Audio_preprocessing

June 1, 2022

1 Preprocessing

In this part of the project process, you are required to load, understand the types and formats, explore, and visualize the data. Make sure you have a clear understanding of the inputs and outputs of your model. You may need to do data augmentation to train a model that is robust against small changes.

[1]:
```
import os
import csv
from pathlib import Path
import librosa   #for audio processing
import itertools
import pandas as pd
import random
import IPython.display as ipd
import matplotlib.pyplot as plt
import plotly.express as px
from IPython.display import Image
import plotly.io as pio
import numpy as np
from scipy.io import wavfile #for audio processing
import warnings
import torch
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
warnings.filterwarnings("ignore")
import os,sys
sys.path.append(os.path.abspath(os.path.join('../scripts')))
from clean import Clean
from eda import EDA
```

[2]:
```
cleaning_audios = Clean()
```

```
2022-06-01 05:46:08,572:logger:Successfully initialized clean class
```

objective: load audio file

result: We are able to download audio files from the swahili or the amharics wav datasets. and we are able to convert the data to the format that we want. In our case we use the load_audios method in the Clean class

[3]:
```
swahilis = cleaning_audios.load_audios('swahili','train',start=0,stop=2)
amharics = cleaning_audios.load_audios('amharics','train',start=0,stop=2)
```

```
2022-06-01 05:46:09,935:logger:successful in operation of loading audios
2022-06-01 05:46:11,105:logger:successful in operation of loading audios
```

This returns an audio time series as a numpy array with a default sampling rate(sr) of 22KHZ mono. We can change this behavior by resampling at 44.1KHz.

Playing Audio:

Using,IPython.display.Audio you can play the audio in your jupyter notebook.

[4]:
```
audio,rate,duration = swahilis[0]
ipd.Audio(audio, rate=rate)
```

[4]:
```
<IPython.lib.display.Audio object>
```

2 Transcription preprocessing

objective: load transcriptions

result: We were able to load transcriptions as given both from the swahili dataset and amharic dataset, and not only were we loading transcriptions but also showed plots of the frequency of the transcriptions,For the case of Amharic, most of the transcriptions are a single characters, which are actually parts of the word.For the case of the Swahili text we notice that the stop words are what form a major chunk of the data, this means we got to do more cleaning so that we can be able to derive more meaningful results from the data

[5]:
```
swahili_train_labels = cleaning_audios.get_labels('swahili','train')
swahili_test_labels = cleaning_audios.get_labels('swahili','test')
amharic_train_labels = cleaning_audios.get_labels('amharic','train')
amharic_test_labels = cleaning_audios.get_labels('amharic','test')
```

[6]:
```
swahili_text_data, swahili_label_data = cleaning_audios.read_data('../data/
 ↪swahili_train_text.txt', '../data/swahili_test_text.txt',
                                                  swahili_train_labels,␣
 ↪swahili_test_labels)
amharic_text_data, amharic_label_data = cleaning_audios.read_data('../data/
 ↪amharic_train_text.txt', '../data/amharic_test_text.txt',
                                                  amharic_train_labels,␣
 ↪amharic_test_labels)
```

```
2022-06-01 05:46:11,406:logger:successfully read file
2022-06-01 05:46:11,412:logger:successfully read file
2022-06-01 05:46:12,488:logger:Successfully read the data
2022-06-01 05:46:12,503:logger:successfully read file
```

```
2022-06-01 05:46:12,506:logger:successfully read file
2022-06-01 05:46:13,540:logger:Successfully read the data
```

[7]:
```
swahili_data = pd.DataFrame({'key': swahili_label_data, 'text':␣
↪swahili_text_data})
amharic_data = pd.DataFrame({'key': amharic_label_data, 'text':␣
↪amharic_text_data})
```

[8]:
```
swahili_recordings = cleaning_audios.load_audios('swahili',files=swahili_data.
↪key.to_list()[0:10])
amharic_recordings = cleaning_audios.load_audios('amharic',files=amharic_data.
↪key.to_list()[0:10])
swahili_data_df = swahili_data.head(10)
amharic_data_df = amharic_data.head(10)
```

```
2022-06-01 05:46:15,381:logger:successful in operation of loading audios
2022-06-01 05:46:18,658:logger:successful in operation of loading audios
```

[9]:
```
durations = []
for recording in swahili_recordings:
    _,_,duration = recording
    durations.append(duration)
swahili_data_df['duration'] = durations
```

[10]:
```
durations = []
for recording in amharic_recordings:
    _,_,duration = recording
    durations.append(duration)
amharic_data_df['duration'] = durations
```

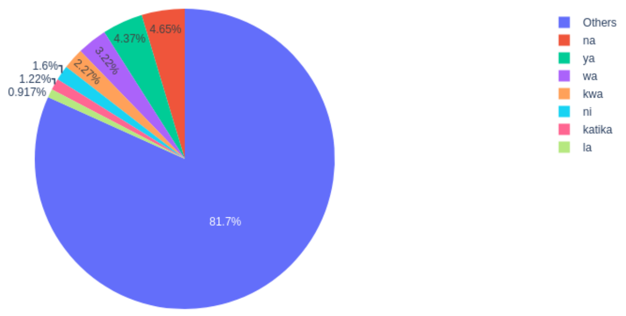
[11]:
```
y = [x in swahili_test_labels for x in swahili_data.key]
swahili_data["category"] = ["Test" if i else "Train" for i in y]
y = [x in amharic_test_labels for x in amharic_data.key]
amharic_data["category"] = ["Test" if i else "Train" for i in y]
```

[12]:
```
words_in_data = pd.DataFrame(' '.join(swahili_data['text']).split())
words_in_data.columns = ['word']
words_data = words_in_data.groupby(['word']).agg({'word': 'count'})
words_data.columns = ['counts']
words_data.reset_index(inplace=True)
words_data = words_data.sort_values("counts", ascending=False)
```

[13]:
```
words_data.loc[words_data['counts'] < 1000, 'word'] = 'Others'
fig = px.pie(words_data, values='counts', names='word', title='Distribution of␣
↪Words', width=800, height=500)
Image(pio.to_image(fig, format='png', width=1200))
```

[13]:

Distribution of Words

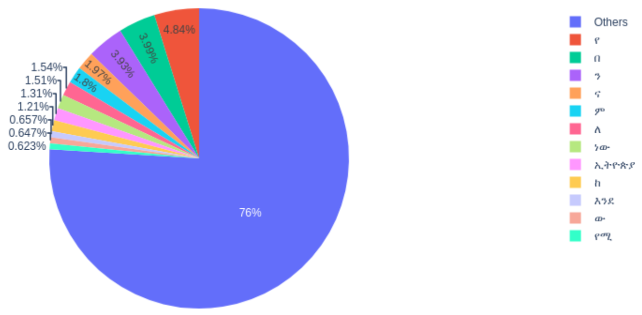


```
[14]: words_in_data = pd.DataFrame(' '.join(amharic_data['text']).split())
      words_in_data.columns = ['word']
      words_data = words_in_data.groupby(['word']).agg({'word': 'count'})
      words_data.columns = ['counts']
      words_data.reset_index(inplace=True)
      words_data = words_data.sort_values("counts", ascending=False)
```

```
[15]: words_data.loc[words_data['counts'] < 1000, 'word'] = 'Others'
      fig = px.pie(words_data, values='counts', names='word', title='Distribution of␣
       ↪Words', width=800, height=500)
      Image(pio.to_image(fig, format='png', width=1200))
```

[15]:

Distribution of Words



3 Converting Channels

objective:Convert into channels Some of the sound files are mono (ie. 1 audio channel) while most of them are stereo (ie. 2 audio channels). Since the Neural network model expects all items to have the same dimensions, we will convert the mono files to stereo, by duplicating the first channel to the second

result: we used a function that we created called convert_channels, where we shift the audio data to the left in the array forming a duplicate of the original, and then saving the incoming file. What does converting the data into stereo help for us in this case. We realize the inputs shall be even when we start doing predictive modeling for the texts, and therefore it is important to understand that concept

[16]:
```
cleaning_audios.convert_channels("../data/amharic_train_wav/tr_10000_tr097082.
 ↪wav","../data/amharic_train_wav/tr_10000_tr097082_stereod.wav")
```

```
2022-06-01 05:46:24,812:logger:succesfully converted to stereo
```

```
_wave_params(nchannels=1, sampwidth=2, framerate=16000, nframes=145408,
comptype='NONE', compname='not compressed')
```

4 Standardizing

Objective: Standardize sampling rate We must standardize and convert all audio to the same sampling rate so that all arrays have the same dimensions.

Result: The sample rate is the number of samples of audio carried per second, measured in Hz or kHz. How do we standardize our sample rates in the data, we can convert the sampling rate so that we can have our data to be consistent, for this case we chose a standard rate of 44,100Hz which is better because by choosing a higher frequency we reduce outliers.

[17]:
```
rates = []
for recording in swahili_recordings:
    _,rate,_ = recording
    rates.append(rate)
swahili_data_df['rate'] = rates
```

[18]:
```
rates = []
for recording in amharic_recordings:
    _,rate,_ = recording
    rates.append(rate)
amharic_data_df['rate'] = rates
```

5 Resizing

objective:Resize to the same length Resize to get an equal-sized audio sample by extending duration by padding it with silence, or by truncating it.

result:In our case we shall pad the data and notice that the data it picks is the fourth element in the amharic audio and the fifth element in the swahili audio, therefore we shall resize the audios to the duration of the fourth element in amharic and fifth in swahili, this is because we notice that this specific elements contain the largest duration in the recordings

```
[19]: audio_rates=[]
      for recording in amharic_recordings:
          audio,rate,duration = recording
          audio_rates.append((audio,rate,duration))

      max_ms = max([i[2] for i in audio_rates[0:len(audio_rates)]])*1000
      max_ms
      audios = np.array([i[0] for i in audio_rates[0:len(audio_rates)]])
      new_audio_rates = []
      for i,x in enumerate(audio_rates):
          audio,rate,_ = x
          new_audio_rates.append(cleaning_audios.pad_trunc(audio,rate,max_ms))
      amharic_data_df['duration'] = amharic_data_df['duration'][3]
```

```
[20]: audio_rates=[]
      for recording in swahili_recordings:
          audio,rate,duration = recording
          audio_rates.append((audio,rate,duration))

      max_ms = max([i[2] for i in audio_rates[0:len(audio_rates)]])*1000
      max_ms
      audios = np.array([i[0] for i in audio_rates[0:len(audio_rates)]])
      new_audio_rates = []
      for i,x in enumerate(audio_rates):
          audio,rate,_ = x
          new_audio_rates.append(cleaning_audios.pad_trunc(audio,rate,max_ms))
      swahili_data_df['duration']=swahili_data_df['duration'][4]
```

6 Data Augumentation

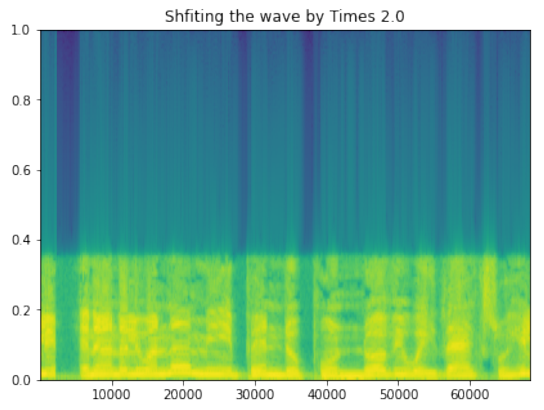
objective: Data argumentation Perform data augmentation on the raw audio signal by applying a Time Shift to shift the audio to the left or the right by a random amount.

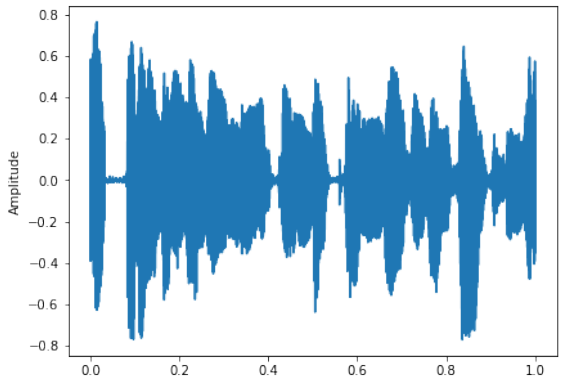
result: Here we shift the wave by sample_rate/10 factor. This will move the wave to the right by given factor along time axis. For achieving this I have used numpy's roll function to generate time shifting.

```
[21]: eda = EDA()
      wav_roll = np.roll(audio,int(rate/10))
      eda.plot_spec(data=wav_roll,sr=20)
      ipd.Audio(wav_roll,rate=rate)
```

```
2022-06-01 05:46:26,027:logger:Successfully initialized eda class
```

```
[21]: <IPython.lib.display.Audio object>
```



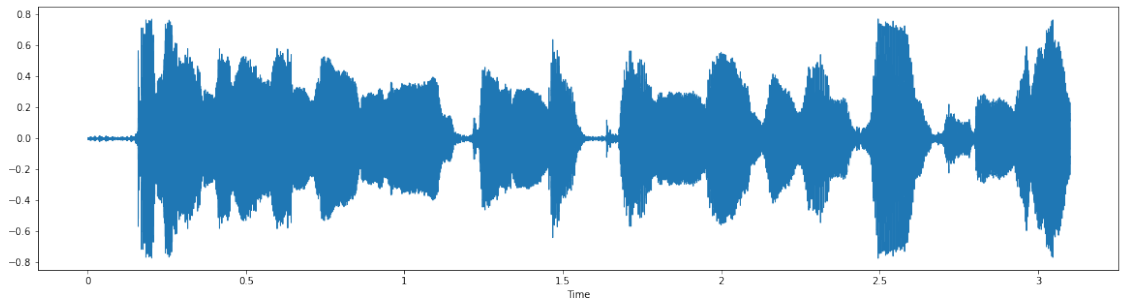


7 Feature Extraction

objective:Feature extraction: Speech recognition methods derive features from the audio, such as Spectrogram or Mel Frequency Cepstrum (MFCC). Convert the augmented audio to a Mel Spectrogram.

result: we shall conduct a feature extraction in the following two steps, we shall examine the spectograms and Mel-Frequency Cepstral Coefficients(MFCCs)

```
[22]: %matplotlib inline
      eda.sound_plots(audio,rate,'waveshow')
```



7.0.1 Spectrogram

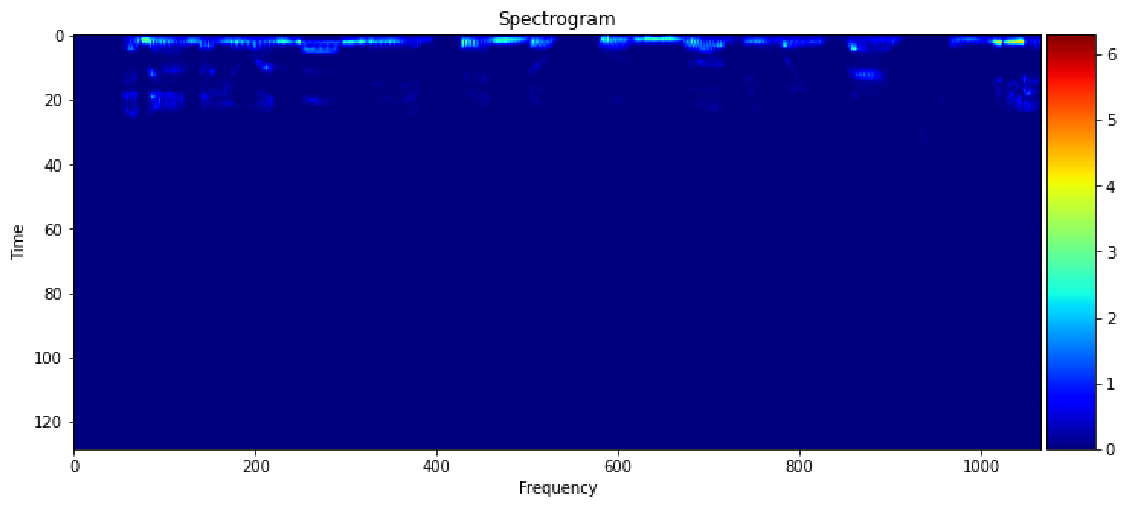
A spectrogram is a visual way of representing the signal strength, or “loudness”, of a signal over time at various frequencies present in a particular waveform. Not only can one see whether there is more or less energy at, for example, 2 Hz vs 10 Hz, but one can also see how energy levels vary over time.

A spectrogram is usually depicted as a heat map, i.e., as an image with the intensity shown by varying the color or brightness.

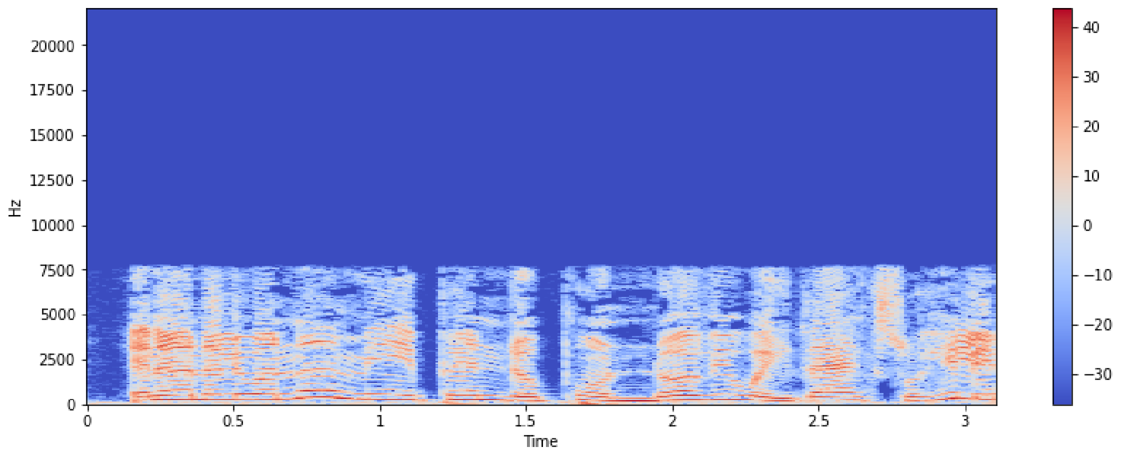
We can display a spectrogram using. librosa.display.specshow.

```
[23]: spe_samples,frequency=eda.spectrogram(audio)
```

```
[24]: eda.plot_spectrogram_feature(spe_samples)
```



```
[25]: eda.sound_plots(audio,rate,'specshow')
```



The vertical axis shows frequencies (from 0 to 8kHz), and the horizontal axis shows the time of the clip.

.stft() converts data into short term Fourier transform. STFT converts signals such that we can know the amplitude of the given frequency at a given time. Using STFT we can determine the amplitude of various frequencies playing at a given time of an audio signal. .specshow is used to display a spectrogram. The vertical axis shows frequencies (from 0 to 10kHz), and the horizontal axis shows the time of the clip.

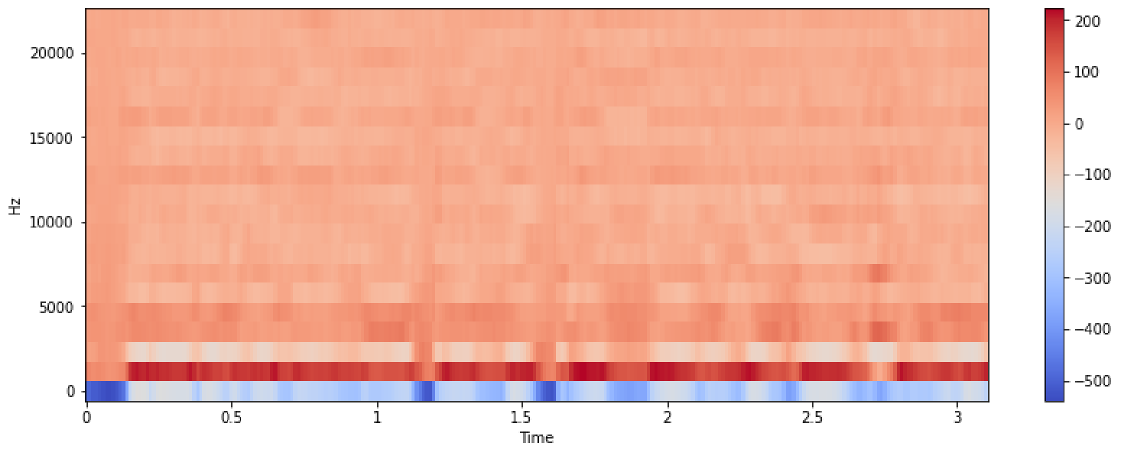
Every audio signal consists of many features. However, we must extract the characteristics that are relevant to the problem we are trying to solve. The process of extracting features to use them for analysis is called feature extraction.

Mel-Frequency Cepstral Coefficients(MFCCs)

The Mel frequency cepstral coefficients (MFCCs) of a signal are a small set of features (usually about 10–20) which concisely describe the overall shape of a spectral envelope. It models the characteristics of the human voice.

[26]:
```
mfcc_features = eda.features(audio,rate,'mfcc')
```

[27]:
```
eda.sound_plots(audio,rate,'specshow',features=mfcc_features)
```



8 Acoustic Modeling

objective: Acoustic modeling: After features are extracted, these vectors are passed to acoustic models. An acoustic model attempts to map the audio signal to the basic units of speech such as phonemes or graphemes.

results: In our case we use store audio features function to perform our acoustic modeling and majorly the basic structures that we developed and shall translate into our model for learning, are chroma_stft, spec_cent,spec_bw, rolloff, zcr, and ofcourse the mfcc features.

[28]:
```
audio_rates=[]
for recording in amharic_recordings:
    audio,rate,_ = recording
    audio_rates.append((audio,rate))
data = []
```

```
for audio,rate in audio_rates:
    data.append(cleaning_audios.store_audio_features(audio,rate))
amharic = pd.DataFrame(data)
amharic_df = pd.concat([amharic_data_df,amharic],axis=1)
```

[29]:
```
audio_rates=[]
for recording in swahili_recordings:
    audio,rate,_ = recording
    audio_rates.append((audio,rate))
data = []
for audio,rate in audio_rates:
    data.append(cleaning_audios.store_audio_features(audio,rate))
swahili = pd.DataFrame(data)
swahili_df = pd.concat([swahili_data_df,swahili],axis=1)
```

[30]:
```
# save the datasets
amharic_df.to_csv("../data/amharic.csv",index=False)
swahili_df.to_csv("../data/swahili.csv",index=False)
```

[31]:
```
amharic_df.head(3)
```

[31]:
```
                 key                                                 text  \
0  tr_10000_tr097082                              …
1  tr_10001_tr097083
2  tr_10002_tr097084

   duration   rate      rmse  chroma_stft   spec_cent      spec_bw  \
0  9.088005  44100  0.148183     0.626604  479.621280   979.304269
1  9.088005  44100  0.138804     0.719108  458.603073  1035.117417
2  9.088005  44100  0.139473     0.659554  555.428268  1070.815135

       rolloff       zcr      mfcc
0   907.885177  0.005419 -5.872562
1   966.260651  0.003081 -6.561193
2  1128.154833  0.004568 -5.345666
```

[32]:
```
swahili_df.head(3)
```

[32]:
```
                                                  key  \
0  SWH-05-20101106_16k-emission_swahili_05h30_-_0…
1  SWH-05-20101106_16k-emission_swahili_05h30_-_0…
2  SWH-05-20101106_16k-emission_swahili_05h30_-_0…

                                                 text  duration   rate  \
0            rais wa tanzania jakaya mrisho kikwete       3.9  44100
1  yanayo andaliwa nami pendo pondo idhaa ya kisw…       3.9  44100
2  inayokutangazia moja kwa moja kutoka jijini da…       3.9  44100
```

```
       rmse  chroma_stft    spec_cent      spec_bw      rolloff       zcr  \
0  0.140494     0.315876  1866.409879  1589.100426  3359.724832  0.054397
1  0.162743     0.321692  1900.991630  1655.337451  3481.883645  0.049550
2  0.164615     0.355232  2063.848819  1775.474533  3859.115658  0.049307

       mfcc
0 -8.142890
1 -6.665521
2 -7.063959
```

9 Model Architecture

Now that we have audio input data & corresponding labels in an array format, it is easier to consume and apply Natural language processing techniques. We can convert audio files labels into integers using label Encoding or One Hot Vector Encoding for machines to learn. The labeled dataset will help us in the neural network model output layer for predicting results. These help in training & validation datasets into nD array. At this stage, we apply other pre-processing techniques like dropping columns, normalization, etc. to conclude our final training data for building models. Moving to the next stage of splitting the dataset into train, test, and validation is what we have been doing for other models. The below diagram is a generic representation of the Convolution Neural Network. We can leverage CNN, RNN, LSTM, etc. deep neural algorithms to build and train the models for speech applications like speech recognition, emotion recognition, music genre classification, voice biometric, and many more. The model trained with the standard size few seconds audio chunk transformed into an array of n dimensions with the respective labels will result in predicting output labels for test audio input. As output labels will vary beyond binary, we are talking about building a multi-class label classification method.

```
[ ]:
```