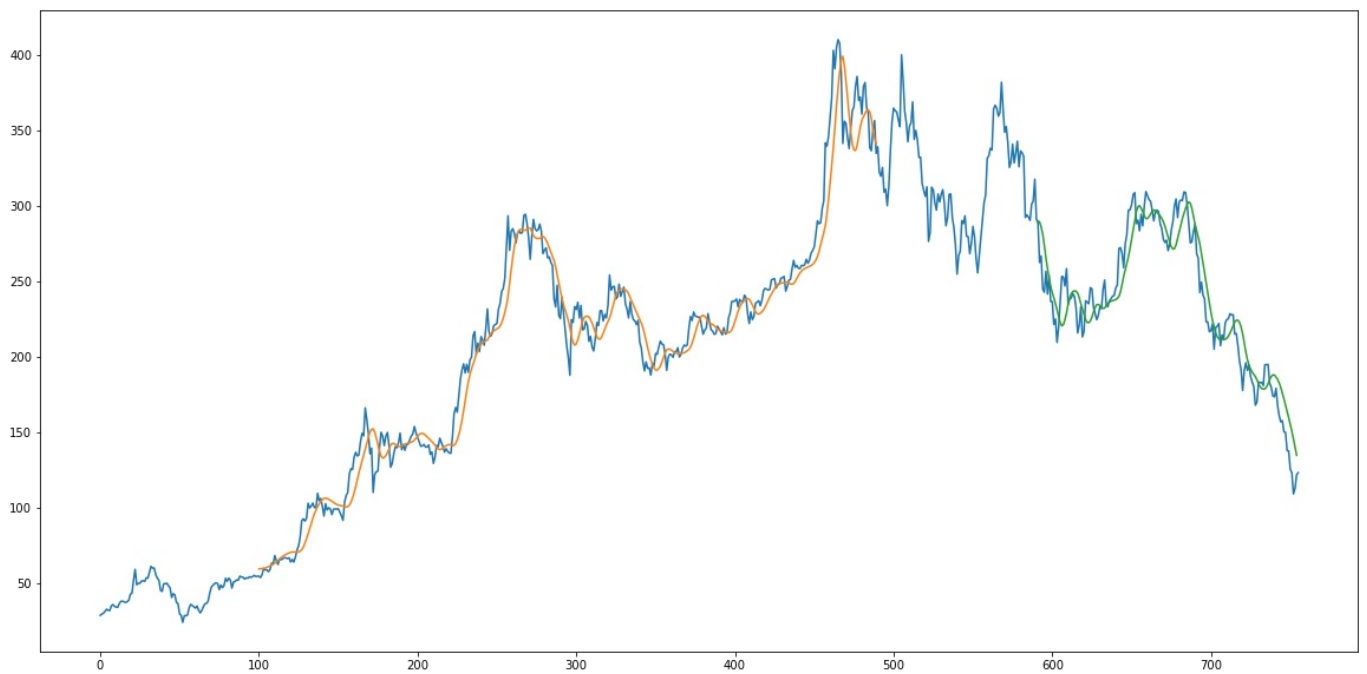
```
In [21]: import numpy as np
look_back=100

trainpredictplot = np.empty_like(close_dataset)
trainpredictplot[:, :] = np.nan
trainpredictplot[look_back:len(train_predict)+look_back, :] = train_predict

testpredictplot= np.empty_like(close_dataset)
testpredictplot[:, :] = np.nan

testpredictplot[len(train_predict)+(look_back*2)+1:len(close_dataset)-1, :] = test_predict.reshape(-1, 1)

plt.plot(scaler.inverse_transform(close_dataset))
plt.plot(trainpredictplot)
plt.plot(testpredictplot)
plt.show()
```



=> the LSTM has predicted stocks almost similar to actual stocks.

```
In [122]: lstm_model.save("lstm_model.h5")
```

```
In [26]: close_dataset = close_dataset.reshape((-1))
```

```
In [31]: close_dataset = close_dataset.reshape((-1))
look_back=100

def predict(num_prediction, lstm_model):
    prediction_list = close_dataset[-look_back:]

    for _ in range(num_prediction):
        x = prediction_list[-look_back:]
        x = x.reshape((1, look_back, 1))
        out = lstm_model.predict(x)[0][0]
        prediction_list = np.append(prediction_list, out)
        prediction_list = prediction_list[look_back-1:]

    return prediction_list

num_prediction = 30
forecast = predict(num_prediction, lstm_model)

print(forecast)
```

```

1/1 [=====] - 0s 35ms/step
1/1 [=====] - 0s 35ms/step
1/1 [=====] - 0s 32ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 31ms/step
1/1 [=====] - 0s 30ms/step
1/1 [=====] - 0s 38ms/step
1/1 [=====] - 0s 42ms/step
1/1 [=====] - 0s 44ms/step
1/1 [=====] - 0s 46ms/step
1/1 [=====] - 0s 31ms/step
1/1 [=====] - 0s 30ms/step
1/1 [=====] - 0s 31ms/step
1/1 [=====] - 0s 34ms/step
1/1 [=====] - 0s 41ms/step
1/1 [=====] - 0s 27ms/step
1/1 [=====] - 0s 28ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 30ms/step
1/1 [=====] - 0s 27ms/step
1/1 [=====] - 0s 37ms/step
1/1 [=====] - 0s 24ms/step
1/1 [=====] - 0s 29ms/step
1/1 [=====] - 0s 31ms/step
1/1 [=====] - 0s 26ms/step
1/1 [=====] - 0s 40ms/step
1/1 [=====] - 0s 26ms/step
[0.25680637 0.26515317 0.25921106 0.25608486 0.25501752 0.25530237
 0.25638941 0.25789961 0.25959757 0.26135123 0.26309484 0.26480088
 0.2664609 0.26807451 0.26964387 0.27117115 0.27265793 0.27410528
 0.27551448 0.27688655 0.27822331 0.27952677 0.28079924 0.28204325
 0.28326136 0.28445619 0.28563032 0.28678605 0.28792545 0.28905061
 0.29016322]

```

In [32]: `#prediction visualisation`

```

import matplotlib.pyplot as plt

plt.figure(figsize=(16,5))
plt.plot(close_dataset[-655:], label='Historical Data')
plt.plot(range(len(close_dataset)-100, len(close_dataset)+num_prediction-99), forecast, label='Predicted Data')

plt.legend()
plt.show()

```

