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, it will be considere d as plagiarised.
 - 2. Please read the instructions on the code cells and markdown cells. We will explain what to write.
 - 3. please return outputs in the same format what we asked. Eg. Don't return List of we are asking for a numpy array.
- 4. Please read the external links that we are given so that you will learn the concept behind the code that you are writing.
 - 5. We are giving instructions at each section if necessary, please follow them.

Every Grader function has to return True.

In [1]:

```
import pandas as pd
import librosa
import os
import tensorflow as tf
##if you need any imports you can do that here.

In [2]:
%load_ext tensorboard

In [3]:
from google.colab import drive
drive.mount('/content/drive')
Mounted at /content/drive
```

We shared recordings.zip, please unzip those.

```
In [4]:
```

```
#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"
from tqdm import tqdm
path=[]
all_files=[]
for i in tqdm(os.listdir('/content/drive/MyDrive/recordings')):
    path.append('/content/drive/MyDrive/recordings'+'/'+i)
    all_files.append(i)

100%| 2000/2000 [00:00<00:00, 1462449.09it/s]</pre>
```

Grader function 1

```
In [5]:

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()
```

Out[5]:

True

Create a dataframe(name=df_audio) with two columns(nath_label)

You can get the label from the first letter of name. Eq: 0 jackson 0 --> 0 0 jackson 43 --> 0 In [6]: allf=[int(list(i[:-4].split(' '))[-3]) for i in all files] df audio=pd.DataFrame(list(zip(path,allf)),columns =['path', 'label']) df audio.head(2) #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 Out[6]: path label 0 /content/drive/MyDrive/recordings/2_yweweler_6... 1 /content/drive/MyDrive/recordings/4_yweweler_1... In [7]: #info df audio.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)

Grader function 2

memory usage: 31.4+ KB

```
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()
Out[8]:
True
In [9]:
from sklearn.utils import shuffle
df audio = shuffle(df audio, random state=33) #don't change the random state
   Train and Validation split
In [10]:
from sklearn.model selection import train test split
X train, X test, y train, y test=train test split(df audio['path'], df audio['label'], test size=0.30, random state=45, stratify=df a
udio[['label']])
#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%
Grader function 3
```

```
In [11]:
def grader split():
    flag_len = (len(X_train) == 1400) and (len(X_test) == 600) and (len(Y_train) == 1400) and (len(Y_train) == 1400)
    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()
Out[11]:
True
In [12]:
# y train=tf.keras.utils.to categorical(y train, 10)
# y test =tf.keras.utils.to categorical(y test, 10)
```

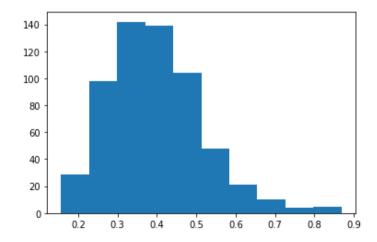
```
Preprocessing
   All files are in the "WAV" format. We will read those raw data files using the librosa
In [13]:
sample rate = 22050
def load wav(x, get duration=True):
    '''This return the array values of audio with sampling rate of 22050 and Duration'''
    #loading the wav file with sampling 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
In [14]:
#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, duration) with same index of X train/y train
X train processed=pd.DataFrame(columns=['raw data', 'duration'])
X test processed=pd.DataFrame(columns=['raw data', 'duration'])
for i in tqdm(X train.index):
    X train processed.loc[i]=load wav(X train[i])
for i in tqdm(X test.index):
    X test processed.loc[i]=load wav(X test[i])
100%|
                1400/1400 [06:46<00:00, 3.44it/s]
100%|
               | 600/600 [02:47<00:00, 3.59it/s]
In [15]:
#plot the histogram of the duration for trian
import matplotlib.pyplot as plt
import seaborn as sns
plt.hist(X train processed['duration'])
Out[15]:
(array([542., 725., 116., 13., 2., 0., 0., 0., 0., 2.]),
array([0.14353741, 0.35746032, 0.57138322, 0.78530612, 0.99922902,
        1.21315193, 1.42707483, 1.64099773, 1.85492063, 2.06884354,
        2.282766441),
<a list of 10 Patch objects>)
```

```
600 -
500 -
400 -
300 -
200 -
100 -
0.5 1.0 1.5 2.0
```

In [16]:

```
#plot the histogram of the duration for trian
import matplotlib.pyplot as plt
import seaborn as sns
plt.hist(X_test_processed['duration'])
```

Out[16]:



In [17]:

```
#print 0 to 100 percentile values with step size of 10 for train data duration.
for j in range(0,101,10):
    print('{} th percentile is {}'.format(j,np.percentile(X_train_processed['duration'],j)))
```

Λ th nercentile is Λ 1435374149659864

```
0 011 00100110110 10 0.11000/11119009001
10 th percentile is 0.2620090702947846
20 th percentile is 0.30259410430839
30 th percentile is 0.33474376417233564
40 th percentile is 0.36007256235827667
50 th percentile is 0.3903854875283447
60 th percentile is 0.41844897959183674
70 th percentile is 0.44775510204081626
80 th percentile is 0.48462585034013606
90 th percentile is 0.5619183673469388
100 th percentile is 2.282766439909297
In [18]:
##print 90 to 100 percentile values with step size of 1.
for j in range(90,101,1):
    print('{} th percentile is {}'.format(j,np.percentile(X train processed['duration'],j)))
90 th percentile is 0.5619183673469388
91 th percentile is 0.576156009070295
92 th percentile is 0.5863274376417237
93 th percentile is 0.6037156462585042
94 th percentile is 0.617911111111111
95 th percentile is 0.6330226757369615
96 th percentile is 0.6436226757369614
97 th percentile is 0.66358231292517
98 th percentile is 0.689717006802721
99 th percentile is 0.7961165532879818
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_test_processed.columns==['raw_data', 'duration']))
    flag_shape = (X_train_processed.shape ==(1400, 2)) and (X_test_processed.shape==(600,2))
    return flag_columns and flag_shape
grader_processed()
```

Out[19]:

In [19]:

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_t est_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 maxim

```
um 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.
In [20]:
max length = 17640
In [21]:
print(X train processed['raw data'].shape[0])
1400
In [22]:
def mask(data):
    maska = []
    for i in tqdm(data):
        masks=[]
        for j in i:
            if j!=0:
                masks.append(True)
            else:
                masks.append(False)
        maska.append(np.array(masks))
    return (np.array (maska))
In [23]:
## as discussed above, Pad with Zero if length of sequence is less than 17640 else Truncate the number.
```

```
## save in the X train pad seq, X test pad seq
## also Create masking vector X train mask, X test mask
from tensorflow.keras.preprocessing.sequence import pad sequences
X train pad seq=pad sequences(X train processed['raw data'], maxlen=max length, dtype='float32', padding='post',truncating='pre')
X test pad seq =pad sequences(X test processed['raw data'], maxlen=max length, dtype='float32', padding='post',truncating='pre')
X train mask = mask(X train pad seq)
X test mask = mask(X test pad seq)
## all the X train pad seq, X test pad seq, X train mask, X test mask will be numpy arrays mask vector dtype must be bool.
                 1400/1400 [00:42<00:00, 32.96it/s]
100%
100%1
                 600/600 [00:17<00:00, 33.43it/s]
```

Grader function 5

```
In [24]:
def grader padoutput():
    flag padshape = (X train pad seq.shape==(1400, 17640)) and (X test pad seq.shape==(600, 17640)) and (y train.shape==(1400,))
    flag maskshape = (X train mask.shape==(1400, 17640)) and (X test mask.shape==(600, 17640)) and (y test.shape==(600,))
    flag dtype = (X train mask.dtype==bool) and (X test mask.dtype==bool)
    return flag padshape and flag maskshape and flag dtype
grader padoutput()
```

Out[24]:

True

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 LS TM cells. Please read LSTM documentation(https://www.tensorflow.org/api docs/python/tf/keras/layers/LSTM) in tensorflow to k now more about mask and also https://www.tensorflow.org/quide/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 (becaus e we have 10 outputs) and then compile with the sparse categorical cross entropy (because we are not converting it to one ho t vectors).
- 3. Use tensorboard to plot the graphs of loss and metric (use micro F1 score as metric) and histograms of gradients.
- 4. make sure that it won't overfit.
- 5. You are free to include any regularization

In [25]:

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

In [26]:

```
## as discussed above, please write the LSTM
input= Input(shape=(17640,1,),dtype=np.float32)
mask1 = Input(shape=(17640,),dtype='bool')
lstm_output=LSTM(20)(inputs=input,mask=mask1)
Densel=Dense(10,activation='softmax')(lstm_output)
model= Model(inputs=[input,mask1],outputs=Dense1)
model.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 17640, 1)]	0	
input_2 (InputLayer)	[(None, 17640)]	0	
lstm (LSTM)	(None, 20)	1760	input_1[0][0] input_2[0][0]
dense (Dense)	(None, 10)	210	lstm[0][0]

Total params: 1,970 Trainable params: 1,970 Non-trainable params: 0

In [27]:

```
from sklearn.metrics import f1_score
def f1_score_func(y_true, y_pred):
    return f1_score(y_true, y_pred, average='micro')

def f1_scores(y_true, y_pred):
    y_pred=tf.math.argmax(y_pred, axis=1)
    return(tf.py_function(f1_score_func, (y_true, y_pred), tf.double))
```

In [28]:

```
re_X_train_pad_seq=X_train_pad_seq.reshape(1400,17640,1)
re_X_test_pad_seq=X_test_pad_seq.reshape(600,17640,1)
```

In [29]:

```
from datetime import datetime
model.compile(loss='SparseCategoricalCrossentropy',optimizer='adam',metrics=['accuracy',f1_scores])
logdir = "logs/fit/" + datetime.now().strftime("%Y%m%d-%H%M%S")
```

In [30]:

```
tensorboard callback = ti.keras.callbacks.TensorBoard(log dir=logdir)
model.fit([re X train pad seq, X train mask], y train, validation data=([re X test pad seq, X test mask], y test), batch size=100, epochs
=7, callbacks=[tensorboard callback])
Epoch 1/7
l accuracy: 0.1000 - val f1 scores: 0.1000
Epoch 2/7
val accuracy: 0.0933 - val f1 scores: 0.0933
Epoch 3/7
val accuracy: 0.0867 - val f1 scores: 0.0867
Epoch 4/7
val accuracy: 0.1000 - val f1 scores: 0.1000
Epoch 5/7
val accuracy: 0.1033 - val f1 scores: 0.1033
Epoch 6/7
val accuracy: 0.0917 - val f1 scores: 0.0917
Epoch 7/7
val accuracy: 0.1000 - val f1 scores: 0.1000
Out[30]:
<tensorflow.python.keras.callbacks.History at 0x7f350bf93b00>
In [ ]:
%tensorboard --logdir=./
```

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

```
In [32]:
```

```
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
```

Out[34]:

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 (#., time_steps, features) average the output of every time step i.e, you should get (#., 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 entrop
y.
4. Use tensorboard to plot the graphs of loss and metric(use micro F1 score as metric) and histograms of gradients.
```

6. You are free to include any regularization

5. make sure that it won't overfit.

```
In [35]:
print(X train spectrogram.shape)
(1400, 64, 35)
In [36]:
input= Input(shape=(64, 35,),dtype='float32')
lstm output=LSTM(100, return sequences=True) (input)
Densel=Dense(50, activation='relu')(tf.math.reduce mean(lstm output, 2))
Dense2=Dense(10, activation='softmax') (Dense1)
model= Model(inputs=input,outputs=Dense2)
model.summary()
Model: "model 1"
Layer (type)
                       Output Shape
                                            Param #
input 3 (InputLayer)
                       [(None, 64, 35)]
                       (None, 64, 100)
1stm 1 (LSTM)
                                            54400
tf.math.reduce mean (TFOpLam (None, 64)
                                            0
dense 1 (Dense)
                       (None, 50)
                                            3250
dense 2 (Dense)
                       (None, 10)
                                            510
______
Total params: 58,160
Trainable params: 58,160
Non-trainable params: 0
In [37]:
from datetime import datetime
model.compile(loss='sparse categorical crossentropy',optimizer='adam',metrics=['accuracy',f1 scores])
logdir = "logs/fit/" + datetime.now().strftime("%Y%m%d-%H%M%S")
In [38]:
tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=logdir)
model.fit(X train spectrogram, y train, validation data=(X test spectrogram, y test), batch size=10, epochs=200, callbacks=[tensorboard
callback])
Epoch 1/200
val accuracy: 0.4383 - val f1 scores: 0.4383
Epoch 2/200
```

```
val accuracy: 0.5067 - val f1 scores: 0.5067
Epoch 3/200
val accuracy: 0.5600 - val f1 scores: 0.5600
Epoch 4/200
val accuracy: 0.6150 - val f1 scores: 0.6150
Epoch 5/200
val accuracy: 0.6433 - val f1 scores: 0.6433
Epoch 6/200
val accuracy: 0.7100 - val f1 scores: 0.7100
Epoch 7/200
val accuracy: 0.7133 - val f1 scores: 0.7133
Epoch 8/200
val accuracy: 0.7667 - val f1 scores: 0.7667
Epoch 9/200
val accuracy: 0.7467 - val f1 scores: 0.7467
Epoch 10/200
val accuracy: 0.7567 - val f1 scores: 0.7567
Epoch 11/200
val accuracy: 0.8067 - val f1 scores: 0.8067
Epoch 12/200
val accuracy: 0.8167 - val f1 scores: 0.8167
Epoch 13/200
val accuracy: 0.7817 - val f1 scores: 0.7817
Epoch 14/200
val accuracy: 0.8017 - val f1 scores: 0.8017
Epoch 15/200
val accuracy: 0.8333 - val f1 scores: 0.8333
Epoch 16/200
val accuracy: 0.8533 - val f1 scores: 0.8533
Epoch 17/200
val accuracy: 0.8533 - val f1 scores: 0.8533
Epoch 18/200
val accuracy: 0.7883 - val f1 scores: 0.7883
Epoch 19/200
```

```
val accuracy: 0.8367 - val f1 scores: 0.8367
Epoch 20/200
val accuracy: 0.8283 - val f1 scores: 0.8283
Epoch 21/200
val accuracy: 0.8450 - val f1 scores: 0.8450
Epoch 22/200
val accuracy: 0.8400 - val f1 scores: 0.8400
Epoch 23/200
val accuracy: 0.8600 - val f1 scores: 0.8600
Epoch 24/200
val accuracy: 0.8533 - val f1 scores: 0.8533
Epoch 25/200
val accuracy: 0.8717 - val f1 scores: 0.8717
Epoch 26/200
val accuracy: 0.8633 - val f1 scores: 0.8633
Epoch 27/200
val accuracy: 0.8667 - val f1 scores: 0.8667
Epoch 28/200
val accuracy: 0.8667 - val f1 scores: 0.8667
Epoch 29/200
val accuracy: 0.8717 - val f1 scores: 0.8717
Epoch 30/200
val accuracy: 0.8433 - val f1 scores: 0.8433
Epoch 31/200
val accuracy: 0.8683 - val f1 scores: 0.8683
Epoch 32/200
val accuracy: 0.8783 - val f1 scores: 0.8783
Epoch 33/200
val accuracy: 0.8783 - val f1 scores: 0.8783
Epoch 34/200
val accuracy: 0.8917 - val f1 scores: 0.8917
Epoch 35/200
val accuracy: 0.8600 - val f1 scores: 0.8600
Epoch 36/200
```

```
val accuracy: 0.8567 - val f1 scores: 0.8567
Epoch 37/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 38/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 39/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 40/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 41/200
val accuracy: 0.8833 - val f1 scores: 0.8833
Epoch 42/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 43/200
val accuracy: 0.8817 - val f1 scores: 0.8817
Epoch 44/200
val accuracy: 0.8783 - val f1 scores: 0.8783
Epoch 45/200
val accuracy: 0.8833 - val f1 scores: 0.8833
Epoch 46/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 47/200
val accuracy: 0.8967 - val f1 scores: 0.8967
Epoch 48/200
val accuracy: 0.8883 - val f1 scores: 0.8883
Epoch 49/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 50/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 51/200
val accuracy: 0.8867 - val f1 scores: 0.8867
Epoch 52/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Enoch 53/200
```

```
LPUU11 00/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 54/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 55/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 56/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 57/200
val accuracy: 0.8900 - val f1 scores: 0.8900
Epoch 58/200
val accuracy: 0.8917 - val f1 scores: 0.8917
Epoch 59/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 60/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 61/200
val accuracy: 0.9300 - val f1 scores: 0.9300
Epoch 62/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 63/200
val accuracy: 0.8917 - val f1 scores: 0.8917
Epoch 64/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 65/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 66/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 67/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 68/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 69/200
val accuracy: 0.9233 - val f1 scores: 0.9233
```

```
Epoch 70/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 71/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 72/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 73/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 74/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 75/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 76/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 77/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 78/200
val accuracy: 0.8783 - val f1 scores: 0.8783
Epoch 79/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 80/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 81/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 82/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 83/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 84/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 85/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 86/200
val accuracy: 0.9150 - val fl scores: 0.9150
```

```
Epoch 87/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 88/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 89/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 90/200
val accuracy: 0.9100 - val fl scores: 0.9100
Epoch 91/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 92/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 93/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 94/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 95/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 96/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 97/200
val accuracy: 0.9283 - val f1 scores: 0.9283
Epoch 98/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 99/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 100/200
val accuracy: 0.9333 - val f1 scores: 0.9333
Epoch 101/200
val accuracy: 0.9283 - val f1 scores: 0.9283
Epoch 102/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 103/200
```

```
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 104/200
val accuracy: 0.9283 - val f1 scores: 0.9283
Epoch 105/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 106/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 107/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 108/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 109/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 110/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 111/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 112/200
val accuracy: 0.9317 - val f1 scores: 0.9317
Epoch 113/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 114/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 115/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 116/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 117/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 118/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 119/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 120/200
```

```
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 121/200
val accuracy: 0.9200 - val f1 scores: 0.9200
Epoch 122/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 123/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 124/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 125/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 126/200
val accuracy: 0.9283 - val f1 scores: 0.9283
Epoch 127/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 128/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 129/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 130/200
val accuracy: 0.8967 - val f1 scores: 0.8967
Epoch 131/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 132/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 133/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 134/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 135/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 136/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 137/200
```

```
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 138/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 139/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 140/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 141/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 142/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 143/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 144/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 145/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 146/200
val accuracy: 0.9200 - val f1 scores: 0.9200
Epoch 147/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 148/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 149/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 150/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 151/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 152/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 153/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 154/200
```

```
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 155/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 156/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 157/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 158/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 159/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 160/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 161/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 162/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 163/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 164/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 165/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 166/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 167/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 168/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 169/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 170/200
val accuracy: 0.9100 - val f1 scores: 0.9100
```

_ 1 1 7 1 / 0 0 0

```
Epocn 1/1/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 172/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 173/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 174/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 175/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 176/200
val accuracy: 0.9283 - val f1 scores: 0.9283
Epoch 177/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 178/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 179/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 180/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 181/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 182/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 183/200
val accuracy: 0.9283 - val f1 scores: 0.9283
Epoch 184/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 185/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 186/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 187/200
val accuracy: 0.9250 - val f1 scores: 0.9250
```

```
Epoch 188/200
val accuracy: 0.9350 - val f1 scores: 0.9350
Epoch 189/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 190/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 191/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 192/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 193/200
val accuracy: 0.9200 - val f1 scores: 0.9200
Epoch 194/200
val accuracy: 0.9300 - val f1 scores: 0.9300
Epoch 195/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 196/200
val accuracy: 0.9317 - val f1 scores: 0.9317
Epoch 197/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 198/200
val accuracy: 0.9317 - val f1 scores: 0.9317
Epoch 199/200
val accuracy: 0.9367 - val f1 scores: 0.9367
Epoch 200/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Out[38]:
<tensorflow.python.keras.callbacks.History at 0x7f34abcb5198>
In [ ]:
%tensorboard --logdir=./
```

3. data augmentation

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.

In [40]:

```
## generating augmented data.
def generate_augmented_data(file_path):
    augmented_data = []
    samples = load_wav(file_path,get_duration=False)
    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_steps=pitch_value)
            augmented_data
    return augmented_data
```

In [41]:

```
temp_path = df_audio.iloc[0].path
aug_temp = generate_augmented_data(temp_path)
```

In [42]:

```
len(aug_temp)
```

Out[42]:

9

As discussed above, for one data point, we will get 9 augmented data points.

Split data into train and test (80-20 split)

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

Do augmentation only on train data, after augmentation we will get 14400 train points.

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

```
In [43]:
```

```
x aug=np.zeros((18000,17640))
y aug=[]
k=0
for i in tqdm(range(df audio.shape[0])):
  temp path=df audio.iloc[i].path
  aug temp = generate augmented data(temp path)
  for j in aug temp:
    if len(j) < = 17640:
      x = aug[k] = np.array(j.tolist()+[0]*(17640-len(j)))
      y aug.append(df audio.iloc[i].label)
    else:
      x aug[k]=np.array((j.tolist())[:17640])
      y aug.append(df audio.iloc[i].label)
    k+=1
               | 2000/2000 [07:43<00:00, 4.32it/s]
In [44]:
X aug train, X aug test, y aug train, y aug test=train test split(x aug,y aug,test size=0.20,random state=45,stratify=y aug)
In [45]:
y aug train=np.array(y aug train)
y aug test=np.array(y aug test)
In [46]:
```

```
X aug train mask = np.array(mask(X aug train))
X aug test mask = np.array(mask(X aug test))
100%|
                14400/14400 [02:18<00:00, 104.24it/s]
                3600/3600 [00:32<00:00, 110.87it/s]
```

In [47]:

```
input= Input(shape=(17640,1,),dtype=np.float32)
mask1 = Input(shape=(17640,),dtype='bool')
lstm output=LSTM(20)(inputs=input, mask=mask1)
Densel=Dense(10, activation='softmax')(lstm output)
model= Model(inputs=[input,mask1],outputs=Dense1)
model.summary()
```

Model: "model 2"

