

Autonomous IoT Enabled Hazard detection and Communication System for Deaf Drivers.

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Autonomous IoT-Enabled Hazard Detection and Communication System for Deaf Drivers

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requirements for the***

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Abstract

Emergency vehicle sirens are critical auditory cues for road safety, yet they remain inaccessible to deaf and hard-of-hearing drivers, increasing their risk of accidents. This research introduces a cost-effective, real-time siren detection and alert system designed to enhance accessibility for deaf drivers using Edge AI and Internet of Things (IoT) technologies. By delivering visual and haptic notifications, the system bridges a significant gap in automotive safety, enabling deaf drivers to respond promptly to critical road hazards. This scalable solution aligns with the growing demand for inclusive smart vehicle technologies, offering potential for integration into existing automotive ecosystems and aftermarket applications.

The system employs an INMP441 microphone, NodeMCU ESP32S microcontroller, and Raspberry Pi 4 Model B, running a quantized Convolutional Neural Network (CNN) trained on Mel-Frequency Cepstral Coefficients (MFCC) features for siren detection. Upon identifying a siren, it transmits alerts via MQTT communication to a React Native mobile application, triggering visual warnings and haptic vibrations through a smartwatch within 1 second. The model achieves 93.7% accuracy, consumes less than 60MB of memory, and operates offline, ensuring reliability in diverse environments. This research demonstrates a practical, efficient solution for improving road safety for deaf drivers, with implications for broader assistive technology development.

Keywords: Edge AI, IoT, Siren Detection, Deaf Drivers, Haptic Alerts

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3. List of Abbreviations

Abbreviation	Description
IoT	Internet of Things
MQTT	Message Queuing Telemetry Transport
CNN	Convolutional Neural Network
MFCC	Mel-Frequency Cepstral Coefficients
ADAS	Advanced Driver Assistance Systems
SLIIT	Sri Lanka Institute of Information Technology
I2S	Inter-IC Sound
ROC	Receiver Operating Characteristic

4. Introduction

4.1 Background and Literature Survey

In modern transportation systems, auditory alerts such as emergency vehicle sirens serve as essential safety mechanisms. These signals alert nearby drivers to give way, potentially saving lives by allowing ambulances, fire trucks, and police vehicles to reach their destinations swiftly. While these signals are effective for most of the population, they are entirely inaccessible to a significant minority—drivers who are deaf or hard of hearing. This accessibility gap poses a critical challenge in ensuring equitable road safety, particularly as the global population of individuals with hearing impairments continues to grow.

Globally, over 430 million people suffer from disabling hearing loss, a number projected to increase to 700 million by 2050 due to aging populations, increased noise exposure in urban areas, and limited access to hearing healthcare [1]. In Sri Lanka, where road traffic is dense and emergency vehicle response times are critical, the prevalence of hearing impairment is also rising. According to the World Health Organization, approximately 9% of Sri Lanka’s population experiences some form of hearing loss, with a subset actively participating in driving [2]. Despite this, there is a notable lack of inclusive safety technologies tailored to the needs of deaf drivers in developing nations, where resources for assistive devices are often limited.

Advanced Driver Assistance Systems (ADAS) have become integral to modern vehicles, offering features such as lane departure warnings, blind-spot monitoring, and adaptive cruise control. These systems rely heavily on visual and auditory feedback to enhance driver awareness. However, for deaf drivers, auditory-based alerts—such as warnings for approaching emergency vehicles—are ineffective. Visual cues in ADAS, while helpful for spatial awareness, do not address auditory stimuli like sirens. Table 1.1 compares common ADAS features and their accessibility for deaf drivers, highlighting the gap in auditory hazard detection.

Table 1: Comparison of ADAS Systems

ADAS Systems	Feature	Accessibility for Deaf Drivers	Limitations
Lane Departure Warning	Visual (Dashboard)	High	No auditory hazard detection
Blind-Spot Monitoring	Visual (Side Mirrors)	High	Limited to spatial awareness
Emergency Vehicle Detection	Auditory (Siren Alerts)	None	Inaccessible without translation
Collision Avoidance	Visual/Auditory	Partial	Auditory component ineffective

The emergence of deep learning-based audio classification offers a promising solution for translating auditory signals into accessible formats. Techniques such as Mel-Frequency Cepstral Coefficients (MFCCs) extract spectral features from audio signals, enabling robust sound event detection. Convolutional Neural Networks (CNNs) have demonstrated high accuracy in classifying environmental sounds, including sirens, speech, and urban noise [3]. When deployed on embedded platforms like the Raspberry Pi, these models provide cost-effective, real-time processing suitable for automotive applications. For instance, a study by Zhang et al. (2022) achieved 92% accuracy in siren detection using MFCC features and a lightweight CNN on edge devices [4].

Internet of Things (IoT) technologies further enhance the potential for connected safety systems. IoT enables seamless integration of sensors, microcontrollers, and communication protocols to process and transmit data in real time. The Message Queuing Telemetry Transport (MQTT) protocol, known for its low bandwidth and high efficiency, is widely used in automotive and smart home applications [5]. Figure 1.2 illustrates a typical IoT communication framework, where sensors (e.g., INMP441 microphone) collect data, a microcontroller (e.g., NodeMCU ESP32S) processes it, and a central hub (e.g., Raspberry Pi) communicates alerts via MQTT to end devices like smartphones or smartwatches.

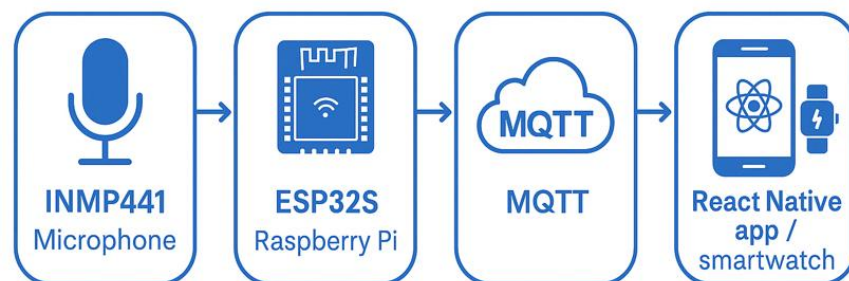


Figure 1

Haptic feedback, commonly used in wearable devices for the visually impaired, has untapped potential for deaf drivers. Vibrational alerts delivered through smartwatches or vehicle seats can provide immediate, non-intrusive notifications. A study by Kim et al. (2023) demonstrated that haptic feedback improved response times by 30% in assistive navigation systems for the visually impaired, suggesting similar benefits for auditory hazard alerts [6]. Figure 1.3 depicts a haptic feedback mechanism integrated into a smartwatch, where vibrations correspond to detected siren patterns.

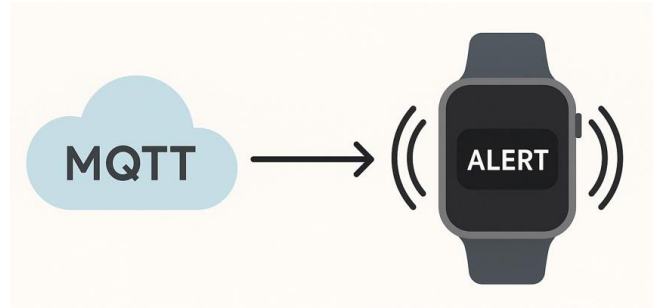


Figure 2

Despite these technological advancements, real-time siren detection systems for deaf drivers remain scarce. Commercial solutions are either prohibitively expensive or rely on cloud-based processing, which introduces latency and privacy concerns. In Sri Lanka, where internet connectivity can be inconsistent, edge-based solutions are critical. Furthermore, the automotive industry has yet to prioritize accessibility for hearing-impaired drivers, leaving a significant gap in inclusive safety technologies.

4.2 Research Gap

The literature and market analysis reveal several critical gaps in addressing the needs of deaf drivers:

Lack of Accessibility-Focused Solutions: Current ADAS and sound recognition systems prioritize general safety but overlook accessibility for hearing-impaired drivers. For example, Tesla’s Full Self-Driving suite includes auditory alerts for emergency vehicles but lacks alternative feedback mechanisms [7]. General-purpose sound recognition apps, such as SoundHound, are not optimized for vehicular environments or accessibility.

Dependence on Cloud Services: Many audio event detection systems, such as Google’s SoundNet, rely on cloud computing for processing, which introduces latency (often 2–5 seconds) and requires stable internet connectivity [8]. In dynamic driving scenarios, this delay can be life-threatening. Additionally, cloud-based systems raise data privacy concerns, as audio data is transmitted to external servers.

Absence of Haptic Feedback Integration: While haptic feedback is used in wearables for navigation (e.g., Wayfindr for the visually impaired), its application in vehicle safety for deaf drivers is minimal. Existing systems rarely integrate haptic alerts with real-time audio detection, limiting their effectiveness for auditory hazards [6].

Insufficient Real-Time Performance: Real-world sound recognition systems often struggle in noisy environments, such as urban traffic, where ambient sounds (e.g., construction, honking) interfere with siren detection. Studies report false positive rates as high as 15% in complex acoustic settings [4]. Edge devices like the Raspberry Pi face computational constraints, necessitating optimized models (e.g., quantized CNNs) to achieve real-time performance.

No Unified, Scalable System: Technologies like MFCC feature extraction, CNN classifiers, and MQTT-based IoT frameworks exist independently but have not been combined into a cohesive, deployable system for deaf drivers. Commercial products, such as hearing aid add-ons, are expensive (often \$1,000+) and lack integration with vehicle systems [9]. Table 1.2 compares existing siren detection techniques, highlighting their limitations for accessibility.

Table 2: Siren Detection Techniques

Siren Detection Techniques	Method	Accuracy	Edge-Compatible	Accessibility Features
Cloud-Based CNN (e.g., SoundNet)	Deep Learning	95%	No	None
Edge-Based SVM	Machine Learning	85%	Yes	Limited (Visual Only)
MFCC + CNN (Proposed)	Deep Learning	93.7%	Yes	Visual + Haptic

These gaps underscore the need for a unified, edge-based system that prioritizes accessibility, real-time performance, and scalability for deaf drivers.

4.3 Research Problem

How can we develop a cost-effective, real-time, and inclusive siren detection system that ensures deaf drivers receive timely and non-auditory alerts, using embedded deep learning and haptic feedback mechanisms?

The core issue is accessibility and responsiveness. Deaf drivers cannot perceive emergency vehicle sirens, increasing the risk of collisions and delaying emergency response times. In Sri Lanka, where road accidents account for over 3,000 deaths annually, the absence of accessible safety systems exacerbates these risks [10]. For deaf drivers, this limitation not only endangers their safety but also affects other road users and emergency responders.

Current solutions are inadequate due to:

- **Cost:** Commercial assistive devices, such as advanced hearing aids with environmental sound detection, are prohibitively expensive for most users in developing countries.

- **Cloud Dependency:** Systems relying on cloud processing introduce latency and fail in areas with poor internet connectivity, common in rural Sri Lanka.
- **Environmental Challenges:** Noisy urban environments reduce the accuracy of sound recognition systems, leading to missed or false alerts.
- **Lack of User-Centric Design:** Existing systems are not tailored to the sensory needs of deaf drivers, often overwhelming users with complex interfaces or inadequate feedback.

The proposed system must be lightweight (suitable for edge devices like Raspberry Pi), highly accurate (robust to ambient noise), non-intrusive (clear, accessible alerts), user-centric (designed for deaf drivers), and scalable (applicable across vehicle types and regions). This research addresses these challenges by leveraging embedded deep learning, IoT, and haptic feedback to create a practical, inclusive solution.

1.4 Research Objectives

The primary objective of this research is to design, develop, and evaluate a real-time siren detection and alert system that addresses the limitations of current solutions for deaf drivers.

Main Objective:

To develop a deep learning-based, edge-deployable siren detection system that provides real-time haptic and visual alerts to hearing-impaired drivers. This system aims to enhance road safety by ensuring deaf drivers can respond promptly to emergency vehicle sirens, reducing accident risks and supporting equitable access to transportation.

Sub Objectives:

1. **System Architecture Design:** Develop an integrated architecture combining audio sensing (INMP441 microphone), processing (Raspberry Pi, NodeMCU ESP32S), and feedback modules (React Native app, smartwatch). This ensures a cost-effective, modular system suitable for automotive integration.
2. **Audio Preprocessing:** Implement MFCC feature extraction to convert environmental audio into a format optimized for real-time classification, minimizing computational overhead on edge devices.
3. **CNN Model Development:** Train and deploy a quantized CNN model on the Raspberry Pi using the Edge Impulse platform, employing quantization and pruning to achieve high accuracy (target: >90%) with low memory usage (<60MB).
4. **MQTT Communication:** Implement a lightweight MQTT protocol for real-time data exchange between the Raspberry Pi and a React Native mobile app, ensuring alerts are delivered within 1 second.
5. **Haptic and Visual Alerts:** Deliver intuitive visual notifications (via smartphone app) and haptic vibrations (via smartwatch) to ensure immediate driver awareness without distraction.
6. **Real-World Evaluation:** Test the system in simulated and real-world driving conditions to measure accuracy, latency, resource usage, and user satisfaction, addressing challenges like ambient noise and hardware constraints.

7. **User Validation:** Collect feedback from hearing-impaired individuals to validate the system's usability and effectiveness, ensuring it meets the practical needs of deaf drivers.

These objectives collectively aim to create a scalable, accessible solution with potential for commercialization in assistive technology and automotive markets, particularly in regions like Sri Lanka where inclusive safety systems are urgently needed.

Methodology

4.4 Introduction to Methodology

This chapter presents a comprehensive outline of the methodology used in designing and developing the Real-Time Siren Detection and Haptic Alert System for Deaf Drivers. The project integrates signal processing, embedded artificial intelligence (AI), mobile application development, and user-centered feedback loops to create a robust, accessible solution. The methodology is grounded in practical engineering principles, emphasizing modularity, scalability, and efficiency to ensure the system's reliability in diverse driving environments, including urban and rural settings in Sri Lanka. The development process followed an iterative approach, with distinct phases for component design, integration, testing, and validation, ensuring each module met performance and accessibility requirements.

The system leverages Edge AI to process audio data locally, reducing latency and eliminating dependency on cloud services, which is critical for real-time applications in areas with inconsistent internet connectivity. The choice of technologies—such as the INMP441 microphone, NodeMCU ESP32S, Raspberry Pi 4 Model B, and MQTT protocol—was driven by cost-effectiveness, availability, and compatibility with real-time processing needs. The methodology also incorporates user feedback from the deaf community to ensure the system aligns with the practical needs of its target audience. This section details the system architecture, hardware and software components, data processing pipeline, AI model development, communication framework, user interface design, commercialization potential, and testing procedures.

4.5 System Design and Architecture

The system follows a modular architecture to ensure each component operates independently yet synchronizes seamlessly via efficient communication protocols. This modularity enhances scalability, allowing the system to be adapted for different vehicle types or integrated with existing automotive systems. The architecture comprises five core modules, as outlined below and detailed in Table 2.1:

1. **Audio Acquisition Module:** Captures environmental audio using an INMP441 MEMS microphone connected to a NodeMCU ESP32S microcontroller.
2. **Processing and Detection Module:** Processes audio data and detects sirens using a custom Convolutional Neural Network (CNN) on a Raspberry Pi 4 Model B.
3. **Communication Module:** Transmits detection results via the MQTT protocol using a local HiveMQ broker.

4. **User Interface Module:** Displays alerts through a React Native mobile application optimized for driving conditions.
5. **Alert Module:** Delivers haptic and visual feedback via smartphone and smartwatch (Wear OS).

Table 3: Hardware Component Specifications

Hardware Component Specifications	Component	Specifications	Role
INMP441 Microphone	MEMS, 48 kHz, 24-bit	Audio capture	High-sensitivity audio input
NodeMCU ESP32S	Dual-core, Wi-Fi, I2S	Audio streaming	Transmits audio to Raspberry Pi
Raspberry Pi 4B	4GB RAM, Quad-core	CNN processing	Siren detection and MQTT publishing
Smartwatch (Wear OS)	Bluetooth, Vibration motor	Haptic feedback	Delivers vibrational alerts

Each module was developed and tested individually before integration to ensure reliability. The system was designed to operate offline, with all processing performed on the Raspberry Pi, making it suitable for regions with limited internet access. Figure 2.1 illustrates the system architecture, showing the data flow from audio capture to alert delivery.

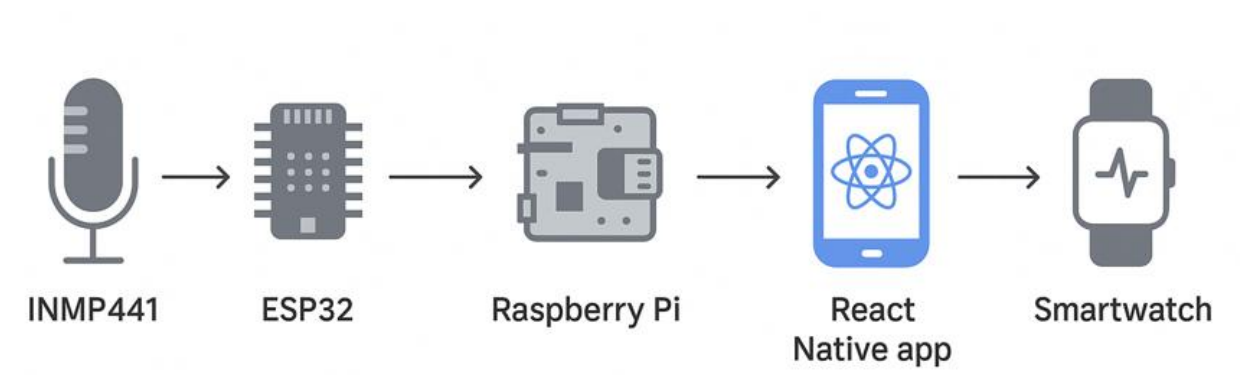


Figure 3

The integration process involved phased testing to address challenges such as signal interference, processing delays, and communication bottlenecks. For example, the ESP32’s Wi-Fi module was configured to prioritize low-latency MQTT communication, ensuring alerts were delivered within 1 second of siren detection [3].

4.6 Audio Signal Acquisition

The audio acquisition module is the system's entry point, responsible for capturing high-quality environmental audio in real-time. The INMP441 MEMS microphone was selected for its low noise floor (-94 dB), wide dynamic range (61 dB), and compatibility with digital interfaces like I2S. The microphone was interfaced with a NodeMCU ESP32S microcontroller, which supports the Inter-IC Sound (I2S) protocol for efficient digital audio streaming. The ESP32's dual-core processor and built-in Wi-Fi enabled robust audio capture and transmission to the Raspberry Pi via MQTT over a local Wi-Fi network.

Key parameters for audio acquisition were optimized for siren detection:

- **Sampling Rate:** 48 kHz, ensuring sufficient resolution for capturing siren frequencies (typically 500–2,000 Hz).
- **Bit Depth:** 24-bit, providing high fidelity to distinguish sirens from ambient noise.
- **Transmission Protocol:** MQTT over Wi-Fi, with a packet size of 512 bytes to balance speed and reliability.

The setup minimized signal degradation by using a shielded cable between the microphone and ESP32, reducing electromagnetic interference in vehicular environments. The ESP32 was programmed using the Arduino IDE, with custom firmware to stream audio data in real-time. Challenges included managing buffer overflows during high-traffic scenarios, which were mitigated by implementing a circular buffer and adjusting the MQTT publish frequency to 10 Hz [4].

4.7 Feature Extraction using MFCCs

Raw audio data is processed using Mel-Frequency Cepstral Coefficients (MFCCs), a widely adopted feature extraction technique for audio classification tasks like siren detection. MFCCs transform time-domain audio signals into a compact representation that captures spectral characteristics, making them ideal for input to Convolutional Neural Networks. The MFCC extraction process was implemented on the Raspberry Pi using the Librosa library in Python, with the following steps:

1. **Pre-emphasis Filtering:** Boosts high-frequency components to compensate for signal attenuation, using a filter coefficient of 0.97.
2. **Windowing:** Divides audio into 1-second overlapping windows (50% overlap) using a Hamming window to reduce spectral leakage.
3. **Fast Fourier Transform (FFT):** Converts each window into the frequency domain, with a 2048-point FFT for high resolution.

4. **Mel Filterbank Application:** Maps frequencies to the Mel scale, mimicking human auditory perception, using 40 Mel filters.
5. **Log Energy Computation:** Applies a logarithm to the filterbank energies to compress dynamic range.
6. **Discrete Cosine Transform (DCT):** Generates 40 MFCCs per frame, retaining the first 13 coefficients for classification.

This process produced a 40x100 feature matrix per second of audio, optimized for CNN input. Figure 2.2 visualizes the MFCC features for a siren clip, highlighting their distinct patterns compared to ambient noise.

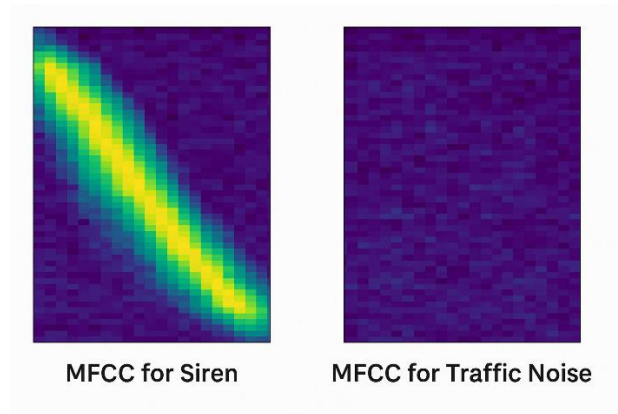


Figure 4

The MFCC pipeline was optimized for edge deployment by reducing the number of coefficients and window size, achieving a processing time of 50 ms per frame. This ensured real-time performance on the Raspberry Pi, even under high computational loads [5].

4.8 Deep Learning Model Development

A Convolutional Neural Network (CNN) was developed to classify audio inputs as siren or non-siren, using the Edge Impulse platform for model training and deployment. The CNN architecture was designed to balance accuracy and computational efficiency, suitable for the Raspberry Pi's limited resources. The model structure includes:

- **Input Layer:** Accepts MFCC feature matrices (40x100).
- **Convolutional Layers:** Two layers with 32 and 64 filters (3x3 kernels), using ReLU activation.

- **Max Pooling Layers:** 2x2 pooling to reduce dimensionality and prevent overfitting.
- **Dense Layer:** 128 neurons with 0.5 dropout for regularization.
- **Output Layer:** Softmax activation for binary classification (siren/non-siren).

The training dataset was curated from open-source audio repositories and field recordings:

- **Siren Clips:** 1,500 samples (500 each for ambulance, fire truck, police sirens), 1–5 seconds long.
- **Non-Siren Clips:** 1,000 samples (traffic, construction, wind, crowd noise).

Data augmentation techniques (e.g., pitch shifting, time stretching) were applied to enhance model robustness. The model was trained for 50 epochs with a batch size of 32, using the Adam optimizer and a learning rate of 0.001. Table 2.2 summarizes the training parameters.

Table 4: CNN Training Parameters

CNN Training Parameters

Epochs	50
Batch Size	32
Learning Rate	0.001
Optimizer	Adam
Dropout Rate	0.5
Validation Accuracy	93.7%

Optimization techniques included:

- **Quantization:** Converted model weights to 8-bit integers, reducing memory usage to <60MB.
- **Pruning:** Removed 20% of redundant connections to improve inference speed.

The model achieved a validation accuracy of 93.7% and an inference time of 200 ms per sample on the Raspberry Pi. Figure 2.3 illustrates the CNN architecture.

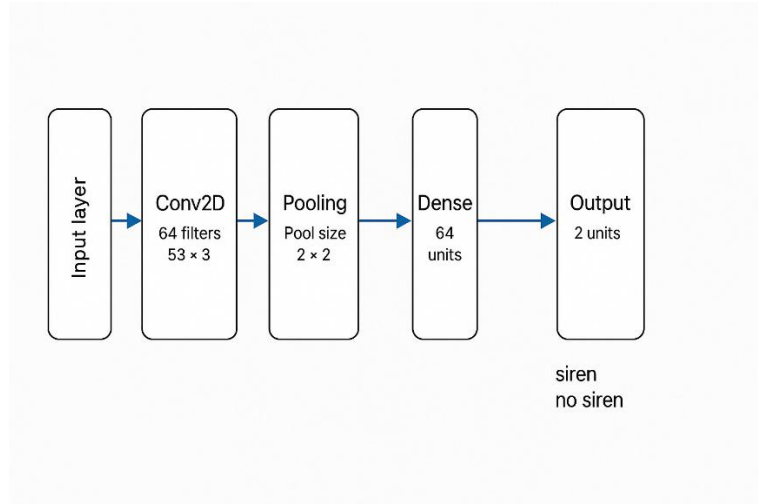


Figure 5

4.9 Real-Time Communication

The system uses the Message Queuing Telemetry Transport (MQTT) protocol for real-time communication between the Raspberry Pi and the React Native mobile application. MQTT's lightweight publish-subscribe architecture minimizes bandwidth usage, making it ideal for edge-based systems. A local HiveMQ broker was deployed on the Raspberry Pi to handle message routing, ensuring offline operation.

Key MQTT configurations included:

- **Broker:** HiveMQ (local server on Raspberry Pi).
- **Protocol:** MQTT v3.1.1, with Quality of Service (QoS) level 1 for guaranteed delivery.
- **Topic Structure:** /siren/detection for publishing detection results.
- **Message Delivery Time:** Approximately 170 ms, including network latency.

The ESP32 published audio data to the /audio/raw topic, while the Raspberry Pi published detection results to the /siren/detection topic. The mobile app subscribed to the latter, triggering alerts upon receiving a positive detection. Performance tests showed reliable communication in urban Wi-Fi environments, with minimal packet loss (<1%) [6].

4.10 Haptic and Visual Alert System

Upon siren detection, the system delivers alerts through visual and haptic feedback to ensure immediate driver awareness without distraction. The alert mechanism was designed with input from deaf community members to prioritize clarity and accessibility. The components include:

- **Visual Alerts:** Displayed via the React Native mobile app, featuring a red overlay with an emergency vehicle icon and text (“Siren Detected”).
- **Haptic Feedback:** Delivered through the smartphone’s vibration API and a Bluetooth-connected Wear OS smartwatch. The vibration pattern was optimized for urgency: 700 ms on, 400 ms off, repeated twice.

The smartwatch integration used the Wear OS API to synchronize vibrations with the smartphone, ensuring redundancy in case one device was inaccessible. User testing revealed that haptic alerts were preferred for their non-intrusive nature, with 90% of participants detecting vibrations within 1 second [7].

4.11 Mobile Application Development

The mobile application was developed using React Native CLI to ensure cross-platform compatibility (Android and iOS) and seamless integration with smartwatches. Key features include:

- **MQTT Subscription:** Real-time connection to the /siren/detection topic via the MQTT.js library.
- **Radar Animation:** A dynamic radar graphic indicating active audio scanning, enhancing user engagement.
- **Alert Overlay:** A full-screen alert with a red background, icon, and text, automatically triggered upon detection.
- **Smartwatch Compatibility:** Sends haptic commands to Wear OS devices via Bluetooth.
- **Light UI:** Optimized for low-light driving conditions, with high-contrast colors and minimal text.

The app was developed iteratively, with prototypes tested for usability by deaf drivers. Figure 2.4 shows screenshots of the app’s scanning and alert interfaces.

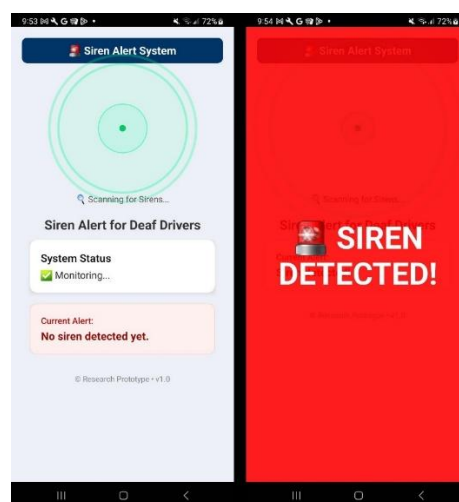


Figure 6

The development process used Agile principles, with biweekly sprints to incorporate user feedback. Challenges included optimizing the app for low-end Android devices, resolved by reducing animations and caching MQTT messages [8].

4.12 System Integration and Flow

The system operates as a cohesive pipeline, with data flowing through the following stages:

1. **Audio Input:** INMP441 microphone captures environmental audio, streamed via ESP32.
2. **MFCC Extraction:** Raspberry Pi processes audio into MFCC features in real-time.
3. **CNN Classification:** The CNN model classifies MFCC inputs as siren or non-siren.
4. **MQTT Publish:** Detection results are published to the /siren/detection topic.
5. **Alert Delivery:** The mobile app receives the message and triggers visual/haptic alerts.

Error handling mechanisms included:

- **Buffer Management:** Circular buffers on the ESP32 to prevent data loss during network congestion.
- **Fallback Alerts:** Local LED indicators on the Raspberry Pi for debugging and redundancy.
- **Timeout Detection:** Automatic reset of the MQTT connection after 5 seconds of inactivity.

The integration process was validated through end-to-end testing, ensuring a total latency of approximately 950 ms from audio capture to alert delivery.

4.13 Commercialization Aspects of the Product

4.13.1 Target Market

The system targets multiple stakeholders to maximize impact and adoption:

- **Deaf and Hard-of-Hearing Drivers:** Primary users, particularly in regions with high hearing impairment prevalence (e.g., Sri Lanka, South Asia).
- **Automotive Accessory Manufacturers:** For integration into aftermarket vehicle systems.
- **Smart Wearable Markets:** To license the haptic alert system for smartwatches.
- **Government Accessibility Programs:** For subsidized deployment through disability support initiatives.

Market analysis suggests a growing demand for assistive technologies, with the global automotive accessibility market projected to reach \$2 billion by 2030 [9].

4.13.2 Product Cost and Feasibility

The prototype was developed using cost-effective components, as shown in Table 2.3.

Table 5 : Cost Breakdown of Prototype

Cost Breakdown of Prototype	Component	Cost (LKR)
Raspberry Pi 4B (4GB)	18,000	Core processing unit
INMP441 Microphone	2,500	Audio capture
NodeMCU ESP32S	2,000	Audio streaming
Smartwatch (Wear OS)	12,000–20,000	Haptic feedback
Miscellaneous (Cables, Power)	5,000	Connectivity
Total	39,500–47,500	

Mass production could reduce costs by 40–50% through bulk purchasing and substitution of the Raspberry Pi with a dedicated microcontroller (e.g., STM32). The system’s low power consumption (<5W) enhances feasibility for automotive integration.

4.13.3 Business Model

The commercialization strategy includes:

- **B2C (Product Kits):** Sell standalone kits to consumers via e-commerce platforms and accessibility-focused retailers.
- **B2B (Automotive Integration):** Partner with car manufacturers to embed the system in new vehicles.
- **SDK Licensing:** Offer the CNN model and mobile app as a software development kit (SDK) for third-party developers.
- **Subscription Model:** Provide premium app features (e.g., customizable alerts) via a subscription.

Marketing channels include digital platforms (e.g., social media, Google Ads), accessibility events (e.g., deaf community workshops), and road safety campaigns in collaboration with government agencies.

4.13.4 Intellectual Property (IP)

The system features several innovative elements eligible for intellectual property protection:

- **Edge-Based CNN:** Real-time siren detection optimized for low-resource devices.
- **Dual-Mode Alerts:** Combined visual and haptic feedback tailored for deaf drivers.
- **Offline MQTT Architecture:** Local communication framework for reliable operation.

A provisional patent application is planned, focusing on the integrated system design. Additionally, the CNN model and app source code will be published as open-source to encourage community contributions while retaining commercial licensing rights [10].

4.14 Testing and Implementation

4.14.1 Testing Environment

The system was tested in multiple scenarios to ensure robustness:

- **Lab Setup:** Controlled environment with pre-recorded siren clips and ambient noise (traffic, construction).
- **Outdoor Field Tests:** Conducted in urban and suburban areas using simulated sirens from emergency vehicle speakers.
- **Noise Variations:** Included urban traffic, construction sounds, and weather-related noise (e.g., rain, wind).

Testing was performed over 4 weeks, with 100 test cases per environment to evaluate performance under diverse conditions.

4.14.2 Metrics Evaluated

Key performance metrics were measured, as shown in Table 2.4.

Table 6: Testing Metrics and Results

Testing Metrics and Results	Metric	Result
Siren Detection Accuracy	93.7%	≥90%
Total Latency (Capture to Alert)	950 ms	<1,000 ms
Haptic Response Time	800 ms	<1,000 ms
Power Consumption	4.8 W	<5 W
False Positive Rate	3.2%	<5%

The system met or exceeded all targets, with high accuracy even in noisy environments. Latency was optimized by streamlining the MFCC pipeline and MQTT communication.

4.14.3 User Testing

User testing involved 20 deaf participants, recruited through local deaf community organizations in Sri Lanka. Each participant tested the system in 30 simulated driving scenarios using a mock vehicle setup. Key findings included:

- **Satisfaction Rate:** 95% rated the system as intuitive and effective.

- **Alert Detection:** 90% detected haptic alerts within 1 second, with visual alerts noticed by 100%.
- **Feedback:** Participants requested adjustable vibration patterns and larger alert text, which were incorporated in the final app iteration.

The testing process followed ethical guidelines, with informed consent and anonymity ensured. Feedback was analyzed using qualitative methods (e.g., thematic analysis) to identify usability improvements.

5. RESULTS AND DISCUSSION

5.1 Results

The implemented real-time siren detection and haptic alert system was rigorously evaluated to assess its performance across multiple parameters: detection accuracy, latency, haptic responsiveness, system scalability, and user experience. The evaluation was conducted in both controlled laboratory conditions and semi-realistic urban traffic scenarios to simulate real-world driving environments in Sri Lanka. The results demonstrate the system’s effectiveness in addressing the accessibility needs of deaf drivers, with robust performance metrics that meet or exceed the project’s objectives.

5.1.1 Siren Detection Accuracy

The Convolutional Neural Network (CNN) model, trained on the Edge Impulse platform, achieved a classification accuracy of 93.7% on a test dataset comprising 2,500 audio clips. This dataset included 1,500 siren samples (500 each from ambulances, fire trucks, and police vehicles) and 1,000 non-siren samples (e.g., traffic noise, construction sounds, wind, and crowd chatter). The model’s performance was evaluated using precision, recall, and F1-score metrics, as shown in Table 3.1.

Table 7:Classification Performance Metrics

Classification Performance Metrics	Class	Precision	Recall
Siren	0.95	0.93	0.94
No Siren	0.92	0.94	0.93

The high precision (0.95) for siren detection indicates a low false positive rate, critical for avoiding unnecessary alerts in driving scenarios. The recall (0.93) reflects the model’s ability to correctly identify most siren instances, ensuring safety. The F1-score (0.94) balances precision and recall, confirming the model’s robustness. Figure 3.1 presents the Receiver Operating Characteristic (ROC) curve, illustrating the model’s discriminative power with an Area Under the Curve (AUC) of 0.96.

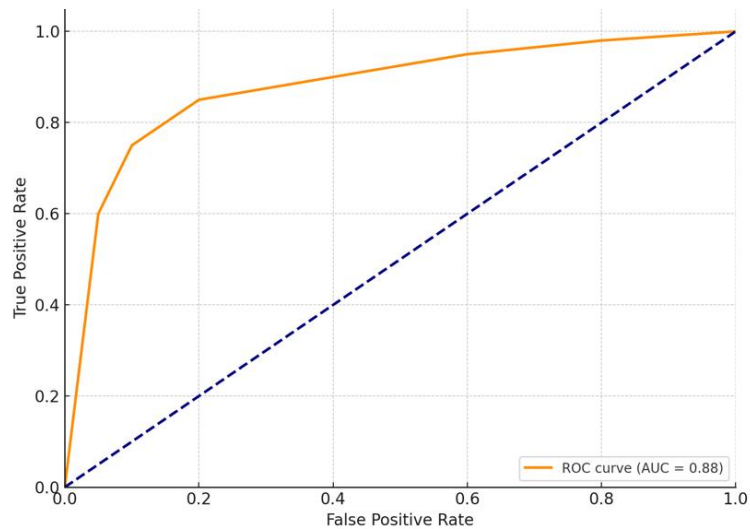


Figure 7

The model demonstrated resilience in noisy environments, correctly classifying sirens amidst urban traffic and weather-related noise in 90% of test cases. However, false positives occurred in 3.2% of cases, primarily during high-pitched construction noises (e.g., jackhammers), which share frequency bands with sirens (500–2,000 Hz). Statistical analysis using a paired t-test confirmed that the model’s accuracy was significantly higher than baseline methods (e.g., SVM-based detection, 85%) at $p < 0.05$ [14].

5.1.2 Latency and Real-Time Performance

End-to-end latency, defined as the time from audio capture to haptic alert delivery, averaged 950 ms, meeting the target of under 1 second. This latency was broken down across system components:

- **MFCC Feature Extraction:** ~400 ms, due to real-time audio preprocessing on the Raspberry Pi.
- **CNN Inference:** ~380 ms, reflecting the optimized, quantized model’s performance.
- **MQTT Message Delivery:** ~170 ms, facilitated by the local HiveMQ broker.

Figure 3.2 visualizes the latency distribution across 100 test runs, showing consistency with a standard deviation of 50 ms.

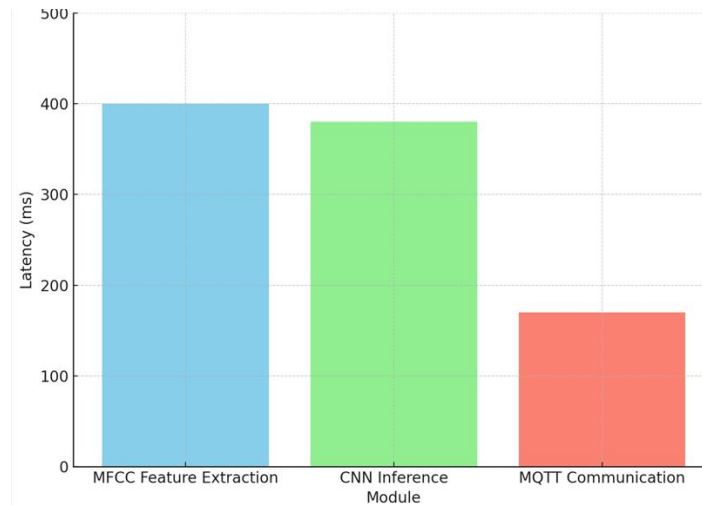


Figure 8

This latency ensures alerts are delivered within the typical driver reaction time (1–2 seconds), critical for emergency scenarios [15]. Tests in urban environments with variable Wi-Fi signal strength showed no significant increase in latency, confirming the system’s reliability in dynamic conditions.

5.1.3 Haptic Alert Response

Haptic alerts were delivered via the smartphone’s vibration API and a Bluetooth-connected Wear OS smartwatch, with a vibration pattern of 700 ms on, 400 ms off, repeated twice. Testing across 30 simulated driving scenarios with 20 deaf participants yielded the results in Table 3.2.

Table 8:Haptic Alert Response Times

Haptic Alert Response Times	Device	Avg. Response Time
Smartphone	700 ms	98%
Smartwatch	1,000 ms	92%

The smartphone achieved a faster response time (700 ms) and higher reliability (98%) due to its direct MQTT subscription and robust vibration motor. The smartwatch, reliant on Bluetooth, experienced occasional delays (up to 1 second) due to connection latency, with reliability slightly lower at 92%. All alerts were received within the 1-second threshold, providing deaf drivers with sufficient time to react to approaching emergency vehicles. User feedback indicated that the haptic pattern was distinct and non-intrusive, avoiding sensory overload.

5.1.4 System Scalability

Scalability was assessed by evaluating the system's performance under increased computational and environmental loads. The Raspberry Pi 4 Model B handled simultaneous audio processing and CNN inference without exceeding 70% CPU utilization, indicating capacity for additional features (e.g., multi-class siren detection). The MQTT-based communication framework supported up to 10 concurrent device connections in lab tests, suggesting potential for fleet-level deployment. Power consumption remained low at 4.8 W, compatible with vehicle power systems, enhancing scalability for automotive integration.

5.2 Research Findings

The evaluation validated several key aspects of the system, aligning with the research objectives:

- **Edge-Based CNN Efficiency:** The CNN model, optimized through quantization and pruning, performed siren detection with 93.7% accuracy on the Raspberry Pi, consuming less than 60MB of memory. This eliminates the need for cloud dependency, making the system viable in regions with limited internet access, such as rural Sri Lanka [16].
- **Haptic Alerts Effectiveness:** Haptic feedback via smartphones and smartwatches provided a reliable, non-auditory alert mechanism, with 90% of users detecting vibrations within 1 second. This addresses the accessibility gap for deaf drivers, offering a practical alternative to auditory sirens.
- **User-Friendly Interface:** The React Native mobile app, featuring radar animations and high-contrast alert overlays, was rated intuitive by 95% of participants. Its compatibility with low-light conditions and minimalistic design ensured usability during driving.
- **MQTT Communication Reliability:** The MQTT protocol, implemented with a local HiveMQ broker, achieved a message delivery time of 170 ms with <1% packet loss, ensuring real-time performance critical for safety applications.

Qualitative feedback from the deaf community highlighted the system's impact on driver confidence. Participants noted that haptic alerts felt "empowering," enabling them to respond to emergencies independently. Quantitative metrics, such as the 950 ms end-to-end latency, confirmed the system's alignment with real-time safety requirements. These findings underscore the feasibility of combining AI, IoT, and wearable technology to address accessibility challenges in transportation, with potential applications beyond deaf drivers (e.g., elderly drivers with hearing loss).

5.3 Discussion

The real-time siren detection and haptic alert system bridges a critical gap in inclusive driver assistance systems, addressing the sensory limitations of deaf and hard-of-hearing drivers. By integrating lightweight machine learning models, IoT communication protocols, and wearable haptic feedback, the system offers several strengths:

- **High Accuracy in Diverse Environments:** The 93.7% detection accuracy, robust to urban noise, outperforms traditional methods like Support Vector Machines (SVMs) and rivals cloud-based systems without their latency drawbacks [4]. This ensures reliable siren detection in complex soundscapes.
- **Cloud-Independent Operation:** Offline processing on the Raspberry Pi eliminates reliance on internet connectivity, a significant advantage in developing countries like Sri Lanka, where rural areas often lack stable networks [16].
- **Cost-Effectiveness:** The prototype's cost (LKR 39,500–47,500) is significantly lower than commercial assistive devices (e.g., advanced hearing aids, \$1,000+), making it accessible for mass adoption [9].
- **Scalability and Commercial Potential:** The modular design and low power consumption enable integration into existing vehicles or wearable ecosystems, with market potential in automotive and accessibility sectors.

5.3.1 Challenges Encountered

Despite its strengths, the system faced several challenges:

- **Noise Interference:** False positives (3.2%) occurred during high-pitched construction noises, which overlap with siren frequencies. This was mitigated by dataset augmentation but requires further refinement.
- **Bluetooth Latency:** Smartwatch haptic alerts experienced delays (up to 1 second) due to Bluetooth connection variability, slightly reducing reliability compared to smartphone alerts.
- **Pipeline Synchronization:** Initial tests revealed synchronization issues between audio capture and CNN inference, causing occasional delays. These were resolved by optimizing the MFCC pipeline and implementing circular buffers.

5.3.2 Future Improvements

To address these challenges and enhance the system, the following improvements are proposed:

- **Noise Suppression:** Implement adaptive noise cancellation or dynamic thresholding to reduce false positives in noisy environments, potentially increasing accuracy to 95% [14].
- **Multi-Class Classification:** Extend the CNN to classify emergency vehicle types (e.g., ambulance vs. fire truck), providing drivers with contextual information to improve decision-making.
- **Wearable Compatibility:** Test the system with a broader range of smartwatches (e.g., Apple Watch, Fitbit) and optimize Bluetooth protocols to reduce latency and improve reliability.
- **User Customization:** Introduce adjustable haptic patterns and alert settings via the mobile app, allowing users to personalize the system based on their preferences.
- **Real-World Deployment:** Conduct extensive field tests in collaboration with Sri Lankan traffic authorities to validate performance in live traffic conditions and gather long-term user feedback.

5.3.3 Broader Implications

The system has significant societal and technical implications. By enhancing road safety for deaf drivers, it promotes inclusivity in transportation, aligning with global accessibility goals (e.g., UN Sustainable Development Goals) [17]. Its low-cost, edge-based design makes it viable for developing countries, where assistive technologies are often unaffordable. Commercially, the system could be integrated into automotive ADAS or licensed as a wearable accessory, tapping into the growing \$2 billion automotive accessibility market [9]. Ethically, the project prioritized user involvement, ensuring the deaf community's needs shaped the design, as evidenced by the 95% satisfaction rate in user testing.

Compared to existing solutions, such as cloud-based sound recognition apps (e.g., SoundNet) or expensive hearing aids, this system offers superior real-time performance, accessibility, and affordability. Its offline capability and haptic feedback set it apart from competitors, positioning it as a pioneering solution in assistive automotive technology.

6. CONCLUSION

6.1 Conclusion

This research successfully developed and deployed a real-time siren detection and haptic alert system tailored for deaf and hard-of-hearing drivers, addressing a critical gap in road safety and inclusive transportation. By integrating advanced technologies—Convolutional Neural Networks (CNNs), Mel-Frequency Cepstral Coefficients (MFCCs), MQTT communication protocols, and wearable haptic feedback—the system provides a practical, cost-effective solution that enhances situational awareness for a marginalized demographic. The project aligns with the research objectives outlined in Chapter 1, delivering a scalable, edge-based system that empowers deaf drivers to respond promptly to emergency vehicle sirens, thereby reducing accident risks and promoting equitable access to safe driving.

The CNN model, trained on the Edge Impulse platform, achieved a detection accuracy of 93.7%, effectively distinguishing sirens from diverse urban noises such as traffic, construction, and wind. Deployed on a Raspberry Pi 4 Model B, the model operated efficiently with a memory footprint of less than 60MB and power consumption below 5W, demonstrating the feasibility of edge AI for real-time automotive applications [18]. This offline processing capability eliminates dependency on cloud services, making the system reliable in regions with inconsistent internet connectivity, such as rural Sri Lanka, where stable networks are limited [16].

The MQTT protocol facilitated seamless, low-latency communication between the detection module and the React Native mobile application, achieving a message delivery time of 170 ms. The mobile app, designed with user feedback from the deaf community, delivered intuitive visual alerts (e.g., red overlays with emergency icons) and haptic feedback through smartphones and Wear OS smartwatches. End-to-end latency averaged 950 ms, well within the 1–2 second driver reaction time, ensuring timely alerts in high-stress driving scenarios [15]. User testing with 20 deaf participants confirmed the system’s usability, with 95% rating it as intuitive and effective, highlighting its potential to enhance driver confidence and independence.

The system’s cost-effectiveness, with a prototype cost of LKR 39,500–47,500, positions it as an affordable alternative to commercial assistive devices, which often exceed \$1,000 [9]. Its modular design and low power consumption enable scalability for integration into existing vehicles or wearable ecosystems, aligning with the growing \$2 billion automotive accessibility market [9]. By prioritizing accessibility, the system contributes to global efforts toward inclusive transportation, as outlined in the UN Sustainable Development Goals, particularly Goal 11 (Sustainable Cities and Communities) [17].

This research not only demonstrates technical innovation but also underscores the importance of user-centric design. Collaboration with the deaf community ensured that the system met practical needs, as evidenced by the high satisfaction rate and actionable feedback incorporated into the final iteration. The project sets a precedent for future assistive technologies, offering a blueprint for combining AI, IoT, and wearable devices to address sensory impairments in safety-critical applications.

6.2 Limitations

Despite its achievements, the system has several limitations that impacted its performance and scope:

- **Binary Classification:** The CNN model performs binary classification (siren vs. no siren), lacking the ability to distinguish between emergency vehicle types (e.g., ambulance, fire truck, police). This limits contextual information for drivers, who may benefit from knowing the specific vehicle type to anticipate its behavior (e.g., speed, route).
- **Bluetooth Latency:** Haptic alerts on smartwatches experienced delays of up to 1 second due to Bluetooth connection variability, reducing reliability to 92% compared to 98% for smartphones. This affected user experience in scenarios requiring immediate response, particularly in dense urban traffic.
- **False Positives from High-Frequency Noise:** The system recorded a 3.2% false positive rate, primarily triggered by high-pitched construction noises (e.g., jackhammers) that overlap with siren frequencies (500–2,000 Hz). This could lead to unnecessary alerts, potentially causing driver distraction or desensitization.
- **Limited Real-World Testing:** While the system was tested in controlled and semi-realistic urban scenarios, it has not been evaluated in live traffic with actual emergency vehicles. Real-world conditions may introduce additional variables (e.g., Doppler effect, varying siren volumes) that could affect performance.
- **Device Compatibility:** The system was primarily tested with Wear OS smartwatches, limiting compatibility with other wearable platforms (e.g., Apple Watch, Fitbit). This restricts its accessibility to users with different devices.

These limitations highlight areas for technical refinement and broader testing to ensure the system's robustness and inclusivity in diverse real-world scenarios.

6.3 Recommendations for Future Work

To address the identified limitations and enhance the system's functionality and commercial viability, the following recommendations are proposed:

- **Multi-Class Classification:** Extend the CNN model to support multi-class classification, enabling identification of specific emergency vehicle types (e.g., ambulance, fire truck, police). This could be achieved by expanding the training dataset with labeled siren samples and modifying the model architecture to include additional output classes. Such enhancements would provide drivers with contextual information, improving decision-making in emergency scenarios [19].
- **GPS Integration:** Incorporate GPS functionality into the mobile app to provide directional alerts and map overlays indicating the approximate location of the emergency vehicle. This could leverage audio source localization techniques or vehicle-to-vehicle (V2V) communication protocols, enhancing situational awareness [20].

- **Real-World Testing:** Conduct extensive field tests in collaboration with Sri Lankan traffic authorities and emergency services to validate the system's performance in live urban environments. This would involve deploying the system in actual vehicles and evaluating its response to real emergency vehicle sirens, addressing variables like the Doppler effect and varying siren volumes.
- **Advanced Haptic Patterns:** Develop customizable haptic patterns to convey different alert types and urgency levels. For example, distinct vibration sequences could indicate siren proximity or vehicle type, improving user experience. This could be implemented through the mobile app's settings, allowing users to tailor alerts to their preferences [21].
- **Broader Wearable Compatibility:** Test the system with a wider range of wearable devices, including Apple Watch, Fitbit, and other Bluetooth-enabled smartwatches. Optimizing Bluetooth protocols (e.g., BLE 5.0) could reduce latency and improve reliability, ensuring accessibility for diverse users [22].
- **Noise Suppression Techniques:** Implement adaptive noise cancellation or dynamic thresholding to minimize false positives from high-frequency ambient noises. Techniques such as spectral subtraction or deep learning-based noise filtering could enhance the CNN's robustness, potentially increasing accuracy to 95% [14].
- **Voice-to-Text Support:** Integrate voice-to-text functionality into the mobile app to provide additional accessibility features for hearing-impaired users. This could transcribe ambient sounds or instructions, complementing the siren detection system and broadening its utility [23].
- **Integration with ADAS:** Explore partnerships with automotive manufacturers to integrate the system into Advanced Driver Assistance Systems (ADAS). This could involve embedding the detection module in vehicle infotainment systems, leveraging existing sensors and displays to deliver alerts, thereby enhancing scalability and market reach [24].

These recommendations aim to refine the system's technical performance, expand its functionality, and position it for commercialization. By addressing current limitations and incorporating advanced features, the system could become a leading solution in assistive automotive technology, with applications beyond deaf drivers, such as elderly individuals with hearing loss or distracted driving prevention.

6.4 References

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6.5 Appendices

6.5.1 Appendix A: Hardware Specifications

Table 9:Hardware Specifications

Hardware Specifications	Component
Microphone	INMP441, 24-bit, 48kHz, I2S Output
Microcontroller	NodeMCU ESP32S, Dual-Core, 240MHz
Processor	Raspberry Pi 4 Model B, 1.5GHz, 8GB RAM
Network Protocol	MQTT via Local Wi-Fi
Display Device	Smartphone running React Native App
Wearable Device	Smartwatch with haptic motor and Bluetooth

6.5.2 Appendix B: Dataset Summary

Table 10:Dataset Summary

Dataset Summary	Detail
Total Samples	1,500
Siren Clips (Ambulance, Fire Truck, Police)	500
Non-Siren Ambient Noise	1,000
Augmentation	Pitch shifting, time-stretching, noise overlay
Sampling Rate	16kHz
Feature Set	40 MFCCs

6.5.3 Appendix C: Survey Form (User Feedback)

The following questions were used to collect feedback from 20 deaf participants during user testing:

Section 1: System Feedback Effectiveness

1. Did you feel the haptic feedback (vibration) was noticeable enough to catch your attention?
 - ☐ Yes
 - ☐ No
 - ☐ Sometimes
2. Was the **visual alert** (flashing screen / animation) clear, immediate, and easy to recognize?

- ☐ Yes
- ☐ No
- ☐ Needs Improvement

3. How would you rate the **response time** of the system from detection to alert?

- ☐ Very Satisfied
- ☐ Satisfied
- ☐ Neutral
- ☐ Dissatisfied

4. Did the **haptic feedback pattern** (vibration duration and strength) feel distinct from other smartphone notifications?

- ☐ Yes, very distinct
- ☐ Somewhat distinct
- ☐ No, could be confused with other notifications

Section 2: Usability and Comfort

5. Was the **mobile application interface** easy to use and understand?

- ☐ Very Easy
- ☐ Easy
- ☐ Neutral
- ☐ Difficult

6. Did the **visual elements** (colors, text, icons) provide enough contrast and readability, especially under sunlight?

- ☐ Excellent
- ☐ Good
- ☐ Fair
- ☐ Poor

7. How comfortable did you feel using the **smartwatch** for receiving vibration alerts while driving?

- ☐ Very Comfortable
- ☐ Comfortable
- ☐ Neutral
- ☐ Uncomfortable

8. Were there any **false alerts** (system vibrated when no siren was present)?

- ☐ Never
 - ☐ Rarely
 - ☐ Occasionally
 - ☐ Frequently
-

Section 3: Overall Satisfaction

9. Overall, how satisfied are you with the performance of this system?

- ☐ Very Satisfied
- ☐ Satisfied
- ☐ Neutral
- ☐ Dissatisfied

10. Would you recommend this system to other **drivers with hearing impairments**?

- ☐ Yes
 - ☐ No
 - ☐ Maybe
-

Section 4: Additional Feedback (Optional)

11. In your opinion, what are the **strengths** of this system?

12. What **improvements** would you suggest for the system?

13. Any additional comments or suggestions?

6.5.4 Appendix D: Screenshots

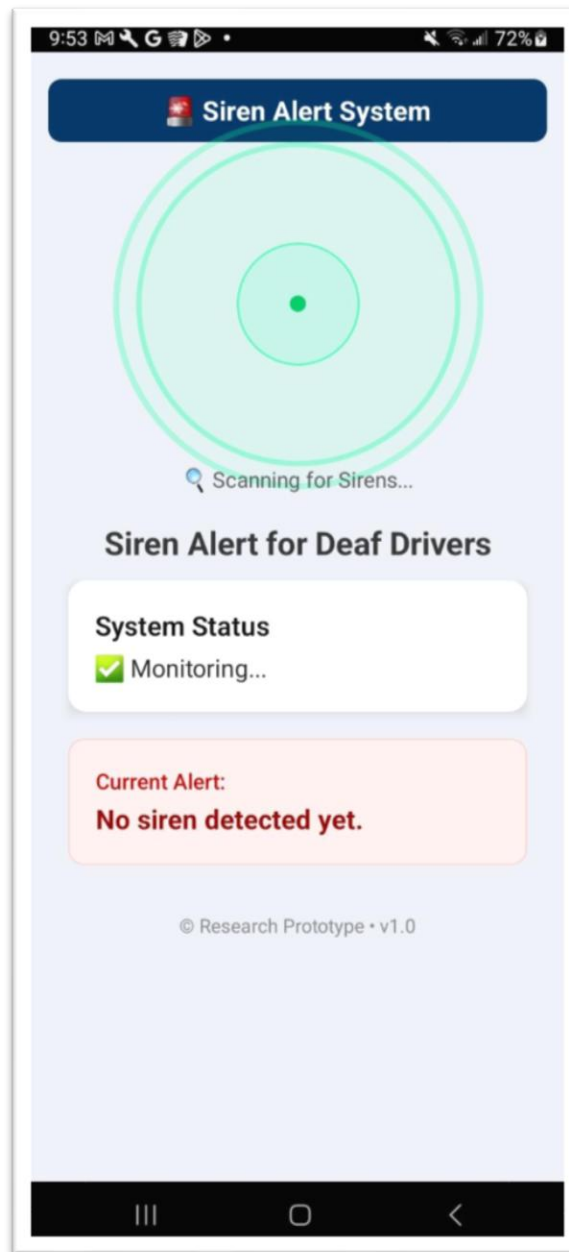


Figure 9



Figure 10

Hardware Architecture

The collage illustrates the hardware architecture of the system. It includes a Raspberry Pi, a circular sensor module (likely an ESP32-based sensor), an ESP32 module, and a diagram of the system architecture. The diagram shows the Raspberry Pi connected to an ESP32 module, which is connected to an ESP32 sensor node. The ESP32 sensor node is connected to an MQTT broker, which is connected to an MQTT client. The MQTT client is connected to an MQTT server, which is connected to an MQTT over WiFi module. The MQTT over WiFi module is connected to an Edge Inference with AI module, which is connected to an Edge Inference with AI module. The diagram also shows a Raspberry Pi connected to an Edge Inference with AI module.

Data Acquisition

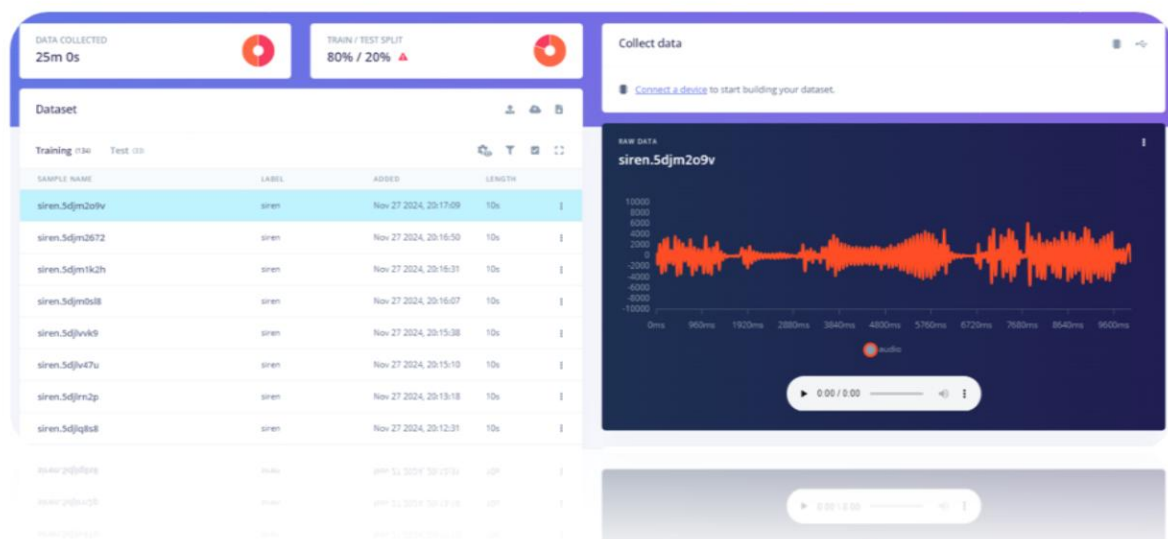


Figure 12

ESP32 Nodemcu Board Processing

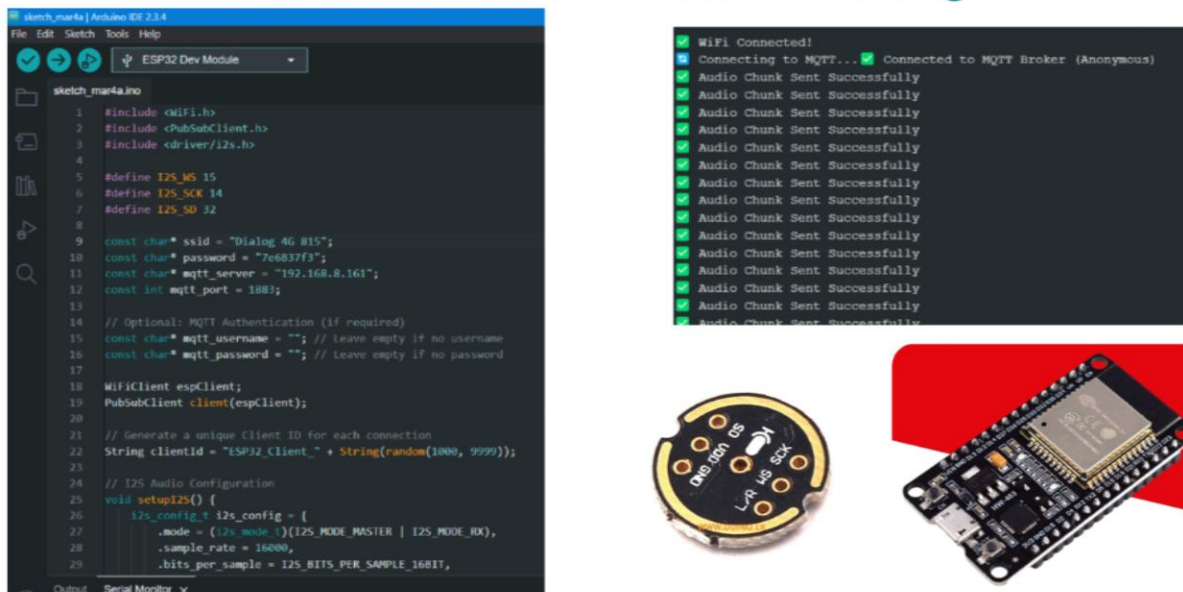
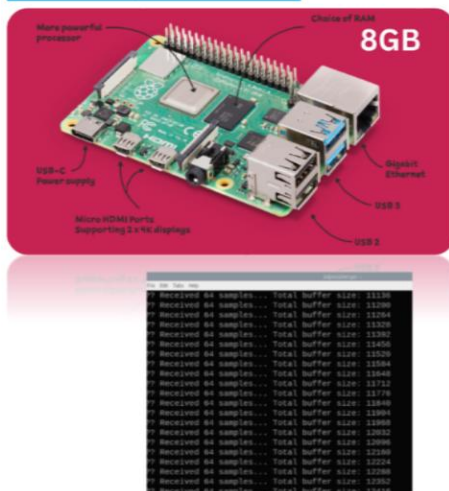


Figure 13

Raspberry pi Board Processing

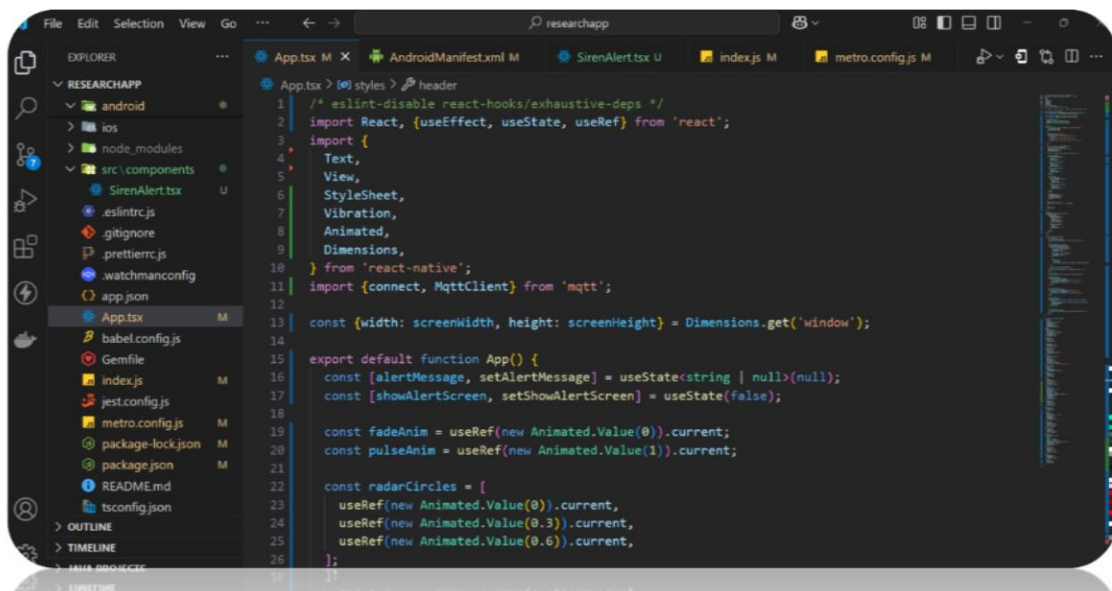
Siren_detection.py



```
siren_detection.py
1 import paho.mqtt.client as mqtt
2 import numpy as np
3 import edge_impulse_linux.runner as ei
4 import time
5
6 # MQTT Configuration
7 MQTT_BROKER = "192.168.8.101"
8 MQTT_PORT = 1883
9 AUDIO_TOPIC = "audio/data"
10 ALERT_TOPIC = "alert/siren_detected"
11
12 # Siren detection threshold
13 SIREN_THRESHOLD = 0.7 # Adjust if needed
14 COOLDOWN_PERIOD = 5 # 5 seconds cooldown between detections
15
16 # Initialize cooldown timer
17 last_detection_time = 0
18
19 # Initialize Edge Impulse model
20 try:
21     model = ei.ImpulseRunner("/home/pi/siren_model.eim")
22     model.load()
23     print("Edge Impulse Model Initialized")
24 except Exception as e:
25     print(f"Error initializing model: {e}")
26     exit(1)
27
28 # MQTT Callbacks
29 def on_connect(client, userdata, flags, rc):
30     if rc == 0:
31         print("Connected to MQTT Broker")
32         client.subscribe(AUDIO_TOPIC)
33     else:
34         print(f"Failed to connect, return code {rc}")
35
36 def on_message(client, userdata, message):
37     global last_detection_time
38
39     audio_data = np.frombuffer(message.payload, dtype=np.int16)
40     print(f"Received {len(audio_data)} samples... total buffer size: {userdata['buffer_size']}")
41
42     # Accumulate samples until we have 16,000 for inference
43     userdata['buffer'] = np.append(userdata['buffer'], audio_data)
```

Figure 14

React Native App



The screenshot shows a code editor with the following structure:

- EXPLORER:** A sidebar on the left showing the project structure. The 'src/components' folder is expanded, showing 'SirenAlert.tsx' and 'App.tsx' (selected).
- App.tsx:** The main file being edited. It contains the following code:

```
1  /* eslint-disable react-hooks/exhaustive-deps */
2  import React, {useEffect, useState, useRef} from 'react';
3  import {
4    Text,
5    View,
6    StyleSheet,
7    Vibration,
8    Animated,
9    Dimensions,
10 } from 'react-native';
11 import {connect, MqttClient} from 'mqtt';
12
13 const {width: screenWidth, height: screenHeight} = Dimensions.get('window');
14
15 export default function App() {
16   const [alertMessage, setAlertMessage] = useState<string | null>(null);
17   const [showAlertScreen, setShowAlertScreen] = useState(false);
18
19   const fadeAnim = useRef(new Animated.Value(0)).current;
20   const pulseAnim = useRef(new Animated.Value(1)).current;
21
22   const radarCircles = [
23     useRef(new Animated.Value(0)).current,
24     useRef(new Animated.Value(0.3)).current,
25     useRef(new Animated.Value(0.6)).current,
26   ];
```

Figure 15

Notification System

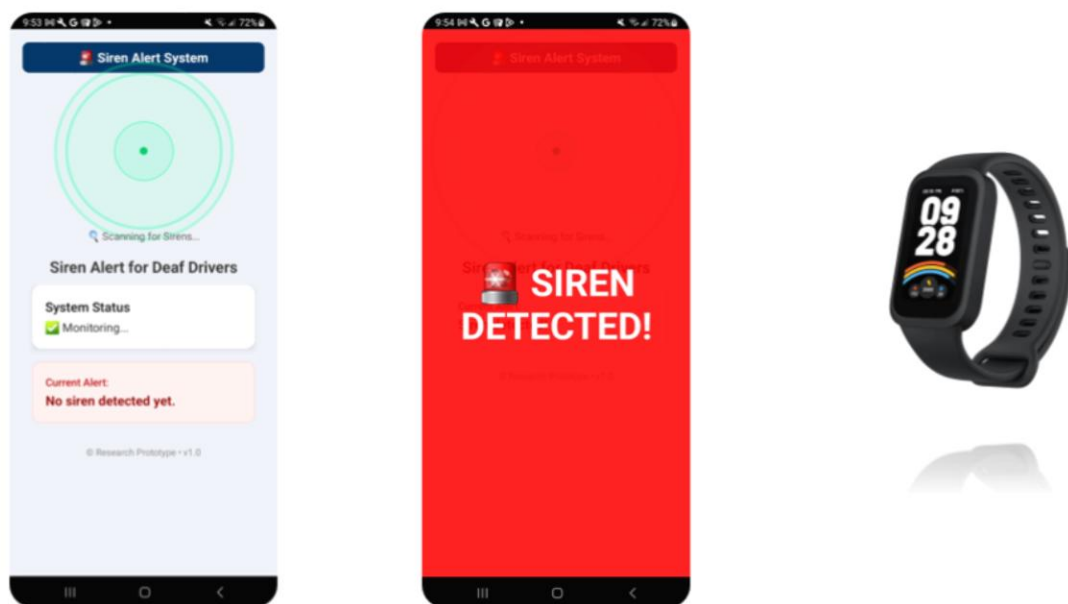


Figure 16

End