# Capstone Project-5

## Speech Emotion Recognition

Deep Learning & ML Engineering Project

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# OVERVIEW

1. Defining Problem Statement

2. Data Collection

3. Exploratory Data Analysis

4. Data augmentation

5. Extracting features from audio

4. Processing features

5. Defining model

6. Training and validating Model

7. Select best model

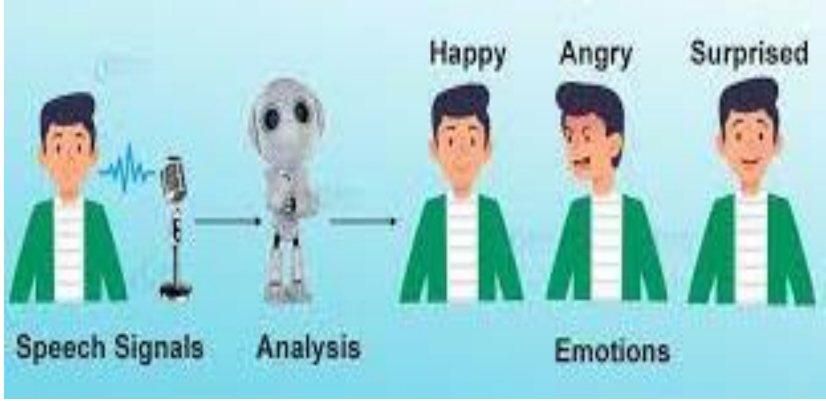
8. Deploy model

# Overview of the Problem Statement

- Speech Emotion Recognition, abbreviated as SER, is the act of attempting to recognize human emotion and affective states from speech. This is capitalizing on the fact that voice often reflects underlying emotion through tone and pitch.

- Tasks for the Project:

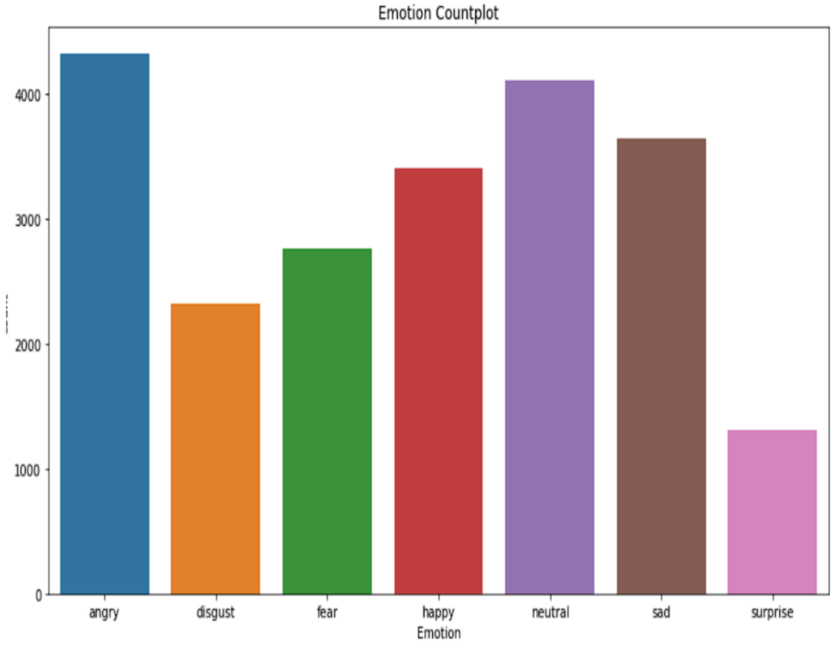
1. Collect data from public databases.
2. Process audio data for applying model.
3. Identify tone/emotion from audio.
4. Deploy model on Azure platform.

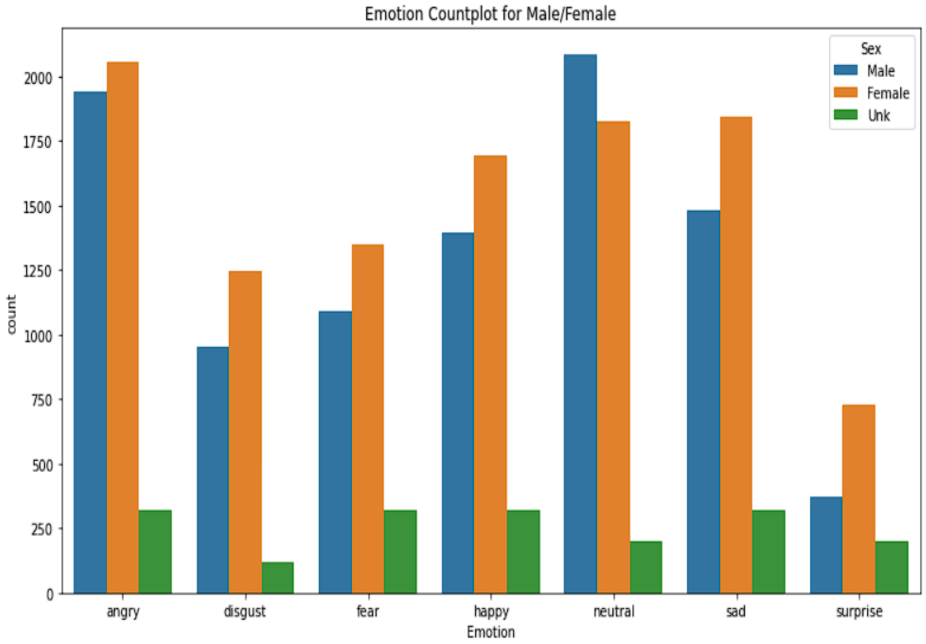


# Dataset used:

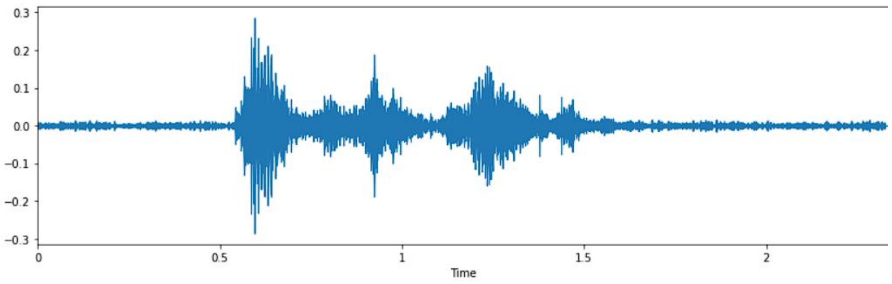
| Name | Language | Gender | Source link | Description |
|---|---|---|---|---|
| CREMA-D | English | Both | https://github.com/CheyneyComputerScience/CREMA-D | 7,442 original clips from 48 male and 43 female actors spoken in 7 diff emotions. |
| TESS | English | Female | https://tspace.library.utoronto.ca/handle/1807/24487 | Toronto Emotional Speech Set: 2 female speakers (young and old), 2800 audio files, random words were spoken in 7 different emotions. |
| SAVEE | English | Male | https://www.kaggle.com/datasets/ejlok1/surrey-audiovisual-expressed-emotion-savee | Surrey Audio-Visual Expressed Emotion: 4 male speakers, 480 audio files, same sentences were spoken in 7 different emotions. |
| RAVDEES | English | Male | https://zenodo.org/record/1188976#.YntXEehBxPY | 2452 audio files, with 12 male speakers and 12 Female speakers, speaking only 2 statements of equal lengths in 8 different emotions by all speakers. |
| BERLIN | German | Both | https://www.kaggle.com/datasets/piyushagni5/berlin-database-of-emotional-speech-emodb | 5 male and 5 female speakers, 535 audio files, 10 different sentences were spoken in 7 different emotions. |
| EMOVO | Italian | Both | http://voice.fub.it/activities/corpora/emovo/index.html | It is a database built from the voices of 3 male and 3 female actors who played 14 sentences simulating 6 emotional states. |
| CASIA | Chinese | Both | http://shachi.org/resources/27 | Chinese Emotional Speech Corpus<br>Four professional speakers are required to utter 500 sentences in 6 emotions. |
| SHEMO | Persian | Both | https://github.com/mansourehk/ShEMO | Sharif Emotional Speech Database: 3000 utterances,87 native-Persian speakers for five basic emotions. |
| CaFE | Canadian French | Both | https://zenodo.org/record/1478765#.Yntal-hBxPY | Canadian French Emotional contains six different sentences, pronounced by 6 male and 6 female actors, in 7 basic emotions. |
| AESDD | GREEK | Both | http://m3c.web.auth.gr/research/aesdd-speech-emotion-recognition/ | Acted Emotional Speech Dynamic Database: 3 female and 2 male actors were recorded. The actors acted these 19 utterances in 5 chosen emotions. |
| J L Corpus | English | Both | https://www.kaggle.com/datasets/tli725/jl-corpus | 2400 recording of 240 sentences by 2 males and 2 female actors in 5 emotions. |

# Emotions Distribution:

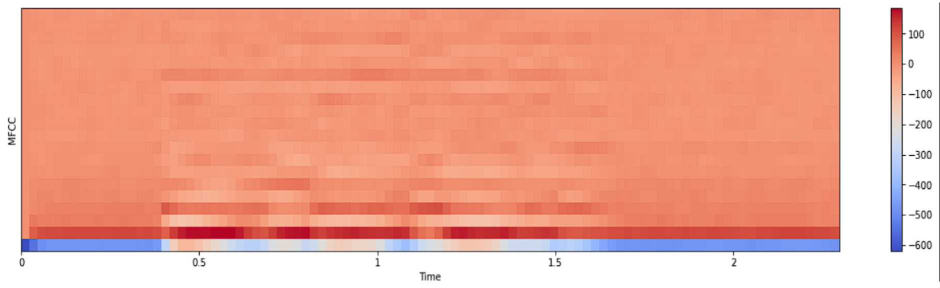


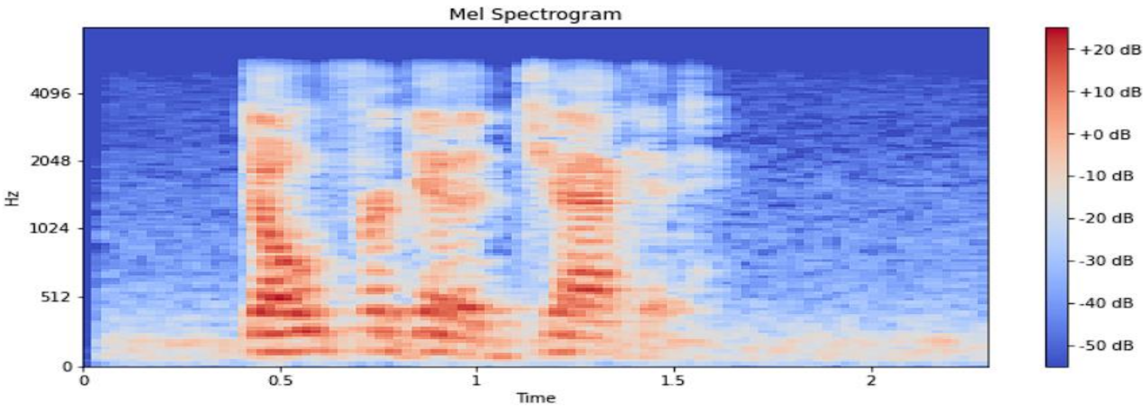
# Audio features:




**Waveform**




**MFCC**




**Mel spectrogram**

# Extracting features from Audio data:

- **ZCR** → The zero-crossing rate (ZCR) is the rate at which a signal transitions from positive to zero to negative or negative to zero to positive.
- **Croma-stft** → Compute a chromagram from a waveform. Chromagram is defined as the whole spectral audio information mapped into one octave.
- **MFCC** → Mel-frequency cepstral coefficients (MFCCs) are coefficients that collectively make up an MFC.
- **RMS** → Compute root-mean-square (RMS) value for each frame from the audio sample.
- **MEL** → Compute a mel-scaled spectrogram

# Data Augmentation:

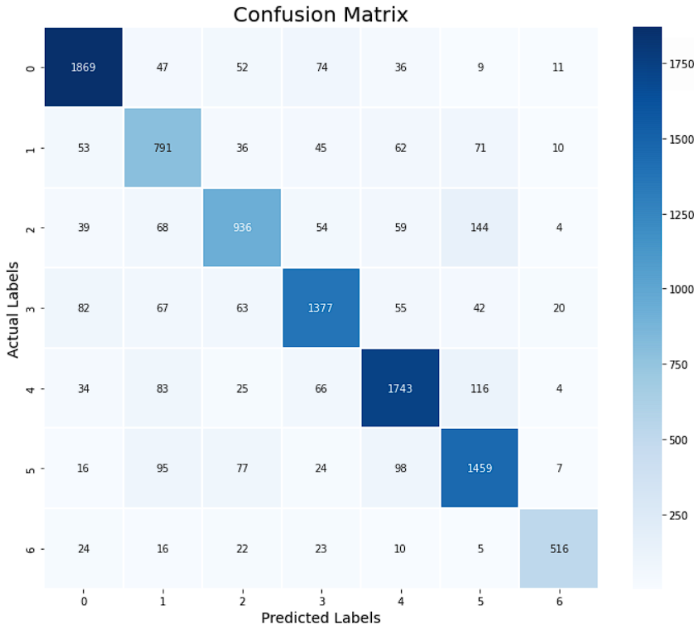
- Add Noise
- Stretch
- Shift
- Alter Pitch

# Model-1 : MLPClassifier

MLPClassifier from sklearn-neural network.
Hidden layer sizes = (256,256,64)
It works well, lets keep this as base model.
Accuracy on train/test set is 91% / 81%.
From the classification report on test set,
Its evident that model is performing
poor on ‘disgust’ and ‘fear’ emotions.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| angry | 0.88 | 0.89 | 0.89 | 2098 |
| disgust | 0.68 | 0.74 | 0.71 | 1068 |
| fear | 0.77 | 0.72 | 0.74 | 1304 |
| happy | 0.83 | 0.81 | 0.82 | 1706 |
| neutral | 0.84 | 0.84 | 0.84 | 2071 |
| sad | 0.79 | 0.82 | 0.81 | 1776 |
| surprise | 0.90 | 0.84 | 0.87 | 616 |
| accuracy | | | 0.82 | 10639 |
| macro avg | 0.81 | 0.81 | 0.81 | 10639 |
| weighted avg | 0.82 | 0.82 | 0.82 | 10639 |

Classification Report
on Test set



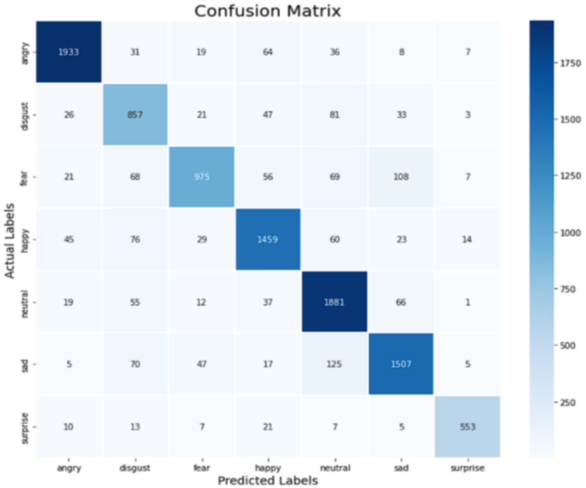

CM for test set

# Model-2 : CNN

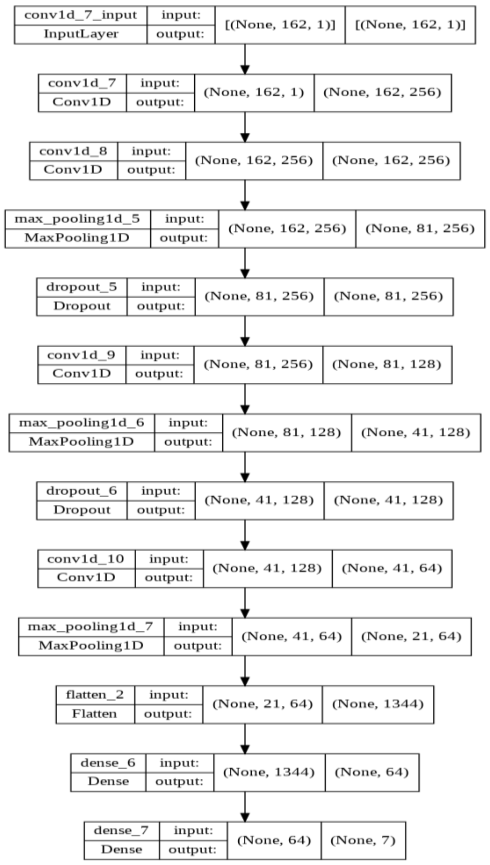
A Custom CNN network .
Dropout technique is used to reduce overfitting.
Accuracy on train/test set is 87% / 86%.
Total parameters: 6L

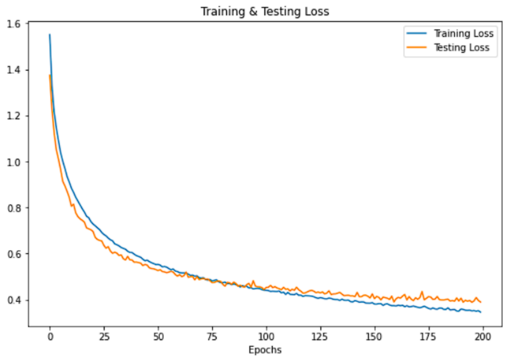
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| angry | 0.94 | 0.92 | 0.93 | 2098 |
| disgust | 0.73 | 0.80 | 0.77 | 1068 |
| fear | 0.88 | 0.75 | 0.81 | 1304 |
| happy | 0.86 | 0.86 | 0.86 | 1706 |
| neutral | 0.83 | 0.91 | 0.87 | 2071 |
| sad | 0.86 | 0.85 | 0.85 | 1776 |
| surprise | 0.94 | 0.90 | 0.92 | 616 |
| accuracy | | | 0.86 | 10639 |
| macro avg | 0.86 | 0.85 | 0.86 | 10639 |
| weighted avg | 0.86 | 0.86 | 0.86 | 10639 |

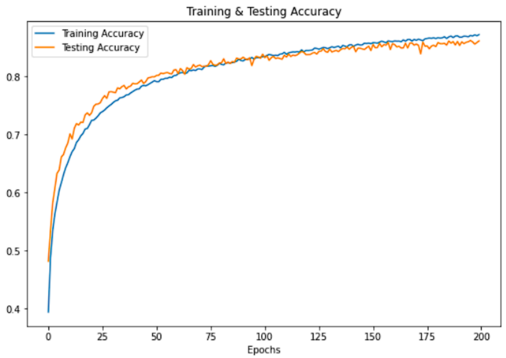
## CM for test set




## Model



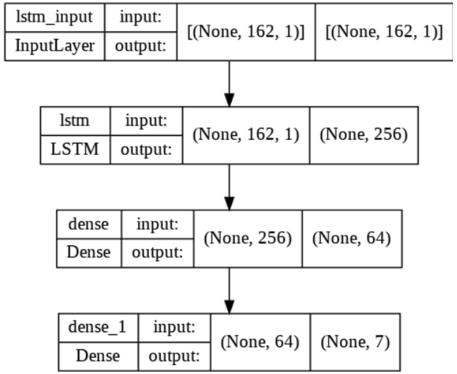




## Model performance

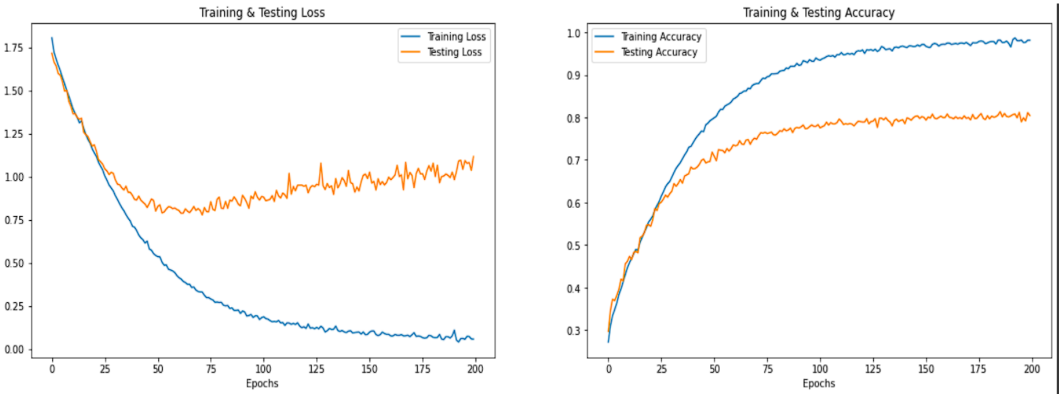
# Model-3 : LSTM

A Custom LSTM network .
There is overfitting.
Accuracy on train/test set is 98% / 80%.
Parameters : 2.8L

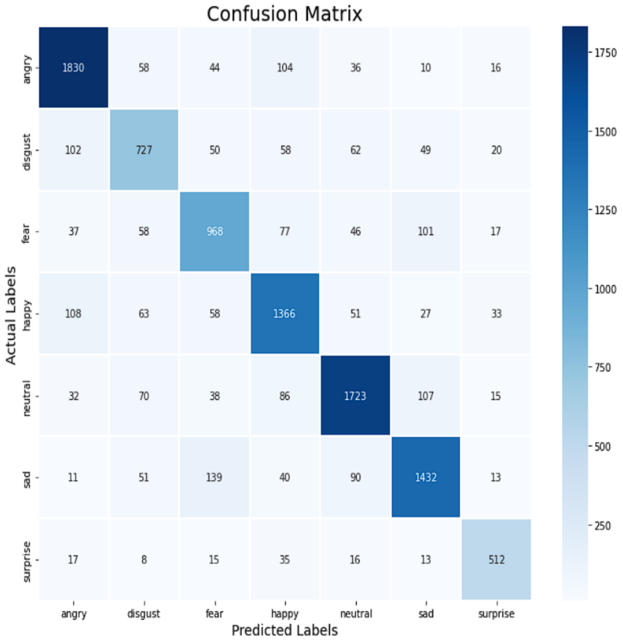
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| angry | 0.86 | 0.87 | 0.86 | 2098 |
| disgust | 0.70 | 0.68 | 0.69 | 1068 |
| fear | 0.74 | 0.74 | 0.74 | 1304 |
| happy | 0.77 | 0.80 | 0.79 | 1706 |
| neutral | 0.85 | 0.83 | 0.84 | 2071 |
| sad | 0.82 | 0.81 | 0.81 | 1776 |
| surprise | 0.82 | 0.83 | 0.82 | 616 |
| accuracy | | | 0.80 | 10639 |
| macro avg | 0.79 | 0.80 | 0.79 | 10639 |
| weighted avg | 0.80 | 0.80 | 0.80 | 10639 |




Model




Model performance



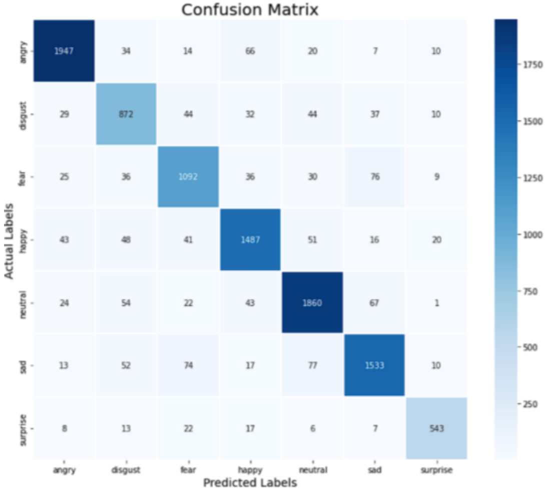

CM for test set

# Model-5 : CNN+ LSTM

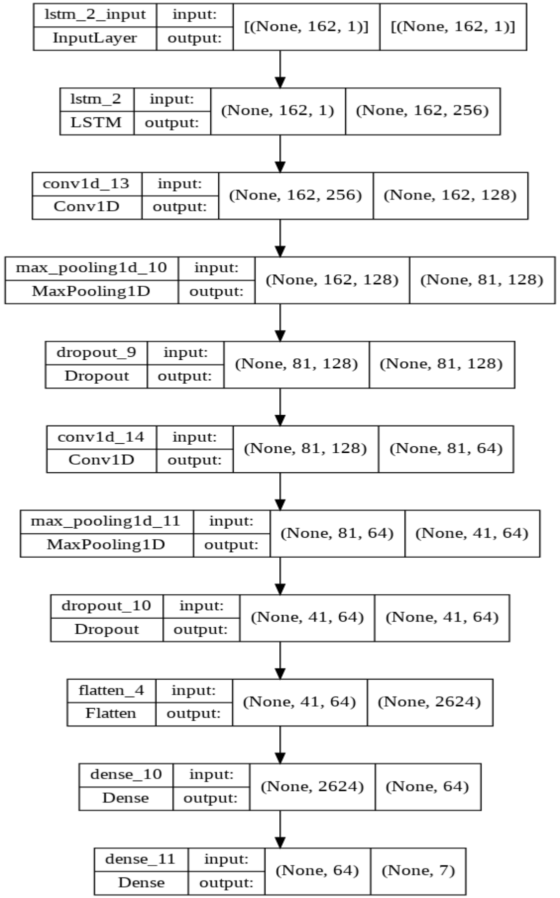
Adding LSTM to CNN network .
Dropout technique is used to reduce overfitting.
Accuracy on train/test set is 99% / 88%.
Parameters: 6.3L

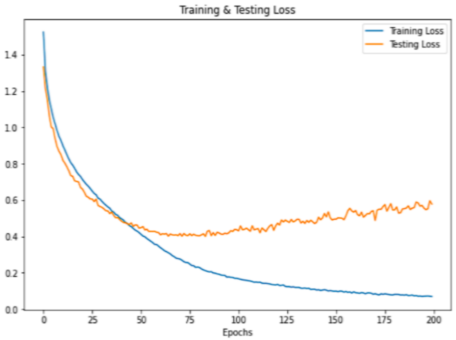
| | precision | recall | f1-score | support |
|---|---|---|---|---|
| angry | 0.93 | 0.93 | 0.93 | 2098 |
| disgust | 0.79 | 0.82 | 0.80 | 1068 |
| fear | 0.83 | 0.84 | 0.84 | 1304 |
| happy | 0.88 | 0.87 | 0.87 | 1706 |
| neutral | 0.89 | 0.90 | 0.89 | 2071 |
| sad | 0.88 | 0.86 | 0.87 | 1776 |
| surprise | 0.90 | 0.88 | 0.89 | 616 |
| accuracy | | | 0.88 | 10639 |
| macro avg | 0.87 | 0.87 | 0.87 | 10639 |
| weighted avg | 0.88 | 0.88 | 0.88 | 10639 |

## CM for test set




## Model





## Model performance

# Model Selection

1. MLP Classifier performed well on the data with 91% and 81% accuracy on Train/Test sets resp. Handling overfitting is a challenge for a ANN network.
2. CNN model with around 6L parameters resulted in accuracy of 95%/86% on train/test sets. Maxpool layer and dropout is utilized in training.
3. LSTM model with over 2.8L parameters resulted in accuracy of 98%/80% on train/test set showing overfitting.
4. A combination of LSTM and CNN helped reducing overfitting and resulted in 99%/88% train/test accuracy. Hence, I have selected this model for deployment.

## Accuracy Table

| | MLP Classifer | CNN | LSTM | LSTM_CNN |
|---|---|---|---|---|
| Train Accuracy | 0.918414 | 0.953702 | 0.984042 | 0.996757 |
| Test Accuracy | 0.816900 | 0.861453 | 0.804399 | 0.877338 |

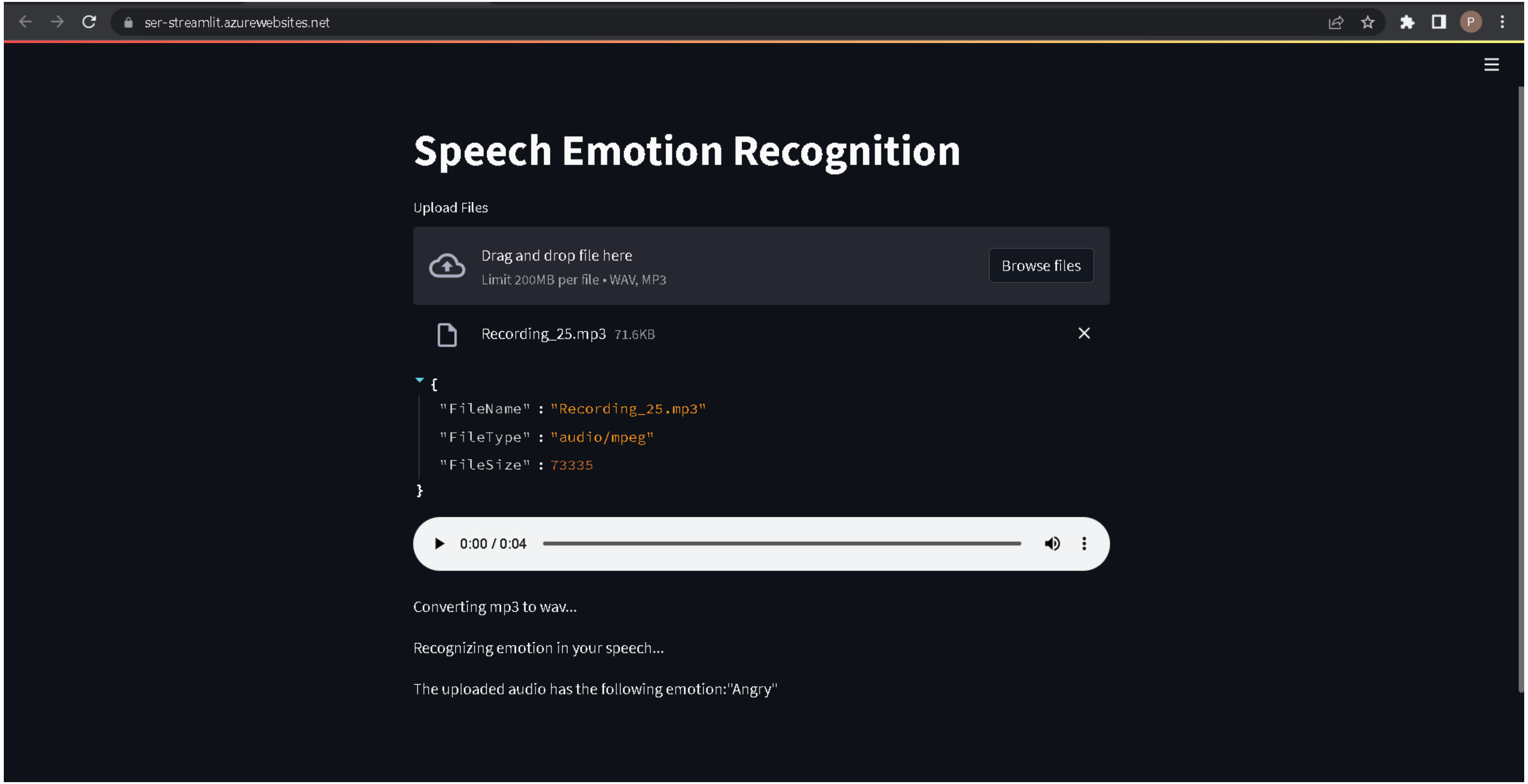
## Prediction Table

| | Actual Labels | MLP Pred | CNN Pred | LSTM Pred | LSTM_CNN Pred |
|---|---|---|---|---|---|
| 0 | neutral | happy | neutral | neutral | neutral |
| 1 | angry | angry | angry | angry | angry |
| 2 | neutral | neutral | neutral | neutral | neutral |
| 3 | neutral | neutral | neutral | neutral | neutral |
| 4 | sad | disgust | neutral | neutral | sad |
| 5 | neutral | neutral | neutral | neutral | neutral |
| 6 | fear | fear | fear | fear | fear |
| 7 | happy | happy | happy | happy | happy |
| 8 | sad | sad | sad | sad | sad |
| 9 | sad | sad | sad | sad | sad |

# Project Structure

```
Structure:
├── model/                          // saved models
│    ├── model_mlpclassifier.sav    // mlp classifer
│    ├── model_cnn.h5               // cnn
│    |── model_lstm.h5              // lstm
│    |── model_lstm_cnn.h5          // lstm + cnn
├── processed data/                 // audiio df and features df
│    ├── new_audio_csv.csv          // audio files path
│    └── df_csv.csv                 // audios more than 1 sec
│    └── all_features.csv           // extracted features
├── app.py                          // main application
├── Dockerfile                      // docker file
├── Notebook.ipynb                  // colab notebook
├── packages.txt                    // system packages
└── requirements.txt                // dependencies
```

# Deployed App



# Summary

Started with...

- Gathering wide range of properly labelled speech recordings in different languages and accent to make sure model generalizes well on real world data.
- Selecting best number of emotions to be classified. Selected emotions are Happy, Sad, Angry, Surprise, Disgust, Fear, Neutral.
- Augmenting Data to generate more data. Techniques used are Noise Insertion, Shifting, Stretching and changing Pitch.
- Extract all important audio features that can be learned by model.
- Trying different neural network models like MLP Classifier, 1-d CNN network, LSTM, LSTM+CNN combination & selecting best model(LSTM+CNN).
- Keeping a check on overfitting while training model by using techniques such as Dropout.
- Dockerizing and creating application using Streamlit.
- Deploying application using Azure web-apps services.
- All models performed poorly on Disgust & Fear emotion as compared to other emotions.
- Using multiple datasets of different properties like gender, language, accent, recording environment is essential in getting a more generalized model.
- Data Augmentation techniques proved to be useful in improving model performance

## Challenges faced:

- Collecting different types of data.
- Understanding how to process audio files.
- Training neural networks and experimenting with architecture of network.
- Handling mp3 audio files.
- Deploying app on Azure- configuring Website port, dockerizing.

Thank You