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Task 1 - STOCK PREDICTION

Problem Statement:

- Perform Stock Price Analysis & Forecasting of stock prices of a company using LSTM.

In [1]:
```
#importing necessary libraries
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
#importing libraries for visualisation
import matplotlib.pyplot as plt
from matplotlib import style
import seaborn as sns
#importing tensorflow
import tensorflow as tf
```

In [2]:
```
tf.__version__
```

Out[2]:
```
'2.13.0'
```

In [3]:
```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving yahoo_stock.csv to yahoo_stock.csv
```

In [4]:
```
import io
data_frame = pd.read_csv(io.BytesIO(uploaded['yahoo_stock.csv']))
```

Performing descriptive analysis. Understand the variables and their corresponding values.

In [5]:
```
# Understanding the dimensions of data
data_frame.shape
```

Out[5]:
```
(1825, 7)
```

In [7]:
```
# Understanding the Data Variables
data_frame.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1825 entries, 0 to 1824
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1825 non-null   object
 1   High       1825 non-null   float64
 2   Low        1825 non-null   float64
 3   Open       1825 non-null   float64
 4   Close      1825 non-null   float64
 5   Volume     1825 non-null   float64
 6   Adj Close  1825 non-null   float64
dtypes: float64(6), object(1)
memory usage: 99.9+ KB
```

In [8]:
```
data_frame.columns
```

Out[8]:
```
Index(['Date', 'High', 'Low', 'Open', 'Close', 'Volume', 'Adj Close'], dtype='obje
ct')
```

- Columns are Open , High, Low, Last , Close, Volume ,Adj Close and the corresponding Dates.

In [9]:
```
# Show the top 5 Rows of data
data_frame.head(5)
```

Out[9]:

	Date	High	Low	Open	Close	Volume	Adj Close
0	2015-11-23	2095.610107	2081.389893	2089.409912	2086.590088	3.587980e+09	2086.590088
1	2015-11-24	2094.120117	2070.290039	2084.419922	2089.139893	3.884930e+09	2089.139893
2	2015-11-25	2093.000000	2086.300049	2089.300049	2088.870117	2.852940e+09	2088.870117
3	2015-11-26	2093.000000	2086.300049	2089.300049	2088.870117	2.852940e+09	2088.870117
4	2015-11-27	2093.290039	2084.129883	2088.820068	2090.110107	1.466840e+09	2090.110107

In [10]:
```
data_frame.tail(5)
```

Out[10]:

	Date	High	Low	Open	Close	Volume	Adj Close
1820	2020-11-16	3628.510010	3600.159912	3600.159912	3626.909912	5.281980e+09	3626.909912
1821	2020-11-17	3623.110107	3588.679932	3610.310059	3609.530029	4.799570e+09	3609.530029
1822	2020-11-18	3619.090088	3567.330078	3612.090088	3567.790039	5.274450e+09	3567.790039
1823	2020-11-19	3585.219971	3543.840088	3559.409912	3581.870117	4.347200e+09	3581.870117
1824	2020-11-20	3581.229980	3556.850098	3579.310059	3557.540039	2.236662e+09	3557.540039

In [11]:

```
#Finding the period of time of stock data available
print('Stock data starting date: ', data_frame["Date"].min())
print('Stock data ending date: ', data_frame["Date"].max())
```

```
Stock data starting date:  2015-11-23
Stock data ending date:  2020-11-20
```

- Time frame of Stock market data is from 23rd November 2015 to 20th November 2020

In [12]:

```
# Arrange in terms of date
data_frame.set_index("Date",inplace=True)
data_frame.head()
```

Out[12]:

Date	High	Low	Open	Close	Volume	Adj Close
2015-11-23	2095.610107	2081.389893	2089.409912	2086.590088	3.587980e+09	2086.590088
2015-11-24	2094.120117	2070.290039	2084.419922	2089.139893	3.884930e+09	2089.139893
2015-11-25	2093.000000	2086.300049	2089.300049	2088.870117	2.852940e+09	2088.870117
2015-11-26	2093.000000	2086.300049	2089.300049	2088.870117	2.852940e+09	2088.870117
2015-11-27	2093.290039	2084.129883	2088.820068	2090.110107	1.466840e+09	2090.110107

In [13]:

```
# Performing Descriptive Analysis
data_frame.describe().T
```

Out[13]:

	count	mean	std	min	25%	50%
High	1825.0	2.660719e+03	4.096809e+02	1.847000e+03	2.348350e+03	2.696250e+03
Low	1825.0	2.632818e+03	4.043101e+02	1.810100e+03	2.322250e+03	2.667840e+03
Open	1825.0	2.647705e+03	4.071700e+02	1.833400e+03	2.341980e+03	2.685490e+03
Close	1825.0	2.647856e+03	4.073012e+02	1.829080e+03	2.328950e+03	2.683340e+03
Volume	1825.0	3.869627e+09	1.087593e+09	1.296540e+09	3.257950e+09	3.609740e+09
Adj Close	1825.0	2.647856e+03	4.073012e+02	1.829080e+03	2.328950e+03	2.683340e+03

- Most of the values in Open, close, high , low and last are similar

In [14]:

```
# Checking for null values
data_frame.isnull().sum()
```

Out[14]:

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

DATA VISUALISATION

In [15]:

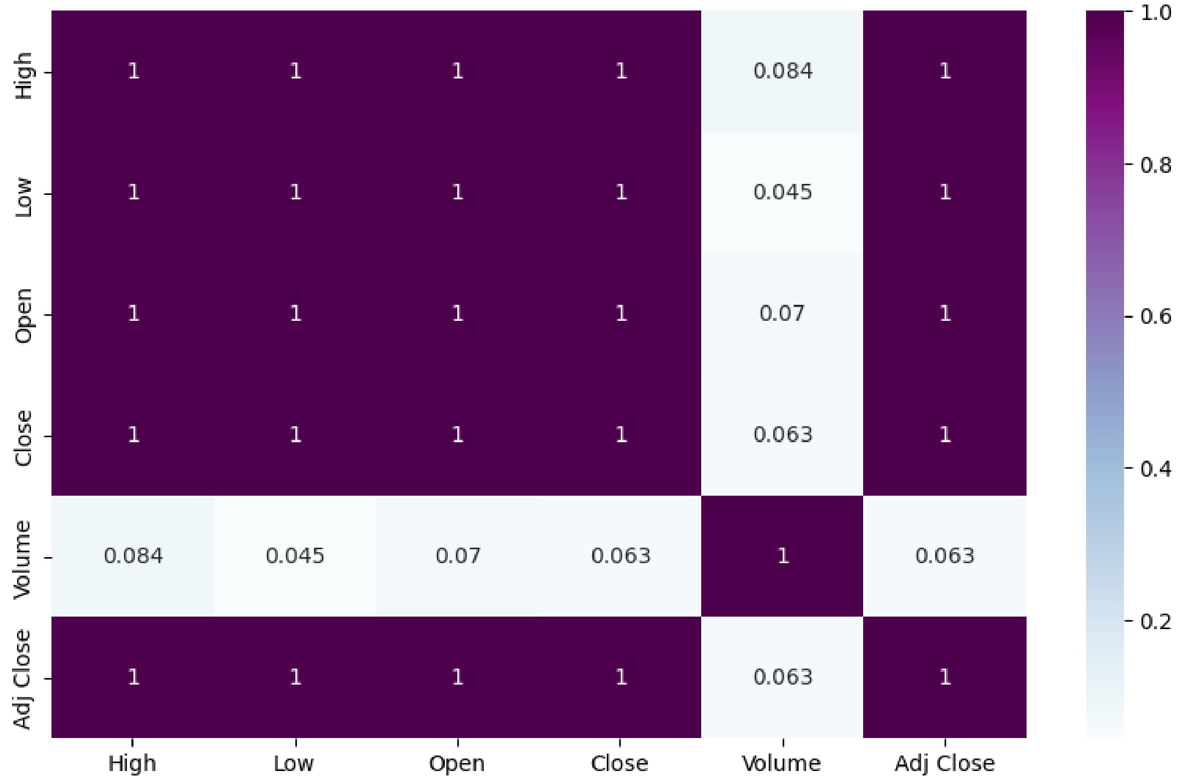
```
# find correlation between variables in data set for plotting heatmap
df_corr=data_frame.corr()
df_corr
```

Out[15]:

	High	Low	Open	Close	Volume	Adj Close
High	1.000000	0.998154	0.999328	0.998958	0.084212	0.998958
Low	0.998154	1.000000	0.998794	0.999020	0.044557	0.999020
Open	0.999328	0.998794	1.000000	0.998344	0.069729	0.998344
Close	0.998958	0.999020	0.998344	1.000000	0.063401	1.000000
Volume	0.084212	0.044557	0.069729	0.063401	1.000000	0.063401
Adj Close	0.998958	0.999020	0.998344	1.000000	0.063401	1.000000

In [16]:

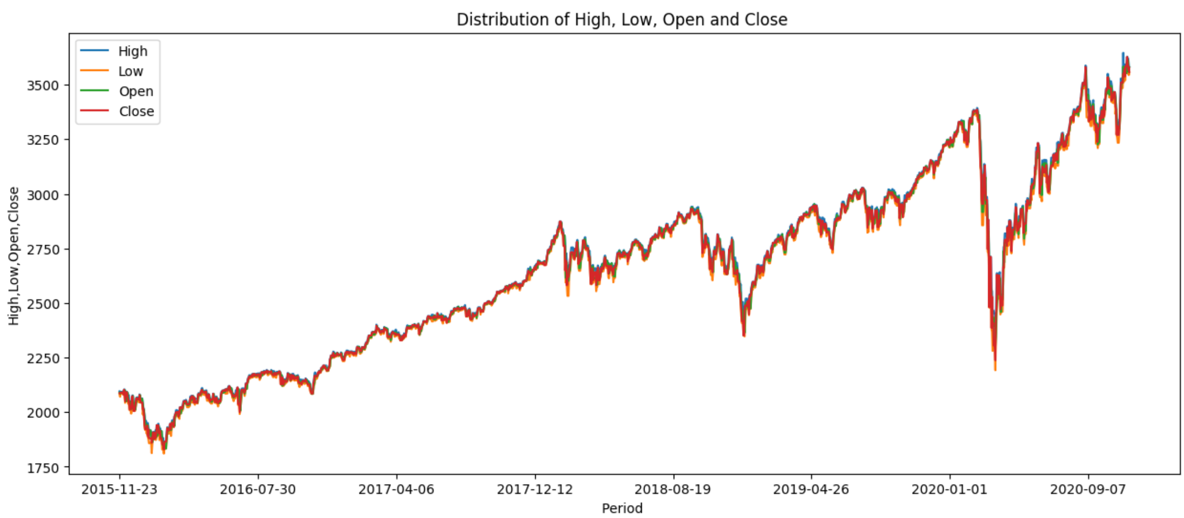
```
# Plotting Heatmap
plt.figure(figsize=(10,6))
sns.heatmap(df_corr,annot=True,cmap="BuPu")
plt.show()
```



- Most of the values are highly correlated with each other

In [17]:
```
# Plotting the distribution of High, Low , Open and Close variables
data_frame[["High", "Low", "Open", "Close"]].plot(figsize=(15,6))
plt.xlabel("Period ")
plt.ylabel("High,Low,Open,Close")
plt.title("Distribution of High, Low, Open and Close ")
plt.legend(loc="best")
```

Out[17]: <matplotlib.legend.Legend at 0x7f2c565debf0>



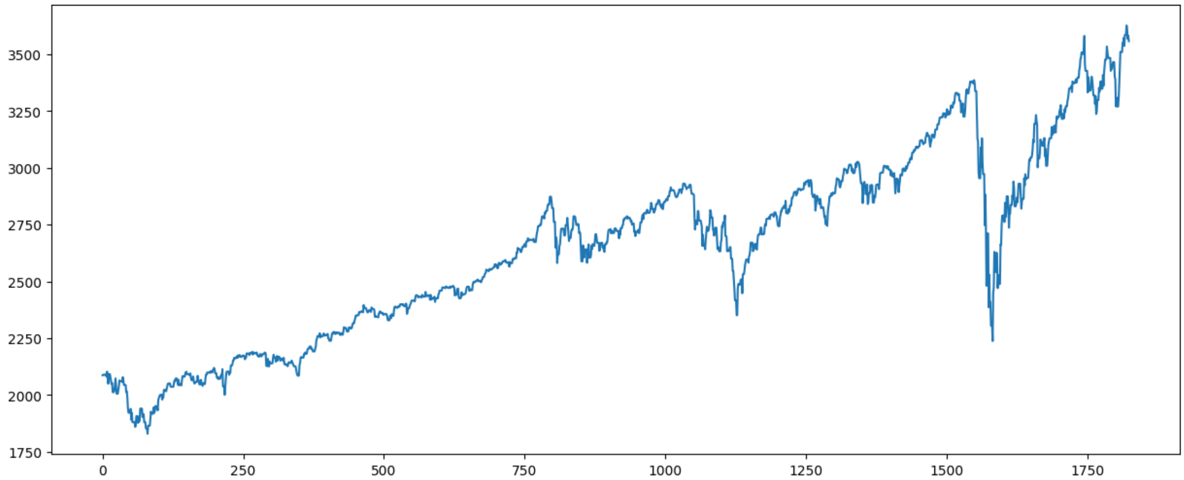
- Here values in Close, Open, High and Low follows similar pattern. So for furthur analysis, Values in 'Close' are only taken.

In [18]:
```
# Taking the Close variable for further analysis
data_frame_column_Close=data_frame.reset_index()['Close']
print(data_frame_column_Close)
```

```
0       2086.590088
1       2089.139893
2       2088.870117
3       2088.870117
4       2090.110107
            ...
1820    3626.909912
1821    3609.530029
1822    3567.790039
1823    3581.870117
1824    3557.540039
Name: Close, Length: 1825, dtype: float64
```

Plotting distribution of Close variable

In [19]:
```
plt.figure(figsize=(15,6))
plt.plot(data_frame_column_Close)
plt.show()
```



In [20]:
```
# Min Max Scaling transforms data by scaling features to a range between 0 and 1
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler(feature_range=(0,1))
data_frame_column_Close=scaler.fit_transform(np.array(data_frame_column_Close).resh
data_frame_column_Close
```

Out[20]:
```
array([[0.14323386],
       [0.14465213],
       [0.14450208],
       ...,
       [0.96711598],
       [0.97494769],
       [0.96141466]])
```

In [21]:
```
# Print Length of train and test dataset
# Train size is taken as 0.75 of total dataset
train_size=int(len(data_frame_column_Close)*0.75)
test_size=len(data_frame_column_Close)-train_size
length=len(data_frame_column_Close)
print('Train size: ', train_size)
print('Test size: ', test_size)
```

```
Train size:  1368
Test size:  457
```

In [22]:
```
# Splitting into train and test data set
train_data,test_data=data_frame_column_Close[0:train_size,:],data_frame_column_Clo
train_data
```

Out[22]:
```
array([[0.14323386],
       [0.14465213],
       [0.14450208],
       ...,
       [0.60882841],
       [0.59595739],
       [0.60926228]])
```

In [23]:
```
# Defining the function stock_close for differentiating feature and target variabl
def stock_close(x, step=1):
        feature,target = [], []

        for i in range(len(x)-step):
                tmp_x = x[i:i+step, 0]
                feature.append(tmp_x)
                target.append(x[i + step, 0])
        return np.array(feature), np.array(target)
```

In [24]:
```
# Defining train and test data
X_train, y_train = stock_close(train_data, 100)
X_test, ytest = stock_close(test_data, 100)
```

In [25]:
```
# Printing dimensions of train dataset
print(X_train.shape), print(y_train.shape)
```

```
(1268, 100)
(1268,)
```

Out[25]:
```
(None, None)
```

In [26]:
```
# Printing dimensions of test dataset
print(X_test.shape), print(ytest.shape)
```

```
(357, 100)
(357,)
```

Out[26]:
```
(None, None)
```

In [27]:
```
# reshape input to be [samples, time steps, features] which is required for LSTM
X_train =X_train.reshape(X_train.shape[0],X_train.shape[1] , 1)
X_test = X_test.reshape(X_test.shape[0],X_test.shape[1] , 1)
```

Building the Neutral Network Model

In [28]:
```
### Create the Stacked LSTM model
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM

#Layers are added to model
# Long short-term memory (LSTM) model is a variation of RNN ( Recurrent Neural Netw
# Stock Prices are highly dependent on time frame
# LSTM capable of processing  long-term dependencies in time-series data.
# Fully connected layer makes the final prediction.
my_model=Sequential()
my_model.add(LSTM(64,return_sequences=True,input_shape=(100,1)))
my_model.add(LSTM(32))
my_model.add(Dense(1))
```

In [29]:
```
# Model Compilation
my_model.compile(loss='mean_squared_error',optimizer='adam')
```

In [30]:
```
# Model Summary
my_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 lstm (LSTM)                 (None, 100, 64)           16896     
                                                                 
 lstm_1 (LSTM)               (None, 32)                12416     
                                                                 
 dense (Dense)               (None, 1)                 33        
                                                                 
=================================================================
Total params: 29345 (114.63 KB)
Trainable params: 29345 (114.63 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [31]:
```
# Fitting the model
# Epoch refers to one cycle through full training dataset. Here 30 Epochs are used
my_model.fit(X_train,y_train,validation_data=(X_test,ytest),epochs=30,batch_size=6
```

```
Epoch 1/30
20/20 [==============================] - 5s 102ms/step - loss: 0.0243 - val_loss:
0.0432
Epoch 2/30
20/20 [==============================] - 1s 71ms/step - loss: 0.0025 - val_loss:
0.0136
Epoch 3/30
20/20 [==============================] - 1s 71ms/step - loss: 9.2325e-04 - val_los
s: 0.0065
Epoch 4/30
20/20 [==============================] - 1s 71ms/step - loss: 4.9597e-04 - val_los
s: 0.0045
Epoch 5/30
20/20 [==============================] - 2s 91ms/step - loss: 4.5381e-04 - val_los
s: 0.0040
Epoch 6/30
20/20 [==============================] - 2s 92ms/step - loss: 4.5282e-04 - val_los
s: 0.0041
Epoch 7/30
20/20 [==============================] - 1s 69ms/step - loss: 4.7682e-04 - val_los
s: 0.0043
Epoch 8/30
20/20 [==============================] - 1s 73ms/step - loss: 4.4176e-04 - val_los
s: 0.0039
Epoch 9/30
20/20 [==============================] - 1s 75ms/step - loss: 4.3982e-04 - val_los
s: 0.0040
Epoch 10/30
20/20 [==============================] - 1s 68ms/step - loss: 4.3888e-04 - val_los
s: 0.0038
Epoch 11/30
20/20 [==============================] - 1s 69ms/step - loss: 4.3497e-04 - val_los
s: 0.0040
Epoch 12/30
20/20 [==============================] - 1s 68ms/step - loss: 4.3190e-04 - val_los
s: 0.0039
Epoch 13/30
20/20 [==============================] - 2s 78ms/step - loss: 4.2432e-04 - val_los
s: 0.0036
Epoch 14/30
20/20 [==============================] - 2s 104ms/step - loss: 4.2298e-04 - val_lo
ss: 0.0035
Epoch 15/30
20/20 [==============================] - 1s 70ms/step - loss: 4.2238e-04 - val_los
s: 0.0036
Epoch 16/30
20/20 [==============================] - 1s 69ms/step - loss: 4.0843e-04 - val_los
s: 0.0034
Epoch 17/30
20/20 [==============================] - 1s 69ms/step - loss: 4.0265e-04 - val_los
s: 0.0033
Epoch 18/30
20/20 [==============================] - 1s 69ms/step - loss: 4.0264e-04 - val_los
s: 0.0032
Epoch 19/30
20/20 [==============================] - 2s 86ms/step - loss: 3.9349e-04 - val_los
s: 0.0032
Epoch 20/30
20/20 [==============================] - 2s 103ms/step - loss: 4.0123e-04 - val_lo
ss: 0.0030
Epoch 21/30
20/20 [==============================] - 2s 85ms/step - loss: 3.9196e-04 - val_los
s: 0.0031
Epoch 22/30
```

```
20/20 [==============================] - 2s 100ms/step - loss: 3.8135e-04 - val_lo
ss: 0.0032
Epoch 23/30
20/20 [==============================] - 1s 70ms/step - loss: 3.8383e-04 - val_los
s: 0.0039
Epoch 24/30
20/20 [==============================] - 1s 69ms/step - loss: 4.1261e-04 - val_los
s: 0.0032
Epoch 25/30
20/20 [==============================] - 1s 69ms/step - loss: 3.6400e-04 - val_los
s: 0.0030
Epoch 26/30
20/20 [==============================] - 1s 70ms/step - loss: 3.5467e-04 - val_los
s: 0.0028
Epoch 27/30
20/20 [==============================] - 1s 70ms/step - loss: 3.5725e-04 - val_los
s: 0.0027
Epoch 28/30
20/20 [==============================] - 1s 71ms/step - loss: 3.4787e-04 - val_los
s: 0.0029
Epoch 29/30
20/20 [==============================] - 1s 67ms/step - loss: 3.4969e-04 - val_los
s: 0.0034
Epoch 30/30
20/20 [==============================] - 2s 101ms/step - loss: 3.5000e-04 - val_lo
ss: 0.0026
```

Out[31]:

```
<keras.src.callbacks.History at 0x7f2c5649dc00>
```

Prediction

In [32]:

```
# Prediction of Close value Prices
X_predict = my_model.predict(X_train)
y_predict = my_model.predict(X_test)
```

```
40/40 [==============================] - 1s 16ms/step
12/12 [==============================] - 0s 15ms/step
```

In [33]:

```
# Inverse Transformation
X_predict = scaler.inverse_transform(X_predict)
y_predict = scaler.inverse_transform(y_predict)
```

In [34]:

```
# Reshaping train and test values
X_train =X_train.reshape(X_train.shape[0],X_train.shape[1])
X_test = X_test.reshape(X_test.shape[0],X_test.shape[1])
y_train =y_train.reshape(-1,1)
ytest = ytest.reshape(-1,1)
# Inverse Transformation
X_test=scaler.inverse_transform(X_test)
X_train=scaler.inverse_transform(X_train)
ytest=scaler.inverse_transform(ytest)
y_train=scaler.inverse_transform(y_train)
```

In [35]:

```
# Length of X_train and X_test
lentrain=len(X_train)
lentest=len(X_test)
```

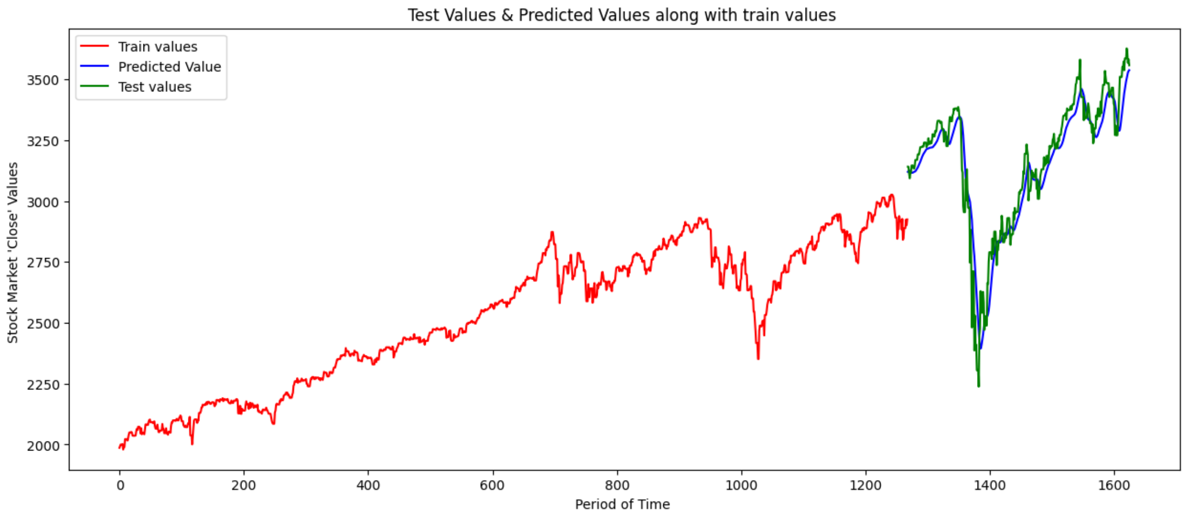
In [36]:

```
# Plotting Close value Price including the Predicted and Actual values
plt.figure(figsize=(15,6))
plt.plot(np.arange(0, lentrain), y_train, 'r', label="Train values")

plt.plot(np.arange(lentrain, lentrain + lentest), y_predict, 'b', label="Predicted
```

```
plt.plot(np.arange(lentrain, lentrain + lentest), ytest, 'g', label="Test values")
plt.legend(loc="best")

plt.xlabel("Period of Time ")
plt.ylabel("Stock Market 'Close' Values ")
plt.title("Test Values & Predicted Values along with train values ")
```

Out[36]:

```
Text(0.5, 1.0, 'Test Values & Predicted Values along with train values ')
```



Test the model

In [37]:

```
# Find Mean Sqaured Error
from sklearn.metrics import mean_squared_error , r2_score
mean_squared_error(ytest, y_predict,squared=False)
```

Out[37]:

```
91.62134192901108
```

In [38]:

```
# Coefficient of Determination or R Squared Value (r2)
r2_score(ytest, y_predict)
```

Out[38]:

```
0.889365381160802
```

--------------------THE END---------------------