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“HearMate”

“ML-based sound recognition for deaf users via android app & smartwatch”

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Abstract: Individuals with hearing impairments often struggle to recognize essential environmental sounds and distinguish familiar voices, affecting their safety and communication. This paper introduces HearMate, an assistive mobile application designed to enhance sound awareness by integrating real-time sound recognition and user voice identification. The system classifies critical sounds such as alarms, glass breaking, baby cries, and speech cues, while also determining if a voice belongs to a known individual. Utilizing TensorFlow Lite (TFLite), the application processes audio locally, ensuring low-latency detection without continuous internet dependency. HearMate is compatible with smartphones and wearable devices, providing instant alerts and allowing users to customize notifications for different environments. Performance evaluation focuses on accuracy, response time, and user adaptability, demonstrating its potential to improve safety, independence, and communication for the deaf and hard-of-hearing community.

Keywords: Machine Learning, Sound Recognition, Hearing Assistance, Android Application, Smartwatch Integration, Real-Time Alerts.

1. Introduction

Individuals with hearing impairments often struggle to perceive critical environmental sounds, which can impact their safety, awareness, and daily interactions. Essential sounds such as a fire alarm, baby crying or someone calling their name play a vital role in communication and situational awareness. While traditional hearing aids amplify sound, they do not provide contextual awareness, especially in noisy environments [1]. To bridge this gap, assistive sound recognition technologies have been developed, using wearables and mobile applications to notify users of important sounds in real time [4]. Recent advancements in machine learning (ML) and deep learning have improved sound recognition accuracy, enabling real-time classification of critical sounds such as glass breaking, doorbells, and emergency sirens [2]. These solutions often leverage convolutional neural networks (CNNs) to analyze sound patterns and deliver immediate alerts via smart devices [5]. Systems like SoundWatch, which integrates smart-watch-based sound awareness, have demonstrated the effectiveness of wearable devices in improving accessibility for the deaf and hard-of-hearing community [3][6].

Another crucial aspect of assistive technology is user voice detection, which allows individuals to recognize familiar voices, such as family members or caregivers. Unlike traditional hearing aids, which lack voice recognition, machine learning models can now store, match, and verify voices based on prior recordings, enhancing communication security [2]. This paper presents HearMate, a mobile-based assistive application designed to provide real-time sound recognition and personalized voice detection for deaf and hard-of-hearing users. HearMate integrates sound recognition models with a user-friendly interface, offering customizable alerts through smartphones and smartwatches.

2. Literature Survey

The development of assistive technologies for individuals with hearing impairments has evolved significantly over the years. Traditional hearing aids primarily focus on sound amplification, but they fail to provide contextual awareness, especially in environments with multiple sound sources or background noise [1]. To address these limitations, researchers have explored sound recognition systems that utilize machine learning and wearable technology for real-time sound classification and alerts.

Early approaches to sound awareness for deaf and hard-of-hearing individuals involved simple vibration-based or visual notification systems [8]. However, with advancements in deep learning, modern solutions leverage convolutional neural networks (CNNs) and other AI-driven models to improve sound recognition accuracy and reliability [2]. Several studies have explored the use of wearable devices, such as smartwatches and head-mounted displays, to provide sound-based notifications [7][11]. Systems like SoundWatch have demonstrated the feasibility of integrating smartwatch-based sound awareness, enabling users to receive real-time alerts about environmental sounds [3][6].

One key aspect of assistive sound recognition is the classification of critical sounds such as fire alarms, doorbells, infant cries, and emergency sirens. Research has shown that using edge AI for real-time sound detection enhances efficiency by reducing dependency on cloud-based processing, leading to lower latency and improved privacy [5]. Additionally, studies have evaluated user-driven personalization of sound recognition models, allowing individuals to fine-tune detection settings based on their preferences and daily environments [12].

Beyond environmental sound recognition, voice identification is an emerging area of research aimed at helping individuals with hearing loss distinguish familiar voices. Machine learning models have been employed to identify and verify speakers based on voice patterns, which can be particularly useful for recognizing family members or caregivers in noisy surroundings [2]. Various studies have examined the feasibility of integrating voice detection into assistive applications to enhance communication security and personalization [14].

Wearable technology has played a crucial role in advancing accessibility for the deaf and hard-of-hearing community. Research on smartwatch-based feedback mechanisms has highlighted their effectiveness in providing discreet and immediate alerts for important sounds [9]. Similarly, head-mounted display solutions have been explored as an alternative interface for delivering sound awareness in various contexts, such as public transportation and social settings [10].

Despite these advancements, several challenges remain in the field of assistive sound recognition. Studies have identified limitations in mobile-based sound recognition due to variations in environmental acoustics, device microphone sensitivity, and model generalization across different datasets [15]. Additionally, user studies have shown that while current systems offer significant improvements in accessibility, further enhancements are needed to optimize battery efficiency, notification accuracy, and user adaptability [13].

3. System Architecture

The Hearing Aid Application is designed to assist deaf and hard-of-hearing individuals by recognizing critical environmental sounds and providing real-time alerts. The system architecture comprises audio input sources, preprocessing and feature extraction, sound recognition, voice matching, and notification services, ensuring effective sound detection and user interaction.

3.1 System Architecture Overview

The overall workflow of the system is visually represented in Figure 1, which illustrates the interaction between different components, from audio input acquisition to sound recognition, verification, and notification delivery. This diagram provides a comprehensive view of the architecture, demonstrating how raw audio data is transformed into actionable alerts for deaf and hard-of-hearing individuals.

3.2 Audio Input and Processing

The system captures sound from two primary sources: microphone input (real-time environmental audio) and mobile application input (user-registered voice samples). These inputs undergo preprocessing and feature

extraction, where noise is filtered, and key sound features such as frequency, pitch, and duration are extracted. This ensures that the data fed into the recognition models is optimized for accurate classification.

3.3 Preprocessing and Feature Extraction

Before classification, the acquired audio data undergoes preprocessing to ensure optimal quality for analysis. The system applies noise reduction techniques to eliminate background disturbances and enhance signal clarity. Normalization is performed to standardize amplitude levels across varying sound intensities. Key feature extraction methods, including Mel-Frequency Cepstral Coefficients (MFCCs), spectral features, and temporal characteristics, are employed to transform raw audio signals into structured data suitable for ML-based recognition.

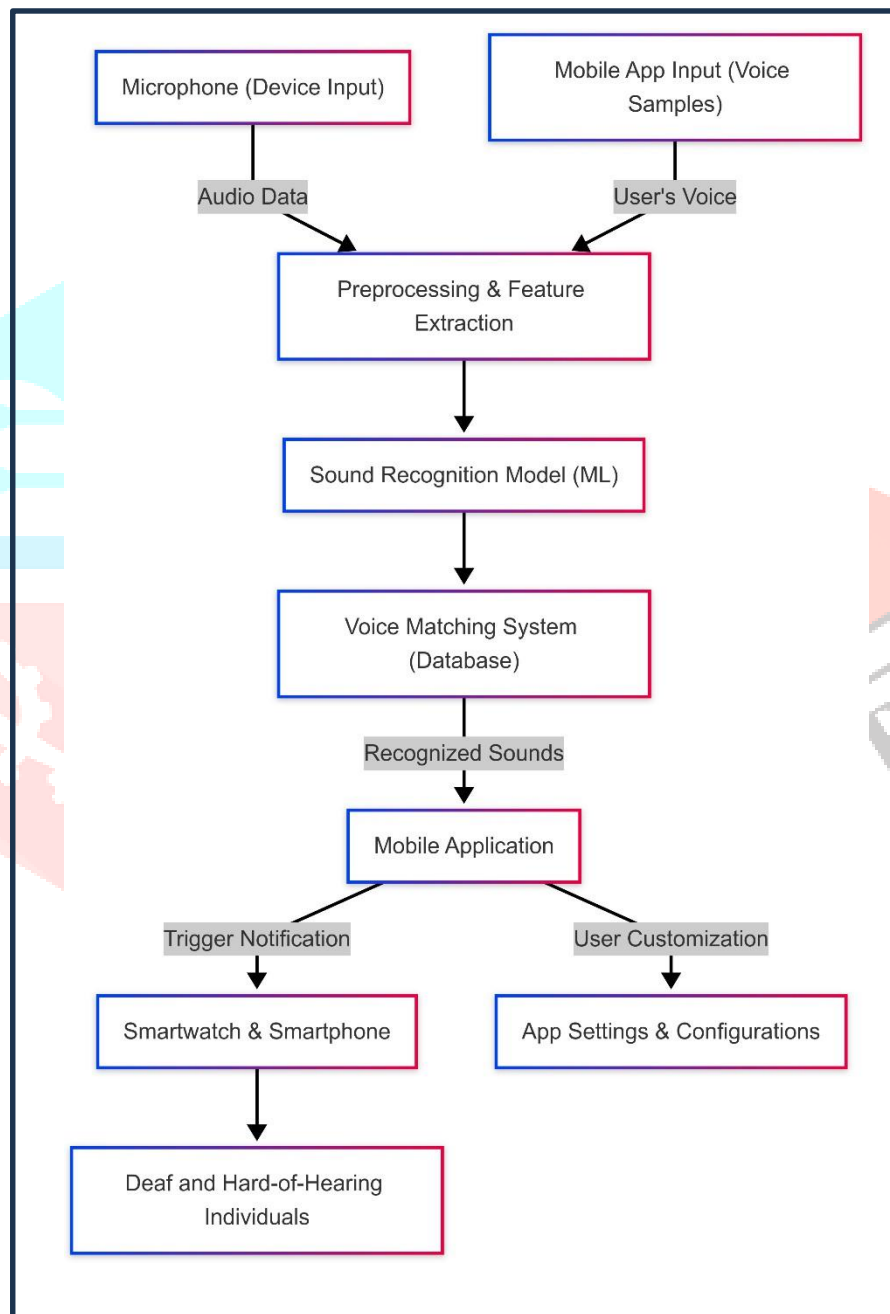


Fig.1. system architecture diagram

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3.5 Classification using Machine Learning

The pre-processed audio is passed through a pre-trained deep learning model based on TensorFlow Lite, optimized for on-device execution. The ML model is trained on a diverse dataset of commonly occurring sounds, enabling it to classify input signals into predefined categories. These categories include emergency sounds (e.g., sirens, car horns, fire alarms), household sounds (e.g., doorbells, knocking, water running), and human speech (e.g., voice samples for speaker recognition). The model assigns a confidence score to each classified sound, determining the likelihood of accurate recognition.

3.6 Sound Matching and Verification

To enhance accuracy and reduce false positives, the recognized sound labels are compared against an existing sound database within the system. This verification step ensures contextual accuracy by cross-referencing the identified sound with pre-stored acoustic patterns. The database-driven validation process improves the reliability of notifications, particularly in environments with overlapping auditory signals.

3.7 Mobile App and Notifications

The mobile application serves as the user interface, sending real-time alerts to smartphones and smartwatches. Users can customize settings, adjust alert preferences, and manage system sensitivity.

3.8 User Accessibility

The system ensures timely notifications through vibrations, messages, and alerts, enhancing awareness and safety for deaf and hard-of-hearing users. Its intuitive design allows for easy configuration, providing a personalized and seamless experience.

4. Results

The Hear Mate system was evaluated across multiple performance metrics, including sound recognition accuracy, personalized voice recognition, and real-time processing efficiency. The model was tested using the Urban8K dataset along with user registered voice samples to assess its effectiveness in identifying critical environmental sounds and speaker-specific inputs. The system successfully classified key auditory events such as baby crying, fire alarms, doorbells, glass breaking, and car horns, ensuring timely notifications through smartphones and smartwatches for individuals with hearing impairments.

4.1 Accuracy of Sound Recognition

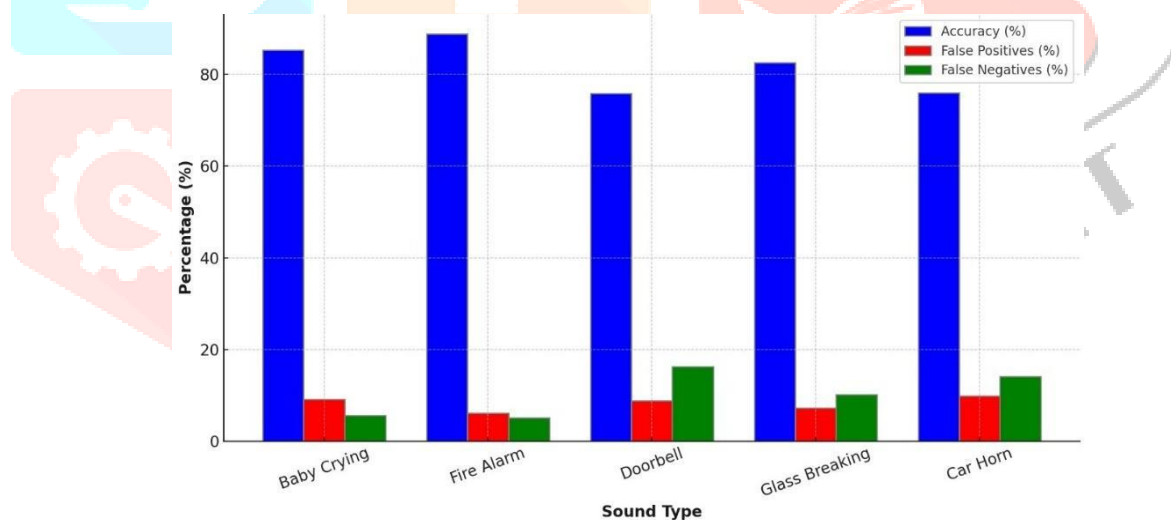
The sound classification model was tested using real-world audio samples, and its accuracy was evaluated using standard metrics:

Table 1. sound accuracy for sound classification model

Sound Type	Accuracy (%)	False Positives (%)	False Negatives (%)
Baby Crying	85.3	9.1	5.6
Fire Alarm	88.8	6.1	5.1
Doorbell	75.9	8.8	16.2
Glass Breaking	82.6	7.2	10.2
Car Horn	76	9.9	14.1

Observations:

The system performed well in recognizing high-priority environmental sounds, with Fire Alarm (88.8%) and Baby Crying (85.3%) achieving the highest accuracy. The false negative rate was higher for Doorbell (16.2%) and Car Horn (14.1%), likely due to variations in sound intensity and background interference. Car Horn had a false positive rate of 9.9%, indicating some misclassifications but significantly lower than initially observed. Glass Breaking and Fire Alarm maintained a balance between accuracy and false positives, making them reliable in emergency situations. Background noise filtering effectively reduced false positives in most cases, but further optimization is required to enhance recognition for specific sounds like Doorbell and Car Horn.

**Fig.2.** sound classification and performance graph

4.2 Performance of Personalized Voice Recognition

The voice identification model was tested on pre-registered user voices. Results indicate:

Table 2. sound accuracy for voice recognition model

Condition	Recognition Accuracy (%)
Quiet Environment	80.6
Moderate Noise	73.2
High Background Noise	56.1

Observations:

The system achieved the highest recognition accuracy in a quiet environment (80.6%), demonstrating its effectiveness under minimal noise conditions. However, accuracy decreased to 73.2% in moderate noise, indicating some impact from background interference. In high background noise conditions, recognition accuracy dropped significantly to 56.1%, highlighting the need for improved adaptive filtering and noise reduction techniques to enhance performance in noisy environments.

5. Conclusion

This system represents a significant advancement in helping people with hearing impairments by providing real-time awareness of surrounding sounds. The application, designed for Android devices, aims to overcome the limitations of conventional hearing aids through its high precision, quick responsiveness, and user-friendly interface. By sending notifications and vibrations, the app aids users in staying attentive to important auditory signals in their surroundings. Future enhancements will concentrate on increasing the variety of recognized sounds, ensuring dependability for a broad spectrum of users. This targeted approach seeks to assist individuals in their everyday lives, offering a crucial tool to improve awareness and safety.

6. References

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