Import libraries

```
!pip install pmdarima
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import tensorflow as tf
import os
from sklearn.preprocessing import MinMaxScaler
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from pmdarima.arima import auto_arima
from statsmodels.tsa.arima.model import ARIMA

import warnings
warnings.filterwarnings('ignore')
```

```
Requirement already satisfied: pmdarima in
/usr/local/lib/python3.10/dist-packages (2.0.4)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.4.2)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (3.0.11)
Requirement already satisfied: numpy>=1.21.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.26.4)
Requirement already satisfied: pandas>=0.19 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (2.2.3)
Requirement already satisfied: scikit-learn>=0.22 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.2.2)
Requirement already satisfied: scipy>=1.3.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (1.13.1)
Requirement already satisfied: statsmodels>=0.13.2 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (0.14.4)
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (2.3.0)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (75.1.0)
Requirement already satisfied: packaging>=17.1 in
/usr/local/lib/python3.10/dist-packages (from pmdarima) (24.2)
Requirement already satisfied: mkl_fft in
/usr/local/lib/python3.10/dist-packages (from numpy>=1.21.2->pmdarima)
(1.3.8)
Requirement already satisfied: mkl_random in
/usr/local/lib/python3.10/dist-packages (from numpy>=1.21.2->pmdarima)
(1.2.4)
Requirement already satisfied: mkl_umath in
/usr/local/lib/python3.10/dist-packages (from numpy>=1.21.2->pmdarima)
```

```
(0.1.1)
Requirement already satisfied: mkl in /usr/local/lib/python3.10/dist-
packages (from numpy>=1.21.2->pmdarima) (2025.0.1)
Requirement already satisfied: tbb4py in
/usr/local/lib/python3.10/dist-packages (from numpy>=1.21.2->pmdarima)
(2022.0.0)
Requirement already satisfied: mkl-service in
/usr/local/lib/python3.10/dist-packages (from numpy>=1.21.2->pmdarima)
(2.4.1)
Requirement already satisfied: python-dateutil>=2.8.2 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima)
(2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima)
(2025.1)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.19->pmdarima)
(2025.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.22-
>pmdarima) (3.5.0)
Requirement already satisfied: patsy>=0.5.6 in
/usr/local/lib/python3.10/dist-packages (from statsmodels>=0.13.2-
>pmdarima) (1.0.1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.2-
>pandas>=0.19->pmdarima) (1.17.0)
Requirement already satisfied: intel-openmp>=2024 in
/usr/local/lib/python3.10/dist-packages (from mkl->numpy>=1.21.2-
>pmdarima) (2024.2.0)
Requirement already satisfied: tbb==2022.* in
/usr/local/lib/python3.10/dist-packages (from mkl->numpy>=1.21.2-
>pmdarima) (2022.0.0)
Requirement already satisfied: tcmlib==1.* in
/usr/local/lib/python3.10/dist-packages (from tbb==2022.*->mkl-
>numpy>=1.21.2->pmdarima) (1.2.0)
Requirement already satisfied: intel-cmplr-lib-rt in
/usr/local/lib/python3.10/dist-packages (from mkl_umath-
>numpy>=1.21.2->pmdarima) (2024.2.0)
Requirement already satisfied: intel-cmplr-lib-ur==2024.2.0 in
/usr/local/lib/python3.10/dist-packages (from intel-openmp>=2024->mkl-
>numpy>=1.21.2->pmdarima) (2024.2.0)
```

Load the Dataset

```
df =
pd.read_csv('/kaggle/input/stock-market-dataset/stocks/NVDA.csv',parse
```

```
_dates=['Date'])
df.head()
```

```
        Date      Open      High       Low     Close  Adj Close
Volume
0 1999-01-22  1.750000  1.953125  1.552083  1.640625   1.509998
67867200.0
1 1999-01-25  1.770833  1.833333  1.640625  1.812500   1.668188
12762000.0
2 1999-01-26  1.833333  1.869792  1.645833  1.671875   1.538759
8580000.0
3 1999-01-27  1.677083  1.718750  1.583333  1.666667   1.533965
6109200.0
4 1999-01-28  1.666667  1.677083  1.651042  1.661458   1.529172
5688000.0
```

Basic Analysis

```
print('Basic information about the data:' ,df.info())
print('\n\nNull values:\n', df.isna().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5334 entries, 0 to 5333
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       5334 non-null   datetime64[ns]
 1   Open       5333 non-null   float64
 2   High       5333 non-null   float64
 3   Low        5333 non-null   float64
 4   Close      5333 non-null   float64
 5   Adj Close  5333 non-null   float64
 6   Volume     5333 non-null   float64
dtypes: datetime64[ns](1), float64(6)
memory usage: 291.8 KB
Basic information about the data: None


Null values:
 Date         0
Open          1
High          1
Low           1
Close         1
Adj Close     1
Volume        1
dtype: int64
```

Drop null values

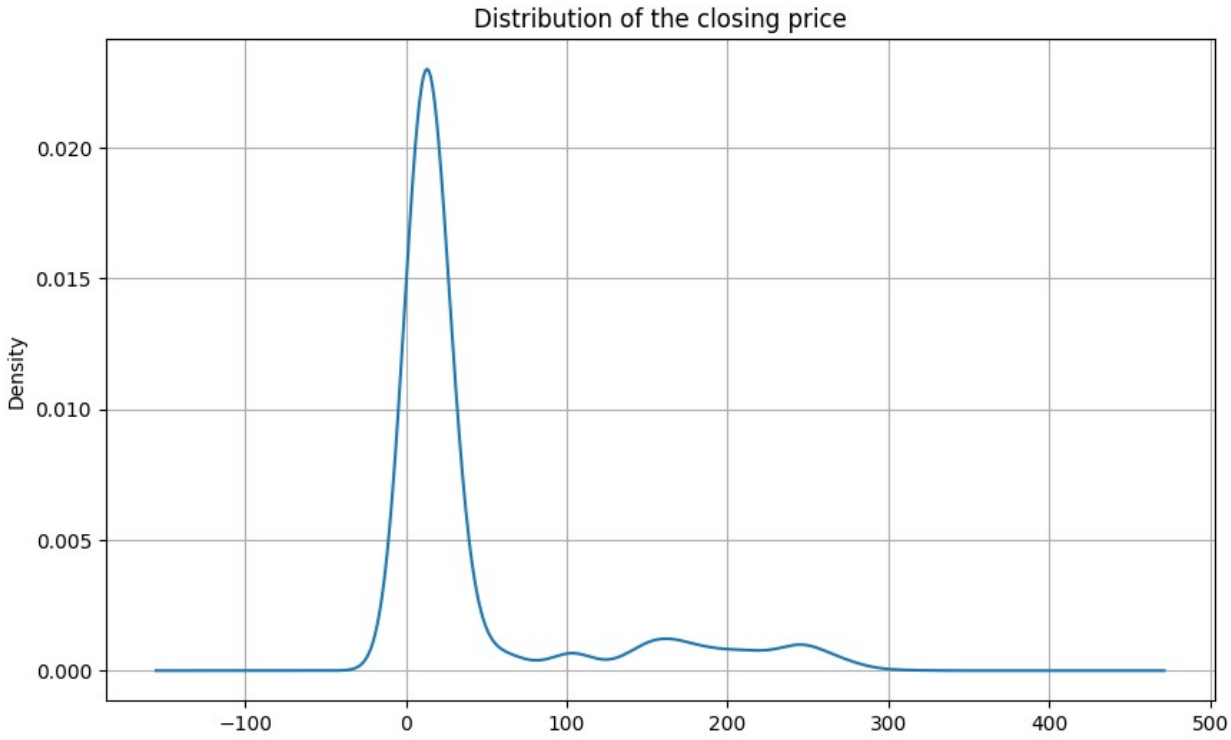
```
df = df.dropna()
df.isna().sum()
```

```
Date          0
Open          0
High          0
Low           0
Close         0
Adj Close     0
Volume        0
dtype: int64
```

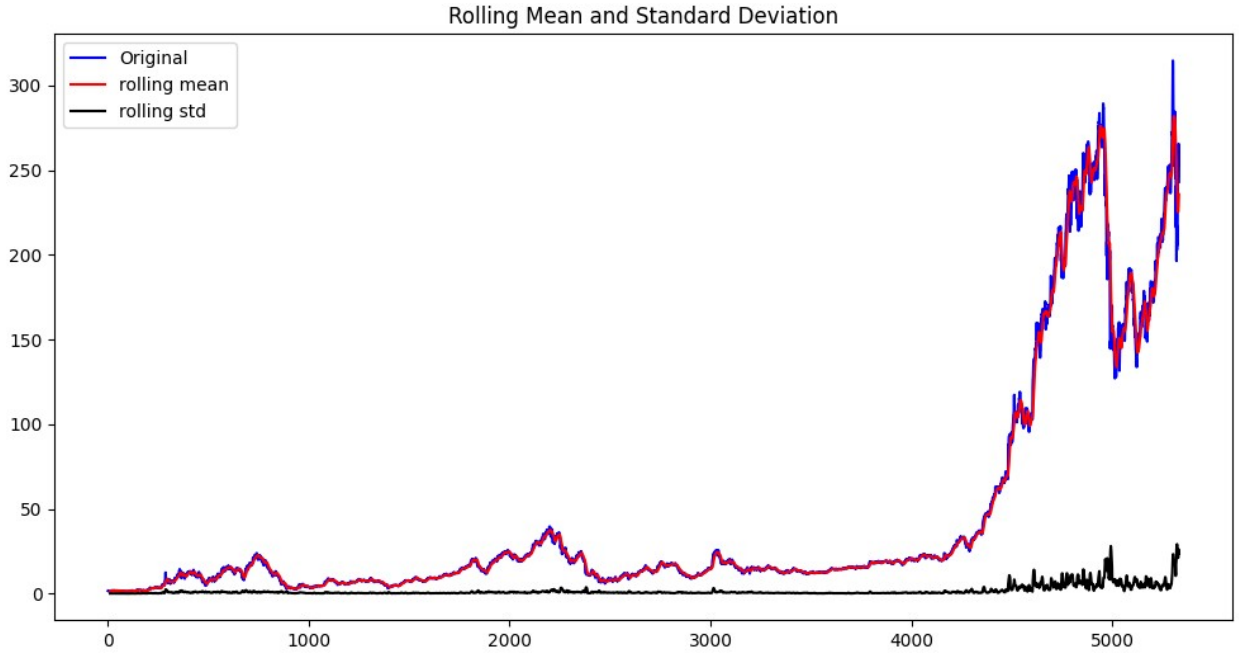
Sessional Trend of the closing price

```
# plot close price
plt.figure(figsize=(10,6))
plt.grid(True)
plt.xlabel('Date')
plt.ylabel('Close Prices')
plt.plot(df['Close'])
plt.title('Closing Price')
plt.show()
```


```
plt.figure(figsize=(10,6))
df_close = df['Close']
df_close.plot(kind='kde', title = 'Distribution of the closing price')
plt.grid(True)
plt.show()
```




```
# stationary test
def test_stationarity(timeseries):
    rolmean = timeseries.rolling(12).mean()
    rolstd = timeseries.rolling(12).std()
    plt.figure(figsize=(12,6))
    plt.plot(timeseries,color='blue',label='Original')
    plt.plot(rolmean,color='red',label='rolling mean')
    plt.plot(rolstd,color='black',label='rolling std')
    plt.legend(loc='best')
    plt.title('Rolling Mean and Standard Deviation')
    plt.show(block=False)
    print('Dicky Fuller Test')
    adft = adfuller(timeseries,autolag='AIC')

    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)

test_stationarity(df_close)
```

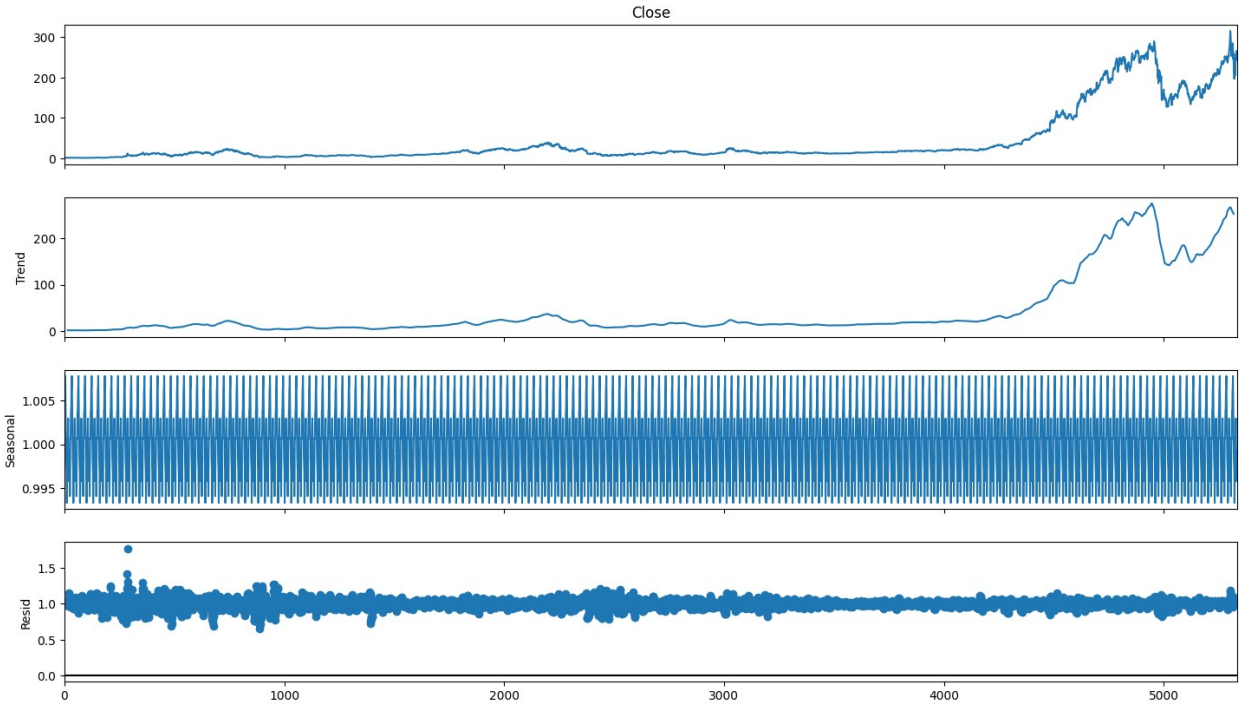



```
Dicky Fuller Test
Test Statistics                    0.214695
p-value                            0.973074
No. of lags used                  32.000000
Number of observations used    5300.000000
critical value (1%)              -3.431584
critical value (5%)              -2.862085
critical value (10%)             -2.567060
dtype: float64
```

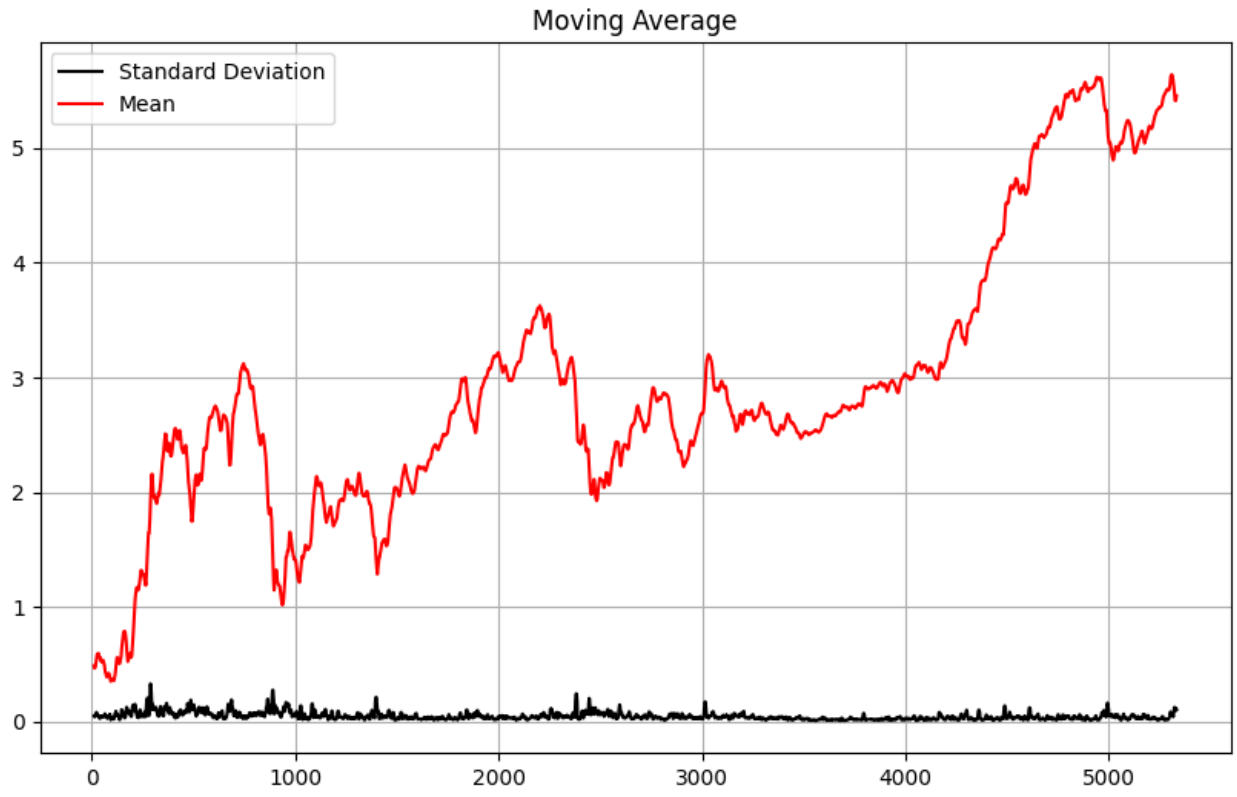
Eliminate Trend and Seasonality

```
result = seasonal_decompose(df_close,model='multiplicative',period=30)
fig = plt.figure()
fig = result.plot()
fig.set_size_inches(16,9)
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```

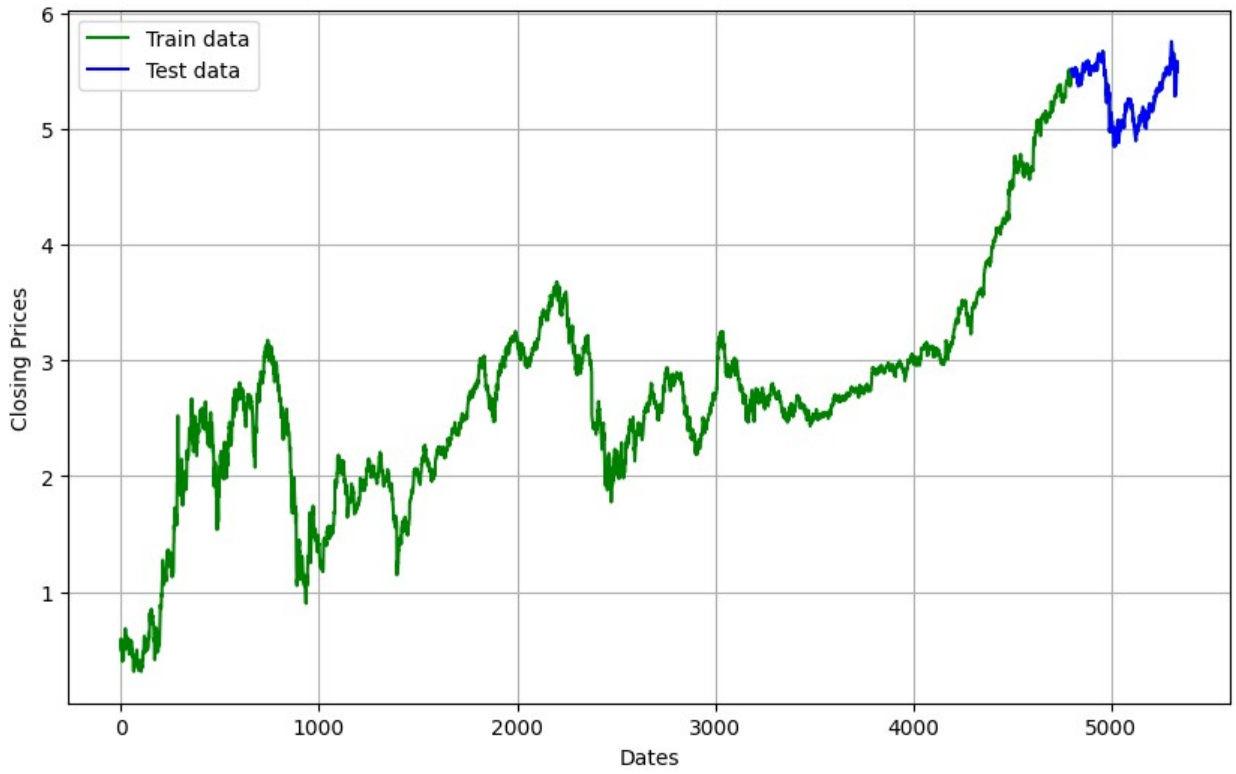



```
#Eliminate trend
from pylab import rcParams

rcParams['figure.figsize'] = 10, 6
df_log = np.log(df_close)
moving_avg = df_log.rolling(12).mean()
std_dev = df_log.rolling(12).std()
plt.legend(loc='best')
plt.title('Moving Average')
plt.plot(std_dev, color ="black", label = "Standard Deviation")
plt.plot(moving_avg, color="red", label = "Mean")
plt.legend()
plt.grid(True)
plt.show()
```



Split data into training and testing part

```
#split data into train and training set

train_data, test_data = df_log[3:int(len(df_log)*0.9)],
df_log[int(len(df_log)*0.9):]
plt.figure(figsize=(10,6))
plt.grid(True)
plt.xlabel('Dates')
plt.ylabel('Closing Prices')
plt.plot(df_log, 'green', label='Train data')
plt.plot(test_data, 'blue', label='Test data')
plt.legend()
plt.show()
```

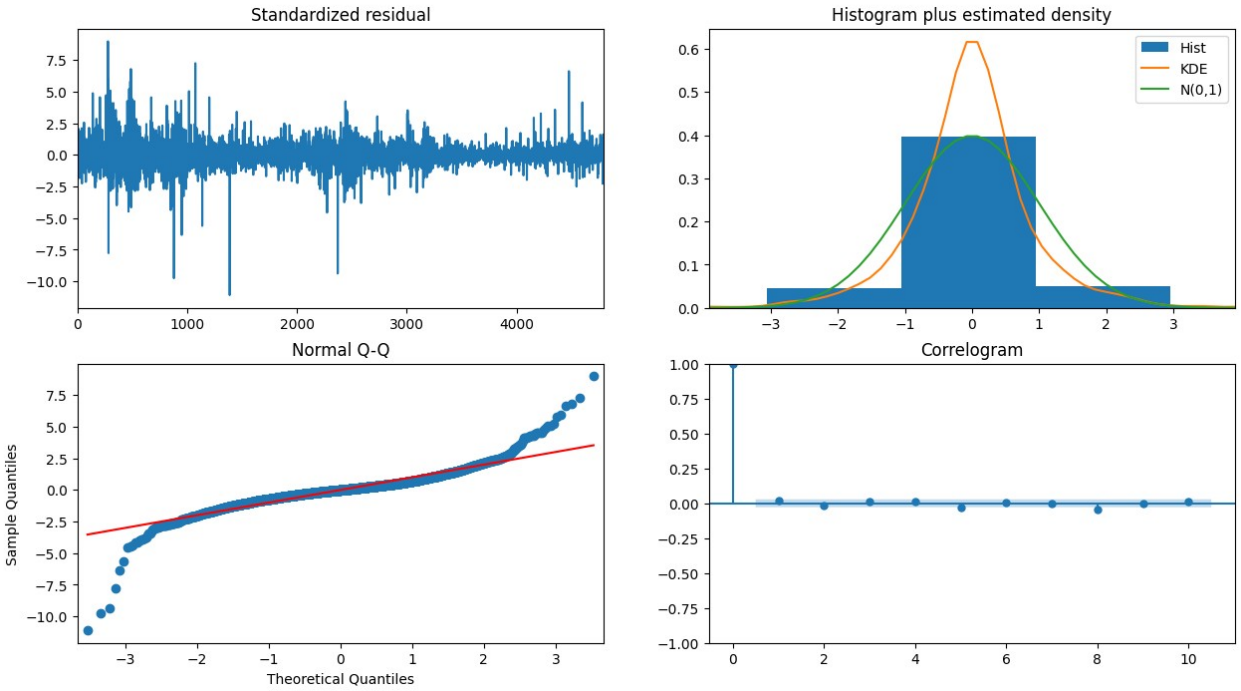


Auto ARIMA Find the Best Parameters

```
model_autoARIMA = auto_arima(train_data, start_p=0, start_q=0,
                      test='adf',       # use adftest to find optimal
'd'
                      max_p=3, max_q=3, # maximum p and q
                      m=1,              # frequency of series
                      d=None,           # let model determine 'd'
                      seasonal=False,   # No Seasonality
                      start_P=0,
                      D=0,
                      trace=True,
                      error_action='ignore',
                      suppress_warnings=True,
                      stepwise=True)
print(model_autoARIMA.summary())
model_autoARIMA.plot_diagnostics(figsize=(15,8))
plt.show()
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=-17432.104, Time=0.86 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=-17431.545, Time=0.47 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=-17431.589, Time=0.39 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=-17430.730, Time=0.32 sec
```

```
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=-17428.141, Time=1.79 sec

Best model:  ARIMA(0,1,0)(0,0,0)[0] intercept
Total fit time: 3.869 seconds
                                SARIMAX Results
                                
==========================================================================
========
Dep. Variable:                           y   No. Observations:
4796
Model:                SARIMAX(0, 1, 0)   Log Likelihood
8718.052
Date:                 Wed, 09 Apr 2025   AIC                            -
17432.104
Time:                         06:59:31   BIC                            -
17419.153
Sample:                               0   HQIC                           -
17427.555
                                  - 4796
                                  
Covariance Type:                    opg

==========================================================================
========
                   coef    std err          z      P>|z|      [0.025
0.975]
--------------------------------------------------------------------------
--------
intercept      0.0010      0.001      1.836      0.066   -7.04e-05
0.002
sigma2         0.0015   1.15e-05    134.629      0.000       0.002
0.002
==========================================================================
==============
Ljung-Box (L1) (Q):                   1.44   Jarque-Bera (JB):
34511.77
Prob(Q):                              0.23   Prob(JB):
0.00
Heteroskedasticity (H):               0.17   Skew:
-0.14
Prob(H) (two-sided):                  0.00   Kurtosis:
16.14
==========================================================================
==============

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



Modeling

```
#Modeling
# Build Model
model = ARIMA(train_data, order=(1,1,2))
fitted = model.fit()
print(fitted.summary())
```

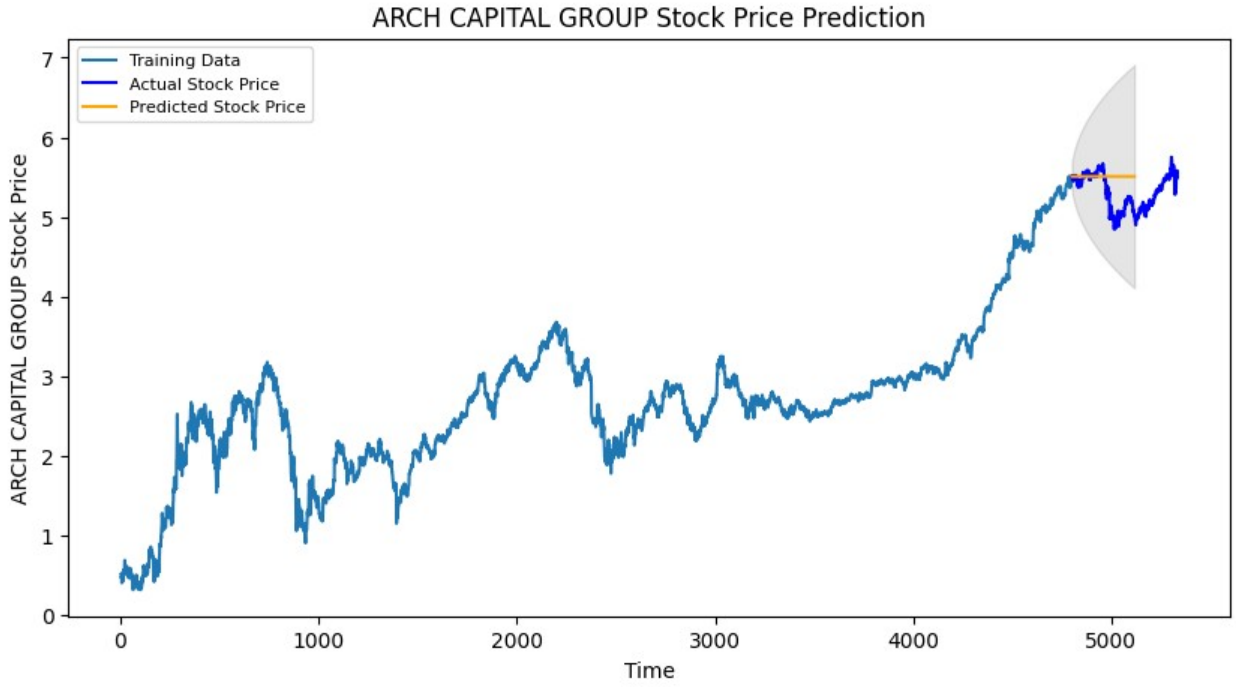
```
                               SARIMAX Results
==============================================================================
Dep. Variable:                  Close   No. Observations:
4796
Model:                 ARIMA(1, 1, 2)   Log Likelihood
8717.191
Date:                Wed, 09 Apr 2025   AIC                              -
17426.382
Time:                        07:03:35   BIC                              -
17400.480
Sample:                             0   HQIC                             -
17417.285
                                - 4796
Covariance Type:                  opg
==============================================================================
```

```
========
                 coef    std err          z      P>|z|      [0.025
0.975]
------------------------------------------------------------------------
--------
ar.L1         -0.7227      1.503     -0.481      0.631      -3.668
2.223
ma.L1          0.7412      1.501      0.494      0.621      -2.200
3.682
ma.L2          0.0112      0.032      0.350      0.726      -0.052
0.074
sigma2         0.0015   1.15e-05    133.814      0.000       0.002
0.002
========================================================================
=============
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
34690.33
Prob(Q):                              0.95   Prob(JB):
0.00
Heteroskedasticity (H):               0.17   Skew:
-0.14
Prob(H) (two-sided):                  0.00   Kurtosis:
16.17
========================================================================
=============

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

Modeling and Forecasting

```
# Forecast
forecast_result = fitted.get_forecast(steps=321)
fc = forecast_result.predicted_mean
conf = forecast_result.conf_int(alpha=0.05)

# Make as pandas series
fc_series = pd.Series(fc, index=test_data.index)
lower_series = pd.Series(conf.iloc[:, 0], index=test_data.index)
upper_series = pd.Series(conf.iloc[:, 1], index=test_data.index)

# Plot
plt.figure(figsize=(10,5), dpi=100)
plt.plot(train_data, label='Training Data')
plt.plot(test_data, color='blue', label='Actual Stock Price')
plt.plot(fc_series, color='orange', label='Predicted Stock Price')
plt.fill_between(lower_series.index, lower_series, upper_series,
```

```
                  color='k', alpha=0.1)
plt.title('ARCH CAPITAL GROUP Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('ARCH CAPITAL GROUP Stock Price')
plt.legend(loc='upper left', fontsize=8)
plt.show()
```



Evaluate Model Performance

```
# Align test data to forecast length
aligned_test = test_data[:len(fc)]

# Then compute metrics
mse = mean_squared_error(aligned_test, fc)
mae = mean_absolute_error(aligned_test, fc)
rmse = math.sqrt(mse)
mape = np.mean(np.abs(fc - aligned_test) / np.abs(aligned_test)) * 100

# Print results
print(f"MSE: {mse:.4f}")
print(f"MAE: {mae:.4f}")
print(f"RMSE: {rmse:.4f}")
print(f"MAPE: {mape:.2f}%")
```

```
MSE: 0.0882
MAE: 0.2178
```

```
RMSE: 0.2970
MAPE: 4.18%
```

'with a MAPE of around 4.18% the model is 95.82 % accurate in predicting the next observations