Stock Market Prediction using Long Short Term Memory (LSTM)

Import all the required libraries

In [1]:
```
import warnings
warnings.simplefilter("ignore")
```

In [2]:
```
import pandas as pd
import datetime as dt
from datetime import date
import matplotlib.pyplot as plt
import yfinance as yf
import numpy as np
import tensorflow as tf
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_absolute_percentage_error
```

```
2023-12-28 23:40:00.790997: I external/local_tsl/tsl/cuda/cudart_stub.cc:31] Could not find cuda drivers on your mac
hine, GPU will not be used.
2023-12-28 23:40:01.195570: E external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already been registered
2023-12-28 23:40:01.195664: E external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to register cuFFT
factory: Attempting to register factory for plugin cuFFT when one has already been registered
2023-12-28 23:40:01.274693: E external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable to register cuBL
AS factory: Attempting to register factory for plugin cuBLAS when one has already been registered
2023-12-28 23:40:01.434397: I external/local_tsl/tsl/cuda/cudart_stub.cc:31] Could not find cuda drivers on your mac
hine, GPU will not be used.
2023-12-28 23:40:03.189963: W tensorflow/compiler/tf2tensorrt/utils/py_utils.cc:38] TF-TRT Warning: Could not find T
ensorRT
```

Define start day to fetch the dataset from the yahoo finance library

In [3]:
```
# I'm using fetching TCS (Tata Consultancy Services Limited) online Data from Yahoo Finance
```

In [4]:
```
START = "2002-01-01"
TODAY = date.today().strftime("%Y-%m-%d")

# Define a function to load the dataset

def load_data(ticker):
    data = yf.download(ticker, START, TODAY)
    data.reset_index(inplace=True)
    return data
```

In [5]:
```
data = load_data('TCS.NS')
df = data
df1 = data
df.head()
```

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

Out[5]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2002-08-12	38.724998	40.000000	38.724998	39.700001	28.128601	212976
1	2002-08-13	39.750000	40.387501	38.875000	39.162498	27.747757	153576
2	2002-08-14	39.250000	39.250000	35.724998	36.462502	25.834730	822776
3	2002-08-15	36.462502	36.462502	36.462502	36.462502	25.834730	0
4	2002-08-16	36.275002	38.000000	35.750000	36.375000	25.772724	811856

In [6]:
```
rows, columns = df.shape
print("Total Rows in Dataset :",rows)
print("Total Columns in Dataset :",columns)
```

```
Total Rows in Dataset : 5309
Total Columns in Dataset : 7
```

In [7]:
```
df = df.drop(['Date', 'Adj Close'], axis = 1)
```

Out[7]:

	Open	High	Low	Close	Volume
0	38.724998	40.000000	38.724998	39.700001	212976
1	39.750000	40.387501	38.875000	39.162498	153576
2	39.250000	39.250000	35.724998	36.462502	822776
3	36.462502	36.462502	36.462502	36.462502	0
4	36.275002	38.000000	35.750000	36.375000	811856

In [8]:
```
df.tail()
```

Out[8]:

	Open	High	Low	Close	Volume
5304	3827.250000	3898.800049	3766.550049	3780.050049	2586083
5305	3756.250000	3806.699951	3743.350098	3787.500000	1517562
5306	3800.000000	3845.949951	3762.000000	3824.000000	2413058
5307	3819.850098	3834.000000	3790.149902	3795.550049	1285231
5308	3799.000000	3818.199951	3768.000000	3811.199951	1293976

In [9]:
```
df.sample(5)
```

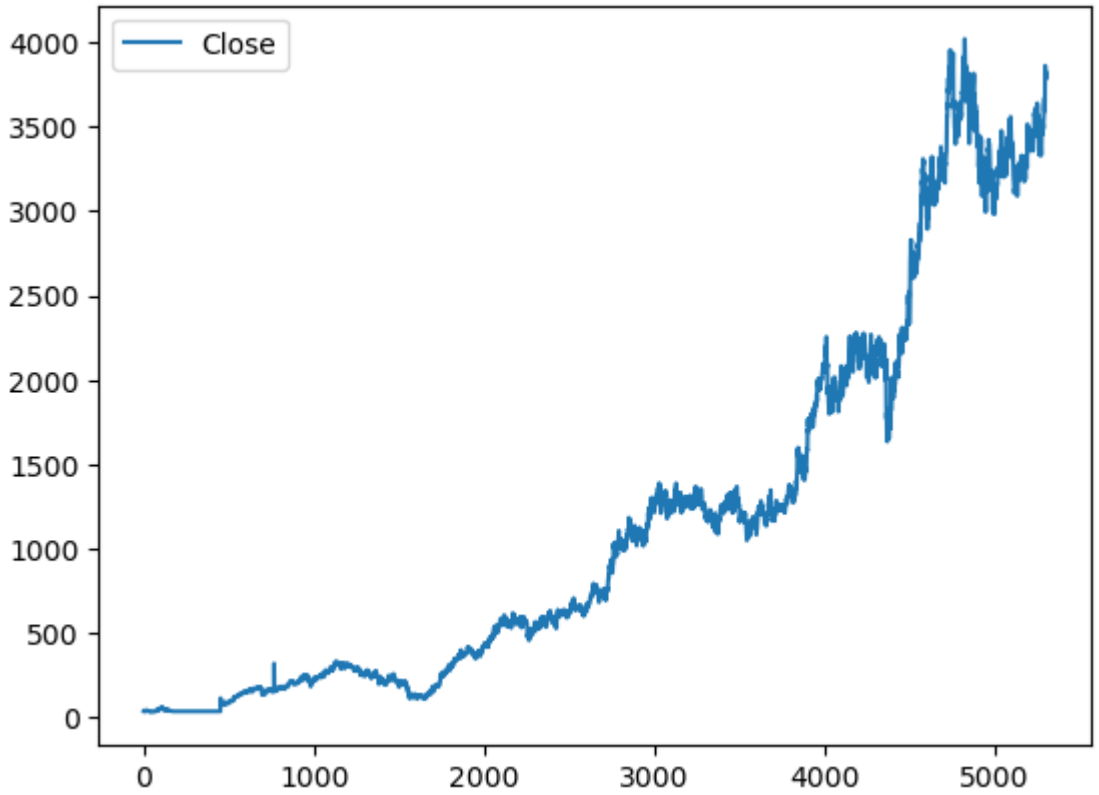
Out[9]:

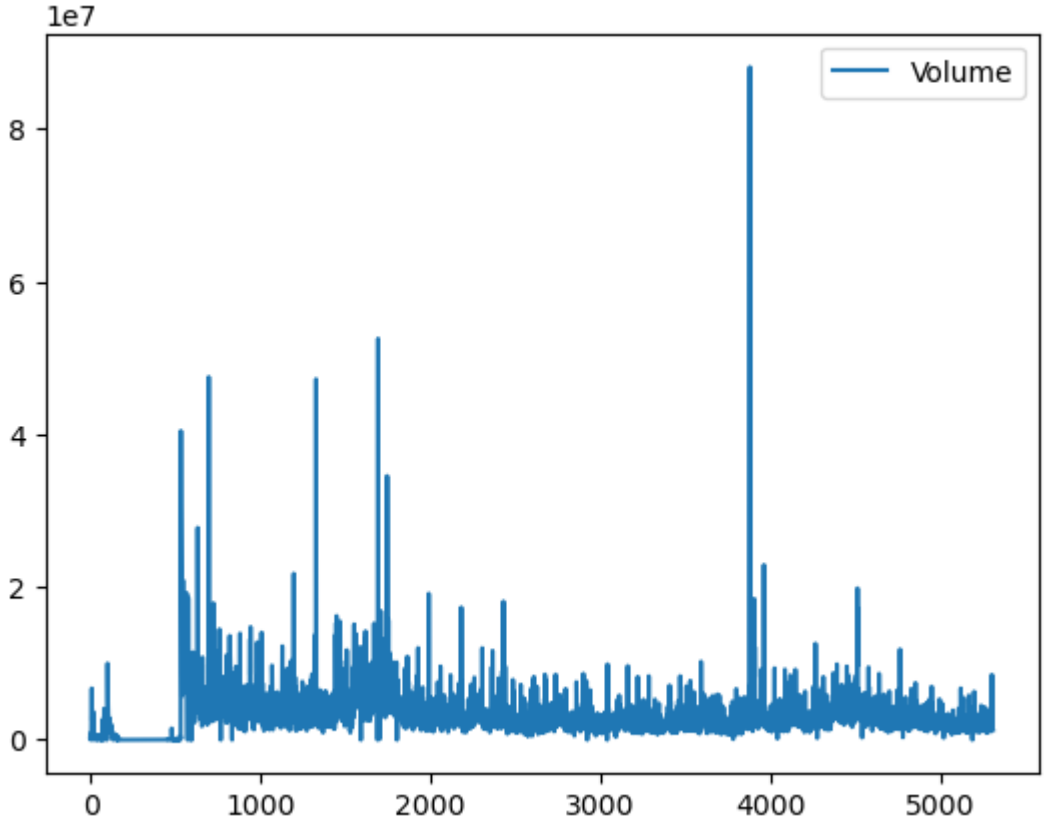
	Open	High	Low	Close	Volume
4300	2053.000000	2082.000000	2045.500000	2078.500000	3334301
3661	1147.000000	1149.375000	1134.000000	1136.574951	2540510
1912	415.000000	418.000000	411.149994	412.524994	1997806
1415	215.649994	216.524994	210.562500	211.537506	1996828
1371	252.762497	255.725006	250.574997	251.300003	2318868

