

```
In [2]: # First we will import the necessary Library

import os
import pandas as pd
import numpy as np
import math
import datetime as dt
import matplotlib as plt

In [3]: # For Evolution we will use these library

from sklearn.metrics import mean_squared_error, mean_absolute_error, explained_variance_score, r2_score
from sklearn.metrics import mean_squared_error, mean_absolute_error, explained_variance_score, r2_score
from sklearn.preprocessing import MinMaxScaler

C:\Users\DELL\anaconda3\lib\site-packages\scipy\_init_.py:155: UserWarning: A NumPy version >=1.18.5 and <1.25.0 is required for this version of SciPy (detected version 1.26.4)
warnings.warn(f"A NumPy version >={np.minversion} and <={np.maxversion}")

In [4]: # For model building we will use these library

import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.layers import LSTM

WARNING:tensorflow:From C:\Users\DELL\anaconda3\lib\site-packages\keras\src\losses.py:2976: The name tf.losses.sparse_softmax_cross_entropy is deprecated. Please use tf.compat.v1.losses.softmax_cross_entropy instead.

In [5]: # For Plotting we will use these library import matplotlib.pyplot as plt

from itertools import cycle
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots

In [6]: df = pd.read_csv('btc.csv')

In [7]: df.shape

Out[7]: (2713, 7)

In [8]: df.head()

Out[8]:
   Date      Open      High      Low      Close  Adj Close  Volume
0  2014-09-17  465.864014  468.174011  452.421997  457.334015  457.334015  21056800
1  2014-09-18  456.859985  456.859985  413.104004  424.440002  424.440002  34483200
2  2014-09-19  424.102997  427.834991  384.532013  394.795990  394.795990  37919700
3  2014-09-20  394.673004  423.295990  389.882996  408.903992  408.903992  36863600
4  2014-09-21  408.084991  412.425995  393.181000  398.821014  398.821014  26580100

In [9]: df.tail()

Out[9]:
   Date      Open      High      Low      Close  Adj Close  Volume
2708  2022-02-15  42586.464844  44667.218750  42491.035156  44575.203125  44575.203125  22721659051
2709  2022-02-16  44578.277344  44578.277344  43456.691406  43961.859375  43961.859375  19792547657
2710  2022-02-17  43937.070313  44132.972656  40249.371094  40538.011719  40538.011719  26246662813
2711  2022-02-18  40562.132613  40929.152344  39637.617188  40030.976563  40030.976563  23310007704
2712  2022-02-19  40022.132813  40246.027344  40010.867188  40126.429688  40126.429688  22263900160

In [10]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2713 entries, 0 to 2712
Data columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
--  --
 0   Date       2713 non-null    object
 1   Open       2713 non-null    float64
 2   High       2713 non-null    float64
 3   Low        2713 non-null    float64
 4   Close      2713 non-null    float64
 5   Adj Close  2713 non-null    float64
 6   Volume     2713 non-null    int64
dtypes: float64(6), int64(1), object(1)
memory usage: 148.5+ KB

In [11]: df.describe()

Out[11]:
   Open      High      Low      Close  Adj Close  Volume
count  2713.000000  2713.000000  2713.000000  2713.000000  2713.000000  2.713000e+03
mean   11311.041069  11614.292482  10975.555057  11323.914637  11323.914637  1.470462e+10
std    16106.428891  16537.390649  15608.572560  16110.365010  16110.365010  2.001627e+10
min     176.897003   211.731003   171.509995   178.102997   178.102997  5.914570e+06
25%    606.396973   609.260986   604.109985   606.718994   606.718994  7.991080e+07
50%    6301.569824   6434.617676   6214.220215  6317.609863  6317.609863  5.088183e+09
75%    10452.399414  10762.644531  10202.387695  10462.259766  10462.259766  2.456992e+10
max    67549.734375  68789.625000  68382.062500  67566.828125  67566.828125  3.509679e+11

In [12]: df.isnull().values.sum()

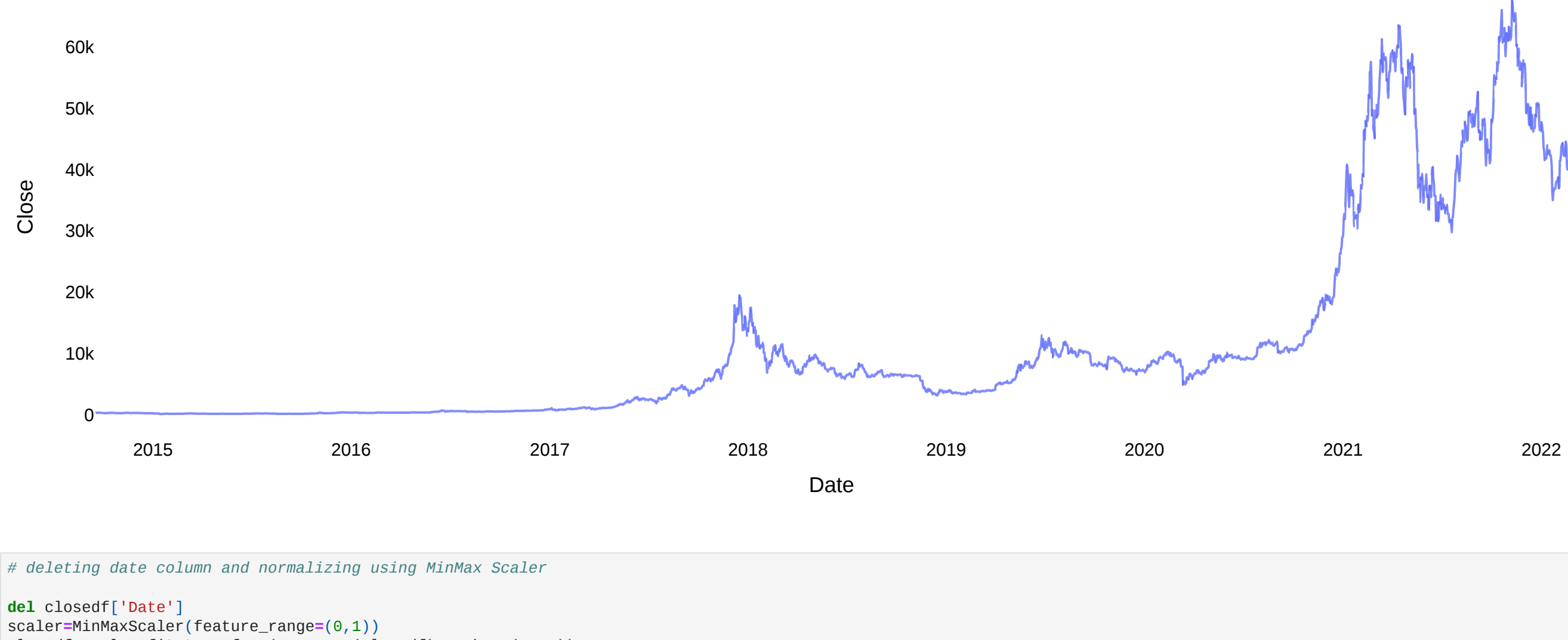
Out[12]: 0

In [13]: # Lets First Take all the Close Price
closedrf = df[['Date','Close']]
print("Shape of close dataframe:", closedrf.shape)

Shape of close dataframe: (2713, 2)

In [14]: fig = px.line(closedrf, x=closedrf.Date, y=closedrf.Close, labels={'date':'Date','close':'Close Stock'})
fig.update_traces(marker_line_width=3, opacity=0.8, marker_line_color='orange')
fig.update_layout(title text="Whole period of timeframe of Bitcoin close price 2014-2022", plot_bgcolor='white',
                    font_size=15, font_color='black')
fig.update_xaxes(showgrid=False)
fig.update_yaxes(showgrid=False)
fig.show()
```

Whole period of timeframe of Bitcoin close price 2014-2022



```
In [15]: # Deleting date column and normalizing using MinMax Scaler

del closedrf['Date']
scaler=MinMaxScaler(feature_range=(0,1))
closedrf=scaler.fit_transform(np.array(closedrf).reshape(-1,1))

In [16]: closedrf.shape

Out[16]: (2713, 1)

In [17]: # We take training set as 80% and 40% testing set

training_size = int(len(closedrf)*0.80)
test_size = len(closedrf) - training_size
train_data, test_data = closedrf[0:training_size,:], closedrf[training_size:len(closedrf),:]
print("train_data: ", train_data.shape)
print("test_data: ", test_data.shape)

train_data: (1627, 1)
test_data: (1086, 1)

In [18]: def create_dataset(dataset, time_step=1):
    dataX = []
    for i in range(len(dataset)-time_step-1):
        a = dataset[i:(i+time_step), 0] ##i=0, 0,1,2,3-----99 100
        dataX.append(a)
        dataY.append(dataset[i + time_step, 0])
    return np.array(dataX), np.array(dataY)

In [19]: time_step = 20
X_train, y_train = create_dataset(train_data, time_step)
X_test, y_test = create_dataset(test_data, time_step)

print("X_train: ", X_train.shape)
print("y_train: ", y_train.shape)
print("X_test: ", X_test.shape)
print("y_test: ", y_test.shape)

X_train: (1086, 20)
y_train: (1086,)
X_test: (1086, 20)
y_test: (1086,)

In [20]: # 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)

print("X_train: ", X_train.shape)
print("X_test: ", X_test.shape)

X_train: (1086, 20, 1)
X_test: (1086, 20, 1)

In [21]: model=Sequential()

model.add(LSTM(10,input_shape=(None,1),activation="relu"))

model.add(Dense(1))

model.compile(loss='mean_squared_error',optimizer="adam")

WARNING:tensorflow:From C:\Users\DELL\anaconda3\lib\site-packages\keras\src\backend.py:873: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\DELL\anaconda3\lib\site-packages\keras\src\optimizers\_init_.py:389: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

In [22]: history = model.fit(X_train,y_train,validation_data=(X_test,y_test),epochs=150,batch_size=32,verbose=1)

Epoch 1/150
WARNING:tensorflow:From C:\Users\DELL\anaconda3\lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.
51/51 [=====] - 2s 11ms/step - loss: 0.0014 - val_loss: 0.0436
Epoch 2/150
51/51 [=====] - 0s 7ms/step - loss: 3.4160e-04 - val_loss: 0.0136
Epoch 3/150
51/51 [=====] - 0s 6ms/step - loss: 5.7750e-05 - val_loss: 0.0144
Epoch 4/150
51/51 [=====] - 0s 6ms/step - loss: 5.2267e-05 - val_loss: 0.0155
Epoch 5/150
51/51 [=====] - 0s 6ms/step - loss: 5.2616e-05 - val_loss: 0.0078
Epoch 6/150
51/51 [=====] - 0s 6ms/step - loss: 5.3882e-05 - val_loss: 0.0057
Epoch 7/150
51/51 [=====] - 0s 6ms/step - loss: 5.3832e-05 - val_loss: 0.0046
Epoch 8/150
51/51 [=====] - 0s 7ms/step - loss: 5.1356e-05 - val_loss: 0.0021
Epoch 9/150
51/51 [=====] - 0s 6ms/step - loss: 4.9432e-05 - val_loss: 0.0029
Epoch 10/150
51/51 [=====] - 0s 6ms/step - loss: 5.1422e-05 - val_loss: 0.0018
Epoch 11/150
51/51 [=====] - 0s 6ms/step - loss: 4.7514e-05 - val_loss: 0.0014
Epoch 12/150
51/51 [=====] - 0s 6ms/step - loss: 4.6319e-05 - val_loss: 0.0011
Epoch 13/150
51/51 [=====] - 0s 7ms/step - loss: 4.5612e-05 - val_loss: 0.0012
Epoch 14/150
51/51 [=====] - 0s 6ms/step - loss: 4.4934e-05 - val_loss: 0.0014
Epoch 15/150
51/51 [=====] - 0s 6ms/step - loss: 4.5411e-05 - val_loss: 0.0012
Epoch 16/150
51/51 [=====] - 0s 6ms/step - loss: 4.4032e-05 - val_loss: 0.0011
Epoch 17/150
51/51 [=====] - 0s 5ms/step - loss: 4.3095e-05 - val_loss: 0.0011
Epoch 18/150
51/51 [=====] - 0s 7ms/step - loss: 4.1808e-05 - val_loss: 0.0020
Epoch 19/150
51/51 [=====] - 0s 8ms/step - loss: 4.4354e-05 - val_loss: 0.0026
Epoch 20/150
51/51 [=====] - 0s 7ms/step - loss: 4.1456e-05 - val_loss: 0.0042
Epoch 21/150
51/51 [=====] - 0s 7ms/step - loss: 3.9440e-05 - val_loss: 0.0028
Epoch 22/150
51/51 [=====] - 0s 7ms/step - loss: 3.9372e-05 - val_loss: 0.0029
Epoch 23/150
51/51 [=====] - 0s 6ms/step - loss: 3.8021e-05 - val_loss: 0.0038
Epoch 24/150
51/51 [=====] - 0s 6ms/step - loss: 3.8789e-05 - val_loss: 0.0044
Epoch 25/150
51/51 [=====] - 0s 7ms/step - loss: 3.7419e-05 - val_loss: 0.0049
Epoch 26/150
51/51 [=====] - 0s 6ms/step - loss: 3.7387e-05 - val_loss: 0.0052
Epoch 27/150
51/51 [=====] - 0s 6ms/step - loss: 3.5654e-05 - val_loss: 0.0062
Epoch 28/150
51/51 [=====] - 0s 7ms/step - loss: 3.6820e-05 - val_loss: 0.0060
Epoch 29/150
51/51 [=====] - 0s 6ms/step - loss: 3.7314e-05 - val_loss: 0.0075
Epoch 30/150
51/51 [=====] - 0s 7ms/step - loss: 3.4327e-05 - val_loss: 0.0074
Epoch 31/150
51/51 [=====] - 0s 7ms/step - loss: 3.4192e-05 - val_loss: 0.0065
Epoch 32/150
51/51 [=====] - 0s 6ms/step - loss: 3.4040e-05 - val_loss: 0.0062
Epoch 33/150
51/51 [=====] - 0s 6ms/step - loss: 3.2595e-05 - val_loss: 0.0077
Epoch 34/150
51/51 [=====] - 0s 6ms/step - loss: 3.2191e-05 - val_loss: 0.0069
Epoch 35/150
51/51 [=====] - 0s 7ms/step - loss: 3.1684e-05 - val_loss: 0.0060
Epoch 36/150
51/51 [=====] - 0s 6ms/step - loss: 3.1640e-05 - val_loss: 0.0057
Epoch 37/150
51/51 [=====] - 0s 6ms/step - loss: 3.0677e-05 - val_loss: 0.0050
Epoch 38/150
51/51 [=====] - 0s 7ms/step - loss: 2.9765e-05 - val_loss: 0.0051
Epoch 39/150
51/51 [=====] - 0s 7ms/step - loss: 3.2827e-05 - val_loss: 0.0047
Epoch 40/150
51/51 [=====] - 0s 8ms/step - loss: 2.9310e-05 - val_loss: 0.0032
Epoch 41/150
51/51 [=====] - 0s 7ms/step - loss: 2.9874e-05 - val_loss: 0.0031
Epoch 42/150
51/51 [=====] - 0s 6ms/step - loss: 2.8639e-05 - val_loss: 0.0034
Epoch 43/150
51/51 [=====] - 0s 7ms/step - loss: 2.8197e-05 - val_loss: 0.0037
Epoch 44/150
51/51 [=====] - 0s 7ms/step - loss: 3.0081e-05 - val_loss: 0.0028
Epoch 45/150
51/51 [=====] - 0s 7ms/step - loss: 2.9428e-05 - val_loss: 0.0022
Epoch 46/150
51/51 [=====] - 0s 7ms/step - loss: 2.7525e-05 - val_loss: 0.0023
Epoch 47/150
51/51 [=====] - 0s 7ms/step - loss: 2.7480e-05 - val_loss: 0.0017
Epoch 48/150
51/51 [=====] - 0s 6ms/step - loss: 2.8058e-05 - val_loss: 0.0027
Epoch 49/150
51/51 [=====] - 0s 7ms/step - loss: 2.7337e-05 - val_loss: 0.0020
Epoch 50/150
51/51 [=====] - 0s 7ms/step - loss: 2.7899e-05 - val_loss: 0.0018
Epoch 51/150
51/51 [=====] - 0s 7ms/step - loss: 2.7759e-05 - val_loss: 0.0023
Epoch 52/150
51/51 [=====] - 0s 7ms/step - loss: 2.6649e-05 - val_loss: 0.0013
Epoch 53/150
51/51 [=====] - 0s 7ms/step - loss: 2.6430e-05 - val_loss: 0.0018
Epoch 54/150
51/51 [=====] - 0s 7ms/step - loss: 2.8175e-05 - val_loss: 0.0014
Epoch 55/150
51/51 [=====] - 0s 7ms/step - loss: 2.6214e-05 - val_loss: 0.0013
Epoch 56/150
51/51 [=====] - 0s 7ms/step - loss: 2.5394e-05 - val_loss: 0.0011
Epoch 57/150
51/51 [=====] - 0s 6ms/step - loss: 2.7095e-05 - val_loss: 0.0014
Epoch 58/150
51/51 [=====] - 0s 6ms/step - loss: 2.5821e-05 - val_loss: 0.0020
Epoch 59/150
51/51 [=====] - 0s 6ms/step - loss: 2.7554e-05 - val_loss: 0.0016
Epoch 60/150
51/51 [=====] - 0s 7ms/step - loss: 2.4879e-05 - val_loss: 0.0011
Epoch 61/150
51/51 [=====] - 0s 5ms/step - loss: 2.4773e-05 - val_loss: 0.0013
Epoch 62/150
51/51 [=====] - 0s 6ms/step - loss: 2.4621e-05 - val_loss: 0.0015
Epoch 63/150
51/51 [=====] - 0s 7ms/step - loss: 2.4394e-05 - val_loss: 0.0017
Epoch 64/150
51/51 [=====] - 0s 5ms/step - loss: 2.5299e-05 - val_loss: 0.0017
Epoch 65/150
51/51 [=====] - 0s 5ms/step - loss: 2.4652e-05 - val_loss: 0.0020
Epoch 66/150
51/51 [=====] - 0s 6ms/step - loss: 2.4991e-05 - val_loss: 0.0022
Epoch 67/150
51/51 [=====] - 0s 6ms/step - loss: 2.6851e-05 - val_loss: 0.0031
Epoch 68/150
51/51 [=====] - 0s 5ms/step - loss: 2.3870e-05 - val_loss: 0.0020
Epoch 69/150
51/51 [=====] - 0s 5ms/step - loss: 2.6786e-05 - val_loss: 0.0018
Epoch 70/150
51/51 [=====] - 0s 5ms/step - loss: 2.4309e-05 - val_loss: 0.0027
Epoch 71/150
51/51 [=====] - 0s 7ms/step - loss: 2.3517e-05 - val_loss: 0.0028
Epoch 72/150
51/51 [=====] - 0s 6ms/step - loss: 2.3076e-05 - val_loss: 0.0021
Epoch 73/150
51/51 [=====] - 0s 6ms/step - loss: 3.0740e-05 - val_loss: 0.0030
Epoch 74/150
51/51 [=====] - 0s 6ms/step - loss: 2.3578e-05 - val_loss: 0.0018
Epoch 75/150
51/51 [=====] - 0s 6ms/step - loss: 2.4079e-05 - val_loss: 0.0036
Epoch 76/150
51/51 [=====] - 0s 6ms/step - loss: 2.3535e-05 - val_loss: 0.0038
Epoch 77/150
51/51 [=====] - 0s 6ms/step - loss: 2.6323e-05 - val_loss: 0.0035
Epoch 78/150
51/51 [=====] - 0s 6ms/step - loss: 2.3816e-05 - val_loss: 0.0040
Epoch 79/150
51/51 [=====] - 0s 6ms/step - loss: 2.2556e-05 - val_loss: 0.0035
Epoch 80/150
51/51 [=====] - 0s 6ms/step - loss: 2.3314e-05 - val_loss: 0.0039
Epoch 81/150
51/51 [=====] - 0s 6ms/step - loss: 2.3640e-05 - val_loss: 0.0035
Epoch 82/150
51/51 [=====] - 0s 6ms/step - loss: 2.2560e-05 - val_loss: 0.0047
Epoch 83/150
51/51 [=====] - 0s 6ms/step - loss: 2.2884e-05 - val_loss: 0.0037
Epoch 84/150
51/51 [=====] - 0s 7ms/step - loss: 2.2936e-05 - val_loss: 0.0040
Epoch 85/150
51/51 [=====] - 0s 6ms/step - loss: 2.2116e-05 - val_loss: 0.0049
Epoch 86/150
51/51 [=====] - 0s 7ms/step - loss: 2.1802e-05 - val_loss: 0.0039
Epoch 87/150
51/51 [=====] - 0s 7ms/step - loss: 2.1796e-05 - val_loss: 0.0047
Epoch 88/150
51/51 [=====] - 0s 7ms/step - loss: 2.1569e-05 - val_loss: 0.0051
Epoch 89/150
51/51 [=====] - 0s 7ms/step - loss: 2.2911e-05 - val_loss: 0.0060
Epoch 90/150
51/51 [=====] - 0s 7ms/step - loss: 2.2433e-05 - val_loss: 0.0053
Epoch 91/150
51/51 [=====] - 0s 6ms/step - loss: 2.1232e-05 - val_loss: 0.0063
Epoch 92/150
51/51 [=====] - 0s 5ms/step - loss: 2.1586e-05 - val_loss: 0.0063
Epoch 93/150
51/51 [=====] - 0s 6ms/step - loss: 2.1134e-05 - val_loss: 0.0054
Epoch 94/150
51/51 [=====] - 0s 6ms/step - loss: 2.1395e-05 - val_loss: 0.0088
Epoch 95/150
51/51 [=====] - 0s 5ms/step - loss: 2.1135e-05 - val_loss: 0.0077
Epoch 96/150
51/51 [=====] - 0s 5ms/step - loss: 2.1092e-05 - val_loss: 0.0085
Epoch 97/150
51/51 [=====] - 0s 5ms/step - loss: 2.1070e-05 - val_loss: 0.0078
Epoch 98/150
51/51 [=====] - 0s 6ms/step - loss: 2.0620e-05 - val_loss: 0.0070
Epoch 99/150
51/51 [=====] - 0s 5ms/step - loss: 2.0039e-05 - val_loss: 0.0066
Epoch 100/150
51/51 [=====] - 0s 6ms/step - loss: 2.1449e-05 - val_loss: 0.0054
Epoch 101/150
51/51 [=====] - 0s 6ms/step - loss: 2.1337e-05 - val_loss: 0.0065
Epoch 102/150
51/51 [=====] - 0s 6ms/step - loss: 2.1476e-05 - val_loss: 0.0060
Epoch 103/150
51/51 [=====] - 0s 6ms/step - loss: 2.1125e-05 - val_loss: 0.0061
Epoch 104/150
51/51 [=====] - 0s 6ms/step - loss: 2.3646e-05 - val_loss: 0.0069
Epoch 105/150
51/51 [=====] - 0s 7ms/step - loss: 2.1293e-05 - val_loss: 0.0073
Epoch 106/150
51/51 [=====] - 0s 6ms/step - loss: 2.0687e-05 - val_loss: 0.0063
Epoch 107/150
51/51 [=====] - 0s 6ms/step - loss: 2.0357e-05 - val_loss: 0.0070
Epoch 108/150
51/51 [=====] - 0s 6ms/step - loss: 2.0562e-05 - val_loss: 0.0077
Epoch 109/150
51/51 [=====] - 0s 5ms/step - loss: 2.0335e-05 - val_loss: 0.0066
Epoch 110/150
51/51 [=====] - 0s 5ms/step - loss: 2.1551e-05 - val_loss: 0.0072
Epoch 111/150
51/51 [=====] - 0s 5ms/step - loss: 1.9950e-05 - val_loss: 0.0070
Epoch 112/150
51/51 [=====] - 0s 6ms/step - loss: 2.0169e-05 - val_loss: 0.0068
Epoch 113/150
51/51 [=====] - 0s 5ms/step - loss: 1.9600e-05 - val_loss: 0.0067
Epoch 114/150
51/51 [=====] - 0s 5ms/step - loss: 1.9578e-05 - val_loss: 0.0073
Epoch 115/150
51/51 [=====] - 0s 6ms/step - loss: 2.1301e-05 - val_loss: 0.0073
Epoch 116/150
51/51 [=====] - 0s 5ms/step - loss: 1.9898e-05 - val_loss: 0.0063
Epoch 117/150
51/51 [=====] - 0s 5ms/step - loss: 1.9482e-05 - val_loss: 0.0079
Epoch 118/150
51/51 [=====] - 0s 5ms/step - loss: 2.0049e-05 - val_loss: 0.0077
Epoch 119/150
51/51 [=====] - 0s 6ms/step - loss: 1.9590e-05 - val_loss: 0.0082
Epoch 120/150
51/51 [=====] - 0s 5ms/step - loss: 1.9921e-05 - val_loss: 0.0093
Epoch 121/150
51/51 [=====] - 0s 5ms/step - loss: 2.0924e-05 - val_loss: 0.0087
Epoch 122/150
51/51 [=====] - 0s 6ms/step - loss: 2.0343e-05 - val_loss: 0.0086
Epoch 123/150
51/51 [=====] - 0s 6ms/step - loss: 2.0100e-05 - val_loss: 0.0086
Epoch 124/150
51/51 [=====] - 0s 5ms/step - loss: 2.1359e-05 - val_loss: 0.0091
Epoch 125/150
51/51 [=====] - 0s 6ms/step - loss: 2.2595e-05 - val_loss: 0.0095
Epoch 126/150
51/51 [=====] - 0s 5ms/step - loss: 1.9373e-05 - val_loss: 0.0092
Epoch 127/150
51/51 [=====] - 0s 6ms/step - loss: 1.9244e-05 - val_loss: 0.0101
Epoch 128/150
51/51 [=====] - 0s 6ms/step - loss: 2.0523e-05 - val_loss: 0.0101
Epoch 129/150
51/51 [=====] - 0s 6ms/step - loss: 1.9571e-05 - val_loss: 0.0094
Epoch 130/150
51/51 [=====] - 0s 6ms/step - loss: 1.9571e-05 - val_loss: 0.0099
Epoch 131/150
51/51 [=====] - 0s 6ms/step - loss: 1.8706e-05 - val_loss: 0.0095
Epoch 132/150
51/51 [=====] - 0s 6ms/step - loss: 1.9619e-05 - val_loss: 0.0097
Epoch 133/150
51/51 [=====] - 0s 7ms/step - loss: 1.8667e-05 - val_loss: 0.0105
Epoch 134/150
51/51 [=====] - 0s 6ms/step - loss: 1.8528e-05 - val_loss: 0.0095
Epoch 135/150
51/51 [=====] - 0s 5ms/step - loss: 1.9352e-05 - val_loss: 0.0098
Epoch 136/150
51/51 [=====] - 0s 6ms/step - loss: 1.8748e-05 - val_loss: 0.0099
Epoch 137/150
51/51 [=====] - 0s 6ms/step - loss: 1.8748e-05 - val_loss: 0.0102
Epoch 138/150
51/51 [=====] - 0s 6ms/step - loss: 1.8533e-05 - val_loss: 0.0103
Epoch 139/150
51/51 [=====] - 0s 6ms/step - loss: 1.9671e-05 - val_loss: 0.0092
Epoch 140/150
51/51 [=====] - 0s 6ms/step - loss: 2.0600e-05 - val_loss: 0.0107
Epoch 141/150
51/51 [=====] - 0s 6ms/step - loss: 1.9540e-05 - val_loss: 0.0122
Epoch 142/150
51/51 [=====] - 0s 6ms/step - loss: 1.8781e-05 - val_loss: 0.0111
Epoch 143/150
51/51 [=====] - 0s 6ms/step - loss: 1.8399e-05 - val_loss: 0.0102
Epoch 144/150
51/51 [=====] - 0s 6ms/step - loss: 1.9294e-05 - val_loss: 0.0100
Epoch 145/150
51/51 [=====] - 0s 6ms/step - loss: 1.9000e-05 - val_loss: 0.0106
Epoch 146/150
51/51 [=====] - 0s 6ms/step - loss: 1.9566e-05 - val_loss: 0.0119
Epoch 147/150
51/51 [=====] - 0s 6ms/step - loss: 1.9412e-05 - val_loss: 0.0107
Epoch 148/150
51/51 [=====] - 0s 6ms/step - loss: 1.8421e-05 - val_loss: 0.0107
Epoch 149/150
51/51 [=====] - 0s 6ms/step - loss: 1.7817e-05 - val_loss: 0.0120
Epoch 150/150
51/51 [=====] - 0s 6ms/step - loss: 1.8533e-05 - val_loss: 0.0117
Epoch 151/150
51/51 [=====] - 0s 6ms/step - loss: 1.8433e-05 - val_loss: 0.0117

In [23]: ## Lets Do the prediction and check performance metrics
train_predict=model.predict(X_train)
test_predict=model.predict(X_test)
train_predict_shape, test_predict_shape

Out[23]: ((1086, 1), (1086, 1))

In [24]: train_predict = scaler.inverse_transform(train_predict)
test_predict = scaler.inverse_transform(test_predict)
original_y_train = scaler.inverse_transform(y_train.reshape(-1,1))
original_y_test = scaler.inverse_transform(y_test.reshape(-1,1))

In [28]: # Evaluation metrics RMSE
print("Train data RMSE: ", math.sqrt(mean_squared_error(original_y_train,train_predict)))
print(".....")
print("Test data RMSE: ", math.sqrt(mean_squared_error(original_ytest,test_predict)))
.....
Train data RMSE: 280.9547894583391
Test data RMSE: 7290.367960666792

In [ ]:
```