# **SPEECH EMOTION ANALYZER**

### A PROJECT REPORT

Submitted by

# SANKALP JAIN [ RA1911026010119 ] AMULYA [ RA1911026010114 ] ENZO DELOYE [VA2111001010001]

*Under the guidance of* 

Dr. A. Revathi

(Assistant Professor, Department of Computational Intelligence)

in partial fulfillment for the award of the degree

of

### **BACHELOR OF TECHNOLOGY**

in

## **COMPUTATIONAL INTELLIGENCE**

of

## FACULTY OF ENGINEERING AND TECHNOLOGY



S.R.M. Nagar, Kattankulathur, Kancheepuram District

**APRIL 2022** 

# SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

(Under Section 3 of UGC Act, 1956)

### **BONAFIDE CERTIFICATE**

Certified that this project report titled "SPEECH EMOTION ANALYZER" is the bonafide work of "SANKALP JAIN [ RA1911026010119 ]", who carried out the project work under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

**SIGNATURE** 

**SIGNATURE** 

Dr. A. Revathi **GUIDE**Assistant Professor
Dept. of Computational Intelligence

Dr. R. Annie Uthra, Professor **HEAD OF THE DEPARTMENT** Dept. of Computational Intelligence

Signature of the Internal Examiner

Signature of the External Examiner

# **ACKNOWLEDGEMENTS**

I would like to express my deepest gratitude to my guide, Dr. A. Revathi, her valuable guidance, consistent encouragement, personal caring, timely help and providing me with an excellent atmosphere for doing the project. All through the work, in spite of her busy schedule, she has extended cheerful and cordial support to me for completing this project work.

**SANKALP JAIN** 

## **ABSTRACT**

The problem of speech emotion recognition can be solved by analyzing one or more of these features. Choosing to follow the lexical features would require a transcript of the speech which would further require an additional step of text extraction from speech if one wants to predict emotions from real-time audio. Similarly, going forward with analyzing visual features would require the excess to the video of the conversations which might not be feasible in every case while the analysis on the acoustic features can be done in real-time while the conversation is taking place as we'd just need the audio data for accomplishing our task. We checked the distribution of labels with respect to emotions and gender and found that while the data is balanced for six emotions viz. neutral, happy, sad, angry, fear and disgust, the number of labels was slightly less for **surprise** and negligible for **boredom**. While the slightly fewer instances of surprise can be overlooked on account of it being a rarer emotion, the imbalance against boredom was rectified later by clubbing sadness and boredom together due to them being similar acoustically. It's also worth noting that boredom could have been combined with neutral emotion but since both **sadness** and **boredom** are negative emotions, it made more sense to combine them. The idea behind creating this project was to build a machine learning model that could detect emotions from the speech we have with each other all the time. Nowadays personalization is something that is needed in all the things we experience everyday. So why not have an emotion detector that will gauge your emotions and in the future recommend you different things based on your mood.

This can be used by multiple industries to offer different services like marketing companies suggesting you to buy products based on your emotions, the automotive industry can detect the person's emotions and adjust the speed of autonomous cars as required to avoid any collisions etc.

## INTRODUCTION

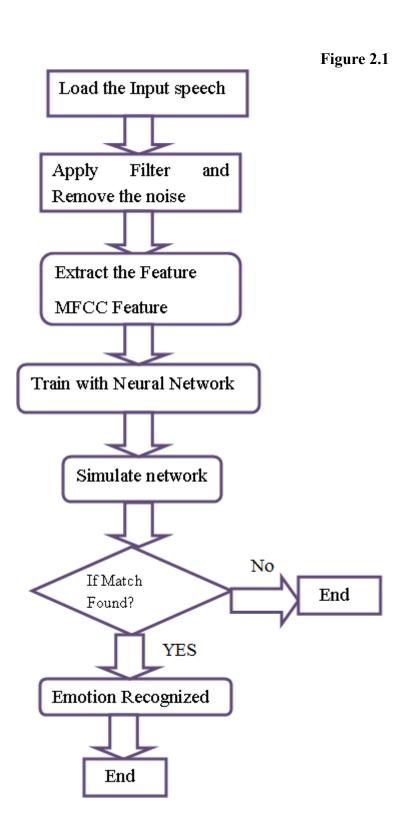
## 1.1 **OBJECTIVE**

The project's goal is to detect emotions through speech using Natural Language Processing and Machine Learning algorithms. The idea behind creating this project was to build a machine learning model that could detect emotions from the speech we have with each other all the time. Nowadays personalization is something that is needed in all the things we experience everyday.

# 1.2 SCOPE

There is big scope for this project. It will help in determining certain emotions through voice which will help organizations to determine certainty of emotion more accurately with visual features .Speech emotion recognition has been formulated as a pattern recognition problem that mainly involves feature extraction and emotion classification. Speech emotion recognition has found increasing applications in practice, e.g., in security, medicine, entertainment, education.

# ARCHITECTURE DIAGRAM



# **IMPLEMENTATION**

## Importing the required libraries

```
In [1]:

import librosa display
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.pyplot as plt
import matplotlib.pyplot import specgram
import keras. preprocessing import sequence
from keras.notels import Sequential
from keras.layers import Dense, Embedding
from keras.sultis import to_categorical
from keras.sultis import to_categorical
from keras.sultis import to_categorical
from keras.layers import to_the_flatten_Doopout, Activation
from keras.layers import ConvID, MaxPoolingID, AveragePoolingID
from keras.sultis import ModelCheckpoint
from keras.callbacks import Model
from keras.callbacks import Model
from keras.callbacks import Model
from keras.callbacks import ConvID, MaxPoolingID, AveragePoolingID

import os

In [3]:

import os

In [4]:

myliste os.listdir('RawOata/')

Using TensorFlow backend.

Out[5]:

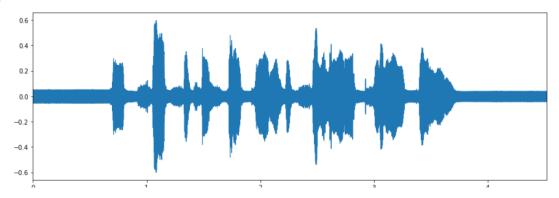
type(mylist)

Out[5]:
```

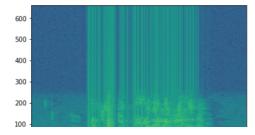
```
In [6]: print(mylist[1800])
f01 (10).wav

In [7]: print(mylist[400][6:-16])
03
```

# Plotting the audio file's waveform and its spectrogram



```
In [10]:
           import matplotlib.pyplot as plt
           import scipy.io.wavfile
           import numpy as np
           import sys
           sr,x = scipy.io.wavfile.read('RawData/f10 (2).wav')
           ## Parameters: 10ms step, 30ms window
           nstep = int(sr * 0.01)
nwin = int(sr * 0.03)
           nfft = nwin
           window = np.hamming(nwin)
           ## will take windows x[n1:n2]. generate
           ## and loop over n2 such that all frames
           ## fit within the waveform
           nn = range(nwin, len(x), nstep)
           X = np.zeros( (len(nn), nfft//2) )
           for i,n in enumerate(nn):
               xseg = x[n-nwin:n]
               z = np.fft.fft(window * xseg, nfft)
X[i,:] = np.log(np.abs(z[:nfft//2]))
           plt.imshow(X.T, interpolation='nearest',
               origin='lower
               aspect='auto')
           plt.show()
```



## Setting the labels

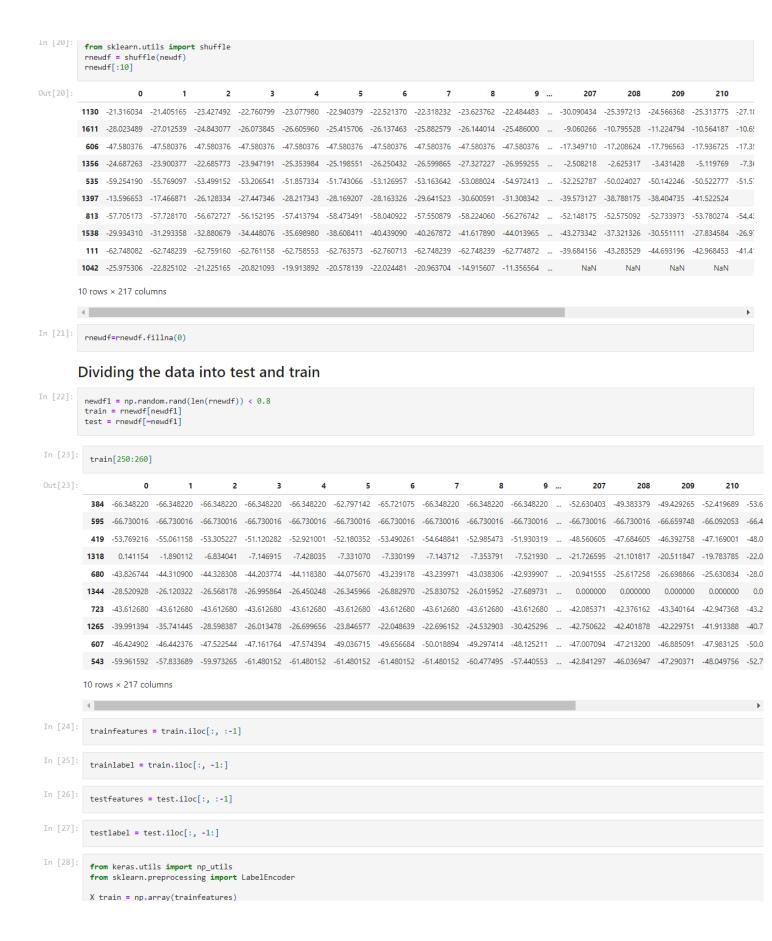
```
In [11]:
                feeling_list=[]
                for item in mylist:
    if item[6:-16]=='02' and int(item[18:-4])%2==0:
                       feeling_list.append('female_calm')

elif item[6:-16]=='02' and int(item[18:-4])%2==1:
    feeling_list.append('male_calm')

elif item[6:-16]=='03' and int(item[18:-4])%2==0:
                       feeling_list.append('female_happy')
elif item[6:-16]=='03' and int(item[18:-4])%2==1:
                              feeling_list.append('male_happy'
                       elif item[6:-16]=='04' and int(item[18:-4])%2==0:
                       feeling_list.append('female_sad')
elif item[6:-16]=='04' and int(item[18:-4])%2==1:
    feeling_list.append('male_sad')
                       elif item[6:-16]=='05' and int(item[18:-4])%2==0:
    feeling_list.append('female_angry')
elif item[6:-16]=='05' and int(item[18:-4])%2==1:
                              feeling_list.append('male_angry
                       elif item[6:-16]=='06' and int(item[18:-4])%2==0:
    feeling_list.append('female_fearful')
elif item[6:-16]=='06' and int(item[18:-4])%2==1:
                              feeling_list.append('male_fearful')
                       elif item[:1]=='a'
                              feeling_list.append('male_angry')
                       elif item[:1]=='f'
                             feeling_list.append('male_fearful')
                       elif item[:1]=='h':
                             feeling_list.append('male_happy')
                       #elif item[:1]=='n
                       #feeling_list.append('neutral')
elif item[:2]=='sa':
                             feeling_list.append('male_sad')
```

```
In [12]: labels = pd.DataFrame(feeling_list)
In [13]: labels[:10]
```

```
In [13]: labels[:10]
Out[13]:
                                                       0 male_calm
                                                       1 female_calm
                                                                           male calm
                                                       3 female_calm
                                                                              male_calm
                                                       5 female_calm
                                                                            male_calm
                                                       7 female_calm
                                                                      male calm
                                                       9 female_calm
                                                    Getting the features of audio files using librosa
 In [14]:
                                                         df = pd.DataFrame(columns=['feature'])
                                                            bookmark=0
                                                             for index,y in enumerate(mylist):
                                                                                  \textbf{if} \  \, \texttt{mylist}[\texttt{index}][6:-16]! = \texttt{'01'} \  \, \texttt{and} \  \, \texttt{mylist}[\texttt{index}][6:-16]! = \texttt{'08'} \  \, \texttt{and} \  \, \texttt{mylist}[\texttt{index}][:2]! = \texttt{'su'} \  \, \texttt{and} \  \, \texttt{mylist}[\texttt{index}][:1]! = \texttt{'n'} \  \, \texttt{not} \  
                                                                                                         X, sample_rate = librosa.load('RawData/'+y, res_type='kaiser_fast',duration=2.5,sr=22050*2,offset=0.5)
sample_rate = np.array(sample_rate)
                                                                                                          mfccs = np.mean(librosa.feature.mfcc(y=X,
                                                                                                                                                                                                                                                                                                                    sr=sample_rate,
                                                                                                                                                                                                                                                                                                                    n mfcc=13),
                                                                                                                                                                                                  axis=0)
                                                                                                         feature = mfccs
#[float(i) for i in feature]
#feature1=feature[:135]
                                                                                                          df.loc[bookmark] = [feature]
                                                                                                         bookmark=bookmark+1
                                                                                                                                                                                                                                                                feature
                                                         0 [-70.2677641611, -70.2677641611, -70.267764161...
                                                         1 [-65.7076524007, -65.7076524007, -63.114722422...
                                                          2 [-65.4824988827, -65.4824988827, -65.482498882...
                                                         3 [-64.5284491035, -64.5284491035, -64.528449103...
                                                          4 [-62.3643105275, -59.9347251381, -61.869599961...
   In [16]: df3 = pd.DataFrame(df['feature'].values.tolist())
                                                             newdf = pd.concat([df3,labels], axis=1)
   In [18]:
                                                             rnewdf = newdf.rename(index=str, columns={"0": "label"})
   In [19]:
                                                             rnewdf[:5]
   Out[19]:
                                                          0 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267764 -70.267
                                                         1 -65.707652 -65.707652 -63.114722 -61.51899 -61.097138 -63.424602 -63.720067 -56.854608 -55.168972 -54.640002 ... -39.792147 -40.613166 -41.209201 -41.439204 -43.99428
                                                          2 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.482499 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.48249 -65.4824
                                                         3 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.52849 -64.528449 -64.528449 -64.528449 -64.528449 -64.528449 -64.5284
                                                          4 -62.364311 -59.934725 -61.869600 -67.495764 -71.071811 -65.679826 -63.394396 -65.503349 -61.856639 -60.005421 ... -39.071328 -41.897121 -40.865430 -38.290605 -36.37235
                                                     5 rows x 217 columns
```



```
from keras.utils import np_utils
           from sklearn.preprocessing import LabelEncoder
           X_train = np.array(trainfeatures)
           y_train = np.array(trainlabel)
           X_test = np.array(testfeatures)
y_test = np.array(testlabel)
           1b = LabelEncoder()
           y_train = np_utils.to_categorical(lb.fit_transform(y_train))
           y_test = np_utils.to_categorical(lb.fit_transform(y_test))
          C:\ProgramData\Anaconda3\lib\site-packages\sklearn\preprocessing\label.py:111: DataConversionWarning: A column-vector y was passed when a 1d array was e
          xpected. Please change the shape of y to (n_samples, ), for example using ravel(). y = column_or_1d(y, warn=True)
In [29]: y_train
..., [0., 0., 0., ..., 1., 0., 0.], [0., 0., 0., ..., 1., 0., 0.], [0., 0., 0., 0., 0., 0., 0.]]
In [30]: X_train.shape
Out[30]: (1378, 216)
```

### Changing dimension for CNN model

```
x_traincnn =np.expand_dims(X_train, axis=2)
                  x_testcnn= np.expand_dims(X_test, axis=2)
In [45]:
                 model = Sequential()
                  model.add(Conv1D(256, 5,padding='same',
                  input_shape=(216,1))
model.add(Activation('relu'))
model.add(Conv1D(128, 5,padding='same'))
                  model.add(Activation('relu'))
model.add(Dropout(0.1))
                  model.add(MaxPooling1D(pool_size=(8)))
                 model.add(maxPoolingID(pool_s1ze=(8)))
model.add(ConvID(128, 5,padding='same',))
model.add(Activation('relu'))
#model.add(ConvID(128, 5,padding='same',))
#model.add(ConvID(128, 5,padding='same',))
#model.add(Activation('relu'))
#model.add(Activation('relu'))
#model.add(Poseput(0.2))
                  #model.add(Dropout(0.2))
model.add(Conv1D(128, 5,padding='same',))
model.add(Activation('relu'))
                  model.add(Flatten())
                  model.add(Dense(10))
                  model.add(Activation('softmax'))
                  opt = keras.optimizers.rmsprop(lr=0.00001, decay=1e-6)
```

```
In [46]: model.summary()
```

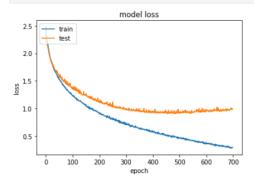
| Output Shape     | Param #   |
|------------------|---|
| (None, 216, 256) | 1536  |
| (None, 216, 256) | 0   |
| (None, 216, 128) | 163968  |
| (None, 216, 128) | 0   |
| (None, 216, 128) | 0   |
| (None, 27, 128)  | 0   |
| (None, 27, 128)  | 82048   |
| (None, 27, 128)  | 0   |
| (None, 27, 128)  | 82048   |
| (None, 27, 128)  | 0   |
| (None, 3456)     | 0   |
| (None, 10)       | 34570   |
| (None, 10)       | 0   |
|                  | (None, 216, 256) (None, 216, 128) (None, 216, 128) (None, 216, 128) (None, 27, 128) |

```
In [47]:
         model.compile(loss='categorical_crossentropy', optimizer=opt,metrics=['accuracy'])
```

#### Removed the whole training part for avoiding unnecessary long epochs list

```
{\tt cnnhistory=model.fit}(x\_{\tt traincnn},\ y\_{\tt train},\ {\tt batch\_size=16},\ {\tt epochs=700},\ {\tt validation\_data=}(x\_{\tt testcnn},\ y\_{\tt test}))
```

```
In [37]:
                    plt.plot(cnnhistory.history['loss'])
plt.plot(cnnhistory.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
                     plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



### Saving the model

```
model_name = 'Emotion_Voice_Detection_Model.h5'
save_dir = os.path.join(os.getcwd(), 'saved_models')
# Save model and weights
if not os.path.isdir(save_dir):
    os.makedirs(save_dir)
model_path = os.path.join(save_dir, model_name)
model.save(model_path)
print('Saved trained model at %s ' % model_path)
```

#### Loading the model

```
In [137...
    # Loading json and creating model
    from keras.models import model_from_json
    json_file = open('model.json', 'r')
    loaded_model_json = json_file.read()
    json_file.close()
    loaded_model = model_from_json(loaded_model_json)
    # Load weights into new model.
    loaded_model.load_weights("saved_models/Emotion_Voice_Detection_Model.h5")
    print("Loaded model from disk")

# evaluate Loaded model on test data
    loaded_model.compile(loss='categorical_crossentropy', optimizer=opt, metrics=['accuracy'])
    score = loaded_model.evaluate(x_testcnn, y_test, verbose=0)
    print("%s: %.2f%%" % (loaded_model.metrics_names[1], score[1]*100))

Loaded model from disk
acc: 72.73%
```

#### Predicting emotions on the test data

```
In [138...
                preds = loaded_model.predict(x_testcnn,
                                                   batch size=32,
                                                   verbose=1)
               319/319 [-----] - 0s
In [139...
               preds
                                                                               1.13181663e-19, ...,
1.14132257e-04],
               array([[ 3.49815641e-12, 1.18043589e-10,
Out[139...
                             1.80016723e-05,
                                                      7.36836637e-06,
                        1.88016723e-05, 7.3683653/e-05,

[ 3.87504338e-16, 5.73074694e-23,

1.75147681e-04, 1.85760673e-05,

[ 8.39285008e-07, 3.43896300e-11,

9.93317604e-01, 1.99900052e-04,
                                                                               1.31673211e-14, ...,
9.99805748e-01],
5.38965035e-03, ...,
                                                                               1.05243188e-03j,
                         [ 3.49616457e-04, 1.94651744e-04,
                                                                               6.65218568e-06, ...,
                             1.67340226e-02,
                                                     6.44345134e-02,
                                                                                9.10043001e-01],
                                                                               6.03030126e-12, ...
2.34207995e-02],
                                                     1.59581254e-11,
9.64888096e-01,
                         [ 4.23396705e-06,
                             6.36715861e-03,
                                                                               0.00000000e+00, ...,
6.36476927e-10]], dtype=float32)
                         [ 3.69524572e-31,
                                                      0.00000000e+00,
                             5.24333927e-07,
                                                     9.99998808e-01,
                preds1=preds.argmax(axis=1)
In [116...
                preds1
1, 7, 2, 5, 8, 1, 8, 4, 4, 8, 5, 2, 9, 6, 6, 3, 9, 5, 9, 6, 1, 7, 5, 7, 8, 4, 7, 5, 7, 3, 5, 6, 8, 7, 1, 6, 0, 0, 4,
                                                                                9, 5, 6, 0, 5, 9, 0, 8, 7, 4,
9, 2, 5, 6, 6, 4, 2, 1, 8, 2,
7, 4, 4, 4, 4, 4, 0, 8, 1, 6,
                         7, 4, 8, 7, 8, 2, 9, 6, 2, 7, 8, 3, 9, 9, 7, 2, 5, 7, 2, 9, 5, 5, 7, 8, 5, 6, 8, 1, 2, 5, 9, 4, 5, 5, 6, 7, 8, 7, 0, 9, 5, 9, 5, 9, 7, 8, 1, 2, 8, 7, 7, 5, 7, 8, 7, 7, 4, 5, 8, 5, 0, 0, 5, 9, 8, 8], dtype=int64)
                abc = preds1.astype(int).flatten()
In [118...
                predictions = (lb.inverse_transform((abc)))
```

```
In [119... preddf = pd.DataFrame({'predictedvalues': predictions})
            preddf[:10]
 Out[119... predictedvalues
            0
                   male_calm
           1 male_sad
           3 female_calm
            4 male_fearful
            5 male_happy
            6 female_calm
            7 female_fearful
               male_angry
            9 male_happy
 In [120...
            actual=y_test.argmax(axis=1)
abc123 = actual.astype(int).flatten()
actualvalues = (lb.inverse_transform((abc123)))
 Out[121...
             actualvalues
              male_calm
          1 male_sad
          2 male_fearful
          3 female_fearful
          4 male_fearful
          5 male_happy
          6 female_calm
          7 female_angry
          8 male_angry
          9 male_happy
In [122... finaldf = actualdf.join(preddf)
```

## Actual v/s Predicted emotions

In [128... finaldf[170:180]

Out[128... actualvalues predictedvalues

|     | actualvalues   | predictedvalues |
|-----|----------------|-----------------|
| 170 | female_fearful | female_fearful  |
| 171 | male_angry     | male_angry      |
| 172 | male_fearful   | male_fearful    |
| 173 | male_happy     | male_happy      |
| 174 | female_happy   | female_happy    |
| 175 | female_angry   | female_angry    |
| 176 | female_angry   | female_sad      |
| 177 | male_sad       | male_calm       |
| 178 | male_angry     | male_calm       |
| 179 | male sad       | male sad        |

Recording live audio file -:

```
In [20]: import pyaudio
            import wave
            CHUNK = 1024
           FORMAT = pyaudio.paInt16 #paInt8
CHANNELS = 2
           RATE = 44100 #sample rate
RECORD_SECONDS = 4
            WAVE_OUTPUT_FILENAME = "output10.wav"
            p = pyaudio.PyAudio()
            stream = p.open(format=FORMAT,
                              channels=CHANNELS,
                              rate=RATE.
                              input=True
                              frames_per_buffer=CHUNK) #buffer
            print("* recording")
            frames = []
            for i in range(0, int(RATE / CHUNK * RECORD_SECONDS)):
                data = stream.read(CHUNK)
frames.append(data) # 2 bytes(16 bits) per channel
            print("* done recording")
            stream.stop_stream()
            stream.close()
            p.terminate()
            wf = wave.open(WAVE_OUTPUT_FILENAME, 'wb')
            wf.setnchannels(CHANNELS)
           wf.setsampwidth(p.get_sample_size(FORMAT))
wf.setframerate(RATE)
            wf.writeframes(b''.join(frames))
           wf.close()
           * recording
* done recording
```

### Predictions live demonstrations-

#### Live Demo

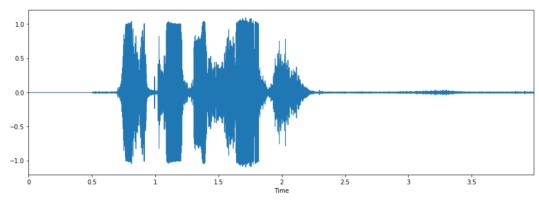
The file 'output10.wav' in the next cell is the file that was recorded live using the code in AudioRecoreder notebook found in the repository

```
In [485... data, sampling_rate = librosa.load('output10.wav')

In [486... % pylab inline import os import pandas as pd import librosa import glob

plt.figure(figsize=(15, 5))
    librosa.display.waveplot(data, sr=sampling_rate)

Out[486... vmatplotlib.collections.PolyCollection at 0x23b43824048>
```



```
In [487...
              #Livedf= pd.DataFrame(columns=['feature'])
X, sample_rate = librosa.load('output10.wav', res_type='kaiser_fast',duration=2.5,sr=22050*2,offset=0.5)
              sample_rate = np.array(sample_rate)
mfccs = np.mean(librosa.feature.mfcc(y=X, sr=sample_rate, n_mfcc=13),axis=0)
featurelive = mfccs
              livedf2 = featurelive
 In [488...
            livedf2= pd.DataFrame(data=livedf2)
 In [489... livedf2 = livedf2.stack().to_frame().T
 In [490...
 Out[490...
                                                                        0
                                                                                                                      0
                                                                                                                                                                         0
                         0
                                     0
                                                0
                                                            0
                                                                                    0
                                                                                                0
                                                                                                          0
                                                                                                                                  0 ...
                                                                                                                                                0
                                                                                                                                                             0
                                                                                                                                                                                     0
                                                                                                                                                                                                 0
              0 -18.203564 -21.471836 -22.52221 -21.71259 -22.264288 -20.707904 -21.726444 -21.76865 -24.302736 -22.250634 ... -24.273819 -24.639939 -24.929152 -24.43919 -25.210171
             1 rows × 216 columns
             4
 In [491... twodim= np.expand_dims(livedf2, axis=2)
 In [492... livepreds = loaded_model.predict(twodim,
                                            batch_size=32,
                                            verbose=1)
             1/1 [-----] - 0s
In [493...
            livepreds
            array([[ 9.24052530e-22, 0.00000000e+00, 3.62402176e-26, 1.30680162e-36, 4.47264152e-28, 1.00000000e+00, 1.80208343e-30, 2.76873961e-27, 3.62227194e-23,
                        1.80208343e-30, 2.76873961e-27, 1.67396652e-11]], dtype=float32)
In [494...
             livepreds1=livepreds.argmax(axis=1)
In [495...
             liveabc = livepreds1.astype(int).flatten()
In [496...
             livepredictions = (lb.inverse_transform((liveabc)))
             livepredictions
Out[496... array(['male_angry'], dtype=object)
```

### Predicted vs actual values-:

#### Actual v/s Predicted emotions

| In [128 fi | finaldf[170:180] |                 |  |
|------------|------------------|-----------------|--|
| Out[128    | actualvalues     | predictedvalues |  |
| 170        | female_fearful   | female_fearful  |  |
| 171        | l male_angry     | male_angry      |  |
| 172        | male_fearful     | male_fearful    |  |
| 173        | male_happy       | male_happy      |  |
| 174        | female_happy     | female_happy    |  |
| 179        | female_angry     | female_angry    |  |
| 176        | female_angry     | female_sad      |  |
| 177        | male_sad         | male_calm       |  |
| 178        | male_angry       | male_calm       |  |
| 179        | male_sad         | male_sad        |  |

#### Made use of two different datasets:

1. [RAVDESS](https://zenodo.org/record/1188976).

This dataset includes around 1500 audio file input from 24 different actors. 12 male and 12 female where these actors record short audios in 8 different emotions i.e 1 = neutral, 2 = calm, 3 = happy, 4 = sad, 5 = angry, 6 = fearful, 7 = disgust, 8 = surprised.

Each audio file is named in such a way that the 7th character is consistent with the different emotions that they represent.

2. [SAVEE](http://kahlan.eps.surrey.ac.uk/savee/Download.html).

This dataset contains around 500 audio files recorded by 4 different male actors. The first two characters of the file name correspond to the different emotions that they portray.

#### **CONCLUSION**

Building the model was a challenging task as it involved a lot of trial and error methods, tuning etc. The model is very well trained to distinguish between male and female voices and it distinguishes with 100% accuracy. The model was tuned to detect emotions with more than 70% accuracy. Accuracy can be increased by including more audio files for training.

#### References

- 1 https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8805181
- 2 https://www.frontiersin.org/articles/10.3389/fcomp.2020.00014/full
- 3 https://link.springer.com/content/pdf/bbm%3A978-3-319-49220-9%2F1.pdf
- 4 https://www.javatpoint.com/nlp
- 5 https://zenodo.org/record/1188976
- 6 http://kahlan.eps.surrey.ac.uk/savee/Download.html