Layer (type)	Output Shape	Param #	Connected to
input_4 (InputLayer)	[(None, 17640, 1)]	0	
input_5 (InputLayer)	[(None, 17640)]	0	

```
1760
1stm 2 (LSTM)
                  (None, 20)
                                    input 4[0][0]
                                    input 5[0][0]
                              210
                                    lstm 2[0][0]
dense 3 (Dense)
                  (None, 10)
Total params: 1,970
Trainable params: 1,970
Non-trainable params: 0
In [54]:
re X aug train=X aug train.reshape(14400,17640,1)
re X aug test=X aug test.reshape(3600,17640,1)
In [55]:
from datetime import datetime
model.compile(loss='SparseCategoricalCrossentropy',optimizer='adam',metrics=['accuracy',f1 scores])
logdir = "logs/fit/" + datetime.now().strftime("%Y%m%d-%H%M%S")
In [56]:
tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=logdir)
model.fit([re X aug train, X aug train mask], y aug train, validation data=([re X aug test, X aug test mask], y aug test), batch size=10
0,epochs=7,callbacks=[tensorboard callback])
Epoch 1/7
6 - val accuracy: 0.1028 - val f1 scores: 0.1028
Epoch 2/7
6 - val accuracy: 0.1075 - val f1 scores: 0.1075
Epoch 3/7
6 - val accuracy: 0.1053 - val f1 scores: 0.1053
Epoch 4/7
6 - val accuracy: 0.0992 - val f1 scores: 0.0992
Epoch 5/7
6 - val accuracy: 0.1011 - val f1 scores: 0.1011
Epoch 6/7
6 - val accuracy: 0.1164 - val f1 scores: 0.1164
Epoch 7/7
6 - val accuracy: 0.0956 - val f1 scores: 0.0956
```

Out [561:

<tensorflow.python.keras.callbacks.History at 0x7f34aa14c7b8>

In []:

```
%tensorboard --logdir=./
```

In [59]:

```
X_aug_train_spectrogram = np.array([convert_to_spectrogram(i) for i in (X_aug_train)])
X_aug_test_spectrogram = np.array([convert_to_spectrogram(i) for i in (X_aug_test)])
```

In [60]:

```
input= Input(shape=(64, 35,),dtype=np.float32)
lstm_output=LSTM(200,return_sequences=True)(input)
Densel=Dense(50,activation='relu')(tf.math.reduce_mean(lstm_output, 2))
Dense2=Dense(10,activation='softmax')(Dense1)
model= Model(inputs=input,outputs=Dense2)
model.summary()
```

Model: "model 3"

Output Shape 	Param #
[(None, 64, 35)]	0
(None, 64, 200)	188800
(None, 64)	0
(None, 50)	3250
(None, 10)	510
	[(None, 64, 35)] (None, 64, 200) (None, 64) (None, 50)

Total params: 192,560 Trainable params: 192,560 Non-trainable params: 0

In [61]:

import keras

In [62]:

```
from datetime import datetime
model.compile(loss='sparse_categorical_crossentropy',optimizer='adam',metrics=['accuracy',fl_scores])
logdir = "logs/fit/" + datetime.now().strftime("%Y%m%d-%H%M%S")
```

In [63]:

```
tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=logdir)
model.fit(X train spectrogram, y train, validation data=(X test spectrogram, y test), batch size=10, epochs=200, callbacks=[tensorboard
callback])
Epoch 1/200
val accuracy: 0.1917 - val f1 scores: 0.1917
Epoch 2/200
val accuracy: 0.4383 - val f1 scores: 0.4383
Epoch 3/200
val accuracy: 0.4867 - val f1 scores: 0.4867
Epoch 4/200
val accuracy: 0.5800 - val f1 scores: 0.5800
Epoch 5/200
val accuracy: 0.6683 - val f1 scores: 0.6683
Epoch 6/200
val accuracy: 0.6600 - val f1 scores: 0.6600
Epoch 7/200
val accuracy: 0.6433 - val f1 scores: 0.6433
Epoch 8/200
val accuracy: 0.7350 - val f1 scores: 0.7350
Epoch 9/200
val accuracy: 0.7183 - val f1 scores: 0.7183
Epoch 10/200
val accuracy: 0.7717 - val f1 scores: 0.7717
Epoch 11/200
val accuracy: 0.6783 - val f1 scores: 0.6783
Epoch 12/200
val accuracy: 0.7900 - val f1 scores: 0.7900
Epoch 13/200
val accuracy: 0.8000 - val f1 scores: 0.8000
Epoch 14/200
val accuracy: 0.8000 - val f1 scores: 0.8000
Epoch 15/200
```

```
val accuracy: 0./950 - val fl scores: 0./950
Epoch 16/200
val accuracy: 0.7833 - val f1 scores: 0.7833
Epoch 17/200
val accuracy: 0.7983 - val f1 scores: 0.7983
Epoch 18/200
val accuracy: 0.8067 - val f1 scores: 0.8067
Epoch 19/200
val accuracy: 0.8417 - val f1 scores: 0.8417
Epoch 20/200
val accuracy: 0.8433 - val f1 scores: 0.8433
Epoch 21/200
val accuracy: 0.8567 - val f1 scores: 0.8567
Epoch 22/200
val accuracy: 0.8167 - val f1 scores: 0.8167
Epoch 23/200
val accuracy: 0.8683 - val f1 scores: 0.8683
Epoch 24/200
val accuracy: 0.8467 - val f1 scores: 0.8467
Epoch 25/200
val accuracy: 0.8550 - val f1 scores: 0.8550
Epoch 26/200
val accuracy: 0.8383 - val f1 scores: 0.8383
Epoch 27/200
val accuracy: 0.8567 - val f1 scores: 0.8567
Epoch 28/200
val accuracy: 0.8500 - val f1 scores: 0.8500
Epoch 29/200
val accuracy: 0.8567 - val f1 scores: 0.8567
Epoch 30/200
val accuracy: 0.8650 - val f1 scores: 0.8650
Epoch 31/200
val accuracy: 0.8567 - val f1 scores: 0.8567
Epoch 32/200
```

```
val accuracy: 0.8650 - val f1 scores: 0.8650
Epoch 33/200
val accuracy: 0.8567 - val f1 scores: 0.8567
Epoch 34/200
val accuracy: 0.8533 - val f1 scores: 0.8533
Epoch 35/200
val accuracy: 0.8800 - val f1 scores: 0.8800
Epoch 36/200
val accuracy: 0.8717 - val f1 scores: 0.8717
Epoch 37/200
val accuracy: 0.8850 - val f1 scores: 0.8850
Epoch 38/200
val accuracy: 0.8617 - val f1 scores: 0.8617
Epoch 39/200
val accuracy: 0.8717 - val f1 scores: 0.8717
Epoch 40/200
val accuracy: 0.8933 - val f1 scores: 0.8933
Epoch 41/200
val accuracy: 0.8900 - val f1 scores: 0.8900
Epoch 42/200
val accuracy: 0.8883 - val f1 scores: 0.8883
Epoch 43/200
val accuracy: 0.8783 - val f1 scores: 0.8783
Epoch 44/200
val accuracy: 0.8900 - val f1 scores: 0.8900
Epoch 45/200
val accuracy: 0.8933 - val f1 scores: 0.8933
Epoch 46/200
val accuracy: 0.8917 - val f1 scores: 0.8917
Epoch 47/200
val accuracy: 0.8800 - val f1 scores: 0.8800
Epoch 48/200
val accuracy: 0.8700 - val f1 scores: 0.8700
Epoch 49/200
```

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1 1 0 / 1 1 0 0001

1 10 /1 10 1

```
val accuracy: 0.8767 - val f1 scores: 0.8767
Epoch 50/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 51/200
val accuracy: 0.8783 - val f1 scores: 0.8783
Epoch 52/200
val accuracy: 0.8867 - val f1 scores: 0.8867
Epoch 53/200
val accuracy: 0.8750 - val f1 scores: 0.8750
Epoch 54/200
val accuracy: 0.8717 - val f1 scores: 0.8717
Epoch 55/200
val accuracy: 0.8917 - val f1 scores: 0.8917
Epoch 56/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 57/200
val accuracy: 0.8867 - val f1 scores: 0.8867
Epoch 58/200
val accuracy: 0.8933 - val f1 scores: 0.8933
Epoch 59/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 60/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 61/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 62/200
val accuracy: 0.8833 - val f1 scores: 0.8833
Epoch 63/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 64/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 65/200
val accuracy: 0.8783 - val f1 scores: 0.8783
Epoch 66/200
```

```
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 67/200
val accuracy: 0.8817 - val f1 scores: 0.8817
Epoch 68/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 69/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 70/200
val accuracy: 0.8967 - val f1 scores: 0.8967
Epoch 71/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 72/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 73/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 74/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 75/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 76/200
val accuracy: 0.8833 - val f1 scores: 0.8833
Epoch 77/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 78/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 79/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 80/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 81/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 82/200
val accuracy: 0.9067 - val f1 scores: 0.9067
```

```
EPOCII 03/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 84/200
val accuracy: 0.8883 - val f1 scores: 0.8883
Epoch 85/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 86/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 87/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 88/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 89/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 90/200
val accuracy: 0.9200 - val f1 scores: 0.9200
Epoch 91/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 92/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 93/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 94/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 95/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 96/200
val accuracy: 0.9200 - val f1 scores: 0.9200
Epoch 97/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 98/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 99/200
```

