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MEMS based Wearable Smart-Glove and its Application of Gesture Detection and Sign Language Classification for Vocally Impaired with Integrated Health Monitoring System

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Abstract: Interactions between individuals with speech difficulties and those without have always posed challenges in communication. Gestures and sign language are recognized as the most natural and expressive means of communication between individuals with speech difficulties and those without. Through the utilization of glove-based communication systems designed for the hearing impaired, this intelligent glove enables individuals with vocal disabilities to engage in communication with others by using their sign language. Each glove is equipped with an embedded signal. The gesture module adapts the resistance of the flex sensor and accelerometer to correspond to specific gestures. Additionally, the design includes a text-to-speech converter that transforms intended actions into spoken output, which is then emitted through a speaker or transmitted via Bluetooth to a connected phone. This prototype also incorporates automatic message alerts for relevant parties, along with health monitoring capabilities for detecting human body temperature and heart rate. Overall, the health monitoring system is a valuable addition to the smart glove-based communication device, and it further enhances its potential to improve the lives of individuals with speech impairments.

Keywords: *Flex sensors, Bluetooth Device, micro-controller, Internet of Things, Health Monitoring, Raspberry Pico, LCD Display, APR 9600, Temperature Sensor, Heart Beat Sensor, Speaker, Analog to Digital Convertor, MEMS acceleration sensors*

1. Introduction

The MEMS (Micro-Electro-Mechanical Systems) based wearable smart-glove [1-2] is a device that is designed to assist individuals with speech impairments in communicating with others using sign language. The smart-glove uses gesture detection and sign language classification to translate the wearer's hand movements into spoken or written language, facilitating easier communication with people who do not comprehend sign language. In addition to its communication capabilities, the smart-glove also incorporates an integrated health monitoring system that can detect changes in body temperature and heart rate. This feature can help individuals and their caregivers monitor their health and detect any potential health issues early. Overall, the MEMS based wearable smart-glove is a promising technological innovation that has the potential to significantly improve the quality of life for individuals with speech impairments. Wireless data gloves resembling ordinary fabric driving gloves are employed, featuring accelerometers and flex sensors. These gloves enable individuals who are not mute to utilize hand gestures, which are then converted into speech and text output.

The output is delivered through a speaker and displayed to facilitate the understanding of non-verbal individuals' expressions. In addition, this device incorporates health monitoring sensors that enable individuals with speech impairments to notify concerned individuals of any changes in their health status. Gestures [3-4] can stem from various physical actions or mental states, but they often originate from hand movements. Developing a system capable of identifying specific human gestures and utilizing them for communication or information transfer is a key focus of gesture recognition research. The prototype extends its capabilities to include health monitoring sensors that send notifications to relevant parties regarding the user's health status. This prototype offers significant advantages, particularly in terms of easy accessibility and affordability for individuals who are deaf and mute. The glove possesses the ability to detect and interpret hand movements, converting them into widely recognized formats. The resulting output encompasses both audio and visual content. The display unit specifically concentrates on transforming the hand movements into textual form, which is then displayed on an LCD

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screen. The LCD display module and the voice synthesis module are both alerted by the gesture detection module [5]. An LCD plus a microprocessor make up the LCD display module. The LCD display module analyzes each signal and subsequently compares it with previously stored values. The microcontroller decides what should be displayed based on this comparison, and after reaching that determination, it notifies the LCD what should be displayed by sending it an eight-bit address. The sensing gadget detects three acceleration directions and four values from flex sensors. Our sensing system generates an analog reading for each of the three acceleration axes. The controller's lookup database contains the acceleration values associated with specific motions [6]. The incoming gesture's values for all three dimensions are compared to their corresponding entries in the database. The margin of error is determined by comparing the signal values on each axis with the previously stored values. Each gesture corresponds to a unique set of commands delivered to the respective voice chip channel. When the incoming acceleration value matches the recorded value, the corresponding instruction is displayed, and the corresponding channel is activated. Due to the weak signal strength (only 5), amplification is necessary before the voice chip's output is played through the speaker. When a recognized motion matches one of the already collected gestures, one of the eight channels in the speech chip is promptly activated. The APR9600 speech chip can also transmit similar information through speakers. This eliminates the need for user training prior to use. The desired results can also be achieved using the Bluetooth module of the user's mobile phone.

2. Literature Review

Deep Learning and Computer vision: According to [7], individuals with hearing or speech difficulties can engage in communication through sign language. Sign language users rely on nonverbal movements to express their thoughts and emotions. However, comprehending sign language poses significant challenges for those who are not familiar with it, necessitating the presence of skilled sign language interpreters during training sessions, meetings, and various contexts such as legal, medical, and educational settings. The need for services which can translate has increased during the previous five years. Presently, there are alternative solutions available, such as utilizing high-speed video for remote human interpretation. However, these options may offer a seemingly straightforward implementation but still face significant challenges when it comes to accurately interpreting sign language. We provide inclusion of two models to recognize the gestures for required sign language in order to address. In the process of training an algorithm to recognize American Sign Language, we utilize a specific dataset containing video recordings of various hand motions. This dataset encompasses a range of motions that were performed repeatedly across different video and contextual scenarios. To ensure ease of use, the videos are captured at a standardized frame rate. We advise utilizing the CNN (Convolutional Neural Network) model Inception for The video stream is utilized for extracting spatial information in order to recognize Sign Language. We can then use an LSTM and an RNN model for extracting temporal information from the video sequences which uses the respective outputs obtained from the Softmax and Pool layers of the CNN.

Cooperative Sequential Hand Gesture Recognition: Referring to source [8-11], the rapid evolution of technologies such as natural language processing and computer vision, has led to the emergence of artificial intelligence (AI). This field has gained significant prominence in recent times, revolutionizing various aspects of our lives. The significance of human hands in communication and human-computer interaction (HCI) has made hand gesture recognition (HGR) a critical field of research. HGR is currently a highly dynamic area of study within computer vision (CV), as it heavily depends on image processing and hardware designed for vision-based applications. However, traditional approaches to vision-based HGR have limitations and can be affected by diverse environmental conditions and complex backgrounds. A novel wearable device has been developed to address these challenges by integrating a smart glove with a pressure sensor array, along with the MYO armband equipped with inertial measurement unit (IMU) and electromyography (EMG) sensors. The pressure sensor array captures the pressure distribution data from each finger, which is then utilized in a classification algorithm to recognize consecutive hand movements. To perform the categorization task, the system incorporates deep learning techniques, which have demonstrated success in numerous applications. The wearable system underwent testing with a dataset comprising 50 test subjects and encompassing ten distinct hand gestures, resulting in an impressive overall accuracy of 92.86%. With its versatility for various applications, this system presents a promising alternative to existing vision-based hand gesture recognition (HGR) methods, particularly in fields such as sign language recognition and human-computer interaction (HCI).

An Effective Glove-based Gesture Recognition System using Wireless Multi-Channel Capacitive Sensors and AI: In a study mentioned in reference [12-15], an innovative gesture recognition system using a wireless multi-channel capacitive sensor and artificial intelligence (AI) was developed. The research focused on utilizing a smart glove integrated with sensors to identify and distinguish between 26 diverse objects. By employing multiple sensors, the device demonstrated its ability to perceive and handle progressively more complex tasks within the physical environment. However, existing smart glove prototypes have limitations in terms of lacking wireless communication support or lacking the necessary sensor interface circuits, thereby restricting their practicality [16]. This study presents a hardware-software approach for 16-channel capacitive pressure sensing and gesture recognition using an efficient and effective Raspberry Pi device. The proposed technique utilizes a code modulation data scheme to capture inputs, enabling the integration of machine learning algorithms directly without the requirement of additional wireless receivers or delay-inducing server decision-making processes [17]. The practicality of this method is evaluated through experimental results and the application of various machine learning strategies.

Soft wrist-worn multi-functional sensor array for real-time hand gesture recognition: In reference to [18-20], hand gesture recognition plays a pivotal role in various applications, including virtual and augmented reality, upper extremity rehabilitation, and machine user interfaces. Wearable technology equipped with sensors, such as pressure sensors, inertial measurement units (IMU), strain sensors, acceleration sensors, and electromyography (EMG), presents a viable approach for achieving real-time hand gesture recognition. This technology allows for continuous and long-term detection of hand gestures. EMG and IMU-based smart bracelets, along with collaborative computing frameworks utilizing multi-sensor data integration in body sensor networks (BSNs), have emerged as commercial options for hand gesture recognition and human-robot interaction [21-22]. However, conventional sensors used in these applications may cause discomfort when worn for extended periods due to compatibility issues with the skin interface. To address this concern, researchers have developed highly stretchable and flexible soft electronics, enabling continuous detection of hand motions while ensuring user comfort. Soft electronics, such as soft wrist-worn sensor systems (SWSS), offer innovative solutions for epidermal electronics, enabling control over the motion of quadrotor aircraft and hand gesture recognition [23]. SWSS devices can be comfortably worn on the posterior side of the wrist and incorporate soft, conductive polymer-based sensors for electromyography (EMG), strain, and pressure detection. By utilizing support vector machines (SVM) and linear discriminant analysis (LDA) techniques, a recognition framework can be constructed based on SWSS data, allowing for performance evaluation of the system [24].

Wearable Bio sensing Gloves: As mentioned in reference [25], wearable sensing gloves and sensory feedback devices have significant applications in healthcare, robotics, prosthetics, and simulated 3D environments, allowing for the recording and enhancement of hand experiences. Recent advancements in soft actuators, flexible bio-electronics, and wireless systems have facilitated the development of ergonomic, lightweight, and cost-effective wearable devices [26-28]. This comprehensive review article covers the latest materials, actuators, sensors, and system-packaging technologies used in the creation of wearable sensing gloves with sensory feedback. The integration of these wearable sensing devices with sensory feedback further enhances their potential as assistive tools for individuals with prosthetic limbs and sensory impairments. The review is divided into two sections: the first focuses on the technology employed in creating pressure, strain, and temperature sensors integrated into versatile wearable sensing gloves, while the second section explores tools and methodologies for incorporating sensory displays. The article also discusses the future direction of the field and highlights current limitations in technology and methodologies. In summary, this research provides an in-depth exploration of the technologies essential for the development of wearable sensing gloves and sensory feedback devices[29-30].

3. Methodology

The gloves consist of two modules, a gesture detection module and a health care system. The gesture detection module is a key component of the smart-glove system that enables it to recognize and interpret hand movements and gestures. The health monitoring system integrated into the smart-glove is another important component that provides real-time health information to the user.

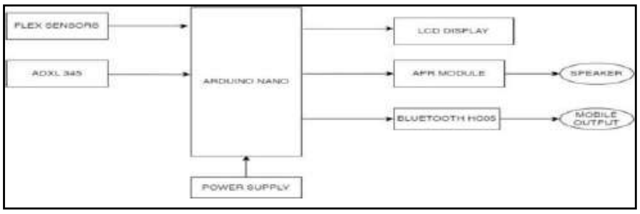

Fig 1: Module 1 - Architecture of Gesture Recognition Module using Arduino Nano

The architecture of the suggested MEMS-based gesture recognition system is shown in Figure 1. The sensing gadget detects flex sensor values and acceleration along three axes. Flex sensors, a MEMS accelerometer, an LCD display, an APR module, and Bluetooth are all integrated into the system utilising the Arduino Nano controller.

Arduino Nano: A compact, breadboard-compatible microcontroller board is the Arduino Nano. The board is equipped with 14 digital input/output pins, 8 analog input pins, and a USB interface for programming and communication with external devices. The Arduino Nano is equipped with a 16 MHz clock speed, 32 KB flash memory,2 KB SRAM, and 1 KB EEPROM, making it suitable for a variety of projects and applications. We store multiple gestures and its output in the microcontroller, which detects the gestures made and gives the corresponding output. The open-source hardware and software of the Arduino Nano enable users to modify and customize the board to their specific needs, making it a flexible and accessible tool for anyone interested in electronics and programming.

Flex Sensors: The resistive carbon components are the foundation of the Flex Sensor's proprietary technology. Flex sensors are attached to the glove. They require a 5-volt input and have an output range of 0 to 5 V, with the voltage output fluctuating in accordance with the degree of bend in the sensor and the resistivity. Resistance will only shift in one direction. Resistance rises to 30- 40 kilo ohms at 90 degrees as the flex sensor is bent. It is simple to detect which of these levels the finger is at any given time, and how much the finger has been bended. The last step is to integrate each finger's movement into a single hand motion and give it a name.

MEMS acceleration sensors: MEMS accelerometer sensors are an important component of the MEMS based wearable smart-glove for gesture detection and sign language classification. The Gesture Vocalizer system uses an accelerometer as a tilt sensor. An ADXL335 accelerometer measures how much the hand is tilting in three directions. 1.5 volts to 3.5 volts is the range of analogue output of accelerometer.

LCD Display: To transform the hand movements into textual format, the system converts them and displays the text on an LCD

Table 1. Example of full page table

Fungal Symptom	*Causal organism*	*Family*	*Order*	*Class*	*Subdivision*	*Affected part*
Mango Anthracnose	Glomerella cingulata	Glomerellaceae	Incertaesedis	Sordariomycetes	Sordariomycetidae	stem, leaf, fruit
Mango Powdery mildew	Oidium mangiferae	Erysiphaceae	Erysiphales	Leotiomycetes	Leotiomycetidae	stem, leaf, fruit
Pomegranate Anthracnose	Glomerella cingulata	Glomerellaceae	Melanconiales	Sordariomycetes	Pezizomycotina	stem, leaf, fruit

screen. Simultaneously, the voice synthesis module receives the signal from the gesture detection module, while the LCD display module analyzes the signal and compares it to pre-existing saved values. The microprocessor decides what should be displayed based on this comparison, and after making this decision, The microcontroller transmits an eight-bit address to the LCD, indicating the content that should be presented on the display. This can help deaf people to understand sign language.

APR Module: Using a flash non-volatile memory method, the APR 9600 is a voice recorder and playback device developed by A plus integrated circuits. It has a analogue storage technique that allows each cell to store up to 256 voltage levels. The response of the built-in anti-aliasing filter is automatically adjusted based on the selected sampling frequency. The signal is subsequently directed to the memory array using a combination of analog read/write operations and sample and hold circuitry. Incoming voice signals are sampled, and instantaneous voltage samples are recorded in non-voltaic flash memory cells which uses 8-bit binary encoding scheme. The recorded signals are retrieved from memory during playback. We store voice outputs for various gestures made using the record mode, and the same is played for the corresponding gestures using its playback mode.

Bluetooth Module and mobile output: HC-05 Bluetooth module is connected to microcontroller. By using Bluetooth and Arduino Bluetooth text to speech mobile application we can provide the text and voice output in the phone as well which can provide additional advantages. Users can customize the pitch, speed, and volume of the speech output to suit their needs, and can also choose from a variety of languages and accents.

Algorithm 1 : Algorithm for detecting gesture

1. Initialize the necessary libraries and variables.
2. Set up the pins for voice output and initialize the LCD display.
3. Begin serial communication and check if the accelerometer Sensor is connected.
4. Enter the main loop.
5. Call the **Flex_Read()** function repeatedly to read the values From flex sensors and accelerometer.
6. Read the analog values from four flex sensors (F1 to F4) using **analogRead()**.
7. Read the X and Y acceleration values from the accelerometer using **accel.getEvent()**.
8. Based on the sensor readings, perform the following actions :
   a. If (F1 is low and F2, F3, and F4) == high, display and output **"Hello."**
   b. If (F2 is low and F1, F3, and F4) == high, display and output **"I Need Food."**
   c. If (F3 is low and F1, F2, and F4) == high, display and output **"I Need Water."**
   d. If (F4 is low and F1, F2, and F3) == high, display and output **"Get Me My Medicines."**
   e. If (F1 and F2 are low, and F3 and F4) == high, display and output **"Super."**
   f. If (F1 and F3 are low, and F2 and F4) == high, display and output **"What is Your Name."**
   g. If (F1 and F4 are low, and F2 and F3) == high, display and output **"Thank You."**
   h. If (F2 and F3 are low, and F1 and F4) == high, display and output **"Sorry I Cannot Speak."**
   i. If (F2 and F4 are low, and F1 and F3) == high, display and output **"The Work Is Finished."**
   j. If (F3 and F4 are low, and F1 and F2) == high, display and output **"Let's Go Out."**
   k. If (F1, F2, and F3 are low, and F4) == high, display and **output "I Need to Use Washroom."**
   l. If (F1, F2, and F4 are low, and F3) == high, display and output **"Too Complicated."**
   m. If (F1 is low, and F2, F3, and F4) == high, display and output **"Take Me Home."**
   n. If (F1 is high, and F2, F3, and F4) == low, display and output **"How Are You??"**
   o. If (F1, F2, F3, and F4) == low, display and output **"Bye Have a Nice Day."**
   p. If the X value from the accelerometer is below -7.5, display and output **"Come."**
   q. If the X value from the accelerometer is above 7.5, display and output **"Go."**
   r. If the Y value from the accelerometer is below -7.5, display and output **"I Agree."**
   s. If the Y value from the accelerometer is above 7.5, display and output **"I Disagree."**
9. Repeat the loop.

The algorithm is designed for a gesture-detecting hand gloves system, which can interpret hand movements and flex sensor values to perform various actions. First, the necessary libraries and variables are initialized. The pins for voice output and the LCD display are set up. Serial communication is started, and the connection to the accelerometer sensor is checked. The program then enters the main loop, where it repeatedly calls the Flex_Read() function. This function reads the analog values from four flex sensors (F1 to F4) using the analogRead() function. It also retrieves the X and Y acceleration values from the accelerometer using the accel.getEvent() function. Based on the sensor readings, specific actions are performed. For example, if F1 is low and F2, F3, and F4 are high, the system displays and outputs "Hello." Similarly, different combinations of flex sensor values trigger specific messages or actions, such as requesting food or water, asking for medicines, expressing gratitude, or indicating agreement or disagreement. Additionally, the algorithm takes into account the accelerometer readings. If the X value is below -7.5, the system displays and outputs "Come." If the X value is above 7.5, it displays and outputs "Go." Similarly, if the Y value is below -7.5, the system displays and outputs "I Agree," while an above 7.5 Y value triggers the display and output of "I Disagree." The main loop continues to execute, allowing real-time gesture detection and response. This algorithm forms the core logic of the gesture-detecting hand gloves system, enabling users to interact with the system through hand movements and flex sensor inputs.

