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 wri

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

                                       section if necessary, please follow them.
```

Saved successfully!

Every Grader function has to return True.

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

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

Importing Libraries

```
import numpy as np
import pandas as pd
import librosa
import librosa.display
import os
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
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()
##if you need any imports you can do that here.
```

Data Preparation

```
#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
```

Saved successfully!

```
     '/content/drive/MyDrive/Audio_Spoken_Digit/recordings/8_nicolas_39.wav',
     Spoken_Digit/recordings/7_theo_29.wav',
     Spoken_Digit/recordings/2_jackson_19.wav',
     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/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

Saved successfully!

```
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
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

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

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

Saved successfully!

```
df_audio.describe()
```

	path	label
count	2000	2000
unique	2000	10
top	/content/drive/MyDrive/Audio_Spoken_Digit/reco...	5
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()
```

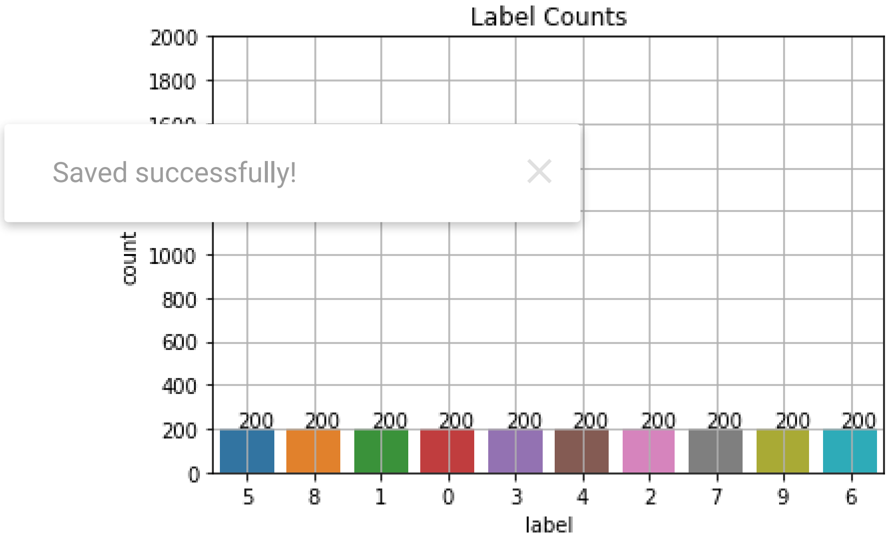
```
True
```

```
df_audio = shuffle(df_audio, random_state=33)
```

```
# Count of Labels.
total = len(df_audio)
print(Counter(df_audio['label']))
ax = sns.countplot(df_audio['label'])
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({'5': 200, '8': 200, '1': 200, '0': 200, '3': 200, '4': 200, '2': 200, '7': 2
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
```



From above all labels are equally numbered.

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)
```

Saved successfully!

```
                        ion(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 174 tasks      | elapsed:    4.7s
[Parallel(n_jobs=-1)]: Done 786 tasks      | elapsed:   50.0s
[Parallel(n_jobs=-1)]: Done 1036 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 1386 tasks      | elapsed:  3.8min
[Parallel(n_jobs=-1)]: Done 1400 out of 1400 | elapsed:  3.9min finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:   13.3s
[Parallel(n_jobs=-1)]: Done 196 tasks      | elapsed:   59.2s
[Parallel(n_jobs=-1)]: Done 446 tasks      | elapsed:  2.2min
[Parallel(n_jobs=-1)]: Done 600 out of 600 | elapsed:  3.0min 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()
```

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

```
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.
```

Saved successfully!

```
)
```

```
(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))
```

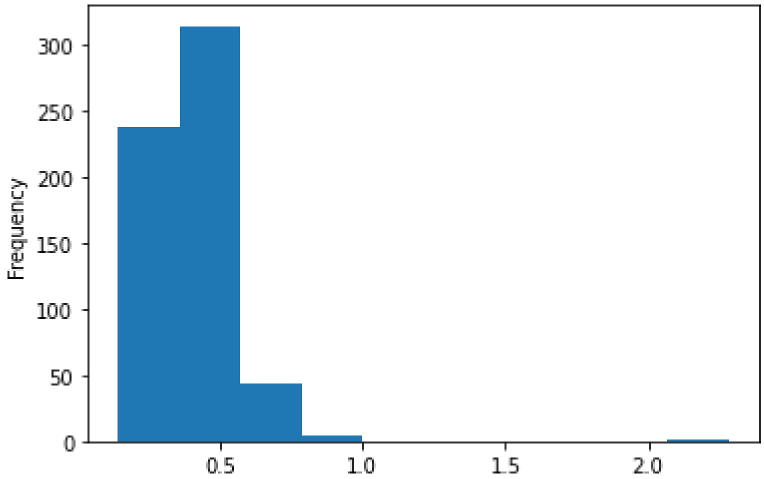
```
del a
del b
```

```
# Train Duration.
X_train_processed['duration'].plot.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f05fc31bf90>
```


```
# Test Duration.
X_test_processed['duration'].plot.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f05ff8a4e10>
```



Saved successfully!

```
ith 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  0.2632517006802721
20 th percentile is  0.30514285714285716
30 th percentile is  0.3346485260770975
40 th percentile is  0.35863945578231293
50 th percentile is  0.39045351473922907
60 th percentile is  0.4159546485260771
70 th percentile is  0.44731519274376413
80 th percentile is  0.481342403628118
90 th percentile is  0.5617823129251701
100 th percentile is  2.195918367346939
```

```
# 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  0.5617823129251701
91 th percentile is  0.5755346938775511
```

```
92 th percentile is  0.5859174603174603
93 th percentile is  0.6012321995464855
94 th percentile is  0.617911111111111
95 th percentile is  0.6330226757369615
96 th percentile is  0.6447981859410431
97 th percentile is  0.6635891156462584
98 th percentile is  0.6956090702947844
99 th percentile is  0.79601179138322
100 th percentile is  2.195918367346939
```

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
```

Updating data suitably for the model.

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.

Saved successfully!

ing sampling rate of 22050 so one sec will give array of
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
```

```
((6789,), (6789,))
```

```
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 = 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_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],
                              ., False, False, False]])
```

Saved successfully!

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. (Model 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
2. Get the final output of the LSTM and give it to Dense layer of any size and then give
3. Use tensorboard to plot the graphs of loss and metric(use micro F1 score as metric) a

                                     ularization
```

Saved successfully!

```
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 =
hangeLearningRate, verbose=1)
```

Saved successfully!

```
metrics = Metrics(Train_data, Val_data)


callbacks = [metrics, checkpoint, reducelr, lrschedule]


reg = tf.keras.regularizers.L2(l2=0.01)


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


model_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 (BatchNorma (None, 128)          512         LSTM[0][0]
__________________________________________________________________________________________________
FC2 (Dense)                     (None, 512)          66048       batch_normalization|
__________________________________________________________________________________________________
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_raw.compile(optimizer=tf.keras.optimizers.RMSprop(0.001),
              loss='sparse_categorical_crossentropy',
              metrics=['sparse_categorical_accuracy'])
```

```
model_history = model_raw.fit(Train, y_train.values, batch_size = 50, validation_data = (V
```

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```
======] - 22s 775ms/step - loss: 2.2931 - sparse_ca
42857143  - val_f1_score :  0.09833333333333333

Epoch 00005: val_sparse_categorical_accuracy did not improve from 0.10500

Epoch 00005: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 6/50

Epoch 00006: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 22s 771ms/step - loss: 2.2915 - sparse_ca
 - train_f1_score :  0.10000000000000002  - val_f1_score :  0.10000000000000002

Epoch 00006: val_sparse_categorical_accuracy did not improve from 0.10500

Epoch 00006: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 7/50

Epoch 00007: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 21s 770ms/step - loss: 2.2876 - sparse_ca
 - train_f1_score :  0.10357142857142858  - val_f1_score :  0.10333333333333333

Epoch 00007: val_sparse_categorical_accuracy did not improve from 0.10500

Epoch 00007: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 8/50

Epoch 00008: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 22s 776ms/step - loss: 2.2858 - sparse_ca
```

```
28/28 [==============================] - 22s 778ms/step - loss: 2.2858 - sparse_ca
 - train_f1_score :  0.10285714285714286  - val_f1_score :  0.10333333333333333

Epoch 00008: val_sparse_categorical_accuracy did not improve from 0.10500

Epoch 00008: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 9/50

Epoch 00009: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 22s 777ms/step - loss: 2.2837 - sparse_ca
 - train_f1_score :  0.10000000000000002  - val_f1_score :  0.10000000000000002

Epoch 00009: val_sparse_categorical_accuracy did not improve from 0.10500

Epoch 00009: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 10/50

Epoch 00010: LearningRateScheduler reducing learning rate to 0.00030250000000000000
28/28 [==============================] - 22s 783ms/step - loss: 2.2796 - sparse_ca
 - train_f1_score :  0.10071428571428571  - val_f1_score :  0.10000000000000002

Epoch 00010: val_sparse_categorical_accuracy did not improve from 0.10500

Epoch 00010: ReduceLROnPlateau reducing learning rate to 3.0250000418163836e-07.
Epoch 11/50

Epoch 00011: LearningRateScheduler reducing learning rate to 0.00030250000000000000
28/28 [==============================] - 22s 776ms/step - loss: 2.2766 - sparse_ca
 - train_f1_score :  0.10142857142857142  - val_f1_score :  0.10333333333333333

Epoch 00011: val_sparse_categorical_accuracy did not improve from 0.10500
```

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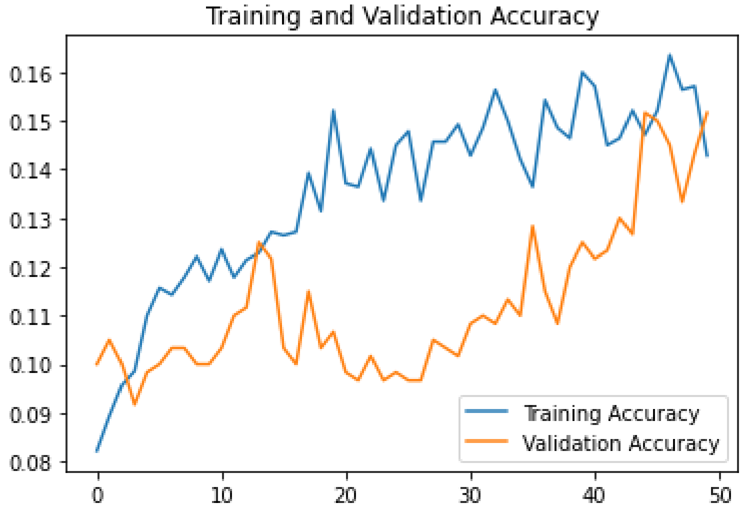
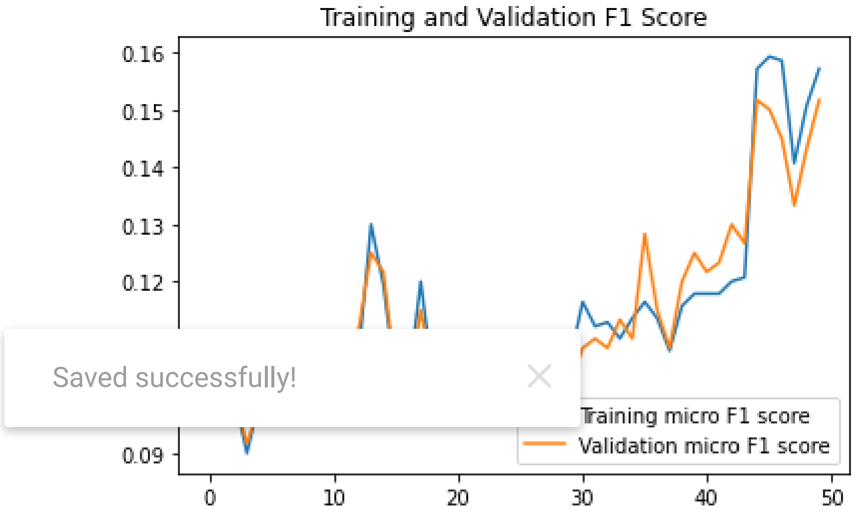
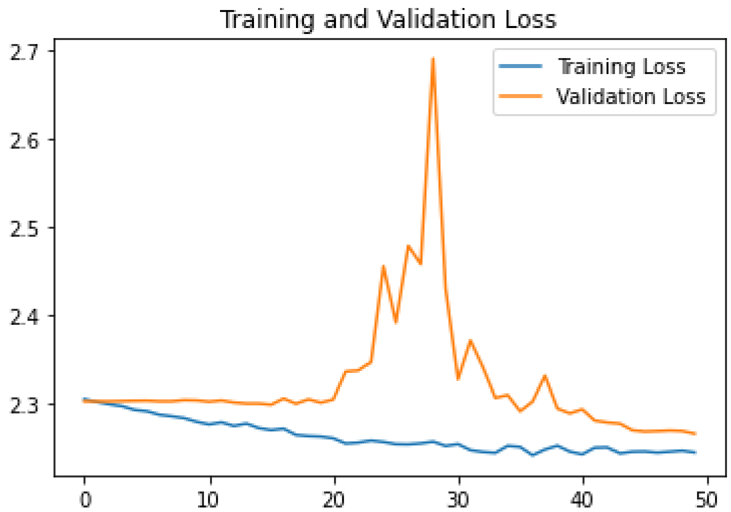
```
categorical_accuracy']
_sparse_categorical_accuracy']

loss = model_history.history['loss']
val_loss = model_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_raw.save('Model_raw_1_0.1517_final.h5')
```

```
model_raw = load_model('/content/model-31-0.1333.hdf5')
```

```
#write the LSTM
y_pred = model_raw.predict(Val)
y_pred = np.argmax(y_pred, axis = 1)


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

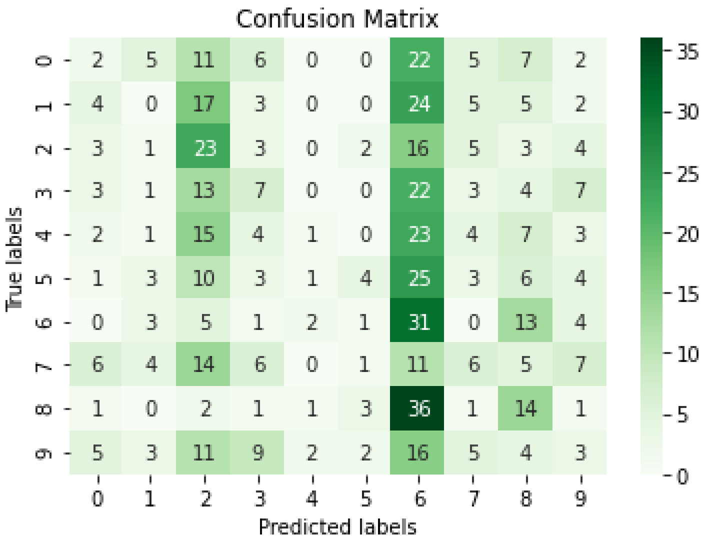
```
Classification Report
              precision    recall  f1-score   support

           0       0.07      0.03      0.05        60
           1       0.00      0.00      0.00        60
           2       0.19      0.38      0.25        60
           3       0.16      0.12      0.14        60
           4       0.14      0.02      0.03        60
           5       0.31      0.07      0.11        60
           6       0.14      0.52      0.22        60
           7       0.16      0.10      0.12        60
           8       0.21      0.23      0.22        60
           9       0.08      0.05      0.06        60

    accuracy                           0.15       600
   macro avg       0.15      0.15      0.12       600
weighted avg       0.15      0.15      0.12       600
```

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

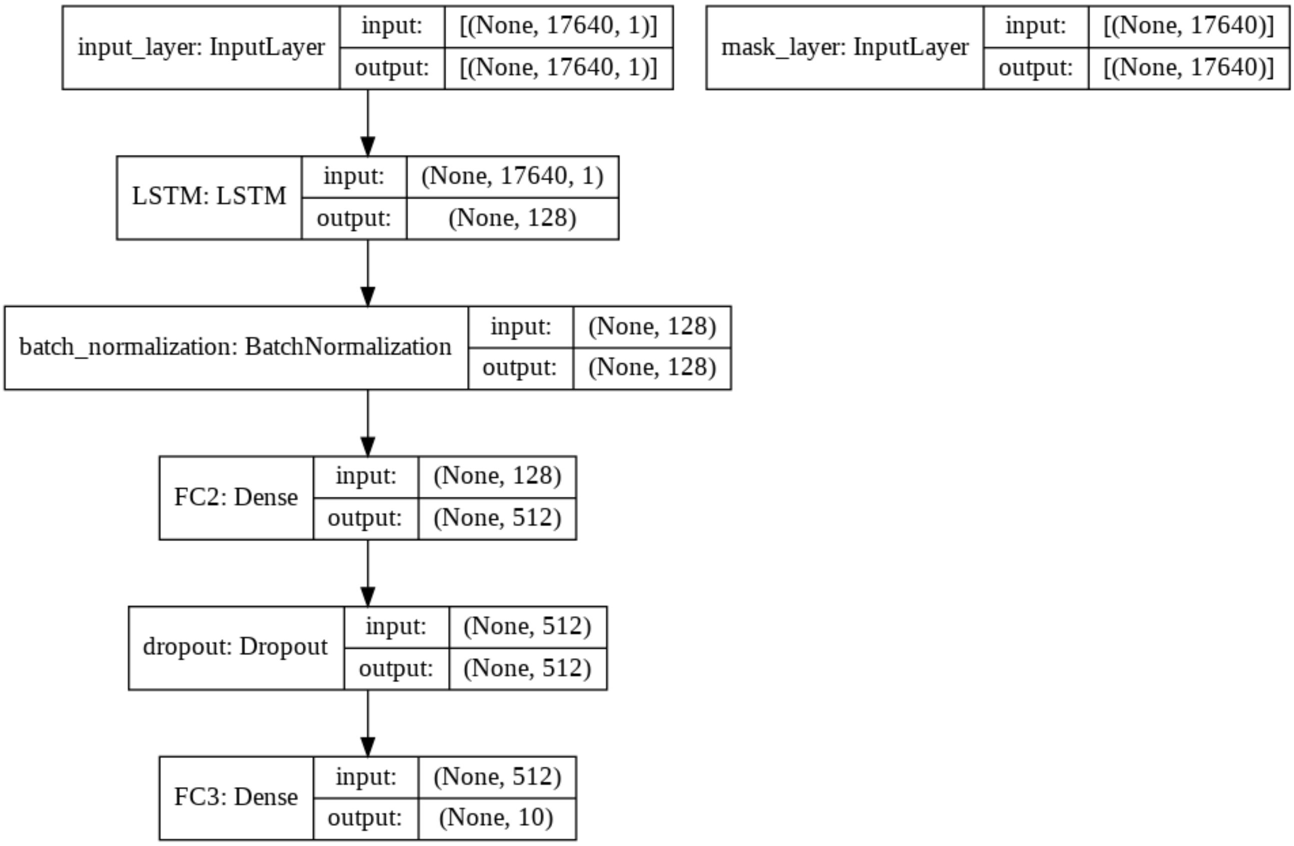


```
.set_ylabel('True labels')
```

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




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



2. (Model 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

```
# Function to convert raw padded audio signal into spectogram.
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
```

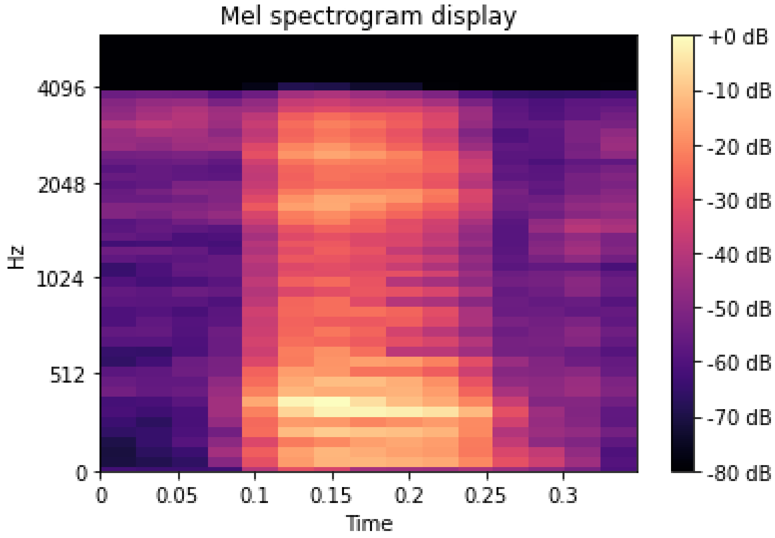
Use convert_to_spectrogram and convert every raw sequence in X_train_pad_seq and X_test_pad-seq.

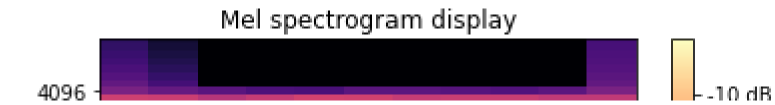
Save those all in the X_train_spectrogram and X_test_spectrogram (These two arrays must be numpy arrays)

```
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)


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")
```

Saved successfully!

```
<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
```


_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.
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 micro F1 score as metric) and histograms of gradients.
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)
```

```
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 (Gl (None, 128)               0
_________________________________________________________________
FC1 (Dense)                  (None, 1024)              132096
_________________________________________________________________
FC2 (Dense)                  (None, 256)               262400
_________________________________________________________________
                              one, 256)                1024
_________________________________________________________________
                              one, 256)                0
_________________________________________________________________
FC3 (Dense)                  (None, 10)                2570
=================================================================
Total params: 482,058
Trainable params: 481,546
Non-trainable params: 512
_________________________________________________________________
```

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```
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]


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 1/50

Epoch 00001: LearningRateScheduler reducing learning rate to 0.001.
28/28 [==============================] - 2s 23ms/step - loss: 2.7975 - sparse_categ
 - train_f1_score :  0.16857142857142857  - val_f1_score :  0.15833333333333333

Epoch 00001: val_sparse_categorical_accuracy improved from -inf to 0.15833, saving
Epoch 2/50

Epoch 00002: LearningRateScheduler reducing learning rate to 0.001.
28/28 [==============================] - 0s 10ms/step - loss: 2.0661 - sparse_categ
 - train_f1_score :  0.32571428571428573  - val_f1_score :  0.325

Epoch 00002: val_sparse_categorical_accuracy improved from 0.15833 to 0.32500, sav
Epoch 3/50

Saved successfully!          ler reducing learning rate to 0.001.
                             =======] - 0s 8ms/step - loss: 1.8349 - sparse_categ
 - train_f1_score :  0.21285714285714286  - val_f1_score :  0.19

Epoch 00003: val_sparse_categorical_accuracy did not improve from 0.32500

Epoch 00003: ReduceLROnPlateau reducing learning rate to 5.500000261235982e-05.
Epoch 4/50

Epoch 00004: LearningRateScheduler reducing learning rate to 0.001.
28/28 [==============================] - 0s 8ms/step - loss: 1.5767 - sparse_categ
 - train_f1_score :  0.28714285714285714  - val_f1_score :  0.24833333333333332

Epoch 00004: val_sparse_categorical_accuracy did not improve from 0.32500
Epoch 5/50

Epoch 00005: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 0s 7ms/step - loss: 1.5362 - sparse_categ
 - train_f1_score :  0.3507142857142857  - val_f1_score :  0.30666666666666664

Epoch 00005: val_sparse_categorical_accuracy did not improve from 0.32500
Epoch 6/50

Epoch 00006: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 0s 7ms/step - loss: 1.3419 - sparse_categ
 - train_f1_score :  0.3985714285714285  - val_f1_score :  0.3416666666666667
```

```
Epoch 00006: val_sparse_categorical_accuracy improved from 0.32500 to 0.34167, sav
Epoch 7/50

Epoch 00007: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 0s 8ms/step - loss: 1.2128 - sparse_categ
 - train_f1_score :  0.5007142857142857  - val_f1_score :  0.42999999999999994

Epoch 00007: val_sparse_categorical_accuracy improved from 0.34167 to 0.43000, sav
Epoch 8/50

Epoch 00008: LearningRateScheduler reducing learning rate to 0.00055.
28/28 [==============================] - 0s 9ms/step - loss: 1.1470 - sparse_categ
 - train_f1_score :  0.495  - val_f1_score :  0.44166666666666665
```

```
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')
```

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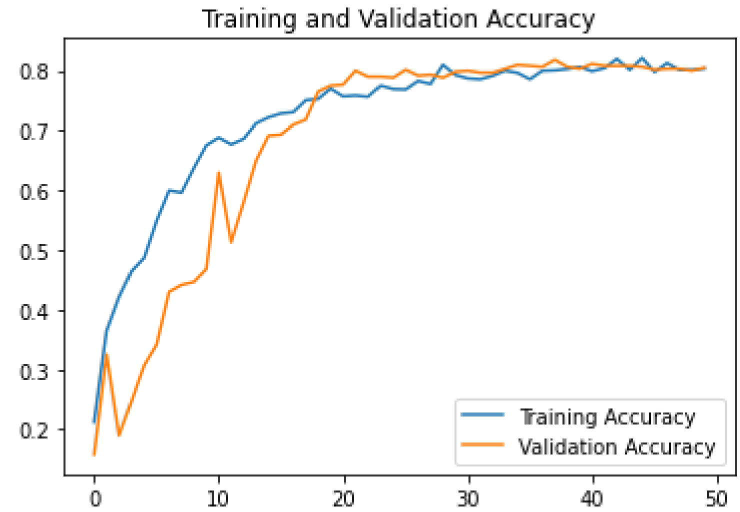
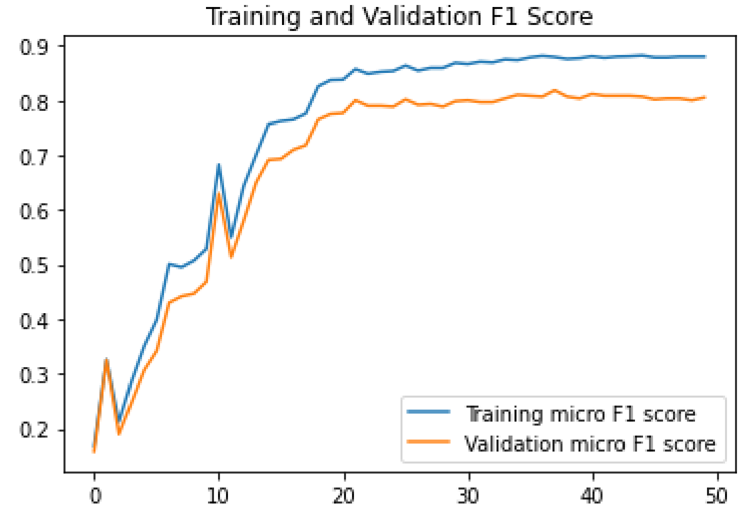
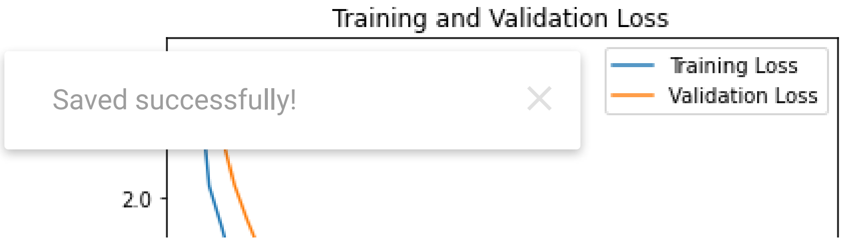
```
ccuracy')
plt.show()

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_spec.predict(X_test_spectrogram)
y_pred = np.argmax(y_pred, axis = 1)
```

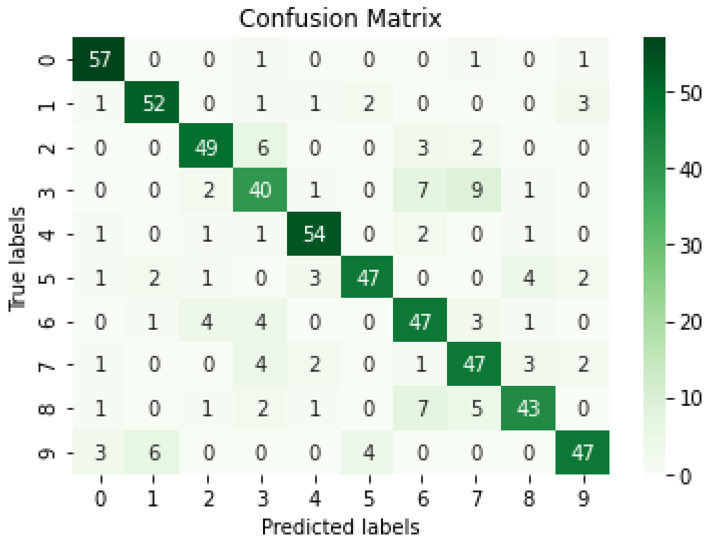
```
print('Classification Report')
print(classification_report(y_test.values, y_pred))
```

```
Classification Report
              precision    recall  f1-score   support

           0       0.88      0.95      0.91        60
           1       0.85      0.87      0.86        60
           2       0.84      0.82      0.83        60
           3       0.68      0.67      0.67        60
           4       0.87      0.90      0.89        60
           5       0.89      0.78      0.83        60
           6       0.70      0.78      0.74        60
           7       0.70      0.78      0.74        60
           8       0.81      0.72      0.76        60
           9       0.85      0.78      0.82        60
```

```
    accuracy                           0.81       600
   macro avg       0.81      0.81      0.81       600
weighted avg       0.81      0.81      0.81       600
```

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

# 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')
```



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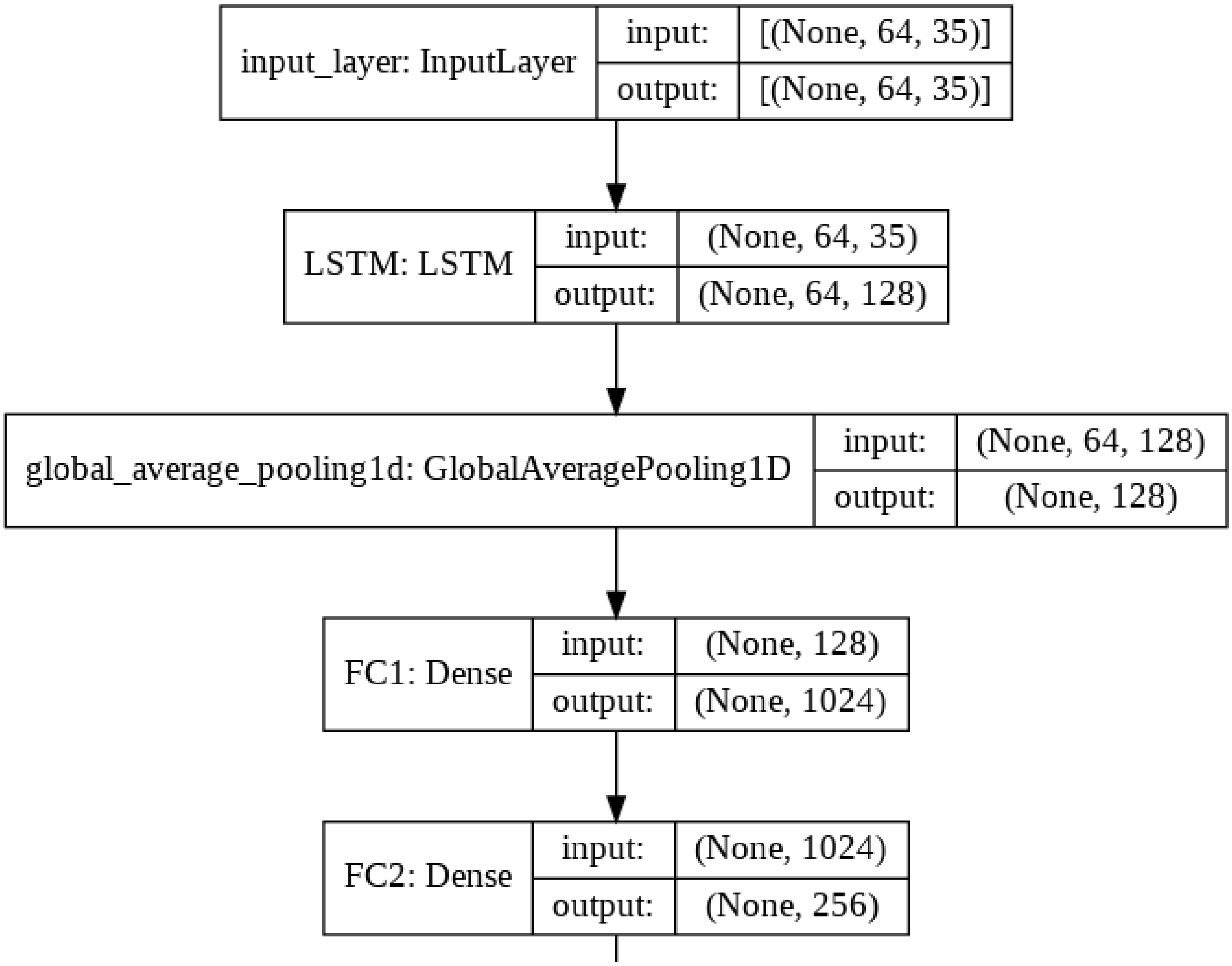
```
al.h5')
```

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



Data Augmentation

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| output: | (None, 256) |

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)
len(aug_temp1)
```

```
10
```

As discussed above, for one data point, we will get 9 augmented data points and original point. We have 2000 data points(train plus test) so, after augmentation we will get 20000 (train - 14000, test - 6000).

do the above steps i.e training with raw data and spectrogram data with augmentation.

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

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  46 tasks      | elapsed:    7.9s
[Parallel(n_jobs=-1)]: Done 196 tasks      | elapsed:   42.3s
[Parallel(n_jobs=-1)]: Done 446 tasks      | elapsed:  1.8min
[Parallel(n_jobs=-1)]: Done 796 tasks      | elapsed:  3.2min
[Parallel(n_jobs=-1)]: Done 1246 tasks      | elapsed:  5.1min
[Parallel(n_jobs=-1)]: Done 1796 tasks      | elapsed:  7.4min
[Parallel(n_jobs=-1)]: Done 2000 out of 2000 | elapsed:  8.2min finished
```

Saved successfully!

```
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.
New_samples, New_labels = shuffle(New_samples, New_labels, random_state=33)#don't change t
```

```
#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_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
```

```
((10232,), (10232,))
```

```
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,
```

Saved successfully!

```
                                ..., 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
```

1. (Model 3) Giving Raw data directly.

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

Saved successfully!

```
                                    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)

Saved successfully!                        ducelr, 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 (BatchNorma (None, 128)         512          LSTM[0][0]

FC2 (Dense)                    (None, 512)          66048        batch_normalization|

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_categorical_crossentropy',
              metrics=['sparse_categorical_accuracy'])
```

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

```
140
```

Saved successfully!

```
ain_dataset, validation_data = test_dataset, epochs =
```

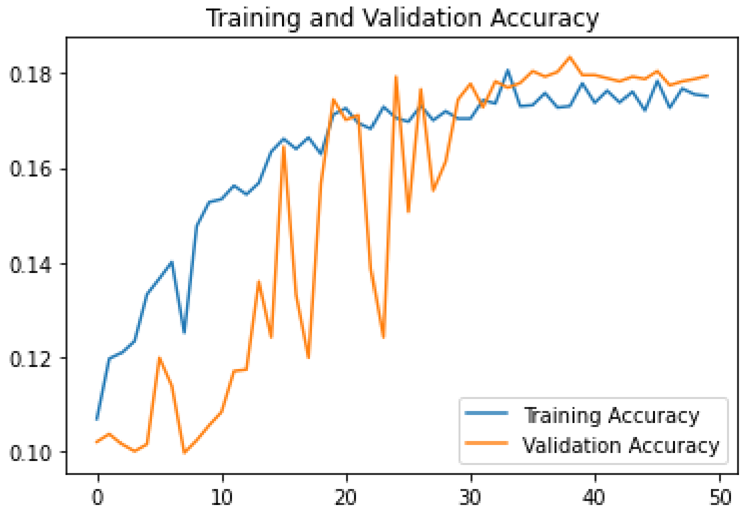
```
Epoch 00007: val_sparse_categorical_accuracy did not improve from 0.11983

Epoch 00007: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 8/50

Epoch 00008: LearningRateScheduler reducing learning rate to 0.00055.
110/110 [==============================] - 112s 1s/step - loss: 3.1387 - sparse_ca
 - train_f1_score :  0.10064285714285715  - val_f1_score :  0.09966666666666667

Epoch 00008: val_sparse_categorical_accuracy did not improve from 0.11983

Epoch 00008: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 9/50

Epoch 00009: LearningRateScheduler reducing learning rate to 0.00055.
110/110 [==============================] - 112s 1s/step - loss: 2.2875 - sparse_ca
 - train_f1_score :  0.103  - val_f1_score :  0.10233333333333333

Epoch 00009: val_sparse_categorical_accuracy did not improve from 0.11983

Epoch 00009: ReduceLROnPlateau reducing learning rate to 5.499999970197678e-07.
Epoch 10/50

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0003025000000000000
```

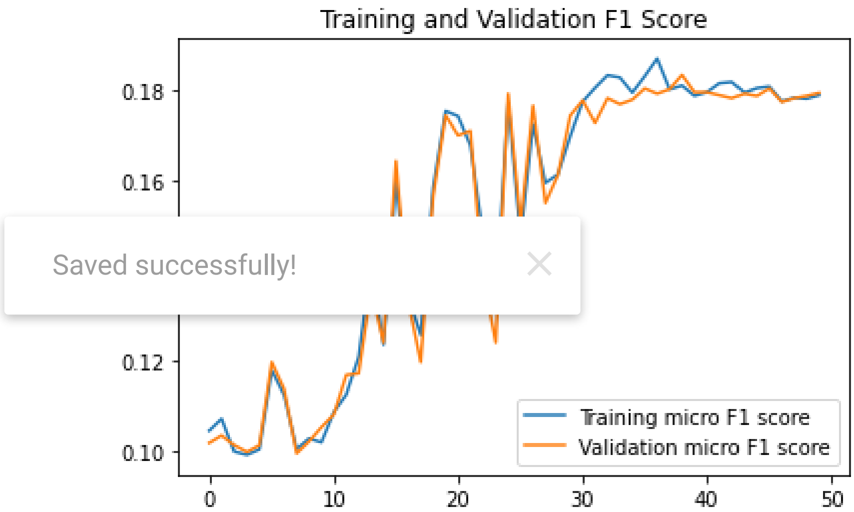
```
110/110 [==============================] - 112s 1s/step - loss: 2.2450 - sparse_ca
 - train_f1_score :  0.10214285714285715  - val_f1_score :  0.1055

Epoch 00010: val_sparse_categorical_accuracy did not improve from 0.11983

Epoch 00010: ReduceLROnPlateau reducing learning rate to 3.0250000418163836e-07.
Epoch 11/50

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0003025000000000000
110/110 [==============================] - 111s 1s/step - loss: 2.2433 - sparse_ca
 - train_f1_score :  0.10885714285714285  - val_f1_score :  0.10833333333333334

Epoch 00011: val_sparse_categorical_accuracy did not improve from 0.11983

Epoch 00011: ReduceLROnPlateau reducing learning rate to 3.0250000418163836e-07.
Epoch 12/50

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0003025000000000000
110/110 [==============================] - 112s 1s/step - loss: 2.2810 - sparse_ca
 - train_f1_score :  0.11271428571428571  - val_f1_score :  0.117

Epoch 00012: val_sparse_categorical_accuracy did not improve from 0.11983

Epoch 00012: ReduceLROnPlateau reducing learning rate to 3.0250000418163836e-07.
Epoch 13/50

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0003025000000000000
110/110 [==============================] - 112s 1s/step - loss: 2.2533 - sparse_ca
 - train_f1_score :  0.121  - val_f1_score :  0.11733333333333333

Epoch 00013: val_sparse_categorical_accuracy did not improve from 0.11983

Epoch 00013: ReduceLROnPlateau reducing learning rate to 3.0250000418163836e-07.
```

Saved successfully!

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

loss = model_history.history['loss']
val_loss = model_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_raw = load_model('/content/model-31-0.1333.hdf5')
```

```
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))
```

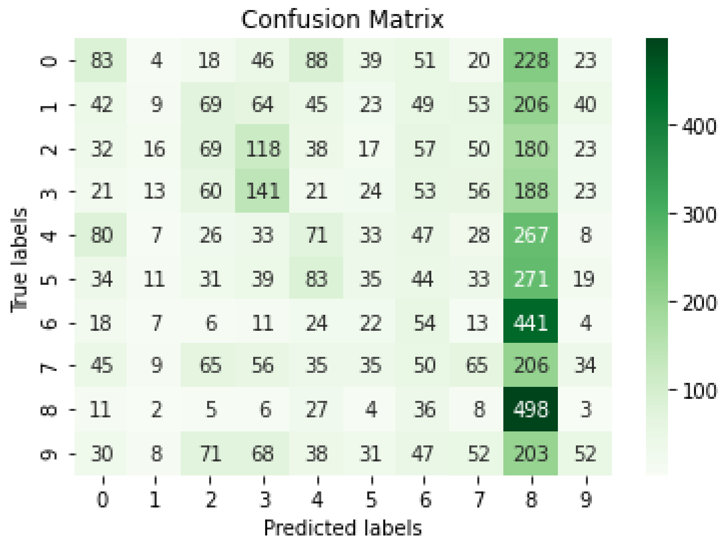
```
Classification Report
              precision    recall  f1-score   support

           0       0.21      0.14      0.17       600
           1       0.10      0.01      0.03       600
           2       0.16      0.12      0.14       600
           3       0.24      0.23      0.24       600
           4       0.15      0.12      0.13       600
           5       0.13      0.06      0.08       600
           6       0.11      0.09      0.10       600
           7       0.17      0.11      0.13       600
           8       0.19      0.83      0.30       600
           9       0.23      0.09      0.13       600

    accuracy                           0.18      6000
   macro avg       0.17      0.18      0.14      6000
weighted avg       0.17      0.18      0.14      6000
```

```
ax= plt.subplot()
```

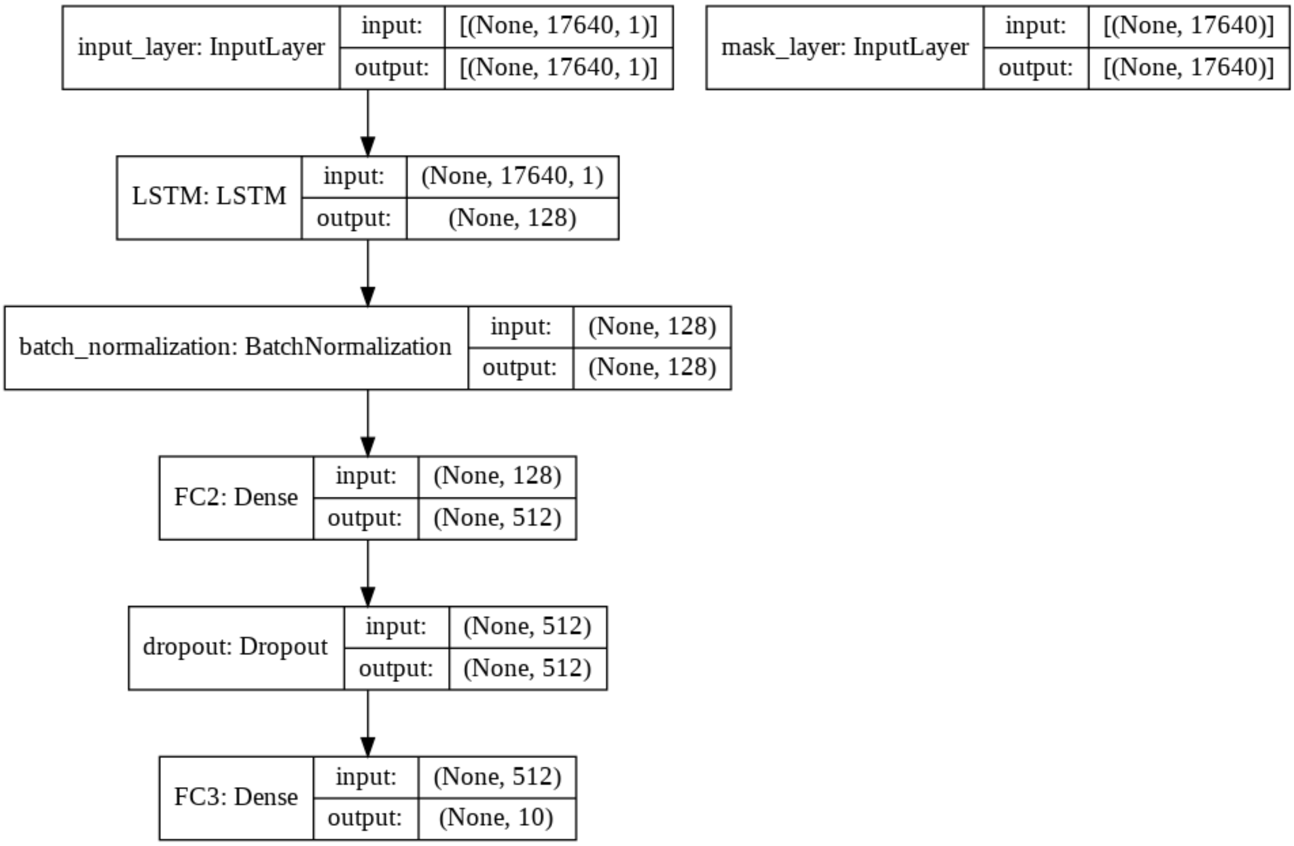
Saved successfully!

```
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')
```




