Regression Modeling for Stock Prediction

In [2]:
```
import numpy as np
import pandas as pd
import yfinance as yf
```

In [3]:
```
# Step 1: Download the Data

tickers = ('AAPL', 'AMZN', 'MSFT', 'QQQ', '^GSPC')
start_date = '2020-01-01'
end_date = '2024-12-31'

df = yf.download(tickers, start_date, end_date)['Close']
df
```

```
C:\Users\sahil\AppData\Local\Temp\ipykernel_1500\2293748721.py:7: FutureWarning: YF.
download() has changed argument auto_adjust default to True
  df = yf.download(tickers, start_date, end_date)['Close']
[*********************100%***********************]  5 of 5 completed
```

Out[3]:

Ticker	AAPL	AMZN	MSFT	QQQ	^GSPC
Date					
2020-01-02	72.468269	94.900497	152.505707	208.848953	3257.850098
2020-01-03	71.763733	93.748497	150.606720	206.935898	3234.850098
2020-01-06	72.335556	95.143997	150.995972	208.269241	3246.280029
2020-01-07	71.995361	95.343002	149.619308	208.240280	3237.179932
2020-01-08	73.153503	94.598503	152.002457	209.805450	3253.050049
...	...	...	...	...	...
2024-12-23	254.120682	225.059998	432.062775	520.901855	5974.069824
2024-12-24	257.037476	229.050003	436.112885	527.965210	6040.040039
2024-12-26	257.853790	227.050003	434.901794	527.606506	6037.589844
2024-12-27	254.439224	223.750000	427.377319	520.593018	5970.839844
2024-12-30	251.064484	221.300003	421.719025	513.669189	5906.939941

1257 rows × 5 columns

In [4]:
```
# Perform Features Engineering
# Shift the value by one

df['AAPL(t-1)'] = df['AAPL'].shift(1)
df['AMZN(t-1)'] = df['AMZN'].shift(1)
df['MSFT(t-1)'] = df['MSFT'].shift(1)
```

```
df['QQQ(t-1)'] = df['QQQ'].shift(1)
df['^GSPC(t-1)'] = df['^GSPC'].shift(1)
```

In [5]:
```
# Moving Average 5 (Technical Indicator)

df['AAPL_MA5'] = df['AAPL'].rolling(window=5).mean()
df['AMZN_MA5'] = df['MSFT'].rolling(window=5).mean()
df['MSFT_MA5'] = df['MSFT'].rolling(window=5).mean()
df['QQQ_MA5'] = df['QQQ'].rolling(window=5).mean()
df['^GSPC_MA5'] = df['^GSPC'].rolling(window=5).mean()
```

In [6]:
```
# Set Y Variable(next day)

df['Target'] = df['AAPL'].shift(-1)
```

In [7]:
```
df.dropna(inplace = True)
df
```

Out[7]:

Ticker	AAPL	AMZN	MSFT	QQQ	^GSPC	AAPL(t-1)	AMZN(t-1
Date							
2020-01-08	73.153503	94.598503	152.002457	209.805450	3253.050049	71.995361	95.34300
2020-01-09	74.707336	95.052498	153.901443	211.583237	3274.699951	73.153503	94.59850
2020-01-10	74.876251	94.157997	153.189301	211.042114	3265.350098	74.707336	95.05249
2020-01-13	76.475906	94.565002	155.031281	213.476944	3288.129883	74.876251	94.15799
2020-01-14	75.443230	93.472000	153.939423	212.636383	3283.149902	76.475906	94.56500
...	...	...	...	...	...	...	.
2024-12-20	253.344177	224.919998	433.402924	515.875793	5930.850098	248.665329	223.28999
2024-12-23	254.120682	225.059998	432.062775	520.901855	5974.069824	253.344177	224.91999
2024-12-24	257.037476	229.050003	436.112885	527.965210	6040.040039	254.120682	225.05999
2024-12-26	257.853790	227.050003	434.901794	527.606506	6037.589844	257.037476	229.05000
2024-12-27	254.439224	223.750000	427.377319	520.593018	5970.839844	257.853790	227.05000

1252 rows × 16 columns

In [8]:

```
# See how many and which columns are in my dataframe
df.columns
```

Out[8]:

```
Index(['AAPL', 'AMZN', 'MSFT', 'QQQ', '^GSPC', 'AAPL(t-1)', 'AMZN(t-1)',
       'MSFT(t-1)', 'QQQ(t-1)', '^GSPC(t-1)', 'AAPL_MA5', 'AMZN_MA5',
       'MSFT_MA5', 'QQQ_MA5', '^GSPC_MA5', 'Target'],
      dtype='object', name='Ticker')
```

In [9]:

```
# Checking if there is any NaN values in the columns
print(df.isna().sum())
```

```
Ticker
AAPL          0
AMZN          0
MSFT          0
QQQ           0
^GSPC         0
AAPL(t-1)     0
AMZN(t-1)     0
MSFT(t-1)     0
QQQ(t-1)      0
^GSPC(t-1)    0
AAPL_MA5      0
AMZN_MA5      0
MSFT_MA5      0
QQQ_MA5       0
^GSPC_MA5     0
Target        0
dtype: int64
```

In [10]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1252 entries, 2020-01-08 to 2024-12-27
Data columns (total 16 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   AAPL        1252 non-null   float64
 1   AMZN        1252 non-null   float64
 2   MSFT        1252 non-null   float64
 3   QQQ         1252 non-null   float64
 4   ^GSPC       1252 non-null   float64
 5   AAPL(t-1)   1252 non-null   float64
 6   AMZN(t-1)   1252 non-null   float64
 7   MSFT(t-1)   1252 non-null   float64
 8   QQQ(t-1)    1252 non-null   float64
 9   ^GSPC(t-1)  1252 non-null   float64
 10  AAPL_MA5    1252 non-null   float64
 11  AMZN_MA5    1252 non-null   float64
 12  MSFT_MA5    1252 non-null   float64
 13  QQQ_MA5     1252 non-null   float64
 14  ^GSPC_MA5   1252 non-null   float64
 15  Target      1252 non-null   float64
dtypes: float64(16)
memory usage: 166.3 KB
```

In [11]:

```
# Run Linear Regression Model

import statsmodels.api as sm

X = df[ [ 'AAPL(t-1)', 'AMZN(t-1)', 'MSFT(t-1)', 'QQQ(t-1)', '^GSPC(t-1)', 'AAPL_MA
       'MSFT_MA5', 'QQQ_MA5', '^GSPC_MA5' ] ]
Y = df['Target']

x_Const = sm.add_constant(X) # Intercept

# Train the model
```

```
model = sm.OLS(Y, x_Const).fit()

# Summary of the Model
model.summary()
```

Out[11]:

OLS Regression Results

Dep. Variable:	Target	**R-squared:**	0.993
Model:	OLS	**Adj. R-squared:**	0.992
Method:	Least Squares	**F-statistic:**	1.827e+04
Date:	Fri, 21 Nov 2025	**Prob (F-statistic):**	0.00
Time:	23:55:42	**Log-Likelihood:**	-3381.7
No. Observations:	1252	**AIC:**	6783.
Df Residuals:	1242	**BIC:**	6835.
Df Model:	9		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.4174	1.138	0.367	0.714	-1.815	2.650
AAPL(t-1)	0.4601	0.081	5.703	0.000	0.302	0.618
AMZN(t-1)	0.0068	0.010	0.695	0.487	-0.012	0.026
MSFT(t-1)	-0.0132	0.052	-0.253	0.800	-0.116	0.089
QQQ(t-1)	0.0499	0.090	0.556	0.578	-0.126	0.226
^GSPC(t-1)	0.0040	0.007	0.574	0.566	-0.010	0.018
AAPL_MA5	0.5243	0.082	6.430	0.000	0.364	0.684
AMZN_MA5	0.0129	0.026	0.487	0.626	-0.039	0.065
MSFT_MA5	0.0129	0.026	0.487	0.626	-0.039	0.065
QQQ_MA5	-0.0530	0.091	-0.583	0.560	-0.231	0.125
^GSPC_MA5	-0.0043	0.007	-0.610	0.542	-0.018	0.010

Omnibus:	26.686	**Durbin-Watson:**	0.805
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	51.277
Skew:	-0.089	**Prob(JB):**	7.33e-12
Kurtosis:	3.975	**Cond. No.**	7.69e+16

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 8.03e-24. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [12]:
```
# Run Linear Regression Model

import statsmodels.api as sm

X = df[ [ 'AAPL(t-1)', '^GSPC(t-1)' ] ]

Y = df['Target']

x_Const = sm.add_constant(X) # Intercept

# Train the model
model = sm.OLS(Y, x_Const).fit()

# Summary of the Model
model.summary()
```

Out[12]: OLS Regression Results

Dep. Variable:	Target	**R-squared:**	0.992
Model:	OLS	**Adj. R-squared:**	0.992
Method:	Least Squares	**F-statistic:**	7.762e+04
Date:	Fri, 21 Nov 2025	**Prob (F-statistic):**	0.00
Time:	23:55:42	**Log-Likelihood:**	-3420.7
No. Observations:	1252	**AIC:**	6847.
Df Residuals:	1249	**BIC:**	6863.
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.7172	0.748	-0.959	0.338	-2.185	0.750
AAPL(t-1)	0.9840	0.007	140.621	0.000	0.970	0.998
^GSPC(t-1)	0.0008	0.000	2.114	0.035	5.8e-05	0.002

Omnibus:	40.865	**Durbin-Watson:**	1.041
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	103.864
Skew:	-0.036	**Prob(JB):**	2.79e-23
Kurtosis:	4.409	**Cond. No.**	3.08e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.08e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [13]:
```
# Predict the value using the Actual Price

df_train_predict = pd.DataFrame()
df_train_predict['Actual'] = df['Target']
df_train_predict['Predicted'] = model.predict(x_Const)
df_train_predict
```

