```
In [116... import pyforest
In [117... df = pd.read_csv("HCLTECH.csv")
```

In [118...

Out[118...

df

		Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close	VWA
	0	2000- 01-11	HCLTECH	EQ	580.00	1550.0	1725.00	1492.00	1560.00	1554.45	1582.7
	1	2000- 01-12	HCLTECH	EQ	1554.45	1560.0	1678.85	1560.00	1678.85	1678.85	1657.0
	2	2000- 01-13	HCLTECH	EQ	1678.85	1790.0	1813.20	1781.00	1813.20	1813.20	1804.6
	3	2000- 01-14	HCLTECH	EQ	1813.20	1958.3	1958.30	1835.00	1958.30	1958.30	1939.9
	4	2000- 01-17	HCLTECH	EQ	1958.30	2115.0	2115.00	1801.65	1801.65	1801.65	1990.5
	•••	•••		•••	•••	•••	•••	•••	•••	•••	
Ę	5295	2021- 04- 26	HCLTECH	EQ	955.65	940.0	954.50	923.05	930.00	928.80	931.7
Ę	5296	2021- 04-27	HCLTECH	EQ	928.80	931.0	938.55	923.40	930.30	928.85	928.0
į	5297	2021- 04- 28	HCLTECH	EQ	928.85	931.2	935.85	921.75	925.90	923.80	926.6
Ę	5298	2021- 04- 29	HCLTECH	EQ	923.80	929.7	929.70	907.10	910.30	909.55	914.3
Ę	5299	2021- 04- 30	HCLTECH	EQ	909.55	905.0	915.00	895.40	900.10	898.95	904.9

5300 rows × 15 columns

```
In [119... df.index
Out[119... RangeIndex(start=0, stop=5300, step=1)
In [120... df = df[(df['Date'] > '2014-12-31')]
In [121... df
```

Out[121...

••		Date	Symbol	Series	Prev Close	Open	High	Low	Last	Close	VW
	3734	2015- 01-01	HCLTECH	EQ	1596.90	1599.00	1611.65	1585.60	1605.50	1606.80	1604.
	3735	2015- 01- 02	HCLTECH	EQ	1606.80	1602.05	1618.95	1600.05	1607.00	1605.25	1608.
	3736	2015- 01- 05	HCLTECH	EQ	1605.25	1615.00	1615.00	1568.70	1581.00	1578.25	1586.
	3737	2015- 01- 06	HCLTECH	EQ	1578.25	1574.00	1574.40	1522.65	1543.05	1536.10	1553.
	3738	2015- 01-07	HCLTECH	EQ	1536.10	1539.50	1548.00	1492.70	1500.00	1499.60	1517.
	•••										
	5295	2021- 04- 26	HCLTECH	EQ	955.65	940.00	954.50	923.05	930.00	928.80	931.
	5296	2021- 04- 27	HCLTECH	EQ	928.80	931.00	938.55	923.40	930.30	928.85	928.
	5297	2021- 04- 28	HCLTECH	EQ	928.85	931.20	935.85	921.75	925.90	923.80	926.
	5298	2021- 04- 29	HCLTECH	EQ	923.80	929.70	929.70	907.10	910.30	909.55	914.
	5299	2021- 04- 30	HCLTECH	EQ	909.55	905.00	915.00	895.40	900.10	898.95	904.

1566 rows × 15 columns

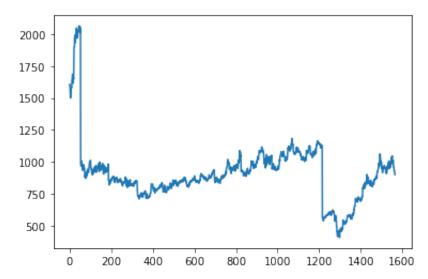
```
In [122... df1 = df.reset_index()
In [123... df1
```

**Prev** Out[123... index **Date Symbol Series** Open High Close Low Last Close 2015-3734 **HCLTECH** 0 EQ 1596.90 1599.00 1611.65 1585.60 1605.50 1606.80 01-01 2015-3735 01-**HCLTECH** 1606.80 1602.05 1618.95 1600.05 1607.00 1605.25 02 2015-3736 01-**HCLTECH** EQ 1605.25 1615.00 1615.00 1568.70 1581.00 1578.25 05 2015-3 3737 01-**HCLTECH** EQ 1578.25 1574.00 1574.40 1522.65 1543.05 1536.10 06 2015-3738 1539.50 1548.00 1492.70 1500.00 1499.60 4 **HCLTECH** EQ 1536.10 01-07 2021-954.50 1561 5295 04-**HCLTECH** EQ 955.65 940.00 923.05 930.00 928.80 26 2021-5296 04- HCLTECH 928.80 931.00 938.55 923.40 930.30 928.85 1562 EQ 27 2021-04- HCLTECH 1563 5297 928.85 931.20 935.85 925.90 923.80 EQ 921.75 28 2021-1564 5298 04- HCLTECH 923.80 929.70 929.70 907.10 910.30 909.55 29 2021-5299 04- HCLTECH 909.55 905.00 915.00 895.40 898.95 1565 EQ 900.10 30

1566 rows × 16 columns

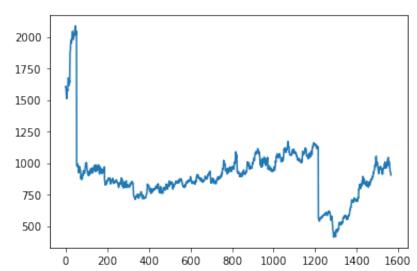
In [124... plt.plot(df1['Close'])

Out[124... [<matplotlib.lines.Line2D at 0x7fcf99e08370>]



In [125... plt.plot(df1['VWAP'])

Out[125... [<matplotlib.lines.Line2D at 0x7fcf9973d8b0>]



```
df1 = df1['VWAP']
In [126...
           df1
In [127...
                   1604.76
          0
Out[127...
          1
                   1608.73
          2
                   1586.98
          3
                   1553.35
                   1517.47
          1561
                    931.70
          1562
                    928.06
          1563
                    926.63
          1564
                    914.34
          1565
                    904.98
          Name: VWAP, Length: 1566, dtype: float64
```

```
In [128...
          from sklearn.preprocessing import MinMaxScaler
          scaler=MinMaxScaler(feature_range=(0,1))
          df1=scaler.fit transform(np.array(df1).reshape(-1,1))
          df1
In [129...
Out[129... array([[0.71168799],
                 [0.71405879],
                 [0.70107014],
                 . . . ,
                 [0.30672304],
                 [0.29938371],
                 [0.29379412]])
          training_size=int(len(df1)*0.70)
In [130...
          test_size=len(df1)-training_size
          train_data,test_data=df1[0:training_size,:],df1[training_size:len(df1),:1]
         training_size,test_size
In [131...
Out[131... (1096, 470)
          import numpy
In [132...
          # convert an array of values into a dataset matrix
          def create dataset(dataset, time step=1):
              dataX, dataY = [], []
              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 numpy.array(dataX), numpy.array(dataY)
In [133...
         time step = 100
          X_train, y_train = create_dataset(train_data, time_step)
          X_test, ytest = create_dataset(test_data, time_step)
         X train[0].shape
In [134...
Out[134... (100,)
         X train.shape
In [135...
Out[135... (995, 100)
In [136... 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)
```

```
In [137...
       from tensorflow.keras.models import Sequential
       from tensorflow.keras.layers import Dense
       from tensorflow.keras.layers import LSTM
       from tensorflow.keras.layers import Dropout
In [138...
      model=Sequential()
       model.add(LSTM(50,return sequences=True,input shape=(100,1)))
       model.add(Dropout(0.2))
       model.add(LSTM(50,return_sequences=True))
       model.add(Dropout(0.2))
       model.add(LSTM(50))
       model.add(Dense(1))
       model.compile(loss='mean_squared_error',optimizer='adam')
      model.summary()
In [139...
      Model: "sequential 3"
      Layer (type)
                           Output Shape
                                             Param #
                       _____
      lstm_7 (LSTM)
                           (None, 100, 50)
                                             10400
      dropout_2 (Dropout)
                           (None, 100, 50)
      lstm_8 (LSTM)
                           (None, 100, 50)
                                             20200
      dropout 3 (Dropout)
                           (None, 100, 50)
      1stm 9 (LSTM)
                           (None, 50)
                                             20200
      dense_2 (Dense)
                           (None, 1)
      _____
      Total params: 50,851
      Trainable params: 50,851
      Non-trainable params: 0
      model history = model.fit(X train,y train,validation data=(X test,ytest),er
In [140...
      Epoch 1/100
      loss: 0.0067
      Epoch 2/100
      loss: 0.0084
      Epoch 3/100
      loss: 0.0080
      Epoch 4/100
      loss: 0.0070
      Epoch 5/100
      _loss: 0.0058
      Epoch 6/100
      val loss: 0.0049
      Epoch 7/100
```

