Spoken Digit Recognition

In this notebook, You will do Spoken Digit Recognition.

Input - speech signal, output - digit number

It contains

1. Reading the dataset. and Preprocess the data set. Detailed instrctions are given below. You have to write the code in the same cell which contains the instrction.
2. Training the LSTM with RAW data
3. Converting to spectrogram and Training the LSTM network
4. Creating the augmented data and doing step 2 and 3 again.

Instructions:

```
1. Don't change any Grader Functions. Don't manipulate any Grader functions. If you manipulate any

2. Please read the instructions on the code cells and markdown cells. We will explain what to writ

3. Please return outputs in the same format what we asked. Eg. Don't return List of we are asking

4. Please read the external links that we are given so that you will learn the concept behind the

5. We are giving instructions at each section if necessary, please follow them.
```

Every Grader function has to return True.

```
import numpy as np
import pandas as pd
import librosa
import librosa.display
import os
from sklearn.utils import shuffle
from sklearn.metrics import confusion_matrix, f1_score, classification_report
import tensorflow as tf
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.callbacks import LearningRateScheduler, ReduceLROnPlateau, ModelChec
from tensorflow.keras.layers import Input, BatchNormalization, Dropout, LSTM, Dense, Avera
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import plot_model
tf.keras.backend.clear_session()
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

```
import seaborn as sns
import glob
from joblib import Parallel, delayed
import time
import librosa.display
from collections import Counter
##if you need any imports you can do that here.
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

We shared recordings.zip, please unzip those.

```
#read the all file names in the recordings folder given by us
#(if you get entire path, it is very useful in future)
#save those files names as list in "all_files"
path = '/content/drive/MyDrive/Audio_Spoken_Digit/recordings'
all_files = []
for files in os.listdir(path):
    names = os.path.join(path, files)
    all_files.append(names)
all_files
```

```
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_nicolas_39.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/7_theo_29.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/2_jackson_19.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/3_nicolas_38.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/5_jackson_49.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_yweweler_40.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/3_theo_26.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/5_theo_46.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/9_nicolas_38.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/2_nicolas_23.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/4_yweweler_38.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_theo_36.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_jackson_47.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/9_yweweler_35.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_yweweler_45.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/3_jackson_19.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/9_jackson_46.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_nicolas_0.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_yweweler_39.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/4_yweweler_24.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/4_nicolas_48.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/7_jackson_35.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/3_yweweler_41.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/4_yweweler_41.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/9_jackson_27.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_nicolas_6.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_theo_7.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/5_jackson_0.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/0_yweweler_15.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_yweweler_21.wav',
'/content/drive/MyDrive/Audio_Spoken_Digit/recordings/4_theo_48.wav'
```

```
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/4_theo_48.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/5_yweweler_41.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/7_yweweler_26.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/0_nicolas_48.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/5_theo_48.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_nicolas_39.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/1_theo_20.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/9_jackson_19.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_theo_13.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/7_jackson_8.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/2_jackson_42.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/2_nicolas_35.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/3_yweweler_12.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/5_nicolas_11.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/3_nicolas_3.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_jackson_6.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/0_theo_44.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_jackson_21.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/4_jackson_41.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_theo_13.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/0_jackson_14.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/7_jackson_0.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/7_jackson_38.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/0_theo_41.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_yweweler_30.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/1_yweweler_45.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/9_theo_31.wav',
 '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/6_theo_22.wav',
```

Grader function 1

```
def grader_files():
    temp = len(all_files)==2000
    temp1 = all([x[-3:]=="wav" for x in all_files])
    temp = temp and temp1
    return temp
grader_files()
```

```
True
```

Create a dataframe(name=df_audio) with two columns(path, label).

You can get the label from the first letter of name.

Eg: 0_jackson_0 --> 0

0_jackson_43 --> 0

```
#Create a dataframe(name=df_audio) with two columns(path, label).
#You can get the label from the first letter of name.
#Eg: 0_jackson_0 --> 0
#0_jackson_43 --> 0
label = []
for files in os.listdir(path):
    label.append(files[0])
len(label)
```

```
2000
```

```
df_audio = pd.DataFrame(list(zip(all_files, label)), columns = ['path', 'label'])
df_audio
```

	path	label
0	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	7
1	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	3
2	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	0
3	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	0
4	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	9
...	...	...
1995	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	2
1996	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	3
1997	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	3
1998	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	0
1999	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	4

2000 rows × 2 columns

```
df_audio.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   path    2000 non-null   object
 1   label   2000 non-null   object
dtypes: object(2)
memory usage: 31.4+ KB
```

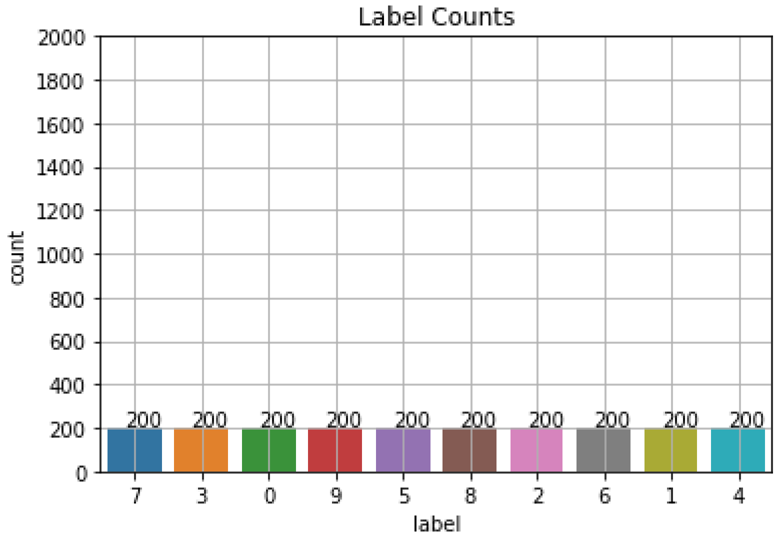
Exploring the sound dataset

```
#It is a good programming practise to explore the dataset that you are dealing with. This
#https://colab.research.google.com/github/Tyler-Hilbert/AudioProcessingInPythonWorkshop/bl
#visualize the data and write code to play 2-3 sound samples in the notebook for better un
#please go through the following reference video https://www.youtube.com/watch?v=37zCgCdV4
```

```
# Count of Labels.
total = len(df_audio)
print(Counter(df_audio['label']))
ax = sns.countplot(df_audio['label'])
for p in ax.patches:
```

```
for p in ax.patches:
  ax.annotate('{}'.format(p.get_height()), (p.get_x()+0.25, p.get_height()+5))

ax.yaxis.set_ticks(np.linspace(0, total, 11))
plt.grid(True)
plt.title("Label Counts")
plt.show()
```

```
Counter({'7': 200, '3': 200, '0': 200, '9': 200, '5': 200, '8': 200, '2': 200, '6': 2
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
```



Creating dataframe

```
#Create a dataframe(name=df_audio) with two columns(path, label).
#You can get the label from the first letter of name.
#Eg: 0_jackson_0 --> 0
#0_jackson_43 --> 0

label = []
for files in os.listdir(path):
    label.append(files[0])
len(label)
```

```
2000
```

```
df_audio = pd.DataFrame(list(zip(all_files, label)), columns = ['path', 'label'])
df_audio
```

	path	label
0	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	7
1	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	3
2	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	0
3	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	0
4	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	9
...	...	...
1995	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	2
1996	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	3
1997	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	3

```
#info
df_audio.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   path    2000 non-null   object
 1   label   2000 non-null   int64 
dtypes: int64(1), object(1)
memory usage: 31.4+ KB
```

```
df_audio.describe()
```

	path	label
count	2000	2000
unique	2000	10
top	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	3
freq	1	200

Grader function 2

```
def grader_df():
    flag_shape = df_audio.shape==(2000,2)
    flag_columns = all(df_audio.columns==['path', 'label'])
    list_values = list(df_audio.label.value_counts())
    flag_label = len(list_values)==10
    flag_label2 = all([i==200 for i in list_values])
    final_flag = flag_shape and flag_columns and flag_label and flag_label2
    return final_flag
grader_df()
```

```
True
```

```
from sklearn.utils import shuffle
df_audio = shuffle(df_audio, random_state=33)#don't change the random state
```

Train and Validation split

```
#split the data into train and validation and save in X_train, X_test, y_train, y_test
#use stratify sampling
#use random state of 45
#use test size of 30%

X = df_audio['path']
Y = df_audio['label'].astype("int32")
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3, stratify = Y, r
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((1400,), (600,), (1400,), (600,))
```

Grader function 3

```
def grader_split():
    flag_len = (len(X_train)==1400) and (len(X_test)==600) and (len(y_train)==1400) and (l
    values_ytrain = list(y_train.value_counts())
    flag_ytrain = (len(values_ytrain)==10) and (all([i==140 for i in values_ytrain]))
    values_ytest = list(y_test.value_counts())
    flag_ytest = (len(values_ytest)==10) and (all([i==60 for i in values_ytest]))
    final_flag = flag_len and flag_ytrain and flag_ytest
    return final_flag
grader_split()
```

```
True
```

Preprocessing

All files are in the "WAV" format. We will read those raw data files using the librosa

```
sample_rate = 22050
def load_wav(x, get_duration=True):
    '''This return the array values of audio with sampling rate of 22050 and Duration'''
    #loading the wav file with sampling rate of 22050
    samples, sample_rate = librosa.load(x, sr=22050)
    if get_duration:
        duration = librosa.get_duration(samples, sample_rate)
        return [samples, duration]
```

```
    else:
        return samples


# Using Parallel jobs to get the samples and duration for train and test.
a = Parallel(n_jobs=-1, verbose = 1)(delayed(load_wav)(train) for train in X_train)
b = Parallel(n_jobs=-1, verbose = 1)(delayed(load_wav)(test) for test in X_test)
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:   29.1s
[Parallel(n_jobs=-1)]: Done 1108 tasks      | elapsed:   41.2s
[Parallel(n_jobs=-1)]: Done 1400 out of 1400 | elapsed:   44.4s finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done 300 tasks      | elapsed:    3.5s
[Parallel(n_jobs=-1)]: Done 600 out of 600 | elapsed:    6.9s finished
```

```
Train_samples = []
Train_duration = []
Test_samples = []
Test_duration = []


a = np.array(a)
Train_samples = a[:,0].tolist()
Train_duration = a[:,1].tolist()
a.dtype
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWar
  """Entry point for launching an IPython kernel.
dtype('O')
```

```
a = np.array(a)
Train_samples = a[:,0].tolist()
Train_duration = a[:,1].tolist()


b = np.array(b)
Test_samples = b[:,0].tolist()
Test_duration = b[:,1].tolist()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWar
  """Entry point for launching an IPython kernel.
```

```
len(Train_samples), len(Test_samples)
```

```
(1400, 600)
```

```
#use load_wav function that was written above to get every wave.
#save it in X_train_processed and X_test_processed
# X_train_processed/X_test_processed should be dataframes with two columns(raw_data, durat

X_train_processed = pd.DataFrame(list(zip(Train_samples, Train_duration)), columns = ['raw
```

