Speech_Emotion_Classifier

January 5, 2023

Speech Emotion Classifier

Importing Libraries

[3]:
```
import os
import sys
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import librosa
import librosa.display

# to play the audio files
from IPython.display import Audio

from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report

import keras
from keras.models import Sequential
from keras.layers import Dense,Conv1D,MaxPooling1D, Flatten, Dropout,␣
↪BatchNormalization
from keras.callbacks import ModelCheckpoint, ReduceLROnPlateau
from keras.utils import np_utils,to_categorical

import warnings
if not sys.warnoptions:
    warnings.simplefilter("ignore")
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

Data Preparation

As we are working with four different datasets, so i will be creating a dataframe storing all emotions of the data in dataframe with their paths.

We will use this dataframe to extract features for our model training.

[5]:
```
Ravdness= "Ravdness/"
Savee= "Savee/"
Crema= "Crema/"
Tess = "Tess/"
```

1. Ravdness Dataset

Here is the filename identifiers as per the official RAVDESS website:

Modality (01 = full-AV, 02 = video-only, 03 = audio-only).

Vocal channel (01 = speech, 02 = song).

Emotion (01 = neutral, 02 = calm, 03 = happy, 04 = sad, 05 = angry, 06 = fearful, 07 = disgust, 08 = surprised).

Emotional intensity (01 = normal, 02 = strong). NOTE: There is no strong intensity for the 'neutral' emotion.

Statement (01 = "Kids are talking by the door", 02 = "Dogs are sitting by the door").

Repetition (01 = 1st repetition, 02 = 2nd repetition).

Actor (01 to 24. Odd numbered actors are male, even numbered actors are female).

So, here's an example of an audio filename. 02-01-06-01-02-01-12.mp4 This means the meta data for the audio file is:

Video-only (02)

Speech (01)

Fearful (06)

Normal intensity (01)

Statement "dogs" (02)

1st Repetition (01)

12th Actor (12) - Female (as the actor ID number is even)

[14]:
```
ravdness_dir_list= os.listdir(Ravdness)
```

[15]:
```
ravdness_dir_list.remove('.DS_Store')
```

[16]:
```
ravdness_dir_list
```

[16]:
```
['Actor_16',
 'Actor_11',
 'Actor_18',
 'Actor_20',
 'Actor_21',
 'Actor_19',
 'Actor_10',
```

```
 'Actor_17',
 'Actor_04',
 'Actor_03',
 'Actor_02',
 'Actor_05',
 'Actor_12',
 'Actor_15',
 'Actor_23',
 'Actor_24',
 'Actor_22',
 'Actor_14',
 'Actor_13',
 'Actor_09',
 'Actor_07',
 'Actor_06',
 'Actor_01',
 'Actor_08']
```

[17]:
```
file_emotion=[]
file_path=[]

for dir in ravdness_dir_list:
    actor = os.listdir(Ravdness+dir)
    for file in actor:
        part= file.split('.')[0]
        part= part.split('-')

        file_emotion.append(int(part[2]))
        file_path.append(Ravdness+dir+'/'+file)
```

[18]:
```
df_emotion = pd.DataFrame(file_emotion,columns=["Emotion"])
```

[19]:
```
df_emotion.head()
```

[19]:

	Emotion
0	5
1	6
2	6
3	5
4	7

[20]:
```
df_path = pd.DataFrame(file_path,columns=["Path"])
```

[21]:
```
df_ravdness = pd.concat([df_emotion,df_path],axis=1)
```

[22]:
```
emotion_mapping= {1:'neutral', 2:'calm', 3:'happy', 4:'sad', 5:'angry', 6:
↪'fear', 7:'disgust', 8:'surprise'}

df_ravdness['Emotion']= df_ravdness['Emotion'].map(emotion_mapping)
```

[23]:
```
df_ravdness.head()
```

[23]:

	Emotion	Path
0	angry	Ravdness/Actor_16/03-01-05-01-02-01-16.wav
1	fear	Ravdness/Actor_16/03-01-06-01-02-02-16.wav
2	fear	Ravdness/Actor_16/03-01-06-02-01-02-16.wav
3	angry	Ravdness/Actor_16/03-01-05-02-01-01-16.wav
4	disgust	Ravdness/Actor_16/03-01-07-01-01-01-16.wav

2. SAVEE DATASET

[24]:
```
savee_dir_list= os.listdir(Savee)
```

[26]:
```
savee_dir_list[:5]
```

[26]: ['JK_sa01.wav', 'JK_sa15.wav', 'DC_n13.wav', 'DC_su09.wav', 'DC_n07.wav']

[27]:
```
file_emotion=[]
file_path=[]
for file in savee_dir_list:
    file_path.append(Savee+file)
    part = file.split('_')[1]
    prefix = part[:-6]
    if prefix=='a':
        file_emotion.append('angry')
    elif prefix=='d':
        file_emotion.append('disgust')
    elif prefix=='f':
        file_emotion.append('fear')
    elif prefix=='h':
        file_emotion.append('happy')
    elif prefix=='n':
        file_emotion.append('neutral')
    elif prefix=='sa':
        file_emotion.append('sad')
    else:
        file_emotion.append('surprise')
```

[28]:
```
file_emotion[:5]
```

[28]: ['sad', 'sad', 'neutral', 'surprise', 'neutral']

[29]:
```
df_emotion=pd.DataFrame(file_emotion,columns=["Emotion"])
df_path= pd.DataFrame(file_path,columns=["Path"])

df_savee = pd.concat([df_emotion,df_path],axis=1)

df_savee.head()
```

[29]:
```
    Emotion               Path
0       sad  Savee/JK_sa01.wav
1       sad  Savee/JK_sa15.wav
2   neutral   Savee/DC_n13.wav
3  surprise  Savee/DC_su09.wav
4   neutral   Savee/DC_n07.wav
```

3. TESS Dataset

[30]:
```
tess_dir_list= os.listdir(Tess)
```

[32]:
```
tess_dir_list.remove('.ipynb_checkpoints')
```

[33]:
```
file_emotion=[]
file_path=[]

for dir in tess_dir_list:
    sub_dir= os.listdir(Tess+dir)
    for file in sub_dir:
        part= file.split('.')[0]
        part=part.split('_')[2]
        if part=='ps':
            file_emotion.append('Surprise')
        else:
            file_emotion.append(part)
        file_path.append(Tess+dir+'/'+file)
```

[34]:
```
file_emotion[:5]
```

[34]:
```
['disgust', 'disgust', 'disgust', 'disgust', 'disgust']
```

[35]:
```
df_emotion= pd.DataFrame(file_emotion,columns=["Emotion"])
df_path=pd.DataFrame(file_path,columns=["Path"])

df_tess= pd.concat([df_emotion,df_path],axis=1)
df_tess.head()
```

[35]:
```
   Emotion                                   Path
0  disgust   Tess/YAF_disgust/YAF_date_disgust.wav
```

```
1  disgust    Tess/YAF_disgust/YAF_rag_disgust.wav
2  disgust  Tess/YAF_disgust/YAF_raise_disgust.wav
3  disgust  Tess/YAF_disgust/YAF_ditch_disgust.wav
4  disgust   Tess/YAF_disgust/YAF_door_disgust.wav
```

4. CREMA dataset
   The audio files in this dataset are named in such a way that the prefix letters describes the emotion classes as follows:
   'a' = 'anger'
   'd' = 'disgust'
   'f' = 'fear'
   'h' = 'happiness'
   'n' = 'neutral'
   'sa' = 'sadness'
   'su' = 'surprise'

[36]:
```
crema_dir_list= os.listdir(Crema)
```

[37]:
```
file_emotion=[]
file_path=[]

for file in crema_dir_list:
    file_path.append(Crema+file)

    part= file.split('_')[2]
    if part == 'SAD':
        file_emotion.append('sad')
    elif part == 'ANG':
        file_emotion.append('angry')
    elif part == 'DIS':
        file_emotion.append('disgust')
    elif part == 'FEA':
        file_emotion.append('fear')
    elif part == 'HAP':
        file_emotion.append('happy')
    elif part == 'NEU':
        file_emotion.append('neutral')
    else:
        file_emotion.append('Unknown')
```

[38]:
```
file_emotion[:5]
```

[38]:
```
['angry', 'angry', 'neutral', 'neutral', 'disgust']
```

[39]:
```
df_emotion=pd.DataFrame(file_emotion,columns=["Emotion"])
df_path=pd.DataFrame(file_path,columns=["Path"])
```

```
df_crema= pd.concat([df_emotion,df_path],axis=1)
df_crema.head()
```

[39]:
```
    Emotion                       Path
0     angry  Crema/1022_ITS_ANG_XX.wav
1     angry  Crema/1037_ITS_ANG_XX.wav
2   neutral  Crema/1060_ITS_NEU_XX.wav
3   neutral  Crema/1075_ITS_NEU_XX.wav
4   disgust  Crema/1073_IOM_DIS_XX.wav
```

Combine all dataframes

[40]:
```
df= pd.concat([df_ravdness,df_savee,df_tess,df_crema],axis=0)
```

[41]:
```
df.to_csv("data.csv",index=False)
df.head()
```

[41]:
```
    Emotion                                          Path
0     angry  Ravdness/Actor_16/03-01-05-01-02-01-16.wav
1      fear  Ravdness/Actor_16/03-01-06-01-02-02-16.wav
2      fear  Ravdness/Actor_16/03-01-06-02-01-02-16.wav
3     angry  Ravdness/Actor_16/03-01-05-02-01-01-16.wav
4   disgust  Ravdness/Actor_16/03-01-07-01-01-01-16.wav
```

[79]:
```
df.shape
```

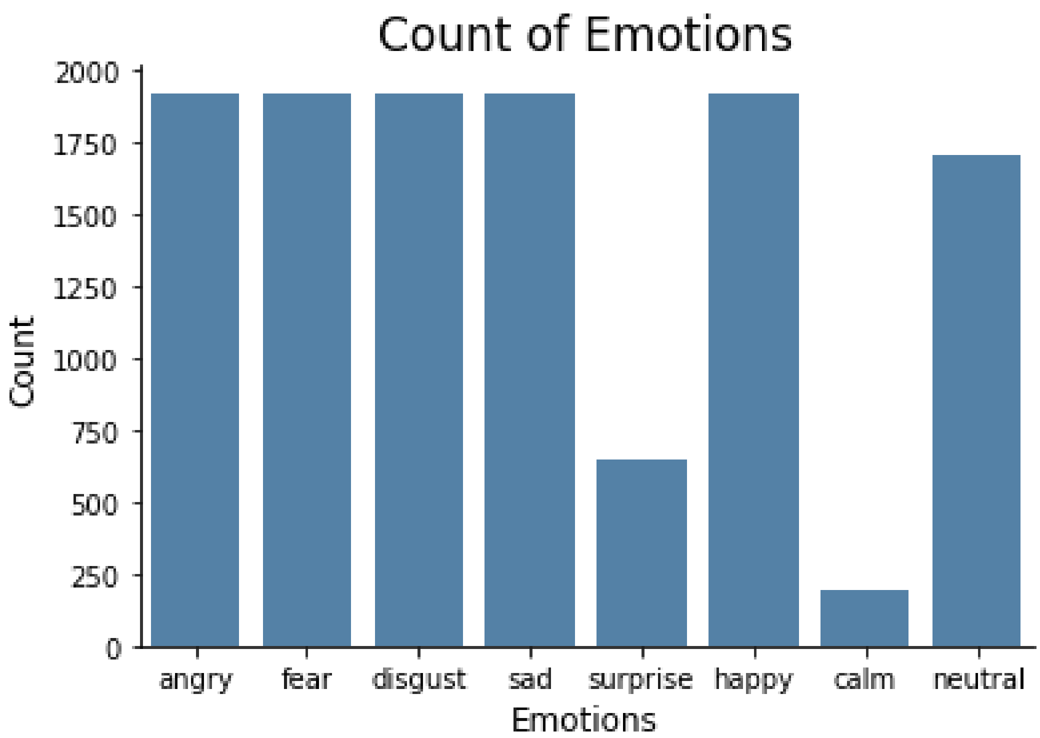
[79]:
```
(9122, 2)
```

Exploratory Data Analysis

[42]:
```
df_copy=df.copy()
df['Emotion'].replace({'Surprise':'surprise'},inplace=True)
```

First let's plot the count of each emotions in our dataset.

[43]:
```
plt.title("Count of Emotions",size=17)
sns.countplot(df['Emotion'],color='steelblue')
plt.xlabel("Emotions",size=12)
plt.ylabel("Count",size=12)
sns.despine(top=True,bottom=False,left=False);
```



We can also plot waveplots and spectograms for audio signals

Waveplots - Waveplots let us know the loudness of the audio at a given time.

Spectograms - A spectrogram is a visual representation of the spectrum of frequencies of sound or other signals as they vary with time. It's a representation of frequencies changing with respect to time for given audio/music signals.

[44]:
```
def create_waveplot(data,sampling_rate,emotion):
    plt.figure(figsize=(12,5))
    plt.title("Waveplot for audio with {} emotion".format(emotion),size=17)
    librosa.display.waveshow(data,sr=sampling_rate)
    plt.show()

def create_spectrogram(data,sampling_rate,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=(12,5))
    plt.title("Spectogram for audio with {} emotion".format(emotion),size=17)
    librosa.display.specshow(Xdb,sr=sampling_rate,x_axis="time",y_axis="hz")
    plt.colorbar()
```

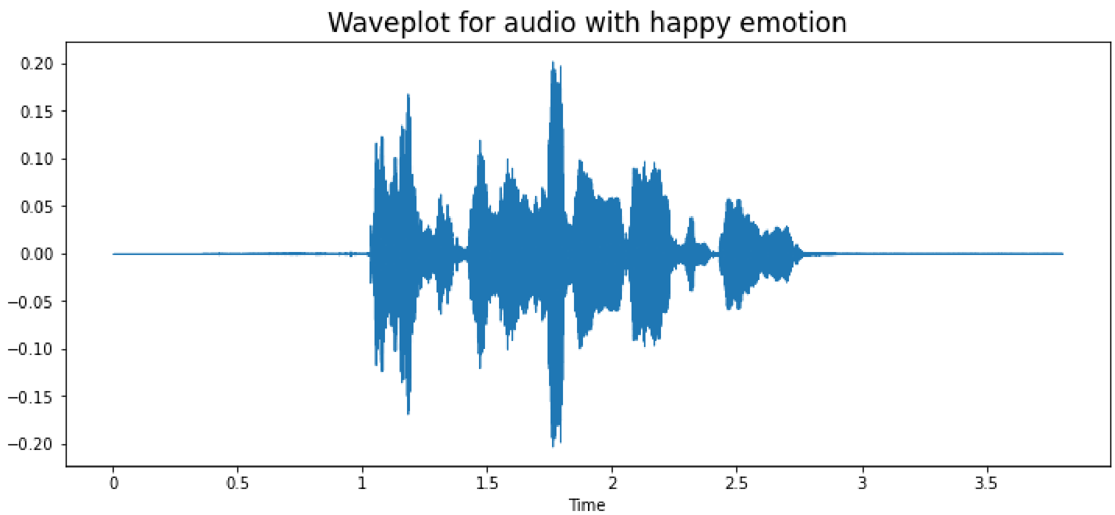
[45]:
```
temp=np.array(df[df["Emotion"]=="happy"]["Path"])[0]
temp
```

[45]:
```
'Ravdness/Actor_16/03-01-03-02-02-02-16.wav'
```

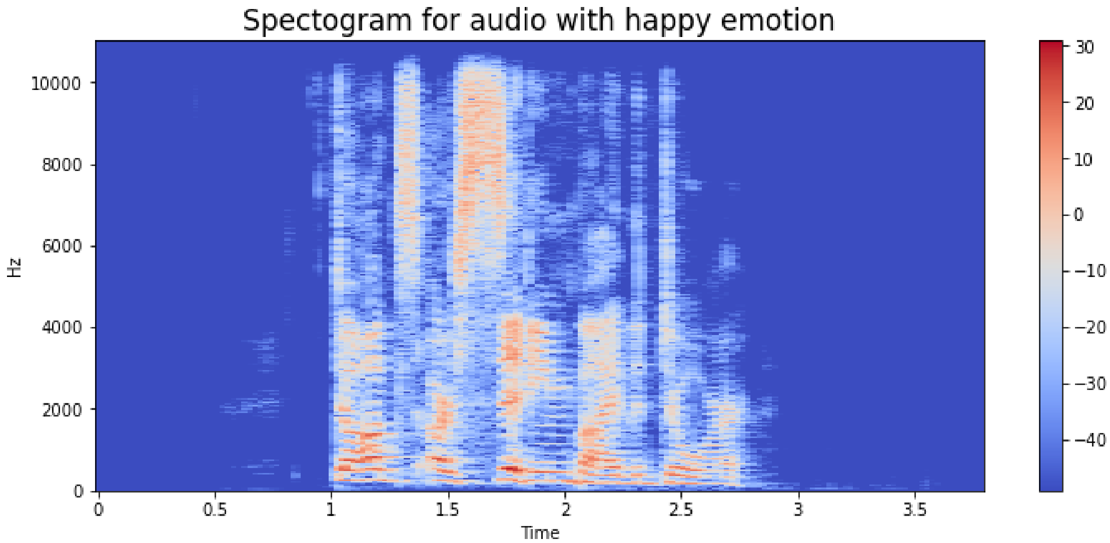
[46]:
```
librosa.load(temp)
```

[46]:
```
(array([ 0.0000000e+00,  0.0000000e+00,  0.0000000e+00, …,
        -5.7374714e-09,  4.6759210e-09,  0.0000000e+00], dtype=float32),
 22050)
```

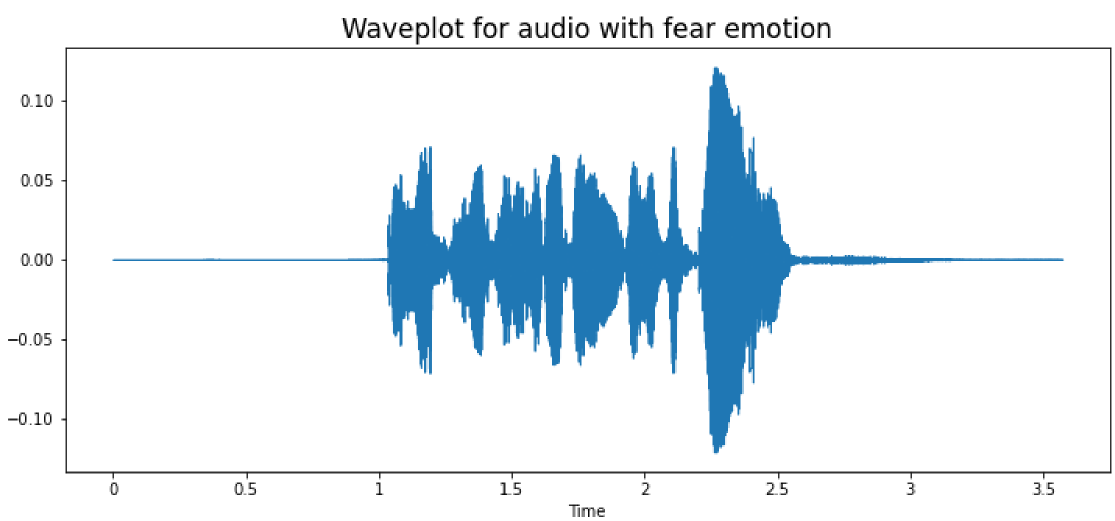
[49]:
```
emotion="happy"

path= np.array(df[df["Emotion"]==emotion]["Path"])[0]
data,sampling_rate= librosa.load(path)
create_waveplot(data,sampling_rate,emotion)
create_spectrogram(data,sampling_rate,emotion)
Audio(path)
```



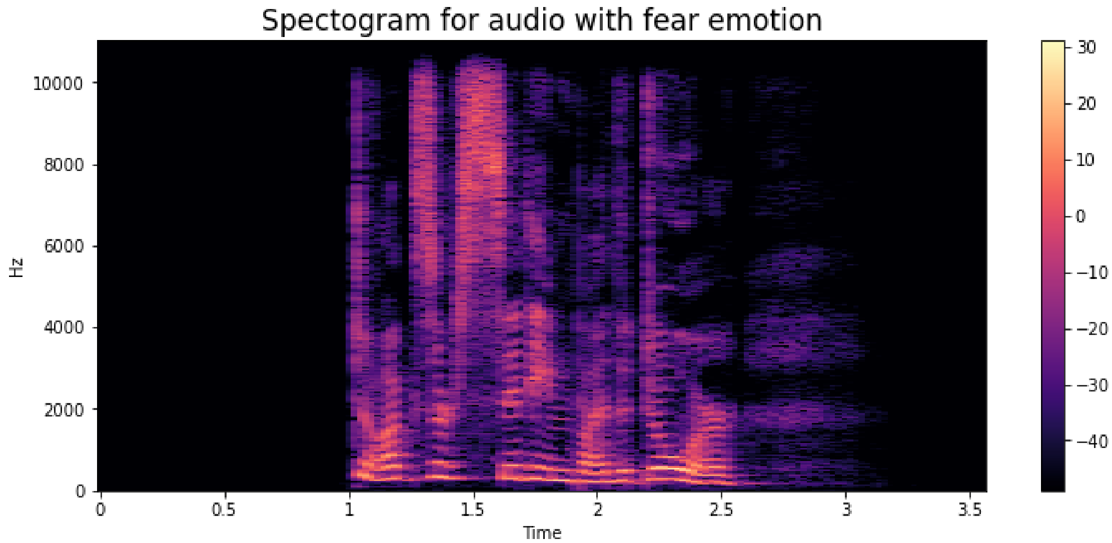
[49]:
```
<IPython.lib.display.Audio object>
```



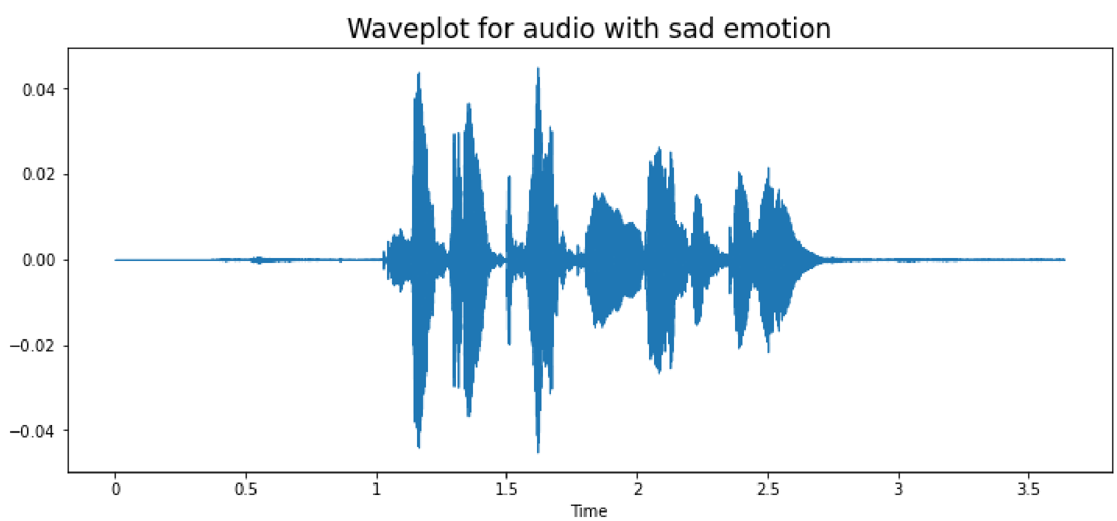
[50]:
```
emotion="fear"

path= np.array(df[df["Emotion"]==emotion]["Path"])[0]
data,sampling_rate= librosa.load(path)
create_waveplot(data,sampling_rate,emotion)
create_spectrogram(data,sampling_rate,emotion)
Audio(path)
```



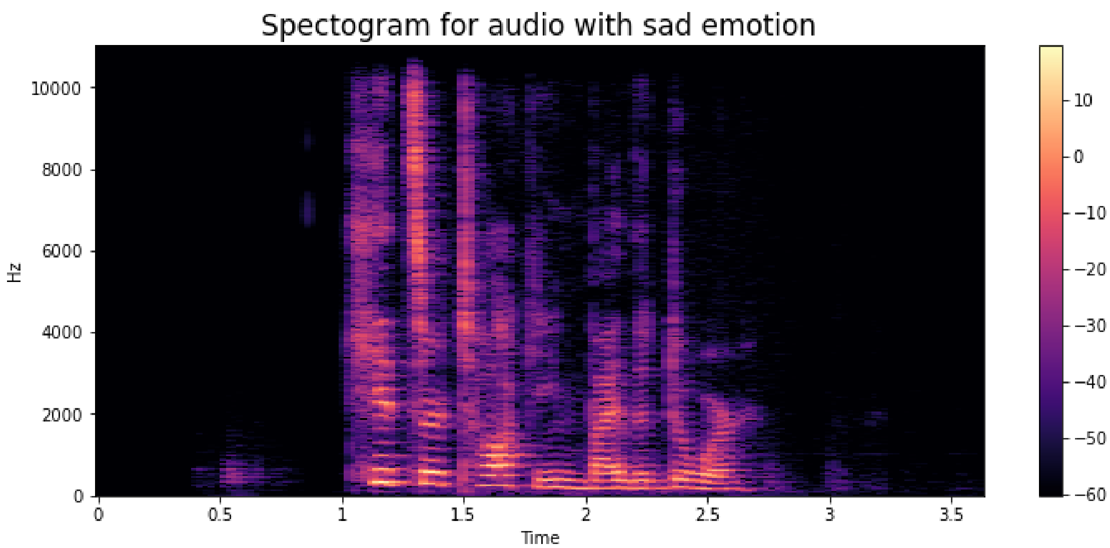
[50]: <IPython.lib.display.Audio object>



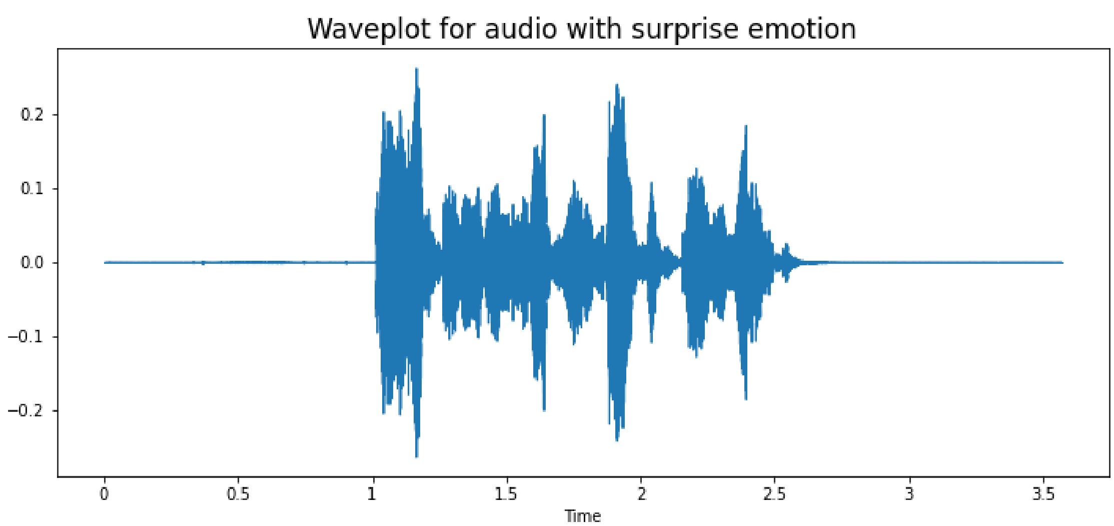
[51]:
```
emotion="sad"

path= np.array(df[df["Emotion"]==emotion]["Path"])[0]
data,sampling_rate= librosa.load(path)
create_waveplot(data,sampling_rate,emotion)
create_spectrogram(data,sampling_rate,emotion)
Audio(path)
```



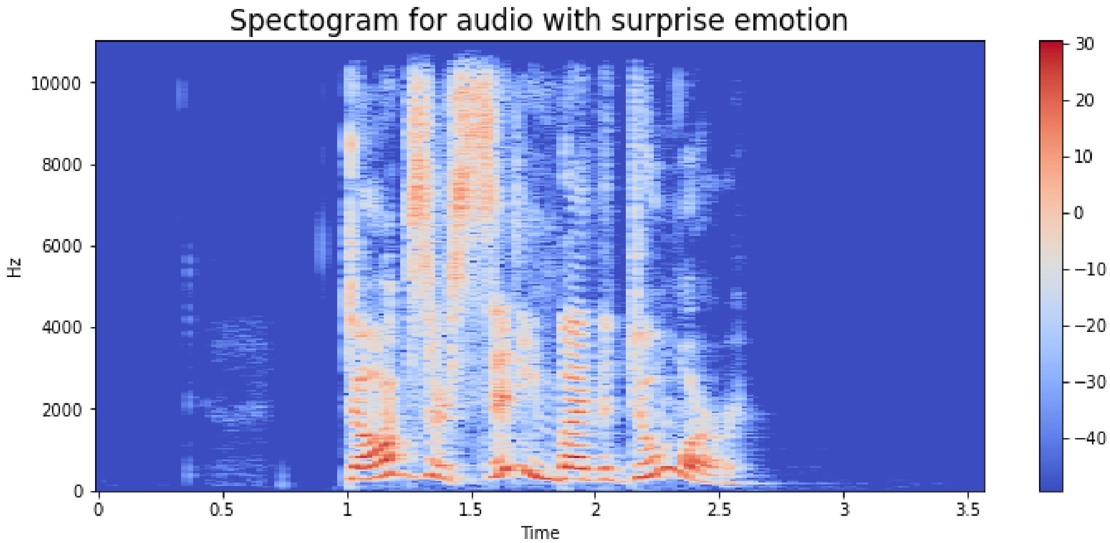
[51]: <IPython.lib.display.Audio object>



[52]:
```
emotion="surprise"

path= np.array(df[df["Emotion"]==emotion]["Path"])[0]
data,sampling_rate= librosa.load(path)
create_waveplot(data,sampling_rate,emotion)
create_spectrogram(data,sampling_rate,emotion)
Audio(path)
```



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



Data Augmentation

Data augmentation is the process by which we create new synthetic data samples by adding small perturbations on our initial training set.

To generate syntactic data for audio, we can apply noise injection, shifting time, changing pitch and speed.

The objective is to make our model invariant to those perturbations and enhace its ability to generalize.

In order to this to work adding the perturbations must conserve the same label as the original training sample.

In images data augmention can be performed by shifting the image, zooming, rotating …

First, let's check which augmentation techniques works better for our dataset.

[53]:
```
data
```

[53]:
```
array([ 1.97388023e-10, -2.77809886e-09,  6.41419584e-09, …,
       -4.48119181e-11,  1.05277636e-11,  0.00000000e+00], dtype=float32)
```

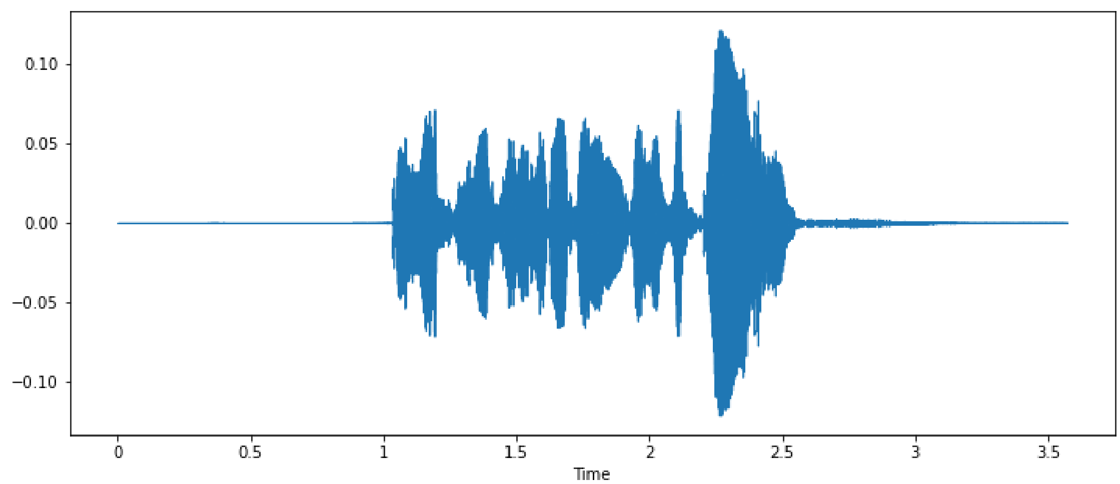
[54]:
```
def noise(data):
    noise_amp = 0.025*np.random.uniform()*np.amax(data)
    data=data+noise_amp*np.random.normal(size=data.shape[0])
    return data

def pitch(data,sampling_rate,pitch_factor=0.8):
    return librosa.effects.pitch_shift(data,sampling_rate,pitch_factor)

def shift(data):
```

```
    shift_range = int(np.random.uniform(low=-7, high = 7)*1000)
    return np.roll(data, shift_range)

def stretch(data,rate=0.9):
    return librosa.effects.time_stretch(data,rate)

path=np.array(df.Path)[1]
data,sample_rate= librosa.load(path)
```

1. Original Audio

[55]:
```
plt.figure(figsize=(12,5))
librosa.display.waveshow(data,sr=sample_rate)
Audio(path)
```

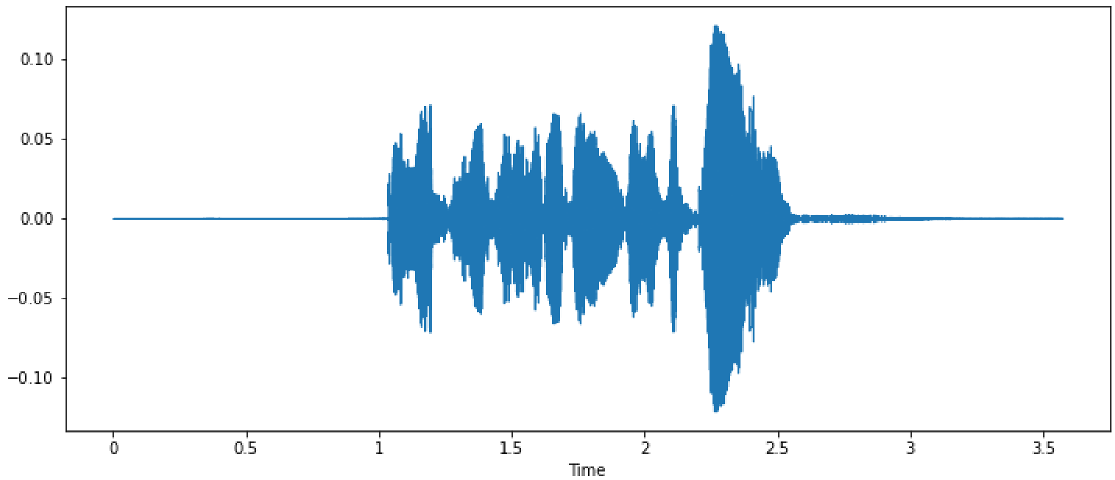
[55]: <IPython.lib.display.Audio object>



2. Audio After Noice Injection

[56]:
```
noice_data= noise(data)
plt.figure(figsize=(12,5))
librosa.display.waveshow(data,sr=sample_rate)
Audio(noice_data,rate=sample_rate)
```

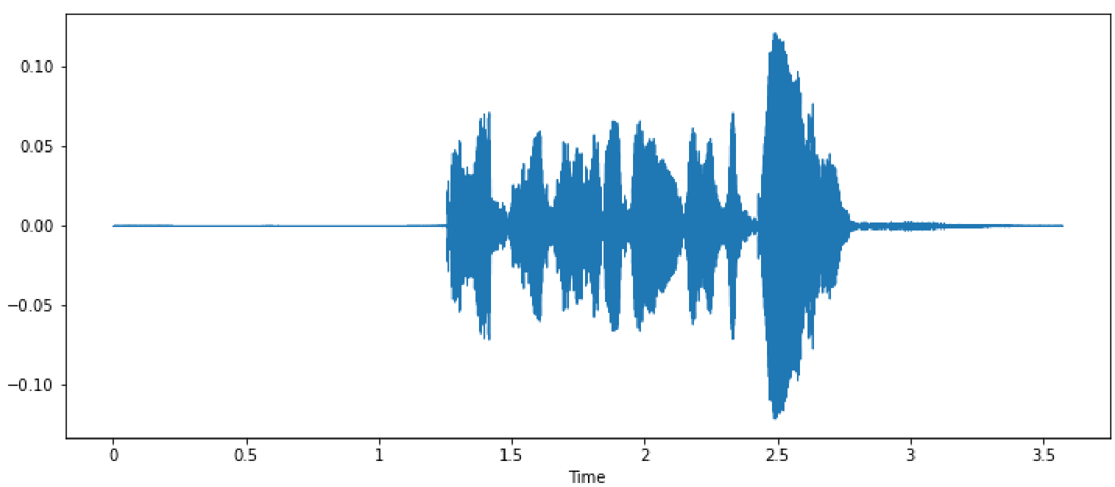
[56]: <IPython.lib.display.Audio object>



3. Audio Shift

[57]:
```
data_shift= shift(data)
plt.figure(figsize=(12,5))
librosa.display.waveshow(data_shift,sr=sample_rate)
Audio(data_shift,rate=sample_rate)
```

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

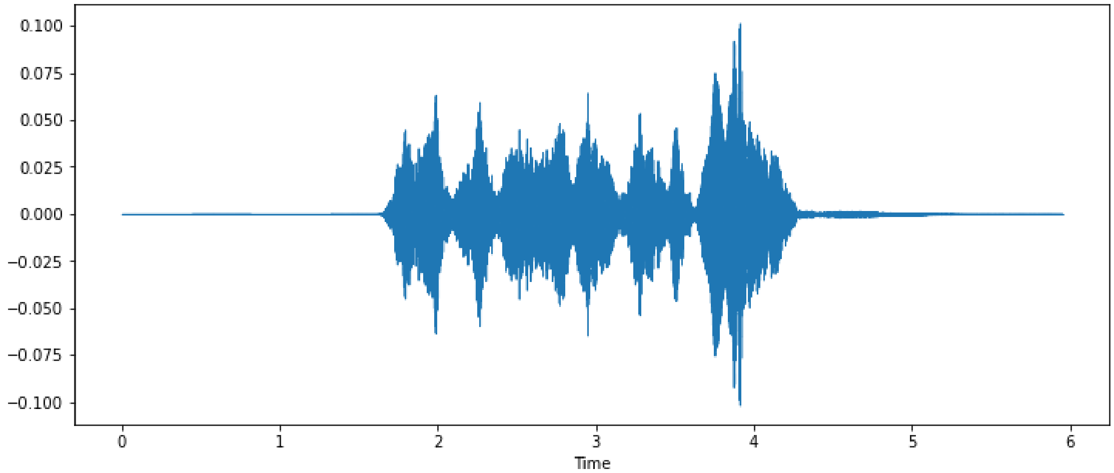


4. Audio Stretch

[58]:
```
data_stretch= stretch(data,rate=0.6)
plt.figure(figsize=(12,5))
librosa.display.waveshow(data_stretch,sr=sample_rate)
```

```
Audio(data_stretch,rate=sample_rate)
```

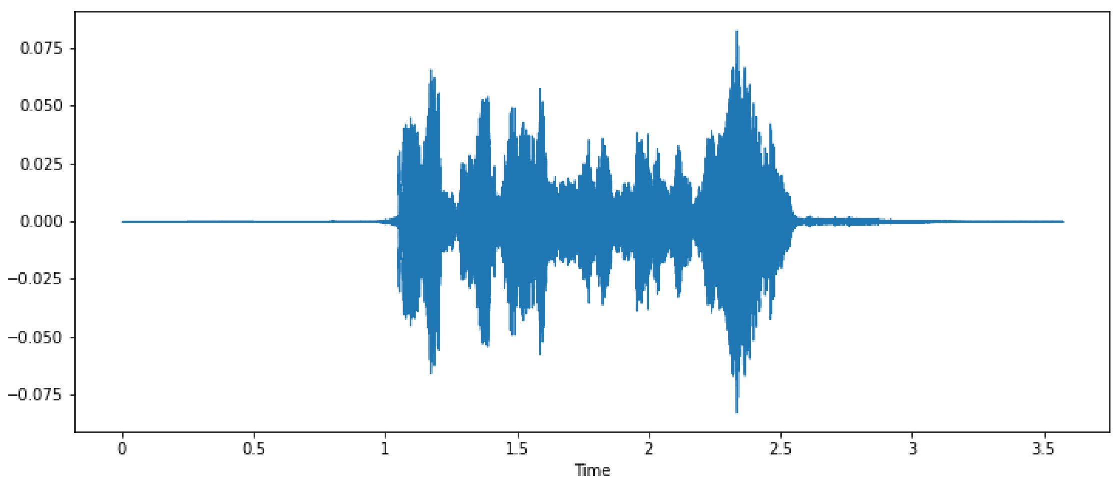
[58]: <IPython.lib.display.Audio object>



5. Audio Pitch

```
[59]: data_pitch= pitch(data,sample_rate,0.5)
plt.figure(figsize=(12,5))
librosa.display.waveshow(data_pitch,sr=sample_rate)
Audio(data_pitch,rate=sample_rate)
```

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



From the above types of augmentation techniques i am using noise, stretching(ie. changing speed) and some pitching.

Feature Extraction

Extraction of features is a very important part in analyzing and finding relations between different things.

As we already know that the data provided of audio cannot be understood by the models directly so we need to convert them into an understandable format for which feature extraction is used.

The audio signal is a three-dimensional signal in which three axes represent time, amplitude and frequency.

There are several transformations that can be performed to extract valuable features from the data.

Zero Crossing Rate: The rate of sign-changes of the signal during the duration of a particular frame. Energy : The sum of squares of the signal values, normalized by the respective frame length. Entropy of Energy : The entropy of sub-frames' normalized energies. It can be interpreted as a measure of abrupt changes. Spectral Centroid : The center of gravity of the spectrum. Spectral Spread : The second central moment of the spectrum. Spectral Entropy : Entropy of the normalized spectral energies for a set of sub-frames. Spectral Flux : The squared difference between the normalized magnitudes of the spectra of the two successive frames. Spectral Rolloff : The frequency below which 90% of the magnitude distribution of the spectrum is concentrated. MFCCs Mel Frequency Cepstral Coefficients form a cepstral representation where the frequency bands are not linear but distributed according to the mel-scale. Chroma Vector : A 12-element representation of the spectral energy where the bins represent the 12 equal-tempered pitch classes of western-type music (semitone spacing). Chroma Deviation : The standard deviation of the 12 chroma coefficients. In this project i am not going deep in feature selection process to check which features are good for our dataset rather i am only extracting 5 features:

Zero Crossing Rate

Chroma_stft

MFCC

RMS(root mean square) value

MelSpectogram to train our model.

[60]:
```
def extract_features(data):
    # Zero Crossing Rate

    result=np.array([])

    zcr=np.mean(librosa.feature.zero_crossing_rate(data).T,axis=0)
    result=np.hstack((result,zcr))

    #Chroma_Stft

    stft = np.abs(librosa.stft(data))
    chroma_stft = np.mean(librosa.feature.chroma_stft(S=stft, sr=sample_rate).
 ↪T, axis=0)
    result = np.hstack((result, chroma_stft)) # stacking horizontally
```

```
    # MFCC
    mfcc = np.mean(librosa.feature.mfcc(y=data, sr=sample_rate).T, axis=0)
    result = np.hstack((result, mfcc)) # stacking horizontally

    # Root Mean Square Value
    rms = np.mean(librosa.feature.rms(y=data).T, axis=0)
    result = np.hstack((result, rms)) # stacking horizontally

    # MelSpectogram
    mel = np.mean(librosa.feature.melspectrogram(y=data, sr=sample_rate).T,␣
↪axis=0)
    result = np.hstack((result, mel)) # stacking horizontally

    return result
```

[61]:
```
np.array(extract_features(data)[:20])
```

[61]:
```
array([ 2.12424538e-01,  5.51800132e-01,  5.10277808e-01,  4.80480254e-01,
        4.46299702e-01,  3.84138763e-01,  4.03150052e-01,  4.07664001e-01,
        4.27179545e-01,  4.73491579e-01,  5.45150876e-01,  5.62913001e-01,
        5.59973657e-01, -5.51948120e+02,  3.88314400e+01, -7.56018877e+00,
        6.31620455e+00, -3.57922673e+00, -7.85105181e+00, -1.59844160e+01])
```

[62]:
```
def get_features(path):
    # duration and offset are used to take care of the no audio in start and␣
↪the ending of each audio files as seen above.
    data, sample_rate = librosa.load(path, duration=2.5, offset=0.6)

    # without augmentation
    res1 = extract_features(data)
    result = np.array(res1)

    # data with noise
    noise_data = noise(data)
    res2 = extract_features(noise_data)
    result = np.vstack((result, res2)) # stacking vertically

    # data with stretching and pitching
    new_data = stretch(data)
    data_stretch_pitch = pitch(new_data, sample_rate)
    res3 = extract_features(data_stretch_pitch)
    result = np.vstack((result, res3)) # stacking vertically

    return result
```

[200]:
```python
X,Y= [],[]

for path,emotion in zip(df["Path"],df["Emotion"]):
    feature= get_features(path)

    for val in feature:
        X.append(val)
        Y.append(emotion)
```

[204]:
```python
len(X)
```

[204]: 36486

[205]:
```python
len(Y)
```

[205]: 36486

[207]:
```python
df["Path"].shape
```

[207]: (12162,)

[209]:
```python
Y[:10]
```

[209]:
```
['angry',
 'angry',
 'angry',
 'fear',
 'fear',
 'fear',
 'fear',
 'fear',
 'fear',
 'angry']
```

[210]:
```python
features = pd.DataFrame(X)
features["labels"]=Y
features.to_csv("features.csv",index=False)
features.head()
```

[210]:

	0	1	2	3	4	5	6	\
0	0.192464	0.516620	0.464575	0.484971	0.538362	0.500001	0.598386	
1	0.266308	0.588017	0.566002	0.600730	0.602344	0.592289	0.643344	
2	0.226546	0.577087	0.478307	0.476140	0.506183	0.482258	0.537989	
3	0.184814	0.552939	0.514264	0.477355	0.408057	0.359502	0.394911	
4	0.308784	0.734920	0.739648	0.729364	0.711060	0.659011	0.653297	

```
         7          8          9  …        153        154        155        156  \
```

```
0  0.544128  0.527744  0.602507  …  0.006685  0.004040  0.004858  0.004599
1  0.567626  0.591652  0.687198  …  0.006771  0.004083  0.004897  0.004646
2  0.570243  0.533903  0.587693  …  0.003240  0.002368  0.001085  0.000946
3  0.405739  0.433439  0.497811  …  0.002602  0.002953  0.003854  0.003141
4  0.575941  0.575158  0.593249  …  0.002967  0.003341  0.004161  0.003606

        157       158       159       160           161  labels
0  0.005219  0.003749  0.000923  0.000175  1.708295e-06   angry
1  0.005262  0.003788  0.000978  0.000228  5.386832e-05   angry
2  0.000686  0.000396  0.000168  0.000018  6.272384e-08   angry
3  0.002715  0.001565  0.000508  0.000056  7.527195e-07    fear
4  0.003147  0.001959  0.000914  0.000437  4.019086e-04    fear

[5 rows x 163 columns]
```

[211]:
```
features.shape
```

[211]:
```
(36486, 163)
```

[213]:
```
X[:1]
```

[213]:
```
[array([ 1.92464193e-01,  5.16620457e-01,  4.64574784e-01,  4.84971434e-01,
         5.38362145e-01,  5.00001192e-01,  5.98385751e-01,  5.44127822e-01,
         5.27743638e-01,  6.02507472e-01,  6.27820551e-01,  6.16499960e-01,
         5.99417984e-01, -4.42239655e+02,  5.50632362e+01, -9.42134476e+00,
         7.01987886e+00, -1.85303936e+01, -7.17252493e+00, -1.66234398e+01,
        -1.56964521e+01, -2.11141605e+01,  2.59504080e-01, -1.40679207e+01,
        -7.06661749e+00, -7.43842745e+00, -6.30661440e+00, -1.17652082e+01,
        -6.34824944e+00, -5.58307409e+00, -8.71648026e+00, -1.11283083e+01,
        -1.68522573e+00,  1.86869409e-02,  2.96468079e-05,  1.43484227e-04,
         2.35352694e-04,  2.12344909e-04,  1.42077776e-03,  2.37771552e-02,
         6.60310388e-02,  4.01816249e-01,  8.08886588e-01,  2.03573868e-01,
         1.86636910e-01,  6.17786646e-01,  2.81607091e-01,  1.22369066e-01,
         1.19166724e-01,  4.24228042e-01,  7.26250947e-01,  6.22547686e-01,
         6.22238636e-01,  2.45175257e-01,  1.97628722e-01,  4.78364408e-01,
         8.08698177e-01,  7.45457172e-01,  2.12040722e-01,  3.40892196e-01,
         3.92136306e-01,  5.71665227e-01,  7.09126890e-01,  2.49673843e-01,
         1.12931386e-01,  2.48106465e-01,  2.34876856e-01,  1.59752145e-01,
         3.48562062e-01,  4.21679139e-01,  3.49740416e-01,  3.21945369e-01,
         4.47214879e-02,  4.55887839e-02,  2.67585013e-02,  9.17579457e-02,
         1.35566354e-01,  6.99822307e-02,  1.07021093e-01,  1.55596659e-01,
         2.17509374e-01,  7.65547305e-02,  5.39707728e-02,  1.07357167e-01,
         2.91637450e-01,  1.80426285e-01,  8.71479213e-02,  2.22560409e-02,
         1.08158281e-02,  2.17125807e-02,  2.34556068e-02,  5.50940000e-02,
         5.04048392e-02,  1.52102299e-02,  1.11309336e-02,  2.36989111e-02,
         2.19254345e-02,  2.01630481e-02,  5.73475705e-03,  1.00871548e-02,
         1.17278611e-02,  4.52592708e-02,  1.00404257e-02,  6.90996740e-03,
```

```
2.52523981e-02,  3.82087193e-02,  1.66740250e-02,  3.71850166e-03,
9.26571526e-03,  7.72680622e-03,  8.16040859e-03,  1.12784095e-02,
2.01424360e-02,  2.81476751e-02,  3.96659076e-02,  5.67275099e-02,
7.39536434e-02,  6.87052310e-02,  1.29024789e-01,  6.28717765e-02,
3.12706046e-02,  2.76769046e-02,  2.38801017e-02,  1.91159099e-02,
1.19583299e-02,  1.03797251e-02,  5.28804446e-03,  4.53299284e-03,
2.36294023e-03,  2.04567332e-03,  3.67039489e-03,  2.73548020e-03,
3.75477178e-03,  2.52783950e-03,  1.96804013e-03,  1.60127121e-03,
1.47715723e-03,  2.96246447e-03,  1.48693798e-03,  1.77240954e-03,
3.12744337e-03,  4.58807359e-03,  8.05071648e-03,  1.21872919e-02,
1.13289272e-02,  8.94001592e-03,  5.09499619e-03,  6.08080905e-03,
6.78576808e-03,  1.05677247e-02,  1.28392028e-02,  1.74394157e-02,
1.27438307e-02,  6.68484252e-03,  4.03970620e-03,  4.85837692e-03,
4.59855841e-03,  5.21945022e-03,  3.74885532e-03,  9.22835548e-04,
1.74872795e-04,  1.70829503e-06])]
```

Data Preparation

As of now we have extracted the data, now we need to normalize and split our data for training and testing.

[63]:
```python
features=pd.read_csv('features.csv')
X = features.iloc[: ,:-1].values
Y = features['labels'].values
```

[64]:
```python
Y
```

[64]:
```
array(['angry', 'angry', 'angry', …, 'neutral', 'neutral', 'neutral'],
      dtype=object)
```

[65]:
```python
# As this is a multiclass classification problem onehotencoding our Y.
ohe = OneHotEncoder()
Y= ohe.fit_transform(np.array(Y).reshape(-1,1)).toarray()
```

[66]:
```python
x_train, x_test, y_train, y_test = train_test_split(X, Y, random_state=0,␣
↪shuffle=True)
x_train.shape, y_train.shape, x_test.shape, y_test.shape
```

[66]:
```
((27364, 162), (27364, 8), (9122, 162), (9122, 8))
```

[67]:
```python
# scaling our data with sklearn's Standard scaler
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
x_train.shape, y_train.shape, x_test.shape, y_test.shape
```

[67]:
```
((27364, 162), (27364, 8), (9122, 162), (9122, 8))
```

[68]:
```
# making our data compatible to model.
x_train = np.expand_dims(x_train, axis=2)
x_test = np.expand_dims(x_test, axis=2)
x_train.shape, y_train.shape, x_test.shape, y_test.shape
```

[68]:
```
((27364, 162, 1), (27364, 8), (9122, 162, 1), (9122, 8))
```

Modelling

[69]:
```
model=Sequential()
model.add(Conv1D(256, kernel_size=5, strides=1, padding='same',␣
↪activation='relu', input_shape=(x_train.shape[1], 1)))
model.add(MaxPooling1D(pool_size=5, strides = 2, padding = 'same'))

model.add(Conv1D(256, kernel_size=5, strides=1, padding='same',␣
↪activation='relu'))
model.add(MaxPooling1D(pool_size=5, strides = 2, padding = 'same'))

model.add(Conv1D(128, kernel_size=5, strides=1, padding='same',␣
↪activation='relu'))
model.add(MaxPooling1D(pool_size=5, strides = 2, padding = 'same'))
model.add(Dropout(0.2))

model.add(Conv1D(64, kernel_size=5, strides=1, padding='same',␣
↪activation='relu'))
model.add(MaxPooling1D(pool_size=5, strides = 2, padding = 'same'))

model.add(Flatten())
model.add(Dense(units=32, activation='relu'))
model.add(Dropout(0.3))

model.add(Dense(units=8, activation='softmax'))
model.compile(optimizer = 'adam' , loss = 'categorical_crossentropy' , metrics␣
↪= ['accuracy'])

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv1d (Conv1D)             (None, 162, 256)          1536

 max_pooling1d (MaxPooling1D  (None, 81, 256)          0
 )

 conv1d_1 (Conv1D)           (None, 81, 256)           327936
```

```
 max_pooling1d_1 (MaxPooling  (None, 41, 256)          0
 1D)

 conv1d_2 (Conv1D)           (None, 41, 128)           163968

 max_pooling1d_2 (MaxPooling  (None, 21, 128)          0
 1D)

 dropout (Dropout)           (None, 21, 128)           0

 conv1d_3 (Conv1D)           (None, 21, 64)            41024

 max_pooling1d_3 (MaxPooling  (None, 11, 64)           0
 1D)

 flatten (Flatten)           (None, 704)               0

 dense (Dense)               (None, 32)                22560

 dropout_1 (Dropout)         (None, 32)                0

 dense_1 (Dense)             (None, 8)                 264

=================================================================
Total params: 557,288
Trainable params: 557,288
Non-trainable params: 0
_________________________________________________________________
2023-01-05 16:32:03.732603: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

[70]:
```python
rlrp = ReduceLROnPlateau(monitor='loss', factor=0.4, verbose=0, patience=2, min_lr=0.0000001)
history=model.fit(x_train, y_train, batch_size=64, epochs=50, validation_data=(x_test, y_test), callbacks=[rlrp])
```

```
Epoch 1/50
428/428 [==============================] - 55s 128ms/step - loss: 1.6623 -
accuracy: 0.3365 - val_loss: 1.3995 - val_accuracy: 0.4485 - lr: 0.0010
Epoch 2/50
428/428 [==============================] - 55s 128ms/step - loss: 1.4364 -
accuracy: 0.4280 - val_loss: 1.3090 - val_accuracy: 0.4954 - lr: 0.0010
```

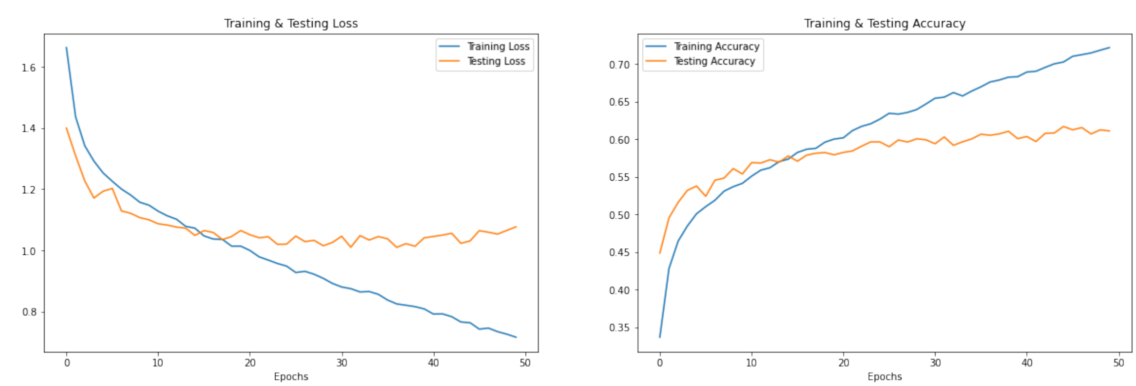
```
Epoch 3/50
428/428 [==============================] - 56s 130ms/step - loss: 1.3416 -
accuracy: 0.4645 - val_loss: 1.2267 - val_accuracy: 0.5160 - lr: 0.0010
Epoch 4/50
428/428 [==============================] - 60s 141ms/step - loss: 1.2915 -
accuracy: 0.4845 - val_loss: 1.1708 - val_accuracy: 0.5319 - lr: 0.0010
Epoch 5/50
428/428 [==============================] - 62s 145ms/step - loss: 1.2527 -
accuracy: 0.5008 - val_loss: 1.1931 - val_accuracy: 0.5377 - lr: 0.0010
Epoch 6/50
428/428 [==============================] - 61s 142ms/step - loss: 1.2257 -
accuracy: 0.5103 - val_loss: 1.2023 - val_accuracy: 0.5240 - lr: 0.0010
Epoch 7/50
428/428 [==============================] - 61s 142ms/step - loss: 1.2001 -
accuracy: 0.5187 - val_loss: 1.1287 - val_accuracy: 0.5454 - lr: 0.0010
Epoch 8/50
428/428 [==============================] - 62s 144ms/step - loss: 1.1807 -
accuracy: 0.5308 - val_loss: 1.1210 - val_accuracy: 0.5482 - lr: 0.0010
Epoch 9/50
428/428 [==============================] - 63s 148ms/step - loss: 1.1571 -
accuracy: 0.5368 - val_loss: 1.1070 - val_accuracy: 0.5610 - lr: 0.0010
Epoch 10/50
428/428 [==============================] - 62s 145ms/step - loss: 1.1474 -
accuracy: 0.5413 - val_loss: 1.0996 - val_accuracy: 0.5537 - lr: 0.0010
Epoch 11/50
428/428 [==============================] - 61s 142ms/step - loss: 1.1279 -
accuracy: 0.5508 - val_loss: 1.0867 - val_accuracy: 0.5688 - lr: 0.0010
Epoch 12/50
428/428 [==============================] - 61s 142ms/step - loss: 1.1126 -
accuracy: 0.5588 - val_loss: 1.0826 - val_accuracy: 0.5683 - lr: 0.0010
Epoch 13/50
428/428 [==============================] - 61s 143ms/step - loss: 1.1015 -
accuracy: 0.5620 - val_loss: 1.0759 - val_accuracy: 0.5727 - lr: 0.0010
Epoch 14/50
428/428 [==============================] - 61s 143ms/step - loss: 1.0784 -
accuracy: 0.5702 - val_loss: 1.0724 - val_accuracy: 0.5694 - lr: 0.0010
Epoch 15/50
428/428 [==============================] - 62s 146ms/step - loss: 1.0724 -
accuracy: 0.5735 - val_loss: 1.0486 - val_accuracy: 0.5777 - lr: 0.0010
Epoch 16/50
428/428 [==============================] - 63s 148ms/step - loss: 1.0470 -
accuracy: 0.5824 - val_loss: 1.0644 - val_accuracy: 0.5707 - lr: 0.0010
Epoch 17/50
428/428 [==============================] - 65s 153ms/step - loss: 1.0369 -
accuracy: 0.5866 - val_loss: 1.0583 - val_accuracy: 0.5788 - lr: 0.0010
Epoch 18/50
428/428 [==============================] - 61s 143ms/step - loss: 1.0359 -
accuracy: 0.5879 - val_loss: 1.0352 - val_accuracy: 0.5813 - lr: 0.0010
```

```
Epoch 19/50
428/428 [==============================] - 68s 159ms/step - loss: 1.0137 -
accuracy: 0.5961 - val_loss: 1.0450 - val_accuracy: 0.5822 - lr: 0.0010
Epoch 20/50
428/428 [==============================] - 64s 150ms/step - loss: 1.0137 -
accuracy: 0.6002 - val_loss: 1.0648 - val_accuracy: 0.5793 - lr: 0.0010
Epoch 21/50
428/428 [==============================] - 62s 144ms/step - loss: 0.9995 -
accuracy: 0.6018 - val_loss: 1.0508 - val_accuracy: 0.5824 - lr: 0.0010
Epoch 22/50
428/428 [==============================] - 68s 159ms/step - loss: 0.9788 -
accuracy: 0.6115 - val_loss: 1.0411 - val_accuracy: 0.5844 - lr: 0.0010
Epoch 23/50
428/428 [==============================] - 69s 162ms/step - loss: 0.9681 -
accuracy: 0.6171 - val_loss: 1.0442 - val_accuracy: 0.5908 - lr: 0.0010
Epoch 24/50
428/428 [==============================] - 64s 150ms/step - loss: 0.9570 -
accuracy: 0.6206 - val_loss: 1.0196 - val_accuracy: 0.5965 - lr: 0.0010
Epoch 25/50
428/428 [==============================] - 60s 141ms/step - loss: 0.9484 -
accuracy: 0.6268 - val_loss: 1.0203 - val_accuracy: 0.5964 - lr: 0.0010
Epoch 26/50
428/428 [==============================] - 62s 145ms/step - loss: 0.9275 -
accuracy: 0.6345 - val_loss: 1.0465 - val_accuracy: 0.5900 - lr: 0.0010
Epoch 27/50
428/428 [==============================] - 63s 146ms/step - loss: 0.9314 -
accuracy: 0.6334 - val_loss: 1.0285 - val_accuracy: 0.5990 - lr: 0.0010
Epoch 28/50
428/428 [==============================] - 64s 148ms/step - loss: 0.9218 -
accuracy: 0.6357 - val_loss: 1.0324 - val_accuracy: 0.5963 - lr: 0.0010
Epoch 29/50
428/428 [==============================] - 63s 147ms/step - loss: 0.9083 -
accuracy: 0.6395 - val_loss: 1.0150 - val_accuracy: 0.6005 - lr: 0.0010
Epoch 30/50
428/428 [==============================] - 67s 156ms/step - loss: 0.8917 -
accuracy: 0.6468 - val_loss: 1.0257 - val_accuracy: 0.5992 - lr: 0.0010
Epoch 31/50
428/428 [==============================] - 66s 155ms/step - loss: 0.8802 -
accuracy: 0.6545 - val_loss: 1.0460 - val_accuracy: 0.5939 - lr: 0.0010
Epoch 32/50
428/428 [==============================] - 64s 150ms/step - loss: 0.8747 -
accuracy: 0.6560 - val_loss: 1.0100 - val_accuracy: 0.6030 - lr: 0.0010
Epoch 33/50
428/428 [==============================] - 64s 149ms/step - loss: 0.8640 -
accuracy: 0.6621 - val_loss: 1.0481 - val_accuracy: 0.5919 - lr: 0.0010
Epoch 34/50
428/428 [==============================] - 69s 160ms/step - loss: 0.8654 -
accuracy: 0.6575 - val_loss: 1.0336 - val_accuracy: 0.5966 - lr: 0.0010
```

```
Epoch 35/50
428/428 [==============================] - 65s 153ms/step - loss: 0.8562 -
accuracy: 0.6641 - val_loss: 1.0449 - val_accuracy: 0.6004 - lr: 0.0010
Epoch 36/50
428/428 [==============================] - 64s 150ms/step - loss: 0.8377 -
accuracy: 0.6697 - val_loss: 1.0377 - val_accuracy: 0.6067 - lr: 0.0010
Epoch 37/50
428/428 [==============================] - 66s 154ms/step - loss: 0.8249 -
accuracy: 0.6761 - val_loss: 1.0096 - val_accuracy: 0.6052 - lr: 0.0010
Epoch 38/50
428/428 [==============================] - 67s 156ms/step - loss: 0.8205 -
accuracy: 0.6788 - val_loss: 1.0218 - val_accuracy: 0.6071 - lr: 0.0010
Epoch 39/50
428/428 [==============================] - 64s 150ms/step - loss: 0.8159 -
accuracy: 0.6826 - val_loss: 1.0132 - val_accuracy: 0.6106 - lr: 0.0010
Epoch 40/50
428/428 [==============================] - 65s 153ms/step - loss: 0.8086 -
accuracy: 0.6832 - val_loss: 1.0409 - val_accuracy: 0.6007 - lr: 0.0010
Epoch 41/50
428/428 [==============================] - 64s 149ms/step - loss: 0.7917 -
accuracy: 0.6894 - val_loss: 1.0451 - val_accuracy: 0.6036 - lr: 0.0010
Epoch 42/50
428/428 [==============================] - 63s 148ms/step - loss: 0.7922 -
accuracy: 0.6904 - val_loss: 1.0498 - val_accuracy: 0.5969 - lr: 0.0010
Epoch 43/50
428/428 [==============================] - 65s 151ms/step - loss: 0.7831 -
accuracy: 0.6956 - val_loss: 1.0557 - val_accuracy: 0.6078 - lr: 0.0010
Epoch 44/50
428/428 [==============================] - 67s 158ms/step - loss: 0.7658 -
accuracy: 0.7003 - val_loss: 1.0227 - val_accuracy: 0.6083 - lr: 0.0010
Epoch 45/50
428/428 [==============================] - 66s 154ms/step - loss: 0.7634 -
accuracy: 0.7027 - val_loss: 1.0307 - val_accuracy: 0.6170 - lr: 0.0010
Epoch 46/50
428/428 [==============================] - 68s 159ms/step - loss: 0.7425 -
accuracy: 0.7103 - val_loss: 1.0642 - val_accuracy: 0.6125 - lr: 0.0010
Epoch 47/50
428/428 [==============================] - 66s 154ms/step - loss: 0.7459 -
accuracy: 0.7125 - val_loss: 1.0591 - val_accuracy: 0.6155 - lr: 0.0010
Epoch 48/50
428/428 [==============================] - 65s 152ms/step - loss: 0.7342 -
accuracy: 0.7148 - val_loss: 1.0531 - val_accuracy: 0.6070 - lr: 0.0010
Epoch 49/50
428/428 [==============================] - 64s 151ms/step - loss: 0.7261 -
accuracy: 0.7184 - val_loss: 1.0651 - val_accuracy: 0.6125 - lr: 0.0010
Epoch 50/50
428/428 [==============================] - 65s 153ms/step - loss: 0.7161 -
accuracy: 0.7219 - val_loss: 1.0766 - val_accuracy: 0.6111 - lr: 0.0010
```

[71]:
```
print("Accuracy of our model on test data : " , model.
 ↪evaluate(x_test,y_test)[1]*100 , "%")

epochs = [i for i in range(50)]
fig , ax = plt.subplots(1,2)
train_acc = history.history['accuracy']
train_loss = history.history['loss']
test_acc = history.history['val_accuracy']
test_loss = history.history['val_loss']

fig.set_size_inches(20,6)
ax[0].plot(epochs , train_loss , label = 'Training Loss')
ax[0].plot(epochs , test_loss , label = 'Testing Loss')
ax[0].set_title('Training & Testing Loss')
ax[0].legend()
ax[0].set_xlabel("Epochs")

ax[1].plot(epochs , train_acc , label = 'Training Accuracy')
ax[1].plot(epochs , test_acc , label = 'Testing Accuracy')
ax[1].set_title('Training & Testing Accuracy')
ax[1].legend()
ax[1].set_xlabel("Epochs")
plt.show()
```

```
286/286 [==============================] - 5s 19ms/step - loss: 1.0766 -
accuracy: 0.6111
Accuracy of our model on test data :  61.105018854141235 %
```



[73]:
```
# predicting on test data.
pred_test = model.predict(x_test)
y_pred = ohe.inverse_transform(pred_test)

y_test = ohe.inverse_transform(y_test)
```

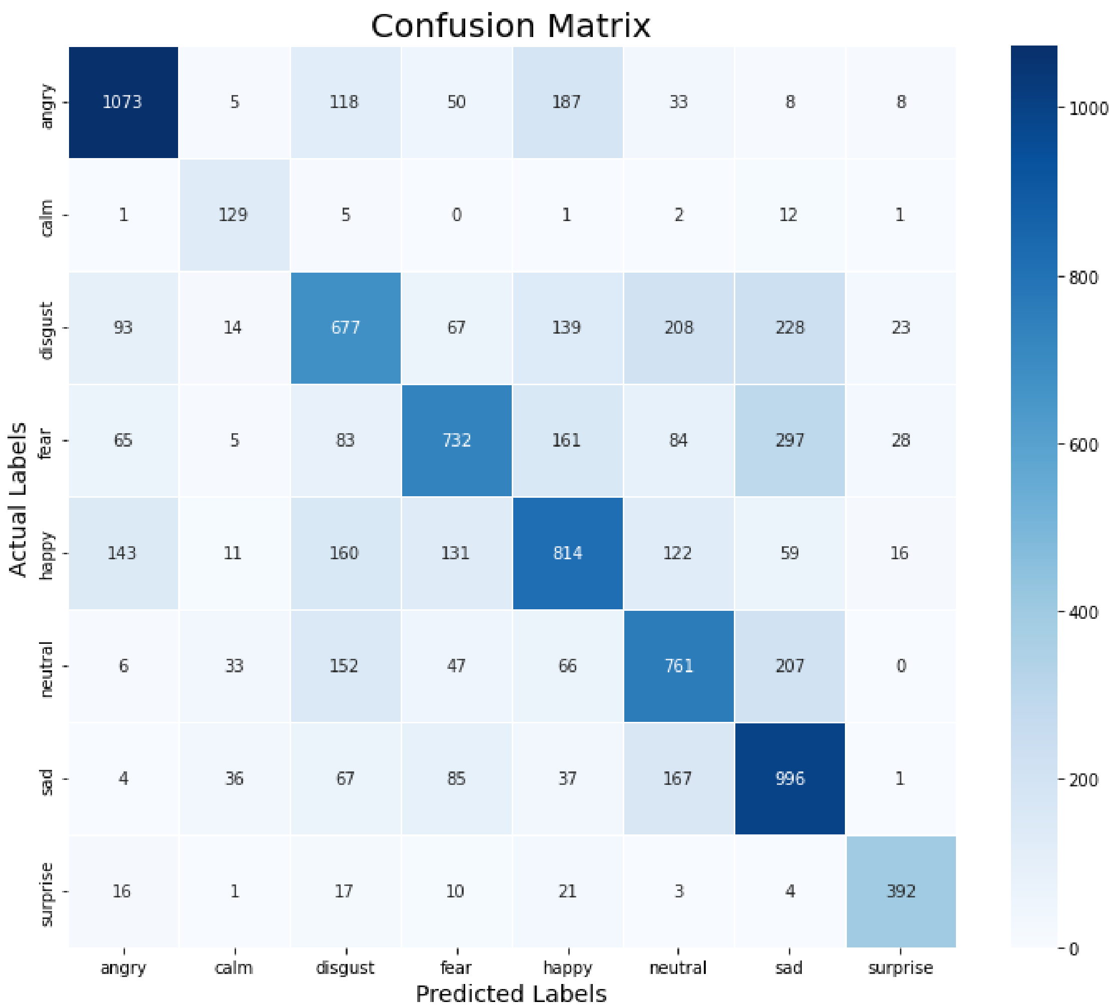
```
286/286 [==============================] - 6s 19ms/step
```

[74]:
```python
df = pd.DataFrame(columns=['Predicted Labels', 'Actual Labels'])
df['Predicted Labels'] = y_pred.flatten()
df['Actual Labels'] = y_test.flatten()

df.head(10)
```

[74]:

	Predicted Labels	Actual Labels
0	happy	happy
1	happy	disgust
2	fear	happy
3	sad	disgust
4	fear	sad
5	surprise	surprise
6	neutral	calm
7	angry	disgust
8	angry	disgust
9	disgust	disgust

[77]:
```python
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize = (12, 10))
cm = pd.DataFrame(cm , index = [i for i in ohe.categories_] , columns = [i for␣
↪i in ohe.categories_])
sns.heatmap(cm, linecolor='white', cmap='Blues', linewidth=1, annot=True,␣
↪fmt='')
plt.title('Confusion Matrix', size=20)
plt.xlabel('Predicted Labels', size=14)
plt.ylabel('Actual Labels', size=14)
plt.show()
```



[78]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

       angry       0.77      0.72      0.74      1482
        calm       0.55      0.85      0.67       151
     disgust       0.53      0.47      0.50      1449
        fear       0.65      0.50      0.57      1455
       happy       0.57      0.56      0.56      1456
     neutral       0.55      0.60      0.57      1272
         sad       0.55      0.72      0.62      1393
    surprise       0.84      0.84      0.84       464

    accuracy                           0.61      9122
   macro avg       0.63      0.66      0.63      9122
weighted avg       0.62      0.61      0.61      9122
```

We can see our model is more accurate in predicting surprise, angry emotions and it makes sense also because audio files of these emotions differ to other audio files in a lot of ways like pitch, speed etc..

We overall achieved 61% accuracy on our test data and its decent but we can improve it more by applying more augmentation techniques and using other feature extraction methods.

```
[ ]:
```