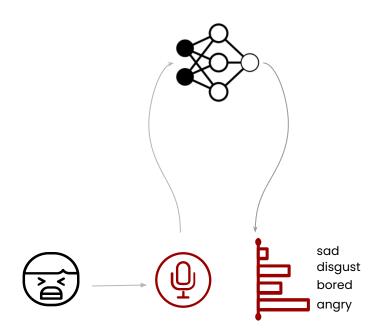
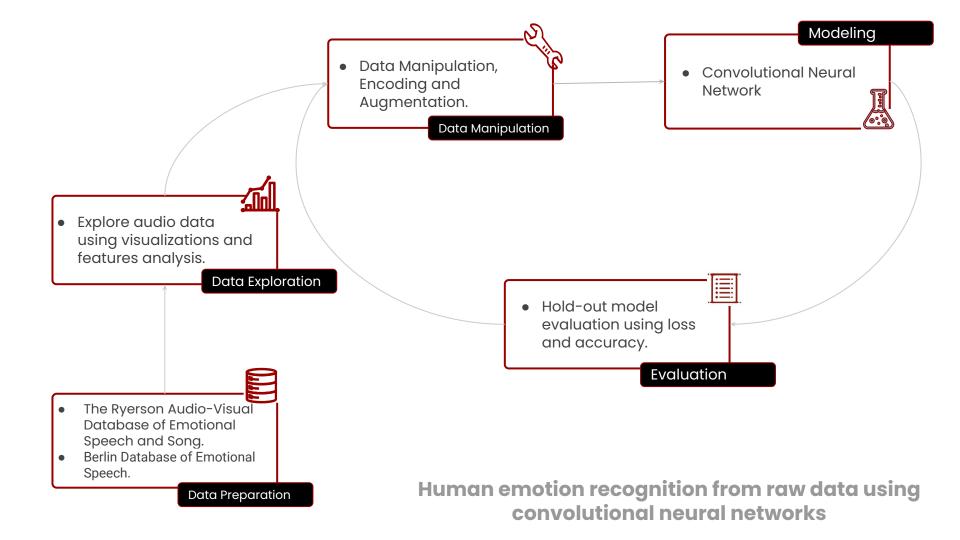
# Emotions Recognition from Audio Speech Using Deep Learning

Pattern Recognition - F20

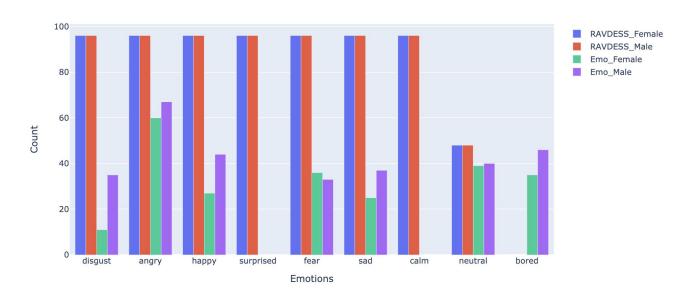
Fatima AlSaadeh



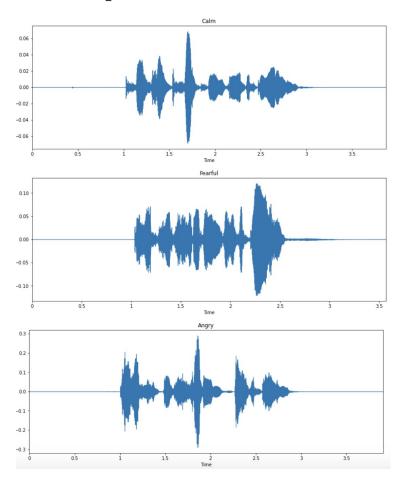


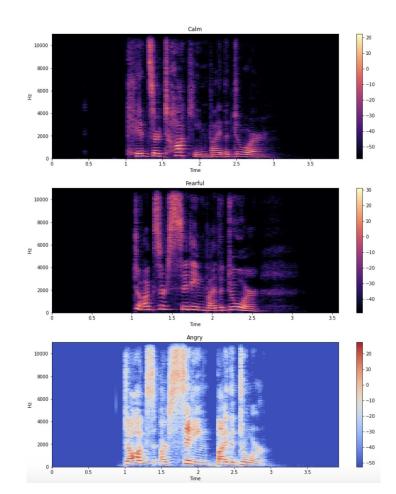
## **Data Preparation**

- 1. The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS):
- The audio-only files contain 1440 files, 24 actors, 12 male and 12 female.
- English.
- 2. Berlin Database of Emotional Speech (EMO-db):
- The audio files contain 535 files, 302 males, 233 females
- Germany



# **Data Exploration**



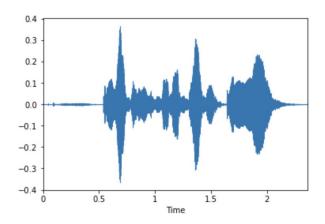


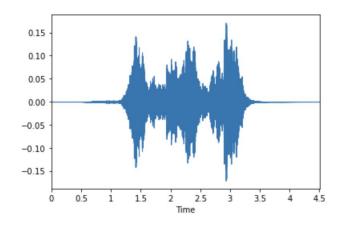
# **Data Manipulation**

Data Standardization

$$x' = rac{x - ar{x}}{\sigma}$$

- Data Augmentation
- Adding white noise.
- Stretching the sound.
- Random Shifting.
- Resampling and Reduction.
- Classes one-hot encoding.





### **Convolutional Neural Networks**

 Require minimal data pre-processing, due to their convolutional layers and their ability to extract features, eliminating the feature engineering by hand step.

$$x_i^l = \sum_{n=1}^j w_{i,j} * x_i^{l-1} + b_i^l$$

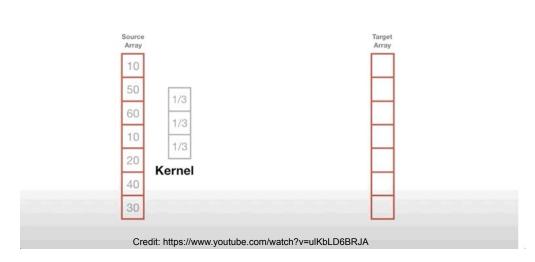
- It takes the raw data as an input and built of different convolutional, pooling and fully connected layers.
- Convolutional Layers have filters which help detect the patterns in the raw input data.

## **Model Architecture**

- Input
- Temporal Convolution: (ConvID)

$$Y = (X - F + 2*P)/S + 1$$

- Batch Normalization.
- Max Pooling.
- Activation function.
- Dropout.
- Average Pooling
- Softmax.

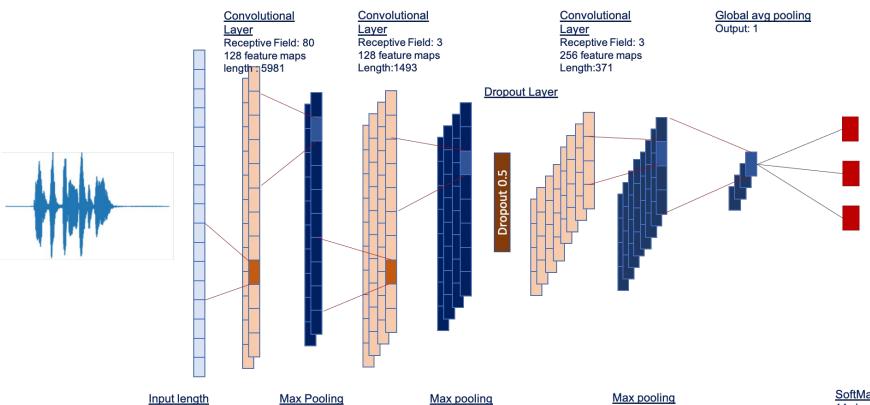


## **Model Architecture**

24000

Pooling length= 4

Output length: 1495



Pooling length:4

Output length: 373

**SoftMax** 14 classes

Pooling length:4

Output length: 92

#### **Evaluation**

#### Evaluation metrics:

- Accuracy.
- o Precision.
- Recall.
- Loss

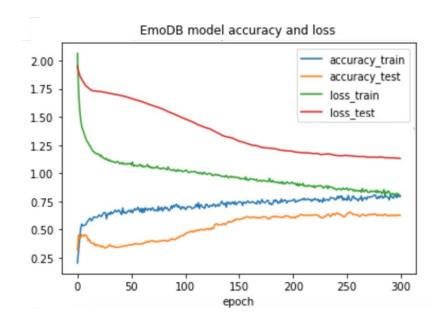
#### Fitting and testing the model to predict the classes in different categories:

- 2 classes: Emotions Intensity strong and natural.
- 4 classes: positive, negative, fearful and surprised.
- 7 classes emotions after we merged the neutral and calm.
- 14 classes: all emotions male and female: male and female, neutral calm, happy, sad, angry, fearful, disgust, surprised.

#### Using holdout evaluation method:

- Split the data into training and testing datasets 80%, 20%
- Further split the training data into training and validation 80%, 20%.

# **Results Analysis**



RAVDESS model accuracy and loss accuracy\_train accuracy\_test 2.5 loss\_train loss\_test 2.0 1.5 1.0 0.5 0.0 200 250 100 150 300 50 epoch

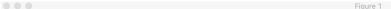
Table 2. Train and test accuracy - EmoDB

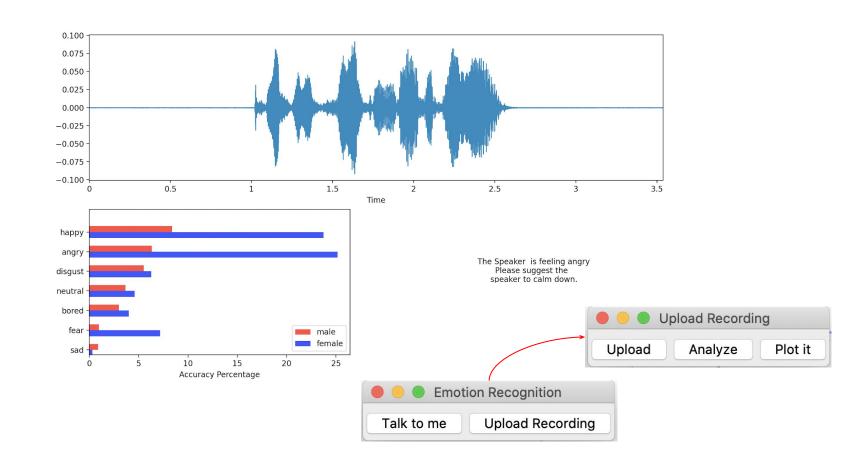
	-		
Classes	Train	Test	
4-classes	87.1%	71.03%	
7-classes	85.9%	60.2%	
14-classes	87.9%	60.7%	

Table 1. Train and test accuracy - RAVDESS

Classes	Train	Test
2-classes	89.0%	68.0%
4-classes	91.8%	55.7%
14-classes	86.5%	51.8%

# **Applications**





### References

- [1] G. Trigeorgis, F. Ringeval, R. Brueckner, E. Marchi, M. A.Nicolaou, B. Schuller, and S. Zafeiriou. Adieu features? end-to-end speech emotion recognition using a deep convolutional recurrent network. 2016
- [2] K. Venkataramanan and H. R. Rajamohan. Emotion recognition from speech.CoRR, abs/1912.10458, 2019
- [3] J. Rintala. Speech Emotion Recognition from Raw Audio using Deep Learning. 2020
- [4] W. Dai, C. Dai, S. Qu, J. Li, and S. Das. Very deep convolutional neural networks for raw waveforms. CoRR, abs/1610.00087, 2016
- [5] Livingstone sr, russo fa (2018) the ryerson audio-visual database of emotional speech and song (ravdess): A dynamic, multimodal set of facial and vocal expressions in north american english. plos one 13(5): e0196391
- [6] Burkhardt, A. Paeschke, M. Rolfes, W. Sendlmeier, and B. Weiss. A database of german emotional speech. volume 5,pages 1517–1520, 01 2005.