machine_learning

November 21, 2020

1 Machine Learning

Recurrent Neural Networks (RNN) with Keras

Recurrent neural networks (RNN) are a class of neural networks that is powerful for modeling sequence data such as time series or natural language. It is prominent in the field of NLP(Natural language processing). Recurrent Neural Network(RNN) are a type of Neural Network where the output from previous step are fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other, but in cases like when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. Thus RNN came into existence, which solved this issue with the help of a Hidden Layer. The main and most important feature of RNN is Hidden state, which remembers some information about a sequence.

Importing nessassary libraries

```
[3]: import numpy as np
import pandas as pd
from keras.models import Sequential
from keras.layers import LSTM,Dense ,Dropout, Bidirectional
from sklearn.preprocessing import MinMaxScaler
```

[4]: from sklearn.preprocessing import OneHotEncoder

Importing the datasets into pandas data frame

```
[5]: #this csv file contains the readings for entire india data = pd.read_csv(r"District91_TempAnalysis_1980_20.csv")
```

```
[6]: #this csv file contains the readings for banglore which was done sepeartaly

→with a different shape file

banglore_temp = pd.read_csv(r"Temp_Analysis_Bangalore_1980_2020.csv")
```

1.1 Predicting Bangalore Mean Temperatures

Here we use explicity the banglore dataset for the prediction.

```
[332]: banglore_temp.head()
```

```
[332]:
                                                  DISPLAY_NA MOVEMENT_I \
       O Raghva Niwas, 38th Cross Road, 4th T Block Eas...
                                                                   162
       1 100 16 A Main Road, Canara Bank Colony, Jayana...
                                                                   163
       2 725-44, TMC Layout, 1st Phase, JP Nagar, Benga...
                                                                   164
       3 State Highway 35, Devasthanagalu, Gunjur Villa...
                                                                   165
       4 Bellandur - Doddakannelli Road, Adarsh Palm Re...
                                                                   166
                  WARD NAME WARD NO
                                                      date
       0
          Pattabhiram Nagar
                                 168
                                      1980-01-01T00:00:00
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                 Byrasandra
                                 169
                                      1980-01-01T00:00:00
       2
           Shakambari Nagar
                                 179
                                      1980-01-01T00:00:00
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                   Varthuru
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                                      1980-01-01T00:00:00
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                 Bellanduru
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                                      1980-01-01T00:00:00
          maximum_2m_air_temperature
                                      minimum_2m_air_temperature
       0
                          305.679810
                                                       288.141510
       1
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                                                       288.141510
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                          305.679810
                                                       288.141510
       3
                                                       288.051396
                          305.614028
       4
                          305.679810
                                                       288.141510
      banglore_temp.info()
[333]:
      <class 'pandas.core.frame.DataFrame'>
      RangeIndex: 31878 entries, 0 to 31877
      Data columns (total 7 columns):
           Column
                                        Non-Null Count Dtype
           _____
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       0
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                                        31878 non-null object
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                                        31878 non-null int64
                                        31878 non-null object
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                                                        object
           maximum_2m_air_temperature
                                        31878 non-null
                                                        float64
           minimum_2m_air_temperature
                                        31878 non-null float64
      dtypes: float64(2), int64(2), object(3)
      memory usage: 1.7+ MB
  [7]: #we group by date to find the mean
       banglore_temp=banglore_temp.groupby('date').mean()
[335]: banglore_temp.head()
[335]:
                            MOVEMENT I
                                        WARD_NO
                                                  maximum_2m_air_temperature
       date
       1980-01-01T00:00:00
                                  99.5
                                            99.5
                                                                  305.580205
       1980-04-01T00:00:00
                                  99.5
                                            99.5
                                                                  306.536743
                                  99.5
       1980-07-01T00:00:00
                                            99.5
                                                                  301.647714
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1980-10-01T00:00:00
                                   99.5
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                                                                   301.881074
       1981-01-01T00:00:00
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                             minimum_2m_air_temperature
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       1980-01-01T00:00:00
                                             288.117520
       1980-04-01T00:00:00
                                             292.963571
       1980-07-01T00:00:00
                                             291.215594
       1980-10-01T00:00:00
                                             286.977627
       1981-01-01T00:00:00
                                             287.973688
      we calculate the mean in the below cell
[336]: col = banglore_temp.loc[: , "maximum_2m_air_temperature":
        →"minimum_2m_air_temperature"]
[337]: banglore_temp['mean_temperature'] = col.mean(axis=1)
[338]: banglore_temp.head()
[338]:
                             MOVEMENT_I WARD_NO maximum_2m_air_temperature
       date
       1980-01-01T00:00:00
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                            minimum_2m_air_temperature mean_temperature
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                                                                296.848862
       1980-04-01T00:00:00
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                                             292.963571
       1980-07-01T00:00:00
                                                                296.431654
                                             291.215594
       1980-10-01T00:00:00
                                             286.977627
                                                                294.429350
       1981-01-01T00:00:00
                                             287.973688
                                                                296.832536
[339]: training set = banglore temp["mean temperature"]
[340]:
      training_set.reset_index(drop=True,inplace=True)
[341]: training_set.head()
[341]: 0
            296.848862
       1
            299.750157
       2
            296.431654
       3
            294.429350
            296.832536
       Name: mean_temperature, dtype: float64
```

```
[342]: len(training_set)
[342]: 161
[343]: training_set = np.asarray(training_set)
[344]: training_set = training_set.reshape((-1,1))
[345]: | training_set=np.round_(training_set, decimals=2)
[367]: test set sample = training set[-1:-35:-1]
       train_set = training_set[0:137]
[368]: print(len(train set))
       print(len(test_set_sample))
      137
      34
      We scale the data, for the purpose of feeding it to the model
[369]: sc = MinMaxScaler(feature_range=(0,1))
       training_set_scaled = sc.fit_transform(train_set)
      Preparing the data to be fed to the model
[370]: x_train = []
       y train = []
       n_future = 4 # next 4 temperature forecast
       n_past = 30 # Past 30
       for i in range(0,len(training_set_scaled)-n_past-n_future+1):
           x_train.append(training_set_scaled[i : i + n_past , 0])
           y_train.append(training_set_scaled[i + n_past : i + n_past + n_future , 0 ])
       x_train , y_train = np.array(x_train), np.array(y_train)
       x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
      Making the RNN model, and fiting the data, and training the model
[372]: regressor = Sequential()
       regressor.add(Bidirectional(LSTM(units=30, return_sequences=True, input_shape = __
       \rightarrow (x_train.shape[1],1)))
       regressor.add(Dropout(0.2))
       regressor.add(LSTM(units= 30 , return_sequences=True))
       regressor.add(Dropout(0.2))
       regressor.add(LSTM(units= 30 , return_sequences=True))
       regressor.add(Dropout(0.2))
       regressor.add(LSTM(units= 30))
       regressor.add(Dropout(0.2))
       regressor.add(Dense(units = n_future,activation='linear'))
```

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regressor.compile(optimizer='adam', loss='mean_squared_error',metrics=['acc'])
regressor.fit(x_train, y_train, epochs=800,batch_size=32 )
```

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Epoch 718/800
Epoch 719/800
```

```
Epoch 720/800
Epoch 721/800
Epoch 722/800
Epoch 723/800
Epoch 724/800
Epoch 725/800
Epoch 726/800
Epoch 727/800
Epoch 728/800
Epoch 729/800
Epoch 730/800
Epoch 731/800
Epoch 732/800
Epoch 733/800
Epoch 734/800
Epoch 735/800
Epoch 736/800
Epoch 737/800
Epoch 738/800
Epoch 739/800
Epoch 740/800
Epoch 741/800
Epoch 742/800
Epoch 743/800
```

```
Epoch 744/800
Epoch 745/800
Epoch 746/800
Epoch 747/800
Epoch 748/800
Epoch 749/800
Epoch 750/800
Epoch 751/800
Epoch 752/800
Epoch 753/800
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Epoch 758/800
Epoch 759/800
Epoch 760/800
Epoch 761/800
Epoch 762/800
Epoch 763/800
Epoch 764/800
Epoch 765/800
Epoch 766/800
Epoch 767/800
```

```
Epoch 768/800
Epoch 769/800
Epoch 770/800
Epoch 771/800
Epoch 772/800
Epoch 773/800
Epoch 774/800
Epoch 775/800
Epoch 776/800
Epoch 777/800
Epoch 778/800
Epoch 779/800
Epoch 780/800
Epoch 781/800
Epoch 782/800
Epoch 783/800
Epoch 784/800
Epoch 785/800
Epoch 786/800
Epoch 787/800
Epoch 788/800
Epoch 789/800
Epoch 790/800
Epoch 791/800
```

```
Epoch 792/800
   Epoch 793/800
   Epoch 794/800
   Epoch 795/800
   Epoch 796/800
   Epoch 797/800
   Epoch 798/800
   Epoch 799/800
   Epoch 800/800
   [372]: <tensorflow.python.keras.callbacks.History at 0x20bf20a0b50>
[375]: testing_sample_scaled = sc.fit_transform(test_set_sample[0:30])
   Predicting for sample test data prepared
[376]: testing_sample_scaled = np.reshape(testing_sample_scaled, (testing_sample_scaled.
    →shape[1],testing_sample_scaled.shape[0],1))
   predicted_temperature = regressor.predict(testing_sample_scaled)
[377]: predicted_temperature = sc.inverse_transform(predicted_temperature)
   The below are the predicted values
[396]: print(predicted_temperature[0])
   [298.21646 299.73602 297.93655 296.91956]
   Now lets see the actual values
[397]: acutal_value = (test_set_sample[30:34])
[398]: acutal_value
[398]: array([[297.59],
       [300.38],
       [296.74],
       [294.47]])
```

Now finding the error between actual and predicted data

```
[399]: error1 = predicted_temperature[0] - acutal_value[0]
```

[400]: print(error1)

The above error indicates that our model performs very well, now lets use it to predict future temperature

Predicting future temperature for next 4 quartely month

```
[401]: testing_sample_scaled = sc.fit_transform(test_set_sample[4:34])
```

```
[402]: testing_sample_scaled = np.reshape(testing_sample_scaled,(testing_sample_scaled.

shape[1],testing_sample_scaled.shape[0],1))

predicted_temperature = regressor.predict(testing_sample_scaled)
```

```
[403]: predicted_temperature = sc.inverse_transform(predicted_temperature)
```

```
[404]: print(predicted_temperature[0])
```

```
[297.91928 299.58896 297.62598 296.5048 ]
```

The above are the predicted mean values for the next quarterly months for banglore

1.2 Predicting Kerala Mean temperature

Here we are using the main ERA5 dataset for this prediction. We predict the mean temperature for kerala state

```
[184]: kerala_data = data[data['STATE_UT'] == 'KERALA']
```

[185]: kerala_data.head()

[185]:	DIST91_ID	NAME	STATE_UT	date	maximum_2m_air_temperature	\
72	171.0	WAYANAD	KERALA	1980-01-01	304.328384	
73	170.0	KANNUR	KERALA	1980-01-01	304.485970	
74	172.0	KOZHIKODE	KERALA	1980-01-01	303.993400	
75	176.0	ERNAKULAM	KERALA	1980-01-01	307.160080	
76	173.0	MALAPPURAM	KERALA	1980-01-01	304.929867	

```
minimum_2m_air_temperature mean_temperature
72
                     286.505651
                                       295.417017
73
                     292.209197
                                        298.347583
74
                     292.673536
                                        298.333468
75
                     293.908322
                                        300.534201
76
                     290.547602
                                        297.738735
```

```
[186]: kerala data.info()
```

Int64Index: 6720 entries, 72 to 313351 Data columns (total 7 columns): Column Non-Null Count Dtype _____ _____ 0 DIST91 ID 6720 non-null float64 1 NAME 6720 non-null object 6720 non-null 2 STATE_UT object 3 6720 non-null datetime64[ns] date 4 maximum_2m_air_temperature 6720 non-null float64 5 minimum_2m_air_temperature 6720 non-null float64 mean_temperature 6720 non-null float64 dtypes: datetime64[ns](1), float64(4), object(2) memory usage: 420.0+ KB Calculating the mean [187]: col = kerala_data.loc[: , "maximum_2m_air_temperature": →"minimum_2m_air_temperature"] [188]: kerala_data['mean_temperature'] = col.mean(axis=1) <ipython-input-188-ada6cff453e5>:1: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer,col_indexer] = value instead See the caveats in the documentation: https://pandas.pydata.org/pandasdocs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy kerala_data['mean_temperature'] = col.mean(axis=1) [189]: kerala_data.head() [189]: DIST91 ID maximum_2m_air_temperature \ NAME STATE UT date 72 171.0 WAYANAD KERALA 1980-01-01 304.328384 73 170.0 KERALA 1980-01-01 304.485970 KANNUR 74 172.0 KERALA 1980-01-01 KOZHIKODE 303.993400 75 176.0 ERNAKULAM KERALA 1980-01-01 307.160080 76 173.0 MALAPPURAM KERALA 1980-01-01 304.929867 minimum_2m_air_temperature mean_temperature 72 286.505651 295.417017 73 292.209197 298.347583 74 292.673536 298.333468 75 293.908322 300.534201 76 290.547602 297.738735 training_set = kerala_data["mean_temperature"] [191]: training_set.reset_index(drop=True,inplace=True)

<class 'pandas.core.frame.DataFrame'>

```
[192]: training_set.head()
[192]: 0
            295.417017
       1
            298.347583
            298.333468
       2
       3
            300.534201
            297.738735
       Name: mean_temperature, dtype: float64
[193]: training_set = np.asarray(training_set)
[194]: training_set = training_set.reshape((-1,1))
[195]: len(training_set)
[195]: 6720
[200]: training_set=np.round_(training_set, decimals=2)
[201]: training set
[201]: array([[295.42],
              [298.35],
              [298.33],
              [299.9],
              [302.9],
              [300.3]])
[202]: test_set_sample = training_set[-1:-100:-1]
       train_set = training_set[0:6621]
[203]: len(train_set)
[203]: 6621
[204]: len(test_set_sample)
[204]: 99
      Scaling the dataset for feeding it to the model
[205]: sc = MinMaxScaler(feature_range=(0,1))
       training_set_scaled = sc.fit_transform(train_set)
      Preparing the data to be fed to the model
[206]: x_train = []
       y_train = []
```

```
n_future = 4 # next 4 days temperature forecast
n_past = 30 # Past 30 days
for i in range(0,len(training_set_scaled)-n_past-n_future+1):
    x_train.append(training_set_scaled[i : i + n_past , 0])
    y_train.append(training_set_scaled[i + n_past : i + n_past + n_future , 0 ])
x_train , y_train = np.array(x_train), np.array(y_train)
x_train = np.reshape(x_train, (x_train.shape[0] , x_train.shape[1], 1) )
```

Making the RNN model, and fiting the data, and training the model

```
[207]: regressor = Sequential()
     regressor.add(Bidirectional(LSTM(units=30, return_sequences=True, input_shape = __
     \hookrightarrow (x_train.shape[1],1)))
     regressor.add(Dropout(0.2))
     regressor.add(LSTM(units= 30 , return_sequences=True))
     regressor.add(Dropout(0.2))
     regressor.add(LSTM(units= 30 , return_sequences=True))
     regressor.add(Dropout(0.2))
     regressor.add(LSTM(units= 30))
     regressor.add(Dropout(0.2))
     regressor.add(Dense(units = n_future,activation='linear'))
     regressor.compile(optimizer='adam', loss='mean_squared_error',metrics=['acc'])
     regressor.fit(x_train, y_train, epochs=500,batch_size=32 )
    Epoch 1/500
    206/206 [============== ] - 6s 28ms/step - loss: 0.0345 - acc:
    0.2495
    Epoch 2/500
    206/206 [=============== ] - 6s 29ms/step - loss: 0.0176 - acc:
    0.2521
    Epoch 3/500
    0.2464
    Epoch 4/500
    0.2577
    Epoch 5/500
    0.2412
    Epoch 6/500
    0.2485
    Epoch 7/500
    206/206 [=============== ] - 6s 30ms/step - loss: 0.0125 - acc:
    0.2491: 1s - loss
    Epoch 8/500
    206/206 [============== ] - 6s 29ms/step - loss: 0.0122 - acc:
    0.2400:
```

```
Epoch 9/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0119 - acc:
0.2523
Epoch 10/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0117 - acc:
0.2498
Epoch 11/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0114 - acc:
0.2523
Epoch 12/500
0.2461
Epoch 13/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0112 - acc:
0.2457
Epoch 14/500
0.2530
Epoch 15/500
206/206 [============= ] - 6s 30ms/step - loss: 0.0108 - acc:
0.2500
Epoch 16/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0106 - acc:
0.2673
Epoch 17/500
0.2702
Epoch 18/500
0.2641
Epoch 19/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0100 - acc:
0.2741
Epoch 20/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0099 - acc:
0.2794
Epoch 21/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0097 - acc:
0.2939
Epoch 22/500
0.2893
Epoch 23/500
0.2961
Epoch 24/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0092 - acc:
0.3109
```

```
Epoch 25/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0090 - acc:
0.3148
Epoch 26/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0088 - acc:
0.3279
Epoch 27/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0084 - acc:
0.3338
Epoch 28/500
0.3713
Epoch 29/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0074 - acc:
0.4168
Epoch 30/500
206/206 [============= ] - 7s 34ms/step - loss: 0.0067 - acc:
0.4355
Epoch 31/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0061 - acc:
0.4391
Epoch 32/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0056 - acc:
0.4762
Epoch 33/500
0.4836
Epoch 34/500
0.4964
Epoch 35/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0048 - acc:
0.5121
Epoch 36/500
0.5162
Epoch 37/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0045 - acc:
0.5217
Epoch 38/500
0.5264
Epoch 39/500
0.5354
Epoch 40/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0041 - acc:
0.5436
```

```
Epoch 41/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0039 - acc:
0.5540
Epoch 42/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0038 - acc:
0.5612
Epoch 43/500
206/206 [================ ] - 6s 30ms/step - loss: 0.0036 - acc:
0.5651
Epoch 44/500
0.5709
Epoch 45/500
206/206 [=============== ] - 7s 36ms/step - loss: 0.0034 - acc:
0.5776
Epoch 46/500
0.5747
Epoch 47/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0033 - acc:
0.5889
Epoch 48/500
206/206 [================ ] - 6s 30ms/step - loss: 0.0032 - acc:
0.5932
Epoch 49/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0030 - acc:
0.6003
Epoch 50/500
0.6140: 1
Epoch 51/500
206/206 [=============== ] - 6s 30ms/step - loss: 0.0029 - acc:
0.6340
Epoch 52/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0028 - acc:
0.6368
Epoch 53/500
206/206 [================ ] - 6s 30ms/step - loss: 0.0027 - acc:
0.6468
Epoch 54/500
0.6457
Epoch 55/500
0.6451
Epoch 56/500
0.6571: 0s - loss: 0.002
```

```
Epoch 57/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0026 - acc:
0.6655
Epoch 58/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0026 - acc:
0.6705
Epoch 59/500
206/206 [================ ] - 6s 30ms/step - loss: 0.0025 - acc:
0.6729
Epoch 60/500
0.6773
Epoch 61/500
0.6721
Epoch 62/500
0.6670
Epoch 63/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0024 - acc:
0.6808: 0s - loss: 0.0024 -
Epoch 64/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0023 - acc:
0.6777
Epoch 65/500
0.6873
Epoch 66/500
0.6864
Epoch 67/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0022 - acc:
0.6982
Epoch 68/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0022 - acc:
0.6884
Epoch 69/500
206/206 [================ ] - 7s 32ms/step - loss: 0.0023 - acc:
0.6878
Epoch 70/500
206/206 [=============== ] - 7s 33ms/step - loss: 0.0023 - acc:
0.6850
Epoch 71/500
0.6831
Epoch 72/500
0.6949
```

```
Epoch 73/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0022 - acc:
0.7023
Epoch 74/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0022 - acc:
0.6964
Epoch 75/500
0.7042
Epoch 76/500
0.6925
Epoch 77/500
206/206 [============ ] - 7s 32ms/step - loss: 0.0023 - acc:
0.6872
Epoch 78/500
0.6982
Epoch 79/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0021 - acc:
0.6978
Epoch 80/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0021 - acc:
0.7001
Epoch 81/500
0.7020
Epoch 82/500
0.7055
Epoch 83/500
206/206 [=============== ] - 6s 30ms/step - loss: 0.0021 - acc:
0.7089
Epoch 84/500
206/206 [============== ] - 7s 32ms/step - loss: 0.0021 - acc:
0.7002
Epoch 85/500
206/206 [================ ] - 7s 34ms/step - loss: 0.0022 - acc:
0.7034
Epoch 86/500
0.7001
Epoch 87/500
206/206 [============ ] - 7s 32ms/step - loss: 0.0020 - acc:
0.7025
Epoch 88/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0020 - acc:
0.7032
```

```
Epoch 89/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0020 - acc:
0.7148
Epoch 90/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0020 - acc:
0.7031
Epoch 91/500
0.7119
Epoch 92/500
0.7072
Epoch 93/500
206/206 [============ ] - 7s 32ms/step - loss: 0.0020 - acc:
0.7081
Epoch 94/500
206/206 [============= ] - 7s 32ms/step - loss: 0.0020 - acc:
0.7113
Epoch 95/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0020 - acc:
0.7121
Epoch 96/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0020 - acc:
0.7143
Epoch 97/500
206/206 [============= ] - 7s 32ms/step - loss: 0.0019 - acc:
0.7107
Epoch 98/500
206/206 [=============== ] - 7s 34ms/step - loss: 0.0020 - acc:
0.7090
Epoch 99/500
206/206 [=============== ] - 7s 35ms/step - loss: 0.0021 - acc:
0.7014
Epoch 100/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0020 - acc:
0.7023
Epoch 101/500
206/206 [=============== ] - 6s 30ms/step - loss: 0.0019 - acc:
0.7117: 1s - loss: 0.0020 - acc: 0 - ETA: 1s - loss:
Epoch 102/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0019 - acc:
0.7152
Epoch 103/500
0.7116
Epoch 104/500
206/206 [=============== ] - 7s 33ms/step - loss: 0.0020 - acc:
0.7037
```

```
Epoch 105/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0019 - acc:
0.7136
Epoch 106/500
206/206 [============== ] - 6s 32ms/step - loss: 0.0019 - acc:
0.7234
Epoch 107/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0019 - acc:
0.7125
Epoch 108/500
206/206 [============= ] - 7s 32ms/step - loss: 0.0019 - acc:
0.7175
Epoch 109/500
206/206 [============ ] - 7s 33ms/step - loss: 0.0019 - acc:
0.7101
Epoch 110/500
206/206 [============= ] - 7s 34ms/step - loss: 0.0018 - acc:
0.7186
Epoch 111/500
206/206 [============ ] - 7s 35ms/step - loss: 0.0019 - acc:
0.7181
Epoch 112/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0019 - acc:
0.7189
Epoch 113/500
0.7221
Epoch 114/500
0.7104
Epoch 115/500
206/206 [=============== ] - 6s 30ms/step - loss: 0.0019 - acc:
0.7107
Epoch 116/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0018 - acc:
0.7162
Epoch 117/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0018 - acc:
0.7149
Epoch 118/500
0.7172
Epoch 119/500
0.7190
Epoch 120/500
0.7248
```

```
Epoch 121/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0019 - acc:
0.7242
Epoch 122/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0020 - acc:
0.7101
Epoch 123/500
206/206 [================ ] - 6s 30ms/step - loss: 0.0019 - acc:
0.7165
Epoch 124/500
206/206 [============= ] - 7s 33ms/step - loss: 0.0018 - acc:
0.7192
Epoch 125/500
206/206 [============ ] - 7s 33ms/step - loss: 0.0018 - acc:
0.7193
Epoch 126/500
0.7256
Epoch 127/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0018 - acc:
0.7172
Epoch 128/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0018 - acc:
0.7310
Epoch 129/500
0.7240
Epoch 130/500
0.7310
Epoch 131/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0018 - acc:
0.7231
Epoch 132/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0018 - acc:
0.7237
Epoch 133/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0018 - acc:
0.7192
Epoch 134/500
0.7184
Epoch 135/500
0.7231
Epoch 136/500
206/206 [=============== ] - 7s 33ms/step - loss: 0.0018 - acc:
0.7286
```

```
Epoch 137/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0018 - acc:
0.7231
Epoch 138/500
206/206 [============== ] - 7s 32ms/step - loss: 0.0018 - acc:
0.7259
Epoch 139/500
206/206 [================ ] - 7s 33ms/step - loss: 0.0018 - acc:
0.7221
Epoch 140/500
206/206 [============= ] - 7s 32ms/step - loss: 0.0017 - acc:
0.7247
Epoch 141/500
206/206 [============= ] - 6s 30ms/step - loss: 0.0017 - acc:
0.7333
Epoch 142/500
0.7224
Epoch 143/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0017 - acc:
0.7209
Epoch 144/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0018 - acc:
0.7155
Epoch 145/500
0.7298
Epoch 146/500
0.7248
Epoch 147/500
206/206 [=============== ] - 6s 27ms/step - loss: 0.0017 - acc:
0.7218
Epoch 148/500
0.7301
Epoch 149/500
206/206 [================ ] - 5s 27ms/step - loss: 0.0017 - acc:
0.7262
Epoch 150/500
0.7204
Epoch 151/500
0.7116
Epoch 152/500
0.7257
```

```
Epoch 153/500
0.7231
Epoch 154/500
206/206 [============== ] - 5s 27ms/step - loss: 0.0017 - acc:
0.7245
Epoch 155/500
206/206 [================ ] - 5s 27ms/step - loss: 0.0017 - acc:
0.7286
Epoch 156/500
0.7315
Epoch 157/500
206/206 [============= ] - 5s 26ms/step - loss: 0.0017 - acc:
0.7309
Epoch 158/500
0.7327
Epoch 159/500
206/206 [============= ] - 5s 27ms/step - loss: 0.0017 - acc:
0.7284
Epoch 160/500
206/206 [================ ] - 5s 26ms/step - loss: 0.0017 - acc:
0.7325
Epoch 161/500
0.7195
Epoch 162/500
0.7312
Epoch 163/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0017 - acc:
0.7268
Epoch 164/500
0.7339
Epoch 165/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0017 - acc:
0.7298
Epoch 166/500
0.7236
Epoch 167/500
0.7263
Epoch 168/500
206/206 [=============== ] - 6s 27ms/step - loss: 0.0017 - acc:
0.7186
```

```
Epoch 169/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0018 - acc:
0.7204
Epoch 170/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0018 - acc:
0.7271
Epoch 171/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0017 - acc:
0.7291
Epoch 172/500
0.7328
Epoch 173/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0017 - acc:
0.7386
Epoch 174/500
0.7277
Epoch 175/500
206/206 [============= ] - 6s 28ms/step - loss: 0.0016 - acc:
0.7269
Epoch 176/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0017 - acc:
0.7351
Epoch 177/500
0.7248
Epoch 178/500
0.7322
Epoch 179/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0016 - acc:
0.7309
Epoch 180/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0016 - acc:
0.7298
Epoch 181/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0016 - acc:
0.7338
Epoch 182/500
0.7325
Epoch 183/500
0.7301
Epoch 184/500
0.7295
```

```
Epoch 185/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0016 - acc:
0.7259
Epoch 186/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0016 - acc:
0.7325
Epoch 187/500
206/206 [================ ] - 6s 30ms/step - loss: 0.0017 - acc:
0.7325
Epoch 188/500
0.7239
Epoch 189/500
206/206 [============ ] - 7s 34ms/step - loss: 0.0016 - acc:
0.7332
Epoch 190/500
0.7269
Epoch 191/500
206/206 [============= ] - 6s 30ms/step - loss: 0.0016 - acc:
0.7313: 0s - loss: 0.0016 - acc
Epoch 192/500
206/206 [================ ] - 6s 30ms/step - loss: 0.0016 - acc:
0.7251
Epoch 193/500
0.7300
Epoch 194/500
0.7322
Epoch 195/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0016 - acc:
0.7335
Epoch 196/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0016 - acc:
0.7348
Epoch 197/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0016 - acc:
0.7306
Epoch 198/500
206/206 [=============== ] - 6s 30ms/step - loss: 0.0016 - acc:
0.7335
Epoch 199/500
0.7366
Epoch 200/500
0.7351
```

```
Epoch 201/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0016 - acc:
0.7341
Epoch 202/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0016 - acc:
0.7266
Epoch 203/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0016 - acc:
0.7312
Epoch 204/500
0.7266
Epoch 205/500
0.7362
Epoch 206/500
0.7356
Epoch 207/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0016 - acc:
0.7407: Os - loss: 0.0016 -
Epoch 208/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0016 - acc:
0.7383
Epoch 209/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0016 - acc:
0.7336
Epoch 210/500
0.7313
Epoch 211/500
206/206 [=============== ] - 6s 28ms/step - loss: 0.0016 - acc:
0.7289
Epoch 212/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0016 - acc:
0.7225
Epoch 213/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0015 - acc:
0.7312
Epoch 214/500
206/206 [=============== ] - 7s 35ms/step - loss: 0.0016 - acc:
0.7292
Epoch 215/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0015 - acc:
0.7398
Epoch 216/500
0.7292
```

```
Epoch 217/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0015 - acc:
0.7256
Epoch 218/500
206/206 [============== ] - 7s 33ms/step - loss: 0.0015 - acc:
0.7322
Epoch 219/500
206/206 [================ ] - 7s 34ms/step - loss: 0.0016 - acc:
0.7330
Epoch 220/500
0.7192
Epoch 221/500
0.7298
Epoch 222/500
0.7400
Epoch 223/500
0.7347
Epoch 224/500
206/206 [================ ] - 7s 34ms/step - loss: 0.0016 - acc:
0.7336
Epoch 225/500
206/206 [============ ] - 7s 34ms/step - loss: 0.0015 - acc:
0.7418
Epoch 226/500
0.7403
Epoch 227/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0016 - acc:
0.7423
Epoch 228/500
206/206 [============== ] - 7s 33ms/step - loss: 0.0015 - acc:
0.7372
Epoch 229/500
206/206 [================ ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7376
Epoch 230/500
206/206 [================ ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7407
Epoch 231/500
0.7321
Epoch 232/500
206/206 [=============== ] - 7s 34ms/step - loss: 0.0015 - acc:
0.7403
```

```
Epoch 233/500
206/206 [============ ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7376
Epoch 234/500
206/206 [============== ] - 7s 34ms/step - loss: 0.0015 - acc:
0.7412
Epoch 235/500
0.7335
Epoch 236/500
0.7230
Epoch 237/500
206/206 [============= ] - 8s 37ms/step - loss: 0.0016 - acc:
0.7260
Epoch 238/500
206/206 [============= ] - 7s 34ms/step - loss: 0.0016 - acc:
0.7283
Epoch 239/500
0.7354
Epoch 240/500
206/206 [================ ] - 7s 32ms/step - loss: 0.0015 - acc:
0.7388
Epoch 241/500
206/206 [============ ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7341
Epoch 242/500
206/206 [=============== ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7366
Epoch 243/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0015 - acc:
0.7394
Epoch 244/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0015 - acc:
0.7336
Epoch 245/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0015 - acc:
0.7406
Epoch 246/500
206/206 [=============== ] - 7s 34ms/step - loss: 0.0017 - acc:
0.7286
Epoch 247/500
206/206 [=============== ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7389
Epoch 248/500
206/206 [=============== ] - 7s 33ms/step - loss: 0.0015 - acc:
0.7436
```

```
Epoch 249/500
206/206 [============ ] - 7s 32ms/step - loss: 0.0015 - acc:
0.7406
Epoch 250/500
206/206 [============== ] - 7s 33ms/step - loss: 0.0015 - acc:
0.7362
Epoch 251/500
206/206 [================ ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7412
Epoch 252/500
206/206 [============= ] - 7s 36ms/step - loss: 0.0015 - acc:
0.7427
Epoch 253/500
206/206 [============ ] - 7s 35ms/step - loss: 0.0014 - acc:
0.7438
Epoch 254/500
206/206 [============= ] - 7s 36ms/step - loss: 0.0015 - acc:
0.7348
Epoch 255/500
206/206 [============ ] - 7s 35ms/step - loss: 0.0016 - acc:
0.7345
Epoch 256/500
206/206 [================ ] - 8s 37ms/step - loss: 0.0015 - acc:
0.7310
Epoch 257/500
206/206 [============= ] - 8s 37ms/step - loss: 0.0015 - acc:
0.7397
Epoch 258/500
206/206 [================ ] - 8s 37ms/step - loss: 0.0015 - acc:
0.7304
Epoch 259/500
206/206 [=============== ] - 8s 37ms/step - loss: 0.0015 - acc:
0.7327
Epoch 260/500
206/206 [============== ] - 8s 38ms/step - loss: 0.0015 - acc:
0.7433
Epoch 261/500
206/206 [=============== ] - 8s 38ms/step - loss: 0.0015 - acc:
0.7420
Epoch 262/500
206/206 [=============== ] - 8s 39ms/step - loss: 0.0015 - acc:
0.7453
Epoch 263/500
0.7365
Epoch 264/500
0.7359
```

```
Epoch 265/500
206/206 [============== ] - 8s 38ms/step - loss: 0.0015 - acc:
0.7403
Epoch 266/500
206/206 [============== ] - 8s 40ms/step - loss: 0.0015 - acc:
0.7391
Epoch 267/500
206/206 [================ ] - 8s 40ms/step - loss: 0.0015 - acc:
0.7368
Epoch 268/500
8s 40ms/step - loss: 0.0015 - acc: 0.7423
Epoch 269/500
0.7365
Epoch 270/500
0.7335
Epoch 271/500
206/206 [============= ] - 8s 37ms/step - loss: 0.0015 - acc:
0.7415
Epoch 272/500
206/206 [================ ] - 8s 38ms/step - loss: 0.0015 - acc:
0.7406
Epoch 273/500
206/206 [============== ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7377
Epoch 274/500
0.7409
Epoch 275/500
206/206 [=============== ] - 8s 37ms/step - loss: 0.0015 - acc:
0.7389
Epoch 276/500
206/206 [============== ] - 8s 37ms/step - loss: 0.0014 - acc:
0.7459
Epoch 277/500
206/206 [================ ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7441
Epoch 278/500
206/206 [================ ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7389
Epoch 279/500
206/206 [=============== ] - 7s 34ms/step - loss: 0.0014 - acc:
0.7410
Epoch 280/500
206/206 [=============== ] - 7s 33ms/step - loss: 0.0015 - acc:
0.7427
```

```
Epoch 281/500
206/206 [============ ] - 7s 34ms/step - loss: 0.0015 - acc:
0.7415: 1s
Epoch 282/500
206/206 [============== ] - 7s 34ms/step - loss: 0.0014 - acc:
0.7401
Epoch 283/500
206/206 [================ ] - 7s 36ms/step - loss: 0.0015 - acc:
0.7433
Epoch 284/500
0.7388
Epoch 285/500
206/206 [============ ] - 7s 33ms/step - loss: 0.0015 - acc:
0.7435
Epoch 286/500
206/206 [============= ] - 7s 33ms/step - loss: 0.0016 - acc:
0.7401
Epoch 287/500
0.7435
Epoch 288/500
206/206 [================ ] - 7s 33ms/step - loss: 0.0015 - acc:
0.7345
Epoch 289/500
0.7413
Epoch 290/500
0.7441
Epoch 291/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0014 - acc:
0.7424
Epoch 292/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0014 - acc:
0.7450
Epoch 293/500
206/206 [================ ] - 7s 33ms/step - loss: 0.0014 - acc:
0.7423
Epoch 294/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0014 - acc:
0.7377
Epoch 295/500
0.7435
Epoch 296/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0014 - acc:
0.7413
```

```
Epoch 297/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0014 - acc:
0.7392
Epoch 298/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0014 - acc:
0.7468
Epoch 299/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0014 - acc:
0.7435
Epoch 300/500
206/206 [============= ] - 7s 33ms/step - loss: 0.0014 - acc:
0.7441
Epoch 301/500
206/206 [=============== ] - 8s 40ms/step - loss: 0.0014 - acc:
0.7457
Epoch 302/500
0.7362: 1s - lo
Epoch 303/500
206/206 [============== ] - 8s 39ms/step - loss: 0.0014 - acc:
0.7391
Epoch 304/500
206/206 [================ ] - 8s 39ms/step - loss: 0.0014 - acc:
0.7442
Epoch 305/500
0.7441
Epoch 306/500
0.7480
Epoch 307/500
206/206 [=============== ] - 6s 30ms/step - loss: 0.0014 - acc:
0.7462
Epoch 308/500
0.7404
Epoch 309/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0015 - acc:
0.7417
Epoch 310/500
0.7454
Epoch 311/500
0.7363
Epoch 312/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0014 - acc:
0.7453
```

```
Epoch 313/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7480
Epoch 314/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0014 - acc:
0.7477
Epoch 315/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7518
Epoch 316/500
0.7418
Epoch 317/500
206/206 [============= ] - 6s 30ms/step - loss: 0.0014 - acc:
0.7388
Epoch 318/500
206/206 [============= ] - 7s 35ms/step - loss: 0.0014 - acc:
0.7497
Epoch 319/500
206/206 [============== ] - 8s 39ms/step - loss: 0.0014 - acc:
0.7500
Epoch 320/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0014 - acc:
0.7464: 1s - loss:
Epoch 321/500
206/206 [============= ] - 6s 31ms/step - loss: 0.0014 - acc:
0.7412
Epoch 322/500
0.7453
Epoch 323/500
206/206 [=============== ] - 7s 36ms/step - loss: 0.0014 - acc:
0.7436
Epoch 324/500
206/206 [============== ] - 7s 34ms/step - loss: 0.0014 - acc:
0.7400
Epoch 325/500
206/206 [================ ] - 7s 35ms/step - loss: 0.0014 - acc:
0.7459
Epoch 326/500
206/206 [=============== ] - 8s 37ms/step - loss: 0.0014 - acc:
0.7409
Epoch 327/500
0.7442
Epoch 328/500
206/206 [=============== ] - 9s 42ms/step - loss: 0.0014 - acc:
0.7470
```

```
Epoch 329/500
206/206 [============= ] - 7s 36ms/step - loss: 0.0015 - acc:
0.7477
Epoch 330/500
206/206 [============== ] - 7s 34ms/step - loss: 0.0014 - acc:
0.7445
Epoch 331/500
206/206 [================ ] - 7s 33ms/step - loss: 0.0014 - acc:
0.7453
Epoch 332/500
206/206 [============= ] - 7s 35ms/step - loss: 0.0015 - acc:
0.7371
Epoch 333/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0014 - acc:
0.7479
Epoch 334/500
0.7457
Epoch 335/500
206/206 [============= ] - 7s 32ms/step - loss: 0.0014 - acc:
0.7492: 1s
Epoch 336/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0014 - acc:
0.7430
Epoch 337/500
206/206 [============ ] - 7s 32ms/step - loss: 0.0014 - acc:
0.7491
Epoch 338/500
0.7459
Epoch 339/500
206/206 [=============== ] - 6s 30ms/step - loss: 0.0014 - acc:
0.7447: Os - loss: 0.0014 - acc
Epoch 340/500
206/206 [============== ] - 6s 31ms/step - loss: 0.0014 - acc:
0.7435
Epoch 341/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7418
Epoch 342/500
0.7404
Epoch 343/500
0.7462
Epoch 344/500
0.7459
```

```
Epoch 345/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7453
Epoch 346/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7407
Epoch 347/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7539
Epoch 348/500
0.7415
Epoch 349/500
206/206 [============= ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7497
Epoch 350/500
0.7436
Epoch 351/500
206/206 [============= ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7447
Epoch 352/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7429
Epoch 353/500
0.7485
Epoch 354/500
0.7479
Epoch 355/500
206/206 [=============== ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7520
Epoch 356/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7495
Epoch 357/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0014 - acc:
0.7543
Epoch 358/500
0.7445
Epoch 359/500
0.7512
Epoch 360/500
206/206 [=============== ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7465
```

```
Epoch 361/500
206/206 [============== ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7494
Epoch 362/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7502
Epoch 363/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7436
Epoch 364/500
0.7471
Epoch 365/500
206/206 [============== ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7453
Epoch 366/500
0.7363
Epoch 367/500
206/206 [============= ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7570
Epoch 368/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7489
Epoch 369/500
0.7476
Epoch 370/500
0.7418
Epoch 371/500
206/206 [=============== ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7511
Epoch 372/500
206/206 [============== ] - 6s 30ms/step - loss: 0.0013 - acc:
0.7511
Epoch 373/500
206/206 [================ ] - 6s 31ms/step - loss: 0.0014 - acc:
0.7457: 0s - loss: 0.0014 - acc: 0.7
Epoch 374/500
206/206 [=============== ] - 7s 33ms/step - loss: 0.0013 - acc:
0.7464
Epoch 375/500
0.7426
Epoch 376/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7456
```

```
Epoch 377/500
206/206 [============== ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7564
Epoch 378/500
0.7480
Epoch 379/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7526
Epoch 380/500
0.7485
Epoch 381/500
206/206 [=============== ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7514
Epoch 382/500
0.7474
Epoch 383/500
206/206 [============= ] - 5s 27ms/step - loss: 0.0013 - acc:
0.7398
Epoch 384/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7523
Epoch 385/500
206/206 [============== ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7429
Epoch 386/500
0.7543
Epoch 387/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0014 - acc:
0.7459
Epoch 388/500
206/206 [============== ] - 5s 26ms/step - loss: 0.0017 - acc:
0.7266
Epoch 389/500
206/206 [================ ] - 5s 27ms/step - loss: 0.0014 - acc:
0.7445
Epoch 390/500
206/206 [=============== ] - 5s 27ms/step - loss: 0.0014 - acc:
0.7424: 0s - loss: 0.0014 - acc:
Epoch 391/500
0.7539
Epoch 392/500
0.7502
```

```
Epoch 393/500
206/206 [============= ] - 5s 26ms/step - loss: 0.0013 - acc:
0.7480
Epoch 394/500
206/206 [============== ] - 5s 26ms/step - loss: 0.0013 - acc:
0.7500
Epoch 395/500
206/206 [================ ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7524
Epoch 396/500
0.7441
Epoch 397/500
206/206 [============== ] - 6s 27ms/step - loss: 0.0013 - acc:
0.7471
Epoch 398/500
206/206 [============= ] - 7s 32ms/step - loss: 0.0013 - acc:
0.7517
Epoch 399/500
206/206 [============ ] - 7s 35ms/step - loss: 0.0013 - acc:
0.7464
Epoch 400/500
206/206 [================ ] - 7s 34ms/step - loss: 0.0013 - acc:
0.7470
Epoch 401/500
206/206 [============= ] - 7s 32ms/step - loss: 0.0014 - acc:
0.7467
Epoch 402/500
206/206 [=============== ] - 7s 32ms/step - loss: 0.0013 - acc:
0.7445
Epoch 403/500
206/206 [=============== ] - 7s 33ms/step - loss: 0.0013 - acc:
0.7482
Epoch 404/500
0.7518
Epoch 405/500
206/206 [=============== ] - 6s 31ms/step - loss: 0.0013 - acc:
0.7486
Epoch 406/500
0.7512
Epoch 407/500
0.7439
Epoch 408/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0014 - acc:
0.7429
```

```
Epoch 409/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7517: 1s - loss
Epoch 410/500
0.7517
Epoch 411/500
0.7477: Os - loss: 0.0013 - acc:
Epoch 412/500
0.7483
Epoch 413/500
0.7485
Epoch 414/500
0.7450
Epoch 415/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7424
Epoch 416/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7474
Epoch 417/500
0.7477
Epoch 418/500
0.7482
Epoch 419/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0014 - acc:
0.7442
Epoch 420/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7444
Epoch 421/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7456
Epoch 422/500
206/206 [=============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7476
Epoch 423/500
0.7482
Epoch 424/500
0.7524
```

```
Epoch 425/500
206/206 [============= ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7470
Epoch 426/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7482
Epoch 427/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7462
Epoch 428/500
0.7497
Epoch 429/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7488
Epoch 430/500
0.7555
Epoch 431/500
206/206 [============= ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7482
Epoch 432/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7562
Epoch 433/500
0.7492
Epoch 434/500
0.7415
Epoch 435/500
206/206 [=============== ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7468
Epoch 436/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7582
Epoch 437/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0014 - acc:
0.7397
Epoch 438/500
0.7492
Epoch 439/500
0.7514
Epoch 440/500
0.7467
```

```
Epoch 441/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7442
Epoch 442/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7502
Epoch 443/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7550
Epoch 444/500
0.7471
Epoch 445/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7594
Epoch 446/500
0.7580
Epoch 447/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7533
Epoch 448/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7498
Epoch 449/500
0.7410: 1s - los
Epoch 450/500
0.7380
Epoch 451/500
0.7354
Epoch 452/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7564
Epoch 453/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7508
Epoch 454/500
0.7562
Epoch 455/500
0.7489
Epoch 456/500
206/206 [=============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7526: Os - loss: 0.0013 - acc:
```

```
Epoch 457/500
206/206 [============== ] - 6s 29ms/step - loss: 0.0012 - acc:
0.7535
Epoch 458/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7597
Epoch 459/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7474
Epoch 460/500
0.7451
Epoch 461/500
0.7500: Os - loss: 0.00
Epoch 462/500
0.7565
Epoch 463/500
0.7509
Epoch 464/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7520
Epoch 465/500
0.7568
Epoch 466/500
0.7512
Epoch 467/500
206/206 [================ ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7520
Epoch 468/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7517
Epoch 469/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0012 - acc:
0.7580
Epoch 470/500
0.7550
Epoch 471/500
0.7477
Epoch 472/500
0.7523
```

```
Epoch 473/500
206/206 [============= ] - 6s 29ms/step - loss: 0.0013 - acc:
0.7539
Epoch 474/500
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7479
Epoch 475/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7521
Epoch 476/500
0.7456
Epoch 477/500
206/206 [============= ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7521
Epoch 478/500
0.7462
Epoch 479/500
206/206 [============= ] - 6s 28ms/step - loss: 0.0012 - acc:
0.7546
Epoch 480/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7543
Epoch 481/500
0.7438
Epoch 482/500
0.7372
Epoch 483/500
206/206 [=============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7488
Epoch 484/500
0.7555
Epoch 485/500
206/206 [================ ] - 6s 28ms/step - loss: 0.0012 - acc:
0.7559
Epoch 486/500
0.7470: 1s - loss: 0
Epoch 487/500
0.7533
Epoch 488/500
206/206 [=============== ] - 6s 28ms/step - loss: 0.0013 - acc:
0.7536- ETA: Os - loss: 0.0013 - acc:
```

```
206/206 [============== ] - 6s 28ms/step - loss: 0.0013 - acc:
   0.7536
   Epoch 490/500
   0.7539
   Epoch 491/500
   206/206 [================ ] - 6s 28ms/step - loss: 0.0012 - acc:
   0.7585
   Epoch 492/500
   0.7488
   Epoch 493/500
   0.7489
   Epoch 494/500
   0.7506
   Epoch 495/500
   0.7514
   Epoch 496/500
   206/206 [================ ] - 6s 28ms/step - loss: 0.0012 - acc:
   0.7453
   Epoch 497/500
   0.7523
   Epoch 498/500
   0.7561
   Epoch 499/500
   206/206 [=============== ] - 6s 28ms/step - loss: 0.0013 - acc:
   0.7538
   Epoch 500/500
   0.7549
[207]: <tensorflow.python.keras.callbacks.History at 0x20b70a2e070>
[213]: testing_sample_scaled = sc.fit_transform(test_set_sample[0:30])
   Predicting for sample test data prepared
[214]: testing_sample_scaled = np.reshape(testing_sample_scaled,(testing_sample_scaled.
    →shape[1],testing_sample_scaled.shape[0],1))
   predicted_temperature = regressor.predict(testing_sample_scaled)
```

Epoch 489/500

```
[215]: predicted_temperature = sc.inverse_transform(predicted_temperature)
      The below are the predicted values
[216]: predicted_temperature
[216]: array([[300.18274, 300.5763, 300.68668, 298.6599]], dtype=float32)
      Seeing the actual value to compare
[217]: test set sample[30:34]
[217]: array([[299.37],
              [299.94],
              [300.47],
              [297.62]])
      Finding the error
      error = predicted_temperature[0] - test_set_sample[30:34][0]
[218]:
[452]: print(error)
      [0.81274 0.6363 0.21668 1.0399 ]
      As the above error on the test data increase that, our model performs very well, now lets predict
      the future
      Predicting future temperature with the current data
[220]: testing_sample_scaled = sc.fit_transform(test_set_sample[70:100])
[221]: testing_sample_scaled = np.reshape(testing_sample_scaled,(testing_sample_scaled.
        predicted_temperature = regressor.predict(testing_sample_scaled)
      predicted_temperature = sc.inverse_transform(predicted_temperature)
[245]: print(predicted_temperature[0])
```

The above values are the predicted mean temperature of Kerala for next 4 months, the values are in kelvin scale

1.3 Predicting INDORE Maximum temperature

[300.33813 301.1022 300.9345 299.91898]

Here we are using the main ERA5 dataset for this prediction, here we predict the mean temperature for INDORE district

```
[518]: indore_data = data[data['NAME'] == 'INDORE']
```

```
[519]: indore_data.head()
[519]:
             DIST91 ID
                          NAME
                                      STATE UT
                                                                date
       393
                 205.0 INDORE MADHYA_PRADESH
                                                 1980-01-01T00:00:00
       1047
                 205.0 INDORE MADHYA PRADESH
                                                 1980-02-01T00:00:00
       1701
                 205.0 INDORE MADHYA_PRADESH
                                                 1980-03-01T00:00:00
       2355
                                MADHYA_PRADESH
                 205.0 INDORE
                                                 1980-04-01T00:00:00
                 205.0 INDORE
                                MADHYA_PRADESH
       3009
                                                 1980-05-01T00:00:00
             maximum_2m_air_temperature minimum_2m_air_temperature
       393
                             302.225027
                                                          283.010331
       1047
                             307.376971
                                                          281.841915
       1701
                             309.569063
                                                          285.828591
       2355
                             314.550475
                                                          292.911056
       3009
                             315.050293
                                                          297.359887
[520]: indore_data.info()
      <class 'pandas.core.frame.DataFrame'>
      Int64Index: 480 entries, 393 to 313659
      Data columns (total 6 columns):
           Column
                                        Non-Null Count Dtype
       0
                                        480 non-null
                                                        float64
           DIST91 ID
       1
           NAME
                                        480 non-null
                                                        object
       2
           STATE UT
                                        480 non-null
                                                        object
       3
           date
                                        480 non-null
                                                        object
                                        480 non-null
                                                        float64
           maximum_2m_air_temperature
           minimum_2m_air_temperature
                                        480 non-null
                                                        float64
      dtypes: float64(3), object(3)
      memory usage: 26.2+ KB
      Preparing the dataset
[521]: training_set = indore_data["maximum_2m_air_temperature"]
[522]: training_set.reset_index(drop=True,inplace=True)
[523]: training_set = np.asarray(training_set)
[524]:
      training_set = training_set.reshape((-1,1))
[525]: len(training_set)
[525]: 480
[526]: test_set_sample = training_set[-1:-61:-1]
       train_set = training_set[0:420]
```

```
[527]: len(test_set_sample)
[527]: 60
    Scaling the data
[528]: sc = MinMaxScaler(feature_range=(0,1))
     training_set_scaled = sc.fit_transform(train_set)
[529]: x train = []
     y_train = []
     n_future = 4 # next 4 days temperature forecast
     n_past = 30 # Past 30 days
     for i in range(0,len(training_set_scaled)-n_past-n_future+1):
        x_train.append(training_set_scaled[i : i + n_past , 0])
        y_train.append(training_set_scaled[i + n_past : i + n_past + n_future , 0 ])
     x train , y train = np.array(x train), np.array(y train)
     x_train = np.reshape(x_train, (x_train.shape[0] , x_train.shape[1], 1) )
    Building the model
[531]: regressor = Sequential()
     regressor.add(Bidirectional(LSTM(units=30, return_sequences=True, input_shape = __
      \hookrightarrow (x_train.shape[1],1)))
     regressor.add(Dropout(0.2))
     regressor.add(LSTM(units= 30 , return_sequences=True))
     regressor.add(Dropout(0.2))
     regressor.add(LSTM(units= 30 , return_sequences=True))
     regressor.add(Dropout(0.2))
     regressor.add(LSTM(units= 30))
     regressor.add(Dropout(0.2))
     regressor.add(Dense(units = n_future,activation='linear'))
     regressor.compile(optimizer='adam', loss='mean_squared_error',metrics=['acc'])
     regressor.fit(x_train, y_train, epochs=300,batch_size=32 )
    Epoch 1/300
     0.2610
    Epoch 2/300
    0.2842
    Epoch 3/300
    0.2481
    Epoch 4/300
    0.2661
    Epoch 5/300
```

```
0.2041
Epoch 6/300
0.2558
Epoch 7/300
0.2584
Epoch 8/300
0.2661
Epoch 9/300
0.2119
Epoch 10/300
0.2429
Epoch 11/300
0.2584
Epoch 12/300
0.2532
Epoch 13/300
0.2713
Epoch 14/300
0.2248
Epoch 15/300
0.2403
Epoch 16/300
0.2222
Epoch 17/300
0.2248
Epoch 18/300
0.2739
Epoch 19/300
0.2868
Epoch 20/300
0.2791
Epoch 21/300
```

```
0.3023
Epoch 22/300
0.2972
Epoch 23/300
0.2868
Epoch 24/300
0.3049
Epoch 25/300
0.3230
Epoch 26/300
0.3566
Epoch 27/300
0.3540
Epoch 28/300
0.4238
Epoch 29/300
0.4444
Epoch 30/300
0.3928
Epoch 31/300
0.4651
Epoch 32/300
0.4264
Epoch 33/300
0.4987
Epoch 34/300
0.4729
Epoch 35/300
0.4780
Epoch 36/300
0.4910
Epoch 37/300
```

```
0.4987
Epoch 38/300
0.4574
Epoch 39/300
0.4832
Epoch 40/300
0.5039
Epoch 41/300
0.5194
Epoch 42/300
0.5013
Epoch 43/300
0.4858
Epoch 44/300
0.5039
Epoch 45/300
0.5297
Epoch 46/300
0.5013
Epoch 47/300
0.5090
Epoch 48/300
0.5271
Epoch 49/300
0.5375
Epoch 50/300
0.5245
Epoch 51/300
0.5271
Epoch 52/300
0.5220
Epoch 53/300
```

```
0.5478
Epoch 54/300
0.5685
Epoch 55/300
0.5530
Epoch 56/300
0.5556
Epoch 57/300
0.5504
Epoch 58/300
0.5788
Epoch 59/300
0.5762
Epoch 60/300
0.5788
Epoch 61/300
0.5659
Epoch 62/300
0.5659
Epoch 63/300
0.5866
Epoch 64/300
0.5943
Epoch 65/300
0.5659
Epoch 66/300
0.5711
Epoch 67/300
0.5969
Epoch 68/300
0.5995
Epoch 69/300
```

```
0.5969
Epoch 70/300
0.5995
Epoch 71/300
0.6279
Epoch 72/300
0.6098
Epoch 73/300
0.5659
Epoch 74/300
0.5788
Epoch 75/300
0.6150
Epoch 76/300
0.5866
Epoch 77/300
0.6098
Epoch 78/300
0.6047
Epoch 79/300
0.5891
Epoch 80/300
0.6098
Epoch 81/300
0.6305
Epoch 82/300
0.6305
Epoch 83/300
0.6150
Epoch 84/300
0.6305
Epoch 85/300
```

```
0.6512
Epoch 86/300
0.6434
Epoch 87/300
0.6460
Epoch 88/300
0.6408
Epoch 89/300
0.6357
Epoch 90/300
0.6460
Epoch 91/300
0.6331
Epoch 92/300
0.6641
Epoch 93/300
0.6486
Epoch 94/300
0.6021
Epoch 95/300
0.6512
Epoch 96/300
0.6253
Epoch 97/300
0.5917
Epoch 98/300
0.6873
Epoch 99/300
0.6279
Epoch 100/300
0.6279
Epoch 101/300
```

```
0.6563
Epoch 102/300
0.6667
Epoch 103/300
0.6693
Epoch 104/300
0.6744
Epoch 105/300
0.6331
Epoch 106/300
0.6150
Epoch 107/300
0.6460
Epoch 108/300
0.6408
Epoch 109/300
0.6382
Epoch 110/300
0.6460
Epoch 111/300
0.6718
Epoch 112/300
0.6848
Epoch 113/300
0.6822
Epoch 114/300
0.6718
Epoch 115/300
0.6925
Epoch 116/300
0.6951
Epoch 117/300
```

```
0.6848
Epoch 118/300
0.6873
Epoch 119/300
0.7054
Epoch 120/300
0.6718
Epoch 121/300
0.7028
Epoch 122/300
0.6822
Epoch 123/300
0.6951
Epoch 124/300
0.6899
Epoch 125/300
0.6951
Epoch 126/300
0.6615
Epoch 127/300
0.6977
Epoch 128/300
0.6873
Epoch 129/300
0.7132
Epoch 130/300
0.7287
Epoch 131/300
0.6899
Epoch 132/300
0.7158
Epoch 133/300
```

```
0.7054
Epoch 134/300
0.7028
Epoch 135/300
0.7080
Epoch 136/300
0.6873
Epoch 137/300
0.6770
Epoch 138/300
0.7003
Epoch 139/300
0.7003
Epoch 140/300
0.7287
Epoch 141/300
0.7003
Epoch 142/300
0.7183: Os - loss: 0.0113 - acc: 0.7
Epoch 143/300
0.6899
Epoch 144/300
0.7339
Epoch 145/300
0.7028
Epoch 146/300
0.6977
Epoch 147/300
0.7339
Epoch 148/300
0.6873
Epoch 149/300
```

```
0.7158
Epoch 150/300
0.7261
Epoch 151/300
0.7261
Epoch 152/300
0.7080
Epoch 153/300
0.7158
Epoch 154/300
0.6925
Epoch 155/300
0.6951
Epoch 156/300
0.7028
Epoch 157/300
0.6899
Epoch 158/300
0.7339
Epoch 159/300
0.7080
Epoch 160/300
0.7054
Epoch 161/300
0.6899
Epoch 162/300
0.7028
Epoch 163/300
0.7132
Epoch 164/300
0.7339
Epoch 165/300
```

```
0.6951
Epoch 166/300
0.7235
Epoch 167/300
0.7209
Epoch 168/300
0.7028
Epoch 169/300
0.7313
Epoch 170/300
0.7209
Epoch 171/300
0.7106
Epoch 172/300
0.6951
Epoch 173/300
0.7339
Epoch 174/300
0.7209
Epoch 175/300
0.7261
Epoch 176/300
0.7313
Epoch 177/300
0.7209
Epoch 178/300
0.7003
Epoch 179/300
0.7106
Epoch 180/300
0.7364
Epoch 181/300
```

```
0.6925
Epoch 182/300
0.7287
Epoch 183/300
0.6925
Epoch 184/300
0.6977
Epoch 185/300
0.7442
Epoch 186/300
0.7028
Epoch 187/300
0.7442
Epoch 188/300
0.7287
Epoch 189/300
0.7132
Epoch 190/300
0.6977
Epoch 191/300
0.6873
Epoch 192/300
0.7313
Epoch 193/300
0.7416
Epoch 194/300
0.7106
Epoch 195/300
0.7209
Epoch 196/300
0.7183
Epoch 197/300
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0.7209
Epoch 198/300
0.7235
Epoch 199/300
0.6951
Epoch 200/300
0.7003
Epoch 201/300
0.7054
Epoch 202/300
0.7287
Epoch 203/300
0.7287
Epoch 204/300
0.6822
Epoch 205/300
0.7313
Epoch 206/300
0.7183
Epoch 207/300
0.7235
Epoch 208/300
0.7080
Epoch 209/300
0.7390
Epoch 210/300
0.7235
Epoch 211/300
0.7261
Epoch 212/300
0.7235
Epoch 213/300
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```
0.7416
Epoch 214/300
0.7390
Epoch 215/300
0.7235
Epoch 216/300
0.7287
Epoch 217/300
0.7183
Epoch 218/300
0.7183
Epoch 219/300
0.7158
Epoch 220/300
0.7158
Epoch 221/300
0.7080
Epoch 222/300
0.7494
Epoch 223/300
0.7313
Epoch 224/300
0.7235
Epoch 225/300
0.7416
Epoch 226/300
0.7287
Epoch 227/300
0.7158
Epoch 228/300
0.7442
Epoch 229/300
```

```
0.7364
Epoch 230/300
0.7132
Epoch 231/300
0.7313
Epoch 232/300
0.7571
Epoch 233/300
0.7235
Epoch 234/300
0.7545
Epoch 235/300
0.7183
Epoch 236/300
0.7209
Epoch 237/300
0.7416
Epoch 238/300
0.7416
Epoch 239/300
0.7287
Epoch 240/300
0.7106
Epoch 241/300
0.7364
Epoch 242/300
0.7468
Epoch 243/300
0.7287
Epoch 244/300
0.7313
Epoch 245/300
```

```
0.7183
Epoch 246/300
0.7235
Epoch 247/300
0.7416
Epoch 248/300
0.7339: Os - loss: 0.0098 - acc:
Epoch 249/300
0.7313
Epoch 250/300
0.7287
Epoch 251/300
0.7287
Epoch 252/300
0.7390
Epoch 253/300
0.7494
Epoch 254/300
0.7390
Epoch 255/300
0.7364
Epoch 256/300
0.7235
Epoch 257/300
0.7158
Epoch 258/300
0.7158
Epoch 259/300
0.7390
Epoch 260/300
0.7339
Epoch 261/300
```

```
0.7364
Epoch 262/300
0.7183
Epoch 263/300
0.7313
Epoch 264/300
0.7235
Epoch 265/300
0.7183
Epoch 266/300
0.7494
Epoch 267/300
0.7519
Epoch 268/300
0.7313
Epoch 269/300
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Epoch 271/300
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Epoch 272/300
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Epoch 273/300
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Epoch 274/300
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Epoch 275/300
0.6693
Epoch 276/300
0.7364
Epoch 277/300
```

```
0.7183
Epoch 278/300
0.7261
Epoch 279/300
0.7183
Epoch 280/300
0.7158
Epoch 281/300
0.7183
Epoch 282/300
0.7313
Epoch 283/300
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Epoch 284/300
0.6925
Epoch 285/300
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Epoch 286/300
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Epoch 287/300
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Epoch 288/300
0.7571
Epoch 289/300
0.7468
Epoch 290/300
0.7519
Epoch 291/300
0.7287
Epoch 292/300
0.7313
Epoch 293/300
```

```
Epoch 294/300
  Epoch 295/300
  Epoch 296/300
  0.7313
  Epoch 297/300
  0.7339
  Epoch 298/300
  0.7183
  Epoch 299/300
  0.7183
  Epoch 300/300
  0.7235
[531]: <tensorflow.python.keras.callbacks.History at 0x20c49bc47f0>
[571]: testing_sample_scaled = sc.fit_transform(test_set_sample[14:34])
  Predicting for sample test data
[572]: testing_sample_scaled = np.reshape(testing_sample_scaled,(testing_sample_scaled.
   →shape[1],testing_sample_scaled.shape[0],1))
```

WARNING:tensorflow:7 out of the last 13 calls to <function
Model.make_predict_function.<locals>.predict_function at 0x0000020C509EE310>
triggered tf.function retracing. Tracing is expensive and the excessive number
of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2)
passing tensors with different shapes, (3) passing Python objects instead of
tensors. For (1), please define your @tf.function outside of the loop. For (2),
@tf.function has experimental_relax_shapes=True option that relaxes argument
shapes that can avoid unnecessary retracing. For (3), please refer to https://ww
w.tensorflow.org/tutorials/customization/performance#python_or_tensor_args and
https://www.tensorflow.org/api_docs/python/tf/function for more details.

```
[573]: predicted_temperature = sc.inverse_transform(predicted_temperature)
```

predicted_temperature = regressor.predict(testing_sample_scaled)

Show predicted data

0.7261

```
[574]: predicted_temperature[0]
[574]: array([306.89902, 307.5554, 307.065, 305.6764], dtype=float32)
      Actual values
[575]: actual_value = (test_set_sample[34:38])
[576]: actual_value
[576]: array([[307.522407],
              [303.71404966],
              [304.23127174],
              [305.16312889]])
      Finding the error
[577]: error = predicted_temperature[0] - actual_value[0]
[578]: print(error)
      [-0.62338967 0.0329824 -0.45740456 -1.8460154 ]
      We see that we get good preformance from this model, so now we use it to predict next 4 months
      maximum temparature
      1.3.1 Predicting Future Temperature with current data
[579]: | testing_sample_scaled = sc.fit_transform(test_set_sample[31:61])
[580]: testing_sample_scaled = np.reshape(testing_sample_scaled, (testing_sample_scaled.
        ⇒shape[1],testing_sample_scaled.shape[0],1))
       predicted_temperature = regressor.predict(testing_sample_scaled)
      predicted_temperature = sc.inverse_transform(predicted_temperature)
[582]:
      predicted_temperature[0]
```

The above values are the predicted temperature values for INDORE district for the next 4 months. The temperature values are in kelvin

[582]: array([307.0098 , 306.61124, 304.31796, 303.4949], dtype=float32)