In [9]:

```
import yfinance as yf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from pandas_datareader import data as pdr
yf.pdr_override()
import datetime as dt
import json
import tensorflow as tf
from tensorflow import keras
```

In [10]:

```
start = '2010-01-01'
end = '2022-12-31'

df = pdr.get_data_yahoo('AAPL', start, end )
df.head()
```

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

Out[10]:

Date	Open	High	Low	Close	Adj Close	Volume
2010-01-04	7.622500	7.660714	7.585000	7.643214	6.515213	493729600
2010-01-05	7.664286	7.699643	7.616071	7.656429	6.526475	601904800
2010-01-06	7.656429	7.686786	7.526786	7.534643	6.422666	552160000
2010-01-07	7.562500	7.571429	7.466071	7.520714	6.410791	477131200
2010-01-08	7.510714	7.571429	7.466429	7.570714	6.453412	447610800

In [11]:

```
df.tail()
```

Out[11]:

Date	Open	High	Low	Close	Adj Close	Volume
2022-12-23	130.919998	132.419998	129.639999	131.860001	131.860001	63814900
2022-12-27	131.380005	131.410004	128.720001	130.029999	130.029999	69007800
2022-12-28	129.669998	131.029999	125.870003	126.040001	126.040001	85438400
2022-12-29	127.989998	130.479996	127.730003	129.610001	129.610001	75703700
2022-12-30	128.410004	129.949997	127.430000	129.929993	129.929993	76960600

In [12]:

```
df = df.reset_index()
df.head()
```

Out[12]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2010-01-04	7.622500	7.660714	7.585000	7.643214	6.515213	493729600
1	2010-01-05	7.664286	7.699643	7.616071	7.656429	6.526475	601904800
2	2010-01-06	7.656429	7.686786	7.526786	7.534643	6.422666	552160000
3	2010-01-07	7.562500	7.571429	7.466071	7.520714	6.410791	477131200
4	2010-01-08	7.510714	7.571429	7.466429	7.570714	6.453412	447610800

In [13]:

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

Out[13]:

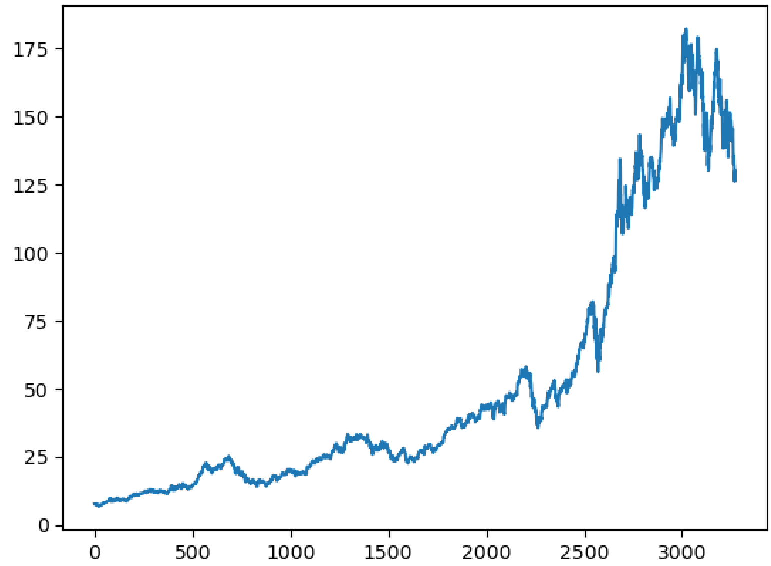
	Open	High	Low	Close	Volume
0	7.622500	7.660714	7.585000	7.643214	493729600
1	7.664286	7.699643	7.616071	7.656429	601904800
2	7.656429	7.686786	7.526786	7.534643	552160000
3	7.562500	7.571429	7.466071	7.520714	477131200
4	7.510714	7.571429	7.466429	7.570714	447610800

In [16]:

```
plt.plot(df.Close)
```

Out[16]:

```
[<matplotlib.lines.Line2D at 0x1825bfc77c0>]
```



In [18]:

```
df
```

Out[18]:

	Open	High	Low	Close	Volume
0	7.622500	7.660714	7.585000	7.643214	493729600
1	7.664286	7.699643	7.616071	7.656429	601904800
2	7.656429	7.686786	7.526786	7.534643	552160000
3	7.562500	7.571429	7.466071	7.520714	477131200
4	7.510714	7.571429	7.466429	7.570714	447610800
...	...	...	...	...	...
3267	130.919998	132.419998	129.639999	131.860001	63814900
3268	131.380005	131.410004	128.720001	130.029999	69007800
3269	129.669998	131.029999	125.870003	126.040001	85438400
3270	127.989998	130.479996	127.730003	129.610001	75703700
3271	128.410004	129.949997	127.430000	129.929993	76960600

3272 rows × 5 columns

In [19]:

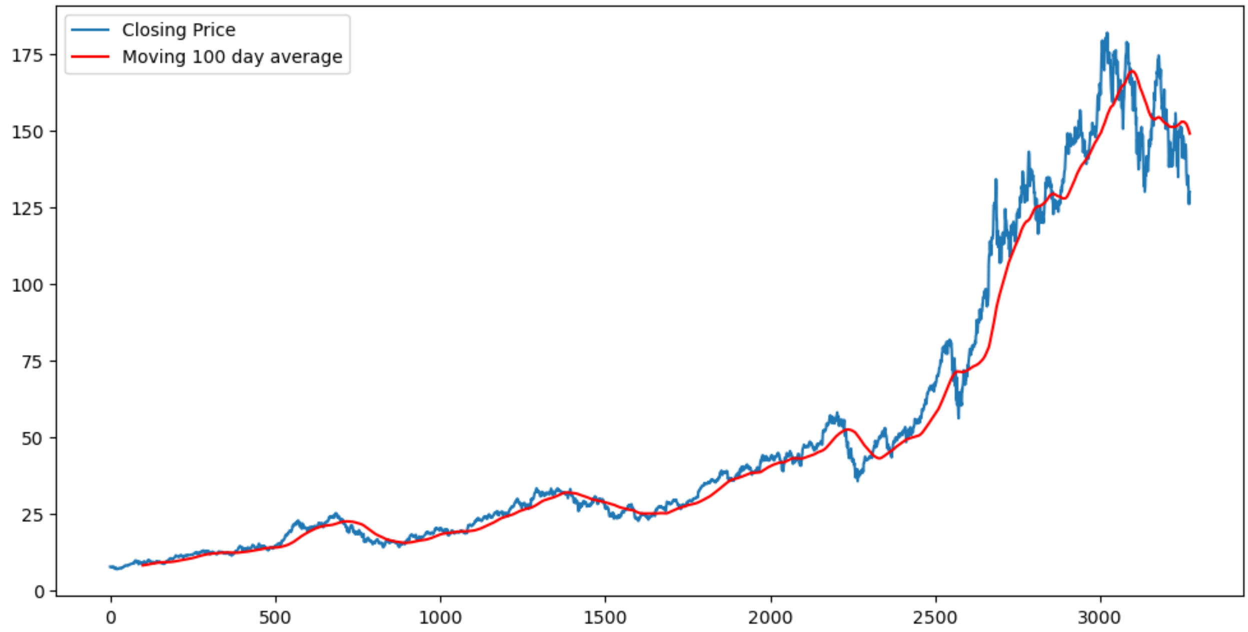
```
ma100 = df.Close.rolling(100).mean() #ma = moving average
ma100
```

Out[19]:

```
0              NaN
1              NaN
2              NaN
3              NaN
4              NaN
           ...
3267    150.515600
3268    150.157800
3269    149.764699
3270    149.412100
3271    149.062199
Name: Close, Length: 3272, dtype: float64
```

In [25]:

```
plt.figure(figsize = (12,6))
plt.plot(df.Close, label = 'Closing Price')
plt.plot(ma100,'r', label='Moving 100 day average')
plt.legend()
plt.show()
```



In [26]:

