Department of Electrical & Electronic Engineering

University of Dhaka

Dhaka, Bangladesh

EEE-5507: Fuzzy Logic, Neural Networks & Deep Learning

Speech Emotion Recognition Using 1D CNN

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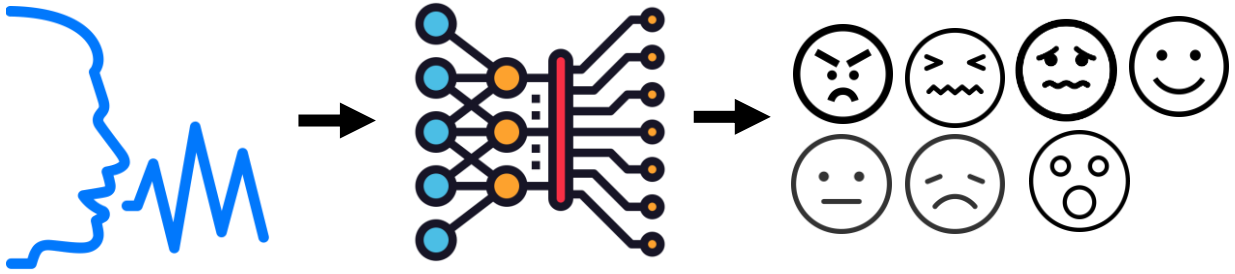
GitHub Link: https://github.com/shasan7/TESS_ML_Project

Speech Emotion Recognition (SER)

What's Emotion Recognition?

- **Emotion Recognition** is the ability to precisely infer human emotions
- Utilizing facial expressions, body language, speech patterns, and text.



Emotion Recognition using speech signals

Why it's important?

Human-Computer Interaction (HCI) & Robotics

→ More intuitive and responsive to user emotions

Mental Health and Well-being

→ Detecting signs of stress, anxiety, or depression, enabling timely interventions

Security & Surveillance

→ Unusual or aggressive behaviors from emotional cues

Marketing and Customer Experience

→Gauge consumer reactions to products, services,

Speech Emotion Recognition (SER)

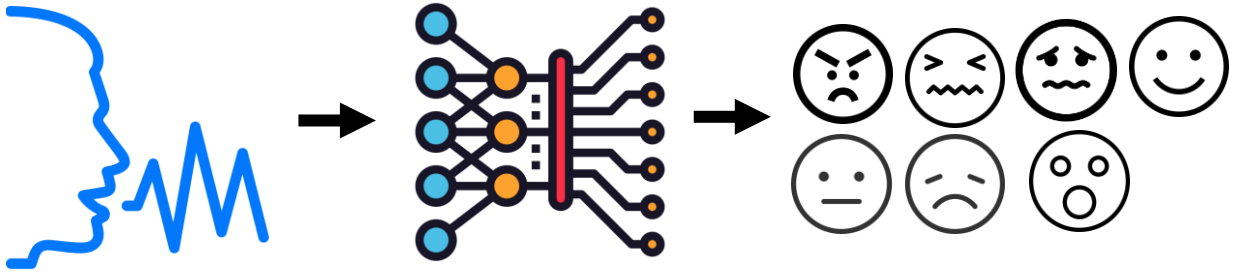
Advantages of Emotion Recognition from speech signals:

Non-Intrusive and Privacy-Friendly
→ Only audio input is required
→ Cameras capture visual data, intruding on privacy

Effective in Low-Visibility Conditions
→ Works in low-light, dark, or visually obstructed environments
→ Suitable for phone calls or virtual meetings without video

Unobstructed by Physical Appearance or Expression Limitations
→ Can detect emotions even if a person's face is obscured, hidden, or masked, eg. in online meetings or while wearing face masks
→ Can detect emotions that are not strongly expressed in facial features, eg. sounds angry but the facial expression is neutral

Works in Unstructured and Natural Conversations
→ Text-based approaches struggles with sarcasm, irony, or subtle emotions that aren't conveyed in words
→ SER works while emotions are conveyed through tone, pitch, and vocal intonation, even if the words themselves are neutral.



Emotion Recognition using speech signals

Emotional Speech Dataset

Toronto Emotional Speech Set (TESS)

→ 2800 speech samples
→ 2 actors, 1400 samples per speaker
→ 7 different emotion classes
→ 400 sample audios for each of the classes

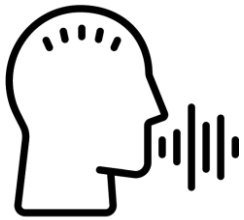
Prior Works

References & Year	Features Extracted	Architecture Used	Performance
[6], 2024	Multiple Time & Freq domain Features	Ensembling A (CNNs), B (BiLSTM-FCN), C (BiLSTM-FCN with transformer) Networks	99.857 %
[7], 2023	MFCC Spectrogram	CNN+LSTM+Attention	99.81 %

[6] Mengsheng Wang, Hongbin Ma, Yingli Wang, Xianhe Sun, Design of smart home system speech emotion recognition model based on ensemble deep learning and feature fusion. https://doi.org/10.1016/j.apacoust.2024.109886
[7] Singh J, Saheer LB, Faust O. Speech Emotion Recognition Using Attention Model. *International Journal of Environmental Research and Public Health*. 2023; 20(6):5140. https://doi.org/10.3390/ijerph20065140

Proposed Approach

Capturing Speech Signal



Human Subject

Pre-processing

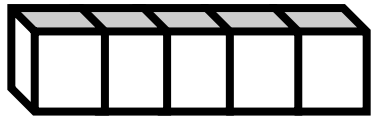
Setting Offset & Clipping
Duration/ Zero Padding

Feature Extraction

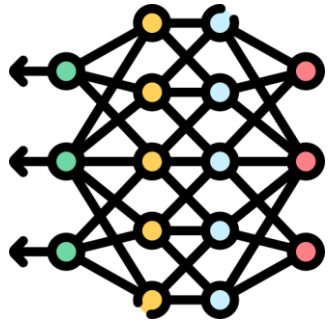
Mel-Frequency
Cepstral Coefficients

Flattening

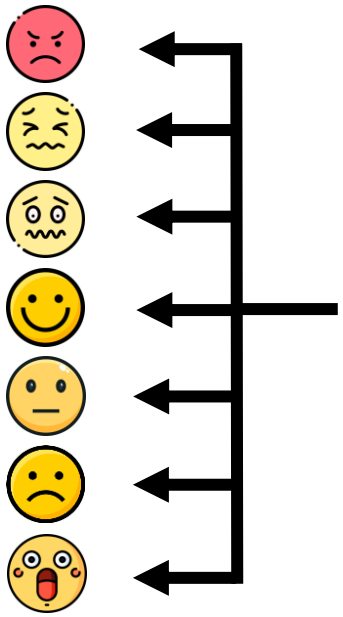
Feature Vector



Train Classifiers
e.g., 1-D CNN

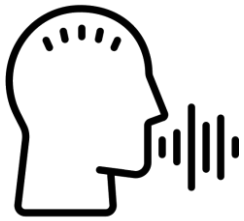


Emotion Recognition

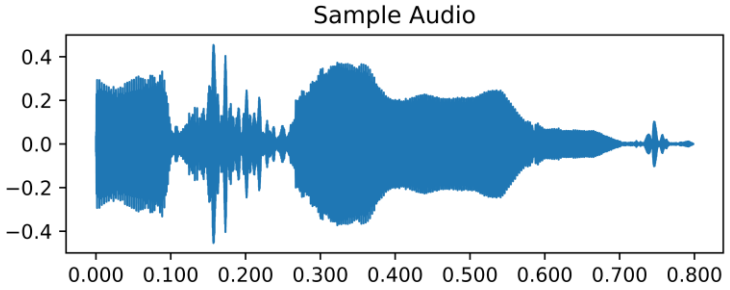


Feature Extraction

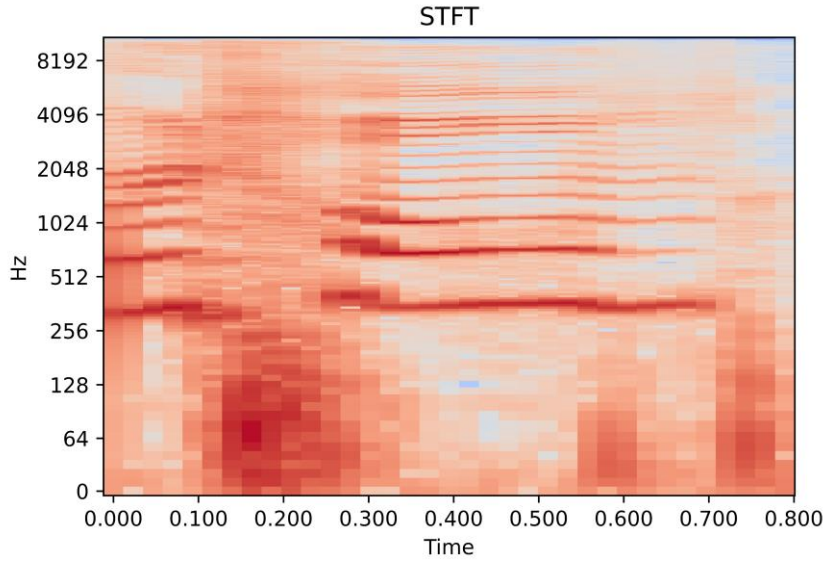
Capturing Speech Signal



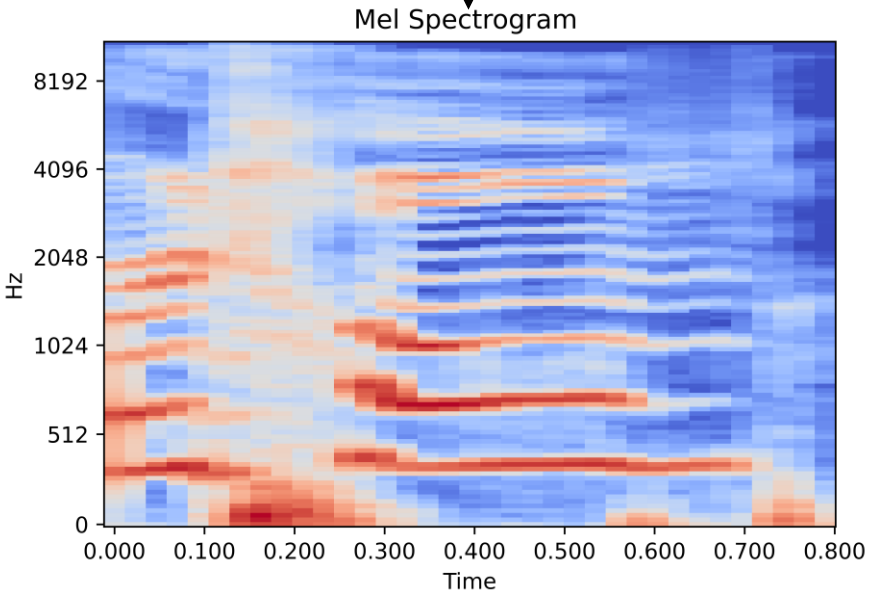
Human Subject



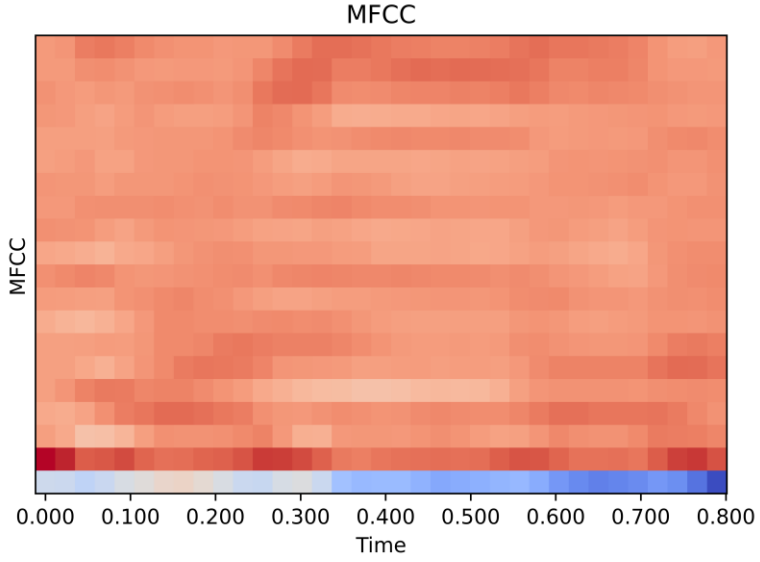
STFT



Mel Scale

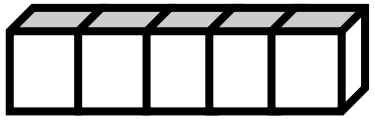


DCT



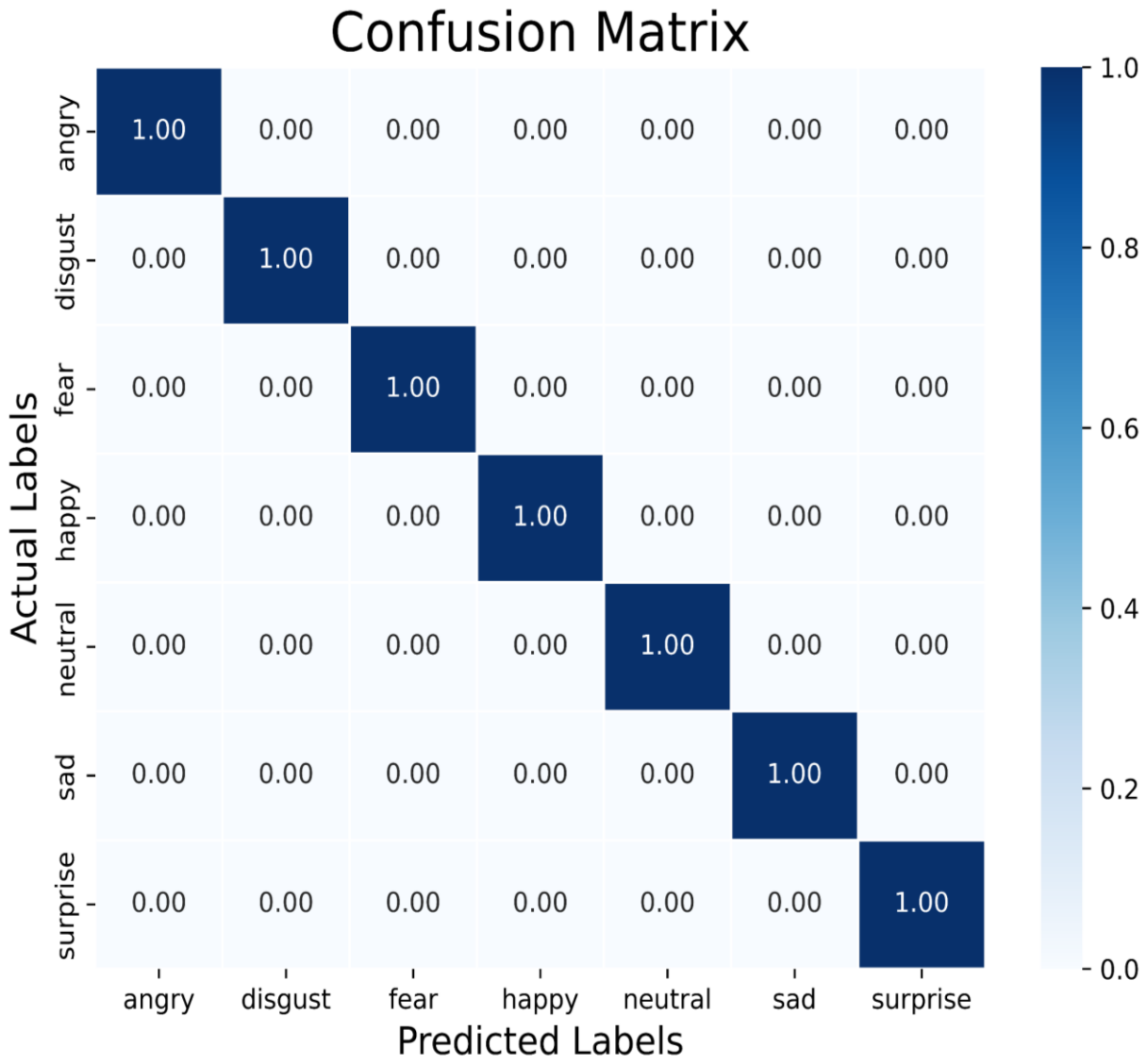
Flattening

Feature Vector



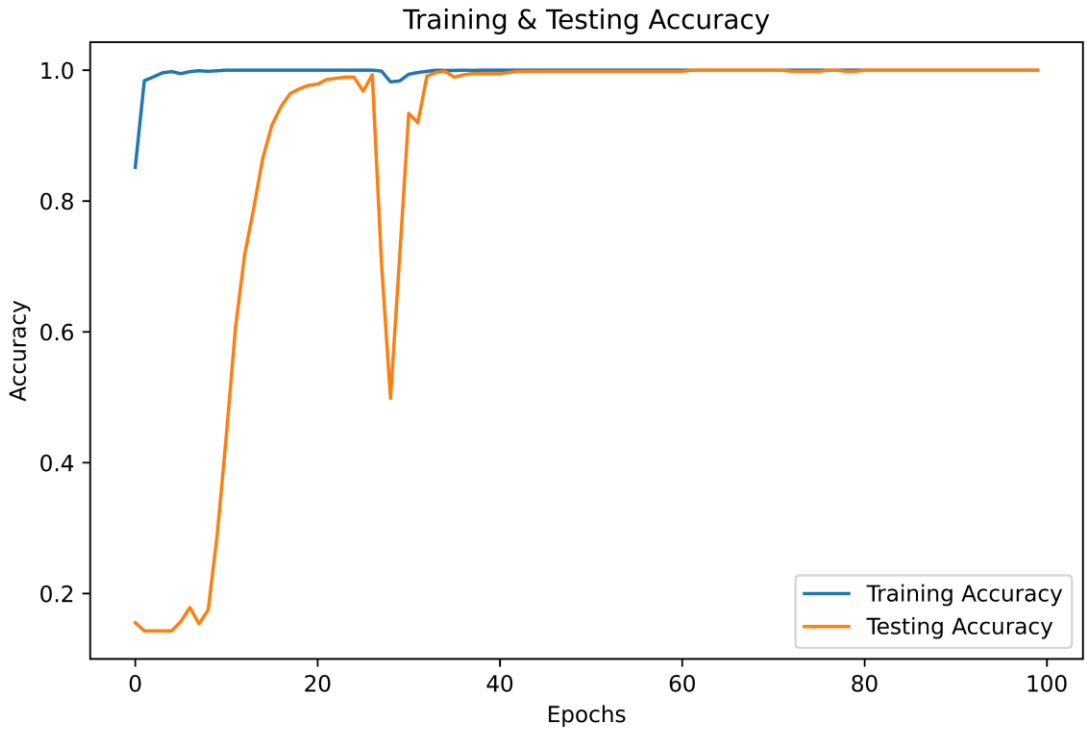
Performance Analysis

Classifier	Result (%)
Decision Tree	78.39
Random Forest	97.68
SVM	98.21
XGBoost	96.96
1D CNN	100

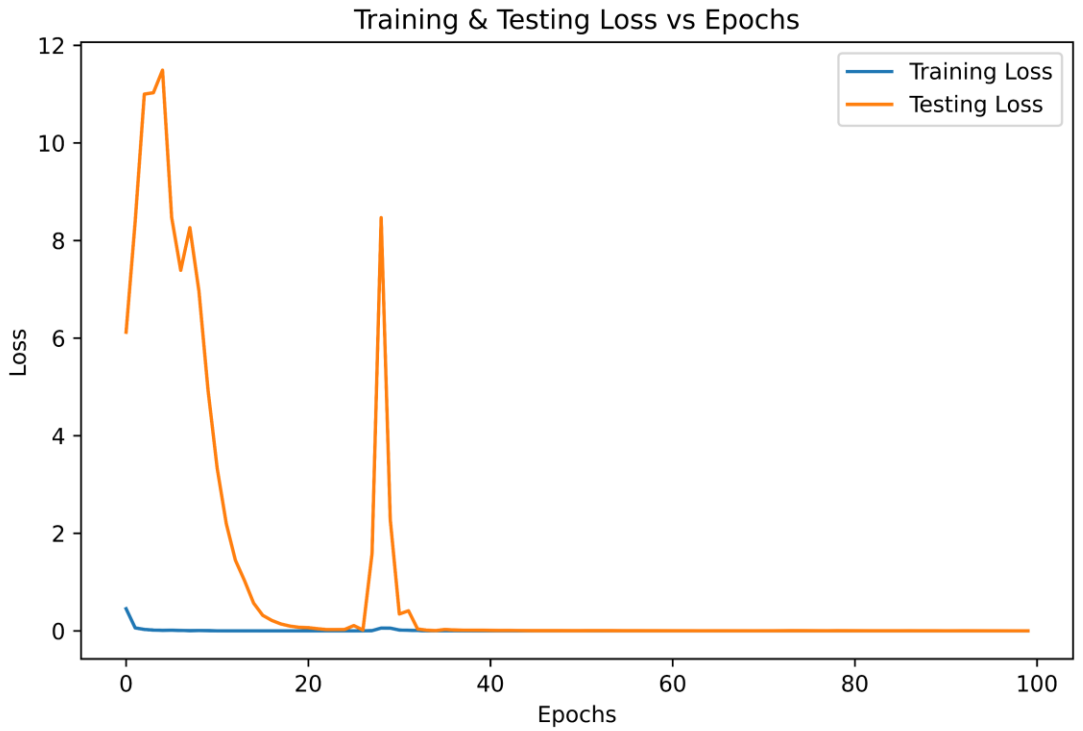


Results obtained using 1D CNN

Performance Analysis



Training & Testing Accuracy vs Epochs



Training & Testing Loss vs Epochs

Performance Analysis

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This Work	MFCC (Flattened)	1D CNN	100 %

1D CNN
Conv1d (filters=128, kernel_size=5)
BN, Relu, MaxPool
Conv1d (filters=128, kernel_size=5)
BN, Relu, MaxPool, *Dropout (0.2)*
Conv1d (filters=256, kernel_size=5)
BN, Relu, MaxPool
Conv1d (filters=256, kernel_size=3)
BN, Relu, MaxPool, *Dropout (0.2)*
Conv1d (filters=256, kernel_size=3)
BN, Relu, MaxPool
Conv1d (filters=512, kernel_size=3)
BN, Relu, MaxPool, *Dropout (0.2)*
Flatten, Dense (256), BN, Dense (7, softmax)

1D CNN Architecture