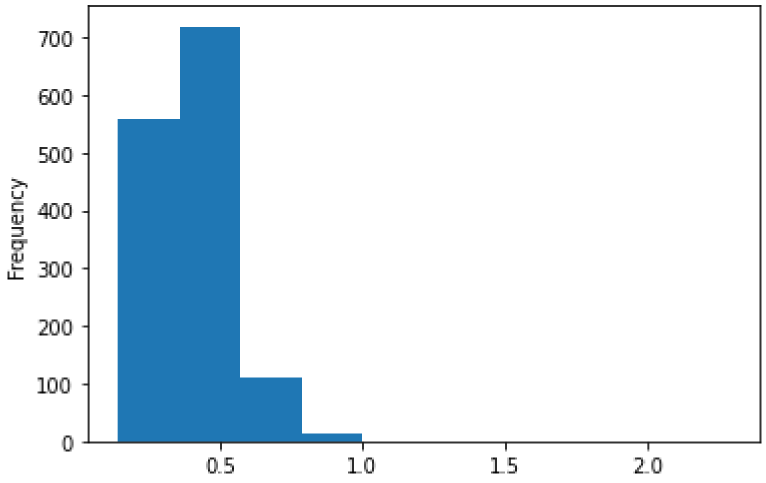
```
X_test_processed = pd.DataFrame(list(zip(Test_samples, Test_duration)), columns = ['raw_da
X_train_processed.shape, X_test_processed.shape
```

```
((1400, 2), (600, 2))
```

```
del a
del b
```

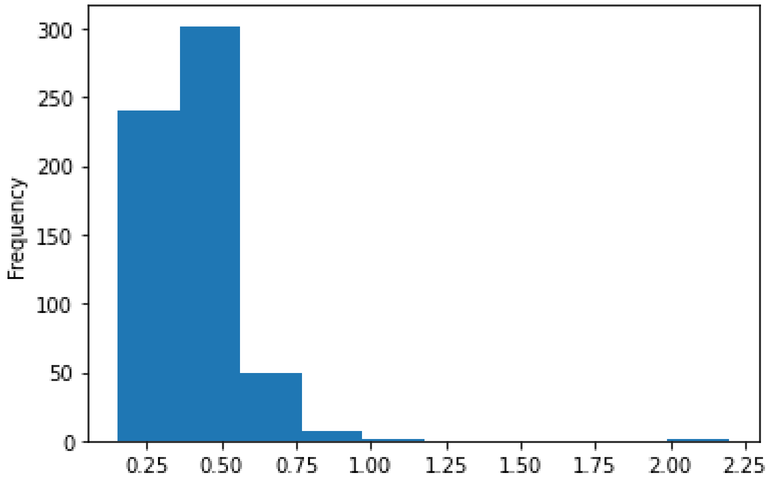
```
# plot the histogram of the duration for train
X_train_processed['duration'].plot.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7eff987f0b90>
```




```
# plot the histogram of the duration for test
X_test_processed['duration'].plot.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7eff98852890>
```

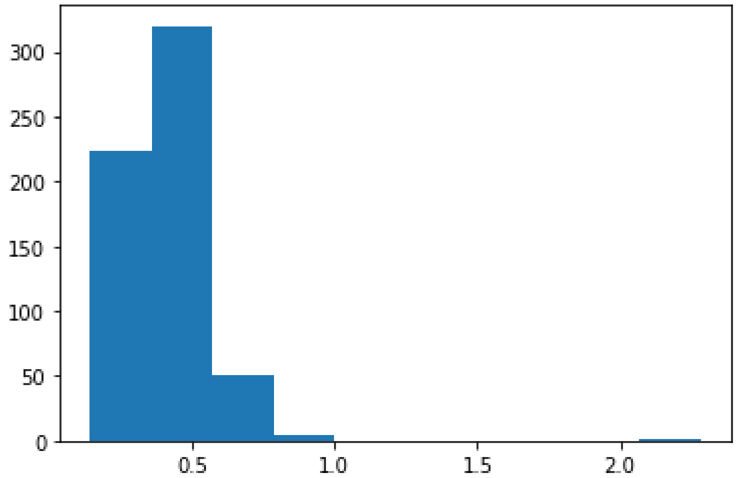



```
#plot the histogram of the duration for trian
```

```
[]
```


```
#plot the histogram of the duration for trian
```

```
(array([224., 320.,  50.,   5.,   0.,   0.,   0.,   0.,   0.,   1.]),
 array([0.14353741, 0.35746032, 0.57138322, 0.78530612, 0.99922902,
        1.21315193, 1.42707483, 1.64099773, 1.85492063, 2.06884354,
        2.28276644]),
 <a list of 10 Patch objects>)
```




```
#print 0 to 100 percentile values with step size of 10 for train data duration.

for i in range(0, 101, 10):
    per = np.percentile(X_train_processed['duration'], i)
    print(i, 'th percentile is ', per)
```

```
0 th percentile is  0.1435374149659864
10 th percentile is  0.2591020408163265
20 th percentile is  0.29586394557823126
30 th percentile is  0.32875283446712017
40 th percentile is  0.357859410430839
50 th percentile is  0.3873922902494331
60 th percentile is  0.4164172335600907
70 th percentile is  0.44616780045351473
80 th percentile is  0.48144217687074836
90 th percentile is  0.555297052154195
100 th percentile is  2.282766439909297
```

```
# Print 90 to 100 percentile values with step size of 1 for train data duration.

for i in range(90, 101):
    per = np.percentile(X_train_processed['duration'], i)
    print(i, 'th percentile is ', per)
```

```
90 th percentile is  0.555297052154195
91 th percentile is  0.5679238095238096
92 th percentile is  0.5795482993197282
93 th percentile is  0.5941251700680278
94 th percentile is  0.6133478458049886
95 th percentile is  0.628310657596372
96 th percentile is  0.6431455782312925
97 th percentile is  0.6611179138321994
98 th percentile is  0.6925750566893424
99 th percentile is  0.784215873015873
100 th percentile is  2.282766439909297
```

Grader function 4

```
def grader_processed():
    flag_columns = (all(X_train_processed.columns==['raw_data', 'duration'])) and (all(X_t
    flag_shape = (X_train_processed.shape ==(1400, 2)) and (X_test_processed.shape==(600,2
    return flag_columns and flag_shape
grader_processed()
```

```
True
```

Based on our analysis 99 percentile values are less than 0.8sec so we will limit maximum length of X_train_processed and X_test_processed to 0.8 sec. It is similar to pad_sequence for a text dataset.

While loading the audio files, we are using sampling rate of 22050 so one sec will give array of length 22050. so, our maximum length is 0.8*22050 = 17640 Pad with Zero if length of sequence is less than 17640 else Truncate the number.

Also create a masking vector for train and test.

masking vector value = 1 if it is real value, 0 if it is pad value. Masking vector data type must be bool.

```
max_length  = 17640
```

```
## as discussed above, Pad with Zero if length of sequence is less than 17640 else Truncat
## save in the X_train_pad_seq, X_test_pad_seq
## also Create masking vector X_train_mask, X_test_mask

## all the X_train_pad_seq, X_test_pad_seq, X_train_mask, X_test_mask will be numpy arrays
```

```
X_train_mask = np.array([np.ones(g.shape[0]) for g in X_train_processed['raw_data'].values
X_train_mask.shape
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWar
  """Entry point for launching an IPython kernel.
(1400,)
```

```
X_test_mask = np.array([np.ones(g.shape[0]) for g in X_test_processed['raw_data'].values])
X_test_mask.shape
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWar
  """Entry point for launching an IPython kernel.
(600,)
```

```
X_train_mask[-50].shape, X_train_processed['raw_data'].values[-50].shape
```

```
((5612,), (5612,))
```

```
#X_train_pad_seq & X_train_mask:

X_train_pad_seq = pad_sequences(X_train_processed['raw_data'], maxlen=max_length, padding=
X_train_mask = pad_sequences(X_train_mask, maxlen=max_length, padding='post', dtype = bool
```

```
#X_test_pad_seq & X_test_mask:

X_test_pad_seq = pad_sequences(X_test_processed['raw_data'], maxlen=max_length, padding='p
X_test_mask = pad_sequences(X_test_mask, maxlen=max_length, padding='post', dtype = bool,
```

```
X_test_pad_seq
```

```
array([[-1.26367854e-02, -1.55794946e-02, -1.13195395e-02, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-1.18654723e-04, -2.41128844e-04, -2.04156895e-04, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-7.05007842e-05, -7.15753195e-05, -4.50172411e-05, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       ...,
       [ 1.53095997e-03,  2.04080902e-03,  2.03249208e-03, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [ 7.05277140e-04,  1.56983704e-04, -3.24962894e-04, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00],
       [-2.44123731e-02, -3.74546014e-02, -4.49726209e-02, ...,
         0.00000000e+00,  0.00000000e+00,  0.00000000e+00]], dtype=float32)
```

```
X_test_mask
```

```
array([[ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False],
       ...,
       [ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False]])
```

Grader function 5

```
def grader_padoutput():
    flag_padshape = (X_train_pad_seq.shape==(1400, 17640)) and (X_test_pad_seq.shape==(600
    flag_maskshape = (X_train_mask.shape==(1400, 17640)) and (X_test_mask.shape==(600, 176
    flag_dtype = (X_train_mask.dtype==bool) and (X_test_mask.dtype==bool)
    return flag_padshape and flag_maskshape and flag_dtype
grader_padoutput()
```

```
True
```

```
# Changing the dimension.
X_T_pad = tf.expand_dims(X_train_pad_seq, axis = 2)
X_T_pad.shape, X_T_pad[0].shape
```

```
(TensorShape([1400, 17640, 1]), TensorShape([17640, 1]))
```

```
X_Te_pad = tf.expand_dims(X_test_pad_seq, axis = 2)
X_Te_pad.shape, X_Te_pad[0].shape
```

```
(TensorShape([600, 17640, 1]), TensorShape([17640, 1]))
```

```
Train = [X_T_pad, X_train_mask]
Val = [X_Te_pad, X_test_mask]
```

```
Train_data = (Train, y_train.values)
Val_data = (Val, y_test.values)
```

1. Giving Raw data directly.

Now we have

Train data: X_train_pad_seq, X_train_mask and y_train
Test data: X_test_pad_seq, X_test_mask and y_test

We will create a LSTM model which takes this input.

Task:

1. Create an LSTM network which takes "X_train_pad_seq" as input, "X_train_mask" as mask input. You can use any number of LSTM cells. Please read LSTM documentation(https://www.tensorflow.org/api_docs/python/tf/keras/layers/LSTM) in tensorflow to know more about mask and also https://www.tensorflow.org/guide/keras/masking_and_padding
2. Get the final output of the LSTM and give it to Dense layer of any size and then give it to Dense layer of size 10(because we have 10 outputs) and then compile with the sparse categorical cross entropy(because we are not converting it to one hot vectors). Also check

the datatype of class labels(y_values) and make sure that you convert your class labels to integer datatype before fitting in the model.

3. While defining your model make sure that you pass both the input layer and mask input layer as input to lstm layer as follows

```
lstm_output = self.lstm(input_layer, mask=masking_input_layer)
```

4. Use tensorboard to plot the graphs of loss and metric(use custom micro F1 score as metric) and histograms of gradients. You can write your code for computing F1 score using this link
5. make sure that it won't overfit.
6. You are free to include any regularization

```
from tensorflow.keras.layers import Input, LSTM, Dense
from tensorflow.keras.models import Model
import tensorflow as tf


tf.keras.backend.clear_session()
class Metrics(tf.keras.callbacks.Callback):

    def __init__(self, x = None, y = None):
        self.training_data = x
        self.validation_data = y

    def on_train_begin(self, logs = {}):
        ## on begin of training, we are creating a instance varible called history
        self.history={'train_f1_score': [], 'val_f1_score': []}


    def on_epoch_end(self, epoch, logs = {}):
        ## on end of each epoch, we will get logs and update the self.history dict
        train_predict = self.model.predict(self.training_data[0], batch_size = 50)
        train_bin = np.argmax(train_predict, axis = 1)
        train_targ = self.training_data[1]
        _train_f1 = f1_score(train_targ, train_bin, average = 'micro')


        val_predict = self.model.predict(self.validation_data[0], batch_size = 50)
        val_bin = np.argmax(val_predict, axis = 1)
        val_targ = self.validation_data[1]
        _val_f1 = f1_score(val_targ, val_bin, average = 'micro')

        self.history['val_f1_score'].append(_val_f1)
        self.history['train_f1_score'].append(_train_f1)

        print(' - train_f1_score : ', _train_f1, ' - val_f1_score : ', _val_f1)
        return
```

```
def changeLearningRate(epoch):
    global initial_learningrate
    epoch = epoch + 1
    if epoch % 5 == 0:
        initial_learningrate *= 0.55
    return initial_learningrate
```

```
import os
save = 'model_save/*.hdf5'
r = glob.glob(save)
for i in r:
    os.remove(i)
```

```
filepath="model_save/model-{epoch:02d}-{val_sparse_categorical_accuracy:.4f}.hdf5"
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_sparse_categorical_accuracy',
reducelr = ReduceLROnPlateau(monitor = 'val_loss', factor = 0.001, patience = 1, verbose =

lrschedule = LearningRateScheduler(changeLearningRate, verbose=1)
initial_learningrate=0.001
```

```
metrics = Metrics(Train_data, Val_data)
callbacks = [metrics, checkpoint, reducelr, lrschedule]
reg = tf.keras.regularizers.L2(l2=0.01)
```

```
## as discussed above, please write the architecture of the model.
## you will have two input layers in your model (data input layer and mask input layer)
## make sure that you have defined the data type of masking layer as bool

input_layer = Input(shape=(17640,1), name = 'input_layer')
input_mask = Input(shape=(17640,), name = 'mask_layer', dtype=bool)
ls = LSTM(units = 128, name = 'LSTM')(input_layer, mask = input_mask)
ls = BatchNormalization()(ls)
dc1 = Dense(512,activation='relu',kernel_initializer=tf.keras.initializers.he_normal(seed
dc1 = Dropout(0.35)(dc1)
out = Dense(10,activation='softmax',kernel_initializer=tf.keras.initializers.glorot_normal
```

```
model_raw1 = Model(inputs = [input_layer,input_mask], outputs = out)
```

```
model_raw1.summary()
```

```
Model: "model"
__________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==========================================================================================
 input_layer (InputLayer)       [(None, 17640, 1)]   0           []

 mask_layer (InputLayer)        [(None, 17640)]      0           []

 LSTM (LSTM)                    (None, 128)          66560       ['input_layer[0][0]
                                                                  'mask_layer[0][0]'
```

```
 batch_normalization (BatchNorm  (None, 128)         512         ['LSTM[0][0]']
 alization)

 FC2 (Dense)                    (None, 512)          66048       ['batch_normalizatio

 dropout (Dropout)              (None, 512)          0           ['FC2[0][0]']

 FC3 (Dense)                    (None, 10)           5130        ['dropout[0][0]']

==================================================================================
Total params: 138,250
Trainable params: 137,994
Non-trainable params: 256
__________________________________________________________________________________
```

```
model_raw1.compile(optimizer=tf.keras.optimizers.RMSprop(0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['sparse_categorical_accuracy'])
```

```
#train your model
#model1.fit([X_train_pad_seq,X_train_mask],y_train_int,.........)s
model_history = model_raw1.fit(Train, y_train.values, batch_size = 40, validation_data = (
```

```
Epoch 00001: LearningRateScheduler setting learning rate to 0.001.
Epoch 1/6
35/35 [==============================] - ETA: 0s - loss: 2.3078 - sparse_categorical_

Epoch 00001: val_sparse_categorical_accuracy improved from -inf to 0.10000, saving mo
35/35 [==============================] - 1411s 41s/step - loss: 2.3078 - sparse_categ

Epoch 00002: LearningRateScheduler setting learning rate to 0.001.
Epoch 2/6
35/35 [==============================] - ETA: 0s - loss: 2.3014 - sparse_categorical_

Epoch 00002: val_sparse_categorical_accuracy did not improve from 0.10000

Epoch 00002: ReduceLROnPlateau reducing learning rate to 1.0000000474974512e-06.
35/35 [==============================] - 1383s 40s/step - loss: 2.3014 - sparse_categ

Epoch 00003: LearningRateScheduler setting learning rate to 0.001.
Epoch 3/6
35/35 [==============================] - ETA: 0s - loss: 2.2984 - sparse_categorical_

Epoch 00003: val_sparse_categorical_accuracy did not improve from 0.10000

Epoch 00003: ReduceLROnPlateau reducing learning rate to 1.0000000474974512e-06.
35/35 [==============================] - 1392s 40s/step - loss: 2.2984 - sparse_categ

Epoch 00004: LearningRateScheduler setting learning rate to 0.001.
Epoch 4/6
35/35 [==============================] - ETA: 0s - loss: 2.5980 - sparse_categorical_

Epoch 00004: val_sparse_categorical_accuracy did not improve from 0.10000
```

```
Epoch 00004: ReduceLROnPlateau reducing learning rate to 1.0000000474974512e-06.
35/35 [==============================] - 1381s 40s/step - loss: 2.5980 - sparse_categ

Epoch 00005: LearningRateScheduler setting learning rate to 0.00055.
Epoch 5/6
35/35 [==============================] - ETA: 0s - loss: 2.3039 - sparse_categorical_

Epoch 00005: val_sparse_categorical_accuracy did not improve from 0.10000

Epoch 00005: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
35/35 [==============================] - 1385s 40s/step - loss: 2.3039 - sparse_categ

Epoch 00006: LearningRateScheduler setting learning rate to 0.00055.
Epoch 6/6
35/35 [==============================] - ETA: 0s - loss: 2.3002 - sparse_categorical_

Epoch 00006: val_sparse_categorical_accuracy did not improve from 0.10000

Epoch 00006: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
35/35 [==============================] - 1394s 40s/step - loss: 2.3002 - sparse_categ
```

```
model_raw1.save('Model_raw_1_0.1517_final.h5')
```

```
model_raw1 = load_model('/content/Model_raw_1_0.1517_final.h5')
```

```
## as discussed above, please write the LSTM
y_pred = model_raw1.predict(Val)
y_pred = np.argmax(y_pred, axis = 1)
```

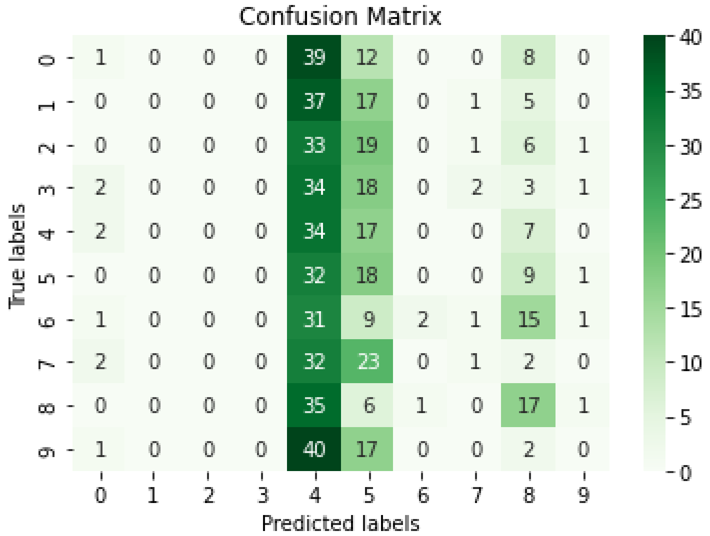
```
print('Classification Report')
print(classification_report(y_test.values, y_pred))
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.11      0.02      0.03        60
           1       0.00      0.00      0.00        60
           2       0.00      0.00      0.00        60
           3       0.00      0.00      0.00        60
           4       0.10      0.57      0.17        60
           5       0.12      0.30      0.17        60
           6       0.67      0.03      0.06        60
           7       0.17      0.02      0.03        60
           8       0.23      0.28      0.25        60
           9       0.00      0.00      0.00        60

    accuracy                           0.12       600
   macro avg       0.14      0.12      0.07       600
weighted avg       0.14      0.12      0.07       600

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Unde
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Unde
  _warn_prf(average, modifier, msg_start, len(result))
```

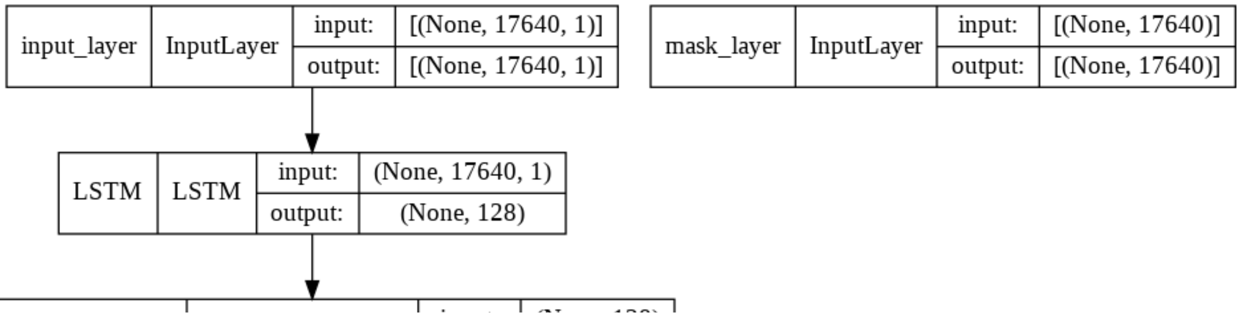
```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Undef
  _warn_prf(average, modifier, msg_start, len(result))
```

```
ax= plt.subplot()
sns.heatmap(confusion_matrix(y_test.values, y_pred), annot=True, ax = ax, fmt='g', cmap='G

ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels')
ax.set_title('Confusion Matrix')
```

```
Text(0.5, 1.0, 'Confusion Matrix')
```




```
plot_model(model_raw1, show_shapes=True, show_layer_names=True)
```



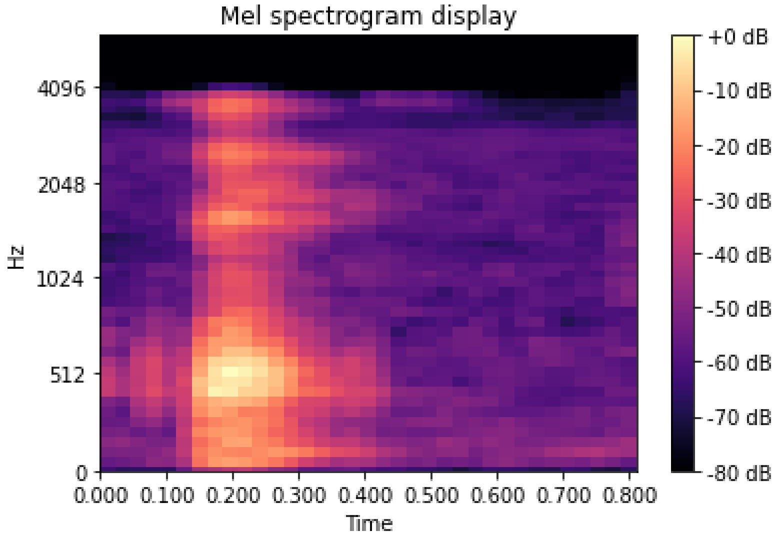
2. Converting into spectrogram and giving spectrogram data as input

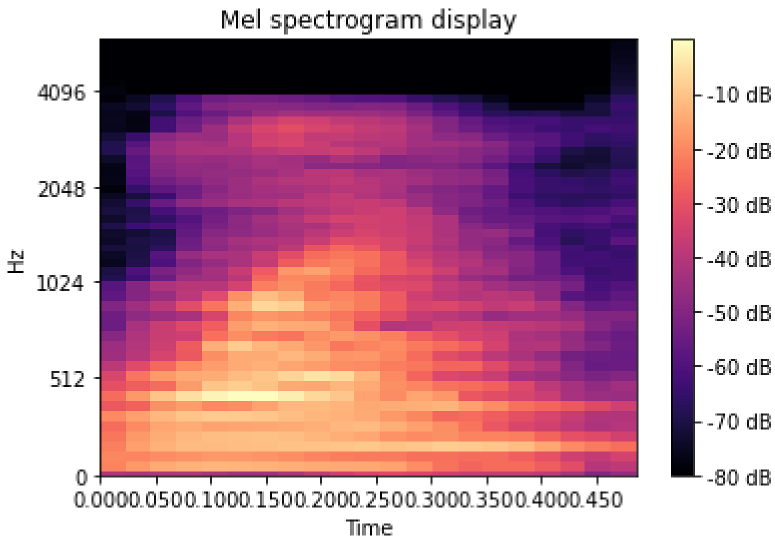
We can use librosa to convert raw data into spectrogram. A spectrogram shows the features in a two-dimensional representation with the intensity of a frequency at a point in time i.e we are converting Time domain to frequency domain. you can read more about this in https://pnsn.org/spectrograms/what-is-a-spectrogram

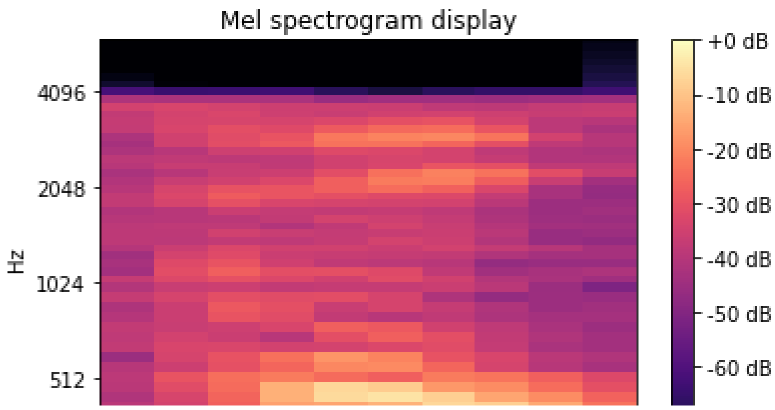
| output: | (None, 512) |

```
def convert_to_spectrogram(raw_data):
    '''converting to spectrogram'''
    spectrum = librosa.feature.melspectrogram(y=raw_data, sr=sample_rate, n_mels=64)
    logmel_spectrum = librosa.power_to_db(S=spectrum, ref=np.max)
    return logmel_spectrum


###use convert_to_spectrogram and convert every raw sequence in X_train_pad_seq and X_test
## save those all in the X_train_spectrogram and X_test_spectrogram ( These two arrays mus
#X_train_spectrogram:
X_train_spectrogram = []
for j in X_train_pad_seq:
    l = convert_to_spectrogram(j)
    X_train_spectrogram.append(l)
X_train_spectrogram = np.array(X_train_spectrogram)


#X_test_spectrogram:
X_test_spectrogram = []
for j in X_test_pad_seq:
    l = convert_to_spectrogram(j)
    X_test_spectrogram.append(l)
X_test_spectrogram = np.array(X_test_spectrogram)


plt.subplots_adjust(wspace=1, hspace=1)
for i in range(0,3):
    fig, ax = plt.subplots()
    img = librosa.display.specshow(convert_to_spectrogram(X_train_processed['raw_data'][i]
    ax.set(title='Mel spectrogram display')
    ax.set_ylim([0,6000])
    fig.colorbar(img, ax=ax, format="%+2.f dB")
```

```
<Figure size 432x288 with 0 Axes>
```







Grader function 6

```
def grader_spectrogram():
    flag_shape = (X_train_spectrogram.shape==(1400,64, 35)) and (X_test_spectrogram.shape
    return flag_shape
grader_spectrogram()
```

```
True
```

Now we have

Train data: X_train_spectrogram and y_train

Test data: X_test_spectrogram and y_test

We will create a LSTM model which takes this input.

Task:

1. Create an LSTM network which takes "X_train_spectrogram" as input and has to return output at every time step.
2. Average the output of every time step and give this to the Dense layer of any size. (ex: Output from LSTM will be (None, time_steps, features) average the output of every time step i.e, you should get (None,time_steps) and then pass to dense layer)
3. give the above output to Dense layer of size 10(output layer) and train the network with sparse categorical cross entropy.
4. Use tensorboard to plot the graphs of loss and metric(use custom micro F1 score as metric) and histograms of gradients. You can write your code for computing F1 score using this link
5. make sure that it won't overfit.
6. You are free to include any regularization

```
tf.keras.backend.clear_session()
reg = tf.keras.regularizers.L2(l2=1.5)


# write the architecture of the model
#print model.summary and make sure that it is following point 2 mentioned above
tf.keras.backend.clear_session()
input_layer = Input(shape=(64,35), name = 'input_layer')
ls = LSTM(units = 128, name = 'LSTM', return_sequences = True)(input_layer)
ad = GlobalAveragePooling1D()(ls)
dc1 = Dense(1024,activation='relu',kernel_initializer=tf.keras.initializers.he_normal(seed
dc1 = Dense(256,activation='relu',kernel_initializer=tf.keras.initializers.he_normal(seed
dc1 = BatchNormalization()(dc1)
dc1 = Dropout(0.6899)(dc1)
out = Dense(10,activation='softmax',kernel_initializer=tf.keras.initializers.glorot_normal


m_spec = Model(inputs = input_layer, outputs = out)


m_spec.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (InputLayer)    [(None, 64, 35)]          0

 LSTM (LSTM)                 (None, 64, 128)           83968

 global_average_pooling1d (G  (None, 128)              0
```

```
 lobalAveragePooling1D)

 FC1 (Dense)                 (None, 1024)              132096

 FC2 (Dense)                 (None, 256)               262400

 batch_normalization (BatchN  (None, 256)              1024
 ormalization)

 dropout (Dropout)           (None, 256)               0

 FC3 (Dense)                 (None, 10)                2570

=================================================================
Total params: 482,058
Trainable params: 481,546
Non-trainable params: 512
_________________________________________________________________
```

```
save = 'model_spec_save/*.hdf5'
r = glob.glob(save)
for i in r:
    os.remove(i)
```

```
filepath="model_spec_save/model-{epoch:02d}-{val_sparse_categorical_accuracy:.4f}.hdf5"
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_sparse_categorical_accuracy',
reducelr = ReduceLROnPlateau(monitor = 'val_loss', factor = 0.055, patience = 1, verbose =

lrschedule = LearningRateScheduler(changeLearningRate, verbose=1)
initial_learningrate=0.001
```

```
Train_data_spec = [X_train_spectrogram, y_train.values]
Test_data_spec = [X_test_spectrogram, y_test.values]
metrics = Metrics(Train_data_spec, Test_data_spec)
callbacks = [metrics, checkpoint, reducelr, lrschedule]
```

```
#compile and fit your model.
#model2.fit([X_train_spectrogram],y_train_int,......)
m_spec.compile(optimizer=tf.keras.optimizers.Adam(0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['sparse_categorical_accuracy'])
```

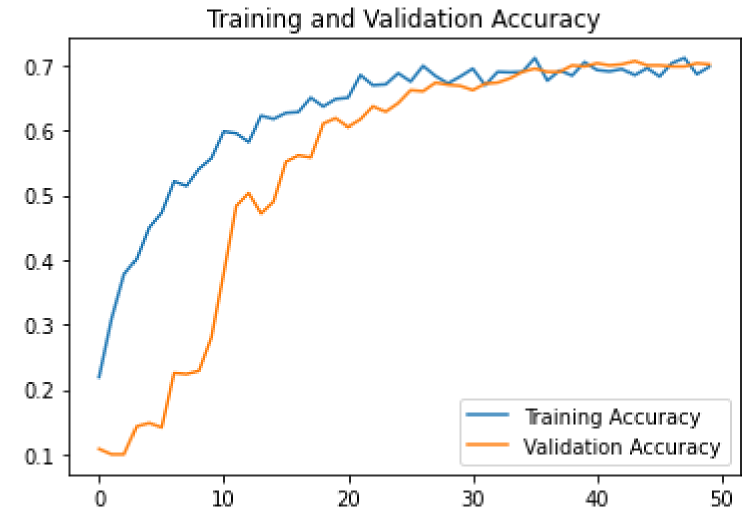
```
tf.keras.backend.clear_session()
model_spec_history = m_spec.fit(X_train_spectrogram, y_train.values, batch_size =50, valid
```

```
Epoch 00042: val_sparse_categorical_accuracy did not improve from 0.70333
28/28 [==============================] - 5s 183ms/step - loss: 0.8912 - sparse_cat

Epoch 00043: LearningRateScheduler setting learning rate to 8.373393789062505e-06.
```

```
Epoch 43/50
28/28 [==============================] - ETA: 0s - loss: 0.9130 - sparse_categoric

Epoch 00043: val_sparse_categorical_accuracy did not improve from 0.70333
28/28 [==============================] - 5s 183ms/step - loss: 0.9130 - sparse_cat

Epoch 00044: LearningRateScheduler setting learning rate to 8.373393789062505e-06.
Epoch 44/50
28/28 [==============================] - ETA: 0s - loss: 0.9075 - sparse_categoric

Epoch 00044: val_sparse_categorical_accuracy improved from 0.70333 to 0.70667, sav
28/28 [==============================] - 5s 185ms/step - loss: 0.9075 - sparse_cat

Epoch 00045: LearningRateScheduler setting learning rate to 4.605366583984378e-06.
Epoch 45/50
28/28 [==============================] - ETA: 0s - loss: 0.8925 - sparse_categoric

Epoch 00045: val_sparse_categorical_accuracy did not improve from 0.70667
28/28 [==============================] - 5s 182ms/step - loss: 0.8925 - sparse_cat

Epoch 00046: LearningRateScheduler setting learning rate to 4.605366583984378e-06.
Epoch 46/50
28/28 [==============================] - ETA: 0s - loss: 0.9129 - sparse_categoric

Epoch 00046: val_sparse_categorical_accuracy did not improve from 0.70667
28/28 [==============================] - 5s 182ms/step - loss: 0.9129 - sparse_cat

Epoch 00047: LearningRateScheduler setting learning rate to 4.605366583984378e-06.
Epoch 47/50
28/28 [==============================] - ETA: 0s - loss: 0.8815 - sparse_categoric

Epoch 00047: val_sparse_categorical_accuracy did not improve from 0.70667
28/28 [==============================] - 5s 183ms/step - loss: 0.8815 - sparse_cat

Epoch 00048: LearningRateScheduler setting learning rate to 4.605366583984378e-06.
Epoch 48/50
28/28 [==============================] - ETA: 0s - loss: 0.8838 - sparse_categoric

Epoch 00048: val_sparse_categorical_accuracy did not improve from 0.70667
28/28 [==============================] - 5s 181ms/step - loss: 0.8838 - sparse_cat

Epoch 00049: LearningRateScheduler setting learning rate to 4.605366583984378e-06.
Epoch 49/50
28/28 [==============================] - ETA: 0s - loss: 0.9120 - sparse_categoric

Epoch 00049: val_sparse_categorical_accuracy did not improve from 0.70667
28/28 [==============================] - 5s 183ms/step - loss: 0.9120 - sparse_cat

Epoch 00050: LearningRateScheduler setting learning rate to 2.532951621191408e-06.
Epoch 50/50
28/28 [==============================] - ETA: 0s - loss: 0.9119 - sparse_categoric
```

```
acc = model_spec_history.history['sparse_categorical_accuracy']
val_acc = model_spec_history.history['val_sparse_categorical_accuracy']

loss = model_spec_history.history['loss']
val_loss = model_spec_history.history['val_loss']
```

```
f1 = metrics.history['train_f1_score']
val_f1 = metrics.history['val_f1_score']

epochs_range = range(50)

#plt.figure(figsize=(8, 8))
#plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.show()

plt.plot(epochs_range, f1, label='Training micro F1 score')
plt.plot(epochs_range, val_f1, label='Validation micro F1 score')
plt.legend(loc='lower right')
plt.title('Training and Validation F1 Score')
plt.show()

#plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



Training and Validation F1 Score

