

Stock Price Prediction System

✓ Load the Data set

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.api as sm
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from sklearn.metrics import mean_squared_error
```

```
df = pd.read_csv('/content/G00GL.csv')
print(df.head())
```



	Date	Open	High	Low	Close	Adj Close	Volume
0	2004-08-19	50.050049	52.082081	48.028027	50.220219	50.220219	44659096
1	2004-08-20	50.555557	54.594597	50.300301	54.209209	54.209209	22834343
2	2004-08-23	55.430431	56.796799	54.579578	54.754753	54.754753	18256126
3	2004-08-24	55.675674	55.855858	51.836838	52.487488	52.487488	15247337
4	2004-08-25	52.532532	54.054054	51.991993	53.053055	53.053055	9188602

✓ Basic info

```
print(df.info())
```

```

↳ <class 'pandas.core.frame.DataFrame'>
RangeIndex: 4431 entries, 0 to 4430
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  -
 0   Date        4431 non-null   object
 1   Open        4431 non-null   float64
 2   High        4431 non-null   float64
 3   Low         4431 non-null   float64
 4   Close       4431 non-null   float64
 5   Adj Close   4431 non-null   float64
 6   Volume      4431 non-null   int64
dtypes: float64(5), int64(1), object(1)
memory usage: 242.4+ KB
None

```

✓ Descriptive statistics

```
print(df.describe())
```

```

↳
count      4431.000000  4431.000000  4431.000000  4431.000000  4431.000000  \
mean       693.087345   699.735595   686.078751   693.097367   693.097367
std        645.118799   651.331215   638.579488   645.187806   645.187806
min         49.644646    50.920921    48.028027    50.055054    50.055054
25%        248.558563   250.853355   245.813309   248.415916   248.415916
50%        434.924927   437.887878   432.687683   435.330322   435.330322
75%       1007.364990  1020.649994   997.274994  1007.790008  1007.790008
max       3025.000000  3030.929932  2977.979980  2996.770020  2996.770020

count      4.431000e+03

```

```
mean    6.444992e+06
std      7.690351e+06
min      4.656000e+05
25%      1.695600e+06
50%      3.778418e+06
75%      8.002390e+06
max      8.215117e+07
```

✓ Check for missing values

```
print(df.isnull().sum())
```


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

✓ Correlation matrix

```
# Convert the 'Date' column to datetime objects
df['Date'] = pd.to_datetime(df['Date'])

# Extract numerical features from the 'Date' column if needed
# For example, you can extract year, month, and day
df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['Day'] = df['Date'].dt.day

# Now you can calculate the correlation matrix
print(df.corr())
```

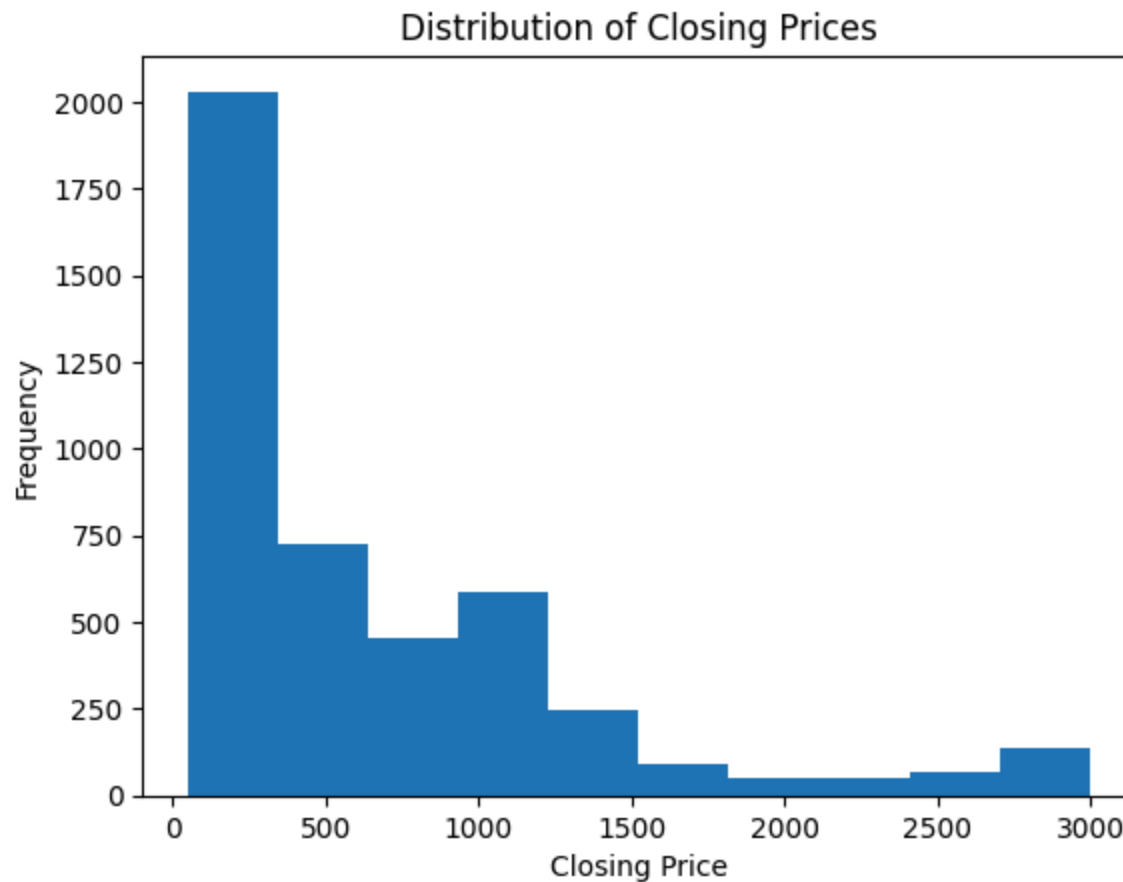


	Date	Open	High	Low	Close	Adj Close \
Date	1.000000	0.851641	0.851575	0.852000	0.851839	0.851839
Open	0.851641	1.000000	0.999915	0.999902	0.999808	0.999808
High	0.851575	0.999915	1.000000	0.999877	0.999903	0.999903
Low	0.852000	0.999902	0.999877	1.000000	0.999914	0.999914
Close	0.851839	0.999808	0.999903	0.999914	1.000000	1.000000
Adj Close	0.851839	0.999808	0.999903	0.999914	1.000000	1.000000
Volume	-0.681369	-0.453884	-0.452855	-0.455447	-0.454252	-0.454252
Year	0.998389	0.849518	0.849495	0.849827	0.849719	0.849719
Month	-0.013969	0.001236	0.000488	0.002091	0.001184	0.001184
Day	-0.002353	-0.004238	-0.004361	-0.004138	-0.004388	-0.004388

	Volume	Year	Month	Day
Date	-0.681369	0.998389	-0.013969	-0.002353
Open	-0.453884	0.849518	0.001236	-0.004238
High	-0.452855	0.849495	0.000488	-0.004361
Low	-0.455447	0.849827	0.002091	-0.004138
Close	-0.454252	0.849719	0.001184	-0.004388
Adj Close	-0.454252	0.849719	0.001184	-0.004388
Volume	1.000000	-0.676220	-0.063534	0.010951
Year	-0.676220	1.000000	-0.070479	-0.007213
Month	-0.063534	-0.070479	1.000000	0.003034
Day	0.010951	-0.007213	0.003034	1.000000

✓ Analyze the distribution of target variable

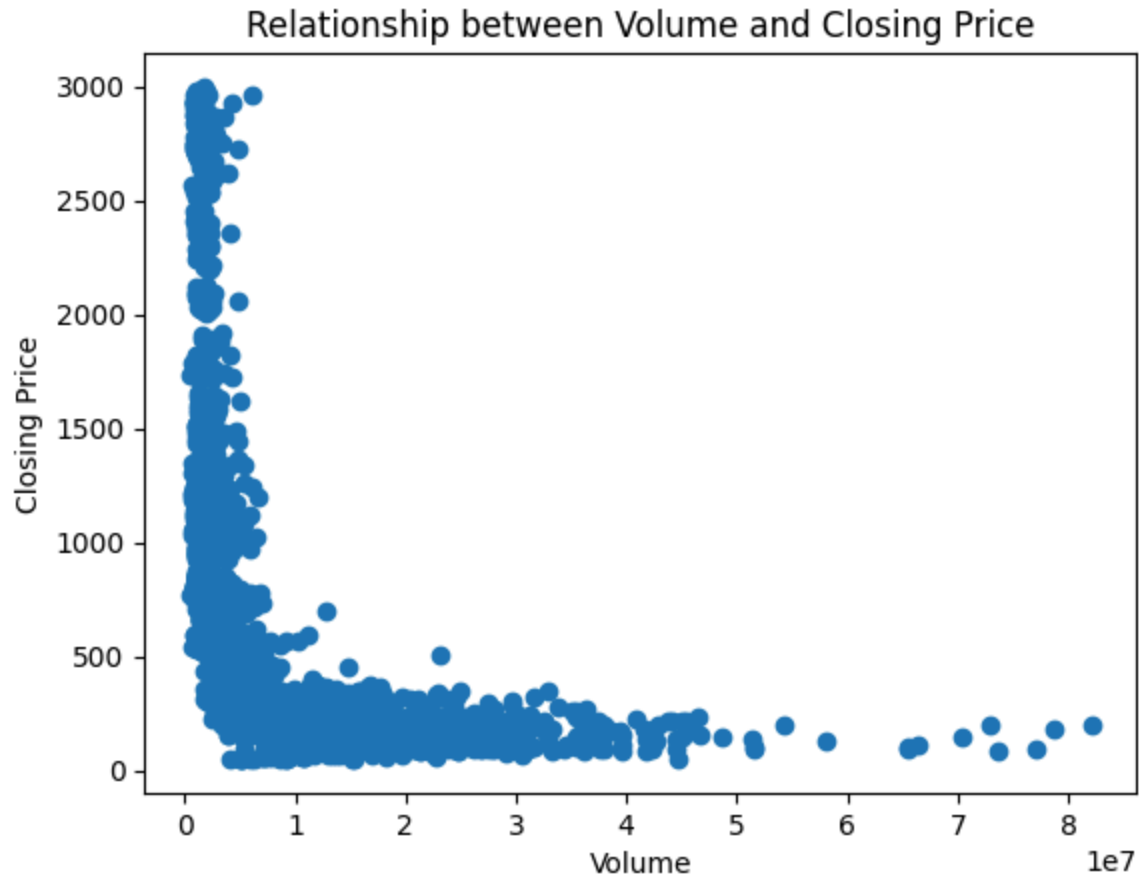
```
plt.hist(df['Close'])  
plt.xlabel('Closing Price')  
plt.ylabel('Frequency')  
plt.title('Distribution of Closing Prices')  
plt.show()
```



✓ Analyze the relationship between features

```
plt.scatter(df['Volume'], df['Close'])  
plt.xlabel('Volume')
```

```
plt.ylabel('Closing Price')  
plt.title('Relationship between Volume and Closing Price')
```



Analyze the correlation between the series and its lagged values.

- ✓ Convert 'Date' column to datetime objects

```
df['Date'] = pd.to_datetime(df['Date'])  
df.set_index('Date', inplace=True)
```

✓ Decompose the time series

```
!pip install statsmodels  
import statsmodels.api as sm  
import pandas as pd
```

```
decomposition = sm.tsa.seasonal_decompose(df['Close'], model='additive', period=12)
```

⇒ Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-packages (0.14.3)
Requirement already satisfied: numpy<3,>=1.22.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (1.26.4)
Requirement already satisfied: scipy!=1.9.2,>=1.8 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (1.13.1)
Requirement already satisfied: pandas!=2.1.0,>=1.4 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (2.2.2)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (0.5.6)
Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from statsmodels) (24.1)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels) (2.9.0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas!=2.1.0,>=1.4->statsmodels) (2024.1)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.6->statsmodels) (1.16.0)

✓ Plot the decomposed components

```
fig = decomposition.plot()  
plt.show()
```



✓ Calculate moving averages

```
df['MA_7'] = df['Close'].rolling(window=7).mean()  
df['MA_30'] = df['Close'].rolling(window=30).mean()  
  
print(df['MA_30'].head())
```



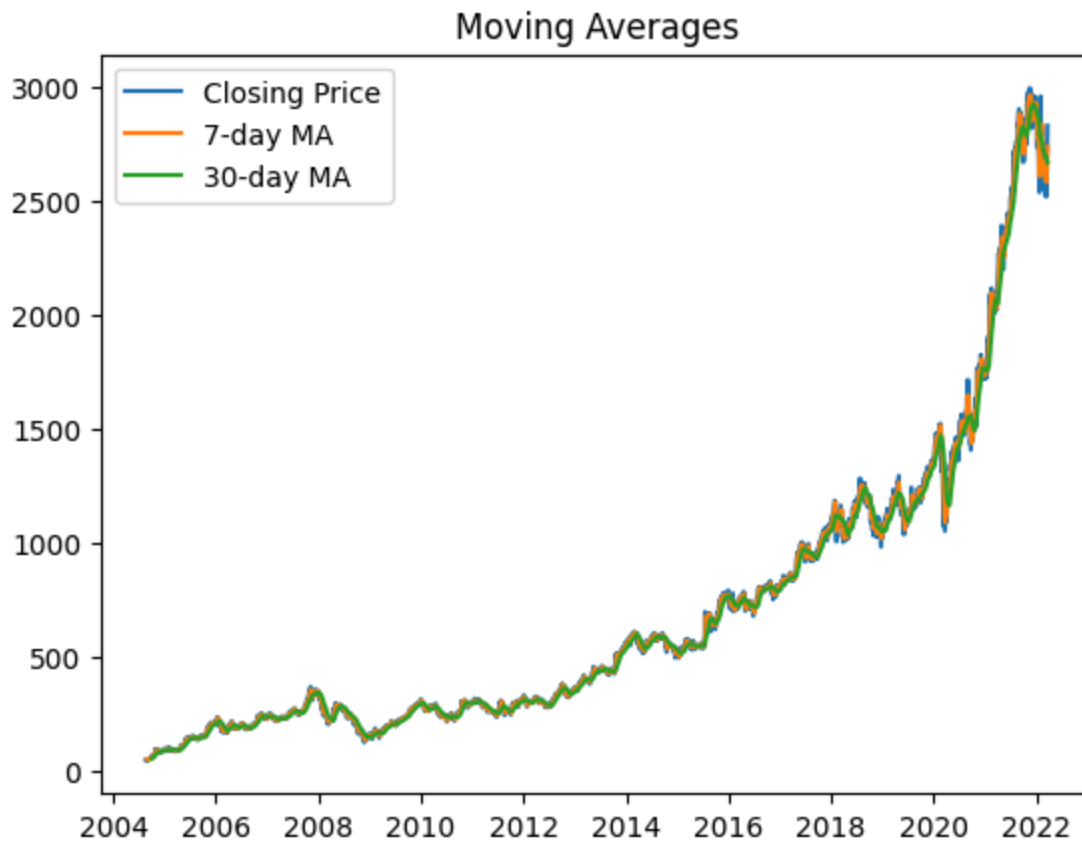
```
Date  
2004-08-19    NaN  
2004-08-20    NaN
```



```
2004-08-23    NaN
2004-08-24    NaN
2004-08-25    NaN
Name: MA_30, dtype: float64
```

✓ Plot moving averages

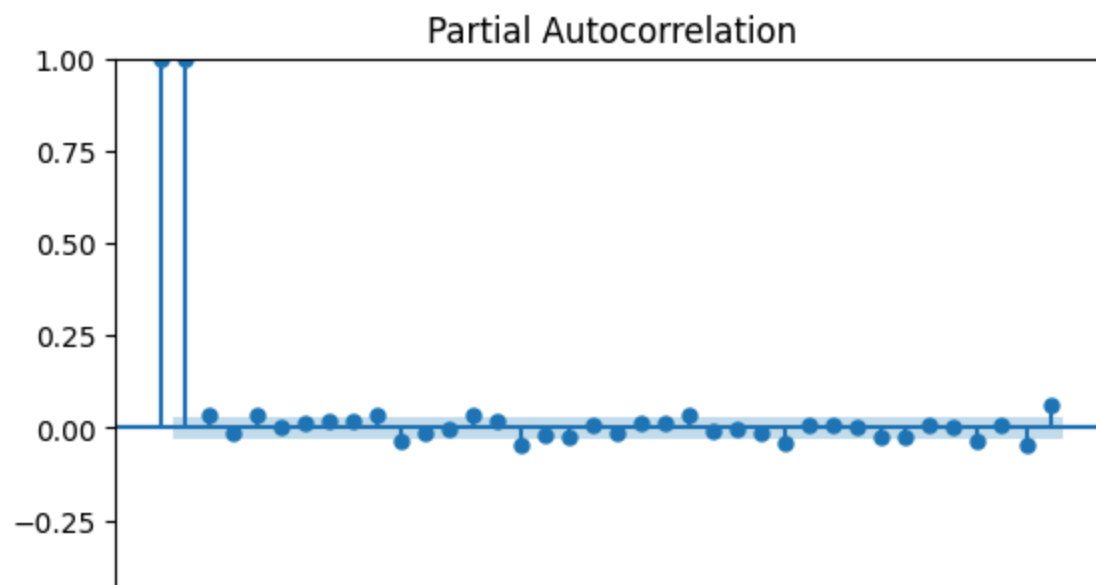
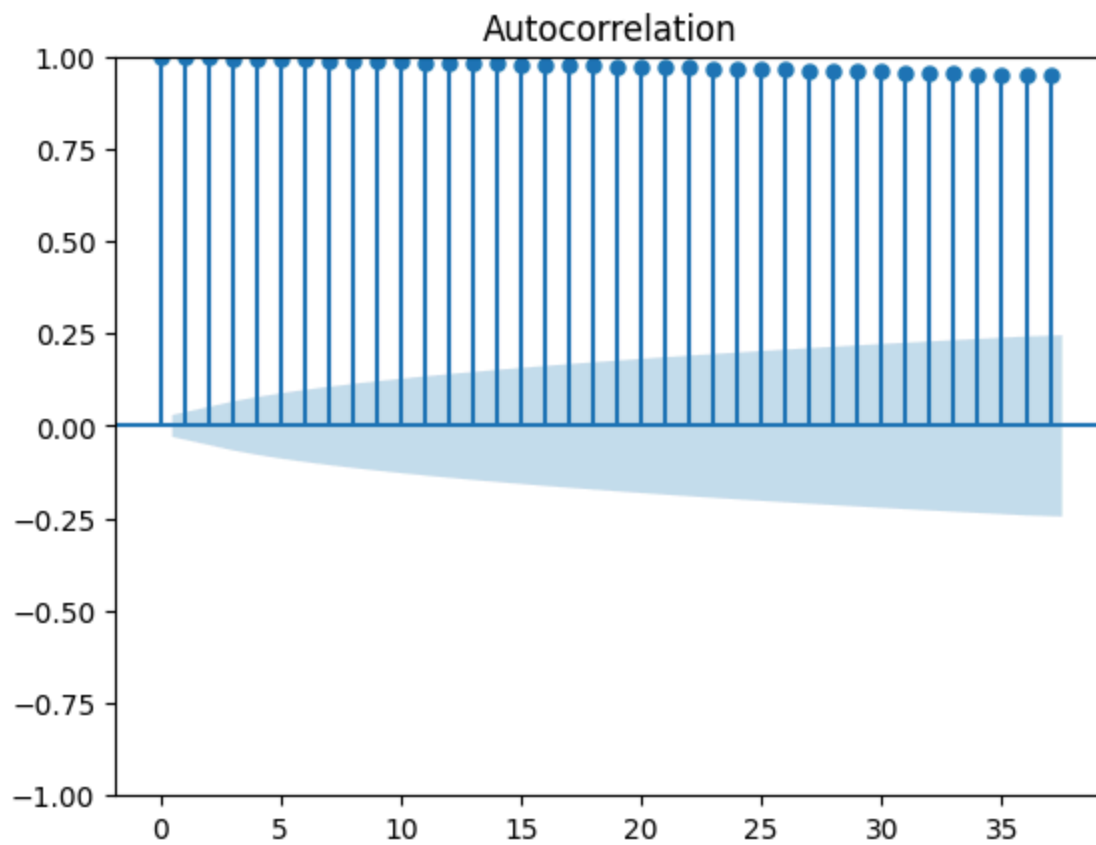
```
plt.plot(df['Close'], label='Closing Price')
plt.plot(df['MA_7'], label='7-day MA')
plt.plot(df['MA_30'], label='30-day MA')
plt.legend()
plt.title('Moving Averages')
plt.show()
```

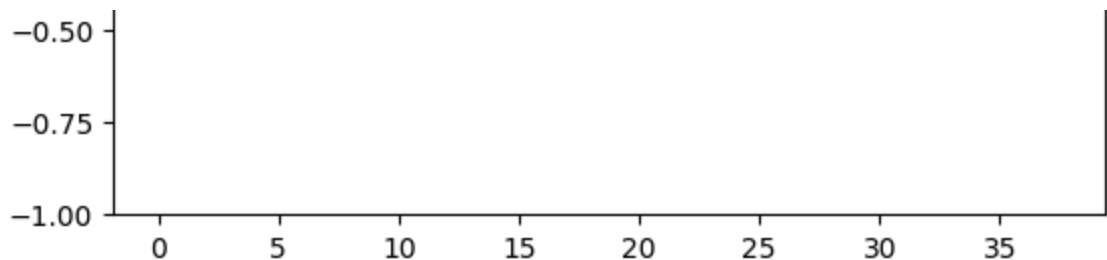


✓ Calculate ACF and PACF

```
plot_acf(df['Close'])  
plt.show()
```

```
plot_pacf(df['Close'])  
plt.show()
```





✓ Feature Engineering

```
df['PriceDifference'] = df['Close'] - df['Open']
```

✓ Handle missing values

```
df.fillna(method='ffill', inplace=True)
```

```
↳ <ipython-input-30-e9443599d05e>:1: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a futu
df.fillna(method='ffill', inplace=True)
```

✓ Scaling (Example: Using MinMaxScaler for numerical features)

```
scaler = MinMaxScaler()
numerical_features = ['Open', 'High', 'Low', 'Close', 'Volume', 'PriceDifference']
df[numerical_features] = scaler.fit_transform(df[numerical_features])
print(df.head())
```

```
↳
Date      Open      High      Low      Close  Adj Close  Volume  Year  \
```

2004-08-19	0.000136	0.000390	0.000000	0.000056	50.220219	0.541020	2004
2004-08-20	0.000306	0.001233	0.000776	0.001410	54.209209	0.273840	2004
2004-08-23	0.001945	0.001972	0.002236	0.001595	54.754753	0.217793	2004
2004-08-24	0.002027	0.001656	0.001300	0.000825	52.487488	0.180959	2004
2004-08-25	0.000971	0.001051	0.001353	0.001017	53.053055	0.106788	2004

Date	Month	Day	MA_7	MA_30	PriceDifference
2004-08-19	8	19	NaN	NaN	0.462611
2004-08-20	8	20	NaN	NaN	0.474721
2004-08-23	8	23	NaN	NaN	0.459671
2004-08-24	8	24	NaN	NaN	0.450936
2004-08-25	8	25	NaN	NaN	0.463829

✓ Creating rolling mean/std features

```
df['Close_RollingMean_7'] = df['Close'].rolling(window=7).mean()
df['Close_RollingStd_7'] = df['Close'].rolling(window=7).std()
```

✓ Adding lagged features

```
df['Close_Lag1'] = df['Close'].shift(1)
df['Close_Lag2'] = df['Close'].shift(2)
```

✓ Handle missing values created by rolling and lagged features

```
df.fillna(method='bfill', inplace=True)

print(df.head())
```



	Open	High	Low	Close	Adj Close	Volume	Year	\
Date								
2004-08-19	0.000136	0.000390	0.000000	0.000056	50.220219	0.541020	2004	
2004-08-20	0.000306	0.001233	0.000776	0.001410	54.209209	0.273840	2004	
2004-08-23	0.001945	0.001972	0.002236	0.001595	54.754753	0.217793	2004	
2004-08-24	0.002027	0.001656	0.001300	0.000825	52.487488	0.180959	2004	
2004-08-25	0.000971	0.001051	0.001353	0.001017	53.053055	0.106788	2004	

	Month	Day	MA_7	MA_30	PriceDifference	\
Date						
2004-08-19	8	19	53.123123	55.474307	0.462611	
2004-08-20	8	20	53.123123	55.474307	0.474721	
2004-08-23	8	23	53.123123	55.474307	0.459671	
2004-08-24	8	24	53.123123	55.474307	0.450936	
2004-08-25	8	25	53.123123	55.474307	0.463829	

	Close_RollingMean_7	Close_RollingStd_7	Close_Lag1	Close_Lag2
Date				
2004-08-19	0.001041	0.000508	0.000056	0.000056
2004-08-20	0.001041	0.000508	0.000056	0.000056
2004-08-23	0.001041	0.000508	0.001410	0.000056
2004-08-24	0.001041	0.000508	0.001595	0.001410
2004-08-25	0.001041	0.000508	0.000825	0.001595

```
<ipython-input-38-2e7246199c50>:1: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version.
df.fillna(method='bfill', inplace=True)
```

Model Building:

✓ Prepare data for LSTM

```
data = df[['Close']].values
train_data, test_data = train_test_split(data, test_size=0.2, shuffle=False)

def create_dataset(dataset, look_back=1):
```

```

dataX, dataY = [], []
for i in range(len(dataset)-look_back-1):
    a = dataset[i:(i+look_back), 0]
    dataX.append(a)
    dataY.append(dataset[i + look_back, 0])
return np.array(dataX), np.array(dataY)

```

```

look_back = 10 # Number of previous time steps to consider
trainX, trainY = create_dataset(train_data, look_back)
testX, testY = create_dataset(test_data, look_back)

```

✓ Reshape input to be [samples, time steps, features]

```

trainX = np.reshape(trainX, (trainX.shape[0], trainX.shape[1], 1))
testX = np.reshape(testX, (testX.shape[0], testX.shape[1], 1))


```

✓ Build LSTM model

```

model = Sequential()
model.add(LSTM(50, return_sequences=True, input_shape=(look_back, 1)))
model.add(LSTM(50))
model.add(Dense(1))
model.compile(loss='mean_squared_error', optimizer='adam')

```

 /usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_shape_tuple` argument to the constructor of RNN layers. It will be ignored in the future. Please use the `build` method instead.
 super().__init__(**kwargs)

✓ Train the model

```
model.fit(trainX, trainY, epochs=100, batch_size=1, verbose=2)
```




```

3533/3533 - 17s - 5ms/step - loss: 1.1550e-05
Epoch 76/100
3533/3533 - 18s - 5ms/step - loss: 1.1584e-05
Epoch 77/100
3533/3533 - 19s - 5ms/step - loss: 1.1078e-05
Epoch 78/100
3533/3533 - 16s - 5ms/step - loss: 1.1579e-05
Epoch 79/100
3533/3533 - 17s - 5ms/step - loss: 1.1312e-05
Epoch 80/100
3533/3533 - 20s - 6ms/step - loss: 1.1707e-05
Epoch 81/100
3533/3533 - 21s - 6ms/step - loss: 1.1621e-05
Epoch 82/100
3533/3533 - 19s - 5ms/step - loss: 1.1353e-05
Epoch 83/100
3533/3533 - 16s - 5ms/step - loss: 1.1389e-05
Epoch 84/100

```

✓ Make predictions

```

trainPredict = model.predict(trainX)
testPredict = model.predict(testX)

```

```

⇒ 111/111 ————— 1s 6ms/step
   28/28 ————— 0s 3ms/step

```

✓ Calculate root mean squared error

```

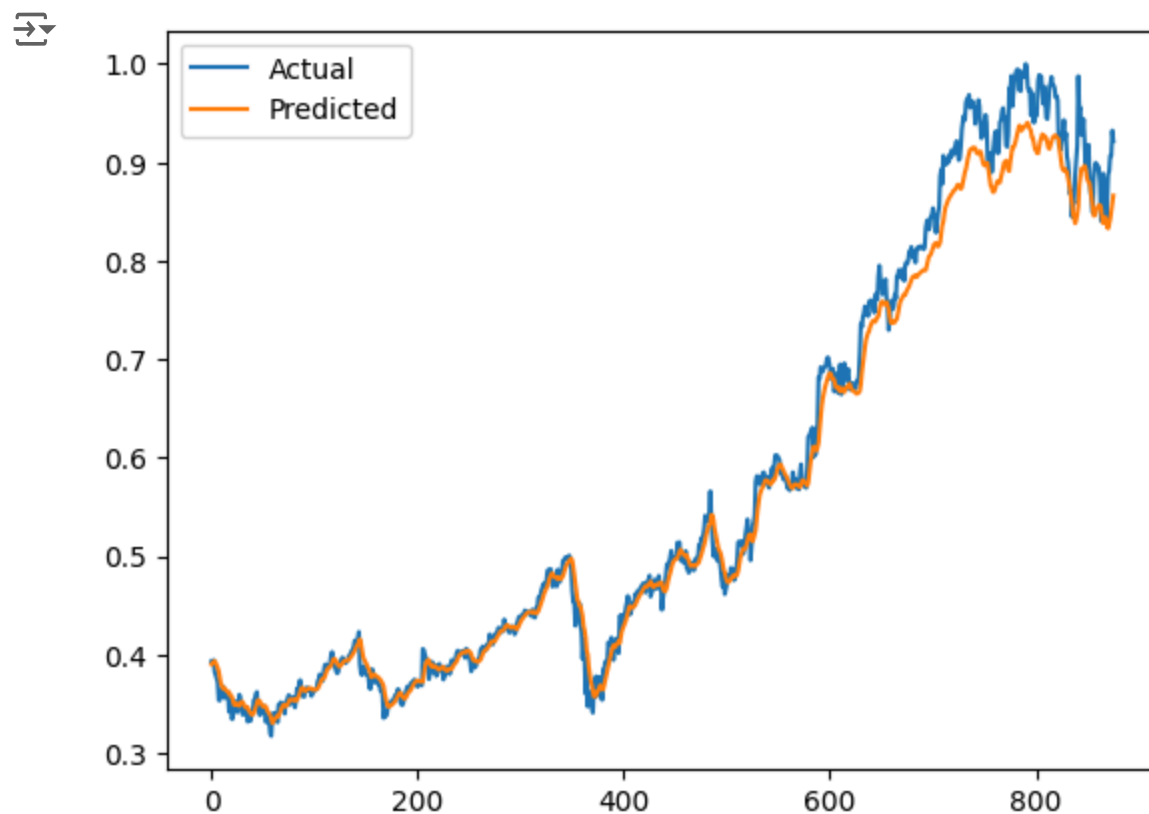
trainScore = np.sqrt(mean_squared_error(trainY, trainPredict))
print('Train Score: %.2f RMSE' % (trainScore))
testScore = np.sqrt(mean_squared_error(testY, testPredict))
print('Test Score: %.2f RMSE' % (testScore))

```

↗ Train Score: 0.00 RMSE
Test Score: 0.02 RMSE

✓ Plot predictions vs actual

```
plt.plot(testY)
plt.plot(testPredict)
plt.legend(['Actual', 'Predicted'])
plt.show()
```



Real-Time Implementation

✓ Install necessary libraries

```
!pip install flask
```

```
from flask import Flask, render_template
import pandas as pd
import numpy as np
from tensorflow.keras.models import load_model
```

```
➡ Requirement already satisfied: flask in /usr/local/lib/python3.10/dist-packages (2.2.5)
Requirement already satisfied: Werkzeug>=2.2.2 in /usr/local/lib/python3.10/dist-packages (from flask) (3.0.4)
Requirement already satisfied: Jinja2>=3.0 in /usr/local/lib/python3.10/dist-packages (from flask) (3.1.4)
Requirement already satisfied: itsdangerous>=2.0 in /usr/local/lib/python3.10/dist-packages (from flask) (2.2.0)
Requirement already satisfied: click>=8.0 in /usr/local/lib/python3.10/dist-packages (from flask) (8.1.7)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from Jinja2>=3.0->flask) (2.
```

✓ Load the trained LSTM model

```
import os
import h5py
from tensorflow.keras.models import load_model

# Get the current working directory
print(os.getcwd())

if os.path.exists('stock_prediction_model.h5'):
    model = load_model('stock_prediction_model.h5')
```

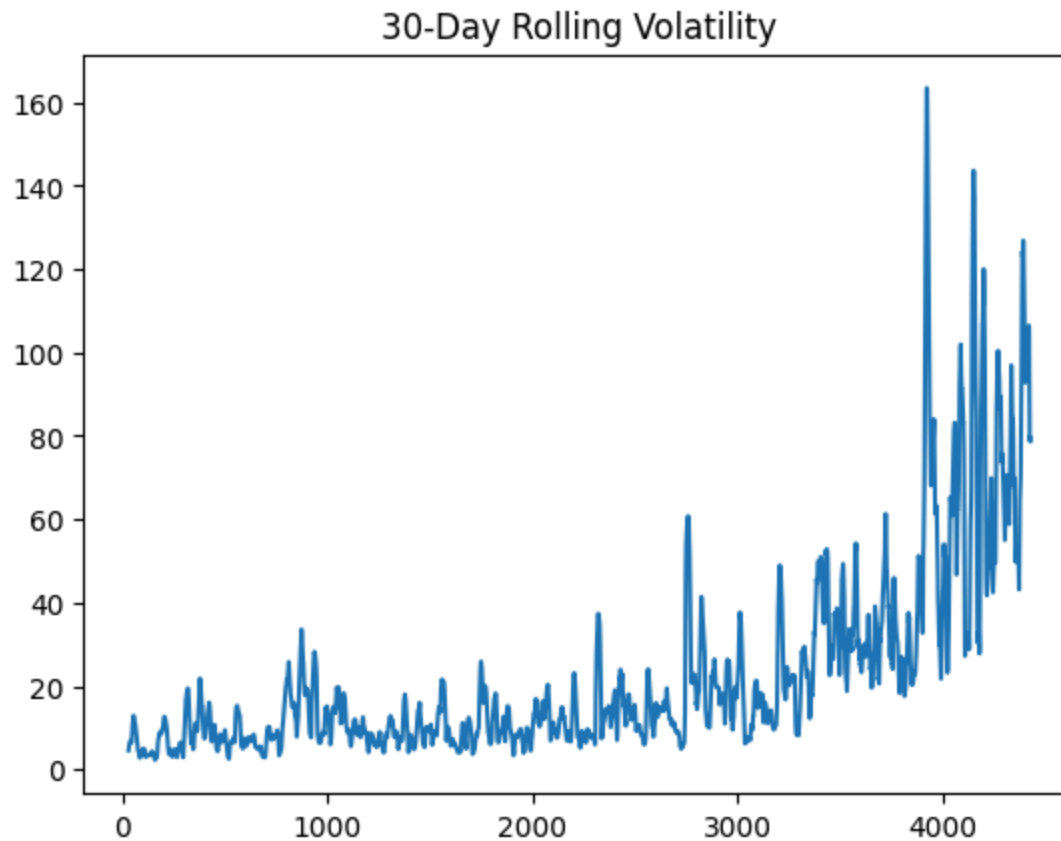
✓ Function to get the latest stock data

```
def get_latest_stock_data():  
    return {'Close': 1500}  
  
app = Flask(__name__)  
  
@app.route('/')  
def index():  
    latest_data = get_latest_stock_data()  
    # Prepare input data for the model  
    input_data = np.array([latest_data['Close']]).reshape(1, -1, 1)  
  
    # Make a prediction  
    prediction = model.predict(input_data)  
  
    return render_template('index.html', prediction=prediction)  
  
if __name__ == '__main__':  
    app.run(debug=True)
```

Volatility Analysis:

✓ Calculate rolling standard deviation to measure volatility

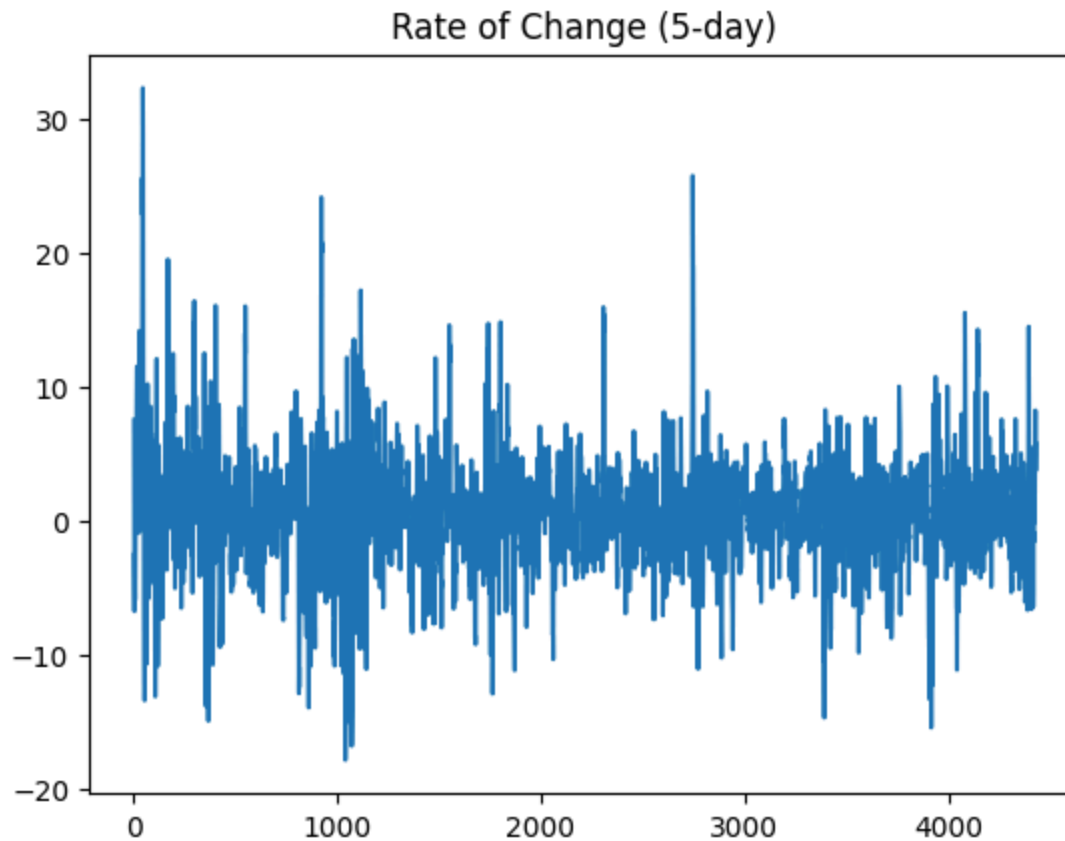
```
df['Close_RollingStd_30'] = df['Close'].rolling(window=30).std()  
plt.plot(df['Close_RollingStd_30'])  
plt.title('30-Day Rolling Volatility')  
plt.show()
```



Rate of Change (ROC)

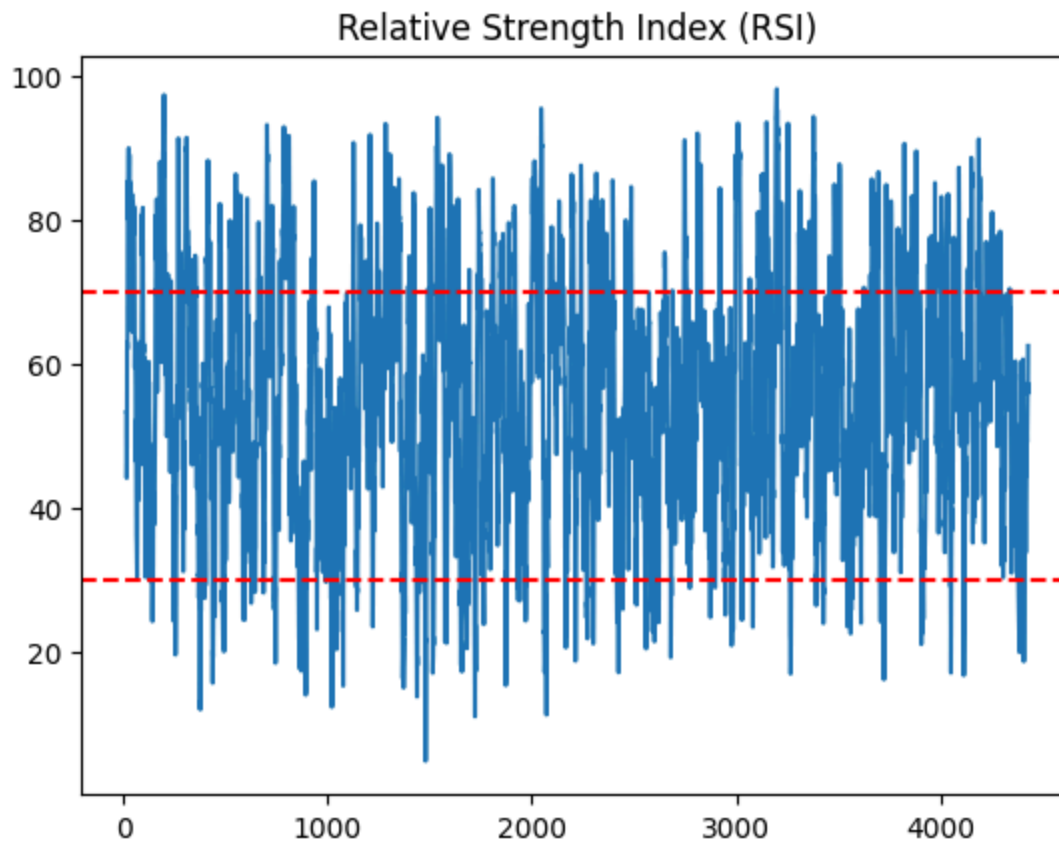
✓ Calculate the percentage change in closing price over a specific period

```
df['ROC_5'] = (df['Close'] - df['Close'].shift(5)) / df['Close'].shift(5) * 100  
plt.plot(df['ROC_5'])  
plt.title('Rate of Change (5-day)')  
plt.show()
```



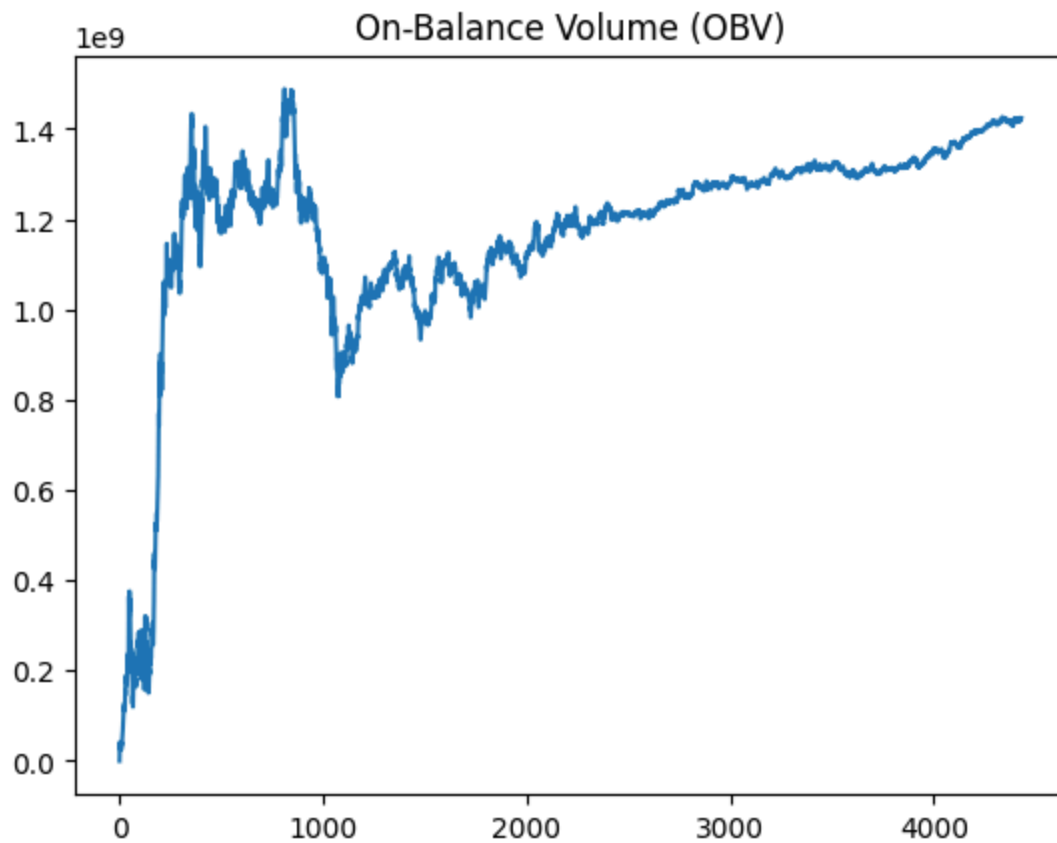
✓ Relative Strength Index (RSI)

```
delta = df['Close'].diff()
gain = (delta.where(delta > 0, 0)).fillna(0)
loss = (-delta.where(delta < 0, 0)).fillna(0)
avg_gain = gain.rolling(window=14).mean()
avg_loss = loss.rolling(window=14).mean()
rs = avg_gain / avg_loss
df['RSI'] = 100 - (100 / (1 + rs))
plt.plot(df['RSI'])
plt.title('Relative Strength Index (RSI)')
plt.axhline(y=70, color='r', linestyle='--')
plt.axhline(y=30, color='r', linestyle='--')
plt.show()
```



✓ On-Balance Volume (OBV)

```
df['OBV'] = np.where(df['Close'] > df['Close'].shift(1), df['Volume'],  
                    np.where(df['Close'] < df['Close'].shift(1), -df['Volume'], 0)).cumsum()  
plt.plot(df['OBV'])  
plt.title('On-Balance Volume (OBV)')  
plt.show()
```




```
df['MA_20'] = df['Close'].rolling(window=20).mean()
```