In [1]:
```
import pandas as pd
tesla = pd.read_csv("TSLA.csv")
```

In [2]:
```
tesla.shape
```

Out[2]:
```
(2416, 7)
```

In [3]:
```
tesla.head()
```

Out[3]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2010-06-29	19.000000	25.00	17.540001	23.889999	23.889999	18766300
1	2010-06-30	25.790001	30.42	23.299999	23.830000	23.830000	17187100
2	2010-07-01	25.000000	25.92	20.270000	21.959999	21.959999	8218800
3	2010-07-02	23.000000	23.10	18.709999	19.200001	19.200001	5139800
4	2010-07-06	20.000000	20.00	15.830000	16.110001	16.110001	6866900

In [4]:
```
tesla.isnull().sum()
```

Out[4]:
```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

In [5]:
```
tesla.describe()
```

Out[5]:

	Open	High	Low	Close	Adj Close	Volume
count	2416.000000	2416.000000	2416.000000	2416.000000	2416.000000	2.416000e+03
mean	186.271147	189.578224	182.916639	186.403651	186.403651	5.572722e+06
std	118.740163	120.892329	116.857591	119.136020	119.136020	4.987809e+06
min	16.139999	16.629999	14.980000	15.800000	15.800000	1.185000e+05
25%	34.342498	34.897501	33.587501	34.400002	34.400002	1.899275e+06
50%	213.035004	216.745002	208.870002	212.960007	212.960007	4.578400e+06
75%	266.450012	270.927513	262.102501	266.774994	266.774994	7.361150e+06
max	673.690002	786.140015	673.520020	780.000000	780.000000	4.706500e+07

In [6]:
```
pd.DataFrame(tesla['Close']).describe(percentiles=(1,0.99,0.9,0.75,0.5,0.3,0.1,0
```

Out[6]:

	Close
count	2416.000000
mean	186.403651
std	119.136020
min	15.800000
1%	19.870001
10%	27.120001
30%	87.414997
50%	212.960007
75%	266.774994
90%	333.919998
99%	424.345500
100%	780.000000
max	780.000000

In [7]:
```
pd.DataFrame(tesla['High']).describe(percentiles=(1,0.99,0.9,0.75,0.5,0.3,0.1,0.
```

Out[7]:

	High
count	2416.000000
mean	189.578224
std	120.892329
min	16.629999
1%	20.202001
10%	27.795000
30%	90.474998
50%	216.745002
75%	270.927513
90%	339.854996
99%	428.470500
100%	786.140015
max	786.140015

In [8]:
```
pd.DataFrame(tesla['Low']).describe(percentiles=(1,0.99,0.9,0.75,0.5,0.3,0.1,0.0
```

Out[8]:

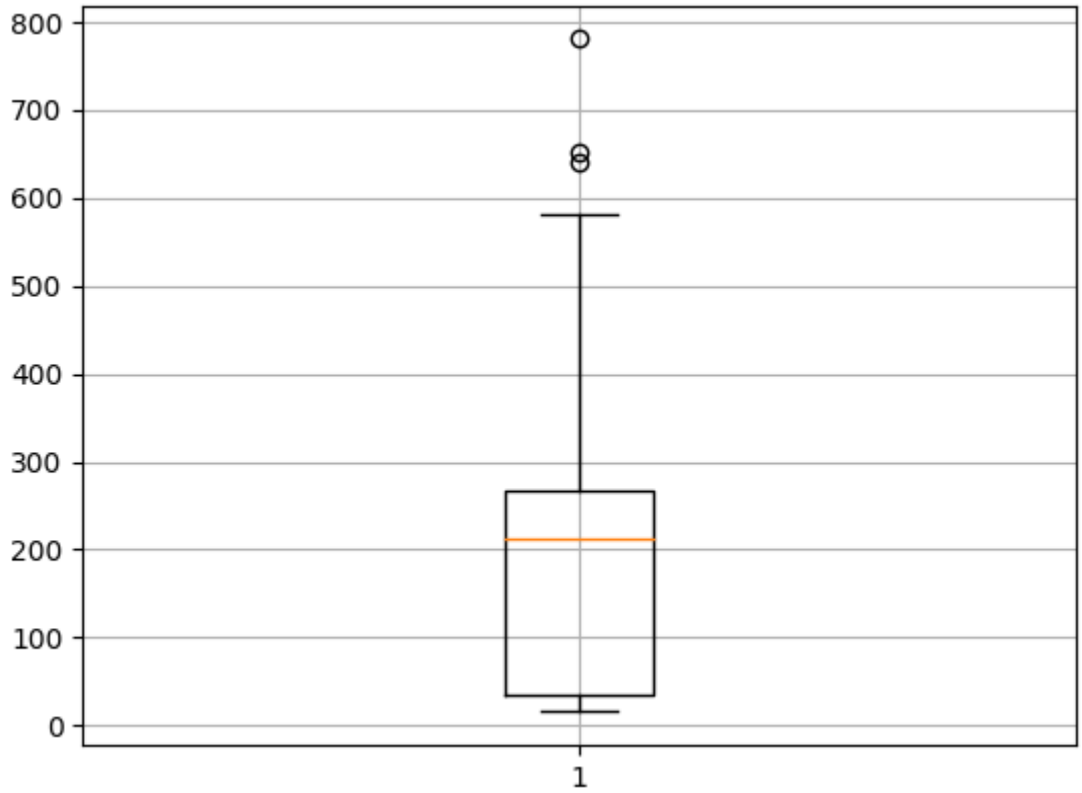
	Low
count	2416.000000
mean	182.916639
std	116.857591
min	14.980000
1%	19.500000
10%	26.534999
30%	82.100003
50%	208.870002
75%	262.102501
90%	327.324997
99%	412.286502
100%	673.520020
max	673.520020

In [9]:
```
pd.DataFrame(tesla['Open']).describe(percentiles=(1,0.99,0.9,0.75,0.5,0.3,0.1,0.
```

Out[9]:

	Open
count	2416.000000
mean	186.271147
std	118.740163
min	16.139999
1%	19.891499
10%	27.200001
30%	85.590001
50%	213.035004
75%	266.450012
90%	333.455002
99%	423.578998
100%	673.690002
max	673.690002

In [10]:
```
import matplotlib.pyplot as plt
# %matplotlib inline
plt.boxplot(tesla['Close'])
plt.grid()
plt.show()
```



In [11]:
```
Close_col_df = pd.DataFrame(tesla['Close'])
Close_median = Close_col_df.median()


Q3 = Close_col_df.quantile(q=0.75)
Q1 = Close_col_df.quantile(q=0.25)
IQR = Q3-Q1


IQR_LL = int(Q1 - 1.5*IQR)
IQR_UL = int(Q3 + 1.5*IQR)


tesla.loc[tesla['Close']>IQR_UL , 'Close'] = int(Close_col_df.quantile(q=0.90))
tesla.loc[tesla['Close']<IQR_LL , 'Close'] = int(Close_col_df.quantile(q=0.01))
```

In [12]:
```
High_col_df = pd.DataFrame(tesla['High'])
High_median = High_col_df.median()


Q3 = High_col_df.quantile(q=0.75)
Q1 = High_col_df.quantile(q=0.25)
IQR = Q3-Q1


IQR_LL = int(Q1 - 1.5*IQR)
IQR_UL = int(Q3 + 1.5*IQR)


tesla.loc[tesla['High']>IQR_UL , 'High'] = int(High_col_df.quantile(q=0.90))
tesla.loc[tesla['High']<IQR_LL , 'High'] = int(High_col_df.quantile(q=0.01))
```

In [13]:
```
Low_col_df = pd.DataFrame(tesla['Low'])
Low_median = High_col_df.median()
```

```
Q3 = Low_col_df.quantile(q=0.75)
Q1 = Low_col_df.quantile(q=0.25)
IQR = Q3-Q1


IQR_LL = int(Q1 - 1.5*IQR)
IQR_UL = int(Q3 + 1.5*IQR)


tesla.loc[tesla['Low']>IQR_UL , 'Low'] = int(Low_col_df.quantile(q=0.90))
tesla.loc[tesla['Low']<IQR_LL , 'Low'] = int(Low_col_df.quantile(q=0.01))
```

In [14]:
```
Open_col_df = pd.DataFrame(tesla['Open'])
Open_median = High_col_df.median()


Q3 = Open_col_df.quantile(q=0.75)
Q1 = Open_col_df.quantile(q=0.25)
IQR = Q3-Q1


IQR_LL = int(Q1 - 1.5*IQR)
IQR_UL = int(Q3 + 1.5*IQR)


tesla.loc[tesla['Open']>IQR_UL , 'Open'] = int(Open_col_df.quantile(q=0.90))
tesla.loc[tesla['Open']<IQR_LL , 'Open'] = int(Open_col_df.quantile(q=0.01))
```

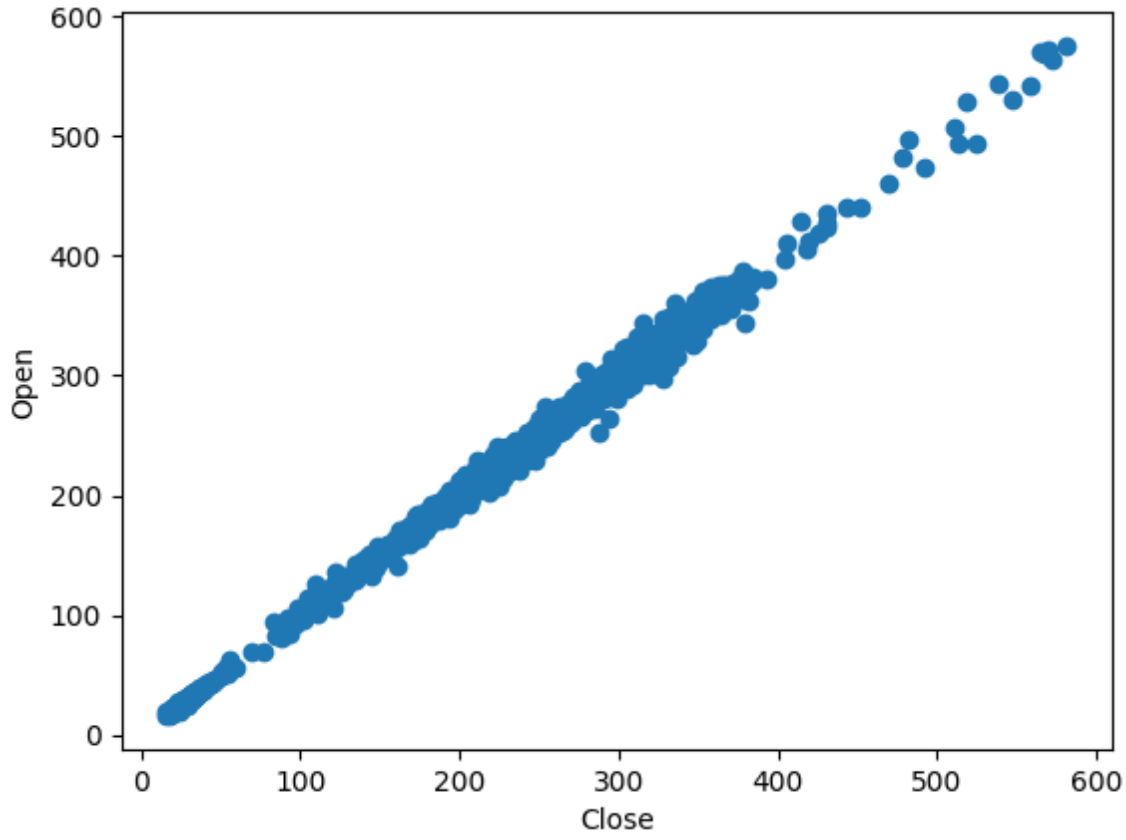
In [15]:
```
tesla.describe()
```

Out[15]:

	Open	High	Low	Close	Adj Close	Volume
count	2416.000000	2416.000000	2416.000000	2416.000000	2416.000000	2.416000e+03
mean	185.879131	189.134093	182.526308	185.959785	186.403651	5.572722e+06
std	117.727539	119.658201	115.842913	117.895176	119.136020	4.987809e+06
min	16.139999	16.629999	14.980000	15.800000	15.800000	1.185000e+05
25%	34.342498	34.897501	33.587501	34.400002	34.400002	1.899275e+06
50%	213.035004	216.745002	208.870002	212.960007	212.960007	4.578400e+06
75%	266.450012	270.927513	262.102501	266.774994	266.774994	7.361150e+06
max	575.690002	594.500000	567.429993	580.989990	780.000000	4.706500e+07

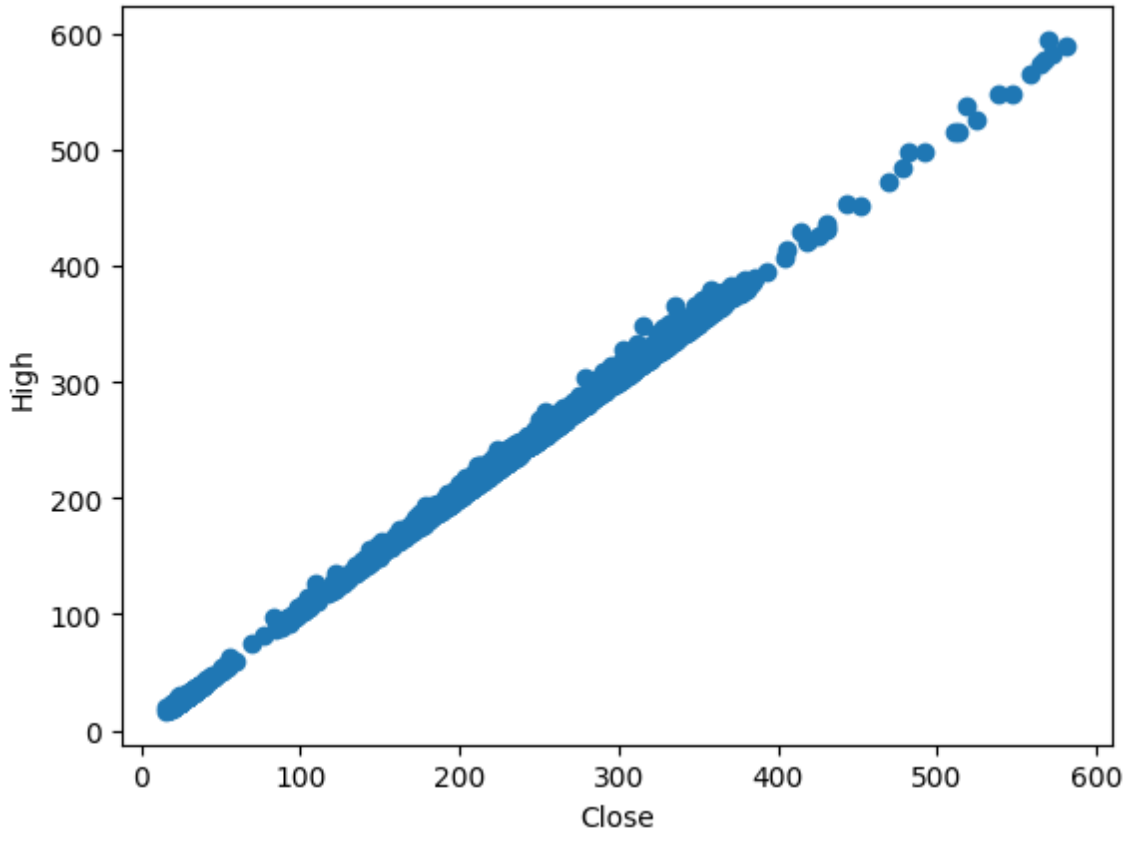
In [16]:
```
x = tesla["Close"]
y=  tesla["Open"]
plt.scatter(x, y)

plt.xlabel('Close')
plt.ylabel('Open')
plt.show()
```



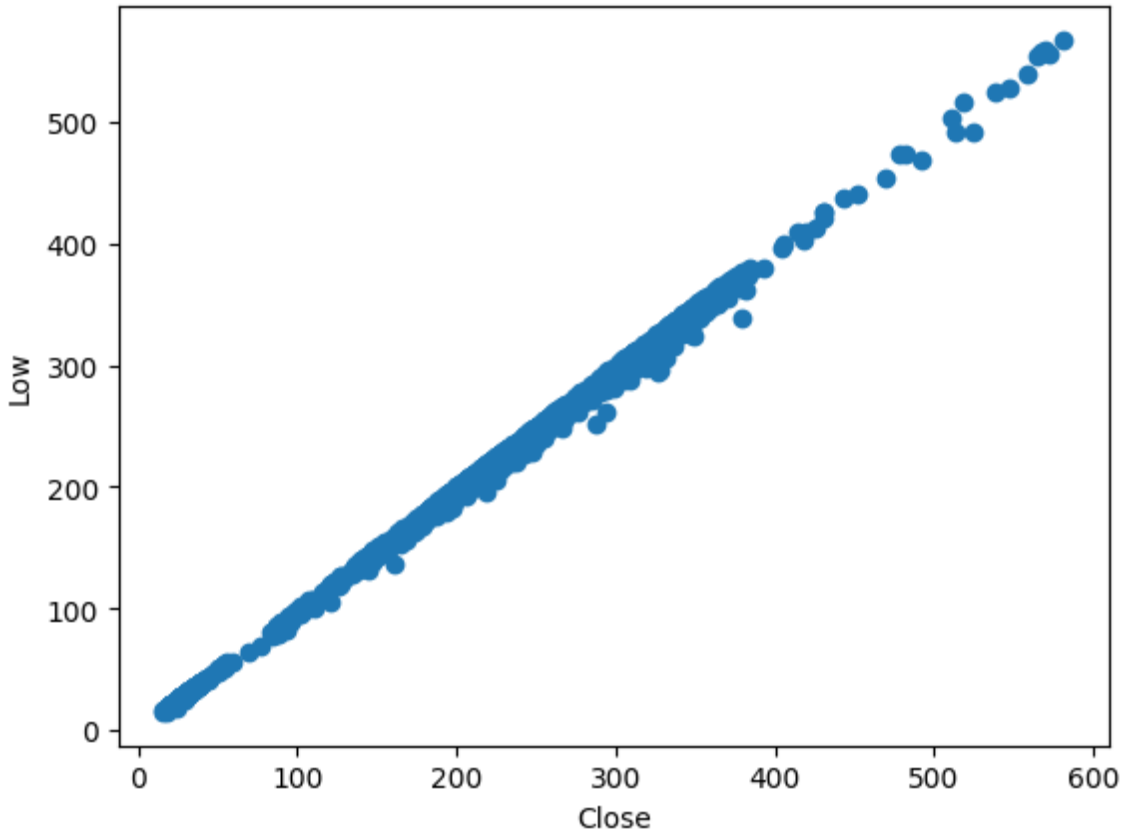
In [17]:
```
x = tesla["Close"]
y=  tesla["High"]
plt.scatter(x, y)

plt.xlabel('Close')
plt.ylabel('High')
plt.show()
```



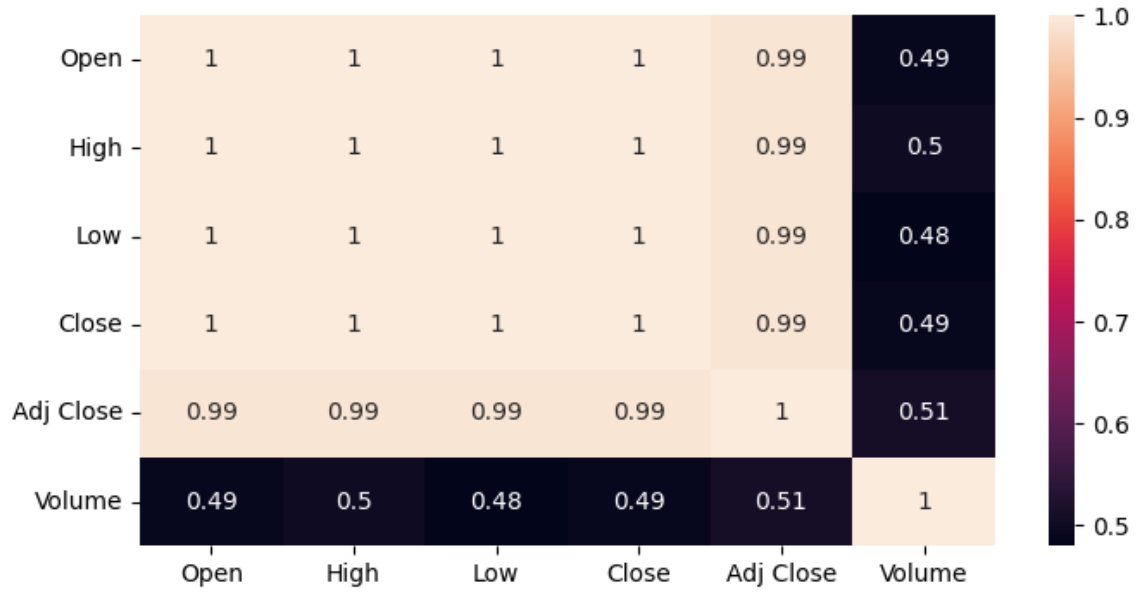
In [18]:
```
x = tesla["Close"]
y=  tesla["Low"]
plt.scatter(x, y)

plt.xlabel('Close')
plt.ylabel('Low')
plt.show()
```



In [19]:
```
correlation_matrix= tesla.corr().round(2)
fgr, ax = plt.subplots(figsize =(8, 4))
import seaborn as sns
c = sns.heatmap(data=correlation_matrix, annot=True)
fgr.savefig("myimage.png")
```

```
C:\Users\hp\AppData\Local\Temp\ipykernel_15872\554146146.py:1: FutureWarning: T
he default value of numeric_only in DataFrame.corr is deprecated. In a future v
ersion, it will default to False. Select only valid columns or specify the valu
e of numeric_only to silence this warning.
  correlation_matrix= tesla.corr().round(2)
```



In [20]:
```
tesla.drop(["Date","Adj Close","Volume"],axis=1,inplace=True)
tesla.head()
```

Out[20]:

	Open	High	Low	Close
0	19.000000	25.00	17.540001	23.889999
1	25.790001	30.42	23.299999	23.830000
2	25.000000	25.92	20.270000	21.959999
3	23.000000	23.10	18.709999	19.200001
4	20.000000	20.00	15.830000	16.110001

In [21]:
```
tesla.describe()
```

Out[21]:

	Open	High	Low	Close
count	2416.000000	2416.000000	2416.000000	2416.000000
mean	185.879131	189.134093	182.526308	185.959785
std	117.727539	119.658201	115.842913	117.895176
min	16.139999	16.629999	14.980000	15.800000
25%	34.342498	34.897501	33.587501	34.400002
50%	213.035004	216.745002	208.870002	212.960007
75%	266.450012	270.927513	262.102501	266.774994
max	575.690002	594.500000	567.429993	580.989990

In [22]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(tesla)
scaled_data
```

Out[22]:
```
array([[0.00511125, 0.01448423, 0.00463391, 0.01431377],
       [0.017246  , 0.0238635 , 0.01506018, 0.01420761],
       [0.01583415, 0.01607628, 0.00957553, 0.01089899],
       ...,
       [0.56627647, 0.55785903, 0.5647932 , 0.56122721],
       [0.56627647, 0.55785903, 0.5647932 , 0.56122721],
       [0.56627647, 0.55785903, 0.5647932 , 0.56122721]])
```

In [23]:
```
tesla_scaled = pd.DataFrame(scaled_data)
tesla_scaled.columns = tesla.columns
tesla_scaled
```

Out[23]:

	Open	High	Low	Close
0	0.005111	0.014484	0.004634	0.014314
1	0.017246	0.023864	0.015060	0.014208
2	0.015834	0.016076	0.009576	0.010899
3	0.012260	0.011196	0.006752	0.006016
4	0.006898	0.005832	0.001539	0.000548
...	...	...	...	...
2411	0.987132	0.969388	0.983075	0.975070
2412	1.000000	0.991867	1.000000	1.000000
2413	0.566276	0.557859	0.564793	0.561227
2414	0.566276	0.557859	0.564793	0.561227
2415	0.566276	0.557859	0.564793	0.561227

2416 rows × 4 columns

In [24]:
```
features = ["Open","High","Low"]
target = ["Close"]
X=tesla_scaled[features]
y=tesla_scaled[target]
```

In [25]:
```
X.head()
```

Out[25]:

	Open	High	Low
0	0.005111	0.014484	0.004634
1	0.017246	0.023864	0.015060
2	0.015834	0.016076	0.009576
3	0.012260	0.011196	0.006752
4	0.006898	0.005832	0.001539

In [26]:
```
y.head()
```

Out[26]:

	Close
0	0.014314
1	0.014208
2	0.010899
3	0.006016
4	0.000548

In [27]:
```
import sklearn
sklearn.set_config(print_changed_only=False)
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_

#Importing neccesary packages
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

In [28]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[28]:
```
((1932, 3), (484, 3), (1932, 1), (484, 1))
```

In [29]:
```
model = LinearRegression()
model.fit(X_train, y_train)
```

Out[29]:
```
LinearRegression
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, positive
=False)
```

In [30]:
```
accuracy = model.score(X_test,y_test)*100
print(accuracy,'%')
```

```
99.9727378794794 %
```

In [31]:
```
y_pred = model.predict(X_test)
h=metrics.r2_score(y_pred,y_test)
print(h)
```

```
0.9997269511147142
```

In [32]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, y_pred)
print("Mean Squared Error:", mse)
```

```
Mean Squared Error: 1.1779989388467442e-05
```

In [33]:
```
import math as m
mse = mean_squared_error(y_test, y_pred)
rms = m.sqrt(mse)

print("RMS:", rms)
```

```
RMS: 0.0034321989144668525
```

In [34]:
```
from sklearn.metrics import mean_absolute_error
mae = mean_absolute_error(y_test, y_pred)
```

```
print("Mean Absolute Error:", mae)
```

```
Mean Absolute Error: 0.002322373145396641
```

In [35]:
```
model.intercept_
```

Out[35]:
```
array([-0.0002602])
```

In [36]:
```
model.coef_
```

Out[36]:
```
array([[-0.62737767,  0.88656411,  0.7484012 ]])
```

In [37]:
```
print("-"*46,"RESULT","-"*46,"\n\n\n")

import pandas as pd
print('*'*100)
table = [[accuracy],[h],[mse],[rms],[mae]]
df = pd.DataFrame(table, columns = ['Performance Score'], index=['Accuracy ',"r2
print(df)
print('*'*100)
```

```
---------------------------------------------- RESULT ------------------------
----------------------



****************************************************************************
********************
                     Performance Score
Accuracy                     99.972738
r2_score                      0.999727
Mean Squared Error            0.000012
RMS                           0.003432
Mean Absolute Error           0.002322
****************************************************************************
********************
```

In [ ]:
```

```