Importing Necessary Libraries

In [1]:

```
import warnings
warnings.filterwarnings("ignore")
import math
import os
import glob
import numpy as np
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
import pandas_datareader as web
from keras.models import Sequential
from keras.layers import Dense, LSTM
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import joblib as jb

```

Optimize Savings

Preprocessing

In [2]:

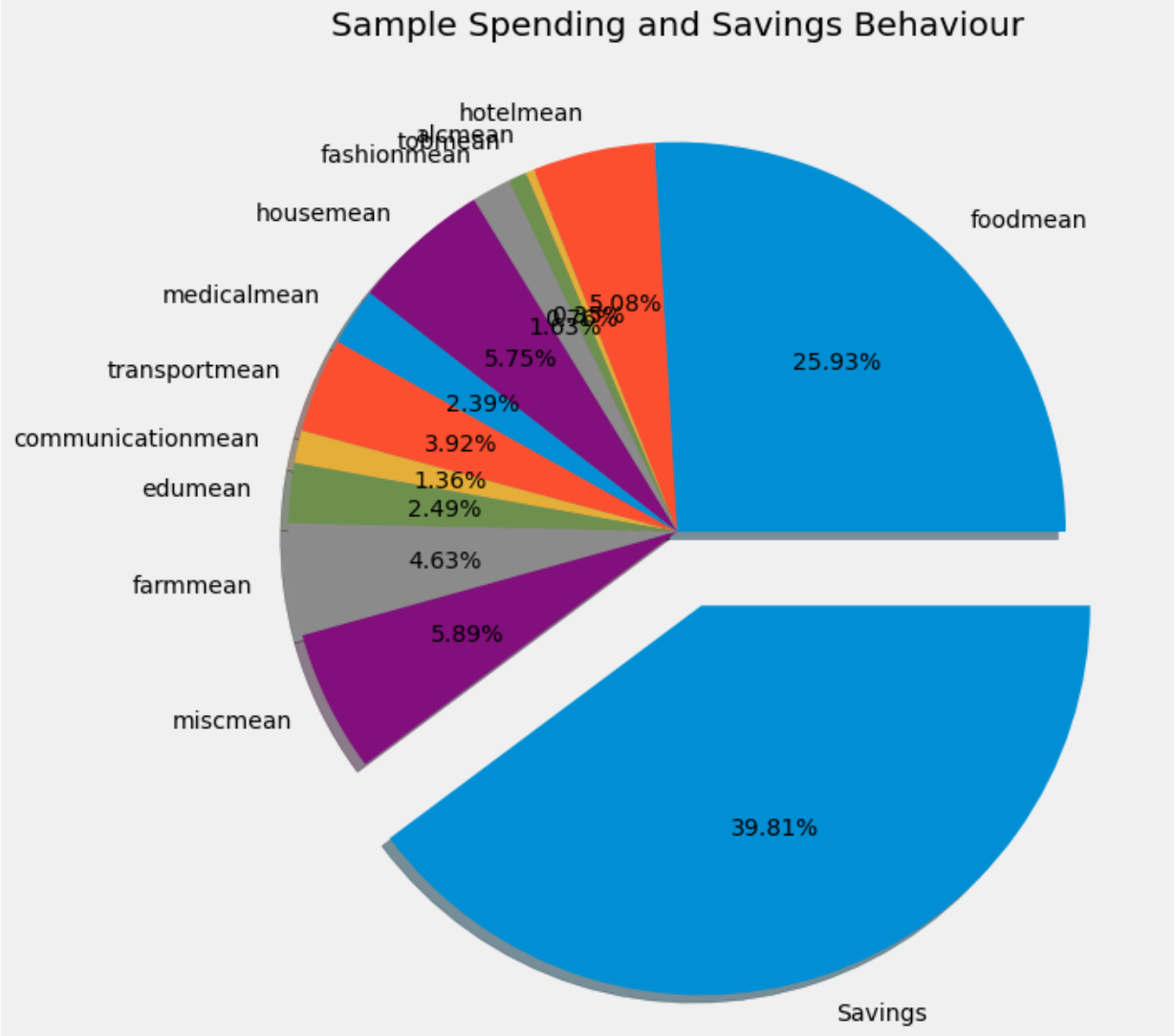
```
raw = pd.read_csv("Family Income and Expenditure.csv")
#raw
#raw.columns
print("Raw dataset Rows = {} and Columns = {}.".format(raw.shape[0],raw.shap
#Dataset Filtering
raw.drop(columns=['Region',
                  'Agricultural Household indicator',
                  'Main Source of Income',
                  'Household Head Highest Grade Completed',
                  'Household Head Job or Business Indicator',
                  'Household Head Occupation',
                  'Household Head Class of Worker',
                  'Type of Household',
                  'Type of Building/House',
                  'Type of Roof',
                  'Type of Walls',
                  'House Floor Area',
                  'House Age',
                  'Number of bedrooms',
                  'Tenure Status',
                  'Toilet Facilities',
                  'Electricity',
                  'Main Source of Water Supply',
                  'Number of Television',
                  'Number of CD/VCD/DVD',
                  'Number of Component/Stereo set',
                  'Number of Refrigerator/Freezer',
                  'Number of Washing Machine',
                  'Number of Airconditioner',
                  'Number of Car, Jeep, Van',
                  'Number of Landline/wireless telephones',
                  'Number of Cellular phone',
                  'Number of Personal Computer',
                  'Number of Stove with Oven/Gas Range',
                  'Number of Motorized Banca',
                  'Number of Motorcycle/Tricycle',
                  'Members with age less than 5 year old',
                  'Members with age 5 - 17 years old',
                  'Total number of family members employed',], inplace = Tru

#raw.info()

#Copy to a new dataset
dataset1=pd.DataFrame()
#dataset1[''] = raw['']
dataset1['Total Household Income'] = raw['Total Household Income'] + raw['To

dataset1['Total Food Expenditure']= (raw['Bread and Cereals Expenditure']+ r
                                     +raw['Meat Expenditure']+raw['Total Fis
                                     +raw['Fruit Expenditure']+raw['Vegetabl

dataset1['Restaurant and hotels Expenditure'] = raw['Restaurant and hotels E

dataset1['Alcoholic Beverages Expenditure'] = raw['Alcoholic Beverages Exper

dataset1['Tobacco Expenditure'] = raw['Tobacco Expenditure']
```

```
57
58  dataset1['Fashion Spendings'] = raw['Clothing, Footwear and Other Wear Exper
59
60  dataset1['Housing Expenditure'] = raw['Housing and water Expenditure'] - raw
61
62  dataset1['Medical Expenditure'] = raw['Medical Care Expenditure']
63
64  dataset1['Transportation Expenditure'] = raw['Transportation Expenditure']
65
66  dataset1['Communication Expenditure'] = raw['Communication Expenditure']
67
68  dataset1['Education Expenditure'] = raw['Education Expenditure']
69
70  dataset1['Farming and Gardening expenses'] = raw['Crop Farming and Gardening
71
72  dataset1['Miscellaneous and Special Occasions Expenditure'] = raw['Miscellar
73
74  dataset1['Sex'] = raw['Household Head Sex']
75
76  dataset1['Age'] = raw['Household Head Age']
77
78  dataset1['Marital Status'] = raw['Household Head Marital Status']
79
80  dataset1['Total Number of Family members'] = raw['Total Number of Family mem
81
82  #dataset1
83  #dataset1.info()
84
85  #print(raw['Total Food Expenditure'] - dataset1['Total Food Expenditure'])
86
87  # Adjusting total Food Expense:
88  food = pd.DataFrame()
89
90  food['Given Total Food Expenditure'] = raw['Total Food Expenditure']
91  food['Calculated Total Food Expenditure'] = dataset1['Total Food Expenditure
92  food['Error'] = (raw['Total Food Expenditure'] - dataset1['Total Food Expend
93  food['Approximate Total Food Expenditure'] = raw['Total Food Expenditure'] -
94
95  # Adding this adjusted value to the Dataset
96  dataset1['Total Food Expenditure'] = food['Approximate Total Food Expenditur
97
98  #dataset1
99  #Saving This to System Disk
100 dataset1.to_csv('Filtered Dataset v2.csv', index=False)
101
102 # Getting Total Expense Value & Savings
103 dataset1['total expense'] = dataset1['Total Food Expenditure']
104 for i in range(2,13):
105     dataset1['total expense'] = dataset1['total expense'] + dataset1.iloc[:,
106
107 dataset1['Savings'] = dataset1['Total Household Income'] - dataset1['total e
108
109 # Getting Unique Categorical Values and Encoding them in the Dataset
110 dataset2 = dataset1.copy()
111
112 #dataset1.iloc[:,13].unique() #Sex male = 1, female = 0
113
```

```
dataset2['Sex'][dataset2['Sex'] == 'Female'] = 0
dataset2['Sex'][dataset2['Sex'] == 'Male'] = 1

#dataset1.iloc[:,15].unique() #Relationship Status

dataset2['Marital Status'][dataset2['Marital Status'] == 'Single'] = 0
dataset2['Marital Status'][dataset2['Marital Status'] == 'Married'] = 1
dataset2['Marital Status'][dataset2['Marital Status'] == 'Widowed'] = 2
dataset2['Marital Status'][dataset2['Marital Status'] == 'Divorced/Separated
dataset2['Marital Status'][dataset2['Marital Status'] == 'Annulled'] = 4
dataset2['Marital Status'][dataset2['Marital Status'] == 'Unknown'] = 5

dataset2.drop(columns=['total expense'], inplace=True)
#dataset2.to_csv('Filtered, Corrected And Encoded Dataset v2.csv', index=Fal
print("Filterred dataset Rows = {} and Columns = {}.".format(dataset2.shape[


#Splitting Data
X = dataset2.iloc[:,0:-1]
Y = dataset2.iloc[:,-1]

from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(X,Y, test_size=0.2, random_

print("Training data:", x_train.shape)
print("Testing data:",x_test.shape)

#Model Training
#Importing Models:
from sklearn.linear_model import LinearRegression

mlr = LinearRegression()

model1_mlr= mlr.fit(x_train,y_train)
M1=model1_mlr.score(x_train,y_train)
print("Multiple Linear Regression Score:",M1)

#Save Model
jb.dump(model1_mlr,"MLR_Training.pkl")


#Counting How many people are in debt

debt = y_train.lt(0).sum() #Less Than

print("People in debt:",debt)
print("Debt percentage in population",round(debt*100/y_train.shape[0],2))

#Making Dictionary for fast acessing
#expenditure mean dictionary creation to get the statsof population
MeanDict = {'incomemean':1 ,'foodmean':2 ,'hotelmean':3 ,'alcmean':4 ,'tobme
            'medicalmean':8 ,'transportmean':9 ,'communicationmean':10 ,'edu
#print(MeanDict)
j=0
for key, value in MeanDict.items():
    MeanDict[key] = x_train.iloc[:,j].mean()
    j+=1
```

```
    if j==13:
        break
#print(MeanDict)

#Mean Percentage
spendper =0
MeanPercentDict = {}
for key,value in MeanDict.items():
    percent= MeanDict[key]*100/MeanDict['incomemean']
    MeanPercentDict[key] = percent
    spendper = spendper + percent
    #print(key,percent,"%")
spendper= spendper - 100 # -100 because 100 is in the income
#print("Total Spending Percentage", spendper)
#print(MeanPercentDict)

#Plotting Population mean data
head = []
val = []
for i, j in MeanPercentDict.items():
    head.append(i)
    val.append(j)
head.append('Savings')
val.append(100-spendper)
head.pop(0) #removing income mean
val.pop(0) #removing income mean value
explode = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.2]
fig = plt.figure(figsize =(30, 10))
plt.title("Sample Spending and Savings Behaviour")
plt.pie(val, labels = head,autopct='%1.2f%%', explode = explode, shadow = Tr
#plt.legend(loc = 'best')
plt.show()
```

```
Raw dataset Rows = 41544 and Columns = 60.
Filterred dataset Rows = 41544 and Columns = 18.
Training data: (33235, 17)
Testing data: (8309, 17)
Multiple Linear Regression Score: 1.0
People in debt: 3436
Debt percentage in population 10.34
```


Sample Spending and Savings Behaviour
hotelmean
fashionmean
housemean
foodmean
medicalmean
5.08%
transportmean
5.75%
25.93%
2.39%
communicationmean
3.92%
edumean
1.36%
2.49%
4.63%
farmmean
5.89%
miscmean
39.81%
Savings

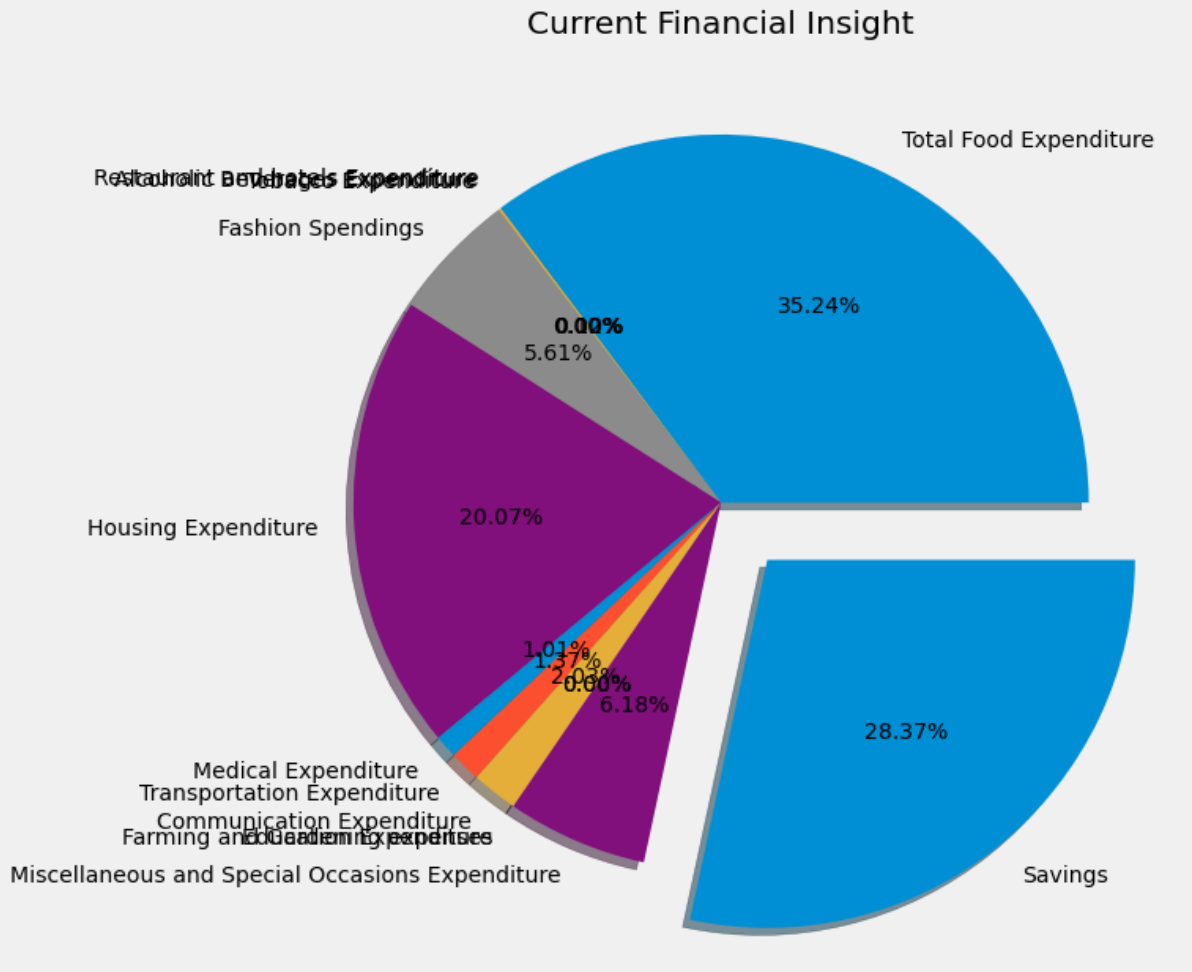
Testing

In [3]:

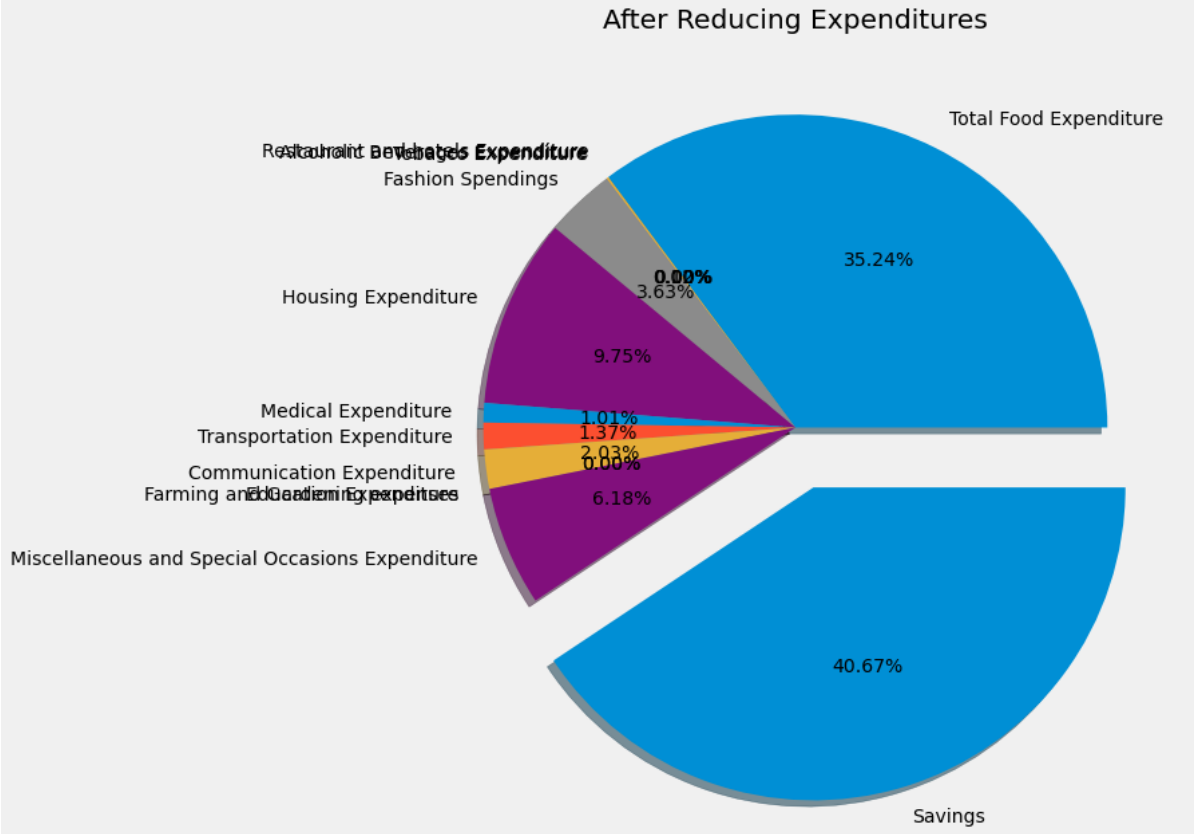
```
 ##############################################   Testing #################


choose = 0



test1 = x_test.iloc[choose,:].values
test1res= y_test.iloc[choose]
#print(test1)
test1 = test1.reshape(1, -1) #make 1d array to 2d
#print(test1)

test1_pred1 = model1_mlr.predict(test1)
print("Current Savings Value:",round(test1_pred1[0],2))


expenditure_names = list(x_train.columns)
expenditure_names.pop(0)
for i in range(4):
    expenditure_names.pop()
#print(L)
expenditure_names.append('Savings')
#print(expenditure_names)

test1v1 = list(test1.flatten()) #2d to 1d conversion
#np.append(test1v3,round(test1_pred1[0],2))
test1v1.pop(0)
for i in range(4):
    test1v1.pop()
#print(L)
test1v1.append(test1_pred1)
#print(len(expenditure_names))

explode = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.2]
fig = plt.figure(figsize =(30, 10))
plt.title("Current Financial Insight")
plt.pie(test1v1, labels = expenditure_names,autopct='%1.2f%%', explode = exp
#plt.legend(loc = 0)
plt.show()

######################  Calculating Inflation Rate ##########################
#  Purchasing Power :
#  Future Value = Present value/(1+inflation rate)^number of years
#  Dataset is of 2012. Inflation rate for 2013 is 2.5837
#  We are calculating Inflation rate for 1 year only

PurchasePower = round((test1_pred1[0]/ (1+0.02587)**1),2)

print("Your Savings will be {} due to Inflation.".format(PurchasePower))

test1v2 = test1

threshold = {'incomemean':1 ,'foodmean':14 ,'hotelmean':1 ,'alcmean':1 ,'tob
             'medicalmean':20 ,'transportmean':2 ,'communicationmean':1 ,'edu
i = 0
```

```
delSave = 0
totalsave = 0
flag = 0

for key,value in MeanPercentDict.items():




    calc_per = test1v2[0][i]*100/test1v2[0][0]

    #print(calc_per)
    if calc_per >= MeanPercentDict[key] + threshold[key]:
        flag+=1
        print("It is a concern in",key[:-4])
        delSave = round((test1v2[0][i]) - (test1v2[0][0] * ((MeanPercentDict
        test1v2[0][i] = test1v2[0][i] - delSave
        print("You can save {} in {} expenditure".format(delSave,key[:-4]))
        totalsave = round(totalsave + delSave,2)
    i+=1
if flag>0:
    print("You can save {} in the above expenditure:".format(totalsave))
else:
    print("Your savings are good")

finalsave = totalsave + round(test1_pred1[0],2)
print("You can save a total Of {} from your salary.".format(finalsave))

test1v2 = list(test1v2.flatten()) #2d to 1d conversion
#np.append(test1v3,round(test1_pred1[0],2))
test1v2.pop(0)
for i in range(4):
    test1v2.pop()


test1v2.append(finalsave)
explode = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0.2]
fig = plt.figure(figsize =(30, 10))
plt.title("After Reducing Expenditures")
plt.pie(test1v2, labels = expenditure_names,autopct='%1.2f%%', explode = exp
#plt.legend(loc = 0)
plt.show()
```

```
Current Savings Value: 21826.5
```




```
Your Savings will be 21276.09 due to Inflation.
It is a concern in fashion
You can save 1522.92 in fashion expenditure
It is a concern in house
You can save 7935.8 in house expenditure
You can save 9458.72 in the above expenditure:
You can save a total Of 31285.22 from your salary.
```



