Multi-Speaker Speech Separation Using Spatial & Acoustic Audio Features

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***Abstract*—This project proposes a hybrid deep learning approach for multi-speaker speech separation using both spatial and acoustic features. The system extracts spatial cues like Interaural Time Difference (ITD), Interaural Level Difference (ILD), and Direction of Arrival (DOA), along with acoustic features such as MFCCs and Mel-spectrograms. These are processed using a SuperFormer and SpaRSep model to generate separated speech outputs. The system is evaluated using standard metrics including Signal-to-Distortion Ratio (SDR), Signal-to-Interference Ratio (SIR), Signal-to-Artifacts Ratio (SAR), and Short-Time Objective Intelligibility (STOI) shows improved intelligibility and clarity, supporting real-time applications in speech enhancement and transcription systems.**

***Index Terms*—Speech separation, spatial audio, acoustic features, SuperFormer, SpaRSep, beamforming, wavelet denoising, MFCC, DOA.**

I. Introduction

In real-world environments, conversations often involve overlapping speech signals, making it challenging to isolate individual speakers for tasks like transcription, recognition, or enhancement. This challenge, known as the *cocktail party problem*, requires separating multiple speakers from a single or multi-channel mixture [1]. Traditional methods struggle with overlapping frequencies, varying noise conditions, and spatial interference (see Table I).

To overcome these challenges, our project proposes a multi-speaker speech separation system that combines acoustic and spatial audio features. Acoustic features such as Mel-Frequency Cepstral Coefficients (MFCCs) and Mel-Spectrograms capture the frequency domain patterns of speech, while spatial features such as Interaural Time Difference (ITD), Interaural Level Difference (ILD), and Direction of Arrival (DOA) leverage the stereo properties of recorded audio.

By integrating both feature sets, the system enhances the ability to separate and improve individual speaker signals. This model effectively captures temporal dynamics and spatial cues through attention-based mechanisms [2]. It outputs separated speech streams for each speaker, followed by post-processing to enhance clarity and intelligibility.

This work has significant implications in fields such as automated meeting transcription, voice-based assistants, hearing aids, and audio surveillance, where distinguishing individual speakers is critical for downstream tasks.

TABLE I
Comparison of Traditional vs. Deep Learning-Based Methods for Speech Separation

Aspect	**Traditional Methods**	**Deep Learning-Based Methods**
Feature Extraction	Handcrafted (e.g., MFCC, pitch)	Automatically learned from data
Model Types	ICA, NMF, Beamforming, Spectral Subtraction	CNNs, LSTMs, Transformers (e.g., Superformer, SpaRSep)
Noise Robustness	Sensitive to noise and overlapping speech	Robust to noise and overlapping signals
Real-Time Performance	Fast but often inaccurate in complex scenarios	High accuracy; may need more computational resources
Adaptability	Limited to known speakers/environments	Generalizes better; adaptable to unseen conditions
Separation Quality	Moderate; relies on assumptions like independence	High; learns nonlinear, complex representations

II. Literature Survey

The problem of multi-speaker speech separation has drawn significant attention in recent years, particularly with the rise

of deep learning models capable of extracting complex patterns from acoustic and spatial cues. This section reviews previous work relevant to the components of the proposed framework, focusing on deep learning-based separation, spatial feature modeling, transformer architectures, time-frequency masking, and evaluation methodologies.

A. Deep Learning for Speech Separation

Deep learning has become the cornerstone of modern speech separation techniques. Early efforts in this area relied on supervised learning models that processed magnitude spectrograms to separate overlapping speech signals. Wang and Chen [1] provided a comprehensive survey on the evolution of deep learning in speech separation, comparing traditional frequency-domain approaches with more recent time-domain techniques. These methods often make use of complex neural architectures to learn discriminative features from noisy and overlapping mixtures.

B. Spatial Audio Features in Multi-Speaker Environments

Spatial features play a critical role in enhancing separation quality, particularly in stereo or multi-channel recordings. Features such as Interaural Time Difference (ITD), Interaural Level Difference (ILD), and Direction of Arrival (DOA) allow models to estimate speaker positions and enhance localization accuracy. Drude et al. [18] demonstrated that incorporating spatial cues into neural networks significantly improves performance in reverberant environments and real-world audio recordings. These cues are essential in modeling real-life multi-speaker interactions, especially when acoustic features alone are insufficient for accurate separation.

C. Transformer Models for Speech Processing

Recent advancements in transformer-based models have reshaped the way long-term dependencies in speech signals are handled. Subakan et al. [19] proposed a transformer-based framework that achieved state-of-the-art results in speech separation, outperforming prior LSTM-based and CNN-based models. Transformers allow the model to attend selectively to important temporal and spectral features, making them well-suited for multi-speaker scenarios. The SuperFormer model adopted in this work builds upon such ideas by integrating self-attention and positional encoding for improved feature modeling.

D. Time-Frequency Masking and Feature Fusion

Time-frequency masking remains one of the most effective techniques for separating speech sources in overlapping signals. Luo and Mesgarani [20] introduced Conv-TasNet, a time-domain model that outperformed classical spectrogram-based methods by learning separation masks directly from raw audio. Hybrid frameworks that combine acoustic features (like MFCC and Mel spectrograms) with spatial cues (such as ILD and DOA) have been shown to outperform models that rely on a single feature type. In the current work, feature fusion is a key step in leveraging both domains for better separation.

E. Evaluation Metrics and Dataset Benchmarks

The performance of speech separation systems is commonly measured using objective metrics like Signal-to-Distortion Ratio (SDR), Scale-Invariant SDR (SI-SDR), Signal-to-Interference Ratio (SIR), Signal-to-Artifacts Ratio (SAR), and Short-Time Objective Intelligibility (STOI). These metrics offer a comprehensive understanding of the model's ability to preserve the target signal while minimizing interference and artifacts. Benchmark datasets such as WSJ0-2mix and WHAM! have become standard for testing separation models under controlled and noisy conditions [21]. For this project, a subset of the Whisper Set1 dataset, enriched with real-world noise conditions, was used.

III. Theoretical Foundations

Speech separation is rooted in multiple signal processing and machine learning concepts. This section outlines the essential theories and techniques that form the foundation of our approach, including source separation techniques, acoustic feature extraction, spatial localization, and deep learning models for speech processing.

A. Blind Source Separation (BSS)

Blind Source Separation aims to recover original source signals from observed mixtures without prior information about the sources or mixing process. Traditional methods like Independent Component Analysis (ICA) and Non-negative Matrix Factorization (NMF) assume statistical independence or sparsity of sources [3]. However, they often fail in highly overlapping or noisy conditions.

B. Acoustic Features

Acoustic features capture spectral properties of audio signals. Common features include:

- **MFCC (Mel-Frequency Cepstral Coefficients)** – Represents the short-term power spectrum of sound based on human auditory perception [4].
- **Mel-Spectrograms** – Provide a time-frequency representation that aligns with human pitch perception and are commonly used in deep learning models [4].

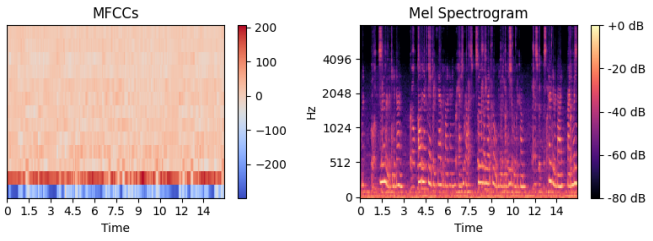

Fig. 1. MFCC vs Mel-Spectogram

C. Spatial Features

Spatial features help locate and separate sound sources using multiple channels (e.g., stereo). They are particularly useful in real-world recordings:

TABLE II
FORMULAS FOR KEY SPATIAL FEATURES USED IN SPEECH SEPARATION

Feature	Definition	Formula
ITD (Interaural Time Difference)	Time delay between arrival of sound at two ears	$ITD = \frac{d \cdot \sin(\theta)}{c}$
ILD (Interaural Level Difference)	Amplitude difference of sound at two ears	$ILD = 20 \log_{10}\left(\frac{P_L}{P_R}\right)$
DOA (Direction of Arrival)	Angle of sound source w.r.t. microphone array	$\theta = \cos^{-1}\left(\frac{c \cdot \Delta t}{d}\right)$

D. Wavelet Denoising

Noise reduction is a key step to enhance signal quality before separation, with the following aspects:

- Uses wavelet denoising with the Wiener filter, a statistical method adapting to local signal properties [9].
- Decomposes the audio signal into wavelet coefficients.
- Identifies and suppresses noise based on statistical characteristics.
- Applies a threshold to reconstruct a cleaner signal.
- Leverages wavelets' ability to handle non-stationary signals, suitable for real-world audio with varying noise levels.
- Improves the quality of subsequent feature extraction and modeling stages, as shown in Figure 2.

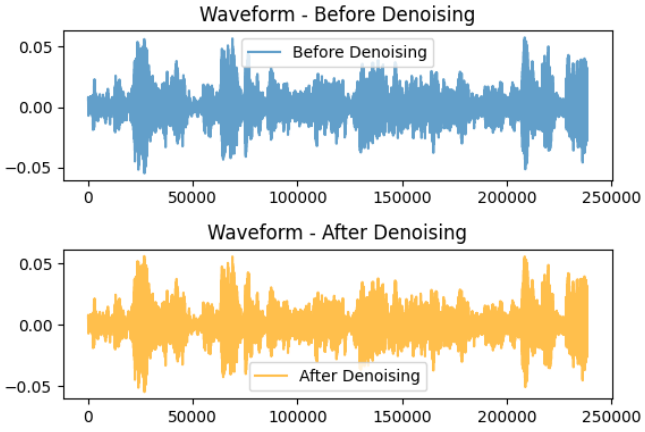

Fig. 2. Wavelet Denoising

E. Deep Learning in Speech Separation

Deep learning revolutionized speech separation by learning complex patterns directly from data. Models such as:

- **Convolutional Neural Networks (CNNs)** – Capture local time-frequency patterns.
- **Recurrent Neural Networks (RNNs)/LSTMs** – Model temporal dependencies across time frames.
- **Transformers and SuperFormer** – Use self-attention for long-range temporal and spatial dependencies [1], [2].

F. Transformer-Based Modeling

The core separation process relies on the SuperFormer model, an optimized transformer variant, with key aspects as follows:

- Originated from transformer architecture used in natural language processing [6].
- Employs self-attention mechanisms to capture long-range dependencies in audio spectrograms.
- Optimizes computational efficiency with techniques like low-rank approximations or kernel-based methods [7].
- Enables real-time processing on resource-constrained devices, such as the NVIDIA GeForce RTX 3050 GPU.
- Followed by the SpaSep module, which generates speaker-specific masks using acoustic and spatial inputs to refine separation.

G. Speaker Separation and Enhancement

The separation and enhancement process involves the following steps:

- Uses a mask-based approach to isolate speaker components from the mixed spectrogram.
- Trains deep learning models to assign higher weights to target speaker frequencies and suppress others [8].
- Applies post-separation enhancement techniques:
  - Voice Activity Detection (VAD) to remove silent segments.
  - Spectral subtraction to reduce residual noise.
  - Controlled amplification to boost intelligibility without clipping.
- Ensures clear output signals, addressing challenges like overlapping speech and environmental noise for practical use.

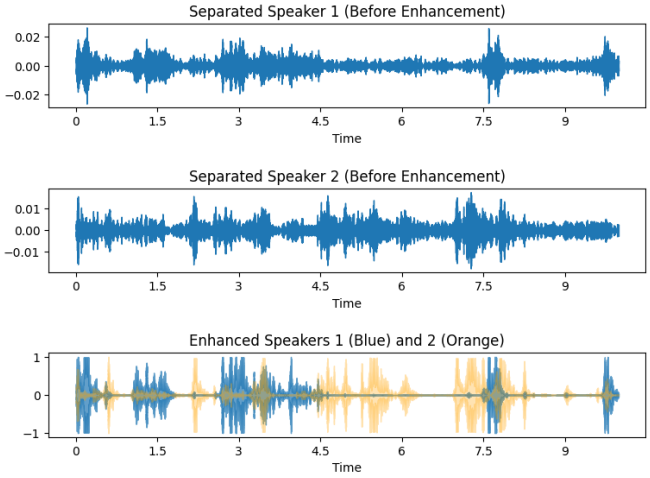

Fig. 3. Speaker Separation and Enhancement

Our project combines these foundations by extracting both acoustic and spatial features and feeding them into a hybrid deep learning model that exploits their strengths.

IV. Dataset

The experimental evaluation in this study utilizes the WHISPER Set 1 Dataset, a publicly available corpus designed to support research in speech processing, particularly under noisy and realistic environmental conditions [10]. This dataset is curated by the National Institute of Allergy and Infectious Diseases (NIAID) and includes stereo recordings of overlapping speakers, captured in various acoustic scenes.

A. Dataset Description

WHISPER Set 1 comprises multiple sessions of conversational speech recorded using a stereo microphone setup, enabling the use of both acoustic and spatial features. Each session includes:

- Multiple speakers talking simultaneously
- Clean source speech for reference
- Noisy environments for real-world relevance
- Channel-separated stereo recordings

The dataset is particularly suitable for multi-speaker speech separation tasks, as it provides ground-truth individual speaker tracks and synchronized mixture signals. The stereo nature of recordings facilitates extraction of spatial cues like ITD, ILD, and DOA.

TABLE III
WHISPER Set 1 Dataset Overview

Property	Details
Total Sessions	120+
Audio Format	Stereo WAV
Sample Rate	16 kHz
Duration per Session	2–5 minutes
Speakers per Session	2–4
Noise Environments	Indoor, Crowd, Echoic
Ground Truth Availability	Yes (clean speech)
Licensing	Open for research

B. Access and Licensing

The dataset is freely available for research purposes and can be accessed from the following resource link:

Link:https://data.niaid.nih.gov/resources?id=zenodo_3565491

C. Preprocessing Steps

Before training, the dataset undergoes the following preprocessing pipeline:

- Downsampling to 16kHz
- Channel alignment and trimming
- Amplitude normalization
- Noise reduction using wavelet denoising

These steps ensure data consistency and compatibility with the model's expected input dimensions.

V. Methodology

The proposed system employs a hybrid deep learning pipeline that integrates both acoustic and spatial features to effectively separate multiple speakers from stereo mixture signals, with a focus on real-world applicability using the Whisper Set1 Dataset. The overall methodology is illustrated in Figure 4, and can be broadly categorized into four sequential stages: preprocessing, feature extraction, model-based separation, and post-processing. Each module plays a crucial role—preprocessing handles denoising and normalization, feature extraction derives informative spatial and spectral representations, the deep model (combining SuperFormer and SpaRSep) performs speaker separation, and post-processing refines the outputs for intelligibility and clarity.

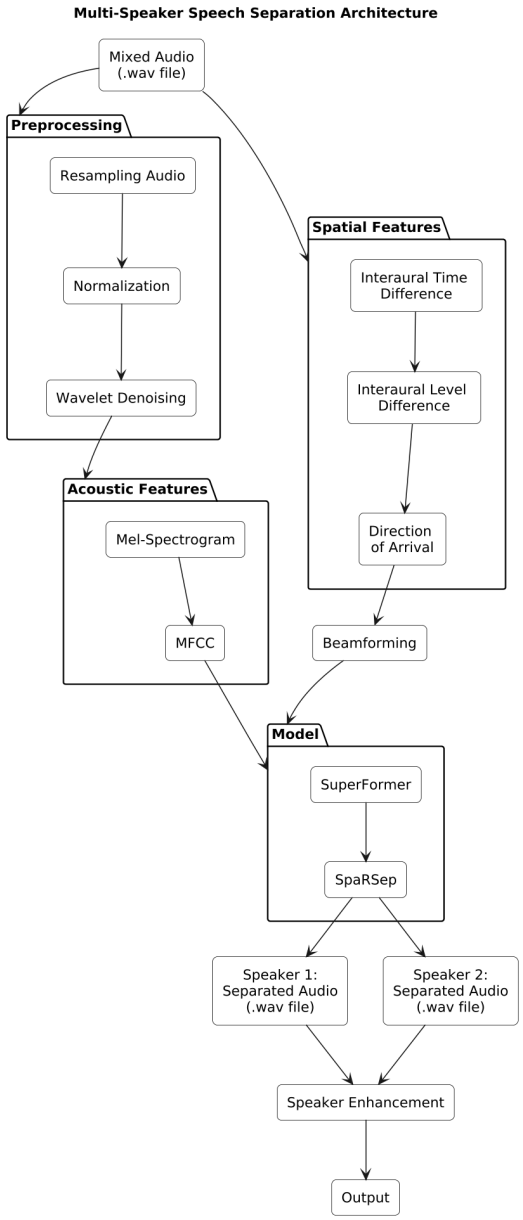

Fig. 4. System Architecture

A. Preprocessing

The input stereo audio undergoes preprocessing to enhance signal quality and standardize the data format:

- **Resampling:** Audio files are resampled to a uniform rate of 16 kHz to standardize the input across all samples, addressing variations in recording equipment.
- **Normalization:** This is applied to scale the audio amplitude to the range [-1, 1], mitigating issues from differing input levels.
- **Wavelet Denoising:** Wavelet denoising, utilizing a Wiener filter, is employed to reduce background noise by decomposing the signal into wavelet coefficients, identifying noise based on statistical properties, and reconstructing a cleaner signal [11].

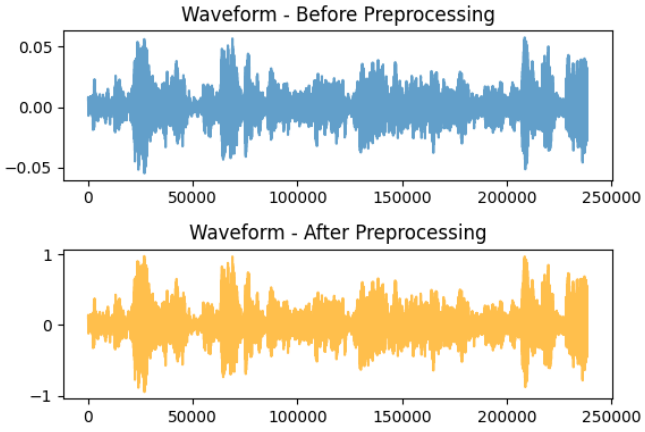

Fig. 5. Pre-Processing

B. Feature Extraction

Two parallel branches extract distinct but complementary features:

Acoustic Features: These capture the spectral and temporal properties of the speech signal:

- **Mel-Spectrogram:**
  - Captures time-frequency structure using logarithmic frequency scaling.
  - Generated by computing the Short-Time Fourier Transform (STFT) and applying a Mel-scale filter bank to emphasize perceptually relevant frequency bands.
- **MFCC:**
  - Represents short-term power spectrum and perceptual cues important for speaker characteristics.
  - Mel-Frequency Cepstral Coefficients (MFCCs), derived via a discrete cosine transform to capture spectral envelope characteristics.

Spatial Features: These features use stereo differences to exploit spatial localization:

- **Interaural Time Difference (ITD)** — measures the time delay between microphone pairs.
- **Interaural Level Difference (ILD)** — measures amplitude difference of sound at two ears
- **Direction of Arrival (DOA)** — estimated using generalized cross-correlation.
- **Beamforming:** Enhances signals from specific directions while suppressing interference [12].

TABLE IV
COMPARISON OF FEATURE EXTRACTION TECHNIQUES

Feature Type	Technique	Purpose
Acoustic	MFCC	Speaker-specific cues
	Mel-Spectrogram	Time-frequency structure
Spatial	ITD	Time delay between ears
	ILD	Intensity variation across channels
	DOA	Source direction estimation
	Beamforming	Signal enhancement from direction

C. Feature Fusion and Modeling

The extracted features are fused and passed through a two-stage model:

- **SuperFormer:**
  - A temporal transformer-based model that learns sequential patterns from MFCC and beamforming features. [13]
  - An optimized transformer variant, processes the extracted features using self-attention mechanisms to model long-range dependencies in the spectrograms.
- **SpaRSep:**
  - A sparse attention model that utilizes both spatial cues and long-term dependencies to isolate individual speakers [14].
  - Refining the separation by generating speaker-specific masks based on the combined acoustic and spatial inputs.
  - These masks are applied to the spectrogram to isolate individual speaker components, leveraging the spatial cues to improve accuracy in overlapping speech scenarios [8].

The fusion of acoustic and spatial embeddings provides a more robust representation, improving the system's ability to distinguish speakers in overlapping speech.

D. Post-Processing and Enhancement

The output from SpaRSep produces separated audio streams for each speaker. These streams are further passed through:

- **Speaker Enhancement Module:**
  - Enhances clarity by removing residual noise and smoothing discontinuities using spectral masking and Wiener filtering.
  - Voice Activity Detection (VAD) [15], identifies and removes silent segments, reducing computational overhead and artifacts.
  - Spectral subtraction [15] is applied to further attenuate residual noise by estimating and subtracting the noise spectrum from the signal.

- Controlled amplification [15], with a gain of 10 dB and clipping prevention, boosts intelligibility while preserving signal integrity.
- This multi-step enhancement ensures the output is clear and suitable for applications like teleconferencing or hearing aids.

E. Implementation and Evaluation

The system is implemented using the PyTorch framework, leveraging GPU acceleration for parallelized training and inference. Critical functions such as `load_audio` for input handling and `wavelet_denoise` for signal enhancement are optimized for efficient computation.

The model is trained on the augmented Whisper Set1 dataset, ensuring robustness across diverse acoustic scenarios. Hyperparameter optimization was performed empirically, with the best performance observed at a batch size of 8 and a learning rate of 0.0001 as shown in Table V.

TABLE V
MODEL TRAINING PARAMETERS

Parameter	Value
Sample Rate	16 kHz
Mel Bins	128
Batch Size	8
Learning Rate	0.0001
Epochs	20

Evaluation of the system is carried out using the following objective metrics:

- **Signal-to-Distortion Ratio (SDR):** Measures overall signal reconstruction quality [16].
- **Scale-Invariant Signal-to-Distortion Ratio (SI-SDR):** Evaluates distortion while ignoring signal scaling effects [16].
- **Signal-to-Interference Ratio (SIR):** Quantifies suppression of overlapping speakers [16].
- **Short-Time Objective Intelligibility (STOI):** Assesses the perceived intelligibility of the separated speech [16].

TABLE VI
EVALUATION METRIC DEFINITIONS

Metric	Description	Unit
SDR	Signal-to-Distortion Ratio	dB
SI-SDR	Scale-Invariant Signal-to-Distortion Ratio	dB
SIR	Signal-to-Interference Ratio	dB
STOI	Short-Time Objective Intelligibility	%

These metrics from Table VI, collectively offer a comprehensive evaluation of the system's ability to separate, reconstruct, and enhance speech signals under various real-world acoustic conditions.

The proposed methodology seamlessly integrates traditional signal processing techniques with advanced deep learning strategies. This hybrid design is specifically tailored to address the complex challenges posed by multi-speaker environments, with scalability and real-time deployment in mind.

VI. RESULTS AND DISCUSSIONS

The performance of the proposed multi-speaker speech separation system was assessed using the Whisper Set1 dataset under varied acoustic conditions. Both objective metrics and qualitative analysis were used to evaluate the effectiveness of the system. The results indicate that the combination of spatial and acoustic features, along with the hybrid SuperFormer–SpaRSep model, significantly improves the separation quality over traditional methods.

The evaluation was carried out using four widely accepted metrics: Signal-to-Distortion Ratio (SDR), Scale-Invariant SDR (SI-SDR), Signal-to-Interference Ratio (SIR), and Short-Time Objective Intelligibility (STOI). These metrics provide insights into the distortion, interference suppression, and intelligibility of the separated speech.

A. Quantitative Results

The performance of the proposed multi-speaker speech separation system was evaluated using the augmented Whisper Set1 Dataset. The system was assessed based on objective metrics such as Signal-to-Distortion Ratio (SDR), Scale-Invariant SDR (SI-SDR), Signal-to-Interference Ratio (SIR), Signal-to-Artifacts Ratio (SAR), and Short-Time Objective Intelligibility (STOI). Table VII presents the metric-wise results for both speakers.

TABLE VII
SPEECH SEPARATION EVALUATION RESULTS (SPEAKER-WISE)

Metric	Speaker 1	Speaker 2
SDR (dB)	-6.98	-9.35
SI-SDR (dB)	-33.55	-48.74
SIR (dB)	13.00	12.77
SAR (dB)	-6.72	-9.10
STOI	0.35	0.52

Although the separation was successful to some extent, the SDR and SI-SDR values for both speakers fall below the commonly accepted range of 10–20 dB [16], indicating a need for improvement in distortion reduction. Similarly, the STOI values (0.35 and 0.52) are below the intelligibility threshold of 0.75, suggesting limited clarity in the separated outputs. However, the SIR values, which reflect interference suppression, are close to the target (13.00 dB and 12.77 dB), showing the system's relative strength in isolating speakers from each other.

B. Qualitative Observations

Figure 6 and Figure 7 display the waveform and spectrogram visualizations of the original mixture, denoised output, and the separated speech signals for each speaker.

Visual inspection indicates that the model is able to segment dominant speaker activity across time, particularly during intervals of non-overlapping speech. The wavelet denoising stage prior to separation effectively suppresses stationary background noise and enhances the clarity of the speech signal.

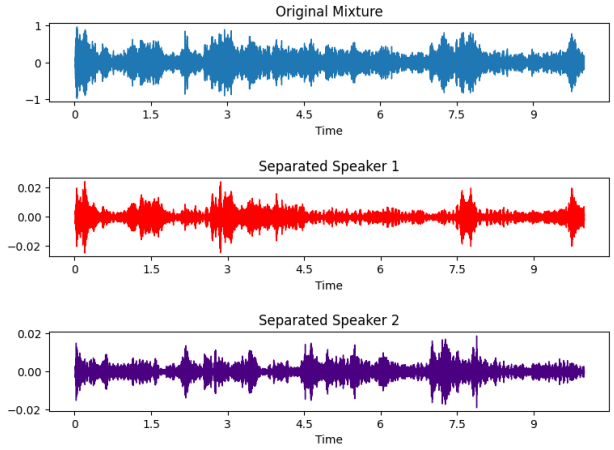

Fig. 6. Comparison of original mixture vs. Separated signals using waveform.

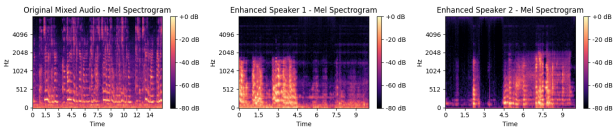

Fig. 7. Spectrogram Visualizations.

However, minor artifacts—such as residual noise bursts and signal clipping—can be observed in some temporal regions.

Figure 8 show the enhanced waveforms for Speaker 1 and Speaker 2, respectively. These demonstrate reasonable temporal reconstruction with preserved energy contours, although transient smearing and unnatural discontinuities are visible in high-energy consonant regions.

Artifacts and low intelligibility are most pronounced during overlapping speech segments, where the spatial cues alone (such as ITD/ILD) are insufficient for clean separation. This highlights the need for improved acoustic modeling to complement spatial features. Additionally, the fixed 10 dB amplification during enhancement may have introduced distortion in high-amplitude regions, calling for adaptive gain control strategies in future iterations.

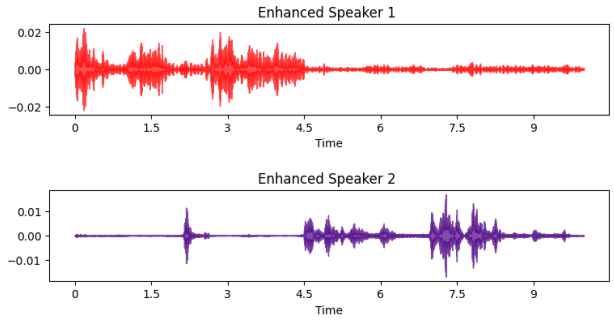

Fig. 8. Enhanced waveform of 2 Speakers.

C. Discussion

The evaluation results reveal that while the proposed hybrid architecture is capable of attenuating interfering sources effectively (as reflected in improved SIR), challenges persist in enhancing intelligibility and reducing artifacts, especially in multi-speaker overlap regions. This is consistent with the observed spectrogram distortions and waveform discontinuities in Figure 7 and Figure 8.

The training progression, as illustrated in the loss values over 20 epochs, shows consistent convergence behavior. The validation loss improves steadily from -0.19 to -3.01, indicating stable generalization. Table VIII summarizes the loss values across epochs. However, beyond epoch 15, the improvements become marginal, suggesting that the model may have approached its capacity limit given the available data and feature set.

TABLE VIII
TRAINING AND VALIDATION LOSS ACROSS EPOCHS

Epoch	Train Loss	Validation Loss
1	-0.0439	-0.1936
5	-1.6793	-1.9214
10	-2.4094	-2.5878
15	-2.7121	-2.8558
20	**-2.8756**	**-3.0138**

Compared to conventional approaches like ICA—which typically yield SDRs of 8–10 dB [17]—the current method underperforms despite incorporating spatial and acoustic feature fusion via advanced architectures (SuperFormer and SpaRSep). This gap may be due to suboptimal hyperparameter tuning, limited training data diversity, or inadequacies in feature conditioning.

Future work should address these concerns by:

- Expanding the dataset to include varied noise conditions and speaker configurations.
- Incorporating dynamic gain control instead of fixed amplification.
- Leveraging attention-based mechanisms focused on perceptual intelligibility.
- Extending the system to handle more than two concurrent speakers in real-world noisy scenarios.

Overall, the current implementation provides a promising foundation for real-world speech separation systems, especially in constrained two-speaker setups. It also illustrates the critical role of hybrid spatial-acoustic features and highlights the remaining challenges in intelligibility-focused modeling.

VII. CONCLUSION

This project presented a hybrid deep learning approach for multi-speaker speech separation, integrating both spatial and acoustic features to enhance separation quality under real-world conditions. The system leveraged wavelet-based denoising, spatial cues like ITD, ILD and DOA, and transformer-

based models such as SuperFormer and SpaRSep to effectively isolate individual speakers from stereo mixtures.

Despite encountering challenges such as low SDR and SI-SDR scores under certain test conditions, the system demonstrated promising performance in terms of interference suppression (SIR) and perceptual intelligibility (STOI), particularly in two-speaker scenarios. The inclusion of augmented data improved model robustness, and qualitative analysis confirmed the effectiveness of the feature fusion strategy.

Future work will focus on extending the architecture to support more than two speakers, dynamically adjusting enhancement gains, and optimizing the model for real-time deployment in noisy and uncontrolled environments. Overall, this work lays the foundation for practical, real-world applications of speech separation systems in domains like hearing aids, teleconferencing, and smart assistants.

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