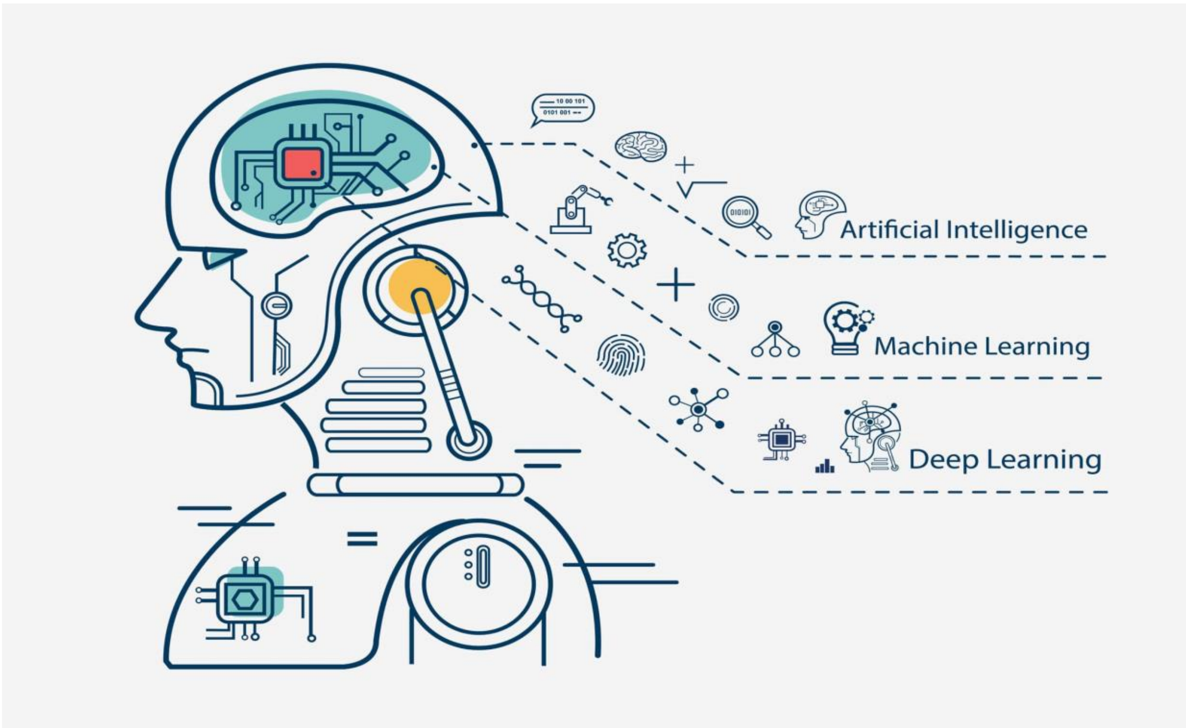
Pattern Recognition



Speech Emotion Recognition

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Speech Emotion Recognition

Importing Libraries

```
! pip install audiomentations
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: audiomentations in /usr/local/lib/python3.10/dist-packages (0.30.0)
Requirement already satisfied: numpy>=1.13.0 in /usr/local/lib/python3.10/dist-packages (from audiomentations) (1.22.4)
Requirement already satisfied: librosa<0.10.0,>0.7.2 in /usr/local/lib/python3.10/dist-packages (from audiomentations) (0.9.2)
Requirement already satisfied: scipy<2,>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from audiomentations) (1.10.1)
Requirement already satisfied: audioread>=2.1.9 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations)
Requirement already satisfied: scikit-learn>=0.19.1 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentatio
Requirement already satisfied: joblib>=0.14 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations) (1.
Requirement already satisfied: decorator>=4.0.10 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations
Requirement already satisfied: resampy>=0.2.2 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations) (
Requirement already satisfied: numba>=0.45.1 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations) (0
Requirement already satisfied: soundfile>=0.10.2 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations
Requirement already satisfied: pooch>=1.0 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations) (1.6.
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from librosa<0.10.0,>0.7.2->audiomentations)
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in /usr/local/lib/python3.10/dist-packages (from numba>=0.45.1->librosa<0.10.0
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from numba>=0.45.1->librosa<0.10.0,>0.7.2->audiome
Requirement already satisfied: appdirs>=1.3.0 in /usr/local/lib/python3.10/dist-packages (from pooch>=1.0->librosa<0.10.0,>0.7.2->audiom
Requirement already satisfied: requests>=2.19.0 in /usr/local/lib/python3.10/dist-packages (from pooch>=1.0->librosa<0.10.0,>0.7.2->audi
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.19.1->librosa<0.10.
Requirement already satisfied: cffi>=1.0 in /usr/local/lib/python3.10/dist-packages (from soundfile>=0.10.2->librosa<0.10.0,>0.7.2->audi
Requirement already satisfied: pycparser in /usr/local/lib/python3.10/dist-packages (from cffi>=1.0->soundfile>=0.10.2->librosa<0.10.0,>
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch>=1.0->libr
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch>=1.0->librosa
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch>=1.0->
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests>=2.19.0->pooch>=1.0->librosa<0.10.
```

```
import numpy as np
import pandas as pd
import os.path
from scipy.io import wavfile
import librosa
import soundfile
import seaborn as sns
```

```
import matplotlib.pyplot as plt
import IPython.display as ipd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder,OneHotEncoder,StandardScaler,MinMaxScaler
from sklearn.metrics import confusion_matrix,f1_score,accuracy_score
from audiomentations import Compose, AddGaussianNoise, TimeStretch, PitchShift, Shift, Gain,SpecCompose, SpecChannelShuffle, SpecFrequencyMask
import tensorflow as tf
from keras import utils
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Conv1D, MaxPooling1D, Conv2D, MaxPooling2D, Flatten, BatchNormalization
from keras import optimizers,regularizers
```

Preprocessing Data

Loading Dataset

```
#kaggle datasets download -d dmitrybabko/speech-emotion-recognition-en
```

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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

Listing the audios files in array (only thier names)

```
#path = '../input/speech-emotion-recognition-en/Crema'
path = '/content/drive/MyDrive/Crema'

files = []

for file in os.listdir(path):
    if file.endswith('.wav'):
        files.append(os.path.join(path, file))

#print(len(files))
#for i in range(5):
#    print(files[i])
```

```
#print("\n")

labels = []

for file in files:
    label = os.path.splitext(os.path.split(file)[1])[0].split('_')[2]
    labels.append(label)

print(len(labels))
print(set(labels))
dict_label={"HAP": "Happy", "ANG": "Anger", "SAD":"Sad", "NEU":"Neutral","DIS":"Disgust", "FEA":"Fear" }
```

```
7451
{'HAP', 'NEU', 'SAD', 'DIS', 'ANG', 'FEA'}
```

loading the raw data of eadh audio in array

```
audios = []

for i in files:
    audio, sr = librosa.load(i, sr= None)
    audios.append(audio)

print(len(audios))
print(len(audios[0]))
for i in range(5):
    print(audios[i])
```

```
7451
36303
[-1.3916016e-02 -1.5411377e-02 -1.4587402e-02 ... -9.1552734e-05
  3.0517578e-05 -6.1035156e-05]
[0.00567627 0.00515747 0.00448608 ... 0.         0.         0.        ]
[-0.00027466 -0.00018311  0.00024414 ...  0.          0.
  0.        ]
[ 0.00100708  0.00045776 -0.00033569 ...  0.          0.
  0.        ]
[ 0.00024414 -0.00039673 -0.00045776 ...  0.          0.
  0.        ]
```

Audio padding

To overcome the problem that the audios are nor the same length, we get the max audio length in the data and make padding for all the audios that have less length

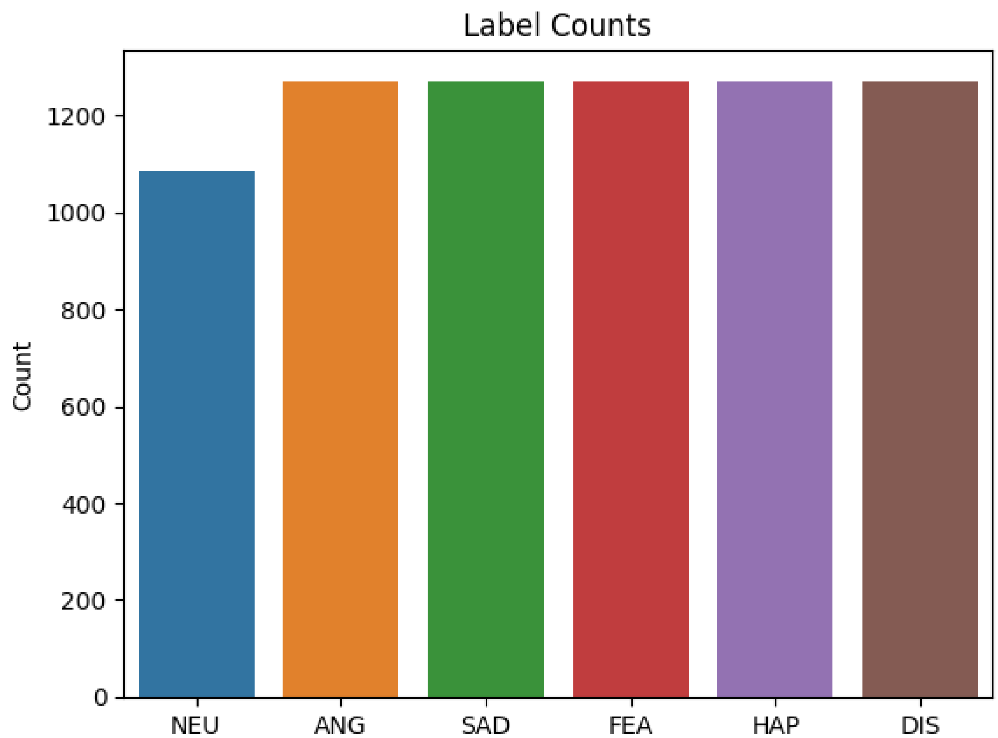
```
max_length = max(len(audio) for audio in audios)

padded_audios = []
for audio in audios:
    padding = max_length - len(audio)
    padded_audio = np.pad(audio, (0, padding), mode='constant')
    padded_audios.append(padded_audio)

print(len(padded_audios))
print(len(padded_audios[0]))
for i in range(5):
    print(padded_audios[i])
```

```
7451
80080
[-0.01391602 -0.01541138 -0.0145874  ...  0.          0.
  0.        ]
[0.00567627 0.00515747 0.00448608 ... 0.         0.         0.        ]
[-0.00027466 -0.00018311  0.00024414 ...  0.          0.
  0.        ]
[ 0.00100708  0.00045776 -0.00033569 ...  0.          0.
  0.        ]
[ 0.00024414 -0.00039673 -0.00045776 ...  0.          0.
  0.        ]
```

Plotting Label Counts

This plot shows the number of audios of each label.

```
sns.countplot(x=labels)
plt.title("Label Counts")
plt.xlabel("Label")
plt.ylabel("Count")
plt.show()
```

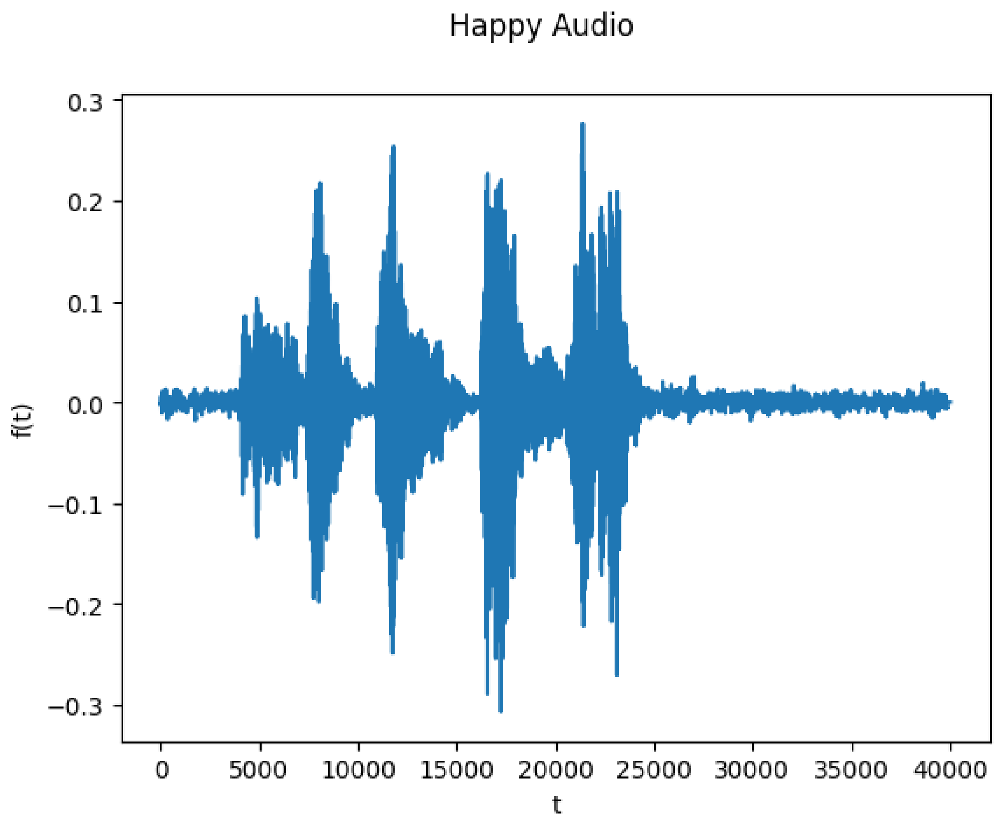


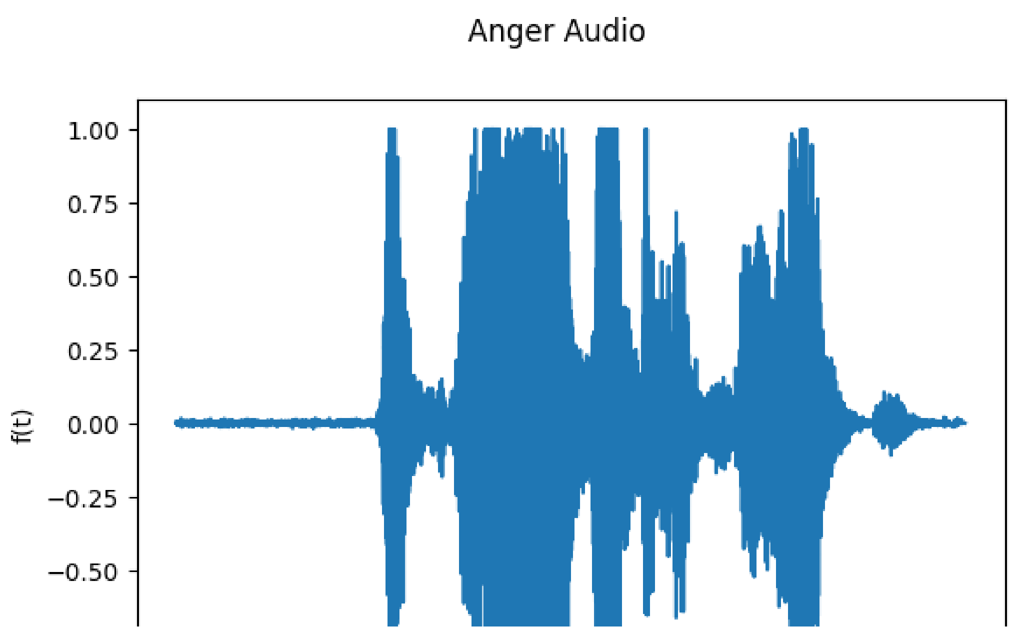
Plotting Raw Signal of Different Audios

This function plots the spectrum of the different types of audios.

```
def plot_audio(start):
  for label in dict_label.keys():
    audio_num=labels.index(label,start)
    fig=plt.figure()
    plt.plot(audios[audio_num])
    fig.suptitle(str(dict_label[labels[audio_num]]+" Audio"))
    plt.xlabel("t")
    plt.ylabel("f(t)")
    plt.show()
```

```
plot_audio(0)
```


Happy Audio
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3
f(t)
0
5000
10000
15000
20000
25000
30000
35000
40000
t


Anger Audio
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
f(t)

Playing Audios

This function makes you able to display the audio according to the label(happiness, anger, fear, neuteral , sad, disgust and so on) and the index of the audio.

```
def play_audio(label,x):
  i=labels.index(label,x)
  print(dict_label[label]+" Audio")
  return ipd.Audio(files[i])
```

```
play_audio("HAP",20)
```

    Happy Audio

```
play_audio("DIS",10)
```

    Disgust Audio

```
play_audio("ANG",30)
```

    Anger Audio

```
play_audio("SAD",60)
```

    Sad Audio

```
play_audio("FEA",60)
```

Fear Audio

```
play_audio("SAD",50)
```

Sad Audio

```
play_audio("HAP",60)
```

Happy Audio

```
play_audio("FEA",70)
```

Fear Audio

```
play_audio("NEU",10)
```

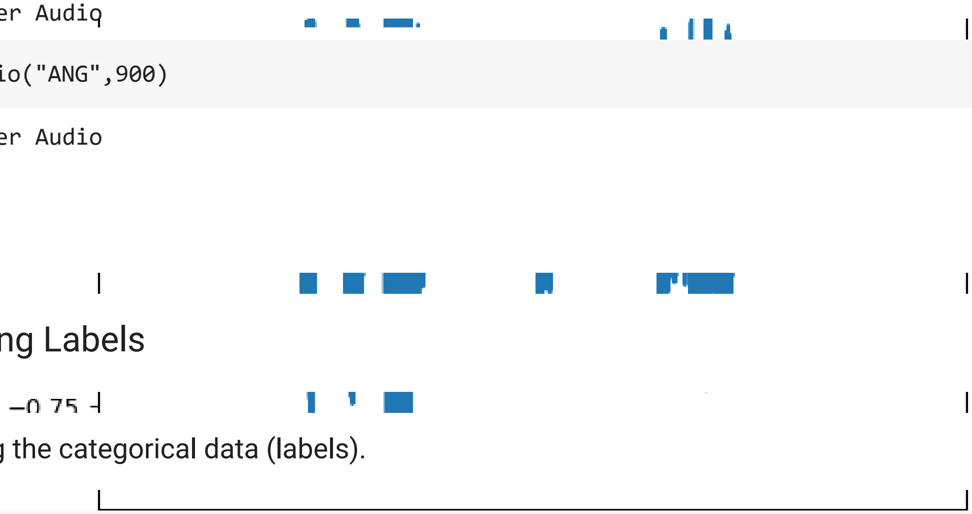
Neutral Audio

```
play_audio("ANG",90)
```

Anger Audio

```
play_audio("ANG",900)
```

Anger Audio



Encoding Labels

Encoding the categorical data (labels).

```
y = np.array(labels)
y = y.reshape(-1, 1)

encoder = OneHotEncoder(sparse_output=False)
encoder.fit(y)

y = encoder.transform(y)
#print(set(y))
print(y.shape)
```

```
(7451, 6)
```

Splitting Data

Splitting the data into train and test sets.

```
X_train_val, X_test, y_train_val, y_test = train_test_split(np.asarray(padded_audios), y, test_size=0.3, random_state=42, stratify = y)
X_train, X_val, y_train, y_val = train_test_split(X_train_val, y_train_val, test_size=0.05, random_state=42, stratify = y_train_val)
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
print(X_val.shape)
print(y_val.shape)
```

```
(4954, 80080)
(4954, 6)
(2236, 80080)
(2236, 6)
(261, 80080)
(261, 6)
```

Data Augmentation

This part to be used in 2D model to enhance the accuracy and training of the model but colab ram is crashed to we didn't use it unfortunately.

```
augmentation = Compose([AddGaussianNoise(p=0.5),
                        TimeStretch(p=0.5),
                        PitchShift(p=0.5),
                        Shift(p=0.5)])
```

```
augmented_audios = []
for audio in X_train:
    augmented_audio = augmentation(samples=audio, sample_rate=sr)
    augmented_audios.append(augmented_audio)
augmented_audios= np.array(augmented_audios)
print(augmented_audios.shape)
```

```
y_train = np.repeat(y_train, len(augmented_audios))
X_train = np.concatenate((padded_audios,augmented_audios),axis=0)

print(X_train.shape)
print(y.shape)
```

Extracting Features

Frequency Domain

Extracting feartues from frequency domain.

MFCCs

```
train_mfcc =  []

for audio in X_train:
    mfccs = np.mean(librosa.feature.mfcc(y=audio),axis= 0)
    train_mfcc.append(mfccs)

#train_mfcc = np.squeeze(np.array(train_mfcc), axis=1)
train_mfcc = np.expand_dims(train_mfcc, -1)
print(train_mfcc.shape)

test_mfcc =  []

for audio in X_test:
    mfccs = np.mean(librosa.feature.mfcc(y=audio),axis= 0)
    test_mfcc.append(mfccs)

#test_mfcc = np.squeeze(np.array(test_mfcc), axis=1)
test_mfcc = np.expand_dims(test_mfcc, -1)
print(test_mfcc.shape)

val_mfcc =  []

for audio in X_val:
    mfccs = np.mean(librosa.feature.mfcc(y=audio),axis= 0)
    val_mfcc.append(mfccs)

#val_mfcc = np.squeeze(np.array(val_mfcc), axis=1)
val_mfcc = np.expand_dims(val_mfcc, -1)
print(val_mfcc.shape)
```

```
(4948, 157, 1)
(2233, 157, 1)
(261, 157, 1)
```

Spectral Roll-off

```
train_sr =  []

for audio in X_train:
```

```
    srf = librosa.feature.spectral_rolloff(y=audio)
    train_sr.append(srf)

train_sr = np.squeeze(np.array(train_sr), axis=1)
train_sr = np.expand_dims(train_sr, -1)
print(train_sr.shape)

test_sr =  []

for audio in X_test:
    srf = librosa.feature.spectral_rolloff(y=audio)
    test_sr.append(srf)

test_sr = np.squeeze(np.array(test_sr), axis=1)
test_sr = np.expand_dims(test_sr, -1)
print(test_sr.shape)

val_sr =  []

for audio in X_val:
    srf = librosa.feature.spectral_rolloff(y=audio)
    val_sr.append(srf)

val_sr = np.squeeze(np.array(val_sr), axis=1)
val_sr = np.expand_dims(val_sr, -1)
print(val_sr.shape)
```

```
(4948, 157, 1)
(2233, 157, 1)
(261, 157, 1)
```

Time Domain

Extracting features from Time domain.

Energy

```
train_energy =  []

for audio in X_train:
```

```
    energy = librosa.feature.rms(y=audio)
    train_energy.append(energy)

train_energy = np.squeeze(np.array(train_energy), axis=1)
train_energy = np.expand_dims(train_energy, -1)
print(train_energy.shape)

test_energy =  []

for audio in X_test:
    energy = librosa.feature.rms(y=audio)
    test_energy.append(energy)

test_energy = np.squeeze(np.array(test_energy), axis=1)
test_energy = np.expand_dims(test_energy, -1)
print(test_energy.shape)

val_energy =  []

for audio in X_val:
    energy = librosa.feature.rms(y=audio)
    val_energy.append(energy)

val_energy = np.squeeze(np.array(val_energy), axis=1)
val_energy = np.expand_dims(val_energy, -1)
print(val_energy.shape)
```

```
(4954, 157, 1)
(2236, 157, 1)
(261, 157, 1)
```

Zero Crossing Rate

```
train_zcr =  []

for audio in X_train:
    zcr = librosa.feature.zero_crossing_rate(audio)
    train_zcr.append(zcr)

train_zcr = np.squeeze(np.array(train_zcr), axis=1)
train_zcr = np.expand_dims(train_zcr, -1)
print(train_zcr.shape)
```

```
test_zcr =  []

for audio in X_test:
    zcr = librosa.feature.zero_crossing_rate(audio)
    test_zcr.append(zcr)

test_zcr = np.squeeze(np.array(test_zcr), axis=1)
test_zcr = np.expand_dims(test_zcr, -1)
print(test_zcr.shape)

val_zcr =  []

for audio in X_val:
    zcr = librosa.feature.zero_crossing_rate(audio)
    val_zcr.append(zcr)

val_zcr = np.squeeze(np.array(val_zcr), axis=1)
val_zcr = np.expand_dims(val_zcr, -1)
print(val_zcr.shape)
```

```
(4954, 157, 1)
(2236, 157, 1)
(261, 157, 1)
```

Mel Spectrogram

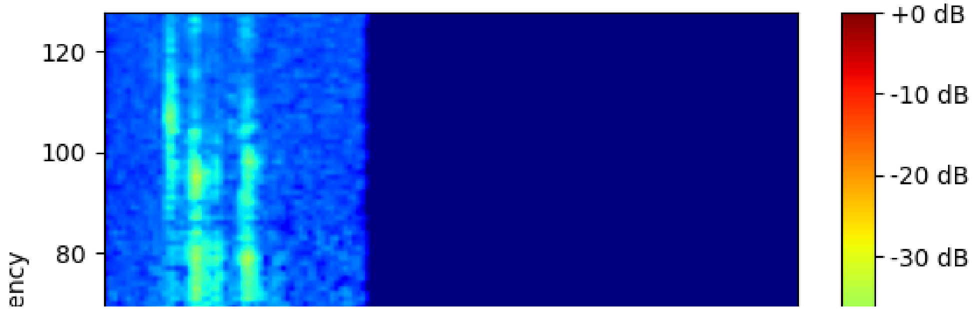
```
train_mel = []

for audio in X_train:
    mel_spec = librosa.feature.melspectrogram(y=audio, sr=sr)
    mel_spec = librosa.power_to_db(mel_spec, ref=np.max)
    train_mel.append(mel_spec)

train_mel = np.array(train_mel)
train_mel = np.expand_dims(train_mel, -1)
print(train_mel.shape)

test_mel = []

for audio in X_test:
    mel_spec = librosa.feature.melspectrogram(y=audio, sr=sr)
    mel_spec = librosa.power_to_db(mel_spec, ref=np.max)
```

```
    test_mel.append(mel_spec)

test_mel = np.array(test_mel)
test_mel = np.expand_dims(test_mel, -1)
print(test_mel.shape)

val_mel = []

for audio in X_val:
    mel_spec = librosa.feature.melspectrogram(y=audio, sr=sr)
    mel_spec = librosa.power_to_db(mel_spec, ref=np.max)
    val_mel.append(mel_spec)

val_mel = np.array(val_mel)
val_mel = np.expand_dims(val_mel, -1)
print(val_mel.shape)
```

```
(4954, 128, 157, 1)
(2236, 128, 157, 1)
(261, 128, 157, 1)
```

Plotting of spectrogram.

```
plt.imshow(mel_spec, aspect='auto', origin='lower', cmap='jet')
plt.colorbar(format='%+2.0f dB')
plt.xlabel('Time')
plt.ylabel('Mel Frequency')
plt.show()
```



CNN Models

Model 1D - Energy

Testing 1D model with energy feature only.