Visualizing Closing Price

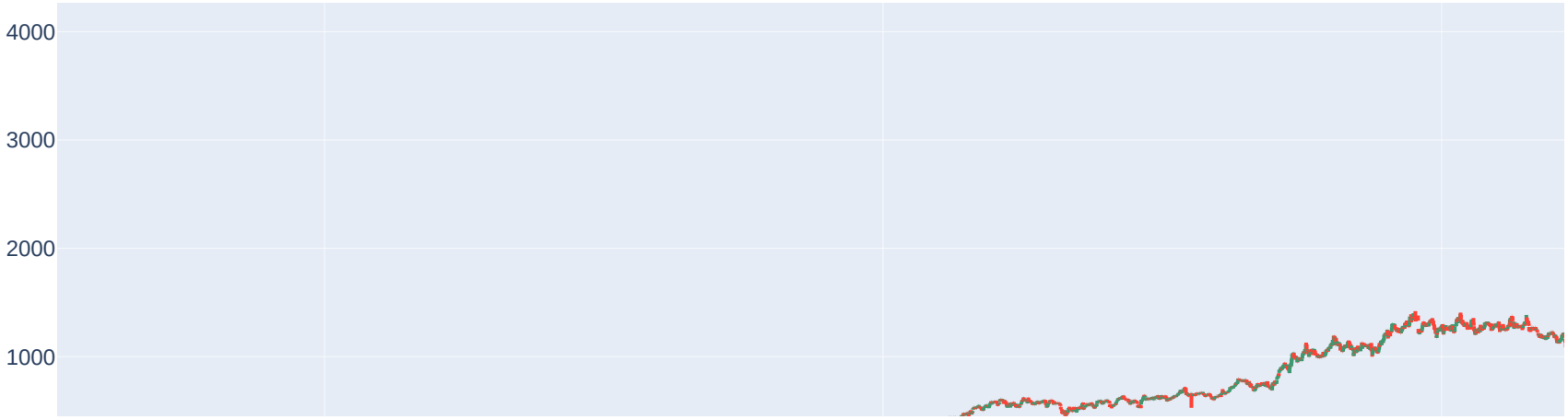
In [10]:
```
df[["Close"]].plot()
#Volume Plot
df[["Volume"]].plot()
```

Out[10]: <Axes: >



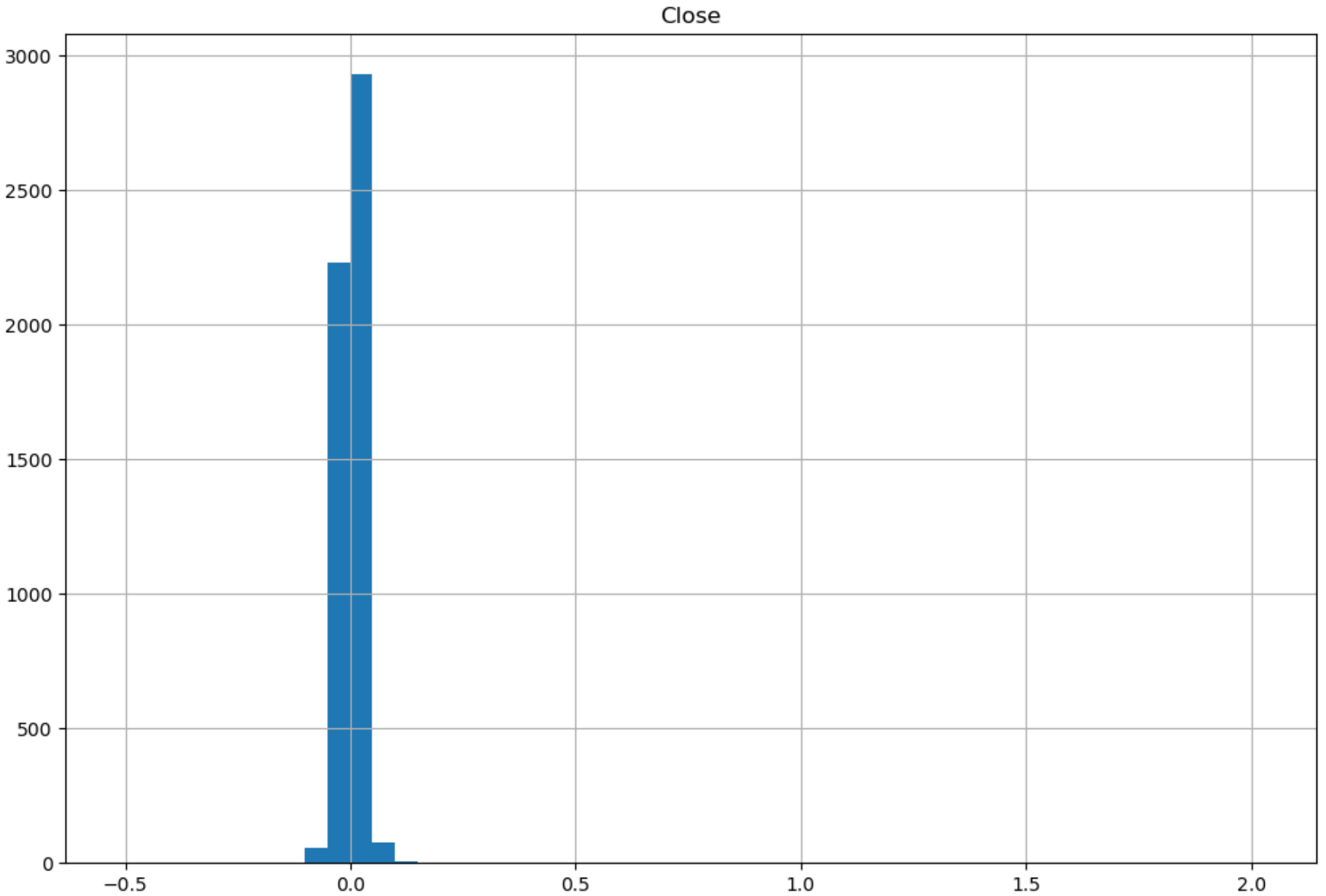


In [11]:
```
import plotly.graph_objects as go

fig = go.Figure(data=go.Ohlc(x = df1['Date'],
        open = df1['Open'],
        high = df1['High'],
        low = df1['Low'],
        close = df1['Close']))
fig.show()
```

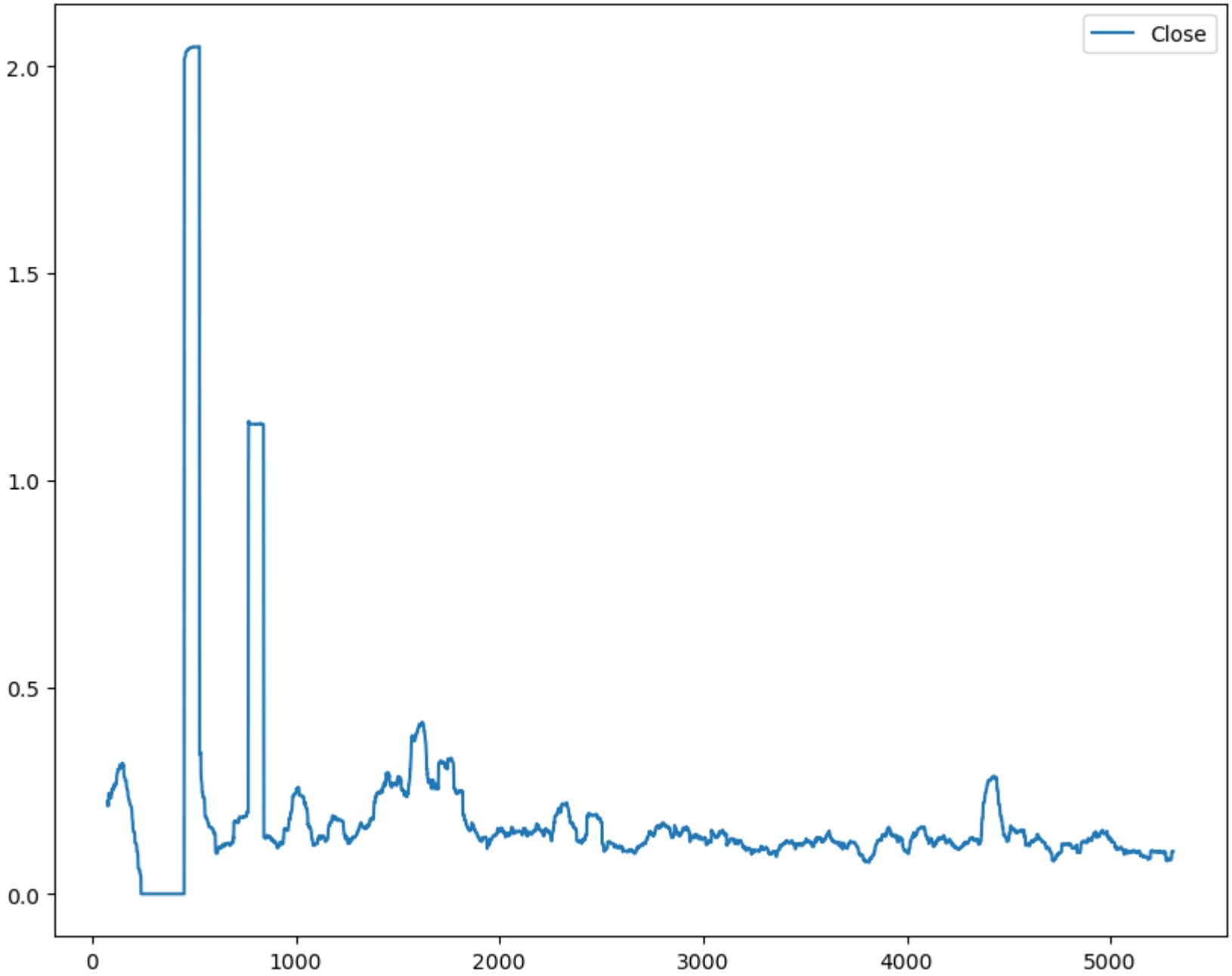


In [12]:
```
daily_close_px = df1[['Close']]
# Calculate the daily percentage change for `daily_close_px`
daily_pct_change = daily_close_px.pct_change()

# Plot the distributions
daily_pct_change.hist(bins=50, sharex=True, figsize=(12,8))
```