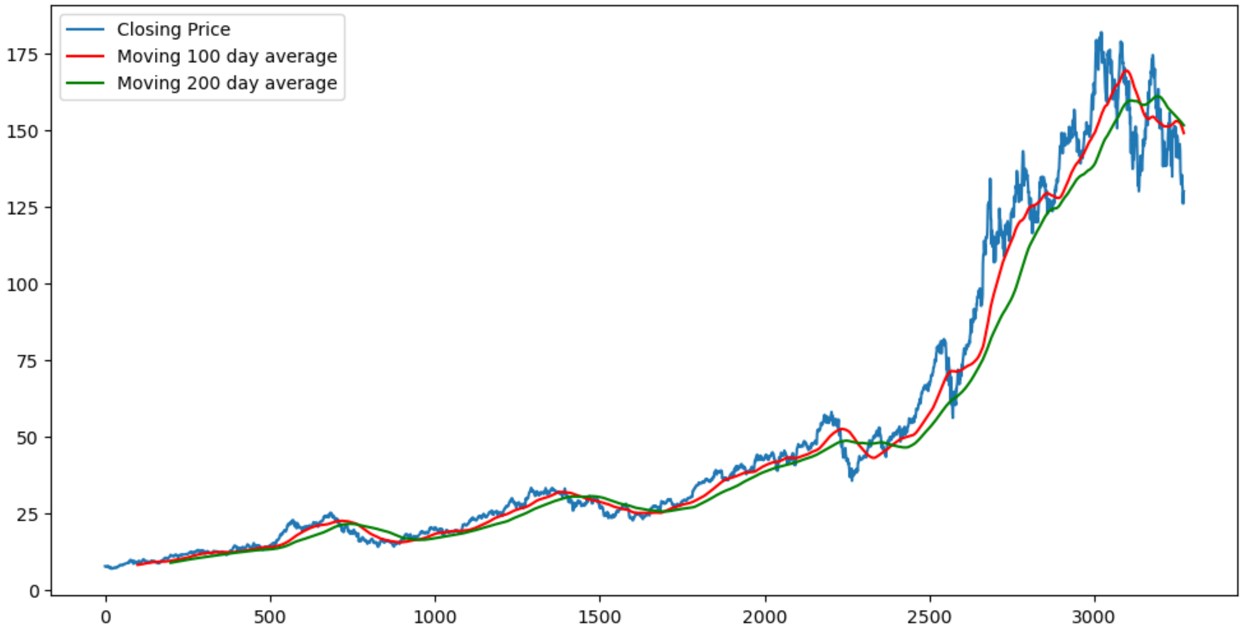
```
ma200 = df.Close.rolling(200).mean() #ma = moving average
ma200
```

Out[26]:

```
0            NaN
1            NaN
2            NaN
3            NaN
4            NaN
          ...
3267    152.1331
3268    152.0096
3269    151.8867
3270    151.7593
3271    151.6110
Name: Close, Length: 3272, dtype: float64
```

In [11]:

```
plt.figure(figsize = (12,6))
plt.plot(df.Close,label='Closing Price')
plt.plot(ma100,'r',label = 'Moving 100 day average')
plt.plot(ma200,'g',label = 'Moving 200 day average')
plt.legend()
plt.show()
```



In [12]:

```
df.shape
```

Out[12]:

```
(3272, 5)
```

In [13]:

```
#Spliting data into training and testing

data_training = pd.DataFrame(df['Close'][0:int(len(df)*0.70)])
data_testing =  pd.DataFrame(df['Close'][int(len(df)*0.70):int(len(df))])

print(data_training.shape)
print(data_testing.shape)
```

```
(2290, 1)
(982, 1)
```

In [14]:

```
data_training.head()
```

Out[14]:

	Close
0	7.643214
1	7.656429
2	7.534643
3	7.520714
4	7.570714

In [15]:

```
from sklearn.preprocessing import MinMaxScaler  #data scaling = reduces the difference between the points in the data
                                                 # which results in greater accuracy. It comes under Data Preproccesing
scaler = MinMaxScaler(feature_range=(0,1))
```

In [16]:

```
data_training_array = scaler.fit_transform(data_training)
data_training_array
```

Out[16]:

```
array([[0.01533047],
       [0.01558878],
       [0.01320823],
       ...,
       [0.71710501],
       [0.71739828],
       [0.70127194]])
```

