LETS GROW MORE - Virtual Internship 2023

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Task 2 - Stock Market Prediction And Forecasting Using Stacked LSTM

Importing Libraries

In [1]:

```
import pandas as pd
import numpy as np
import math
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
import tensorflow as tf
from tensorflow.python.keras.models import Sequential
from tensorflow.python.keras.layers import Dense
from tensorflow.python.keras.layers import LSTM
%matplotlib inline
from warnings import filterwarnings
filterwarnings("ignore")
```

Import Data

In [2]:

```
df = pd.read_csv('NSE-TATAGLOBAL.csv')
df.head()
```

Out[2]:

	Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
0	2018-09-28	234.05	235.95	230.20	233.50	233.75	3069914	7162.35
1	2018-09-27	234.55	236.80	231.10	233.80	233.25	5082859	11859.95
2	2018-09-26	240.00	240.00	232.50	235.00	234.25	2240909	5248.60
3	2018-09-25	233.30	236.75	232.00	236.25	236.10	2349368	5503.90
4	2018-09-24	233.55	239.20	230.75	234.00	233.30	3423509	7999.55

Data Exploration

In [3]:

```
df.shape
```

Out[3]:

```
(2035, 8)
```

In [4]:

```
# check basic info of data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2035 entries, 0 to 2034
Data columns (total 8 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   Date                  2035 non-null   object 
 1   Open                  2035 non-null   float64
 2   High                  2035 non-null   float64
 3   Low                   2035 non-null   float64
 4   Last                  2035 non-null   float64
 5   Close                 2035 non-null   float64
 6   Total Trade Quantity  2035 non-null   int64  
 7   Turnover (Lacs)       2035 non-null   float64
dtypes: float64(6), int64(1), object(1)
memory usage: 127.3+ KB
```

In [5]:

```
# get statistical summaries of dataset
df.describe()
```

Out[5]:

	Open	High	Low	Last	Close	Total Trade Quantity	T
count	2035.000000	2035.000000	2035.000000	2035.000000	2035.00000	2.035000e+03	2035
mean	149.713735	151.992826	147.293931	149.474251	149.45027	2.335681e+06	3899
std	48.664509	49.413109	47.931958	48.732570	48.71204	2.091778e+06	4570
min	81.100000	82.800000	80.000000	81.000000	80.95000	3.961000e+04	37
25%	120.025000	122.100000	118.300000	120.075000	120.05000	1.146444e+06	1427
50%	141.500000	143.400000	139.600000	141.100000	141.25000	1.783456e+06	2512
75%	157.175000	159.400000	155.150000	156.925000	156.90000	2.813594e+06	4539
max	327.700000	328.750000	321.650000	325.950000	325.75000	2.919102e+07	55755

In [6]:

```
df_close = df.reset_index()['Close']
df_close
```

Out[6]:

```
0       233.75
1       233.25
2       234.25
3       236.10
4       233.30
         ...
2030    118.65
2031    117.60
2032    120.65
2033    120.90
2034    121.55
Name: Close, Length: 2035, dtype: float64
```

In [7]:

```
# check is there any null values present of not
df.isnull().sum()
```

Out[7]:

```
Date                    0
Open                    0
High                    0
Low                     0
Last                    0
Close                   0
Total Trade Quantity    0
Turnover (Lacs)         0
dtype: int64
```

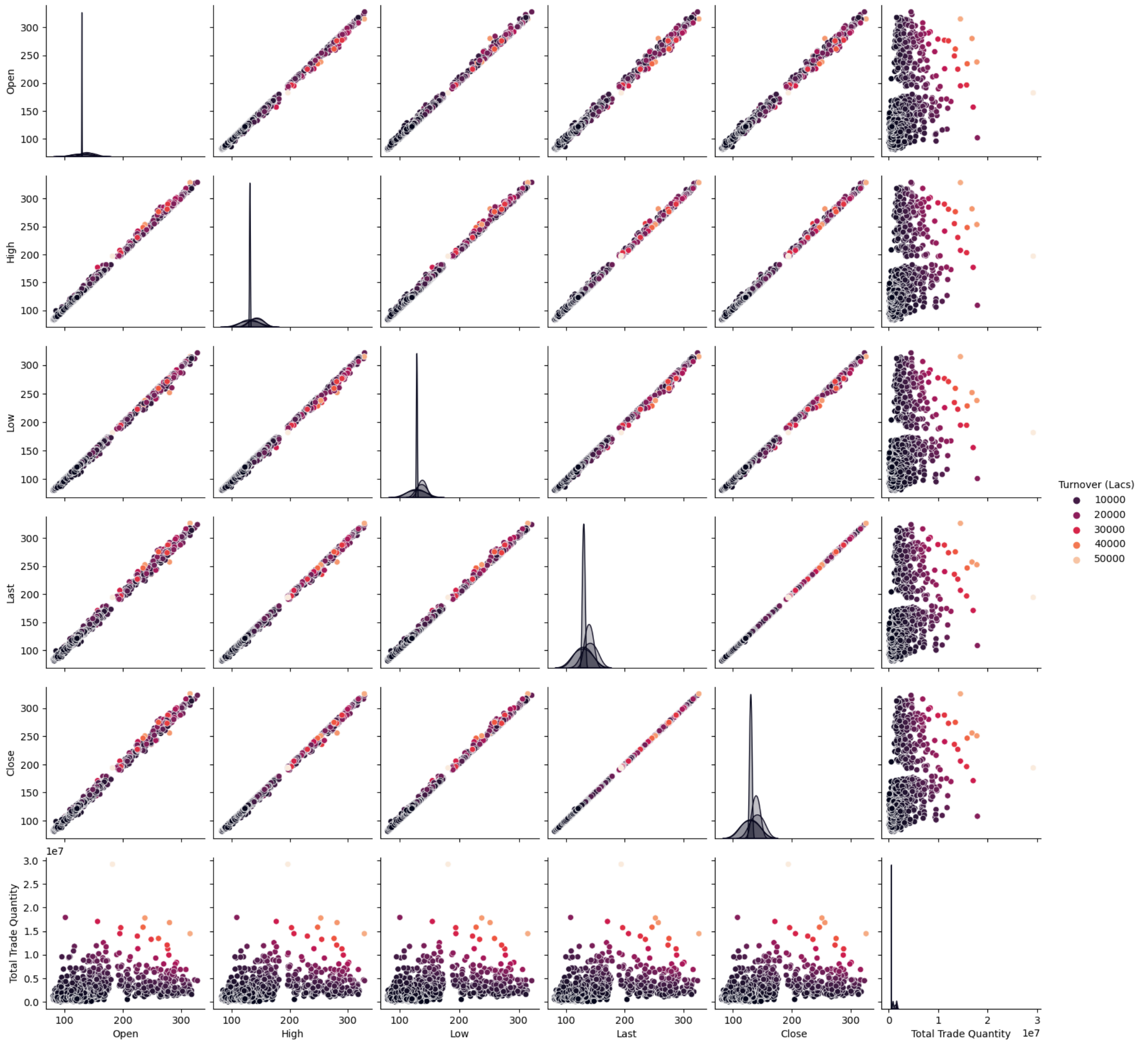
Here we can see no null values present in dataset

Exploratory Data Analysis (EDA)

Data visualization

In [8]:

```
sns.pairplot(df, hue= 'Turnover (Lacs)', palette= "rocket")
plt.show()
```

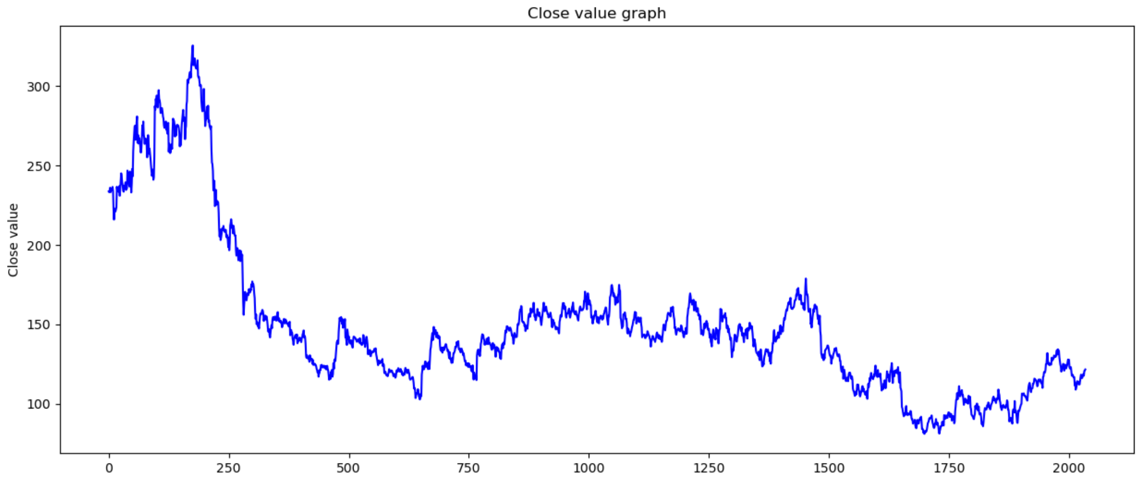


Let us plot the Close value graph using pyplot

- **Let us plot the Close value graph using pyplot**

In [9]:

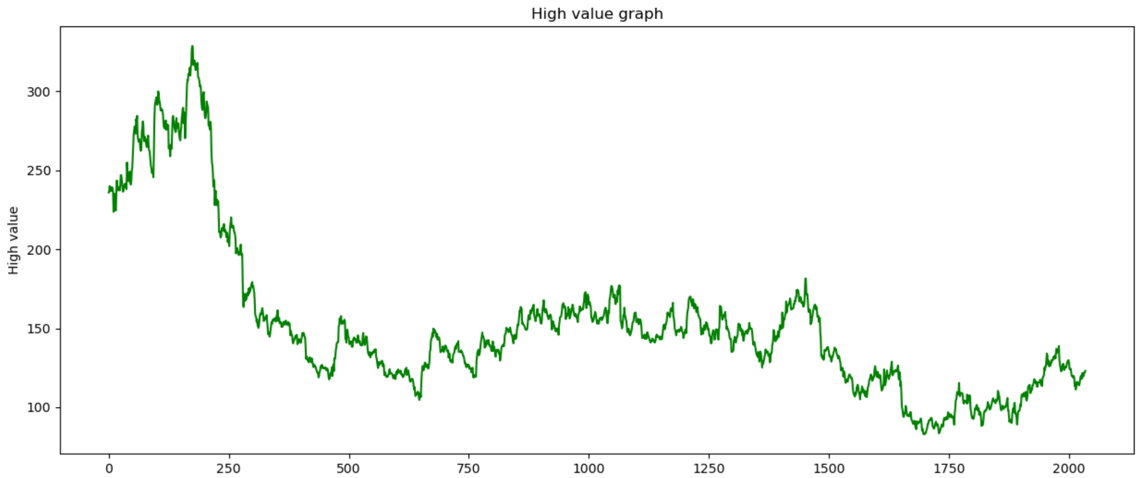
```
plt.figure(figsize=(15,6))
plt.plot(df_close, c= "b")
plt.ylabel("Close value")
plt.title('Close value graph')
plt.show()
```



- **Let us plot the High value graph using pyplot**

In [10]:

```
plt.figure(figsize=(15,6))

df_high=df.reset_index()['High']
plt.plot(df_high, c="g")
plt.ylabel("High value")
plt.title('High value graph')
plt.show()
```



- **Since LSTM are sensitive to the scale of the data, so we apply MinMax Scaler to transform our values between 0 and 1**

In [11]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range = (0,1))
df_high = scaler.fit_transform(np.array(df_high).reshape(-1,1))
df_high
```

Out[11]:

```
array([[0.62268754],
       [0.62614353],
       [0.6391543 ],
       ...,
       [0.15917869],
       [0.15938199],
       [0.16344786]])
```

In [12]:

```
df_high.shape
```

Out[12]:

```
(2035, 1)
```

Train Test Split

- In time-series data the one data is dependent on other data. The training size should be 75% of the total length of the data frame, the test size should be the difference between the length of the dataset and the training size.

In [13]:

```
training_size = int(len(df_high) * 0.75)
test_size = len(df_high) - training_size
train_data, test_data = df_high[0:training_size,:], df_high[training_size:len(df_hig
```

In [14]:

```
print('Training Data :',train_data.size)
print('Training Data :',test_data.size)
```

```
Training Data : 1526
Training Data : 509
```

Data Preprocessing

In [15]:

```
def create_dataset(dataset, time_step = 1):
    dataX, dataY = [], []
    for i in range(len(dataset) - time_step - 1):
        a = dataset[i:(i+time_step), 0]
        dataX.append(a)
        dataY.append(dataset[i+time_step, 0])
    return np.array(dataX), np.array(dataY)
```

In [16]:

```
time_step = 100
x_train, y_train = create_dataset(train_data, time_step)
x_test, y_test = create_dataset(test_data, time_step)
```

LSTM

- Reshape the input to be [samples, time steps, features] which is the requirement of LSTM

In [17]:

```
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 [18]:

```
print("X Training Data :",x_train.shape)
print("X testing Data :",x_test.shape)
print("Y Training Data :",y_train.shape)
print("Y Tresting Data :",y_test.shape)
```

```
X Training Data : (1425, 100, 1)
X testing Data : (408, 100, 1)
Y Training Data : (1425,)
Y Tresting Data : (408,)
```

- **Import required modules for the stacked LSTM.**

In [19]:

```
import math
from sklearn.metrics import mean_squared_error
import tensorflow as tf
from tensorflow.python.keras.models import Sequential
from tensorflow.python.keras.layers import Dense
from tensorflow.python.keras.layers import LSTM
```

In [20]:

```
#checking my tensorflow version
tf.__version__
```

Out[20]:

```
'2.11.0'
```

Creating model

In [21]:

```
#Create the LSTM Model
model = Sequential()
model.add(LSTM(50, return_sequences = True, input_shape = (100,1)))
model.add(LSTM(50, return_sequences = True))
model.add(LSTM(50))
model.add(Dense(1))
model.compile(loss = 'mean_squared_error', optimizer = 'adam')
```

In [22]:

```
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 [23]:

```
model.fit(x_train, y_train, validation_data = (x_test, y_test), epochs = 10, batch_s
```

```
Epoch 1/10
23/23 [==============================] - 14s 275ms/step - loss: 0.0303 - v
al_loss: 0.0071
Epoch 2/10
23/23 [==============================] - 5s 228ms/step - loss: 0.0029 - va
l_loss: 0.0011
Epoch 3/10
23/23 [==============================] - 5s 231ms/step - loss: 0.0015 - va
l_loss: 0.0018
Epoch 4/10
23/23 [==============================] - 5s 223ms/step - loss: 0.0014 - va
l_loss: 0.0013
Epoch 5/10
23/23 [==============================] - 5s 221ms/step - loss: 0.0015 - va
l_loss: 0.0013
Epoch 6/10
23/23 [==============================] - 5s 220ms/step - loss: 0.0014 - va
l_loss: 0.0010
Epoch 7/10
23/23 [==============================] - 5s 223ms/step - loss: 0.0013 - va
l_loss: 0.0011
Epoch 8/10
23/23 [==============================] - 5s 223ms/step - loss: 0.0012 - va
l_loss: 0.0015
Epoch 9/10
23/23 [==============================] - 5s 225ms/step - loss: 0.0011 - va
l_loss: 9.5912e-04
Epoch 10/10
23/23 [==============================] - 5s 224ms/step - loss: 0.0011 - va
l_loss: 9.2192e-04
```

Out[23]:

```
<tensorflow.python.keras.callbacks.History at 0x220437eeb50>
```

In [32]:

```
#Lets predict and check performance metrics
train_predict = model.predict(x_train)
test_predict = model.predict(x_test)
```

In [33]:

```
#Transform back to original form
train_predict = scaler.inverse_transform(train_predict)
test_predict = scaler.inverse_transform(test_predict)
```

Calculating RMSE

In [34]:

```
#Calculate RMSE performance metrics
math.sqrt(mean_squared_error(y_train, train_predict))
```

Out[34]:

164.14558794369935

In [35]:

```
#Test Data RMSE
math.sqrt(mean_squared_error(y_test, test_predict))
```

Out[35]:

110.79035236747968

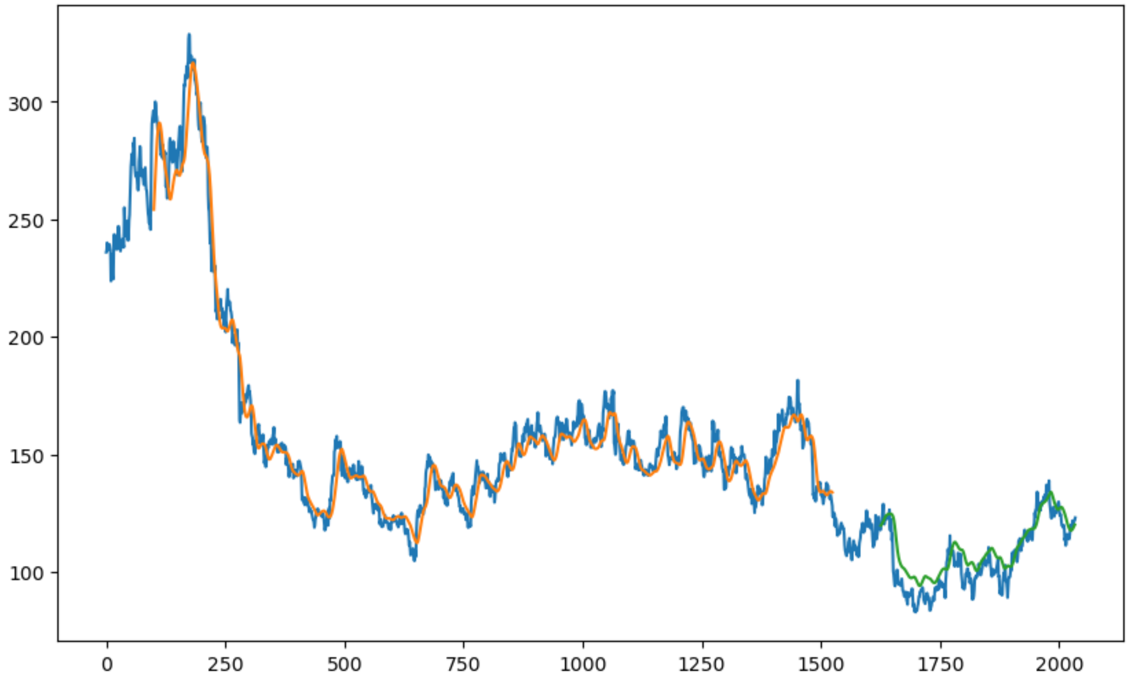
Plotting the graph according to train and test data

In [36]:

```
#Plotting

#Shift train prediction for plotting
look_back = 100
trainPredictPlot = np.empty_like(df_high)
trainPredictPlot[:,:] = np.nan
trainPredictPlot[look_back:len(train_predict) + look_back, :] = train_predict

#Shift test prediction for plotting
testPredictPlot = np.empty_like(df_high)
testPredictPlot[:,:] = np.nan
testPredictPlot[len(train_predict) + (look_back * 2)+1:len(df_high) - 1, :] = test_p
```

In [37]:

```
#Plot baseline and predictions
plt.figure(figsize=(10,6))

plt.plot(scaler.inverse_transform(df_high))
plt.plot(trainPredictPlot)
plt.plot(testPredictPlot)
plt.show()

print("Green indicates the Predicted Data")
print("Blue indicates the Complete Data")
print("Orange indicates the Train Data")
```




```
Green indicates the Predicted Data
Blue indicates the Complete Data
Orange indicates the Train Data
```

In [38]:

```
#Predict the next 28 days Stock Price
print("Length of Test Data : ",len(test_data))
print("Shape of x Test Data :",x_test.shape)
```

```
Length of Test Data :  509
Shape of x Test Data : (408, 100, 1)
```

In [39]:

```
x_input=test_data[409:].reshape(1,-1)
x_input.shape
```

Out[39]:

```
(1, 100)
```

Predicting values for next 30 days

In [40]:

```
temp_input = list(x_input)
temp_input = temp_input[0].tolist()
```

In [41]:

```
lst_output=[]
n_steps=100
i=0
while(i<30):

    if(len(temp_input)>100):
        x_input=np.array(temp_input[1:])
        print("{} day input {}".format(i,x_input))
        x_input=x_input.reshape(1,-1)
        x_input = x_input.reshape((1, n_steps, 1))

        yhat = model.predict(x_input, verbose=0)
        print("{} day output {}".format(i,yhat))
        temp_input.extend(yhat[0].tolist())
        temp_input=temp_input[1:]

        lst_output.extend(yhat.tolist())
        i=i+1
    else:
        x_input = x_input.reshape((1, n_steps,1))
        yhat = model.predict(x_input, verbose=0)
        print(yhat[0])
        temp_input.extend(yhat[0].tolist())
        print(len(temp_input))
        lst_output.extend(yhat.tolist())
        i=i+1


print(lst_output)
```

```
[0.15512641]
101
1 day input [0.13254727 0.13397032 0.13356373 0.13498679 0.14108559 0.1
3498679
 0.12644847 0.12685505 0.12482212 0.14515145 0.1467778  0.15003049
 0.15368977 0.17198618 0.16548079 0.17625534 0.17564546 0.19129904
 0.20817239 0.20309006 0.18479366 0.17930474 0.1896727  0.17483228
 0.17849156 0.17645863 0.18540354 0.18377719 0.19190892 0.18987599
 0.19028258 0.19394186 0.20004066 0.19638138 0.19495832 0.20349665
 0.19597479 0.21162838 0.22036999 0.20979874 0.21528766 0.21589754
 0.21610083 0.22748526 0.19150234 0.1833706  0.17340923 0.16751372
 0.1622281  0.17056312 0.17462899 0.17930474 0.18174426 0.16853019
 0.16548079 0.1742224  0.1713763  0.17300264 0.17157959 0.17767839
 0.18459036 0.18702988 0.18987599 0.19109575 0.18581012 0.17015654
 0.16751372 0.16974995 0.16609067 0.15531612 0.15003049 0.15064037
 0.14860744 0.14596463 0.15043708 0.14413499 0.12441553 0.12827811
 0.11547062 0.12034966 0.13478349 0.13498679 0.12868469 0.13295385
 0.12807481 0.12624517 0.13051433 0.13905265 0.14718439 0.15104696
 0.14515145 0.14311852 0.15816223 0.15328319 0.14921732 0.15531612
 0.15017869 0.15038109 0.16244786 0.15512641]
```

In [42]:

```
day_new = np.arange(1,101)
day_pred = np.arange(101,131)
```

In [43]:

```
print(day_new.shape)
print(day_pred.shape)
```

```
(100,)
(30,)
```

In [44]:

```
ds3 = df_high.tolist()
ds3.extend(lst_output)

len(df_high)
```

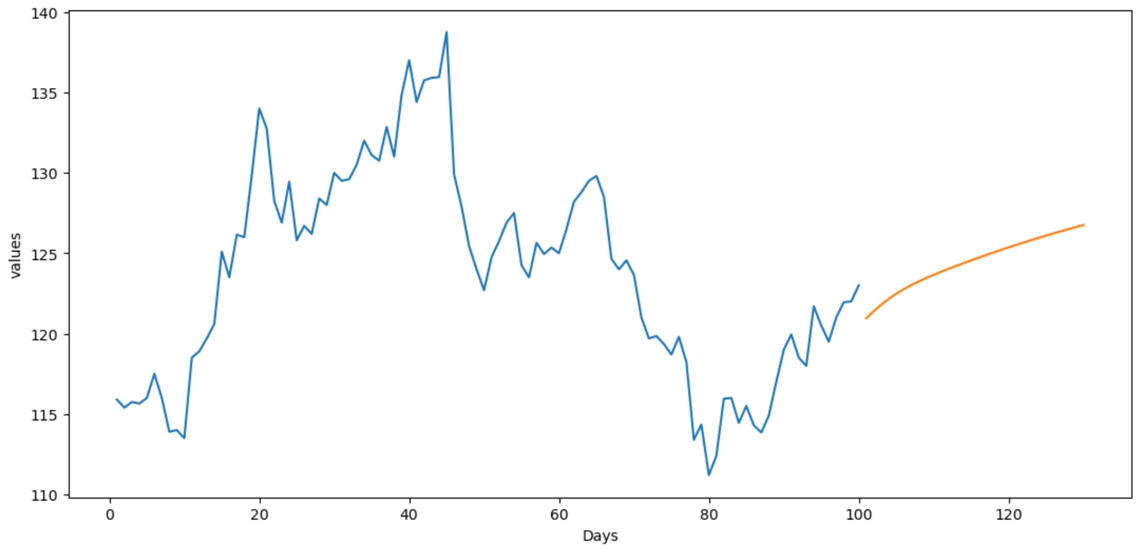
Out[44]:

```
2035
```

- **Graph of actual values in last 100 days**

In [45]:

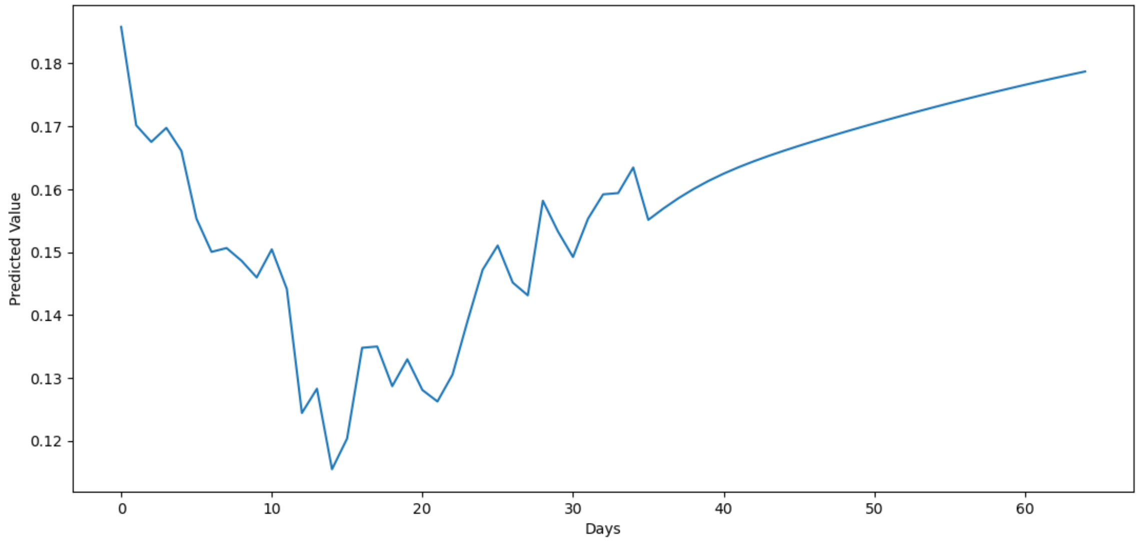
```
plt.figure(figsize=(13,6))

plt.plot(day_new, scaler.inverse_transform(df_high[1935:]))
plt.plot(day_pred, scaler.inverse_transform(lst_output))
plt.xlabel('Days')
plt.ylabel('values')

plt.show()
```



- **Graph of predicted values for last 65 days**

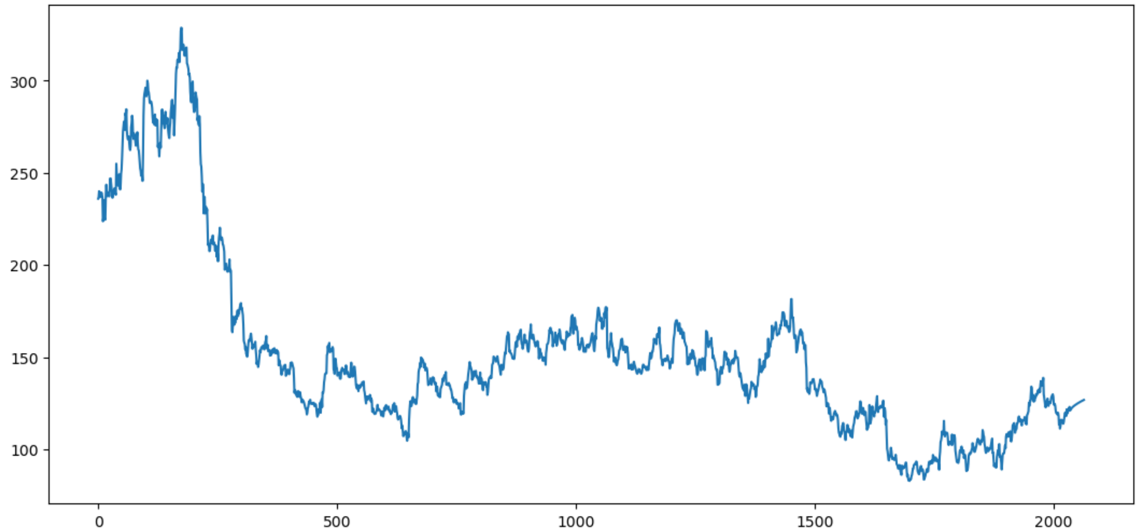
In [46]:

```
plt.figure(figsize=(13,6))

ds3=df_high.tolist()
ds3.extend(lst_output)
plt.plot(ds3[2000:])
plt.xlabel("Days")
plt.ylabel("Predicted Value")
plt.show()
```



In [47]:

```
plt.figure(figsize=(13,6))

ds3=scaler.inverse_transform(ds3).tolist()
plt.plot(ds3)

plt.show()
```



Model Created Successfully !

Thank You!

In [ ]:

```
1
```