Preprocessing Stocks

Separating Different stocks

In [4]:

```
raw = pd.read_csv("BSE_30.csv")

#print(raw)
#print(raw.info())
#print(raw.describe())

raw = raw.dropna()
raw.reset_index(drop=True, inplace=True)

raw['Date'] = pd.to_datetime(raw['Date']).dt.date


Company = raw['Symbol'].unique()
print("Company stocks are",Company)
print("\nNumber of companies in dataset are",raw['Symbol'].nunique())

company_dict = {}
for i in Company:
    company_dict[i] = pd.DataFrame()
#print(company_dict)

for i in range(0, len(raw)):
    company_dict[raw['Symbol'][i]] = company_dict[raw['Symbol'][i]].append(r


for name in company_dict:
    temp = company_dict[name]
    #print(temp)
    temp.to_csv(r"C:/Users/DIBYA/Capstone Project/StocksData"+ '/'+'{}.csv'.
    #print("Executing ",name)
print("Extracted to directory")
```

```
Company stocks are ['ADANIPORTS' 'ASIANPAINT' 'AXISBANK' 'BAJAJ-AUTO' 'BHARTIAR
TL'
 'COALINDIA' 'DRREDDY' 'HDFC' 'HDFCBANK' 'HEROMOTOCO' 'HINDUNILVR'
 'ICICIBANK' 'INDUSINDBK' 'INFY' 'ITC' 'KOTAKBANK' 'LT' 'M&M' 'MARUTI'
 'ONGC' 'RELIANCE' 'SBIN' 'SUNPHARMA' 'TATAMOTORS' 'TATAMTRDVR'
 'TATASTEEL' 'TCS' 'WIPRO' 'YESBANK' 'POWERGRID']

Number of companies in dataset are 30
Extracted to directory
```

Categorizing as Low, Medium and High risk

In [5]:

```
def GetValues(dataset = None):
    df = dataset
    df['Returns'] = (df['Adj Close'] / df['Adj Close'].shift(1)) - 1
    #print(df)

    nan_values = df['Returns'].isna().sum() #NaN Values count
    zero_values = df['Returns'].eq(0).sum() #Equal )
    negative_values = df['Returns'].lt(0).sum() #Less Than
    positive_values = df['Returns'].gt(0).sum() #Greater Than


    print("Total Values = {}\nNull Values = {}\nZero Values = {}\nNegative V
          .format(nan_values + zero_values + negative_values + positive_valu
                  nan_values, zero_values, negative_values, positive_values)
    Difference = positive_values - negative_values
    percentage = (Difference*100)/(positive_values + negative_values)

    print("Difference = ",Difference)
    print("Difference % = ", percentage)
    if percentage <= 1.30:
        print("Stock is High Risk")
        return 'High',percentage
    elif 1.30 < percentage <= 2.7:
        print("Stock is Medium Risk")
        return 'Medium',percentage
    else:
        print("Stock is Low Risk")
        return 'Low',percentage
```

In [6]:

```
StockRisk = pd.DataFrame(columns = ['Stock', 'Risk', 'Percentage'])

path = os.getcwd()
csv_files = glob.glob(os.path.join('C:/Users/DIBYA/Capstone Project/StocksDa

risk_dict={}
# loop over the list of csv files
for f in csv_files:
    templist = []
    # read the csv file
    df = pd.read_csv(f)

    # print the location and filename
    #print('Location:', f)

    temp = f.split("\\")[-1]
    #print('File Name with Extension:', temp)
    print('File Name:', temp[:-4])

    if temp[:-4] not in risk_dict:
        df = pd.read_csv(f)

        risk_dict[temp[:-4]], percent = GetValues(dataset = df)

    StockRisk = StockRisk.append({'Stock':temp[:-4], 'Risk': risk_dict[temp[
    print()
    print()

#print("Risk Dictionary",risk_dict)
print("Risk DataFrame")
StockRisk
```

```
File Name: ADANIPORTS
Total Values = 2461
Null Values = 1
Zero Values = 22
Negative Values 1223
Positive Values 1215
Difference =  -8
Difference % =  -0.3281378178835111
Stock is High Risk


File Name: ASIANPAINT
Total Values = 2462
Null Values = 1
Zero Values = 16
Negative Values 1165
Positive Values 1280
Difference =  115
Difference % =  4.703476482617587
Stock is Low Risk


File Name: AXISBANK
```

Total Values = 2462
Null Values = 1
Zero Values = 10
Negative Values 1224
Positive Values 1227
Difference = 3
Difference % = 0.12239902080783353
Stock is High Risk

File Name: BAJAJ-AUTO
Total Values = 2446
Null Values = 1
Zero Values = 6
Negative Values 1204
Positive Values 1235
Difference = 31
Difference % = 1.2710127101271014
Stock is High Risk

File Name: BHARTIARTL
Total Values = 2461
Null Values = 1
Zero Values = 16
Negative Values 1257
Positive Values 1187
Difference = -70
Difference % = -2.8641571194762685
Stock is High Risk

File Name: COALINDIA
Total Values = 1846
Null Values = 1
Zero Values = 13
Negative Values 915
Positive Values 917
Difference = 2
Difference % = 0.1091703056768559
Stock is High Risk

File Name: DRREDDY
Total Values = 2461
Null Values = 1
Zero Values = 9
Negative Values 1192
Positive Values 1259
Difference = 67
Difference % = 2.733578131374949
Stock is Low Risk

File Name: HDFC
Total Values = 2461
Null Values = 1

Zero Values = 15
Negative Values 1220
Positive Values 1225
Difference = 5
Difference % = 0.20449897750511248
Stock is High Risk

File Name: HDFCBANK
Total Values = 2461
Null Values = 1
Zero Values = 16
Negative Values 1178
Positive Values 1266
Difference = 88
Difference % = 3.600654664484452
Stock is Low Risk

File Name: HEROMOTOCO
Total Values = 2462
Null Values = 1
Zero Values = 14
Negative Values 1231
Positive Values 1216
Difference = -15
Difference % = -0.6129955046996322
Stock is High Risk

File Name: HINDUNILVR
Total Values = 2461
Null Values = 1
Zero Values = 15
Negative Values 1202
Positive Values 1243
Difference = 41
Difference % = 1.6768916155419222
Stock is Medium Risk

File Name: ICICIBANK
Total Values = 2462
Null Values = 1
Zero Values = 13
Negative Values 1239
Positive Values 1209
Difference = -30
Difference % = -1.2254901960784315
Stock is High Risk

File Name: INDUSINDBK
Total Values = 2461
Null Values = 1
Zero Values = 16
Negative Values 1180

Positive Values 1264
Difference = 84
Difference % = 3.436988543371522
Stock is Low Risk

File Name: INFY
Total Values = 2462
Null Values = 1
Zero Values = 11
Negative Values 1189
Positive Values 1261
Difference = 72
Difference % = 2.938775510204082
Stock is Low Risk

File Name: ITC
Total Values = 2461
Null Values = 1
Zero Values = 22
Negative Values 1173
Positive Values 1265
Difference = 92
Difference % = 3.7735849056603774
Stock is Low Risk

File Name: KOTAKBANK
Total Values = 2461
Null Values = 1
Zero Values = 11
Negative Values 1188
Positive Values 1261
Difference = 73
Difference % = 2.9808084932625563
Stock is Low Risk

File Name: LT
Total Values = 2461
Null Values = 1
Zero Values = 13
Negative Values 1252
Positive Values 1195
Difference = -57
Difference % = -2.3293829178586023
Stock is High Risk

File Name: M&M
Total Values = 2462
Null Values = 1
Zero Values = 9
Negative Values 1205
Positive Values 1247
Difference = 42

Difference % = 1.7128874388254487
Stock is Medium Risk

File Name: MARUTI
Total Values = 2461
Null Values = 1
Zero Values = 6
Negative Values 1218
Positive Values 1236
Difference = 18
Difference % = 0.7334963325183375
Stock is High Risk

File Name: ONGC
Total Values = 2461
Null Values = 1
Zero Values = 11
Negative Values 1238
Positive Values 1211
Difference = -27
Difference % = -1.1024908125765618
Stock is High Risk

File Name: POWERGRID
Total Values = 2461
Null Values = 1
Zero Values = 51
Negative Values 1212
Positive Values 1197
Difference = -15
Difference % = -0.6226650062266501
Stock is High Risk

File Name: RELIANCE
Total Values = 2461
Null Values = 1
Zero Values = 15
Negative Values 1227
Positive Values 1218
Difference = -9
Difference % = -0.36809815950920244
Stock is High Risk

File Name: SBIN
Total Values = 2462
Null Values = 1
Zero Values = 14
Negative Values 1205
Positive Values 1242
Difference = 37
Difference % = 1.5120555782590928
Stock is Medium Risk

File Name: SUNPHARMA
Total Values = 2461
Null Values = 1
Zero Values = 8
Negative Values 1195
Positive Values 1257
Difference = 62
Difference % = 2.528548123980424
Stock is Medium Risk

File Name: TATAMOTORS
Total Values = 2461
Null Values = 1
Zero Values = 11
Negative Values 1234
Positive Values 1215
Difference = -19
Difference % = -0.7758268681094325
Stock is High Risk

File Name: TATAMTRDVR
Total Values = 2319
Null Values = 1
Zero Values = 108
Negative Values 1078
Positive Values 1132
Difference = 54
Difference % = 2.4434389140271495
Stock is Medium Risk

File Name: TATASTEEL
Total Values = 2462
Null Values = 1
Zero Values = 9
Negative Values 1233
Positive Values 1219
Difference = -14
Difference % = -0.5709624796084829
Stock is High Risk

File Name: TCS
Total Values = 2461
Null Values = 1
Zero Values = 13
Negative Values 1186
Positive Values 1261
Difference = 75
Difference % = 3.064977523498161
Stock is Low Risk

```
File Name: WIPRO
Total Values = 2461
Null Values = 1
Zero Values = 14
Negative Values 1181
Positive Values 1265
Difference =  84
Difference % =  3.4341782502044156
Stock is Low Risk


File Name: YESBANK
Total Values = 2461
Null Values = 1
Zero Values = 11
Negative Values 1190
Positive Values 1259
Difference =  69
Difference % =  2.8174765210289916
Stock is Low Risk


Risk DataFrame
```

Out[6]:

	Stock	Risk	Percentage
0	ADANIPORTS	High	-0.328138
1	ASIANPAINT	Low	4.703476
2	AXISBANK	High	0.122399
3	BAJAJ-AUTO	High	1.271013
4	BHARTIARTL	High	-2.864157
5	COALINDIA	High	0.109170
6	DRREDDY	Low	2.733578
7	HDFC	High	0.204499
8	HDFCBANK	Low	3.600655
9	HEROMOTOCO	High	-0.612996
10	HINDUNILVR	Medium	1.676892
11	ICICIBANK	High	-1.225490
12	INDUSINDBK	Low	3.436989
13	INFY	Low	2.938776
14	ITC	Low	3.773585
15	KOTAKBANK	Low	2.980808
16	LT	High	-2.329383
17	M&M	Medium	1.712887
18	MARUTI	High	0.733496
19	ONGC	High	-1.102491

	Stock	Risk	Percentage
20	POWERGRID	High	-0.622665
21	RELIANCE	High	-0.368098
22	SBIN	Medium	1.512056
23	SUNPHARMA	Medium	2.528548
24	TATAMOTORS	High	-0.775827
25	TATAMTRDVR	Medium	2.443439
26	TATASTEEL	High	-0.570962
27	TCS	Low	3.064978
28	WIPRO	Low	3.434178
29	YESBANK	Low	2.817477

Predicting Stock using LSTM model

In [7]:

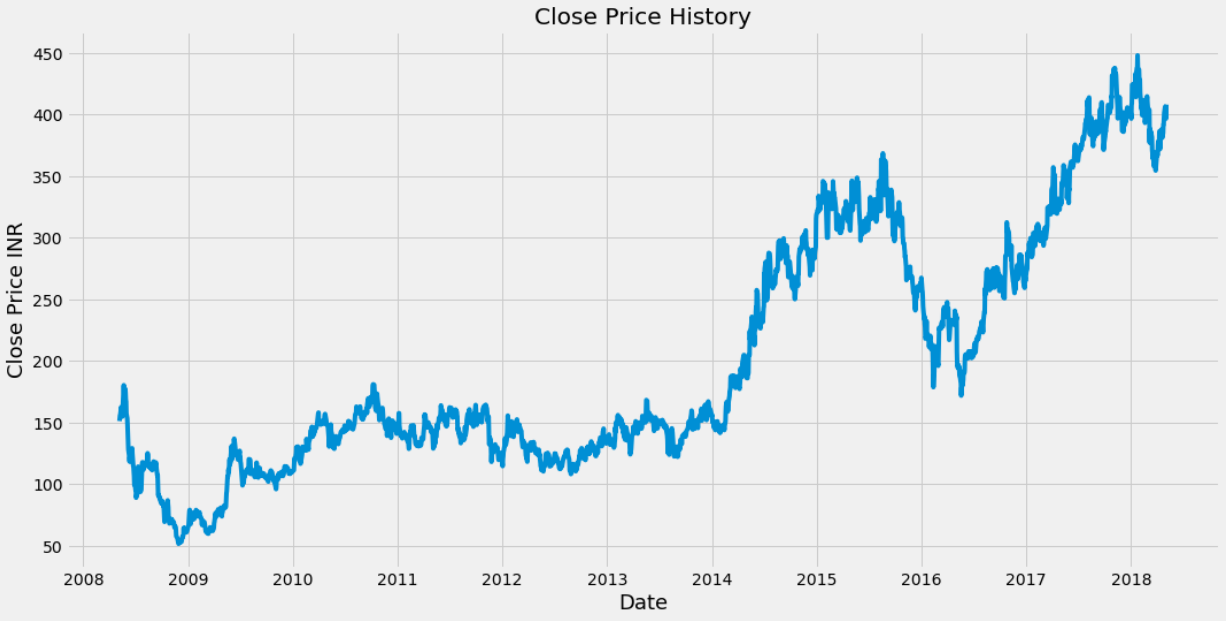
```
def StockPredict(dataset = None, batch_size = 30, epochs = 5 ):


    df = dataset
    df['Date'] = pd.to_datetime(df.Date)
    df.set_index('Date', inplace=True)

    plt.figure(figsize=(16,8))
    plt.title('Close Price History')
    plt.plot(df['Close'])
    plt.xlabel('Date', fontsize = 18)
    plt.ylabel('Close Price INR', fontsize = 18)
    plt.show()

################    training data ##############################
    data = df.filter(['Close'])
    dataset = data.values
    training_data_len = math.ceil(len(dataset)*0.8)

    scaler = MinMaxScaler(feature_range=(0,1))
    scaled_data = scaler.fit_transform(dataset)

    train_data = scaled_data[0:training_data_len, :]
    x_train = []
    y_train = []

    for i in range(60, len(train_data)):
        x_train.append(train_data[i-60:i,0])
        y_train.append(train_data[i,0])

    x_train, y_train = np.array(x_train), np.array(y_train)
    x_train = np.reshape(x_train, (x_train.shape[0],x_train.shape[1],1))

################    Model Making and Training ##############################

    model = Sequential()
    model.add(LSTM(60,return_sequences = True, input_shape= (x_train.shape[1
    model.add(LSTM(60,return_sequences = False))
    model.add(Dense(25))
    model.add(Dense(1))

    model.compile(optimizer = 'adam', loss = 'mean_squared_error')
    model.fit(x_train, y_train, batch_size = batch_size , epochs = epochs)


################    testing data ##############################
    test_data = scaled_data[training_data_len-60:, :]

    x_test = []
    y_test = dataset[training_data_len:, :]

    for i in range(60, len(test_data)):
        x_test.append(test_data[i-60:i,0])

    x_test = np.array(x_test)
```

```
    x_test = np.reshape(x_test, (x_test.shape[0],x_test.shape[1],1))
    predictions = model.predict(x_test)
    predictions = scaler.inverse_transform(predictions)

###################  RMSE value  ##############################
    rmse = np.sqrt(np.mean(predictions - y_test)**2)
    print(rmse)

    train = data[:training_data_len]
    valid = data[training_data_len:]
    valid['Predictions'] = predictions

        #Ploting the validation and test
    plt.figure(figsize =(16,8))
    plt.title('LSTM Model')
    plt.xlabel('Date', fontsize = 18)
    plt.ylabel('Close Price INR', fontsize = 18)
    plt.plot(train['Close'])
    plt.plot(valid[['Close','Predictions']])
    plt.legend(['Train', 'Actual', 'Predictions'], loc = 'best')
    plt.show()

    print("Predicted close Stock Price of the next day is \n {},Actual is {}

    return valid.iloc[0,1]


```

In [8]:

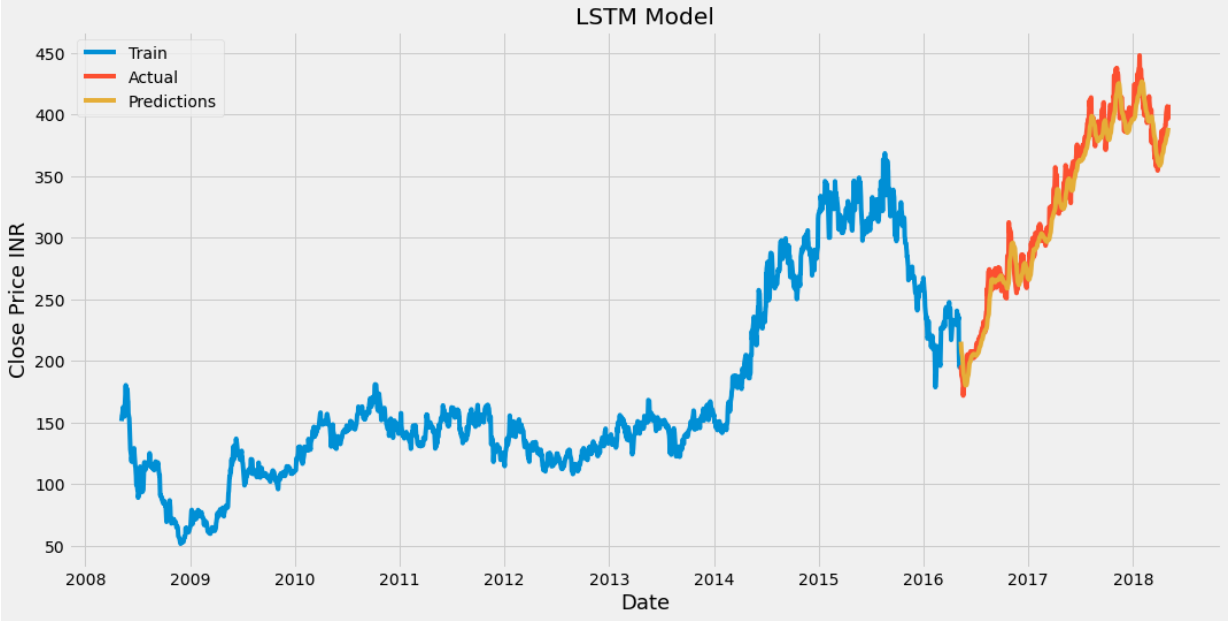
```
path = os.getcwd()
csv_files = glob.glob(os.path.join('C:/Users/DIBYA/Capstone Project/StocksDa

StockClose = pd.DataFrame( columns = ['Stock','Closing Price'])

company_dict={}
# loop over the list of csv files
for f in csv_files:

    # read the csv file
    df = pd.read_csv(f)

    # print the location and filename
    #print('Location:', f)

    temp = f.split("\\")[-1]
    #print('File Name with Extension:', temp)
    print('Stock Name:', temp[:-4])

    if temp[:-4] not in company_dict:
        df = pd.read_csv(f)

        company_dict[temp[:-4]] = StockPredict(dataset = df)

    StockClose = StockClose.append({'Stock':temp[:-4],'Closing Price': compa
    print()
    print()
StockClose.to_csv("C:/Users/DIBYA/Capstone Project/StockClose.csv",index = F
#print(company_dict)
StockClose
```

```
Stock Name: ADANIPORTS
```

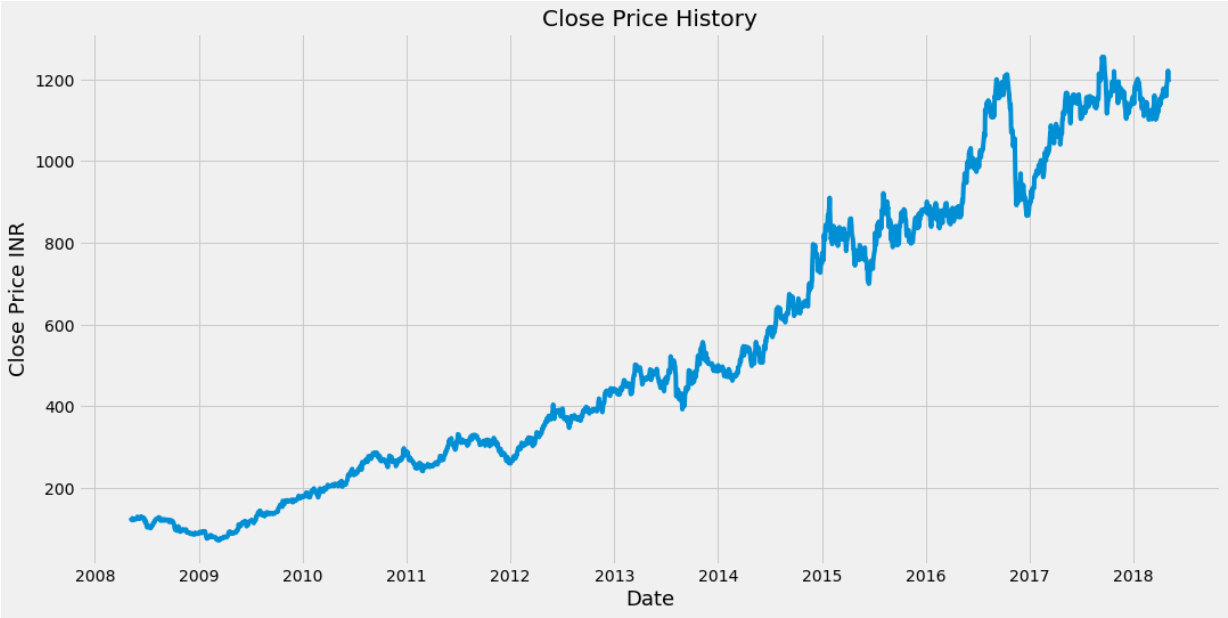



```
Epoch 1/5
64/64 [==============================] - 6s 38ms/step - loss: 0.0089
Epoch 2/5
64/64 [==============================] - 3s 47ms/step - loss: 6.2448e-04
Epoch 3/5
```

```
64/64 [==============================] - 3s 46ms/step - loss: 5.8343e-04
Epoch 4/5
64/64 [==============================] - 3s 44ms/step - loss: 5.8253e-04
Epoch 5/5
64/64 [==============================] - 3s 47ms/step - loss: 5.3031e-04
5.938259464434864
```