```
model_raw1.save('Model_raw_1_0.1517_final.h5')
```

```
model_raw1 = load_model('/content/Model_raw_1_0.1517_final.h5')
```

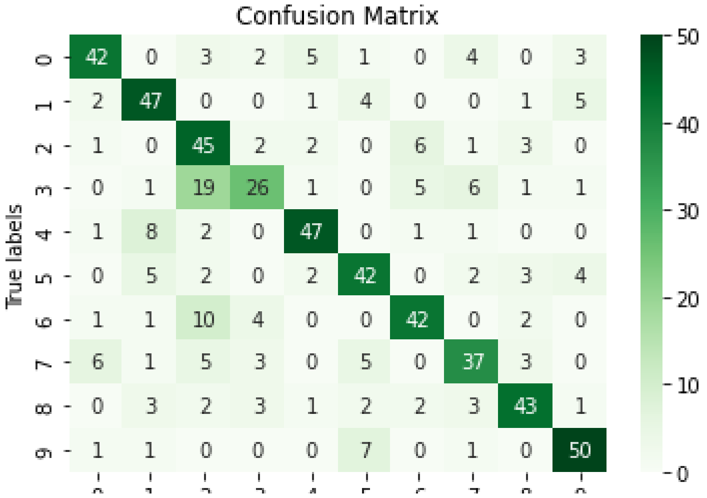
```
## as discussed above, please write the LSTM
y_pred = m_spec.predict(X_test_spectrogram)
y_pred = np.argmax(y_pred, axis = 1)
```

```
print('Classification Report')
print(classification_report(y_test.values, y_pred))
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.78      0.70      0.74        60
           1       0.70      0.78      0.74        60
           2       0.51      0.75      0.61        60
           3       0.65      0.43      0.52        60
           4       0.80      0.78      0.79        60
           5       0.69      0.70      0.69        60
           6       0.75      0.70      0.72        60
           7       0.67      0.62      0.64        60
           8       0.77      0.72      0.74        60
           9       0.78      0.83      0.81        60

    accuracy                           0.70       600
   macro avg       0.71      0.70      0.70       600
weighted avg       0.71      0.70      0.70       600
```

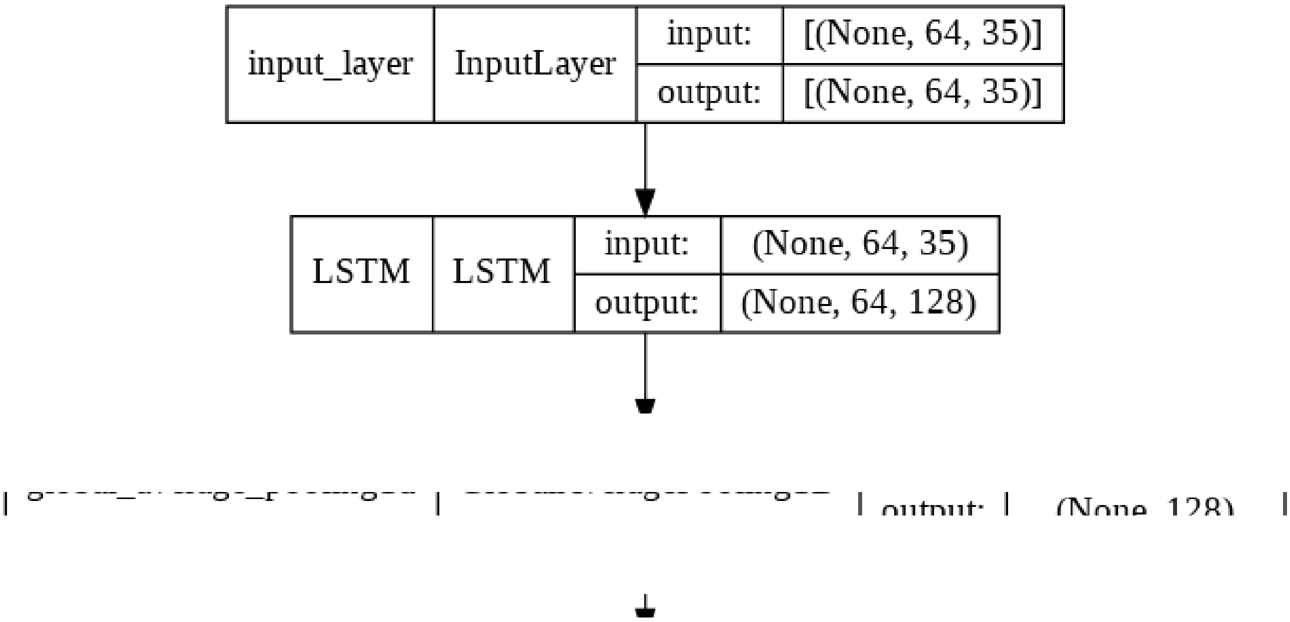
```
ax= plt.subplot()
sns.heatmap(confusion_matrix(y_test.values, y_pred), annot=True, ax = ax, fmt='g', cmap='G

ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels')
ax.set_title('Confusion Matrix')
```

```
Text(0.5, 1.0, 'Confusion Matrix')
```




```
m_spec.save('Model_Spect_1_0.805_final.h5')
```

```
m_spec = load_model('/content/Model_Spect_1_0.805_final.h5')
plot_model(m_spec, show_shapes=True, show_layer_names=True)
```



3. Data augmentation with raw features

Till now we have done with 2000 samples only. It is very less data. We are giving the process of generating augmented data below.

There are two types of augmentation:

1. time stretching - Time stretching either increases or decreases the length of the file. For time stretching we move the file 30% faster or slower
2. pitch shifting - pitch shifting moves the frequencies higher or lower. For pitch shifting we shift up or down one half-step.

```
## generating augmented data.
def generate_augmented_data(file_path, label):
    augmented_data = []
    samples = load_wav(file_path,get_duration=False)
    augmented_data.append(samples)
    for time_value in [0.7, 1, 1.3]:
        for pitch_value in [-1, 0, 1]:
            time_stretch_data = librosa.effects.time_stretch(samples, rate=time_value)
            final_data = librosa.effects.pitch_shift(time_stretch_data, sr=sample_rate, n_
            augmented_data.append(final_data)
    return augmented_data, np.full(len(augmented_data), label)
```

```
Y = df_audio['label'].astype("int32")
```

```
temp_path, temp_lab = df_audio.iloc[1].path, Y.iloc[1]
aug_temp1,auj= generate_augmented_data(temp_path, temp_lab)
```

Follow the steps

1. Split data 'df_audio' into train and test (80-20 split)

2. We have 2000 data points(1600 train points, 400 test points)

```
X_train, X_test, y_train, y_test=train_test_split(df_audio['path'],df_audio['label'],rando
```

3. Do augmentation only on X_train,pass each point of X_train to generate_augmented_data function.After augmentation we will get 14400 train points. Make sure that you are augmenting the corresponding class labels (y_train) also.
4. Preprocess your X_test using load_wav function.
5. Convert the augmented_train_data and test_data to numpy arrays.
6. Perform padding and masking on augmented_train_data and test_data.
7. After padding define the model similar to model 1 and fit the data

Note - While fitting your model on the augmented data for model 3 you might face Resource exhaust error. One simple hack to avoid that is save the augmented_train_data,augment_y_train,test_data and y_test to Drive or into your local system. Then restart the runtime so that now you can train your model with full RAM capacity. Upload these files again in the new runtime session perform padding and masking and then fit your model.

```
a = Parallel(n_jobs=-1, verbose = 1)(delayed(generate_augmented_data)(i, j) for i, j in (X
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:   11.4s
[Parallel(n_jobs=-1)]: Done 196 tasks      | elapsed:   37.1s
[Parallel(n_jobs=-1)]: Done 446 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 796 tasks      | elapsed:  2.3min
[Parallel(n_jobs=-1)]: Done 1246 tasks      | elapsed:  3.6min
[Parallel(n_jobs=-1)]: Done 1796 tasks      | elapsed:  5.2min
[Parallel(n_jobs=-1)]: Done 2000 out of 2000 | elapsed:  5.8min finished
```

```
a = np.array(a)
New_samples = a[:,0].ravel()
New_labels = a[:,1].astype('int32').ravel()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWar
  """Entry point for launching an IPython kernel.
```

```
len(New_samples), len(New_labels)
```

```
(20000, 20000)
```

```
# Shuffling the above dataset, don't change the random state
New_samples, New_labels = shuffle(New_samples, New_labels, random_state=33)
```

```
X_train, X_test, y_train, y_test = train_test_split(New_samples, New_labels, test_size = 0
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((14000,), (6000,), (14000,), (6000,))
```

```
X_train_mask = np.array([np.ones(g.shape[0]) for g in X_train])
X_train_mask.shape
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWar
  """Entry point for launching an IPython kernel.
(14000,)
```

```
X_test_mask = np.array([np.ones(g.shape[0]) for g in X_test])
X_test_mask.shape
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: VisibleDeprecationWar
  """Entry point for launching an IPython kernel.
(6000,)
```

```
max_length  = 17640
X_train_mask[-50].shape, X_train[-50].shape
```

```
((7770,), (7770,))
```

```
X_train_pad_seq = pad_sequences(X_train, maxlen=max_length, padding='post', dtype = np.flo
X_train_mask = pad_sequences(X_train_mask, maxlen=max_length, padding='post', dtype = bool
```

```
X_test_pad_seq = pad_sequences(X_test, maxlen=max_length, padding='post', dtype = np.float
X_test_mask = pad_sequences(X_test_mask, maxlen=max_length, padding='post', dtype = bool,
```

```
X_test_mask
```

```
array([[ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False],
       ...,
       [ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False],
       [ True,  True,  True, ..., False, False, False]])
```

```
X_T_pad = tf.expand_dims(X_train_pad_seq, axis = 2)
X_T_pad.shape, X_T_pad[0].shape
```

```
(TensorShape([14000, 17640, 1]), TensorShape([17640, 1]))
```

```
X_Te_pad = tf.expand_dims(X_test_pad_seq, axis = 2)
X_Te_pad.shape, X_Te_pad[0].shape
```

```
(TensorShape([6000, 17640, 1]), TensorShape([17640, 1]))
```

```
td1 = tf.data.Dataset.from_tensor_slices((X_T_pad, X_train_mask))
td2 = tf.data.Dataset.from_tensor_slices((y_train))
td = tf.data.Dataset.zip((td1, td2))


BATCH_SIZE = 128
SHUFFLE_BUFFER_SIZE = 100
train_dataset = td.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE)


td1 = tf.data.Dataset.from_tensor_slices((X_Te_pad, X_test_mask))
td2 = tf.data.Dataset.from_tensor_slices((y_test))
td = tf.data.Dataset.zip((td1, td2))


test_dataset = td.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE)


Train = [X_T_pad, X_train_mask]
Val = [X_Te_pad, X_test_mask]


Train_data = (Train, y_train)
Val_data = (Val, y_test)


del a


#Model:3- Data augmentation with raw features:

tf.keras.backend.clear_session()
class Metrics(tf.keras.callbacks.Callback):

    def __init__(self, x = None, y = None):
        self.training_data = x
        self.validation_data = y

    def on_train_begin(self, logs = {}):
        ## on begin of training, we are creating a instance varible called history
        self.history={'train_f1_score': [], 'val_f1_score': []}


    def on_epoch_end(self, epoch, logs = {}):
        ## on end of each epoch, we will get logs and update the self.history dict
        train_predict = self.model.predict(self.training_data[0], batch_size = 128)
        train_bin = np.argmax(train_predict, axis = 1)
        train_targ = self.training_data[1]
        _train_f1 = f1_score(train_targ, train_bin, average = 'micro')


        val_predict = self.model.predict(self.validation_data[0], batch_size = 128)
        val_bin = np.argmax(val_predict, axis = 1)
        val_targ = self.validation_data[1]
        _val_f1 = f1_score(val_targ, val_bin, average = 'micro')
```

```
        self.history['val_f1_score'].append(_val_f1)
        self.history['train_f1_score'].append(_train_f1)

        print(' - train_f1_score : ', _train_f1, ' - val_f1_score : ', _val_f1)
        return


def changeLearningRate(epoch):
    global initial_learningrate
    epoch = epoch + 1
    if epoch % 5 == 0:
        initial_learningrate *= 0.55
    return initial_learningrate


import os
save = 'model_aug_raw_save/*.hdf5'
r = glob.glob(save)
for i in r:
    os.remove(i)


filepath="model_aug_raw_save/model-{epoch:02d}-{val_sparse_categorical_accuracy:.4f}.hdf5"
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_sparse_categorical_accuracy',
reducelr = ReduceLROnPlateau(monitor = 'val_loss', factor = 0.001, patience = 1, verbose =

lrschedule = LearningRateScheduler(changeLearningRate, verbose=1)
initial_learningrate=0.001


metrics = Metrics(Train_data, Val_data)
callbacks = [metrics, checkpoint, reducelr, lrschedule]
reg = tf.keras.regularizers.L2(l2=0.01)


tf.keras.backend.clear_session()
input_layer = Input(shape=(17640,1), name = 'input_layer')
input_mask = Input(shape=(17640,), name = 'mask_layer', dtype=bool)
ls = LSTM(units = 128, name = 'LSTM')(input_layer, mask = input_mask)
ls = BatchNormalization()(ls)
dc1 = Dense(512,activation='relu',kernel_initializer=tf.keras.initializers.he_normal(seed
dc1 = Dropout(0.35)(dc1)
out = Dense(10,activation='softmax',kernel_initializer=tf.keras.initializers.glorot_normal


model_aug_raw = Model(inputs = [input_layer,input_mask], outputs = out)


model_aug_raw.summary()
```

```
Model: "model"
__________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==========================================================================================
 input_layer (InputLayer)       [(None, 17640, 1)]   0           []
```

```
 mask_layer (InputLayer)        [(None, 17640)]      0           []

 LSTM (LSTM)                    (None, 128)          66560       ['input_layer[0][0]
                                                                  'mask_layer[0][0]'

 batch_normalization (BatchNorm  (None, 128)         512         ['LSTM[0][0]']
 alization)

 FC2 (Dense)                    (None, 512)          66048       ['batch_normalizati

 dropout (Dropout)              (None, 512)          0           ['FC2[0][0]']

 FC3 (Dense)                    (None, 10)           5130        ['dropout[0][0]']

==================================================================================
Total params: 138,250
Trainable params: 137,994
Non-trainable params: 256
__________________________________________________________________________________
```

```
model_aug_raw.compile(optimizer=tf.keras.optimizers.RMSprop(0.001),loss='sparse_categorica
```

```
train_steps = X_train.shape[0]//100
valid_steps = X_test.shape[0]//100
train_steps
```

```
140
```

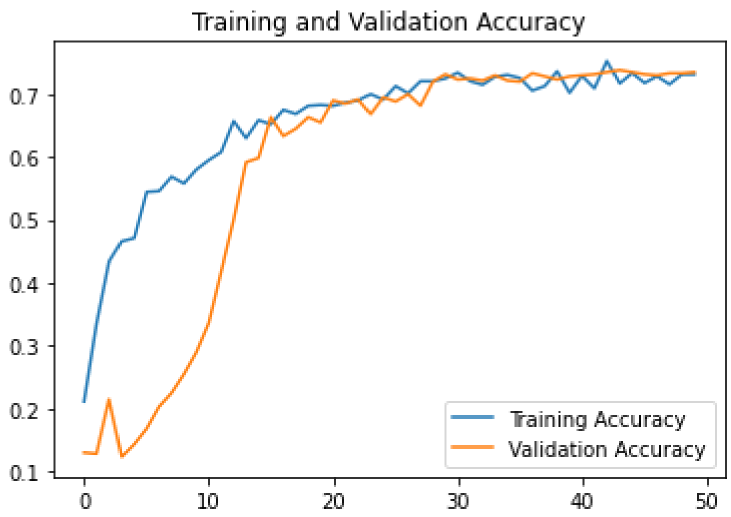
```
#tf.keras.backend.clear_session()
model_spec_history = m_spec.fit(X_train_spectrogram, y_train.values, batch_size =50, valid

#model_history = model_aug_raw.fit(train_dataset, validation_data = test_dataset, epochs =
```

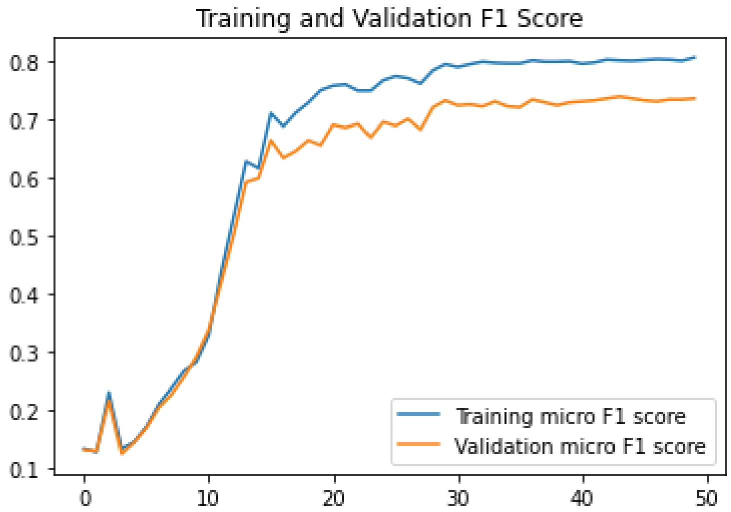
```
Epoch 00003: ReduceLROnPlateau reducing learning rate to 5.500000261235982e-05.
28/28 [==============================] - 5s 188ms/step - loss: 1.7642 - sparse_cat

Epoch 00004: LearningRateScheduler setting learning rate to 0.001.
Epoch 4/50
28/28 [==============================] - ETA: 0s - loss: 1.5385 - sparse_categoric

Epoch 00004: val_sparse_categorical_accuracy did not improve from 0.21500

Epoch 00004: ReduceLROnPlateau reducing learning rate to 5.500000261235982e-05.
28/28 [==============================] - 5s 182ms/step - loss: 1.5385 - sparse_cat

Epoch 00005: LearningRateScheduler setting learning rate to 0.00055.
Epoch 5/50
28/28 [==============================] - ETA: 0s - loss: 1.5168 - sparse_categoric

Epoch 00005: val_sparse_categorical_accuracy did not improve from 0.21500

Epoch 00005: ReduceLROnPlateau reducing learning rate to 3.0249999836087226e-05.
28/28 [==============================] - 5s 188ms/step - loss: 1.5168 - sparse_cat
```

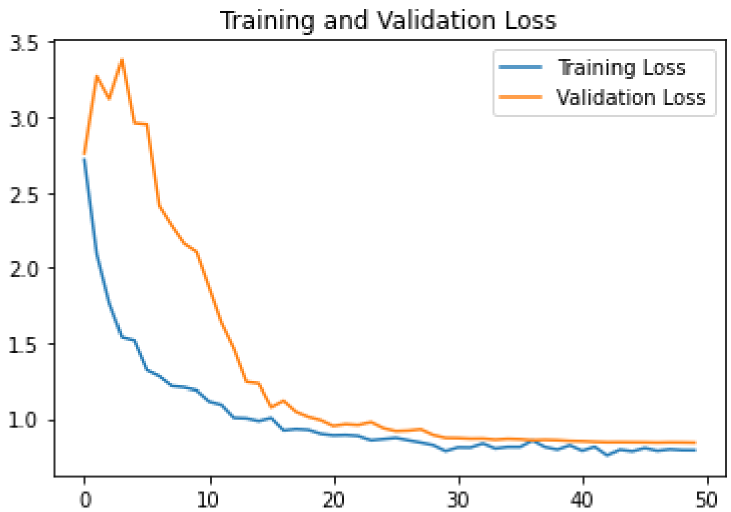
```
Epoch 00006: LearningRateScheduler setting learning rate to 0.00055.
Epoch 6/50
28/28 [==============================] - ETA: 0s - loss: 1.3212 - sparse_categoric

Epoch 00006: val_sparse_categorical_accuracy did not improve from 0.21500

Epoch 00006: ReduceLROnPlateau reducing learning rate to 3.0249999836087226e-05.
28/28 [==============================] - 5s 190ms/step - loss: 1.3212 - sparse_cat

Epoch 00007: LearningRateScheduler setting learning rate to 0.00055.
Epoch 7/50
28/28 [==============================] - ETA: 0s - loss: 1.2809 - sparse_categoric

Epoch 00007: val_sparse_categorical_accuracy did not improve from 0.21500
28/28 [==============================] - 5s 194ms/step - loss: 1.2809 - sparse_cat

Epoch 00008: LearningRateScheduler setting learning rate to 0.00055.
Epoch 8/50
28/28 [==============================] - ETA: 0s - loss: 1.2160 - sparse_categoric

Epoch 00008: val_sparse_categorical_accuracy improved from 0.21500 to 0.22500, sav
28/28 [==============================] - 5s 187ms/step - loss: 1.2160 - sparse_cat

Epoch 00009: LearningRateScheduler setting learning rate to 0.00055.
Epoch 9/50
28/28 [==============================] - ETA: 0s - loss: 1.2074 - sparse_categoric

Epoch 00009: val_sparse_categorical_accuracy improved from 0.22500 to 0.25500, sav
28/28 [==============================] - 5s 188ms/step - loss: 1.2074 - sparse_cat

Epoch 00010: LearningRateScheduler setting learning rate to 0.0003025000000000003
Epoch 10/50
28/28 [==============================] - ETA: 0s - loss: 1.1878 - sparse_categoric

Epoch 00010: val_sparse_categorical_accuracy improved from 0.25500 to 0.29000, sav
```

```
acc = model_spec_history.history['sparse_categorical_accuracy']
val_acc = model_spec_history.history['val_sparse_categorical_accuracy']

loss = model_spec_history.history['loss']
val_loss = model_spec_history.history['val_loss']

f1 = metrics.history['train_f1_score']
val_f1 = metrics.history['val_f1_score']

epochs_range = range(50)

#plt.figure(figsize=(8, 8))
#plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.show()

plt.plot(epochs_range, f1, label='Training micro F1 score')
plt.plot(epochs_range, val_f1, label='Validation micro F1 score')
```

```
plt.legend(loc='lower right')
plt.title('Training and Validation F1 Score')
plt.show()

#plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```








```
model_aug_raw.save('Model_Aug_raw_2_0.1795_final.h5')
```

```
model_raw1 = load_model('/content/Model_Aug_raw_2_0.1795_final.h5')


y_pred = model_aug_raw.predict(Val)
y_pred = np.argmax(y_pred, axis = 1)


print('Classification Report')
print(classification_report(y_test, y_pred))
```

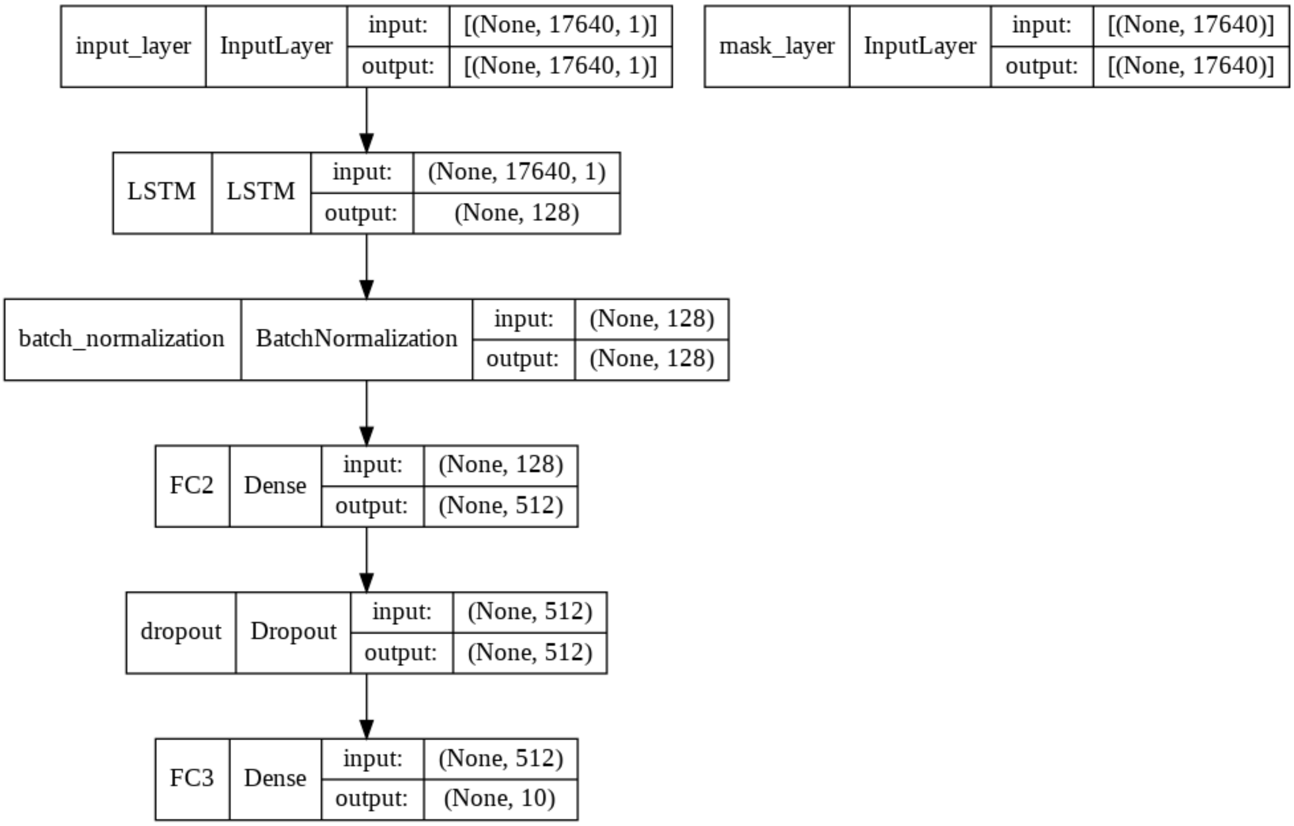
```
Classification Report
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        60
           1       0.00      0.00      0.00        60
           2       0.00      0.00      0.00        60
           3       0.00      0.00      0.00        60
           4       0.00      0.00      0.00        60
           5       0.07      0.33      0.12        60
           6       0.19      0.08      0.12        60
           7       0.00      0.00      0.00        60
           8       0.03      0.02      0.02        60
           9       0.09      0.38      0.15        60

    accuracy                           0.08       600
   macro avg       0.04      0.08      0.04       600
weighted avg       0.04      0.08      0.04       600

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Unde
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Unde
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: Unde
  _warn_prf(average, modifier, msg_start, len(result))
```

```
ax= plt.subplot()
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, ax = ax, fmt='g', cmap='Greens')

ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels')
ax.set_title('Confusion Matrix')
```

```
Text(0.5, 1.0, 'Confusion Matrix')
```

Confusion Matrix

```
from tensorflow.keras.utils import plot_model
plot_model(model_aug_raw, show_shapes=True, show_layer_names=True)
```



4. Data augmentation with spectogram data

1. use convert_to_spectrogram and convert the padded data from train and test data to spectogram data.
2. The shape of train data will be 14400 x 64 x 35 and shape of test_data will be 400 x 64 x35
3. Define the model similar to model 2 and fit the data

```
def convert_to_spectrogram(raw_data):
    '''converting to spectrogram'''
    spectrum = librosa.feature.melspectrogram(y=raw_data, sr=sample_rate, n_mels=64)
    logmel_spectrum = librosa.power_to_db(S=spectrum, ref=np.max)
    return logmel_spectrum
```

```
X_train_spectrogram = []
for j in X_train_pad_seq:
    l = convert_to_spectrogram(j)
    X_train_spectrogram.append(l)
X_train_spectrogram = np.array(X_train_spectrogram)
```

```
X_test_spectrogram = []
for j in X_test_pad_seq:
    l = convert_to_spectrogram(j)
    X_test_spectrogram.append(l)
X_test_spectrogram = np.array(X_test_spectrogram)
```

```
def grader_spectrogram():
    flag_shape = (X_train_spectrogram.shape==(14000,64, 35)) and (X_test_spectrogram.shape
    return flag_shape
grader_spectrogram()
```

```
False
```

```
td1 = tf.data.Dataset.from_tensor_slices((X_train_spectrogram, y_train))
```

```
BATCH_SIZE = 128
SHUFFLE_BUFFER_SIZE = 100
train_spec_dataset = td1.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE)
```

```
td1 = tf.data.Dataset.from_tensor_slices((X_test_spectrogram, y_test))
```

```
test_spec_dataset = td1.shuffle(SHUFFLE_BUFFER_SIZE).batch(BATCH_SIZE)
```

```
reg = tf.keras.regularizers.L2(l2=1.5)
```

```
tf.keras.backend.clear_session()
input_layer = Input(shape=(64,35), name = 'input_layer')
ls = LSTM(units = 128, name = 'LSTM', return_sequences = True)(input_layer)
ad = GlobalAveragePooling1D()(ls)
dc1 = Dense(1024,activation='relu',kernel_initializer=tf.keras.initializers.he_normal(seed
dc1 = Dense(256,activation='relu',kernel_initializer=tf.keras.initializers.he_normal(seed
dc1 = BatchNormalization()(dc1)
dc1 = Dropout(0.6599)(dc1)
out = Dense(10,activation='softmax',kernel_initializer=tf.keras.initializers.glorot_normal
```

```
m_aug_spec = Model(inputs = input_layer, outputs = out)

m_aug_spec.summary()
```

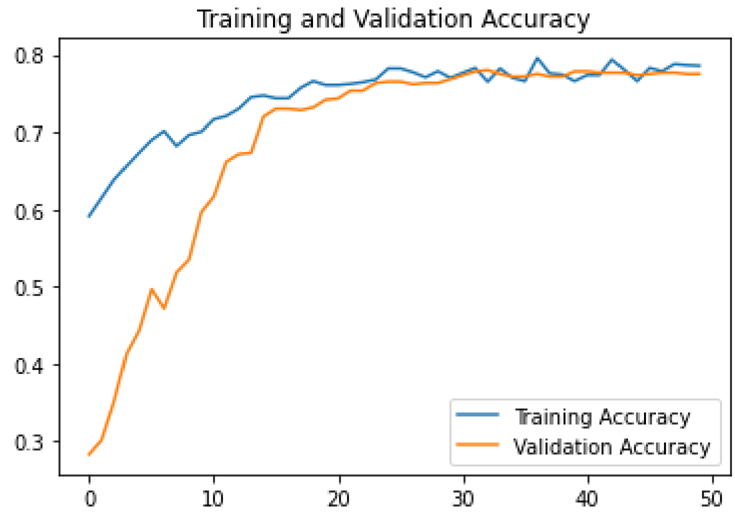
```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (InputLayer)    [(None, 64, 35)]          0

 LSTM (LSTM)                 (None, 64, 128)           83968

 global_average_pooling1d (G  (None, 128)              0
 lobalAveragePooling1D)

 FC1 (Dense)                 (None, 1024)              132096

 FC2 (Dense)                 (None, 256)               262400

 batch_normalization (BatchN  (None, 256)              1024
 ormalization)

 dropout (Dropout)           (None, 256)               0

 FC3 (Dense)                 (None, 10)                2570

=================================================================
Total params: 482,058
Trainable params: 481,546
Non-trainable params: 512
_________________________________________________________________
```

