Project-3

Time-Series

STOCK PRICE FORECASTING

#Value_freeContent

Adani Power Ltd.

krishnakumarprajapat366@gmail.com

@krishan kumar

v9lrsp6nn

November 9, 2023

1 Adani Power ltd. :- Stock Price Forecasting

2 Steps that we are follow in time series (Forecasting)

1. Data Ingesiton
2. EDA of the data
3. Processing of the data
4. Model Building
5. Model Evalution

[ ]:

```

```

3 Data Ingesiton

[1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import os
import sys
import warnings
warnings.filterwarnings('ignore')
```

[2]:

```
# load the dataset (adani power limited)

data = pd.read_csv('Adani_power_LTD_data_file.csv')
data.head()
```

[2]:

```
         Date        Open        High         Low       Close   Adj Close  \
0  2022/11/09  348.600006  366.000000  345.000000  365.799988  365.799988
1  2022/11/10  365.799988  377.000000  358.000000  371.399994  371.399994
2  2022/11/11  376.000000  378.000000  353.000000  360.200012  360.200012
3  2022/11/14  348.149994  365.049988  342.200012  359.799988  359.799988
4  2022/11/15  355.899994  358.500000  353.000000  357.049988  357.049988

    Volume
```

```
0  3891628
1  2938662
2  3406069
3  3238002
4  1265382
```

[ ]:

4 Univariate Analysis

[3]:
```
stock_data = data[['Date','Close']]
stock_data
```

[3]:
```
          Date       Close
0    2022/11/09  365.799988
1    2022/11/10  371.399994
2    2022/11/11  360.200012
3    2022/11/14  359.799988
4    2022/11/15  357.049988
..          …           …
245  2023/11/03  384.649994
246  2023/11/06  394.000000
247  2023/11/07  383.799988
248  2023/11/08  393.399994
249  2023/11/09  401.100006

[250 rows x 2 columns]
```

[4]:
```
# checking the information
stock_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    250 non-null    object
 1   Close   250 non-null    float64
dtypes: float64(1), object(1)
memory usage: 4.0+ KB
```

[5]:
```
# convert data time [ Obj--> int ]

pd.to_datetime(stock_data.Date)
stock_data['Date'] = pd.to_datetime(stock_data.Date)
```

```
# now check the updated info()
stock_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 250 entries, 0 to 249
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   Date    250 non-null    datetime64[ns]
 1   Close   250 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 4.0 KB
```

[ ]:

```

```

[6]:

```
# set the date as a index
stock_data = stock_data.set_index('Date')
```

[7]:

```
stock_data
```

[7]:

```
                 Close
Date
2022-11-09  365.799988
2022-11-10  371.399994
2022-11-11  360.200012
2022-11-14  359.799988
2022-11-15  357.049988
…                  …
2023-11-03  384.649994
2023-11-06  394.000000
2023-11-07  383.799988
2023-11-08  393.399994
2023-11-09  401.100006

[250 rows x 1 columns]
```

[ ]:

```

```

4.1 Observation:

we convert this date column into index because of: 1. Retriving of the data will be easy

2. visualization will be easy

3. those lib has been degine in such a way it required date column as a index(scipy statsmodel)

[ ]:

```

```

5 EDA of the Data:

Steps:

1. Summary Statistics

- Compute summary statistics such as mean, median, mode, standard deviation, to get an overview of the data.

2. Visualize the Time Series Data

- Plot the Time Series data

- Plot the rolling mean and rolling standard deviation of the Time Series data.

- Decompose the Time Series Data check for any trends, seasonality, and Noise.

- Plot the decomposed components to get a better understanding of the Time Series data.

3. Stationarity Check

- Check for stationarity.
- Check for stationarity of the Time Series data using the Augmented Dickey-Fuller test.

4. Check for Autocorrelation

- Plot the autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify the order of the ARIMA model.

5. Outlier Detection

- Detect and handle outliers using statistical methods or machine learning techniques.

6. Check for Autocorrelation

- Plot the autocorrelation function (ACF) and partial autocorrelation function (PACF) to identify the order of the ARIMA model.

[8]:
```
stock_data.describe()
```

[8]:
```
            Close
count  250.000000
mean   273.129200
std     65.525775
min    139.350006
25%    235.625004
50%    273.075012
75%    325.787506
max    401.100006
```

[9]:
```
stock_data.head(5)
```

[9]:
```
                 Close
Date
2022-11-09  365.799988
```

```
2022-11-10  371.399994
2022-11-11  360.200012
2022-11-14  359.799988
2022-11-15  357.049988
```

[ ]:

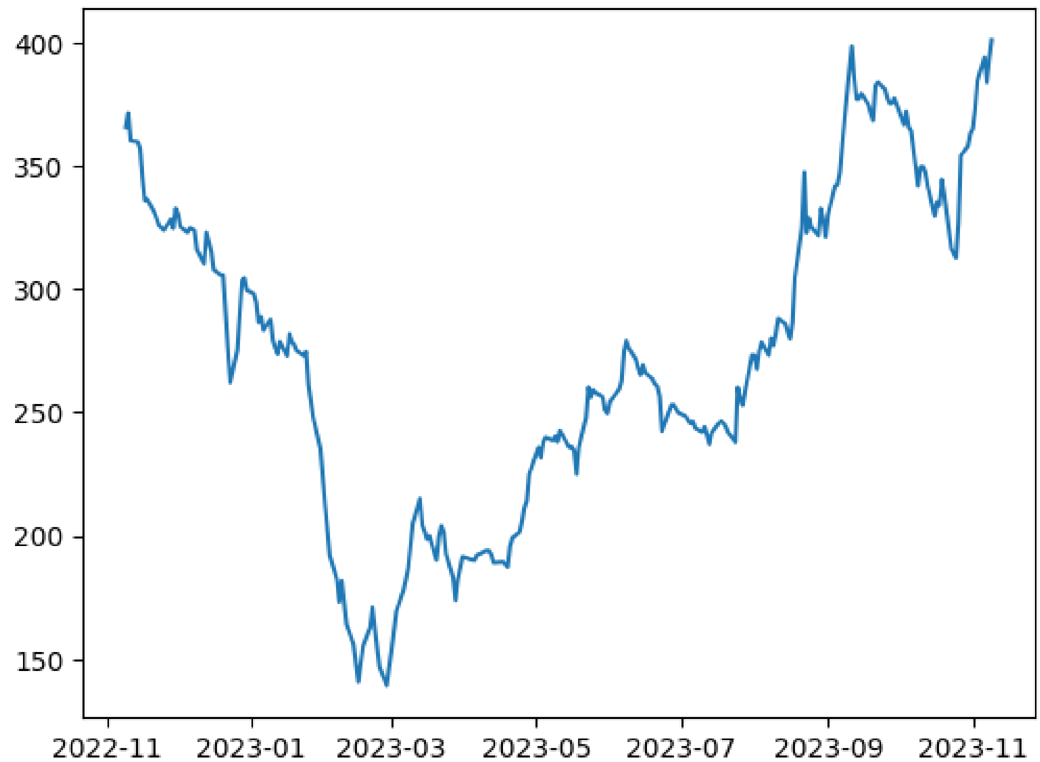
```

```

[10]:

```
# Plot the Stock data
plt.plot(stock_data.Close)
```

[10]:

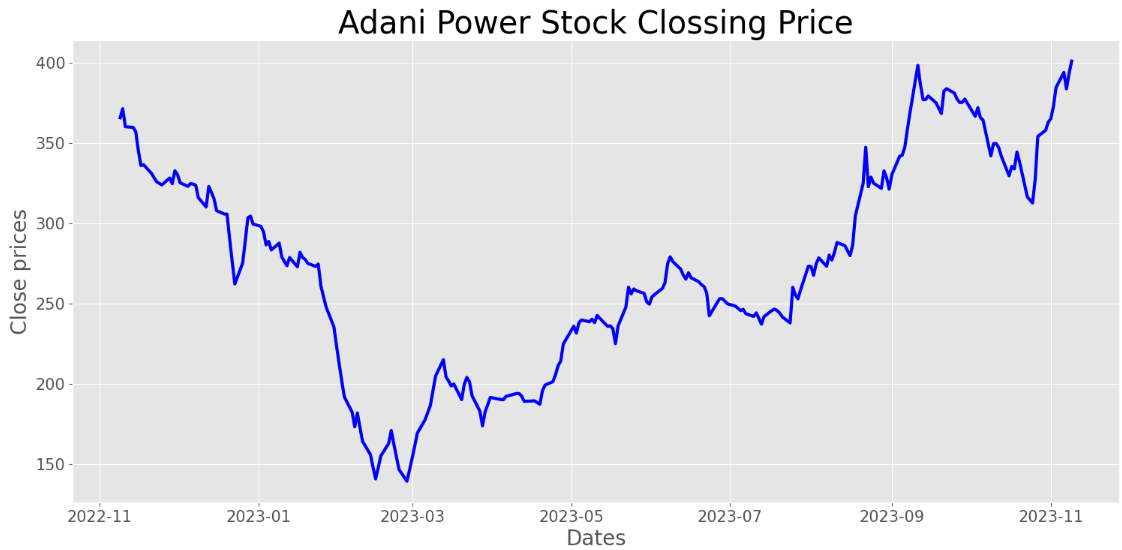
```
[<matplotlib.lines.Line2D at 0x1e1cd560f50>]
```



[11]:

```
# making this plot more readable :
# plot the close price
plt.style.use('ggplot')
plt.figure(figsize=(18,8))
plt.grid(True)
plt.xlabel('Dates', fontsize= (20))
plt.xticks(fontsize = 15)
plt.ylabel('Close prices', fontsize = 20)
plt.yticks(fontsize= 15)
plt.plot(stock_data['Close'], linewidth = 3, color = 'blue')
```

```
plt.title('Adani Power Stock Clossing Price', fontsize= 30 )
plt.show()
```



[ ]:

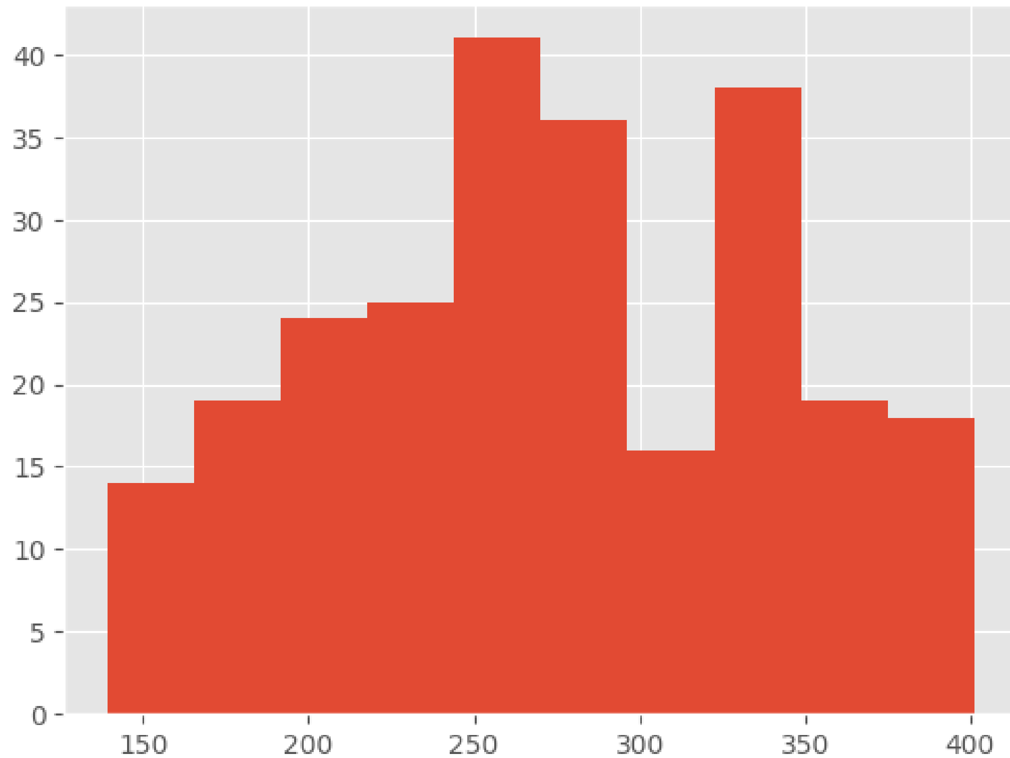
```

```

[12]:

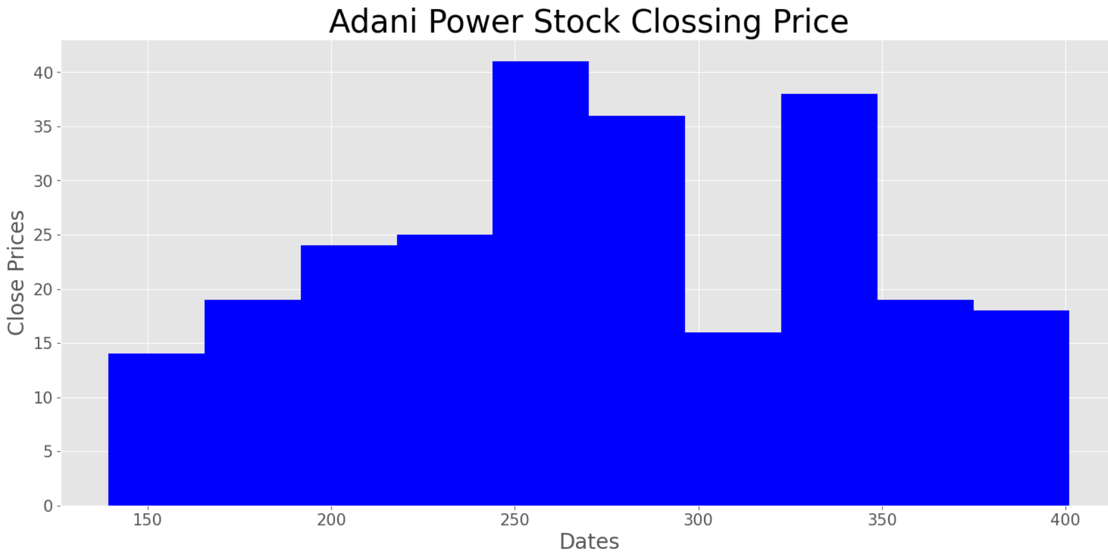
```
# Showing this stock data into histograme
plt.hist(stock_data.Close)
```

[12]:

```
(array([14., 19., 24., 25., 41., 36., 16., 38., 19., 18.]),
 array([139.350006, 165.525006, 191.700006, 217.875006, 244.050006,
        270.225006, 296.400006, 322.575006, 348.750006, 374.925006,
        401.100006]),
 <BarContainer object of 10 artists>)
```



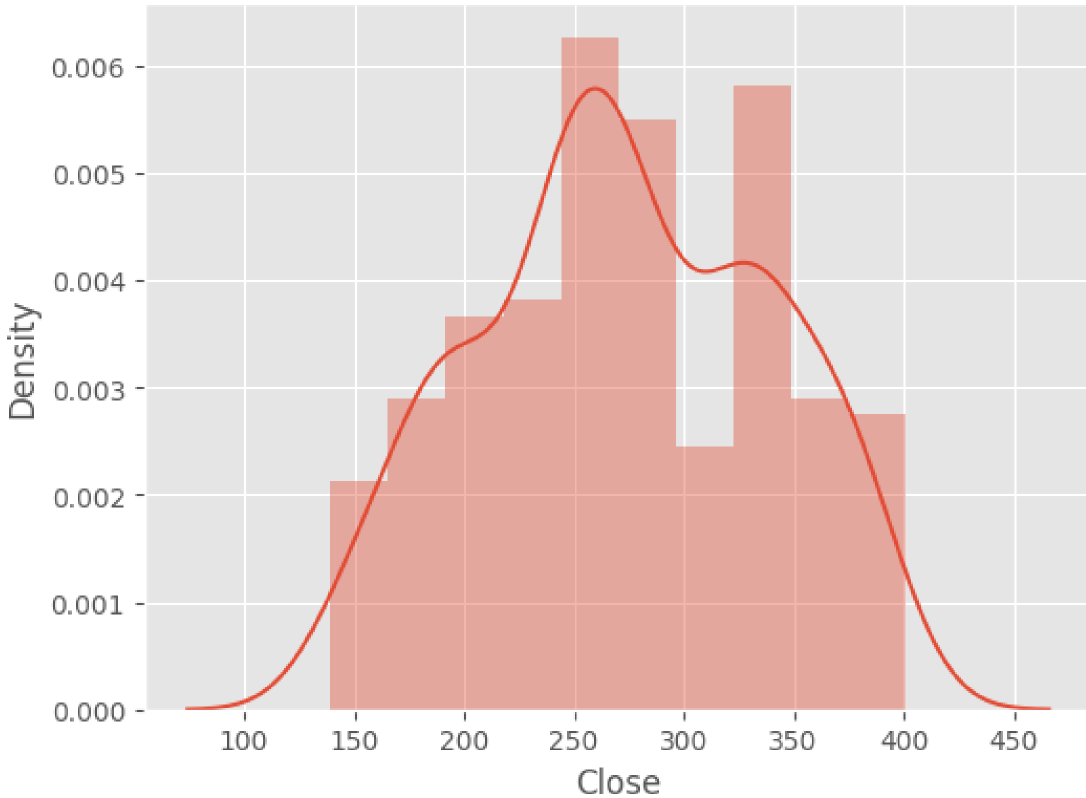
[13]:
```
# making histograme  more readable
# plotting close price
plt.style.use('ggplot')
plt.figure(figsize=(18,8))
plt.grid(True)
plt.xlabel('Dates', fontsize = 20)
plt.xticks(fontsize = 15)
plt.ylabel('Close Prices', fontsize = 20)
plt.yticks(fontsize = 15)
plt.hist(stock_data['Close'], linewidth = 3, color = 'blue')
plt.title('Adani Power Stock Clossing Price', fontsize = 30)
plt.show()
```




```
[ ]:
```

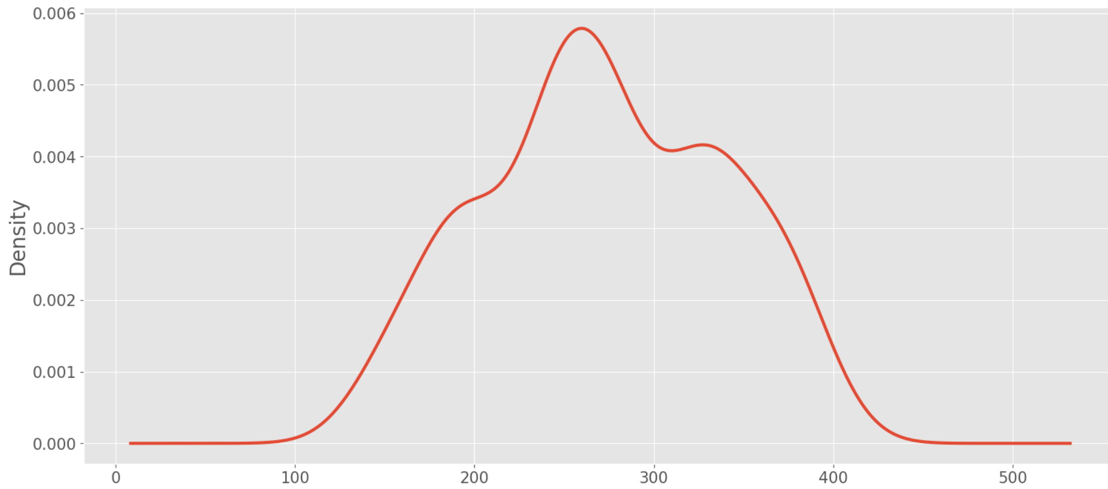
```
[14]: # showing in displot aslo
import seaborn as sns
sns.distplot(stock_data.Close)
```

```
[14]: <Axes: xlabel='Close', ylabel='Density'>
```




```
[ ]:
```

```
[15]: # Distribution of the Close price
df_close = stock_data['Close']
df_close.plot(kind = 'kde',figsize = (18,8), linewidth= 3 )
plt.xticks(fontsize = 15)
plt.grid("both")
plt.ylabel('Density', fontsize = 20)
plt.yticks(fontsize = 15)
plt.show()
```



[ ]:

[16]:
```
# Plot the Rolling mean and Standard deviation of the Time Series Data
```

[17]:
```
stock_data['Close']
```

[17]:
```
Date
2022-11-09    365.799988
2022-11-10    371.399994
2022-11-11    360.200012
2022-11-14    359.799988
2022-11-15    357.049988
                 …
2023-11-03    384.649994
2023-11-06    394.000000
2023-11-07    383.799988
2023-11-08    393.399994
2023-11-09    401.100006
Name: Close, Length: 250, dtype: float64
```

[18]:
```
# Rolling mean
stock_data['Close'].rolling(12)
```

[18]:
```
Rolling [window=12,center=False,axis=0,method=single]
```

[19]:
```
# check the rolling mean
rolmean = stock_data['Close'].rolling(12).mean()
rolmean
```

[19]:

```
Date
2022-11-09           NaN
2022-11-10           NaN
2022-11-11           NaN
2022-11-14           NaN
2022-11-15           NaN
                  …
2023-11-03    347.595838
2023-11-06    352.600004
2023-11-07    355.879168
2023-11-08    360.470835
2023-11-09    367.525001
Name: Close, Length: 250, dtype: float64
```

[20]:

```
# Check the rolling standard deviation
rolstd = stock_data['Close'].rolling(12).std()
rolstd
```

[20]:

```
Date
2022-11-09          NaN
2022-11-10          NaN
2022-11-11          NaN
2022-11-14          NaN
2022-11-15          NaN
                 …
2023-11-03    22.552848
2023-11-06    25.693257
2023-11-07    27.034590
2023-11-08    28.421093
2023-11-09    26.969857
Name: Close, Length: 250, dtype: float64
```

[ ]:

```

```

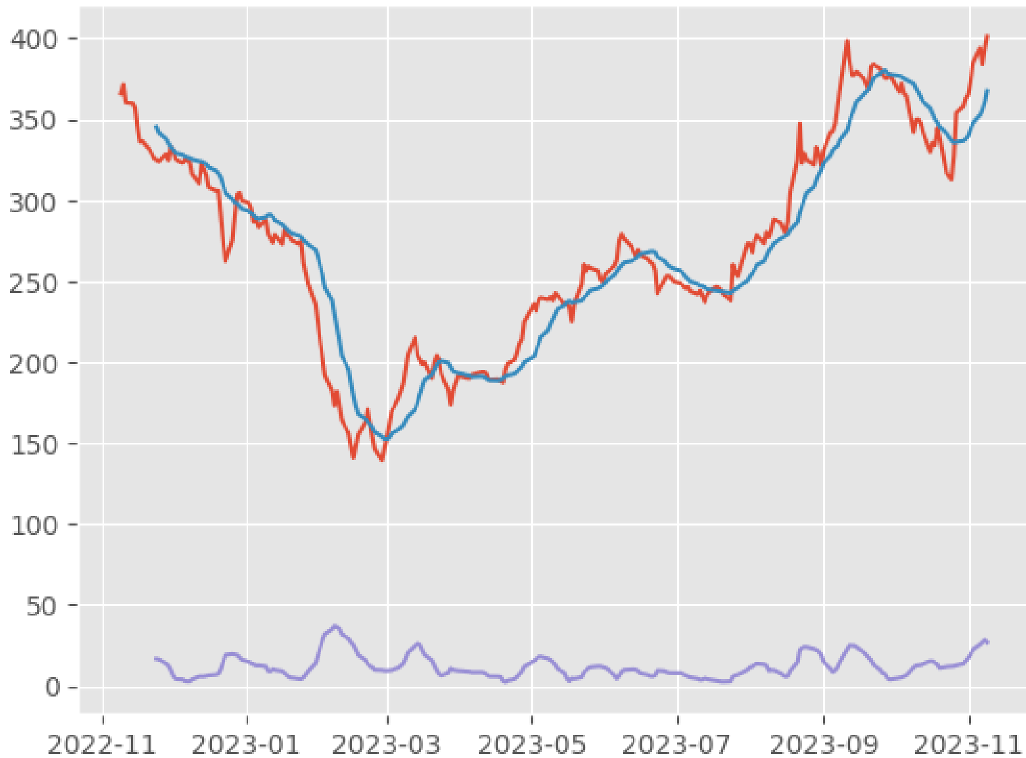
6 Plotting the data Before Smoothning

[21]:

```
# now plot those values
plt.plot(stock_data.Close)   ##time series data
plt.plot(rolmean)   ## rolling mean
plt.plot(rolstd)      ## rolling std
```

[21]:

```
[<matplotlib.lines.Line2D at 0x1e1e2151550>]
```



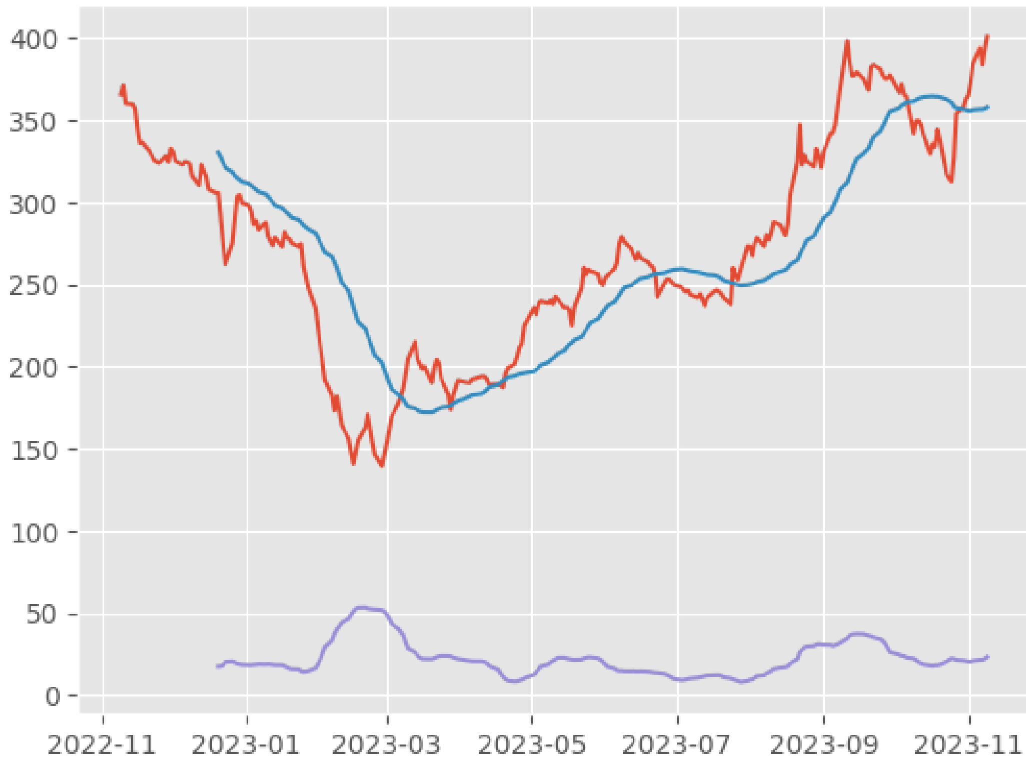

```
[ ]:
```

7 Plotting After Smoothning

```
[22]: rolmean = stock_data['Close'].rolling(30).mean()     ## smoothning by changing␣
      ↪the rolling mean values

      rolstd = stock_data['Close'].rolling(30).std()      ## smoothning by changing␣
      ↪the rolling std values
```

```
[23]: # now plot those values after smothining
      plt.plot(stock_data.Close)    ##time series data
      plt.plot(rolmean)    ## rolling mean
      plt.plot(rolstd)       ## rolling std
```

```
[23]: [<matplotlib.lines.Line2D at 0x1e1e2177fd0>]
```



[ ]:

8 Stationarity Check

[24]:
```
# importing the adfuller for checking the stationarity
from statsmodels.tsa.stattools import adfuller
adft = adfuller(stock_data.Close)
```

[25]:
```
adft
```

[25]:
```
(-0.875900424719507,
 0.795805131159639,
 1,
 248,
 {'1%': -3.4569962781990573,
  '5%': -2.8732659015936024,
  '10%': -2.573018897632674},
 1631.1543128405356)
```

[26]:
```
adft[0:4]
```

[26]: (-0.875900424719507, 0.795805131159639, 1, 248)

[27]:
```
## indexing on adft values
pd.Series(adft[0:4], index= ['test stats', 'P-value', 'lag', 'data points'])
```

[27]:
```
test stats      -0.875900
P-value          0.795805
lag              1.000000
data points    248.000000
dtype: float64
```

[ ]:
```

```

8.1 make a criteria for the p-value

null hypothesis = data is non stationary

P-value= 0.795805

$p < 0.05$ reject null hypothesis

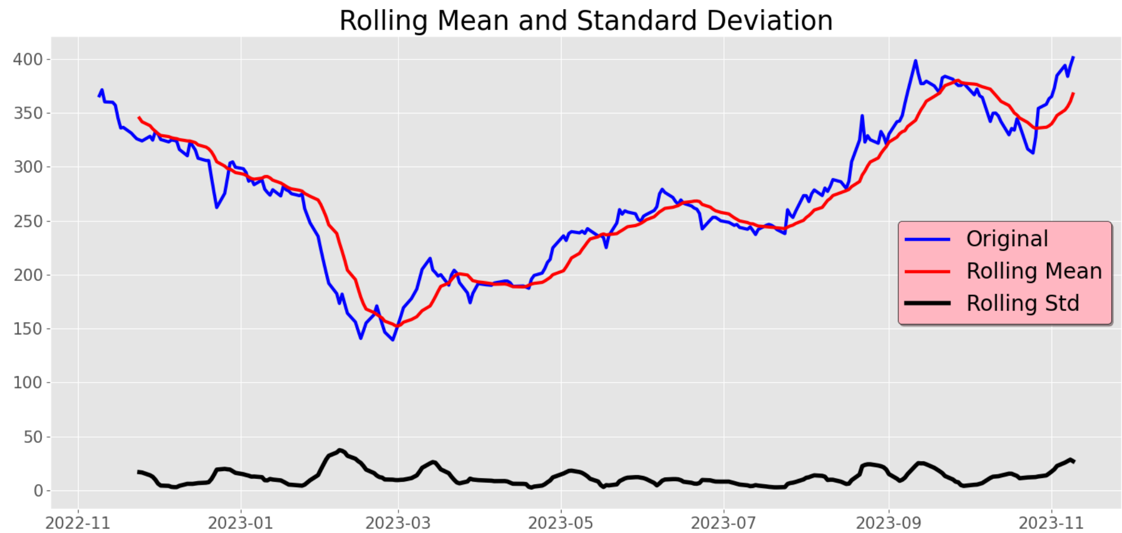
$p > 0.05$ accept null hypothesis

[ ]:
```

```

[28]:
```
# creating a function where all stationarity details shuould be present

#Test for staionarity
def test_stationarity(timeseries):

    # Determing rolling statistics
    rolmean = timeseries.rolling(12).mean() # rolling mean
    rolstd = timeseries.rolling(12).std() # rolling standard deviation

    # Plot rolling statistics:
    plt.figure(figsize = (18,8))
    plt.grid('both')
    plt.plot(timeseries, color='blue',label='Original', linewidth = 3)
    plt.plot(rolmean, color='red', label='Rolling Mean',linewidth = 3)
    plt.plot(rolstd, color='black', label = 'Rolling Std',linewidth = 4)
    plt.legend(loc='best', fontsize = 20,␣
 ↪shadow=True,facecolor='lightpink',edgecolor = 'k')
    plt.title('Rolling Mean and Standard Deviation', fontsize = 25)
    plt.xticks(fontsize = 15)
    plt.yticks(fontsize = 15)
    plt.show(block=False)

    print("Results of dickey fuller test")
    adft = adfuller(timeseries,autolag='AIC')
```

```
    # output for adft will give us without defining what the values are.
    # hence we manually write what values does it explains using a for loop
    output = pd.Series(adft[0:4],index=['Test Statistics','p-value','No. of␣
↪lags used','Number of observations used'])
    for key,values in adft[4].items():
        output['critical value (%s)'%key] =  values
    print(output)
```

[29]:
```
test_stationarity(stock_data.Close)
```



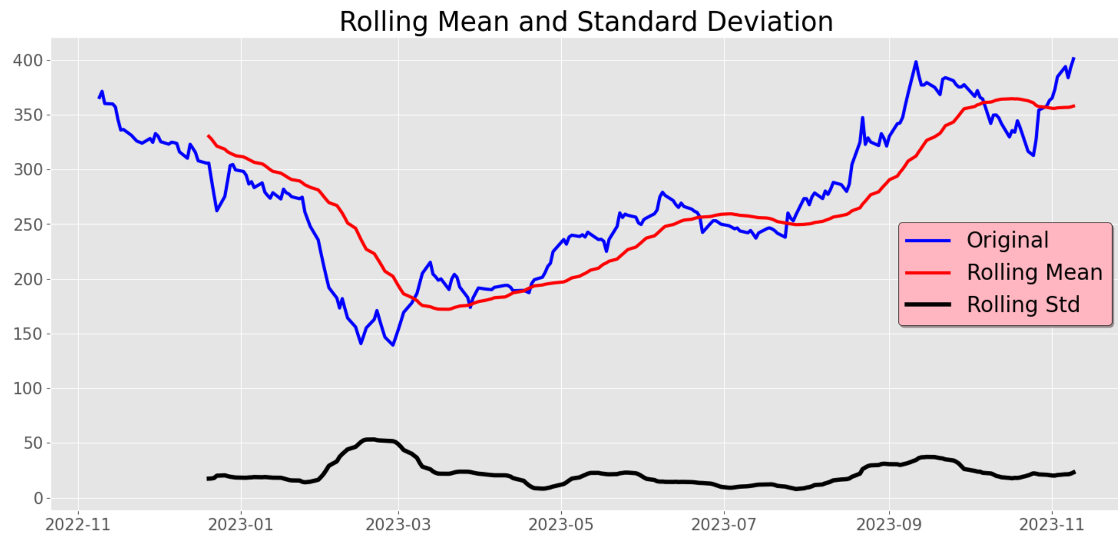

```
Results of dickey fuller test
Test Statistics                 -0.875900
p-value                          0.795805
No. of lags used                 1.000000
Number of observations used    248.000000
critical value (1%)             -3.456996
critical value (5%)             -2.873266
critical value (10%)            -2.573019
dtype: float64
```

[ ]:
```

```

[30]:
```
## smothning on stock data

# creating a function where all stationarity details shuould be present

#Test for staionarity
def test_stationarity(timeseries):
```

```
# Determing rolling statistics
rolmean = timeseries.rolling(30).mean() # rolling mean
rolstd = timeseries.rolling(30).std() # rolling standard deviation

# Plot rolling statistics:
plt.figure(figsize = (18,8))
plt.grid('both')
plt.plot(timeseries, color='blue',label='Original', linewidth = 3)
plt.plot(rolmean, color='red', label='Rolling Mean',linewidth = 3)
plt.plot(rolstd, color='black', label = 'Rolling Std',linewidth = 4)
plt.legend(loc='best', fontsize = 20,␣
↪shadow=True,facecolor='lightpink',edgecolor = 'k')
plt.title('Rolling Mean and Standard Deviation', fontsize = 25)
plt.xticks(fontsize = 15)
plt.yticks(fontsize = 15)
plt.show(block=False)

print("Results of dickey fuller test")
adft = adfuller(timeseries,autolag='AIC')

# output for dft will give us without defining what the values are.
# hence we manually write what values does it explains using a for loop
output = pd.Series(adft[0:4],index=['Test Statistics','p-value','No. of␣
↪lags used','Number of observations used'])
for key,values in adft[4].items():
    output['critical value (%s)'%key] =  values
print(output)
```

[31]:
```
test_stationarity(stock_data.Close)
```



```
Results of dickey fuller test
Test Statistics                 -0.875900
p-value                          0.795805
No. of lags used                 1.000000
Number of observations used    248.000000
critical value (1%)             -3.456996
critical value (5%)             -2.873266
critical value (10%)            -2.573019
dtype: float64
```

[ ]:

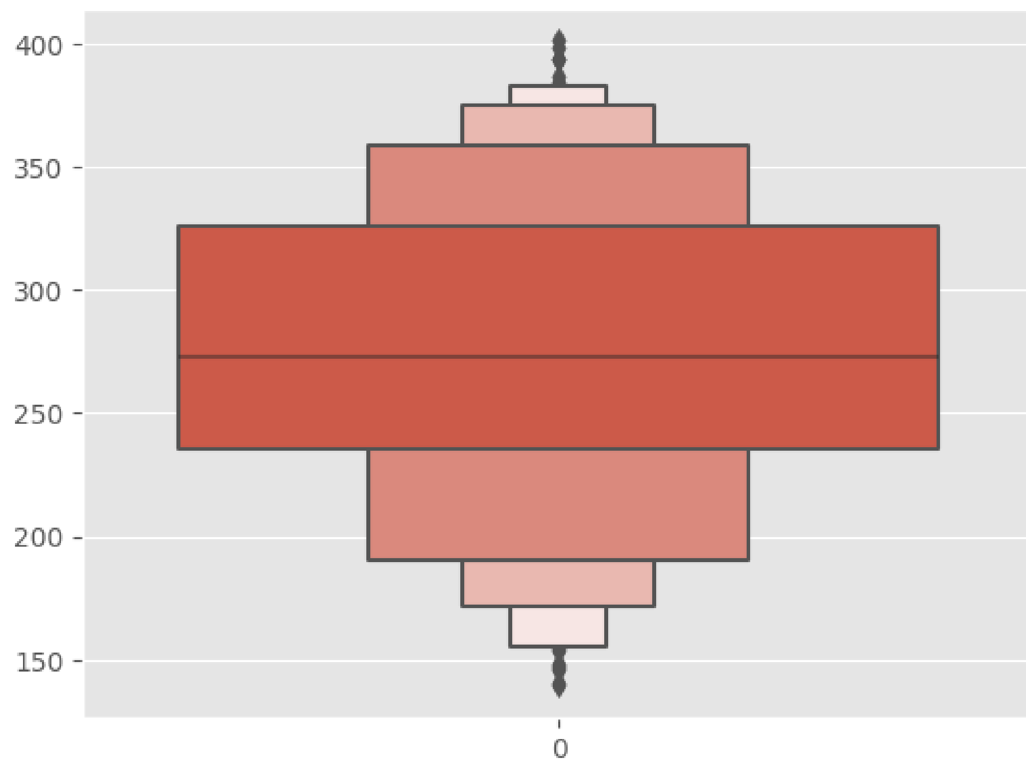
9 Outlier Dectection

[32]:
```
# there is no missing value in the dataset
stock_data.Close.isnull().sum()
```

[32]: 0

[33]:
```
sns.boxenplot(stock_data.Close)
```

[33]: <Axes: >



[34]:
```
stock_data.Close.describe()
```

[34]:
```
count    250.000000
mean     273.129200
std       65.525775
min      139.350006
25%      235.625004
50%      273.075012
75%      325.787506
max      401.100006
Name: Close, dtype: float64
```

[35]:
```
# finding the IQR
iqr_25 = stock_data.Close.quantile(0.25)
iqr_75 = stock_data.Close.quantile(0.75)
```

[36]:
```
iqr_25
```

[36]:
```
235.62500375000002
```

[37]:
```
iqr_75
```

[37]:
```
325.787506
```

[38]:
```
iqr = iqr_75 - iqr_25
iqr
```

[38]:
```
90.16250224999999
```

[39]:
```
upper_limit = iqr_75 + 1.5*iqr
lower_limit = iqr_25 - 1.5*iqr

