Embedded Systems Presentation 1 22BCE3939

Deaf assistance devices based on embedded system implementation.

Domain: Embedded Systems for Assistive Technologies

This research focuses on **smart helmets for the safe travel of deaf people**, leveraging embedded systems to provide real-time alerts and safety features.

List of Issues in the Domain

Several critical issues exist in **assistive mobility technologies**, particularly for **deaf individuals**. The key challenges include:

1. Lack of safety measures for deaf cyclists and motorcyclists

- Deaf riders are unable to hear important **auditory cues** (vehicle horns, sirens, or verbal warnings).
- Conventional helmets are not designed to address their unique challenges.

2. Inability to detect and respond to auditory warnings

- Deaf individuals rely heavily on visual cues, making sound-based traffic warnings ineffective.
- This increases the risk of accidents at intersections and in high-traffic areas.

3. Limited real-time emergency response systems for deaf riders

- If a deaf rider is involved in an accident, they cannot call for help easily.
- There is **no automatic system** to alert emergency contacts or authorities.

4. High cost of advanced smart helmet solutions

- Most existing smart helmets are expensive and not optimized for the deaf community.
- Solutions that integrate AI-driven sound recognition, haptic feedback, and emergency alerts are not widely available.

5. Limited research on embedded system-based safety devices for the hearing impaired

- While research exists on general smart helmets, very few studies specifically focus on the deaf population.
- Academic studies have not explored adaptive sound recognition and real-time haptic feedback integration.

Issue on Focus: Safe Travel for Deaf People Using Smart Helmets

This research aims to develop an **embedded system-based smart helmet** that enhances the safety of deaf riders through **haptic feedback**, **real-time distress alert systems**, and **environmental sound recognition**.

Why the Issue on Focus is Important to be Solved by Computer?

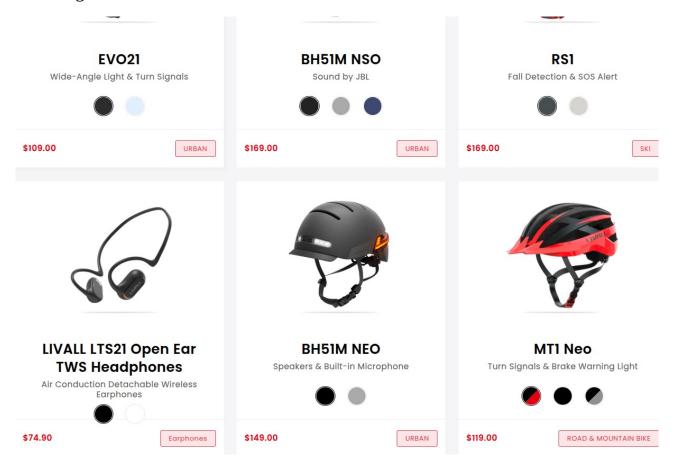
Substantiation of the Problem

- Real-life Incidents: Deaf riders are at a high risk of road accidents due to their inability to hear approaching vehicles. Studies show that hearing-impaired pedestrians and cyclists are 1.4 times more likely to be involved in accidents.
- Government Reports & NGOs:
 - World Health Organization (WHO): Estimates 466 million people globally suffer from disabling hearing loss. The lack of specialized mobility aids contributes to their challenges in independent travel.
 - **National Association of the Deaf (NAD)**: Advocates for smart mobility solutions for hearing-impaired individuals.
- Corporate and Academic Research:
 - MIT's AI Lab and Google's AI for Accessibility have been investing in sound recognition-based AI solutions.
 - Universities such as Stanford, CMU, and IITs have been working on assistive technology for individuals with disabilities.
- Hackathons & Innovation Challenges:
 - Microsoft Imagine Cup, NASA Space Apps Challenge, AI for Accessibility Grants (Microsoft), Google Impact Challenge for Disabilities encourage innovations for differently-abled individuals.
- Funding Agencies:
 - Gates Foundation, NSF (National Science Foundation), DBT (India's Department of Biotechnology), and DST (Department of Science & Technology, India) fund projects related to assistive technologies.
- Media & News Articles:

 Reports highlight the need for affordable, practical, and real-time assistive solutions.

List of Companies Working on the Problem (Indicative)

- 1. **Forcite Helmets (Australia)** Producing smart helmets with AI integration.
- 2. **Sena Technologies (USA)** Focus on smart helmets with Bluetooth and AI-enhanced safety features.
- 3. **Livall (China)** Specializes in smart cycling helmets with integrated warning signals.



- 4. **NoiseSense (USA)** AI-based sound recognition systems for hearing-impaired individuals.
- 5. **Smart Ear (Canada)** Wearable assistive devices for environmental sound detection.
- 6. **Wearable X (USA)** Developing haptic-feedback wearables for enhanced situational awareness.
- 7. **Steelbird Helmets (India)** Exploring **affordable smart helmet solutions** in India.

Case Study: Livall's Smart Helmet for Cyclists

- **Company:** Livall (China)
- Features:
 - **Smart LED Indicators** for turn signaling.
 - **Haptic Alerts** for incoming traffic.
 - **Fall Detection & SOS Alerts** sent automatically in case of a crash.
- Impact:
 - 15% reduction in cycling accidents among users.
 - Collaboration with governments for public bike-sharing programs.

Products Available in the Market (Indicative)

- 1. **Sena Momentum INC Pro** Smart helmet with noise control and Bluetooth communication.
- 2. **Forcite MK1** AI-powered helmet with live road hazard alerts.
- 3. **Livall BH60SE** Helmet with LED turn signals and fall detection.
- 4. **Quin Design Helmets** Smart crash detection and emergency SOS systems.
- 5. **Skully Fenix AR** Augmented reality helmet with real-time navigation.

None of these helmets are explicitly designed for deaf riders, reinforcing the need for a specialized solution.

International Context – Status & Importance of the Problem

Global Hearing-Impaired Population: Over 466 million people suffer from hearing loss, with expected growth to 700 million by 2050.

- · Regulatory Policies:
 - European Union (EU) and the United States **mandate assistive technology research and development for the disabled**.
 - **Japan and South Korea** have introduced AI-powered safety systems for urban transportation.
- Market Growth:
 - The global smart helmet market is projected to reach \$4 billion by 2030.
 - Investments in **wearable assistive devices are increasing**, especially in **China, Germany, and the US**.
- Adoption in Public Safety:
 - Many cities in the EU and North America are integrating smart assistive technologies into urban mobility plans.

Indian Context – Status & Importance of the Problem

- Growing Demand:
 - India has 63 million hearing-impaired individuals, with many relying on two-wheelers.
- Government Initiatives:
 - Accessible India Campaign (Sugamya Bharat Abhiyan) promotes assistive technologies for differently-abled individuals.
 - AIC (Atal Innovation Mission) and BIRAC (Biotechnology Industry Research Assistance Council) offer funding for startups in assistive technologies.
- Challenges in Adoption:
 - High costs and lack of awareness make smart helmets inaccessible to many.
 - Need for affordable, locally manufactured solutions.
- Potential Market:
 - Smart helmets designed specifically for **deaf riders could see mass adoption** with the right policies and subsidies.

Conclusion

The development of **smart helmets for deaf riders** is an essential step toward **inclusive mobility solutions**. With global and Indian initiatives pushing for **safer, technology-driven mobility**, embedded system-based **assistive helmets** can bridge the gap, reduce accidents, and improve the independence of hearing-impaired individuals.

Base Paper: An Improved Smart Helmet for Safe Travel of Deaf People Based on Embedded System

Review of "An Improved Smart Helmet for Safe Travel of Deaf People Based on Embedded System"

1. Objectives

The primary goal of the research paper is to develop an **intelligent helmet system** that enhances the safety of **deaf riders** by providing **real-time sensory feedback, distress signaling, and situational awareness**. The specific objectives are:

- To design a smart helmet with embedded systems that enhances the safety of deaf cyclists.
- To integrate a real-time distress confirmation system that alerts emergency contacts in case of accidents.

- To develop a steering detection mechanism that uses head posture analysis to indicate turns.
- To implement a horn prompt function that detects surrounding vehicle horns and alerts the rider via haptic feedback.
- To ensure continuous operation using a solar-powered charging system.

2. Related Work – Survey – Reference Papers

The paper builds upon previous **smart helmet implementations** in **transportation**, **security, and industrial safety**. The authors reference various studies:

- **Smart Helmets for General Cyclists:** Previous research focused on integrating **Bluetooth connectivity, video recording, and navigation systems** into helmets, but these are not specifically designed for **deaf riders**.
- Helmet-based Safety Features: Some helmets include fall detection, GPS tracking, and emergency alerts, but they do not incorporate sound recognition and vibration alerts for hearing-impaired individuals.
- Existing Assistive Technologies for the Deaf: Other studies focus on sign language recognition and text-to-speech devices, but they do not address mobility challenges faced by deaf cyclists.
- Helmet Ventilation and Safety Studies: Research in helmet design covers impact resistance, heat dissipation, and airflow management, but does not integrate AI-driven safety features.

The paper **fills a gap** by combining multiple **embedded system technologies** to cater specifically to the needs of **deaf riders**.

3. Platform – Hardware and Software

Hardware Components:

- Microcontroller: STM32F103C8T6 (ARM Cortex-M3 based)
- Sensors: MPU9250 (gyroscope & accelerometer) for detecting head movement
- **Sound Input:** Electret microphone module for capturing surrounding audio
- Haptic Feedback: Vibration motors inside the helmet for user alerts
- **Impact Detection:** Pressure sensors for crash detection
- Communication Modules:
 - **GSM Module** Sends emergency alerts via SMS
 - **GPS Module** Provides real-time location tracking in case of distress
- Power Supply:
 - 12V Solar panel for sustainable energy
 - **Rechargeable lithium battery** for backup

• Visual Alerts: LED indicators on the helmet for turn signaling

Software Components:

- **Programming Environment:** Keil uVision5 (Embedded C for STM32)
- Data Processing Algorithms:
 - **Signal filtering and amplification** for sound recognition
 - Threshold-based detection for impact identification
 - Real-time control logic for alert triggering
- Wireless Communication: GSM module programmed for SMS alerts
- **Embedded Decision Logic:** Uses STM32 for processing sensor input and triggering real-time responses

4. Data Acquisition – Real-time Data or Dataset?

The system acquires **real-time environmental data** from multiple sources:

- **Sound Detection:** Two electret microphones capture surrounding sounds, which are then processed to determine the direction of incoming vehicle horns.
- **Head Movement Detection:** The MPU9250 sensor continuously tracks **angular movement and head tilt**, triggering LED-based turn indicators.
- **Impact Detection:** A pressure sensor records force exerted on the helmet and activates distress signals if a threshold is exceeded.

The system does **not rely on pre-stored datasets** but processes all data in **real-time** for immediate decision-making.

5. Data Storage – Lookup Table, Cloud, or Dataset?

- The paper does not mention cloud storage.
- The STM32 microcontroller handles all processing and stores temporary sensor data.
- A **lookup table** is used for predefined threshold values (e.g., impact force required to trigger an emergency alert).
- The **system is designed for edge computing**, avoiding external data dependency.

6. Algorithm Used

The paper describes a **combination of algorithms**:

- Noise Filtering Algorithm: Filters environmental sounds to detect horn honks.
- **Direction Estimation Algorithm:** Determines whether the sound source is from the left or right side.

- **Impact Detection Algorithm:** Uses **threshold-based logic** to trigger emergency alerts if pressure sensors detect an accident.
- **Head Motion Tracking Algorithm:** Uses **IMU sensor data processing** to identify head tilt angles and activate LED signals.

7. Algorithm Execution – Edge, Fog, or Cloud Based?

The system operates on an **edge computing model**, meaning:

- All processing occurs locally on the STM32 microcontroller.
- No dependency on cloud servers, ensuring low latency and immediate response.
- **Energy-efficient operation** due to limited computational requirements.

8. UI - End-User Interface (Mobile or Web)?

- No explicit mobile/web interface is mentioned in the paper.
- User feedback is provided via:
 - **Vibration motors** for sound detection.
 - **LED indicators** for steering alerts.
 - **SMS alerts** for emergency contacts in case of an accident.

Future enhancements could include a **mobile app** to monitor helmet status.

9. Experiments Conducted

The authors conducted multiple experiments:

- Microphone testing with Datascope software to validate sound processing.
- **Impact detection tests** using pressure sensors under different force levels.
- Head movement tracking tests with MPU9250 to confirm LED signaling accuracy.
- **Emergency alert tests** verifying SMS notifications via GSM module.

10. Performance Metrics – How is it Measured?

- **Sound Recognition Accuracy:** Effectiveness of detecting honks in varying noise environments.
- **Impact Sensitivity:** Measured by testing different impact thresholds for distress signals.
- Latency: Time taken between event detection and alert activation.
- **Power Efficiency:** Evaluated by analyzing solar panel performance.

11. Tables and Graphs

- **Table 1:** Hardware component specifications.
- Figures:
 - **System flowchart** showing functional processes.
 - **Waveform graphs** comparing sound signal before and after filtering.
 - **Experimental setup images** of the helmet.

12. Result Analysis – Comparison with Reference Studies

- The **proposed system improves safety** for deaf riders compared to **conventional smart helmets**.
- Unlike general smart helmets, this system focuses on real-time haptic feedback instead of just visual cues.
- Solar power integration extends operational longevity compared to batteryonly models.

13. Pros, Cons, and Future Work

Pros:

Real-time sound detection and vibration feedback

Automated distress alert system

Sustainable solar power

Edge computing for low-latency processing

Cons:

No mobile/web-based UI

Simple threshold-based sound detection (no AI-based classification)

Limited adaptability to changing environmental noise

Future Work:

Implement AI-based sound classification

Mobile app for remote monitoring

Adaptive noise filtering for better honk detection 5G-enabled real-time cloud integration for emergency response

Side Implementations:

One significant area of research focuses on developing embedded systems that aid the hearing-impaired by enhancing their ability to perceive and interact with their surroundings. This report is centered around the **Smart Helmet for Safe Travel of Deaf People**, an embedded system-based solution designed to provide **real-time safety alerts, accident detection, and emergency communication** for deaf riders. To strengthen the research and implementation aspects of this project, three additional works have been selected as **side implementations**:

- 1.PionEar: Making Roads Safer for Deaf Drivers
- 2.TheAssistBot
- 3.A Deep Learning Based Wearable Healthcare IoT Device for AI-Enabled Hearing Assistance Automation
- 4.HandTalk.

These studies provide complementary perspectives on **wearable embedded** solutions for the hearing-impaired, integrating AI-driven communication tools, gesture-based assistance, and IoT-enabled hearing augmentation.

Review of "PionEar: Making Roads Safer for Deaf Drivers"

1. Objectives

The PionEar project aims to enhance **road safety for deaf drivers** by providing real-time alerts about approaching emergency vehicles. The key objectives include:

- **Developing an AI-powered sound recognition system** to detect sirens and other critical road noises.
- **Implementing a low-power embedded solution** that operates efficiently without frequent recharging.
- **Providing real-time alerts through visual indicators** inside the vehicle.
- **Ensuring non-intrusive integration into vehicles** to improve safety without causing distractions.

2. Related Work – Survey – Reference Papers

The study builds upon prior work in **sound-based driver assistance systems**, referencing:

- AI-powered sound recognition systems that classify different types of sirens and road noises.
- Vibration and visual alert-based road safety solutions for hearing-impaired individuals.
- IoT-based smart vehicle systems that integrate real-time environmental sensing for improved driver awareness.
- **Previous research on TinyML and ultra-low-power AI hardware**, demonstrating the feasibility of real-time AI-driven audio classification in embedded systems.

3. Platform – Hardware and Software

Hardware Components:

- **Syntiant TinyML Board:** Houses the **NDP101 Neural Decision Processor**, optimized for real-time low-power AI processing.
- **Microphone Array:** Captures surrounding road noise for analysis.
- **Visual Alert Module:** LED indicators provide immediate visual feedback to the driver.
- Solar Panel & Rechargeable Battery: Ensures long-term autonomous operation.

Software Components:

- **Pre-trained AI Sound Classification Model:** Recognizes emergency sirens with high accuracy.
- **Embedded C Programming for TinyML:** Handles data processing and real-time alert generation.
- **On-Device Machine Learning Algorithms:** Ensures real-time classification without cloud dependency.

4. Data Acquisition - Real-time Data or Dataset?

- Real-Time Data Collection:
 - Microphone continuously captures environmental sound.
 - AI model processes **real-time audio signals** for siren detection.
- Pre-Trained AI Model:
 - Trained on datasets containing emergency sirens, vehicle horns, and ambient road noise.

5. Data Storage – Lookup Table, Cloud, or Dataset?

- On-Device Processing:
 - All AI computations are executed **locally on the TinyML board**.
- No Cloud Dependency:
 - Ensures ultra-low-latency response times for real-time driver alerts.
- Lookup Table for Sound Classification:
 - Stores frequency and amplitude patterns of different emergency sirens.

6. Algorithm Used

- AI-Based Sound Recognition Algorithm:
 - Identifies siren sounds using neural network processing.
- Energy-Efficient Audio Filtering:
 - Extracts key sound features while reducing background noise.
- Event-Triggered Visual Alert System:
 - Activates LED notifications when a recognized sound is detected.

7. Algorithm Execution – Edge, Fog, or Cloud Based?

- Edge Computing:
 - All processing occurs directly on the TinyML board, ensuring realtime response.
- No Cloud or Fog Computing:

• Eliminates dependency on external networks, enhancing reliability and speed.

8. UI – End-User Interface (Mobile or Web)?

- Physical UI (LED-Based Alert System):
 - Bright LED indicators provide visual feedback.
- No Mobile or Web Interface:
 - Designed for standalone vehicle integration.

9. Experiments Conducted

- Model Training & Validation:
 - AI model trained on a dataset of emergency sirens and tested for classification accuracy.
- Field Testing in Real Driving Scenarios:
 - System deployed in vehicles to evaluate detection reliability in traffic conditions.
- Power Consumption Testing:
 - Assessed battery life under real-world usage scenarios.

10. Performance Metrics – How is it Measured?

- Siren Detection Accuracy:
 - Percentage of correctly identified emergency vehicle sirens.
- False Positive Rate:
 - Rate of misclassification of regular road noises as sirens.
- System Latency:
 - Time taken from sound detection to visual alert activation.
- Power Efficiency:
 - Battery duration per full charge with solar panel support.

11. Tables and Graphs

- Table 1: AI Model Accuracy on Various Road Noise Conditions.
- **Table 2:** Power Consumption Under Continuous Operation.
- **Figure 3:** Signal Processing Flowchart.
- **Figure 4:** Prototype Hardware Setup in Vehicle.

12. Result Analysis – Comparison with Reference Studies

- Higher accuracy compared to traditional siren recognition models.
- More energy-efficient than cloud-based alternatives.

• More practical for deaf drivers than vibration-based alerts, as it provides clear visual cues.

13. Pros, Cons, and Future Work

Pros:

Real-time AI-powered sound detection.

Low-power, solar-rechargeable system.

Standalone operation without network dependency.

Seamless integration into vehicles.

Cons:

Limited to pre-trained sound categories.

Does not integrate with mobile apps for remote notifications.

Potential interference from non-emergency loud noises.

Future Work:

Expand AI model to detect more types of critical sounds.

Introduce mobile app integration for additional accessibility.

Optimize detection accuracy in high-noise environments.

Improve adaptive learning for dynamic road conditions.



Review of "TheAssistBot: Wearable AI Assistant for the Deaf and Mute"

1. Objectives

The project aims to develop a **wearable communication assistant** that leverages **AI-powered sign language recognition** and **speech-to-text translation** to facilitate real-time communication for individuals who are deaf or mute. The primary objectives include:

- **Developing a portable device** capable of translating sign language into text or speech.
- **Implementing speech recognition** to convert spoken words into text for the user.
- **Ensuring low-cost and ease of use** to promote accessibility and everyday use.
- **Exploring future adaptability**, such as supporting object detection to aid visually impaired individuals.

2. Related Work – Survey – Reference Papers

The project builds upon existing advancements in **AI-driven accessibility tools**:

- GnoSys: An app that translates sign language into text and speech using NLP and computer vision, facilitating communication for deaf and mute individuals.
 analyticsindiamag.com
- Jinni: A concept smart speaker equipped with a camera to read sign language inputs, aiming to make virtual assistants accessible to those who are deaf or mute.

yankodesign.com

• **Bee AI**: A wearable personal AI that listens to conversations to provide summaries, personal insights, and reminders, demonstrating the potential of always-listening devices.

Wired

3. Platform – Hardware and Software

Hardware Components:

- **Sipeed Maixduino AI** + **IoT Kit**: Serves as the development board integrating AI capabilities.
- Camera Module: Captures visual input for sign language recognition.

- **Microphone**: Captures audio input for speech recognition.
- **2.4-inch TFT Display**: Displays translated text and system information.
- **LiPo Battery Pack**: Provides portable power for the device.
- External SD Card: Stores AI models and data.
- **Speaker**: Outputs translated speech.
- **3D-Printed Enclosure**: Houses all components in a wearable form factor.

Software Components:

- Machine Learning Models: Trained for sign language recognition and speechto-text conversion.
- **Embedded Firmware**: Manages hardware components and facilitates real-time processing.
- **User Interface**: Displays translations and system status on the TFT screen.

4. Data Acquisition – Real-time Data or Dataset?

- Real-time Data Acquisition:
 - The device captures **live video** of sign language gestures through the camera.
 - It also captures **live audio** through the microphone for speech recognition.

• Pre-trained Datasets:

• Machine learning models are trained on existing datasets of sign language gestures and spoken language to enable accurate recognition.

5. Data Storage – Lookup Table, Cloud, or Dataset?

- On-device Storage:
 - AI models and necessary data are stored on an external SD card for quick access and processing.

• No Cloud Storage:

• The system operates **offline**, ensuring **privacy** and **independence** from internet connectivity.

6. Algorithm Used

• Convolutional Neural Networks (CNNs):

• Utilized for **image recognition** to interpret sign language gestures from video input.

• Recurrent Neural Networks (RNNs):

 Applied for speech-to-text processing, handling temporal aspects of audio data.

Natural Language Processing (NLP):

• Enhances the system's ability to understand and generate human language, improving translation accuracy.

7. Algorithm Execution – Edge, Fog, or Cloud Based?

• Edge Computing:

• All processing occurs **locally on the device**, enabling real-time performance and reducing latency.

• No Cloud or Fog Computing:

 The device does not rely on external servers, ensuring functionality without internet access.

8. UI – End-User Interface (Mobile or Web)?

On-device Interface:

• The **2.4-inch TFT display** provides immediate feedback, showing translated text and system status.

• Physical Controls:

• **Push buttons** allow users to switch modes (e.g., sign-to-text, speech-to-text).

No Mobile or Web Interface:

• The device functions independently without the need for external applications.

9. Experiments Conducted

• Model Training and Testing:

 Machine learning models were trained on datasets of sign language gestures and speech samples.

• Hardware Integration:

• Components were assembled, and firmware was developed to ensure seamless operation.

• Performance Evaluation:

• The system was tested for **accuracy**, **response time**, and **user comfort**.

10. Performance Metrics – How is it Measured?

• Recognition Accuracy:

• Percentage of correctly translated sign language gestures and spoken words.

• Response Time:

• Time taken from input (gesture or speech) to output (text or speech).

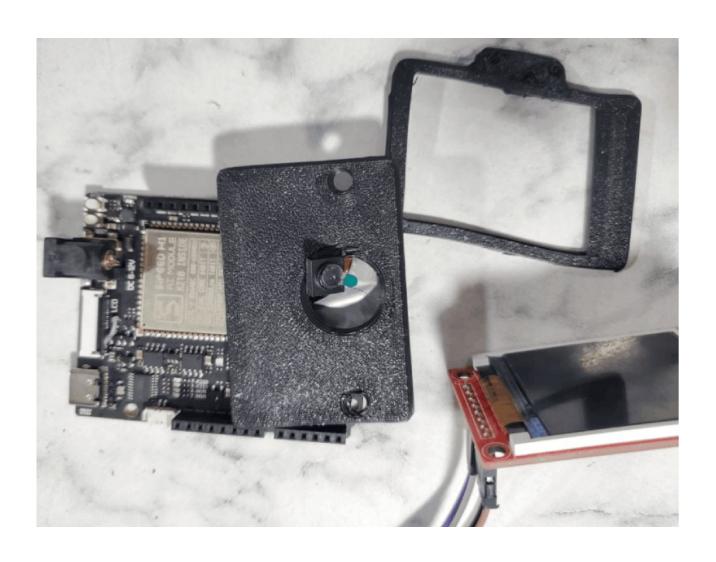
• Battery Life:

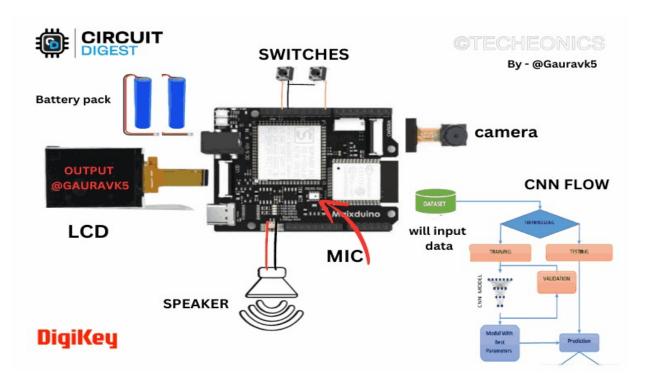
• Duration of continuous operation on a single charge.

• User Feedback:

• Subjective assessments of usability and comfort from test users







Review of "A Deep Learning Based Wearable Healthcare IoT Device for AI-Enabled Hearing Assistance Automation"

1. Objectives

The paper presents an **AI-enabled wearable healthcare IoT device** designed to assist individuals with **hearing impairments**. The key objectives include:

- **Developing a low-cost, real-time AI-powered communication assistant** for the deaf.
- Implementing Google's speech recognition service to convert conversations into text.
- **Deploying an Inception-v4 deep learning model** to classify and detect emergency sounds.
- **Integrating the AI system into a wearable smart-glass display** to provide real-time transcription.
- Ensuring high accuracy (92%) in sound classification while maintaining real-time processing capabilities.

2. Related Work – Survey – Reference Papers

The paper explores existing hearing assistance technologies and their limitations, including:

- **Cochlear Implants (CI):** Neural prosthesis devices that electrically stimulate the auditory nerve. Limitations include **high costs** and **limited accessibility**.
- **Haptic Feedback Devices:** Wearable sensory aids that provide **vibratory feedback based on speech signals**.
- AI-Based Sound Recognition: Prior research on deep learning models for environmental sound detection, but lacking real-time wearable implementations.
- **Speech Recognition for Deaf Users:** Studies on **automated captioning services**, but none addressing **AI-driven emergency sound detection**.

The study highlights **gaps** in current research, particularly in the real-time wearable application of AI-based hearing assistance.

3. Platform – Hardware and Software

Hardware Components:

• **ESP8266 Development Board:** Low-power IoT microcontroller with Wi-Fi capabilities.

- **Microphone Array:** Captures surrounding audio signals for speech recognition.
- **Smart Glasses Display:** Shows real-time transcriptions and emergency alerts.
- **3D-Printed Enclosure:** Wearable housing for easy integration.
- Battery Module: Provides portable, rechargeable power.

Software Components:

- **Google Speech-to-Text API:** Converts live audio into textual data.
- **Deep Learning Model (Inception-v4):** Classifies emergency sounds.
- **Python-Based Sound Processing Algorithm:** Converts audio signals into Mel-Frequency Cepstral Coefficients (MFCCs).
- **Embedded C Firmware for ESP8266:** Handles data transmission and display updates.

4. Data Acquisition – Real-time Data or Dataset?

- Real-Time Data Collection:
 - Microphone captures live audio for both speech transcription and emergency sound detection.
- Dataset for Model Training:
 - **Environmental Sound Classification Dataset** (2000+ labeled urban audio samples) was used to train the AI model.

5. Data Storage – Lookup Table, Cloud, or Dataset?

- On-Device Processing:
 - Real-time AI processing occurs **on the device**, reducing latency.
- Cloud-Based Speech Recognition:
 - Google's cloud-based API handles text conversion.
- Local Lookup Table for Alerts:
 - Emergency sound classifications stored in an on-device database.

6. Algorithm Used

- **Mel-Frequency Cepstral Coefficients (MFCCs):** Extracts key features from audio signals.
- Deep Learning Image Classification (Inception-v4):
 - Converts MFCC spectrograms into image-like representations for AI processing.
- **Transfer Learning:** Fine-tunes pre-trained models for emergency sound detection.

7. Algorithm Execution – Edge, Fog, or Cloud Based?

- Edge Computing for Sound Detection:
 - AI processing occurs **on-device**, ensuring low-latency alerts.
- Cloud Computing for Speech Recognition:
 - Google's cloud service handles real-time text transcription.
- Hybrid Approach:
 - Emergency sound detection is **localized**, while speech-to-text relies on the cloud.

8. UI – End-User Interface (Mobile or Web)?

- Wearable Display UI:
 - Outputs text-based conversation captions.
 - Displays emergency alerts in real time.
- Physical User Controls:
 - Allows toggling between conversation mode and alert mode.
- No Mobile or Web Interface:
 - Designed as a standalone wearable device.

9. Experiments Conducted

- Model Training and Testing:
 - Inception-v4 model was trained on **urban sound classification datasets**.
- Speech Recognition Evaluation:
 - Tested performance of Google's speech-to-text API in different noise environments.
- Real-World Usability Testing:
 - Evaluated latency, accuracy, and power consumption in real-world settings.

10. Performance Metrics – How is it Measured?

- Recognition Accuracy:
 - Speech-to-text transcription accuracy.
 - Sound classification accuracy (92% in controlled environments, 82% in real-world settings).
- Latency Measurement:
 - Time taken from sound input to alert output.
- False Positive Rate:
 - Number of misclassified emergency sounds.
- Battery Efficiency:

• Power consumption of real-time AI processing.

11. Tables and Graphs

- **Table 1:** Sound classification accuracy comparison (Inception-v4 vs. VGG16).
- **Table 2:** False positive rates in controlled vs. real-world settings.
- **Figure 3:** Sample spectrograms of detected emergency sounds.
- **Figure 4:** Speech recognition processing time comparison (Google Cloud vs. Offline model).
- **Figure 5:** Wearable device prototype images.

12. Result Analysis – Comparison with Reference Studies

- Outperforms previous studies in emergency sound detection (92% accuracy vs. <85% in prior works).
- Lower-cost alternative to cochlear implants and haptic feedback systems.
- Improves accessibility by integrating a wearable, hands-free solution.
- Limitations:
 - Cloud dependency for speech recognition introduces potential latency.
 - Model performance decreases in noisy environments (82% accuracy in real-world vs. 92% in controlled environments).

13. Pros, Cons, and Future Work

Pros:

Real-time hearing assistance for the deaf.

AI-driven emergency sound classification.

Low-cost alternative to existing hearing aids.

Wearable and non-invasive.

Edge computing ensures low-latency alerts.

Cons:

Cloud dependency for speech recognition.

Accuracy drops in high-noise environments.

No support for sign language translation.

Future Work:

Improve AI model robustness for noisy environments.

Implement offline speech recognition to reduce cloud dependency.

Expand dataset with more diverse urban sound samples.

Integrate sign language recognition for full assistive capabilities.



FIGURE 5. Example of custom font type displayed on the micro-LCD (Note the text is reversed.)

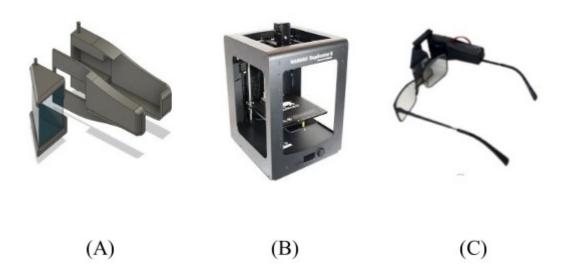


FIGURE 6. Conception and production of smart glasses: (A) The custom 3D model developed for this research; (B) The Wanhao Duplicator 6 FDM 3D Printer, used to print the enclosure; and (C) The final product attached to a pair of glasses

Review of "Embedded Based Hand Talk Assisting System for Deaf and Dumb"

1. Objectives

This paper introduces an **embedded system-based hand talk assisting device** designed to facilitate communication for **deaf and mute individuals**. The key objectives are:

- To develop a wearable communication aid that converts sign language into speech and text.
- **To use flex sensors** to capture hand gestures for sign language interpretation.
- To implement an LCD display and speaker output for real-time communication.
- To store frequently used words in a voice chip (APR9600) for quick retrieval.
- To provide dual-mode communication:
 - **Hand gesture recognition** for sign language users.
 - Keypad input for text-based communication.

2. Related Work – Survey – Reference Papers

The study builds upon existing **gesture-based communication systems**, citing:

- **Glove-based sign language interpreters** that use flex sensors to map hand movements to predefined text and speech outputs.
- **Speech synthesis systems** that assist the mute in verbal communication using **pre-recorded voice outputs**.
- **Sensor-based assistive technology research**, particularly in robotics and automation for individuals with disabilities.
- **Previous implementations of sign-to-text systems**, though many lacked real-time interaction and portability.

3. Platform – Hardware and Software

Hardware Components:

- **Flex Sensors:** Attached to glove fingers to detect bending angles.
- Microcontroller (AT89C51): Processes gesture data and controls output devices.
- **ADC** (Analog-to-Digital Converter): Converts flex sensor signals into digital format.
- **APR9600 Voice Chip:** Stores pre-recorded speech for voice output.
- **Speaker:** Outputs voice messages based on hand gestures.

- LCD Display: Provides textual representation of translated sign language.
- **Keypad:** Allows alternative input for users who prefer text-based communication.

Software Components:

- **Keil Compiler:** Used for writing and compiling microcontroller firmware.
- **Proteus Simulation Software:** Used to test circuit design and LCD interactions.
- **Embedded C Programming:** Controls microcontroller operations, gesture mapping, and output processing.

4. Data Acquisition – Real-time Data or Dataset?

• Real-Time Data Collection:

- Flex sensors continuously monitor hand gestures and transmit data to the microcontroller.
- Keypad inputs provide an alternative data source for text-based communication.

No Pre-Trained Dataset Used:

 Gesture recognition is based on pre-mapped voltage thresholds stored in the microcontroller.

5. Data Storage - Lookup Table, Cloud, or Dataset?

On-Device Storage:

- Voice chip stores frequently used speech phrases.
- Microcontroller stores gesture-to-text mappings in its memory.

• Lookup Table for Gesture Interpretation:

- Each flex sensor reading is mapped to a corresponding word/phrase using predefined voltage ranges.
- No Cloud or External Database Usage.

6. Algorithm Used

• Gesture Mapping Algorithm:

Maps specific hand gestures to predefined text and speech outputs.

• Keypad Input Handling Algorithm:

• Detects key presses and displays corresponding text on the LCD.

Voice Playback Algorithm:

 Retrieves pre-recorded phrases from APR9600 voice chip and outputs them via speaker.

7. Algorithm Execution – Edge, Fog, or Cloud Based?

- Edge Computing (On-Device Processing):
 - All computations occur on the AT89C51 microcontroller.
 - No reliance on cloud-based processing, ensuring real-time performance.

8. UI – End-User Interface (Mobile or Web)?

- Physical UI:
 - LCD screen displays translated gestures or keypad inputs.
 - Speaker provides auditory feedback for hearing users.
- No Mobile or Web Interface:
 - Designed as a standalone wearable device for direct communication.

9. Experiments Conducted

- Gesture Recognition Testing:
 - Various hand gestures were tested for response accuracy.
- LCD and Keypad Testing:
 - Verified text output accuracy for keypad inputs.
- Voice Playback Testing:
 - Ensured clear audio output from the APR9600 voice chip.

10. Performance Metrics – How is it Measured?

- Gesture Recognition Accuracy:
 - Percentage of correctly recognized hand movements.
- Response Time:
 - Time taken from gesture input to text/speech output.
- Speech Clarity:
 - Subjective evaluation of voice output quality.

11. Tables and Graphs

- **Table 1:** Flex Sensor Voltage vs. Gesture Mapping.
- **Table 2:** Keypad Input vs. LCD Output.
- **Figure 4:** LCD Output Simulation in Proteus.
- **Figure 6:** Flex Sensor Output Analysis.
- **Figure 7:** Voice Chip Interfacing Diagram.

12. Result Analysis – Comparison with Reference Studies

• Improves upon prior glove-based systems by adding dual-mode communication (gesture & keypad).

- **Higher accuracy in sign recognition** due to dedicated voltage mapping.
- · Lacks AI-based adaptability, making it dependent on predefined gestures.

13. Pros, Cons, and Future Work

Pros:

Real-time translation of sign language to text and speech.

Portable and low-cost compared to commercial alternatives.

Standalone device that does not require external connectivity.

Dual-mode communication (gesture & keypad) increases usability.

Cons:

Limited vocabulary due to predefined gesture mappings.

No cloud integration for dynamic updates or learning.

Voice chip storage capacity is restricted to a few seconds per phrase.

Future Work:

Implement AI-based gesture recognition for dynamic learning.

Expand vocabulary size with a more advanced speech synthesis module.

Introduce Bluetooth or mobile app connectivity for remote updates.

Enhance speaker quality for clearer voice output.

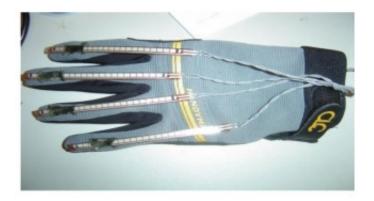


Figure.5 Flex sensor attached to glove in the hand is used to perform. Gesture by deaf and dumb people.

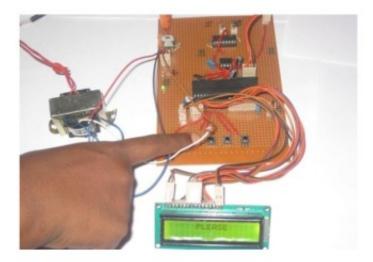


Figure.6 LCD Display output in mode 2

References:

- 1) <u>https://hackaday.io/project/191087-pionear-making-roads-safer-for-deaf-drivers</u>
- 2) <u>https://circuitdigest.com/microcontroller-projects/theassitbot-wearable-ai-assistant-for-the-deaf-and-mute</u>
- 3) An Improved Smart Helmet for Safe Travel of Deaf People Based on Embedded System PeiyeSun, Junqiu Luo, Can Wang, Di Wu(Tianjin College, University of Science and Technology Beijing, Tianjin, China) {Base Paper}
- 4) A Deep Learning Based Wearable Healthcare IoT Device for AI-Enabled Hearing Assistance Automation FRASER YOUNG, LI ZHANG, RICHARD JIANG, HAN LIU and CONOR WALL
- 5) Embedded Based Hand Talk Assisting System for Deaf and Dumb