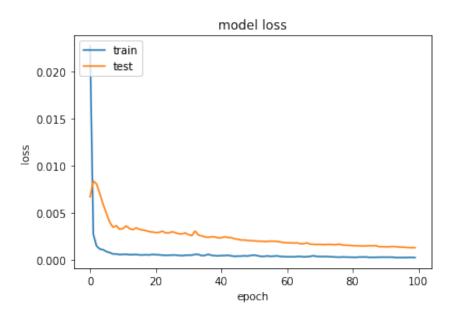
```
16/16 [============= ] - 3s 166ms/step - loss: 7.2642e-04 -
val loss: 0.0040
Epoch 8/100
val loss: 0.0034
Epoch 9/100
val loss: 0.0036
Epoch 10/100
val_loss: 0.0032
Epoch 11/100
val loss: 0.0033
Epoch 12/100
val loss: 0.0036
Epoch 13/100
val loss: 0.0033
Epoch 14/100
val loss: 0.0032
Epoch 15/100
val loss: 0.0034
Epoch 16/100
val_loss: 0.0032
Epoch 17/100
val loss: 0.0031
Epoch 18/100
val loss: 0.0031
Epoch 19/100
val loss: 0.0030
Epoch 20/100
val loss: 0.0029
Epoch 21/100
val loss: 0.0029
Epoch 22/100
val_loss: 0.0029
Epoch 23/100
val_loss: 0.0030
Epoch 24/100
val loss: 0.0028
Epoch 25/100
val loss: 0.0028
Epoch 26/100
val loss: 0.0030
Epoch 27/100
```

```
val loss: 0.0029
Epoch 28/100
val loss: 0.0027
Epoch 29/100
val loss: 0.0027
Epoch 30/100
val_loss: 0.0028
Epoch 31/100
val loss: 0.0027
Epoch 32/100
val loss: 0.0025
Epoch 33/100
val loss: 0.0030
Epoch 34/100
val loss: 0.0026
Epoch 35/100
16/16 [=============] - 3s 183ms/step - loss: 4.5899e-04 -
val loss: 0.0025
Epoch 36/100
val_loss: 0.0024
Epoch 37/100
val_loss: 0.0024
Epoch 38/100
val loss: 0.0024
Epoch 39/100
val loss: 0.0024
Epoch 40/100
val loss: 0.0023
Epoch 41/100
val loss: 0.0023
Epoch 42/100
val_loss: 0.0024
Epoch 43/100
val loss: 0.0023
Epoch 44/100
val loss: 0.0023
Epoch 45/100
val loss: 0.0022
Epoch 46/100
val loss: 0.0022
Epoch 47/100
val_loss: 0.0021
```

```
Epoch 48/100
val loss: 0.0021
Epoch 49/100
val loss: 0.0020
Epoch 50/100
val loss: 0.0020
Epoch 51/100
val loss: 0.0020
Epoch 52/100
val loss: 0.0020
Epoch 53/100
val_loss: 0.0020
Epoch 54/100
val loss: 0.0019
Epoch 55/100
16/16 [============== ] - 3s 185ms/step - loss: 3.5764e-04 -
val loss: 0.0019
Epoch 56/100
val loss: 0.0020
Epoch 57/100
val loss: 0.0020
Epoch 58/100
val loss: 0.0019
Epoch 59/100
val_loss: 0.0019
Epoch 60/100
val_loss: 0.0018
Epoch 61/100
val loss: 0.0018
Epoch 62/100
val loss: 0.0018
Epoch 63/100
val loss: 0.0018
Epoch 64/100
val_loss: 0.0018
Epoch 65/100
val loss: 0.0017
Epoch 66/100
val loss: 0.0017
Epoch 67/100
val loss: 0.0018
Epoch 68/100
```

```
val loss: 0.0016
Epoch 69/100
val loss: 0.0016
Epoch 70/100
val loss: 0.0016
Epoch 71/100
16/16 [=============] - 3s 184ms/step - loss: 3.0620e-04 -
val loss: 0.0016
Epoch 72/100
16/16 [============= ] - 3s 191ms/step - loss: 3.0371e-04 -
val loss: 0.0016
Epoch 73/100
val loss: 0.0016
Epoch 74/100
val_loss: 0.0016
Epoch 75/100
val loss: 0.0016
Epoch 76/100
val loss: 0.0016
Epoch 77/100
val loss: 0.0016
Epoch 78/100
val loss: 0.0015
Epoch 79/100
val_loss: 0.0015
Epoch 80/100
val_loss: 0.0015
Epoch 81/100
val loss: 0.0015
Epoch 82/100
val loss: 0.0015
Epoch 83/100
val loss: 0.0015
Epoch 84/100
val_loss: 0.0014
Epoch 85/100
val loss: 0.0015
Epoch 86/100
val loss: 0.0015
Epoch 87/100
val loss: 0.0015
Epoch 88/100
```