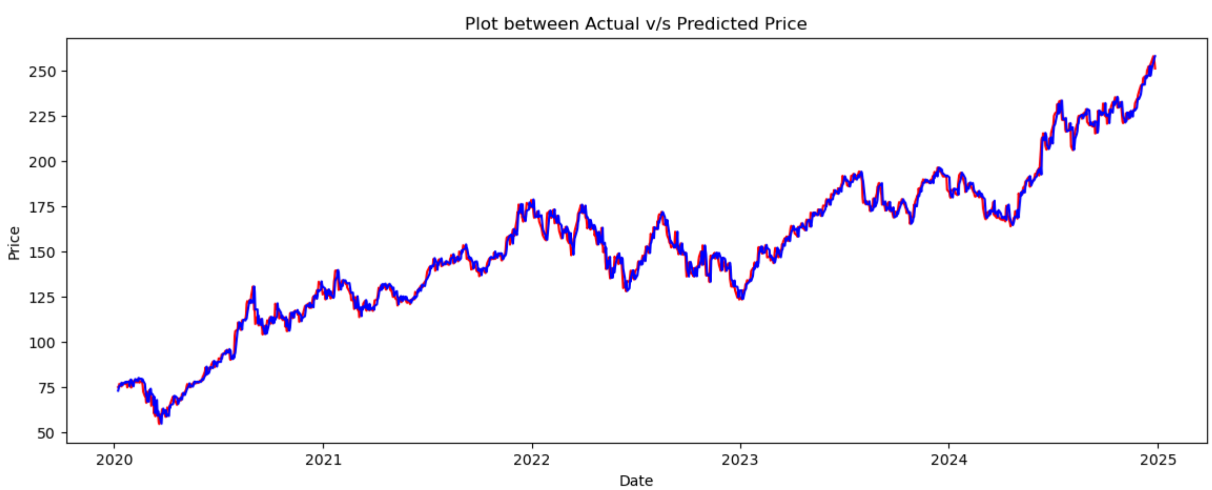
Out[13]:

Date	Actual	Predicted
2020-01-08	74.707336	72.734141
2020-01-09	74.876251	73.886544
2020-01-10	76.475906	75.432966
2020-01-13	75.443230	75.591649
2020-01-14	75.119904	77.184070
...	...	...
2024-12-20	254.120682	248.696998
2024-12-23	257.037476	253.352384
2024-12-24	257.853790	254.151282
2024-12-26	254.439224	257.074565
2024-12-27	251.064484	257.875851

1252 rows × 2 columns

In [14]:

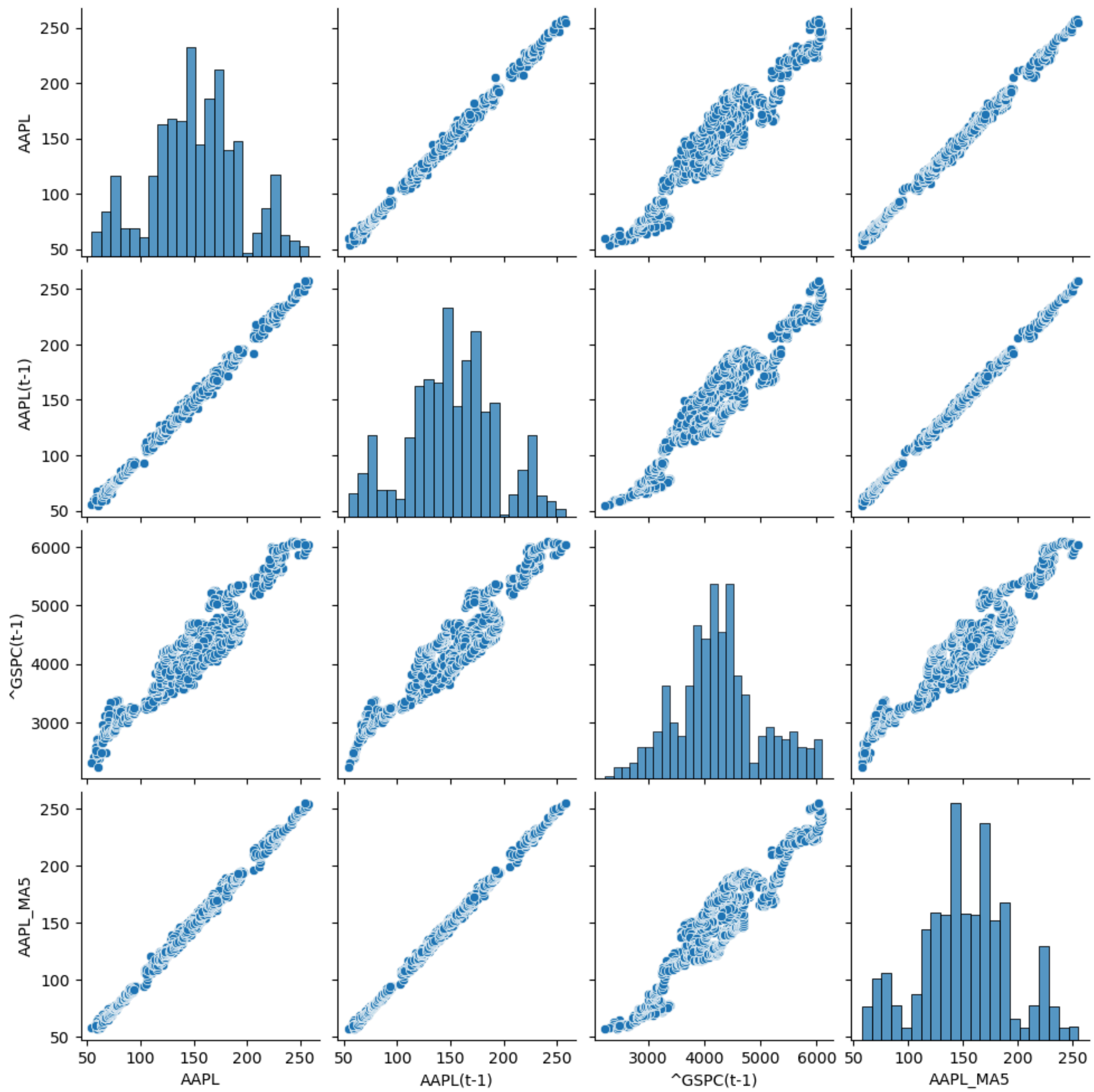
```
# Plot between Actual vs Predict

import matplotlib.pyplot as plt

plt.figure( figsize = (14,5))
plt.plot(df_train_predict.index, df_train_predict['Actual'], label='Actual', color
plt.plot(df_train_predict.index, df_train_predict['Predicted'], label='Predicted',
plt.title('Plot between Actual v/s Predicted Price')
plt.xlabel('Date')
plt.ylabel('Price')
plt.show()
```



Check the assumption of the LR model

In [16]:
```
# 1) Linearity between dependent and independent

import seaborn as sns

df = df[['AAPL', 'AAPL(t-1)', '^GSPC(t-1)', 'AAPL_MA5']]
sns.pairplot(df)
```

Out[16]: <seaborn.axisgrid.PairGrid at 0x12b425a0d70>



In [17]:
```
# 2) Multicollinearity => using VIF

from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = pd.DataFrame()
vif['features'] = x_Const.columns
```

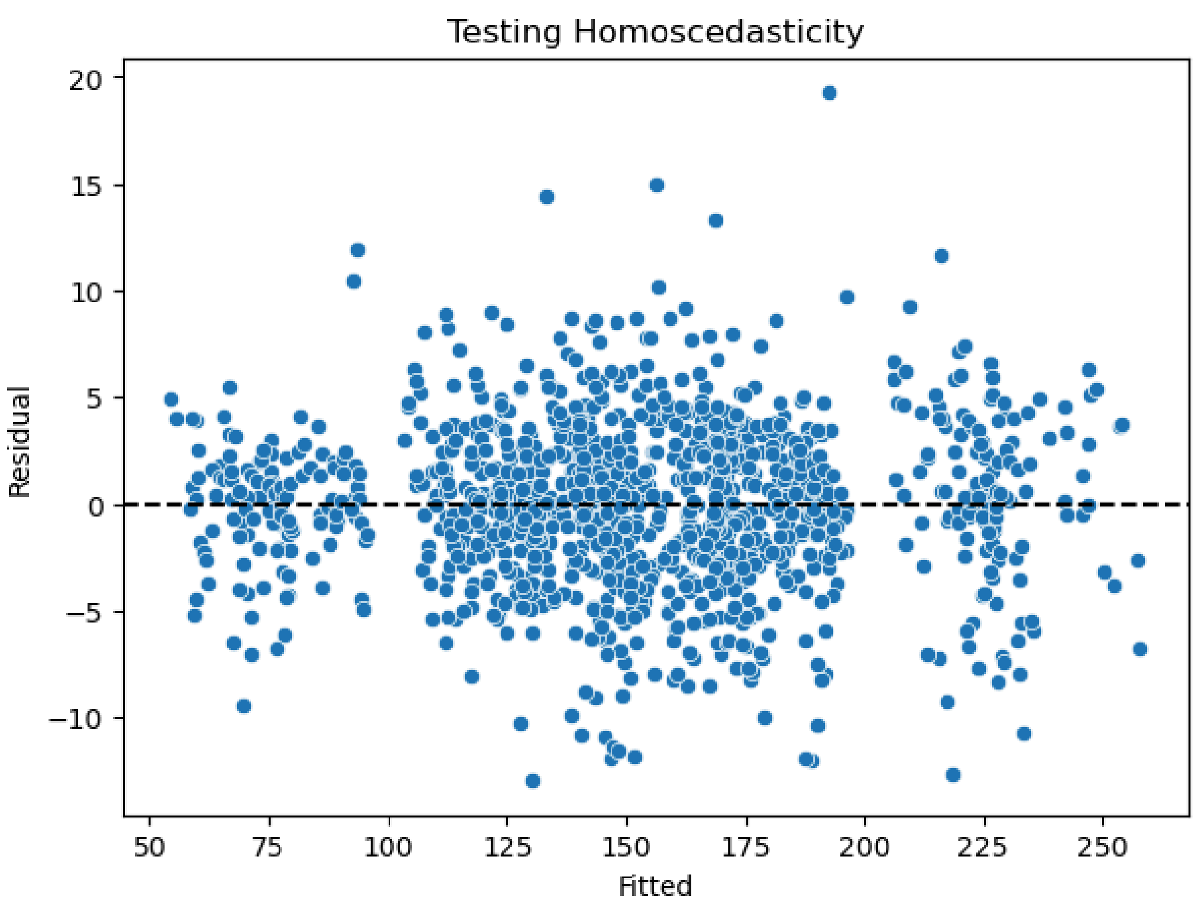
```
vif['vif'] = [variance_inflation_factor(x_Const.values, i) for i in range(x_Const.s
vif = vif[1:]
vif
```

Out[17]:

	features	vif
1	AAPL(t-1)	7.634911
2	^GSPC(t-1)	7.634911

In [18]:

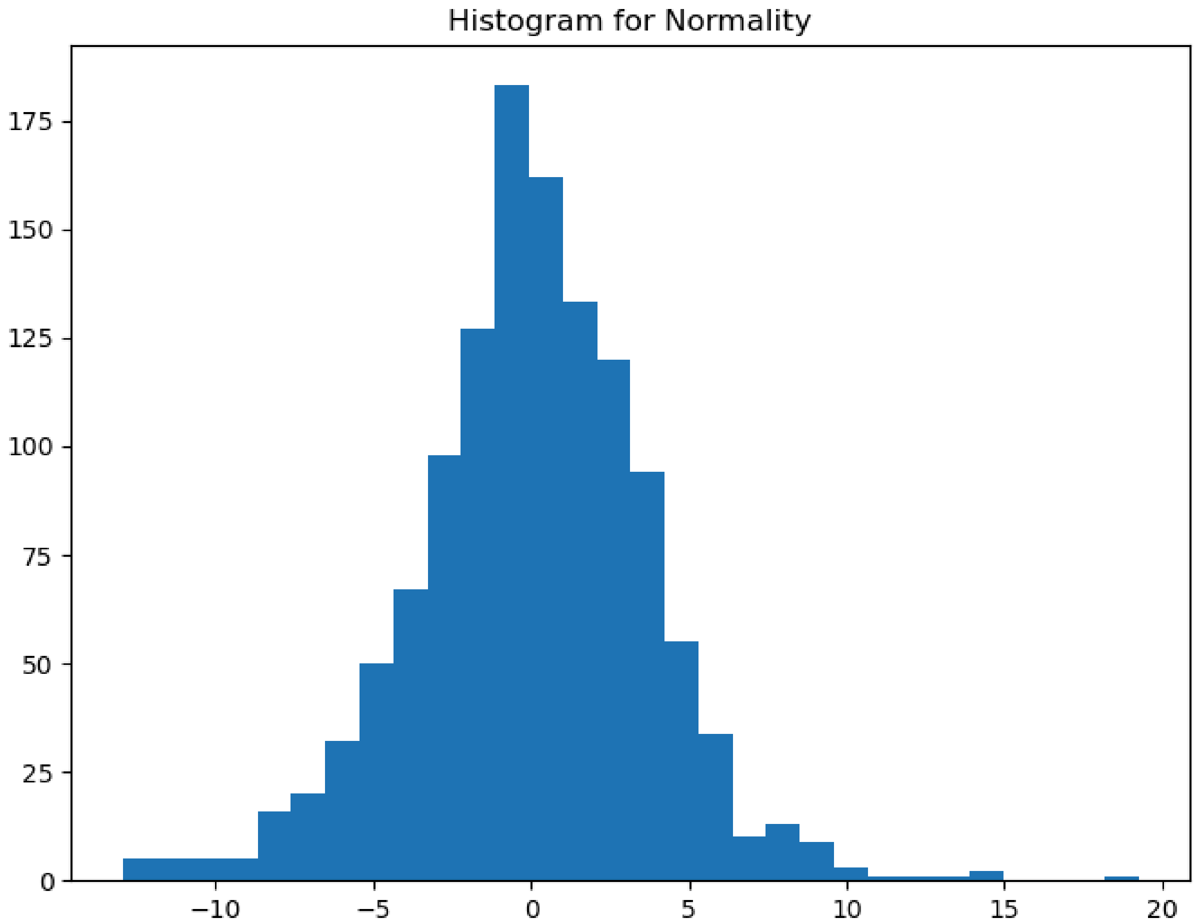
```
# Homoscedasticity => fitting residual with predicted value

residual = model.resid # Actual - Predicted
fitted = model.fittedvalues # Predict Y Value

plt.figure( figsize = (7,5))
sns.scatterplot(x = fitted, y = residual)
plt.axhline(0, color='black', linestyle='--')
plt.title('Testing Homoscedasticity')
plt.xlabel('Fitted')
plt.ylabel('Residual')
plt.show()

# This graph does not look like the funnel
```



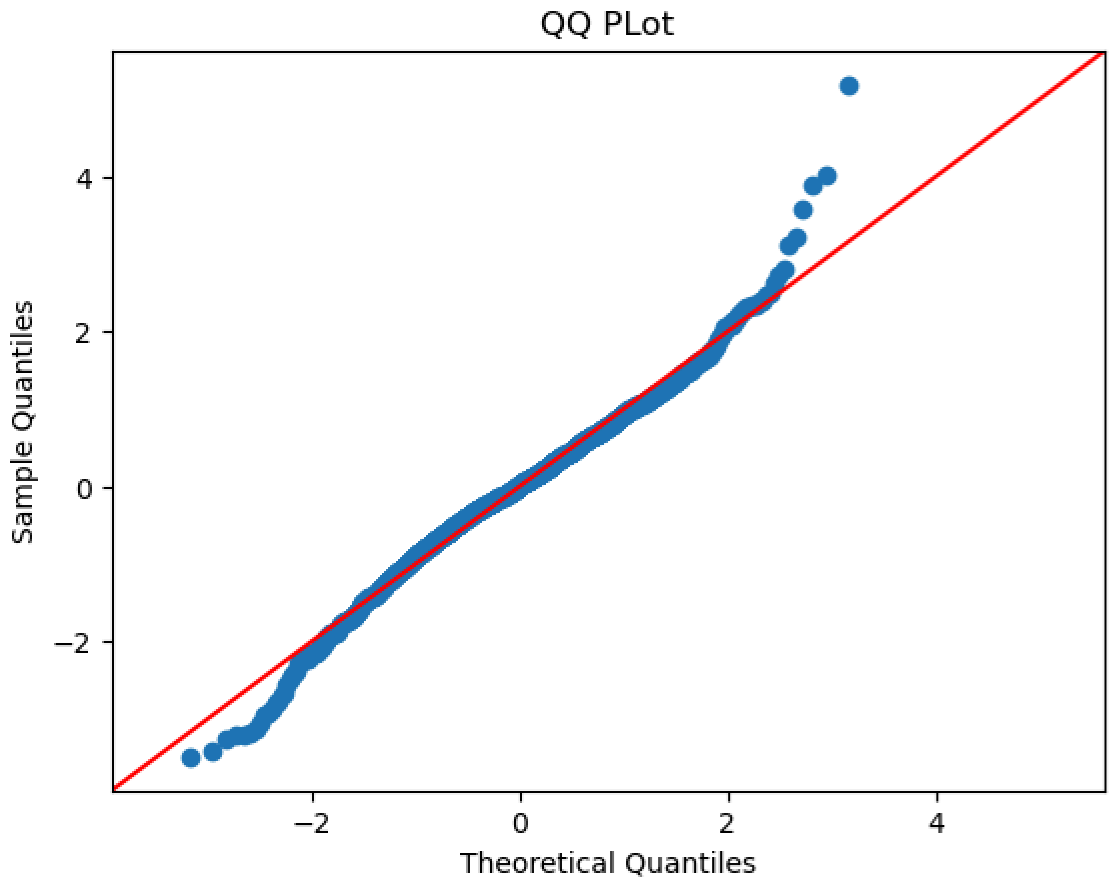
In [19]:

```
# 4) Normality of residual => Histogram or QQ plot
# Histogram
```

```
plt.figure(figsize = (8,6))
plt.hist(residual, bins=30)
plt.title('Histogram for Normality')
plt.show()
```



In [20]:
```
# QQ Plot

sm.qqplot(residual, line ='45', fit = True)
plt.title('QQ PLot')
plt.show()
```



In [21]:
```
# Auto Correlation of Residual => Durbin Watson Test

from statsmodels.stats.stattools import durbin_watson

dw = durbin_watson(residual)
dw
```

Out[21]: 1.0410072213200119

Predict the stock price for the year 2025

In [23]:
```
# Step 1: Download the data from Yahoo Finance

tickers = ('AAPL', '^GSPC')
start_date = '2025-01-01'
end_date = '2025-03-31'

df = yf.download(tickers, start_date, end_date)['Close']
df.head()
```

```
C:\Users\sahil\AppData\Local\Temp\ipykernel_1500\3989341984.py:7: FutureWarning: YF.
download() has changed argument auto_adjust default to True
  df = yf.download(tickers, start_date, end_date)['Close']
[*********************100%***********************]  2 of 2 completed
```

Out[23]:

Ticker	AAPL	^GSPC
Date		
2025-01-02	242.752090	5868.549805
2025-01-03	242.264297	5942.470215
2025-01-06	243.896912	5975.379883
2025-01-07	241.119476	5909.029785
2025-01-08	241.607269	5918.250000

In [24]:

```
# Step 2: Feature Engineer

df['AAPL(t-1)'] = df['AAPL'].shift(1)
df['^GSPC(t-1)'] = df['^GSPC'].shift(1)
df = df.dropna()
df.head()
```

Out[24]:

Ticker	AAPL	^GSPC	AAPL(t-1)	^GSPC(t-1)
Date				
2025-01-03	242.264297	5942.470215	242.752090	5868.549805
2025-01-06	243.896912	5975.379883	242.264297	5942.470215
2025-01-07	241.119476	5909.029785	243.896912	5975.379883
2025-01-08	241.607269	5918.250000	241.119476	5909.029785
2025-01-10	235.783600	5827.040039	241.607269	5918.250000

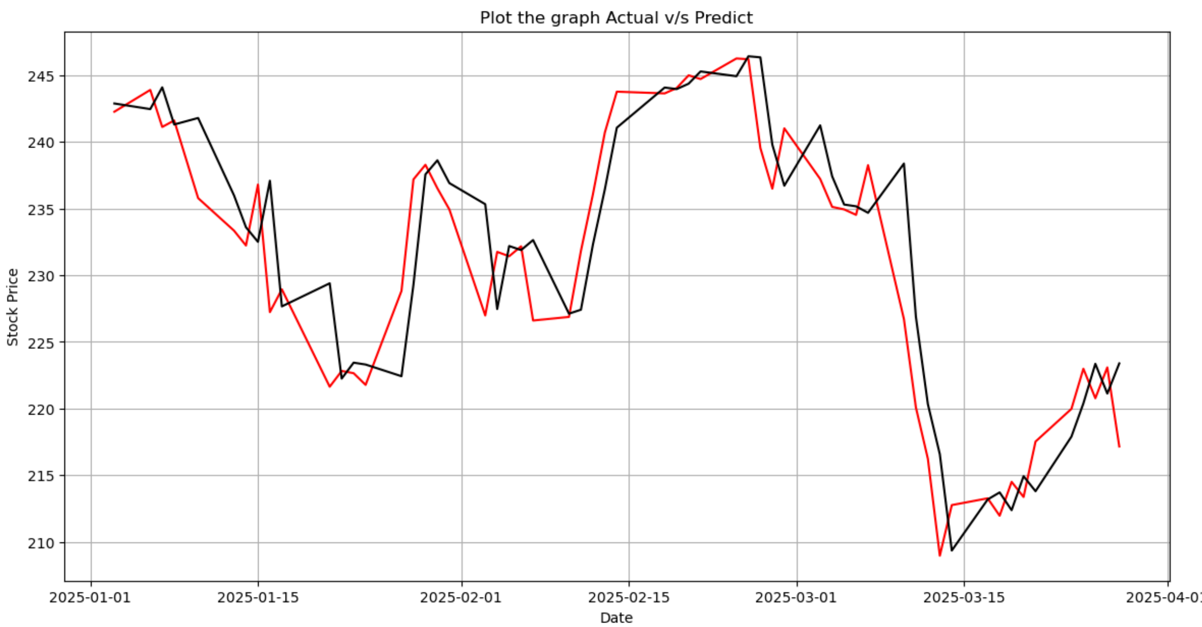
In [25]:

```
X_test = df[ ['AAPL(t-1)', '^GSPC(t-1)'] ]
x_test = sm.add_constant(X_test)

df_result = pd.DataFrame()
df_result['Actual'] = df['AAPL']
df_result['Predicted'] = model.predict(x_test)
df_result.head()
```

Out[25]:

	Actual	Predicted
Date		
2025-01-03	242.264297	242.879509
2025-01-06	243.896912	242.459055
2025-01-07	241.119476	244.092067
2025-01-08	241.607269	241.305608
2025-01-10	235.783600	241.793027

In [26]:
```
# Plot Actual V/S Predicted

plt.figure( figsize = (14,7))
plt.plot(df_result.index, df_result['Actual'], label='Actual', color='red')
plt.plot(df_result.index, df_result['Predicted'], label='predict', color='black')
plt.title('Plot the graph Actual v/s Predict')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.grid(True)
plt.show()
```



In [27]:
```
# Risk Metrics => Calculate RMSE and MSE

from sklearn.metrics import mean_squared_error, r2_score

r2 = r2_score(df_result['Actual'], df_result['Predicted'])

mse = mean_squared_error(df_result['Actual'], df_result['Predicted']) # MSE

rmse = np.sqrt(mse) # RMSE

print('R2 =', r2)
print("MSE:", mse)
print("RMSE:", rmse)
```

```
R2 = 0.8348121724833452
MSE: 17.23421034626402
RMSE: 4.151410645342619
```

In [ ]: