Stock Price Prediction Using LSTM

Import Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv("Stocks_dataset.csv")
df.head()
```

Out[2]:

	symbol	date	close	high	low	open	volume	adjClose	adjHigh	adjLow	adjOpen	adjVolume	divC
0	GOOG	2016-06-14 00:00:00+00:00	718.27	722.47	713.1200	716.48	1306065	718.27	722.47	713.1200	716.48	1306065	
1	GOOG	2016-06-15 00:00:00+00:00	718.92	722.98	717.3100	719.00	1214517	718.92	722.98	717.3100	719.00	1214517	
2	GOOG	2016-06-16 00:00:00+00:00	710.36	716.65	703.2600	714.91	1982471	710.36	716.65	703.2600	714.91	1982471	
3	GOOG	2016-06-17 00:00:00+00:00	691.72	708.82	688.4515	708.65	3402357	691.72	708.82	688.4515	708.65	3402357	
4	GOOG	2016-06-20 00:00:00+00:00	693.71	702.48	693.4100	698.77	2082538	693.71	702.48	693.4100	698.77	2082538	

In [3]:
```
#Shape of Data
df.shape
```

Out[3]: (1258, 14)

In [4]:
```
#Statistical Descritpion
df.describe()
```

Out[4]:

	close	high	low	open	volume	adjClose	adjHigh	adjLow	adjOpe
count	1258.000000	1258.000000	1258.000000	1258.000000	1.258000e+03	1258.000000	1258.000000	1258.000000	1258.00000
mean	1216.317067	1227.430934	1204.176430	1215.260779	1.601590e+06	1216.317067	1227.430936	1204.176436	1215.26077
std	383.333358	387.570872	378.777094	382.446995	6.960172e+05	383.333358	387.570873	378.777099	382.44699
min	668.260000	672.300000	663.284000	671.000000	3.467530e+05	668.260000	672.300000	663.284000	671.00000
25%	960.802500	968.757500	952.182500	959.005000	1.173522e+06	960.802500	968.757500	952.182500	959.00500
50%	1132.460000	1143.935000	1117.915000	1131.150000	1.412588e+06	1132.460000	1143.935000	1117.915000	1131.15000
75%	1360.595000	1374.345000	1348.557500	1361.075000	1.812156e+06	1360.595000	1374.345000	1348.557500	1361.07500
max	2521.600000	2526.990000	2498.290000	2524.920000	6.207027e+06	2521.600000	2526.990000	2498.290000	2524.92000

In [5]:
```
#Data Summary
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
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   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
```

In [6]:
```
#Check Null values
df.isnull().sum()
```

Out[6]:
```
symbol         0
date           0
close          0
high           0
low            0
open           0
volume         0
adjClose       0
adjHigh        0
adjLow         0
adjOpen        0
adjVolume      0
divCash        0
splitFactor    0
dtype: int64
```

In [7]:
```
#No null values in data
df = df[['date','open','close']] #Require columns extracting
df['date'] = pd.to_datetime(df['date'].apply(lambda x: x.split()[0])) #Convert to datetime dtype
df.set_index('date', drop=True, inplace=True)
df.head()
```

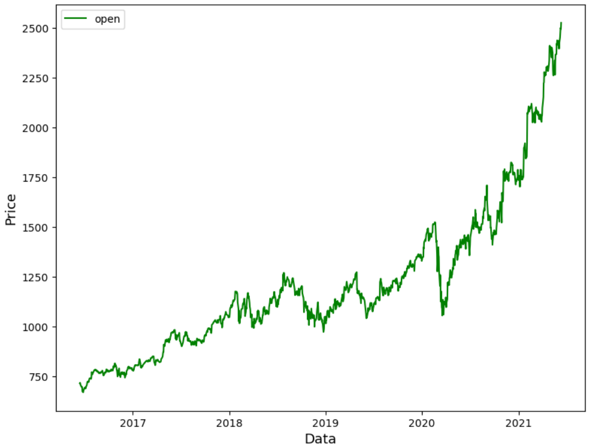
Out[7]:

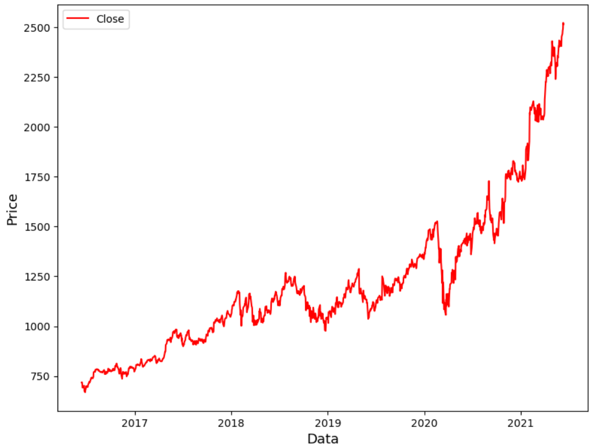
date	open	close
2016-06-14	716.48	718.27
2016-06-15	719.00	718.92
2016-06-16	714.91	710.36
2016-06-17	708.65	691.72
2016-06-20	698.77	693.71

In [8]:
```
# Now we plotting open and closing price on date index
fig, ax = plt.subplots(1,2, figsize=(20,7))
ax[0].plot(df['open'], label = 'open', color = 'green')
ax[0].set_xlabel('Data', size=13)
ax[0].set_ylabel('Price', size=13)
ax[0].legend()

ax[1].plot(df['close'], label = 'Close', color = 'red')
ax[1].set_xlabel('Data', size=13)
ax[1].set_ylabel('Price', size=13)
ax[1].legend()
```

Out[8]: <matplotlib.legend.Legend at 0x29d0d5f90f0>





Data Preprocessing

In [9]:
```
# we'll normalizing all the values of all columns using MinMaxScaler
from sklearn.preprocessing import MinMaxScaler
mms = MinMaxScaler()
df[df.columns] = mms.fit_transform(df)
df.head()
```

Out[9]:

date	open	close
2016-06-14	0.024532	0.026984
2016-06-15	0.025891	0.027334
2016-06-16	0.023685	0.022716
2016-06-17	0.020308	0.012658
2016-06-20	0.014979	0.013732

In [10]:
```
#split data into Training and testing
training_size = round(len(df) * 0.75) #75% for training
training_size
```

Out[10]: 944

In [11]:
```
training_data = df[:training_size]
testing_data = df[training_size:]
training_data.shape, testing_data.shape
```

Out[11]: ((944, 2), (314, 2))

In [18]:
```
# we'll create sequence of data for training and testing

def create_sequence(dataset):
    sequence = []
    labels = []

    start_idx = 0

    for stop_idx in range(50, len(dataset)): #selecting 50 rows at a time
        sequence.append(dataset.iloc[start_idx:stop_idx])
        labels.append(dataset.iloc[stop_idx])
        start_idx += 1
    return (np.array(sequence), np.array(labels))
```

In [19]:
```
train_seq, train_label, = create_sequence(training_data)
test_seq, test_label = create_sequence(testing_data)
train_seq.shape, train_label.shape, test_seq.shape, test_label.shape
```

Out[19]:
```
((894, 50, 2), (894, 2), (264, 50, 2), (264, 2))
```

Create LSTM Model

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

In [27]:
```
#import Sequential from keras.models
model = Sequential()
#import Dense, Dropout, LSTM, Bidirectional from keras.layers
model.add(LSTM(units=50, return_sequences=True, input_shape=(train_seq.shape[1], train_seq.shape[2])))

model.add(Dropout(0.1))
model.add(LSTM(units=50))

model.add(Dense(2))

model.compile(loss = 'mean_squared_error', optimizer = 'adam', metrics = ['mean_absolute_error'])

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 50, 50)            10600

 dropout (Dropout)           (None, 50, 50)            0

 lstm_1 (LSTM)               (None, 50)                20200

 dense (Dense)               (None, 2)                 102

=================================================================
Total params: 30902 (120.71 KB)
Trainable params: 30902 (120.71 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [28]:
```
# fitting the model by iterating the dataset over 100 times(100 epochs)
model.fit(train_seq, train_label, epochs = 100, validation_data = (test_seq, test_label), verbose = 1
```

```
Epoch 1/100
28/28 [==============================] - 4s 46ms/step - loss: 0.0082 - mean_absolute_error: 0.0618
- val_loss: 0.0116 - val_mean_absolute_error: 0.0830
Epoch 2/100
28/28 [==============================] - 1s 21ms/step - loss: 7.3860e-04 - mean_absolute_error: 0.
0216 - val_loss: 0.0037 - val_mean_absolute_error: 0.0466
Epoch 3/100
28/28 [==============================] - 1s 22ms/step - loss: 4.4218e-04 - mean_absolute_error: 0.
0155 - val_loss: 0.0027 - val_mean_absolute_error: 0.0403
Epoch 4/100
28/28 [==============================] - 1s 22ms/step - loss: 4.5139e-04 - mean_absolute_error: 0.
0154 - val_loss: 0.0033 - val_mean_absolute_error: 0.0446
Epoch 5/100
28/28 [==============================] - 1s 22ms/step - loss: 4.2917e-04 - mean_absolute_error: 0.
0151 - val_loss: 0.0032 - val_mean_absolute_error: 0.0439
Epoch 6/100
28/28 [==============================] - 1s 22ms/step - loss: 4.1802e-04 - mean_absolute_error: 0.
0150 - val_loss: 0.0034 - val_mean_absolute_error: 0.0449
Epoch 7/100
```

In [29]:
```
# predicting the values after running the model
test_predicted = model.predict(test_seq)
test_predicted[:5]
```

```
9/9 [==============================] - 1s 7ms/step
```

Out[29]:
```
array([[0.4009781 , 0.39791748],
       [0.40054685, 0.39778033],
       [0.39749146, 0.39499703],
       [0.40202242, 0.3990669 ],
       [0.40562916, 0.40245682]], dtype=float32)
```

In [31]:
```
# Inversing normalization/scaling on predicted data
test_inverse_predicted = mms.inverse_transform(test_predicted)
test_inverse_predicted[:5]
```

Out[31]:
```
array([[1414.3813, 1405.7363],
       [1413.5818, 1405.4822],
       [1407.9174, 1400.3237],
       [1416.3174, 1407.8666],
       [1423.004 , 1414.1494]], dtype=float32)
```

PREDICTED DATA VS VISUALIZING ACTUAL

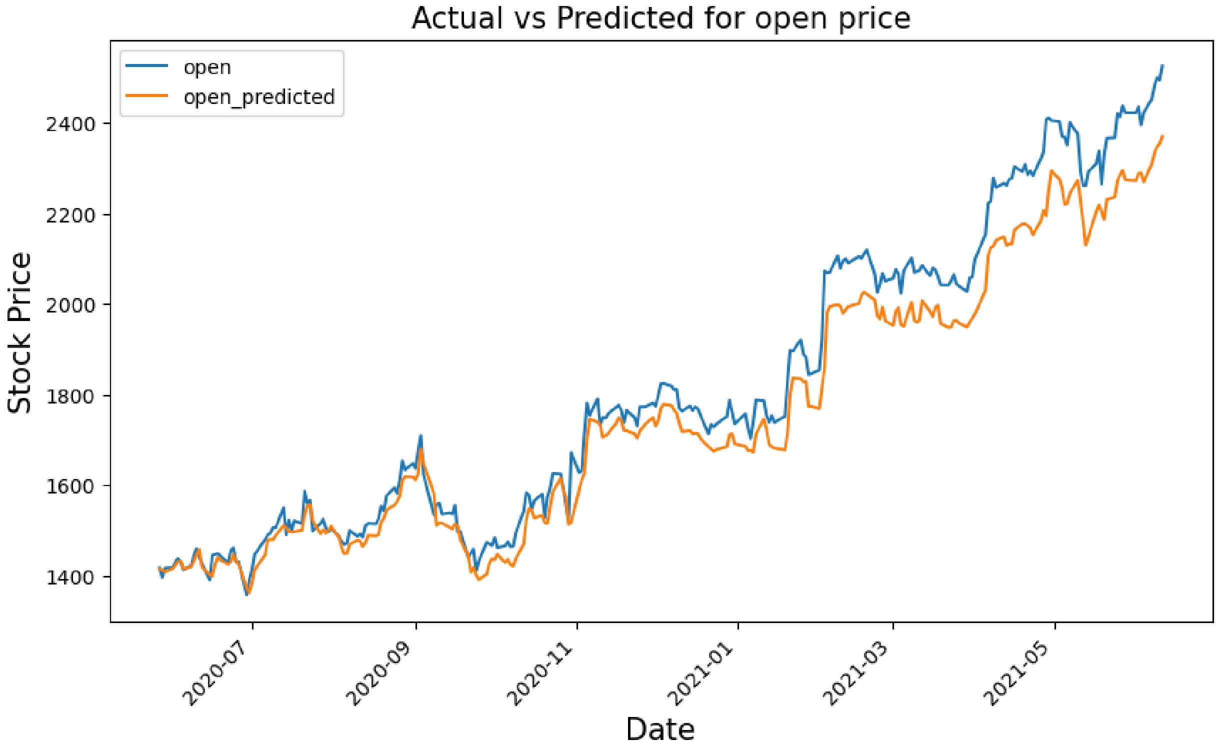
In [32]:
```
# Merging actual and predicted data for better visualization
df_merge = pd.concat([df.iloc[-264:].copy(),
                          pd.DataFrame(test_inverse_predicted,columns=['open_predicted','close_predic
                                 index=df.iloc[-264:].index)], axis=1)
```

In [34]:
```
# Inversing normalization/scaling
df_merge[['open','close']] = mms.inverse_transform(df_merge[['open','close']])
df_merge.head()
```

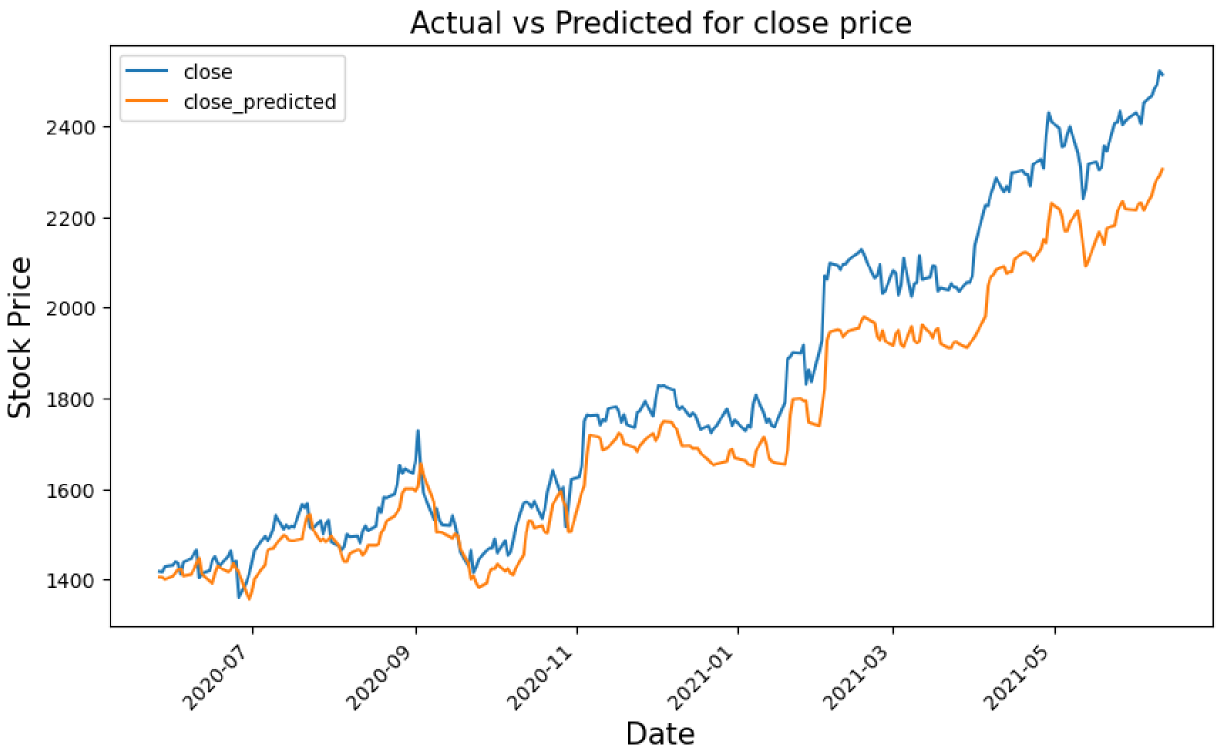
Out[34]:

date	open	close	open_predicted	close_predicted
2020-05-27	1417.25	1417.84	1414.381348	1405.736328
2020-05-28	1396.86	1416.73	1413.581787	1405.482178
2020-05-29	1416.94	1428.92	1407.917358	1400.323730
2020-06-01	1418.39	1431.82	1416.317383	1407.866577
2020-06-02	1430.55	1439.22	1423.004028	1414.149414

In [35]:
```
# plotting the actual open and predicted open prices on date index
df_merge[['open','open_predicted']].plot(figsize=(10,6))
plt.xticks(rotation=45)
plt.xlabel('Date',size=15)
plt.ylabel('Stock Price',size=15)
plt.title('Actual vs Predicted for open price',size=15)
plt.show()
```



In [36]:
```
# plotting the actual close and predicted close prices on date index
df_merge[['close','close_predicted']].plot(figsize=(10,6))
plt.xticks(rotation=45)
plt.xlabel('Date',size=15)
plt.ylabel('Stock Price',size=15)
plt.title('Actual vs Predicted for close price',size=15)
plt.show()
```



PREDICTING UPCOMING 10 DAYS

In [37]:
```
# Creating a dataframe and adding 10 days to existing index

df_merge = df_merge.append(pd.DataFrame(columns=df_merge.columns,
                                        index=pd.date_range(start=df_merge.index[-1], periods=11, fre
df_merge['2021-06-09':'2021-06-16']
```

Out[37]:

	open	close	open_predicted	close_predicted
2021-06-09	2499.50	2491.40	2346.817871	2283.711426
2021-06-10	2494.01	2521.60	2352.575928	2290.069092
2021-06-11	2524.92	2513.93	2369.620605	2304.991699
2021-06-12	NaN	NaN	NaN	NaN
2021-06-13	NaN	NaN	NaN	NaN
2021-06-14	NaN	NaN	NaN	NaN
2021-06-15	NaN	NaN	NaN	NaN
2021-06-16	NaN	NaN	NaN	NaN

In [38]:
```
# creating a DataFrame and filling values of open and close column
upcoming_prediction = pd.DataFrame(columns=['open','close'],index=df_merge.index)
upcoming_prediction.index=pd.to_datetime(upcoming_prediction.index)
```

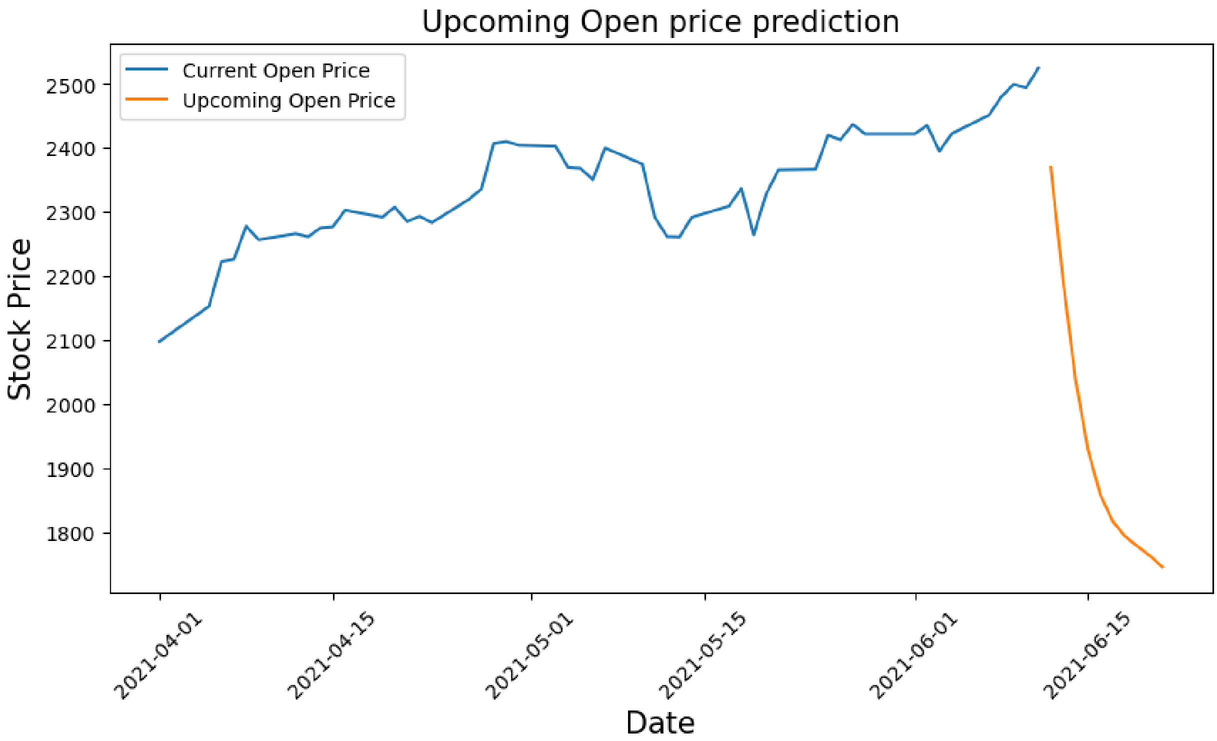
In [39]:
```
curr_seq = test_seq[-1:]

for i in range(-10,0):
  up_pred = model.predict(curr_seq)
  upcoming_prediction.iloc[i] = up_pred
  curr_seq = np.append(curr_seq[0][1:],up_pred,axis=0)
  curr_seq = curr_seq.reshape(test_seq[-1:].shape)
```

