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Advanced Computer Science Masters Project

Interim Progress Report (IPR)

Human Emotion Detection from the audio using Deep Learning

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Contents

1. Background Research

This project aims to develop a deep learning model which can detect the human emotion from the audio file provided as the input. This project also aimed to solve a research question "Will the high emotion level audio provide more accurate emotion detection (Anger, Disgust, Fear, Happy, Neutral, and Sad) compared to low and medium emotional level audio?".

For this project CREMA-D dataset [1] is considered from the Kaggle and considered the original dataset which is available in GitHub [2] with some extra important data files (VideoDemographics.csv, finishedResponses.csv) which linked with the original dataset and will are crucial for data analysis.

The Research started with finding human emotion projects and papers across the internet, mainly on IEEE Xplore and other platforms like ResearchGate. The first task in this project is to identify the relevant papers which are similar to this idea to seek some help to start the project, in this process [3,4,5,6,7] papers have been found which are relatively close to my research idea and also the dataset.

The dataset considered from the Kaggle consists of only audio files with some specific notation like " 1001_DFA_DIS_XX.wav". 1001 represents the actor's id, DFA represents dialogue the actor has told, DIS represents emotion, and XX represents tone level in the audio. According to [5], the dataset consists of 7442 clips of 91 actors with diverse backgrounds like Caucasian, African

American, Asian, few unknown and each actor has chosen to tell from 12 sentences with 6 emotions (anger, disgust, fear, happy, neutral, sad) in 3 tone levels (Low, Medium, High).

This project is considered to have two output variables “Emotion” and “Tone Level”. The emotion column has a nearly equal distribution of data for 6 emotions, whereas the “Tone Level” column has some missed values, which need to fill with the relative data existing in some other dataset by merging based on clip name. In the process of figuring a solution for this, it has been observed that there is a file named "**finishedResponses.csv**" related to the crema-d dataset, in which they have given a hint for assigning the tone levels i.e., "dispVal" - the displayed value "dispLevel" - a numeric representation of the displayed value, 20 for low, 50 for med, 80 for hi. Those unspecified XX values in the Tone_Level column will be replaced by their actual tone level referring to these two columns and merging them. To get more information about the data, "VideoDemographics.csv” has been merged with the data considered in the beginning.

After merging the required data, the next challenge is to clean the data by removing the null values in the data and then subset the data with the required columns for the analysis. The later step is data augmentation for the audio data because the original data has only 7442 records, for the better training of the model it is necessary to have more records. Hence it is necessary to learn about the augmentation techniques and how they can be done. Augmentation techniques like Pitching, shifting, stretching, and adding noise are used according to the brief description given in [8] about these techniques.

Now, the major part is to extract the features of the data after augmentation because it is very important to get the main features from the audio using feature extraction which will help in the prediction of emotions very well [7]. The feature extraction techniques like Zero-Crossing Rate, MFCC, Chroma STFT, RMS, and Mel Scale Spectrogram have been studied and applied in the project based on the above methods discussed in the paper [3, 4, 7] which helped a lot for the project. Then the next step in the project is to perform one hot encoding for the output variables and then standardize the data using a standard scaler.

Firstly, a baseline model has to be built, just to make sure everything is in place. A CNN model with one hidden layer with one input and two output variables has been developed to test at the first place. The paper [7], “deep learning-based audio processing speech emotion detection” has been used to understand the structure for building CNN model.

The above is the complete background research I have done to understand the needs for doing emotion detection model using deep learning and achieved the results for the base line model which are shown in next section.

2) Project Plan

Human Emotion Detection from the audio using Deep Learning

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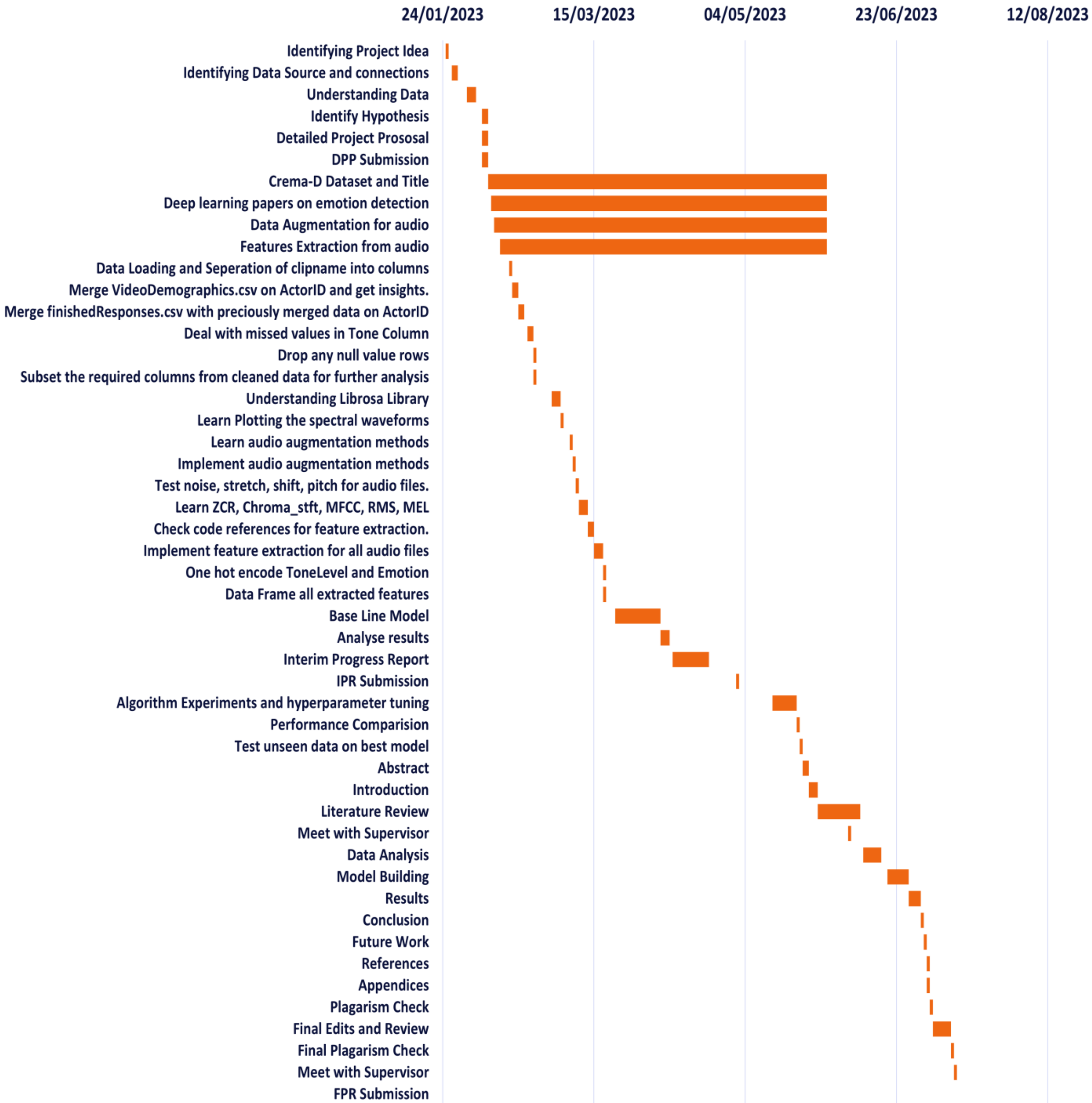
	Milestone description	Progress	Start	End	Days
Project Idea and Data	Identifying Project Idea	100%	25/01/2023	26/01/2023	1
	Identifying Data Source and connections	100%	27/01/2023	29/01/2023	2
	Understanding Data	100%	01/02/2023	04/02/2023	3
	Identify Hypothesis	100%	06/02/2023	07/02/2023	2
	Detailed Project Prososal	100%	06/02/2023	07/02/2023	2
	DPP Submission	100%	06/02/2023	07/02/2023	2
Literature Research (Identify Papers on)	Crema-D Dataset and Title	90%	08/02/2023	31/05/2023	112
	Deep learning papers on emotion detection	85%	09/02/2023	31/05/2023	111
	Data Augmentation for audio	80%	10/02/2023	31/05/2023	110
	Features Extraction from audio	100%	12/02/2023	31/05/2023	108
Data Cleaning and Merging	Data Loading and Seperation of clipname into columns	100%	15/02/2023	15/02/2023	1
	Merge VideoDemographics.csv on ActorID and get insights.	100%	16/02/2023	17/02/2023	2
	Merge finishedResponses.csv with preciously merged data on ActorID	100%	18/02/2023	19/02/2023	2
	Deal with missed values in Tone Column	100%	21/02/2023	22/02/2023	2
	Drop any null value rows	100%	23/02/2023	23/02/2023	1
	Subset the required columns from cleaned data for further analysis	100%	23/02/2023	23/02/2023	1

Data Augmentation and Feature Extarction	Understanding Librosa Library	100%	01/03/2023	03/03/2023	3
	Learn Plotting the spectral waveforms	100%	04/03/2023	04/03/2023	1
	Learn audio augmentation methods	100%	07/03/2023	07/03/2023	1
	Implement audio augmentation methods	100%	08/03/2023	08/03/2023	1
	Test noise, stretch, shift, pitch for audio files.	100%	09/03/2023	09/03/2023	1
	Learn ZCR, Chroma_stft, MFCC, RMS, MEL	100%	10/03/2023	12/03/2023	3
	Check code references for feature extraction.	100%	13/03/2023	14/03/2023	2
	Implement feature extraction for all audio files	100%	15/03/2023	17/03/2023	3
	One hot encode ToneLevel and Emotion	100%	18/03/2023	18/03/2023	1
	Data Frame all extracted features	100%	18/03/2023	18/03/2023	1
Model Building	Base Line Model	100%	22/03/2023	05/04/2023	15
	Analyse results	100%	06/04/2023	08/04/2023	3
	Interim Progress Report	100%	10/04/2023	21/04/2023	12
	IPR Submission	100%	01/05/2023	01/05/2023	1
	Algorithm Experiments and hyperparameter tuning		13/05/2023	20/05/2023	8
	Performance Comparision		21/05/2023	21/05/2023	1
	Test unseen data on best model		22/05/2023	22/05/2023	1

Dissertation Report	Abstract	23/05/2023	24/05/2023	2
	Introduction	25/05/2023	27/05/2023	3
	Literature Review	28/05/2023	10/06/2023	14
	Meet with Supervisor	07/06/2023	07/06/2023	1
	Data Analysis	12/06/2023	17/06/2023	6
	Model Building	20/06/2023	26/06/2023	7
	Results	27/06/2023	30/06/2023	4
	Conclusion	01/07/2023	01/07/2023	1
	Future Work	02/07/2023	02/07/2023	1
	References	03/07/2023	03/07/2023	1
	Appendices	03/07/2023	03/07/2023	1
	Plagarism Check	04/07/2023	04/07/2023	1
	Final Edits and Review	05/07/2023	10/07/2023	6
	Final Plagarism Check	11/07/2023	11/07/2023	1
	Meet with Supervisor	12/07/2023	12/07/2023	1
	FPR Submission	28/08/2023	28/08/2023	1

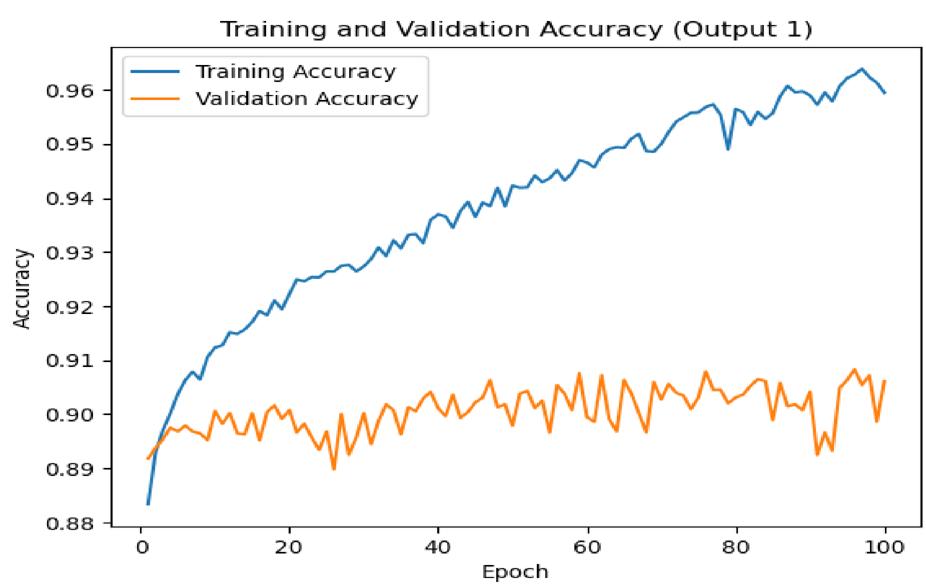
Gantt Chart for Project Plan

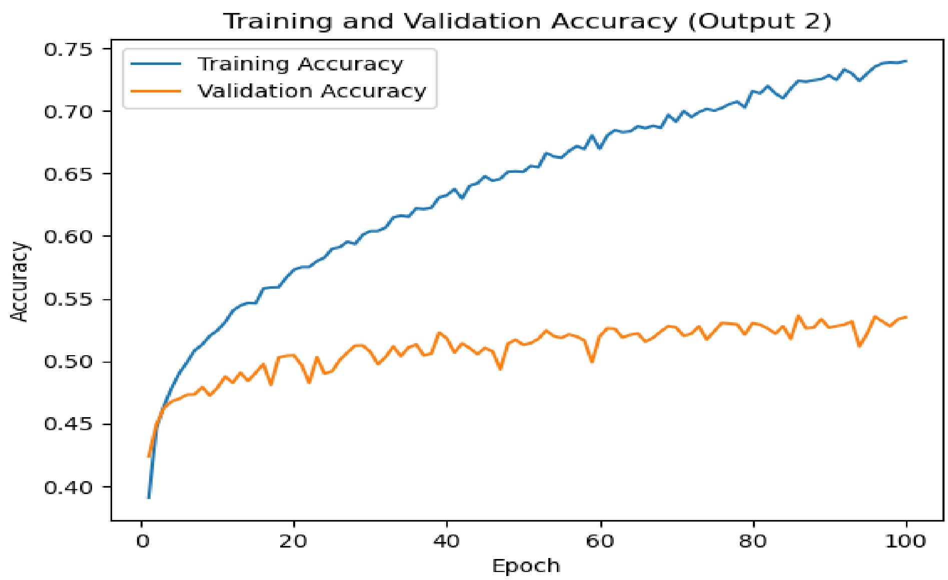


3) Summary of Progress to Date

As mentioned in the above project plan, Data understanding and merging the required columns for analysis has taken a lot of time, but successfully completed the part of data cleaning by finding and dropping the unwanted null values from the data. Later, Understanding the techniques of audio augmentation and feature extraction has been completed along with the practical implementation of code and tested to make sure practical data augmentation techniques and features extraction techniques are working.

Finally, the baseline deep learning model has been implemented with the help of the architecture mentioned in the journal [7] by feeding the extracted features of the audio to the model. The performance has been tracked and achieved 95% accuracy on the training data for output variable 1 and 73% accuracy for output variable 2. On testing data, output variable 1 achieved 90% accuracy and 53.49% for output variable 2. The graph for the results achieved are shown below.





This project has been successfully completed with the baseline model to date. Still, a lot of work needs to be done to get better results with advanced deep-learning architectures. And later I have to start writing a dissertation report for this project.

The source code for the project implemented to date is shown in the appendices.

4) Consideration of ethical, legal, professional, and social issues

The consideration for this project is the secondary data which is already available on Kaggle and GitHub. Source code is referred through online sources and my own version of the code is implemented with the help of architecture in the journal [7], the implementation and libraries used are completely legal and there are no social issues associated with concept or project implementation.

Appendices

Source Code for the Human Emotion Detection using deep learning project is given below:

```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

import os
import sys

import librosa
import librosa.display
import seaborn as sns


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

from IPython.display import Audio

import tensorflow as tf
from tensorflow.keras.callbacks import ReduceLROnPlateau
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, LSTM, Flatten, Dropout, BatchNormalization
from tensorflow.keras.callbacks import ModelCheckpoint

import librosa
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers

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

import tensorflow as tf
from tensorflow import keras
from tensorflow.python.keras.callbacks import ReduceLROnPlateau
```

```
from tensorflow.python.keras.models import Sequential
from tensorflow.python.keras.layers import Dense, Conv1D, MaxPooling1D, Flatten, Dropout, Activation
from tensorflow.python.keras.utils import np_utils
from tensorflow.python.keras.callbacks import ModelCheckpoint
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.utils import to_categorical


Crema = os.listdir("AudioWAV")
Crema.sort()
Crema[0:20]
```

1) Seperate the file name to get, dialouge, emotion and tone level, Concatenate the path to respective audiofiles in a folder AudioWAV. Add them as seperate columns.

```
c = pd.DataFrame(Crema, columns=["FileName"])
c

# To store the values in seperate columns

clipName = []
actor_id = []
dialouge = []
emotion = []
tone = []
path = []

#Seperating the FileName based on "_" seperator to get the dialouge, emotion and tone level in seperate columns.
# also adding the path for the audio file in the folder AudioWAV

for i in c["FileName"]:
  c_split = i.split(".")
  clipName.append(c_split[0])
  c_split_1 = c_split[0].split("_")
  actor_id.append(c_split_1[0])
  dialouge.append(c_split_1[1])
  emotion.append(c_split_1[2])
  tone.append(c_split_1[3])
  path.append("AudioWav/" + i)
```

```
# Adding to the respective empty columns by converting to the list.

c["clipName"] = list(clipName)
c["ActorID"] = list(actor_id)
c["Dialouge"] = list(dialouge)
c["Emotion"] = list(emotion)
c["Tone_Level"] = list(tone)
c["File_Path"] = list(path)

# Converting the ActorID to integer type as it is in object type, for future use of merging.
c["ActorID"] = c["ActorID"].astype(np.int64)

c.head()
c.info()
c['ActorID'].unique()
```

2) Merging the VideoDemographics.csv file based on the ActorID to get the gender of the voice in the audio.

```
gend = pd.read_csv("VideoDemographics.csv")
gend.head()

# Merging c (actual data), gend (videodemographics.csv) files to get the gender based on the ActorID as unique column.

c_gend=pd.merge(c,gend, left_on='ActorID', right_on='ActorID', how='left')
c_gend

c_gend.info()

# checking the duplicates in the filepath.
(c_gend.File_Path.value_counts()==1).value_counts()

c_gend["Race"].value_counts()

c_gend["Ethnicity"].value_counts()

# SInce this the important column for the analysis of the hypothesis question, analysing this column is important.
c_gend["Tone_Level"].value_counts()
```

c_gend["Emotion"].value_counts()

tone_fill = pd.read_csv("finishedResponses.csv")
tone_fill.head()

#We just need, the dispVal and clipName for filling the missing data.
tone_fill_disp_value = tone_fill[["clipName","dispVal"]].sort_values(["clipName","dispVal"])
tone_fill_disp_value

 # there are 219688 rows in the above data, but we just need the unique values. hence removing the duplicates.

clips_unique_tone_value=tone_fill_disp_value.drop_duplicates()

clips_unique_tone_value

we are not considering any null values, after removing the null values, we have got 7442 which is the exact rows.

which we have in c_gend dataframe.

clips_unique_tone_value =
clips_unique_tone_value[~clips_unique_tone_value.dispVal.isnull()==True]

clips_unique_tone_value

clips_unique_tone_value["dispVal"].value_counts()

#Merging clips_unique_tone_value and c_gend on clipname using left join to get the dispVal values for respective audio clip.
HED = pd.merge(c_gend, clips_unique_tone_value, on='clipName', how='left')
HED.info()

#checking if there are any null values in dispVal column.

HED[HED.dispVal.isnull()==True]

```
# There is one Null Value in dispVal, so we are removing that.


HED = HED.dropna().reset_index(drop = True)
HED

# Now all the values are non-null for all 7441 records.
# Its time to add the Respective tone level based on the dispVal of the audio.

for i in range(len(HED["Tone_Level"])):

   if i < len(HED["Tone_Level"]) and HED["Tone_Level"][i] in ("XX","X"):

      if i < len(HED["dispVal"]):

         if HED["dispVal"][i] == 20.0:

            HED["Tone_Level"][i] = "LO"

         elif HED["dispVal"][i] == 50.0:

            HED["Tone_Level"][i] = "MD"

         elif HED["dispVal"][i] == 80.0:

            HED["Tone_Level"][i] = "HI"

HED["Tone_Level"].value_counts()



HED.head()


# Now we just need audiofile path,Dialouge in the audiofile, tone_level of the audio, emotion in
the
# audio. so we are having only these four columns for model building.

HED_DATA = HED[["File_Path","Tone_Level","Emotion"]]


for i in range(len(HED_DATA["Emotion"])):
   if i < len(HED_DATA["Emotion"]):
      if HED_DATA["Emotion"][i] == "ANG":
```

```
            HED_DATA["Emotion"][i] = "ANGER"
        elif HED_DATA["Emotion"][i] == "DIS":
            HED_DATA["Emotion"][i] = "DISGUST"
        elif HED_DATA["Emotion"][i] == "FEA":
            HED_DATA["Emotion"][i] = "FEAR"
        elif HED_DATA["Emotion"][i] == "HAP":
            HED_DATA["Emotion"][i] = "HAPPY"
        elif HED_DATA["Emotion"][i] == "NEU":
            HED_DATA["Emotion"][i] = "NEUTRAL"
        elif HED_DATA["Emotion"][i] == "SAD":
            HED_DATA["Emotion"][i] = "SAD"

HED_DATA.head()


HED_DATA["Emotion"].value_counts()


for i in range(len(HED_DATA["Tone_Level"])):
    if i < len(HED_DATA["Tone_Level"]):
        if HED_DATA["Tone_Level"][i] == "MD":
            HED_DATA["Tone_Level"][i] = "MEDIUM"
        elif HED_DATA["Tone_Level"][i] == "LO":
            HED_DATA["Tone_Level"][i] = "LOW"
        elif HED_DATA["Tone_Level"][i] == "HI":
            HED_DATA["Tone_Level"][i] = "HIGH"




HED_DATA["Tone_Level"].unique()


HED_DATA.head()


from imblearn.over_sampling import RandomOverSampler
from collections import Counter
import pandas as pd

X = HED_DATA["File_Path"]
y1 = HED_DATA['Tone_Level']
y2 = HED_DATA["Emotion"]
```

```
print('Original dataset shape %s' % Counter(y2))
```

3) converting audiowaves into spectral values.¶

Now, its time to convert the audio file into values using data augmentation techniques at first and extracting features

```
def create_waveplot(data, sr, e):

    plt.figure(figsize=(10, 3))

    plt.title('Waveplot for audio with {} emotion'.format(e), size=15)

    librosa.display.waveshow(data, sr=sr)

    plt.show()


def create_spectrogram(data, sr, e):

    X = librosa.stft(data)

    Xdb = librosa.amplitude_to_db(abs(X))

    plt.figure(figsize=(12, 3))

    plt.title('Spectrogram for audio with {} emotion'.format(e), size=15)

    librosa.display.specshow(Xdb, sr=sr, x_axis='time', y_axis='hz')

    plt.colorbar()


emotion='FEAR'

path = np.array(HED_DATA.File_Path[HED_DATA.Emotion==emotion])[1]

data, sampling_rate = librosa.load(path)

create_waveplot(data, sampling_rate, emotion)
```

```
create_spectrogram(data, sampling_rate, emotion)

Audio(path)




#Data Augmentation

def add_noise(aug_data):

    noise_add = 0.035*np.random.uniform()*np.amax(aug_data)

    aug_data = aug_data + noise_add*np.random.normal(size=aug_data.shape[0])

    return aug_data


def wav_stretch(aug_data):
    """
    Streching the sound. Note that this expands the dataset slightly
    """
    aug_data = librosa.effects.time_stretch(aug_data, rate = 0.5)
    return aug_data


def wav_shift(aug_data):

    wav_shift_range = int(np.random.uniform(low=-10, high = 10)*1000)

    return np.roll(aug_data, wav_shift_range)


def add_pitch(aug_data, sampling_rate, steps):

    return librosa.effects.pitch_shift(aug_data, sr=sampling_rate, n_steps = steps)
```

```
file_path = np.array(HED_DATA.File_Path)[2]

data, sample_rate = librosa.load(file_path)
data.shape

plt.figure(figsize=(14,4))
librosa.display.waveshow(y=data, sr=sample_rate)
Audio(file_path)

x = add_noise(data)
plt.figure(figsize = (14, 4))
# orginial plot
librosa.display.waveshow(data, sr = sampling_rate)
plt.title('Original Audio Waveform', size = 24)
plt.show()
plt.figure(figsize = (14, 4))
librosa.display.waveshow(x, sr = sampling_rate)
plt.title('Augmented Audio Waveform with Noise', size = 24)
plt.show()
Audio(x, rate = sampling_rate)


x = wav_stretch(data)
plt.figure(figsize = (14, 4))
# orginial plot
librosa.display.waveshow(data, sr = sampling_rate)
plt.title('Original Audio Waveform', size = 24)
plt.show()
plt.figure(figsize = (14, 4))
librosa.display.waveshow(x, sr = sampling_rate)
plt.title('Augmented Audio Waveform with Stretch', size = 24)
plt.show()
Audio(x, rate = sampling_rate)


x = wav_shift(data)
plt.figure(figsize = (14, 4))
# orginial plot
librosa.display.waveshow(data, sr = sampling_rate)
plt.title('Original Audio Waveform', size = 24)
plt.show()
plt.figure(figsize = (14, 4))
librosa.display.waveshow(x, sr = sampling_rate)
plt.title('Augmented Audio Waveform with Shift', size = 24)
```

```
plt.show()
Audio(x, rate = sampling_rate)




x = add_pitch(data,sample_rate, steps=5)
plt.figure(figsize = (14, 4))
# orginial plot
librosa.display.waveshow(data, sr = sampling_rate)
plt.title('Original Audio Waveform', size = 24)
plt.show()
plt.figure(figsize = (14, 4))
librosa.display.waveshow(x, sr = sampling_rate)
plt.title('Augmented Audio Waveform with Pitch Shift', size = 24)
plt.show()
Audio(x, rate = sampling_rate)


# Features extraction from data
def extract_features(data):
   # ZCR
   result = np.array([])
   zcr = np.mean(librosa.feature.zero_crossing_rate(y=data).T, axis=0)
   result=np.hstack((result, zcr)) # stacking horizontally

   # 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
```

```
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, offset=0.6, sr=8025)

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


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

   # data with stretching and pitching
   new_data = wav_stretch(data)
   data_stretch_pitch = add_pitch(new_data, sample_rate, steps=5)
   res3 = extract_features(data_stretch_pitch)
   result = np.vstack((result, res3)) # stacking vertically

   return result



X, Y1,Y2 = [], [], []
for file_path, tone_level, emotion in zip(HED_DATA.File_Path, HED_DATA.Tone_Level, HED_DATA.Emotion):
   feature = get_features(file_path)
   for element in feature:
      X.append(element)
      Y1.append(tone_level)
      Y2.append(emotion)


len(X), len(Y1), len(Y2), HED_DATA.File_Path.shape


HED_Features = pd.DataFrame(X)
HED_Features['Tone_Level'] = Y1
HED_Features['Emotion'] = Y2
```

```
HED_Features.to_csv('HED_Spectral_Features.csv', index=False)
HED_Features.head()


X_train = HED_Features.iloc[: ,:-2].values
Y1_train = HED_Features['Tone_Level'].values
Y2_train = HED_Features['Emotion'].values

encoder = OneHotEncoder()
Y1 = encoder.fit_transform(np.array(Y1_train).reshape(-1,1)).toarray()
Y2 = encoder.fit_transform(np.array(Y2_train).reshape(-1,1)).toarray()

x_train, x_test, y1_train, y1_test, y2_train, y2_test = train_test_split(X_train, Y1, Y2, random_state=0, shuffle=True)
x_train.shape, y1_train.shape, y2_train.shape, x_test.shape, y1_test.shape, y2_test.shape



X_train


scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
x_train.shape, y1_train.shape, y2_train.shape, x_test.shape, y1_test.shape, y2_test.shape


# Baseline model

from tensorflow.keras.layers import Input, Conv1D, Activation, Flatten, Dense
from tensorflow.keras.models import Model

# Define input layer
inputs = Input(shape=(x_train.shape[1], 1))

# Define convolutional layers
conv = Conv1D(64, 8, padding='same')(inputs)
conv = Activation('relu')(conv)

# Define flatten layer
flatten = Flatten()(conv)

# Define output layers
output_1 = Dense(y1_train.shape[1], activation='softmax')(flatten)
```

```
output_2 = Dense(y2_train.shape[1], activation='softmax')(flatten)

# Define the model with input and output layers
model = Model(inputs=inputs, outputs=[output_1, output_2])

# Compile the model
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

# Train the model
history = model.fit(x_train, [y1_train, y2_train], epochs=100, batch_size=64,
validation_data=(x_test, [y1_test, y2_test]))


import matplotlib.pyplot as plt

# Get training and validation accuracy for each epoch
acc = history.history['dense_accuracy']
val_acc = history.history['val_dense_accuracy']
acc2 = history.history['dense_1_accuracy']
val_acc2 = history.history['val_dense_1_accuracy']

# Plot the training and validation accuracy for the first output
plt.plot(range(1, len(acc) + 1), acc, label='Training Accuracy')
plt.plot(range(1, len(val_acc) + 1), val_acc, label='Validation Accuracy')
plt.title('Training and Validation Accuracy (Output 1)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Plot the training and validation accuracy for the second output
plt.plot(range(1, len(acc2) + 1), acc2, label='Training Accuracy')
plt.plot(range(1, len(val_acc2) + 1), val_acc2, label='Validation Accuracy')
plt.title('Training and Validation Accuracy (Output 2)')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()



import matplotlib.pyplot as plt
```

```
# Plot the training loss for both output layers
plt.plot(history.history['dense_loss'])
plt.plot(history.history['dense_1_loss'])
plt.title('Training Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['y1_train', 'y2_train'], loc='upper right')
plt.show()

# Plot the validation loss for both output layers
plt.plot(history.history['val_dense_loss'])
plt.plot(history.history['val_dense_1_loss'])
plt.title('Validation Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['y1_test', 'y2_test'], loc='upper right')
plt.show()
```

The entire implemented source code for this project is pushed to the GitHub link given below.

Navigate to the below link to watch the project progress in detail.

Source Code Link:

https://github.com/kksairam19061996/MSc_Project_Sairam/blob/main/Human%20Emotion%20Detection%20from%20the%20audio%20using%20Deep%20Learning.ipynb

GitHub MSc Project Repository: https://github.com/kksairam19061996/MSc_Project_Sairam

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