Building Model

```
model = Sequential()
model.add(Conv1D(16, 12, activation='relu', input_shape=(train_energy.shape[1], 1)))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 8, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 5, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
#model.add(Dense(32, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(6, activation='softmax'))

model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.001),
             metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv1d_12 (Conv1D)          (None, 146, 16)           208       
                                                                 
 max_pooling1d_12 (MaxPoolin  (None, 73, 16)           0         
 g1D)                                                            
                                                                 
 conv1d_13 (Conv1D)          (None, 66, 24)            3096      
                                                                 
 max_pooling1d_13 (MaxPoolin  (None, 33, 24)           0         
 g1D)                                                            
                                                                 
 conv1d_14 (Conv1D)          (None, 29, 24)            2904      
                                                                 
 max_pooling1d_14 (MaxPoolin  (None, 14, 24)           0         
 g1D)                                                            
                                                                 
 flatten_4 (Flatten)         (None, 336)               0         
                                                                 
 dense_8 (Dense)             (None, 64)                21568     
                                                                 
 dropout_4 (Dropout)         (None, 64)                0         
                                                                 
 dense_9 (Dense)             (None, 6)                 390       
                                                                 
=================================================================
Total params: 28,166
Trainable params: 28,166
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(train_energy, y_train,
                    epochs=50,
                    batch_size=128,
                    validation_data=(val_energy, y_val))
```

```
Epoch 1/50
39/39 [==============================] - 2s 28ms/step - loss: 1.7254 - accuracy: 0.2084 - val_loss: 1.6094 - val_accuracy: 0.2874
Epoch 2/50
39/39 [==============================] - 1s 23ms/step - loss: 1.5927 - accuracy: 0.3145 - val_loss: 1.4802 - val_accuracy: 0.3870
Epoch 3/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5160 - accuracy: 0.3608 - val_loss: 1.4089 - val_accuracy: 0.4444
Epoch 4/50
39/39 [==============================] - 1s 24ms/step - loss: 1.4870 - accuracy: 0.3895 - val_loss: 1.3773 - val_accuracy: 0.4751
Epoch 5/50
```

```
39/39 [==============================] - 1s 22ms/step - loss: 1.4643 - accuracy: 0.4000 - val_loss: 1.3642 - val_accuracy: 0.4828
Epoch 6/50
39/39 [==============================] - 1s 22ms/step - loss: 1.4571 - accuracy: 0.4052 - val_loss: 1.3585 - val_accuracy: 0.4713
Epoch 7/50
39/39 [==============================] - 1s 21ms/step - loss: 1.4477 - accuracy: 0.4084 - val_loss: 1.3491 - val_accuracy: 0.4943
Epoch 8/50
39/39 [==============================] - 1s 22ms/step - loss: 1.4473 - accuracy: 0.4139 - val_loss: 1.3467 - val_accuracy: 0.4636
Epoch 9/50
39/39 [==============================] - 1s 22ms/step - loss: 1.4364 - accuracy: 0.4165 - val_loss: 1.3451 - val_accuracy: 0.4904
Epoch 10/50
39/39 [==============================] - 1s 21ms/step - loss: 1.4296 - accuracy: 0.4115 - val_loss: 1.3239 - val_accuracy: 0.5019
Epoch 11/50
39/39 [==============================] - 1s 21ms/step - loss: 1.4227 - accuracy: 0.4204 - val_loss: 1.3145 - val_accuracy: 0.4904
Epoch 12/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4177 - accuracy: 0.4210 - val_loss: 1.3118 - val_accuracy: 0.5134
Epoch 13/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4158 - accuracy: 0.4274 - val_loss: 1.3099 - val_accuracy: 0.5019
Epoch 14/50
39/39 [==============================] - 1s 19ms/step - loss: 1.4085 - accuracy: 0.4333 - val_loss: 1.3049 - val_accuracy: 0.5057
Epoch 15/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4074 - accuracy: 0.4335 - val_loss: 1.2946 - val_accuracy: 0.5096
Epoch 16/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4074 - accuracy: 0.4272 - val_loss: 1.2987 - val_accuracy: 0.5096
Epoch 17/50
39/39 [==============================] - 1s 22ms/step - loss: 1.3986 - accuracy: 0.4317 - val_loss: 1.3333 - val_accuracy: 0.4789
Epoch 18/50
39/39 [==============================] - 1s 23ms/step - loss: 1.3952 - accuracy: 0.4319 - val_loss: 1.3007 - val_accuracy: 0.5172
Epoch 19/50
39/39 [==============================] - 1s 22ms/step - loss: 1.4048 - accuracy: 0.4307 - val_loss: 1.2958 - val_accuracy: 0.5096
Epoch 20/50
39/39 [==============================] - 1s 21ms/step - loss: 1.3944 - accuracy: 0.4313 - val_loss: 1.3080 - val_accuracy: 0.5057
Epoch 21/50
39/39 [==============================] - 1s 23ms/step - loss: 1.3928 - accuracy: 0.4400 - val_loss: 1.2761 - val_accuracy: 0.5057
Epoch 22/50
39/39 [==============================] - 1s 23ms/step - loss: 1.3869 - accuracy: 0.4418 - val_loss: 1.2910 - val_accuracy: 0.5019
Epoch 23/50
39/39 [==============================] - 1s 22ms/step - loss: 1.3861 - accuracy: 0.4456 - val_loss: 1.2755 - val_accuracy: 0.5172
Epoch 24/50
39/39 [==============================] - 1s 22ms/step - loss: 1.3833 - accuracy: 0.4402 - val_loss: 1.2925 - val_accuracy: 0.5096
Epoch 25/50
39/39 [==============================] - 1s 22ms/step - loss: 1.3889 - accuracy: 0.4357 - val_loss: 1.2690 - val_accuracy: 0.5364
Epoch 26/50
39/39 [==============================] - 1s 21ms/step - loss: 1.3753 - accuracy: 0.4448 - val_loss: 1.2580 - val_accuracy: 0.5326
Epoch 27/50
39/39 [==============================] - 1s 22ms/step - loss: 1.3780 - accuracy: 0.4438 - val_loss: 1.2675 - val_accuracy: 0.5172
Epoch 28/50
39/39 [==============================] - 1s 20ms/step - loss: 1.3695 - accuracy: 0.4410 - val_loss: 1.2669 - val_accuracy: 0.5211
Epoch 29/50
```

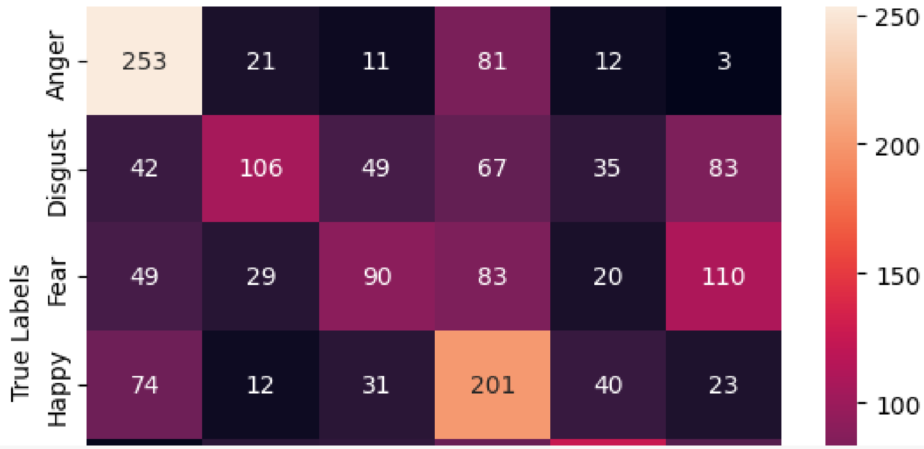
```
39/39 [==============================] - 1s 21ms/step - loss: 1.3710 - accuracy: 0.4430 - val_loss: 1.2571 - val_accuracy: 0.5326
```

Evaluating Model

```
y_pred = model.predict(test_energy)
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 0s 3ms/step


Acurracy score = 0.44872369010300045


F1 score (macro average) = 0.436351352454696


F1 score (weighted average) = 0.43693261772795944
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
#print(precisions)
#print(recalls)

class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])

k=1
print("Most Confusing Classes:\n")
```

```
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - FEA:
	F1-score = 0.2835	Precision = 0.3543	Recall = 0.2362
2 - DIS:
	F1-score = 0.3442	Precision = 0.4530	Recall = 0.2775
3 - NEU:
	F1-score = 0.4124	Precision = 0.4421	Recall = 0.3865
4 - HAP:
	F1-score = 0.4413	Precision = 0.3792	Recall = 0.5276
5 - SAD:
	F1-score = 0.5113	Precision = 0.4502	Recall = 0.5916
6 - ANG:
	F1-score = 0.6255	Precision = 0.5911	Recall = 0.6640
```

Model 1D - Zero Crossing Rate

Testing 1D model with Zero crossing rate feature only.

Building Model

```
model = Sequential()
model.add(Conv1D(16, 12, activation='relu', input_shape=(train_zcr.shape[1], 1)))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 8, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 5, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
#model.add(Dense(32, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(6, activation='softmax'))

model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.001),
```

```
              metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_15 (Conv1D)          (None, 146, 16)           208

 max_pooling1d_15 (MaxPoolin  (None, 73, 16)           0
 g1D)

 conv1d_16 (Conv1D)          (None, 66, 24)            3096

 max_pooling1d_16 (MaxPoolin  (None, 33, 24)           0
 g1D)

 conv1d_17 (Conv1D)          (None, 29, 24)            2904

 max_pooling1d_17 (MaxPoolin  (None, 14, 24)           0
 g1D)

 flatten_5 (Flatten)         (None, 336)               0

 dense_10 (Dense)            (None, 64)                21568

 dropout_5 (Dropout)         (None, 64)                0

 dense_11 (Dense)            (None, 6)                 390

=================================================================
Total params: 28,166
Trainable params: 28,166
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(train_zcr, y_train,
                    epochs=50,
                    batch_size=128,
                    validation_data=(val_zcr, y_val))
```

```
Epoch 1/50
39/39 [==============================] - 2s 29ms/step - loss: 1.7773 - accuracy: 0.1789 - val_loss: 1.7373 - val_accuracy: 0.1954
Epoch 2/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7441 - accuracy: 0.2591 - val_loss: 1.6983 - val_accuracy: 0.2414
Epoch 3/50
```

```
39/39 [==============================] - 1s 20ms/step - loss: 1.7107 - accuracy: 0.2801 - val_loss: 1.6455 - val_accuracy: 0.3142
Epoch 4/50
39/39 [==============================] - 1s 20ms/step - loss: 1.6579 - accuracy: 0.3173 - val_loss: 1.5946 - val_accuracy: 0.3678
Epoch 5/50
39/39 [==============================] - 1s 19ms/step - loss: 1.6157 - accuracy: 0.3426 - val_loss: 1.5881 - val_accuracy: 0.3525
Epoch 6/50
39/39 [==============================] - 1s 21ms/step - loss: 1.5925 - accuracy: 0.3482 - val_loss: 1.5510 - val_accuracy: 0.3563
Epoch 7/50
39/39 [==============================] - 1s 21ms/step - loss: 1.5815 - accuracy: 0.3498 - val_loss: 1.5439 - val_accuracy: 0.3755
Epoch 8/50
39/39 [==============================] - 1s 21ms/step - loss: 1.5773 - accuracy: 0.3549 - val_loss: 1.5665 - val_accuracy: 0.3372
Epoch 9/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5576 - accuracy: 0.3630 - val_loss: 1.5819 - val_accuracy: 0.3180
Epoch 10/50
39/39 [==============================] - 1s 21ms/step - loss: 1.5706 - accuracy: 0.3517 - val_loss: 1.5419 - val_accuracy: 0.3793
Epoch 11/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5427 - accuracy: 0.3723 - val_loss: 1.5312 - val_accuracy: 0.3716
Epoch 12/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5341 - accuracy: 0.3739 - val_loss: 1.5386 - val_accuracy: 0.3716
Epoch 13/50
39/39 [==============================] - 1s 20ms/step - loss: 1.5366 - accuracy: 0.3763 - val_loss: 1.5258 - val_accuracy: 0.3525
Epoch 14/50
39/39 [==============================] - 1s 21ms/step - loss: 1.5384 - accuracy: 0.3630 - val_loss: 1.5199 - val_accuracy: 0.3755
Epoch 15/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5200 - accuracy: 0.3842 - val_loss: 1.5329 - val_accuracy: 0.3678
Epoch 16/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5172 - accuracy: 0.3820 - val_loss: 1.5161 - val_accuracy: 0.3870
Epoch 17/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5132 - accuracy: 0.3836 - val_loss: 1.5185 - val_accuracy: 0.3716
Epoch 18/50
39/39 [==============================] - 1s 22ms/step - loss: 1.5116 - accuracy: 0.3874 - val_loss: 1.5256 - val_accuracy: 0.3525
Epoch 19/50
39/39 [==============================] - 1s 21ms/step - loss: 1.5108 - accuracy: 0.3858 - val_loss: 1.5185 - val_accuracy: 0.3946
Epoch 20/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4993 - accuracy: 0.3937 - val_loss: 1.5269 - val_accuracy: 0.3678
Epoch 21/50
39/39 [==============================] - 1s 20ms/step - loss: 1.5038 - accuracy: 0.3846 - val_loss: 1.5316 - val_accuracy: 0.3678
Epoch 22/50
39/39 [==============================] - 1s 24ms/step - loss: 1.4944 - accuracy: 0.3981 - val_loss: 1.5175 - val_accuracy: 0.3678
Epoch 23/50
39/39 [==============================] - 1s 25ms/step - loss: 1.4959 - accuracy: 0.3959 - val_loss: 1.5312 - val_accuracy: 0.3410
Epoch 24/50
39/39 [==============================] - 1s 23ms/step - loss: 1.4948 - accuracy: 0.3909 - val_loss: 1.5277 - val_accuracy: 0.3257
Epoch 25/50
39/39 [==============================] - 1s 21ms/step - loss: 1.5028 - accuracy: 0.3899 - val_loss: 1.5062 - val_accuracy: 0.3755
Epoch 26/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4930 - accuracy: 0.3981 - val_loss: 1.5280 - val_accuracy: 0.3257
Epoch 27/50
```

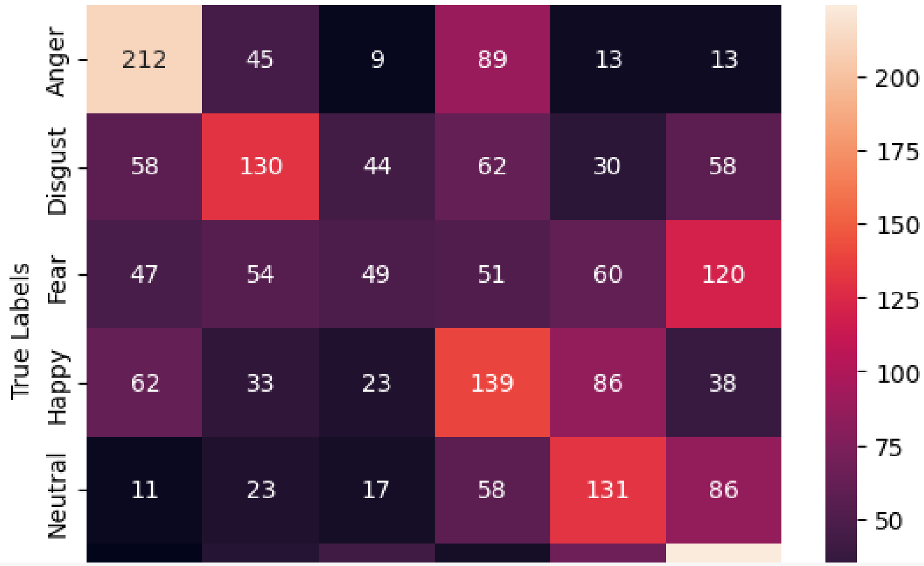
```
39/39 [==============================] - 1s 20ms/step - loss: 1.4873 - accuracy: 0.3961 - val_loss: 1.5223 - val_accuracy: 0.3640
Epoch 28/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4810 - accuracy: 0.3973 - val_loss: 1.5163 - val_accuracy: 0.3678
Epoch 29/50
39/39 [==============================] - 1s 20ms/step - loss: 1.4766 - accuracy: 0.4084 - val_loss: 1.5189 - val_accuracy: 0.3563
```

Evaluating Model

```
y_pred = model.predict(test_zcr)
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 0s 3ms/step


Acurracy score = 0.39632781012091356


F1 score (macro average) = 0.38286335100423435


F1 score (weighted average) = 0.38328540496165664
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
#print(precisions)
#print(recalls)

class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])
```

```
k=1
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - FEA:
        F1-score = 0.1735       Precision = 0.2663      Recall = 0.1286
2 - HAP:
        F1-score = 0.3488       Precision = 0.3341      Recall = 0.3648
3 - NEU:
        F1-score = 0.3675       Precision = 0.3385      Recall = 0.4018
4 - DIS:
        F1-score = 0.3746       Precision = 0.4167      Recall = 0.3403
5 - SAD:
        F1-score = 0.4864       Precision = 0.4156      Recall = 0.5864
6 - ANG:
        F1-score = 0.5464       Precision = 0.5367      Recall = 0.5564
```

Model 1D - Energy and Zero Crossing Rate

This model gave us the best results, with accuracy reaching 48%.

Building Model

```
model = Sequential()
model.add(Conv1D(16, 12, activation='relu', input_shape=((np.concatenate((train_energy, train_zcr), axis=1)).shape[1], 1)))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 8, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 5, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
#model.add(Dense(32, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(6, activation='softmax'))
```

```
model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.001),
             metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv1d_18 (Conv1D)          (None, 303, 16)           208       
                                                                 
 max_pooling1d_18 (MaxPoolin  (None, 151, 16)          0         
 g1D)                                                            
                                                                 
 conv1d_19 (Conv1D)          (None, 144, 24)           3096      
                                                                 
 max_pooling1d_19 (MaxPoolin  (None, 72, 24)           0         
 g1D)                                                            
                                                                 
 conv1d_20 (Conv1D)          (None, 68, 24)            2904      
                                                                 
 max_pooling1d_20 (MaxPoolin  (None, 34, 24)           0         
 g1D)                                                            
                                                                 
 flatten_6 (Flatten)         (None, 816)               0         
                                                                 
 dense_12 (Dense)            (None, 64)                52288     
                                                                 
 dropout_6 (Dropout)         (None, 64)                0         
                                                                 
 dense_13 (Dense)            (None, 6)                 390       
                                                                 
=================================================================
Total params: 58,886
Trainable params: 58,886
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(np.concatenate((train_energy, train_zcr), axis=1), y_train,
                    epochs=50,
                    batch_size=128,
                    validation_data=(np.concatenate((val_energy, val_zcr), axis=1), y_val))
```

```
Epoch 1/50
39/39 [==============================] - 2s 37ms/step - loss: 1.7090 - accuracy: 0.2387 - val_loss: 1.5530 - val_accuracy: 0.3372
Epoch 2/50
39/39 [==============================] - 1s 31ms/step - loss: 1.5649 - accuracy: 0.3482 - val_loss: 1.4812 - val_accuracy: 0.3946
Epoch 3/50
39/39 [==============================] - 1s 33ms/step - loss: 1.5159 - accuracy: 0.3804 - val_loss: 1.3936 - val_accuracy: 0.4789
Epoch 4/50
39/39 [==============================] - 1s 33ms/step - loss: 1.4814 - accuracy: 0.3931 - val_loss: 1.3811 - val_accuracy: 0.4100
Epoch 5/50
39/39 [==============================] - 1s 35ms/step - loss: 1.4526 - accuracy: 0.4095 - val_loss: 1.3580 - val_accuracy: 0.4751
Epoch 6/50
39/39 [==============================] - 1s 36ms/step - loss: 1.4331 - accuracy: 0.4163 - val_loss: 1.3452 - val_accuracy: 0.4598
Epoch 7/50
39/39 [==============================] - 1s 35ms/step - loss: 1.4296 - accuracy: 0.4224 - val_loss: 1.3220 - val_accuracy: 0.4674
Epoch 8/50
39/39 [==============================] - 1s 34ms/step - loss: 1.4150 - accuracy: 0.4220 - val_loss: 1.3241 - val_accuracy: 0.4674
Epoch 9/50
39/39 [==============================] - 1s 35ms/step - loss: 1.3992 - accuracy: 0.4349 - val_loss: 1.3076 - val_accuracy: 0.4674
Epoch 10/50
39/39 [==============================] - 1s 37ms/step - loss: 1.3881 - accuracy: 0.4353 - val_loss: 1.3304 - val_accuracy: 0.4559
Epoch 11/50
39/39 [==============================] - 1s 36ms/step - loss: 1.3812 - accuracy: 0.4509 - val_loss: 1.3078 - val_accuracy: 0.4713
Epoch 12/50
39/39 [==============================] - 1s 31ms/step - loss: 1.3650 - accuracy: 0.4527 - val_loss: 1.2955 - val_accuracy: 0.4943
Epoch 13/50
39/39 [==============================] - 1s 34ms/step - loss: 1.3619 - accuracy: 0.4513 - val_loss: 1.2965 - val_accuracy: 0.4713
Epoch 14/50
39/39 [==============================] - 1s 35ms/step - loss: 1.3521 - accuracy: 0.4543 - val_loss: 1.2925 - val_accuracy: 0.4751
Epoch 15/50
39/39 [==============================] - 1s 31ms/step - loss: 1.3455 - accuracy: 0.4596 - val_loss: 1.2779 - val_accuracy: 0.4789
Epoch 16/50
39/39 [==============================] - 1s 31ms/step - loss: 1.3502 - accuracy: 0.4559 - val_loss: 1.2726 - val_accuracy: 0.4828
Epoch 17/50
39/39 [==============================] - 1s 31ms/step - loss: 1.3366 - accuracy: 0.4598 - val_loss: 1.2646 - val_accuracy: 0.4789
Epoch 18/50
39/39 [==============================] - 1s 33ms/step - loss: 1.3265 - accuracy: 0.4626 - val_loss: 1.2694 - val_accuracy: 0.4713
Epoch 19/50
39/39 [==============================] - 1s 31ms/step - loss: 1.3149 - accuracy: 0.4685 - val_loss: 1.2591 - val_accuracy: 0.4943
Epoch 20/50
39/39 [==============================] - 1s 31ms/step - loss: 1.3152 - accuracy: 0.4802 - val_loss: 1.2680 - val_accuracy: 0.4828
Epoch 21/50
39/39 [==============================] - 1s 32ms/step - loss: 1.3111 - accuracy: 0.4764 - val_loss: 1.2713 - val_accuracy: 0.4943
Epoch 22/50
39/39 [==============================] - 1s 35ms/step - loss: 1.3085 - accuracy: 0.4691 - val_loss: 1.2734 - val_accuracy: 0.4866
Epoch 23/50
39/39 [==============================] - 1s 33ms/step - loss: 1.2910 - accuracy: 0.4830 - val_loss: 1.2598 - val_accuracy: 0.4866
Epoch 24/50
39/39 [==============================] - 1s 33ms/step - loss: 1.2875 - accuracy: 0.4810 - val_loss: 1.2622 - val_accuracy: 0.5019
```

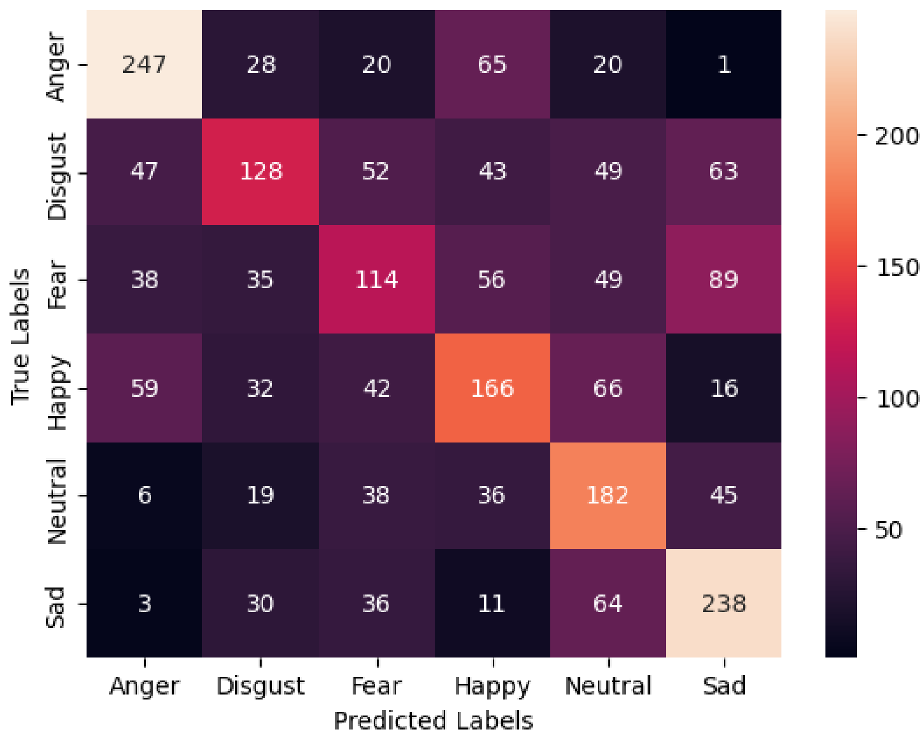
```
Epoch 25/50
39/39 [==============================] - 1s 32ms/step - loss: 1.2850 - accuracy: 0.4893 - val_loss: 1.2797 - val_accuracy: 0.4789
Epoch 26/50
39/39 [==============================] - 1s 31ms/step - loss: 1.2867 - accuracy: 0.4822 - val_loss: 1.2581 - val_accuracy: 0.5057
Epoch 27/50
39/39 [==============================] - 1s 33ms/step - loss: 1.2827 - accuracy: 0.4877 - val_loss: 1.2608 - val_accuracy: 0.4981
Epoch 28/50
39/39 [==============================] - 1s 32ms/step - loss: 1.2781 - accuracy: 0.4879 - val_loss: 1.2532 - val_accuracy: 0.4981
Epoch 29/50
39/39 [==============================] - 1s 35ms/step - loss: 1.2806 - accuracy: 0.4919 - val_loss: 1.2702 - val_accuracy: 0.4866
```

Evaluating Model

```
y_pred = model.predict(np.concatenate((test_energy, test_zcr), axis=1))
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 0s 6ms/step


Acurracy score = 0.48141513658755036


F1 score (macro average) = 0.47466678367205245


F1 score (weighted average) = 0.4745046872848074
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
```

```
#print(precisions)
#print(recalls)

class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])

k=1
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - FEA:
        F1-score = 0.3338       Precision = 0.3775      Recall = 0.2992
2 - DIS:
        F1-score = 0.3914       Precision = 0.4706      Recall = 0.3351
3 - HAP:
        F1-score = 0.4380       Precision = 0.4403      Recall = 0.4357
4 - NEU:
        F1-score = 0.4815       Precision = 0.4233      Recall = 0.5583
5 - SAD:
        F1-score = 0.5707       Precision = 0.5265      Recall = 0.6230
6 - ANG:
        F1-score = 0.6325       Precision = 0.6175      Recall = 0.6483
```

Another 1D model

```
model = Sequential()
model.add(Conv1D(256, 12, activation='relu', input_shape=((np.concatenate((train_energy, train_zcr), axis=1)).shape[1], 1)))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(128, 8, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(64, 5, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Flatten())
#model.add(Dense(128, activation='relu'))
#model.add(Dropout(0.3))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(BatchNormalization())
```

```python
model.add(Dense(6, activation='softmax'))

model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.0001),
             metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv1d_21 (Conv1D)          (None, 303, 256)          3328      
                                                                 
 max_pooling1d_21 (MaxPoolin  (None, 151, 256)         0         
 g1D)                                                            
                                                                 
 conv1d_22 (Conv1D)          (None, 144, 128)          262272    
                                                                 
 max_pooling1d_22 (MaxPoolin  (None, 72, 128)          0         
 g1D)                                                            
                                                                 
 conv1d_23 (Conv1D)          (None, 68, 64)            41024     
                                                                 
 max_pooling1d_23 (MaxPoolin  (None, 34, 64)           0         
 g1D)                                                            
                                                                 
 flatten_7 (Flatten)         (None, 2176)              0         
                                                                 
 dense_18 (Dense)            (None, 64)                139328    
                                                                 
 dropout_11 (Dropout)        (None, 64)                0         
                                                                 
 batch_normalization_5 (Batc  (None, 64)               256       
 hNormalization)                                                 
                                                                 
 dense_19 (Dense)            (None, 6)                 390       
                                                                 
=================================================================
Total params: 446,598
Trainable params: 446,470
Non-trainable params: 128
_________________________________________________________________
```

```python
history = model.fit(np.concatenate((train_energy, train_zcr), axis=1), y_train,
                    epochs=25,
```

```
                  batch_size=128,
                  validation_data=(np.concatenate((val_energy, val_zcr), axis=1), y_val))
```

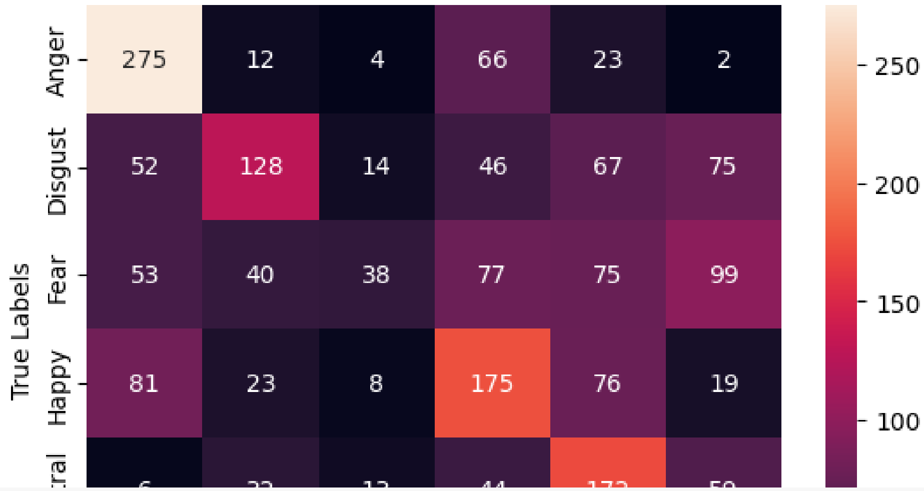
```
Epoch 1/25
39/39 [==============================] - 46s 1s/step - loss: 1.7234 - accuracy: 0.2662 - val_loss: 1.7800 - val_accuracy: 0.3525
Epoch 2/25
39/39 [==============================] - 44s 1s/step - loss: 1.5988 - accuracy: 0.3516 - val_loss: 1.7661 - val_accuracy: 0.3908
Epoch 3/25
39/39 [==============================] - 45s 1s/step - loss: 1.5539 - accuracy: 0.3692 - val_loss: 1.7529 - val_accuracy: 0.4368
Epoch 4/25
39/39 [==============================] - 44s 1s/step - loss: 1.5163 - accuracy: 0.3815 - val_loss: 1.7410 - val_accuracy: 0.4100
Epoch 5/25
39/39 [==============================] - 44s 1s/step - loss: 1.5032 - accuracy: 0.3958 - val_loss: 1.7293 - val_accuracy: 0.3908
Epoch 6/25
39/39 [==============================] - 45s 1s/step - loss: 1.4869 - accuracy: 0.4025 - val_loss: 1.7148 - val_accuracy: 0.4330
Epoch 7/25
39/39 [==============================] - 45s 1s/step - loss: 1.4628 - accuracy: 0.4150 - val_loss: 1.6949 - val_accuracy: 0.4368
Epoch 8/25
39/39 [==============================] - 44s 1s/step - loss: 1.4578 - accuracy: 0.4142 - val_loss: 1.6663 - val_accuracy: 0.4330
Epoch 9/25
39/39 [==============================] - 44s 1s/step - loss: 1.4490 - accuracy: 0.4235 - val_loss: 1.6403 - val_accuracy: 0.4521
Epoch 10/25
39/39 [==============================] - 44s 1s/step - loss: 1.4445 - accuracy: 0.4312 - val_loss: 1.6016 - val_accuracy: 0.4444
Epoch 11/25
39/39 [==============================] - 45s 1s/step - loss: 1.4236 - accuracy: 0.4378 - val_loss: 1.5699 - val_accuracy: 0.4483
Epoch 12/25
39/39 [==============================] - 45s 1s/step - loss: 1.4216 - accuracy: 0.4374 - val_loss: 1.5470 - val_accuracy: 0.4444
Epoch 13/25
39/39 [==============================] - 44s 1s/step - loss: 1.4237 - accuracy: 0.4419 - val_loss: 1.5230 - val_accuracy: 0.4483
Epoch 14/25
39/39 [==============================] - 44s 1s/step - loss: 1.4016 - accuracy: 0.4497 - val_loss: 1.4814 - val_accuracy: 0.4713
Epoch 15/25
39/39 [==============================] - 44s 1s/step - loss: 1.4043 - accuracy: 0.4514 - val_loss: 1.4647 - val_accuracy: 0.4521
Epoch 16/25
39/39 [==============================] - 45s 1s/step - loss: 1.3877 - accuracy: 0.4528 - val_loss: 1.4502 - val_accuracy: 0.4521
Epoch 17/25
39/39 [==============================] - 44s 1s/step - loss: 1.3866 - accuracy: 0.4520 - val_loss: 1.4205 - val_accuracy: 0.4559
Epoch 18/25
39/39 [==============================] - 44s 1s/step - loss: 1.3834 - accuracy: 0.4621 - val_loss: 1.3999 - val_accuracy: 0.4598
Epoch 19/25
39/39 [==============================] - 45s 1s/step - loss: 1.3750 - accuracy: 0.4621 - val_loss: 1.4250 - val_accuracy: 0.4483
Epoch 20/25
39/39 [==============================] - 44s 1s/step - loss: 1.3779 - accuracy: 0.4574 - val_loss: 1.3968 - val_accuracy: 0.4674
Epoch 21/25
39/39 [==============================] - 44s 1s/step - loss: 1.3657 - accuracy: 0.4647 - val_loss: 1.3949 - val_accuracy: 0.4330
Epoch 22/25
39/39 [==============================] - 44s 1s/step - loss: 1.3661 - accuracy: 0.4651 - val_loss: 1.3750 - val_accuracy: 0.4866
Epoch 23/25
```

```
39/39 [==============================] - 44s 1s/step - loss: 1.3486 - accuracy: 0.4711 - val_loss: 1.3917 - val_accuracy: 0.4368
Epoch 24/25
39/39 [==============================] - 45s 1s/step - loss: 1.3542 - accuracy: 0.4653 - val_loss: 1.3639 - val_accuracy: 0.4751
Epoch 25/25
39/39 [==============================] - 44s 1s/step - loss: 1.3443 - accuracy: 0.4717 - val_loss: 1.3925 - val_accuracy: 0.4674
```

```
y_pred = model.predict(np.concatenate((test_energy, test_zcr), axis=1))
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 4s 57ms/step


Acurracy score = 0.4601967799642218


F1 score (macro average) = 0.4343275560587625


F1 score (weighted average) = 0.4348376787576417
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
#print(precisions)
#print(recalls)

class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])

k=1
```

```
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - FEA:
        F1-score = 0.2830       Precision = 0.3603      Recall = 0.2330
2 - DIS:
        F1-score = 0.4060       Precision = 0.4770      Recall = 0.3534
3 - HAP:
        F1-score = 0.4222       Precision = 0.3995      Recall = 0.4476
4 - NEU:
        F1-score = 0.4255       Precision = 0.3756      Recall = 0.4908
5 - SAD:
        F1-score = 0.5378       Precision = 0.4967      Recall = 0.5864
6 - ANG:
        F1-score = 0.6539       Precision = 0.6384      Recall = 0.6702
```

Model 1D - MFCCs

Building Model

```
model = Sequential()
model.add(Conv1D(16, 12, activation='relu', input_shape=(train_mfcc.shape[1], 1)))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 8, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 5, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
#model.add(Dense(32, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(6, activation='softmax'))

model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.001),
             metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv1d_21 (Conv1D)          (None, 146, 16)           208       
                                                                 
 max_pooling1d_21 (MaxPoolin  (None, 73, 16)           0         
 g1D)                                                            
                                                                 
 conv1d_22 (Conv1D)          (None, 66, 24)            3096      
                                                                 
 max_pooling1d_22 (MaxPoolin  (None, 33, 24)           0         
 g1D)                                                            
                                                                 
 conv1d_23 (Conv1D)          (None, 29, 24)            2904      
                                                                 
 max_pooling1d_23 (MaxPoolin  (None, 14, 24)           0         
 g1D)                                                            
                                                                 
 flatten_7 (Flatten)         (None, 336)               0         
                                                                 
 dense_14 (Dense)            (None, 64)                21568     
                                                                 
 dropout_7 (Dropout)         (None, 64)                0         
                                                                 
 dense_15 (Dense)            (None, 6)                 390       
                                                                 
=================================================================
Total params: 28,166
Trainable params: 28,166
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(train_mfcc, y_train,
                    epochs=50,
                    batch_size=128,
                    validation_data=(val_mfcc, y_val))
```

```
Epoch 25/50
39/39 [==============================] - 1s 21ms/step - loss: 1.3595 - accuracy: 0.4450 - val_loss: 1.4107 - val_accuracy: 0.3985
Epoch 26/50
39/39 [==============================] - 1s 21ms/step - loss: 1.3636 - accuracy: 0.4590 - val_loss: 1.4106 - val_accuracy: 0.4138
Epoch 27/50
39/39 [==============================] - 1s 21ms/step - loss: 1.3354 - accuracy: 0.4576 - val_loss: 1.4167 - val_accuracy: 0.3831
```

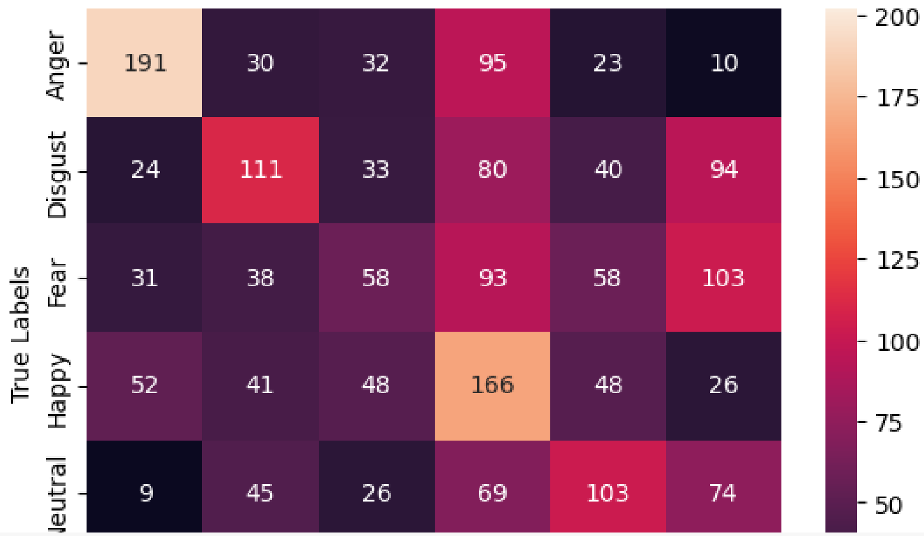
```
Epoch 49/50
39/39 [==============================] - 1s 22ms/step - loss: 1.1249 - accuracy: 0.5558 - val_loss: 1.5392 - val_accuracy: 0.3793
Epoch 50/50
39/39 [==============================] - 1s 22ms/step - loss: 1.1191 - accuracy: 0.5521 - val_loss: 1.5481 - val_accuracy: 0.3563
```

Evaluating Model

```
y_pred = model.predict(test_mfcc)
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 0s 3ms/step


Acurracy score = 0.37214509628302733


F1 score (macro average) = 0.365114083038715


F1 score (weighted average) = 0.3663917421448286
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
#print(precisions)
#print(recalls)

class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])
```

```
k=1
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - FEA:
        F1-score = 0.1865       Precision = 0.2407      Recall = 0.1522
2 - NEU:
        F1-score = 0.3140       Precision = 0.3121      Recall = 0.3160
3 - DIS:
        F1-score = 0.3199       Precision = 0.3558      Recall = 0.2906
4 - HAP:
        F1-score = 0.3640       Precision = 0.3126      Recall = 0.4357
5 - SAD:
        F1-score = 0.4534       Precision = 0.3969      Recall = 0.5288
6 - ANG:
        F1-score = 0.5528       Precision = 0.6161      Recall = 0.5013
```

Model 1D - Spectral Roll-off

This model gave us the worst results by far.

Building Model

```
model = Sequential()
model.add(Conv1D(16, 12, activation='relu', input_shape=(train_sr.shape[1], 1)))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 8, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 5, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
#model.add(Dense(32, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(6, activation='softmax'))
```

```
model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.001),
             metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_24 (Conv1D)          (None, 146, 16)           208

 max_pooling1d_24 (MaxPoolin  (None, 73, 16)           0
 g1D)

 conv1d_25 (Conv1D)          (None, 66, 24)            3096

 max_pooling1d_25 (MaxPoolin  (None, 33, 24)           0
 g1D)

 conv1d_26 (Conv1D)          (None, 29, 24)            2904

 max_pooling1d_26 (MaxPoolin  (None, 14, 24)           0
 g1D)

 flatten_8 (Flatten)         (None, 336)               0

 dense_16 (Dense)            (None, 64)                21568

 dropout_8 (Dropout)         (None, 64)                0

 dense_17 (Dense)            (None, 6)                 390

=================================================================
Total params: 28,166
Trainable params: 28,166
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(train_sr, y_train,
                    epochs=50,
                    batch_size=128,
                    validation_data=(val_sr, y_val))
```

```
Epoch 1/50
39/39 [==============================] - 2s 27ms/step - loss: 179.7276 - accuracy: 0.1692 - val_loss: 19.6667 - val_accuracy: 0.2184
```

```
Epoch 2/50
39/39 [==============================] - 1s 21ms/step - loss: 14.7119 - accuracy: 0.1742 - val_loss: 6.2626 - val_accuracy: 0.1877
Epoch 3/50
39/39 [==============================] - 1s 22ms/step - loss: 5.3804 - accuracy: 0.1684 - val_loss: 3.2832 - val_accuracy: 0.1916
Epoch 4/50
39/39 [==============================] - 1s 22ms/step - loss: 2.7428 - accuracy: 0.1908 - val_loss: 2.2282 - val_accuracy: 0.1686
Epoch 5/50
39/39 [==============================] - 1s 21ms/step - loss: 2.0660 - accuracy: 0.1865 - val_loss: 1.9669 - val_accuracy: 0.1648
Epoch 6/50
39/39 [==============================] - 1s 22ms/step - loss: 1.9271 - accuracy: 0.1880 - val_loss: 1.9352 - val_accuracy: 0.1648
Epoch 7/50
39/39 [==============================] - 1s 22ms/step - loss: 1.8584 - accuracy: 0.1878 - val_loss: 1.9356 - val_accuracy: 0.1609
Epoch 8/50
39/39 [==============================] - 1s 21ms/step - loss: 1.8285 - accuracy: 0.1896 - val_loss: 1.9182 - val_accuracy: 0.1648
Epoch 9/50
39/39 [==============================] - 1s 19ms/step - loss: 1.8152 - accuracy: 0.1916 - val_loss: 1.9090 - val_accuracy: 0.1609
Epoch 10/50
39/39 [==============================] - 1s 21ms/step - loss: 1.7972 - accuracy: 0.1908 - val_loss: 1.8916 - val_accuracy: 0.1648
Epoch 11/50
39/39 [==============================] - 1s 20ms/step - loss: 1.7890 - accuracy: 0.1948 - val_loss: 1.9022 - val_accuracy: 0.1609
Epoch 12/50
39/39 [==============================] - 1s 20ms/step - loss: 1.7785 - accuracy: 0.1956 - val_loss: 1.8865 - val_accuracy: 0.1648
Epoch 13/50
39/39 [==============================] - 1s 19ms/step - loss: 1.7695 - accuracy: 0.1979 - val_loss: 1.8975 - val_accuracy: 0.1648
Epoch 14/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7675 - accuracy: 0.1954 - val_loss: 1.8973 - val_accuracy: 0.1609
Epoch 15/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7673 - accuracy: 0.1962 - val_loss: 1.8914 - val_accuracy: 0.1648
Epoch 16/50
39/39 [==============================] - 1s 21ms/step - loss: 1.7541 - accuracy: 0.1989 - val_loss: 1.8919 - val_accuracy: 0.1648
Epoch 17/50
39/39 [==============================] - 1s 21ms/step - loss: 1.7573 - accuracy: 0.2013 - val_loss: 1.8996 - val_accuracy: 0.1571
Epoch 18/50
39/39 [==============================] - 1s 19ms/step - loss: 1.7554 - accuracy: 0.1975 - val_loss: 1.8978 - val_accuracy: 0.1571
Epoch 19/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7499 - accuracy: 0.2033 - val_loss: 1.9188 - val_accuracy: 0.1609
Epoch 20/50
39/39 [==============================] - 1s 20ms/step - loss: 1.7512 - accuracy: 0.1979 - val_loss: 1.8866 - val_accuracy: 0.1877
Epoch 21/50
39/39 [==============================] - 1s 20ms/step - loss: 1.7461 - accuracy: 0.1999 - val_loss: 1.9324 - val_accuracy: 0.1724
Epoch 22/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7504 - accuracy: 0.1964 - val_loss: 1.8910 - val_accuracy: 0.1686
Epoch 23/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7468 - accuracy: 0.1989 - val_loss: 1.8834 - val_accuracy: 0.1916
Epoch 24/50
39/39 [==============================] - 1s 26ms/step - loss: 1.7362 - accuracy: 0.2035 - val_loss: 1.9160 - val_accuracy: 0.1724
Epoch 25/50
39/39 [==============================] - 1s 26ms/step - loss: 1.7442 - accuracy: 0.1991 - val_loss: 1.9079 - val_accuracy: 0.1762
```

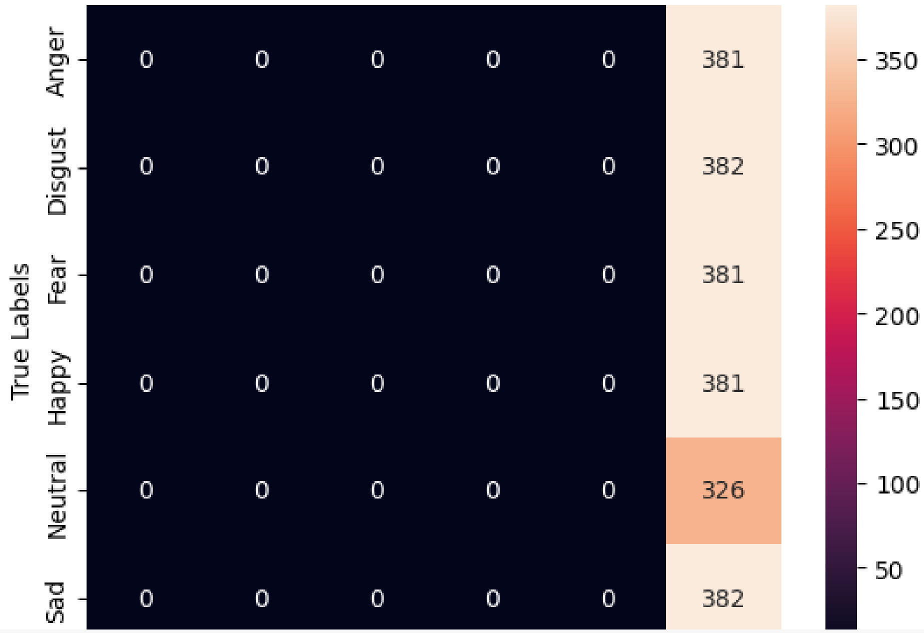
```
Epoch 26/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7374 - accuracy: 0.2078 - val_loss: 1.9109 - val_accuracy: 0.1801
Epoch 27/50
39/39 [==============================] - 1s 21ms/step - loss: 1.7371 - accuracy: 0.2049 - val_loss: 1.8901 - val_accuracy: 0.1762
Epoch 28/50
39/39 [==============================] - 1s 22ms/step - loss: 1.7401 - accuracy: 0.2049 - val_loss: 1.9109 - val_accuracy: 0.1916
Epoch 29/50
```

Evaluating Model

```
y_pred = model.predict(test_mfcc)
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 0s 4ms/step


Acurracy score = 0.17107030900134348


F1 score (macro average) = 0.04869343530911408


F1 score (weighted average) = 0.04998000614800245
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
#print(precisions)
#print(recalls)
```

```
class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])

k=1
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - ANG:
        F1-score = nan  Precision = nan Recall = 0.0000
2 - DIS:
        F1-score = nan  Precision = nan Recall = 0.0000
3 - FEA:
        F1-score = nan  Precision = nan Recall = 0.0000
4 - HAP:
        F1-score = nan  Precision = nan Recall = 0.0000
5 - NEU:
        F1-score = nan  Precision = nan Recall = 0.0000
6 - SAD:
        F1-score = 0.2922       Precision = 0.1711      Recall = 1.0000
/tmp/ipykernel_34/2911065269.py:13: RuntimeWarning: invalid value encountered in long_scalars
  precision = TP / (TP + FP)
```

Model 1D - Energy, Zero Crossing Rate and MFCCs

Building Model

```
model = Sequential()
model.add(Conv1D(16, 12, activation='relu', input_shape=((np.concatenate((train_mfcc,train_energy,train_zcr), axis=1)).shape[1], 1)))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 8, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Conv1D(24, 5, activation='relu'))
model.add(MaxPooling1D(pool_size=2, strides=2))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
#model.add(Dense(32, activation='relu'))
model.add(Dropout(0.2))
```

```
model.add(Dense(6, activation='softmax'))

model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.001),
             metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d_27 (Conv1D)          (None, 460, 16)           208

 max_pooling1d_27 (MaxPoolin  (None, 230, 16)          0
 g1D)

 conv1d_28 (Conv1D)          (None, 223, 24)           3096

 max_pooling1d_28 (MaxPoolin  (None, 111, 24)          0
 g1D)

 conv1d_29 (Conv1D)          (None, 107, 24)           2904

 max_pooling1d_29 (MaxPoolin  (None, 53, 24)           0
 g1D)

 flatten_9 (Flatten)         (None, 1272)              0

 dense_18 (Dense)            (None, 64)                81472

 dropout_9 (Dropout)         (None, 64)                0

 dense_19 (Dense)            (None, 6)                 390

=================================================================
Total params: 88,070
Trainable params: 88,070
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit((np.concatenate((train_mfcc, train_energy,train_zcr), axis=1)), y_train,
                    epochs=50,
                    batch_size=128,
                    validation_data=((np.concatenate((val_mfcc,val_energy,val_zcr), axis=1)), y_val))
```

```
Epoch 1/50
39/39 [==============================] - 3s 53ms/step - loss: 2.0548 - accuracy: 0.1975 - val_loss: 1.7181 - val_accuracy: 0.2261
Epoch 2/50
39/39 [==============================] - 2s 44ms/step - loss: 1.6412 - accuracy: 0.3145 - val_loss: 1.5258 - val_accuracy: 0.3372
Epoch 3/50
39/39 [==============================] - 2s 45ms/step - loss: 1.5426 - accuracy: 0.3575 - val_loss: 1.4569 - val_accuracy: 0.3908
Epoch 4/50
39/39 [==============================] - 2s 45ms/step - loss: 1.5170 - accuracy: 0.3650 - val_loss: 1.3878 - val_accuracy: 0.4483
Epoch 5/50
39/39 [==============================] - 2s 44ms/step - loss: 1.4805 - accuracy: 0.3765 - val_loss: 1.3771 - val_accuracy: 0.4444
Epoch 6/50
39/39 [==============================] - 2s 44ms/step - loss: 1.4726 - accuracy: 0.3943 - val_loss: 1.3645 - val_accuracy: 0.4444
Epoch 7/50
39/39 [==============================] - 2s 54ms/step - loss: 1.4569 - accuracy: 0.3983 - val_loss: 1.3597 - val_accuracy: 0.4636
Epoch 8/50
39/39 [==============================] - 2s 50ms/step - loss: 1.4441 - accuracy: 0.4072 - val_loss: 1.3612 - val_accuracy: 0.4444
Epoch 9/50
39/39 [==============================] - 2s 45ms/step - loss: 1.4336 - accuracy: 0.4167 - val_loss: 1.3412 - val_accuracy: 0.4483
Epoch 10/50
39/39 [==============================] - 2s 47ms/step - loss: 1.4296 - accuracy: 0.4091 - val_loss: 1.3414 - val_accuracy: 0.4636
Epoch 11/50
39/39 [==============================] - 2s 43ms/step - loss: 1.4200 - accuracy: 0.4254 - val_loss: 1.3283 - val_accuracy: 0.4483
Epoch 12/50
39/39 [==============================] - 2s 43ms/step - loss: 1.4096 - accuracy: 0.4258 - val_loss: 1.3198 - val_accuracy: 0.4674
Epoch 13/50
39/39 [==============================] - 2s 42ms/step - loss: 1.4046 - accuracy: 0.4337 - val_loss: 1.3268 - val_accuracy: 0.4674
Epoch 14/50
39/39 [==============================] - 2s 42ms/step - loss: 1.3919 - accuracy: 0.4337 - val_loss: 1.2956 - val_accuracy: 0.4828
Epoch 15/50
39/39 [==============================] - 2s 43ms/step - loss: 1.3860 - accuracy: 0.4406 - val_loss: 1.3141 - val_accuracy: 0.4789
Epoch 16/50
39/39 [==============================] - 2s 44ms/step - loss: 1.3970 - accuracy: 0.4305 - val_loss: 1.3176 - val_accuracy: 0.4636
Epoch 17/50
39/39 [==============================] - 2s 42ms/step - loss: 1.3800 - accuracy: 0.4450 - val_loss: 1.2926 - val_accuracy: 0.4713
Epoch 18/50
39/39 [==============================] - 2s 42ms/step - loss: 1.3821 - accuracy: 0.4414 - val_loss: 1.2904 - val_accuracy: 0.5019
Epoch 19/50
39/39 [==============================] - 2s 43ms/step - loss: 1.3760 - accuracy: 0.4416 - val_loss: 1.2972 - val_accuracy: 0.4751
Epoch 20/50
39/39 [==============================] - 2s 44ms/step - loss: 1.3670 - accuracy: 0.4434 - val_loss: 1.3036 - val_accuracy: 0.4828
Epoch 21/50
39/39 [==============================] - 2s 44ms/step - loss: 1.3636 - accuracy: 0.4503 - val_loss: 1.2929 - val_accuracy: 0.4904
Epoch 22/50
39/39 [==============================] - 2s 46ms/step - loss: 1.3523 - accuracy: 0.4630 - val_loss: 1.2739 - val_accuracy: 0.5019
Epoch 23/50
39/39 [==============================] - 2s 47ms/step - loss: 1.3545 - accuracy: 0.4580 - val_loss: 1.2820 - val_accuracy: 0.4904
Epoch 24/50
39/39 [==============================] - 2s 44ms/step - loss: 1.3710 - accuracy: 0.4531 - val_loss: 1.2895 - val_accuracy: 0.4828
```

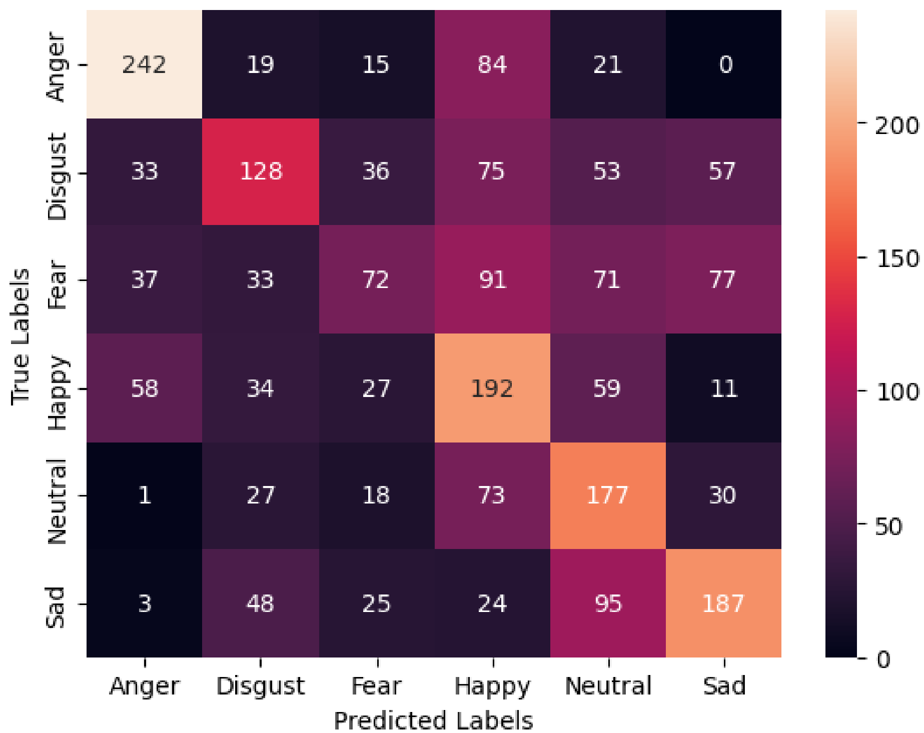
```
Epoch 25/50
39/39 [==============================] - 2s 58ms/step - loss: 1.3356 - accuracy: 0.4592 - val_loss: 1.2969 - val_accuracy: 0.4751
Epoch 26/50
39/39 [==============================] - 2s 47ms/step - loss: 1.3388 - accuracy: 0.4578 - val_loss: 1.2878 - val_accuracy: 0.4904
Epoch 27/50
39/39 [==============================] - 2s 48ms/step - loss: 1.3292 - accuracy: 0.4685 - val_loss: 1.2722 - val_accuracy: 0.4789
Epoch 28/50
39/39 [==============================] - 2s 50ms/step - loss: 1.3350 - accuracy: 0.4648 - val_loss: 1.2827 - val_accuracy: 0.4789
Epoch 29/50
39/39 [==============================] - 2s 48ms/step - loss: 1.3268 - accuracy: 0.4671 - val_loss: 1.2684 - val_accuracy: 0.4943
```

Evaluating Model

```
y_pred = model.predict((np.concatenate((test_mfcc, test_energy,test_zcr), axis=1)))
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 1s 6ms/step


Acurracy score = 0.44693237796686075


F1 score (macro average) = 0.4391544645220722


F1 score (weighted average) = 0.4391018836581617
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
```

```
#print(precisions)
#print(recalls)

class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])

k=1
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - FEA:
        F1-score = 0.2509       Precision = 0.3731      Recall = 0.1890
2 - DIS:
        F1-score = 0.3815       Precision = 0.4429      Recall = 0.3351
3 - HAP:
        F1-score = 0.4174       Precision = 0.3562      Recall = 0.5039
4 - NEU:
        F1-score = 0.4414       Precision = 0.3718      Recall = 0.5429
5 - SAD:
        F1-score = 0.5027       Precision = 0.5166      Recall = 0.4895
6 - ANG:
        F1-score = 0.6411       Precision = 0.6471      Recall = 0.6352
```

Model 2D - Mel Spectrogram

Building Model

We build our own model but we have noticed that the accuracy not so good as shown.

```
model = Sequential()
model.add(Conv2D(16, (7, 7), activation='relu', input_shape=(train_mel.shape[1], train_mel.shape[2], 1)))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(BatchNormalization())
model.add(Conv2D(24, (7, 7), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
```

```
model.add(BatchNormalization())
model.add(Conv2D(24, (7, 7), activation='relu'))
model.add(Flatten())
model.add(Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.00001)))
model.add(BatchNormalization())
model.add(Dropout(0.2))
model.add(Dense(6, activation='softmax'))

model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.00001),
             metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d_3 (Conv2D)           (None, 122, 151, 16)      800       
                                                                 
 max_pooling2d_2 (MaxPooling  (None, 61, 75, 16)       0         
 2D)                                                             
                                                                 
 batch_normalization_3 (Batc  (None, 61, 75, 16)       64        
 hNormalization)                                                 
                                                                 
 conv2d_4 (Conv2D)           (None, 55, 69, 24)        18840     
                                                                 
 max_pooling2d_3 (MaxPooling  (None, 27, 34, 24)       0         
 2D)                                                             
                                                                 
 batch_normalization_4 (Batc  (None, 27, 34, 24)       96        
 hNormalization)                                                 
                                                                 
 conv2d_5 (Conv2D)           (None, 21, 28, 24)        28248     
                                                                 
 flatten_1 (Flatten)         (None, 14112)             0         
                                                                 
 dense_2 (Dense)             (None, 64)                903232    
                                                                 
 batch_normalization_5 (Batc  (None, 64)               256       
 hNormalization)                                                 
                                                                 
 dropout_1 (Dropout)         (None, 64)                0         
                                                                 
 dense_3 (Dense)             (None, 6)                 390       
```

```
=================================================================
Total params: 951,926
Trainable params: 951,718
Non-trainable params: 208
_________________________________________________________________
```

```
history = model.fit(train_mel, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_data=(val_mel, y_val))
```

```
Epoch 1/10
39/39 [==============================] - 229s 6s/step - loss: 2.3071 - accuracy: 0.1964 - val_loss: 2.3234 - val_accuracy: 0.2031
Epoch 2/10
39/39 [==============================] - 222s 6s/step - loss: 1.9433 - accuracy: 0.2920 - val_loss: 2.2687 - val_accuracy: 0.2069
Epoch 3/10
39/39 [==============================] - 223s 6s/step - loss: 1.7613 - accuracy: 0.3472 - val_loss: 2.1264 - val_accuracy: 0.2222
Epoch 4/10
39/39 [==============================] - 223s 6s/step - loss: 1.6761 - accuracy: 0.3707 - val_loss: 1.9395 - val_accuracy: 0.2529
Epoch 5/10
39/39 [==============================] - 223s 6s/step - loss: 1.6030 - accuracy: 0.3941 - val_loss: 1.7752 - val_accuracy: 0.3103
Epoch 6/10
39/39 [==============================] - 221s 6s/step - loss: 1.5754 - accuracy: 0.3957 - val_loss: 1.6510 - val_accuracy: 0.3602
Epoch 7/10
39/39 [==============================] - 226s 6s/step - loss: 1.5214 - accuracy: 0.4194 - val_loss: 1.6229 - val_accuracy: 0.3870
Epoch 8/10
39/39 [==============================] - 222s 6s/step - loss: 1.4913 - accuracy: 0.4321 - val_loss: 1.5827 - val_accuracy: 0.4100
Epoch 9/10
39/39 [==============================] - 224s 6s/step - loss: 1.4522 - accuracy: 0.4440 - val_loss: 1.5170 - val_accuracy: 0.3946
Epoch 10/10
39/39 [==============================] - 222s 6s/step - loss: 1.4486 - accuracy: 0.4444 - val_loss: 1.5055 - val_accuracy: 0.4100
```

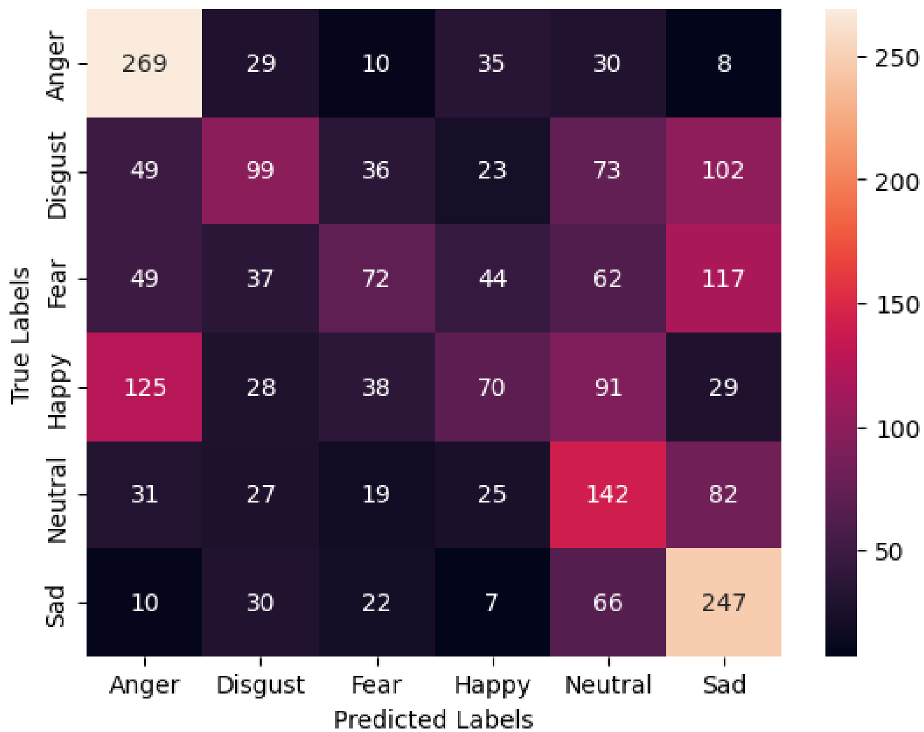
Evaluating Model

```
y_pred = model.predict(test_mel)
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

```
70/70 [==============================] - 26s 365ms/step
```

```
Acurracy score = 0.4025974025974026

F1 score (macro average) = 0.37678596107610596

F1 score (weighted average) = 0.3772434861554859
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```



```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
#print(precisions)
#print(recalls)

class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])

k=1
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - FEA:
        F1-score = 0.2665       Precision = 0.2934      Recall = 0.2441
2 - DIS:
        F1-score = 0.2778       Precision = 0.3696      Recall = 0.2225
3 - NEU:
        F1-score = 0.3156       Precision = 0.4150      Recall = 0.2546
4 - HAP:
        F1-score = 0.3703       Precision = 0.3679      Recall = 0.3727
5 - SAD:
```

```
        F1-score = 0.4513       Precision = 0.4422      Recall = 0.4607
6 - ANG:
        F1-score = 0.5485       Precision = 0.4231      Recall = 0.7795
```

Model 2D - Research Paper

This model is replicated from a model in this research paper with some modifications and it gives higher accuracy and less confusing classes.

Emotion Recognition in Audio and Video Using Deep Neural Networks

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Building Model

This was the CNN model architecture used in the original research paper, we have replicated it here. However, since the research paper was used on a different dataset, we have modified the input and output layers accordingly.

CNN

INPUT	200x300
CONV 1	16 filters of 12x16
ReLU	
MaxPool2D	Size 2 with Stride 2
CONV 2	24 filters of 8x12
ReLU	
MaxPool2D	Size 2 with Stride 2
CONV 3	24 filters of 5x7
ReLU	
MaxPool2D	Size 2 with Stride 2
Flatten	
Linear	64
ReLU	
Dropout	0.2
Linear	4

```
model = Sequential()
model.add(Conv2D(16, (12, 6), activation='relu', input_shape=(train_mel.shape[1], train_mel.shape[2], 1)))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Conv2D(24, (8, 12), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Conv2D(24, (5, 7), activation='relu'))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(6, activation='softmax'))

model.compile(loss='categorical_crossentropy',
             optimizer=optimizers.Adam(learning_rate=0.001),
             metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_18"
_________________________________________________________________
```

```
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_21 (Conv2D)          (None, 117, 152, 16)      1168

 max_pooling2d_16 (MaxPoolin  (None, 58, 76, 16)       0
 g2D)

 conv2d_22 (Conv2D)          (None, 51, 65, 24)        36888

 max_pooling2d_17 (MaxPoolin  (None, 25, 32, 24)       0
 g2D)

 conv2d_23 (Conv2D)          (None, 21, 26, 24)        20184

 flatten_18 (Flatten)        (None, 13104)             0

 dense_36 (Dense)            (None, 64)                838720

 dropout_18 (Dropout)        (None, 64)                0

 dense_37 (Dense)            (None, 6)                 390

=================================================================
Total params: 897,350
Trainable params: 897,350
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(train_mel, y_train,
                    epochs=10,
                    batch_size=128,
                    validation_data=(val_mel, y_val))
```

```
Epoch 1/10
39/39 [==============================] - 155s 4s/step - loss: 3.2869 - accuracy: 0.1776 - val_loss: 1.7848 - val_accuracy: 0.2184
Epoch 2/10
39/39 [==============================] - 154s 4s/step - loss: 1.7462 - accuracy: 0.2478 - val_loss: 1.5522 - val_accuracy: 0.3333
Epoch 3/10
39/39 [==============================] - 154s 4s/step - loss: 1.5277 - accuracy: 0.3832 - val_loss: 1.3663 - val_accuracy: 0.4483
Epoch 4/10
39/39 [==============================] - 154s 4s/step - loss: 1.3874 - accuracy: 0.4464 - val_loss: 1.3026 - val_accuracy: 0.4598
Epoch 5/10
39/39 [==============================] - 153s 4s/step - loss: 1.3019 - accuracy: 0.4893 - val_loss: 1.3870 - val_accuracy: 0.4521
Epoch 6/10
39/39 [==============================] - 154s 4s/step - loss: 1.2287 - accuracy: 0.5253 - val_loss: 1.2957 - val_accuracy: 0.4444
Epoch 7/10
39/39 [==============================] - 156s 4s/step - loss: 1.1668 - accuracy: 0.5451 - val_loss: 1.2497 - val_accuracy: 0.4713
```

```
Epoch 8/10
39/39 [==============================] - 154s 4s/step - loss: 1.0673 - accuracy: 0.5835 - val_loss: 1.2772 - val_accuracy: 0.4789
Epoch 9/10
39/39 [==============================] - 153s 4s/step - loss: 0.9423 - accuracy: 0.6372 - val_loss: 1.3159 - val_accuracy: 0.4751
Epoch 10/10
39/39 [==============================] - 155s 4s/step - loss: 0.8536 - accuracy: 0.6688 - val_loss: 1.3401 - val_accuracy: 0.5096
```

Evaluating Model

```
y_pred = model.predict(test_mel)
print("\n")
print("Acurracy score =",accuracy_score(y_test.argmax(axis=1),y_pred.argmax(axis=1)))
print("\n")
print("F1 score (macro average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'macro'))
print("\n")
print("F1 score (weighted average) =",f1_score(y_test.argmax(axis=1),y_pred.argmax(axis=1),average = 'weighted'))
```

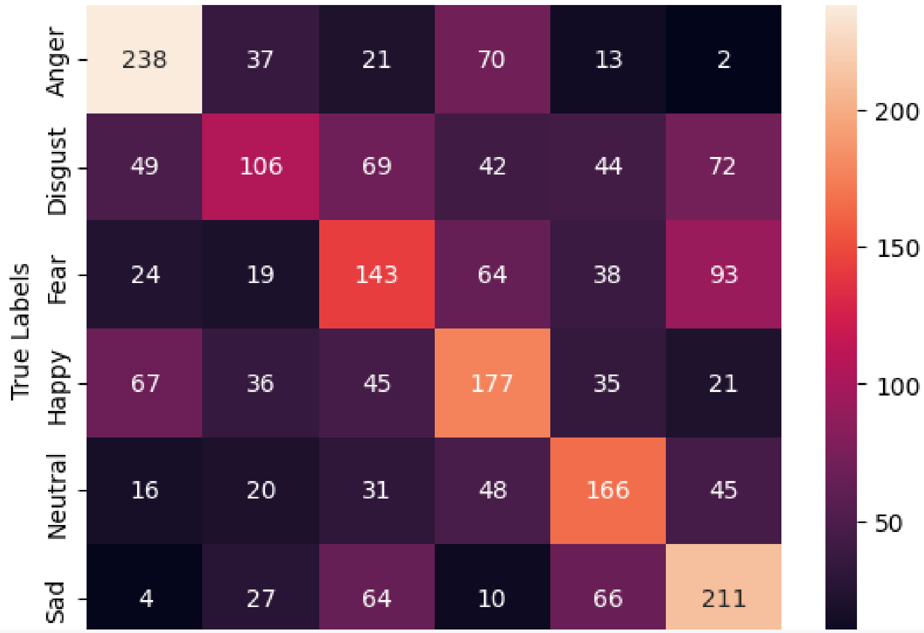
```
70/70 [==============================] - 15s 208ms/step


Acurracy score = 0.46618898343036275


F1 score (macro average) = 0.4614819803410712


F1 score (weighted average) = 0.46092974621199106
```

```
con_mat = confusion_matrix(y_test.argmax(axis=1),y_pred.argmax(axis=1))
#unique_labels = np.unique(labels)
#print(unique_labels)
ax = sns.heatmap(con_mat, annot=True, fmt="d",
                 xticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'],
                 yticklabels = ['Anger', 'Disgust', 'Fear', 'Happy', 'Neutral', 'Sad'])
#ax = sns.heatmap(con_mat, annot=True, fmt="d", xticklabels=unique_labels, yticklabels=unique_labels)
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```




```
class_labels = list(np.unique(labels))
#print(class_labels)

precisions = []
recalls = []
f1_scores = []

for i in range(len(class_labels)):
    TP = con_mat[i, i]
    FP = np.sum(con_mat[:, i]) - TP
    FN = np.sum(con_mat[i, :]) - TP

    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    f1 = 2 * (precision * recall) / (precision + recall)

    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)

#print(f1_scores)
#print(precisions)
#print(recalls)
```

```
class_idxs = list(range(len(class_labels)))
sorted_classes = sorted(class_idxs, key=lambda x: f1_scores[x])

k=1
print("Most Confusing Classes:\n")
for j in sorted_classes:
    label = class_labels[j]
    print(f"{k} - {label}:\n\tF1-score = {f1_scores[j]:.4f}\tPrecision = {precisions[j]:.4f}\tRecall = {recalls[j]:.4f} ")
    k+=1
```

```
Most Confusing Classes:

1 - DIS:
        F1-score = 0.3381       Precision = 0.4327      Recall = 0.2775
2 - FEA:
        F1-score = 0.3793       Precision = 0.3834      Recall = 0.3753
3 - HAP:
        F1-score = 0.4470       Precision = 0.4307      Recall = 0.4646
4 - NEU:
        F1-score = 0.4826       Precision = 0.4586      Recall = 0.5092
5 - SAD:
        F1-score = 0.5109       Precision = 0.4752      Recall = 0.5524
6 - ANG:
        F1-score = 0.6110       Precision = 0.5980      Recall = 0.6247
```

These were the results obtained in the original paper, note that the datasets used were different, so labels and accuracies will also be slightly different

Architecture	Accuracy(%)	Data Aug.	Emotion
CNN	52.23	No	H,S,A,N
CNN	51.90	Yes	H,S,A,N