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



2. (Model 4) 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

```
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)
```

Use convert_to_spectrogram and convert every raw sequence in X_train_pad_seq and X_test_pad-seq.

Save those all in the X_train_spectrogram and X_test_spectrogram (These two arrays must be numpy arrays)

```
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)
```

Grader function 7

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

Saved successfully!

```
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)
```

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.
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 micro F1 score as metric) and histograms of gradients.
5. make sure that it won't overfit.
6. You are free to include any regularization

```
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
```

Saved successfully!

```
yer, 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 (Gl (None, 128)               0
_________________________________________________________________
FC1 (Dense)                  (None, 1024)              132096
_________________________________________________________________
FC2 (Dense)                  (None, 256)               262400
_________________________________________________________________
batch_normalization (BatchNo (None, 256)               1024
_________________________________________________________________
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'])
```

Saved successfully!

```
train_spec_dataset, validation_data = test_spec_datase
```

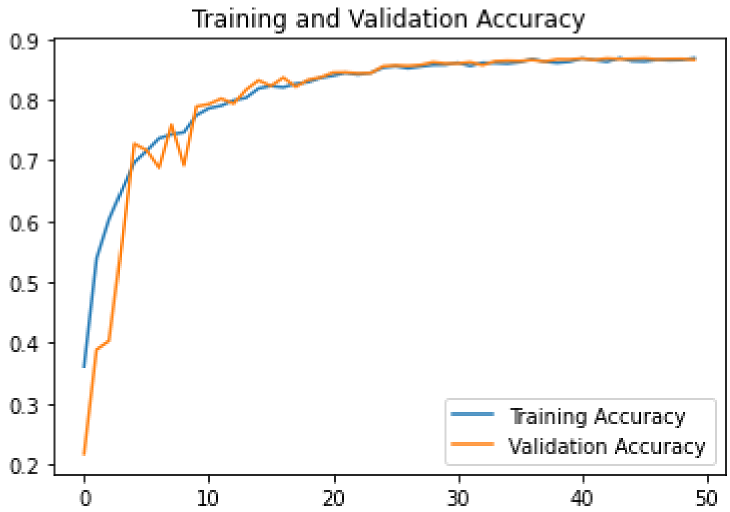
```
Epoch 00006: LearningRateScheduler reducing learning rate to 0.00055.
110/110 [==============================] - 1s 10ms/step - loss: 0.8274 - sparse_ca
 - train_f1_score :  0.7325  - val_f1_score :  0.7166666666666667

Epoch 00006: val_sparse_categorical_accuracy did not improve from 0.72750

Epoch 00006: ReduceLROnPlateau reducing learning rate to 3.0249999836087226e-05.
Epoch 7/50

Epoch 00007: LearningRateScheduler reducing learning rate to 0.00055.
110/110 [==============================] - 1s 10ms/step - loss: 0.7762 - sparse_ca
 - train_f1_score :  0.7030714285714286  - val_f1_score :  0.688

Epoch 00007: val_sparse_categorical_accuracy did not improve from 0.72750

Epoch 00007: ReduceLROnPlateau reducing learning rate to 3.0249999836087226e-05.
Epoch 8/50

Epoch 00008: LearningRateScheduler reducing learning rate to 0.00055.
110/110 [==============================] - 1s 10ms/step - loss: 0.7559 - sparse_ca
 - train_f1_score :  0.7702857142857142  - val_f1_score :  0.7588333333333335

Epoch 00008: val_sparse_categorical_accuracy improved from 0.72750 to 0.75883, sav
Epoch 9/50
```

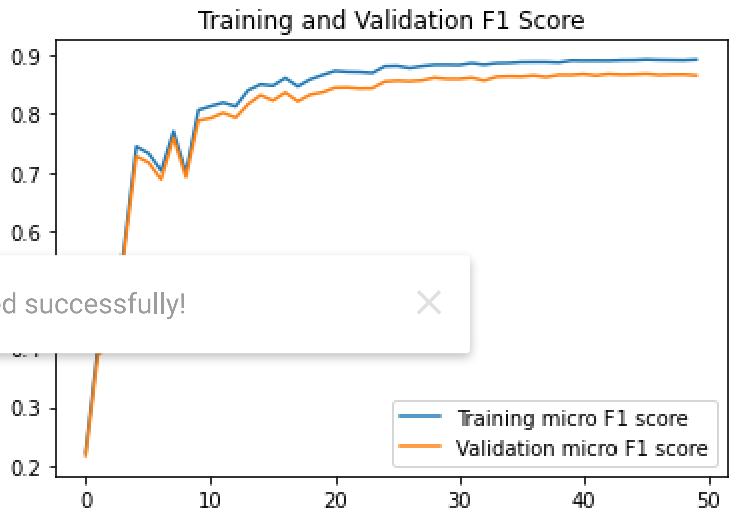
```
Epoch 00009: LearningRateScheduler reducing learning rate to 0.00055.
110/110 [==============================] - 1s 10ms/step - loss: 0.7339 - sparse_ca
 - train_f1_score :  0.7  - val_f1_score :  0.692

Epoch 00009: val_sparse_categorical_accuracy did not improve from 0.75883

Epoch 00009: ReduceLROnPlateau reducing learning rate to 3.0249999836087226e-05.
Epoch 10/50

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0003025000000000000
110/110 [==============================] - 1s 10ms/step - loss: 0.6635 - sparse_ca
 - train_f1_score :  0.8067142857142857  - val_f1_score :  0.7888333333333334

Epoch 00010: val_sparse_categorical_accuracy improved from 0.75883 to 0.78883, sav
Epoch 11/50

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0003025000000000000
110/110 [==============================] - 1s 10ms/step - loss: 0.6383 - sparse_ca
 - train_f1_score :  0.8132857142857143  - val_f1_score :  0.7928333333333333

Epoch 00011: val_sparse_categorical_accuracy improved from 0.78883 to 0.79283, sav
Epoch 12/50

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0003025000000000000
110/110 [==============================] - 1s 10ms/step - loss: 0.6282 - sparse_ca
 - train_f1_score :  0.8192142857142857  - val_f1_score :  0.8018333333333333

Epoch 00012: val_sparse_categorical_accuracy improved from 0.79283 to 0.80183, sav
Epoch 13/50

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0003025000000000000
```