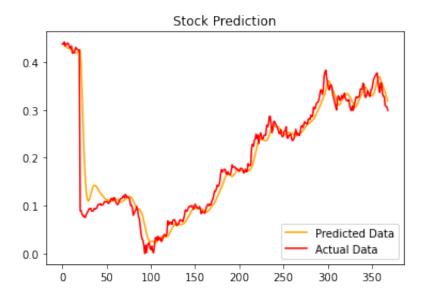
```
val loss: 0.0015
   Epoch 89/100
   val loss: 0.0014
   Epoch 90/100
   val loss: 0.0014
   Epoch 91/100
   val loss: 0.0014
   Epoch 92/100
   val loss: 0.0014
   Epoch 93/100
   val loss: 0.0014
   Epoch 94/100
   val loss: 0.0014
   Epoch 95/100
   val_loss: 0.0013
   Epoch 96/100
   val loss: 0.0013
   Epoch 97/100
   val loss: 0.0013
   Epoch 98/100
   val loss: 0.0013
   Epoch 99/100
   val loss: 0.0013
   Epoch 100/100
   val_loss: 0.0013
In [141...
   plt.plot(model_history.history['loss'])
   plt.plot(model_history.history['val_loss'])
   plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
```



```
In [142... train_predict=model.predict(X_train)
    test_predict=model.predict(X_test)

In [143... plt.plot(test_predict, color='orange', label='Predicted Data')
    plt.plot(ytest, color='red', label='Actual Data')
```

```
In [143... plt.plot(test_predict, color='orange', label='Predicted Data')
   plt.plot(ytest, color='red', label='Actual Data')
   plt.title('Stock Prediction')
   plt.legend()
   plt.show()
```



```
In [144... train_predict=scaler.inverse_transform(train_predict) test_predict=scaler.inverse_transform(test_predict)
```

```
In [
           len(test_data)
In [145...
Out[145... 470
         Taking last 100 values for future prediction
           x_input=test_data[370:].reshape(1,-1)
In [166...
           x input.shape
Out[166... (1, 100)
           test_data
In [167...
Out[167... array([[0.4060339]],
                 [0.41626357],
                 [0.41049482],
                 [0.40967669],
                  [0.40515007],
                 [0.39813919],
                 [0.40082052],
                 [0.40322715],
                 [0.40023529],
                 [0.397333],
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                 [0.36216513],
                 [0.36339532],
                 [0.36613637],
                 [0.35203698],
                 [0.35607391],
                  [0.36439858],
                 [0.37007178],
```

[0.3924421], [0.40600404], [0.39768533], [0.39483082], [0.38898444], [0.3904953], [0.39866471], [0.39438891], [0.39524884], [0.40282107], [0.40185962], [0.40267178], [0.41904045], [0.42035425], [0.409187], [0.41961374], [0.42089171], [0.41810885], [0.41368376], [0.40136396], [0.38868585], [0.38400397], [0.3888889], [0.39006533], [0.38414132], [0.3864942], [0.37630633], [0.38014619], [0.37056147], [0.37584053], [0.38347248], [0.37619884], [0.37504628], [0.39631182], [0.38687042], [0.39726731], [0.39535036], [0.39607295], [0.37965053], [0.38457129], [0.39693886], [0.40458872], [0.40449915], [0.40632651], [0.40492911], [0.4088705], [0.38974285], [0.40532922], [0.42675003], [0.42414036], [0.43033311], [0.43415505], [0.43668709], [0.4436502], [0.4410465], [0.44560894], [0.44222891], [0.4385264], [0.43768438], [0.44213336], [0.43368925],

[0.43807255], [0.43846668], [0.43991186], [0.4366632], [0.43111541], [0.42929999], [0.43373703], [0.41918975], [0.4193689], [0.41923155], [0.42488683], [0.43060184], [0.428028], [0.42660671], [0.42506002], [0.42532278], [0.0893738], [0.08942157], [0.08305565], [0.07866041], [0.07889331], [0.07534009], [0.07634933], [0.08269734], [0.0853727], [0.08953504], [0.09330921], [0.09355405], [0.09452745], [0.08855566], [0.08895577], [0.08943352], [0.09446773], [0.09295687], [0.09404374], [0.09568598], [0.10219523],[0.102243 [0.10238633], [0.10400468], [0.1009113], [0.10162194], [0.10267297], [0.10709807], [0.10867462], [0.10758776], [0.10847755], [0.1085731], [0.10437493], [0.10648297], [0.10960622], [0.11499277], [0.11467627], [0.11071697], [0.11676042], [0.11625879], [0.10871045], [0.10552749], [0.10208177],[0.10371206], [0.10828645],

[0.11381633], [0.1147121], [0.11507041], [0.11811005], [0.12051668], [0.1165335], [0.12350257], [0.12094068], [0.11650961], [0.11769799], [0.11672459], [0.11315346], [0.10094115], [0.10146667], [0.09562029], [0.07998615], [0.0841664], [0.08883037], [0.09176251], [0.09873756], [0.09046066], [0.07766312], [0.07213324], [0.05559736], [0.03983183], [0.03053376], [0.02769716], [0.01754512], [0. [0.01725847], [0.00164821], [0.01747346], [0.01917542], [0.02291973], [0.01089254], [0.00812163], [0.01556845], [0.00524323], [0.00147503], [0.01802286], [0.03244473], [0.03379436], [0.02724927], [0.03584865], [0.03104136], [0.02841975], [0.03247459], [0.02521887], [0.02895123], [0.03625473], [0.0397542], [0.03910328], [0.03635625], [0.04102022], [0.06837699], [0.06028521], [0.06513431], [0.06258435], [0.06582703], [0.06090628], [0.06986993],

[0.07054475], [0.07010881], [0.06508653], [0.05846382], [0.05938347], [0.06109738], [0.06636449], [0.070491],[0.0695176], [0.06927276], [0.06654962], [0.07246169], [0.08072068], [0.09117131], [0.08836457], [0.08897966], [0.09380487], [0.0982001], [0.09883311], [0.0979254], [0.10012899], [0.09922128], [0.09256871], [0.09645037], [0.10315669], [0.09845092], [0.09745363], [0.09430052], [0.09442593], [0.09806275], [0.09149976], [0.08322286], [0.08908118], [0.08623264], [0.08580864], [0.08411265], [0.09050844], [0.09759695], [0.1021594], [0.10314474], [0.09976471], [0.10275061], [0.10192053], [0.1104363], [0.11292654], [0.12143036], [0.13026861], [0.13007154], [0.13515951], [0.14291686], [0.14089242], [0.14221219], [0.15093697], [0.16727579], [0.17543923], [0.1707036], [0.17403585], [0.175911],[0.17588711],[0.1674848], [0.16602769],

[0.1712112], [0.16616504], [0.16556189], [0.16543648], [0.17388059], [0.1854778], [0.18058691], [0.18086161], [0.18130352], [0.17677691], [0.1778578], [0.17569004], [0.17303857], [0.17162922], [0.176968], [0.17850275], [0.17717104], [0.17435833], [0.16842237], [0.17024377], [0.17643054], [0.17068568], [0.17259665], [0.18793818], [0.18411026], [0.18378779], [0.18525685], [0.22131451], [0.22839705], [0.22448553], [0.23568264], [0.23987483], [0.24948941], [0.24031077], [0.24753067], [0.22950183], [0.24420438], [0.25213491], [0.24634825], [0.23883574], [0.2404959], [0.24708875], [0.2479248], [0.24705889], [0.2681632], [0.2646279], [0.26990099], [0.28650256], [0.28687878], [0.26932172], [0.25267835], [0.25994602], [0.27631469], [0.275825], [0.27096994], [0.26711216], [0.26265124], [0.2587636], [0.25102416], [0.25085695], [0.25862625],

[0.24647366], [0.24421035], [0.24590037], [0.25559855], [0.25684666], [0.26506384], [0.24251436], [0.24074671], [0.2474172], [0.24685585], [0.24971037], [0.24218591], [0.23591554], [0.23783248], [0.24106322], [0.25042101], [0.259737 [0.24846824], [0.25166314], [0.24739929], [0.24656324], [0.25454752], [0.26548784], [0.26726146], [0.26348131], [0.27027721], [0.27558016], [0.27284508], [0.2714656], [0.27088633], [0.28075173], [0.28123544], [0.28015455], [0.28924361], [0.28629952], [0.28659811], [0.30591088], [0.30228003], [0.30345647], [0.31268289], [0.31523284], [0.31601514], [0.32106728], [0.33185233], [0.34159232], [0.34156843], [0.33244951], [0.34258363], [0.37081228], [0.37994315], [0.38300668], [0.36635733], [0.35639638], [0.34462002], [0.34216561], [0.35124273], [0.352879], [0.34456627], [0.33055645], [0.32399345], [0.31532242],

[0.30737994], [0.299957 ], [0.31992667], [0.32954125], [0.32636426], [0.32015359], [0.32308574], [0.3303773],[0.32418455], [0.32959499], [0.3352025], [0.32490714], [0.32204665], [0.31885772], [0.31904284], [0.32174806], [0.30892663], [0.30070945], [0.29886417], [0.30851458], [0.29932997], [0.30824585], [0.31793209], [0.32659716], [0.3274989], [0.3256357], [0.32786317], [0.32931432], [0.34353315], [0.34421991], [0.34304346], [0.35586489], [0.3540017], [0.3299115], [0.32614927], [0.33104017], [0.3399023], [0.33695224], [0.32978012], [0.328323], [0.34230296], [0.34378994], [0.35314176], [0.36408208], [0.36785028], [0.37124822], [0.37516572], [0.37739319], [0.36007501], [0.34517539], [0.3367492], [0.35649193], [0.35588281], [0.33386482], [0.32887241], [0.32825731], [0.30975074], [0.30757701], [0.30672304], [0.29938371], [0.29379412]])

```
In [168...
          x input
Out[168... array([[0.26548784, 0.26726146, 0.26348131, 0.27027721, 0.27558016,
                 0.27284508, 0.2714656 , 0.27088633, 0.28075173, 0.28123544,
                 0.28015455, 0.28924361, 0.28629952, 0.28659811, 0.30591088,
                 0.30228003, 0.30345647, 0.31268289, 0.31523284, 0.31601514,
                 0.32106728, 0.33185233, 0.34159232, 0.34156843, 0.33244951,
                 0.34258363, 0.37081228, 0.37994315, 0.38300668, 0.36635733,
                 0.35639638, 0.34462002, 0.34216561, 0.35124273, 0.352879
                 0.34456627, 0.33055645, 0.32399345, 0.31532242, 0.30737994,
                           , 0.31992667, 0.32954125, 0.32636426, 0.32015359,
                 0.32308574, 0.3303773 , 0.32418455, 0.32959499, 0.3352025 ,
                 0.32490714, 0.32204665, 0.31885772, 0.31904284, 0.32174806,
                 0.30892663, 0.30070945, 0.29886417, 0.30851458, 0.29932997,
                 0.30824585, 0.31793209, 0.32659716, 0.3274989 , 0.3256357
                 0.32786317, 0.32931432, 0.34353315, 0.34421991, 0.34304346,
                 0.35586489, 0.3540017 , 0.3299115 , 0.32614927, 0.33104017,
                 0.3399023 , 0.33695224, 0.32978012, 0.328323 , 0.34230296,
                 0.34378994, 0.35314176, 0.36408208, 0.36785028, 0.37124822,
                 0.37516572, 0.37739319, 0.36007501, 0.34517539, 0.3367492 ,
                 0.35649193, 0.35588281, 0.33386482, 0.32887241, 0.32825731,
                 0.30975074, 0.30757701, 0.30672304, 0.29938371, 0.29379412
          temp input=list(x input)
In [169...
          temp_input=temp_input[0].tolist()
```

Function to predict future and add it as input so that next day prediction can be made based on previous day prediction

Making Prediction for next 2 months

```
In [170...
          from numpy import array
          lst output=[]
          n steps=100
          i=0
          while(i<60):</pre>
              if(len(temp_input)>100):
                  #print(temp input)
                  x input=np.array(temp input[1:])
                  x_input=x_input.reshape(1,-1)
                  x_input = x_input.reshape((1, n_steps, 1))
                  #print(x input)
                  yhat = model.predict(x input, verbose=0)
                  yhat actual = scaler.inverse transform(yhat)
                  print("{} day output {}".format(i+1,yhat_actual[0][0]))
                  temp input.extend(yhat[0].tolist())
                  temp_input=temp_input[1:]
                  #print(temp input)
                  lst output.extend(yhat.tolist())
                  i=i+1
              else:
                  x_input = x_input.reshape((1, n_steps,1))
                  yhat = model.predict(x_input, verbose=0)
                  yhat_actual = scaler.inverse_transform(yhat)
                  print("{} day output {}".format(i+1, yhat actual[0][0]))
                  temp input.extend(yhat[0].tolist())
                  lst output.extend(yhat.tolist())
                  i=i+1
         1 day output 928.9598999023438
         2 day output 924.3707885742188
         3 day output 923.0628051757812
         4 day output 924.1746826171875
         5 day output 926.8358154296875
         6 day output 930.3850708007812
         7 day output 934.381591796875
         8 day output 938.545166015625
         9 day output 942.694091796875
         10 day output 946.70166015625
         11 day output 950.4720458984375
         12 day output 953.9291381835938
         13 day output 957.0140991210938
         14 day output 959.6846923828125
```

15 day output 961.9151000976562

- 16 day output 963.6959228515625
- 17 day output 965.0333251953125
- 18 day output 965.9468994140625
- 19 day output 966.4677124023438
- 20 day output 966.635986328125
- 21 day output 966.4985961914062
- 22 day output 966.1063842773438
- 23 day output 965.512451171875
- 24 day output 964.7698364257812
- 25 day output 963.9293212890625
- 26 day output 963.0386352539062
- 27 day output 962.1412353515625
- 28 day output 961.2742919921875
- 29 day output 960.4700317382812
- 30 day output 959.7537841796875
- 31 day output 959.1448364257812
- 32 day output 958.6560668945312
- 33 day output 958.2954711914062
- 34 day output 958.0643920898438
- 35 day output 957.9609985351562
- 36 day output 957.9788818359375
- 37 day output 958.1083984375
- 38 day output 958.337890625
- 39 day output 958.6537475585938
- 40 day output 959.0413208007812
- 41 day output 959.4852905273438
- 42 day output 959.970947265625
- 43 day output 960.48388671875
- 44 day output 961.010498046875
- 45 day output 961.5386962890625
- 46 day output 962.0579833984375
- 47 day output 962.5594482421875
- 48 day output 963.0355224609375
- 49 day output 963.4810791015625

```
50 day output 963.8920288085938
51 day output 964.2664794921875
52 day output 964.6035766601562
53 day output 964.90380859375
54 day output 965.1688842773438
55 day output 965.4015502929688
56 day output 965.60498046875
57 day output 965.7831420898438
58 day output 965.9402465820312
59 day output 966.0803833007812
60 day output 966.2079467773438
```