ser

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#### 0.1 Problem Statement

Speech is the most natural way of expressing ourselves as humans. It is only natural then to extend this communication medium to computer applications. We define speech emotion recognition (SER) systems as a collection of methodologies that process and classify speech signals to detect the embedded emotions. SER is not a new field, it has been around for over two decades, and has regained attention thanks to the recent advancements. We have built different models with different features extracted from audios to try to detect the embedded emotions in each audio. We used the CREMA dataset in this model which can be found here.

### 0.2 Imports

```
[880]: import numpy as np
      import pandas as pd
      import matplotlib.pyplot as plt
      import os
      import seaborn as sns
      import random
      import IPython.display
      import librosa
      from sklearn.model_selection import train_test_split
      from sklearn.preprocessing import LabelEncoder, StandardScaler
      import tensorflow as tf
      import tensorflow.keras.layers as L
      from tensorflow.keras.optimizers import Adam
      from tensorflow.keras.regularizers import 12
      from tensorflow.keras.regularizers import 11_12
      from tensorflow.python.keras.callbacks import EarlyStopping, ReduceLROnPlateau
      from tensorflow.python.keras import backend as K
      from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
      from tensorflow.keras.models import Sequential
      from tensorflow.keras.layers import Conv1D, MaxPooling1D, LSTM, Dense, Dropout
```

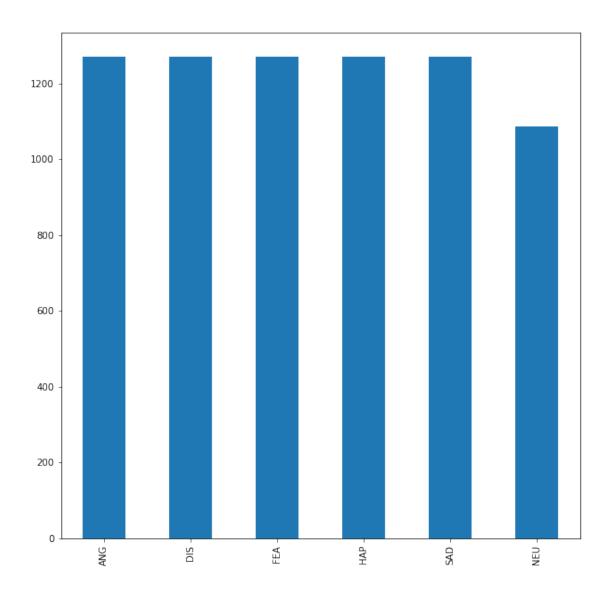
```
[878]: config = tf.compat.v1.ConfigProto( device_count = {'GPU': 1 , 'CPU': 6} )
sess = tf.compat.v1.Session(config=config)
K.set_session(sess)
```

### 0.3 Download the Dataset and Understand the Format (10 points)

We start by loading each audio as a normalized numpy array using librosa's load function. We set the duration to 2.5 seconds, and the offset to 0.3. So, 2.5 seconds will be retained from each audio, starting at 0.3 seconds. This is important to ensure that all audios have the same feature space dimensions. However, we can still skip this and retain the whole audio, then pad the feature spaces later on (We have implemented this as well).

```
[881]: audios = []
       labels = []
       audio_files = os.listdir('Crema')
       for file in audio files:
           labels.append(file.split('_')[2])
           # fs, data = wavfile.read(os.path.join('Crema', file))
           data, fs = librosa.load(os.path.join('Crema',file),sr=None,duration=2.
        5,offset=0.3)
           audios.append([data,fs])
[882]: aud = []
       for audio,fs in audios:
           audio = librosa.util.fix_length(audio, size=35000)
           aud.append([audio,fs])
       audios=aud
[883]: print(len(labels))
       print(len(audios))
      7442
      7442
      audios[1000][0].shape
[884]:
[884]: (35000,)
[885]:
      set(labels)
[885]: {'ANG', 'DIS', 'FEA', 'HAP', 'NEU', 'SAD'}
[886]: fs_list = [x for _,x in audios]
       set(fs_list) # all files have a sample rate of 16kHz
[886]: {16000}
```

```
[887]: df = pd.concat([pd.Series(audios,name='data'),pd.
        ⇔Series(labels,name='label')],axis=1)
       df['label'].value_counts().plot(kind='bar',figsize=(10,10))
[887]:
                                                            data label
             [[0.0006713867, 0.0006713867, 0.00048828125, 0...
       0
                                                                 ANG
       1
             [[0.008575439, 0.008636475, 0.009094238, 0.009...
                                                                 DIS
       2
             [[3.0517578e-05, -0.000579834, -0.0010070801, ...
                                                                 FEA
       3
             [[0.004699707, 0.0038452148, 0.0040283203, 0.0...
                                                                 HAP
             [[0.0045776367, 0.0049438477, 0.0043029785, 0...
       4
                                                                NEU
             [[0.0020751953, 0.0020446777, 0.002166748, 0.0...
       7437
                                                                 DIS
             [[-0.004119873, -0.0042419434, -0.004272461, -...
       7438
                                                                 FEA
       7439
             [[-0.0035705566, -0.0033569336, -0.0028381348,...
                                                                 HAP
       7440 [[-0.00894165, -0.008422852, -0.008148193, -0...
                                                                NEU
       7441
             [[-0.0051879883, -0.0052490234, -0.0053100586,...
                                                                 SAD
```



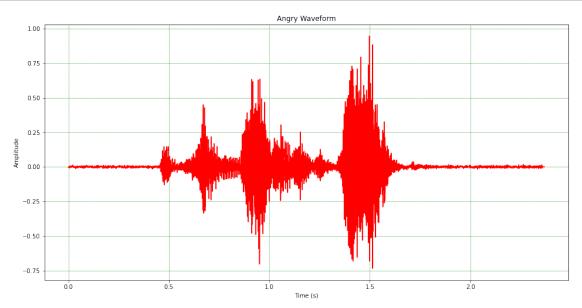
## 0.4 Exploring the Dataset

We implement a load\_audio() function that plots and outputs a random audio of the desired emotion. We also plot the spectrogram of that audio using create\_spectrogram().

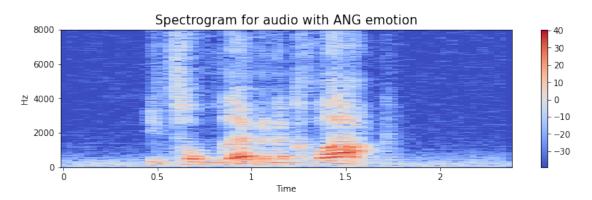
```
[900]: def load_audio(audioss,emotion):
           # audios = list(df[df['label'] == emotion]['data'])
           audios = []
           for a in audioss:
               if a['label'] == emotion:
                   audios.append(a)
           idx = random.randint(0,len(audios)-1) # choosing a random file of that
        \hookrightarrow emotion
           # audio = audios[idx][0]
           audio = audios[idx]['audio']
           # fs = audios[idx][1]
           fs = audios[idx]['sr']
           duration = len(audio)/fs
           time = np.arange(0,duration,1/fs) # time vector
           plt.figure(figsize=(16,8))
           plt.plot(time,audio,color=colors[emotion])
           plt.xlabel('Time (s)')
           plt.ylabel('Amplitude')
           plt.title(emotions[emotion] + ' Waveform')
           plt.grid(color = 'green', linestyle = '--', linewidth = 0.5)
           plt.show()
           return audio, fs
[896]: audioss[0]['label']
[896]: 'ANG'
[901]: def create_spectrogram(data, fs, emotion):
           # stft function converts the data into short term fourier transform
           X = librosa.stft(data)
           Xdb = librosa.amplitude_to_db(abs(X))
           plt.figure(figsize=(12, 3))
           plt.title('Spectrogram for audio with {} emotion'.format(emotion), size=15)
           librosa.display.specshow(Xdb, sr=fs, x_axis='time', y_axis='hz')
           plt.colorbar()
```

## 0.4.1 Angry Emotion

```
[902]: # ANGRY
audio,fs = load_audio(audioss,'ANG')
create_spectrogram(audio,fs,'ANG')
IPython.display.Audio(audio,rate=fs)
```



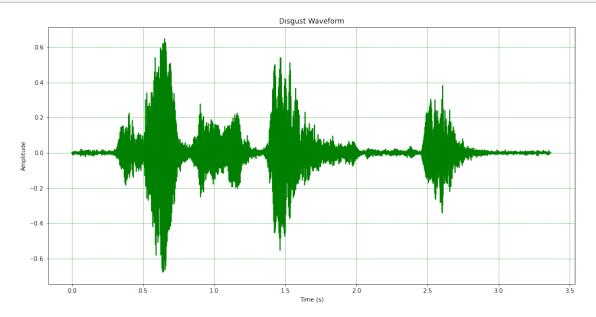
[902]: <IPython.lib.display.Audio object>



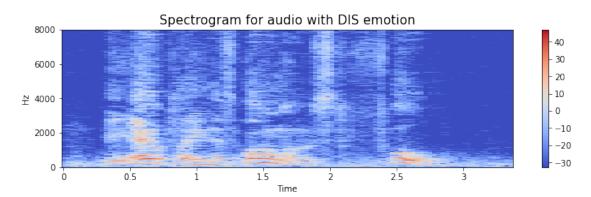
## 0.4.2 Disgusted Emotion

```
[903]: # DISGUSTED
audio,fs = load_audio(audioss,'DIS')
create_spectrogram(audio,fs,'DIS')
```

## IPython.display.Audio(audio,rate=fs)

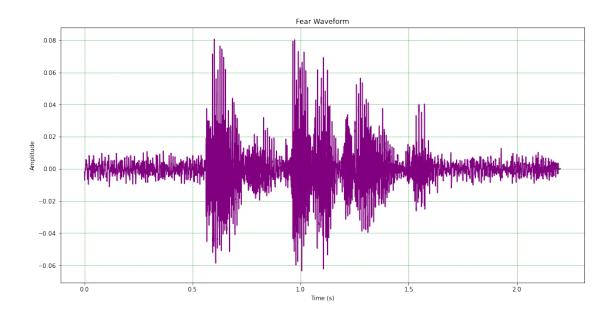


[903]: <IPython.lib.display.Audio object>

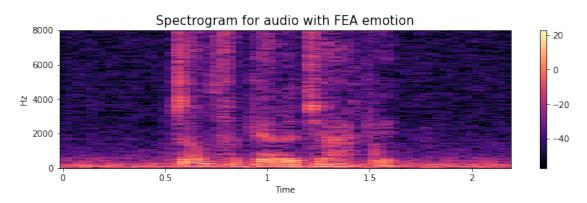


### 0.4.3 Fear Emotion

```
[904]: # FEAR
audio,fs = load_audio(audioss,'FEA')
create_spectrogram(audio,fs,'FEA')
IPython.display.Audio(audio,rate=fs)
```

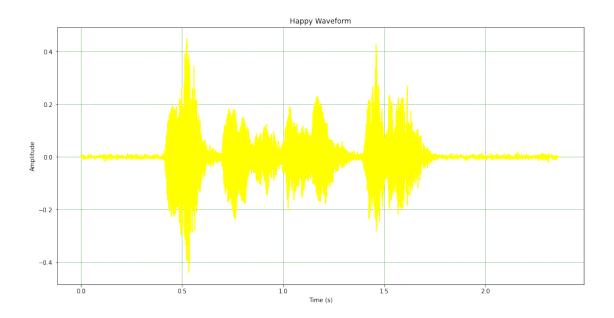


# [904]: <IPython.lib.display.Audio object>

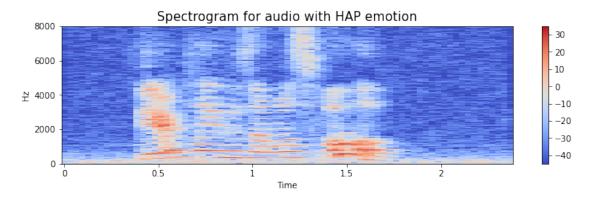


# 0.4.4 Happy Emotion

```
[906]: # HAPPY
audio,fs = load_audio(audioss,'HAP')
create_spectrogram(audio,fs,'HAP')
IPython.display.Audio(audio,rate=fs)
```

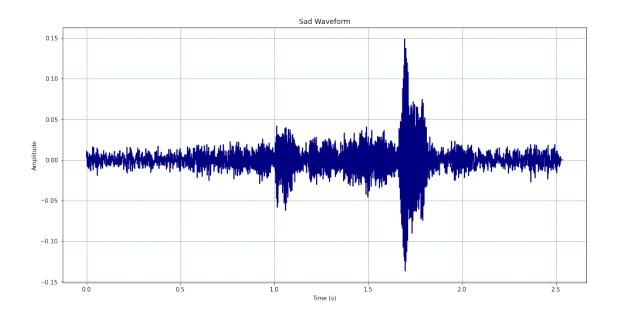


[906]: <IPython.lib.display.Audio object>

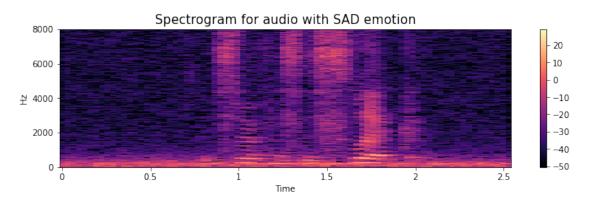


## 0.4.5 Sad Emotion

```
[907]: # SAD
audio,fs = load_audio(audioss,'SAD')
create_spectrogram(audio,fs,'SAD')
IPython.display.Audio(audio,rate=fs)
```

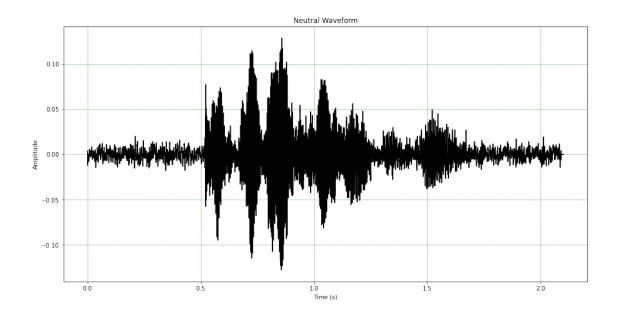


# [907]: <IPython.lib.display.Audio object>

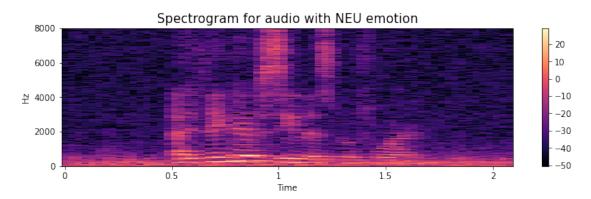


# 0.4.6 Neutral Emotion

```
[908]: # NEUTRAL
audio,fs = load_audio(audioss,'NEU')
create_spectrogram(audio,fs,'NEU')
IPython.display.Audio(audio,rate=fs)
```



[908]: <IPython.lib.display.Audio object>



#### 0.5 Splitting the Dataset into Train, Test and Validation

We split the data into 70% train and validation, and 30% test. Then, we further split the train and validation set into 95% train and 5% validation. We proceed by encoding the labels using sklearn's LabelEncoder().

```
[909]: X_trainval, X_test, y_trainval, y_test = train_test_split(df['data'].

_to_numpy(), np.array(labels), test_size=0.3, random_state=42,stratify=labels)

X_train, X_val, y_train, y_val = train_test_split(X_trainval, y_trainval,__

_test_size=0.05, random_state=42,stratify=y_trainval)
```

```
[910]: le = LabelEncoder()
    y_train = le.fit_transform(y_train)
    y_test = le.transform(y_test)
    y_val = le.transform(y_val)
```

#### 0.6 Create the Feature Space (30 Points)

We experimented with many feature combinations and tried multiple dimensionality reduction techniques (i.e PCA, LDA) to try to capture trends and temporal patterns in speech emotion changes. We created two feature spaces, a 1-dimensional feature space, and a 2-dimensional one. Here are some features we tried:

- 1. Zero Crossing Rate: The rate of sign-changes of the signal during the duration of a particular frame.
- 2. Energy: The sum of squares of the signal values, normalized by the respective frame length.
- 3. Spectral Rolloff : The frequency below which 90% of the magnitude distribution of the spectrum is concentrated.
- 4. MFCCs: Mel Frequency Cepstral Coefficients form a cepstral representation where the frequency bands are not linear but distributed according to the mel-scale.
- 5. Delta MFCC: In addition to the MFCC features, these features capture the changes in the MFCC coefficients over time, providing more information about the speech signal dynamics.

- 6. Chroma Features: Chroma features such as chroma energy and chroma deviation can provide useful information related to the pitch content or musicality of speech, which may be relevant for certain emotional states or variations in speech patterns.
- 7. Pitch mean, standard deviation, and range.

After many experimentations, we were able to yield the best results using ZCR, ENERGY, MFCCS, and SPECTRAL ROLLOFF with no dimensionality reduction. (1-dimensional feature space)

The 2-dimensional feature space consisted of the mel spectrogram of each audio with n\_mels=128.

Note: We tried using zcr, energy, and specral rolloff as arrays and as mean values. Mean values provide a global summary of the feature, while using an array of values captures the temporal dynamics. We settled on incorporating them as arrays.

```
[]: # OBSOLETE. LEFT FOR REFERENCE.
     def create_feature_space(X,y=None,mel_spectrogram=False,training = False,_
      -max_len_zcr=None,max_len_en=None,max_len_mfccs=None,max_len_mel=None,clf=None,mean=None,std
         # labels = \Gamma7
         if not mel_spectrogram: # time/freq domain feature space
             feature_space = []
             zcrs=[]
             energies=[]
             mfccs=[]
             rolloff=[]
             # lfccs = []
             # transform = transforms.LFCC(
             # speckwargs={"n_fft": 400, "hop_length": 512, "center": False})
             for i,data in enumerate(X):
                 # audio = np.array(data[0][0],dtype='float')
                 audio = data[0]
                 fs = data[1]
                 # zero_crosses = np.nonzero(np.diff(audio > 0))[0]
                 # zcr = zero crosses.size/len(audio) # zero crossing rate
                 # zero crossing rate
                 # zcr=np.squeeze(librosa.feature.
      ⇒zero_crossing_rate(audio, frame_length=2048,hop_length=512))
                 zcr=np.mean(librosa.feature.
      -zero_crossing_rate(audio,frame_length=2048,hop_length=512).T,axis=0)
                 # print(zcr.shape)
                 zcrs.append(zcr)
                 # normalized energy
```

```
# energy=np.squeeze(librosa.feature.
⇔rms(y=audio, frame_length=2048, hop_length=512))
           # energy = np.array([sum(audio[j:j+2048]**2)/2048 \text{ for } j \text{ in } range(0, j)
\hookrightarrow len(audio), 512)])
           # print(energy.shape)
           energy=np.mean(librosa.feature.
→rms(y=audio,frame_length=2048,hop_length=512).T,axis=0)
           energies.append(energy)
           # mel frequency cepstral coefficient (MFCC)
           mfcc=np.ravel(librosa.feature.mfcc(y=audio,sr=fs).T)
           # print(mfcc.shape)
           mfccs.append(mfcc)
           roll = np.squeeze(librosa.feature.spectral_rolloff(y=audio,__
⇔sr=fs,hop_length=512))
           rolloff.append(roll)
           # lfcc = transform(tf.convert_to_tensor(audio)[0])
           # lfccs.append(lfcc.numpy())
           # feature space.append(np.concatenate((zcr,energy,mfcc), axis=None))
           # labels.append(data[1])
           if i%1000==0:
               print(f'audio #{i} checkpoint')
       # max_len = max([len(i) for i in zcrs]) # find the longest list of scr_
→to pad the others until they have equal length
       # if not training:
           zcrs, = pad(zcrs, max len=max len zcr)
             energies,_ = pad(energies, max_len=max_len_en)
            mfccs,_ = pad(mfccs,max_len=max_len_mfccs)
       # else:
           zcrs, max len z = pad(zcrs)
            energies, max_len_e = pad(energies)
       #
           mfccs, max\_len\_m = pad(mfccs)
       # lfccs = pad(lfccs)
      for i in range(X.shape[0]):
           # feature_space.append(np.
→concatenate((zcrs[i],energies[i],mfccs[i],lfccs[i]), axis=None))
           feature_space.append(np.
concatenate((zcrs[i],energies[i],mfccs[i],rolloff[i]), axis=None))
```

```
# labels = np.array(labels)
       feature_space = np.array(feature_space)
       # if training:
           # clf = LinearDiscriminantAnalysis(n_components=5).
⇔fit(feature_space,y)
           # feature space=clf.transform(feature space)
           # return feature_space, max_len_z, max_len_e, max_len_m, clf
           # return feature_space,clf
       # else:
           # feature_space=clf.transform(feature_space)
      return feature_space
  else:
      mels=[]
       for i,data in enumerate(X):
           audio = data[0]
           fs = data[1]
           mel = librosa.feature.melspectrogram(y=audio, sr=fs,_
\rightarrown_fft=2048,n_mels=128).T
           # mel = librosa.feature.melspectrogram(y=audio, sr=fs, | 
\rightarrow n_fft=1024, n_mels=128)
           # mel_db = librosa.power_to_db(mel, ref=np.max)
           mels.append(mel)
           # labels.append(data[1])
           if i%1000==0:
               print(f'audio #{i} checkpoint')
      mels=np.array(mels)
       # if training:
           # mels, max_len_mels = pad(mels, mel_spectrogram=True)
           # mean value = np.mean(mels,axis=0)
           # std_value = np.std(mels,axis=0)
           # norm_mels = (mels - mean_value) / std_value
           # return norm_mels, max_len_mels, mean_value, std_value
           # return norm_mels, mean_value, std_value
       # else:
           # mels,_ = pad(mels,mel_spectrogram=True,max_len=max_len_mel)
           # norm_mels = (mels - mean) / stddev
      return mels
```

```
result = np.hstack((result,zcr))
       # rms = np.mean(librosa.feature.
\rightarrow rms(y=audio, frame\_length=2048, hop\_length=512).T, axis=0)
       rms = np.squeeze(librosa.feature.

y=audio,frame_length=2048,hop_length=512))

       result = np.hstack((result, rms))
       # rolloff = np.mean(librosa.feature.spectral_rolloff(y=audio, ___)
\hookrightarrow sr = 16000, n \ fft = 2048, hop \ length = 512).T, axis = 0
       rolloff = np.squeeze(librosa.feature.spectral_rolloff(y=audio,_
⇒sr=16000,n_fft=2048,hop_length=512))
       result = np.hstack((result, rolloff))
       # stft = np.abs(librosa.stft(audio))
       \# chroma_stft = np.mean(librosa.feature.chroma_stft(S=stft, sr=16000).
\hookrightarrow T, axis=0)
       # result = np.hstack((result, chroma_stft))
       \# mfcc = np.mean(librosa.feature.mfcc(y=audio, sr=16000).T, axis=0)
       mfcc = np.ravel(librosa.feature.mfcc(y=audio, sr=16000).T)
       result = np.hstack((result, mfcc))
       # delta_mfcc = np.mean(librosa.feature.delta(mfcc).T,axis=0)
       # result = np.hstack((result, delta mfcc))
       # delta2_mfcc = np.mean(librosa.feature.delta(mfcc, order=2).T,axis=0)
       # result = np.hstack((result, delta2_mfcc))
       # Extract chroma features
       \# chroma = librosa.feature.chroma_stft(y=audio, sr=16000)
       # chroma_energy = np.mean(chroma, axis=1)
       # # chroma_deviation = np.std(chroma, axis=1)
       # result = np.hstack((result, chroma_energy))
       # result = np.hstack((result, chroma_deviation))
       # pitch, magnitudes = librosa.core.piptrack(y=audio, sr=16000)
       # pitch_mean = np.mean(pitch, axis=0)
       # pitch_std = np.std(pitch, axis=0)
       # pitch_range = np.max(pitch, axis=0) - np.min(pitch, axis=0)
       # result = np.hstack((result, pitch_mean))
       # result = np.hstack((result, pitch_std))
       # result = np.hstack((result, pitch_range))
       return result
```

```
else:
               mel = librosa.feature.melspectrogram(y=audio, sr=16000, n_fft=2048)
               return mel
[912]: X_trainn = np.array(np.array([x for x, in X_train]))
       X_testt = np.array(np.array([x for x,_ in X_test]))
       X_vall = np.array(np.array([x for x,_ in X_val]))
 []: sc=StandardScaler()
       X_trainn=sc.fit_transform(X_trainn)
       X_testt=sc.transform(X_testt)
       X vall=sc.transform(X vall)
 []: # Apply data augmentation techniques (example: random cropping)
       def random_crop(mel_spectrogram, crop_size):
          h, w = mel_spectrogram.shape
          max_x = h - crop_size
          max_y = w - crop_size
          x = np.random.randint(0, max_x)
          y = np.random.randint(0, max y)
           cropped = mel_spectrogram[x:x+crop_size, y:y+crop_size]
          return cropped
 []: features_train = []
       features_test = []
       features_val = []
       for i in range(X_trainn.shape[0]):
          features train.append(extract features(X trainn[i]))
       for i in range(X_testt.shape[0]):
          features_test.append(extract_features(X_testt[i]))
       for i in range(X_vall.shape[0]):
          features val.append(extract features(X vall[i]))
 []: features_train = np.array(features_train)
       features_test = np.array(features_test)
       features_val = np.array(features_val)
 []: X_trainn = np.array(np.array([x for x, in X_train]))
       X_testt = np.array(np.array([x for x, in X_test]))
       X_vall = np.array(np.array([x for x,_ in X_val]))
[932]: mels_train = []
      mels_test=[]
       mels_val=[]
       for i in range(X_trainn.shape[0]):
```

```
mels_train.append(extract_features(X_trainn[i],mel_spectrogram=True))
      for i in range(X_testt.shape[0]):
          mels_test.append(extract_features(X_testt[i],mel_spectrogram=True))
      for i in range(X_vall.shape[0]):
          mels_val.append(extract_features(X_vall[i],mel_spectrogram=True))
[933]: mels_train=np.array(mels_train)
      mels_test = np.array(mels_test)
      mels_val=np.array(mels_val)
[935]: mels_train = np.expand_dims(mels_train,axis=3)
      mels_test = np.expand_dims(mels_test,axis=3)
      mels_val = np.expand_dims(mels_val,axis=3)
[936]: mels_train.shape
[936]: (4948, 128, 69, 1)
 []: | # lda = LinearDiscriminantAnalysis(n_components=5).fit(features_train,y_train)
       # features_trainn = lda.transform(features_train)
       # features_testt = lda.transform(features_test)
       # features_vall = lda.transform(features_val)
      from sklearn.decomposition import PCA
      pca = PCA(n_components=50)
      features_trainn = pca.fit_transform(X_trainn)
      features_testt = pca.transform(X_testt)
      features_vall = pca.transform(X_vall)
```

### 0.7 Building the Model (40 points)

We tried two different models for the 1-dimensional feature space. The major difference was that one of the models had LSTM layers while the other did not. Also, the model with no LSTM layers was much deeper, with 5,554,310 trainable parameters in contrast to just 189,190 trainable parameters. Obviously, The model with LSTM layers was much faster, and actually yielded better results. We were able to reach a test accuracy of 52.53% using that model. The other model yielded a test accuracy of 50.8%

```
L.BatchNormalization(),
   L.MaxPool1D(pool_size=5,strides=2,padding='same'),
   L.Conv1D(256,kernel_size=5,strides=1,padding='same',activation='relu'),
   L.BatchNormalization(),
   L.MaxPool1D(pool_size=5,strides=2,padding='same'),
   L.Conv1D(256,kernel_size=3,strides=1,padding='same',activation='relu'),
   L.BatchNormalization(),
   L.MaxPool1D(pool_size=5,strides=2,padding='same'),
   L.Dropout(0.3),
   L.Conv1D(128,kernel_size=3,strides=1,padding='same',activation='relu'),
   L.BatchNormalization(),
   L.MaxPool1D(pool_size=3,strides=2,padding='same'),
   L.Flatten(),
   L.Dense(512,activation='relu'),
   L.BatchNormalization(),
   L.Dense(6,activation='softmax')
])
opt = tf.keras.optimizers.Adam(learning_rate=0.0001)
model.compile(loss='sparse_categorical_crossentropy', optimizer=opt_
→,metrics=['acc'])
model.summary()
```

Model: "sequential\_122"

Layer (type)	1 1	Param #
conv1d_386 (Conv1D)		3072
<pre>batch_normalization_446 (Ba tchNormalization)</pre>	(None, 1587, 512)	2048
<pre>max_pooling1d_377 (MaxPooli ng1D)</pre>	(None, 794, 512)	0
conv1d_387 (Conv1D)	(None, 794, 512)	1311232
<pre>batch_normalization_447 (Ba tchNormalization)</pre>	(None, 794, 512)	2048
<pre>max_pooling1d_378 (MaxPooli ng1D)</pre>	(None, 397, 512)	0
conv1d_388 (Conv1D)	(None, 397, 256)	655616
<pre>batch_normalization_448 (Ba tchNormalization)</pre>	(None, 397, 256)	1024

```
max_pooling1d_379 (MaxPooli (None, 199, 256)
     ng1D)
     conv1d_389 (Conv1D)
                                (None, 199, 256)
                                                         196864
     batch_normalization_449 (Ba (None, 199, 256)
                                                         1024
     tchNormalization)
     max_pooling1d_380 (MaxPooli (None, 100, 256)
     ng1D)
     dropout_65 (Dropout)
                                (None, 100, 256)
                                                         0
     conv1d_390 (Conv1D)
                                (None, 100, 128)
                                                         98432
     batch_normalization_450 (Ba (None, 100, 128)
                                                         512
     tchNormalization)
     max_pooling1d_381 (MaxPooli (None, 50, 128)
                                                         0
     ng1D)
                                (None, 6400)
     flatten_52 (Flatten)
     dense_243 (Dense)
                                (None, 512)
                                                         3277312
                                                         2048
     batch_normalization_451 (Ba (None, 512)
     tchNormalization)
     dense 244 (Dense)
                                (None, 6)
                                                         3078
    ______
    Total params: 5,554,310
    Trainable params: 5,549,958
    Non-trainable params: 4,352
[]: # Define the model architecture
    modelopt = Sequential()
    modelopt.add(Conv1D(filters=32, kernel_size=5, activation='relu', __
     →input_shape=(features_train.shape[1], 1)))
    modelopt.add(MaxPooling1D(pool_size=2,padding='same'))
    # modelopt.add(BatchNormalization())
    modelopt.add(Conv1D(filters=64, kernel size=3, activation='relu'))
    modelopt.add(MaxPooling1D(pool_size=2,padding='same'))
```

modelopt.add(Conv1D(filters=256, kernel\_size=3, activation='relu'))

modelopt.add(MaxPooling1D(pool\_size=2,padding='same'))

# modelopt.add(BatchNormalization())

Model: "sequential\_123"

Layer (type)	Output Shape	Param #
conv1d_391 (Conv1D)	(None, 1583, 32)	192
<pre>max_pooling1d_382 (MaxPooli ng1D)</pre>	(None, 792, 32)	0
conv1d_392 (Conv1D)	(None, 790, 64)	6208
<pre>max_pooling1d_383 (MaxPooli ng1D)</pre>	(None, 395, 64)	0
conv1d_393 (Conv1D)	(None, 393, 256)	49408
<pre>max_pooling1d_384 (MaxPooli ng1D)</pre>	(None, 197, 256)	0
lstm_88 (LSTM)	(None, 197, 64)	82176
lstm_89 (LSTM)	(None, 64)	33024
dense_245 (Dense)	(None, 256)	16640
dense_246 (Dense)	(None, 6)	1542

Total params: 189,190 Trainable params: 189,190 Non-trainable params: 0

```
[]: histopt = modelopt.fit(features_train, y_train, batch_size=128, epochs=100,__
   →verbose=1, validation_data=(features_val, y_val),
   →callbacks=[early_stop,lr_reduction])
  Epoch 1/100
  0.2439 - val_loss: 1.7191 - val_acc: 0.2759 - lr: 1.0000e-04
  Epoch 2/100
  0.3193 - val_loss: 1.5996 - val_acc: 0.3257 - lr: 1.0000e-04
  Epoch 3/100
  0.3660 - val_loss: 1.5106 - val_acc: 0.4023 - lr: 1.0000e-04
  Epoch 4/100
  0.4072 - val_loss: 1.4872 - val_acc: 0.3831 - lr: 1.0000e-04
  Epoch 5/100
  0.4119 - val_loss: 1.4562 - val_acc: 0.3985 - lr: 1.0000e-04
  Epoch 6/100
  0.4214 - val_loss: 1.4534 - val_acc: 0.4061 - lr: 1.0000e-04
  Epoch 7/100
  0.4240 - val_loss: 1.4236 - val_acc: 0.4215 - lr: 1.0000e-04
  Epoch 8/100
  39/39 [============ - - 73s 2s/step - loss: 1.4265 - acc:
  0.4325 - val_loss: 1.4411 - val_acc: 0.4176 - lr: 1.0000e-04
  Epoch 9/100
  0.4382 - val_loss: 1.4458 - val_acc: 0.4368 - lr: 1.0000e-04
  Epoch 10/100
  0.4250 - val_loss: 1.4170 - val_acc: 0.4406 - lr: 1.0000e-04
  Epoch 11/100
  0.4422 - val_loss: 1.3979 - val_acc: 0.4444 - lr: 1.0000e-04
  Epoch 12/100
  0.4523 - val_loss: 1.4430 - val_acc: 0.3985 - lr: 1.0000e-04
  Epoch 13/100
  0.4475 - val_loss: 1.4317 - val_acc: 0.3985 - lr: 1.0000e-04
  Epoch 14/100
```

0.4458 - val\_loss: 1.4323 - val\_acc: 0.4406 - lr: 1.0000e-04

Epoch 15/100

```
0.4493 - val_loss: 1.4016 - val_acc: 0.4253 - lr: 1.0000e-04
Epoch 16/100
0.4501 - val_loss: 1.3992 - val_acc: 0.4368 - lr: 1.0000e-04
Epoch 17/100
0.4491 - val_loss: 1.4169 - val_acc: 0.3985 - lr: 1.0000e-04
Epoch 18/100
0.4584 - val_loss: 1.4021 - val_acc: 0.4368 - lr: 1.0000e-04
Epoch 19/100
39/39 [============== ] - ETA: Os - loss: 1.3557 - acc: 0.4689
Epoch 00019: ReduceLROnPlateau reducing learning rate to 7.499999810534064e-05.
0.4689 - val_loss: 1.4187 - val_acc: 0.4138 - lr: 1.0000e-04
Epoch 20/100
0.4614 - val_loss: 1.3958 - val_acc: 0.4330 - lr: 7.5000e-05
Epoch 21/100
0.4557 - val_loss: 1.3781 - val_acc: 0.4444 - lr: 7.5000e-05
Epoch 22/100
0.4713 - val_loss: 1.3920 - val_acc: 0.4444 - lr: 7.5000e-05
Epoch 23/100
0.4604 - val_loss: 1.3880 - val_acc: 0.4521 - lr: 7.5000e-05
0.4679 - val_loss: 1.3746 - val_acc: 0.4215 - lr: 7.5000e-05
Epoch 25/100
0.4729 - val_loss: 1.3750 - val_acc: 0.4559 - lr: 7.5000e-05
Epoch 26/100
0.4780 - val_loss: 1.3621 - val_acc: 0.4483 - lr: 7.5000e-05
Epoch 27/100
0.4634 - val_loss: 1.3901 - val_acc: 0.4368 - lr: 7.5000e-05
Epoch 28/100
0.4671 - val_loss: 1.3899 - val_acc: 0.4598 - lr: 7.5000e-05
Epoch 29/100
0.4695 - val_loss: 1.4047 - val_acc: 0.4330 - lr: 7.5000e-05
Epoch 30/100
```

```
0.4612 - val_loss: 1.3621 - val_acc: 0.4713 - lr: 7.5000e-05
Epoch 31/100
0.4818 - val_loss: 1.4135 - val_acc: 0.4061 - lr: 7.5000e-05
Epoch 32/100
0.4879 - val_loss: 1.3768 - val_acc: 0.4751 - lr: 7.5000e-05
Epoch 33/100
0.4834 - val_loss: 1.3687 - val_acc: 0.4751 - lr: 7.5000e-05
Epoch 34/100
0.4812 - val_loss: 1.3799 - val_acc: 0.4828 - lr: 7.5000e-05
Epoch 35/100
0.4885 - val_loss: 1.3757 - val_acc: 0.4674 - lr: 7.5000e-05
Epoch 36/100
0.4749 - val_loss: 1.3644 - val_acc: 0.4674 - lr: 7.5000e-05
Epoch 37/100
0.4838 - val_loss: 1.4007 - val_acc: 0.4330 - lr: 7.5000e-05
Epoch 38/100
0.4840 - val_loss: 1.3676 - val_acc: 0.4406 - lr: 7.5000e-05
Epoch 39/100
0.4776 - val_loss: 1.3757 - val_acc: 0.4330 - lr: 7.5000e-05
0.4923 - val_loss: 1.3728 - val_acc: 0.4636 - lr: 7.5000e-05
Epoch 41/100
0.4976 - val_loss: 1.3532 - val_acc: 0.4751 - lr: 7.5000e-05
Epoch 42/100
Epoch 00042: ReduceLROnPlateau reducing learning rate to 5.6249997214763425e-05.
0.5044 - val_loss: 1.4133 - val_acc: 0.4368 - lr: 7.5000e-05
Epoch 43/100
0.4964 - val_loss: 1.3666 - val_acc: 0.4330 - lr: 5.6250e-05
0.5063 - val_loss: 1.3693 - val_acc: 0.4636 - lr: 5.6250e-05
Epoch 45/100
0.4998 - val_loss: 1.3426 - val_acc: 0.4674 - lr: 5.6250e-05
```

```
Epoch 46/100
0.5075 - val_loss: 1.3607 - val_acc: 0.4789 - lr: 5.6250e-05
Epoch 47/100
0.5073 - val_loss: 1.3575 - val_acc: 0.4521 - lr: 5.6250e-05
Epoch 48/100
0.5141 - val_loss: 1.3375 - val_acc: 0.5057 - lr: 5.6250e-05
Epoch 49/100
0.5202 - val_loss: 1.3472 - val_acc: 0.4828 - lr: 5.6250e-05
Epoch 50/100
0.5162 - val_loss: 1.3541 - val_acc: 0.4521 - lr: 5.6250e-05
Epoch 51/100
0.5172 - val_loss: 1.3473 - val_acc: 0.4828 - lr: 5.6250e-05
Epoch 52/100
0.5109 - val_loss: 1.3486 - val_acc: 0.4674 - lr: 5.6250e-05
Epoch 53/100
0.5188 - val_loss: 1.3298 - val_acc: 0.4828 - lr: 5.6250e-05
Epoch 54/100
0.5301 - val_loss: 1.3329 - val_acc: 0.4828 - lr: 5.6250e-05
Epoch 55/100
39/39 [=========== ] - 73s 2s/step - loss: 1.2189 - acc:
0.5249 - val_loss: 1.3547 - val_acc: 0.4943 - lr: 5.6250e-05
Epoch 56/100
Epoch 00056: ReduceLROnPlateau reducing learning rate to 4.218749927531462e-05.
0.5257 - val_loss: 1.3703 - val_acc: 0.4866 - lr: 5.6250e-05
Epoch 57/100
0.5329 - val_loss: 1.3372 - val_acc: 0.4789 - lr: 4.2188e-05
Epoch 58/100
39/39 [============ - 69s 2s/step - loss: 1.2112 - acc:
0.5279 - val_loss: 1.3572 - val_acc: 0.4713 - lr: 4.2188e-05
Epoch 59/100
0.5249 - val_loss: 1.3572 - val_acc: 0.4636 - lr: 4.2188e-05
Epoch 60/100
0.5378 - val_loss: 1.3386 - val_acc: 0.4598 - lr: 4.2188e-05
Epoch 61/100
```

```
0.5263 - val_loss: 1.3393 - val_acc: 0.4789 - lr: 4.2188e-05
Epoch 62/100
0.5382 - val_loss: 1.3154 - val_acc: 0.4789 - lr: 4.2188e-05
Epoch 63/100
0.5473 - val_loss: 1.3151 - val_acc: 0.5057 - lr: 4.2188e-05
Epoch 64/100
Epoch 00064: ReduceLROnPlateau reducing learning rate to 3.164062582072802e-05.
0.5471 - val_loss: 1.3297 - val_acc: 0.4828 - lr: 4.2188e-05
Epoch 65/100
0.5493 - val_loss: 1.3112 - val_acc: 0.5172 - lr: 3.1641e-05
Epoch 66/100
0.5477 - val_loss: 1.2970 - val_acc: 0.5172 - lr: 3.1641e-05
Epoch 67/100
0.5604 - val_loss: 1.3335 - val_acc: 0.4866 - lr: 3.1641e-05
Epoch 68/100
39/39 [============ - 70s 2s/step - loss: 1.1634 - acc:
0.5491 - val_loss: 1.3186 - val_acc: 0.5134 - lr: 3.1641e-05
Epoch 69/100
0.5568 - val_loss: 1.3337 - val_acc: 0.4904 - lr: 3.1641e-05
0.5572 - val_loss: 1.3495 - val_acc: 0.4866 - lr: 3.1641e-05
Epoch 71/100
0.5523 - val_loss: 1.3895 - val_acc: 0.4598 - lr: 3.1641e-05
Epoch 72/100
0.5509 - val_loss: 1.3216 - val_acc: 0.4981 - lr: 3.1641e-05
Epoch 73/100
Epoch 00073: ReduceLROnPlateau reducing learning rate to 2.3730469365546014e-05.
0.5588 - val_loss: 1.3497 - val_acc: 0.4674 - lr: 3.1641e-05
0.5641 - val_loss: 1.3296 - val_acc: 0.4866 - lr: 2.3730e-05
Epoch 75/100
0.5679 - val_loss: 1.3408 - val_acc: 0.4674 - lr: 2.3730e-05
```

```
Epoch 76/100
0.5592 - val_loss: 1.3126 - val_acc: 0.5019 - lr: 2.3730e-05
Epoch 77/100
0.5622 - val_loss: 1.3163 - val_acc: 0.4943 - lr: 2.3730e-05
Epoch 78/100
0.5645 - val_loss: 1.3257 - val_acc: 0.4904 - lr: 2.3730e-05
Epoch 79/100
0.5663 - val_loss: 1.3001 - val_acc: 0.5211 - lr: 2.3730e-05
Epoch 80/100
0.5713 - val_loss: 1.3142 - val_acc: 0.4943 - lr: 2.3730e-05
Epoch 81/100
0.5707 - val_loss: 1.3346 - val_acc: 0.4866 - lr: 2.3730e-05
Epoch 82/100
0.5695 - val_loss: 1.3052 - val_acc: 0.5172 - lr: 2.3730e-05
Epoch 83/100
0.5669 - val_loss: 1.2936 - val_acc: 0.5249 - lr: 2.3730e-05
Epoch 84/100
0.5780 - val_loss: 1.3268 - val_acc: 0.5172 - lr: 2.3730e-05
Epoch 85/100
0.5740 - val_loss: 1.3105 - val_acc: 0.5057 - lr: 2.3730e-05
Epoch 86/100
0.5756 - val_loss: 1.3395 - val_acc: 0.4751 - lr: 2.3730e-05
Epoch 87/100
0.5699 - val_loss: 1.3355 - val_acc: 0.4866 - lr: 2.3730e-05
Epoch 88/100
0.5770 - val_loss: 1.3077 - val_acc: 0.5211 - lr: 2.3730e-05
Epoch 89/100
0.5762 - val_loss: 1.3249 - val_acc: 0.5057 - lr: 2.3730e-05
39/39 [=========== ] - 70s 2s/step - loss: 1.0990 - acc:
0.5798 - val_loss: 1.3275 - val_acc: 0.4981 - lr: 2.3730e-05
Epoch 91/100
Epoch 00091: ReduceLROnPlateau reducing learning rate to 1.7797852706280537e-05.
```

```
0.5770 - val_loss: 1.3347 - val_acc: 0.4904 - lr: 2.3730e-05
  Epoch 92/100
  0.5792 - val_loss: 1.3217 - val_acc: 0.4866 - lr: 1.7798e-05
  Epoch 93/100
  0.5839 - val_loss: 1.3240 - val_acc: 0.4904 - lr: 1.7798e-05
  Epoch 94/100
  0.5837 - val_loss: 1.3017 - val_acc: 0.5172 - lr: 1.7798e-05
  0.5887 - val_loss: 1.2979 - val_acc: 0.5096 - lr: 1.7798e-05
  Epoch 96/100
  0.5897 - val_loss: 1.3096 - val_acc: 0.4943 - lr: 1.7798e-05
  Epoch 97/100
  0.5869 - val_loss: 1.3011 - val_acc: 0.5172 - lr: 1.7798e-05
  Epoch 98/100
  0.5859 - val_loss: 1.3044 - val_acc: 0.5211 - lr: 1.7798e-05
  Epoch 99/100
  Epoch 00099: ReduceLROnPlateau reducing learning rate to 1.3348389529710403e-05.
  0.5907 - val_loss: 1.3056 - val_acc: 0.5057 - lr: 1.7798e-05
  Epoch 100/100
  0.5901 - val_loss: 1.3062 - val_acc: 0.5134 - lr: 1.3348e-05
[]: histopt = modelopt.fit(features_train, y_train, batch_size=128, epochs=50,__
   overbose=1, validation_data=(features_val, y_val), ∪
   →callbacks=[early_stop,lr_reduction])
  Epoch 1/50
  0.3207 - val_loss: 1.4396 - val_acc: 0.4253 - lr: 1.0000e-04
  Epoch 2/50
  0.4236 - val_loss: 1.3934 - val_acc: 0.4713 - lr: 1.0000e-04
  0.4491 - val_loss: 1.3718 - val_acc: 0.4598 - lr: 1.0000e-04
  Epoch 4/50
  0.4721 - val_loss: 1.3697 - val_acc: 0.4751 - lr: 1.0000e-04
```

```
Epoch 5/50
0.4612 - val_loss: 1.3567 - val_acc: 0.4483 - lr: 1.0000e-04
0.4800 - val_loss: 1.3859 - val_acc: 0.4406 - lr: 1.0000e-04
Epoch 7/50
0.4861 - val_loss: 1.3745 - val_acc: 0.4598 - lr: 1.0000e-04
Epoch 8/50
0.4642 - val_loss: 1.4411 - val_acc: 0.3870 - lr: 1.0000e-04
Epoch 9/50
0.4685 - val_loss: 1.3733 - val_acc: 0.4291 - lr: 1.0000e-04
Epoch 10/50
0.4875 - val_loss: 1.3715 - val_acc: 0.4406 - lr: 1.0000e-04
Epoch 11/50
0.5030 - val_loss: 1.3559 - val_acc: 0.4636 - lr: 1.0000e-04
Epoch 12/50
Epoch 00012: ReduceLROnPlateau reducing learning rate to 7.499999810534064e-05.
0.4986 - val_loss: 1.3488 - val_acc: 0.4751 - lr: 1.0000e-04
Epoch 13/50
0.5101 - val_loss: 1.3433 - val_acc: 0.4636 - lr: 7.5000e-05
Epoch 14/50
39/39 [============ - - 73s 2s/step - loss: 1.2497 - acc:
0.5143 - val_loss: 1.3913 - val_acc: 0.4406 - lr: 7.5000e-05
Epoch 15/50
0.5093 - val_loss: 1.3841 - val_acc: 0.4483 - lr: 7.5000e-05
Epoch 16/50
0.5150 - val_loss: 1.3157 - val_acc: 0.4789 - lr: 7.5000e-05
Epoch 17/50
39/39 [============ - - 73s 2s/step - loss: 1.2300 - acc:
0.5271 - val_loss: 1.3416 - val_acc: 0.4713 - lr: 7.5000e-05
Epoch 18/50
0.5327 - val_loss: 1.3366 - val_acc: 0.4828 - lr: 7.5000e-05
Epoch 19/50
0.5190 - val_loss: 1.3272 - val_acc: 0.4789 - lr: 7.5000e-05
Epoch 20/50
```

```
0.5342 - val_loss: 1.3081 - val_acc: 0.4789 - lr: 7.5000e-05
Epoch 21/50
0.5392 - val_loss: 1.3111 - val_acc: 0.4713 - lr: 7.5000e-05
Epoch 22/50
0.5366 - val_loss: 1.3371 - val_acc: 0.4713 - lr: 7.5000e-05
Epoch 23/50
0.5348 - val_loss: 1.3229 - val_acc: 0.4406 - lr: 7.5000e-05
Epoch 24/50
39/39 [============ ] - 75s 2s/step - loss: 1.1841 - acc:
0.5432 - val_loss: 1.2731 - val_acc: 0.4943 - lr: 7.5000e-05
Epoch 25/50
0.5511 - val_loss: 1.3193 - val_acc: 0.4828 - lr: 7.5000e-05
Epoch 26/50
0.5558 - val_loss: 1.2705 - val_acc: 0.4789 - lr: 7.5000e-05
Epoch 27/50
0.5501 - val_loss: 1.2958 - val_acc: 0.4981 - lr: 7.5000e-05
Epoch 28/50
0.5594 - val_loss: 1.3664 - val_acc: 0.4330 - lr: 7.5000e-05
Epoch 29/50
0.5635 - val_loss: 1.3036 - val_acc: 0.4943 - lr: 7.5000e-05
Epoch 30/50
39/39 [============ - - 72s 2s/step - loss: 1.1676 - acc:
0.5475 - val_loss: 1.3894 - val_acc: 0.4751 - lr: 7.5000e-05
Epoch 31/50
0.5580 - val_loss: 1.2555 - val_acc: 0.5096 - lr: 7.5000e-05
Epoch 32/50
0.5675 - val_loss: 1.3003 - val_acc: 0.4904 - lr: 7.5000e-05
Epoch 33/50
39/39 [============ - - 72s 2s/step - loss: 1.1819 - acc:
0.5453 - val_loss: 1.3105 - val_acc: 0.4751 - lr: 7.5000e-05
Epoch 34/50
0.5594 - val_loss: 1.2994 - val_acc: 0.4943 - lr: 7.5000e-05
Epoch 35/50
0.5683 - val_loss: 1.3316 - val_acc: 0.4828 - lr: 7.5000e-05
Epoch 36/50
```

```
0.5728 - val_loss: 1.2785 - val_acc: 0.5096 - lr: 7.5000e-05
Epoch 37/50
0.5661 - val_loss: 1.2963 - val_acc: 0.4943 - lr: 7.5000e-05
Epoch 38/50
0.5616 - val_loss: 1.2602 - val_acc: 0.5211 - lr: 7.5000e-05
Epoch 39/50
0.5699 - val_loss: 1.2877 - val_acc: 0.4943 - lr: 7.5000e-05
0.5901 - val_loss: 1.2908 - val_acc: 0.4866 - lr: 7.5000e-05
0.5754 - val_loss: 1.2206 - val_acc: 0.5326 - lr: 7.5000e-05
Epoch 42/50
0.5930 - val_loss: 1.2551 - val_acc: 0.4943 - lr: 7.5000e-05
Epoch 43/50
0.5938 - val_loss: 1.2587 - val_acc: 0.5287 - lr: 7.5000e-05
Epoch 44/50
0.5930 - val_loss: 1.3312 - val_acc: 0.4943 - lr: 7.5000e-05
Epoch 45/50
0.5974 - val_loss: 1.3186 - val_acc: 0.4943 - lr: 7.5000e-05
Epoch 46/50
0.5914 - val_loss: 1.2842 - val_acc: 0.5057 - lr: 7.5000e-05
Epoch 47/50
0.6013 - val_loss: 1.2967 - val_acc: 0.5096 - lr: 7.5000e-05
Epoch 48/50
0.5968 - val_loss: 1.2619 - val_acc: 0.5249 - lr: 7.5000e-05
Epoch 49/50
Epoch 00049: ReduceLROnPlateau reducing learning rate to 5.6249997214763425e-05.
0.5984 - val_loss: 1.3311 - val_acc: 0.4713 - lr: 7.5000e-05
Epoch 50/50
0.6065 - val_loss: 1.2516 - val_acc: 0.5211 - lr: 5.6250e-05
```

```
[]: histopt = modelopt.fit(features_train, y_train, batch_size=128, epochs=50,__
      overbose=1, validation_data=(features_val, y_val), ∪
      →callbacks=[early_stop,lr_reduction])
```

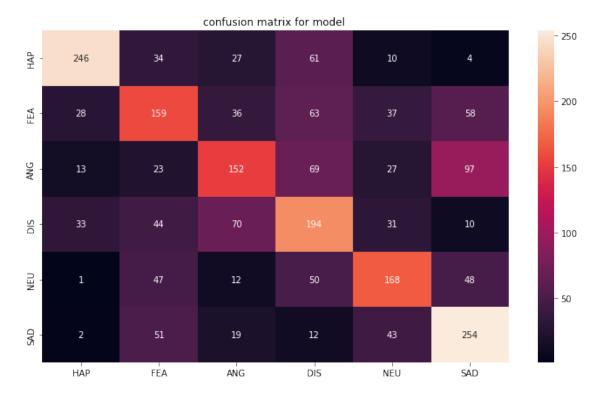
### 0.8 Big Picture (20 Points)

We compute the accuracy, f1-score, precision, recall and loss on test data based on our model.

```
1. TESTING THE FIRST MODEL ON 1-DIMENSIONAL FEATURE VECTORS
[]: loss,accuracy=modelopt.evaluate(features_test,y_test,verbose=0)
    print(f'Test Loss: {loss}')
    print(f'Test Accuracy: {accuracy*100}%')
    Test Loss: 1.2662875652313232
    Test Accuracy: 52.53022909164429%
[]: import plotly.express as px
    fig=px.line(histopt.history,y=['acc','val_acc'],
                labels={'index':'epoch','value':'acc'},
               title=f'Epoch accuracy and validation accuracy chart for the model')
    fig.show()
[]: fig=px.line(histopt.history,y=['loss','val_loss'],
               labels={'index':'epoch','value':'loss'},
               title=(f'Epoch loss and validation loss chart for the model'))
    fig.show()
[]: import plotly.express as px
    fig=px.line(histopt.history,y=['acc','val_acc'],
               labels={'index':'epoch','value':'acc'},
                title=f'Epoch accuracy and validation accuracy chart for the model')
    fig.show()
[]:|fig=px.line(histopt.history,y=['loss','val_loss'],
                labels={'index':'epoch','value':'loss'},
                title=(f'Epoch loss and validation loss chart for the model'))
    fig.show()
[]: from sklearn.metrics import confusion_matrix
    from sklearn.metrics import classification_report
    y_pred = modelopt.predict(features_test)
    y_pred = np.argmax(y_pred, axis=1)
    conf=confusion_matrix(y_test,y_pred)
    cm=pd.DataFrame(
         conf,index=[i for i in set(labels)],
         columns=[i for i in set(labels)]
```

```
plt.figure(figsize=(12,7))
ax=sns.heatmap(cm,annot=True,fmt='d')
ax.set_title(f'confusion matrix for model ')
plt.show()
```

70/70 [=======] - 19s 239ms/step



```
[]: from sklearn.metrics import f1_score,precision_score,recall_score
    prec=precision_score(y_test,y_pred,average='weighted')
    rec=recall_score(y_test,y_pred,average='weighted')
    f1score=f1_score(y_test,y_pred,average='weighted')
    print(f'Test precision: {prec}')
    print(f'Test recall: {rec}')
    print(f'Test f1-score: {f1score}')
```

Test precision: 0.5316831795330076 Test recall: 0.5253022839229736 Test f1-score: 0.5252374785837246

#### 2. TESTING THE SECOND MODEL ON 1-DIMENSIONAL FEATURE VECTORS

```
[]: hist = model.fit(features_train, y_train, batch_size=128, epochs=100,
verbose=1, validation_data=(features_val, y_val),
callbacks=[early_stop,lr_reduction])
```

```
Epoch 1/100
0.3013 - val_loss: 5.0133 - val_acc: 0.1724 - lr: 1.0000e-04
Epoch 2/100
0.3373 - val_loss: 2.0859 - val_acc: 0.2299 - lr: 1.0000e-04
Epoch 3/100
39/39 [================== ] - 17s 443ms/step - loss: 1.6632 - acc:
0.3559 - val_loss: 1.8614 - val_acc: 0.1724 - lr: 1.0000e-04
Epoch 4/100
0.3612 - val_loss: 1.6996 - val_acc: 0.2567 - lr: 1.0000e-04
Epoch 5/100
0.3775 - val_loss: 1.6211 - val_acc: 0.3333 - lr: 1.0000e-04
Epoch 6/100
0.3705 - val_loss: 1.5418 - val_acc: 0.3180 - lr: 1.0000e-04
Epoch 7/100
0.3800 - val_loss: 1.5074 - val_acc: 0.3678 - lr: 1.0000e-04
Epoch 8/100
0.3789 - val_loss: 1.5081 - val_acc: 0.3563 - lr: 1.0000e-04
Epoch 9/100
0.3899 - val_loss: 1.5001 - val_acc: 0.3487 - lr: 1.0000e-04
Epoch 10/100
39/39 [=============== ] - 17s 428ms/step - loss: 1.4954 - acc:
0.3965 - val_loss: 1.4750 - val_acc: 0.3755 - lr: 1.0000e-04
Epoch 11/100
0.3897 - val_loss: 1.4807 - val_acc: 0.4023 - lr: 1.0000e-04
Epoch 12/100
0.3921 - val_loss: 1.4441 - val_acc: 0.4100 - lr: 1.0000e-04
Epoch 13/100
0.3812 - val_loss: 1.5706 - val_acc: 0.3716 - lr: 1.0000e-04
Epoch 14/100
0.3955 - val_loss: 1.4787 - val_acc: 0.3678 - lr: 1.0000e-04
0.4022 - val_loss: 1.4492 - val_acc: 0.3793 - lr: 1.0000e-04
Epoch 16/100
0.4004 - val_loss: 1.4540 - val_acc: 0.3908 - lr: 1.0000e-04
```

```
Epoch 17/100
0.4044 - val_loss: 1.5814 - val_acc: 0.3333 - lr: 1.0000e-04
Epoch 18/100
0.4000 - val_loss: 1.4826 - val_acc: 0.3870 - lr: 1.0000e-04
Epoch 19/100
0.4115 - val_loss: 1.4606 - val_acc: 0.3716 - lr: 1.0000e-04
Epoch 20/100
0.4121 - val_loss: 1.4335 - val_acc: 0.3870 - lr: 1.0000e-04
Epoch 21/100
0.4192 - val_loss: 1.4160 - val_acc: 0.4138 - lr: 1.0000e-04
Epoch 22/100
0.4198 - val_loss: 1.4437 - val_acc: 0.4253 - lr: 1.0000e-04
Epoch 23/100
0.4276 - val_loss: 1.5748 - val_acc: 0.3218 - lr: 1.0000e-04
Epoch 24/100
39/39 [================== ] - 17s 439ms/step - loss: 1.4059 - acc:
0.4361 - val_loss: 1.4105 - val_acc: 0.4483 - lr: 1.0000e-04
Epoch 25/100
0.4186 - val_loss: 1.3992 - val_acc: 0.4368 - lr: 1.0000e-04
Epoch 26/100
39/39 [============== ] - 17s 444ms/step - loss: 1.3990 - acc:
0.4266 - val_loss: 1.4498 - val_acc: 0.3831 - lr: 1.0000e-04
Epoch 27/100
0.4327 - val_loss: 1.4232 - val_acc: 0.3946 - lr: 1.0000e-04
Epoch 28/100
0.4418 - val_loss: 1.4173 - val_acc: 0.4100 - lr: 1.0000e-04
Epoch 29/100
0.4337 - val_loss: 1.4052 - val_acc: 0.4253 - lr: 1.0000e-04
Epoch 30/100
0.4329 - val_loss: 1.3921 - val_acc: 0.4215 - lr: 1.0000e-04
0.4307 - val_loss: 1.4065 - val_acc: 0.4291 - lr: 1.0000e-04
Epoch 32/100
0.4460 - val_loss: 1.3753 - val_acc: 0.4444 - lr: 1.0000e-04
```

```
Epoch 33/100
0.4335 - val_loss: 1.4012 - val_acc: 0.4368 - lr: 1.0000e-04
Epoch 34/100
Epoch 00034: ReduceLROnPlateau reducing learning rate to 4.999999873689376e-05.
0.4378 - val_loss: 1.4264 - val_acc: 0.4023 - lr: 1.0000e-04
Epoch 35/100
0.4483 - val_loss: 1.4051 - val_acc: 0.4253 - lr: 5.0000e-05
Epoch 36/100
0.4572 - val_loss: 1.4039 - val_acc: 0.4368 - lr: 5.0000e-05
Epoch 37/100
39/39 [============== ] - 17s 443ms/step - loss: 1.3374 - acc:
0.4450 - val_loss: 1.3481 - val_acc: 0.4406 - lr: 5.0000e-05
Epoch 38/100
39/39 [============== ] - 17s 442ms/step - loss: 1.3403 - acc:
0.4503 - val_loss: 1.3652 - val_acc: 0.4751 - lr: 5.0000e-05
Epoch 39/100
39/39 [================== ] - 17s 439ms/step - loss: 1.3268 - acc:
0.4624 - val_loss: 1.3727 - val_acc: 0.4674 - lr: 5.0000e-05
Epoch 40/100
0.4675 - val_loss: 1.3795 - val_acc: 0.4138 - lr: 5.0000e-05
Epoch 41/100
0.4600 - val_loss: 1.4155 - val_acc: 0.4023 - lr: 5.0000e-05
Epoch 42/100
0.4739 - val_loss: 1.3670 - val_acc: 0.4368 - lr: 5.0000e-05
Epoch 43/100
0.4656 - val_loss: 1.3820 - val_acc: 0.4291 - lr: 5.0000e-05
Epoch 44/100
39/39 [================= ] - 17s 441ms/step - loss: 1.3144 - acc:
0.4667 - val_loss: 1.4513 - val_acc: 0.3793 - lr: 5.0000e-05
Epoch 45/100
0.4665 - val_loss: 1.3616 - val_acc: 0.4598 - lr: 5.0000e-05
Epoch 46/100
39/39 [================ ] - 18s 453ms/step - loss: 1.3057 - acc:
0.4762 - val_loss: 1.3781 - val_acc: 0.4483 - lr: 5.0000e-05
Epoch 47/100
0.4784 - val_loss: 1.3501 - val_acc: 0.4598 - lr: 5.0000e-05
Epoch 48/100
```

```
Epoch 00048: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-05.
0.4747 - val_loss: 1.3730 - val_acc: 0.4100 - lr: 5.0000e-05
Epoch 49/100
0.4852 - val_loss: 1.3641 - val_acc: 0.4444 - lr: 2.5000e-05
Epoch 50/100
0.4871 - val_loss: 1.3500 - val_acc: 0.4789 - lr: 2.5000e-05
Epoch 51/100
0.4913 - val_loss: 1.3780 - val_acc: 0.4215 - lr: 2.5000e-05
Epoch 52/100
0.4883 - val_loss: 1.3833 - val_acc: 0.4061 - lr: 2.5000e-05
Epoch 53/100
0.4905 - val_loss: 1.4071 - val_acc: 0.4253 - lr: 2.5000e-05
Epoch 54/100
0.5020 - val_loss: 1.3653 - val_acc: 0.4483 - lr: 2.5000e-05
Epoch 55/100
0.5002 - val_loss: 1.3916 - val_acc: 0.4521 - lr: 2.5000e-05
Epoch 56/100
0.5044 - val_loss: 1.3818 - val_acc: 0.4330 - lr: 2.5000e-05
0.5010 - val_loss: 1.3588 - val_acc: 0.4636 - lr: 2.5000e-05
Epoch 58/100
0.5067 - val_loss: 1.3703 - val_acc: 0.4406 - lr: 2.5000e-05
Epoch 59/100
0.4956 - val_loss: 1.3678 - val_acc: 0.4559 - lr: 2.5000e-05
Epoch 60/100
Epoch 00060: ReduceLROnPlateau reducing learning rate to 1.249999968422344e-05.
0.5087 - val_loss: 1.3908 - val_acc: 0.4253 - lr: 2.5000e-05
0.5135 - val_loss: 1.3579 - val_acc: 0.4406 - lr: 1.2500e-05
Epoch 62/100
0.5182 - val_loss: 1.3775 - val_acc: 0.4483 - lr: 1.2500e-05
```

```
0.5188 - val_loss: 1.3598 - val_acc: 0.4521 - lr: 1.2500e-05
  Epoch 64/100
  0.5168 - val_loss: 1.3858 - val_acc: 0.4559 - lr: 1.2500e-05
  Epoch 65/100
  0.5180 - val_loss: 1.3824 - val_acc: 0.4291 - lr: 1.2500e-05
  Epoch 66/100
  0.5224 - val_loss: 1.3670 - val_acc: 0.4713 - lr: 1.2500e-05
  Epoch 67/100
  0.5261 - val_loss: 1.3805 - val_acc: 0.3985 - lr: 1.2500e-05
  Epoch 68/100
  0.5176 - val_loss: 1.3579 - val_acc: 0.4483 - lr: 1.2500e-05
  Epoch 69/100
  0.5232 - val_loss: 1.3822 - val_acc: 0.4444 - lr: 1.2500e-05
  Epoch 70/100
  Epoch 00070: ReduceLROnPlateau reducing learning rate to 6.24999984211172e-06.
  0.5342 - val_loss: 1.3690 - val_acc: 0.4444 - lr: 1.2500e-05
[]: import plotly.express as px
   fig=px.line(hist.history,y=['acc','val_acc'],
          labels={'index':'epoch','value':'acc'},
          title=f'According to the epoch accuracy and validation accuracy_
   ⇔chart for the model')
   fig.show()
[]:|fig=px.line(hist.history,y=['loss','val_loss'],
          labels={'index':'epoch','value':'loss'},
          title=f'According to the epoch loss and validation loss chart for \sqcup
   fig.show()
[]: hist2 = model.fit(features_train, y_train, batch_size=64, epochs=50, verbose=1, ___
   avalidation_data=(features_val, y_val), callbacks=[early_stop,lr_reduction])
  Epoch 1/50
  0.2850 - val_loss: 2.4579 - val_acc: 0.2452 - lr: 1.0000e-04
  Epoch 2/50
  78/78 [============== ] - 167s 2s/step - loss: 1.7202 - acc:
```

Epoch 63/100

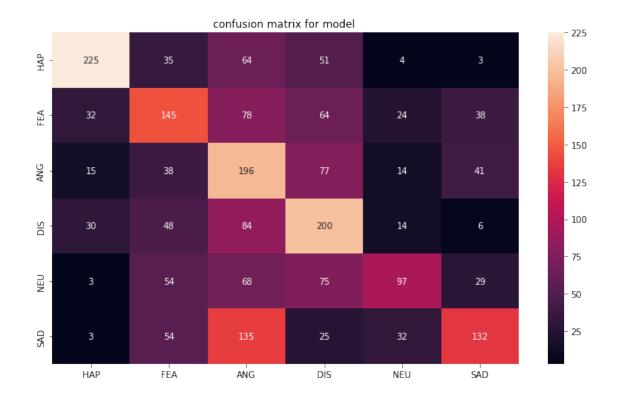
```
0.3432 - val_loss: 1.9398 - val_acc: 0.2452 - lr: 1.0000e-04
Epoch 3/50
78/78 [============== ] - 169s 2s/step - loss: 1.6271 - acc:
0.3652 - val_loss: 1.7943 - val_acc: 0.2375 - lr: 1.0000e-04
Epoch 4/50
78/78 [============== ] - 167s 2s/step - loss: 1.5450 - acc:
0.3884 - val_loss: 1.7942 - val_acc: 0.2912 - lr: 1.0000e-04
Epoch 5/50
78/78 [============== ] - 170s 2s/step - loss: 1.5145 - acc:
0.4014 - val_loss: 1.4952 - val_acc: 0.3602 - lr: 1.0000e-04
Epoch 6/50
0.4101 - val_loss: 1.5317 - val_acc: 0.3602 - lr: 1.0000e-04
Epoch 7/50
0.4169 - val_loss: 1.5331 - val_acc: 0.3333 - lr: 1.0000e-04
Epoch 8/50
0.4337 - val_loss: 1.5030 - val_acc: 0.3793 - lr: 1.0000e-04
Epoch 9/50
0.4424 - val_loss: 1.4835 - val_acc: 0.3755 - lr: 1.0000e-04
Epoch 10/50
0.4545 - val_loss: 1.4623 - val_acc: 0.4215 - lr: 1.0000e-04
Epoch 11/50
0.4636 - val_loss: 1.5009 - val_acc: 0.3870 - lr: 1.0000e-04
Epoch 12/50
78/78 [============== ] - 169s 2s/step - loss: 1.3316 - acc:
0.4656 - val_loss: 1.4026 - val_acc: 0.4215 - lr: 1.0000e-04
Epoch 13/50
78/78 [============== ] - 173s 2s/step - loss: 1.3084 - acc:
0.4755 - val_loss: 1.4503 - val_acc: 0.3678 - lr: 1.0000e-04
Epoch 14/50
78/78 [=============== ] - 153s 2s/step - loss: 1.3112 - acc:
0.4832 - val_loss: 1.4790 - val_acc: 0.4138 - lr: 1.0000e-04
Epoch 15/50
78/78 [============== ] - 146s 2s/step - loss: 1.2806 - acc:
0.4956 - val_loss: 1.3788 - val_acc: 0.4406 - lr: 1.0000e-04
Epoch 16/50
0.4897 - val_loss: 1.4003 - val_acc: 0.4674 - lr: 1.0000e-04
Epoch 17/50
0.5032 - val_loss: 1.4312 - val_acc: 0.3985 - lr: 1.0000e-04
Epoch 18/50
78/78 [============== ] - 147s 2s/step - loss: 1.2283 - acc:
```

```
0.5119 - val_loss: 1.4717 - val_acc: 0.3908 - lr: 1.0000e-04
Epoch 19/50
78/78 [============== ] - 144s 2s/step - loss: 1.2026 - acc:
0.5212 - val_loss: 1.4051 - val_acc: 0.4444 - lr: 1.0000e-04
Epoch 20/50
78/78 [============== ] - 159s 2s/step - loss: 1.1922 - acc:
0.5261 - val_loss: 1.3725 - val_acc: 0.4521 - lr: 1.0000e-04
Epoch 21/50
Epoch 00021: ReduceLROnPlateau reducing learning rate to 4.999999873689376e-05.
78/78 [============== ] - 165s 2s/step - loss: 1.1762 - acc:
0.5325 - val_loss: 1.3543 - val_acc: 0.4330 - lr: 1.0000e-04
Epoch 22/50
0.5588 - val_loss: 1.4055 - val_acc: 0.4138 - lr: 5.0000e-05
Epoch 23/50
0.5649 - val_loss: 1.3242 - val_acc: 0.5019 - lr: 5.0000e-05
Epoch 24/50
78/78 [============== ] - 159s 2s/step - loss: 1.0742 - acc:
0.5825 - val_loss: 1.3460 - val_acc: 0.4636 - lr: 5.0000e-05
Epoch 25/50
78/78 [=============== ] - 172s 2s/step - loss: 1.0549 - acc:
0.5823 - val_loss: 1.2937 - val_acc: 0.4751 - lr: 5.0000e-05
Epoch 26/50
0.6051 - val_loss: 1.4161 - val_acc: 0.4406 - lr: 5.0000e-05
Epoch 27/50
78/78 [=============== ] - 155s 2s/step - loss: 1.0186 - acc:
0.6043 - val_loss: 1.2856 - val_acc: 0.5172 - lr: 5.0000e-05
Epoch 28/50
0.6085 - val_loss: 1.3790 - val_acc: 0.4483 - lr: 5.0000e-05
Epoch 29/50
0.6318 - val_loss: 1.4974 - val_acc: 0.4176 - lr: 5.0000e-05
Epoch 30/50
78/78 [=============== ] - 153s 2s/step - loss: 0.9711 - acc:
0.6261 - val_loss: 1.3993 - val_acc: 0.4521 - lr: 5.0000e-05
Epoch 31/50
78/78 [============== ] - 153s 2s/step - loss: 0.9475 - acc:
0.6372 - val_loss: 1.3605 - val_acc: 0.4751 - lr: 5.0000e-05
Epoch 32/50
Epoch 00032: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-05.
78/78 [============== ] - 153s 2s/step - loss: 0.9601 - acc:
0.6308 - val_loss: 1.4399 - val_acc: 0.4368 - lr: 5.0000e-05
Epoch 33/50
```

```
78/78 [============== ] - 153s 2s/step - loss: 0.8949 - acc:
0.6681 - val_loss: 1.3813 - val_acc: 0.4598 - lr: 2.5000e-05
Epoch 34/50
0.6886 - val_loss: 1.3938 - val_acc: 0.4368 - lr: 2.5000e-05
Epoch 35/50
78/78 [=============== ] - 154s 2s/step - loss: 0.8350 - acc:
0.6886 - val_loss: 1.3697 - val_acc: 0.4444 - lr: 2.5000e-05
Epoch 36/50
78/78 [============== ] - 153s 2s/step - loss: 0.8131 - acc:
0.7025 - val_loss: 1.4371 - val_acc: 0.4176 - lr: 2.5000e-05
Epoch 37/50
Epoch 00037: ReduceLROnPlateau reducing learning rate to 1.249999968422344e-05.
78/78 [============== ] - 153s 2s/step - loss: 0.7939 - acc:
0.7100 - val_loss: 1.3735 - val_acc: 0.4904 - lr: 2.5000e-05
Epoch 38/50
0.7270 - val_loss: 1.4090 - val_acc: 0.4713 - lr: 1.2500e-05
Epoch 39/50
78/78 [=============== ] - 153s 2s/step - loss: 0.7336 - acc:
0.7346 - val_loss: 1.3952 - val_acc: 0.4598 - lr: 1.2500e-05
Epoch 40/50
0.7371 - val_loss: 1.4452 - val_acc: 0.4789 - lr: 1.2500e-05
Epoch 41/50
78/78 [============== ] - 153s 2s/step - loss: 0.7064 - acc:
0.7506 - val_loss: 1.4392 - val_acc: 0.4828 - lr: 1.2500e-05
Epoch 42/50
Epoch 00042: ReduceLROnPlateau reducing learning rate to 6.24999984211172e-06.
78/78 [============== ] - 162s 2s/step - loss: 0.6931 - acc:
0.7510 - val_loss: 1.4309 - val_acc: 0.4598 - lr: 1.2500e-05
Epoch 43/50
78/78 [=============== ] - 163s 2s/step - loss: 0.6755 - acc:
0.7593 - val_loss: 1.4500 - val_acc: 0.4483 - lr: 6.2500e-06
Epoch 44/50
78/78 [=============== ] - 159s 2s/step - loss: 0.6569 - acc:
0.7680 - val_loss: 1.3964 - val_acc: 0.5019 - lr: 6.2500e-06
Epoch 45/50
78/78 [============== ] - 160s 2s/step - loss: 0.6571 - acc:
0.7668 - val_loss: 1.3912 - val_acc: 0.4943 - lr: 6.2500e-06
78/78 [============== ] - 160s 2s/step - loss: 0.6436 - acc:
0.7771 - val_loss: 1.3933 - val_acc: 0.4713 - lr: 6.2500e-06
Epoch 47/50
Epoch 00047: ReduceLROnPlateau reducing learning rate to 3.12499992105586e-06.
```

```
0.7658 - val_loss: 1.4162 - val_acc: 0.4713 - lr: 6.2500e-06
[]: fig=px.line(hist2.history,y=['acc','val_acc'],
              labels={'index':'epoch','value':'acc'},
              title=f'According to the epoch accuracy and validation accuracy_
     ⇔chart for the model')
    fig.show()
[]: fig=px.line(hist2.history,y=['loss','val_loss'],
              labels={'index':'epoch','value':'loss'},
              title=f'According to the epoch loss and validation loss chart for U
     fig.show()
[]: loss,accuracy=model.evaluate(features_test,y_test,verbose=0)
    print(f'Test Loss: {loss}')
    print(f'Test Accuracy: {accuracy}')
    Test Loss: 1.3888615369796753
    Test Accuracy: 0.4455888867378235
[]: from sklearn.metrics import confusion_matrix
    from sklearn.metrics import classification_report
    y_pred = model.predict(features_test)
    y_pred = np.argmax(y_pred, axis=1)
    conf=confusion_matrix(y_test,y_pred)
    cm=pd.DataFrame(
        conf,index=[i for i in set(labels)],
        columns=[i for i in set(labels)]
    plt.figure(figsize=(12,7))
    ax=sns.heatmap(cm,annot=True,fmt='d')
    ax.set_title(f'confusion matrix for model ')
    plt.show()
```

70/70 [========= ] - 14s 192ms/step



```
[938]: model2D=tf.keras.Sequential([
           L.Conv2D(32,kernel_size=5, strides=1,padding='same',_
        activation='relu',input_shape=(mels_train.shape[1],mels_train.shape[2],1)),
           L.BatchNormalization(),
           L.MaxPool2D(pool_size=5,strides=2,padding='same'),
           L.Conv2D(64,kernel_size=5,strides=1,padding='same',activation='relu'),
           L.BatchNormalization(),
           L.MaxPool2D(pool_size=5,strides=2,padding='same'),
           # L.Conv2D(256,kernel_size=5,strides=1,padding='same',activation='relu'),
           L.Conv2D(128,kernel_size=5,strides=1,padding='same',activation='relu'),
           L.BatchNormalization(),
           L.MaxPool2D(pool size=3, strides=2, padding='same'),
           L.Conv2D(256,kernel_size=3,strides=1,padding='same',activation='relu'),
           L.BatchNormalization(),
           L.MaxPool2D(pool_size=3,strides=2,padding='same'),
           # L.Conv2D(256,kernel_size=3,strides=1,padding='same',activation='relu'),
           # L.BatchNormalization(),
           # L.MaxPool2D(pool_size=5,strides=2,padding='same'),
           # L. Conv2D(128, kernel_size=3, strides=1, paddinq='same', activation='relu'),
           # L.BatchNormalization(),
           # L.GlobalAveragePooling2D(),
```

```
L.Flatten(),
    # L.Dropout(rate=0.1),
    # L.Dense(512,activation='relu'),
    L.Dense(512,activation='relu'),
    # L.BatchNormalization(),
    # L.Dense(64,activation='relu'),
    # L.BatchNormalization(),
    L.Dropout(0.3),
    L.Dense(6,activation='softmax')
])
 ⇒compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics='acc')
# model2D.summary()
opt = tf.keras.optimizers.Adam(learning_rate=0.0001)
\verb|model2D.compile(loss='sparse\_categorical\_crossentropy', optimizer=opt_{\sqcup})|

¬,metrics=['acc'])

model2D.summary()
```

Model: "sequential\_140"

Layer (type)		
conv2d_169 (Conv2D)		
<pre>batch_normalization_521 (BatchNormalization)</pre>	(None, 128, 69, 32)	128
<pre>max_pooling2d_143 (MaxPooli ng2D)</pre>	(None, 64, 35, 32)	0
conv2d_170 (Conv2D)	(None, 64, 35, 64)	51264
<pre>batch_normalization_522 (BatchNormalization)</pre>	(None, 64, 35, 64)	256
<pre>max_pooling2d_144 (MaxPooli ng2D)</pre>	(None, 32, 18, 64)	0
conv2d_171 (Conv2D)	(None, 32, 18, 128)	204928
<pre>batch_normalization_523 (BatchNormalization)</pre>	(None, 32, 18, 128)	512
<pre>max_pooling2d_145 (MaxPooli ng2D)</pre>	(None, 16, 9, 128)	0

```
batch_normalization_524 (Ba (None, 16, 9, 256)
                                        1024
    tchNormalization)
    max_pooling2d_146 (MaxPooli (None, 8, 5, 256)
    ng2D)
    flatten_69 (Flatten)
                      (None, 10240)
    dense_279 (Dense)
                       (None, 512)
                                        5243392
    dropout_72 (Dropout)
                       (None, 512)
    dense_280 (Dense)
                       (None, 6)
                                        3078
    ______
    Total params: 5,800,582
    Trainable params: 5,799,622
    Non-trainable params: 960
    _____
[939]: early_stop=EarlyStopping(monitor='val_acc', mode='auto', patience=20, restore_best_weights=True)
    lr reduction=ReduceLROnPlateau(monitor='val acc',patience=5,verbose=1,factor=0.
     →75,min_lr=0.00001)
[922]: history2D = model2D.fit(mels_train, y_train, batch_size=128, epochs=70,__
     →lr_reduction])
    Epoch 1/70
    0.3250 - val_loss: 84.9503 - val_acc: 0.3027 - lr: 1.0000e-04
    Epoch 2/70
    0.3965 - val_loss: 76.0143 - val_acc: 0.3103 - lr: 1.0000e-04
    Epoch 3/70
    0.4190 - val_loss: 68.1409 - val_acc: 0.2874 - lr: 1.0000e-04
    0.4274 - val_loss: 60.2869 - val_acc: 0.2605 - lr: 1.0000e-04
    39/39 [============ ] - 122s 3s/step - loss: 56.3771 - acc:
    0.4376 - val_loss: 52.8989 - val_acc: 0.3372 - lr: 1.0000e-04
    Epoch 6/70
    0.4523 - val_loss: 46.1609 - val_acc: 0.3027 - lr: 1.0000e-04
```

(None, 16, 9, 256)

295168

conv2d\_172 (Conv2D)

```
Epoch 7/70
39/39 [============ ] - 121s 3s/step - loss: 42.8162 - acc:
0.4527 - val_loss: 39.9457 - val_acc: 0.2950 - lr: 1.0000e-04
Epoch 8/70
0.4792 - val_loss: 34.3501 - val_acc: 0.3103 - lr: 1.0000e-04
0.4814 - val_loss: 29.4316 - val_acc: 0.3333 - lr: 1.0000e-04
Epoch 10/70
Epoch 00010: ReduceLROnPlateau reducing learning rate to 4.999999873689376e-05.
39/39 [============ ] - 124s 3s/step - loss: 26.9128 - acc:
0.4905 - val_loss: 25.1072 - val_acc: 0.2950 - lr: 1.0000e-04
Epoch 11/70
0.4984 - val_loss: 23.0734 - val_acc: 0.3487 - lr: 5.0000e-05
Epoch 12/70
39/39 [============== ] - 99s 3s/step - loss: 21.6802 - acc:
0.5253 - val_loss: 21.2599 - val_acc: 0.3372 - lr: 5.0000e-05
Epoch 13/70
0.5317 - val_loss: 19.5197 - val_acc: 0.3410 - lr: 5.0000e-05
Epoch 14/70
39/39 [============== ] - 98s 3s/step - loss: 18.2971 - acc:
0.5358 - val_loss: 18.0314 - val_acc: 0.3218 - lr: 5.0000e-05
Epoch 15/70
39/39 [============ ] - 103s 3s/step - loss: 16.8446 - acc:
0.5350 - val_loss: 16.7022 - val_acc: 0.3333 - lr: 5.0000e-05
Epoch 16/70
Epoch 00016: ReduceLROnPlateau reducing learning rate to 2.499999936844688e-05.
0.5453 - val_loss: 15.3416 - val_acc: 0.3487 - lr: 5.0000e-05
Epoch 17/70
0.5602 - val_loss: 14.7186 - val_acc: 0.3563 - lr: 2.5000e-05
Epoch 18/70
0.5705 - val_loss: 14.0835 - val_acc: 0.3716 - lr: 2.5000e-05
Epoch 19/70
0.5766 - val_loss: 13.4665 - val_acc: 0.3563 - lr: 2.5000e-05
Epoch 20/70
0.5859 - val_loss: 12.9965 - val_acc: 0.3678 - lr: 2.5000e-05
Epoch 21/70
39/39 [============= ] - 95s 2s/step - loss: 12.2648 - acc:
```

```
0.5853 - val_loss: 12.4989 - val_acc: 0.3678 - lr: 2.5000e-05
Epoch 22/70
0.5821 - val_loss: 12.0580 - val_acc: 0.3563 - lr: 2.5000e-05
Epoch 23/70
0.5837 - val_loss: 11.7204 - val_acc: 0.3870 - lr: 2.5000e-05
Epoch 24/70
0.5891 - val_loss: 11.2257 - val_acc: 0.3678 - lr: 2.5000e-05
Epoch 25/70
0.5829 - val_loss: 10.7376 - val_acc: 0.3985 - lr: 2.5000e-05
Epoch 26/70
0.5948 - val_loss: 10.4245 - val_acc: 0.3946 - lr: 2.5000e-05
Epoch 27/70
0.5859 - val_loss: 10.1512 - val_acc: 0.3793 - lr: 2.5000e-05
Epoch 28/70
0.6031 - val_loss: 9.9324 - val_acc: 0.4061 - lr: 2.5000e-05
Epoch 29/70
0.5903 - val_loss: 9.5365 - val_acc: 0.4100 - lr: 2.5000e-05
Epoch 30/70
0.6008 - val_loss: 9.2244 - val_acc: 0.4215 - lr: 2.5000e-05
39/39 [============== ] - 103s 3s/step - loss: 8.6864 - acc:
0.6091 - val_loss: 9.0418 - val_acc: 0.4330 - lr: 2.5000e-05
Epoch 32/70
39/39 [============== ] - 103s 3s/step - loss: 8.3927 - acc:
0.6164 - val_loss: 8.8639 - val_acc: 0.3602 - lr: 2.5000e-05
Epoch 33/70
0.6174 - val_loss: 8.6749 - val_acc: 0.3563 - lr: 2.5000e-05
Epoch 34/70
0.6227 - val_loss: 8.5880 - val_acc: 0.3755 - lr: 2.5000e-05
Epoch 35/70
39/39 [============== ] - 105s 3s/step - loss: 7.7224 - acc:
0.6112 - val_loss: 8.1109 - val_acc: 0.4138 - lr: 2.5000e-05
Epoch 36/70
Epoch 00036: ReduceLROnPlateau reducing learning rate to 1.249999968422344e-05.
39/39 [=============== ] - 102s 3s/step - loss: 7.5364 - acc:
0.6150 - val_loss: 8.1473 - val_acc: 0.3870 - lr: 2.5000e-05
```

```
Epoch 37/70
0.6336 - val_loss: 7.8307 - val_acc: 0.4138 - lr: 1.2500e-05
Epoch 38/70
0.6409 - val_loss: 7.7058 - val_acc: 0.4253 - lr: 1.2500e-05
Epoch 39/70
0.6358 - val_loss: 7.6868 - val_acc: 0.4291 - lr: 1.2500e-05
Epoch 40/70
0.6413 - val_loss: 7.4741 - val_acc: 0.4100 - lr: 1.2500e-05
Epoch 41/70
Epoch 00041: ReduceLROnPlateau reducing learning rate to 6.24999984211172e-06.
0.6465 - val_loss: 7.3652 - val_acc: 0.4023 - lr: 1.2500e-05
Epoch 42/70
0.6597 - val_loss: 7.3747 - val_acc: 0.4176 - lr: 6.2500e-06
Epoch 43/70
0.6550 - val_loss: 7.2937 - val_acc: 0.4215 - lr: 6.2500e-06
Epoch 44/70
39/39 [============== ] - 102s 3s/step - loss: 6.6303 - acc:
0.6568 - val_loss: 7.2149 - val_acc: 0.4023 - lr: 6.2500e-06
Epoch 45/70
0.6607 - val_loss: 7.2294 - val_acc: 0.4253 - 1r: 6.2500e-06
Epoch 46/70
Epoch 00046: ReduceLROnPlateau reducing learning rate to 3.12499992105586e-06.
0.6562 - val_loss: 7.2276 - val_acc: 0.4023 - lr: 6.2500e-06
Epoch 47/70
0.6603 - val_loss: 7.1733 - val_acc: 0.4176 - lr: 3.1250e-06
Epoch 48/70
39/39 [============== ] - 102s 3s/step - loss: 6.4842 - acc:
0.6647 - val_loss: 7.0787 - val_acc: 0.4100 - lr: 3.1250e-06
Epoch 49/70
0.6649 - val_loss: 7.0740 - val_acc: 0.4061 - lr: 3.1250e-06
Epoch 50/70
0.6603 - val_loss: 7.1167 - val_acc: 0.4023 - lr: 3.1250e-06
Epoch 51/70
```

```
Epoch 00051: ReduceLROnPlateau reducing learning rate to 1.56249996052793e-06.
    0.6556 - val_loss: 7.1132 - val_acc: 0.4023 - lr: 3.1250e-06
[940]: \# opt = tf.keras.optimizers.Adam(learning_rate=0.0001)
     \# model2D.compile(loss='sparse_categorical_crossentropy', optimizer=opt_\subseteq
     →, metrics=['acc'])
     history2D = model2D.fit(mels_train, y_train, batch_size=128, epochs=50,__
     overbose=1, validation_data=(mels_val, y_val), callbacks = [early_stop, ____
      →lr_reduction])
    Epoch 1/50
    39/39 [=============== ] - 110s 3s/step - loss: 2.1346 - acc:
    0.3454 - val_loss: 4.3059 - val_acc: 0.2529 - lr: 1.0000e-04
    Epoch 2/50
    0.3842 - val_loss: 1.6857 - val_acc: 0.3295 - lr: 1.0000e-04
    39/39 [================ ] - 110s 3s/step - loss: 1.4706 - acc:
    0.4143 - val_loss: 1.6260 - val_acc: 0.3027 - lr: 1.0000e-04
    Epoch 4/50
    39/39 [============== ] - 109s 3s/step - loss: 1.4532 - acc:
    0.4347 - val_loss: 1.7235 - val_acc: 0.2874 - lr: 1.0000e-04
    Epoch 5/50
    0.4359 - val_loss: 1.5401 - val_acc: 0.3372 - lr: 1.0000e-04
    Epoch 6/50
    39/39 [================ ] - 102s 3s/step - loss: 1.3717 - acc:
    0.4525 - val_loss: 1.6128 - val_acc: 0.2835 - lr: 1.0000e-04
    Epoch 7/50
    0.4600 - val_loss: 1.6166 - val_acc: 0.3257 - lr: 1.0000e-04
    Epoch 8/50
    39/39 [================= ] - 102s 3s/step - loss: 1.3086 - acc:
    0.4788 - val_loss: 1.6206 - val_acc: 0.3257 - lr: 1.0000e-04
    Epoch 9/50
    0.4830 - val_loss: 1.6273 - val_acc: 0.3257 - lr: 1.0000e-04
    Epoch 10/50
    Epoch 00010: ReduceLROnPlateau reducing learning rate to 7.499999810534064e-05.
    0.5067 - val_loss: 1.5841 - val_acc: 0.3372 - lr: 1.0000e-04
    Epoch 11/50
    39/39 [============== ] - 101s 3s/step - loss: 1.2279 - acc:
    0.5101 - val_loss: 1.5841 - val_acc: 0.3410 - lr: 7.5000e-05
    Epoch 12/50
```

```
0.5236 - val_loss: 1.7961 - val_acc: 0.3180 - lr: 7.5000e-05
Epoch 13/50
0.5483 - val_loss: 1.4447 - val_acc: 0.4483 - lr: 7.5000e-05
Epoch 14/50
0.5578 - val_loss: 1.6422 - val_acc: 0.3793 - lr: 7.5000e-05
Epoch 15/50
0.5831 - val_loss: 1.6323 - val_acc: 0.3908 - lr: 7.5000e-05
Epoch 16/50
39/39 [============ ] - 98s 3s/step - loss: 1.0701 - acc:
0.5837 - val_loss: 1.6098 - val_acc: 0.3755 - lr: 7.5000e-05
Epoch 17/50
0.5889 - val_loss: 1.4675 - val_acc: 0.4483 - lr: 7.5000e-05
Epoch 18/50
Epoch 00018: ReduceLROnPlateau reducing learning rate to 5.6249997214763425e-05.
39/39 [============= ] - 101s 3s/step - loss: 1.0347 - acc:
0.5998 - val_loss: 1.5620 - val_acc: 0.3640 - lr: 7.5000e-05
Epoch 19/50
39/39 [================ ] - 107s 3s/step - loss: 0.9899 - acc:
0.6209 - val_loss: 1.6272 - val_acc: 0.3908 - lr: 5.6250e-05
Epoch 20/50
0.6332 - val_loss: 1.9032 - val_acc: 0.3333 - lr: 5.6250e-05
Epoch 21/50
39/39 [============== ] - 109s 3s/step - loss: 0.9472 - acc:
0.6300 - val_loss: 1.8207 - val_acc: 0.3870 - lr: 5.6250e-05
Epoch 22/50
39/39 [=============== ] - 112s 3s/step - loss: 0.9061 - acc:
0.6512 - val_loss: 1.5841 - val_acc: 0.4138 - lr: 5.6250e-05
Epoch 23/50
Epoch 00023: ReduceLROnPlateau reducing learning rate to 4.218749927531462e-05.
39/39 [================= ] - 117s 3s/step - loss: 0.8947 - acc:
0.6570 - val_loss: 1.6974 - val_acc: 0.3908 - lr: 5.6250e-05
Epoch 24/50
0.6791 - val_loss: 1.6231 - val_acc: 0.3985 - lr: 4.2188e-05
Epoch 25/50
39/39 [============== ] - 105s 3s/step - loss: 0.8353 - acc:
0.6855 - val_loss: 1.5725 - val_acc: 0.4138 - lr: 4.2188e-05
Epoch 26/50
39/39 [============== ] - 102s 3s/step - loss: 0.8007 - acc:
0.7019 - val_loss: 1.8773 - val_acc: 0.3563 - lr: 4.2188e-05
Epoch 27/50
```

```
39/39 [=============== ] - 103s 3s/step - loss: 0.7954 - acc:
0.7041 - val_loss: 1.6710 - val_acc: 0.4061 - lr: 4.2188e-05
Epoch 28/50
Epoch 00028: ReduceLROnPlateau reducing learning rate to 3.164062582072802e-05.
39/39 [============== ] - 108s 3s/step - loss: 0.7809 - acc:
0.7001 - val_loss: 1.6689 - val_acc: 0.4100 - lr: 4.2188e-05
Epoch 29/50
0.7209 - val_loss: 1.7262 - val_acc: 0.3870 - lr: 3.1641e-05
Epoch 30/50
0.7262 - val_loss: 1.5889 - val_acc: 0.4521 - lr: 3.1641e-05
Epoch 31/50
39/39 [=============== ] - 112s 3s/step - loss: 0.7395 - acc:
0.7268 - val_loss: 1.6569 - val_acc: 0.3946 - lr: 3.1641e-05
Epoch 32/50
39/39 [============== ] - 114s 3s/step - loss: 0.6962 - acc:
0.7395 - val_loss: 1.6024 - val_acc: 0.4521 - lr: 3.1641e-05
Epoch 33/50
39/39 [================== ] - 112s 3s/step - loss: 0.6754 - acc:
0.7492 - val_loss: 1.7905 - val_acc: 0.3602 - lr: 3.1641e-05
Epoch 34/50
0.7540 - val_loss: 1.6673 - val_acc: 0.4406 - lr: 3.1641e-05
Epoch 35/50
Epoch 00035: ReduceLROnPlateau reducing learning rate to 2.3730469365546014e-05.
39/39 [=============== ] - 116s 3s/step - loss: 0.6521 - acc:
0.7635 - val_loss: 1.6467 - val_acc: 0.4406 - lr: 3.1641e-05
Epoch 36/50
0.7690 - val_loss: 1.7007 - val_acc: 0.4100 - lr: 2.3730e-05
Epoch 37/50
39/39 [================== ] - 110s 3s/step - loss: 0.6335 - acc:
0.7656 - val_loss: 1.7215 - val_acc: 0.4061 - lr: 2.3730e-05
Epoch 38/50
39/39 [================ ] - 107s 3s/step - loss: 0.6249 - acc:
0.7650 - val_loss: 1.7074 - val_acc: 0.4291 - lr: 2.3730e-05
Epoch 39/50
39/39 [============== ] - 103s 3s/step - loss: 0.6077 - acc:
0.7821 - val_loss: 1.6960 - val_acc: 0.3946 - lr: 2.3730e-05
39/39 [================ ] - 104s 3s/step - loss: 0.6071 - acc:
0.7732 - val_loss: 1.7206 - val_acc: 0.4636 - lr: 2.3730e-05
Epoch 41/50
39/39 [================ ] - 101s 3s/step - loss: 0.5743 - acc:
0.7928 - val_loss: 1.7366 - val_acc: 0.4023 - lr: 2.3730e-05
```

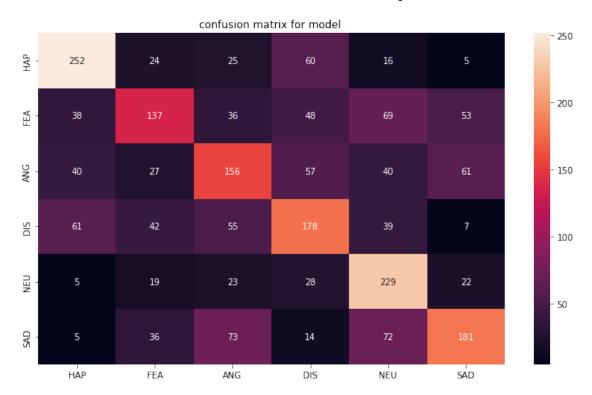
```
Epoch 42/50
0.7878 - val_loss: 2.0084 - val_acc: 0.3563 - lr: 2.3730e-05
39/39 [============== ] - 108s 3s/step - loss: 0.5705 - acc:
0.7955 - val_loss: 1.7986 - val_acc: 0.4291 - lr: 2.3730e-05
39/39 [================ ] - 115s 3s/step - loss: 0.5426 - acc:
0.8080 - val_loss: 1.6625 - val_acc: 0.4598 - lr: 2.3730e-05
Epoch 45/50
Epoch 00045: ReduceLROnPlateau reducing learning rate to 1.7797852706280537e-05.
0.7971 - val_loss: 1.7655 - val_acc: 0.4253 - lr: 2.3730e-05
Epoch 46/50
39/39 [============== ] - 108s 3s/step - loss: 0.5342 - acc:
0.8090 - val_loss: 1.8823 - val_acc: 0.3870 - lr: 1.7798e-05
Epoch 47/50
39/39 [============== ] - 102s 3s/step - loss: 0.5313 - acc:
0.8086 - val_loss: 1.8564 - val_acc: 0.4521 - lr: 1.7798e-05
Epoch 48/50
0.8222 - val_loss: 1.7960 - val_acc: 0.4521 - lr: 1.7798e-05
Epoch 49/50
39/39 [============== ] - 108s 3s/step - loss: 0.5178 - acc:
0.8096 - val_loss: 1.8814 - val_acc: 0.4138 - lr: 1.7798e-05
Epoch 50/50
39/39 [============= ] - 106s 3s/step - loss: 0.5097 - acc:
0.8171 - val_loss: 1.7588 - val_acc: 0.4674 - lr: 1.7798e-05
```

## 3. TESTING THE 2D CNN MODEL ON THE 2-DIMENSIONAL FEATURE MATRICES

```
[941]: loss,accuracy=model2D.evaluate(mels_test,y_test,verbose=0)
    print(f'Test Loss: {loss}')
    print(f'Test Accuracy: {accuracy*100}%')
    y_pred = model2D.predict(mels_test)
    y_pred = np.argmax(y_pred, axis=1)
    conf=confusion_matrix(y_test,y_pred)
    cm=pd.DataFrame(
        conf,index=[i for i in set(labels)],
        columns=[i for i in set(labels)]
    )
    plt.figure(figsize=(12,7))
    ax=sns.heatmap(cm,annot=True,fmt='d')
    ax.set_title(f'confusion matrix for model ')
    plt.show()
```

Test Loss: 1.5859235525131226 Test Accuracy: 50.73891878128052%

70/70 [======] - 12s 149ms/step



```
[943]: from sklearn.metrics import f1_score,precision_score,recall_score
prec=precision_score(y_test,y_pred,average='weighted')
rec=recall_score(y_test,y_pred,average='weighted')
f1score=f1_score(y_test,y_pred,average='weighted')
print(f'Test precision: {prec}')
print(f'Test recall: {rec}')
print(f'Test f1-score: {f1score}')
```

Test precision: 0.5067107992243727 Test recall: 0.5073891625615764 Test f1-score: 0.5023103752175271

fig.show()