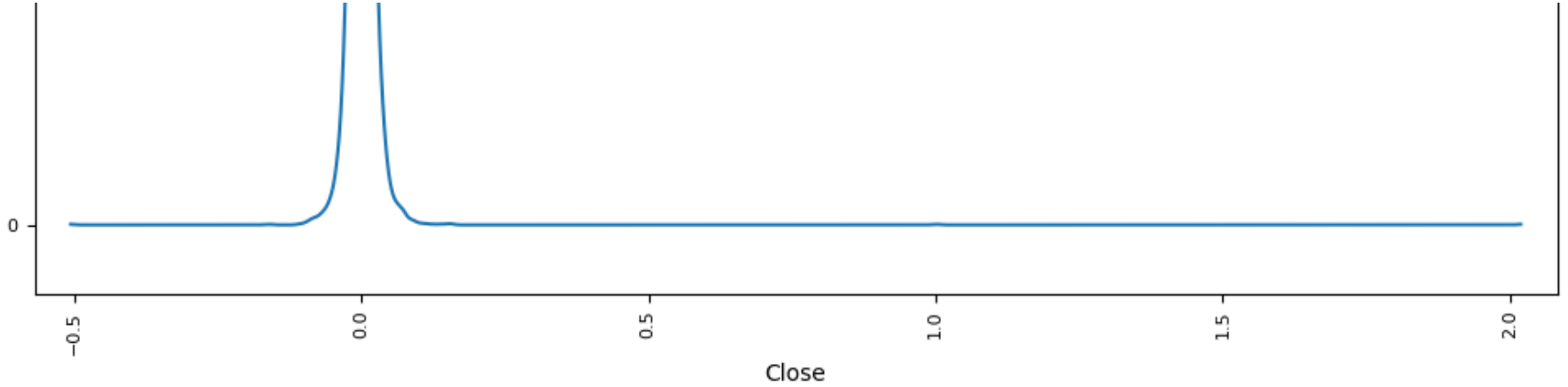
```
# Show the resulting plot
plt.show()
```



In [13]:
```
# Define the minumum of periods to consider
min_periods = 75

# Calculate the volatility
vol = daily_pct_change.rolling(min_periods).std() * np.sqrt(min_periods)

# Plot the volatility
vol.plot(figsize=(10, 8))

# Show the plot
plt.show()
```



In [14]:
```
# Plot a scatter matrix with the `daily_pct_change` data
pd.plotting.scatter_matrix(daily_pct_change, diagonal='kde', alpha=0.1,figsize=(12,12))

# Show the plot
plt.show()
```

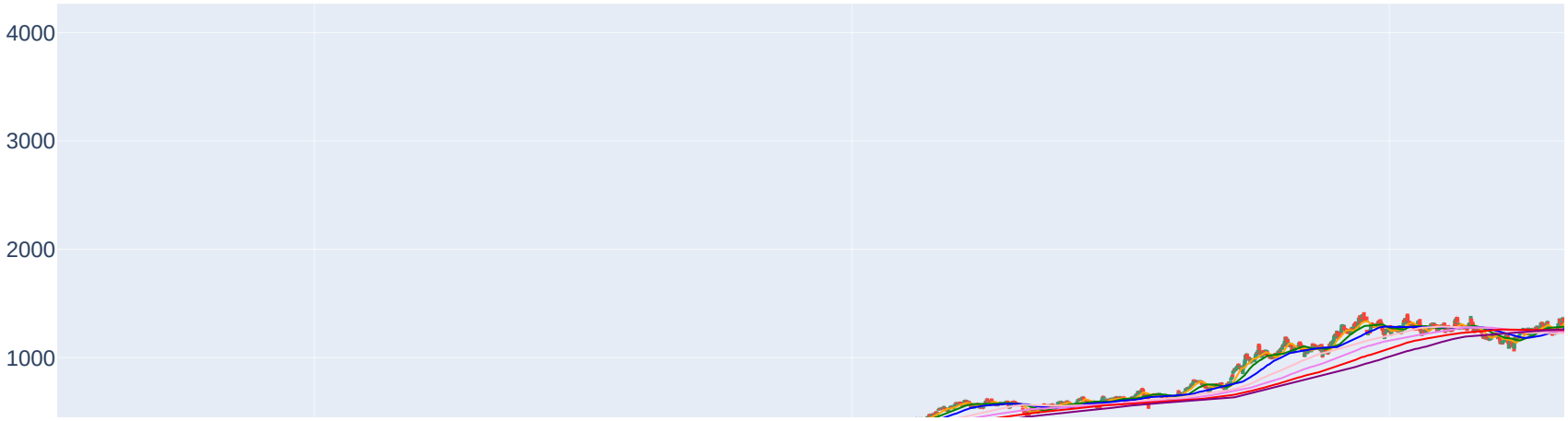


SMA chart plotting for 20, 50, 100, 200, 300, 400, 500 day moving averages

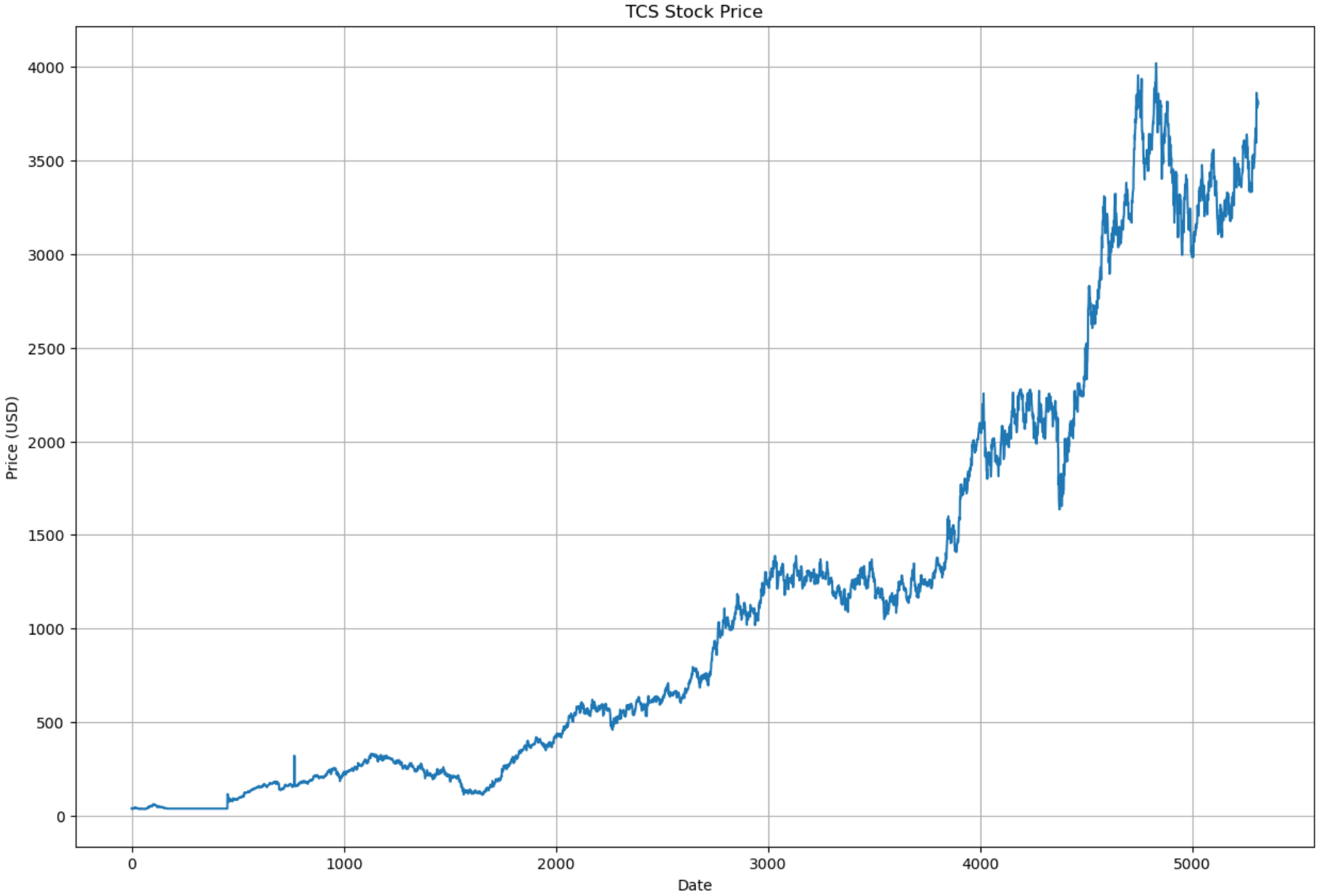
In [15]:
```
df1['SMA20'] = df1.Close.rolling(20).mean()
df1['SMA50'] = df1.Close.rolling(50).mean()
df1['SMA100'] = df1.Close.rolling(100).mean()
df1['SMA200'] = df1.Close.rolling(200).mean()
df1['SMA300'] = df1.Close.rolling(300).mean()
df1['SMA400'] = df1.Close.rolling(400).mean()
df1['SMA500'] = df1.Close.rolling(500).mean()

fig = go.Figure(data=[go.Ohlc(x = df1['Date'],
                              open = df1['Open'],
                              high = df1['High'],
                              low = df1['Low'],
                              close = df1['Close'], name = "OHLC"),
                      go.Scatter(x = df1.Date, y = df1.SMA20, line=dict(color='orange', width=1), name="SMA20"),
                      go.Scatter(x = df1.Date, y = df1.SMA50, line=dict(color='green', width=1), name="SMA50"),
                      go.Scatter(x = df1.Date, y = df1.SMA100, line=dict(color='blue', width=1), name="SMA100"),
                      go.Scatter(x = df1.Date, y = df1.SMA200, line=dict(color='red', width=1), name="SMA200"),
                      go.Scatter(x = df1.Date, y = df1.SMA300, line=dict(color='pink', width=1), name="SMA300"),
                      go.Scatter(x = df1.Date, y = df1.SMA400, line=dict(color='violet', width=1), name="SMA400"),
                      go.Scatter(x = df1.Date, y = df1.SMA500, line=dict(color='purple', width=1), name="SMA500")])
fig.show()
```

In [16]:
```
df1['EMA20'] = df1.Close.ewm(span=20, adjust=False).mean()
df1['EMA50'] = df1.Close.ewm(span=50, adjust=False).mean()
df1['EMA100'] = df1.Close.ewm(span=100, adjust=False).mean()
df1['EMA200'] = df1.Close.ewm(span=200, adjust=False).mean()
df1['EMA300'] = df1.Close.ewm(span=300, adjust=False).mean()
df1['EMA400'] = df1.Close.ewm(span=400, adjust=False).mean()
df1['EMA500'] = df1.Close.ewm(span=500, adjust=False).mean()
```

```
fig = go.Figure(data = [go.Ohlc(x = df1['Date'],
                                open = df1['Open'],
                                high = df1['High'],
                                low = df1['Low'],
                                close = df1['Close'], name = "OHLC"),
                        go.Scatter(x = df1.Date, y = df1.SMA20, line=dict(color='orange', width=1), name="EMA20"),
                        go.Scatter(x = df1.Date, y = df1.SMA50, line=dict(color='green', width=1), name="EMA50"),
                        go.Scatter(x = df1.Date, y = df1.SMA100, line=dict(color='blue', width=1), name="EMA100"),
                        go.Scatter(x = df1.Date, y = df1.SMA200, line=dict(color='pink', width=1), name="EMA200"),
                        go.Scatter(x = df1.Date, y = df1.SMA300, line=dict(color='violet', width=1), name="EMA300"),
                        go.Scatter(x = df1.Date, y = df1.SMA400, line=dict(color='red', width=1), name="EMA400"),
                        go.Scatter(x = df1.Date, y = df1.SMA500, line=dict(color='purple', width=1), name="EMA500")])
fig.show()
```



In [17]:
```
plt.figure(figsize=(15, 10))
plt.plot(df['Close'])
plt.title("TCS Stock Price")
plt.xlabel("Date")
plt.ylabel("Price (USD)")
plt.grid(True)
plt.show()
```



In [18]:
```
df
```

Out[18]:

	Open	High	Low	Close	Volume
0	38.724998	40.000000	38.724998	39.700001	212976
1	39.750000	40.387501	38.875000	39.162498	153576
2	39.250000	39.250000	35.724998	36.462502	822776
3	36.462502	36.462502	36.462502	36.462502	0
4	36.275002	38.000000	35.750000	36.375000	811856
...	...	...	...	...	...
5304	3827.250000	3898.800049	3766.550049	3780.050049	2586083
5305	3756.250000	3806.699951	3743.350098	3787.500000	1517562
5306	3800.000000	3845.949951	3762.000000	3824.000000	2413058
5307	3819.850098	3834.000000	3790.149902	3795.550049	1285231
5308	3799.000000	3818.199951	3768.000000	3811.199951	1293976

5309 rows × 5 columns

Plotting moving averages of 100 day

In [19]:
```
moving_average_100 = df.Close.rolling(200).mean()
```

In [20]:
```
moving_average_100
```

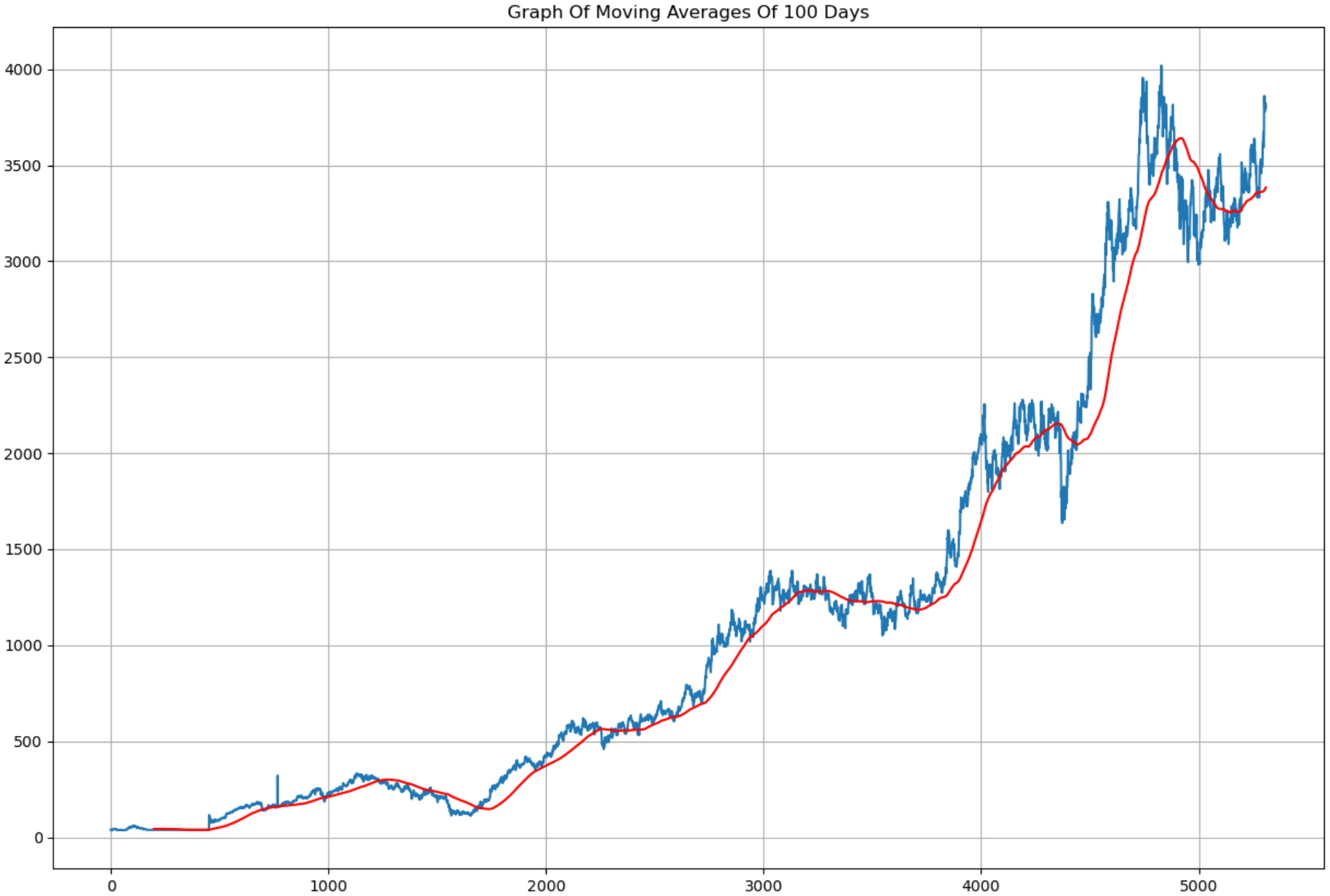
Out[20]:
```
0              NaN
1              NaN
2              NaN
3              NaN
4              NaN
           ...
5304    3374.338247
5305    3376.616497
5306    3379.172246
5307    3381.221497
5308    3383.670247
Name: Close, Length: 5309, dtype: float64
```

In [21]:
```
moving_average_100.describe()
```

Out[21]:
```
count    5110.000000
mean     1133.830330
std      1063.894758
min        38.387501
25%       241.267747
50%       726.603124
75%      1758.078746
max      3640.561985
Name: Close, dtype: float64
```

In [22]:
```
plt.figure(figsize = (15,10))
plt.plot(df.Close)
plt.plot(moving_average_100, 'r')
plt.grid(True)
plt.title('Graph Of Moving Averages Of 100 Days')
```

Out[22]:
```
Text(0.5, 1.0, 'Graph Of Moving Averages Of 100 Days')
```



Defining 200 days moving averages and plotting comparision graph with 100 days moving averages

---

In [23]:
```
moving_average_200 = df.Close.rolling(200).mean()
```

In [24]:
```
moving_average_200
```

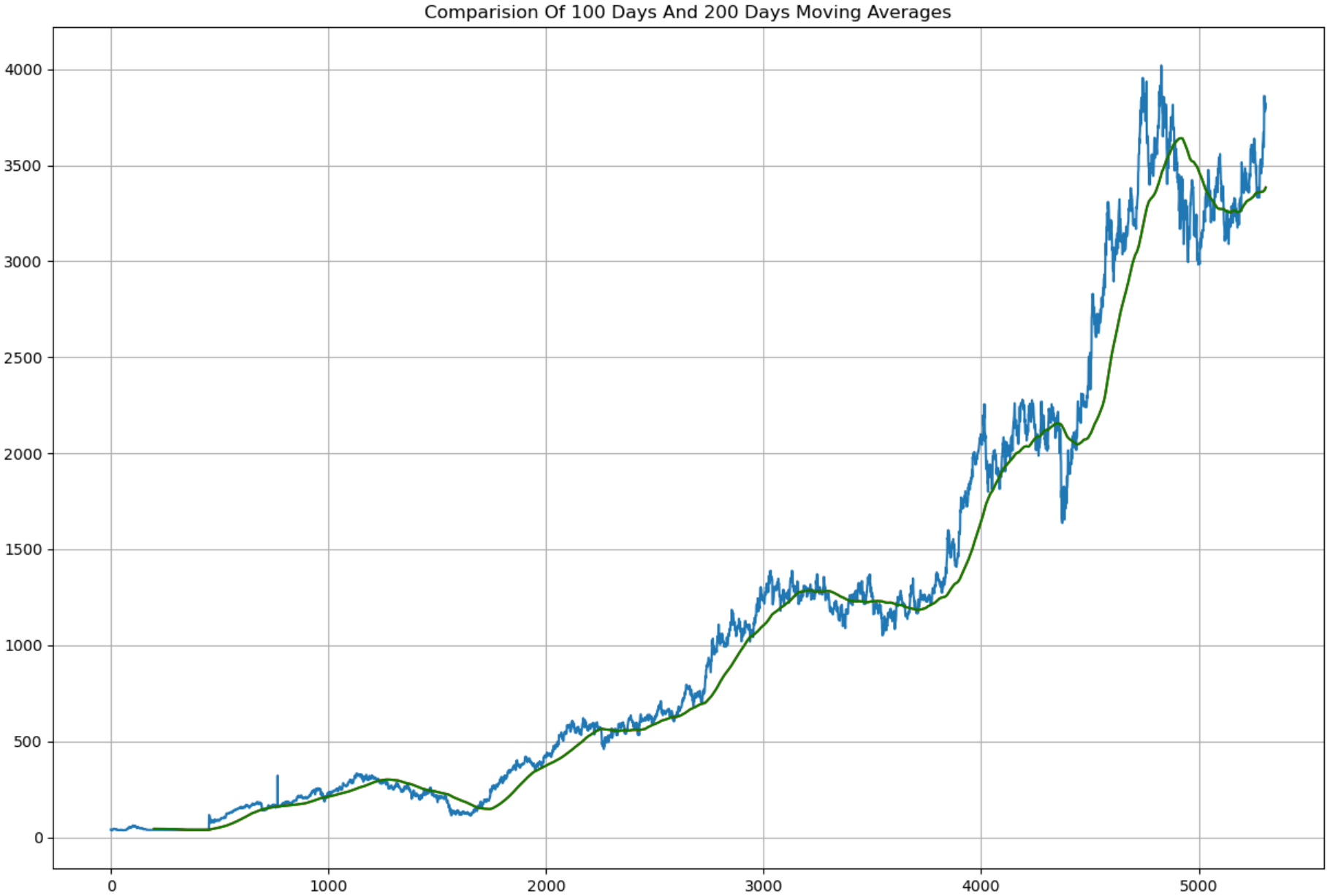
Out[24]:
```
0              NaN
1              NaN
2              NaN
3              NaN
4              NaN
           ...
5304    3374.338247
5305    3376.616497
5306    3379.172246
5307    3381.221497
5308    3383.670247
Name: Close, Length: 5309, dtype: float64
```

In [25]:
```
moving_average_200.describe
```

Out[25]:
```
<bound method NDFrame.describe of 0              NaN
1              NaN
2              NaN
3              NaN
4              NaN
           ...
5304    3374.338247
5305    3376.616497
5306    3379.172246
5307    3381.221497
5308    3383.670247
Name: Close, Length: 5309, dtype: float64>
```

In [26]:
```
plt.figure(figsize = (15,10))
plt.plot(df.Close)
plt.plot(moving_average_100, 'r')
plt.plot(moving_average_200, 'g')
plt.grid(True)
plt.title('Comparision Of 100 Days And 200 Days Moving Averages')
```

Out[26]:
```
Text(0.5, 1.0, 'Comparision Of 100 Days And 200 Days Moving Averages')
```



In [27]:
```
df.shape # i have dropped two Columns from loaded Dataset like Date and Adj Close
```

Out[27]: (5309, 5)

Spliting the dataset into training (67%) and testing (33%) set

In [28]:
```
# Splitting data into training and testing

train = pd.DataFrame(data[0:int(len(data)*0.67)])
test = pd.DataFrame(data[int(len(data)*0.67): int(len(data))])

print(train.shape)
print(test.shape)
```

```
(3557, 21)
(1752, 21)
```

In [29]:
```
train.head()
```

Out[29]:

	Date	Open	High	Low	Close	Adj Close	Volume	SMA20	SMA50	SMA100	...	SMA300	SMA400	SMA500	
0	2002-08-12	38.724998	40.000000	38.724998	39.700001	28.128601	212976	NaN	NaN	NaN	...	NaN	NaN	NaN	3
1	2002-08-13	39.750000	40.387501	38.875000	39.162498	27.747757	153576	NaN	NaN	NaN	...	NaN	NaN	NaN	3
2	2002-08-14	39.250000	39.250000	35.724998	36.462502	25.834730	822776	NaN	NaN	NaN	...	NaN	NaN	NaN	3
3	2002-08-15	36.462502	36.462502	36.462502	36.462502	25.834730	0	NaN	NaN	NaN	...	NaN	NaN	NaN	3
4	2002-08-16	36.275002	38.000000	35.750000	36.375000	25.772724	811856	NaN	NaN	NaN	...	NaN	NaN	NaN	3

5 rows × 21 columns

In [30]:
```
train.tail()
```

Out[30]:

	Date	Open	High	Low	Close	Adj Close	Volume	SMA20	SMA50	SMA100	...	
3552	2016-11-21	1063.099976	1070.000000	1052.500000	1066.449951	924.593872	1793366	1136.617499	1171.703501	1225.988752	...	12
3553	2016-11-22	1066.000000	1088.724976	1061.025024	1067.500000	925.504456	1318860	1129.276251	1168.213000	1223.437002	...	12
3554	2016-11-23	1074.500000	1081.474976	1063.599976	1078.175049	934.759460	1275808	1122.492505	1165.371001	1221.349003	...	12
3555	2016-11-24	1077.449951	1103.800049	1068.500000	1094.224976	948.674561	3026234	1117.242505	1164.034500	1219.812002	...	12
3556	2016-11-25	1106.000000	1153.625000	1096.099976	1150.175049	997.182129	4276148	1114.845007	1163.513501	1218.994003	...	12

5 rows × 21 columns

In [31]:
```
train.sample(5)
```

Out[31]:

	Date	Open	High	Low	Close	Adj Close	Volume	SMA20	SMA50	SMA100	...
2058	2010-10-21	487.024994	496.924988	485.000000	493.100006	382.249969	3752354	476.611249	453.750999	426.199500	...
2120	2011-01-20	590.000000	609.375000	590.000000	606.099976	470.741516	4545208	576.311246	554.383000	515.760499	...
153	2003-03-13	42.212502	42.724998	41.000000	41.924999	29.705076	390112	45.473750	49.991000	47.649375	...
1170	2007-03-16	310.350006	314.462494	303.787506	309.412506	224.759613	4224284	310.409381	317.559504	300.423127	...
3227	2015-07-22	1280.500000	1284.500000	1260.525024	1264.025024	1069.319336	1320628	1280.772498	1282.233499	1283.352251	...	1

5 rows × 21 columns

In [32]:
```
test.head()
```

Out[32]:

	Date	Open	High	Low	Close	Adj Close	Volume	SMA20	SMA50	SMA100	...	SMA
3557	2016-11-28	1147.0	1159.724976	1125.949951	1141.300049	989.487671	1924296	1111.457507	1162.749001	1217.892504	...	1224.146
3558	2016-11-29	1137.5	1146.000000	1126.275024	1129.925049	979.625610	1442296	1107.986261	1162.063003	1216.426254	...	1223.570
3559	2016-11-30	1132.5	1147.375000	1121.150024	1138.025024	986.648376	3445832	1106.137512	1161.554004	1215.302253	...	1223.118
3560	2016-12-01	1138.5	1145.000000	1127.025024	1131.724976	981.185974	1123052	1105.122510	1160.571504	1214.148503	...	1222.657
3561	2016-12-02	1129.0	1135.400024	1102.599976	1110.925049	963.153076	1998032	1102.682513	1158.675505	1212.831254	...	1222.126

5 rows × 21 columns

In [33]:
```
test.tail()
```

Out[33]:

	Date	Open	High	Low	Close	Adj Close	Volume	SMA20	SMA50	SMA100	...	
5304	2023-12-20	3827.250000	3898.800049	3766.550049	3780.050049	3780.050049	2586083	3613.032495	3511.515000	3491.664500	...	3
5305	2023-12-21	3756.250000	3806.699951	3743.350098	3787.500000	3787.500000	1517562	3625.900000	3514.497998	3495.656499	...	3
5306	2023-12-22	3800.000000	3845.949951	3762.000000	3824.000000	3824.000000	2413058	3641.687500	3518.400000	3499.927500	...	3
5307	2023-12-26	3819.850098	3834.000000	3790.149902	3795.550049	3795.550049	1285231	3658.609998	3522.113003	3504.329001	...	3
5308	2023-12-27	3799.000000	3818.199951	3768.000000	3811.199951	3811.199951	1293976	3675.662500	3527.486001	3508.226501	...	3

5 rows × 21 columns

In [34]:
```
test.sample(5)
```

Out[34]:

	Date	Open	High	Low	Close	Adj Close	Volume	SMA20	SMA50	SMA100	...	
4476	2020-08-19	2276.350098	2284.600098	2252.500000	2256.600098	2122.070068	2843005	2257.264990	2183.912983	2039.275493	...	2
5113	2023-03-10	3312.899902	3337.250000	3290.000000	3331.000000	3289.323242	1024404	3418.905005	3392.502007	3337.480002	...	3
5188	2023-07-03	3314.300049	3318.800049	3268.750000	3272.300049	3255.389404	1687264	3234.237488	3245.025996	3274.064500	...	3
5198	2023-07-17	3510.000000	3549.899902	3477.050049	3491.699951	3473.655762	2743228	3287.107483	3274.313994	3257.640493	...	3
5302	2023-12-18	3858.100098	3929.000000	3830.149902	3859.199951	3859.199951	2521612	3584.709998	3503.805000	3483.640999	...	3

5 rows × 21 columns

Using MinMax scaler for normalization of the dataset

In [35]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler(feature_range=(0,1))
```

In [36]:
```
train_close = train.iloc[:, 4:5].values
test_close = test.iloc[:, 4:5].values
```

In [37]:
```
data_training_array = scaler.fit_transform(train_close)
data_training_array
```

Out[37]:
```
array([[3.12378868e-03],
       [2.72638213e-03],
       [7.30118150e-04],
       ...,
       [7.70928485e-01],
       [7.82795125e-01],
```

In [38]:
```
x_train = []
y_train = []

for i in range(100, data_training_array.shape[0]):
    x_train.append(data_training_array[i-100: i])
    y_train.append(data_training_array[i, 0])

x_train, y_train = np.array(x_train), np.array(y_train)
```

In [39]:
```
x_train.shape
```

Out[39]:
```
(3457, 100, 1)
```

ML Model (LSTM)

In [40]:
```
from tensorflow.keras.layers import Dense, Dropout, LSTM
from tensorflow.keras.models import Sequential
```

In [41]:
```
model = Sequential()
model.add(LSTM(units = 50, activation = 'relu', return_sequences=True
              ,input_shape = (x_train.shape[1], 1)))
model.add(Dropout(0.2))


model.add(LSTM(units = 60, activation = 'relu', return_sequences=True))
model.add(Dropout(0.3))


model.add(LSTM(units = 80, activation = 'relu', return_sequences=True))
model.add(Dropout(0.4))


model.add(LSTM(units = 120, activation = 'relu'))
model.add(Dropout(0.5))
```

```
model.add(Dense(units = 1))
```

In [42]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 100, 50)           10400

 dropout (Dropout)           (None, 100, 50)           0

 lstm_1 (LSTM)               (None, 100, 60)           26640

 dropout_1 (Dropout)         (None, 100, 60)           0

 lstm_2 (LSTM)               (None, 100, 80)           45120

 dropout_2 (Dropout)         (None, 100, 80)           0

 lstm_3 (LSTM)               (None, 120)               96480

 dropout_3 (Dropout)         (None, 120)               0

 dense (Dense)               (None, 1)                 121

=================================================================
Total params: 178761 (698.29 KB)
Trainable params: 178761 (698.29 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Training the model

In [43]:
```
import tensorflow as tf
adam', loss = 'mean_squared_error', metrics=[tf.keras.metrics.MeanAbsoluteError()])
```

```
model.fit(x_train, y_train,epochs = 100)
```

```
Epoch 1/100
109/109 [==============================] - 34s 258ms/step - loss: 0.0254 - mean_absolute_error: 0.0955
Epoch 2/100
109/109 [==============================] - 30s 272ms/step - loss: 0.0098 - mean_absolute_error: 0.0669
Epoch 3/100
109/109 [==============================] - 30s 274ms/step - loss: 0.0058 - mean_absolute_error: 0.0497
Epoch 4/100
109/109 [==============================] - 28s 255ms/step - loss: 0.0063 - mean_absolute_error: 0.0511
Epoch 5/100
109/109 [==============================] - 38s 349ms/step - loss: 0.0048 - mean_absolute_error: 0.0440
Epoch 6/100
109/109 [==============================] - 26s 241ms/step - loss: 0.0046 - mean_absolute_error: 0.0435
Epoch 7/100
109/109 [==============================] - 27s 252ms/step - loss: 0.0048 - mean_absolute_error: 0.0443
Epoch 8/100
109/109 [==============================] - 26s 242ms/step - loss: 0.0040 - mean_absolute_error: 0.0412
Epoch 9/100
109/109 [==============================] - 28s 259ms/step - loss: 0.0038 - mean_absolute_error: 0.0398
Epoch 10/100
109/109 [==============================] - 26s 241ms/step - loss: 0.0042 - mean_absolute_error: 0.0403
Epoch 11/100
109/109 [==============================] - 36s 329ms/step - loss: 0.0033 - mean_absolute_error: 0.0366
Epoch 12/100
109/109 [==============================] - 42s 380ms/step - loss: 0.0039 - mean_absolute_error: 0.0411
Epoch 13/100
109/109 [==============================] - 35s 319ms/step - loss: 0.0033 - mean_absolute_error: 0.0364
Epoch 14/100
109/109 [==============================] - 35s 324ms/step - loss: 0.0033 - mean_absolute_error: 0.0370
Epoch 15/100
109/109 [==============================] - 42s 382ms/step - loss: 0.0032 - mean_absolute_error: 0.0364
Epoch 16/100
109/109 [==============================] - 30s 269ms/step - loss: 0.0030 - mean_absolute_error: 0.0359
Epoch 17/100
109/109 [==============================] - 35s 318ms/step - loss: 0.0033 - mean_absolute_error: 0.0381
Epoch 18/100
109/109 [==============================] - 34s 311ms/step - loss: 0.0029 - mean_absolute_error: 0.0357
Epoch 19/100
109/109 [==============================] - 32s 296ms/step - loss: 0.0028 - mean_absolute_error: 0.0355
Epoch 20/100
109/109 [==============================] - 38s 352ms/step - loss: 0.0029 - mean_absolute_error: 0.0364
Epoch 21/100
```

```
109/109 [==============================] - 29s 264ms/step - loss: 0.0030 - mean_absolute_error: 0.0371
Epoch 22/100
109/109 [==============================] - 35s 320ms/step - loss: 0.0028 - mean_absolute_error: 0.0358
Epoch 23/100
109/109 [==============================] - 40s 366ms/step - loss: 0.0029 - mean_absolute_error: 0.0360
Epoch 24/100
109/109 [==============================] - 33s 297ms/step - loss: 0.0027 - mean_absolute_error: 0.0359
Epoch 25/100
109/109 [==============================] - 33s 298ms/step - loss: 0.0029 - mean_absolute_error: 0.0370
Epoch 26/100
109/109 [==============================] - 35s 324ms/step - loss: 0.0028 - mean_absolute_error: 0.0370
Epoch 27/100
109/109 [==============================] - 40s 367ms/step - loss: 0.0029 - mean_absolute_error: 0.0370
Epoch 28/100
109/109 [==============================] - 31s 281ms/step - loss: 0.0027 - mean_absolute_error: 0.0359
Epoch 29/100
109/109 [==============================] - 32s 295ms/step - loss: 0.0026 - mean_absolute_error: 0.0358
Epoch 30/100
109/109 [==============================] - 39s 358ms/step - loss: 0.0027 - mean_absolute_error: 0.0370
Epoch 31/100
109/109 [==============================] - 31s 283ms/step - loss: 0.0027 - mean_absolute_error: 0.0362
Epoch 32/100
109/109 [==============================] - 30s 274ms/step - loss: 0.0025 - mean_absolute_error: 0.0353
Epoch 33/100
109/109 [==============================] - 30s 276ms/step - loss: 0.0026 - mean_absolute_error: 0.0350
Epoch 34/100
109/109 [==============================] - 32s 294ms/step - loss: 0.0025 - mean_absolute_error: 0.0354
Epoch 35/100
109/109 [==============================] - 44s 401ms/step - loss: 0.0024 - mean_absolute_error: 0.0346
Epoch 36/100
109/109 [==============================] - 42s 382ms/step - loss: 0.0024 - mean_absolute_error: 0.0346
Epoch 37/100
109/109 [==============================] - 43s 393ms/step - loss: 0.0025 - mean_absolute_error: 0.0348
Epoch 38/100
109/109 [==============================] - 43s 393ms/step - loss: 0.0025 - mean_absolute_error: 0.0350
Epoch 39/100
109/109 [==============================] - 43s 392ms/step - loss: 0.0026 - mean_absolute_error: 0.0358
Epoch 40/100
109/109 [==============================] - 41s 379ms/step - loss: 0.0025 - mean_absolute_error: 0.0355
```



```
109/109 [==============================] - 41s 378ms/step - loss: 0.0026 - mean_absolute_error: 0.0367
```

```
Epoch 42/100
109/109 [==============================] - 41s 380ms/step - loss: 0.0026 - mean_absolute_error: 0.0360
Epoch 43/100
109/109 [==============================] - 40s 366ms/step - loss: 0.0029 - mean_absolute_error: 0.0383
Epoch 44/100
109/109 [==============================] - 41s 373ms/step - loss: 0.0027 - mean_absolute_error: 0.0368
Epoch 45/100
109/109 [==============================] - 41s 372ms/step - loss: 0.0027 - mean_absolute_error: 0.0366
Epoch 46/100
109/109 [==============================] - 37s 339ms/step - loss: 0.0026 - mean_absolute_error: 0.0369
Epoch 47/100
109/109 [==============================] - 29s 264ms/step - loss: 0.0026 - mean_absolute_error: 0.0370
Epoch 48/100
109/109 [==============================] - 38s 346ms/step - loss: 0.0026 - mean_absolute_error: 0.0367
Epoch 49/100
109/109 [==============================] - 42s 387ms/step - loss: 0.0023 - mean_absolute_error: 0.0344
Epoch 50/100
109/109 [==============================] - 37s 340ms/step - loss: 0.0024 - mean_absolute_error: 0.0355
Epoch 51/100
109/109 [==============================] - 37s 342ms/step - loss: 0.0025 - mean_absolute_error: 0.0361
Epoch 52/100
109/109 [==============================] - 34s 316ms/step - loss: 0.0025 - mean_absolute_error: 0.0352
Epoch 53/100
109/109 [==============================] - 33s 304ms/step - loss: 0.0025 - mean_absolute_error: 0.0356
Epoch 54/100
109/109 [==============================] - 33s 303ms/step - loss: 0.0029 - mean_absolute_error: 0.0383
Epoch 55/100
109/109 [==============================] - 35s 322ms/step - loss: 0.0026 - mean_absolute_error: 0.0361
Epoch 56/100
109/109 [==============================] - 33s 303ms/step - loss: 0.0023 - mean_absolute_error: 0.0352
Epoch 57/100
109/109 [==============================] - 34s 309ms/step - loss: 0.0024 - mean_absolute_error: 0.0354
Epoch 58/100
109/109 [==============================] - 31s 289ms/step - loss: 0.0023 - mean_absolute_error: 0.0346
Epoch 59/100
109/109 [==============================] - 38s 344ms/step - loss: 0.0024 - mean_absolute_error: 0.0356
Epoch 60/100
109/109 [==============================] - 33s 306ms/step - loss: 0.0024 - mean_absolute_error: 0.0347
Epoch 61/100
109/109 [==============================] - 36s 329ms/step - loss: 0.0024 - mean_absolute_error: 0.0354
Epoch 62/100
```

```
109/109 [==============================] - 35s 320ms/step - loss: 0.0025 - mean_absolute_error: 0.0368
Epoch 63/100
109/109 [==============================] - 34s 310ms/step - loss: 0.0024 - mean_absolute_error: 0.0353
Epoch 64/100
109/109 [==============================] - 35s 321ms/step - loss: 0.0025 - mean_absolute_error: 0.0356
Epoch 65/100
109/109 [==============================] - 35s 325ms/step - loss: 0.0023 - mean_absolute_error: 0.0349
Epoch 66/100
109/109 [==============================] - 34s 316ms/step - loss: 0.0026 - mean_absolute_error: 0.0355
Epoch 67/100
109/109 [==============================] - 33s 301ms/step - loss: 0.0025 - mean_absolute_error: 0.0360
Epoch 68/100
109/109 [==============================] - 35s 322ms/step - loss: 0.0023 - mean_absolute_error: 0.0344
Epoch 69/100
109/109 [==============================] - 39s 358ms/step - loss: 0.0024 - mean_absolute_error: 0.0346
Epoch 70/100
109/109 [==============================] - 40s 368ms/step - loss: 0.0023 - mean_absolute_error: 0.0343
Epoch 71/100
109/109 [==============================] - 36s 333ms/step - loss: 0.0030 - mean_absolute_error: 0.0382
Epoch 72/100
109/109 [==============================] - 33s 301ms/step - loss: 0.0025 - mean_absolute_error: 0.0363
Epoch 73/100
109/109 [==============================] - 33s 305ms/step - loss: 0.0025 - mean_absolute_error: 0.0361
Epoch 74/100
109/109 [==============================] - 31s 287ms/step - loss: 0.0023 - mean_absolute_error: 0.0347
Epoch 75/100
109/109 [==============================] - 31s 286ms/step - loss: 0.0025 - mean_absolute_error: 0.0357
Epoch 76/100
109/109 [==============================] - 32s 295ms/step - loss: 0.0024 - mean_absolute_error: 0.0350
Epoch 77/100
109/109 [==============================] - 32s 291ms/step - loss: 0.0023 - mean_absolute_error: 0.0338
Epoch 78/100
109/109 [==============================] - 31s 282ms/step - loss: 0.0024 - mean_absolute_error: 0.0351
Epoch 79/100
109/109 [==============================] - 31s 283ms/step - loss: 0.0024 - mean_absolute_error: 0.0361
Epoch 80/100
109/109 [==============================] - 32s 294ms/step - loss: 0.0022 - mean_absolute_error: 0.0343
Epoch 81/100
109/109 [==============================] - 32s 296ms/step - loss: 0.0040 - mean_absolute_error: 0.0386
```



```
109/109 [==============================] - 31s 284ms/step - loss: 0.0027 - mean_absolute_error: 0.0361
```

```
Epoch 83/100
109/109 [==============================] - 31s 286ms/step - loss: 0.0024 - mean_absolute_error: 0.0348
Epoch 84/100
109/109 [==============================] - 34s 314ms/step - loss: 0.0030 - mean_absolute_error: 0.0386
Epoch 85/100
109/109 [==============================] - 32s 296ms/step - loss: 0.0025 - mean_absolute_error: 0.0351
Epoch 86/100
109/109 [==============================] - 31s 285ms/step - loss: 0.0025 - mean_absolute_error: 0.0356
Epoch 87/100
109/109 [==============================] - 29s 269ms/step - loss: 0.0025 - mean_absolute_error: 0.0351
Epoch 88/100
109/109 [==============================] - 27s 249ms/step - loss: 0.0025 - mean_absolute_error: 0.0362
Epoch 89/100
109/109 [==============================] - 26s 236ms/step - loss: 0.0024 - mean_absolute_error: 0.0352
Epoch 90/100
109/109 [==============================] - 27s 248ms/step - loss: 0.0025 - mean_absolute_error: 0.0363
Epoch 91/100
109/109 [==============================] - 26s 238ms/step - loss: 0.0025 - mean_absolute_error: 0.0358
Epoch 92/100
109/109 [==============================] - 26s 236ms/step - loss: 0.0025 - mean_absolute_error: 0.0357
Epoch 93/100
109/109 [==============================] - 27s 246ms/step - loss: 0.0029 - mean_absolute_error: 0.0383
Epoch 94/100
109/109 [==============================] - 26s 235ms/step - loss: 0.0024 - mean_absolute_error: 0.0359
Epoch 95/100
109/109 [==============================] - 27s 249ms/step - loss: 0.0024 - mean_absolute_error: 0.0351
Epoch 96/100
109/109 [==============================] - 27s 248ms/step - loss: 0.0024 - mean_absolute_error: 0.0352
Epoch 97/100
109/109 [==============================] - 36s 331ms/step - loss: 0.0023 - mean_absolute_error: 0.0347
Epoch 98/100
109/109 [==============================] - 33s 304ms/step - loss: 0.0024 - mean_absolute_error: 0.0352
Epoch 99/100
109/109 [==============================] - 36s 328ms/step - loss: 0.0022 - mean_absolute_error: 0.0339
Epoch 100/100
109/109 [==============================] - 34s 308ms/step - loss: 0.0023 - mean_absolute_error: 0.0346
```

Out[43]: <keras.src.callbacks.History at 0x7f9356a5dd50>

In [44]:
```
model.save('keras_model.h5')
```

In [45]:
```
test_close.shape
```

Out[45]:
```
(1752, 1)
```

In [46]:
```
past_100_days = pd.DataFrame(train_close[-100:])
```

In [47]:
```
test_df = pd.DataFrame(test_close)
```

Defining the final dataset for testing by including last 100 coloums of the training dataset to get the prediction from the 1st column of the testing dataset.

In [48]:
```
final_df = pd.concat([past_100_days, test_df], ignore_index=True)
```

In [49]:
```
final_df.head()
```

Out[49]:

	0
0	1251.449951
1	1276.550049
2	1250.425049
3	1247.099976
4	1242.650024

In [50]:
```
input_data = scaler.fit_transform(final_df)
input_data
```

Out[50]:
```
array([[0.06766715],
       [0.07612242],
       [0.0673219 ],
       ...,
       [0.93426142],
       [0.92467771],
       [0.92994957]])
```

In [51]:
```
input_data.shape
```

Out[51]: (1852, 1)

Testing the model

In [52]:
```
x_test = []
y_test = []
for i in range(100, input_data.shape[0]):
   x_test.append(input_data[i-100: i])
   y_test.append(input_data[i, 0])
```

In [53]:
```
x_test, y_test = np.array(x_test), np.array(y_test)
print(x_test.shape)
print(y_test.shape)
```

```
(1752, 100, 1)
(1752,)
```

Making prediction and plotting the graph of predicted vs actual values

---

In [54]:
```
# Making predictions

y_pred = model.predict(x_test)
```

```
55/55 [==============================] - 5s 86ms/step
```

In [55]:
```
y_pred.shape
```

Out[55]: (1752, 1)

In [56]:
```
y_test
```

Out[56]:
```
array([0.03056183, 0.02673003, 0.0294586 , ..., 0.93426142, 0.92467771,
       0.92994957])
```

In [57]:
```
y_pred
```

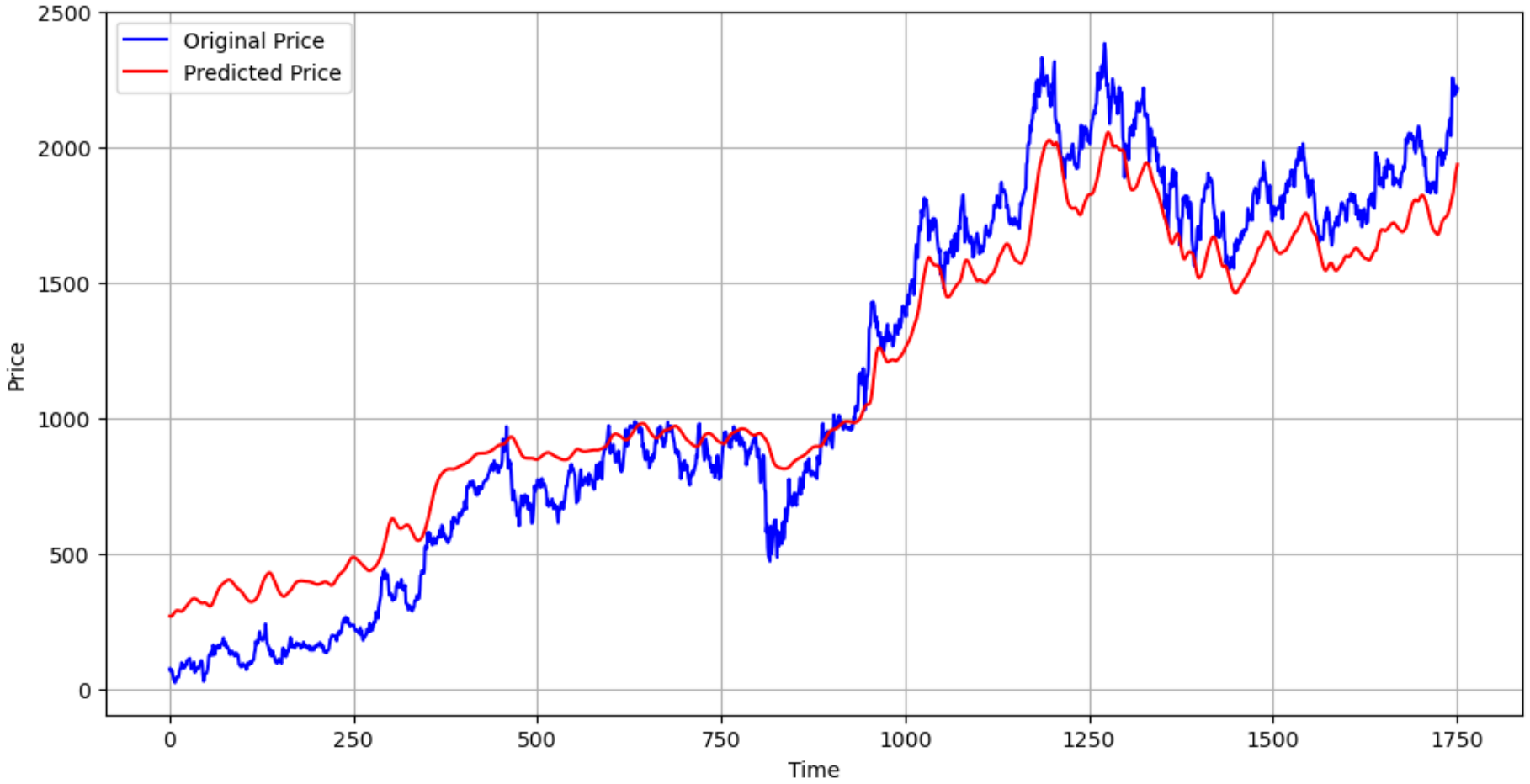
Out[57]:
```
array([[0.11212508],
       [0.11159423],
       [0.11180729],
       ...,
       [0.8013097 ],
       [0.8074249 ],
       [0.8124113 ]], dtype=float32)
```

In [58]:
```
scaler.scale_
```

Out[58]:
```
array([0.00033686])
```

In [59]:
```
scale_factor = 1/0.00041967
y_pred = y_pred * scale_factor
y_test = y_test * scale_factor
```

In [60]:
```
plt.figure(figsize = (12,6))
plt.plot(y_test, 'b', label = "Original Price")
plt.plot(y_pred, 'r', label = "Predicted Price")
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.grid(True)
plt.show()
```



Model evaluation

Calculation of mean absolute error

In [61]:
```
from sklearn.metrics import mean_absolute_error

mae = mean_absolute_error(y_test, y_pred)
mae_percentage = (mae / np.mean(y_test)) * 100
print("Mean absolute error on test set: {:.2f}%".format(mae_percentage))
```

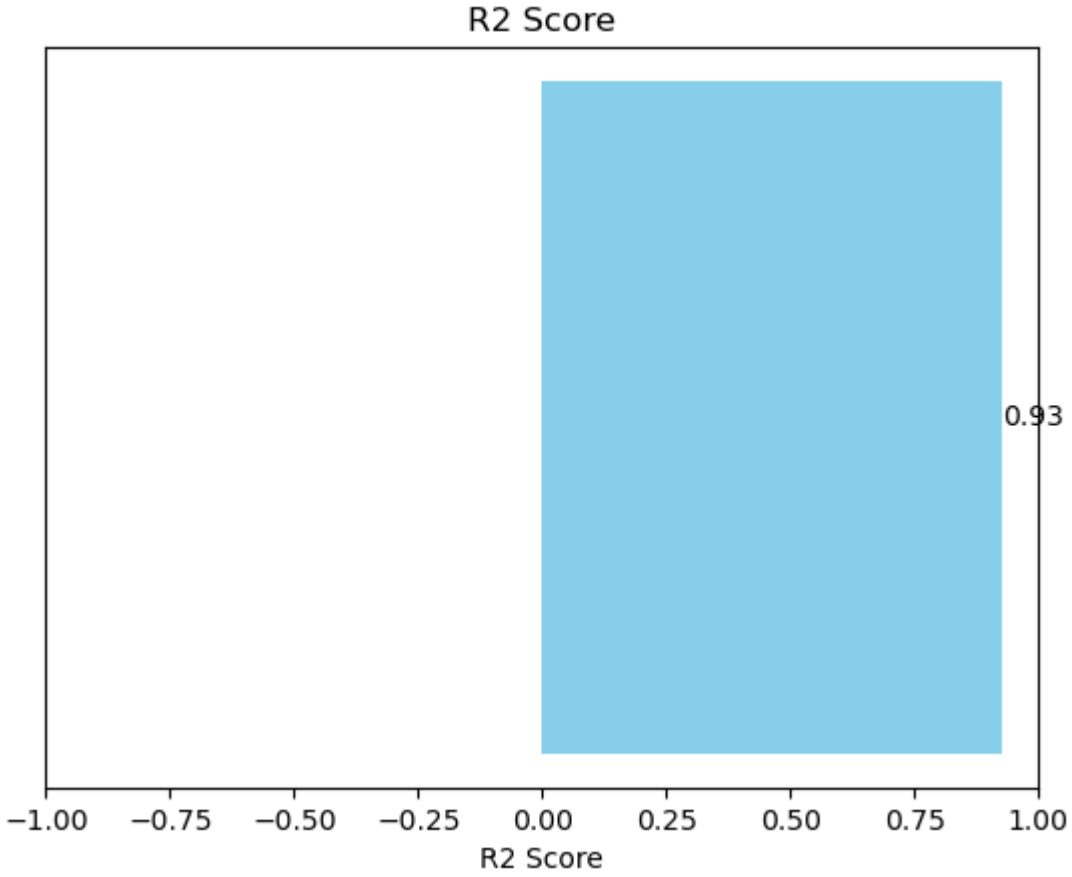
```
Mean absolute error on test set: 14.20%
```

Calculation of R2 score

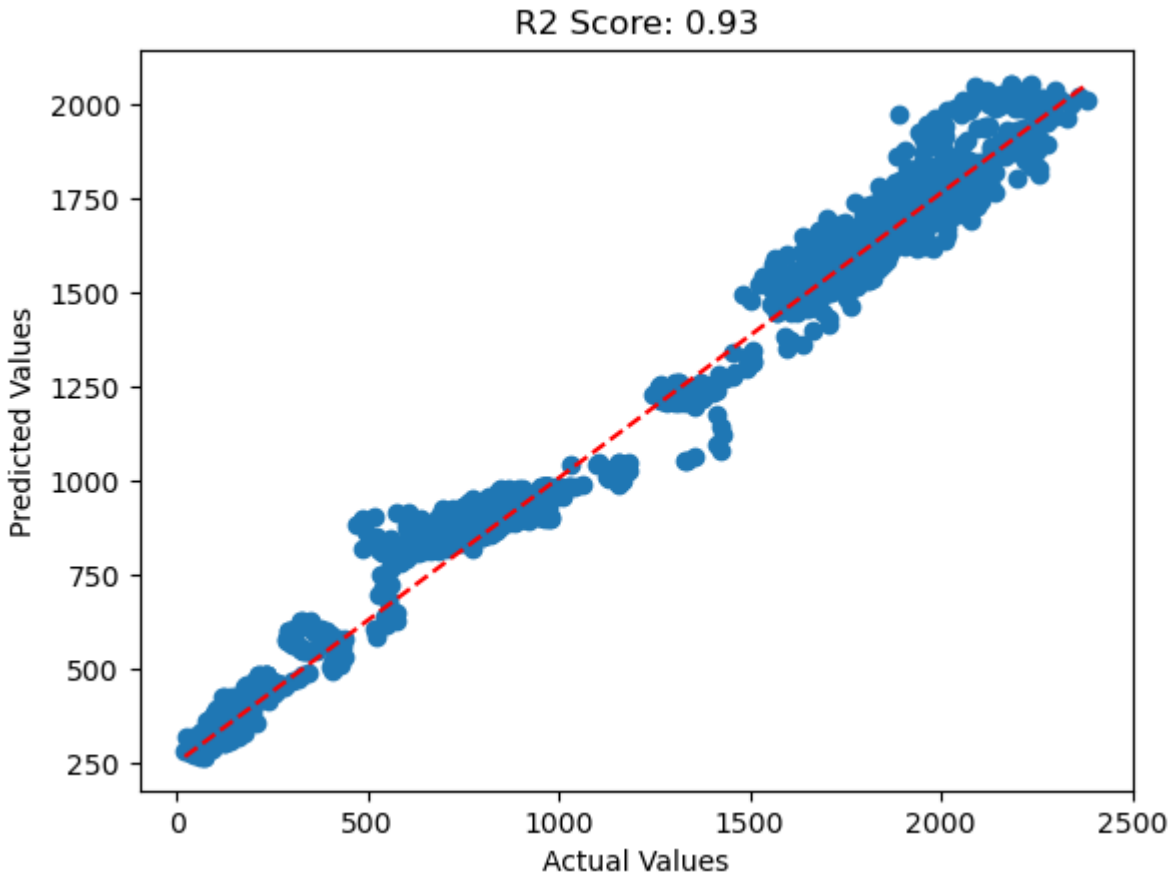
In [62]:
```
from sklearn.metrics import r2_score

# Actual values
actual = y_test

# Predicted values
predicted = y_pred

# Calculate the R2 score
r2 = r2_score(actual, predicted)

print("R2 score:", r2)
```

```
R2 score: 0.9272452174290756
```

In [63]:
```
# Plotting the R2 score
fig, ax = plt.subplots()
ax.barh(0, r2, color='skyblue')
ax.set_xlim([-1, 1])
ax.set_yticks([])
ax.set_xlabel('R2 Score')
ax.set_title('R2 Score')

# Adding the R2 score value on the bar
ax.text(r2, 0, f'{r2:.2f}', va='center', color='black')

plt.show()
```



In [64]:
```
plt.scatter(actual, predicted)
plt.plot([min(actual), max(actual)], [min(predicted), ma<b><x(predicted)], 'r--')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title(f'R2 Score: {r2:.2f}')
plt.show()
```



In [65]:
```
print("The Error Rate of Prediction Model:",(mean_absolute_percentage_error(y_pred,y_test))*100)
print("The Accuracy of Prediction Model:",(1-mean_absolute_percentage_error(y_pred,y_test))*100)
```

```
The Error Rate of Prediction Model: 20.53598044414941
The Accuracy of Prediction Model: 79.46401955585058
```

In [66]:
```
plt.plot(y_test,color='red',label='original test data')
plt.plot(y_pred,color='green',label='predicted data')
plt.xlabel('time')
plt.ylabel('google stock price')
plt.legend()
plt.show()
```

In [ ]:

In [ ]: