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In [ ]:

```
#Experiment 9
#Use LSTM to predict stock price
```

LSTM stands for 'long short-term memory' in deep learning which is a recurrent neural netowk (RNN)

Importing Libraries:

In [4]:

```
import numpy as np #numpy arrays for mathematical computations
import matplotlib.pyplot as plt #for visualising the data in graphical form
import pandas as pd #to read our csv file for preprocessing and further operations
```

In [5]:

```
dataset_train=pd.read_csv('NSE-TATAGLOBAL.csv') #reading the input data csv file
dataset_train.head() #summarising what's in the input data csv file
```

Out[5]:

	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

In [6]:

```
dataset_train.shape
```

Out[6]:

```
(2035, 8)
```

2035 rows and 8 columns, data given for each (7) days.

In [7]:

```
training_set=dataset_train.iloc[:,1:2] #we take only the first column which is open, and select a
ll the rows
training_set.head()
```

Out[7]:

	Open
0	234.05
1	234.55
2	240.00
3	233.30
4	233.55

In [8]:

```
training_set.shape
```

Out[8]:

```
(2035, 1)
```

Now we have taken all the rows and only one column from our input dataset

Converting training_set values into numpy array

In [9]:

```
training_set=training_set.values
```

to get optimal results, we normalise all the values first

PREPROCESSING:

In [10]:

```
from sklearn.preprocessing import MinMaxScaler #Transform features by scaling each feature in a r
ange of 0 and 1
scale=MinMaxScaler(feature_range=(0,1)) #we normalize the values, so that value is in range 0 to
1
training_set_scaled= scale.fit_transform(training_set) #MinMax Regularization
```

In [11]:

```
training_set_scaled.shape
```

Out[11]:

```
(2035, 1)
```

The shape is still the same, column shows the stock price of 2035 rows of each day

In [12]:

```
training_set_scaled[10] #opening value of the stock on the 11th day
```

Out[12]:

```
array([0.54845904])
```

In [13]:

```
#iniitialising matrix X-train and y_train
X_train=[]
y_train=[]
for i in range(60,2035):
  X_train.append(training_set_scaled[i-60:i,0]) # for i =60, rows from 0 to 59 will be appended a
s columns to X_train
  y_train.append(training_set_scaled[i,0]) # for i=60, rows from 60 to 2034 will append in y_trai
n
X_train,y_train=np.array(X_train), np.array(y_train)
```

In [14]:

```
X_train.shape #2035 -60 = 1975, i.e. first 60 rows are not appended in X_train but all other rows
with 60 columns are appended
```

Out[14]:

```
(1975, 60)
```

In [15]:

```
y_train.shape #no column suggests that it is a vector not a matrix
```

Out[15]:

```
(1975,)
```

In [16]:

```
X_train = np.reshape(X_train,(X_train.shape[0], X_train.shape[1], 1)) #we reshape the X_train wit
h one additional dimension
```

In [17]:

```
X_train.shape # now we have one more dimension
```

Out[17]:

```
(1975, 60, 1)
```

In [18]:

```
from keras.models import Sequential
from keras.layers import Dense #fully connected layer to the neural network
from keras.layers import LSTM #
from keras.layers import Dropout #to avoid overfitting, we use the dropout layer in our neural ne
tworks
```

BUILDING THE MODEL:

In [19]:

```
model=Sequential() #adding layers to our neural network model one by one

#First Hidden layer consists of 50 LSTM neurons
#1 Layer:
model.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1],1))) #input layer w
ill be LSTM which will use first column and the dimension of the training data
model.add(Dropout(0.2))

#2 Layer
model.add(LSTM(units=50, return_sequences=True))
model.add(Dropout(0.3))

#3 Layer
model.add(LSTM(units=50, return_sequences=True))
model.add(Dropout(0.3))

#4 Layer/ Output Layer
model.add(LSTM(units=50))
model.add(Dropout(0.2))

model.add(Dense(units=1)) #output is 1, since we are trying to predict stock value of one day
```

COMPILING THE MODEL:

In [20]:

```
model.compile(optimizer='adam', loss="mean_squared_error") #we use mean_squred_error to calculate
the loss
#adam optimizer will handle sparse gradient
```

FITTING THE MODEL:

In [21]:

```
model.fit(X_train, y_train, epochs=150, batch_size=32) # fitting the model, training it with 150
epochs
```

```
Epoch 1/150
62/62 [==============================] - 13s 103ms/step - loss: 0.0286
Epoch 2/150
62/62 [==============================] - 6s 102ms/step - loss: 0.0031
Epoch 3/150
62/62 [==============================] - 6s 103ms/step - loss: 0.0031
Epoch 4/150
62/62 [==============================] - 6s 102ms/step - loss: 0.0027
```

```
Epoch 5/150
62/62 [==============================] - 7s 105ms/step - loss: 0.0029
Epoch 6/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0024
Epoch 7/150
62/62 [==============================] - 6s 105ms/step - loss: 0.0021
Epoch 8/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0021
Epoch 9/150
62/62 [==============================] - 7s 105ms/step - loss: 0.0019
Epoch 10/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0025
Epoch 11/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0022
Epoch 12/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0017
Epoch 13/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0020
Epoch 14/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0021
Epoch 15/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0015
Epoch 16/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0015
Epoch 17/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0016
Epoch 18/150
62/62 [==============================] - 7s 105ms/step - loss: 0.0017
Epoch 19/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0016
Epoch 20/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0016
Epoch 21/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0015
Epoch 22/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0015
Epoch 23/150
62/62 [==============================] - 7s 109ms/step - loss: 0.0016
Epoch 24/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0015
Epoch 25/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0014
Epoch 26/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0014
Epoch 27/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0016
Epoch 28/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0019
Epoch 29/150
62/62 [==============================] - 7s 109ms/step - loss: 0.0017
Epoch 30/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0012
Epoch 31/150
62/62 [==============================] - 7s 108ms/step - loss: 0.0013
Epoch 32/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0013
Epoch 33/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0012
Epoch 34/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0010
Epoch 35/150
62/62 [==============================] - 7s 107ms/step - loss: 9.9740e-04
Epoch 36/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0011
Epoch 37/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0011
Epoch 38/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0011
Epoch 39/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0010
Epoch 40/150
62/62 [==============================] - 7s 109ms/step - loss: 0.0010
```

```
Epoch 41/150
62/62 [==============================] - 7s 114ms/step - loss: 9.9816e-04
Epoch 42/150
62/62 [==============================] - 8s 123ms/step - loss: 9.9368e-04
Epoch 43/150
62/62 [==============================] - 7s 107ms/step - loss: 9.8046e-04
Epoch 44/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0011
Epoch 45/150
62/62 [==============================] - 7s 107ms/step - loss: 8.1730e-04
Epoch 46/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0011
Epoch 47/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0010
Epoch 48/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0010
Epoch 49/150
62/62 [==============================] - 7s 108ms/step - loss: 7.8339e-04
Epoch 50/150
62/62 [==============================] - 7s 109ms/step - loss: 0.0011
Epoch 51/150
62/62 [==============================] - 7s 108ms/step - loss: 9.9118e-04
Epoch 52/150
62/62 [==============================] - 7s 106ms/step - loss: 8.5422e-04
Epoch 53/150
62/62 [==============================] - 7s 106ms/step - loss: 8.9537e-04
Epoch 54/150
62/62 [==============================] - 7s 107ms/step - loss: 7.7167e-04
Epoch 55/150
62/62 [==============================] - 7s 106ms/step - loss: 8.7156e-04
Epoch 56/150
62/62 [==============================] - 7s 106ms/step - loss: 9.5567e-04
Epoch 57/150
62/62 [==============================] - 7s 107ms/step - loss: 7.7805e-04
Epoch 58/150
62/62 [==============================] - 7s 106ms/step - loss: 8.8036e-04
Epoch 59/150
62/62 [==============================] - 7s 106ms/step - loss: 8.4485e-04
Epoch 60/150
62/62 [==============================] - 7s 108ms/step - loss: 9.2739e-04
Epoch 61/150
62/62 [==============================] - 7s 107ms/step - loss: 7.6772e-04
Epoch 62/150
62/62 [==============================] - 7s 108ms/step - loss: 7.9462e-04
Epoch 63/150
62/62 [==============================] - 7s 107ms/step - loss: 7.7790e-04
Epoch 64/150
62/62 [==============================] - 7s 106ms/step - loss: 0.0010
Epoch 65/150
62/62 [==============================] - 7s 108ms/step - loss: 7.7881e-04
Epoch 66/150
62/62 [==============================] - 7s 108ms/step - loss: 7.8288e-04
Epoch 67/150
62/62 [==============================] - 7s 106ms/step - loss: 9.3848e-04
Epoch 68/150
62/62 [==============================] - 7s 106ms/step - loss: 8.0238e-04
Epoch 69/150
62/62 [==============================] - 7s 106ms/step - loss: 8.1360e-04
Epoch 70/150
62/62 [==============================] - 7s 107ms/step - loss: 0.0010
Epoch 71/150
62/62 [==============================] - 7s 106ms/step - loss: 7.4430e-04
Epoch 72/150
62/62 [==============================] - 7s 105ms/step - loss: 7.6628e-04
Epoch 73/150
62/62 [==============================] - 7s 105ms/step - loss: 8.6437e-04
Epoch 74/150
62/62 [==============================] - 7s 107ms/step - loss: 7.6607e-04
Epoch 75/150
62/62 [==============================] - 7s 108ms/step - loss: 8.2354e-04
Epoch 76/150
62/62 [==============================] - 7s 106ms/step - loss: 7.0704e-04
```

```
62/62 [==============================] - 7s 106ms/step - loss: [illegible]
Epoch 77/150
62/62 [==============================] - 7s 106ms/step - loss: 8.2456e-04
Epoch 78/150
62/62 [==============================] - 7s 108ms/step - loss: 6.5271e-04
Epoch 79/150
62/62 [==============================] - 7s 106ms/step - loss: 5.8699e-04
Epoch 80/150
62/62 [==============================] - 7s 107ms/step - loss: 7.7280e-04
Epoch 81/150
62/62 [==============================] - 7s 107ms/step - loss: 6.9240e-04
Epoch 82/150
62/62 [==============================] - 7s 107ms/step - loss: 6.0727e-04
Epoch 83/150
62/62 [==============================] - 7s 107ms/step - loss: 7.7091e-04
Epoch 84/150
62/62 [==============================] - 7s 107ms/step - loss: 9.3221e-04
Epoch 85/150
62/62 [==============================] - 7s 108ms/step - loss: 6.8761e-04
Epoch 86/150
62/62 [==============================] - 7s 107ms/step - loss: 7.0139e-04
Epoch 87/150
62/62 [==============================] - 7s 107ms/step - loss: 7.5117e-04
Epoch 88/150
62/62 [==============================] - 7s 107ms/step - loss: 7.3301e-04
Epoch 89/150
62/62 [==============================] - 7s 106ms/step - loss: 7.3193e-04
Epoch 90/150
62/62 [==============================] - 7s 106ms/step - loss: 7.4713e-04
Epoch 91/150
62/62 [==============================] - 7s 105ms/step - loss: 8.1118e-04
Epoch 92/150
62/62 [==============================] - 7s 108ms/step - loss: 6.3065e-04
Epoch 93/150
62/62 [==============================] - 7s 107ms/step - loss: 9.1737e-04
Epoch 94/150
62/62 [==============================] - 7s 108ms/step - loss: 7.6149e-04
Epoch 95/150
62/62 [==============================] - 7s 107ms/step - loss: 6.7583e-04
Epoch 96/150
62/62 [==============================] - 7s 108ms/step - loss: 7.0747e-04
Epoch 97/150
62/62 [==============================] - 7s 106ms/step - loss: 6.7283e-04
Epoch 98/150
62/62 [==============================] - 7s 108ms/step - loss: 7.8816e-04
Epoch 99/150
62/62 [==============================] - 7s 107ms/step - loss: 6.1270e-04
Epoch 100/150
62/62 [==============================] - 7s 107ms/step - loss: 7.1653e-04
Epoch 101/150
62/62 [==============================] - 7s 107ms/step - loss: 8.2203e-04
Epoch 102/150
62/62 [==============================] - 7s 106ms/step - loss: 5.8431e-04
Epoch 103/150
62/62 [==============================] - 7s 106ms/step - loss: 6.4470e-04
Epoch 104/150
62/62 [==============================] - 7s 107ms/step - loss: 7.2346e-04
Epoch 105/150
62/62 [==============================] - 7s 108ms/step - loss: 6.8499e-04
Epoch 106/150
62/62 [==============================] - 7s 107ms/step - loss: 6.3572e-04
Epoch 107/150
62/62 [==============================] - 7s 107ms/step - loss: 6.6830e-04
Epoch 108/150
62/62 [==============================] - 7s 108ms/step - loss: 6.6839e-04
Epoch 109/150
62/62 [==============================] - 7s 107ms/step - loss: 6.5072e-04
Epoch 110/150
62/62 [==============================] - 7s 108ms/step - loss: 6.7144e-04
Epoch 111/150
62/62 [==============================] - 7s 108ms/step - loss: 6.1604e-04
Epoch 112/150
62/62 [==============================] - 7s 108ms/step - loss: 6.0746e-04
```

```
Epoch 113/150
62/62 [==============================] - 7s 108ms/step - loss: 7.6479e-04
Epoch 114/150
62/62 [==============================] - 7s 107ms/step - loss: 6.6314e-04
Epoch 115/150
62/62 [==============================] - 7s 107ms/step - loss: 7.4306e-04
Epoch 116/150
62/62 [==============================] - 7s 107ms/step - loss: 5.7719e-04
Epoch 117/150
62/62 [==============================] - 7s 107ms/step - loss: 6.8334e-04
Epoch 118/150
62/62 [==============================] - 7s 107ms/step - loss: 5.7441e-04
Epoch 119/150
62/62 [==============================] - 7s 107ms/step - loss: 5.9341e-04
Epoch 120/150
62/62 [==============================] - 7s 107ms/step - loss: 6.7147e-04
Epoch 121/150
62/62 [==============================] - 7s 108ms/step - loss: 7.1403e-04
Epoch 122/150
62/62 [==============================] - 7s 108ms/step - loss: 7.5054e-04
Epoch 123/150
62/62 [==============================] - 7s 106ms/step - loss: 7.1714e-04
Epoch 124/150
62/62 [==============================] - 7s 108ms/step - loss: 6.0862e-04
Epoch 125/150
62/62 [==============================] - 7s 106ms/step - loss: 6.2236e-04
Epoch 126/150
62/62 [==============================] - 7s 107ms/step - loss: 7.8451e-04
Epoch 127/150
62/62 [==============================] - 7s 106ms/step - loss: 6.1008e-04
Epoch 128/150
62/62 [==============================] - 7s 106ms/step - loss: 5.2075e-04
Epoch 129/150
62/62 [==============================] - 7s 107ms/step - loss: 6.1249e-04
Epoch 130/150
62/62 [==============================] - 7s 109ms/step - loss: 5.1797e-04
Epoch 131/150
62/62 [==============================] - 7s 107ms/step - loss: 6.3500e-04
Epoch 132/150
62/62 [==============================] - 7s 106ms/step - loss: 6.5958e-04
Epoch 133/150
62/62 [==============================] - 7s 107ms/step - loss: 6.4578e-04
Epoch 134/150
62/62 [==============================] - 7s 107ms/step - loss: 5.8043e-04
Epoch 135/150
62/62 [==============================] - 7s 107ms/step - loss: 6.8500e-04
Epoch 136/150
62/62 [==============================] - 7s 106ms/step - loss: 6.6813e-04
Epoch 137/150
62/62 [==============================] - 7s 107ms/step - loss: 7.3075e-04
Epoch 138/150
62/62 [==============================] - 7s 107ms/step - loss: 5.7956e-04
Epoch 139/150
62/62 [==============================] - 7s 106ms/step - loss: 5.8980e-04
Epoch 140/150
62/62 [==============================] - 7s 108ms/step - loss: 5.5038e-04
Epoch 141/150
62/62 [==============================] - 7s 107ms/step - loss: 7.3794e-04
Epoch 142/150
62/62 [==============================] - 7s 107ms/step - loss: 5.2422e-04
Epoch 143/150
62/62 [==============================] - 7s 106ms/step - loss: 7.7568e-04
Epoch 144/150
62/62 [==============================] - 7s 107ms/step - loss: 6.2101e-04
Epoch 145/150
62/62 [==============================] - 7s 108ms/step - loss: 5.2212e-04
Epoch 146/150
62/62 [==============================] - 7s 108ms/step - loss: 6.4941e-04
Epoch 147/150
62/62 [==============================] - 7s 107ms/step - loss: 6.1679e-04
Epoch 148/150
62/62 [==============================] - 7s 107ms/step - loss: 5.7327e-04
```

```
Epoch 149/150
62/62 [==============================] - 7s 108ms/step - loss: 5.7250e-04
Epoch 150/150
62/62 [==============================] - 7s 108ms/step - loss: 6.3782e-04
```

Out[21]:

```
<tensorflow.python.keras.callbacks.History at 0x7f76d08d5810>
```

In [22]:

```
dataset_test=pd.read_csv('tatatest.csv')
dataset_test.head()
```

Out[22]:

	Date	Open	High	Low	Last	Close	Total Trade Quantity	Turnover (Lacs)
0	2018-10-24	220.10	221.25	217.05	219.55	219.80	2171956	4771.34
1	2018-10-23	221.10	222.20	214.75	219.55	218.30	1416279	3092.15
2	2018-10-22	229.45	231.60	222.00	223.05	223.25	3529711	8028.37
3	2018-10-19	230.30	232.70	225.50	227.75	227.20	1527904	3490.78
4	2018-10-17	237.70	240.80	229.45	231.30	231.10	2945914	6961.65

In [23]:

```
dataset_test.shape #16 rows and 8 columns in test dataset
```

Out[23]:

```
(16, 8)
```

In [24]:

```
stock_price = dataset_test.iloc[:,1:2].values
```

In [25]:

```
stock_price.shape #we take all the rows and only 1 column
```

Out[25]:

```
(16, 1)
```

In [26]:

```
test_total=pd.concat((dataset_train['Open'],dataset_test['Open']),axis=0) #2035 rows from trainin
g dataset, and 16 rows from testing dataset is concatenated
test_total.shape #2035+16 = 2051 rows in total
```

Out[26]:

```
(2051,)
```

In [27]:

```
input_samples=test_total[len(dataset_train)-60:].values #last 60 values are taken now
input_samples.shape #last 60 values are from training dataset, and 16 values from testing
dataset
```

Out[27]:

```
(76,)
```

60 + 16 = 76 rows in total

In [28]:

```
input_samples = input_samples.reshape(-1,1) #reshaping the input_samples
input_samples.shape
```

Out[28]:

```
(76, 1)
```

In [29]:

```
input_samples=scale.transform(input_samples)
```

In [30]:

```
X_test=[]
for i in range(60,76):
  X_test.append(input_samples[i-60:i,0]) #for i =60, 0 to 75 rows are appended in X_test
X_test=np.array(X_test)
X_test=np.reshape(X_test, (X_test.shape[0], X_test.shape[1],1))
```

In [31]:

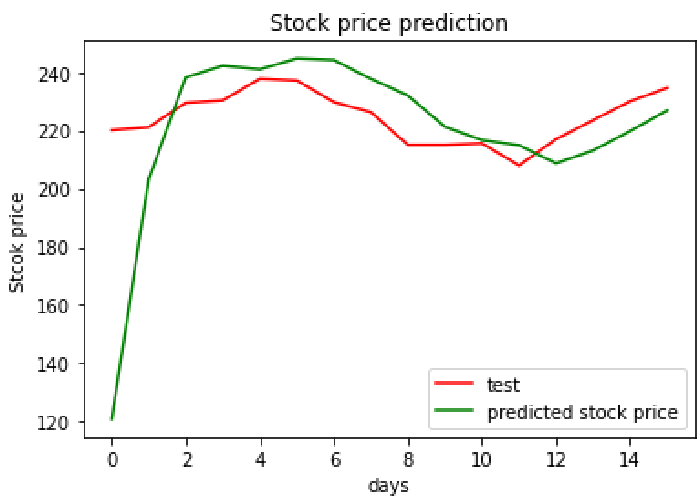
```
pred_stock_price=model.predict(X_test)
pred_stock_price=scale.inverse_transform(pred_stock_price) #predicting the stock prices
```

In [32]:

```
#setting green and red color respectively for predicted and test stock price
plt.plot(dataset_test['Open'],color='red', label='test')
plt.plot(pred_stock_price, color='green', label='predicted stock price')
#setting labels for plotting graph
plt.title('Stock price prediction')
plt.xlabel('days')
plt.ylabel('Stcok price')
plt.legend()
```

Out[32]:

```
<matplotlib.legend.Legend at 0x7f76cc9abc10>
```



CONCLUSION:

1) The Graph shows that the foirst few days that the differnevce beetewwn the ios lagrge, this differnece reduce after the number of days are increased.

2) Differnece can be reuduced by increasing the number of epochs.