

**Speech Emotion Recognition**

CZ4042 Neural Networks & Deep Learning

Final Project

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# Introduction

The most basic ways of human expression are speech and body language. We depend on these recognitions to determine emotions, which plays a vital role in communications. As the technology advancement in the past few decades produced artificial intelligence that can perform speech recognition such as Siri and Alexa or facial recognition systems, human has been trying to extend the understanding of emotions to computers in various ways.

Since emotions are subjective and have different understandings depending on individuals, emotion detection has always been challenging. There is no standard agreement on measuring or categorising them but are evaluated by various factors such as knowledge or cultures, which others can easily misunderstand. As a result, the crucial task of automatic recognition of human emotions became a research field of significant interest.

Among all sources of emotion recognition such as facial expressions, physiological measurements, or communication content, speech signals are the most convenient and effective method since it is easy to acquire and non-invasive. It is also generally known that emotional changes are subconsciously reflected in speech utterances. Therefore more research can be done on this domain to better improve how AI understand emotions.

# Objective

In this project, we aim to determine if the tone of a person’s speech can be correctly mapped to the different emotions: Anger, Sadness, Happiness, Fear, Disgust, Surprised, and Neutral. We propose the use of a deep learning classifier compared to the common traditional classifier such as Hidden Markov Model or Support Vector Machine. This is done by extracting, experimenting and training with various time-series signal features and methods. These insights will then produce the most optimal results, which in turn be used to detect the speaker’s emotions in real-time.

# Literature Review

## Existing Techniques

Previous researches done on speech emotion recognition are discussed in this section. Naturally, most of the methods used are typically the traditional classifiers and did not include the recent trends and advances of deep neural networks such as Convolutional Neural Network or Recurrent Neural Network.

## Database

### Emo-DB

Emo-DB is a freely available German emotional database that is created by the Institute of Communication Science, Technical University, Berlin, Germany. The emotions that Emo-DB was trying to capture are anger, boredom, anxiety, happiness, sadness, disgust and neutral.

### RAVDESS Emotional speech audio

RAVDESS is also a freely available emotional database. It contains audio recordings in a North American accent. The emotions that RAVDESS emotional speech audio was trying to capture are neutral, calm, happy, sad, angry, fearful, disgust and surprised.

# Methodology

## Features Extraction

## Librosa

Librosa is an open-source python package for music and audio analysis. It allows for feature extraction. The user can choose from a selection of feature extraction functions from their library

## Opensmile

## OpenSMILE is an open-source toolkit for audio feature extraction. This toolkit was a project started in 2008 at the Technical University Munich (TUM). For this project, we used the openSMILE Python library to extract the features needed to execute this project. The feature sets available in the Python library are as follows:

1. ComParE\_2016
2. GeMAPS *(deprecated)*
3. GeMAPSv01a
4. GeMAPSv01b
5. eGeMAPS *(deprecated)*
6. eGeMAPSv01a
7. eGeMAPSv01b *(deprecated)*
8. eGeMAPSv02
9. emobase

However, the feature sets GeMAPS, eGeMAPSv01b, and eGeMAPS are deprecated. Therefore for the future experiments, we will exclude the usage of these feature sets.

## Classifier

During the extraction of the features from the Emo-DB and RAVDESS audiofiles, we combined the data extracted from the two databases into a single CSV file. The combined range of emotions identified by the two datasets are as follows:

1. Neutral
2. Calm
3. Happy
4. Sad
5. Angry
6. Fearful
7. Disgust
8. Surprised
9. Boredom

# Experiments & Results

* 1. Model

We experimented with various models to find out which model yielded better results. We are using the sequential API to build our models.

* + 1. CNN Model

model = Sequential()

model.add(Conv1D(256, kernel\_size=8, strides = 1, activation='relu', input\_shape=(num\_of\_features,1)))

model.add(BatchNormalization())

model.add(MaxPooling1D(pool\_size=2))

model.add(Dropout(0.5))

model.add(Conv1D(128, kernel\_size=8, strides = 1, activation='relu'))

model.add(BatchNormalization())

model.add(MaxPooling1D(pool\_size=2))

model.add(Dropout(0.5))

model.add(Conv1D(64, kernel\_size=8, strides = 1, activation='relu'))

model.add(BatchNormalization())

model.add(MaxPooling1D(pool\_size=2))

model.add(Dropout(0.7))

model.add(Flatten())

model.add(Dense(64, activation='relu'))

model.add(Dense(32, activation='relu'))

model.add(Dense(9, activation='softmax'))

* + 1. Effectiveness of feature sets

By comparing the val\_acc obtained by training the model using datasets with different feature combinations, the following results have been obtained.

A picture containing chart

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Figure - Training accuracy for CNN model

It is observed that the cross-validation accuracy of emobase and ComParE\_2016 feature sets are greater the eGeMAPSv01a, GeMAPSv01a, eGeMAPSv02 on the CNN model)

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Figure - Training accuracy for LSTM model

Chart

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Figure - Cross-validation loss for LSTM model

Conversely, the cross-validation accuracy of eGeMAPSv01a, GeMAPSv01a, eGeMAPSv02 feature sets are greater than the emobase and ComParE\_2016 features sets. Regardless, the cross-validation accuracies of emobase and ComParE\_2016 feature sets using the CNN network are still higher than the rest of the calculated cross-validation accuracies.

However, as the emobase dataset contains 988 different features and the ComParE\_2016 dataset contains 6373 features. While emobase dataset is more compact and offers similar results compared to ComParE\_2016 dataset, the use of emobase is more efficient.

* + 1. RNN Model

In additional to develop a classification model in CNN, we also try to implement a RNN architecture to analyze the speech audio. The model we chose to analyze the audio file and identify the expressed emotion is LSTM model, which is a most popular time-series analysis model in RNN architecture.

We build the model with 2 hidden LSTM layers with 128 neurons and an output layer with 9 neurons, as shown in the Figure 2. Basically, the input’s shape of the LSTM is 3-dimension; the structure of the input is [samples, timesteps, feature]. Hence, we unify the timesteps of all input audio during the data preprocesing (Figure 3), and do the feature extraction before training the model. The feature extraction library used here is librosa instead of openSmile, because Librosa generates the features from the timeseries of audio files which are more appropriate for the LSTM model. The Code Snippet 1 shows the features generated for the training model, which includes root-mean-square (RMS) value for each frame, the zero-Graphical user interface, text

Description automatically generatedcrossing rate of an audio time series and Mel-frequency cepstral coefficients (MFCCs).

Figure 2: The structure of the training model

Chart, scatter chart

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Figure 3: The audio wavefroms of before and after data preprocessing. We normalised the audio signal, trimmed the silence in the beginning and end, extended the right-side signal for length equalization, and reduced noice.

Word

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Code Snippet 1: To generate the feature of the audio signal.

Chart, line chart

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# Conclusion