CS 753 Project

Speech to Sign-Language(with emotions) for the Hearing-Impaired

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2. Motivation
3. Subtasks
4. Speech to text conversion
5. ESPNet Model
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Problem Statement

Given a speech utterence from a speaker who is trying to convey a message to a person who is hearing-impaired and/or voiceless, then speech has to be converted in a form that the other person can understand, i.e. in a sign language.

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- Most of the literature in the field of ASL and Speech are based on the conversion of sign-to-speech.
- But the converse model that completes the cycle of sign-to-speech, i.e. speech-to-sign, is mostly unexplored.
- In this project, we explore the speech-to-sign paradigm Deep Learning ASR models.
- This project could be used as a conversation model for the speech and/or hearing-impaired to interact with people who dont have knowledge of sign-language.

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Subtasks

- Speech to text conversion (ASR)
- Speech to emotion recognition
- Text to Sign Language Conversion (Future Work)

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Task1: Speech to Text

- The speech2text problem is one of the most classical problems in ASR.
- It started from a statistical modelling problem with separate model components like the acoustic model, language model and the pronunciation model.
- On the advent of the era of Deep Learning, this changed to an End-to-End modelling paradigm.
- It started with Tandem and Hybrid networks, with the present state-of-the-art(SOTA) model being the Conformer-based model.

Task1: Speech to Text

- Dataset: LIBRISPEECH[1]
- We initially wanted to train our own Speech2Text network using a CTC-Beam Search based CNN-LSTM model.
- But due to constraint in resources could not train the model.(code is present but only able to run 30 epochs over 4days)
- So, we reverted to the ESPNet Toolkit[2].
- From this toolkit we used the model here
- It uses a conformer based architecture for the acoustic model and a transformer based architecture for the language model.
- We have used the pre-trained models for both.
- The metrics claimed by the model on `test-clean` are:

Metric	Sub	Del	Ins	Err
WER	2.1	0.2	0.3	2.6
CER	1.2	0.8	0.7	2.7

[1] Panayotov et al. 2015.
[2] Guo et al. 2020.

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Short Description of ESPNet Architecture

The Conformer-based model architecture[3] is as follows:

- The input speech signal is converted into a sequence of 80 dimensional log-mel filterbank features with/without 3-dimensional pitch features.
- Then, passed through a Conformer-based encoder.
- The output of the above block is passed through a Transformer-based decoder.
- The encoder-decoder model was trained using joint-CTC-attention training and decoding.
- Followed by a token/word-level language model (transformer based) via shallow fusion.

[3] Guo et al. 2020.

ESPNet Architecture (Contd.)

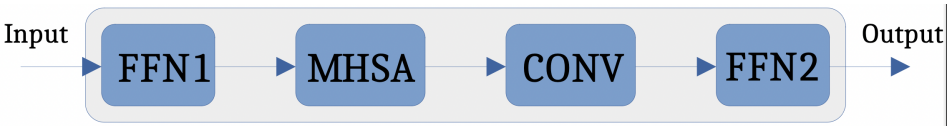

Figure: Conformer Module Architecture

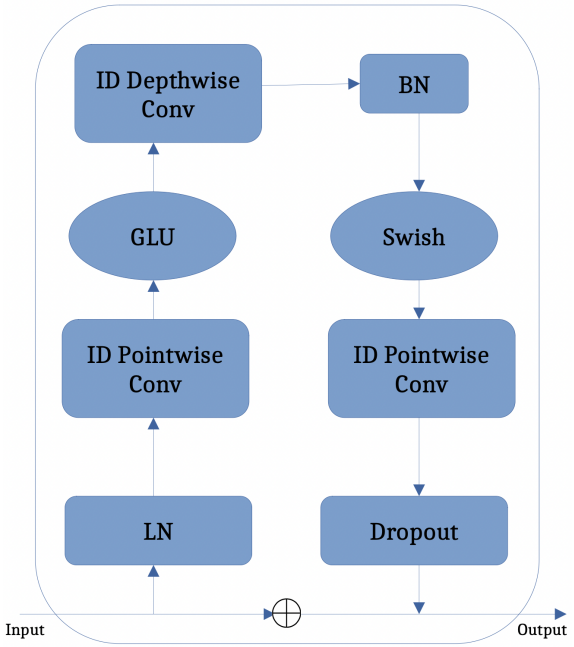

Figure: Conv Module in the Conformer Model

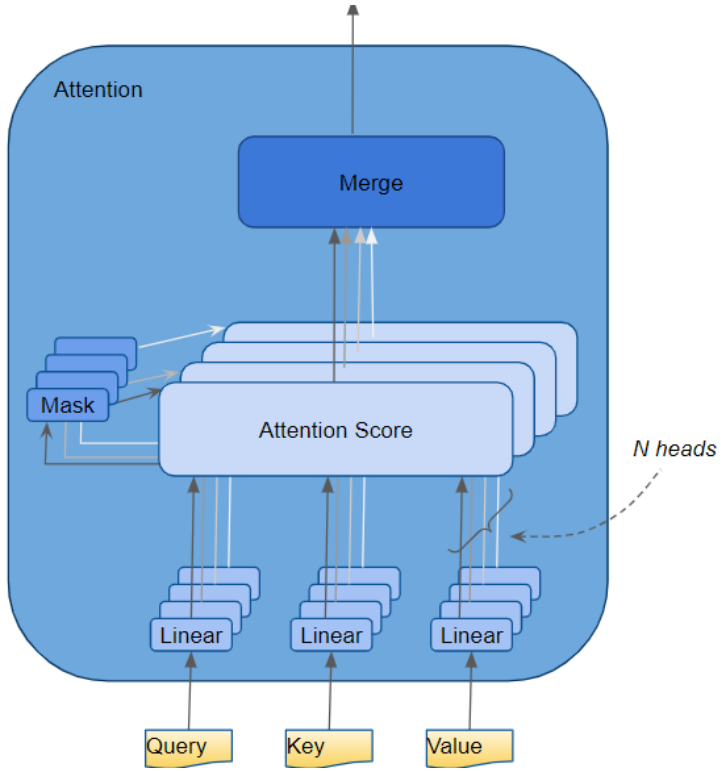

Figure: Multi-Head Attention Module

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Emotion Recogition

- **Motivation**:
  Often the emotion carried out by an utterence cannot be properly conveyed using sign-language.
- **Dataset**: RAVDESS[4]
- **Data Pre-processing**:
  - Convert the input speech signal into 40-dimensional MFCC features.
- **Model**:
  - The model used is a CNN-based model with a softmax layer, trained on Sparse Categorical Cross-Entropy Loss.
  - Model Accuracy: 72%

[4] Livingstone and Russo 2018.

Results from the model trained

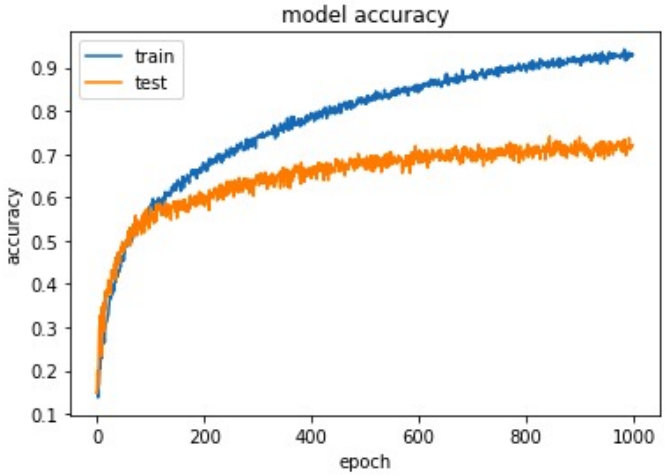
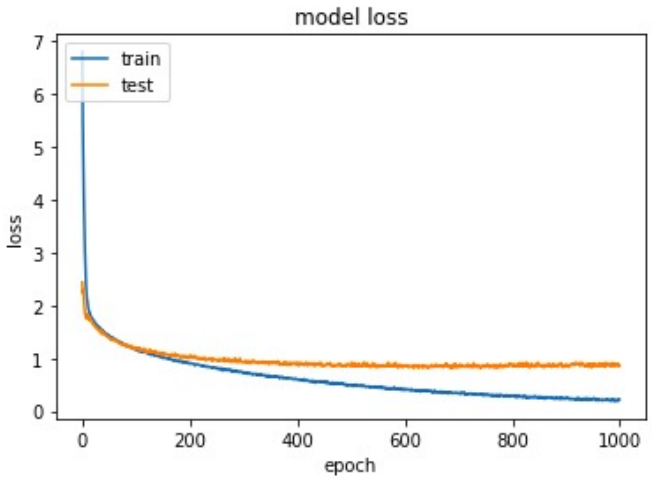


Figure: Train and Validation Accuracy Plot



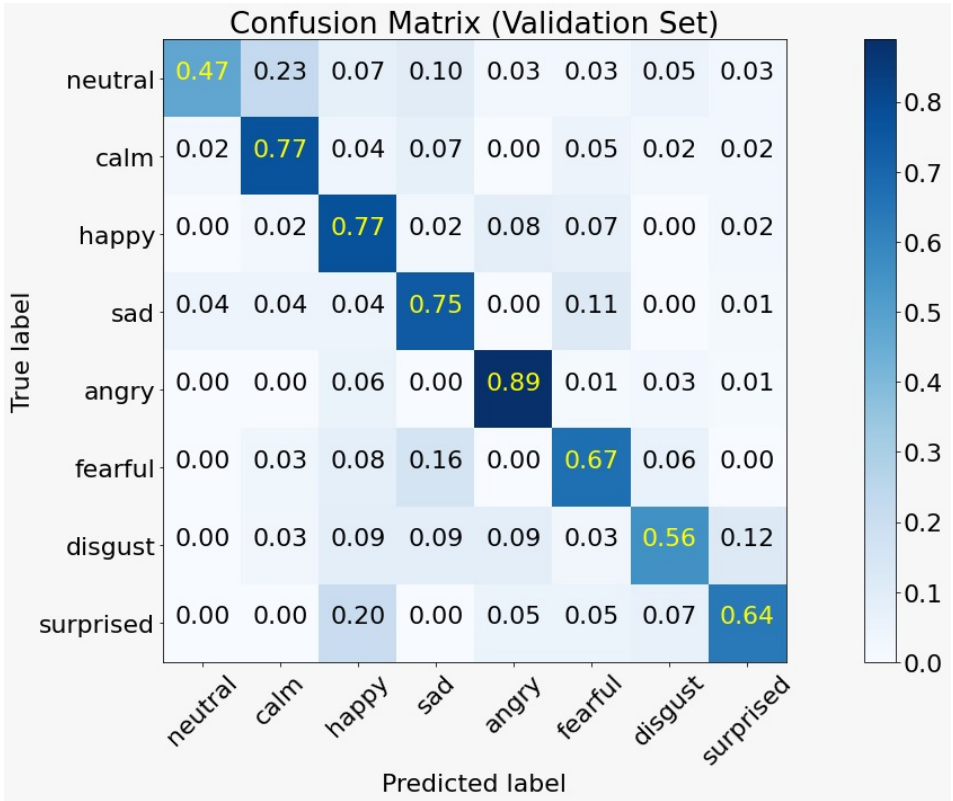


Figure: Confusion Matrix

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Text to Speech Conversion

- We thought of building a speech to sign-language tool, by first converting the speech to text and for every word map to american sign-language (ASL) representation.
- **Disclaimer: We could not implement the text ot sign language part.
- We came across several datasets that converted the letters to ASL hand-images, but that was not what we intended.
- There were other Unity and Blender based Avatar models, but that were not truly capable of direct text to ASL conversion, because of limited datasets.
- We got an architecture that treated this problem as a GAN-based model, but we could not implement it due constraints.
- The Workflow was as follows:
  - Translate text to ASL glossary using Transformer model.
  - Align the ASL Glossary to poses using OpenPose.
  - Interpolate the poses generated using a Fully-Connected neural network (FCN).
  - Generate avatar images for each pose using pix2pix GAN and compile as a video.

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Web Tool for the pipeline

- We created a toolkit using the `streamlit` module of python where we can record a 10sec audio and can detect text and emotion.

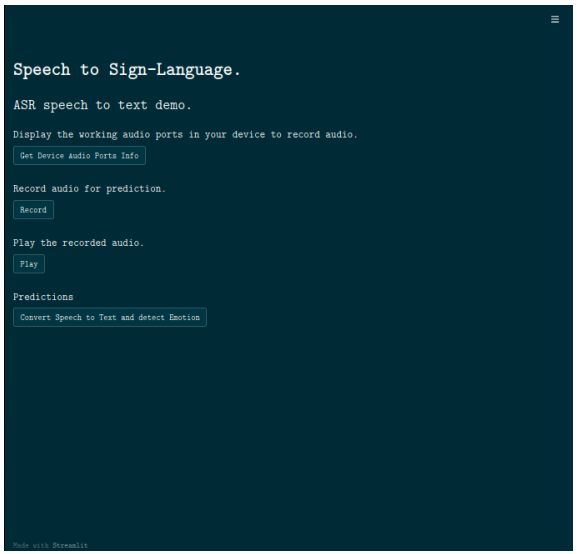

Figure: The Tool Overview

Figure: Play the Audio

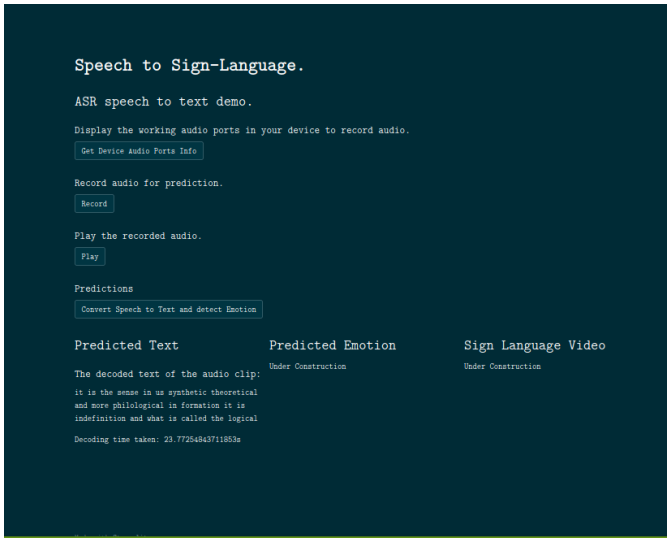

Figure: Audio Decoding

The accuracy of the toolkit depends on the accuracy of the models in general and we hope to integrate the text to ASL feature in future.

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Work Load Division

- **Soham Naha**: Speech2text, Webapp Integration using `streamlit`, Presentation
- **Mohit Agarwala**: Presentation, Speech to ASL research
- **Abhinav Goud Bingi**: Speech to Emotion

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