Comparaison des Modèles ARIMA, SARIMA et LSTM pour la Prédiction des Prix de Clôture des Actions

Par: Mr HACHIMI ATMANE

In [359…

```
# Importer les bibliothèques nécessaires
import yfinance as yf
from datetime import datetime
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.stattools import adfuller
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.statespace.sarimax import SARIMAX
from keras.models import Sequential
from keras.layers import Dense, LSTM
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

In [360…

```
#download data from yfinance
end = datetime.now()
start = datetime(end.year - 3, end.month, end.day)

data = yf.download('AAPL', start=start, end=end)
```

```
[*********************100%%***********************]  1 of 1 completed
```

In [361…

```
#display the data
data.head()
```

Out[361...

Date	Open	High	Low	Close	Adj Close	Volume
2021-12-14	175.250000	177.740005	172.210007	174.330002	171.520370	139380400
2021-12-15	175.110001	179.500000	172.309998	179.300003	176.410278	131063300
2021-12-16	179.279999	181.139999	170.750000	172.259995	169.483704	150185800
2021-12-17	169.929993	173.470001	169.690002	171.139999	168.381775	195432700
2021-12-20	168.279999	170.580002	167.460007	169.750000	167.014175	107499100

In [362...

```
#display data infos
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 755 entries, 2021-12-14 to 2024-12-13
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Open       755 non-null    float64
 1   High       755 non-null    float64
 2   Low        755 non-null    float64
 3   Close      755 non-null    float64
 4   Adj Close  755 non-null    float64
 5   Volume     755 non-null    int64  
dtypes: float64(5), int64(1)
memory usage: 41.3 KB
```

In [363...

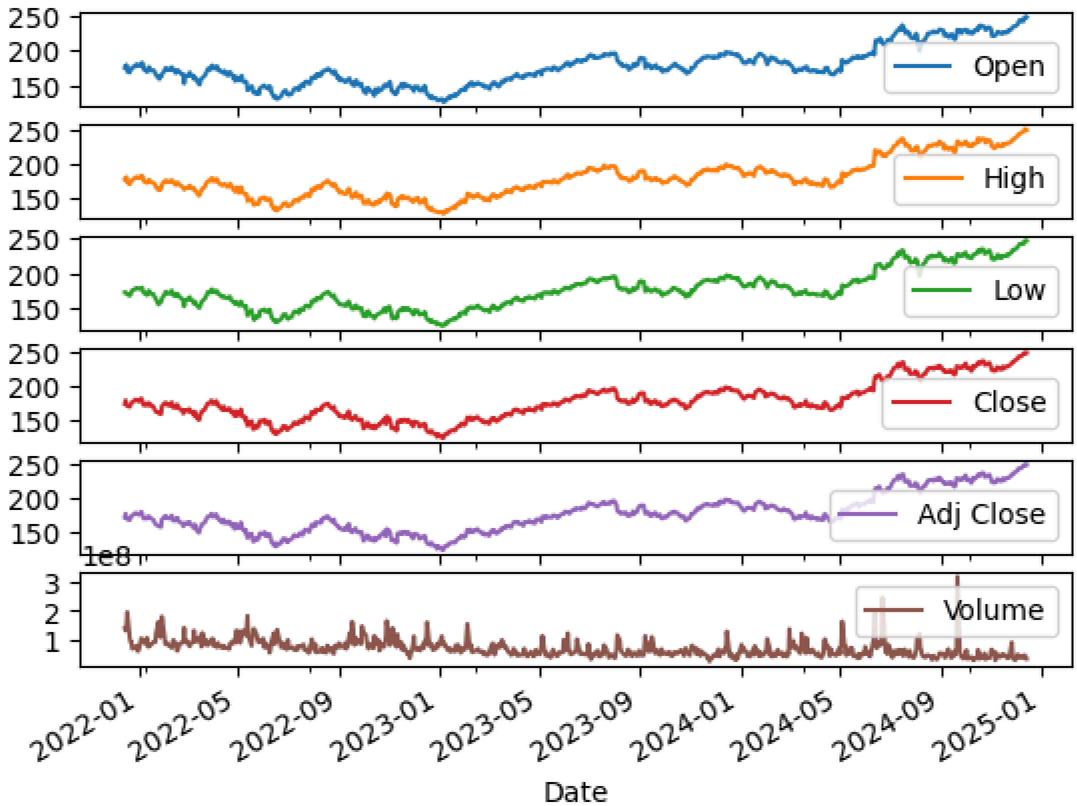
```
#verify the index of the data
data.index
```

Out[363...

```
DatetimeIndex(['2021-12-14', '2021-12-15', '2021-12-16', '2021-12-17',
               '2021-12-20', '2021-12-21', '2021-12-22', '2021-12-23',
               '2021-12-27', '2021-12-28',
               ...
               '2024-12-02', '2024-12-03', '2024-12-04', '2024-12-05',
               '2024-12-06', '2024-12-09', '2024-12-10', '2024-12-11',
               '2024-12-12', '2024-12-13'],
              dtype='datetime64[ns]', name='Date', length=755, freq=None)
```

In [364...

```
#plot evry column vs time

data.plot(subplots=True)
plt.show()
```



In [365…

```
# Check for missing values in the dataset
data.isnull().sum()
```

Out[365…

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

In [366…

```
# Count the number of duplicate rows in the DataFrame and return the count
data.duplicated().sum()
```

Out[366…

```
0
```

In [367…

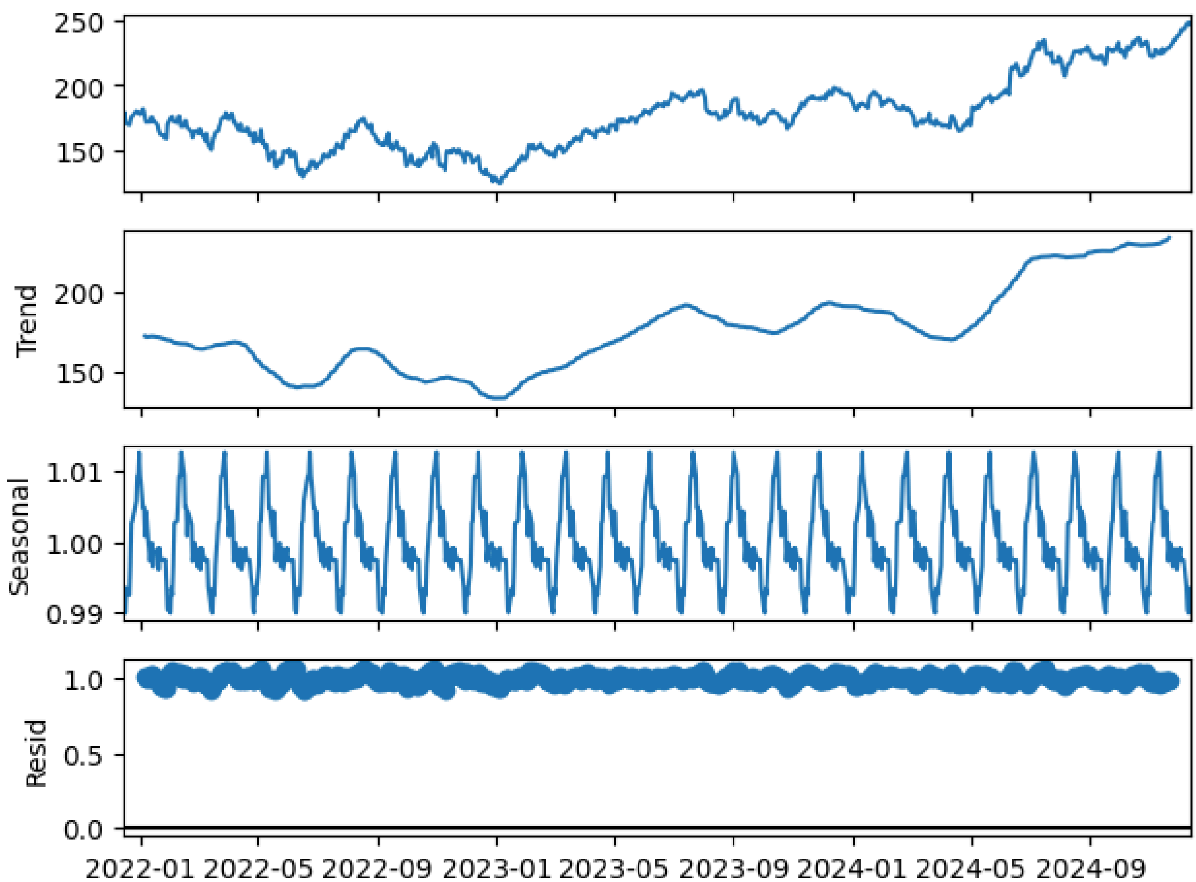
```
#create a new dataframe with the one column closing price
df = data['Close'].to_frame()
df.head()
```

Out[367...

Date	Close
2021-12-14	174.330002
2021-12-15	179.300003
2021-12-16	172.259995
2021-12-17	171.139999
2021-12-20	169.750000

In [ ]:

```
#use the seaosnal_decompose function from statsmodels to decompose
# the closing price into trend, seasonal and residual components
from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(df, model='multiplicative', period=30)
result.plot()
plt.show()
```



Description du graphique de décomposition saisonnière

Le graphique de décomposition saisonnière de la série temporelle des prix de clôture se compose de quatre sous-graphiques :

1. **Observed (Observé)** :

- Le sous-graphe "Observed" montre les valeurs originales des prix de clôture sur la période spécifiée. On peut observer les fluctuations quotidiennes des prix de clôture.

2. **Trend (Tendance)** :

   - Le sous-graphe "Trend" montre la tendance à long terme des prix de clôture. On peut voir une tendance générale à la hausse des prix de clôture sur la période. Cette composante lisse les fluctuations à court terme pour révéler la direction générale de la série.

3. **Seasonal (Saisonnalité)** :

   - Le sous-graphe "Seasonal" montre les variations saisonnières répétitives des prix de clôture. On peut observer des motifs périodiques qui se répètent à intervalles réguliers. Cette composante capture les motifs saisonniers dans les prix de clôture.

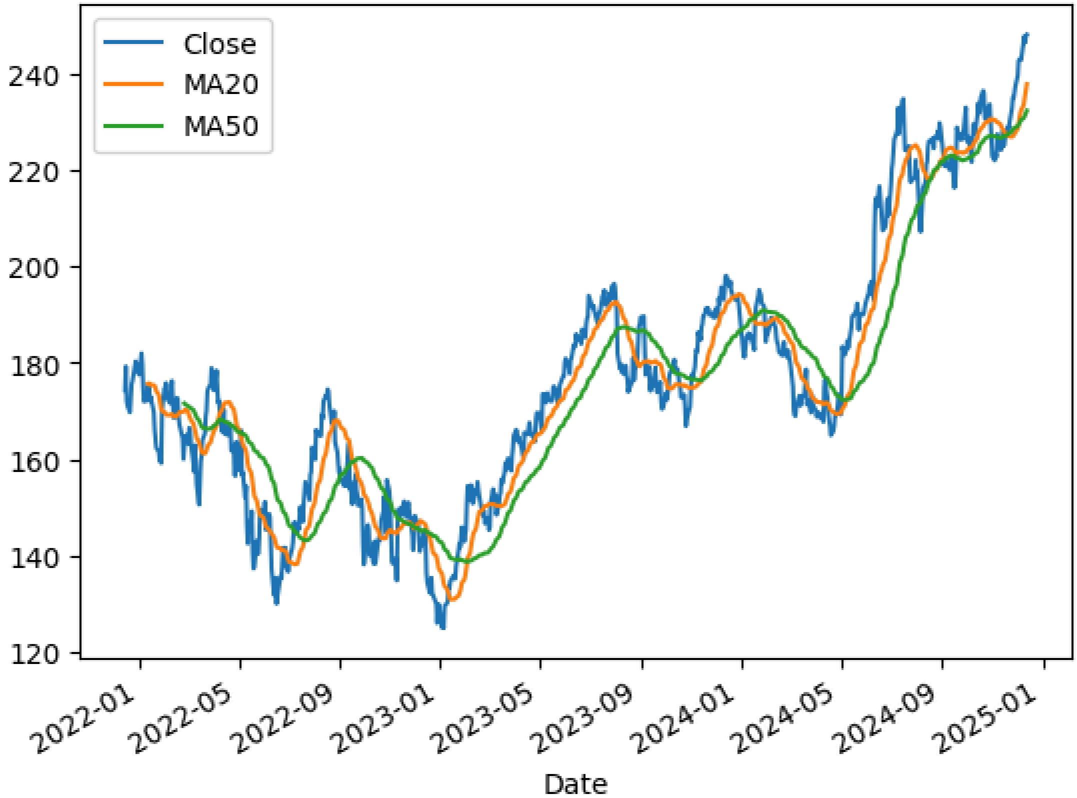
4. **Residual (Résidu)** :

   - Le sous-graphe "Residual" montre les résidus ou les erreurs après avoir retiré la tendance et la saisonnalité. On peut voir les variations aléatoires ou les bruits qui ne sont pas expliqués par la tendance ou la saisonnalité. Cette composante représente les variations imprévisibles dans les prix de clôture.

En résumé, la décomposition saisonnière permet de séparer la série temporelle en ses composantes de tendance, de saisonnalité et de résidu, ce qui facilite l'analyse et la compréhension des motifs sous-jacents dans les prix de clôture.

In [369…

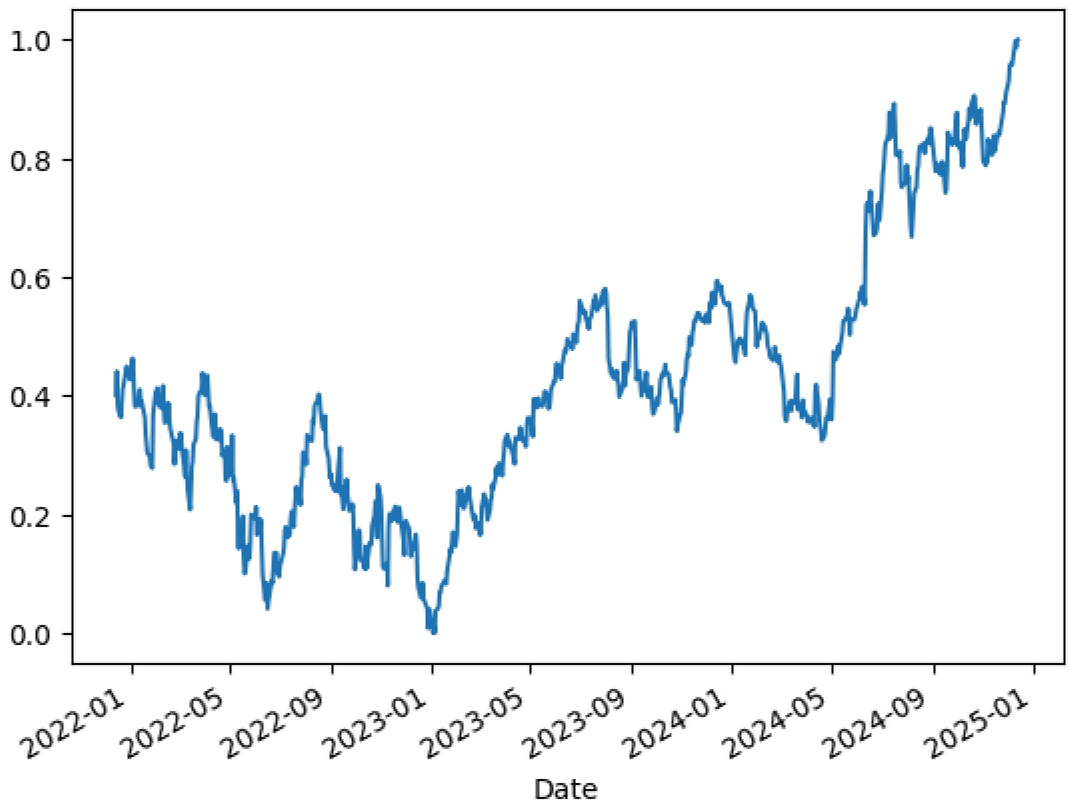
```
#the moving average of the closing price over a 20-day and 50-day period for visual
df['MA20'] = df['Close'].rolling(window=20).mean()
df['MA50'] = df['Close'].rolling(window=50).mean()
df[['Close', 'MA20', 'MA50']].plot()
plt.show()
```



Calculer les **moyennes mobiles** sur 20 et 50 jours permet de lisser les fluctuations quotidiennes des prix de clôture des actions, facilitant ainsi l'identification des tendances à court et à long terme. Cela aide les investisseurs à prendre des décisions éclairées en visualisant les mouvements de prix plus stables et en détectant les signaux de trading potentiels.

In [370…

```
#Scale the closing price using MinMaxScaler for better visualization and analysis
scaler = MinMaxScaler()
df['Close_scaled'] = scaler.fit_transform(df[['Close']])
df['Close_scaled'].plot()
plt.show()
```



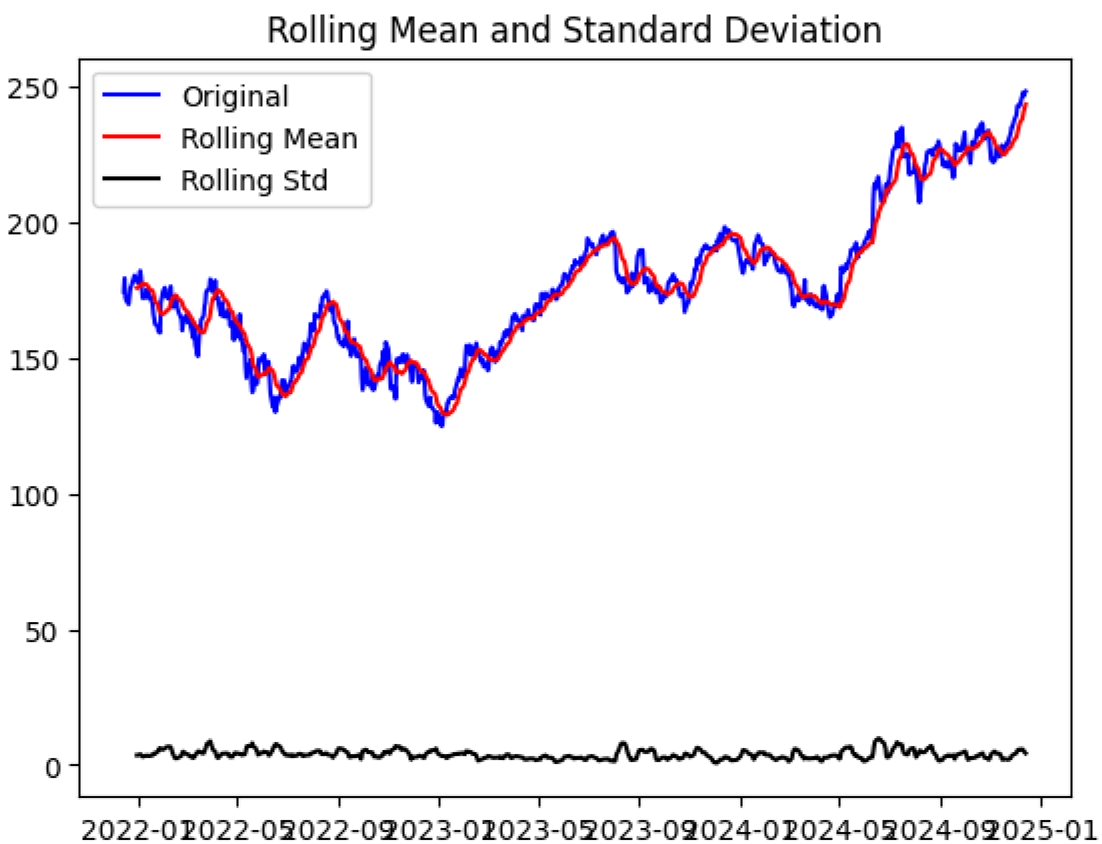
Scaling des données est une étape cruciale pour assurer que les caractéristiques sont sur une échelle commune, améliorer les performances des algorithmes de machine learning, éviter les problèmes de stabilité numérique et faciliter la visualisation des données.

In [371…
```
#display the scaled closing price
df['Close_scaled'].head()
```

Out[371…
```
Date
2021-12-14    0.400536
2021-12-15    0.440907
2021-12-16    0.383722
2021-12-17    0.374624
2021-12-20    0.363334
Name: Close_scaled, dtype: float64
```

In [372…
```
# Define a function to test the stationarity of a time series using the Augmented D
def test_stationarity(timeseries):

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

    #Plot rolling statistics:
    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)
```

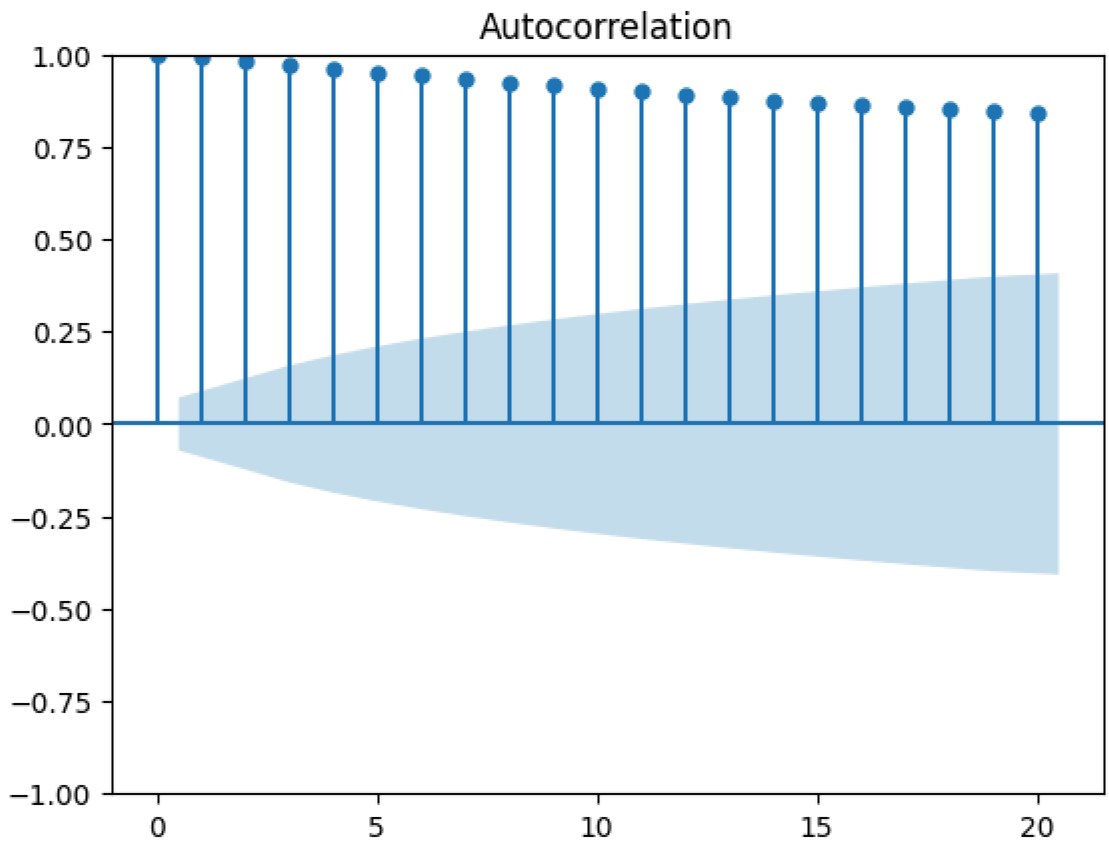
```
    print("Results of dickey fuller test")
    adft = adfuller(timeseries,autolag='AIC')

    # 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 us
    for key,values in adft[4].items():
        output['critical value (%s)'%key] =  values
    print(output)

test_stationarity(df['Close'])
```

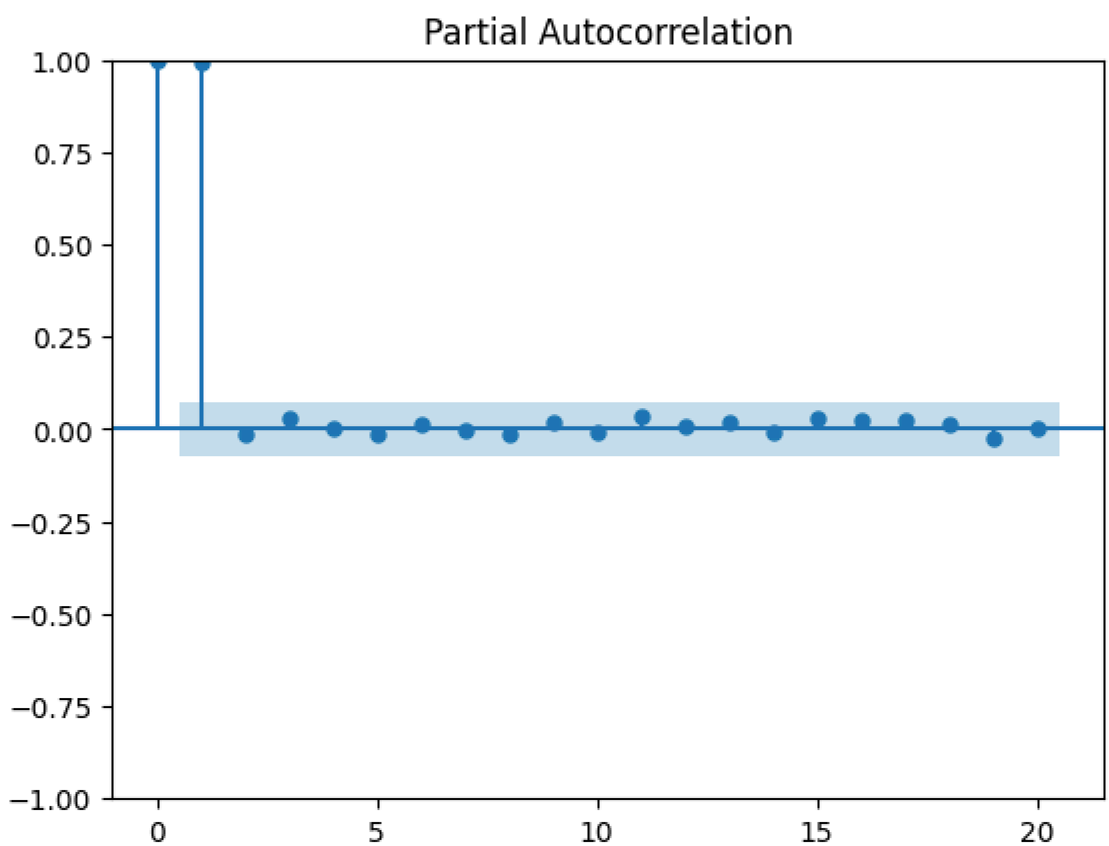



```
Results of dickey fuller test
Test Statistics                 -0.271963
p-value                          0.929382
No. of lags used                 0.000000
Number of observations used    754.000000
critical value (1%)             -3.439053
critical value (5%)             -2.865381
critical value (10%)            -2.568815
dtype: float64
```

In [373…

```
#plot the autocorrelation and partial autocorrelation functions
plot_acf(df['Close'], lags=20)
plt.show()

plot_pacf(df['Close'], lags=20)
plt.show()
```





Analyse des graphes ACF et PACF

1-**ACF (Autocorrelation Function)**

Observation : Les coefficients sont significatifs (en dehors de la zone bleue) pour de nombreux retards (lags) au début, et ils décroissent lentement au fur et à mesure. Interprétation : Cela indique la présence d'une dépendance à long terme dans les données. La décroissance lente suggère une possible non-stationnarité dans les données ou une série avec une tendance. Conclusion : Une différenciation peut être nécessaire pour rendre la série stationnaire, un prérequis pour les modèles ARIMA.

2- **PACF (Partial Autocorrelation Function)**

Observation : Seuls les premiers retards (1 ou 2) sont significatifs ; les suivants sont proches de zéro. Interprétation : Cela indique que la dépendance est principalement capturée par le premier ou les deux premiers termes d'autoregression. Conclusion : Cela suggère qu'un modèle AR(1) ou AR(2) pourrait être suffisant pour expliquer les dépendances dans les données. Conclusions générales Les données montrent une non-stationnarité potentielle. Une différenciation est probablement nécessaire. La structure PACF suggère qu'un modèle AR(1) ou AR(2) peut être un bon point de départ. Si la différenciation est effectuée (modèle ARIMA), le paramètre d sera potentiellement égal à 1. Étapes suivantes Différencier les données et réanalyser les graphes ACF et PACF. Tester un modèle ARIMA(p, d, q) en commençant par p=1 , d=1, q=0

En conclusion, les résultats indiquent que la série temporelle testée est non-stationnaire. Pour rendre la série stationnaire, vous pouvez envisager de différencier les données ou d'appliquer une transformation appropriée.

In [375…

```
#transform the closing price to make it stationary

# Log transformation
df['close_log'] = np.log(df['Close'])

# Differencing
df['close_log_diff'] = df['close_log'].diff()

# Remove infinite values and NaNs
df['close_log_diff'].replace([np.inf, -np.inf], np.nan, inplace=True)
df['close_log_diff'].dropna(inplace=True)
```

Transformation logarithmique (log) :

La transformation logarithmique est utilisée pour stabiliser la variance de la série temporelle. Cela est particulièrement utile si la série présente une tendance exponentielle ou si les variations augmentent avec le temps.

Différenciation (diff()) :

La différenciation est utilisée pour éliminer les tendances et rendre la série temporelle stationnaire en termes de moyenne. En prenant la différence entre les valeurs consécutives, les tendances linéaires sont éliminées.

- **diff()** : Cette méthode calcule la différence entre chaque élément et l'élément précédent dans la série temporelle. Elle est souvent utilisée pour transformer une série non stationnaire en une série stationnaire en éliminant les tendances.

En résumé, appliquer la transformation logarithmique suivie de la différenciation peut aider à rendre une série temporelle stationnaire en stabilisant la variance et en éliminant les tendances.

In [415…

```
df.head()
```

Out[415…

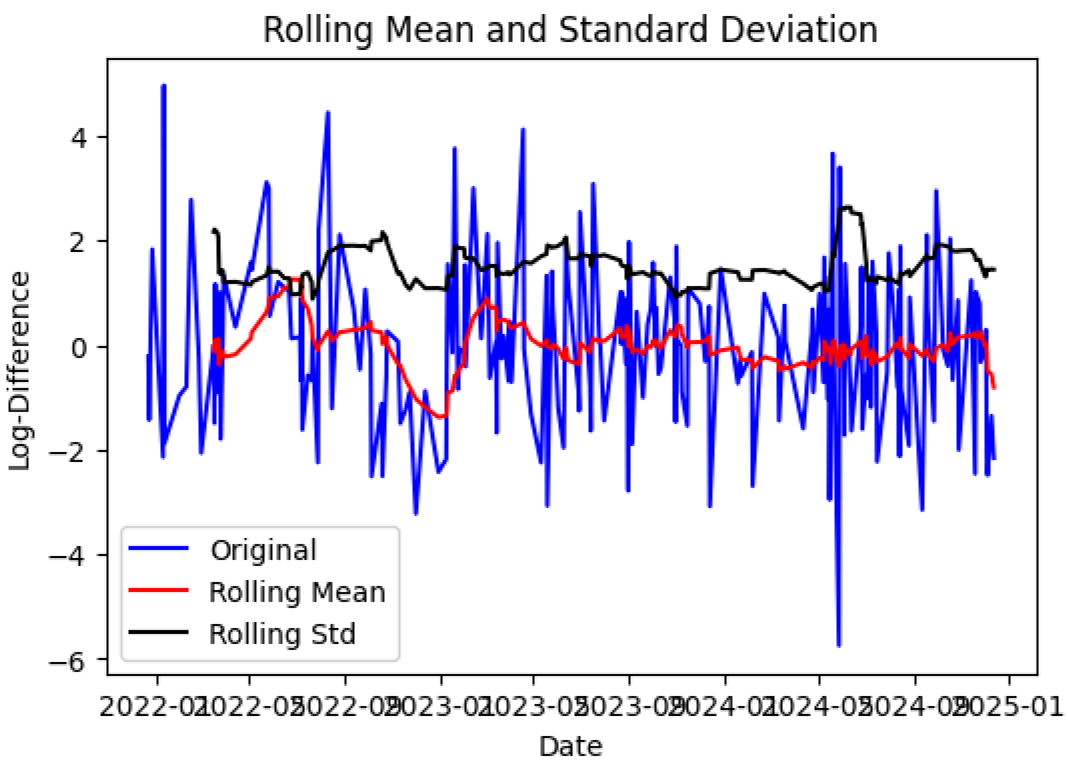
	Close	MA20	MA50	Close_scaled	close_log	close_log_diff
Date						
2021-12-14	174.330002	NaN	NaN	0.400536	5.160950	NaN
2021-12-15	179.300003	NaN	NaN	0.440907	5.189060	0.028110
2021-12-16	172.259995	NaN	NaN	0.383722	5.149005	-0.040055
2021-12-17	171.139999	NaN	NaN	0.374624	5.142482	-0.006523
2021-12-20	169.750000	NaN	NaN	0.363334	5.134327	-0.008155

In [376…

```
#retest the stationarity of the closing price
def test_stationarity(timeseries):

    # Transformation to make the data stationary
    timeseries_log = np.log(timeseries)
    timeseries_log_diff = timeseries_log.diff().dropna()

    # Remove infinite values and NaNs
    timeseries_log_diff.replace([np.inf, -np.inf], np.nan, inplace=True)
    timeseries_log_diff.dropna(inplace=True)

    # Determing rolling statistics
    rolmean = timeseries_log_diff.rolling(window=12).mean()
    rolstd = timeseries_log_diff.rolling(window=12).std()

    # Plot rolling statistics
    plt.figure(figsize=(6, 4))
    plt.plot(timeseries_log_diff, 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.xlabel('Date')
    plt.ylabel('Log-Difference')
    plt.show()

    # Perform ADF test
    adft = adfuller(timeseries_log_diff, autolag='AIC')
```

```
    # Output the ADF test results
    output = pd.Series(adft[0:4], index=['Test Statistic', 'p-value', 'Number of La
    for key, value in adft[4].items():
        output[f'Critical Value ({key})'] = value
    print(output)


test_stationarity(df['close_log_diff'])
```

```
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\pandas\core\arraylike.
py:396: RuntimeWarning: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\pandas\core\arraylike.
py:396: RuntimeWarning: invalid value encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

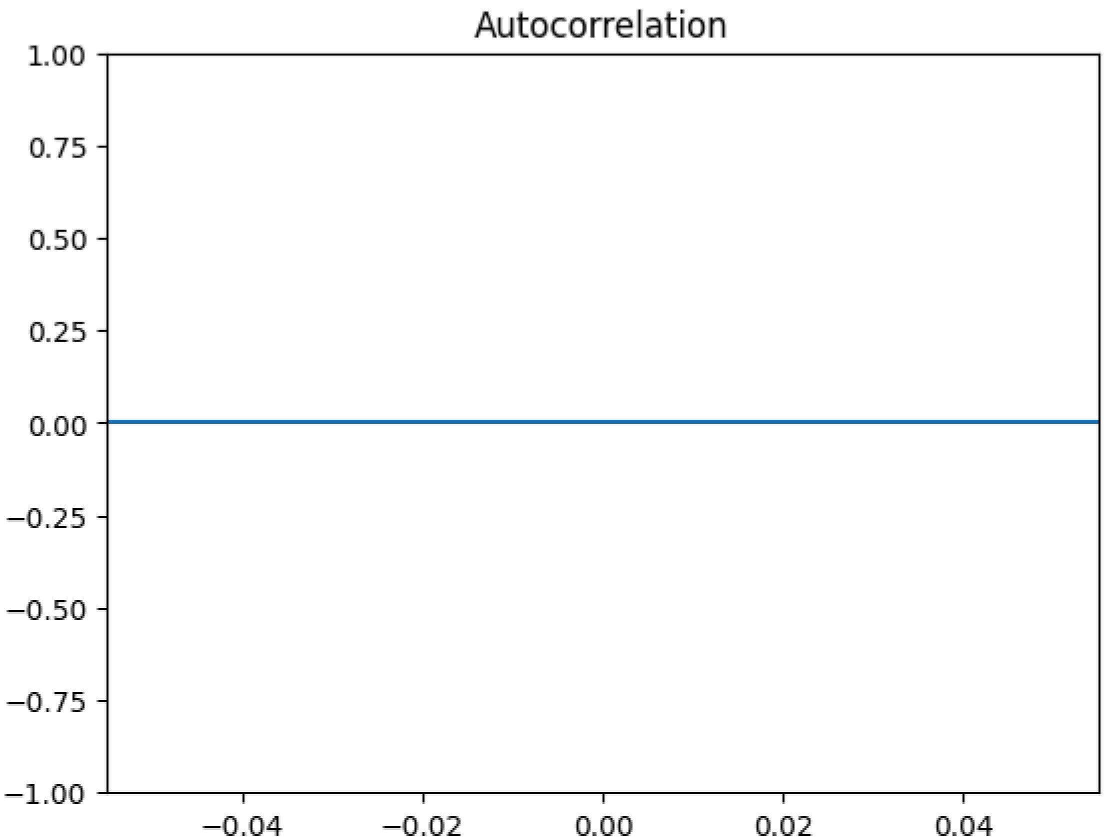


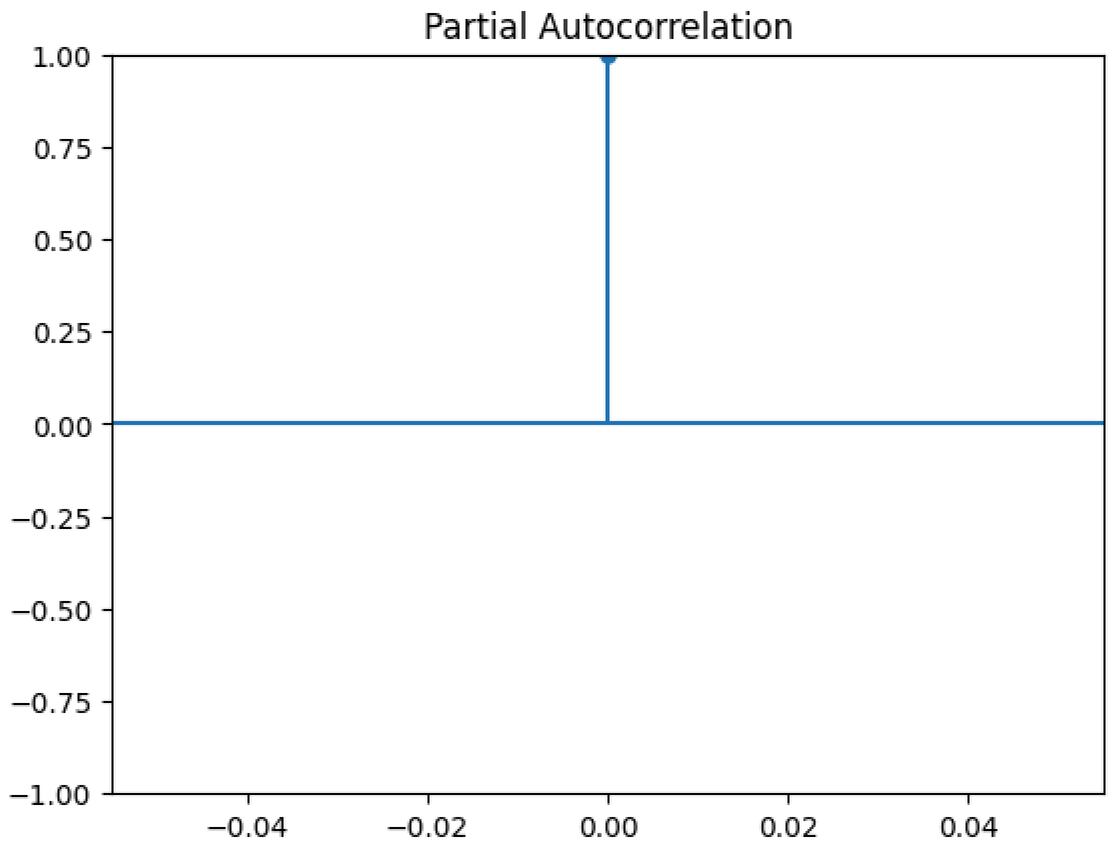

```
Test Statistic                -1.736206e+01
p-value                        5.196850e-30
Number of Lags Used            0.000000e+00
Number of Observations Used    2.120000e+02
Critical Value (1%)           -3.461578e+00
Critical Value (5%)           -2.875272e+00
Critical Value (10%)          -2.574089e+00
dtype: float64
```

En conclusion, les résultats indiquent que la série temporelle différenciée en logarithme est stationnaire. Cela signifie que les propriétés statistiques de la série (telles que la moyenne et la variance) ne changent pas au fil du temps, ce qui est une condition préalable importante pour nos modèles de prévision de séries temporelles.

In [377…

```
#acf and pacf of the transformed closing price
plot_acf(df['close_log_diff'], lags=20)
plt.show()

plot_pacf(df['close_log_diff'], lags=20)
plt.show()
```





BUILD MODEL ARIMA

Commençant avec un modèle ARIMA(p, d, q) avec d=1 (différenciation pour stationnarité), p=1 ou 2 (basé sur PACF), et q=0 (faible influence MA suggérée).

In [378…
```
#replace the infinite values with NaNs
df['close_log_diff'].replace([np.inf, -np.inf], np.nan, inplace=True)

#drop the NaNs
df['close_log_diff'].dropna(inplace=True)
```

In [379…
```
#split the data into training and testing sets
train_size = int(len(df) * 0.8)
train_log_diff, test_log_diff = df['close_log_diff'][:train_size], df['close_log_di

train_log_diff.head()
```

Out[379…
```
Date
2021-12-14         NaN
2021-12-15    0.028110
2021-12-16   -0.040055
2021-12-17   -0.006523
2021-12-20   -0.008155
Name: close_log_diff, dtype: float64
```

In [380…
```
#drop the NaNs
train_log_diff.dropna(inplace=True)
```

In [381…

```
#check for missing values
train_log_diff.isna().sum()
```

Out[381…

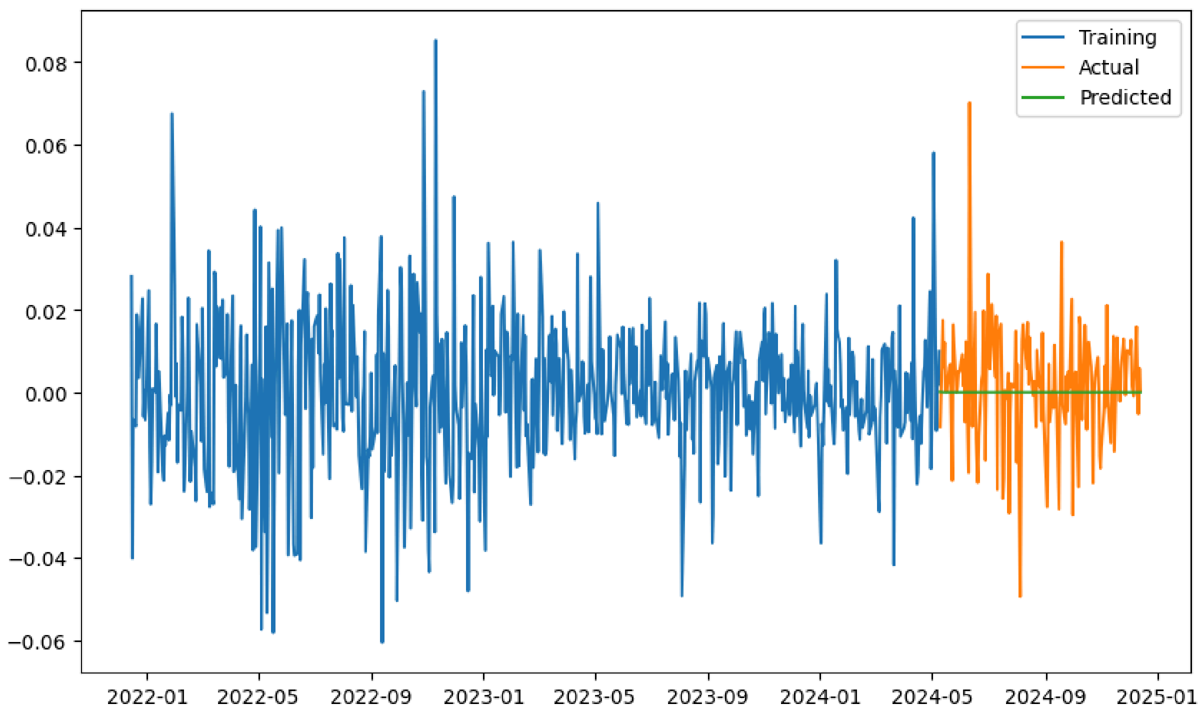
```
0
```

In [382…

```
#build the ARIMA model with the training data and make predictions on the testing d

# Ensure the data is in the correct format
train_log_diff = train_log_diff.dropna()

# Build the ARIMA model
model = ARIMA(train_log_diff, order=(1, 1, 1))
model_fit = model.fit()
print(model_fit.summary())

# Make predictions
predictions1 = model_fit.forecast(steps=len(test_log_diff))

# Plot the predictions
plt.figure(figsize=(10, 6))
plt.plot(train_log_diff ,label='Training')
plt.plot(test_log_diff, label='Actual')
plt.plot(test_log_diff.index, predictions1, label='Predicted')
plt.legend()
plt.show()
```

```
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:473: ValueWarning: A date index has been provided, but it has no associa
ted frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:473: ValueWarning: A date index has been provided, but it has no associa
ted frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:473: ValueWarning: A date index has been provided, but it has no associa
ted frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\base\mode
l.py:607: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Ch
eck mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:836: ValueWarning: No supported index is available. Prediction results w
ill be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:836: FutureWarning: No supported index is available. In the next versio
n, calling this method in a model without a supported index will result in an except
ion.
  return get_prediction_index(
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:          close_log_diff   No. Observations:                  603
Model:                  ARIMA(1, 1, 1)   Log Likelihood                1567.717
Date:                 Sat, 14 Dec 2024   AIC                          -3129.433
Time:                         16:11:14   BIC                          -3116.233
Sample:                              0   HQIC                         -3124.295
                                 - 603
Covariance Type:                   opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0085      0.036      0.235      0.814      -0.062       0.079
ma.L1         -0.9999      0.648     -1.542      0.123      -2.271       0.271
sigma2         0.0003      0.000      1.544      0.123   -8.54e-05       0.001
===================================================================================
Ljung-Box (L1) (Q):                   0.01   Jarque-Bera (JB):               104.24
Prob(Q):                              0.93   Prob(JB):                         0.00
Heteroskedasticity (H):               0.39   Skew:                             0.15
Prob(H) (two-sided):                  0.00   Kurtosis:                         5.02
===================================================================================

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



In [383…

```
mse = mean_squared_error(test_log_diff, predictions1)
mse

#calculate the accuracy of the model
accuracy = 100 - (mse * 100)
print(f'Model Accuracy: {accuracy}%', '\n', f'mean_squared_error : {mse}')
```

```
Model Accuracy: 99.98017605931706%
 mean_squared_error : 0.0001982394068293454
```

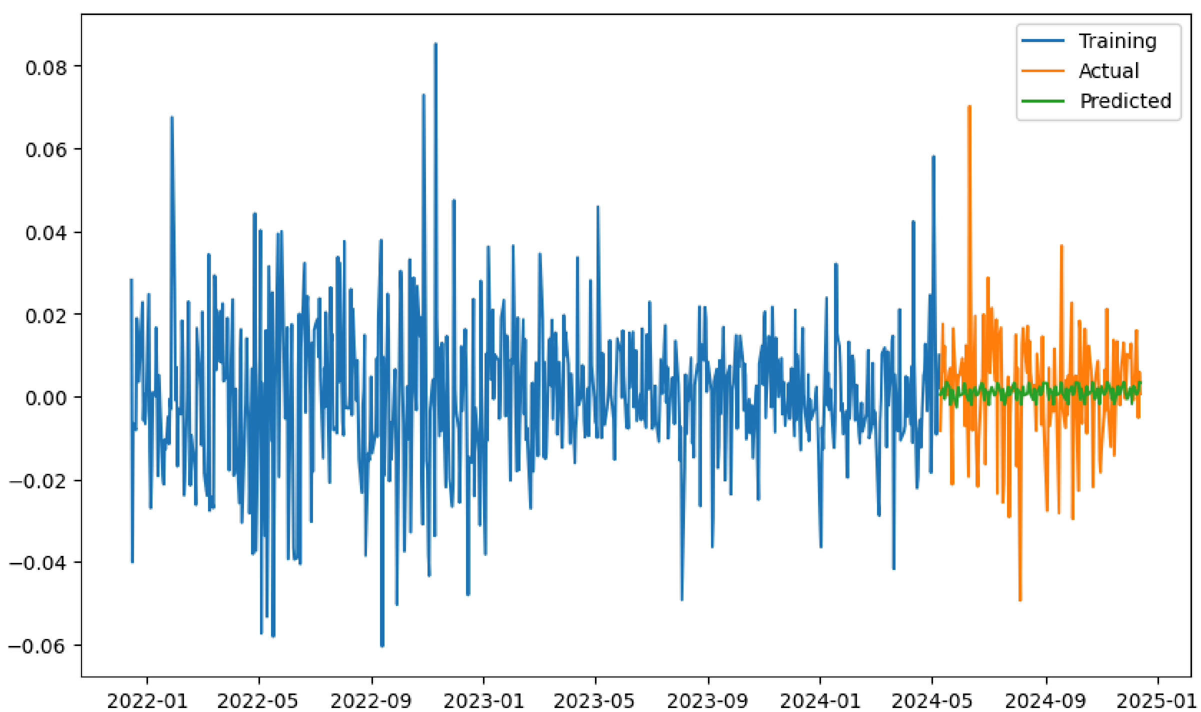
BUILD MODEL SARIMA

In [384…

```
# Build the SARIMA model with the training data and make predictions on the testing

# Build the SARIMA model
model = SARIMAX(train_log_diff, order=(1, 1, 1), seasonal_order=(1, 1, 1, 12))
model_fit = model.fit()
print(model_fit.summary())

# Make predictions
predictions2 = model_fit.forecast(steps=len(test_log_diff))


# Plot the predictions
plt.figure(figsize=(10, 6))
plt.plot(train_log_diff ,label='Training')
plt.plot(test_log_diff, label='Actual')
plt.plot(test_log_diff.index, predictions2, label='Predicted')
plt.legend()
plt.show()
```

```
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:473: ValueWarning: A date index has been provided, but it has no associa
ted frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:473: ValueWarning: A date index has been provided, but it has no associa
ted frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\base\mode
l.py:607: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Ch
eck mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:836: ValueWarning: No supported index is available. Prediction results w
ill be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\statsmodels\tsa\base\t
sa_model.py:836: FutureWarning: No supported index is available. In the next versio
n, calling this method in a model without a supported index will result in an except
ion.
  return get_prediction_index(
```

```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                   close_log_diff   No. Observations:
603
Model:             SARIMAX(1, 1, 1)x(1, 1, 1, 12)   Log Likelihood                15
06.908
Date:                          Sat, 14 Dec 2024   AIC                          -30
03.817
Time:                                  16:11:15   BIC                          -29
81.916
Sample:                                       0   HQIC                         -29
95.285
                                          - 603
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0051      0.037      0.138      0.890      -0.067       0.078
ma.L1         -0.9973      0.035    -28.420      0.000      -1.066      -0.929
ar.S.L12      -0.0442      0.039     -1.148      0.251      -0.120       0.031
ma.S.L12      -0.9992      1.283     -0.779      0.436      -3.513       1.515
sigma2         0.0003      0.000      0.791      0.429      -0.000       0.001
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                86.19
Prob(Q):                              0.96   Prob(JB):                         0.00
Heteroskedasticity (H):               0.41   Skew:                             0.18
Prob(H) (two-sided):                  0.00   Kurtosis:                         4.84
===================================================================================

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



In [385…

```
#calculate the mean squared error of the predictions
mse = mean_squared_error(test_log_diff, predictions2)


#calculate the accuracy of the model
accuracy = 100 - (mse * 100)
print(f"accuracy = " ,accuracy,"error = "  , mse)
```

```
accuracy =  99.98053953763929 error =  0.00019460462360715368
```

BUILD MODEL LSTM

In [386…

```
#display the data
df.head()
```

Out[386…

Date	Close	MA20	MA50	Close_scaled	close_log	close_log_diff
2021-12-14	174.330002	NaN	NaN	0.400536	5.160950	NaN
2021-12-15	179.300003	NaN	NaN	0.440907	5.189060	0.028110
2021-12-16	172.259995	NaN	NaN	0.383722	5.149005	-0.040055
2021-12-17	171.139999	NaN	NaN	0.374624	5.142482	-0.006523
2021-12-20	169.750000	NaN	NaN	0.363334	5.134327	-0.008155

In [387…

```
# Create a new dataframe with only the 'Close column
data1 = df.filter(['Close'])
# Convert the dataframe to a numpy array
dataset = data1.values
# Get the number of rows to train the model on
training_data_len = int(np.ceil( len(dataset) * .95 ))

training_data_len
```

Out[387…

```
718
```

In [388…

```
#reshape the Close_scaled column to a 2D array
scaled_data = df['Close_scaled'].values.reshape(-1,1)
```

In [390…

```
# Create the training data set
# Create the scaled training data set
train_data = scaled_data[0:int(training_data_len), :]
# Split the data into x_train and y_train data sets
x_train = []
y_train = []

for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])
    if i<= 61:
```

```
        print(x_train)
        print(y_train)
        print()

# Convert the x_train and y_train to numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)

# Reshape the data
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
```

```
[array([0.40053612, 0.44090653, 0.38372183, 0.37462432, 0.36333361,
       0.38965158, 0.41117699, 0.41637559, 0.44927302, 0.44082522,
       0.44155637, 0.43197138, 0.42685409, 0.46291929, 0.44415561,
       0.40532855, 0.38160994, 0.38299081, 0.3831533 , 0.40662823,
       0.41028348, 0.3831533 , 0.39030142, 0.36373977, 0.33474126,
       0.32077   , 0.30371216, 0.29729507, 0.28234912, 0.28161809,
       0.27780036, 0.36804486, 0.40419136, 0.4028105 , 0.41280153,
       0.38892043, 0.38477784, 0.37884822, 0.40459753, 0.41637559,
       0.38258464, 0.35431728, 0.3562668 , 0.38802691, 0.38607752,
       0.3562668 , 0.34343273, 0.31922677, 0.2847048 , 0.30639271,
       0.32353186, 0.32572493, 0.31012913, 0.3374218 , 0.33474126,
       0.30988546, 0.2784502 , 0.26334176, 0.30809843, 0.27211441])]
[0.24132886927125385]

[array([0.40053612, 0.44090653, 0.38372183, 0.37462432, 0.36333361,
       0.38965158, 0.41117699, 0.41637559, 0.44927302, 0.44082522,
       0.44155637, 0.43197138, 0.42685409, 0.46291929, 0.44415561,
       0.40532855, 0.38160994, 0.38299081, 0.3831533 , 0.40662823,
       0.41028348, 0.3831533 , 0.39030142, 0.36373977, 0.33474126,
       0.32077   , 0.30371216, 0.29729507, 0.28234912, 0.28161809,
       0.27780036, 0.36804486, 0.40419136, 0.4028105 , 0.41280153,
       0.38892043, 0.38477784, 0.37884822, 0.40459753, 0.41637559,
       0.38258464, 0.35431728, 0.3562668 , 0.38802691, 0.38607752,
       0.3562668 , 0.34343273, 0.31922677, 0.2847048 , 0.30639271,
       0.32353186, 0.32572493, 0.31012913, 0.3374218 , 0.33474126,
       0.30988546, 0.2784502 , 0.26334176, 0.30809843, 0.27211441]), array([0.440906
53, 0.38372183, 0.37462432, 0.36333361, 0.38965158,
       0.41117699, 0.41637559, 0.44927302, 0.44082522, 0.44155637,
       0.43197138, 0.42685409, 0.46291929, 0.44415561, 0.40532855,
       0.38160994, 0.38299081, 0.3831533 , 0.40662823, 0.41028348,
       0.3831533 , 0.39030142, 0.36373977, 0.33474126, 0.32077   ,
       0.30371216, 0.29729507, 0.28234912, 0.28161809, 0.27780036,
       0.36804486, 0.40419136, 0.4028105 , 0.41280153, 0.38892043,
       0.38477784, 0.37884822, 0.40459753, 0.41637559, 0.38258464,
       0.35431728, 0.3562668 , 0.38802691, 0.38607752, 0.3562668 ,
       0.34343273, 0.31922677, 0.2847048 , 0.30639271, 0.32353186,
       0.32572493, 0.31012913, 0.3374218 , 0.33474126, 0.30988546,
       0.2784502 , 0.26334176, 0.30809843, 0.27211441, 0.24132887])]
[0.24132886927125385, 0.20794408870696612]
```

In [409…

```
from keras.layers import Dropout

# Build the improved LSTM model
model = Sequential()
model.add(LSTM(256, return_sequences=True, input_shape=(x_train.shape[1], 1)))
```

```python
model.add(Dropout(0.2))
model.add(LSTM(128, return_sequences=True))
model.add(Dropout(0.2))
model.add(LSTM(64, return_sequences=False))
model.add(Dropout(0.2))
model.add(Dense(50))
model.add(Dense(1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Train the model
model.fit(x_train, y_train, batch_size=32, epochs=100)
```

```
Epoch 1/100
```

```
C:\Users\darck\AppData\Roaming\Python\Python311\site-packages\keras\src\layers\rnn\r
nn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a laye
r. When using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)
```

```
21/21 ━━━━━━━━━━━━━━━━━━━━ 5s 66ms/step - loss: 0.0579
Epoch 2/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 68ms/step - loss: 0.0062
Epoch 3/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0051
Epoch 4/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 67ms/step - loss: 0.0043
Epoch 5/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0048
Epoch 6/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0047
Epoch 7/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0033
Epoch 8/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0037
Epoch 9/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0034
Epoch 10/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 68ms/step - loss: 0.0038
Epoch 11/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0045
Epoch 12/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0025
Epoch 13/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 67ms/step - loss: 0.0030
Epoch 14/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0027
Epoch 15/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 65ms/step - loss: 0.0025
Epoch 16/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 68ms/step - loss: 0.0022
Epoch 17/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0023
Epoch 18/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 68ms/step - loss: 0.0024
Epoch 19/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0023
Epoch 20/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0022
Epoch 21/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 75ms/step - loss: 0.0026
Epoch 22/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0021
Epoch 23/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0020
Epoch 24/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0024
Epoch 25/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0023
Epoch 26/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 74ms/step - loss: 0.0019
Epoch 27/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0016
Epoch 28/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0021
Epoch 29/100
```

```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0019
Epoch 30/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0025
Epoch 31/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0017
Epoch 32/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0020
Epoch 33/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 70ms/step - loss: 0.0017
Epoch 34/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 71ms/step - loss: 0.0015
Epoch 35/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 77ms/step - loss: 0.0015
Epoch 36/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 73ms/step - loss: 0.0017
Epoch 37/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0016
Epoch 38/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0018
Epoch 39/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 73ms/step - loss: 0.0014
Epoch 40/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 65ms/step - loss: 0.0017
Epoch 41/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0016
Epoch 42/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0017
Epoch 43/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0014
Epoch 44/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0015
Epoch 45/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0014
Epoch 46/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0013
Epoch 47/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0014
Epoch 48/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0014
Epoch 49/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0014
Epoch 50/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0018
Epoch 51/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0013
Epoch 52/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 73ms/step - loss: 0.0014
Epoch 53/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0013
Epoch 54/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 74ms/step - loss: 0.0014
Epoch 55/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0013
Epoch 56/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 73ms/step - loss: 0.0013
Epoch 57/100
```

```
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0014
Epoch 58/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0013
Epoch 59/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0013
Epoch 60/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0012
Epoch 61/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 73ms/step - loss: 0.0012
Epoch 62/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0014
Epoch 63/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0012
Epoch 64/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0013
Epoch 65/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0012
Epoch 66/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0013
Epoch 67/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0012
Epoch 68/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0012
Epoch 69/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0014
Epoch 70/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0013
Epoch 71/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0012
Epoch 72/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0012
Epoch 73/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0011
Epoch 74/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0012
Epoch 75/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0012
Epoch 76/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0014
Epoch 77/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0013
Epoch 78/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 67ms/step - loss: 0.0011
Epoch 79/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0012
Epoch 80/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 83ms/step - loss: 0.0010
Epoch 81/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 78ms/step - loss: 0.0013
Epoch 82/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 79ms/step - loss: 0.0011
Epoch 83/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 78ms/step - loss: 0.0013
Epoch 84/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 80ms/step - loss: 0.0011
Epoch 85/100
```

```
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 79ms/step - loss: 0.0013
Epoch 86/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 80ms/step - loss: 0.0013
Epoch 87/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 79ms/step - loss: 0.0012
Epoch 88/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 78ms/step - loss: 9.7751e-04
Epoch 89/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 79ms/step - loss: 0.0011
Epoch 90/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 77ms/step - loss: 0.0011
Epoch 91/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 77ms/step - loss: 0.0013
Epoch 92/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 78ms/step - loss: 0.0014
Epoch 93/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 77ms/step - loss: 0.0014
Epoch 94/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 73ms/step - loss: 0.0011
Epoch 95/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 70ms/step - loss: 0.0010
Epoch 96/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0011
Epoch 97/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 1s 69ms/step - loss: 0.0013
Epoch 98/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 73ms/step - loss: 0.0012
Epoch 99/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 71ms/step - loss: 0.0010
Epoch 100/100
21/21 ━━━━━━━━━━━━━━━━━━━━ 2s 72ms/step - loss: 0.0012
```

Out[409…

```
<keras.src.callbacks.history.History at 0x2f002088b90>
```

In [410…

```
model.summary()
```

Model: "sequential_8"

Layer (type)	Output Shape	Param #
lstm_24 (LSTM)	(None, 60, 256)	264,192
dropout (Dropout)	(None, 60, 256)	0
lstm_25 (LSTM)	(None, 60, 128)	197,120
dropout_1 (Dropout)	(None, 60, 128)	0
lstm_26 (LSTM)	(None, 64)	49,408
dropout_2 (Dropout)	(None, 64)	0
dense_16 (Dense)	(None, 50)	3,250
dense_17 (Dense)	(None, 1)	51

Total params: 1,542,065 (5.88 MB)

Trainable params: 514,021 (1.96 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 1,028,044 (3.92 MB)

In [411…

```
# Create the testing data set
# Create a new array containing scaled values from index 1543 to 2002
test_data = scaled_data[training_data_len - 60: , :]
# Create the data sets x_test and y_test
x_test = []
y_test = dataset[training_data_len:, 0]  # Select only the 'Close' column
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])

# Convert the data to a numpy array
x_test = np.array(x_test)

# Reshape the data
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1 ))

# Get the models predicted price values
predictions3 = model.predict(x_test)
predictions3 = scaler.inverse_transform(predictions3)

# Get the root mean squared error (RMSE)
rmse = np.sqrt(np.mean(((predictions3 - y_test.reshape(-1, 1)) ** 2)))
rmse

#calculate the mean squared error of the predictions
mse = mean_squared_error(y_test, predictions3)
mse
```

2/2 ━━━━━━━━━━━━━━━━━━━━ **2s** 357ms/step

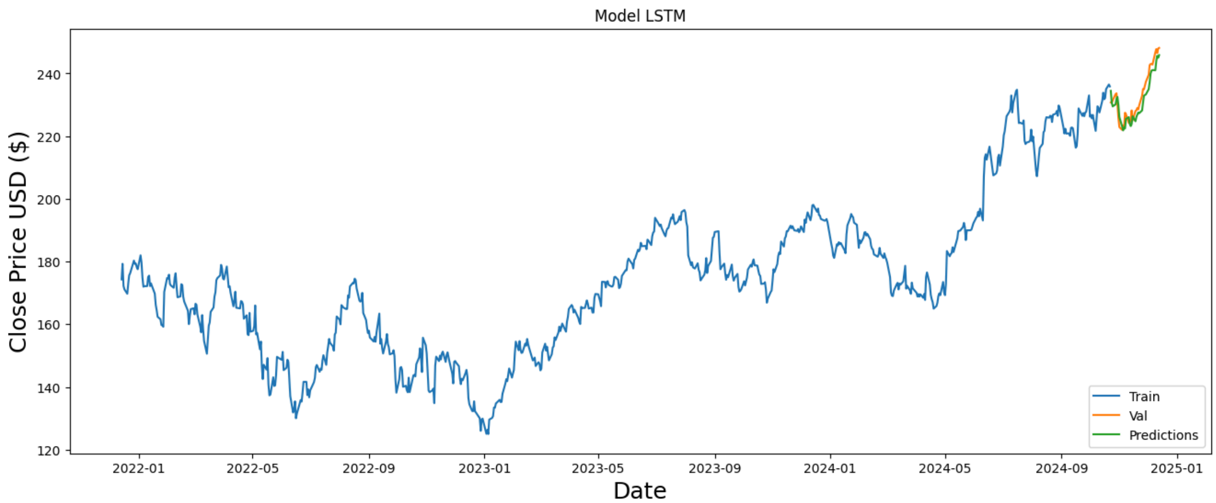
Out[411…

```
9.220745615642267
```

In [412…

```
# Plot the data
train = data1[:training_data_len]
valid = data1[training_data_len:]
valid['Predictions'] = predictions3

# Visualize the data
plt.figure(figsize=(16,6))
plt.title('Model LSTM')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train['Close'])
plt.plot(valid[['Close', 'Predictions']])
plt.legend(['Train', 'Val', 'Predictions'], loc='lower right')
plt.show()

# Show the accurate
```

```
C:\Users\darck\AppData\Local\Temp\ipykernel_26764\2554651337.py:4: SettingWithCopyWa
rning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/u
ser_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions3
```



In [413…

```
# Calculer les métriques d'évaluation pour LSTM
mae = mean_absolute_error(y_test, predictions3)
print(f'Mean Absolute Error: {mae}')

mse = mean_squared_error(y_test, predictions3)
print(f'Mean Squared Error: {mse}')
```

```
Mean Absolute Error: 2.6506764179951436
Mean Squared Error: 9.220745615642267
```

In [414…

```
valid.head()
```

Out[414…

	Close	Predictions
Date		
2024-10-23	230.759995	234.465393
2024-10-24	230.570007	230.687195
2024-10-25	231.410004	229.500397
2024-10-28	233.399994	230.136993
2024-10-29	233.669998	231.900864