# RESEARCH AND DEVELOPMENT CS402

# Run-time conversion of speech from one language to another using deep learning

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# Objectives of the Study

*Objective 1:* To implement the project using machine learning libraries

*Objective 2:* To switch from machine learning libraries to deep learning libraries and neural nets

**Speech Recognition:**
Deepspeech and Tensorflow (or) HMM model

**Speech Translation:**
Tensorflow, NLTK and Keras

**Speech Synthesis:**
Tensorflow ,Matplotlib and Tensorboard

# Rationale of the Study

Language is a genuine problem when difficult to understand. Through our research, we aim to considerable solve the following problems:

- **Lingual Barrier -** To make language easy to understand and also to widen our knowledge in the fields of machine learning and deep learning.
- **Conferences** - To make speeches in international conferences accessible to all the dignitaries.
- **Education** - To instantaneously translate a teacher's lecture to different languages in a classroom.
- **Tourism** – To enable a tourist to communicate effectively with people in a new country.
- **Blind People** - To translate on-screen text to a blind person's native language.

# Rationale of the Study (Continued)

**Why not use previous models**

- **Pre-1970**

1. Speech recognition was implemented for less vocabulary of words(16-200 words).
2. User had to give a pause after every word for the system to recognize.

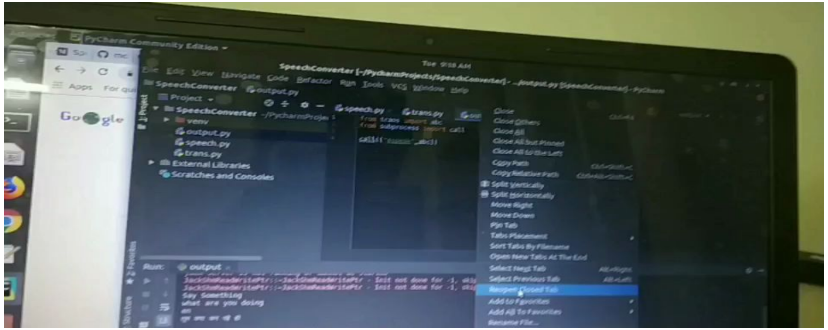
- **1970-2000**

1. Introduction of HMM model.
2. 30 seconds of speech required 100 minutes to be translated into another language.

- **2000s**

1. Introduction of LSTM which outperforms HMM models.
2. There was a increase in the performance and decrease in word error

# Results of the work done: Machine learning




**Successfully implemented with ML libraries and noted the Shortcomings -**

- Output is not that accurate
- Bad quality microphone is prone to noise
- Not real time

# Results of the work done: Deep learning (Continued)

```
| Adam | epoch: 003 | loss: 0.20745 - acc: 0.9607 -- iter: 09792/
Training Step: 468  | total loss: 0.20083 | time: 0.928s
| Adam | epoch: 003 | loss: 0.20083 - acc: 0.9631 -- iter: 09856/
Training Step: 469  | total loss: 0.19530 | time: 0.934s
| Adam | epoch: 003 | loss: 0.19530 - acc: 0.9668 -- iter: 09920/
Training Step: 470  | total loss: 0.19072 | time: 0.939s
| Adam | epoch: 003 | loss: 0.19072 - acc: 0.9670 -- iter: 09984/
Training Step: 471  | total loss: 0.19505 | time: 0.945s
| Adam | epoch: 003 | loss: 0.19505 - acc: 0.9640 -- iter: 10000/
--
predicted digit for 9_Alex_120.wav : result = 9
नौ
```

# Results of the work done: Deep learning

**Speech Recognition**

- In this approach  we build an LSTM recurrent neural network using the TFLearn high level Tensorflow-based library to train on a labeled dataset of spoken digits. Then we test it on spoken digits
- We label the Dataset with the help of the  extracted features (Frequency and width) from the .wav file and perform classification for phoneme
- This module is almost complete as there are few errors while training the model due to lack of high end GPU (RTX 1080 8 gb)

# Results of the work done: Deep learning

**Speech Synthesis**

- We use a TTS engine
- In this approach we convert raw text containing symbols like numbers and abbreviations into the  equivalent of written-out words
- we  assigns phonetic transcriptions to each word .
- Converting  the symbolic linguistic representation into sound .
- Yet to implement

# Results of the work done: Deep learning

**Speech Translation :**

We use Neural MachineTranslation:

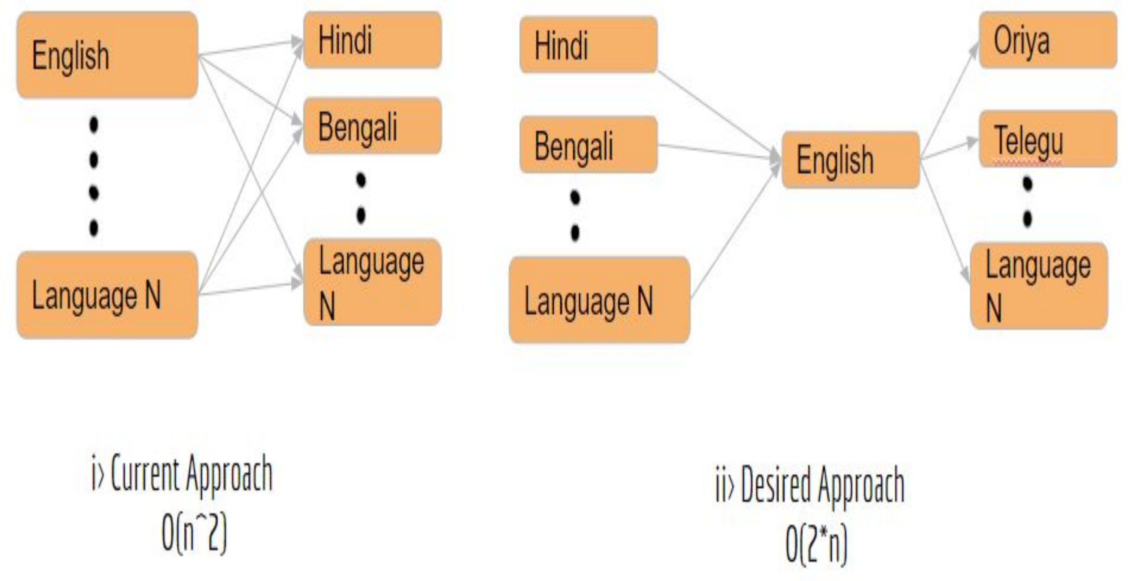
- RNN Encoder–Decoder : It consists of two recurrent neural networks (RNN) that act as an encoder and a decoder pair.
- The encoder maps a variable-length source sequence to a fixed-length vector, and the decoder maps the vector representation back to a variable-length target sequence.

# Future work

- Mastering the skills required in order to overcome the errors faced.
- Implementing the other two phases(Translation, Synthesis) using deep learning with large corpus and high-end GPU.
- Modifying the model according to our novelty for better performance.

# Novelty

- We have decided to train our model with human voice signal so that the synthesis becomes more real and with emotions.
- We plan on using English as an intermediate language for optimizing the complexity from O(n^2) to O(2*n)



# Difficulties faced

- Getting the required Dataset.
- Need of high-end GPU and good quality microphone.
- Problem using google colab.

# References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