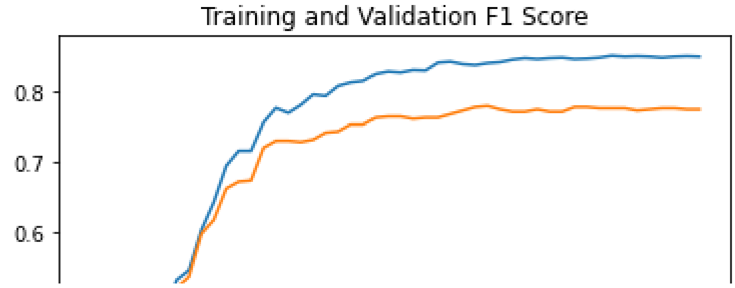
```
save = 'model_aug_spec_save/*.hdf5'
r = glob.glob(save)
for i in r:
    os.remove(i)


filepath="model_aug_spec_save/model-{epoch:02d}-{val_sparse_categorical_accuracy:.4f}.hdf5
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_sparse_categorical_accuracy',
reducelr = ReduceLROnPlateau(monitor = 'val_loss', factor = 0.055, patience = 1, verbose =

lrschedule = LearningRateScheduler(changeLearningRate, verbose=1)
initial_learningrate=0.001



Train_data_spec = [X_train_spectrogram, y_train]
Test_data_spec = [X_test_spectrogram, y_test]
metrics = Metrics(Train_data_spec, Test_data_spec)
callbacks = [metrics, checkpoint, reducelr, lrschedule]


m_aug_spec.compile(optimizer=tf.keras.optimizers.Adam(0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['sparse_categorical_accuracy'])
```

```
model_spec_history = m_aug_spec.fit(train_spec_dataset, validation_data = test_spec_datase
```

```
Epoch 00001: LearningRateScheduler setting learning rate to 0.00055.
Epoch 1/50
11/11 [==============================] - ETA: 0s - loss: 1.1839 - sparse_categoric

Epoch 00001: val_sparse_categorical_accuracy improved from 0.24667 to 0.28333, sav
11/11 [==============================] - 4s 408ms/step - loss: 1.1839 - sparse_cat

Epoch 00002: LearningRateScheduler setting learning rate to 0.00055.
Epoch 2/50
11/11 [==============================] - ETA: 0s - loss: 1.1018 - sparse_categoric

Epoch 00002: val_sparse_categorical_accuracy improved from 0.28333 to 0.30167, sav
11/11 [==============================] - 4s 411ms/step - loss: 1.1018 - sparse_cat

Epoch 00003: LearningRateScheduler setting learning rate to 0.00055.
Epoch 3/50
11/11 [==============================] - ETA: 0s - loss: 1.0339 - sparse_categoric

Epoch 00003: val_sparse_categorical_accuracy improved from 0.30167 to 0.35167, sav
11/11 [==============================] - 4s 399ms/step - loss: 1.0339 - sparse_cat

Epoch 00004: LearningRateScheduler setting learning rate to 0.00055.
Epoch 4/50
11/11 [==============================] - ETA: 0s - loss: 0.9789 - sparse_categoric

Epoch 00004: val_sparse_categorical_accuracy improved from 0.35167 to 0.41333, sav
11/11 [==============================] - 4s 404ms/step - loss: 0.9789 - sparse_cat

Epoch 00005: LearningRateScheduler setting learning rate to 0.0003025000000000003
Epoch 5/50
11/11 [==============================] - ETA: 0s - loss: 0.9360 - sparse_categoric

Epoch 00005: val_sparse_categorical_accuracy improved from 0.41333 to 0.44333, sav
11/11 [==============================] - 4s 412ms/step - loss: 0.9360 - sparse_cat

Epoch 00006: LearningRateScheduler setting learning rate to 0.0003025000000000003
Epoch 6/50
11/11 [==============================] - ETA: 0s - loss: 0.9141 - sparse_categoric

Epoch 00006: val_sparse_categorical_accuracy improved from 0.44333 to 0.49667, sav
11/11 [==============================] - 4s 404ms/step - loss: 0.9141 - sparse_cat

Epoch 00007: LearningRateScheduler setting learning rate to 0.0003025000000000003
Epoch 7/50
11/11 [==============================] - ETA: 0s - loss: 0.8778 - sparse_categoric

Epoch 00007: val_sparse_categorical_accuracy did not improve from 0.49667

Epoch 00007: ReduceLROnPlateau reducing learning rate to 1.663750022999011e-05.
11/11 [==============================] - 4s 397ms/step - loss: 0.8778 - sparse_cat

Epoch 00008: LearningRateScheduler setting learning rate to 0.0003025000000000003
Epoch 8/50
11/11 [==============================] - ETA: 0s - loss: 0.8765 - sparse_categoric

Epoch 00008: val_sparse_categorical_accuracy improved from 0.49667 to 0.51833, sav
```

```
acc = model_spec_history.history['sparse_categorical_accuracy']
val_acc = model_spec_history.history['val_sparse_categorical_accuracy']

loss = model_spec_history.history['loss']
val_loss = model_spec_history.history['val_loss']

f1 = metrics.history['train_f1_score']
val_f1 = metrics.history['val_f1_score']

epochs_range = range(50)

#plt.figure(figsize=(8, 8))
#plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.show()

plt.plot(epochs_range, f1, label='Training micro F1 score')
plt.plot(epochs_range, val_f1, label='Validation micro F1 score')
plt.legend(loc='lower right')
plt.title('Training and Validation F1 Score')
plt.show()

#plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```





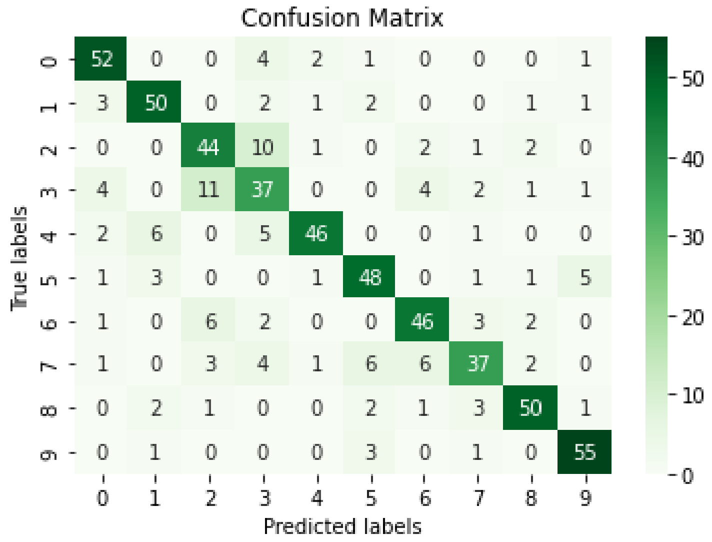

```
## as discussed above, please write the LSTM
y_pred = m_aug_spec.predict(X_test_spectrogram)
y_pred = np.argmax(y_pred, axis = 1)
#p = p.round()
```

```
print('Classification Report')
print(classification_report(y_test, y_pred))
```

```
    Classification Report
                  precision    recall  f1-score   support

               0       0.81      0.87      0.84        60
               1       0.81      0.83      0.82        60
               2       0.68      0.73      0.70        60
               3       0.58      0.62      0.60        60
               4       0.88      0.77      0.82        60
               5       0.77      0.80      0.79        60
               6       0.78      0.77      0.77        60
               7       0.76      0.62      0.68        60
               8       0.85      0.83      0.84        60
               9       0.86      0.92      0.89        60

        accuracy                           0.78       600
       macro avg       0.78      0.78      0.77       600
    weighted avg       0.78      0.78      0.77       600
```

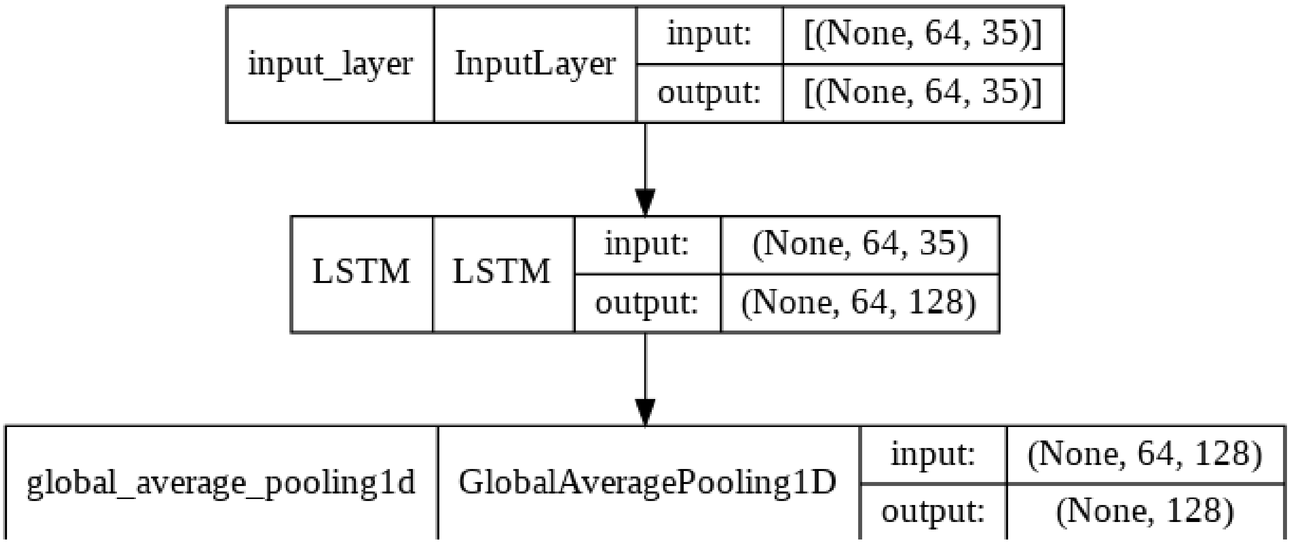
```
ax= plt.subplot()
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, ax = ax, fmt='g', cmap='Greens')

# labels, title and ticks
ax.set_xlabel('Predicted labels');ax.set_ylabel('True labels')
ax.set_title('Confusion Matrix')
```

```
Text(0.5, 1.0, 'Confusion Matrix')
```




```
m_aug_spec.save('Model_Aug_Spect_2_0.805_final.h5')
```

```
plot_model(m_aug_spec, show_shapes=True, show_layer_names=True)
```



Observation:

1. Micro F1 score for model 1 is: 0.10000000000
2. Micro F1 score for model 2 is: 0.80241004573
3. Micro F1 score for model 3 is: 0.10214937002
4. Micro F1 score for model 4 is: 0.87520014689

Spectrogram data gives good F1 score than using raw data.