In [17]:

```
data_training_array.shape
```

Out[17]:

```
(2290, 1)
```

In [18]:

```
x_train = []  # this is the steps we take, for example 100 days data
y_train = []  #this is the predicted value, ie value on 101 day after analysing 100 days.

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 [19]:

```
x_train.shape
```

Out[19]:

```
(2190, 100, 1)
```

In [20]:

```
y_train.shape
```

Out[20]:

```
(2190,)
```

In [21]:

```
#ML Model
```

In [22]:

```
from keras.layers import Dense, Dropout, LSTM
from keras.models import Sequential, model_from_json
```

In [23]:

```
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))  #connects the whole model
```

In [24]:

```
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: 178,761
Trainable params: 178,761
Non-trainable params: 0
_________________________________________________________________
```

In [25]:

```
model.compile(optimizer = 'adam', loss = 'mean_squared_error')
model.fit(x_train , y_train, epochs = 50)
```

```
Epoch 1/50
69/69 [==============================] - 20s 206ms/step - loss: 0.0347
Epoch 2/50
69/69 [==============================] - 14s 199ms/step - loss: 0.0070
Epoch 3/50
69/69 [==============================] - 14s 201ms/step - loss: 0.0065
Epoch 4/50
69/69 [==============================] - 14s 199ms/step - loss: 0.0063
Epoch 5/50
69/69 [==============================] - 14s 204ms/step - loss: 0.0054
Epoch 6/50
69/69 [==============================] - 15s 217ms/step - loss: 0.0047
Epoch 7/50
69/69 [==============================] - 15s 215ms/step - loss: 0.0049
Epoch 8/50
69/69 [==============================] - 14s 207ms/step - loss: 0.0049
Epoch 9/50
69/69 [==============================] - 16s 234ms/step - loss: 0.0048
Epoch 10/50
69/69 [==============================] - 15s 218ms/step - loss: 0.0040
Epoch 11/50
69/69 [==============================] - 14s 206ms/step - loss: 0.0038
Epoch 12/50
69/69 [==============================] - 14s 209ms/step - loss: 0.0038
Epoch 13/50
69/69 [==============================] - 15s 220ms/step - loss: 0.0033
Epoch 14/50
69/69 [==============================] - 17s 243ms/step - loss: 0.0035
Epoch 15/50
69/69 [==============================] - 15s 219ms/step - loss: 0.0037
Epoch 16/50
69/69 [==============================] - 14s 204ms/step - loss: 0.0039
Epoch 17/50
69/69 [==============================] - 15s 213ms/step - loss: 0.0034
Epoch 18/50
69/69 [==============================] - 15s 214ms/step - loss: 0.0033
Epoch 19/50
69/69 [==============================] - 14s 208ms/step - loss: 0.0031
Epoch 20/50
69/69 [==============================] - 15s 218ms/step - loss: 0.0028
Epoch 21/50
69/69 [==============================] - 15s 220ms/step - loss: 0.0030
Epoch 22/50
69/69 [==============================] - 16s 227ms/step - loss: 0.0029
Epoch 23/50
69/69 [==============================] - 15s 218ms/step - loss: 0.0022
Epoch 24/50
69/69 [==============================] - 15s 224ms/step - loss: 0.0024
Epoch 25/50
69/69 [==============================] - 15s 221ms/step - loss: 0.0025
Epoch 26/50
69/69 [==============================] - 15s 211ms/step - loss: 0.0024
Epoch 27/50
69/69 [==============================] - 14s 209ms/step - loss: 0.0023
Epoch 28/50
69/69 [==============================] - 15s 223ms/step - loss: 0.0022
Epoch 29/50
69/69 [==============================] - 15s 222ms/step - loss: 0.0022
Epoch 30/50
69/69 [==============================] - 16s 229ms/step - loss: 0.0020
Epoch 31/50
69/69 [==============================] - 16s 228ms/step - loss: 0.0021
Epoch 32/50
69/69 [==============================] - 16s 237ms/step - loss: 0.0022
Epoch 33/50
69/69 [==============================] - 16s 233ms/step - loss: 0.0023
Epoch 34/50
69/69 [==============================] - 16s 232ms/step - loss: 0.0020
Epoch 35/50
69/69 [==============================] - 16s 226ms/step - loss: 0.0018
Epoch 36/50
69/69 [==============================] - 16s 233ms/step - loss: 0.0018
Epoch 37/50
69/69 [==============================] - 15s 215ms/step - loss: 0.0020
Epoch 38/50
69/69 [==============================] - 16s 238ms/step - loss: 0.0020
Epoch 39/50
69/69 [==============================] - 15s 224ms/step - loss: 0.0021
Epoch 40/50
69/69 [==============================] - 16s 235ms/step - loss: 0.0017
Epoch 41/50
69/69 [==============================] - 16s 225ms/step - loss: 0.0017
Epoch 42/50
69/69 [==============================] - 14s 204ms/step - loss: 0.0018
Epoch 43/50
69/69 [==============================] - 15s 220ms/step - loss: 15.4308
```