print('Upper Limit', upper_limit)
print('Lower Limit', lower_limit)
```

```
Upper Limit 461.031259375
Lower Limit 100.38125037500004
```

[40]:
```
stock_data[stock_data.Close > upper_limit]
```

[40]:
```
Empty DataFrame
Columns: [Close]
Index: []
```

[41]:
```
stock_data[stock_data.Close < lower_limit]
```

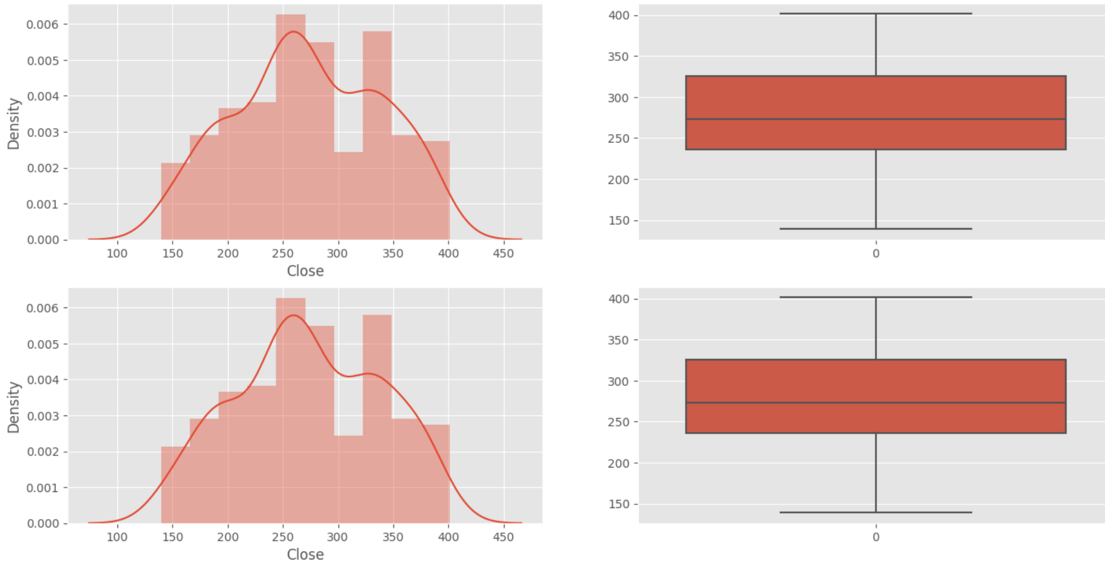
[41]: Empty DataFrame
Columns: [Close]
Index: []

[42]:
```
# Capping

new_df_cap = stock_data.copy()

new_df_cap['Close'] = np.where(
    new_df_cap['Close'] > upper_limit,
    upper_limit,
    np.where(
        new_df_cap['Close'] < lower_limit,
        lower_limit,
        new_df_cap['Close']
    )
)
```

[43]:
```
new_df_cap.shape
```

[43]: (250, 1)

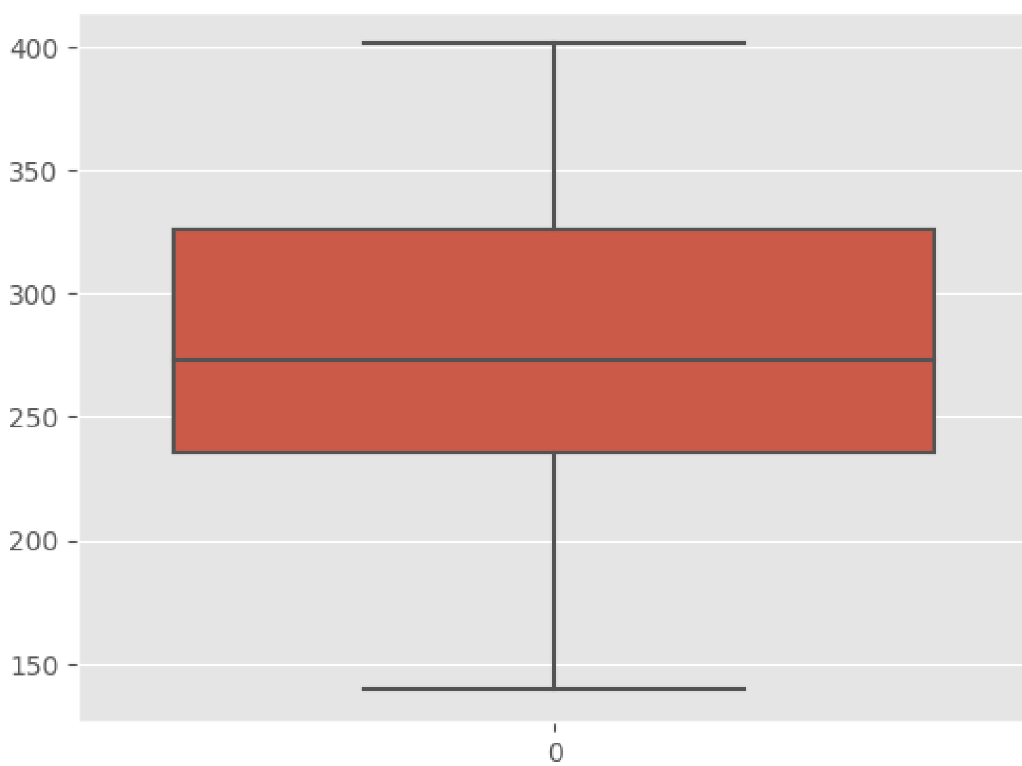
[44]:
```
# camparing

plt.figure(figsize=(16,8))
plt.subplot(2,2,1)
sns.distplot(stock_data['Close'])

plt.subplot(2,2,2)
sns.boxplot(stock_data['Close'])

plt.subplot(2,2,3)
sns.distplot(new_df_cap['Close'])

plt.subplot(2,2,4)
sns.boxplot(new_df_cap['Close'])

plt.show()
```



[ ]:

[45]:
```
sns.boxplot(stock_data['Close'])
```

[45]: <Axes: >



10 Observation :

now we capping all the outliers from the data set. now our data is completly outlier free.

[ ]:

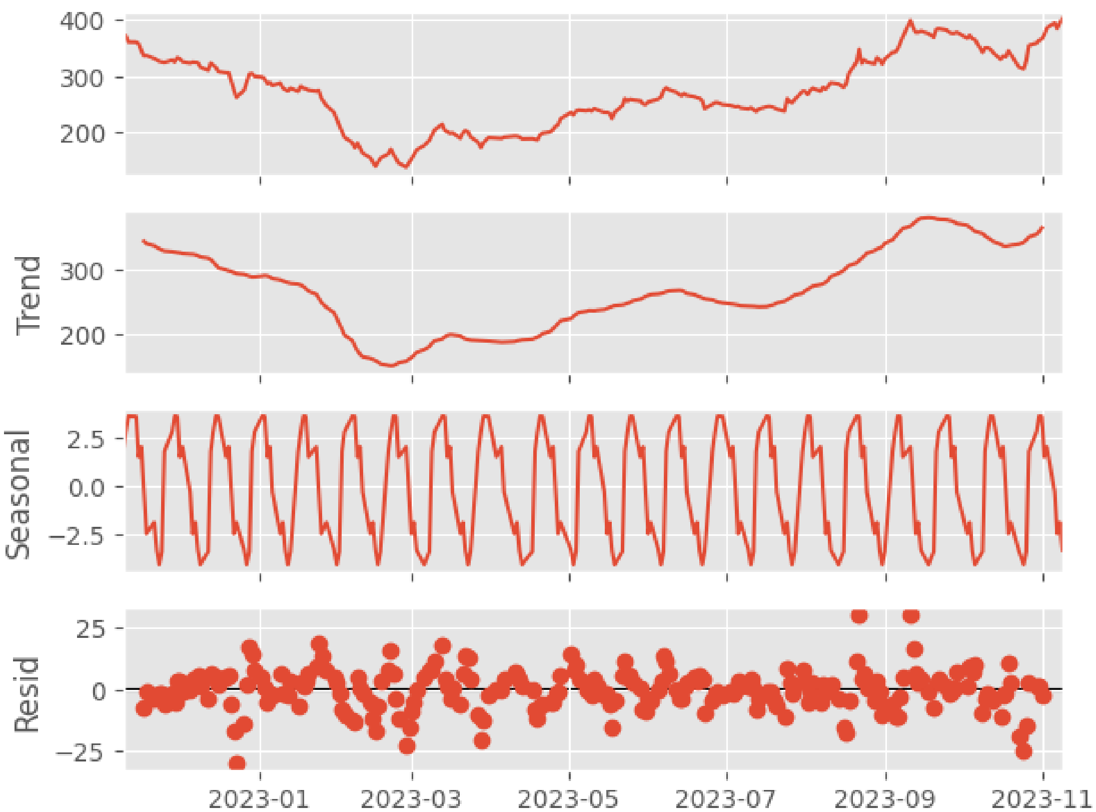
11 Time series Decomposition

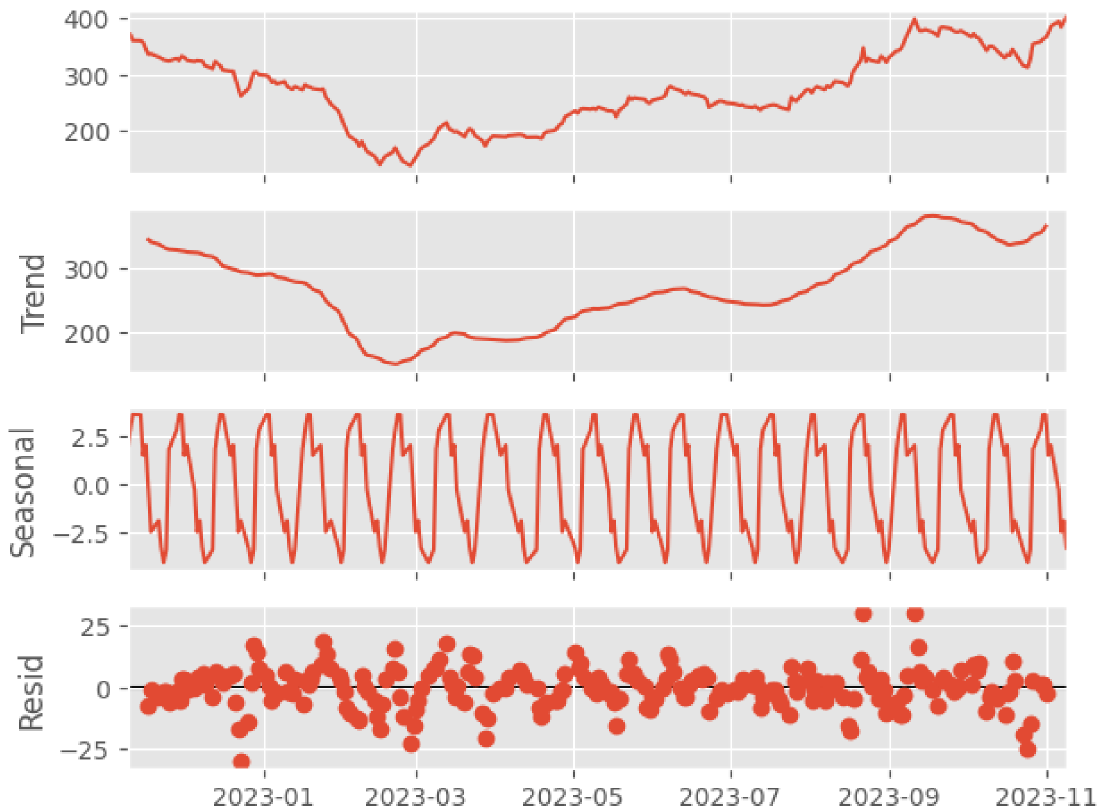
[46]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

result = seasonal_decompose(stock_data[['Close']], period= 12)
result
```

[46]:
```
<statsmodels.tsa.seasonal.DecomposeResult at 0x1e1e2528390>
```

[47]:
```
# plot the result
result.plot()
```

[47]:





12 Observation

1. Here we got two plot: one for additive and second for multiplicative, we can go with one also but defolt this go will both perametter, we can chage it with our conviniant.
2. And we also check seperatly the trend, seasonl, resid values with graph

[ ]:

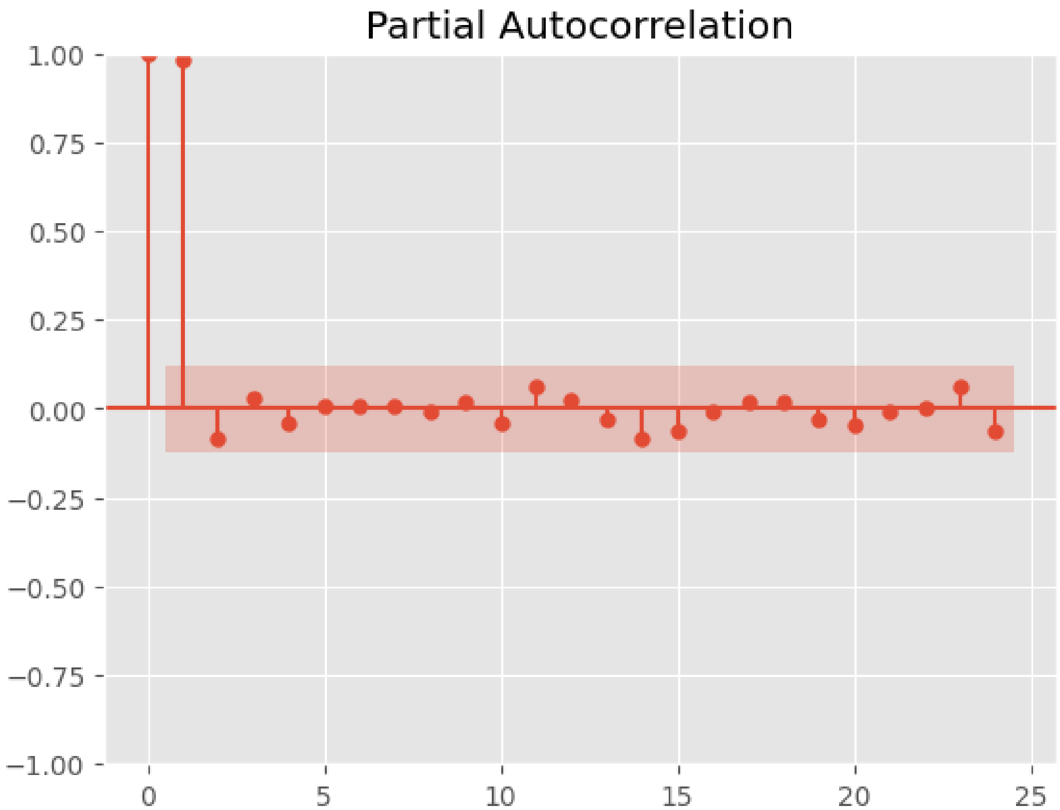
```

```

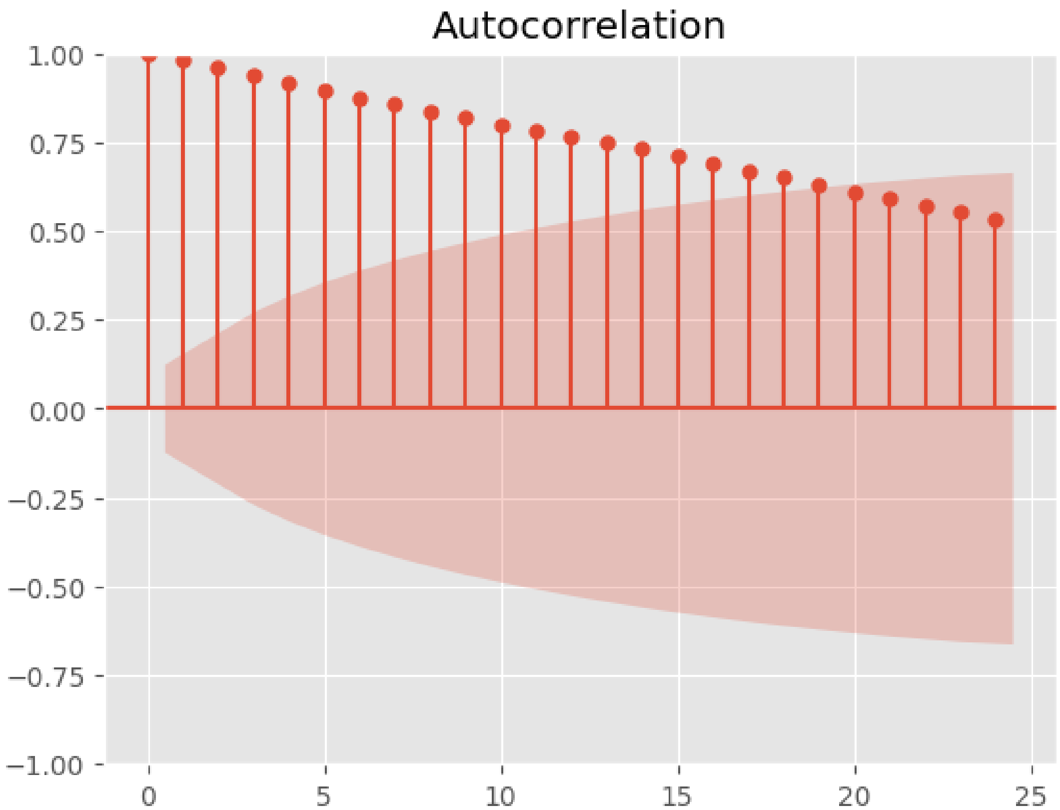
13 ACF AND PACF

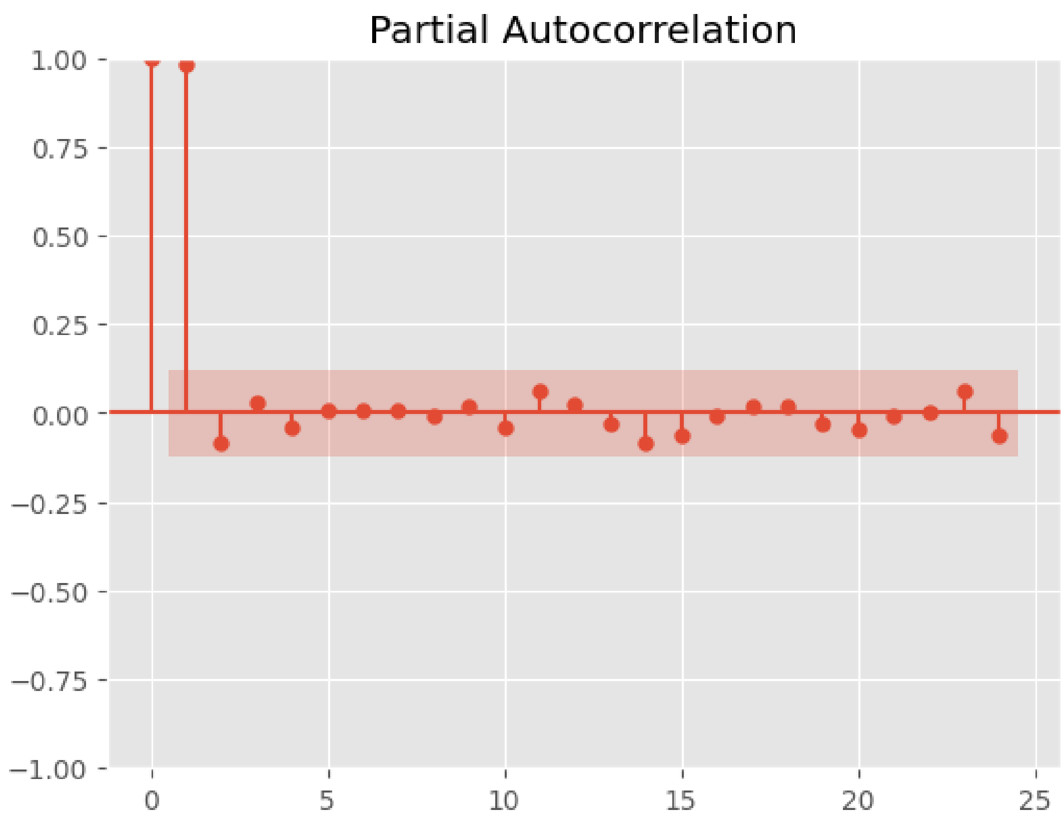
[48]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
plot_acf(stock_data.Close)
plot_pacf(stock_data.Close)
```

[48]:


Partial Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25


Autocorrelation
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00
0
5
10
15
20
25



[ ]:

14 Preprocessing of the data

1. fill the miss(here not required)
2. convert data into stationary time series
3. if necessary then normalize the data(here not required)
4. split the data into train and test
5. clean the data by removing the outlier (here not required)

[49]:
```
# non stationary to stationary
df_close = stock_data['Close']
df_close
```

[49]:
```
Date
2022-11-09    365.799988
2022-11-10    371.399994
2022-11-11    360.200012
```

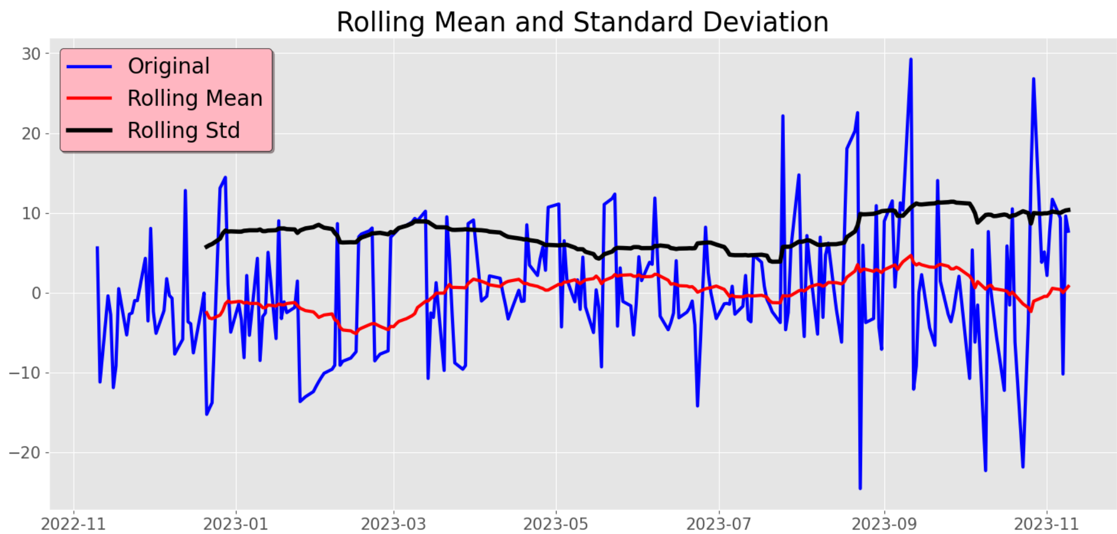
```
2022-11-14    359.799988
2022-11-15    357.049988
                 …
2023-11-03    384.649994
2023-11-06    394.000000
2023-11-07    383.799988
2023-11-08    393.399994
2023-11-09    401.100006
Name: Close, Length: 250, dtype: float64
```

[50]:
```python
df_close.diff(2)      ## chaninging values in diff
```

[50]:
```
Date
2022-11-09          NaN
2022-11-10          NaN
2022-11-11    -5.599976
2022-11-14   -11.600006
2022-11-15    -3.150024
                 …
2023-11-03    19.449982
2023-11-06    21.049988
2023-11-07    -0.850006
2023-11-08    -0.600006
2023-11-09    17.300018
Name: Close, Length: 250, dtype: float64
```

[51]:
```python
df_close = df_close.diff()
df_close = df_close.dropna()
```

[52]:
```python
# now passing df-close data into test-stationarity function
test_stationarity(df_close)
```



```
Results of dickey fuller test
Test Statistics                 -1.250145e+01
p-value                          2.800604e-23
No. of lags used                 0.000000e+00
Number of observations used      2.480000e+02
critical value (1%)             -3.456996e+00
critical value (5%)             -2.873266e+00
critical value (10%)            -2.573019e+00
dtype: float64
```

[53]:
```
# train test split our data
df_close[0:-40]   ##training data
```

[53]:
```
Date
2022-11-10     5.600006
2022-11-11   -11.199982
2022-11-14    -0.400024
2022-11-15    -2.750000
2022-11-16   -11.899994
                …
2023-09-05     0.700012
2023-09-06     5.099976
2023-09-07    11.250000
2023-09-08    10.350006
2023-09-11    29.250000
Name: Close, Length: 209, dtype: float64
```

[54]:
```
df_close[-40:]   ##testing data
```

[54]:
```
Date
2023-09-12   -12.100006
2023-09-13    -9.199982
2023-09-14     0.049988
2023-09-15     2.250000
2023-09-18    -4.399994
2023-09-20    -6.600006
2023-09-21    14.050018
2023-09-22     1.449982
2023-09-25    -2.750000
2023-09-26    -3.649994
2023-09-27    -2.149994
2023-09-28     0.049988
2023-09-29     2.050018
2023-10-03   -10.750000
2023-10-04     5.349976
```

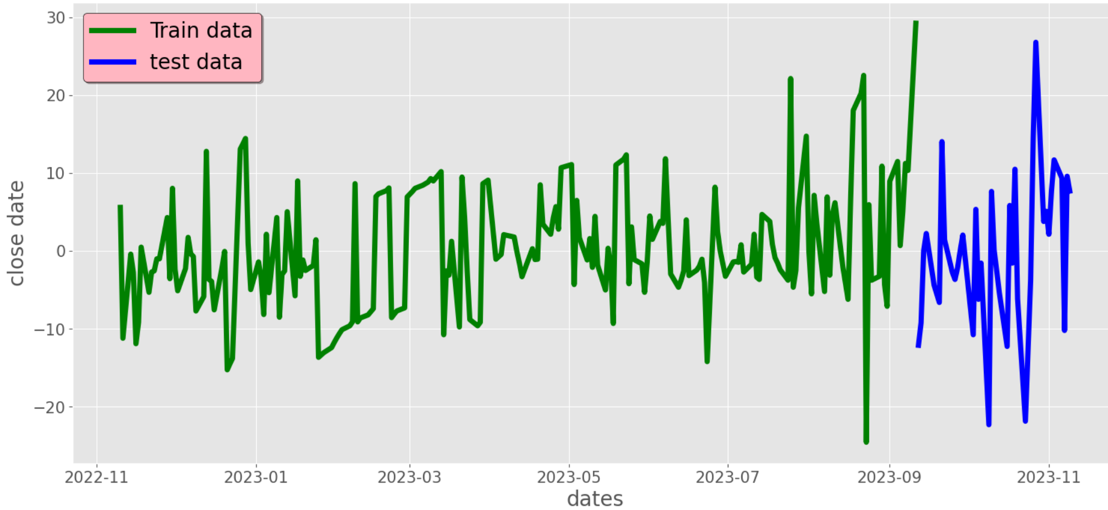
```
2023-10-05    -6.199982
2023-10-06    -1.550018
2023-10-09   -22.299988
2023-10-10     7.649994
2023-10-11     0.149994
2023-10-12    -2.549988
2023-10-13    -5.350006
2023-10-16   -12.250000
2023-10-17     5.850006
2023-10-18    -1.549988
2023-10-19    10.500000
2023-10-20    -6.150024
2023-10-23   -21.849976
2023-10-25    -3.750000
2023-10-26    14.649994
2023-10-27    26.799988
2023-10-30     3.800018
2023-10-31     5.099976
2023-11-01     2.150024
2023-11-02     7.750000
2023-11-03    11.699982
2023-11-06     9.350006
2023-11-07   -10.200012
2023-11-08     9.600006
2023-11-09     7.700012
Name: Close, dtype: float64
```

[55]:

```
##ploting the train test splited data into graph

# split data into train and testing data
train_data = df_close[0:-40]
test_data = df_close[-40:]
plt.figure(figsize= (18,8))
plt.grid(True)
plt.xlabel('dates', fontsize = 20 )
plt.ylabel('close date', fontsize = 20)
plt.xticks(fontsize = 15 )
plt.yticks(fontsize = 15 )
plt.plot(train_data, 'green', label = 'Train data', linewidth = 5)
plt.plot(test_data, 'blue', label = 'test data', linewidth = 5)
plt.legend(fontsize = 20, shadow = True, facecolor = 'lightpink', edgecolor =
 ↪'k')
```

[55]:

```
<matplotlib.legend.Legend at 0x1e1e2485050>
```

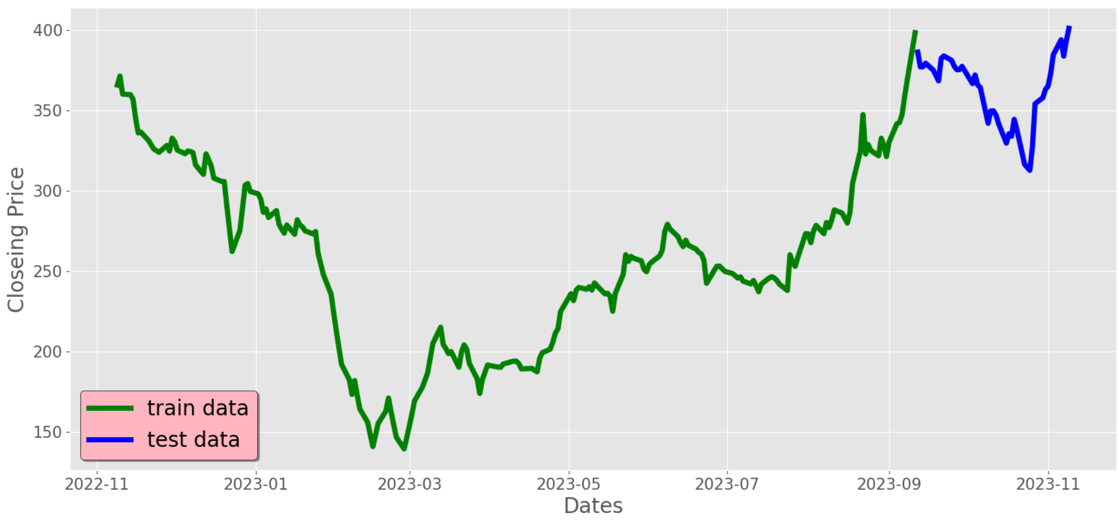



```
[ ]:
```

15 Model Building

```
[56]: train_data = stock_data['Close'][0:-40]        ##train data
      test_data = stock_data['Close'][-40:]            ## testing data
      plt.figure(figsize=(18,8))
      plt.grid(True)
      plt.xlabel('Dates', fontsize = 20)
      plt.ylabel('Closeing Price', fontsize = 20)
      plt.xticks(fontsize = 15)
      plt.yticks(fontsize = 15)
      plt.plot(train_data, 'green', label = 'train data', linewidth = 5)
      plt.plot(test_data, 'blue', label = 'test data', linewidth = 5)
      plt.legend(fontsize = 20, shadow = True, facecolor = 'lightpink', edgecolor =
       ↪'k')
```

```
[56]: <matplotlib.legend.Legend at 0x1e1e2dab9d0>
```



[57]:
```
stock_data['Close']
```

[57]:
```
Date
2022-11-09    365.799988
2022-11-10    371.399994
2022-11-11    360.200012
2022-11-14    359.799988
2022-11-15    357.049988
                 ...
2023-11-03    384.649994
2023-11-06    394.000000
2023-11-07    383.799988
2023-11-08    393.399994
2023-11-09    401.100006
Name: Close, Length: 250, dtype: float64
```

[58]:
```
249-40   ## 0-->209 == training data, 209-->249 == testing data
```

[58]:
```
209
```

[59]:
```
# importing the libraries
import statsmodels.api as sm
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
```

[60]:
```
history = [x for x in train_data]
```

[61]:
```
# passing train data into the arima model
model = ARIMA(history, order= (1,1,1) )      ##p,d,q values ---> lags values
```

[62]:
```python
model = model.fit()    ##fiting the model
```

[63]:
```python
model.summary()
```

[63]:

Dep. Variable:	y	**No. Observations:**	210
Model:	ARIMA(1, 1, 1)	**Log Likelihood**	-713.376
Date:	Thu, 09 Nov 2023	**AIC**	1432.752
Time:	19:21:42	**BIC**	1442.779
Sample:	0 - 210	**HQIC**	1436.806
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.4868	0.168	2.893	0.004	0.157	0.817
ma.L1	-0.2124	0.201	-1.058	0.290	-0.606	0.181
sigma2	53.9485	4.249	12.697	0.000	45.621	62.276

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	26.51
Prob(Q):	0.98	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.48	**Skew:**	0.16
Prob(H) (two-sided):	0.10	**Kurtosis:**	4.71

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

[ ]:
```python

```

16 Now we want to predict Or Forecast the next value

[64]:
```python
model.forecast()
```

[64]: array([407.18606043])

[65]:
```python
# geting the MSE value
mean_squared_error([test_data[0]], model.forecast())
```

[65]: 436.22802153554466

[66]:
```python
## geting the RMSE value
np.sqrt(mean_squared_error([test_data[0]], model.forecast()))
```

[66]: 20.886072429625074

[ ]:
```python

```

[67]:
```python
def train_arima_model(X, y, arima_order):
    history = [x for x in X]  ## prepare training dataset
    predictions = list()     ## make prediction list
```

```python
    for t in range(len(y)):
        model  = ARIMA(history, order= arima_order)
        model_fit = model.fit()
        yhat  = model_fit.forecast()[0]
        predictions.append(yhat)
        history.append(y[t])

    # calculate out of sample error
    rmse = np.sqrt(mean_squared_error(y, predictions))
    return rmse
```

[68]:
```python
## evaluate different combinations of p,d,q values for an ARIMA model to get␣
↪the best order for ARIMA model
def evaluate_models(dataset, test, p_values, d_values, q_values):
    dataset = dataset.astype('float32')
    best_score, best_cfg = float('inf'), None

    for p in p_values:
        for d in d_values:
            for q in q_values:
                order = (p,d,q)
                try:
                    rmse = train_arima_model(dataset, test, order)
                    if rmse < best_score:
                        best_score, best_cfg = rmse, order
                    print('ARIMA%s RMSE= %.3f'  %(order, rmse))
                except:
                    continue
    print('Best ARIMA%s RMSE= %.3f'  %(best_cfg, best_score))
```

[ ]:
```python
import warnings
warnings.filterwarnings('ignore')

p_values = range(0,3)
d_values = range(0,3)
q_values = range(0,3)

evaluate_models(train_data, test_data, p_values, d_values, q_values)
```

```
ARIMA(0, 0, 0) RMSE= 100.786
ARIMA(0, 0, 1) RMSE= 52.635
ARIMA(0, 0, 2) RMSE= 44.402
ARIMA(0, 1, 0) RMSE= 9.550
ARIMA(0, 1, 1) RMSE= 9.727
ARIMA(0, 1, 2) RMSE= 9.878
ARIMA(0, 2, 0) RMSE= 13.903
```

```
ARIMA(0, 2, 1) RMSE= 10.235
ARIMA(0, 2, 2) RMSE= 10.088
ARIMA(1, 0, 0) RMSE= 9.548
ARIMA(1, 0, 1) RMSE= 9.720
ARIMA(1, 0, 2) RMSE= 9.872
ARIMA(1, 1, 0) RMSE= 9.869
ARIMA(1, 1, 1) RMSE= 9.950
ARIMA(1, 1, 2) RMSE= 9.952
ARIMA(1, 2, 0) RMSE= 12.823
ARIMA(1, 2, 1) RMSE= 10.118
ARIMA(1, 2, 2) RMSE= 10.140
ARIMA(2, 0, 0) RMSE= 9.864
ARIMA(2, 0, 1) RMSE= 9.952
```

[ ]:
```
# now with best arima values create our final model

history = [x for x in train_data]
predictions = list()
conf_list = list()
for t in range(len(test_data)):
    model = ARIMA(history,order=(1,0,0))
    model_fit = model.fit()
    fc = model_fit.forecast(alpha = 0.05)
    predictions.append(fc)
    history.append(test_data[t])
print('RMSE of ARIMA Model:', np.sqrt(mean_squared_error(test_data,␣
↪predictions)))
```

17 Observation:

- For our model the best ARIMA Value is == **(1,0,0)**
- **RMSE of ARIMA** Model = **9.547**

[ ]:
```

```

[ ]:
```
## now ploting the predicted data

plt.figure(figsize=(18,8))
plt.grid(True)
plt.plot(range(len(test_data)),test_data, label = 'True Test Close Value',␣
↪linewidth = 5)
plt.plot(range(len(predictions)), predictions, label = 'Predictions on test␣
↪data', linewidth = 5)
plt.xticks(fontsize = 15)
plt.xticks(fontsize = 15)
plt.legend(fontsize = 20, shadow=True,facecolor='lightpink',edgecolor = 'k')
plt.show()
```

[ ]:

```

```

[ ]:

```
# Now converted forecast values into series
fc_series = pd.Series(predictions, index= test_data.index)
```

18 Now plot the fc-series

[ ]:

```
plt.figure(figsize=(12,5), dpi=100)
plt.plot(train_data, label='Training', color = 'blue')
plt.plot(test_data, label='Test', color = 'green', linewidth = 3)
plt.plot(fc_series, label='Forecast', color = 'red')
plt.title('Forecast vs Actuals on test data')
plt.legend(loc='upper left', fontsize=8)
plt.show()
```

[ ]:

```
# now plotting forecast the future calues in the plot
from statsmodels.graphics.tsaplots import plot_predict
fig = plt.figure(figsize=(18,8))
ax1 = fig.add_subplot(111)
plot_predict(result=model_fit,start=1, end=len(df_close)+60, ax = ax1)
plt.grid("both")
plt.legend(['Forecast','Close','95% confidence interval'],fontsize = 20,␣
 ↪shadow=True,facecolor='lightblue',edgecolor = 'k')
plt.show()
```

[ ]:

```
# Let's check with SARIMA Model also

## evaluate parameters for sarimax
import warnings
warnings.filterwarnings('ignore')

history = [x for x in train_data]
predictions = list()
conf_list = list()
for t in range(len(test_data)):
    model = sm.tsa.statespace.SARIMAX(history, order = (0,1,0), seasonal_order␣
 ↪= (1,1,1,3))
    model_fit = model.fit()
    fc = model_fit.forecast()
    predictions.append(fc)
    history.append(test_data[t])
print('RMSE of SARIMA Model:', np.sqrt(mean_squared_error(test_data,␣
 ↪predictions)))
```

[ ]:
```python
plt.figure(figsize=(18,8))
plt.title('Forecast vs Actual', fontsize = 25)
plt.plot(range(40), predictions, label = 'Predictions', linewidth = 4)
plt.plot(range(40), test_data, label = 'Close', linewidth = 4)
plt.legend(fontsize = 25, shadow=True,facecolor='lightpink',edgecolor = 'k')
```

19 Observation :

- in this Adani Power Limited stock price data there is no need to apply or include sessional factor beacause our actual data in zik-zak.
- we make sure that our order of arima is should be in correct format.
- Here we forecaste the Close price for the next 60 days.

[ ]:

[ ]:

[ ]:

[ ]:

[ ]: