IMPORTING LIBRARIES:

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
#here we are loading data using pandas
df=pd.read_csv(r'C:\Users\Hp\Downloads\archive (4) (1).zip')
```

In [3]:
```
df
```

Out[3]:

	Unnamed: 0	Date	Close	Volume	Open	High	Low
0	0	2024-01-19	2029.3	166078.0	2027.4	2041.9	2022.2
1	1	2024-01-18	2021.6	167013.0	2009.1	2025.6	2007.7
2	2	2024-01-17	2006.5	245194.0	2031.7	2036.1	2004.6
3	3	2024-01-16	2030.2	277995.0	2053.4	2062.8	2027.6
4	4	2024-01-12	2051.6	250946.0	2033.2	2067.3	2033.1
...	...	...	...	...	...	...	...
2506	2528	2014-01-28	1250.5	81426.0	1254.9	1261.9	1248.0
2507	2529	2014-01-27	1263.5	63419.0	1269.9	1280.1	1252.0
2508	2530	2014-01-24	1264.5	34998.0	1264.3	1273.2	1256.9
2509	2531	2014-01-23	1262.5	41697.0	1235.1	1267.1	1230.8
2510	2532	2014-01-22	1238.6	80262.0	1240.5	1243.5	1235.5

2511 rows × 7 columns

Analyzing the each attribute from the above data: Given goldstock prices GoldStock:which refers to the market where shares of companies involved in the production,exploration,or distribution of gold brought and sold. 1.Date: stock price on particular date. 2.close:At the end of the day,the price of the gold stock per share. 3.Volume:Throughout given date,total shares of the gold stock were bought and sold. 4.Open:when the market opened ,the first trade of the gold stock per share. 5.High:The highest price that the gold stock reached on the particular date. 6.Low:The lowest price that the gold stock reached on the particular date.

In [4]:
```
df.head()
```

Out[4]:

	Unnamed: 0	Date	Close	Volume	Open	High	Low
0	0	2024-01-19	2029.3	166078.0	2027.4	2041.9	2022.2
1	1	2024-01-18	2021.6	167013.0	2009.1	2025.6	2007.7
2	2	2024-01-17	2006.5	245194.0	2031.7	2036.1	2004.6
3	3	2024-01-16	2030.2	277995.0	2053.4	2062.8	2027.6
4	4	2024-01-12	2051.6	250946.0	2033.2	2067.3	2033.1

In [5]:
```
df.tail()
```

Out[5]:

	Unnamed: 0	Date	Close	Volume	Open	High	Low
2506	2528	2014-01-28	1250.5	81426.0	1254.9	1261.9	1248.0
2507	2529	2014-01-27	1263.5	63419.0	1269.9	1280.1	1252.0
2508	2530	2014-01-24	1264.5	34998.0	1264.3	1273.2	1256.9
2509	2531	2014-01-23	1262.5	41697.0	1235.1	1267.1	1230.8
2510	2532	2014-01-22	1238.6	80262.0	1240.5	1243.5	1235.5

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
Unnamed: 0    0
Date          0
Close         0
Volume        0
Open          0
High          0
Low           0
dtype: int64
```

In [7]:
```
df.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
df['Date']=pd.to_datetime(df['Date'])
df['dayofweek']=df['Date'].dt.dayofweek
df['Month']=df['Date'].dt.month
df['Year']=df['Date'].dt.year
```

In [9]:
```
df1 = df.drop(df.columns[1], axis=1)
df1
```

Out[9]:

	Unnamed: 0	Close	Volume	Open	High	Low	dayofweek	Month	Year
0	0	2029.3	166078.0	2027.4	2041.9	2022.2	4	1	2024
1	1	2021.6	167013.0	2009.1	2025.6	2007.7	3	1	2024
2	2	2006.5	245194.0	2031.7	2036.1	2004.6	2	1	2024
3	3	2030.2	277995.0	2053.4	2062.8	2027.6	1	1	2024
4	4	2051.6	250946.0	2033.2	2067.3	2033.1	4	1	2024
...	...	...	...	...	...	...	...	...	...
2506	2528	1250.5	81426.0	1254.9	1261.9	1248.0	1	1	2014
2507	2529	1263.5	63419.0	1269.9	1280.1	1252.0	0	1	2014
2508	2530	1264.5	34998.0	1264.3	1273.2	1256.9	4	1	2014
2509	2531	1262.5	41697.0	1235.1	1267.1	1230.8	3	1	2014
2510	2532	1238.6	80262.0	1240.5	1243.5	1235.5	2	1	2014

2511 rows × 9 columns

In [10]:
```
df2 = df1.drop(df1.columns[0], axis=1)
df2
```

Out[10]:

	Close	Volume	Open	High	Low	dayofweek	Month	Year
0	2029.3	166078.0	2027.4	2041.9	2022.2	4	1	2024
1	2021.6	167013.0	2009.1	2025.6	2007.7	3	1	2024
2	2006.5	245194.0	2031.7	2036.1	2004.6	2	1	2024
3	2030.2	277995.0	2053.4	2062.8	2027.6	1	1	2024
4	2051.6	250946.0	2033.2	2067.3	2033.1	4	1	2024
...	...	...	...	...	...	...	...	...
2506	1250.5	81426.0	1254.9	1261.9	1248.0	1	1	2014
2507	1263.5	63419.0	1269.9	1280.1	1252.0	0	1	2014
2508	1264.5	34998.0	1264.3	1273.2	1256.9	4	1	2014
2509	1262.5	41697.0	1235.1	1267.1	1230.8	3	1	2014
2510	1238.6	80262.0	1240.5	1243.5	1235.5	2	1	2014

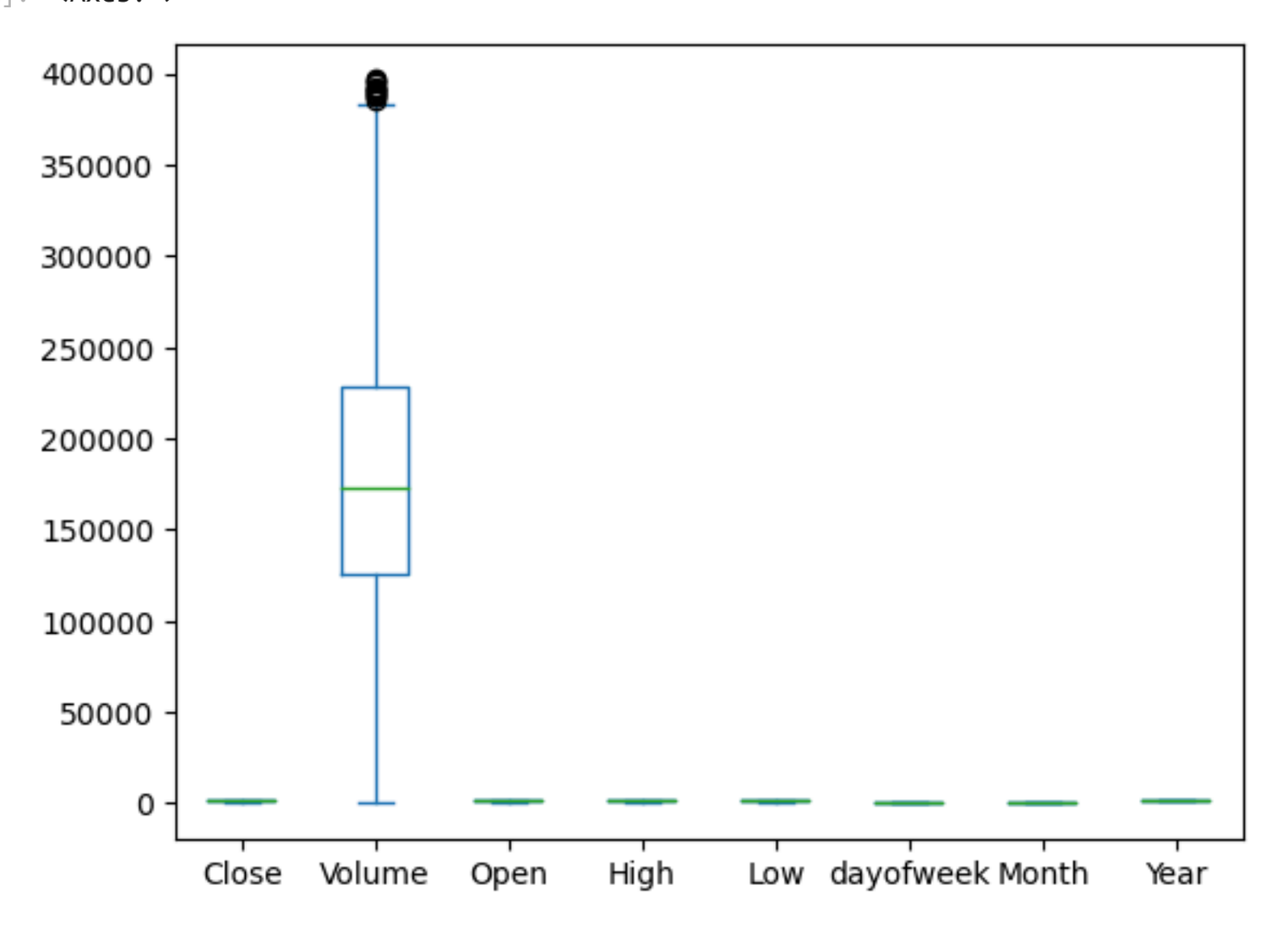
2511 rows × 8 columns

In [11]:
```
Q1 = df2.quantile(0.25)
Q3 = df2.quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
data_cleaned = df2[~((df2 < lower_bound) | (df2 > upper_bound)).any(axis=1)]

print("Original Data:")
print(df2)

print("\nCleaned Data:")
print(data_cleaned)
```

```
Original Data:
       Close    Volume    Open    High     Low  dayofweek  Month  Year
0     2029.3  166078.0  2027.4  2041.9  2022.2          4      1  2024
1     2021.6  167013.0  2009.1  2025.6  2007.7          3      1  2024
2     2006.5  245194.0  2031.7  2036.1  2004.6          2      1  2024
3     2030.2  277995.0  2053.4  2062.8  2027.6          1      1  2024
4     2051.6  250946.0  2033.2  2067.3  2033.1          4      1  2024
...      ...       ...     ...     ...     ...        ...    ...   ...
2506  1250.5   81426.0  1254.9  1261.9  1248.0          1      1  2014
2507  1263.5   63419.0  1269.9  1280.1  1252.0          0      1  2014
2508  1264.5   34998.0  1264.3  1273.2  1256.9          4      1  2014
2509  1262.5   41697.0  1235.1  1267.1  1230.8          3      1  2014
2510  1238.6   80262.0  1240.5  1243.5  1235.5          2      1  2014

[2511 rows x 8 columns]

Cleaned Data:
       Close    Volume    Open    High     Low  dayofweek  Month  Year
0     2029.3  166078.0  2027.4  2041.9  2022.2          4      1  2024
1     2021.6  167013.0  2009.1  2025.6  2007.7          3      1  2024
2     2006.5  245194.0  2031.7  2036.1  2004.6          2      1  2024
3     2030.2  277995.0  2053.4  2062.8  2027.6          1      1  2024
4     2051.6  250946.0  2033.2  2067.3  2033.1          4      1  2024
...      ...       ...     ...     ...     ...        ...    ...   ...
2506  1250.5   81426.0  1254.9  1261.9  1248.0          1      1  2014
2507  1263.5   63419.0  1269.9  1280.1  1252.0          0      1  2014
2508  1264.5   34998.0  1264.3  1273.2  1256.9          4      1  2014
2509  1262.5   41697.0  1235.1  1267.1  1230.8          3      1  2014
2510  1238.6   80262.0  1240.5  1243.5  1235.5          2      1  2014

[2437 rows x 8 columns]
```

In [12]:
```
data_cleaned.plot(kind='box')
```

Out[12]:
```
<Axes: >
```



In [13]:
```
#Summary statistics
data_cleaned.describe()
```

Out[13]:

	Close	Volume	Open	High	Low	dayofweek	Month	Year
count	2437.000000	2437.000000	2437.000000	2437.000000	2437.000000	2437.000000	2437.000000	2437.000000
mean	1498.066147	176976.345917	1497.833238	1507.382725	1488.429093	2.019286	6.554370	2018.528929
std	301.038475	82812.354274	301.184398	303.356911	298.731184	1.400811	3.441396	2.914153
min	1049.600000	1.000000	1051.500000	1062.700000	1045.400000	0.000000	1.000000	2014.000000
25%	1247.400000	125228.000000	1247.000000	1255.100000	1240.700000	1.000000	4.000000	2016.000000
50%	1329.500000	172801.000000	1330.800000	1337.600000	1323.600000	2.000000	7.000000	2018.000000
75%	1807.200000	228720.000000	1807.400000	1816.500000	1794.100000	3.000000	10.000000	2021.000000
max	2093.100000	396657.000000	2094.400000	2098.200000	2074.600000	4.000000	12.000000	2024.000000

In [14]:
```
#correlation matrix
correlation_matrix=data_cleaned.corr()
correlation_matrix
```

Out[14]:

	Close	Volume	Open	High	Low	dayofweek	Month	Year
Close	1.000000	0.019988	0.999130	0.999623	0.999616	0.008208	0.013139	0.893486
Volume	0.019988	1.000000	0.022064	0.024467	0.017113	0.050983	-0.005889	0.104433
Open	0.999130	0.022064	1.000000	0.999536	0.999523	0.006848	0.013119	0.893521
High	0.999623	0.024467	0.999536	1.000000	0.999426	0.008177	0.012042	0.892439
Low	0.999616	0.017113	0.999523	0.999426	1.000000	0.007288	0.014914	0.894628
dayofweek	0.008208	0.050983	0.006848	0.008177	0.007288	1.000000	-0.017887	0.008763
Month	0.013139	-0.005889	0.013119	0.012042	0.014914	-0.017887	1.000000	-0.023847
Year	0.893486	0.104433	0.893521	0.892439	0.894628	0.008763	-0.023847	1.000000

Building an algorithm

In [15]:
```
#importing some libraries to build a model
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error as mse
from sklearn.metrics import r2_score
```

In [16]:
```
x=df[['Volume','Open','High','Low','dayofweek','Month','Year']]
y=df[['Close']]
x_train,x_test,y_train,y_test= train_test_split(x,y,test_size=0.2,random_state=49)
```

Here we choose target variable as 'close'. we choose 'Volume','Open','High','Low','dayofweek','Month','Year'variables as input variables.

In [17]:
```
x
```

Out[17]:

	Volume	Open	High	Low	dayofweek	Month	Year
0	166078.0	2027.4	2041.9	2022.2	4	1	2024
1	167013.0	2009.1	2025.6	2007.7	3	1	2024
2	245194.0	2031.7	2036.1	2004.6	2	1	2024
3	277995.0	2053.4	2062.8	2027.6	1	1	2024
4	250946.0	2033.2	2067.3	2033.1	4	1	2024
...	...	...	...	...	...	...	...
2506	81426.0	1254.9	1261.9	1248.0	1	1	2014
2507	63419.0	1269.9	1280.1	1252.0	0	1	2014
2508	34998.0	1264.3	1273.2	1256.9	4	1	2014
2509	41697.0	1235.1	1267.1	1230.8	3	1	2014
2510	80262.0	1240.5	1243.5	1235.5	2	1	2014

2511 rows × 7 columns

In [18]:
```
y
```

Out[18]:

	Close
0	2029.3
1	2021.6
2	2006.5
3	2030.2
4	2051.6
...	...
2506	1250.5
2507	1263.5
2508	1264.5
2509	1262.5
2510	1238.6

2511 rows × 1 columns

In [19]:
```
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
#feature Scaling
scaler =StandardScaler().fit(x_train)
```

In [20]:
```
scaler
```

Out[20]:
```
▾ StandardScaler
StandardScaler()
```

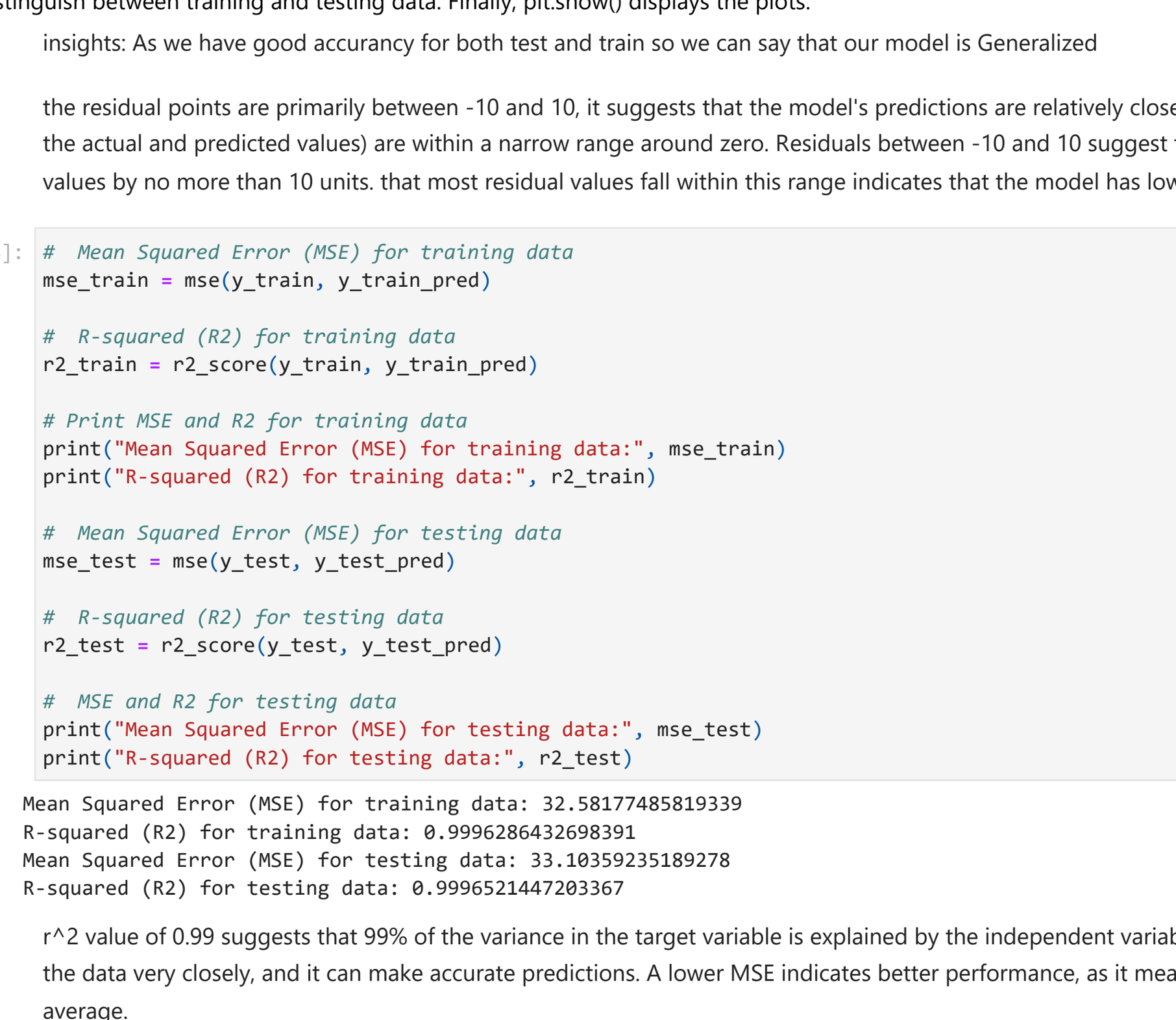
In [21]:
```
#creating a linear model
from sklearn.linear_model import LinearRegression
lm=LinearRegression()
lm.fit(x_train,y_train)
```

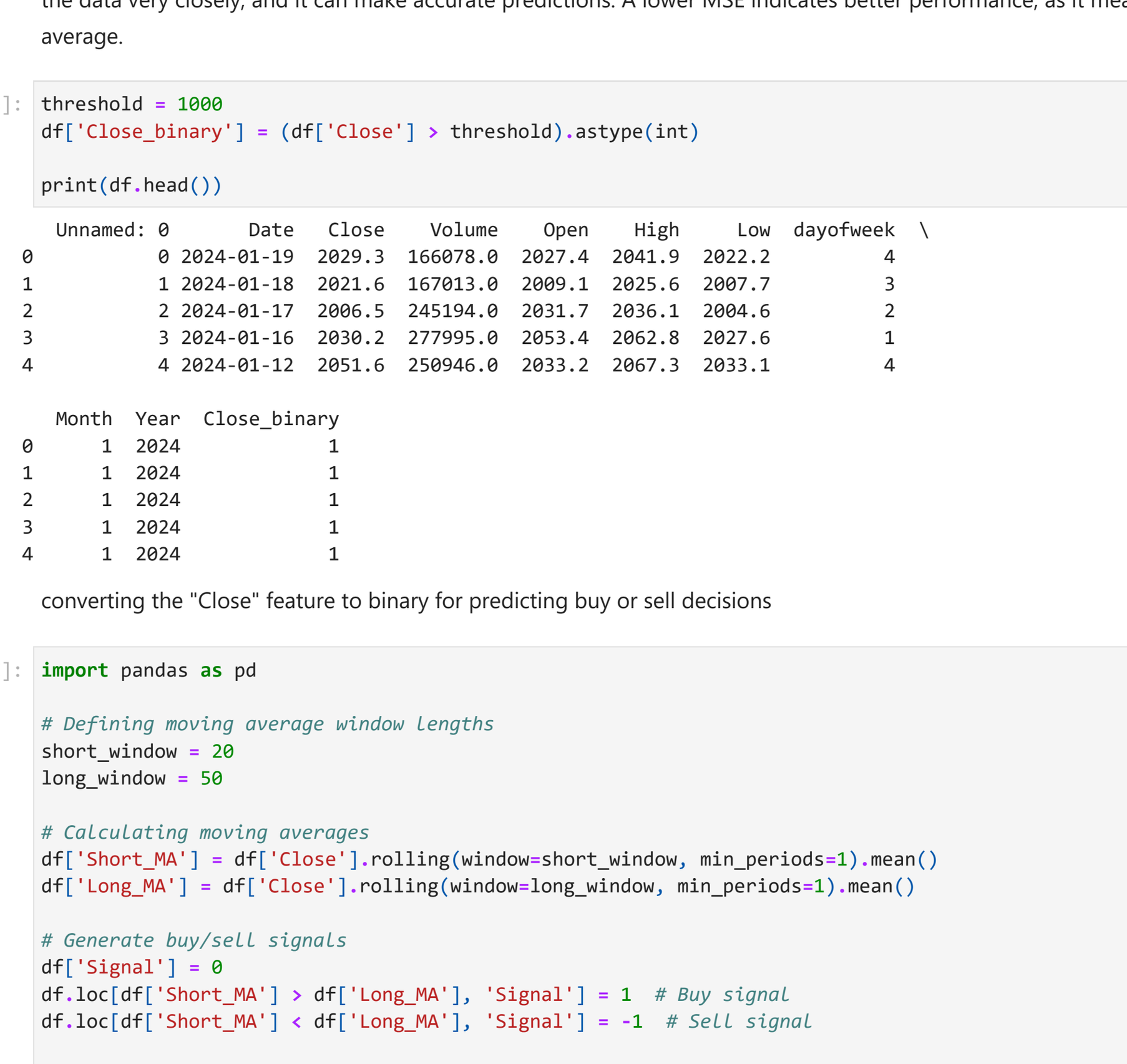
Out[21]:
```
▾ LinearRegression
LinearRegression()
```

In [22]:
```
y_pred=lm.predict(x_test)
len(y_train)
```

Out[22]:
```
2008
```

In [23]:
```
# predictions on the training data
y_train_pred = lm.predict(x_train)

# Plotting the actual vs predicted values for the training data
plt.figure(figsize=(8, 6))
plt.scatter(y_train, y_train_pred, color='blue', label='Training Data')
plt.plot([y_train.min(), y_train.max()], [y_train.min(), y_train.max()], linestyle='--', color='red')  # Plotting the diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted (Training Data)')
plt.legend()
plt.show()

# predictions on the testing data
y_test_pred = lm.predict(x_test)

# Plotting the actual vs predicted values for the testing data
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_test_pred, color='green', label='Testing Data')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], linestyle='--', color='red')  # Plotting the diagonal line
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.title('Actual vs Predicted (Testing Data)')
plt.legend()
plt.show()
```





y_train and y_train_pred are the actual and predicted target values, respectively, for the training data. y_test and y_test_pred are the actual and predicted target values, respectively, for the testing data. plt.scatter() is used to create a scatter plot of actual vs predicted values for both training and testing data. The label argument is used to label each plot. plt.legend() adds a legend to the plot to distinguish between training and testing data. Finally, plt.show() displays the plots.

insights: As we have good accurancy for both test and train so we can say that our model is Generalized

the residual points are primarily between -10 and 10, it suggests that the model's predictions are relatively close to the actual values, as the residuals (the differences between the actual and predicted values) are within a narrow range around zero. Residuals between -10 and 10 suggest that the model's predictions typically deviate from the actual values by no more than 10 units. that most residual values fall within this range indicates that the model has low prediction error.

In [24]:
```
#  Mean Squared Error (MSE) for training data
mse_train = mse(y_train, y_train_pred)

#  R-squared (R2) for training data
r2_train = r2_score(y_train, y_train_pred)

# Print MSE and R2 for training data
print("Mean Squared Error (MSE) for training data:", mse_train)
print("R-squared (R2) for training data:", r2_train)

#  Mean Squared Error (MSE) for testing data
mse_test = mse(y_test, y_test_pred)

#  R-squared (R2) for testing data
r2_test = r2_score(y_test, y_test_pred)

#  MSE and R2 for testing data
print("Mean Squared Error (MSE) for testing data:", mse_test)
print("R-squared (R2) for testing data:", r2_test)
```

```
Mean Squared Error (MSE) for training data: 32.58177485819339
R-squared (R2) for training data: 0.9996286432698391
Mean Squared Error (MSE) for testing data: 33.10359235189278
R-squared (R2) for testing data: 0.9996521447203367
```

r^2 value of 0.99 suggests that 99% of the variance in the target variable is explained by the independent variables in the model.This high r2 value indicates that the model fits the data very closely, and it can make accurate predictions. A lower MSE indicates better performance, as it means that the model's predictions are closer to the actual values on average.

In [25]:
```
threshold = 1000
df['Close_binary'] = (df['Close'] > threshold).astype(int)

print(df.head())
```

```
   Unnamed: 0       Date   Close    Volume    Open    High     Low  dayofweek  \
0           0 2024-01-19  2029.3  166078.0  2027.4  2041.9  2022.2          4
1           1 2024-01-18  2021.6  167013.0  2009.1  2025.6  2007.7          3
2           2 2024-01-17  2006.5  245194.0  2031.7  2036.1  2004.6          2
3           3 2024-01-16  2030.2  277995.0  2053.4  2062.8  2027.6          1
4           4 2024-01-12  2051.6  250946.0  2033.2  2067.3  2033.1          4

   Month  Year  Close_binary
0      1  2024             1
1      1  2024             1
2      1  2024             1
3      1  2024             1
4      1  2024             1
```

converting the "Close" feature to binary for predicting buy or sell decisions

In [26]:
```
import pandas as pd

# Defining moving average window lengths
short_window = 20
long_window = 50

# Calculating moving averages
df['Short_MA'] = df['Close'].rolling(window=short_window, min_periods=1).mean()
df['Long_MA'] = df['Close'].rolling(window=long_window, min_periods=1).mean()

# Generate buy/sell signals
df['Signal'] = 0
df.loc[df['Short_MA'] > df['Long_MA'], 'Signal'] = 1  # Buy signal
df.loc[df['Short_MA'] < df['Long_MA'], 'Signal'] = -1  # Sell signal

# Determine whether to buy or sell
df['Action'] = 'Hold'
df.loc[df['Signal'] == 1, 'Action'] = 'Buy'
df.loc[df['Signal'] == -1, 'Action'] = 'Sell'

# Display the DataFrame with buy/sell signals
print(df[['Close', 'Short_MA', 'Long_MA', 'Signal', 'Action']])
```

```
       Close     Short_MA      Long_MA  Signal Action
0     2029.3  2029.300000  2029.300000       0   Hold
1     2021.6  2025.450000  2025.450000       0   Hold
2     2006.5  2019.133333  2019.133333       0   Hold
3     2030.2  2021.900000  2021.900000       0   Hold
4     2051.6  2027.840000  2027.840000       0   Hold
...      ...          ...          ...     ...    ...
2506  1250.5  1286.365000  1310.842000      -1   Sell
2507  1263.5  1282.405000  1309.930000      -1   Sell
2508  1264.5  1278.730000  1309.254000      -1   Sell
2509  1262.5  1275.675000  1308.434000      -1   Sell
2510  1238.6  1271.760000  1307.514000      -1   Sell

[2511 rows x 5 columns]
```

(SMA) for the 'Close' prices of a stock over two different periods: a short-term period (20 days) and a long-term period (50 days).(sma used to smooth out short-term fluctuations and highlight longer-term trends or cycles in data.)

it generates a buy signal, and when the short-term moving average crosses below the long-term moving average, it generates a sell signal. The actions ('Buy', 'Sell', or 'Hold') are determined based on these signals.

In [27]:
```
new_data=[[400000,1900,2000,1800,5,1,2024]]
y_pred_new=lm.predict(new_data)
```

```
C:\Users\Hp\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X does not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```

In [28]:
```
# Defining new data as a DataFrame with proper column names
new_data = pd.DataFrame([[400000, 1900, 2000, 1800, 5, 1, 2024]], columns=['Volume', 'Open', 'High', 'Low', 'dayofweek', 'Month', 'Year'])

# Making predictions on the new data
y_pred_new = lm.predict(new_data)

# Printing the predicted value
print("Predicted value:", y_pred_new)
```

```
Predicted value: [[1898.31040042]]
```

In [29]:
```
# Defining thresholds for buy and sell signals
buy_threshold = 0.5  # Adjust threshold as needed
sell_threshold = -0.5  # Adjust threshold as needed

# Determining action based on predicted value
if y_pred_new > buy_threshold:
    action = "Buy"
elif y_pred_new < sell_threshold:
    action = "Sell"
else:
    action = "Hold"

# Printing the recommended action
print("Recommended Action:", action)
```

```
Recommended Action: Buy
```

In [ ]: