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Speech Emotion Recognition Using Deep Learning

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ABSTRACT: Communication is an integral part of the human social life. We communicate using the different semantics known to us and we express our thoughts, ideas and opinions via tone and linguistics. It has been observed that humans convey information using various emotions such as anger, fear, sadness, calm, disgust, happiness, etc. Humans have been able to perceive such emotions because of years of social interaction among them, but such gifted abilities are restricted and limited to humans only. Machines, which us humans are dependent on nowadays do not have this luxury. Machines are not as capable as us humans to process such delicate and intricate information on their own and hence, there is a need to train them accordingly resulting in easier and better communication. In the field of human computer inter- action (HCI), emotion recognition from the computer is still a challenging issue, especially when the recog- nition is based solely on voice, which is the basic mean and the most integral part of human communication. In human computer interaction systems, emotion recognition could provide the users with improved personalization services by being adaptive to their emotions. Therefore, emotion detection from speech could have many potential applications in order to make the machine more flexible to the user and thus enriching and bettering user's needs and experience. In the proposed system we will be using various Deep Learning (ML) techniques to build and train a model which is capable of detecting and recognizing the various emotions known to man. By this project, one of our aims is to enrich customer experiences in call centers by analyzing various call recordings and recognize the emotional aspects of speech irrespective of the semantic contents.

KEYWORDS: Speech, Emotion, Noise.

I. INTRODUCTION

In order for any conversation to be fruitful, the use of emotions is very necessary. Emotions play a very important and crucial role in communication. It is a medium of expression which humans rely on heavily. The importance of emotion recognition in human speech has increased in recent times to improve both the naturalness and efficiency of human-machine interactions. Recognizing human emotions is itself a very complex task due to the ambiguity of classifying emotions as occurring and natural. A number of studies have been conducted with the aim of extracting spectral and prosodic features that would lead to the correct identification of emotions. Speech Emotion Recognition (SER) can be stated as the extraction of the emotional state of a user from their speech signal. There exists few universal emotions like Anger, Happiness, Sadness. These emotions with the help of any intelligent system and finite computational resources can be trained to identify as required. In this work, spectral and prosodic features are used for speech emotion recognition because both of these features contain emotional and semantic content. Fundamental frequency, loudness, pitch, intensity of speech and glottal parameters are prosodic features that are used to model the different emotions. Potential features are extracted from each utterance for computational mapping between the emotions and speech patterns. Pitch can be detected from the selected elements. Emotions can be classified as Natural and Artificial emotions and can be further divided into an emotion set like anger, sadness, joy, fear, etc. Various machine learning techniques, including k-nearest neighbor, radial basis function, and neural network back propagation have been used to create recognition agents. In particular, the role of speech emotion recognition is one of the most important problems in the field of para linguistics. This field has recently expanded its applications because it is a decisive factor in optimal human- computer interaction, including dialog systems. The goal of speech

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emotion recognition is to predict the emotional content of speech and classify speech according to one of several labels (i.e., happy, sad, neutral, and angry). Different types of deep learning methods have been used to improve the performance of emotion classifiers; however, this task is still considered challenging for several reasons. First, due to the cost associated with involving humans, there is not enough data available to train complex neural network-based models. Second, emotion characteristics must be learned from low- level speech signals. Feature-based models show limited skill when applied to this problem. To overcome this problem, we propose a model that uses a high level text transcription to utilize the information contained within the information contained within low resource datasets to a greater degree. With this project we plan to build a system given the problem definition stated above along with gathering relevant data regarding speech ex- pressing different emotions. Along with this, we aim to improve man and machine interface. We are building a Multi-Layer Perceptron and a classifier to recognize emotion given a speech signal. The models are evaluated on the IEMOCAP dataset under different settings, namely, Audio-only, Text- only and Audio + Text .Our project involves building a model using Natural Language Processing (NLP) and deep learning techniques to improve the learning performance, lowering computational complexity, and building better generalizing models and decreasing the required storage. With this project we generate a model to recognize the emotions available and recognize the emotional aspects of speech irrespective of the semantic contents.

II. RELATED WORK

[1] The difficulty of recognizing emotions from speech signals as a component of Human- Computer Interaction. Many techniques, including traditional and Deep Learning methods, have been used for speech emotion recognition. The paper presents an overview of Deep Learning techniques in speech-based emotion recognition, covering the databases used, emotions extracted, contributions made, and limitations. Understanding emotions from voice signals is a crucial yet difficult aspect of human-computer interaction (HCI).

[2] Many methods, including many well-known speech analysis and classification methods, have been used to extract emotions from signals in the literature on speech emotion recognition (SER). Recently, deep learning approaches have been put out as an alternative to conventional SER techniques. In order to recognise speech-based emotions, this paper provides an overview of deep learning approaches and reviews some current work that uses these techniques. The review discusses the databases used, the emotions that were retrieved, the advancements made in speech emotion identification, and any associated constraints.

[3] .Although a few good surveys exist for SER, they either don't cover all aspects of SER in natural environments or don't discuss the specifics in detail. This survey focuses on SER in a natural environment, discussing SER techniques for natural environment along with their advantages and disadvantages in terms of speaker, text, language, and recording environments. In the recent past, the deep learning techniques have become very popular due to minimal speech processing and enhanced accuracy. Special attention has been given to deep-learning techniques and the related issues in this survey. Recent databases, features, and feature selection algorithms for SER, which have not been discussed in the existing surveys and can be promising for SER in a natural environment, have also been discussed in this paper.

III. PROPOSED SYSTEM

STEP 1: DATASET

In our paper we make use of the IEMOCAP, which researchers at the University of Southern California published in 2008(USC).There are five recorded sessions in it, ten speakers, totaling almost 12 hours of audio and video with transcriptions of the conversations.. It is labeled with eight classified emotion categories, including surprised, fear, rage, happiness, sadness, neutral, and thrilled. Addition- ally, it has dimensional labels with activation and valence values ranging from 1 to 5, but they are not employed in this work. We further divided each utterance file to produce wav files for each sentence because the dataset has already been divided into numerous utterances for each session.

STEP 2: IMPLEMENTATION

This section shows the process of our data pre-processing and feature extraction. Four models are ensembled to generate better results.

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1. Data Pre-Processing*:* The data pre- processing steps are as follows:

a. For Audio: A first frequency analysis of the dataset showed that it is unbalanced. The under representation of the emotions ”fear” and ”surprise” was addressed using upsampling methods. Once we recognised that ”happy” was underrepresented and that the two feelings were very similar to one another, we combined instances from the ”happy” and ”excited” classes. Additionally, we eliminate examples labelled as ”others” since they matched situations that even a human would have labelled as unclear. The aforementioned operations were used to generate a total of 7837 samples.

b) For Text: The available transcriptions were first normalized to lowercase and any special symbols were removed.

2. Feature Extraction*:* We now describe the handcrafted features used to train both, the ML- and the DL-based models.

i. Audio Features*:*

a. Standard Deviation: Standard deviation is a statistical measure that describes how much variation or dispersion there is in a set of data. In speech emotion recognition, standard deviation can be used to analyze the variability of features extracted from speech signals, such as pitch, intensity, and format frequencies.

b. RMS: RMS also known as root mean square shows the average loudness of the audio. RMS loudness measures the audio signal taking into account the energy of the wave. This measurement represents the perceived loudness more accurately than peak levels.

c) Silence: Silence in audio refers to the absence or near-absence of sound in an audio signal. In other words, it is a period of time during which there is little or no audible sound present in the audio signal. Silence can occur for various reasons, such as during pauses in speech or music, in between tracks on an album, or due to technical issues during audio recording or processing. In audio processing, detecting silence can be useful for tasks such as audio segmentation, where we want to divide a long audio signal into smaller chunks based on the presence or absence of sound. Detecting silence can also be useful for removing or reducing noise in an audio signal, as we can filter out or attenuate parts of the signal that are below a certain threshold.

d. Harmonics: In audio, harmonics refer to the additional frequencies that are produced by a sound source in addition to its fundamental frequency. These additional frequencies are integer multiples of the fundamental frequency and are also known as overtones. The presence and strength of harmonics in an audio signal can have a significant impact on its perceived timbre or tone color. The unique pattern of harmonics produced by different instruments or voices is what allows us to distinguish between them even when they are playing the same note at the same volume.

ii) Text Features:

a) Term Frequency-Inverse Document Frequency (TFIDF): TFIDF is a numeric value that represents the relationship between a word and a document in a collection or corpus. This value has two components:

- Term Frequency: Term frequency refers to the number of times a specific word or term appears in a given document or text. It is a simple measure that quantifies the importance or relevance of a term within a document.

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- Inverse Document Frequency: Inverse Document Frequency (IDF) is a statistical measure that quantifies how rare or unique a term is in a collection or corpus of documents. It is calculated by taking the logarithm of the ratio of the total number of documents in the corpus to the number of documents that contain the term.

TFIDF value for a term is calculated by taking the product of TF and IDF values.

IV. PROPOSED SYSTEM

To achieve results for our proposed system, we performed audio classification and text classification separately. But our classification did not yield the accuracy we were aiming for, hence to improve our accuracy rate we combined both, the audio and text classification. After performing these combined classification problems, we observed that we obtained a better accuracy rate when both the classification problems are combined.

Our combined data of audio and text yielded us better accuracy results but not how much we expected it to be. Following are the results of the various machine learning models we used to get results.

1. Random Forest:

Random Forest consists of a large number of Decision Trees that operate as an ensemble. Each individual decision tree has a class prediction and the one class with the most votes becomes the prediction of the model. After applying random forest model on our dataset we achieved an accuracy rate of **66%**

2. XGBoost:

XGBoost is an optimized distributed gradient boosting library for efficient training of machine learning models. This method combines the results of multiple weak models to achieve a stronger and better result. After applying XGBoost model on our dataset we achieved an accuracy rate of **61.8%**

3. Support Vector Classifier:

Support Vector Classifier is a supervised machine learning algorithm typically used for classification tasks. SVC works by mapping data points to a high-dimensional space and then finding the optimal hyperplane that divides the data into two classes. After applying support vector classifier model on our dataset we achieved an accuracy rate of **63.8%**

4. Multinomial Naive Bayes:

Multinomial Naive Bayes (MNB) is a popular machine learning algorithm for text classification problems in Natural Language Processing (NLP). It is particularly useful for problems that involve text data with discrete features such as word frequency counts. MNB works on the principle of Bayes theorem and assumes that the features are conditionally independent given the class variable. After applying support vector classifier model on our dataset we achieved an accuracy rate of **59.8%**

5. Multilayer Perceptron:

A fully connected multi-layer neural network is called a Multilayer Perceptron (MLP). It has 3 layers including one hidden layer. If it has more than 1 hidden layer, it is called a deep ANN. An MLP is a typical example of a feedforward artificial neural network. After applying support vector classifier model on our dataset we achieved an accuracy rate of **66.3%**

6. Logistic Regression: Logistic regression predicts the output of a categorical dependent variable. It is a Machine Learning method that is used to solve classification issues. It is a predictive analytic technique that is based on the probability idea. After applying support vector classifier model on our dataset we achieved an accuracy rate of **63.3%**

The above mentioned accuracy rates are a better result than what we had achieved earlier from individually training on text and speech. to generate even better results we ensembled the following models, i.e, MultiLayer

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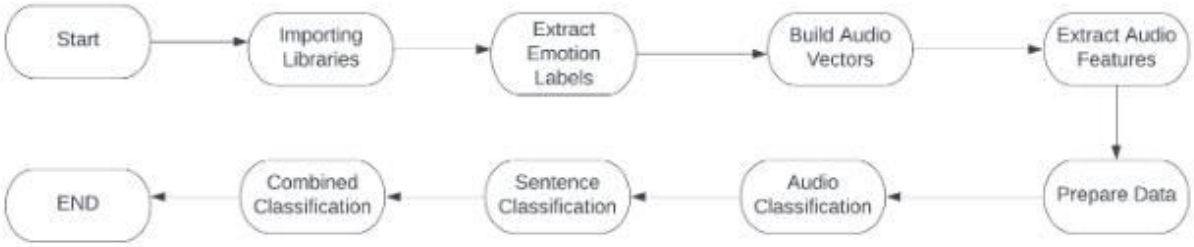
Perceptron, Random Forest, Logistic Regression, XGBoost and ensembled using the soft voting ensembling technique which yielded us an accuracy rate of **70%**

SYSTEM FLOWCHART:



V. RESULTS

The mentioned accuracy rates in section IV are a better result than what we had achieved earlier from individually training on text and speech. To generate even better results we ensembled the following models, i.e, MultiLayer Perceptron, Random Forest, Logistic Regression ,XGBoost and ensembled using the soft voting ensembling technique which yielded us an accuracy rate of **70%**.

1. Multilayer perceptron: Following is the confusion matrix for the combined audio+text classification. We obtained an accuracy of **66.3**%

2. Random Forest classifier: Following is the confusion matrix for the combined audio+text classification. We obtained an accuracy of **66**%

3. Logistic Regression: Following is the confusion matrix for the combined audio+text classification. We obtained an accuracy of **63.3**%

4) XGBoost: Following is the confusion matrix for the combined audio+text classification. We obtained an accuracy of **61.8**%

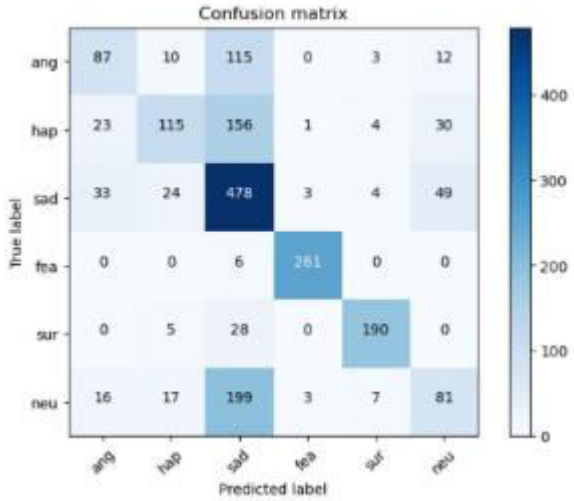


Fig.1. MultiLayer Perceptron

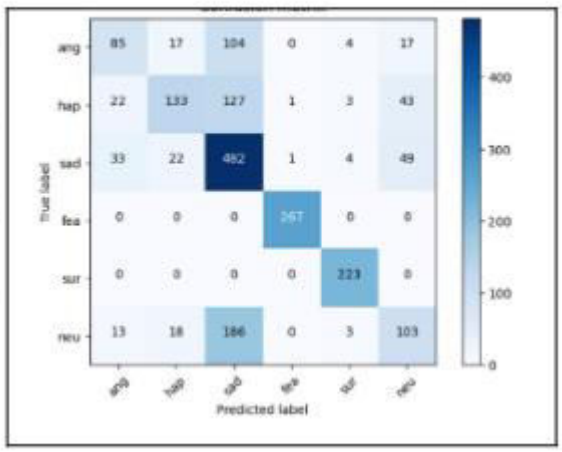


Fig. 2. Random Forest

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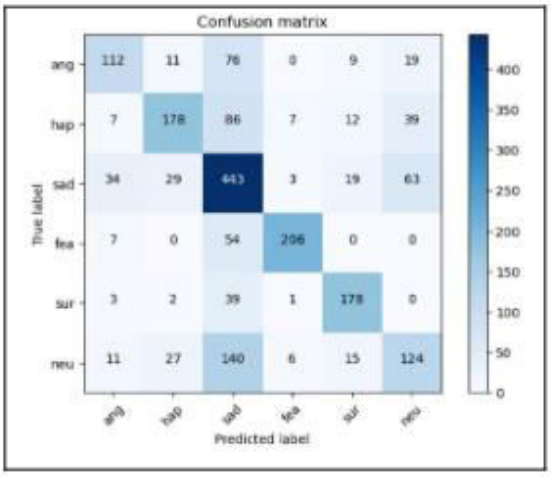


Fig. 3. Logistic Regression

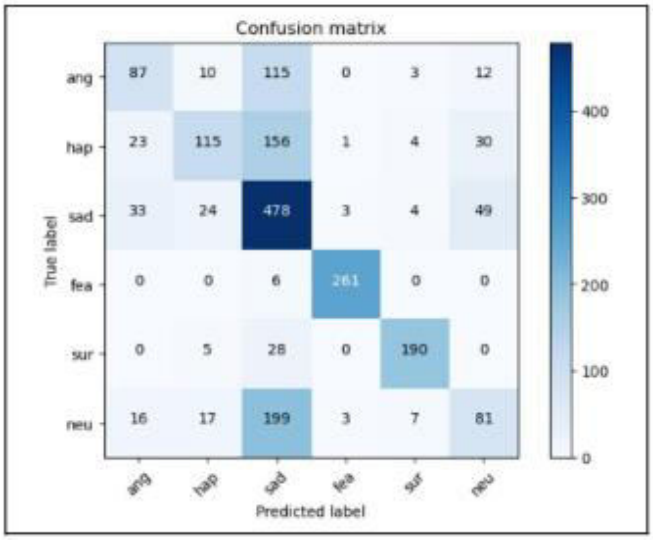
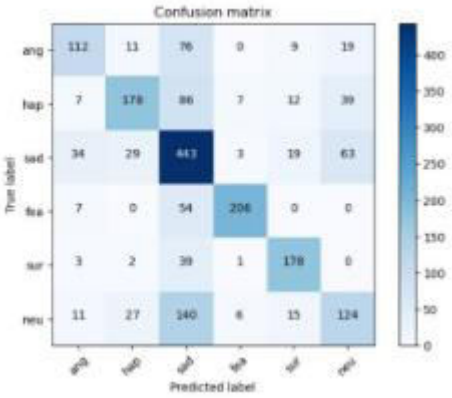


Fig 4. XG Boost

After ensembling the above models using soft voting we got an accuracy of **71.3**%.

Result as follows:



VI. Conclusion and Future Work

In this project, we have proposed a system that plans to make use of the deep neural network, to extract the emotional characteristic parameter from emotional speech signal automatically. We have combined deep learning networks and proposed a classifier model which is based on it. Through this project, we showed how we can make use of Deep Learning Techniques to obtain the un derlying emotion from speech audio data as well as a text model and obtain some insights on the human expression of emotion through voice. This system can be employed in a variety of setups like call centers for complaints or marketing, in voice based virtual assistants or chat bots, in linguistic research, etc. In future work we will continue to further study speech emotion recognition based on Deep Learning Techniques and further expand the training dataset. Our ultimate aim is to study how to improve the recognition rate of speech emotion and better the process of finding any trigger words if possible applicable in our dataset.

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A few possible steps that can be implanted to make the models more robust and accurate are the following:

1. An accurate implementation of the pace of the speaking can be explored to check if it can resolve some of the deficiencies of the model.
2. Exploring other acoustic features of sound data to check their applicability in the domain of speech emotion recognition.

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