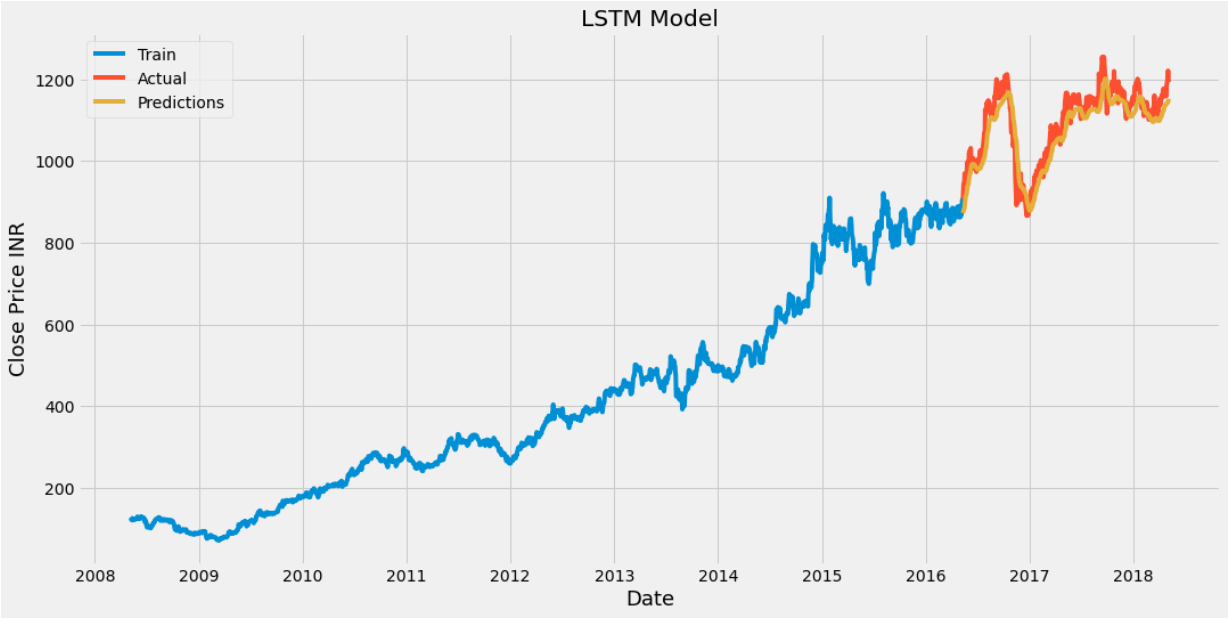



```
Predicted close Stock Price of the next day is
 215.63653564453125,Actual is 193.300003


Stock Name: ASIANPAINT
```



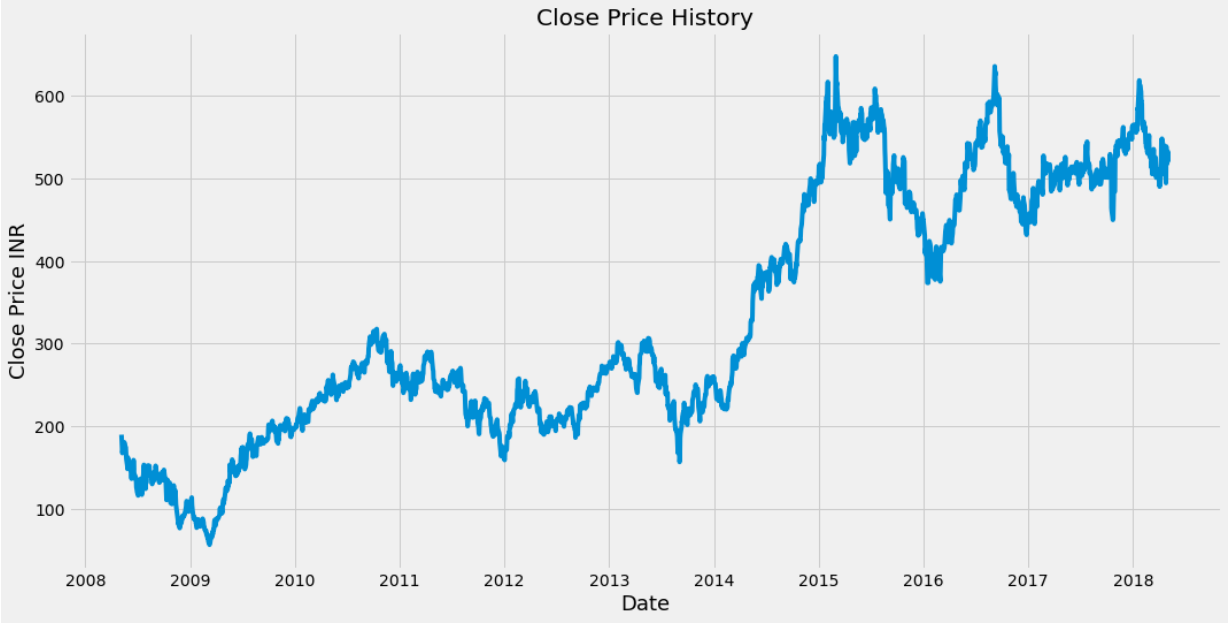

```
Epoch 1/5
64/64 [==============================] - 6s 51ms/step - loss: 0.0054
Epoch 2/5
64/64 [==============================] - 3s 47ms/step - loss: 2.1985e-04
Epoch 3/5
64/64 [==============================] - 3s 47ms/step - loss: 2.2535e-04
Epoch 4/5
```

```
64/64 [==============================] - 3s 51ms/step - loss: 2.2613e-04
Epoch 5/5
64/64 [==============================] - 3s 45ms/step - loss: 2.3995e-04
22.30351121308118
```



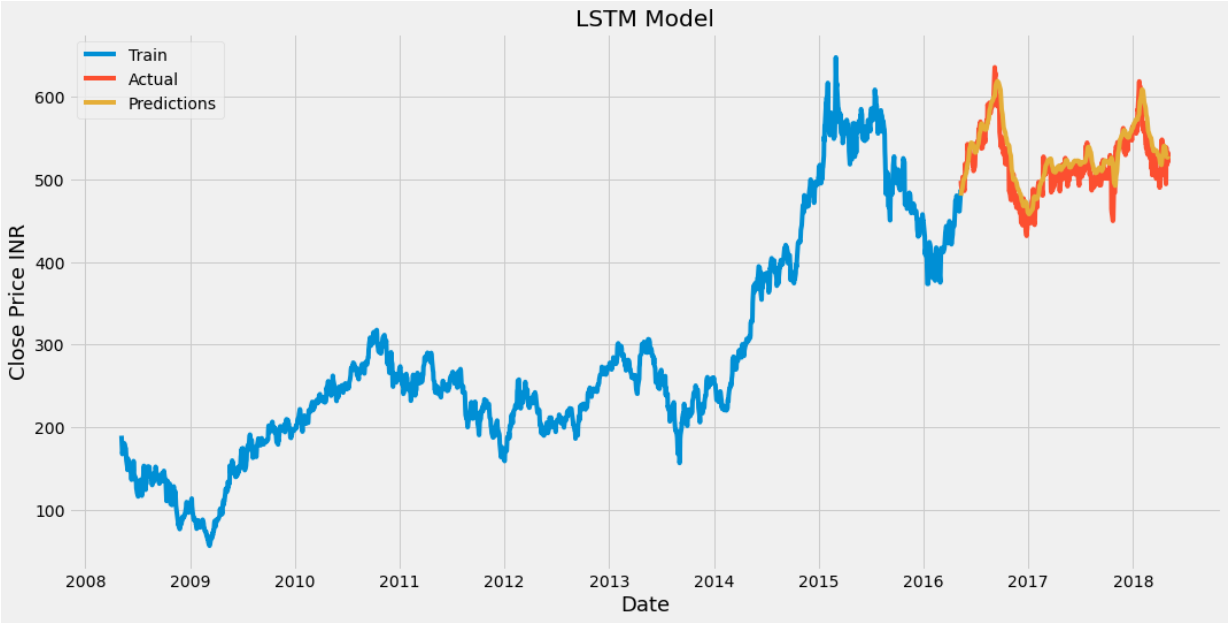

```
Predicted close Stock Price of the next day is
 872.8787231445312,Actual is 907.400024
```

```
Stock Name: AXISBANK
```



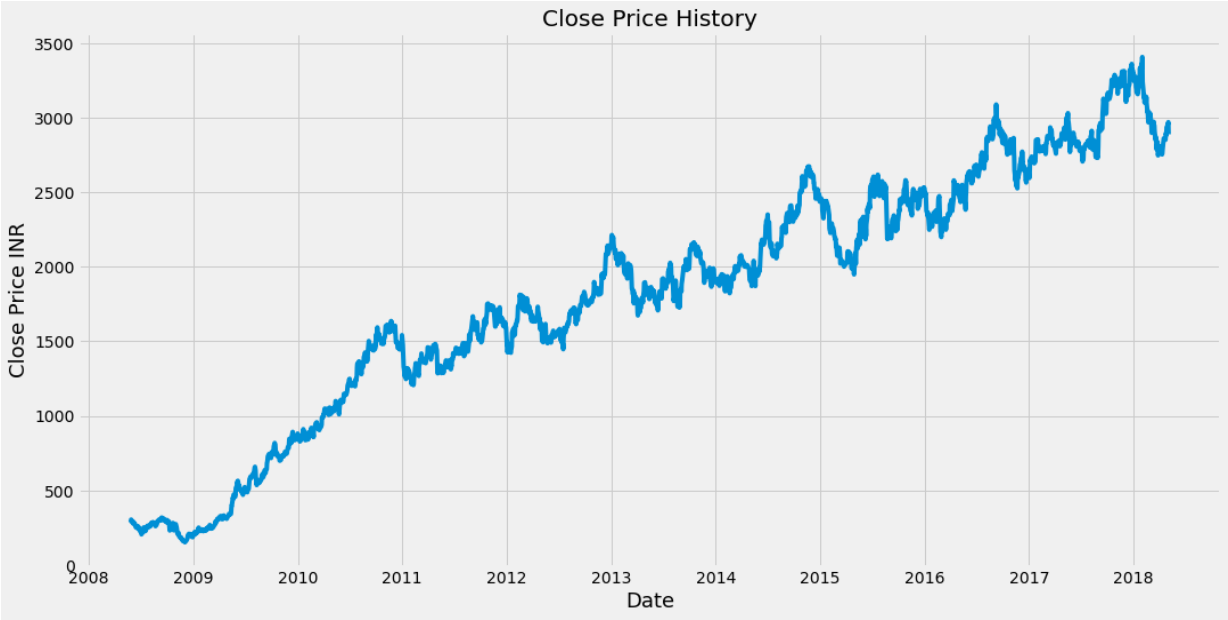

```
Epoch 1/5
64/64 [==============================] - 6s 41ms/step - loss: 0.0083
Epoch 2/5
64/64 [==============================] - 3s 44ms/step - loss: 6.3966e-04
Epoch 3/5
64/64 [==============================] - 3s 46ms/step - loss: 6.0916e-04
Epoch 4/5
64/64 [==============================] - 3s 46ms/step - loss: 6.2290e-04
Epoch 5/5
```

```
64/64 [==============================] - 3s 45ms/step - loss: 5.5983e-04
11.27795094089018
```



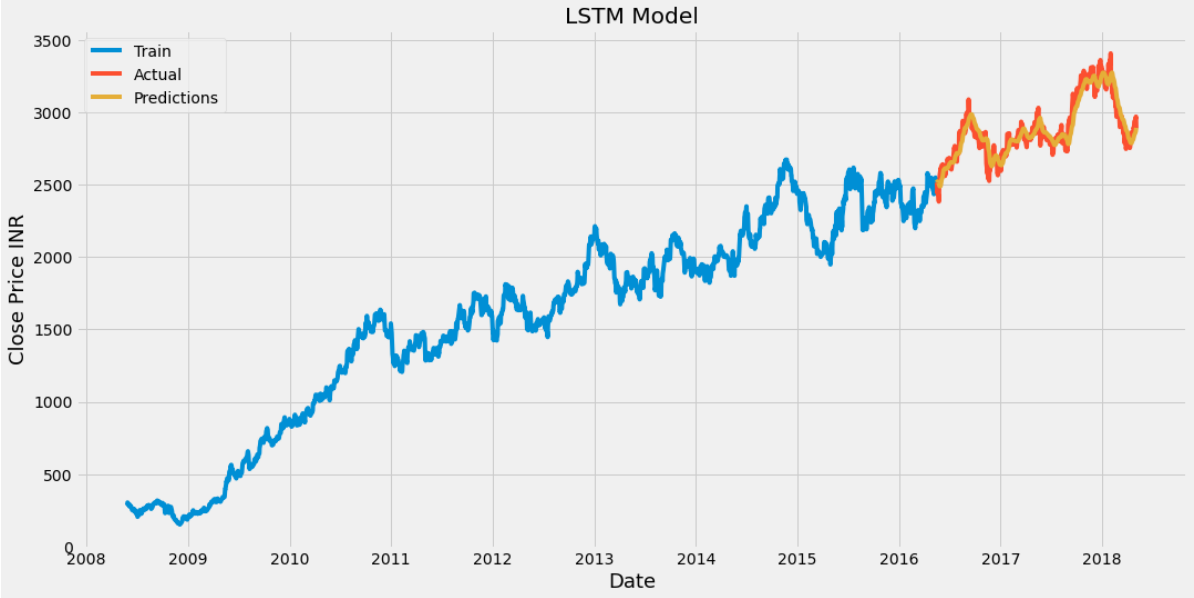

```
Predicted close Stock Price of the next day is
 480.4407958984375,Actual is 498.399994
```

```
Stock Name: BAJAJ-AUTO
```

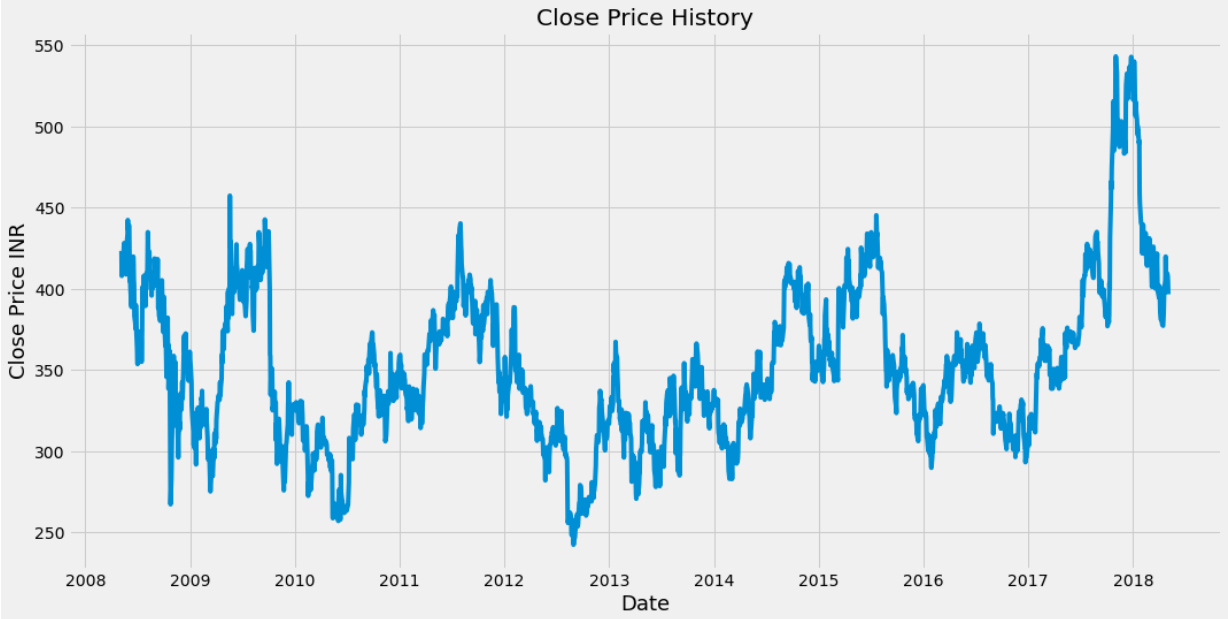



```
Epoch 1/5
64/64 [==============================] - 5s 43ms/step - loss: 0.0180
Epoch 2/5
64/64 [==============================] - 3s 47ms/step - loss: 4.1476e-04
Epoch 3/5
64/64 [==============================] - 3s 47ms/step - loss: 3.9011e-04
Epoch 4/5
64/64 [==============================] - 3s 45ms/step - loss: 3.9963e-04
Epoch 5/5
```

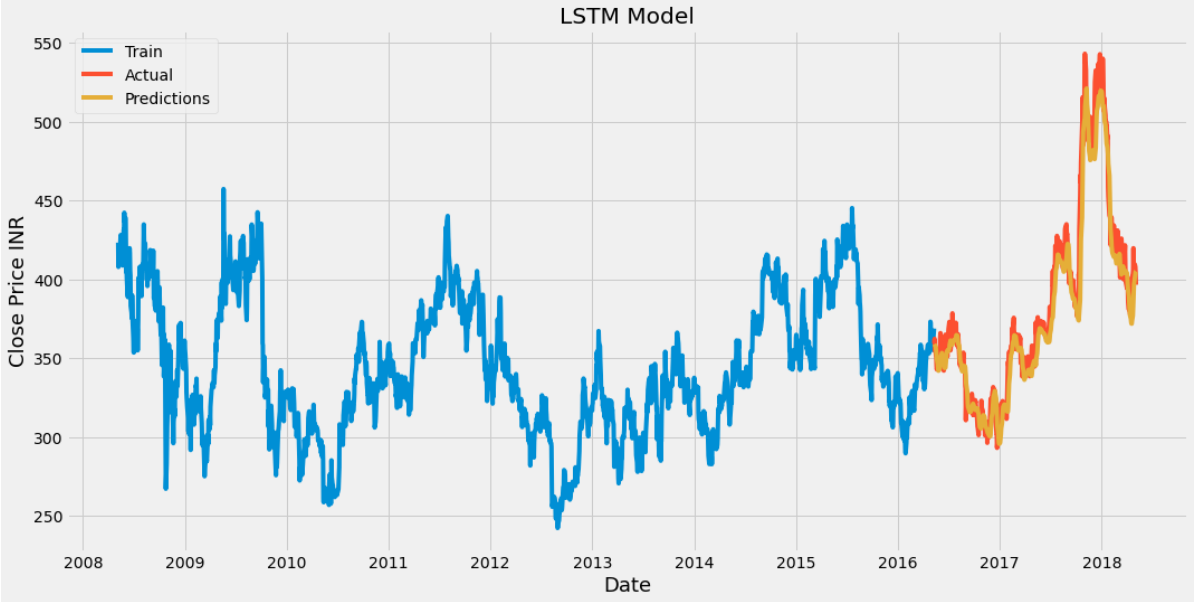
```
64/64 [==============================] - 3s 46ms/step - loss: 3.7460e-04
```




```
Predicted close Stock Price of the next day is
 2517.074462890625,Actual is 2518.600098

Stock Name: BHARTIARTL
```

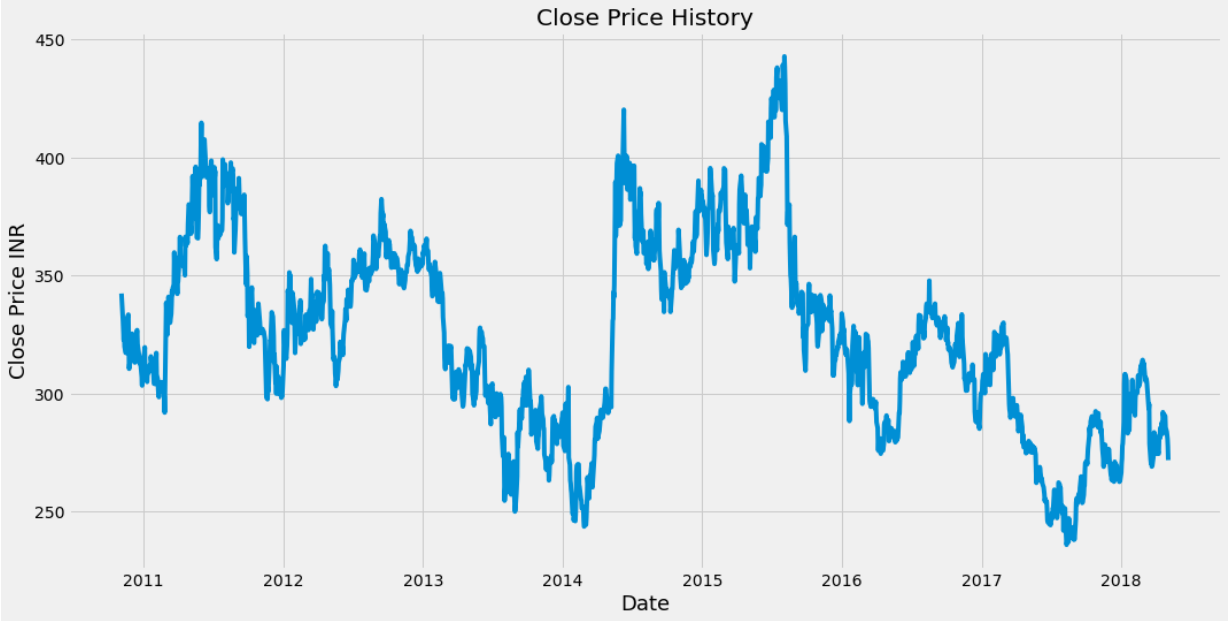



```
Epoch 1/5
64/64 [==============================] - 5s 44ms/step - loss: 0.0109
Epoch 2/5
64/64 [==============================] - 3s 47ms/step - loss: 0.0024
Epoch 3/5
64/64 [==============================] - 3s 44ms/step - loss: 0.0020
Epoch 4/5
64/64 [==============================] - 3s 46ms/step - loss: 0.0018
Epoch 5/5
64/64 [==============================] - 3s 50ms/step - loss: 0.0017
6.179609909576663
```

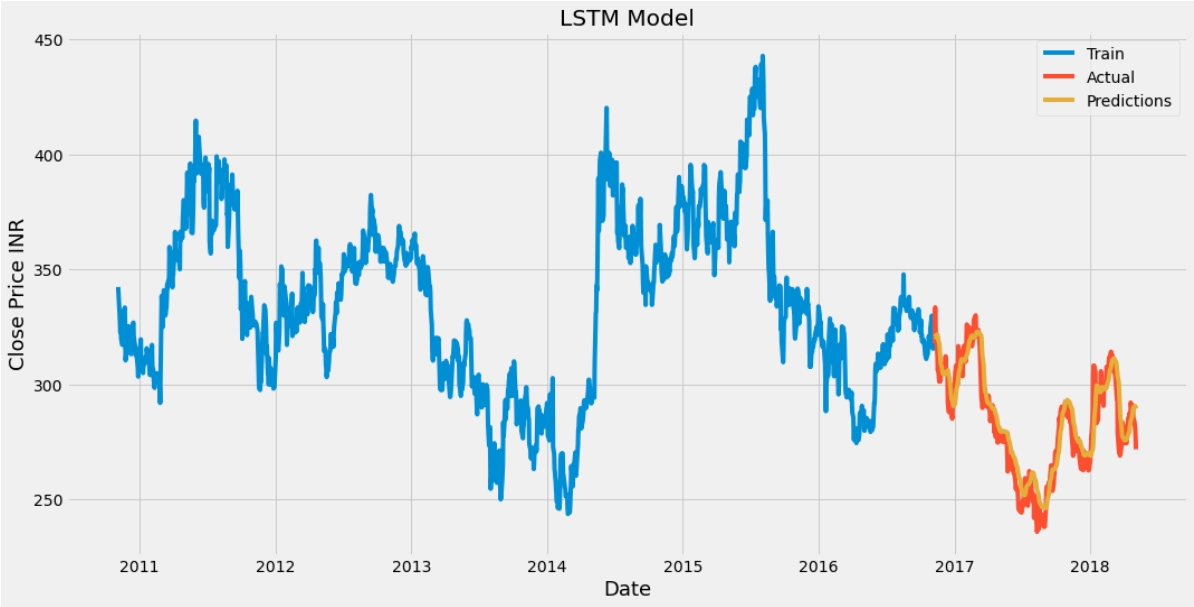



```
Predicted close Stock Price of the next day is
 358.9405517578125,Actual is 359.450012
```

```
Stock Name: COALINDIA
```

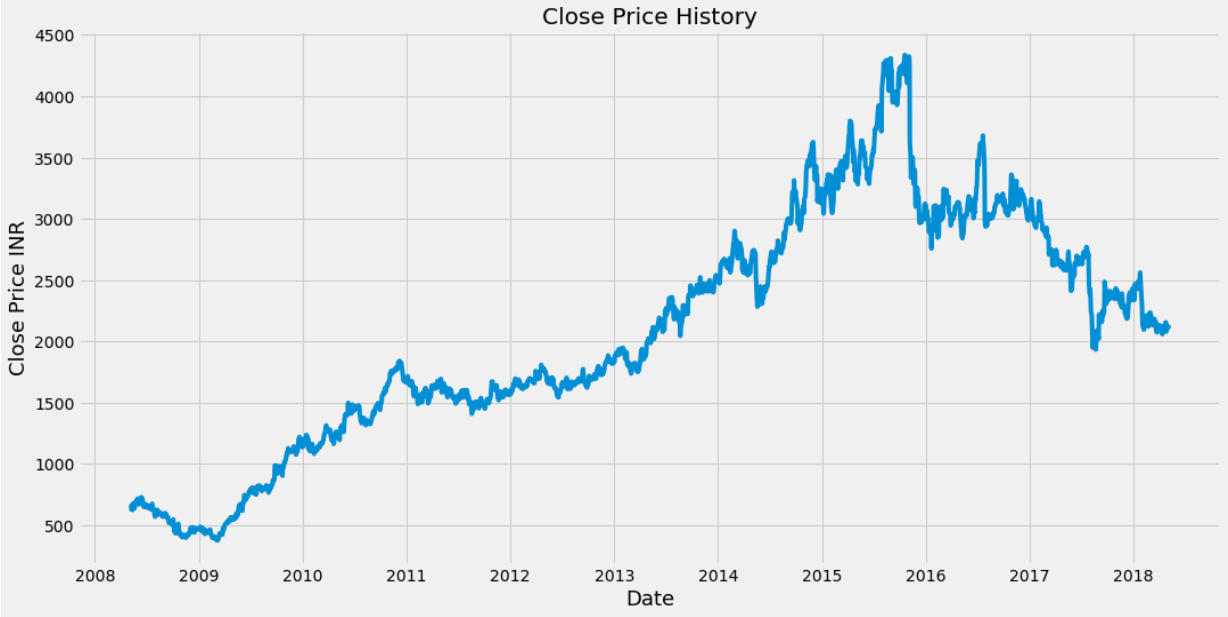



```
Epoch 1/5
48/48 [==============================] - 5s 45ms/step - loss: 0.0312
Epoch 2/5
48/48 [==============================] - 2s 48ms/step - loss: 0.0043
Epoch 3/5
48/48 [==============================] - 2s 47ms/step - loss: 0.0038
Epoch 4/5
48/48 [==============================] - 2s 48ms/step - loss: 0.0034
Epoch 5/5
48/48 [==============================] - 2s 47ms/step - loss: 0.0034
2.7591184757262024
```



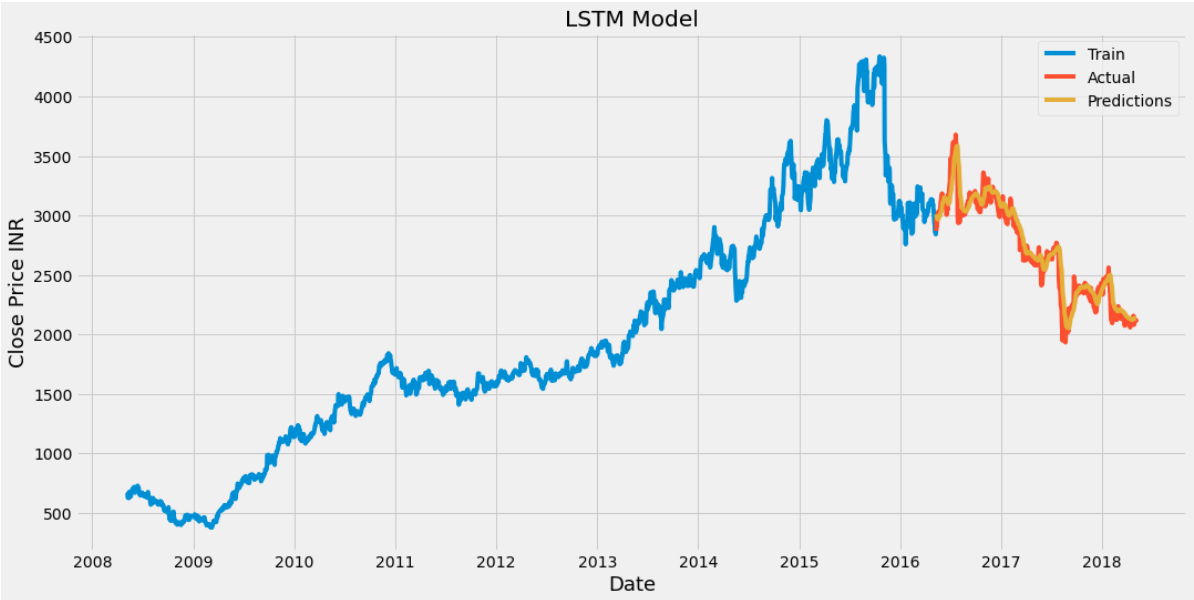

```
Predicted close Stock Price of the next day is
 320.72613525390625,Actual is 317.899994
```

```
Stock Name: DRREDDY
```

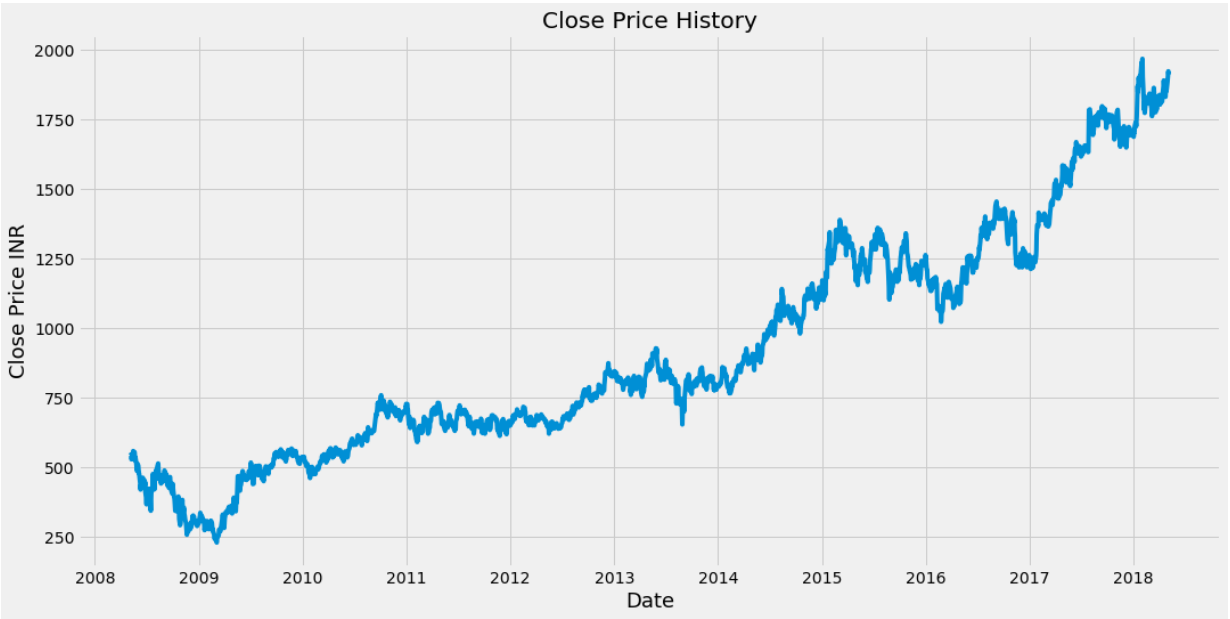



```
Epoch 1/5
64/64 [==============================] - 5s 46ms/step - loss: 0.0136: 0s
Epoch 2/5
64/64 [==============================] - 3s 48ms/step - loss: 5.6016e-04
Epoch 3/5
64/64 [==============================] - 3s 43ms/step - loss: 5.2340e-04
Epoch 4/5
```

```
64/64 [==============================] - 3s 45ms/step - loss: 5.6137e-04
Epoch 5/5
64/64 [==============================] - 3s 47ms/step - loss: 5.3400e-04
31.494602864932666
```

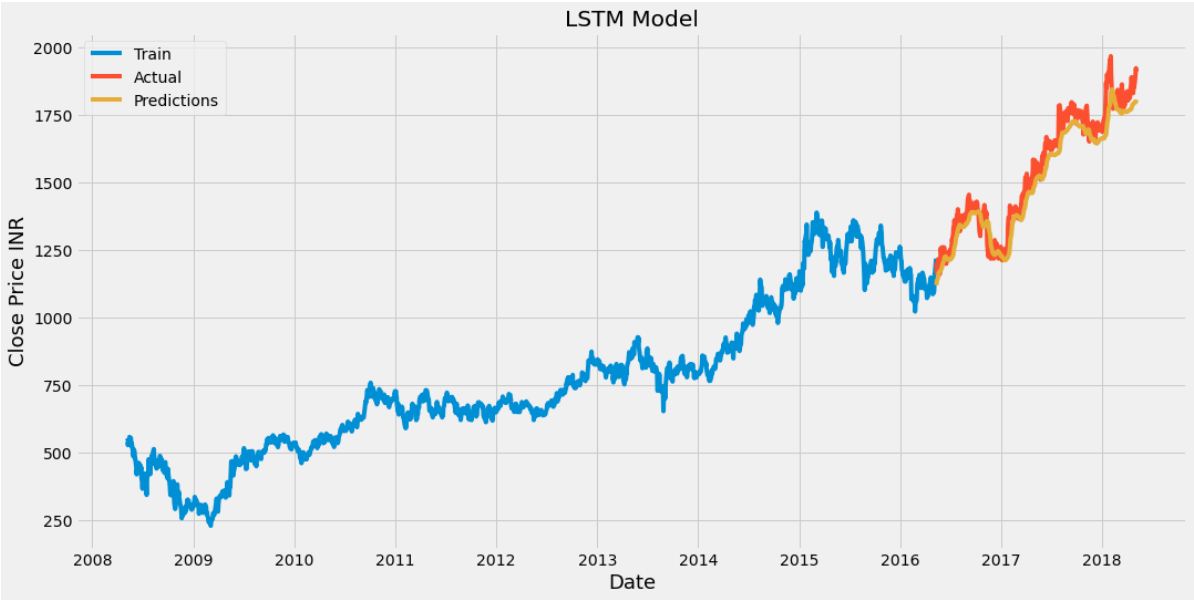



```
Predicted close Stock Price of the next day is
 3009.2451171875,Actual is 2869.199951

Stock Name: HDFC
```



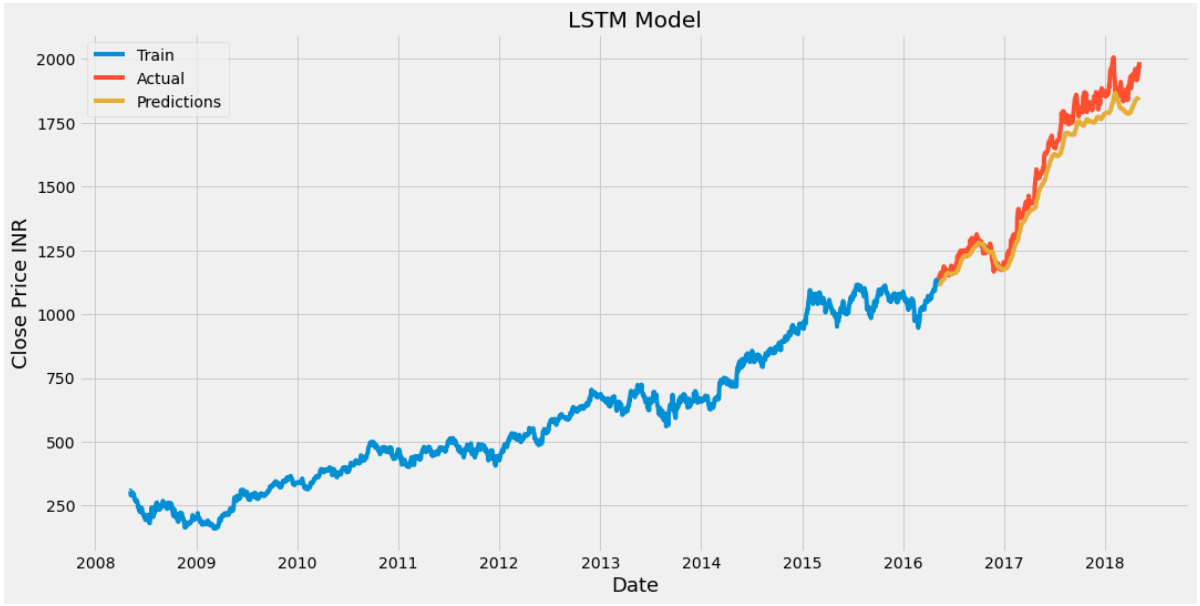

```
Epoch 1/5
```

```
64/64 [==============================] - 5s 43ms/step - loss: 0.0083
Epoch 2/5
64/64 [==============================] - 3s 46ms/step - loss: 3.3615e-04
Epoch 3/5
64/64 [==============================] - 3s 47ms/step - loss: 3.3260e-04
Epoch 4/5
64/64 [==============================] - 3s 47ms/step - loss: 3.2002e-04
Epoch 5/5
64/64 [==============================] - 3s 46ms/step - loss: 3.3092e-04
40.74575061860073
```



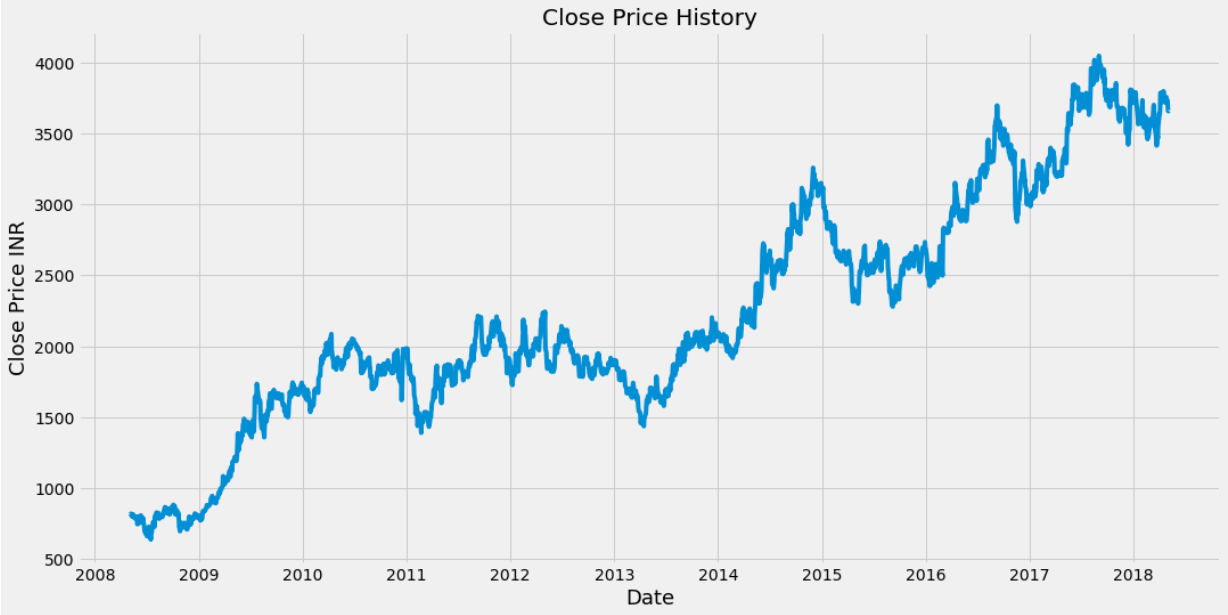

```
Predicted close Stock Price of the next day is
 1120.618408203125,Actual is 1203.650024


Stock Name: HDFCBANK
```


```
Epoch 1/5
64/64 [==============================] - 6s 45ms/step - loss: 0.0042: 0s - lo
Epoch 2/5
64/64 [==============================] - 3s 49ms/step - loss: 1.3689e-04
Epoch 3/5
64/64 [==============================] - 3s 51ms/step - loss: 1.2604e-04
Epoch 4/5
64/64 [==============================] - 3s 48ms/step - loss: 1.2567e-04
Epoch 5/5
64/64 [==============================] - 3s 49ms/step - loss: 1.2028e-04:
52.122500042381226
```

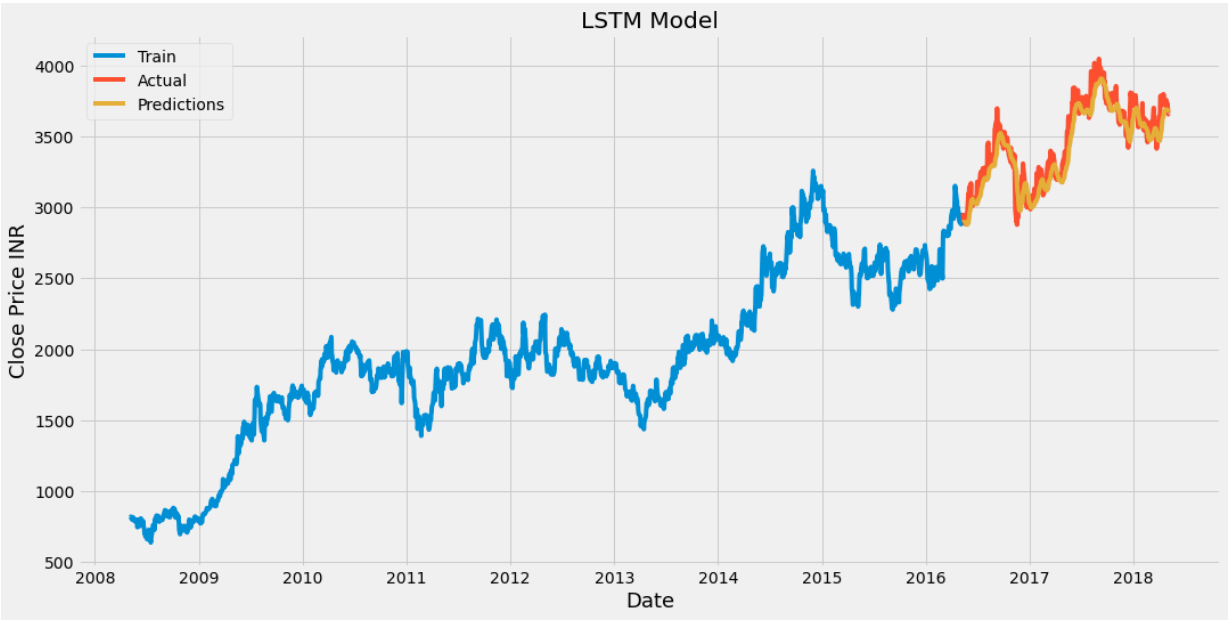



```
Predicted close Stock Price of the next day is
 1110.8172607421875,Actual is 1138.0
```

