

ML POWERED PERSONALIZED HEARING AID

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Abstract - This project focuses on individuals using hearing aids who face difficulty hearing in noisy environments by introducing devices that aim to amplify all sounds equally by reducing background noise effectively. By combining traditional signal processing with advanced machine learning to deliver intelligent noise suppression, MVDR beamforming helps to isolate sounds from specific directions thereby focusing on speaker's voice supported by dual microphone. Voice Activity Detection aids to detect and process speech segments by further processing them into the time frequency domain. In order to further enhance the clarity by classifying and adjusting audio frames, a post processing module like Support Vector Machine is applied. It runs with low delay, making it ideal for real-time hearing aids. Its modular design fits easily into other audio systems. By combining classic beamforming with AI, it offers a smarter way to help people hear better in noisy places

Key Words: Audio Processing, MVDR, VAD, Beamforming, Noise Reduction, Machine learning, Signal-to-Noise Ratio (SNR), Hearing Assistance.

1. INTRODUCTION

This project aims to provide an intelligent, ML-powered hearing aid system for improving relevant sound in a noisy environment. Our system mainly enhances speech while suppressing background noise using advanced signal processing steps.

The key components of this project are Short-Time Fourier Transform (STFT), Voice Activity Detection (VAD), MVDR beamforming, and SVM-based classification. Real-time audio is given as input and then processed, filtered, and reconstructed to deliver the final clear audio to the user.

1.1 Motivation

Due to increasing noise pollution in the public and daily environment, it becomes difficult for individuals with hearing problems to differentiate human speech from background noise. Normal hearing aids amplify all the sounds in the surroundings, making it difficult to focus on the required and essential sounds that need enhancement. So, there is a demanding need for such a hearing aid that will amplify only the relevant sounds while reducing the background noise. The advanced technologies in Machine Learning and signal processing help to tackle these problems and provide a better and more natural hearing experience.

1.2 Scope

The system mainly focuses on enhancing the human speech or relevant sound in noisy environments for hearing aid applications. This project includes dual microphone beamforming, noise suppression, and classification using machine learning knowledge. It does not rely on IoT integration, biometric authentication, or commercial deployment. Instead of this, it provides a software solution that can well integrate with hearing aid devices or the mobile application for being user-friendly.

2. SYSTEM ARCHITECTURE

The system arch is designed to enhance the real-time audio signals for hearing aid users by considering signal processing with machine learning. The process starts with acquisition of noisy audio input from the surrounding environment, through the microphone. This raw input is then first converted into the frequency domain using the STFT, i.e., the Short-Time Fourier Transform. STFT divides the audio signal into smaller overlapping windows and also applies Fourier transform to each segment frame. This generates the time-frequency representation, where each frame tells about how frequency content evolves over time. STFT allows the system to analyze speech features while also detecting and analyzing background noise, making it ideal for further enhancement stages.

Next, the system applies Voice Activity Detection (VAD) to differentiate between human speech and non-speech segments. This step helps to focus only on segments where speech is actually present, enhancing both accuracy and computation. Following this, the Minimum Variance Distortion less Response (MVDR) beamforming algorithm is used to spatially filter out the incoming audio signal. MVDR works by steering the beam of the microphone array towards the specific speech source while reducing the power from all other directions. This is done by calculating the beamformer weight vector that maintains the desired signal without distortion while suppressing the background interferences. MVDR dynamically adapts to the noisy environment by calculating the covariance matrix, helping to suppress moving noise sources.

The beamformed signal is then passed to the adaptive filtering stage, where a noise covariance matrix is continuously estimated. This helps to apply targeted noise reduction by adapting filter coefficients in real-time,

considering that non-speech elements are suppressed without distorting the required speech. The system extracts the meaningful features from the enhanced audio signal by using Mel-Frequency Cepstral Coefficients (MFCCs). MFCCs focus on how the human ear perceives sound by focusing on important frequency bands using the Mel scale. This process involves taking the log of spectrum power and applying a Discrete Cosine Transform (DCT) to form decorrelated coefficients. These features capture the shape and energy of speech, making it ideal for classification and improvement.

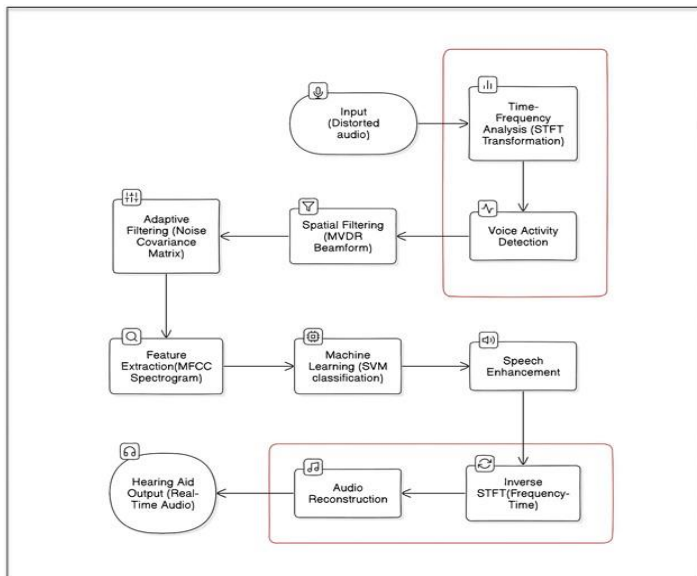


Fig - 1 : Architecture Diagram

The extracted features then pass into a machine learning classifier, a Support Vector Machine (SVM), which is trained to differentiate between the speech and non-speech components based on their spectral features. The SVM works by finding the optimal hyperplane in the feature space that separates out the two classes with minimum margin, ensuring the classification even in overlapping conditions. The supervised machine learning approach allows making fine-grained decisions on a frame-by-frame basis, determining which part of the signal should be preserved and which should be suppressed.

Once classification is done, the system enhances the identified speech segments while suppressing the noise dominance. This targeted enhancement preserves the efficiency and naturalness of speech while minimizing distortion. The processed signal, which is still in the frequency domain, is then passed to the inverse Short-Time Fourier Transform (iSTFT) to convert the signal back into the time domain, by converting the frequency-filtered frames into continuous audio waveforms. The final output, which is a noise-suppressed audio stream, can be delivered directly to the earphones or the hearing aid device.

3. MATHEMATICAL MODEL

The Hearing Aid System S is a real-time audio processing channel designed to improve speech in a noisy environment. It is mathematically given as:

$$S = \{I, P, O\}$$

Where:

I: Input audio signal from a dual microphone array, sampled at 16 kHz.

P: The collection of steps including Short-Time Fourier Transform (STFT), Voice Activity Detection (VAD), MVDR beamforming, Mel-Frequency Cepstral Coefficient (MFCC) extraction, Support Vector Machine (SVM) classification, speech enhancement, and inverse STFT.

O: Enhanced output audio signal with suppressed background noise, delivered with end-to-end latency below 50 ms.

The system passes input through a flow of transformations: $I \rightarrow \text{STFT} \rightarrow \text{VAD} \rightarrow \text{MVDR Beamforming} \rightarrow \text{MFCC Extraction} \rightarrow \text{SVM Classification} \rightarrow \text{Speech Enhancement} \rightarrow \text{Inverse STFT} \rightarrow O$.

3.1 Short-Time Fourier Transform (STFT):

The STFT converts the time-domain audio into the frequency domain, allowing spectral analysis for noise reduction and speech enhancement.

For a discrete-time audio signal $x_m[n]$ from microphone $m \in \{1,2\}$, the STFT is defined as:

$$\text{STFT: } X(t, f) = \sum [x(n) \times w(n - t)] \times \exp(-j \times 2\pi \times f \times n)$$

Where:

$x(n)$ = the original time-domain signal.

$w(n - t)$ = window function centered at time t.

f = frequency bin.

$\exp(-j \times 2\pi \times f \times n)$ = complex sinusoid for the Fourier transform.

$X(t, f)$ = complex-valued output showing frequency content at time t.

Description:

1. Divide the input audio into small overlapping signals.

2. Apply the window function to minimize the edge effect.
3. Calculate the DFT for each segment.

2. Measure the background noise covariance.
3. Design the filter that preserves speech from specific direction and reduce noise from all other directions.
4. Apply this filter to microphone inputs to get clear audio.

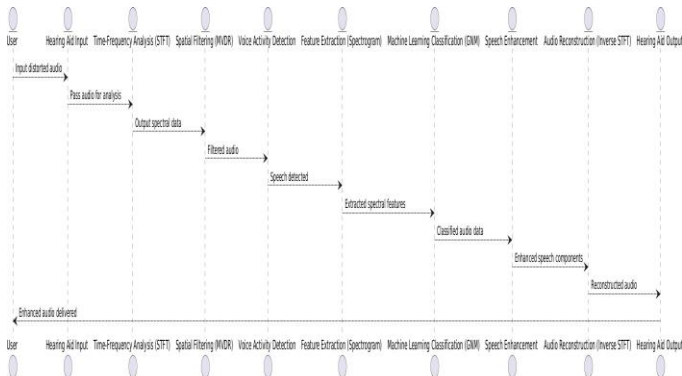


Fig -2 : Sequence Diagram

3.2 MVDR BEAMFORMING:

MVDR beamforming enhances speech from a particular direction while reducing noise from other directions using dual microphone array.

Formula :

$$\text{MVDR Weights (w): } w = R^{-1} \times d / (d^H \times R^{-1} \times d)$$

Where:

R = noise covariance matrix.

d = steering vector in the direction of targeted source.

R^{-1} = inverse of the noise covariance matrix.

d^H = conjugate transpose of the steering vector.

w = beamforming weights.

Output Signal :

$$y = w^H \times x$$

x = input vector of microphone signals.

w^H = Hermitian of weight vector.

y = enhanced output.

Description :

1. Consider the direction of the desired speech source.

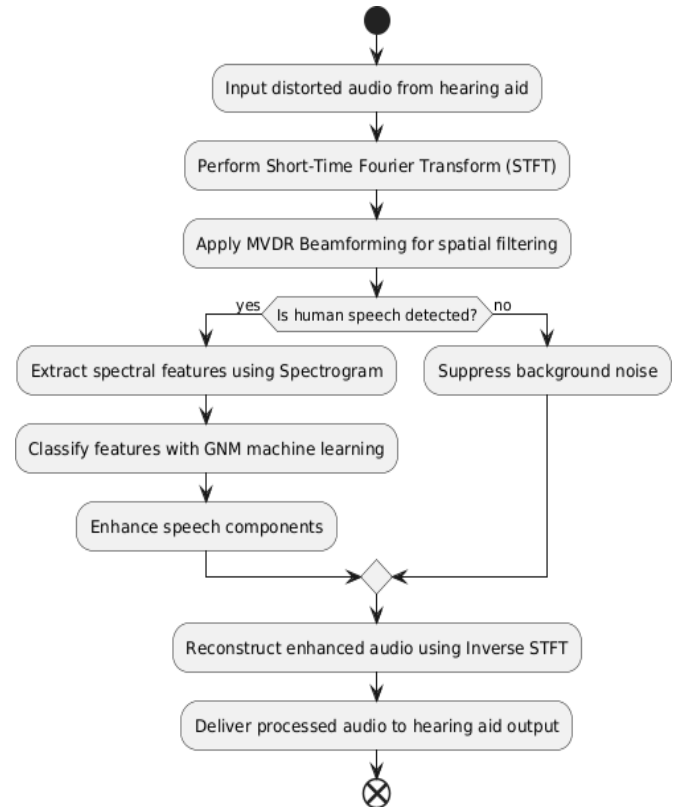


Fig-3 : Activity Diagram

4. PROJECT IMPLEMENTATION

The proposed system is a real-time speech enhancement framework designed to improve auditory experiences in challenging acoustic environments, such as those encountered by users of hearing assistive devices. It integrates advanced signal processing techniques with machine learning models to perform noise suppression, beamforming, and speech classification. The system operates on live stereo audio input captured from a dual-microphone array, and outputs a processed audio stream with enhanced speech clarity and reduced background interference.

The implementation is modular, comprising the following key stages:

- * Audio acquisition and preprocessing
- * Voice Activity Detection (VAD)
- * Beamforming and noise filtering

* Feature extraction and classification

* Speech enhancement and signal reconstruction

These stages are optimized to run with minimal latency (<50ms), ensuring a seamless and real-time auditory feedback experience.

4.1 TOOLS AND TECHNOLOGY:

Frameworks and Libraries

LibROSA: A cornerstone for audio analysis, LibROSA was utilized for extracting critical audio features such as Mel-Frequency Cepstral Coefficients (MFCCs) and for visualizing time-frequency representations like spectrograms.

NumPy and SciPy : These foundational scientific libraries enabled high-performance numerical operations, including the computation of the Short-Time Fourier Transform (STFT) and its inverse. They provided efficient array manipulations necessary for real-time signal processing.

SoundDevice: Used for capturing and playing back audio in real-time, this library was essential for interfacing with microphone arrays and delivering processed audio output.
FastAPI / Streamlit (Optional UI) : To support a visual inspection of audio waveforms, spectrograms, and processing metrics, a lightweight interface was optionally developed using FastAPI and/or Streamlit.

Development Environment

Jupyter Notebook: Initial prototyping, algorithmic experimentation, and visualization were conducted within Jupyter Notebooks, enabling rapid iterations and effective debugging.

Visual Studio Code and GIT: VS Code served as the primary development environment, integrated with GIT for version control and collaborative development.

Python Virtual Environment (VEnv): Project dependencies and libraries were isolated and managed using Python's virtual environment, ensuring reproducibility and clean deployments.

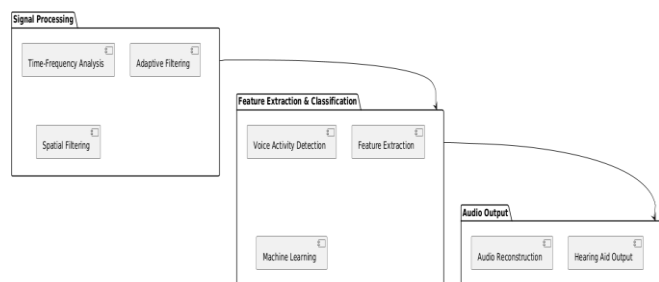


Fig-4 : Package Diagram

4.1 ALGORITHMIC IMPLEMENTATION:

Audio Acquisition and Preprocessing

The system begins by capturing stereo audio signals sampled at 16kHz from a dual-microphone array. Audio is segmented into frames of 20 milliseconds with a 50% overlap, balancing temporal resolution with computational efficiency. Each frame undergoes a Short-Time Fourier Transform (STFT) using a 512-sample Hamming window and a 256-sample hop size. The resulting complex spectrogram is normalized to standardize the amplitude dynamic range, ensuring consistency across frames and preparing the data for downstream processing.

Voice Activity Detection (VAD)

An essential component of the pipeline is the Voice Activity Detection (VAD) module, responsible for distinguishing speech frames from background noise. The implementation supports both energy-based and machine-learning-based VAD algorithms. By analyzing the magnitude spectrum of the incoming signal, the system identifies and retains only speech-active frames, thereby reducing computational burden and focusing enhancement efforts on segments of auditory interest. Spectrogram normalization is also reapplied at this stage to harmonize the input characteristics for subsequent modules.

MVDR Beamforming and Noise Filtering

To address spatial noise suppression, the system employs a Minimum Variance Distortionless Response (MVDR) beamformer. The noise covariance matrix is first estimated from the non-speech frames identified during the VAD stage. Beamforming then steers the microphone array towards the speech source while minimizing interference from other directions. This spatial filtering is further complemented by an adaptive Wiener-style noise suppression technique, which dynamically updates the noise model to remain effective under changing acoustic conditions.

Feature Extraction and Classification

Following beamforming, the system extracts 13-dimensional MFCCs along with their first-order temporal derivatives (deltas) from the cleaned spectrogram. These features are concatenated into frame-level vectors that serve as input to a Support Vector Machine (SVM) classifier. The classifier is trained to distinguish between speech and noise frames, and its hyperparameters—such as kernel type and regularization constant (C)—are tuned to maximize classification accuracy and minimize false positives.

Speech Enhancement and Signal Reconstruction

Based on the classifier's output, a gain mask is computed and applied to the spectrogram. This mask selectively amplifies frames containing speech while attenuating residual noise. The enhanced spectrogram is then converted back to the time domain via inverse STFT. Overlap-add techniques are used to ensure continuity in the output signal, which is

subsequently delivered in real time with latency maintained below 50 milliseconds—well within acceptable thresholds for hearing aid applications.

This end-to-end system demonstrates a robust and efficient approach to real-time speech enhancement, integrating classical signal processing techniques with modern machine learning classifiers. It is capable of operating in dynamic and noisy environments, providing a significant improvement in speech intelligibility and listening comfort for end-users.

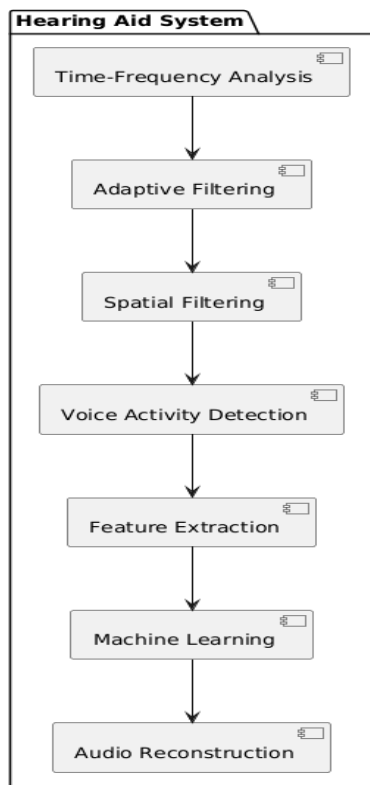


Fig-5 : Component Diagram

5. RESULTS

To improve speech clarity and reduce background noise in natural noisy environments, ML Powered Personalized Hearing Aid system was thoroughly checked in both quantitative and qualitative metrics. This system thus helped to understand whether the system met desired requirements.

Quantitative Evaluation

In this we made use of standard classification metrics like precision, recall, f1-score. They were derived by comparing the predicted labels with the actual ones, which helped to understand systems accuracy.

Qualitative Evaluation

We got the results by listening to the improved audio and comparing it with the original clean speech and the noisy versions under different conditions

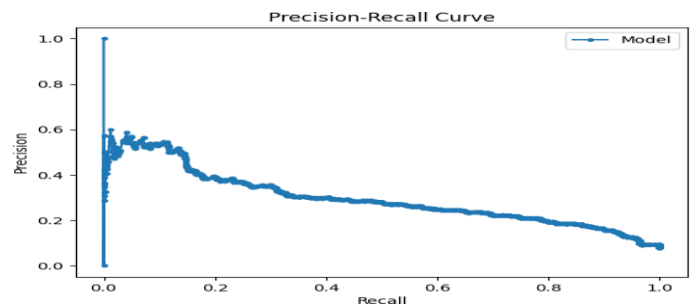


Fig-6: Precision – Recall Curve



Fig-7: Confusion Matrix

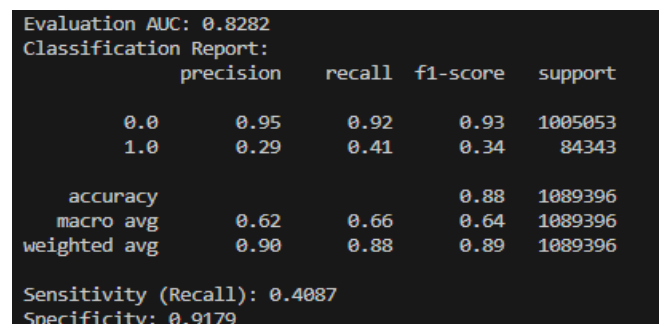


Fig-8: evaluation model

6. CONCLUSIONS

This project presents an intelligent audio enhancement system aimed at improving hearing aid performance by focusing on real-time speech clarity and noise suppression. By combining traditional signal processing methods with machine learning algorithms such as MVDR, VAD, and SVM, the system effectively isolates speech from background noise, offering users a clearer and more comfortable listening experience. Unlike conventional hearing aids that amplify all sounds equally, this solution adapts to various acoustic environments, prioritizing relevant speech and minimizing auditory distractions. Its modular and scalable design also allows for easy integration of future improvements and advanced features. In summary, the

platform demonstrates a promising approach to enhancing speech intelligibility and reducing listening fatigue. As technology evolves, such intelligent systems can lead to more personalized and context-aware hearing solutions, significantly improving everyday communication for hearing aid users.

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