# IMPORTING LIBRARIES AND DATA TO BE USED

In [2]:
```
#importing libraries to be used
import numpy as np # for linear algebra
import pandas as pd # data preprocessing
import matplotlib.pyplot as plt # data visualization library
import seaborn as sns # data visualization library
%matplotlib inline
import warnings
warnings.filterwarnings('ignore') # ignore warnings

from sklearn.preprocessing import MinMaxScaler # for normalization
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM, Bidirectional
```

In [3]:
```
df = pd.read_csv('C:/Users/KAVYA/Downloads/GOOG.csv') # data_importing
df.head(10) # fetching first 10 rows of dataset
```

Out[3]:

| | symbol | date | close | high | low | open | volume | adjClose | adjHigh | adjLow | adjOpen | adjVolume | divCash | splitFactor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **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 | 0.0 | 1.0 |
| **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 | 0.0 | 1.0 |
| **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 | 0.0 | 1.0 |
| **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 | 0.0 | 1.0 |
| **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 | 0.0 | 1.0 |
| **5** | GOOG | 2016-06-21 00:00:00+00:00 | 695.94 | 702.77 | 692.0100 | 698.40 | 1465634 | 695.94 | 702.77 | 692.0100 | 698.40 | 1465634 | 0.0 | 1.0 |
| **6** | GOOG | 2016-06-22 00:00:00+00:00 | 697.46 | 700.86 | 693.0819 | 699.06 | 1184318 | 697.46 | 700.86 | 693.0819 | 699.06 | 1184318 | 0.0 | 1.0 |
| **7** | GOOG | 2016-06-23 00:00:00+00:00 | 701.87 | 701.95 | 687.0000 | 697.45 | 2171415 | 701.87 | 701.95 | 687.0000 | 697.45 | 2171415 | 0.0 | 1.0 |
| **8** | GOOG | 2016-06-24 00:00:00+00:00 | 675.22 | 689.40 | 673.4500 | 675.17 | 4449022 | 675.22 | 689.40 | 673.4500 | 675.17 | 4449022 | 0.0 | 1.0 |
| **9** | GOOG | 2016-06-27 00:00:00+00:00 | 668.26 | 672.30 | 663.2840 | 671.00 | 2641085 | 668.26 | 672.30 | 663.2840 | 671.00 | 2641085 | 0.0 | 1.0 |

# GATHERING INSIGHTS

In [4]:
```
# shape of data
print("Shape of data:",df.shape)
```

```
Shape of data: (1258, 14)
```

In [5]:
```
# statistical description of data
df.describe()
```

Out[5]:

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

In [6]:
```
# summary of data
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 [7]:

```
# checking null values
df.isnull().sum()
```

Out[7]:

```
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
```

# There are no null values in the dataset

In [8]:

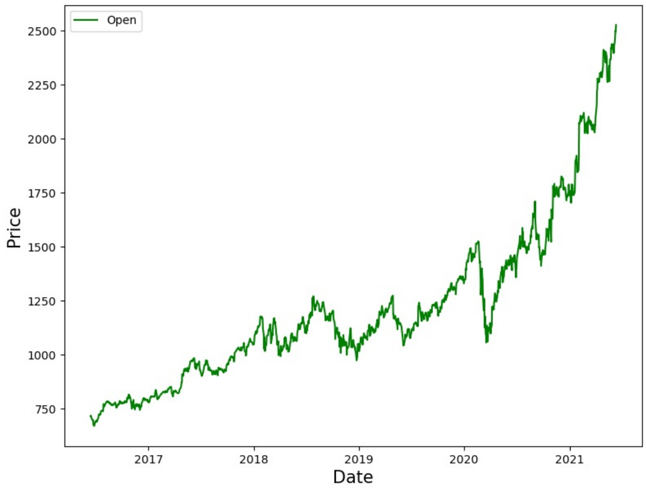
```
df = df[['date','open','close']] # Extracting required columns
df['date'] = pd.to_datetime(df['date'].apply(lambda x: x.split()[0])) # converting object dtype of date column
df.set_index('date',drop=True,inplace=True) # Setting date column as index
df.head(10)
```

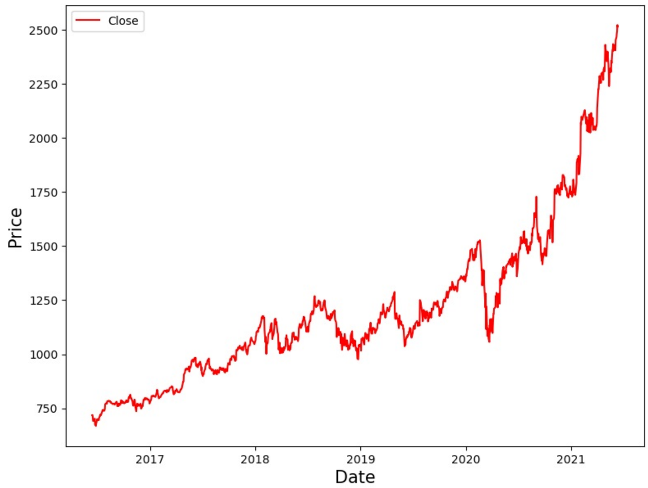
Out[8]:

| 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 |
| **2016-06-21** | 698.40 | 695.94 |
| **2016-06-22** | 699.06 | 697.46 |
| **2016-06-23** | 697.45 | 701.87 |
| **2016-06-24** | 675.17 | 675.22 |
| **2016-06-27** | 671.00 | 668.26 |

In [9]:

```
# 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('Date',size=15)
ax[0].set_ylabel('Price',size=15)
ax[0].legend()

ax[1].plot(df['close'],label='Close',color='red')
ax[1].set_xlabel('Date',size=15)
ax[1].set_ylabel('Price',size=15)
ax[1].legend()

fig.show()
```




# DATA PRE-PROCESSING

In [10]:

```
# normalizing all the values of all columns using MinMaxScaler
MMS = MinMaxScaler()
df[df.columns] = MMS.fit_transform(df)
df.head(10)
```

Out[10]:

| 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 |
| 2016-06-21 | 0.014779 | 0.014935 |
| 2016-06-22 | 0.015135 | 0.015755 |
| 2016-06-23 | 0.014267 | 0.018135 |
| 2016-06-24 | 0.002249 | 0.003755 |
| 2016-06-27 | 0.000000 | 0.000000 |

In [11]:

```
# splitting the data into training and test set
training_size = round(len(df) * 0.75) # Selecting 75 % for training and 25 % for testing
training_size
```

Out[11]:

```
944
```

In [12]:

```
train_data = df[:training_size]
test_data  = df[training_size:]

train_data.shape, test_data.shape
```

Out[12]:

```
((944, 2), (314, 2))
```

In [13]:

```
# Function to create sequence of data for training and testing

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

  start_idx = 0

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

In [14]:

```
train_seq, train_label = create_sequence(train_data)
test_seq, test_label = create_sequence(test_data)
train_seq.shape, train_label.shape, test_seq.shape, test_label.shape
```

Out[14]:

```
((894, 50, 2), (894, 2), (264, 50, 2), (264, 2))
```

# CREATING LSTM MODEL

In [15]:

```python
# imported Sequential from keras.models
model = Sequential()
# importing 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"
_________________________________________________________________
 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: 30,902
Trainable params: 30,902
Non-trainable params: 0
_________________________________________________________________
```

In [16]:

```python
# 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 [==============================] - 13s 162ms/step - loss: 0.0084 - mean_absolute_error: 0.0648 - val_loss
: 0.0221 - val_mean_absolute_error: 0.1258
Epoch 2/100
28/28 [==============================] - 2s 76ms/step - loss: 9.1405e-04 - mean_absolute_error: 0.0240 - val_lo
ss: 0.0063 - val_mean_absolute_error: 0.0644
Epoch 3/100
28/28 [==============================] - 2s 72ms/step - loss: 4.7781e-04 - mean_absolute_error: 0.0161 - val_lo
ss: 0.0052 - val_mean_absolute_error: 0.0592
Epoch 4/100
28/28 [==============================] - 2s 73ms/step - loss: 4.6453e-04 - mean_absolute_error: 0.0158 - val_lo
ss: 0.0032 - val_mean_absolute_error: 0.0433
Epoch 5/100
28/28 [==============================] - 2s 75ms/step - loss: 4.4336e-04 - mean_absolute_error: 0.0153 - val_lo
ss: 0.0035 - val_mean_absolute_error: 0.0460
Epoch 6/100
28/28 [==============================] - 2s 76ms/step - loss: 4.2706e-04 - mean_absolute_error: 0.0151 - val_lo
ss: 0.0044 - val_mean_absolute_error: 0.0533
Epoch 7/100
28/28 [==============================] - 2s 76ms/step - loss: 4.6415e-04 - mean_absolute_error: 0.0158 - val_lo
ss: 0.0059 - val_mean_absolute_error: 0.0625
Epoch 8/100
28/28 [==============================] - 2s 77ms/step - loss: 4.1368e-04 - mean_absolute_error: 0.0149 - val_lo
ss: 0.0039 - val_mean_absolute_error: 0.0485
Epoch 9/100
28/28 [==============================] - 2s 79ms/step - loss: 4.1483e-04 - mean_absolute_error: 0.0149 - val_lo
ss: 0.0037 - val_mean_absolute_error: 0.0469
Epoch 10/100
28/28 [==============================] - 2s 78ms/step - loss: 4.0273e-04 - mean_absolute_error: 0.0147 - val_lo
ss: 0.0032 - val_mean_absolute_error: 0.0432
Epoch 11/100
28/28 [==============================] - 2s 77ms/step - loss: 4.3347e-04 - mean_absolute_error: 0.0153 - val_lo
ss: 0.0062 - val_mean_absolute_error: 0.0650
Epoch 12/100
28/28 [==============================] - 2s 78ms/step - loss: 3.8743e-04 - mean_absolute_error: 0.0145 - val_lo
ss: 0.0054 - val_mean_absolute_error: 0.0592
Epoch 13/100
28/28 [==============================] - 2s 78ms/step - loss: 3.8162e-04 - mean_absolute_error: 0.0142 - val_lo
ss: 0.0053 - val_mean_absolute_error: 0.0587
Epoch 14/100
28/28 [==============================] - 2s 78ms/step - loss: 3.6166e-04 - mean_absolute_error: 0.0137 - val_lo
ss: 0.0031 - val_mean_absolute_error: 0.0419
Epoch 15/100
28/28 [==============================] - 2s 78ms/step - loss: 3.6923e-04 - mean_absolute_error: 0.0141 - val_lo
ss: 0.0053 - val_mean_absolute_error: 0.0578
Epoch 16/100
28/28 [==============================] - 2s 78ms/step - loss: 3.6820e-04 - mean_absolute_error: 0.0142 - val_lo
ss: 0.0070 - val_mean_absolute_error: 0.0684
Epoch 17/100
28/28 [==============================] - 2s 78ms/step - loss: 3.6576e-04 - mean_absolute_error: 0.0140 - val_lo
ss: 0.0053 - val_mean_absolute_error: 0.0589
Epoch 18/100
```

```
28/28 [==============================] - 2s 77ms/step - loss: 3.4324e-04 - mean_absolute_error: 0.0135 - val_lo
ss: 0.0064 - val_mean_absolute_error: 0.0648
Epoch 19/100
28/28 [==============================] - 2s 78ms/step - loss: 3.2163e-04 - mean_absolute_error: 0.0131 - val_lo
ss: 0.0057 - val_mean_absolute_error: 0.0607
Epoch 20/100
28/28 [==============================] - 2s 77ms/step - loss: 3.2105e-04 - mean_absolute_error: 0.0131 - val_lo
ss: 0.0049 - val_mean_absolute_error: 0.0559
Epoch 21/100
28/28 [==============================] - 2s 78ms/step - loss: 3.1451e-04 - mean_absolute_error: 0.0128 - val_lo
ss: 0.0088 - val_mean_absolute_error: 0.0798
Epoch 22/100
28/28 [==============================] - 2s 77ms/step - loss: 3.2065e-04 - mean_absolute_error: 0.0134 - val_lo
ss: 0.0043 - val_mean_absolute_error: 0.0524
Epoch 23/100
28/28 [==============================] - 2s 78ms/step - loss: 3.0431e-04 - mean_absolute_error: 0.0129 - val_lo
ss: 0.0047 - val_mean_absolute_error: 0.0551
Epoch 24/100
28/28 [==============================] - 2s 77ms/step - loss: 3.0412e-04 - mean_absolute_error: 0.0129 - val_lo
ss: 0.0063 - val_mean_absolute_error: 0.0658
Epoch 25/100
28/28 [==============================] - 2s 77ms/step - loss: 2.9042e-04 - mean_absolute_error: 0.0125 - val_lo
ss: 0.0051 - val_mean_absolute_error: 0.0583
Epoch 26/100
28/28 [==============================] - 2s 77ms/step - loss: 2.9271e-04 - mean_absolute_error: 0.0125 - val_lo
ss: 0.0029 - val_mean_absolute_error: 0.0426
Epoch 27/100
28/28 [==============================] - 2s 77ms/step - loss: 3.0456e-04 - mean_absolute_error: 0.0128 - val_lo
ss: 0.0023 - val_mean_absolute_error: 0.0367
Epoch 28/100
28/28 [==============================] - 2s 78ms/step - loss: 3.0565e-04 - mean_absolute_error: 0.0128 - val_lo
ss: 0.0048 - val_mean_absolute_error: 0.0558
Epoch 29/100
28/28 [==============================] - 2s 76ms/step - loss: 2.7566e-04 - mean_absolute_error: 0.0121 - val_lo
ss: 0.0022 - val_mean_absolute_error: 0.0353
Epoch 30/100
28/28 [==============================] - 2s 76ms/step - loss: 2.6982e-04 - mean_absolute_error: 0.0120 - val_lo
ss: 0.0021 - val_mean_absolute_error: 0.0358
Epoch 31/100
28/28 [==============================] - 2s 77ms/step - loss: 2.6578e-04 - mean_absolute_error: 0.0120 - val_lo
ss: 0.0036 - val_mean_absolute_error: 0.0491
Epoch 32/100
28/28 [==============================] - 2s 89ms/step - loss: 2.9437e-04 - mean_absolute_error: 0.0129 - val_lo
ss: 0.0021 - val_mean_absolute_error: 0.0358
Epoch 33/100
28/28 [==============================] - 2s 64ms/step - loss: 2.8215e-04 - mean_absolute_error: 0.0123 - val_lo
ss: 0.0022 - val_mean_absolute_error: 0.0361
Epoch 34/100
28/28 [==============================] - 2s 78ms/step - loss: 2.6206e-04 - mean_absolute_error: 0.0121 - val_lo
ss: 0.0029 - val_mean_absolute_error: 0.0423
Epoch 35/100
28/28 [==============================] - 2s 77ms/step - loss: 2.5252e-04 - mean_absolute_error: 0.0116 - val_lo
ss: 0.0034 - val_mean_absolute_error: 0.0473
Epoch 36/100
28/28 [==============================] - 2s 76ms/step - loss: 2.5735e-04 - mean_absolute_error: 0.0118 - val_lo
ss: 0.0022 - val_mean_absolute_error: 0.0368
Epoch 37/100
28/28 [==============================] - 2s 75ms/step - loss: 2.5474e-04 - mean_absolute_error: 0.0116 - val_lo
ss: 0.0022 - val_mean_absolute_error: 0.0372
Epoch 38/100
28/28 [==============================] - 2s 68ms/step - loss: 2.3630e-04 - mean_absolute_error: 0.0113 - val_lo
ss: 0.0050 - val_mean_absolute_error: 0.0586
Epoch 39/100
28/28 [==============================] - 2s 74ms/step - loss: 2.4119e-04 - mean_absolute_error: 0.0112 - val_lo
ss: 0.0059 - val_mean_absolute_error: 0.0644
Epoch 40/100
28/28 [==============================] - 2s 70ms/step - loss: 2.3362e-04 - mean_absolute_error: 0.0112 - val_lo
ss: 0.0035 - val_mean_absolute_error: 0.0474
Epoch 41/100
28/28 [==============================] - 2s 75ms/step - loss: 2.3213e-04 - mean_absolute_error: 0.0112 - val_lo
ss: 0.0027 - val_mean_absolute_error: 0.0415
Epoch 42/100
28/28 [==============================] - 2s 74ms/step - loss: 2.2727e-04 - mean_absolute_error: 0.0111 - val_lo
ss: 0.0024 - val_mean_absolute_error: 0.0396
Epoch 43/100
28/28 [==============================] - 2s 75ms/step - loss: 2.2635e-04 - mean_absolute_error: 0.0111 - val_lo
ss: 0.0043 - val_mean_absolute_error: 0.0545
Epoch 44/100
28/28 [==============================] - 2s 72ms/step - loss: 2.3254e-04 - mean_absolute_error: 0.0111 - val_lo
ss: 0.0022 - val_mean_absolute_error: 0.0367
Epoch 45/100
28/28 [==============================] - 2s 73ms/step - loss: 2.4993e-04 - mean_absolute_error: 0.0118 - val_lo
ss: 0.0034 - val_mean_absolute_error: 0.0475
Epoch 46/100
28/28 [==============================] - 2s 76ms/step - loss: 2.2562e-04 - mean_absolute_error: 0.0109 - val_lo
ss: 0.0030 - val_mean_absolute_error: 0.0448
Epoch 47/100
28/28 [==============================] - 2s 69ms/step - loss: 2.1701e-04 - mean_absolute_error: 0.0108 - val_lo
ss: 0.0021 - val_mean_absolute_error: 0.0365
```

Type

```
Epoch 48/100
28/28 [==============================] - 2s 77ms/step - loss: 2.2386e-04 - mean_absolute_error: 0.0110 - val_lo
ss: 0.0050 - val_mean_absolute_error: 0.0607
Epoch 49/100
28/28 [==============================] - 2s 83ms/step - loss: 1.9933e-04 - mean_absolute_error: 0.0104 - val_lo
ss: 0.0033 - val_mean_absolute_error: 0.0472
Epoch 50/100
28/28 [==============================] - 2s 83ms/step - loss: 2.1095e-04 - mean_absolute_error: 0.0106 - val_lo
ss: 0.0038 - val_mean_absolute_error: 0.0511
Epoch 51/100
28/28 [==============================] - 2s 76ms/step - loss: 2.0873e-04 - mean_absolute_error: 0.0106 - val_lo
ss: 8.6034e-04 - val_mean_absolute_error: 0.0221
Epoch 52/100
28/28 [==============================] - 2s 74ms/step - loss: 1.9468e-04 - mean_absolute_error: 0.0103 - val_lo
ss: 0.0045 - val_mean_absolute_error: 0.0552
Epoch 53/100
28/28 [==============================] - 2s 72ms/step - loss: 1.9288e-04 - mean_absolute_error: 0.0102 - val_lo
ss: 0.0035 - val_mean_absolute_error: 0.0480
Epoch 54/100
28/28 [==============================] - 2s 76ms/step - loss: 2.1123e-04 - mean_absolute_error: 0.0108 - val_lo
ss: 0.0051 - val_mean_absolute_error: 0.0598
Epoch 55/100
28/28 [==============================] - 2s 72ms/step - loss: 2.0095e-04 - mean_absolute_error: 0.0101 - val_lo
ss: 0.0037 - val_mean_absolute_error: 0.0490
Epoch 56/100
28/28 [==============================] - 2s 76ms/step - loss: 1.8876e-04 - mean_absolute_error: 0.0101 - val_lo
ss: 0.0026 - val_mean_absolute_error: 0.0418
Epoch 57/100
28/28 [==============================] - 2s 76ms/step - loss: 1.8531e-04 - mean_absolute_error: 0.0099 - val_lo
ss: 0.0014 - val_mean_absolute_error: 0.0285
Epoch 58/100
28/28 [==============================] - 2s 75ms/step - loss: 1.7605e-04 - mean_absolute_error: 0.0096 - val_lo
ss: 0.0029 - val_mean_absolute_error: 0.0436
Epoch 59/100
28/28 [==============================] - 2s 76ms/step - loss: 2.0312e-04 - mean_absolute_error: 0.0103 - val_lo
ss: 0.0026 - val_mean_absolute_error: 0.0403
Epoch 60/100
28/28 [==============================] - 2s 75ms/step - loss: 2.0422e-04 - mean_absolute_error: 0.0104 - val_lo
ss: 9.0172e-04 - val_mean_absolute_error: 0.0228
Epoch 61/100
28/28 [==============================] - 2s 70ms/step - loss: 1.8638e-04 - mean_absolute_error: 0.0100 - val_lo
ss: 9.2860e-04 - val_mean_absolute_error: 0.0230
Epoch 62/100
28/28 [==============================] - 2s 70ms/step - loss: 1.8993e-04 - mean_absolute_error: 0.0101 - val_lo
ss: 0.0021 - val_mean_absolute_error: 0.0363
Epoch 63/100
28/28 [==============================] - 2s 71ms/step - loss: 1.7831e-04 - mean_absolute_error: 0.0097 - val_lo
ss: 0.0040 - val_mean_absolute_error: 0.0520
Epoch 64/100
28/28 [==============================] - 2s 66ms/step - loss: 1.8095e-04 - mean_absolute_error: 0.0098 - val_lo
ss: 0.0050 - val_mean_absolute_error: 0.0579
Epoch 65/100
28/28 [==============================] - 2s 71ms/step - loss: 1.7173e-04 - mean_absolute_error: 0.0095 - val_lo
ss: 0.0025 - val_mean_absolute_error: 0.0395
Epoch 66/100
28/28 [==============================] - 2s 68ms/step - loss: 1.6561e-04 - mean_absolute_error: 0.0092 - val_lo
ss: 0.0030 - val_mean_absolute_error: 0.0441
Epoch 67/100
28/28 [==============================] - 2s 74ms/step - loss: 1.7168e-04 - mean_absolute_error: 0.0096 - val_lo
ss: 0.0039 - val_mean_absolute_error: 0.0525
Epoch 68/100
28/28 [==============================] - 2s 66ms/step - loss: 1.7348e-04 - mean_absolute_error: 0.0097 - val_lo
ss: 0.0031 - val_mean_absolute_error: 0.0450
Epoch 69/100
28/28 [==============================] - 2s 77ms/step - loss: 1.6919e-04 - mean_absolute_error: 0.0096 - val_lo
ss: 0.0021 - val_mean_absolute_error: 0.0373
Epoch 70/100
28/28 [==============================] - 2s 77ms/step - loss: 1.5923e-04 - mean_absolute_error: 0.0092 - val_lo
ss: 0.0013 - val_mean_absolute_error: 0.0267
Epoch 71/100
28/28 [==============================] - 2s 69ms/step - loss: 1.5958e-04 - mean_absolute_error: 0.0091 - val_lo
ss: 0.0022 - val_mean_absolute_error: 0.0365
Epoch 72/100
28/28 [==============================] - 2s 73ms/step - loss: 1.5513e-04 - mean_absolute_error: 0.0090 - val_lo
ss: 0.0015 - val_mean_absolute_error: 0.0304
Epoch 73/100
28/28 [==============================] - 2s 67ms/step - loss: 1.5671e-04 - mean_absolute_error: 0.0090 - val_lo
ss: 0.0027 - val_mean_absolute_error: 0.0416
Epoch 74/100
28/28 [==============================] - 2s 74ms/step - loss: 1.6093e-04 - mean_absolute_error: 0.0091 - val_lo
ss: 0.0030 - val_mean_absolute_error: 0.0454
Epoch 75/100
28/28 [==============================] - 2s 76ms/step - loss: 1.4674e-04 - mean_absolute_error: 0.0088 - val_lo
ss: 0.0030 - val_mean_absolute_error: 0.0453
Epoch 76/100
28/28 [==============================] - 2s 76ms/step - loss: 1.4612e-04 - mean_absolute_error: 0.0087 - val_lo
ss: 0.0034 - val_mean_absolute_error: 0.0485
Epoch 77/100
28/28 [==============================] - 2s 77ms/step - loss: 1.4620e-04 - mean_absolute_error: 0.0087 - val_lo
```

```
ss: 0.0020 - val_mean_absolute_error: 0.0356
Epoch 78/100
28/28 [==============================] - 2s 75ms/step - loss: 1.6000e-04 - mean_absolute_error: 0.0092 - val_lo
ss: 0.0021 - val_mean_absolute_error: 0.0358
Epoch 79/100
28/28 [==============================] - 2s 75ms/step - loss: 1.5322e-04 - mean_absolute_error: 0.0090 - val_lo
ss: 0.0039 - val_mean_absolute_error: 0.0522
Epoch 80/100
28/28 [==============================] - 2s 76ms/step - loss: 1.5051e-04 - mean_absolute_error: 0.0091 - val_lo
ss: 0.0036 - val_mean_absolute_error: 0.0513
Epoch 81/100
28/28 [==============================] - 2s 76ms/step - loss: 1.6520e-04 - mean_absolute_error: 0.0095 - val_lo
ss: 0.0022 - val_mean_absolute_error: 0.0365
Epoch 82/100
28/28 [==============================] - 2s 75ms/step - loss: 1.4147e-04 - mean_absolute_error: 0.0085 - val_lo
ss: 0.0019 - val_mean_absolute_error: 0.0343
Epoch 83/100
28/28 [==============================] - 2s 73ms/step - loss: 1.3314e-04 - mean_absolute_error: 0.0083 - val_lo
ss: 0.0041 - val_mean_absolute_error: 0.0543
Epoch 84/100
28/28 [==============================] - 2s 71ms/step - loss: 1.3426e-04 - mean_absolute_error: 0.0084 - val_lo
ss: 0.0028 - val_mean_absolute_error: 0.0432
Epoch 85/100
28/28 [==============================] - 2s 75ms/step - loss: 1.2755e-04 - mean_absolute_error: 0.0080 - val_lo
ss: 0.0031 - val_mean_absolute_error: 0.0454
Epoch 86/100
28/28 [==============================] - 2s 76ms/step - loss: 1.3597e-04 - mean_absolute_error: 0.0084 - val_lo
ss: 0.0033 - val_mean_absolute_error: 0.0465
Epoch 87/100
28/28 [==============================] - 2s 68ms/step - loss: 1.3157e-04 - mean_absolute_error: 0.0082 - val_lo
ss: 0.0027 - val_mean_absolute_error: 0.0432
Epoch 88/100
28/28 [==============================] - 2s 72ms/step - loss: 1.3880e-04 - mean_absolute_error: 0.0085 - val_lo
ss: 0.0019 - val_mean_absolute_error: 0.0354
Epoch 89/100
28/28 [==============================] - 2s 72ms/step - loss: 1.3528e-04 - mean_absolute_error: 0.0085 - val_lo
ss: 0.0021 - val_mean_absolute_error: 0.0366
Epoch 90/100
28/28 [==============================] - 2s 72ms/step - loss: 1.5266e-04 - mean_absolute_error: 0.0090 - val_lo
ss: 0.0012 - val_mean_absolute_error: 0.0265
Epoch 91/100
28/28 [==============================] - 2s 76ms/step - loss: 1.3766e-04 - mean_absolute_error: 0.0085 - val_lo
ss: 0.0015 - val_mean_absolute_error: 0.0286
Epoch 92/100
28/28 [==============================] - 2s 76ms/step - loss: 1.3259e-04 - mean_absolute_error: 0.0084 - val_lo
ss: 0.0025 - val_mean_absolute_error: 0.0402
Epoch 93/100
28/28 [==============================] - 2s 76ms/step - loss: 1.2394e-04 - mean_absolute_error: 0.0082 - val_lo
ss: 0.0019 - val_mean_absolute_error: 0.0354
Epoch 94/100
28/28 [==============================] - 2s 75ms/step - loss: 1.2022e-04 - mean_absolute_error: 0.0078 - val_lo
ss: 0.0013 - val_mean_absolute_error: 0.0282
Epoch 95/100
28/28 [==============================] - 2s 72ms/step - loss: 1.3169e-04 - mean_absolute_error: 0.0083 - val_lo
ss: 0.0010 - val_mean_absolute_error: 0.0254
Epoch 96/100
28/28 [==============================] - 2s 74ms/step - loss: 1.4499e-04 - mean_absolute_error: 0.0087 - val_lo
ss: 0.0027 - val_mean_absolute_error: 0.0430
Epoch 97/100
28/28 [==============================] - 2s 72ms/step - loss: 1.1930e-04 - mean_absolute_error: 0.0080 - val_lo
ss: 0.0039 - val_mean_absolute_error: 0.0529
Epoch 98/100
28/28 [==============================] - 2s 71ms/step - loss: 1.1981e-04 - mean_absolute_error: 0.0079 - val_lo
ss: 0.0023 - val_mean_absolute_error: 0.0386
Epoch 99/100
28/28 [==============================] - 2s 72ms/step - loss: 1.2681e-04 - mean_absolute_error: 0.0081 - val_lo
ss: 0.0028 - val_mean_absolute_error: 0.0441
Epoch 100/100
28/28 [==============================] - 2s 71ms/step - loss: 1.2679e-04 - mean_absolute_error: 0.0081 - val_lo
ss: 0.0028 - val_mean_absolute_error: 0.0424
```

Out[16]:

```
<keras.callbacks.History at 0x23b61997760>
```

In [17]:

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

Out[17]:

```
9/9 [==============================] - 2s 19ms/step
array([[0.3987828 , 0.40509373],
       [0.39797232, 0.40461183],
       [0.39309195, 0.3999965 ],
       [0.3959207 , 0.4024696 ],
       [0.39985454, 0.4062231 ]], dtype=float32)
```

In [18]:

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

Out[18]:
```
array([[1410.3114, 1419.0365],
       [1408.8088, 1418.1433],
       [1399.761 , 1409.5895],
       [1405.0052, 1414.173 ],
       [1412.2983, 1421.1295]], dtype=float32)
```

# VISUALIZING ACTUAL VS PREDICTED DATA

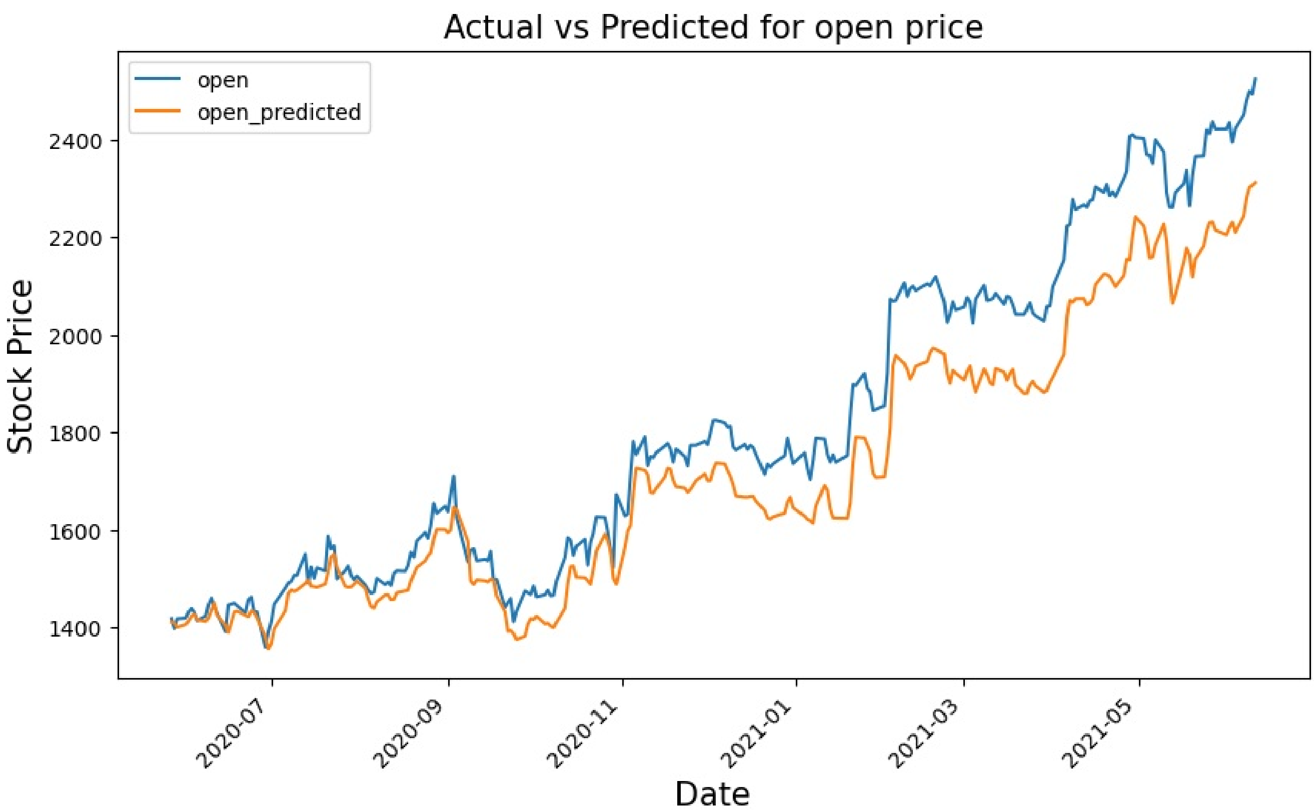
In [19]:
```
# Merging actual and predicted data for better visualization
df_merge = pd.concat([df.iloc[-264:].copy(),
                          pd.DataFrame(test_inverse_predicted,columns=['open_predicted','close_predicted'],
                                       index=df.iloc[-264:].index)], axis=1)
```

In [20]:
```
# Inversing normalization/scaling
df_merge[['open','close']] = MMS.inverse_transform(df_merge[['open','close']])
df_merge.head()
```

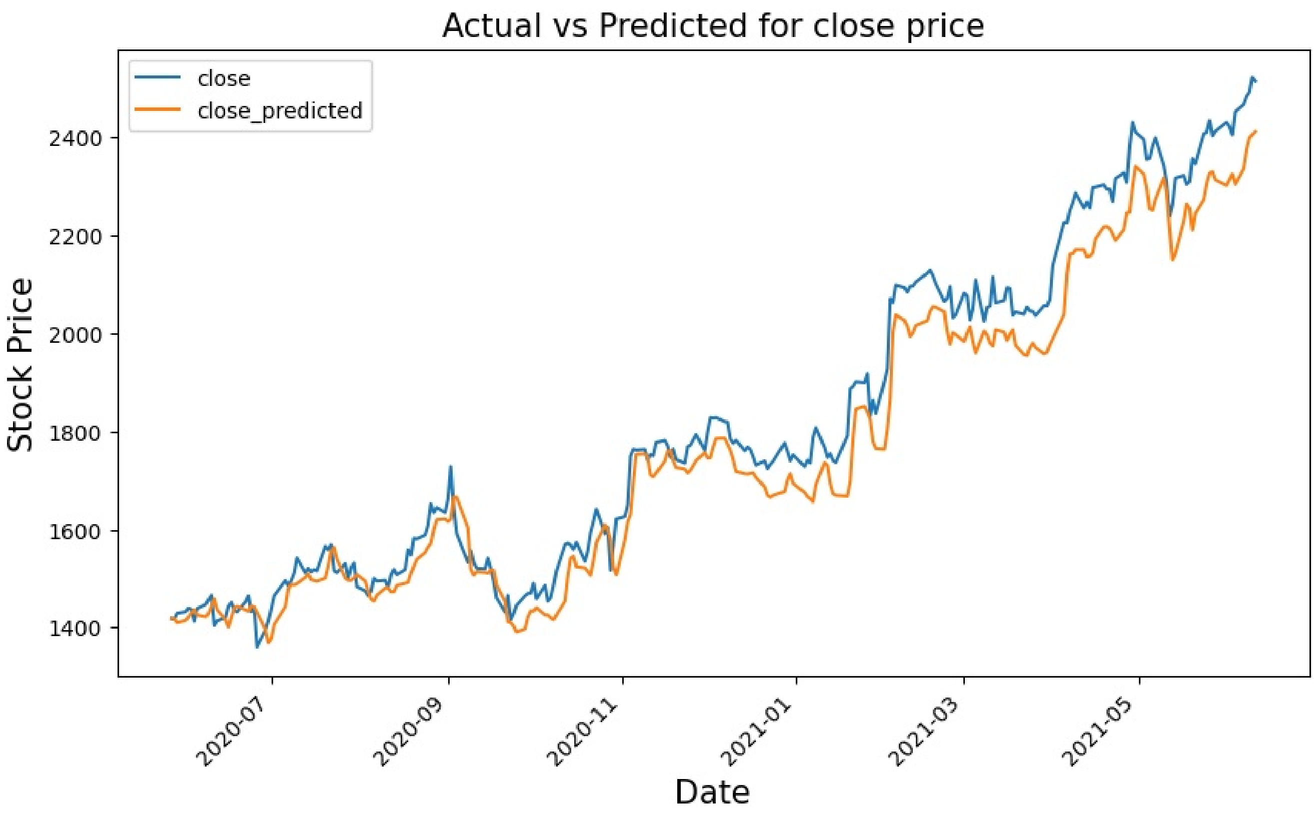
Out[20]:

| date | open | close | open_predicted | close_predicted |
|---|---|---|---|---|
| **2020-05-27** | 1417.25 | 1417.84 | 1410.311401 | 1419.036499 |
| **2020-05-28** | 1396.86 | 1416.73 | 1408.808838 | 1418.143311 |
| **2020-05-29** | 1416.94 | 1428.92 | 1399.760986 | 1409.589478 |
| **2020-06-01** | 1418.39 | 1431.82 | 1405.005249 | 1414.172974 |
| **2020-06-02** | 1430.55 | 1439.22 | 1412.298340 | 1421.129517 |

In [21]:
```
# 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 [22]:
```
# 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 [23]:
```
# 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, freq='D', clo
df_merge['2021-06-09':'2021-06-16']
```

Out[23]:

| | open | close | open_predicted | close_predicted |
|---|---|---|---|---|
| **2021-06-09** | 2499.50 | 2491.40 | 2301.978027 | 2398.498047 |
| **2021-06-10** | 2494.01 | 2521.60 | 2306.009033 | 2404.821045 |
| **2021-06-11** | 2524.92 | 2513.93 | 2311.519531 | 2410.579346 |
| **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 [24]:
```
# 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)
```

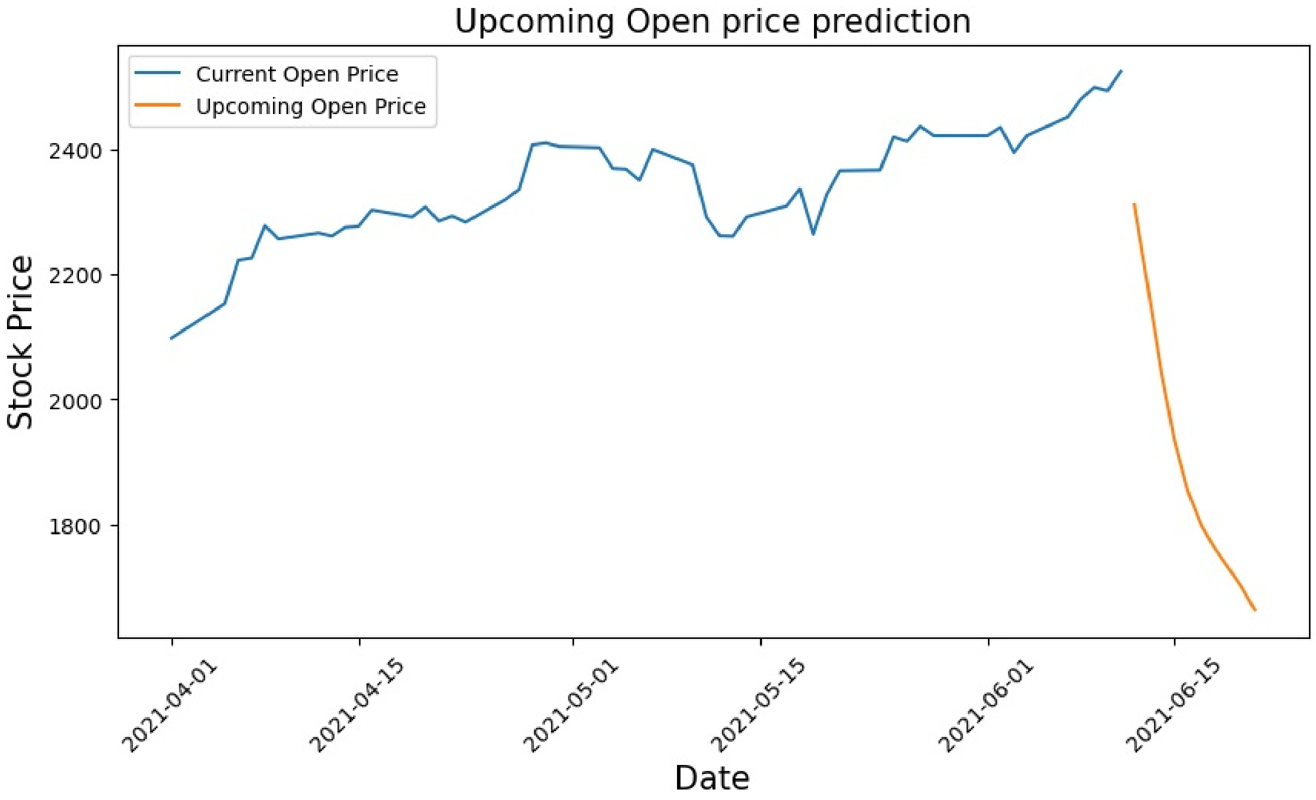
In [25]:
```
curr_seq = test_seq[-1:]

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 50ms/step
1/1 [==============================] - 0s 47ms/step
1/1 [==============================] - 0s 44ms/step
1/1 [==============================] - 0s 49ms/step
1/1 [==============================] - 0s 66ms/step
1/1 [==============================] - 0s 50ms/step
1/1 [==============================] - 0s 54ms/step
1/1 [==============================] - 0s 50ms/step
1/1 [==============================] - 0s 54ms/step
1/1 [==============================] - 0s 50ms/step
```

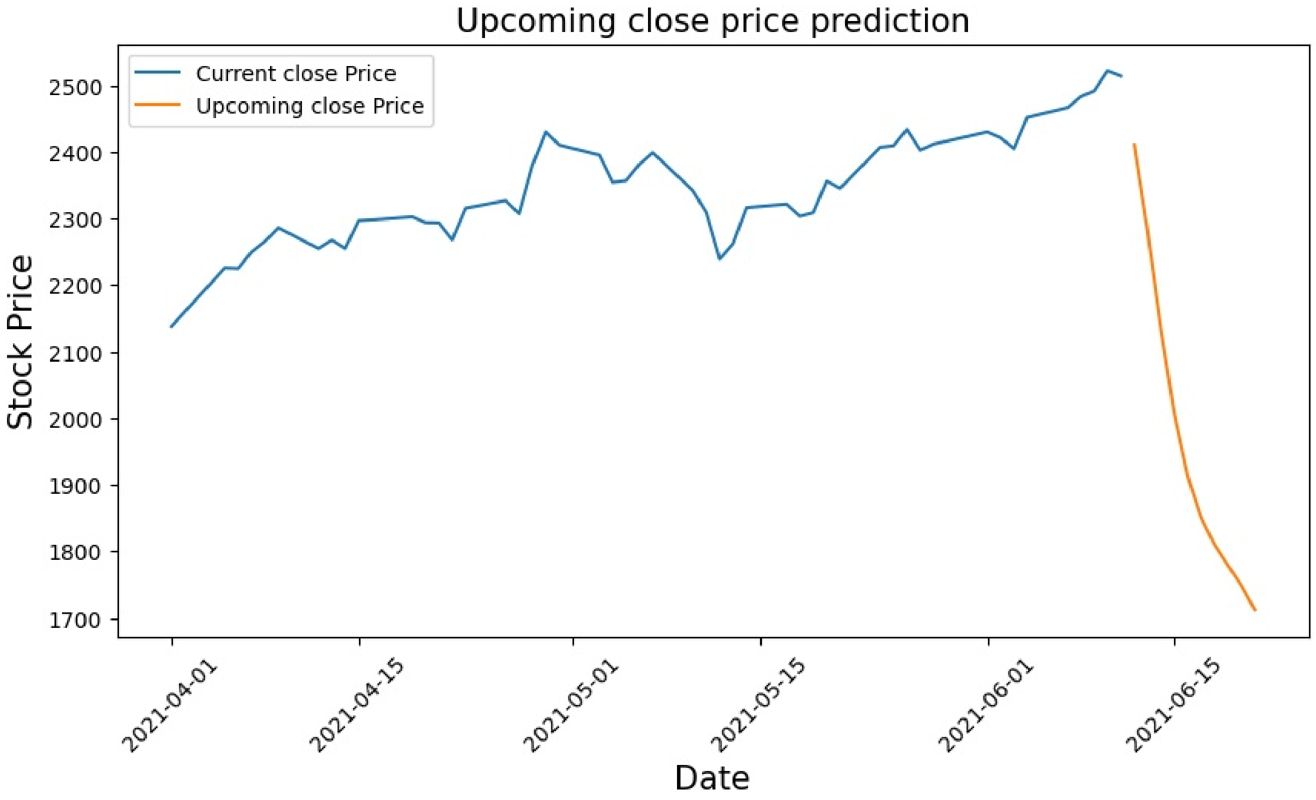
In [26]:
```
# inversing Normalization/scaling
upcoming_prediction[['open','close']] = MMS.inverse_transform(upcoming_prediction[['open','close']])
```

In [27]:
```
# 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 [28]:
```
# 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()
```



# THANK YOU!

In [ ]:

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