```
Epoch 44/50
69/69 [==============================] - 15s 212ms/step - loss: 0.0043
Epoch 45/50
69/69 [==============================] - 16s 232ms/step - loss: 0.0029
Epoch 46/50
69/69 [==============================] - 16s 227ms/step - loss: 0.0026
Epoch 47/50
69/69 [==============================] - 15s 213ms/step - loss: 0.0024
Epoch 48/50
69/69 [==============================] - 16s 226ms/step - loss: 0.0023
Epoch 49/50
69/69 [==============================] - 16s 237ms/step - loss: 0.0025
Epoch 50/50
69/69 [==============================] - 17s 246ms/step - loss: 0.0024
```

Out[25]:

```
<keras.callbacks.History at 0x20de7492d90>
```

In [26]:

```
model.save('keras_model4.keras')
```

In [27]:

```
data_testing.head()
```

Out[27]:

	Close
2290	42.602501
2291	42.357498
2292	42.722500
2293	42.544998
2294	42.700001

In [28]:

```
past_100_days = data_training.tail(100)
```

In [29]:

```
final_df = pd.concat([past_100_days, data_testing],ignore_index = True, axis = 0)
```

In [30]:

```
final_df.head()
```

Out[30]:

	Close
0	55.959999
1	54.470001
2	54.560001
3	54.592499
4	55.007500

In [31]:

```
input_data = scaler.fit_transform(final_df)
input_data
```

Out[31]:

```
array([[0.13937014],
       [0.1291969 ],
       [0.1298114 ],
       ...,
       [0.61785443],
       [0.64222927],
       [0.64441407]])
```

In [32]:

```
input_data.shape
```

Out[32]:

```
(1082, 1)
```

In [33]:

```
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 [34]:

```
x_test , y_test = np.array(x_test), np.array(y_test)
print(x_test.shape)
print(y_test.shape)
```

```
(982, 100, 1)
(982,)
```

In [35]:

```
#Making Predictions

y_predicted = model.predict(x_test)
```

```
31/31 [==============================] - 2s 62ms/step
```

In [36]:

```
y_predicted.shape
```

Out[36]:

```
(982, 1)
```

In [37]:

```
y_test
```

Out[37]:

```
array([0.04816933, 0.04649653, 0.04898865, 0.04777672, 0.04883503,
       0.04818639, 0.04905691, 0.05093454, 0.04927882, 0.05253905,
       0.05468976, 0.05486046, 0.05578219, 0.05284628, 0.05595289,
       0.05745499, 0.05690876, 0.05518478, 0.05173679, 0.05243663,
       0.06266108, 0.06609201, 0.06745755, 0.07090551, 0.07498506,
       0.07822822, 0.0756849 , 0.07846719, 0.09029614, 0.08340019,
       0.07945721, 0.07612869, 0.07899633, 0.07942306, 0.08152257,
       0.08372451, 0.08846975, 0.09073996, 0.09132031, 0.09355637,
       0.09884784, 0.09782367, 0.09973542, 0.09688486, 0.09674831,
       0.0973628 , 0.09739694, 0.10401981, 0.10526585, 0.10640949,
       0.1114449 , 0.1108987 , 0.10768968, 0.1060169 , 0.10654605,
       0.09982077, 0.11663396, 0.11429546, 0.11873346, 0.11315182,
       0.10355893, 0.1036272 , 0.09990612, 0.0938636 , 0.0743023 ,
       0.07932065, 0.08317828, 0.08174448, 0.079901  , 0.06981308,
       0.0758044 , 0.06928394, 0.06395836, 0.06278058, 0.06151744,
       0.06006658, 0.06163694, 0.05612359, 0.05310233, 0.06392421,
       0.06887427, 0.07344884, 0.08186395, 0.08601178, 0.08981821,
       0.08875993, 0.08869163, 0.08628489, 0.08824784, 0.0960314 ,
```

In [38]:

```
y_predicted
```

Out[38]:

```
array([[0.09207357],
       [0.09277508],
       [0.09351471],
       [0.09425803],
       [0.09497693],
       [0.09565249],
       [0.09627241],
       [0.09683166],
       [0.09733434],
       [0.09778409],
       [0.09819143],
       [0.09857252],
       [0.09894121],
       [0.09930849],
       [0.09967425],
       [0.10003999],
       [0.1004099 ],
       [0.1007849 ],
```

In [42]:

```
scaler.scale_  #gives the factor with which the above data is scaled down so that we can scale it up again
```

Out[42]:

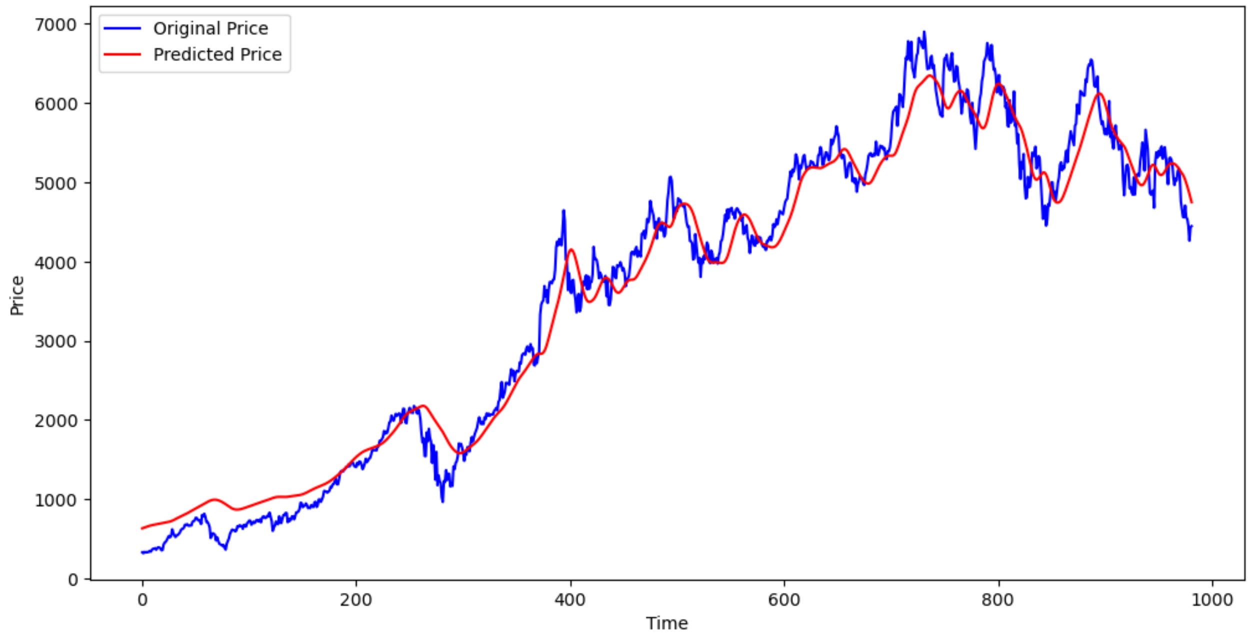
```
array([0.00682769])
```

In [44]:

```
scale_factor = 1/0.00682769
y_predicted = y_predicted * scale_factor
y_test = y_test * scale_factor
```

In [45]:

```
plt.figure(figsize=(12,6))
plt.plot(y_test, 'b', label = "Original Price")
plt.plot(y_predicted, 'r', label = "Predicted Price")
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.show()
```



In [ ]: