

Speech and Text Emotion Detection using Different Approaches

Course: AI5100

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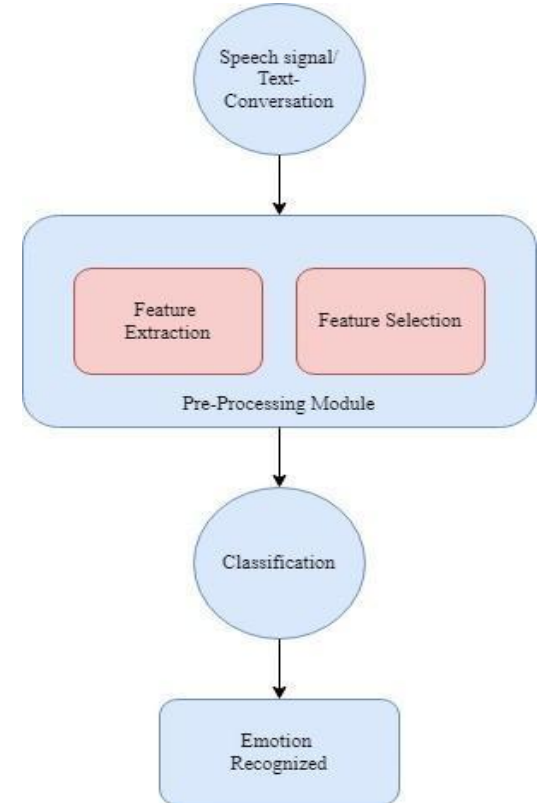
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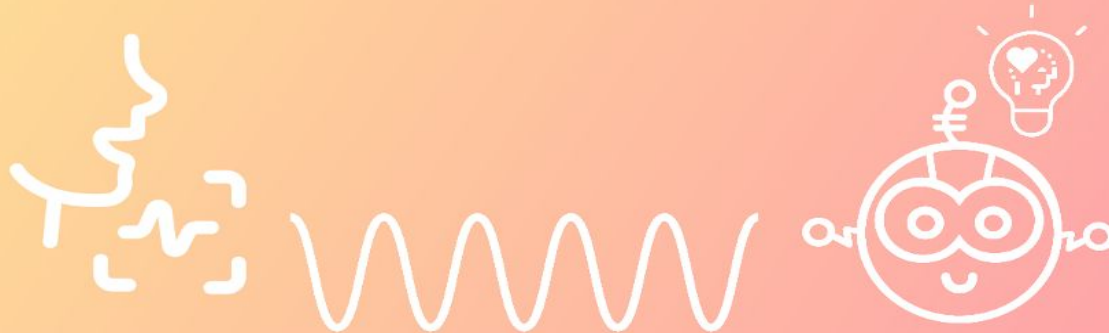
Problem Statement

- Detecting and recognizing human emotion is a big challenge in computer vision and artificial intelligence.
- The main aim of our project is to develop a robust system which can detect as well as recognize human emotions from provided information.
- Information provided is in the form of speech or text.



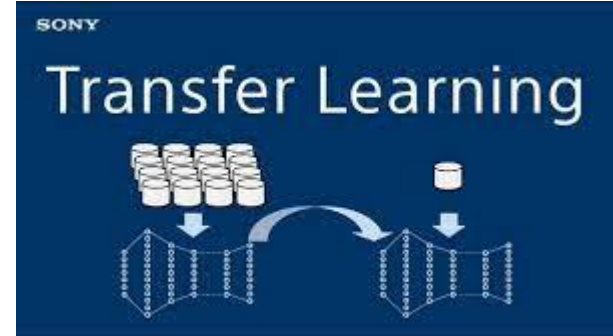
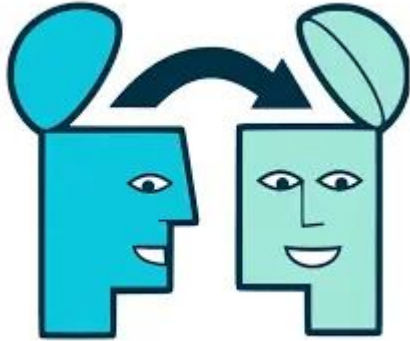
Motivation?

- Emotion recognition provides benefits to many institutions and aspects of life.
- It is useful and important for security, healthcare purposes and robotic applications.
- This system can also be used to detect and recognize racial differences in emotion recognition.
- In the automobile industry, car manufacturers use AI to help them understand human emotions.



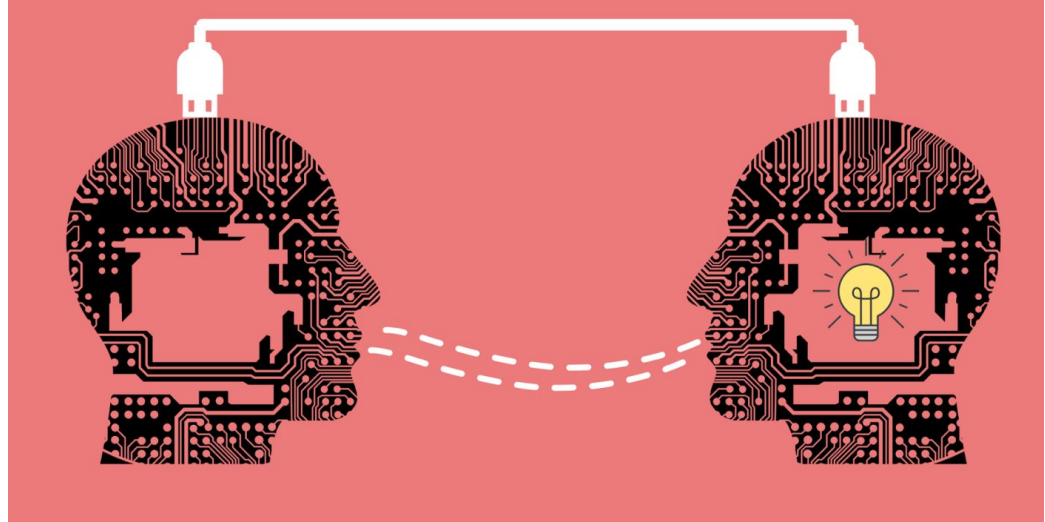
Transfer Learning

- Transfer Learning is a machine learning method where we reuse a pre-trained model as the starting point for a model on a new task.
- It helps us utilize knowledge from previously learned task and apply it newer (related) ones.



Why Transfer Learning?

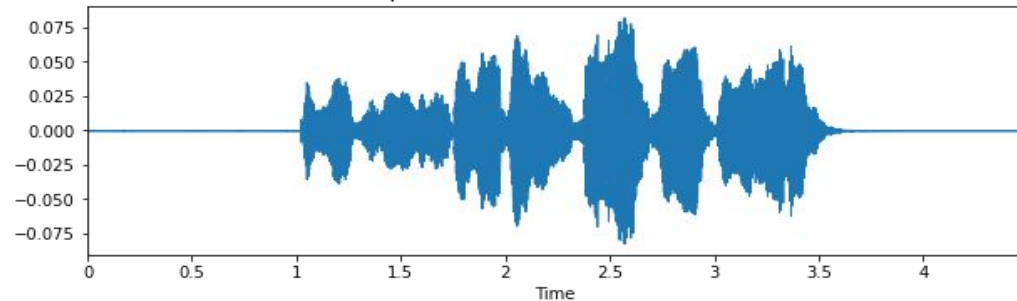
- Quicker Development
- Less Data
- Better Results



Methodology

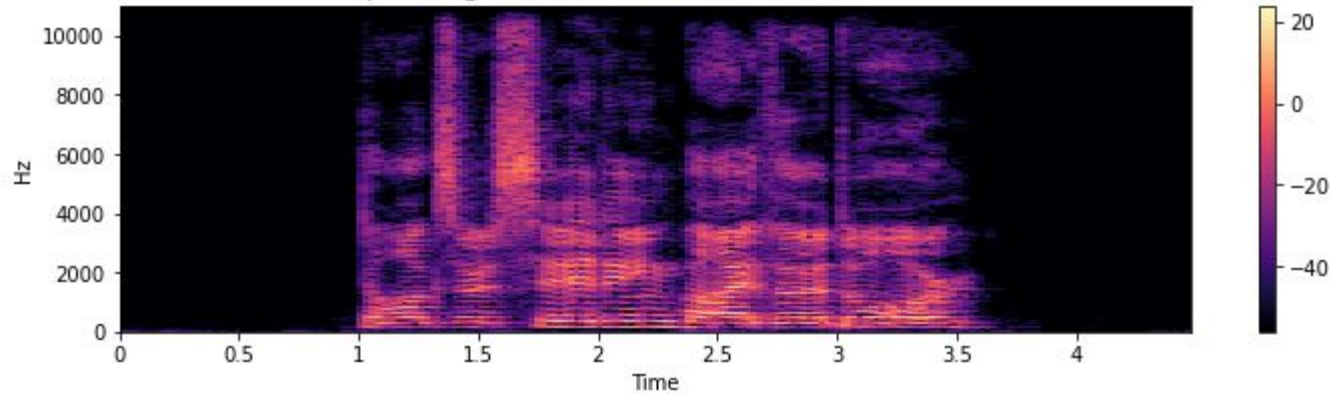
Speech Emotion Recognition (using CNN)

- Datasets used: TESS, RAVDESS and SAVEE
- Step 1: Extracted labels from each dataset separately.
- Step 2: Data Visualization
 - Amplitude envelope of speech signal



Methodology contd.

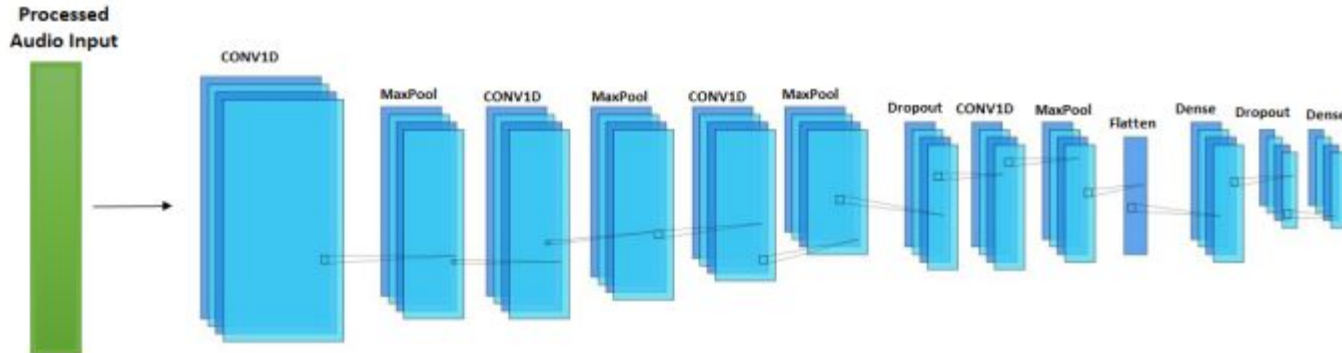
- Spectrogram of audio file



- Step 3: Data Augmentation
 - Added gaussian noise, pitch shift and signal stretching

Methodology contd.

- Step 4: Feature Extraction
 - Features extracted:
 - Zero-crossing rate
 - Chromagram
 - Mel Frequency Cepstral Coefficients (MFCC)
 - Root Mean Square value (RMS)
- Step 5: Training
 - Model used was a CNN with 1D convolution layers

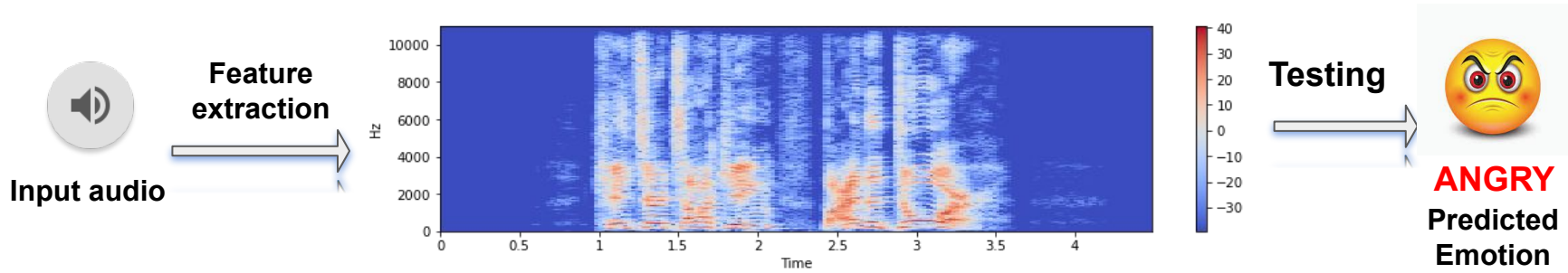


Methodology contd.

Speech Emotion Recognition (using Transfer Learning)

- Datasets used: TESS, RAVDESS AND SAVEE
- Step 1: Extracted labels from each of the datasets
- Step 2: Feature Extraction
 - Extracted 3D audio spectrogram
- Step 3: Training
 - Used pre-trained AlexNet model

Instance



One of the extracted features: Spectrogram for input audio

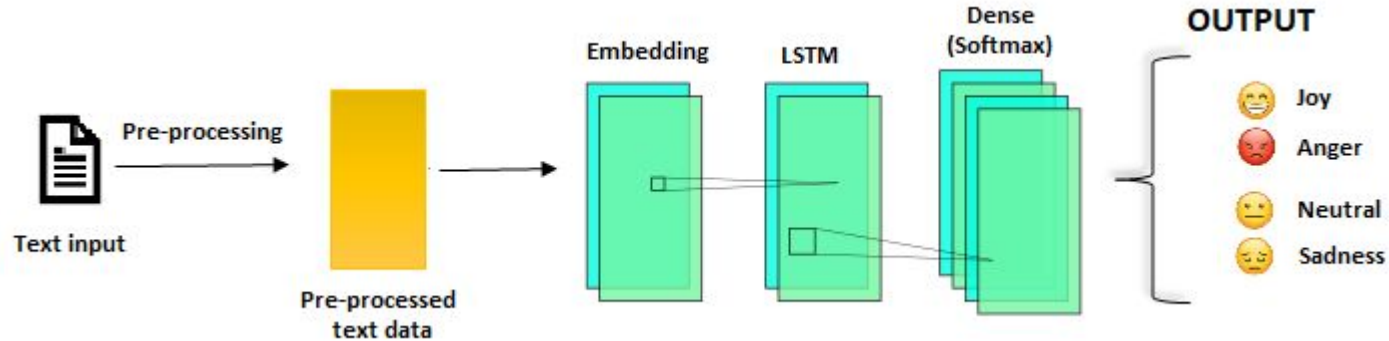
Methodology contd.

Text Emotion Recognition (using LSTM)

- Dataset used: IEMOCAP (text)
- Step 1 - Data Visualization
- Step 2 - Data pre-processing:
 - Label encoded target classes
 - Lower casing
 - Removal of Stop words
 - Stemming
 - Tokenization

Methodology contd.

- Step 3 - Model training:
 - Used an embedding, an LSTM and a dense layer.



Instance

Input text

**“No we won't. It's pointless
it's like a waiting up to see
Santa Claus.”**

Pre-process



**“pointless like wait see santa
clau”**

Predication



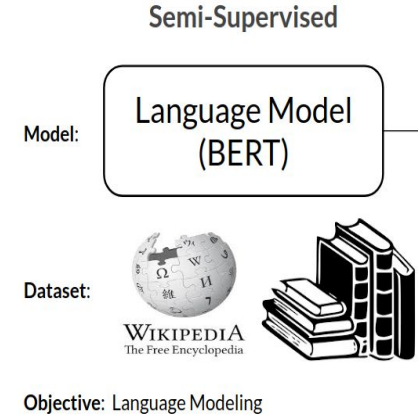
SAD

Predicted emotion

Methodology contd.

Text Emotion Recognition (using Transfer Learning)

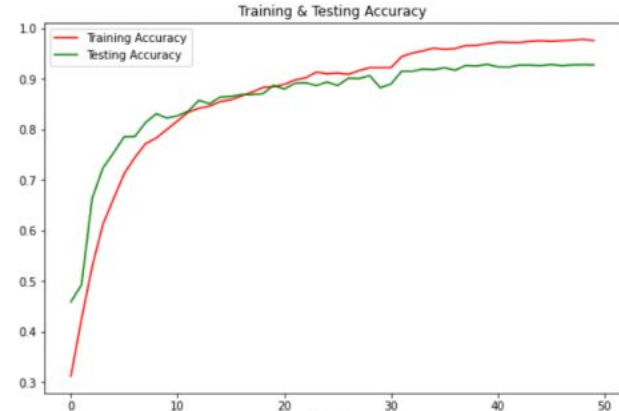
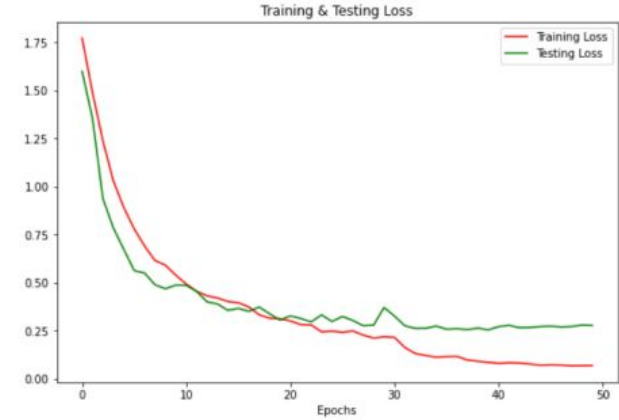
- Dataset used : IEMOCAP (text)
- Pre-trained Model : BERT (**bert-based-uncased**)
- Step 1 - Input Formatting
 - Add Special Tokens
 - Fixed Sentence Length and Attention mask
- Step 2 - Tokenization using bert tokenizer
- Step 3 - Train using **BertForSequenceClassification**
- Step 4 - Use Adam optimiser to update model parameters



Results

- Speech Emotion Recognition
- Accuracy and Loss

	Training loss	Training accuracy	Testing loss	Testing accuracy
Approach1	0.0692	0.9751	0.2775	0.9270
Approach2	0.0425	0.9871	0.1469	0.9438



Results

- Text Emotion Recognition
- Accuracy and Loss

	Training loss	Training accuracy	Testing loss	Testing accuracy
Approach1	0.2893	0.8771	1.5738	0.6116
Approach2	0.1573	0.9042	1.236	0.8247

Conclusion

- Transfer learning approach for emotion detection and classification performs better than CNN for speech-emotion-recognition and LSTM for text-emotion recognition.
- Transfer learning has potential of leveraging multiple sources of emotion-specific speech/text data to improve emotion recognition performance.

References

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Group member contributions

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THANK YOU!