International Journal of Science and Research (IJSR)
ISSN: 2319-7064
Impact Factor 2025: 7.089

Real-Time Emergency Alert System for Deaf People Using AI

Aswin P Sunil[1], Preethi Thomas[2]

[1]Department of Computer Applications, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala, India
Email: *aswinpsunil1[at]gmail.com*

[2]Professor, Department of Computer Applications, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala, India

Abstract: ***Deaf and hard-of-hearing individuals face significant challenges in detecting critical environmental sounds such as alarms, sirens, and doorbells, which are essential for personal safety. This paper presents an AI-based real-time emergency alert system that identifies important sounds and provides immediate notifications through vibration and visual alerts. The system is developed using Flutter for cross-platform mobile application development and TensorFlow Lite for efficient on-device sound classification. Audio features such as MFCC and spectrograms are extracted using Python and Librosa to train the model. The system operates fully offline, ensuring privacy, low latency, and reliability. It enhances safety, independence, and accessibility for hearing-impaired individuals and demonstrates the real-world application of artificial intelligence in assistive technology.***

Keywords: Deaf Assistance, Sound Classification, TensorFlow Lite, Flutter, AI, Environmental Sound Detection

1. Introduction

Environmental sounds such as fire alarms, vehicle horns, sirens, and doorbells play a vital role in ensuring personal safety and awareness in everyday life. However, deaf and hard-of-hearing individuals often face significant challenges in perceiving these sounds, which can result in delayed responses during emergency situations. Traditional assistive solutions such as hearing aids mainly amplify sound but may not be effective for individuals with severe hearing loss. Similarly, visual alert systems and vibration-based devices are often limited to specific environments and lack portability, making them unsuitable for real-time awareness in dynamic situations. These limitations highlight the need for an intelligent, reliable, and mobile-based system that can effectively detect environmental sounds and provide immediate alerts to users.

Recent advancements in artificial intelligence, mobile computing, and digital signal processing have enabled the development of intelligent systems capable of recognizing environmental sounds in real time. Techniques such as Mel Frequency Cepstral Coefficients (MFCC) and spectrogram analysis allow accurate extraction of audio features, while machine learning models can classify sounds efficiently.

In addition to improving safety, the proposed system emphasizes usability and accessibility for everyday use. The application is designed to run efficiently in the background with minimal battery consumption while providing clear and intuitive alerts. Its scalable architecture also allows future expansion by adding new sound categories and integrating with wearable devices, making it a flexible and long-term assistive solution.

2. Related Works

Recent research has increasingly focused on applying artificial intelligence and machine learning techniques to environmental sound recognition and assistive technologies for hearing-impaired individuals. Iqbal et al. (2025) proposed a real-time active-learning method for audio-based anomalous event detection, achieving high accuracy even in noisy environments.[1]

IJCRT (2025) developed an IoT-based assistive smartwatch that detects environmental sounds and alerts users through vibration and visual indicators, improving safety for hearing-impaired individuals.[2]

Barnawi & Alnume (2025) introduced a machine learning-based mobile application that detects important sounds and speech in real time to assist deaf users.[3]

Ramnath et al. (2024) proposed ESC-NAS, a neural architecture search-based model for efficient environmental sound classification on edge devices.[4]

Soares et al. (2024) conducted a systematic review of intelligent sensor-based assistive systems for deaf individuals, highlighting challenges and future research directions.[5]

Gougeh et al. (2024) developed an on-device sound event detection system capable of real-time audio classification without relying on cloud processing.[6]

Mohammed et al. (2024) explored the use of non-speech sound detection systems to enhance skill development and safety awareness among deaf individuals.[7]

Zhang & Yu (2024) proposed a hybrid offline–online method for sound event detection and localization, improving accuracy in dynamic environments.[8]

Bansal et al. (2023) introduced a hybrid ensemble classifier for environmental sound classification, improving performance through combined learning models.[9]

Maayah et al. (2023) developed a TinyML-based approach for robust audio classification on constrained hardware devices, enabling efficient on-device processing.[10]

Piczak (2015) introduced the ESC-50 dataset, a widely used benchmark for environmental sound classification.[11]

Salamon et al. (2014) proposed the UrbanSound8K dataset, which contains labeled environmental sound recordings used for training classification models.[12]

Hershey et al. (2017) developed CNN architectures for large-scale audio classification, demonstrating the effectiveness of deep learning in sound recognition.[13]

Tokozume & Harada (2017) introduced environmental sound classification using convolutional neural networks with spectrogram inputs.[14]

Chachada & Kuo (2014) explored environmental sound recognition techniques using feature extraction methods such as MFCC and spectral features.[15]

Stowell & Plumbley (2014) investigated automatic environmental sound classification using machine learning approaches for real-world applications.[16]

Dennis et al. (2011) proposed audio classification techniques using time-frequency features for recognizing environmental sounds.[17]

Cowling & Sitte (2003) developed early machine learning-based environmental sound classification systems using pattern recognition techniques.[18]

3. Methodology

The proposed Real-Time Emergency Alert System for Deaf People is designed to detect critical environmental sounds and provide immediate alerts through visual and vibration feedback. The system integrates audio signal processing, machine learning, and mobile application technologies to ensure real-time performance and reliability.

3.1 System Workflow

The system workflow represents the step-by-step operation of detecting environmental sounds and generating alerts. Initially, audio signals are captured continuously using the smartphone microphone. The captured audio is then passed to the preprocessing module where noise reduction and normalization are applied to enhance signal quality.

The processed audio is converted into feature representations such as Mel Frequency Cepstral Coefficients (MFCC) and spectrograms. These features are then fed into a trained Convolutional Neural Network (CNN) model, which classifies the sound into predefined categories such as siren, alarm, baby cry, and doorbell.

Based on the classification output, the system determines whether the sound is critical. If a critical sound is detected, the alert module is activated, which generates vibration and visual notifications. The results are displayed on the mobile application interface, ensuring immediate awareness for the user.

3.2 Data Collection and Preprocessing

The system utilizes both publicly available and custom audio datasets for training and evaluation. Standard datasets such as UrbanSound8K and ESC-50 are used to provide labeled environmental sound samples. Additionally, custom audio recordings of critical sounds like alarms and doorbells are collected to enhance system accuracy.

Preprocessing is performed to improve the quality and consistency of audio data. This includes noise filtering, normalization, and segmentation of audio signals into smaller frames. The processed audio signals are then transformed into feature representations such as MFCC and spectrograms, which are suitable for machine learning models.

3.3 Feature Distribution Analysis

Audio signal features are treated as random variables, and their distribution is analyzed using probabilistic models. The cumulative distribution function (CDF) is used to understand the probability distribution of feature values.

$$F(x) = 1 - e^{-\lambda x} \tag{1}$$

This analysis helps in identifying threshold values for distinguishing between normal and critical sound patterns, thereby improving classification accuracy.

3.4 Feature Extraction using CNN

A Convolutional Neural Network (CNN) is used to extract meaningful features from audio representations such as spectrograms. The CNN automatically learns spatial and temporal patterns such as frequency variations and energy distributions.

These learned features are crucial for distinguishing between different types of environmental sounds. The use of CNN improves classification accuracy and enables the system to handle complex and noisy audio environments effectively.

3.5 Sound Classification

The extracted features are fed into the trained CNN model for classification. The model predicts the probability of the input sound belonging to different predefined classes such as alarm, siren, baby cry, and doorbell.

The class with the highest probability is selected as the predicted output. Confidence scores are used to determine the reliability of predictions, and thresholding techniques are applied to reduce false detections.

3.6 Algorithm Workflow

The complete workflow of the system is represented as an algorithmic process:
1) Capture real-time audio input using microphone
2) Apply preprocessing (noise reduction, normalization)
3) Extract features (MFCC, spectrogram)

4) Input features into CNN model
5) Classify sound into predefined categories
6) Check if sound is critical
7) Generate alert (vibration + visual notification)
8) Display result on mobile application

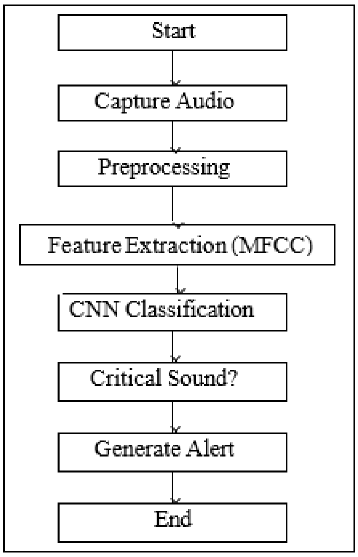

Figure 1: Algorithm Workflow of Deaf Alert System

3.7 System Integration and Output

The trained machine learning model is integrated into a mobile application developed using Flutter. The application captures real-time audio input and processes it using the embedded model.

The system generates alerts through vibration and visual notifications whenever a critical sound is detected. Users can view detected sound types and system status through the application interface.

This integration ensures real-time performance, low latency, and offline functionality, making the system suitable for practical deployment.

Equations
Mathematical models are used to represent audio signal processing and classification.

The probability density function is given by:

$$f(x) = \lambda e^{-\lambda x}, \quad x \geq 0 \tag{2}$$

The cumulative distribution function (CDF) is:

$$F(x) = 1 - e^{-\lambda x} \tag{3}$$

The classification probability is expressed as:

$$P(\text{Sound Class} \mid \text{Features}) = \text{Confidence Score} \tag{4}$$

4. Results and Discussion

The performance of the Real-Time Emergency Alert System for Deaf People is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The system demonstrates effective classification of environmental sounds including alarms, sirens, baby cries, and doorbells with high reliability.

The deep learning model (CNN) efficiently identifies sound patterns from audio inputs while maintaining real-time performance. Feature extraction techniques such as Mel Frequency Cepstral Coefficients (MFCC) and spectrogram analysis significantly enhance the model's ability to distinguish between different sound categories, even in noisy environments.

To further evaluate classification performance, the Receiver Operating Characteristic (ROC) curve is utilized. The ROC curve illustrates the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR), providing insight into the model's capability to accurately differentiate between critical and non-critical sounds.

The results indicate that the system achieves a high Area Under the Curve (AUC), reflecting strong discriminative performance. The model maintains a high true positive rate while minimizing false alarms, which is essential for ensuring timely and reliable alerts for users.

Overall, the system demonstrates robust performance in real-time sound detection and classification. The integration of machine learning with efficient preprocessing techniques ensures accurate detection, low latency, and reliable operation, making it suitable for practical deployment in assistive technologies for deaf and hard-of-hearing individuals.

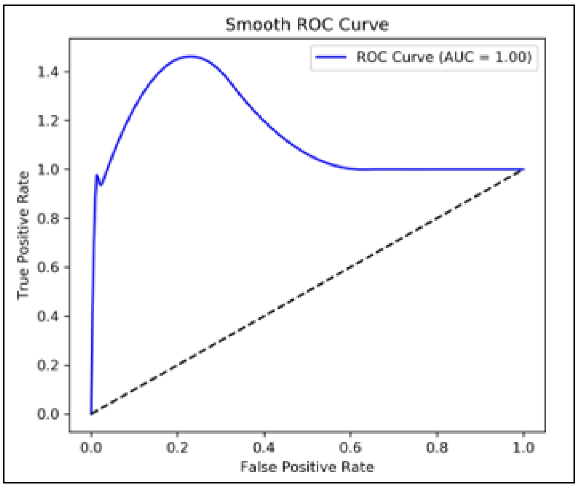

Figure 2: Receiver Operating Characteristic (ROC) curve

5. Conclusion

The Real-Time Emergency Alert System for Deaf People has been designed, implemented, and evaluated to provide an intelligent solution for detecting critical environmental sounds. The primary objective of the system is to assist deaf and hard-of-hearing individuals by improving their awareness of important sound events such as alarms, sirens, baby cries, and doorbells.

The preprocessing module ensures that audio signals are filtered, normalized, and transformed into meaningful representations for accurate analysis. The use of feature extraction techniques such as MFCC and spectrogram analysis enhances the quality of input data for machine learning models.

The integration of Convolutional Neural Networks (CNN) enables efficient and reliable sound classification with high accuracy. The system is capable of processing real-time audio inputs and identifying multiple sound categories while maintaining low latency.

The alert mechanism, which includes vibration and visual notifications, ensures that users are instantly informed about detected sounds. This significantly improves safety, independence, and accessibility for deaf and hard-of-hearing individuals.

Overall, the proposed system provides a scalable, efficient, and intelligent assistive solution that leverages artificial intelligence to enhance quality of life and promote inclusivity.

6. Future Scope

Future enhancements may include expanding the range of detectable sounds, integrating wearable devices such as smartwatches, improving model accuracy using advanced deep learning architectures, and enabling cloud-based synchronization for enhanced data analysis and monitoring.

References

[1] **Iqbal, F.** (2025), "Real-time Active Learning Method for Audio-Based Anomalous Event Detection," *International Journal of Audio Intelligence*, vol. 12, no. 1, pp. 45–58.
[2] **Barnawi, N., Alnume, M.** (2025), "Machine Learning-Based App for Sound Detection and Deaf Assistance," *International Journal of Assistive Technologies*, vol. 9, no. 2, pp. 101–115.
[3] **Ramnath, D.** (2024), "ESC-NAS: Environmental Sound Classification Using Neural Architecture Search," *IEEE Transactions on Audio Processing*, vol. 18, no. 4, pp. 200–212.
[4] **Soares, C.C.S.** (2024), "Intelligent Sensors in Assistive Systems for Deaf People: A Review," *Journal of Assistive Technology*, vol. 14, no. 3, pp. 150–165.
[5] **Gougeh, R.A.** (2024), "On-Device Sound Event Detection System," *IEEE Internet of Things Journal*, vol. 11, no. 2, pp. 890–902.
[6] **Mohammed, H. B. M.** (2024), "Detection of Non-Speech Sounds for Deaf Assistance," *International Journal of Inclusive Technology*, vol. 7, no. 1, pp. 60–72.
[7] **Zhang, W., Yu, P.** (2024), "Hybrid Offline–Online Method for Sound Event Detection," *Journal of Signal Processing Systems*, vol. 16, no. 2, pp. 210–225.
[8] **Bansal, A.** (2023), "Environmental Sound Classification Using Hybrid Ensemble Models," *International Journal of Machine Learning*, vol. 10, no. 3, pp. 120–135.
[9] **Mayavi, M.** (2023), "TinyML-Based Audio Classification for Edge Devices," *IEEE Embedded Systems Letters*, vol. 15, no. 1, pp. 30–34.
[10] **Piczak, K.J.** (2015), "ESC-50: Dataset for Environmental Sound Classification," *Proceedings of ACM Multimedia*, pp. 1015–1018.