Stock Name: HEROMOTOCO

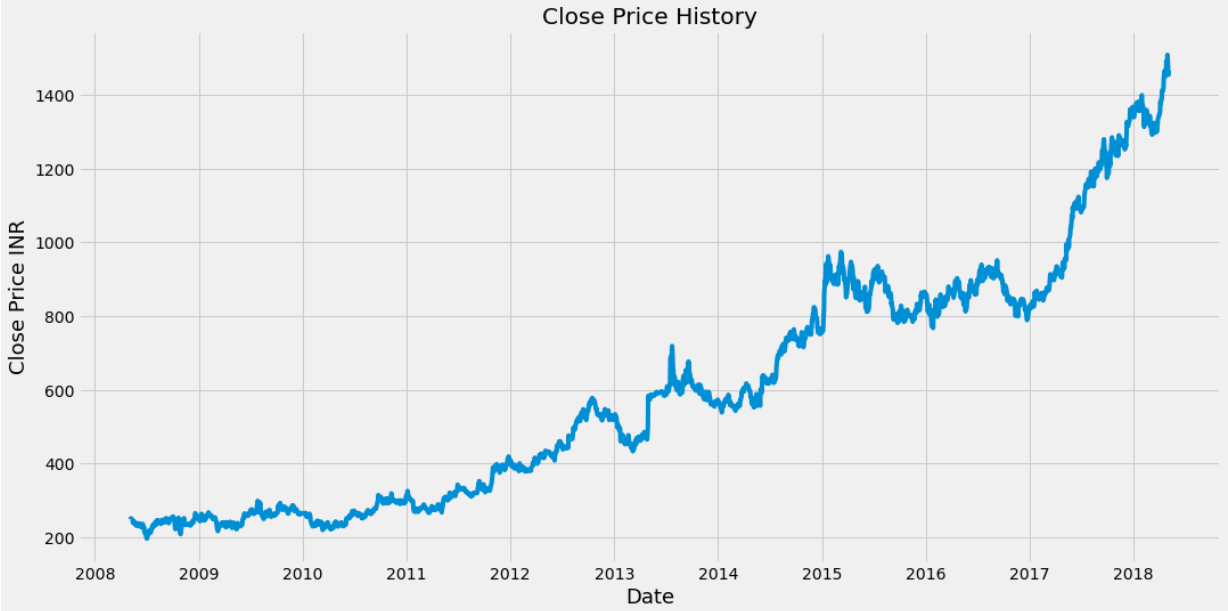



```
Epoch 1/5
64/64 [==============================] - 5s 45ms/step - loss: 0.0083
Epoch 2/5
64/64 [==============================] - 3s 48ms/step - loss: 5.8332e-04
Epoch 3/5
64/64 [==============================] - 3s 46ms/step - loss: 5.5444e-04
Epoch 4/5
64/64 [==============================] - 3s 48ms/step - loss: 5.3869e-04
Epoch 5/5
64/64 [==============================] - 3s 46ms/step - loss: 4.9776e-04
54.582212385607214
```




```
Predicted close Stock Price of the next day is
 2893.832275390625,Actual is 2960.649902
```

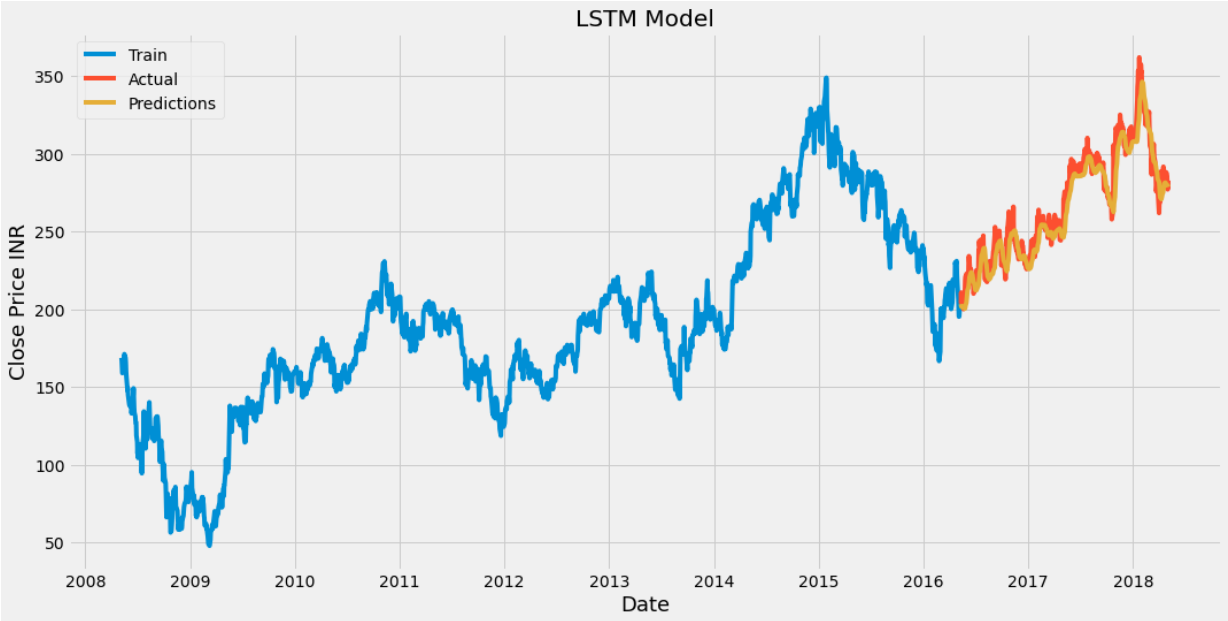
Stock Name: HINDUNILVR




```
Epoch 1/5
64/64 [==============================] - 5s 43ms/step - loss: 0.0036: 1s
Epoch 2/5
64/64 [==============================] - 3s 44ms/step - loss: 2.4326e-04
Epoch 3/5
64/64 [==============================] - 3s 44ms/step - loss: 2.3883e-04
Epoch 4/5
64/64 [==============================] - 3s 45ms/step - loss: 2.1837e-04
Epoch 5/5
64/64 [==============================] - 3s 41ms/step - loss: 2.0268e-04
0.1934227750015881
```

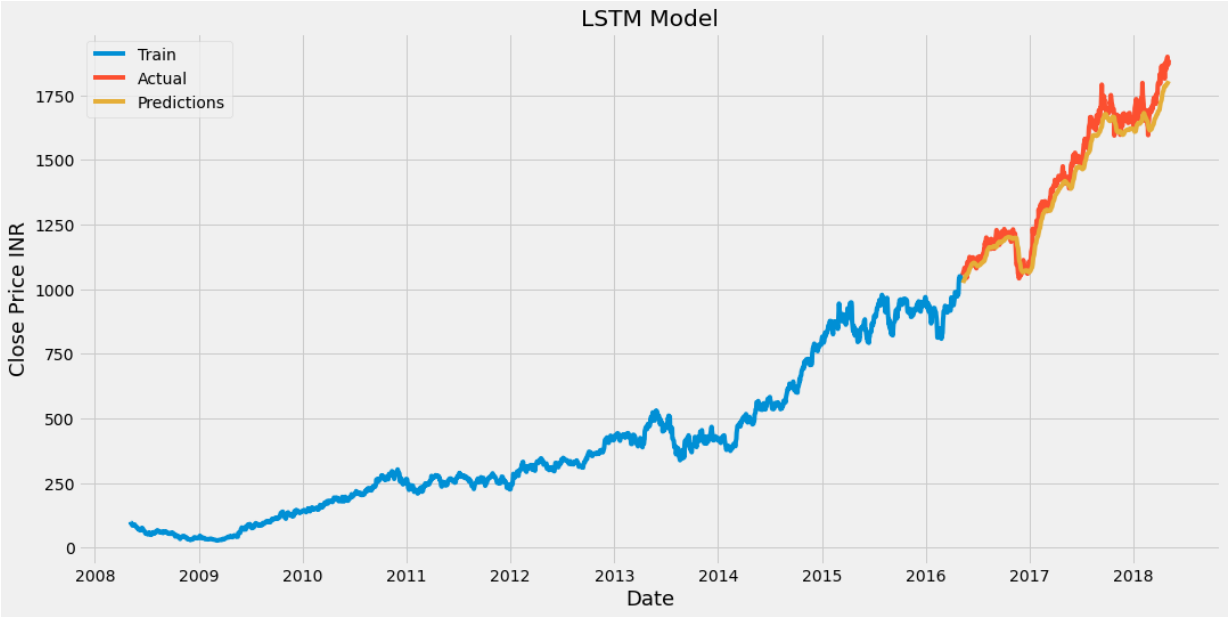

```
Predicted close Stock Price of the next day is
 880.9915161132812,Actual is 862.700012


Stock Name: ICICIBANK
```


```
Epoch 1/5
64/64 [==============================] - 5s 48ms/step - loss: 0.0082
Epoch 2/5
64/64 [==============================] - 3s 48ms/step - loss: 8.3572e-04
Epoch 3/5
64/64 [==============================] - 3s 48ms/step - loss: 8.0524e-04
Epoch 4/5
64/64 [==============================] - 3s 47ms/step - loss: 7.7978e-04
Epoch 5/5
64/64 [==============================] - 3s 48ms/step - loss: 7.6073e-04
5.037314007169399
```



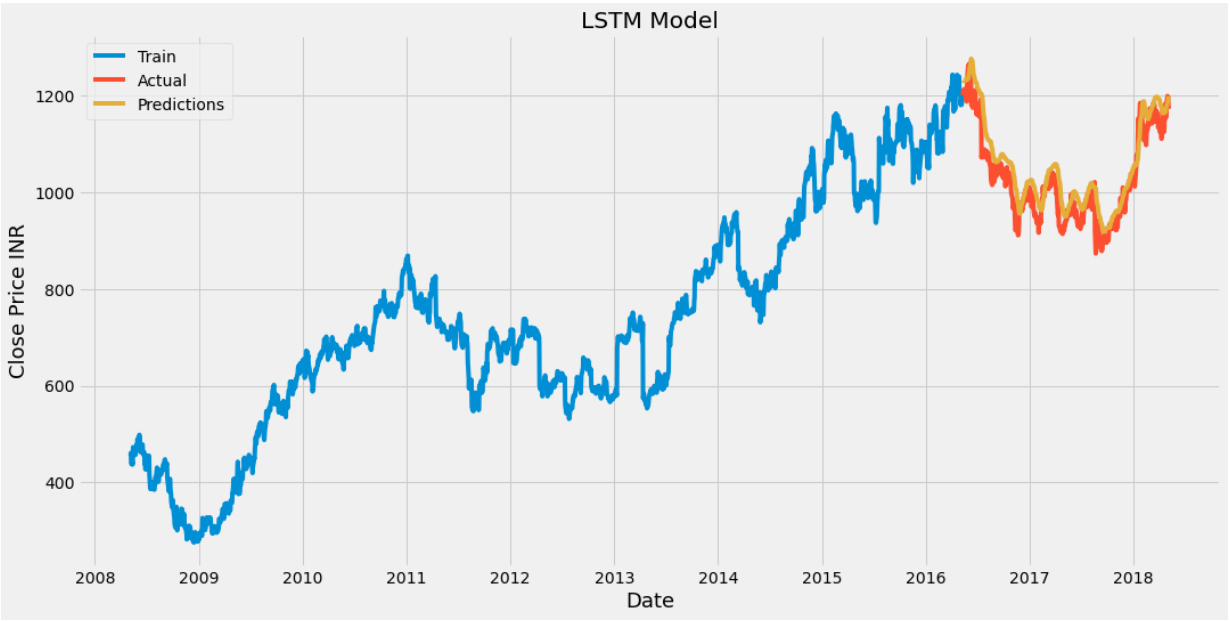

```
Predicted close Stock Price of the next day is
 203.36627197265625,Actual is 203.727005


Stock Name: INDUSINDBK
```


```
Epoch 1/5
64/64 [==============================] - 6s 45ms/step - loss: 0.0020
Epoch 2/5
64/64 [==============================] - 3s 48ms/step - loss: 1.1990e-04
Epoch 3/5
64/64 [==============================] - 3s 46ms/step - loss: 1.1748e-04
Epoch 4/5
64/64 [==============================] - 3s 46ms/step - loss: 1.2367e-04
Epoch 5/5
64/64 [==============================] - 3s 47ms/step - loss: 1.2641e-04
39.44631077223863
```

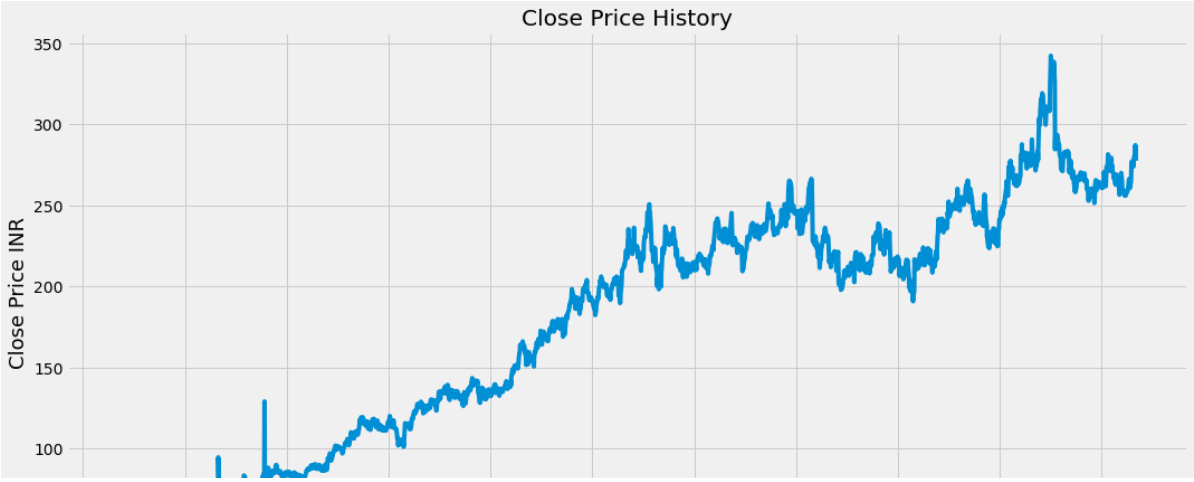



```
Predicted close Stock Price of the next day is
 1023.6333618164062,Actual is 1053.300049


Stock Name: INFY
```

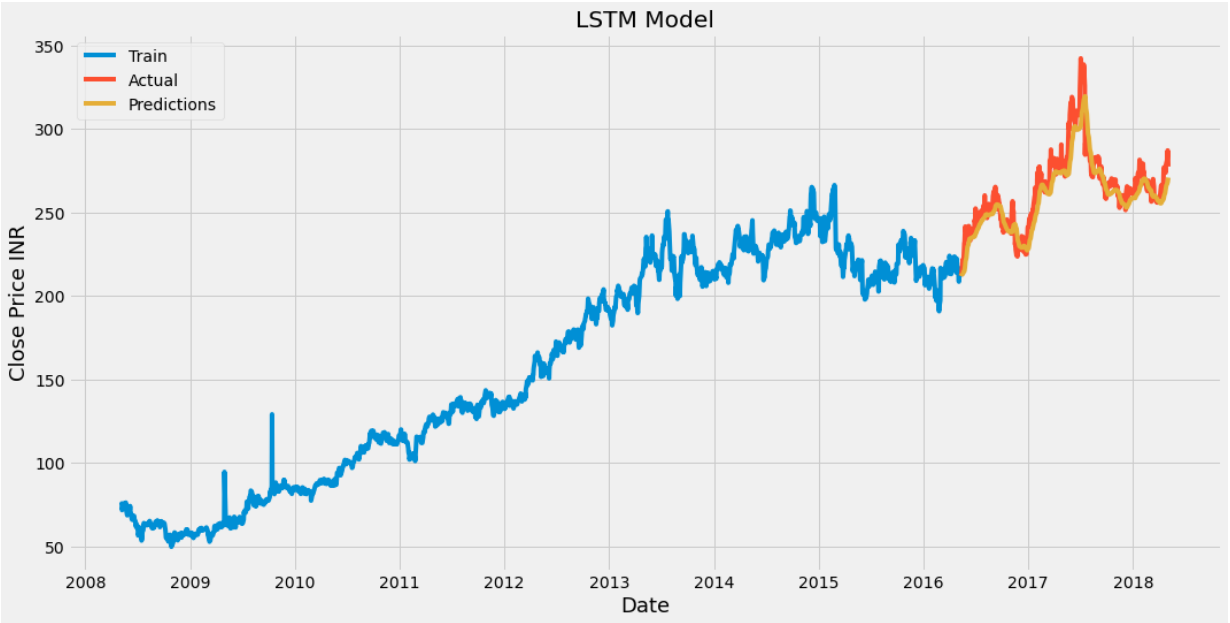

```
Epoch 1/5
64/64 [==============================] - 6s 49ms/step - loss: 0.0140
Epoch 2/5
64/64 [==============================] - 3s 51ms/step - loss: 9.6026e-04
Epoch 3/5
64/64 [==============================] - 3s 49ms/step - loss: 9.1925e-04
Epoch 4/5
64/64 [==============================] - 3s 49ms/step - loss: 8.9559e-04
Epoch 5/5
64/64 [==============================] - 3s 48ms/step - loss: 8.2142e-04
28.000096764545223
```



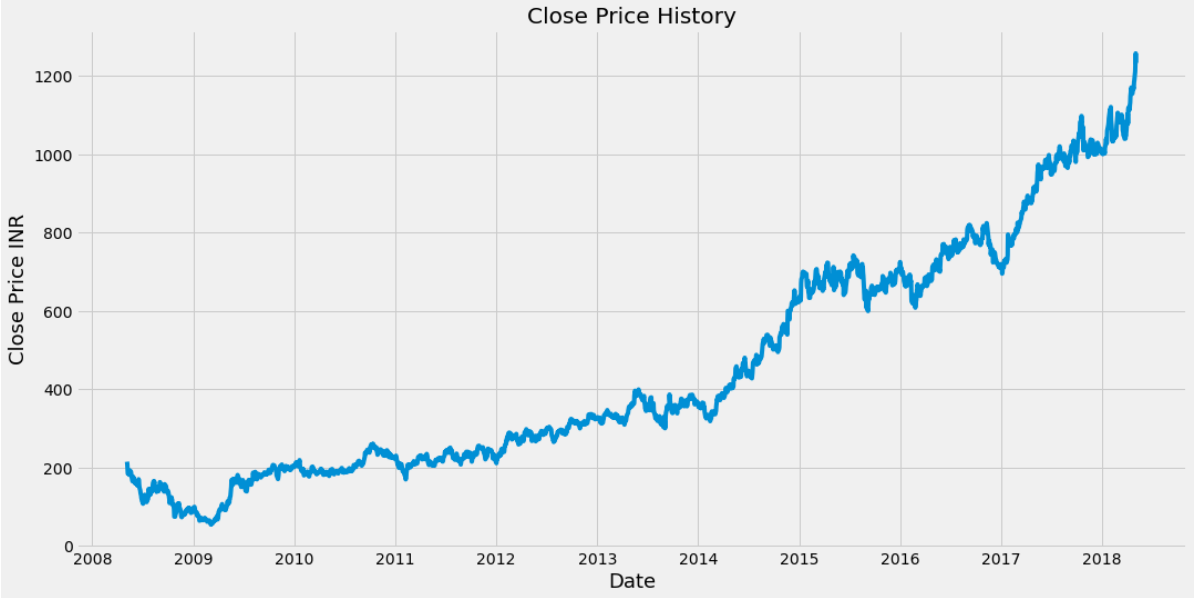

```
Predicted close Stock Price of the next day is
 1232.069091796875,Actual is 1201.050049


Stock Name: ITC
```




```
Epoch 1/5
64/64 [==============================] - 5s 45ms/step - loss: 0.0104
Epoch 2/5
64/64 [==============================] - 3s 45ms/step - loss: 4.3398e-04
Epoch 3/5
64/64 [==============================] - 3s 46ms/step - loss: 4.2439e-04
Epoch 4/5
64/64 [==============================] - 3s 48ms/step - loss: 4.5888e-04
Epoch 5/5
64/64 [==============================] - 3s 44ms/step - loss: 4.3576e-04
4.950621375309642
```

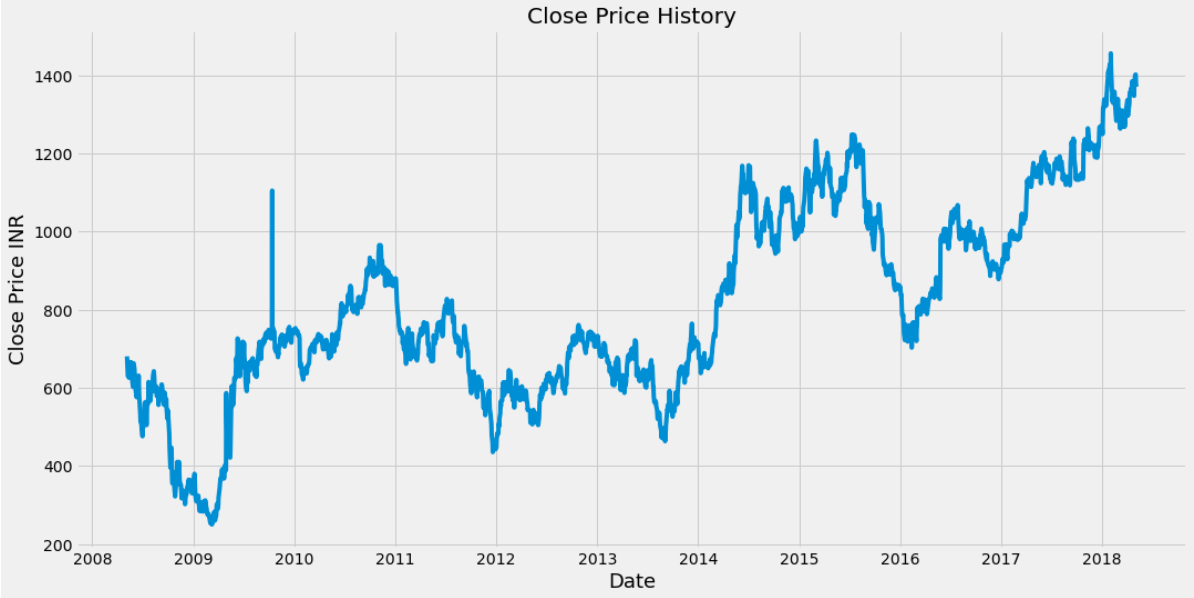



```
Predicted close Stock Price of the next day is
 213.74490356445312,Actual is 212.0


Stock Name: KOTAKBANK
```

