

# **Enhancing Forensic Audio Investigations: A Multi-Speaker Speech Understanding and Analysis System**

Himani (M23CSA516) & Ankit Kumar Chauhan (M23CSA509)

Speech Understanding

Course Instructor: Dr. Richa Singh

Dept. of Computer Science and Engineering, Indian Institute of Technology Jodhpur, Jodhpur, Rajasthan, 342030, India

atistical models (LR, SVC, KNN

# Abstract

- This project focuses on developing a multicomponent speech understanding system that processes audio containing multiple speakers.
- The system uses Speaker Diarization, Emotion Classification, Gender Classification, and Speaker Identification to enhance forensic audio investigations.
- It leverages state-of-the-art techniques such as **Sep Former** for **speech separation** and **enhancement**, and deep learning models for **emotion** and **gender recognition**.
- The system is modular, allowing independent development of each component with robust integration for final deployment.

# Methodology

#### Dataset Preparation

- VoxCeleb Dataset: We utilized the VoxCeleb dataset, which contains real-world audio recordings of multiple speakers, to build our training dataset.
- Mixing Audio: Audio from the VoxCeleb dataset was mixed to simulate real-world multi-speaker environments.

#### Audio Acquisition & Preprocessing

- Upload mixed audio file containing multiple speakers.
- Standardize audio format and extract **MFCC** features using **Librosa**.
- Pad or trim audio to ensure consistent frame length.

#### Speaker Diarization & Separation

- Use **SepFormer** model (sepformer-whamr) for separating overlapping speech.
- Save separated audio sources for individual speaker analysis.

#### > Speech Enhancement

- Apply SepFormer Enhancement Model (sepformer-wham-enhancement) to improve speech quality by reducing noise.
- > Feature Extraction
- Extract features like Zero Crossing Rate (ZCR), Root Mean Square Error (RMSE), and MFCC.

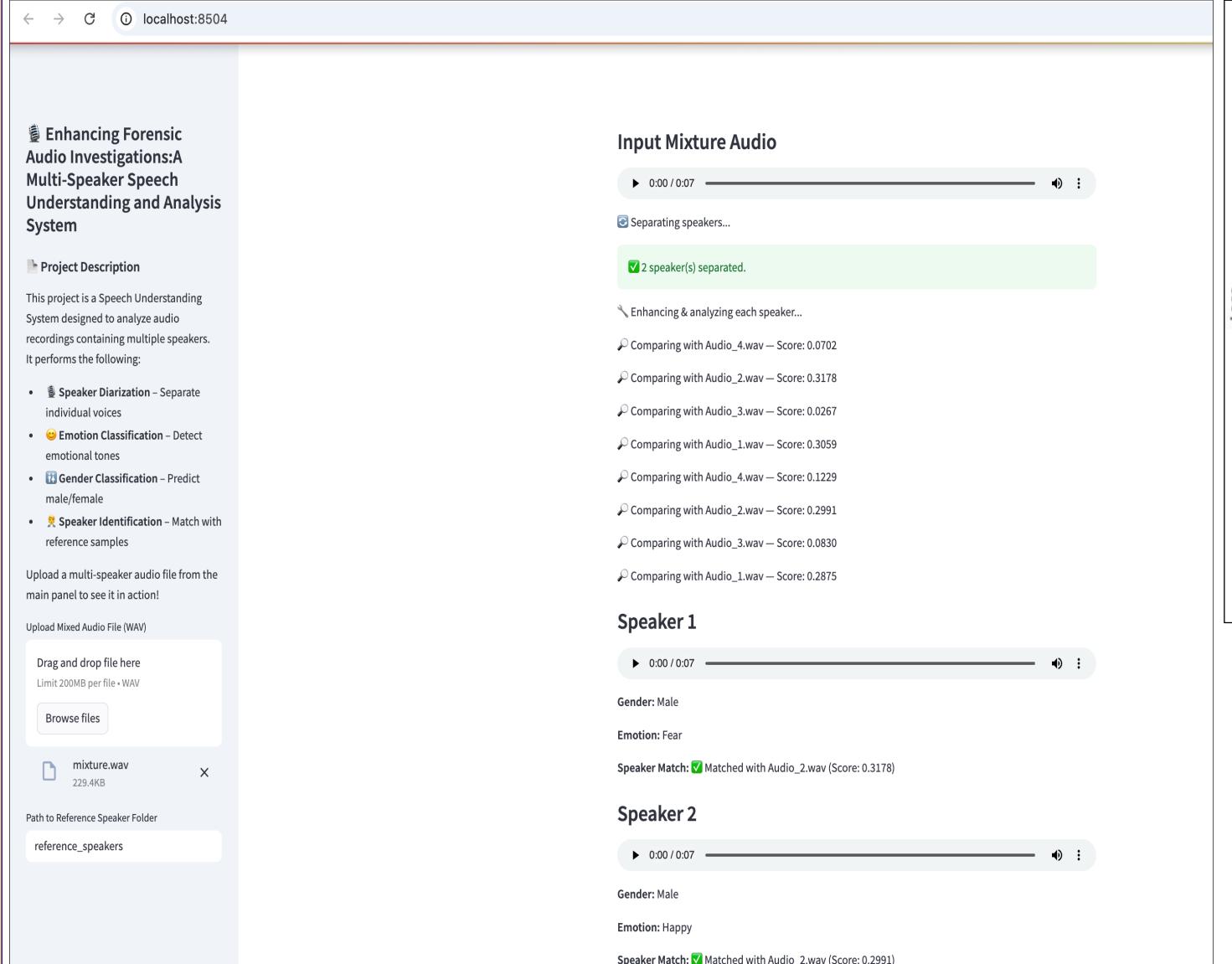
# Forensic Analysis - Compile final reports of speaker identity, Gender & emotion Speaker Diarization - Compare features with known DB - Identity verification - Similarity scoring & confidence Feature Extraction - MFCCs, pitch, energy - Spectral/formant analysis - Additional acoustic features Gender Classification

# System Architecture

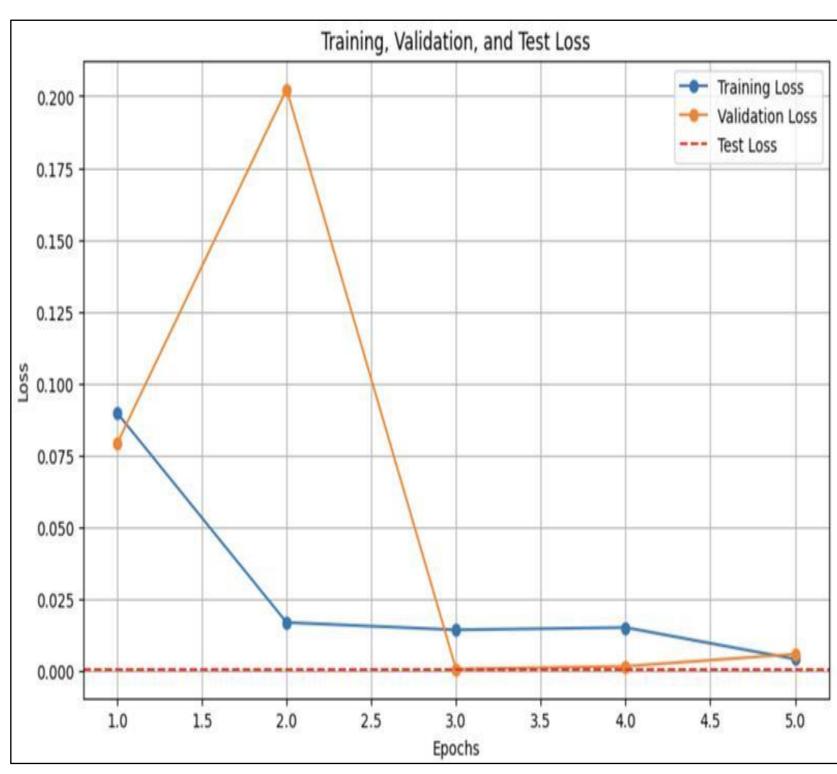
- > Gender Classification Model Training
- Use an LSTM-Based Model for gender classification.
- Train using MFCC features and Binary Cross-Entropy Loss.
- Output: Male or Female.
- > Emotion Classification Model Training
- CNN-Based Model for emotion recognition using 1D Convolutional Layers.
- Output: 7 emotional classes (Neutral, Calm, Happy, Sad, Angry, Fear, Disgust, Surprise).
- > Speaker Identification
- Use **SpeechBrain's ECAPA-TDNN-based Speaker Recognition** to match speakers with a reference database.

# Results and Analysis

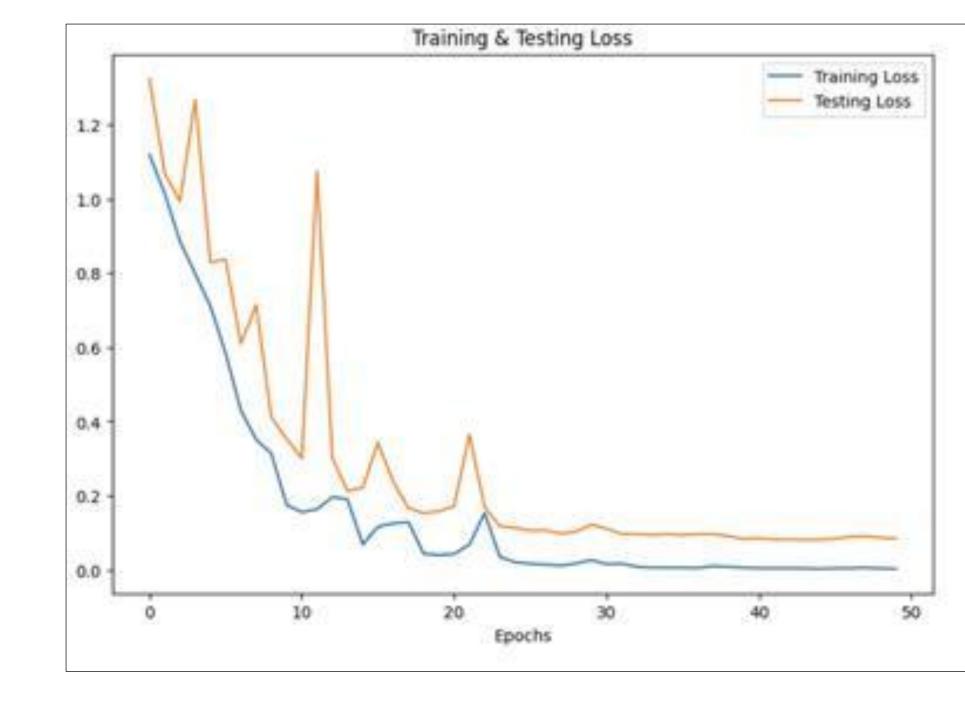
# **Application Deployed on Streamlit**

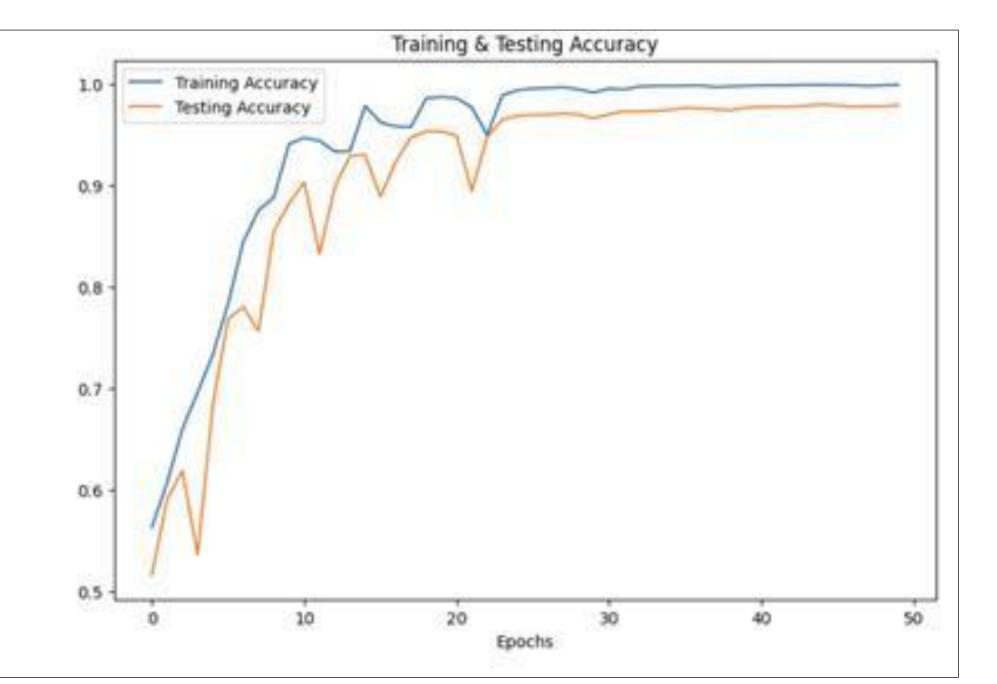


# Loss Graph: Gender Prediction Model



## Loss & Accuracy Graph: Emotion Recognition Model





# Problem with existing system

Current systems struggle with overlapping speech, rely on isolated task solutions, and use outdated models, limiting accuracy, especially in emotion recognition. They also lack modularity and fail to perform well in real-world conditions with noise, accents, and variable recordings.

#### Conclusion

This Multi-Speaker Speech Understanding and Analysis System leverages cutting-edge models for speech separation, emotion recognition, gender classification, and speaker identification. By utilizing the SepFormer model for separation and enhancement, combined with advanced neural networks for classification tasks, the system effectively processes complex audio scenarios.

## References

[1] D. Snyder, D. Garcia-Romero, G. Sell, D. Povey, and S. Khudanpur, "X-vectors: Robust DNN embeddings for speaker recognition," in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018, pp. 5329–5333.

[2] B. Schuller, M. Valstar, F. Eyben, G. McKeown, R. Cowie, and M. Pantic, "Cross-corpus acoustic emotion recognition: Variances and strategies," IEEE Transactions on Affective Computing, vol. 1, no. 2, pp. 119–131, 2010.