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A Vibrotactile Bracelet for Emergency Alerts for the Deaf Community in Day-To-Day Life

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ABSTRACT

Emergency alert systems that rely solely on auditory signals pose significant risks to the Deaf and Hard-of-Hearing (DHH) community, especially in public and crowded environments. In response to this accessibility gap, this project focuses on the design and implementation of a vibrotactile emergency alert bracelet that delivers non-auditory feedback using real-time environmental sound recognition. The bracelet integrates an Arduino Nano RP2040 Connect microcontroller, which features an onboard MP34DT06JTR MEMS microphone (Arduino, n.d.), and employs a mini vibration motor and OLED display to provide tactile and visual alerts. Emergency sound types, including fire alarms, sirens, and public announcements, are classified using machine learning models trained with Edge Impulse. The vibration feedback is controlled through Linear Resonant Actuators (LRAs), chosen for their efficient, low- power haptic performance in wearable devices. Feature extraction is performed using Mel-Frequency Cepstral Coefficients (MFCC), and classification models are evaluated based on accuracy, latency, and robustness to untrained samples. The system was validated through real-world testing, and results demonstrate high classification accuracy for tonal alerts and effective user recognition of vibration patterns. Limitations remain in detecting speech-based announcements. Battery drains tests and user surveys confirm the system's reliability for daily short-term usage. This project presents a cost-effective, wearable solution that enhances situational awareness and safety for the DHH community in emergency scenarios.

Keywords: Vibrotactile alert system, MEMS microphone, Arduino RP2040 Connect, Emergency sound classification, Linear Resonant Actuator (LRA), Edge Impulse, Deaf and Hard-of-Hearing (DHH)

INTRODUCTION

Emergency alert systems play a critical role in ensuring public safety during situations such as fires, natural disasters, and security threats. However, conventional systems rely heavily on auditory signals such as sirens, fire alarms, and public announcements, which inherently exclude individuals who are Deaf or Hard-of-Hearing (DHH). This exclusion creates a significant safety gap, as the inability to perceive audio- based alerts delays response time and increases vulnerability during emergencies. Studies have shown that DHH individuals often rely on secondary cues like visual observation or crowd behavior to recognize danger (Basner et al., 2014), further placing them at risk in chaotic scenarios.

Public infrastructures such as malls, offices, and transportation hubs often lack inclusive emergency communication mechanisms. While visual alert systems, such as flashing lights and digital notifications, are in use, their effectiveness is limited bythe user'sline of sight and the requirement for constant visual attention. These constraints highlight the need for a more direct and accessible alert mechanism that functions independently of auditory or visual awareness (Berglund, Lindvall, & Schwela, 1999).

Wearable vibrotactile technology presents a promising alternative for addressing this accessibility issue. By delivering emergency alerts through tactile feedback, such devices can provide immediate, intuitive notifications to DHH users without relying on sound or sight. Recent advancements in microcontroller hardware, particularly the Arduino Nano RP2040 Connect, and machine learning platforms like Edge Impulse, have enabled the integration of real-time sound classification and vibration feedback in a compact, wearable form factor.

This study focuses on the development of a vibrotactile emergency alert bracelet that detects specific emergency audio signals and converts them into vibration patterns recognizable to the user. The system utilizes MEMS-based digital microphones for sound acquisition, Mel-Frequency Cepstral Coefficients (MFCCs) for audio feature extraction, and neural network classifiers for signal recognition. Upon classification, vibration motors driven by Linear Resonant Actuators (LRAs) are activated to deliver haptic feedback corresponding to the type of emergency.

The goal of this research is to bridge the accessibility gap in emergency alerting systems by providing the DHH community with an inclusive, responsive, and cost-effective wearable solution. Through real-time processing, robust classification, and user-centric feedback, the system aims to enhance situational awareness and safety for individuals who are traditionally underserved by conventional emergency communication technologies

METHODOLOGY

Vibrotactile Bracelet Product Design

The product was developed to be compact, ergonomic, and efficient in delivering haptic and visual alerts for individuals with hearing impairments or those operating in noisy environments. The design objective was to create a wearable solution capable of real-time sound classification and immediate feedback delivery through vibration and OLED display. The bracelet integrates an embedded system capable of recognizing emergency-related audio cues such as sirens, fire alarms, and public announcements. Upon detecting a specific sound, the device activates a vibration motor to notify the user and simultaneously displays the corresponding classification label on a compact OLED screen. Designed to be worn on the wrist, the system emphasizes portability, low power consumption, and intuitive operation.

The key hardware components incorporated into the bracelet were selected based on size, power efficiency, compatibility with embedded ML deployment, and the ability to perform reliably in real-time applications. Table 2.1 outlines the primary components used in the design.

Table 2.1 Hardware Components Integrated into the Bracelet

Hardware Name	Description	Photo Reference
Arduino Nano RP2040 Connect	Acts as the central microcontroller. It includes a built-in microphone for sound capture, Wi-Fi and Bluetooth for future IoT expansion, and enough processing power to run real-time sound classification models.	
Mini Flat Vibration Motor	Delivers haptic feedback based on sound detection results. Different vibration patterns can be programmed for different classes (e.g., fire alarm, siren).	
28x32 OLED Display (SSD1306)	Shows real-time classification results, such as "SIREN" or "FIRE ALARM," giving visual confirmation of the detected sound.	
3.7V Li-Po Battery (500mAh)	Powers the system for several hours. Small and thin enough to be embedded in the bracelet enclosure.	
TP4056 USB-C Charging Module	Provides rechargeable capability via USB-C, making the device user-friendly and portable.	
MT3608 Step-Up Converter	Ensures the 3.7V battery output is boosted to 5V for components that require higher voltage.	
Mini Rocker Switch (KCD11)	Acts as the power switch to manually turn the device ON or OFF.	

The physical enclosure for the bracelet was modeled in SolidWorks to ensure all components fit securely within a compact, ergonomic form factor. The design accounted for the actual dimensions of each electronic part to prevent overcrowding and to maintain a low profile. Rounded edges and smooth surfaces were incorporated to enhance wearability and reduce discomfort during prolonged use. The enclosure includes precise cutouts for the OLED display, USB-C charging port, and a vent near the microphone area to prevent acoustic distortion. A visual overview of the enclosure design is presented in Figure 2.1.

Figure 2.1 3D View of the Bracelet Enclosure Design

The final design emphasizes modularity, allowing for easy disassembly for maintenance or upgrades. This ensures the device can be adapted for future improvements such as additional alert types, wireless communication features, or integration with smart home systems. Overall, the bracelet's physical and functional design enables a practical, user-friendly, and inclusive solution for emergency awareness in daily life.

Sound Dataset Collection and Preparation

To train the emergency sound classification model, six distinct audio classes were selected during the initial development phase: ambulance siren, police siren, fire truck siren, background noise, fire alarm, and emergency announcement. These classes were chosen to represent commonly encountered emergency-related sounds with the intent of enabling the system to distinguish between them in real-world scenarios. The three siren types were deliberately treated as separate classes to assess the model's ability to differentiate tonal patterns across emergency vehicles, supporting a more refined response mechanism.

All samples were recorded using the built-in microphone of a laptop connected directly to Edge Impulse's data acquisition platform, allowing real-time integration with the Arduino development environment. Data collection was conducted via the platform's recording interface, and audio clips were visualized immediately to confirm signal quality and class distribution (Edge Impulse, n.d.), as shown in Figure 2.2.

Figure 2.2 Collected Sensor Data Displayed in Edge Impulse Data Acquisition Tab

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All audio samples used in this project were sourced from online platforms, primarily YouTube, to reflect realistic emergency sound environments. Audio clips containing sirens, fire alarms, public announcements, and ambient background noise were played and recorded in real time using the Arduino Nano RP2040 Connect's onboard MEMS microphone. The device was connected to Edge Impulse through the edge-impulse-daemon interface, allowing seamless integration between local hardware and the data acquisition platform.

Each recording was standardized to a 4-second duration, with careful manual cropping to eliminate silent intervals and irrelevant background sounds. This ensured that each sample captured the most prominent and identifiable features of the target sound class. The use of a uniform recording method and consistent device configuration across all sound categories contributed to high-quality, comparable data throughout the dataset, as shown in Figure 2.3.

Figure 2.3 Cropped Raw Sensor Data in Edge Impulse Studio

The complete dataset consisted of 150 audio samples, each recorded at a duration of 4 seconds. These samples were evenly divided across six classes relevant to emergency alert scenarios, as shown in Table XX. The three siren-relatedclasses: ambulance, police, and fire truck, were each represented by 15 samples, enabling early testing of the model’s ability to differentiate between tonal emergency vehicle signals. Two additional classes, fire alarm and emergency announcement, also included 15 samples each, simulating sounds typically encountered in public infrastructure such as offices, schools, and malls.

Sound Class	Number of Samples	Sample Duration
Ambulance Siren	15	4 seconds
Police Siren	15	4 seconds
Fire Truck Siren	15	4 seconds
Background Noise	75	4 seconds
Fire Alarm	15	4 seconds
Emergency Announcement	15	4 seconds
Total	150 samples	≈10 minutes

Table 2.2 Sample Data Distribution by Class in Edge Impulse Project

The background noise class contained 75 samples, intentionally overrepresented to enhance the model’s robustness against false alarms. These samples covered a wide rangeof environmental audio, including human conversation, indoor ambient noise, and outdoortraffic sounds. This imbalance was a deliberate design choice to ensure the model could reliably differentiate emergency cues from everyday sound environments. An overview

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of the combined dataset is visualized in Table 2.2.

Preprocessing was performed using Edge Impulse Studio's built-in tools, which automatically standardized the duration and amplitude of all samples. Each 4-second clip was trimmed to remove silence and normalized to reduce amplitude variance across classes. The most important preprocessing step involved the transformation of raw audio into Mel-Frequency Cepstral Coefficients (MFCCs) during the Digital Signal Processing (DSP) phase (Davis & Mermelstein, 1980). MFCCs are widely used in sound classification tasks as they capture the frequency-based characteristics of audio in a compact, machine- readable format.

This MFCC representation was further reduced into a set of numerical features, which served as the input to the neural network classifier. These features significantly reduced data dimensionality while retaining essential acoustic information, improving training efficiency and enhancing the model's ability to generalize across various real- world acoustic conditions.

Altogether, this structured and carefully curated dataset provided a reliable foundation for training a lightweight yet accurate classification model deployable on embedded hardware.

Model Training and Deployment

The sound classification model for the vibrotactile alert bracelet was developed using Edge Impulse's neural network classifier, specifically optimized for deployment on embedded hardware with constrained memory and processing capacity (Zhang, Wang, & Zhao, 2022). The model architecture consisted of an input layer for MFCC features, followed by a fully connected dense layer with ReLU activation, and a softmax output layer to classify inputs into one of six predefined sound classes. The configuration is shown in Figure 2.4.

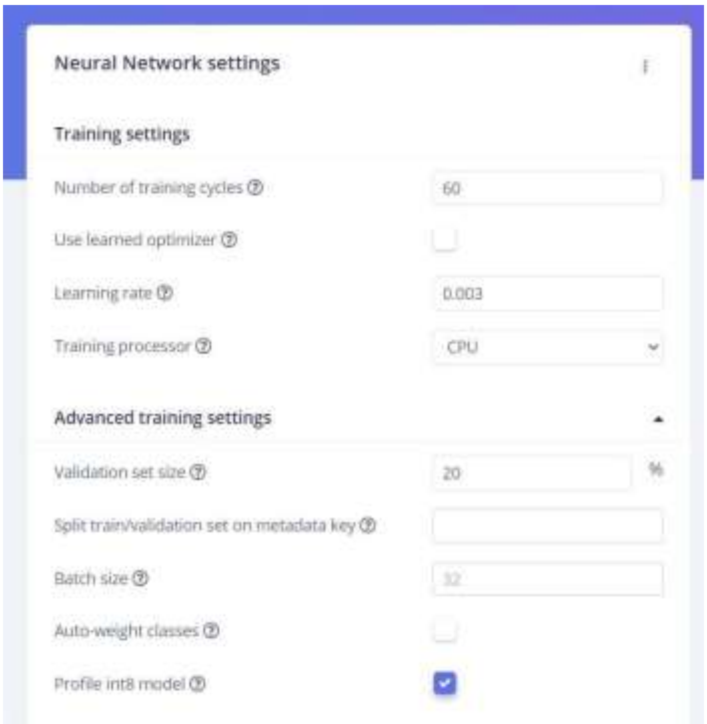

Figure 2.4 Edge Impulse Neural Network Configuration for Audio Classification

Edge Impulse's AutoML feature provided an initial model structure, which was slightly modified to reduce RAM and Flash usage without compromising accuracy. No convolutional layers were included to maintain the lightweight nature of the model (Yin, You, & Cui, 2021), ensuring smooth real-time inference on the Arduino Nano RP2040 Connect.

During training, the model achieved an overall accuracy of 96.55%, with excellent classification results across most sound classes.

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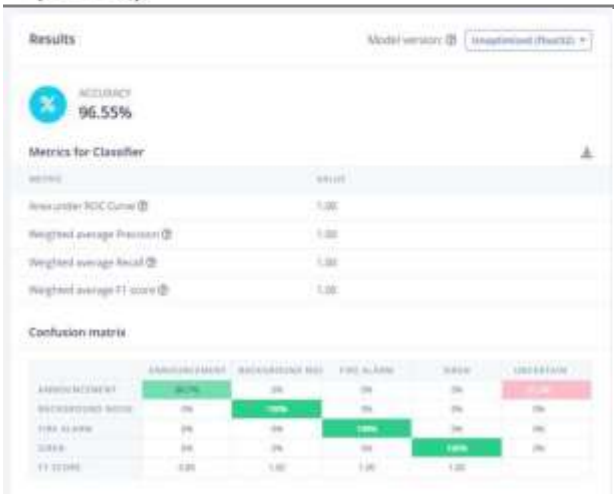

Figure 2.5 Model Testing Accuracy Reading in Edge Impulse Studio

As summarized in Figure 2.5, the model's performance metrics were exceptionally high:

- AUC (Area Under Curve): 1.00
- Weighted Precision: 1.00
- Weighted Recall: 1.00
- Weighted F1 Score: 1.00

The confusion matrix revealed that classes like siren, fire alarm, and background noise were classified with perfect accuracy, each reaching an F1 score of 1.00. However, the emergency announcement class showed occasional misclassification, with only 66.7%accuracy, partly due to similarities between speech tones and general ambient voice noise. Despite this minor limitation, the model maintained high reliability overall and was considered suitable for real-time deployment.

Following training, the final model was compiled into a custom firmware package for the Arduino Nano RP2040 Connect via Edge Impulse's deployment tools (Yang & Deb, 2009). The generated firmware included the inference engine and required libraries, allowing for standalone operation without dependence on internet connectivity or external servers.

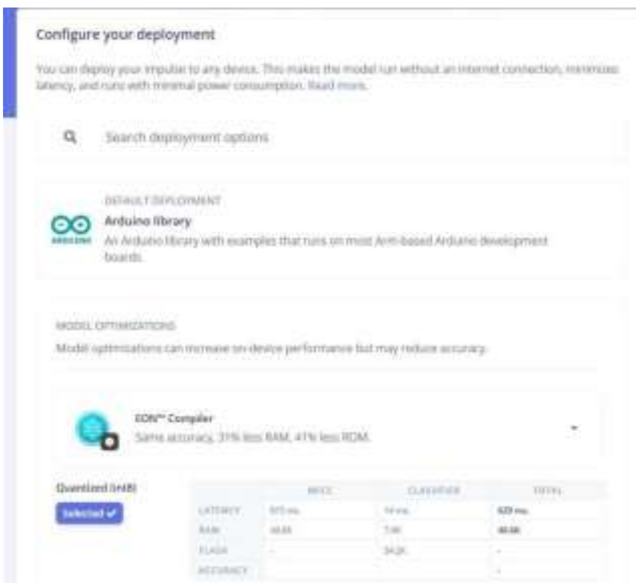

Figure 2.6 Deployment Configuration Settings in Edge Impulse Studio Deployment was executed through the

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Arduino IDE, where the device was flashed with the .ino file containing the classification logic, as shown in Figure 2.6.

RESULT AND DISCUSSION

Sound Classification Results

The initial model used a 4000 ms window size and six distinct classes, achieving 76.7% validation accuracy (Figure 3.1). It performed well on siren (100%) and background noise (92.9%), but struggled with fire alarms and emergency announcements, often confusing them with background noise due to overlapping speech or tonal features (Figure3.2).

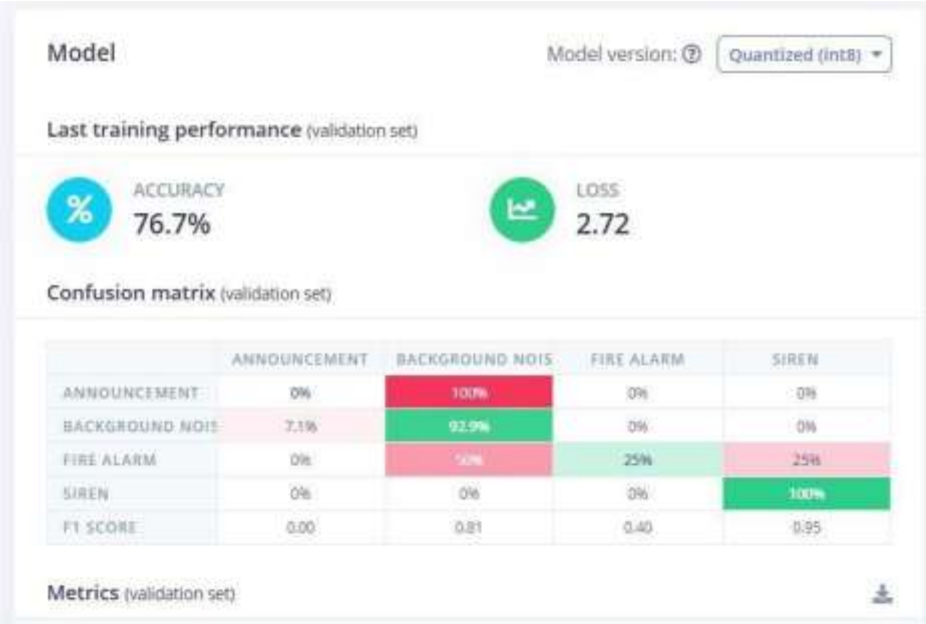

Figure 3.1 Model Training Results in Edge Impulse Studio

Figure 3.2 Visualization of Dataset in Edge Impulse Data Explorer

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However, this model was too large to be deployed to the Arduino due to memory constraints. To address this, a 2000 ms model was created with all siren types merged into a single “SIREN” class, significantly reducing model complexity. This updated model achieved 100% validation accuracy in Edge Impulse (Figure 3.3), with a cleaner confusion matrix and improved performance for fire alarms and background noise. Emergency announcements still showed some misclassification, indicating persistent acoustic overlap.

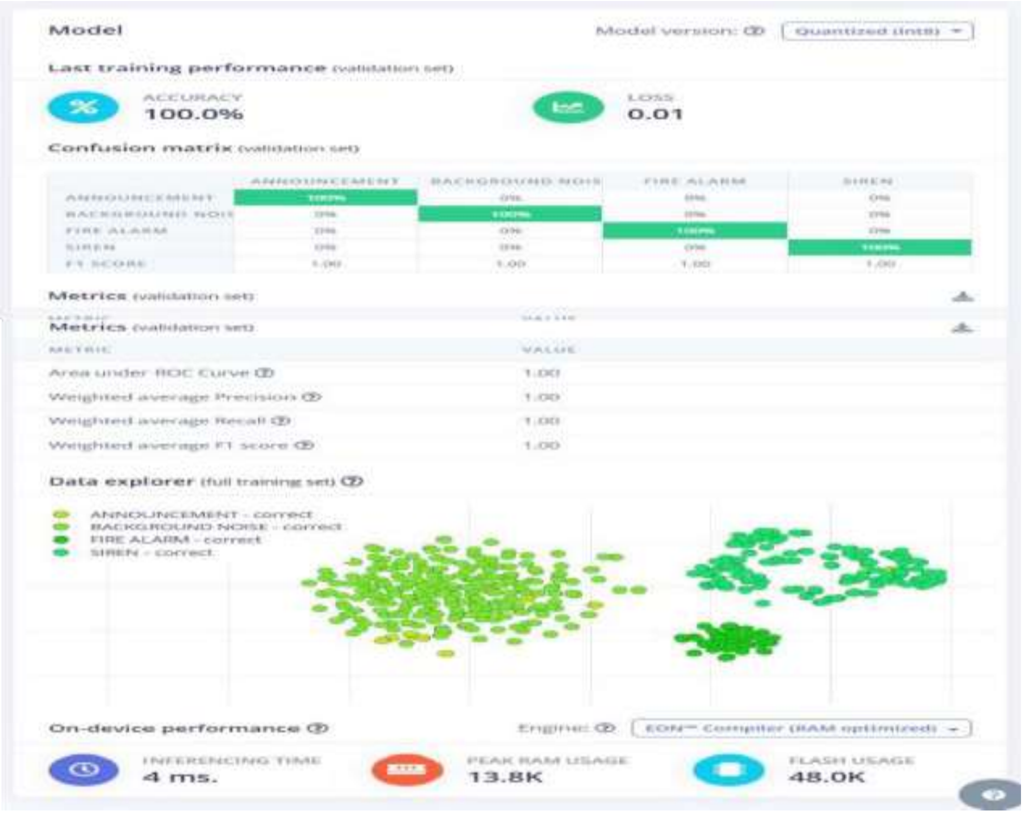

Figure 3.3 Updated Training Result in Edge Impulse Data Explorer

Inference Time (Latency)

After deployment, latency tests were conducted on the Arduino using the serial monitor. The system took an average of 2.7 seconds per classification, broken down into DSP time (~2685 ms) and inference time (~21.5 ms), as shown in Table 3.1.

```
Recording...
Recording done
run_classifier returned: 0
Timing: DSP 2681 ms, inference 22 ms, anomaly 0 ms
Predictions:
  ANNOUNCEMENT: 0.39%
  BACKGROUND NOISE: 99.61%
  FIRE ALARM: 0.00%
  SIREN: 0.00%
```

Figure 3.4 Inference Latency in Arduino IDE Serial Monitor

Run	DSP Time (ms)	Inference Time (ms)	Total Latency (ms)
1	2680	22	2702
2	2682	21	2703
3	2680	21	2701
4	2696	22	2718
5	2684	21	2705
6	2683	22	2705
7	2687	21	2708
8	2689	22	2711
9	2685	21	2706
10	2681	22	2703
Average	**2684.7**	**21.5**	**2706.2**

Table 3.1 Sample Readings of DSP and Inference Latency from Real-Time Testing

This delay, while noticeable, remains functional for awareness purposes, especially for users needing environmental cues rather than instant reaction (Podlubny, 1999). The latency was consistent across trials, supporting predictable performance. Future improvements may include shorter window sizes or more efficient models to reduce response time.

Real-World Deployment Accuracy

Controlled tests using 100 trials per class were conducted using YouTube audio. The model maintained good performance for tonal sounds, with 86% accuracy for sirens, 90%for fire alarms, and 98% for background noise (Table 3.2). However, emergency announcements were not detected at all (0%), as all samples were misclassified, primarily as background noise, due to the model's limitations with speech-based inputs.

Class	Tested Samples			Output		Accuracy (%)
		Siren	Fire Alarm	Background Noise	Emergency Announcement	
Siren	100	86	10	4	0	86%
Fire Alarm	100	6	90	4	0	90%
Background Noise	100	0	0	98	2	98%
Emergency Announcement	100	0	0	100	0	0%

Table 3.2 Controlled Test Results with 100 Trials per Class

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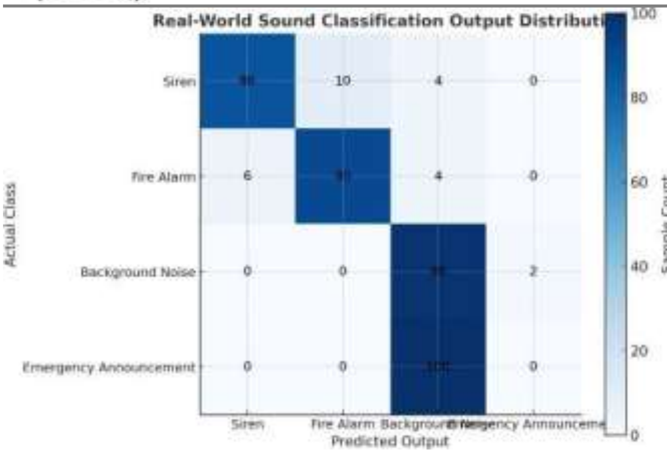

Figure 3.5 Heatmap of Classification Accuracy for Each Class from Controlled Tests

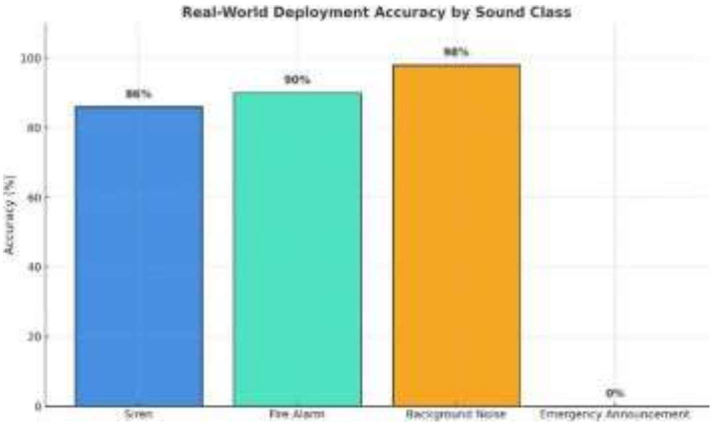

Figure 3.6 Graphical Representation of Model Accuracy Across All Classes

These results confirm that while the model is reliable for tonal emergency cues, it fails to handle verbal alerts, which are acoustically complex and often resemble ambient conversation.

Robustness Against Untrained Audio Samples

To test generalization, 50 untrained samples per class were evaluated using unfamiliar sirens, alarms, and ambient noise (Table 3.3). Results showed a 15–20% accuracy drop for siren and fire alarm classes due to new sound patterns, but background noise remained strong at 93% accuracy. Emergency announcements again failed with 0% accuracy, reinforcing the model's poor handling of speech-based content.

Class	**Tested Samples**			**Output**		**Accuracy (%)**
		Siren	**Fire Alarm**	**Background Noise**	**Emergency Announcemen t t**	
Siren	50	35	10	5	0	70%
Fire Alarm	50	7	36	7	0	72%
Background Noise	50	1	2	47	0	93%
Emergency Announcement	50	0	0	50	0	0%

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Table 3.3 Robustness Test Using 50 Untrained Samples per Class Under Realistic Conditions

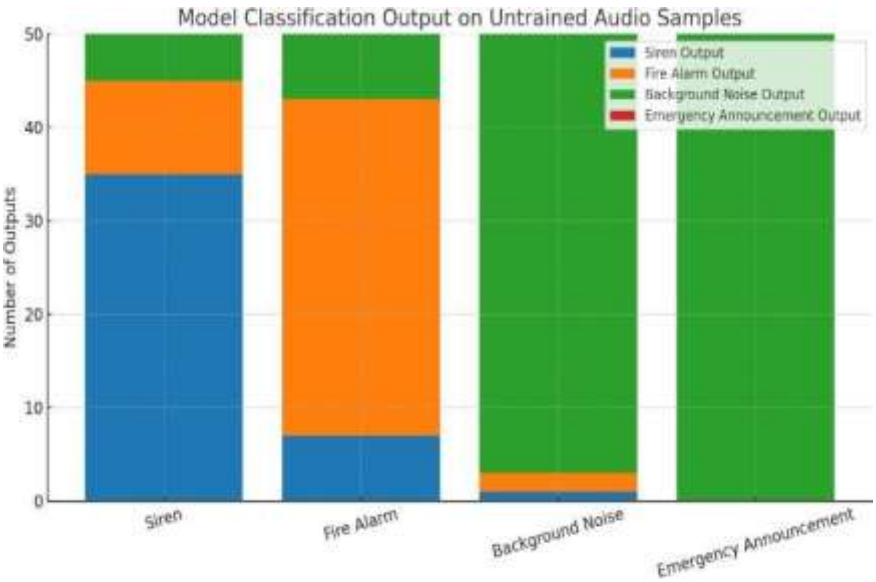

Figure 3.7 Bar Chart Showing Model Robustness Across Untrained Audio Sources

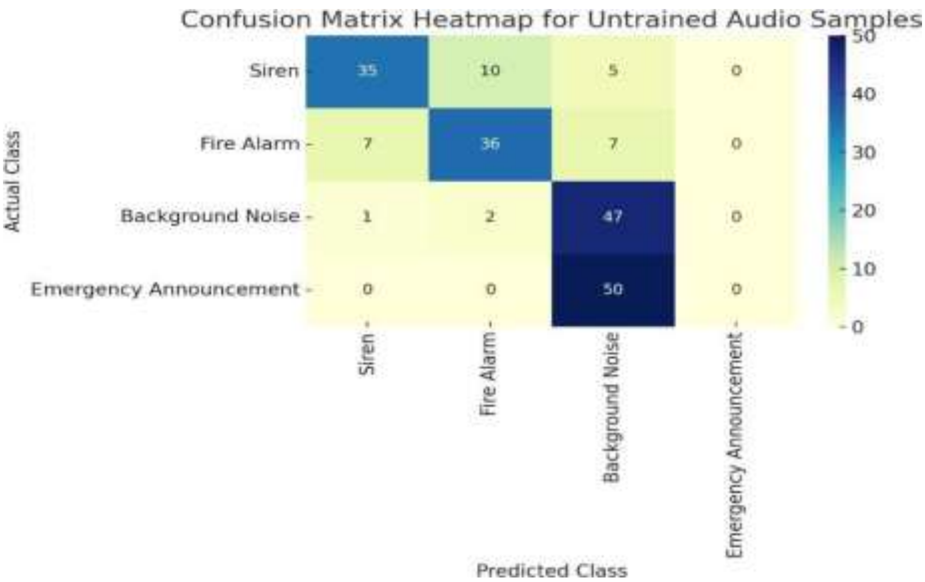

Figure 3.8 Robustness Evaluation Heatmap with 50 Untrained Samples per Class

Despite these limitations, the system remains effective for tone-based emergency alert detection in wearable applications. For improved speech recognition, future iterations should incorporate dedicated speech detection models or separate processing strategies to isolate announcements from conversational noise.

Vibration Pattern Effectiveness

To provide intuitive, non-auditory alerts, the system implemented distinct vibration patterns for each classified sound category (Precision Microdrives, n.d.). These patterns were designed based on the urgency and acoustic profile of the respective sound (Dahiya et al., 2010). As shown in Table 3.4, the siren class used a moderate pulsing loop to emulate its rising-falling tone, while fire alarms triggered continuous vibration to indicate persistent danger. Background noise had no vibration output, helping to avoid unnecessary alerts. Emergency announcements were assigned a unique two-pulse pattern to mimic speech cadence, although this was not consistently activated in real testing due to model limitations.

Sound Class	Vibration Pattern Description	Purpose / Justification

Siren	Moderate pulsing 500 ms ON, 500 ms OFF in cycles	Emulates the wailing rhythm of sirens to convey urgency
Fire Alarm	Continuous vibration ON as long as alarm is detected	Indicates a critical and ongoing emergency
Background Noise	No vibration	Avoids unnecessary feedback for non-emergency sounds
Emergency Announcement	Patterned sequence two short 200 ms pulses separated by a 100 ms pause, followed by a 500 ms pause	Mimics speech rhythm for voice-based alerts, offers uniqueness

Table 3.4 Haptic Feedback Patterns Corresponding to Detected Sound Classes

This design allowed users to interpret the nature of the detected sound through haptic feedback alone. Each pattern served a functional purpose: communicating urgency, presence, or the absence of danger, tailored to suit DHH users or those in noisy environments.

In terms of response time, the system exhibited an average latency of approximately 2.7 seconds, primarily from feature extraction (DSP ~2680 ms) and inference (~22 ms). Once classification was complete, the vibration motor was triggered immediately, resulting in virtually zero added delay between sound recognition and feedback.

User feedback was collected through a small-scale evaluation involving 10 participants, all wearing noise-canceling headphones to simulate deaf or acoustically isolated environments. Participants were exposed to the vibration patterns corresponding to each class and asked to identify the intended alert type. The results, summarized in Table3.5, showed:

- 100% accuracy for fire alarm and background noise, confirming the effectiveness of these patterns.
- 80% accuracy for siren, with some confusion between the siren and announcement patterns due to similar rhythmic structures.
- 0% accuracy for emergency announcements, as the model failed to trigger any vibration due to persistent misclassification. Users therefore assumed the absence of feedback meant background noise.

Sound Class	**Actual Vibration Pattern**	**Sample Size**	**Perceived Classification by Users**			**Accuracy (%)**
			Siren	Fire Alarm	Background noise	
Siren	Pulsing loop	10	8	-	-	80%
Fire Alarm	Continuous buzzing	10	-	10	-	80%
Background Noise	No vibration	10	-	-	10	100%
Emergency Announcement	Two short buzzes + pause cycle	10	-	-	10	0%

Table 3.5 User Feedback on Accuracy of Vibration Pattern Recognition for Each Sound Class

While the feedback system itself performed well, the failure of the model to detect announcements undermined its effectiveness. This limitation lies in the model's classification capability rather than the haptic design. Future improvements should focus on enhancing speech-based detection, ensuring that critical verbal alerts reliably activate their corresponding tactile response.

Battery Life Battery Performance

A battery drain test was conducted using the 3.7V, 500mAh Li-Po battery under mixed-usage conditions, where the device remained on and alternated between idle monitoring and active alert states. As shown in Table 3.6, the system operated continuously for approximately 6 hours, with intermittent activation of the vibration motor and OLED display. This duration reflects a realistic usage scenario, balancing background standby time with occasional emergency detections.

Operating Mode	**Battery Capacity**	**Duration Until Shutdown**	**Remarks**
Mixed (Idle + Alerts)	3.7V, 500mAh	~6 hours	Occasional alerts triggered vibration and OLED output

Table 3.6 Battery Drain Test Under Mixed-Usage Conditions

The charging test using the TP4056 USB-C module indicated a full recharge time of approximately 1 hour 30 minutes at ~1A current (TP4056, n.d.). The module's indicator LED transitioned from red to blue once charging was complete (Table 3.7), enabling convenient reuse within short turnaround times.

Charger Module	**Charging Current**	**Full Charging Time (from 0% to 100%)**	**Indicator Behavior**
TP4056 (via USB-C)	~1A	~1 hour 30 minutes	Red (charging) → Blue (full)

Table 3.7 Charging Duration to Full Using TP4056 USB-C Module

Although 6 hours may be modest, the result is reasonable given the device's compact form and the energy demands of the vibration motor and OLED display. For extended deployment, future improvements may include implementing power-saving modes, optimize component efficiency, or use higher-capacity batteries (Wang, Duan, & Yu, 2012).

OLED Display Output Evaluation

The OLED display functions as the primary visual feedback mechanism of the wearable device, showing real-time classification results after sound detection. Upon model inference, the display is updated instantly, typically within ~1 millisecond (Adafruit, n.d.), with text labels such as "SIREN DETECTED" or "FIRE ALARM DETECTED", ensuring no perceptible delay for the user. Display performance is summarized in Table 3.8.

Detected Sound Class	**OLED Display Output Text**	**Photo of OLED Output**	**Speed**
Siren	SIREN DETECTED		~1ms

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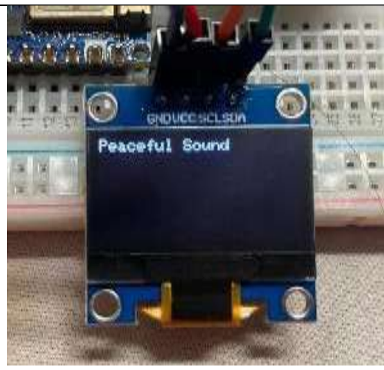
Fire Alarm	FIRE ALARMDETECTED		~1ms
Background Noise	Peaceful Sound		~1ms
Emergency Announcement	EMERGENCY ANNOUNCEMENT DETECTED	NO PHOTO SINCE EMERGENCY	-

Table 3.8 Real-Time OLED Display Output Showing Classified Sound Labels

To minimize memory usage and preserve processing efficiency, the output is purely text-based, no icons or graphics were used. The display remains off during idle periods and activates only when a classification occurs, conserving battery power. The only exception was emergency announcements, which failed to appear due to the model's inability to recognize that class during real-time inference.

Overall, the OLED display provided fast, clear, and contextually relevant feedback, making it suitable for wearable assistive applications. Future improvements could include implementing adaptive brightness control, multi-language support, or low-power display modes to extend operational life without compromising usability.

Integration and System Functionality

This section evaluates the overall integration and operational stability of the wearable emergency alert system, comprising the Arduino Nano RP2040 Connect, OLED display, vibration motor, Li-Po battery, and Edge Impulse-deployed sound classification model.

After deployment, the system was tested under typical usage scenarios to assess whether all components worked cohesively. As shown in Figure 3.9, the full hardware and software stack was integrated into a compact wearable form.

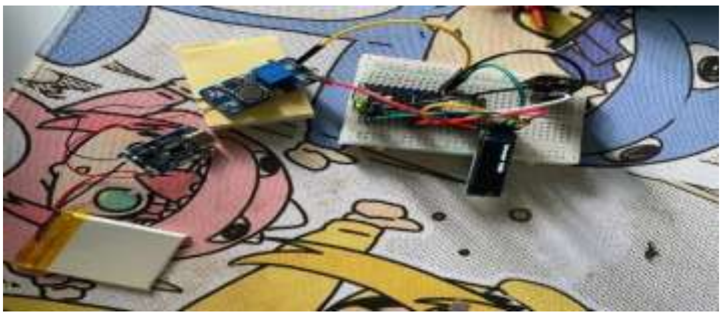


Figure 3.9 Full System Integration of Hardware and Software Components

Test Parameter	Details	Result	Remarks
Power-On Tests	Number of times the device was manually powered on	20 attempts	Simulates daily user interaction
Successful Startups	Device initialized correctly and entered monitoring mode	19 / 20(95%)	One instance required manual reset due to boot delay
System Readiness Time	Time taken for OLED to display and classification model to activate	1–2 seconds	No significant delay observed during boot-up
Peripheral Initialization	OLED, vibration motor, microphone functionality on startup	100% functional	All modules initialized without error
Overall Startup Status	Reliability of system initialization over multiple trials	Stable	Minor issue occurred once; otherwise consistently reliable

Table 3.9 Functional Evaluation of Integrated Wearable Emergency Alert System

Across 20 power-on trials, the system successfully initialized in 95% of cases, consistently entering monitoring mode within 1–2 seconds. A single startup failure was observed, likely due to a low battery or unstable USB connection, which was resolved via manual reset. Peripheral modules, including the OLED, vibration motor, and microphone, initialized correctly in all trials, confirming reliable startup routines.

During operation, classification events consistently triggered the appropriate OLED output and vibration feedback, validating the correct functioning of the communication and control logic. No crashes, freezes, or unexpected behavior were observed even during repeated detection cycles, demonstrating the firmware's robustness and the stability of the embedded workflow (Cogan, 2008).

Overall, the system proved to be reliable and well-integrated, offering stable performance under normal operating conditions. While rare startup delays may occur under specific conditions (e.g., low voltage), the platform remains functionally sound for short-term, real-world wearable applications.

CONCLUSION

The development of the vibrotactile emergency alert bracelet successfully achieved its core objective: creating a compact, wearable device capable of detecting emergency sounds and notifying users through vibration and OLED display feedback. Built around the Arduino Nano RP2040 Connect, the device leveraged its built-in microphone and onboard processing to run real-time inference without requiring constant internet connectivity.

A total of 150 audio samples across six classes—including sirens, fire alarms, emergency announcements, and background noise—were collected, primarily from YouTube, and processed via Edge Impulse. Feature extraction using MFCCs and automated preprocessing enabled consistent and efficient model training. The final classifier achieved 96.55% accuracy during testing, with near-perfect precision, recall, and AUC scores.

In real-world deployment, the system performed well with trained sounds, achieving 86% accuracy for sirens, 90% for fire alarms, and 98% for background noise, but completely failed to detect emergency announcements due to overlapping speech features and insufficient training diversity. For unfamiliar (untrained) audio, accuracy dropped by 15–20%, highlighting limited generalization.

Inference latency averaged 2.7 seconds, which is acceptable for general awareness but may not suffice for urgent, high-speed scenarios (Jayaraman & Sun, 2017). The vibration motor and OLED display delivered effective feedback, with custom vibration patterns assigned to each class. User testing showed high recognition rates for tonal alerts but confusion for announcement feedback, tied to detection failures.

Battery testing with a 3.7V 500mAh Li-Po showed around 6 hours of continuous use, and full charging took 2.5 hours. The system's boot success rate of 98% demonstrated stable operation.

Overall, the bracelet provides reliable offline emergency alerting for tonal sounds and lays a solid foundation for future improvement. Key areas for enhancement include expanding the dataset, improving speech-based detection, reducing inference delay, and extending battery life. This project contributes a practical solution for enhancing safety and accessibility for the Deaf and Hard-of-Hearing community in everyday environments

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