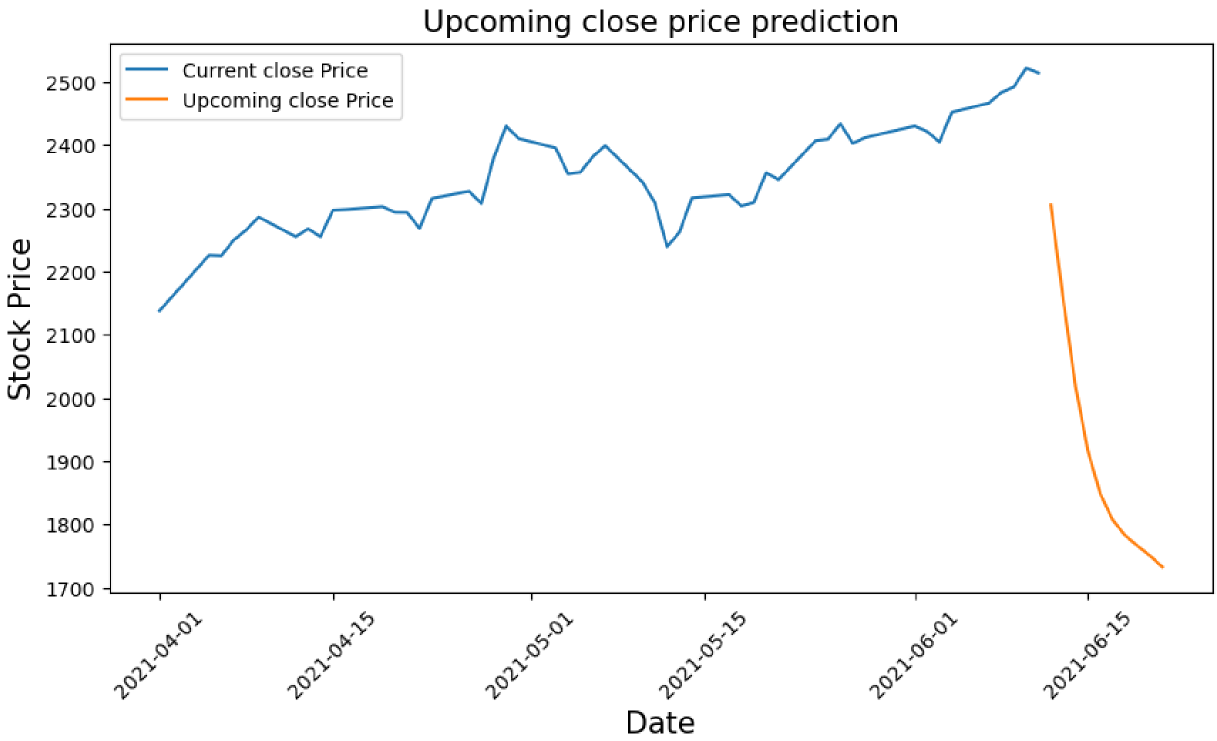
```
1/1 [==============================] - 0s 24ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 20ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 21ms/step
1/1 [==============================] - 0s 18ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 19ms/step
1/1 [==============================] - 0s 19ms/step
```

In [41]:
```
# inversing Normalization/scaling
upcoming_prediction[['open','close']] = mms.inverse_transform(upcoming_prediction[['open','close']])
```

In [42]:
```
# plotting Upcoming Open price on date index
fig,ax=plt.subplots(figsize=(10,5))
ax.plot(df_merge.loc['2021-04-01':,'open'],label='Current Open Price')
ax.plot(upcoming_prediction.loc['2021-04-01':,'open'],label='Upcoming Open Price')
plt.setp(ax.xaxis.get_majorticklabels(), rotation=45)
ax.set_xlabel('Date',size=15)
ax.set_ylabel('Stock Price',size=15)
ax.set_title('Upcoming Open price prediction',size=15)
ax.legend()
fig.show()
```



In [43]:
```
# plotting Upcoming Close price on date index
fig,ax=plt.subplots(figsize=(10,5))
ax.plot(df_merge.loc['2021-04-01':,'close'],label='Current close Price')
ax.plot(upcoming_prediction.loc['2021-04-01':,'close'],label='Upcoming close Price')
plt.setp(ax.xaxis.get_majorticklabels(), rotation=45)
ax.set_xlabel('Date',size=15)
ax.set_ylabel('Stock Price',size=15)
ax.set_title('Upcoming close price prediction',size=15)
ax.legend()
fig.show()
```



You can find the project on [GitHub. (https://github.com/Vyas-Rishabh/Stock_Price_Prediction_Using_LSTM)](https://github.com/Vyas-Rishabh/Stock_Price_Prediction_Using_LSTM)