val accuracy: 0.9067 - val f1 scores: 0.9067

```
Epoch 100/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 101/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 102/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 103/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 104/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 105/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 106/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 107/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 108/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 109/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 110/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 111/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 112/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 113/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 114/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 115/200
val accuracy: 0.8933 - val f1 scores: 0.8933
Epoch 116/200
```

113 300112011. 0 0003 - 1131 fl 00000. 0 0003

```
val accuracy: 0.3000 - val il Scores: 0.3003
Epoch 117/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 118/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 119/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 120/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 121/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 122/200
val accuracy: 0.8917 - val f1 scores: 0.8917
Epoch 123/200
val accuracy: 0.8917 - val f1 scores: 0.8917
Epoch 124/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 125/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 126/200
val accuracy: 0.8967 - val f1 scores: 0.8967
Epoch 127/200
val_accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 128/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 129/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 130/200
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 131/200
val accuracy: 0.8833 - val f1 scores: 0.8833
Epoch 132/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 133/200
```

```
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 134/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 135/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 136/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 137/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 138/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 139/200
val accuracy: 0.8967 - val f1 scores: 0.8967
Epoch 140/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 141/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 142/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 143/200
val accuracy: 0.9117 - val f1 scores: 0.9117
Epoch 144/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 145/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 146/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 147/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 148/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 149/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 150/200
```

140/140 [========== 0 0483 = 10 0483

```
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 151/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 152/200
140/140 [============] - 1s 9ms/step - loss: 0.1319 - accuracy: 0.9657 - f1 scores: 0.9657 - val loss: 0.2898 -
val accuracy: 0.8983 - val f1 scores: 0.8983
Epoch 153/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 154/200
val accuracy: 0.8750 - val f1 scores: 0.8750
Epoch 155/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 156/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 157/200
val accuracy: 0.9000 - val f1 scores: 0.9000
Epoch 158/200
val accuracy: 0.8933 - val f1 scores: 0.8933
Epoch 159/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 160/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 161/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 162/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 163/200
val accuracy: 0.9233 - val f1 scores: 0.9233
Epoch 164/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 165/200
val accuracy: 0.9017 - val f1 scores: 0.9017
Epoch 166/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 167/200
```

```
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 168/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 169/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 170/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 171/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 172/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 173/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 174/200
val accuracy: 0.9067 - val f1 scores: 0.9067
Epoch 175/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 176/200
val accuracy: 0.9167 - val f1 scores: 0.9167
Epoch 177/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 178/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 179/200
val accuracy: 0.9267 - val f1 scores: 0.9267
Epoch 180/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 181/200
val accuracy: 0.9217 - val f1 scores: 0.9217
Epoch 182/200
val accuracy: 0.9133 - val f1 scores: 0.9133
Epoch 183/200
val accuracy: 0.9083 - val f1 scores: 0.9083
```

Enoch 184/200

```
LPUU11 101/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 185/200
val accuracy: 0.9250 - val f1 scores: 0.9250
Epoch 186/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 187/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 188/200
val accuracy: 0.9200 - val f1 scores: 0.9200
Epoch 189/200
val accuracy: 0.9150 - val f1 scores: 0.9150
Epoch 190/200
val accuracy: 0.9033 - val f1 scores: 0.9033
Epoch 191/200
val accuracy: 0.9283 - val f1 scores: 0.9283
Epoch 192/200
val accuracy: 0.8950 - val f1 scores: 0.8950
Epoch 193/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 194/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 195/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 196/200
val accuracy: 0.9083 - val f1 scores: 0.9083
Epoch 197/200
val accuracy: 0.9050 - val f1 scores: 0.9050
Epoch 198/200
val accuracy: 0.9183 - val f1 scores: 0.9183
Epoch 199/200
val accuracy: 0.9100 - val f1 scores: 0.9100
Epoch 200/200
val accuracy: 0.9083 - val f1 scores: 0.9083
```

```
Out[63]:
<tensorflow.python.keras.callbacks.History at 0x7f331e6a3f98>
In []:
%tensorboard --logdir=./
In []:
```