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Speech Emotion Recognition Using Neural Networks

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ABSTRACT

Speech is the most natural and easy method for people to communicate, and interpreting speech is one of the most sophisticated tasks that the human brain conducts. The goal of Speech Emotion Recognition (SER) is to identify human emotion from speech. This is due to the fact that tone and pitch of the voice frequently reflect underlying emotions. Librosa was used to analyse audio and music, sound file was used to read and write sampled sound file formats, and sklearn was used to create the model. The current study looked on the effectiveness of Convolutional Neural Networks (CNN) in recognising spoken emotions. The networks' input characteristics are spectrograms of voice samples. Mel-Frequency Cepstral Coefficients (MFCC) are used to extract characteristics from audio. Our own voice dataset is utilised to train and test our algorithms. The emotions of the speech (happy, sad, angry, neutral, shocked, disgusted) will be determined based on the evaluation.

KEYWORDS: *Speech emotion, Energy, Pitch, Librosa, Sklearn, Sound file, CNN, Spectrogram, MFCC*

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I. INTRODUCTION

Speech emotion recognition (SER) is a technique that extracts emotional features from speech by analysing distinctive characteristics and the acquired emotional change. At the moment, voice emotion recognition is a developing artificial intelligence cross-field [1]. A voice emotion processing and recognition system is made up of three parts: speech signal acquisition, feature extraction, and emotion recognition. In this method, the extraction quality has a direct impact on the accuracy of speech emotion identification. In feature extraction, the entire emotion sentence was frequently used as a unit for feature extraction and extraction contents. The neural networks of the human brain are highly capable of learning high-level abstract notions from low-level information acquired by the sensory periphery. Humans communicate through voice, and interpreting speech is one of the most sophisticated operations that the human brain conducts. It has been argued that children who are not able to understand the emotional states of the speakers developed poor social skills and in some cases they show psychopathological symptoms [2, 3]. This highlights the importance of recognizing the emotional states of speech in effective communication. Detection of emotion from facial expressions and biological measurements such as heart beats or skin resistance formed the preliminary framework of research in emotion recognition[4].

More recently, emotion recognition from speech signal has received growing attention. The traditional approach toward this problem was based on the fact that there are relationships between acoustic features and emotion. In other words, the emotion is encoded by acoustic and prosodic correlates of speech signals such as speaking rate, intonation, energy, formant frequencies, fundamental frequency (pitch), intensity (loudness), duration (length), and spectral characteristic (timbre) [5, 6]. There are a variety of machine learning algorithms that have been examined to classify emotions based on their acoustic correlates in speech utterances. In the current study, we investigated the capability of convolutional neural networks in classifying speech emotions using our own dataset. There are a variety of machine learning algorithms that have been examined to classify emotions based on their acoustic correlates in speech utterances. In the current study, we investigated the capability of convolutional neural networks in classifying speech emotions using our own dataset. The specific contribution of this study is using wideband spectrograms instead of narrow-band spectrograms as well as assessing the effect of data augmentation on the accuracy of models. Our results revealed that wide-band spectrograms and data augmentation equipped CNNs to achieve the state-of-the art accuracy and surpass human performance.

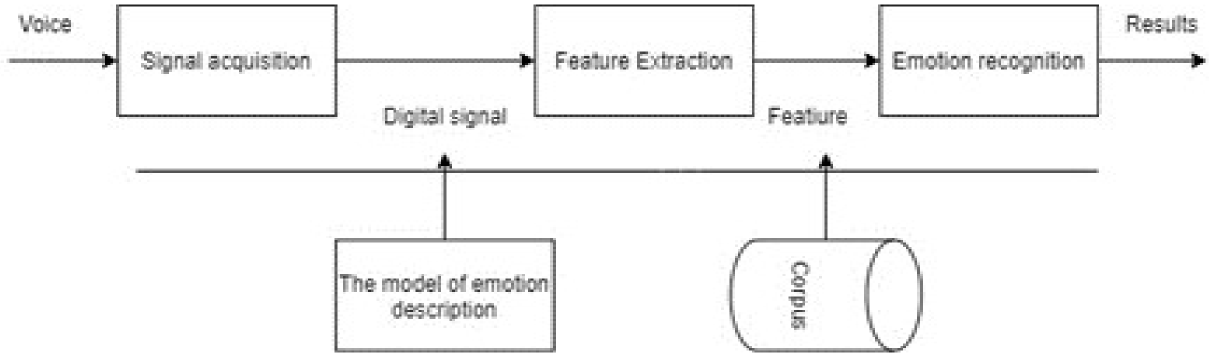

Fig.1. Speech emotion recognition block diagram

II. RELATED WORK

Most of the papers published in last decade use spectral and prosodic features extracted from raw audio signals. The process of emotion recognition from speech involves extracting the characteristics from a corpus of emotional speech selected or implemented, and after that, the classification of emotions is done on the basis of the extracted characteristics. The performance of the classification of emotions strongly depends on the good extraction of the characteristics (such as combination of MFCC acoustic feature with the energy prosodic feature [7]. Yixiong Pan in [8] used SVM for three class emotion classification on Berlin Database of Emotional Speech [9] and achieved 95.1% accuracy.

Norooziet.al. Proposed a versatile emotion recognition system based on the analysis of visual and auditory signals. He used 88 features (Mel frequency cepstral coefficients

(MFCC), filter bank energies (FBEs)) using the Principal Component Analysis (PCA) infeature extraction to reduce the dimension of features previously extracted revealed that wide-band spectrograms and data augmentation equipped CNNs to achieve the state-of-the art accuracy and surpass human performance.

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H.M Fayek in [14] explored various DNN architecture and reported accuracy around 60% on two different database eNTERFACE [15] and SAVEE [16] with 6 and 7 classes respectively. Fei Wang used combination of Deep Auto Encoder, various features and SVM in [17] and reported 83.5% accuracy on 6 classes of Chinese emotion corpus CASIA. In contrast to these traditional approaches more novel papers have been published recently employing Deep Neural Networks into their experiments with the promising results. Many authors agree that the most important audio characteristics to recognize emotions are spectral energy distribution, Teager Energy Operator (TEO) [18], MFCC, Zero Crossing Rate (ZCR), and the energy parameters of the filter bank energies (FBEs) [19].

III. TRADITIONAL SYSTEM

The traditional system was based on the analysis and comparison of all kinds of emotional characteristic parameters, selecting emotional characteristics with high emotional resolution for feature extraction. In general, the traditional emotional feature extraction concentrates on the analysis of the emotional features in the speech from time construction, amplitude construction, and fundamental frequency construction and signal feature [28].

IV. PROPOSED METHOD

Convolutional Neural Network (CNN) is used to classify the emotions (happy, sad, angry, neutral, surprised, disgust) and to predict the output by showing its accuracy.

The given speech is plotted as spectrogram by using matplot library and this is used as input for CNN to build the model.

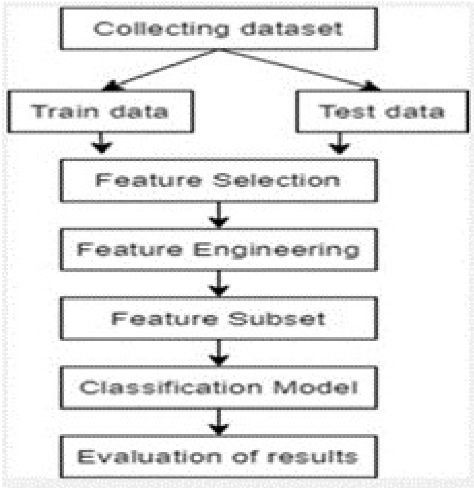

Fig.2. Flow diagram of proposed system

A. Data Set Collection

The first step is to create an empty dataset that will hold the training data for the model. After creating an empty dataset, the data's (audio) have to be recorded and labeled in different classes. Once the labeling is done, the data's have to be preprocessed which will produce the clear pitch of the data by removing its unwanted background noise. After preprocessing the data's are classified into train dataset and test dataset, where the train dataset hold 75% of the data and the test dataset holds 25% of the data.

B. Feature Extraction of Speech Emotion

Human speech consists of many parameters which show the emotions compromise in it. As there is change in emotions these parameters also gets changed. Hence it's necessary to select proper feature vector to identify the emotions. Features are categorized as excitation source features, spectral features, and prosodic features. Excitation source features are achieved by suppressing characteristics of vocal tract (VT). Spectral features used for emotion recognition are linear prediction coefficients (LPC), Perceptual Linear prediction coefficients (PLPCs), Mel-frequency cepstral coefficients (MFCC), linear prediction cepstrum coefficients (LPCC), and perceptual linear prediction (PLP). The accuracy of differentiating different emotions can be achieved by using MFCC, LFPC

[20, 21].

C. Mel-Frequency Cepstral Coefficients

The Mel-Frequency Cepstral Coefficients (MFCC) feature extraction method is a leading approach for speech feature extraction. The various steps involved in MFCC feature extraction are:

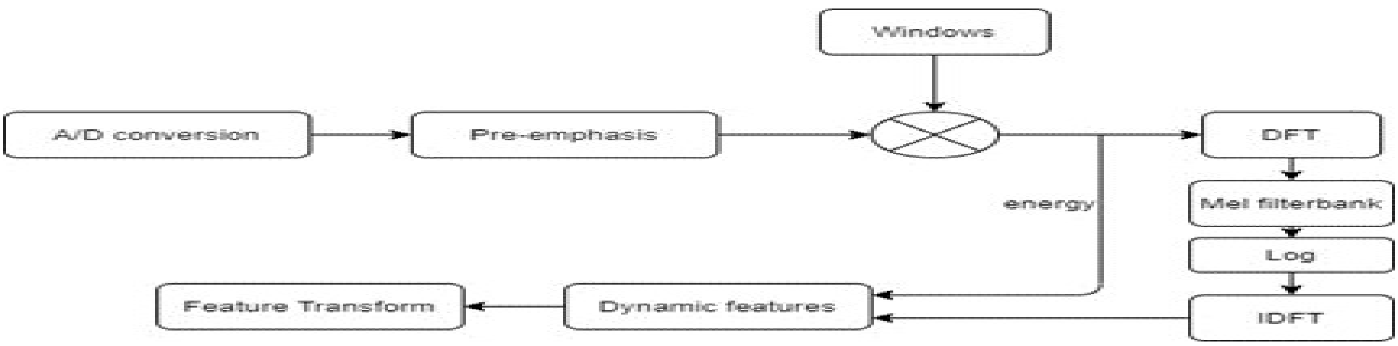

Fig.3. Flow of MFCC A/D conversion:

This converts the analog signal into discrete space.
Pre-emphasis**:**
This boosts the amount of energy in the high frequencies.

Windowing:
Windowing involves the slicing of audio waveform into sliding frames. *Discrete Fourier Transform:*

DFT is used to extract information in the frequency domain [22, 23].

D. Classifiers
After extracting features of speech, it is essential to select a proper classifier. Classifiers are used to classify emotions. In the current study, we use Convolutional Neural Network (CNN). The term Convolutional comes from the fact that Convolution-the mathematical operation is employed in these networks. Convolutional Neural Networks is one of the most popular Deep Learning Models that have manifested remarkable success in the research areas. CNN is a deep learning algorithm that takes image as an input, assign importance to various aspects in the image and will be able to differentiate from other. Generally CNNs have three building blocks: the convolutional layer, the pooling layer, and the fully connected layer. Following, we describe these building blocks along with some basic concept such as soft max unit, rectified linear unit, and drop out.

- **Input layer:** This layer holds the raw input image.
- **Convolution Layer:** This layer computes the output volume by computing dot product between all filters and image patch.
- **Activation Function Layer:** This layer will apply element wise activation function to the output of convolution layer.
- **Pool Layer:** This layer is periodically inserted in CNN and its main function is to reduce the size of volume which makes computation fast and reduces memory. The two types are Maxpooling and average pooling.
- **Fully-Connected Layer:** This layer takes input from the previous layer and computes the class scores and outputs the 1-D array of size equal to the number of classes [24, 25].

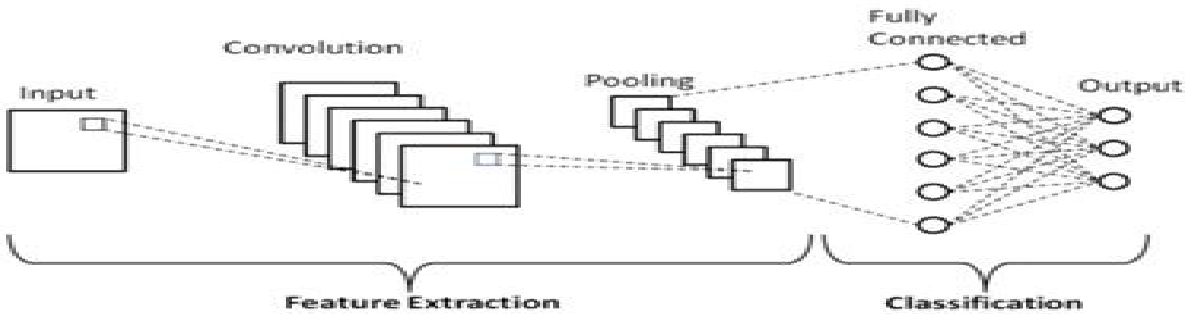

Fig.4. CNN Algorithm

V. APPLICATION
The applications of speech emotion recognition system are, psychiatric diagnosis, conversation with robots, intelligent toys, mobile based emotion recognition, emotion recognition in call centre where emotions of customer can be identified and can help to get better service quality, intelligent tutoring system, lie detection, games[26,27]. It is also used in healthcare, Psychology, cognitive science and marketing, voice-based virtual assistants.

VI. CONCLUSION
In this research, we suggested a technique for extracting the emotional characteristic parameter from an emotional speech signal using the CNN algorithm, one of the Deep Learning methods. Previous research relied heavily on narrow-band spectrograms, which offer better frequency resolution than wide-band spectrograms and can discern individual harmonics. Wide-band spectrograms, on the other hand, offer better temporal resolution than narrow-band spectrograms and reveal distinct glottal pulses that are connected with basic frequency and pitch. On training data, CNNs perform admirably. The current study's findings demonstrated CNNs' ability to learn the fundamental emotional properties of speech signals from their low-level representation utilising wide-band spectrums.

VII. FUTURE SCOPE
For future work, we suggest to use audio-visual database or audio-visual-linguistic databases to train Deep Learning models where facial expressions and semantic information are taken into account as well as speech signals, which allows improving the recognition rate of each emotion. In future, we can think about using other types of features and apply our system on other bases that are larger and used other method for feature extraction.

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