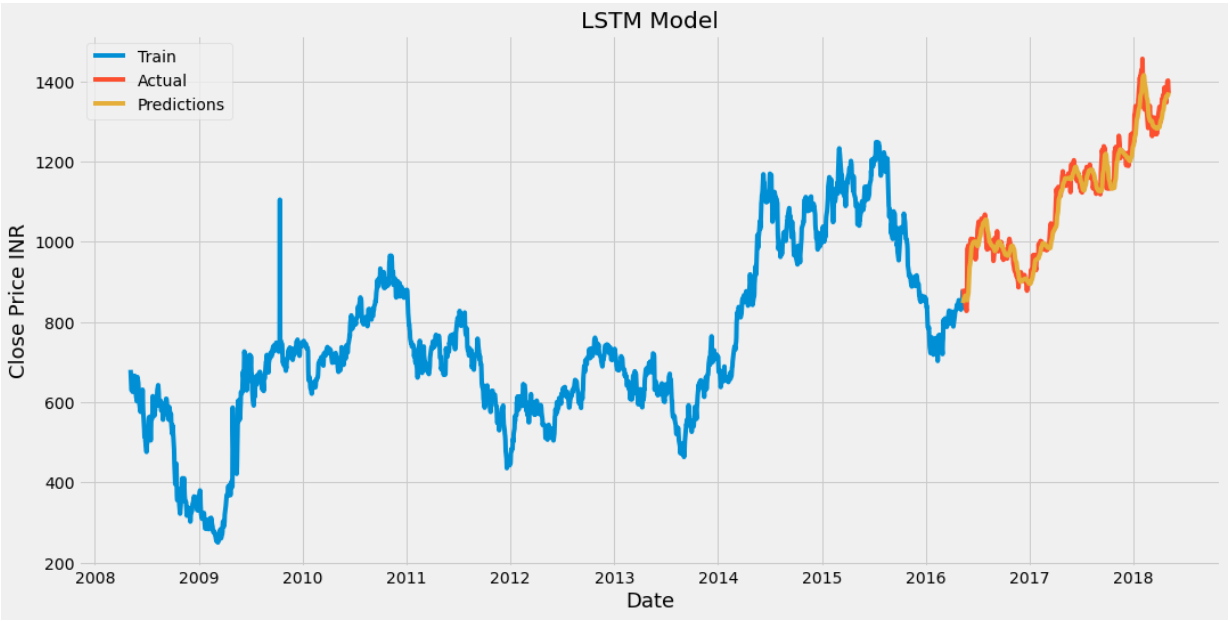



```
Epoch 1/5
64/64 [==============================] - 6s 46ms/step - loss: 0.0044: 0s - los
s: 0.006 - ETA: 0s
Epoch 2/5
64/64 [==============================] - 3s 48ms/step - loss: 1.8001e-04
Epoch 3/5
64/64 [==============================] - 3s 50ms/step - loss: 1.6614e-04
Epoch 4/5
64/64 [==============================] - 3s 48ms/step - loss: 1.5947e-04
Epoch 5/5
64/64 [==============================] - 3s 50ms/step - loss: 1.7974e-04
52.994513670477644
```


```
Predicted close Stock Price of the next day is
 677.8251342773438,Actual is 731.150024


Stock Name: LT
```



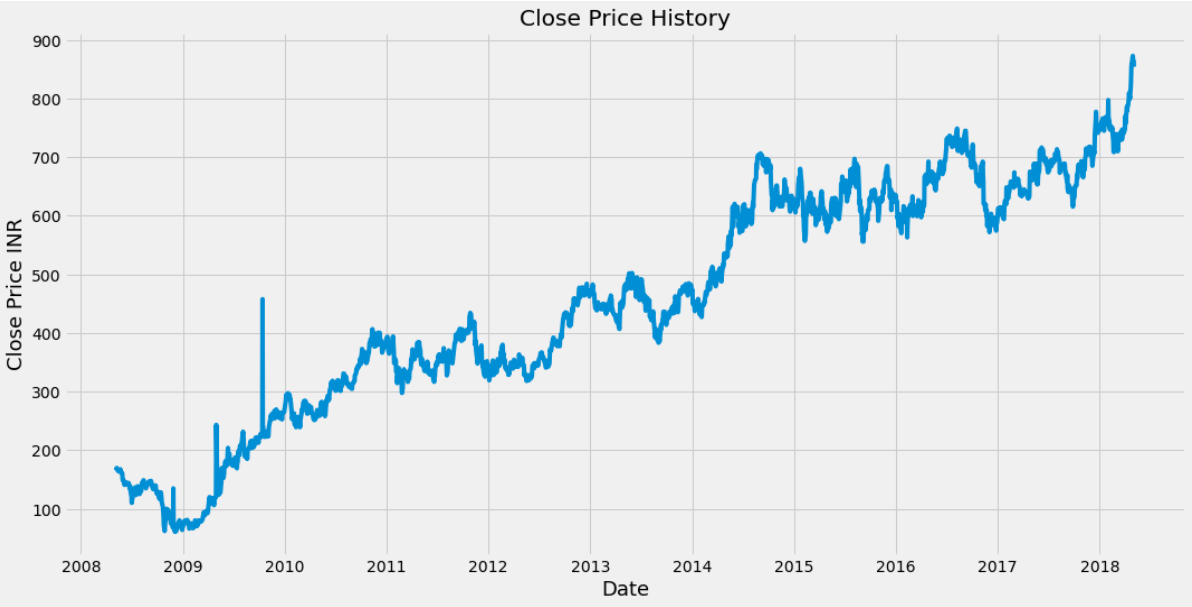

```
Epoch 1/5
64/64 [==============================] - 6s 49ms/step - loss: 0.0112
Epoch 2/5
64/64 [==============================] - 3s 51ms/step - loss: 0.0011
Epoch 3/5
64/64 [==============================] - 3s 51ms/step - loss: 0.0010
Epoch 4/5
64/64 [==============================] - 3s 49ms/step - loss: 9.1120e-04
Epoch 5/5
64/64 [==============================] - 3s 52ms/step - loss: 8.9834e-04
6.990886905019371
```



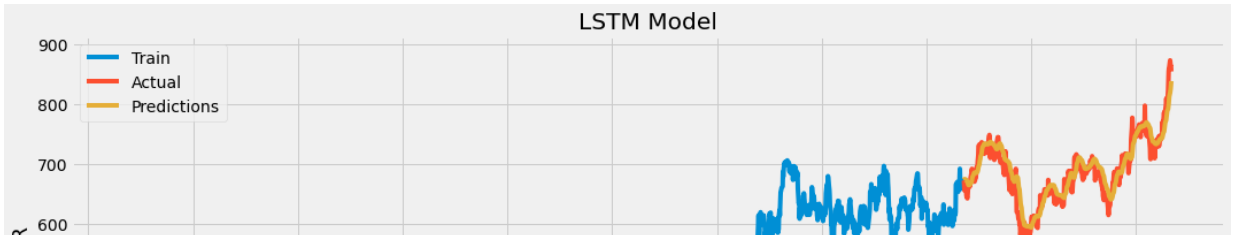

```
Predicted close Stock Price of the next day is
```

846.7249755859375,Actual is 882.666992

Stock Name: M&M



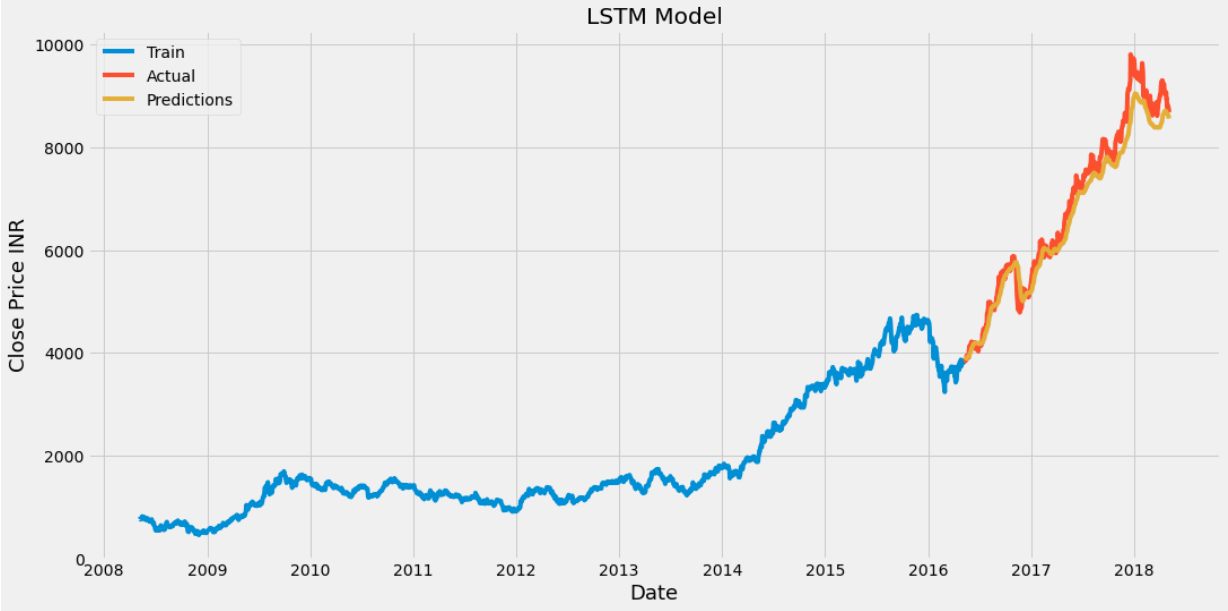

```
Epoch 1/5
64/64 [==============================] - 6s 45ms/step - loss: 0.0177
Epoch 2/5
64/64 [==============================] - 3s 49ms/step - loss: 5.3441e-04
Epoch 3/5
64/64 [==============================] - 3s 46ms/step - loss: 5.3417e-04
Epoch 4/5
64/64 [==============================] - 3s 47ms/step - loss: 5.3343e-04
Epoch 5/5
64/64 [==============================] - 3s 47ms/step - loss: 5.1195e-04
4.088627514124428
```




```
Predicted close Stock Price of the next day is
 673.84033203125,Actual is 673.075012
```

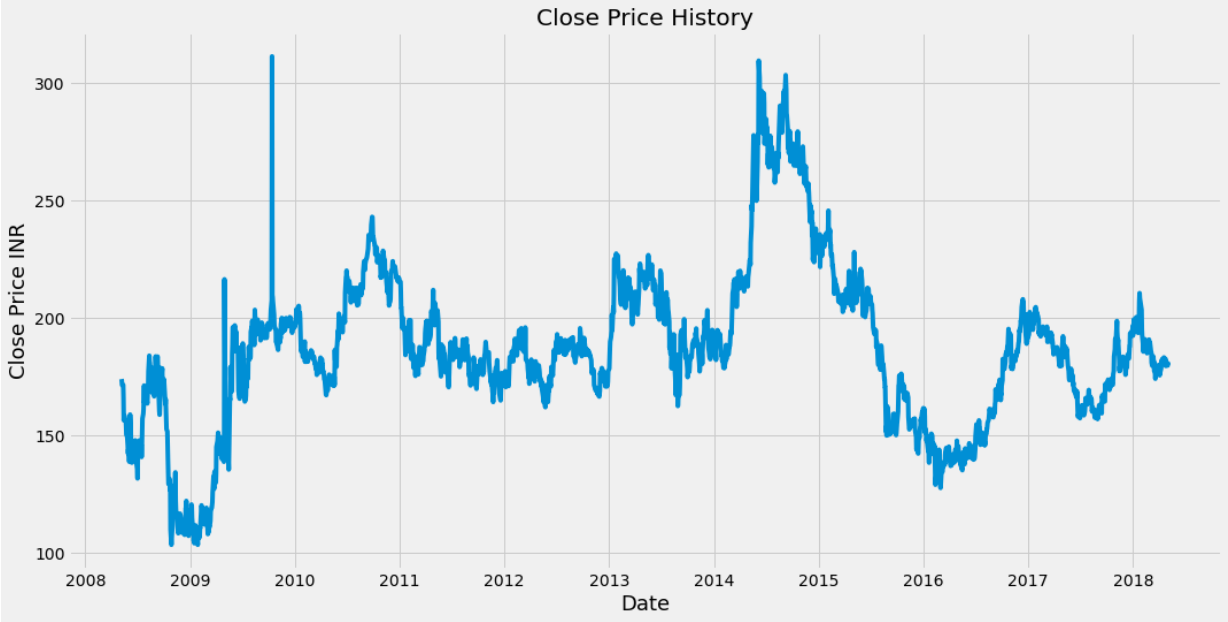
```
Stock Name: MARUTI
```


```
Epoch 1/5
64/64 [==============================] - 5s 41ms/step - loss: 0.0025
Epoch 2/5
64/64 [==============================] - 3s 46ms/step - loss: 1.0008e-04
Epoch 3/5
64/64 [==============================] - 3s 42ms/step - loss: 9.3028e-05
Epoch 4/5
64/64 [==============================] - 3s 46ms/step - loss: 9.3900e-05
Epoch 5/5
64/64 [==============================] - 3s 42ms/step - loss: 9.7123e-05
215.90841799583967
```

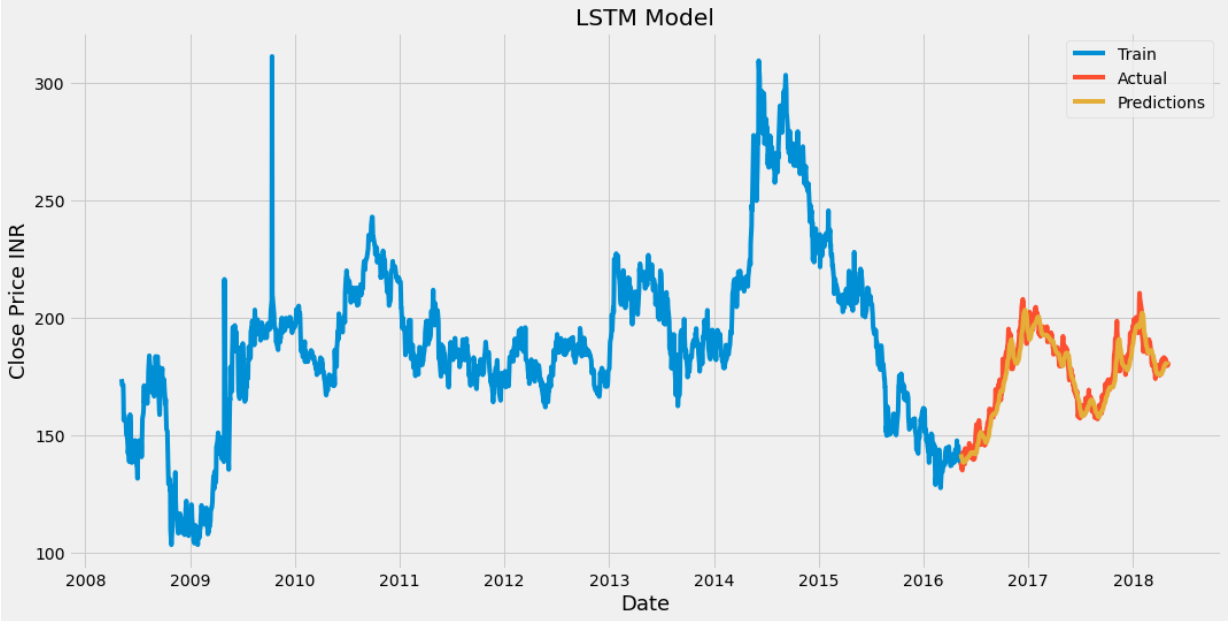


Predicted close Stock Price of the next day is
3862.08837890625,Actual is 3889.850098

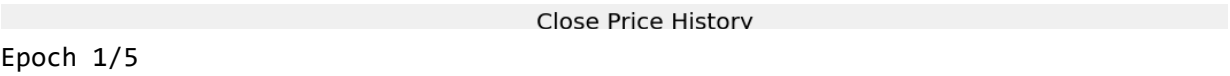
Stock Name: ONGC



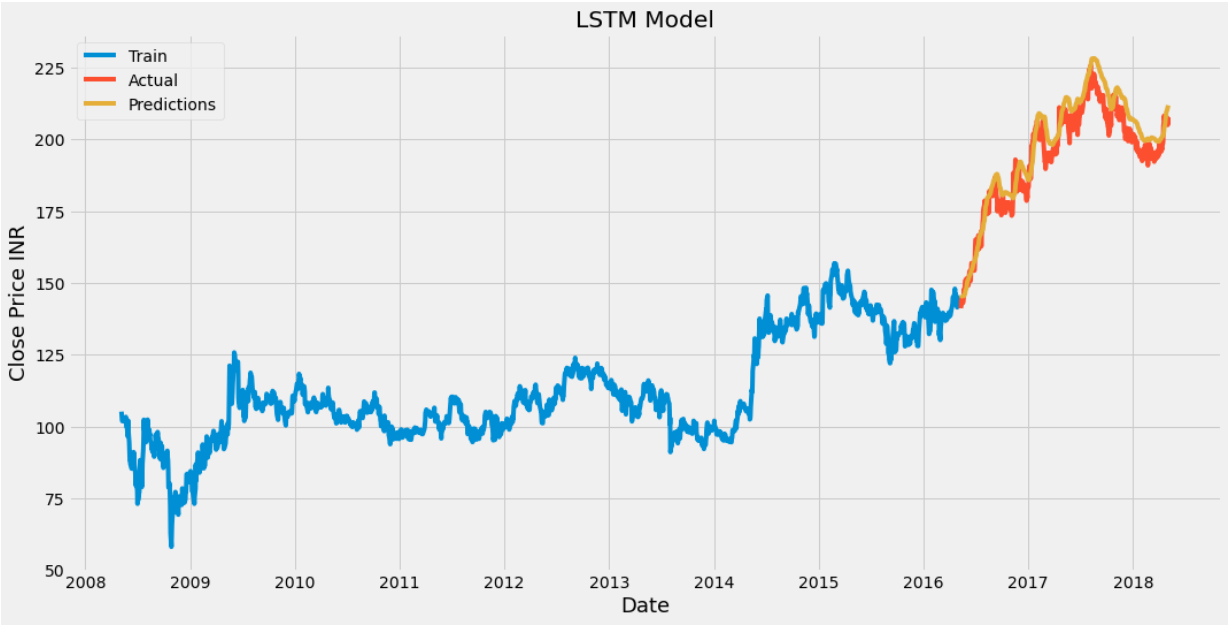
```
Epoch 1/5
64/64 [==============================] - 5s 45ms/step - loss: 0.0115
Epoch 2/5
64/64 [==============================] - 3s 47ms/step - loss: 0.0020
Epoch 3/5
64/64 [==============================] - 3s 48ms/step - loss: 0.0018
Epoch 4/5
64/64 [==============================] - 3s 49ms/step - loss: 0.0016
Epoch 5/5
64/64 [==============================] - 3s 46ms/step - loss: 0.0016
1.4907529301221891
```



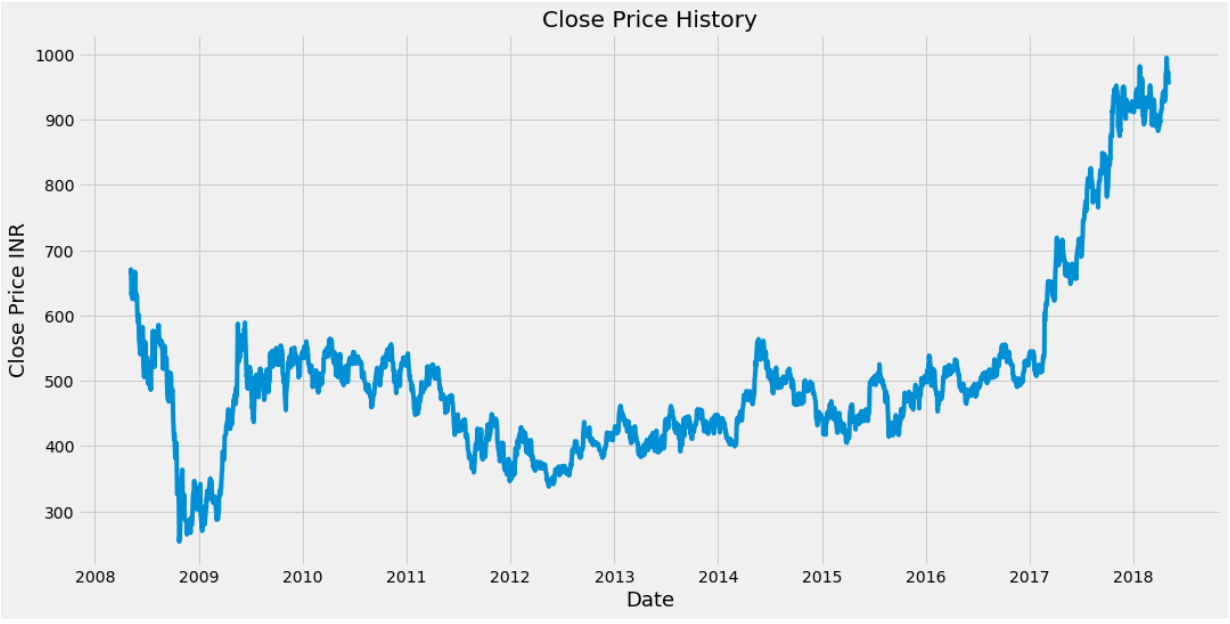

```
Predicted close Stock Price of the next day is
 142.05758666992188,Actual is 137.100006


Stock Name: POWERGRID
```




```
Epoch 1/5
64/64 [==============================] - 6s 48ms/step - loss: 0.0091
Epoch 2/5
64/64 [==============================] - 3s 52ms/step - loss: 5.5101e-04
Epoch 3/5
64/64 [==============================] - 4s 57ms/step - loss: 5.2287e-04
Epoch 4/5
64/64 [==============================] - 3s 52ms/step - loss: 5.0987e-04
Epoch 5/5
64/64 [==============================] - 3s 53ms/step - loss: 4.9237e-04
4.058662598529598
```

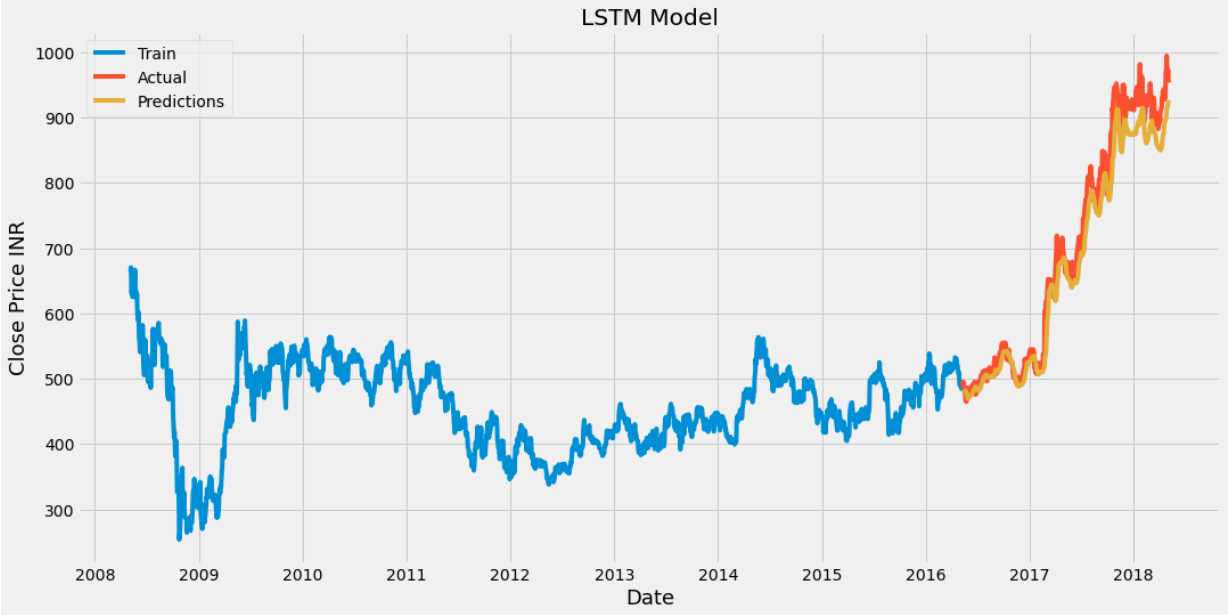



```
Predicted close Stock Price of the next day is
 145.8404998779297,Actual is 141.149994


Stock Name: RELIANCE
```



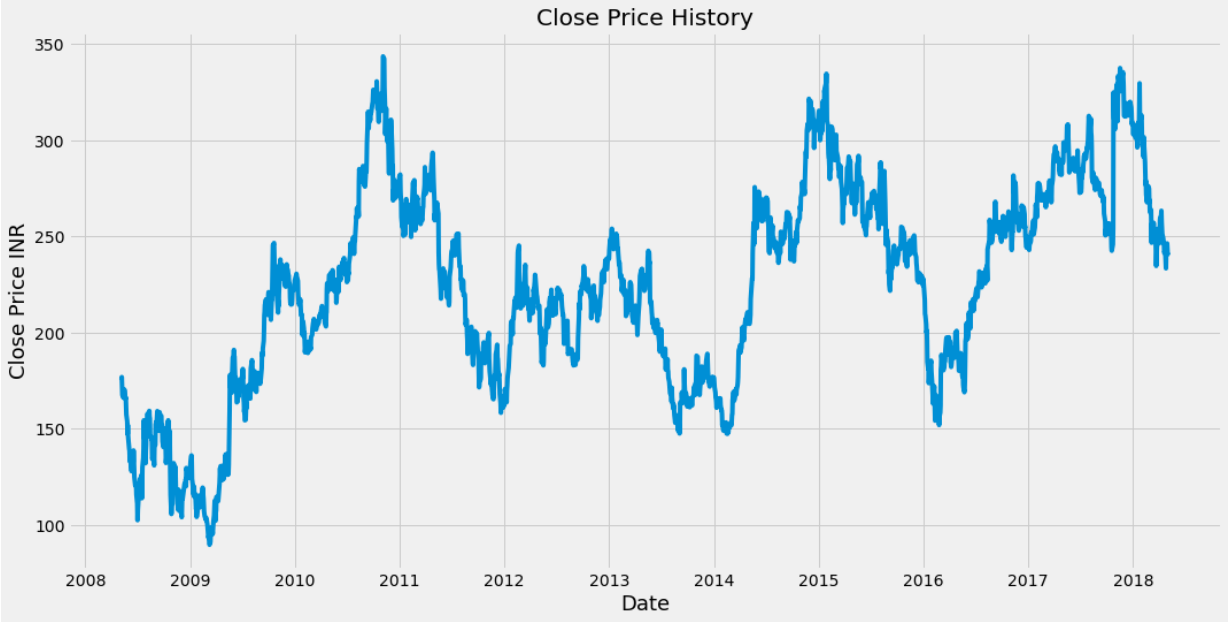

```
Epoch 1/5
```

```
64/64 [==============================] - 6s 47ms/step - loss: 0.0036
Epoch 2/5
64/64 [==============================] - 3s 50ms/step - loss: 6.9041e-04
Epoch 3/5
64/64 [==============================] - 3s 51ms/step - loss: 6.2690e-04
Epoch 4/5
64/64 [==============================] - 3s 50ms/step - loss: 5.5981e-04
Epoch 5/5
64/64 [==============================] - 3s 48ms/step - loss: 5.5393e-04
24.094891501036106
```



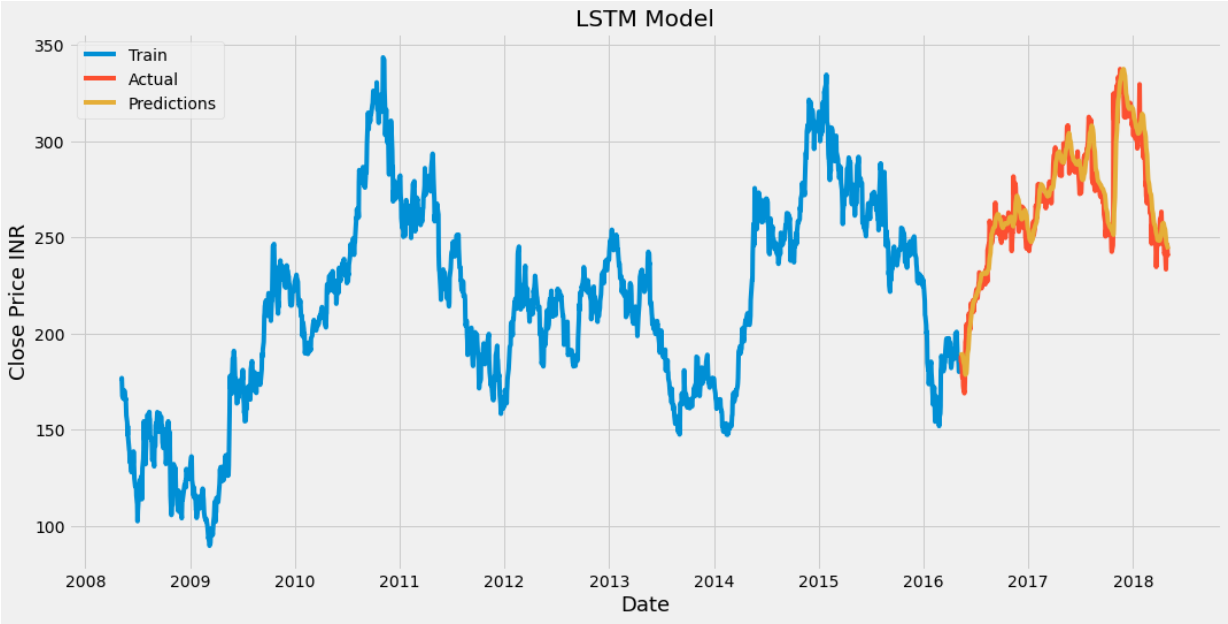

```
Predicted close Stock Price of the next day is
 483.5892028808594,Actual is 487.424988
```

```
Stock Name: SBIN
```



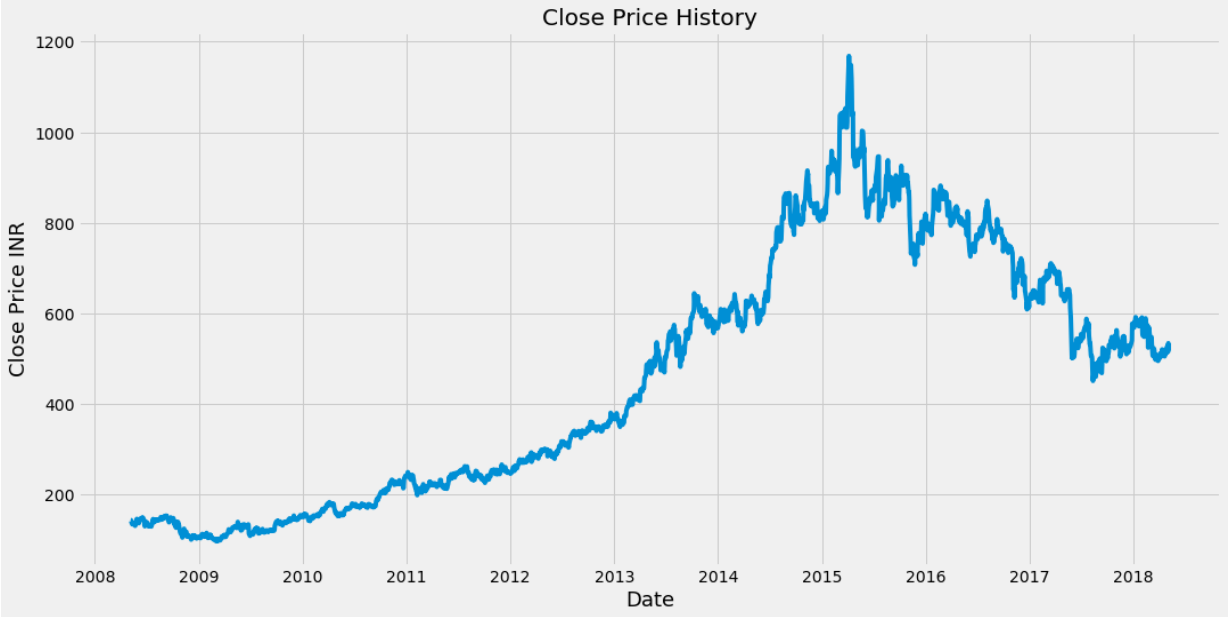

```
Epoch 1/5
64/64 [==============================] - 5s 44ms/step - loss: 0.0202
Epoch 2/5
```

```
64/64 [==============================] - 3s 45ms/step - loss: 0.0022
Epoch 3/5
64/64 [==============================] - 3s 44ms/step - loss: 0.0020
Epoch 4/5
64/64 [==============================] - 3s 45ms/step - loss: 0.0018
Epoch 5/5
64/64 [==============================] - 3s 47ms/step - loss: 0.0016
1.7796645333817651
```



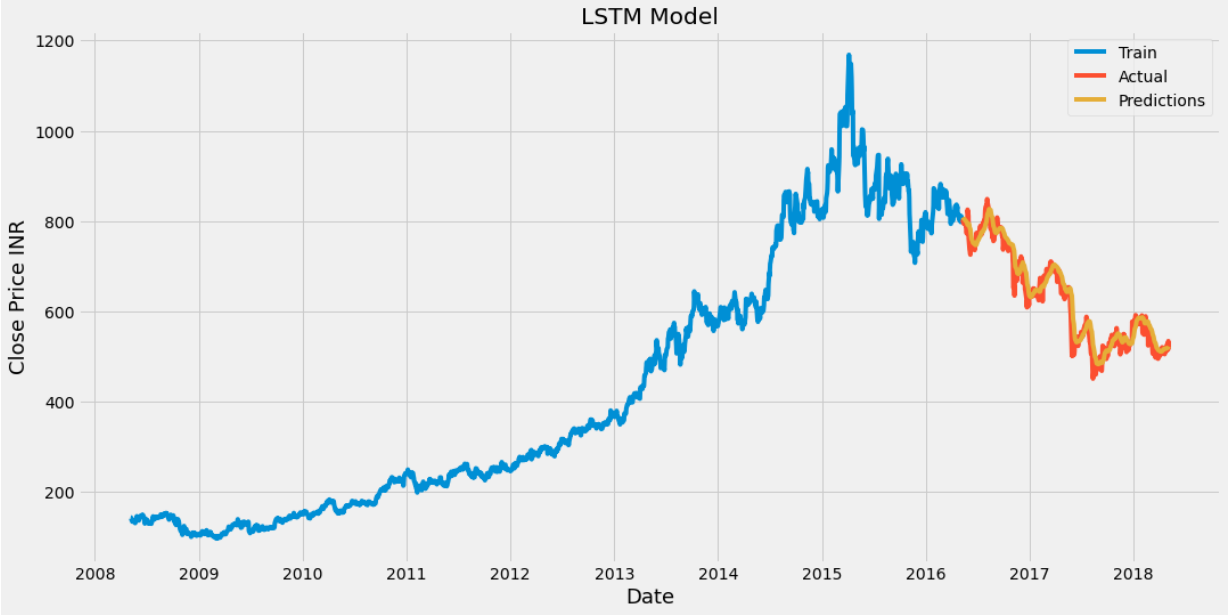

```
Predicted close Stock Price of the next day is
 190.20327758789062,Actual is 184.949997
```

```
Stock Name: SUNPHARMA
```

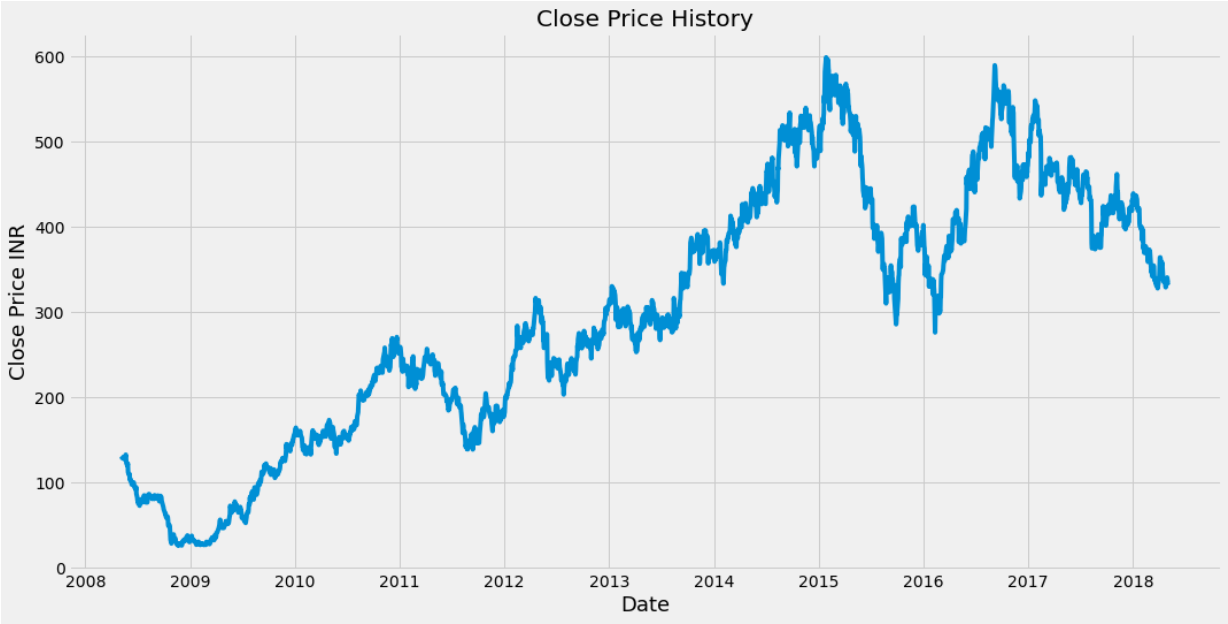



```
Epoch 1/5
64/64 [==============================] - 6s 49ms/step - loss: 0.0068:
Epoch 2/5
64/64 [==============================] - 4s 56ms/step - loss: 4.9005e-04
```

```
Epoch 3/5
64/64 [==============================] - 3s 50ms/step - loss: 5.0482e-04: 0s
- loss: 5.0844
Epoch 4/5
64/64 [==============================] - 3s 51ms/step - loss: 4.6458e-04
Epoch 5/5
64/64 [==============================] - 3s 52ms/step - loss: 5.3039e-04
8.081276003441786
```

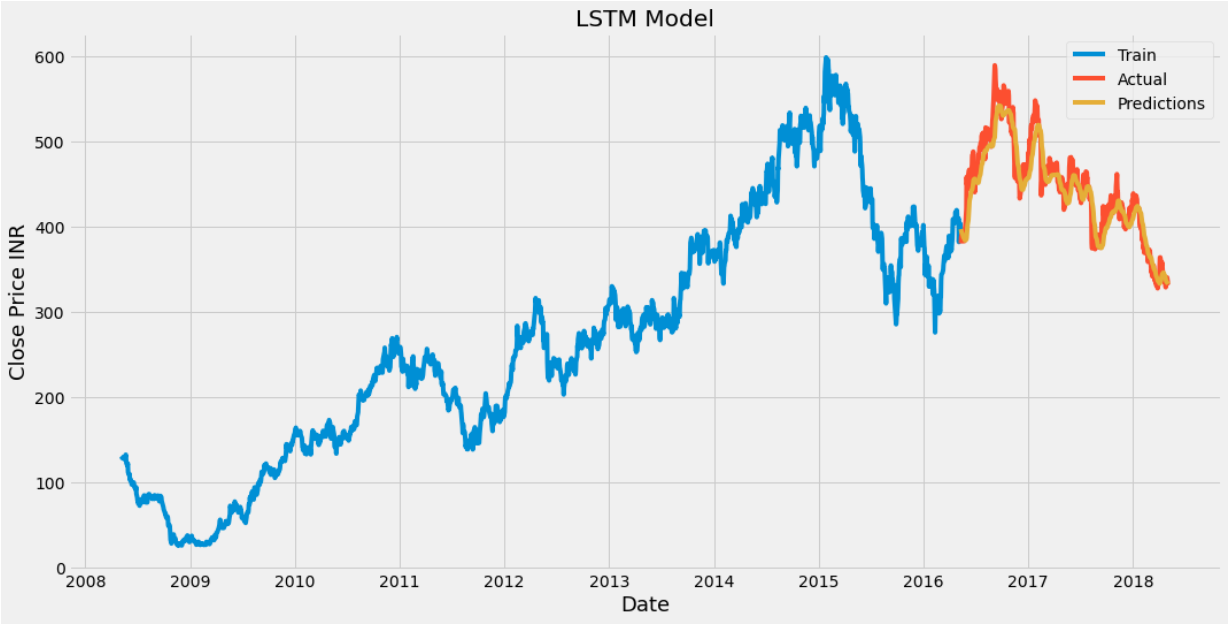



```
Predicted close Stock Price of the next day is
 808.4512939453125,Actual is 796.099976


Stock Name: TATAMOTORS
```



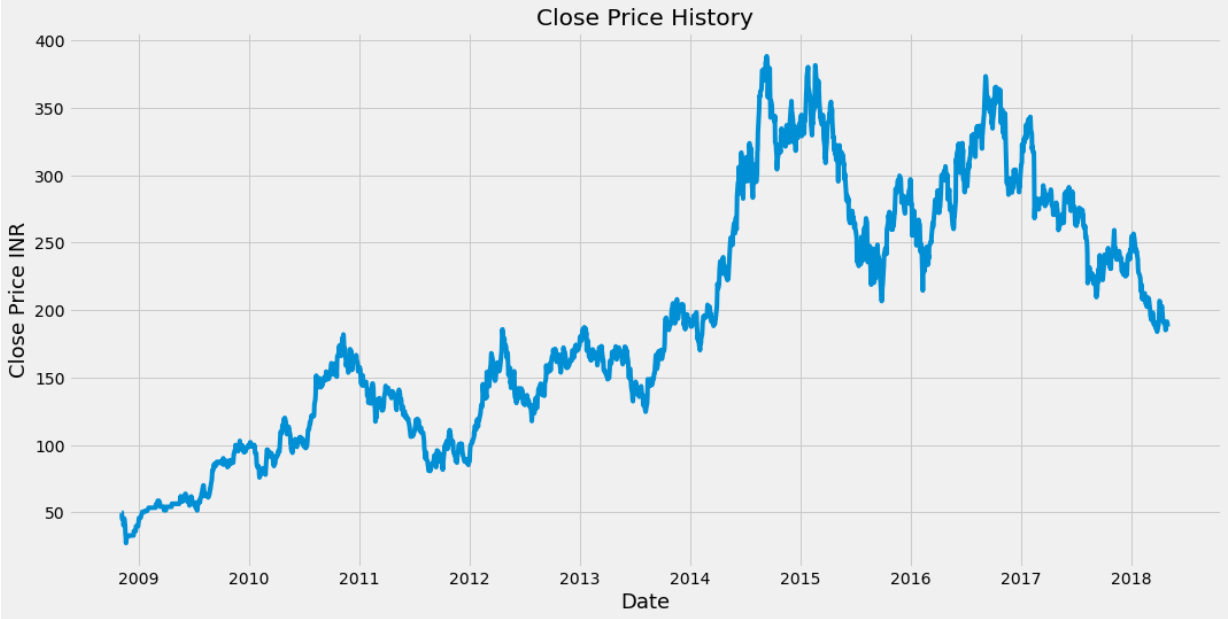

```
Epoch 1/5
64/64 [==============================] - 6s 48ms/step - loss: 0.0123: 1s - lo
ss:  - ETA: 0s - loss: 0 - ETA: 0s -
Epoch 2/5
64/64 [==============================] - 3s 48ms/step - loss: 7.3648e-04
Epoch 3/5
```

```
64/64 [==============================] - 3s 48ms/step - loss: 7.0488e-04
Epoch 4/5
64/64 [==============================] - 3s 53ms/step - loss: 7.0421e-04
Epoch 5/5
64/64 [==============================] - 3s 49ms/step - loss: 6.4779e-04
7.56991020667397
```



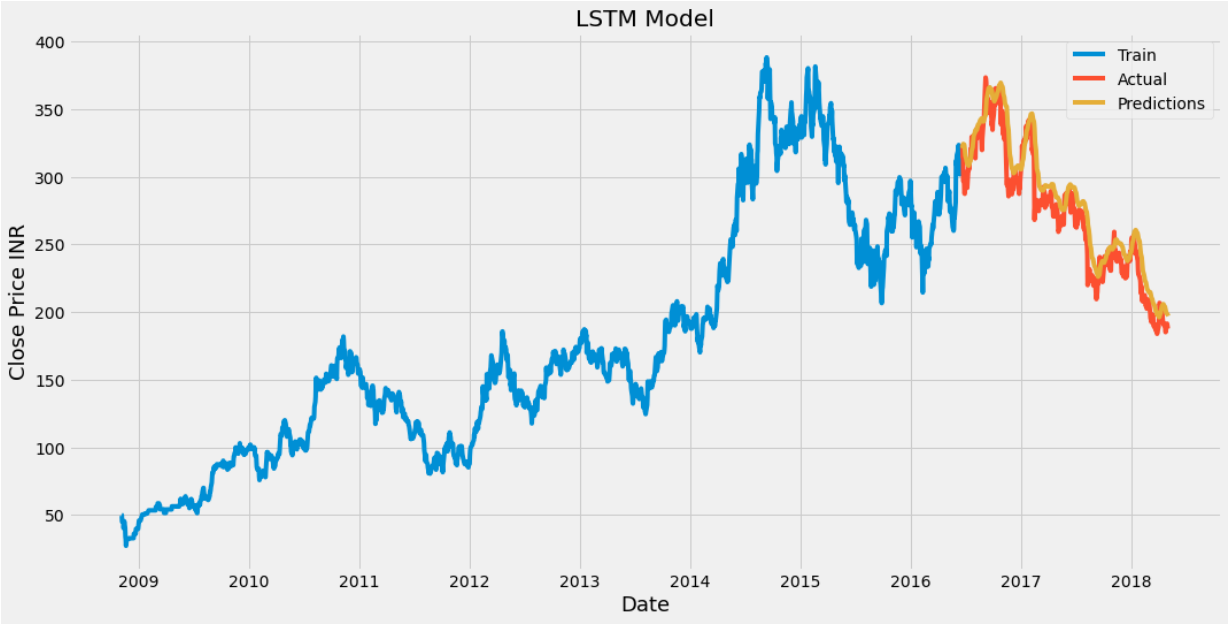

```
Predicted close Stock Price of the next day is
 397.0318298339844,Actual is 380.100006
```

```
Stock Name: TATAMTRDVR
```

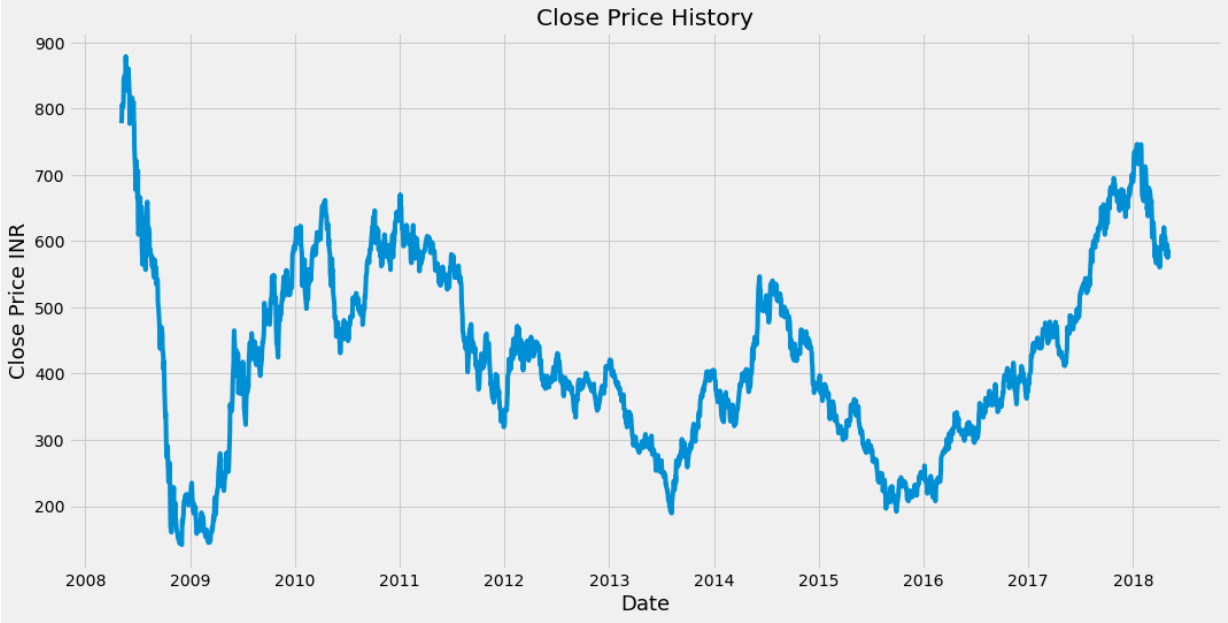



```
Epoch 1/5
60/60 [==============================] - 6s 51ms/step - loss: 0.0132
Epoch 2/5
60/60 [==============================] - 3s 52ms/step - loss: 0.0010
Epoch 3/5
60/60 [==============================] - 3s 53ms/step - loss: 9.3884e-04
```

```
Epoch 4/5
60/60 [==============================] - 3s 51ms/step - loss: 9.7480e-04
Epoch 5/5
60/60 [==============================] - 4s 65ms/step - loss: 9.5922e-04
```

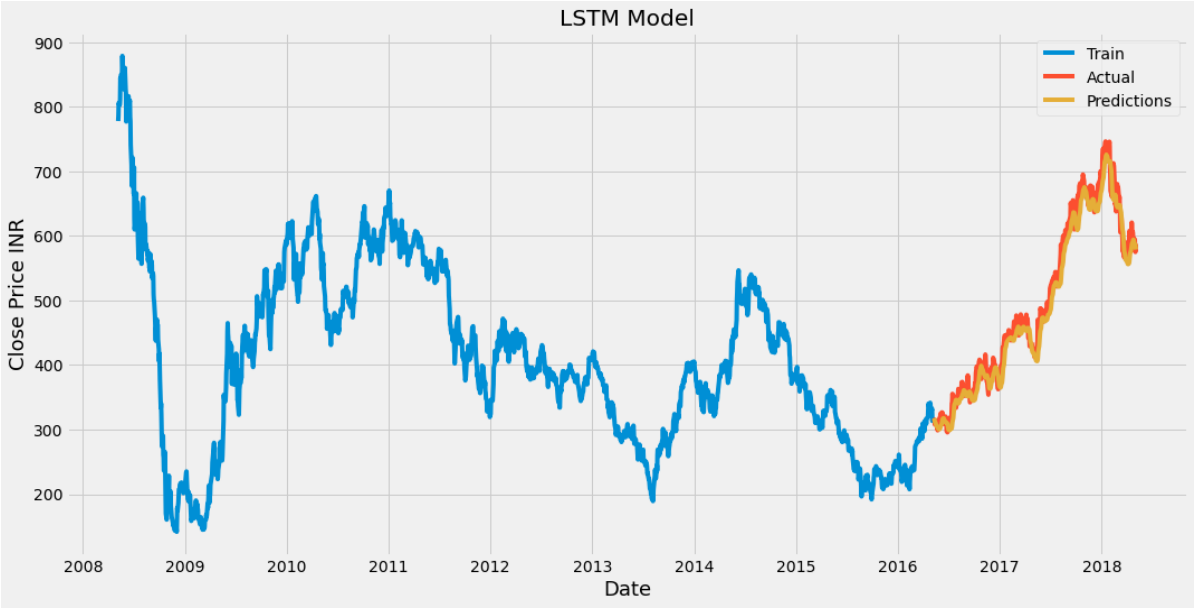



```
Predicted close Stock Price of the next day is
 321.1720886230469,Actual is 323.850006


Stock Name: TATASTEEL
```

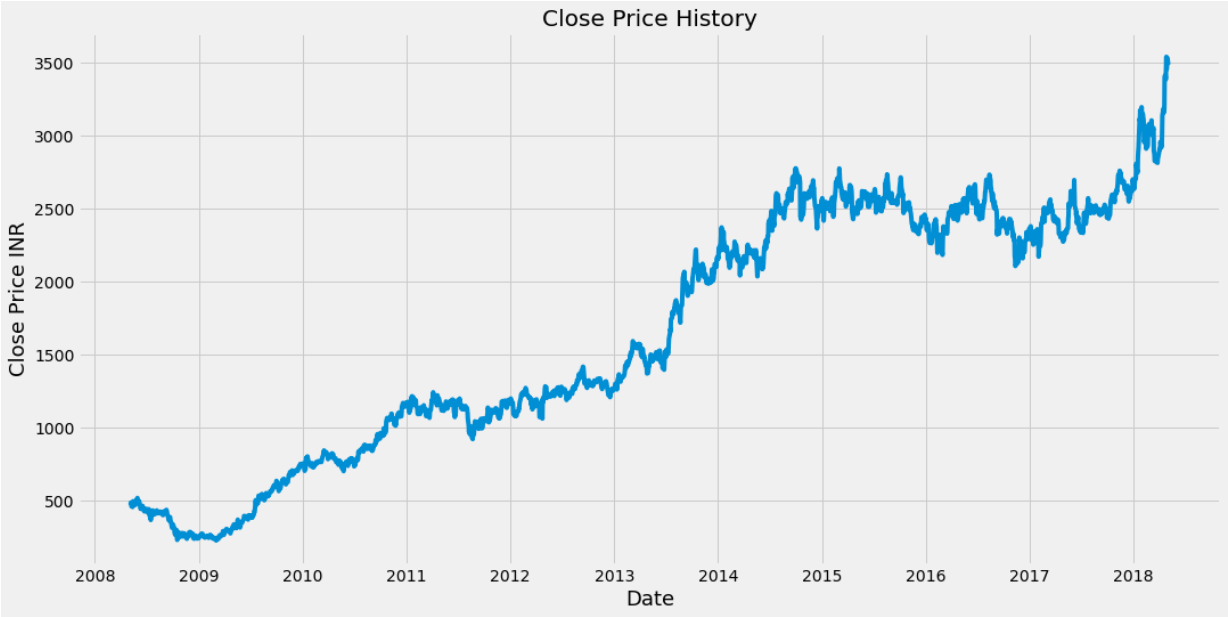



```
Epoch 1/5
64/64 [==============================] - 7s 54ms/step - loss: 0.0100
Epoch 2/5
64/64 [==============================] - 4s 59ms/step - loss: 0.0012
Epoch 3/5
64/64 [==============================] - 3s 52ms/step - loss: 0.0011
Epoch 4/5
64/64 [==============================] - 3s 50ms/step - loss: 9.3300e-04
Epoch 5/5
```

```
64/64 [==============================] - 3s 48ms/step - loss: 8.6411e-04
12.245516398945629
```

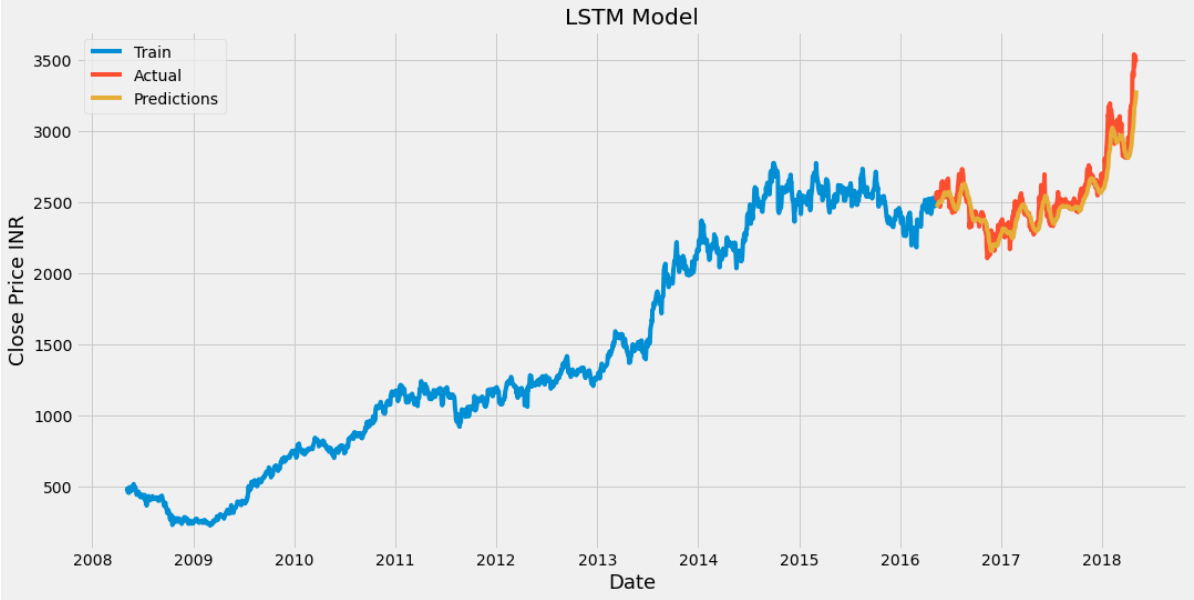



```
Predicted close Stock Price of the next day is
 317.5965576171875,Actual is 313.462006

Stock Name: TCS
```

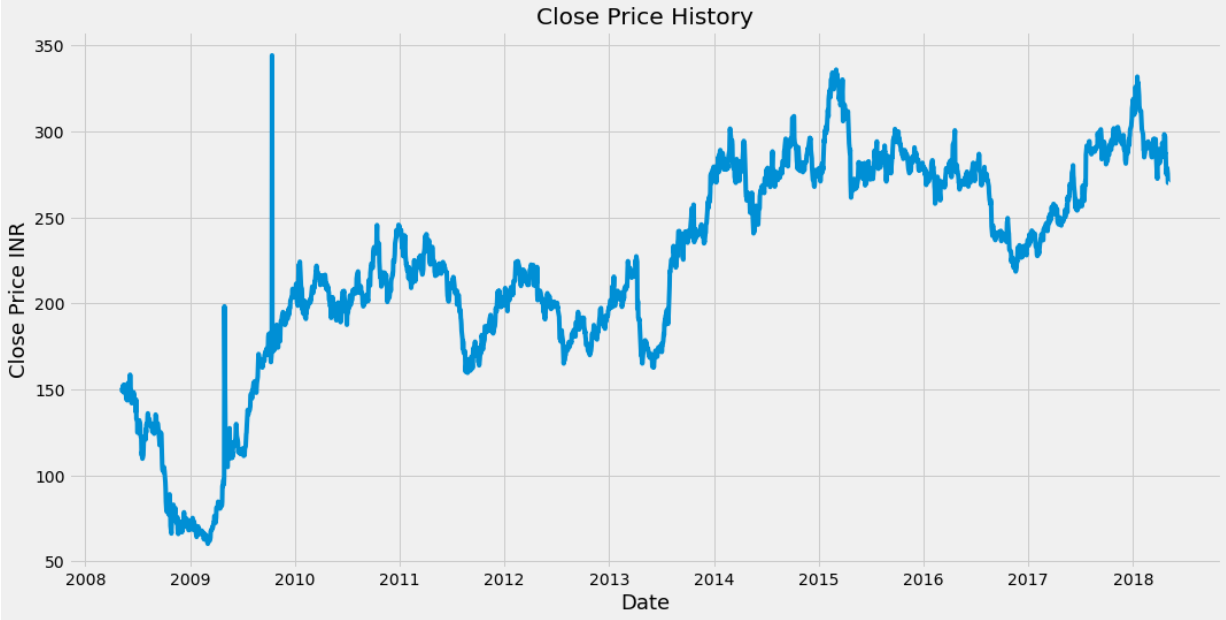



```
Epoch 1/5
64/64 [==============================] - 5s 48ms/step - loss: 0.0093
Epoch 2/5
64/64 [==============================] - 3s 50ms/step - loss: 2.5971e-04
Epoch 3/5
64/64 [==============================] - 3s 47ms/step - loss: 2.5582e-04
Epoch 4/5
64/64 [==============================] - 3s 51ms/step - loss: 2.4243e-04
Epoch 5/5
```

```
64/64 [==============================] - 3s 48ms/step - loss: 2.5078e-04
44.04986821354166 4
```

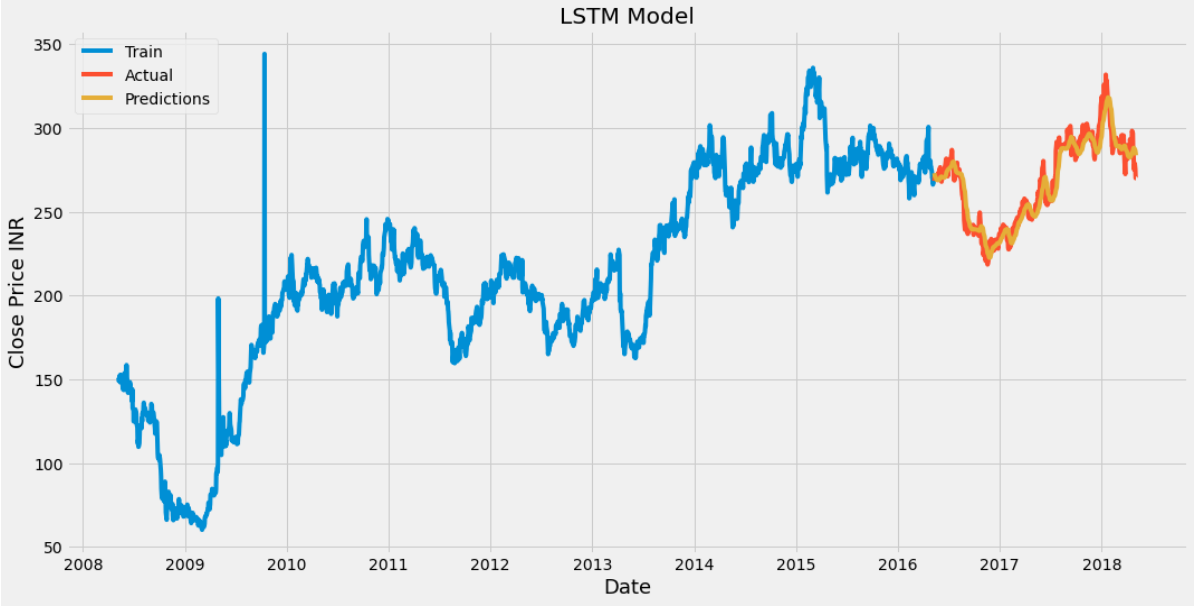



```
Predicted close Stock Price of the next day is
 2466.040771484375,Actual is 2517.75

Stock Name: WIPRO
```




```
Epoch 1/5
64/64 [==============================] - 6s 50ms/step - loss: 0.0243
Epoch 2/5
64/64 [==============================] - 3s 52ms/step - loss: 0.0013
Epoch 3/5
64/64 [==============================] - 4s 55ms/step - loss: 0.0012
Epoch 4/5
64/64 [==============================] - 3s 53ms/step - loss: 0.0011 ETA: 1s -
```

```
Epoch 5/5
64/64 [==============================] - 4s 55ms/step - loss: 0.0011
1.2402970222426006
```




```
Predicted close Stock Price of the next day is
 273.1091613769531,Actual is 268.575012


Stock Name: YESBANK
```


```
Epoch 1/5
64/64 [==============================] - 6s 45ms/step - loss: 0.0037
Epoch 2/5
```

```
64/64 [==============================] - 3s 50ms/step - loss: 3.3691e-04
Epoch 3/5
64/64 [==============================] - 3s 53ms/step - loss: 3.3717e-04
Epoch 4/5
64/64 [==============================] - 3s 54ms/step - loss: 3.5380e-04
Epoch 5/5
64/64 [==============================] - 3s 53ms/step - loss: 3.1176e-04: 0s -
loss: 3
4.301543344222402
```


```
Predicted close Stock Price of the next day is
 185.07762145996094,Actual is 191.25
```

Out[8]:

	Stock	Closing Price
0	ADANIPORTS	215.636536
1	ASIANPAINT	872.878723
2	AXISBANK	480.440796
3	BAJAJ-AUTO	2517.074463
4	BHARTIARTL	358.940552
5	COALINDIA	320.726135
6	DRREDDY	3009.245117
7	HDFC	1120.618408
8	HDFCBANK	1110.817261

	Stock	Closing Price
9	HEROMOTOCO	2893.832275
10	HINDUNILVR	880.991516
11	ICICIBANK	203.366272
12	INDUSINDBK	1023.633362
13	INFY	1232.069092
14	ITC	213.744904
15	KOTAKBANK	677.825134
16	LT	846.724976
17	M&M	673.840332
18	MARUTI	3862.088379
19	ONGC	142.057587
20	POWERGRID	145.840500
21	RELIANCE	483.589203
22	SBIN	190.203278
23	SUNPHARMA	808.451294
24	TATAMOTORS	397.031830
25	TATAMTRDVR	321.172089
26	TATASTEEL	317.596558
27	TCS	2466.040771
28	WIPRO	273.109161
29	YESBANK	185.077621

Recommend Stocks on the Basis of risk

0 : No Risk
1 : Low Risk
2 : Medium Risk
3 : High Risk

In [11]:

```
NoRisk = pd.read_csv("NoRisk.csv")
Risk = pd.read_csv('StockRisk.csv')
Close = pd.read_csv('StockClose.csv')

Risk['Risk'][Risk['Risk'] == 'Low'] = 1
Risk['Risk'][Risk['Risk'] == 'Medium'] = 2
Risk['Risk'][Risk['Risk'] == 'High'] = 3

print("What is your risk taking apettite for your funds?")

print("0 : No Risk Very Low Return\n1 : Low Risk Low Return\n2 : Medium Risk
risk = int(input("Enter Corresponsing Number : "))


if risk == 0:
    print(NoRisk)
else:
    print("How much you want to invest?")
    invest = int(input("Enter Ammount : "))

    Temp1 = pd.DataFrame((Risk['Stock'][Risk['Risk'] == risk]).reset_index(d
    Temp2 = pd.DataFrame((Close['Stock'][Close['Closing Price'] <= invest]).
    Result = pd.merge(pd.merge(Temp1,Temp2, how='inner'),Close, how='inner')
    print(Result)
```

```
What is your risk taking apettite for your funds?
0 : No Risk Very Low Return
1 : Low Risk Low Return
2 : Medium Risk Medium Return
3 : High Risk High Return
Enter Corresponsing Number : 2
How much you want to invest?
Enter Ammount : 800
        Stock  Closing Price
0         M&M      673.84033
1        SBIN      190.20328
2  TATAMTRDVR      321.17210
```

In [ ]:

```
1
```