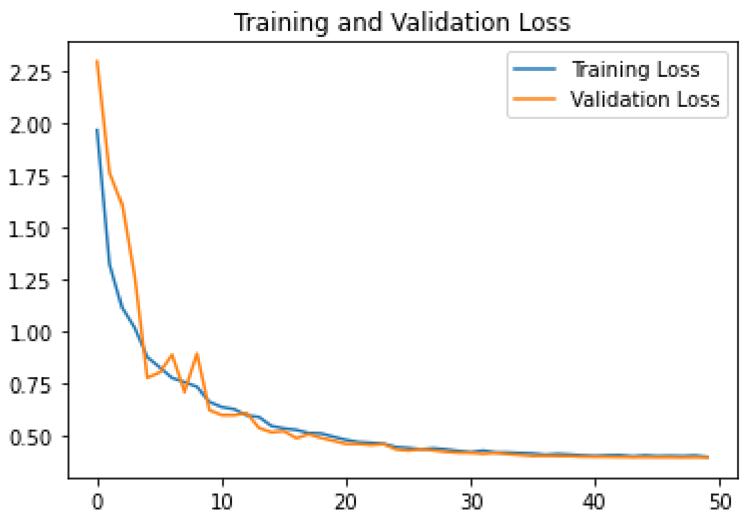
Saved successfully!

```
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)
```

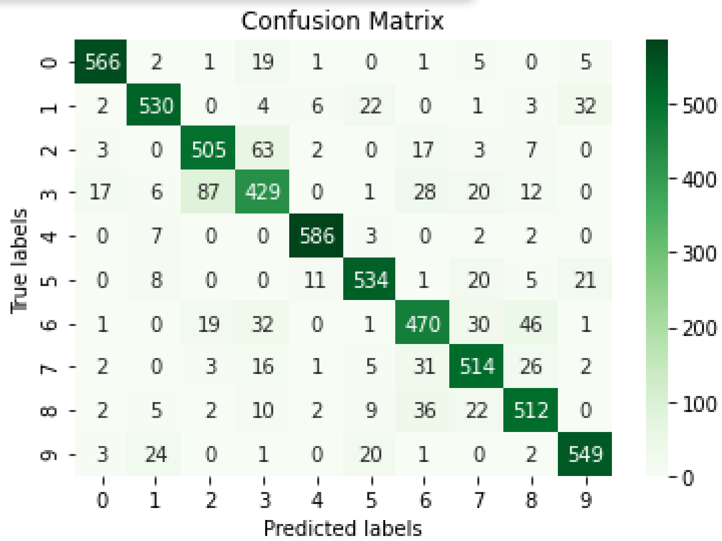
```
y_pred = np.argmax(y_pred, axis = 1)
#p = p.round()

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

```
Classification Report
              precision    recall  f1-score   support

           0       0.95      0.94      0.95       600
           1       0.91      0.88      0.90       600
           2       0.82      0.84      0.83       600
           3       0.75      0.71      0.73       600
           4       0.96      0.98      0.97       600
           5       0.90      0.89      0.89       600
           6       0.80      0.78      0.79       600
           7       0.83      0.86      0.84       600
           8       0.83      0.85      0.84       600
           9       0.90      0.92      0.91       600

    accuracy                           0.87      6000
   macro avg       0.87      0.87      0.87      6000
weighted avg       0.87      0.87      0.87      6000
```

```
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')
```

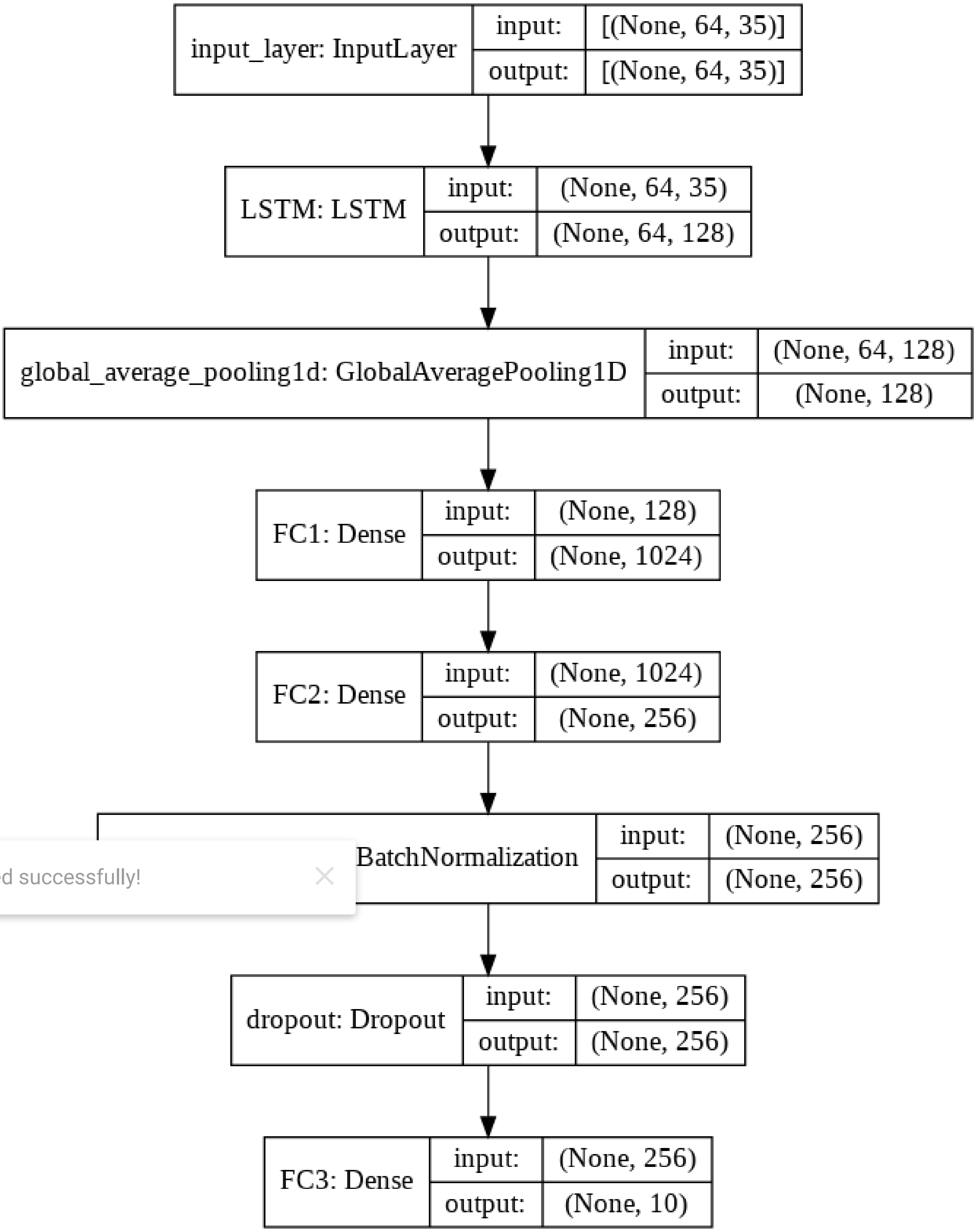
Saved successfully!

```
x')
```




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

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



Saved successfully!

Observations:

Data	Model	Test_F1_Score
Original - Raw Data	Model - 1	0.1517
Original - Spectogram	Model - 2	0.805
Augmented - Raw Data	Model - 3	0.1795
Augmented - Spectogram	Model - 4	0.8658

1. Micro F1 score for model 1 is: 0.15175246013
2. Micro F1 score for model 2 is: 0.80541004575
3. Micro F1 score for model 2 is: 0.17958463700
4. Micro F1 score for model 2 is: 0.86580286491

Spectrogram data gives good F1 score than using raw data.

Saved successfully!

0s completed at 12:33 AM