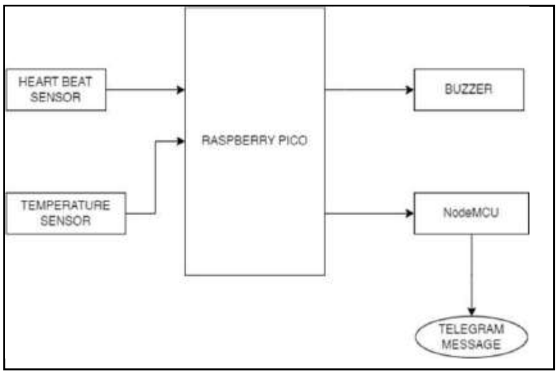

Fig 2: Module 2 - Architecture of Health Monitoring Module using Raspberry Pico

Raspberry pi pico: The Raspberry Pi Foundation created the Raspberry Pico, is costs less and a microcontroller board with high performance. This device incorporates a powerful dual-core ARM Cortex-M0+ processor with a clock speed of up to 133 MHz, accompanied by 264 KB of RAM. The board is designed to be highly versatile, with a variety of input/output (I/O) options, including 26 multi-function general-purpose input/output (GPIO) pins, 3 analogue inputs, and 2 programmable I2C, SPI, and UART controllers. Raspberry Pico is designed to be highly programmable, with support for a range of programming languages, which includes C/C++, CircuitPython and Micropython.

Heart rate and Temperature sensors: The heart rate sensor will measure the individual's pulse rate by detecting the change in blood volume in the capillaries of the fingertip. It is used to monitor the pulses of the heart. These pulse signals are sent to the microcontroller and compared with the threshold pulse value to identify abnormal pulse rate. Temperature sensors can detect variations in body for every degree Celsius change in temperature. These two sensors will be connected to the Raspberry Pi Pico via its analog-to- digital converter (ADC) pins. These can detect any medical emergencies in the user’s body.

Node MCU: Based on the ESP8266 Wi-Fi chip, NodeMCU is a board with open-source firmware. It is intended to make the development of IoT projects simple. Providing a low- cost and easy-to-use platform. The board features an ESP8266 chip that provides Wi-Fi connectivity, along with a USB-to- serial interface for easy programming and debugging. NodeMCU is programmable with the Luascripting language, which allows for quick and easy development of IoT applications. It also supports programming with Arduino IDE and MicroPython, making it a versatile platform for a range of projects.

Buzzer: A buzzer is used in the health monitoring system of the MEMS based wearable smart-glove as an alert mechanism to notify the user of any abnormal health conditions or changes in their vital signs. For example, if the user's heart rate falls outside of a predetermined normal rate.

The health monitoring system can activate the buzzer and alert the user of the potential health concern. This can be particularly important for vocally impaired individuals who may have difficulty communicating their symptoms or who may not be able to hear or see traditional alarm systems.

The algorithm describes a health monitoring system that is designed to continuously monitor a person's heartbeat and body temperature. It consists of two main functions: HEART_BEAT_MONITOR () and TEMP_READING ().In the HEART_BEAT_MONITOR () function, the system resets the heartbeat count and clears the display. It then starts measuring the heartbeat for a specific duration. If the measured heartbeat falls below a certain threshold, the count is incremented. After the measurement period, the system analyzes the heartbeat value. If it exceeds a predefined threshold, indicating an abnormality, an alert buzzer is triggered, and an emergency message is sent to notify the caretaker. In the TEMP_READING() function, the system reads the temperature from a sensor. It converts the sensor value into degrees Celsius. The system then checks if the temperature value is outside a normal range. If it is, indicating a potential issue, the alert buzzer is activated, and an emergency message is sent to inform the caretaker about the abnormal temperature reading. The main loop of the algorithm ensures that these monitoring functions are repeated continuously, allowing real-time monitoring of the person's health. Whenever abnormal values are detected, the system generates alerts and sends emergency messages to ensure timely attention from the caretaker.

Before presenting the UML diagram illustrating the key components and interactions of our project's modules, it is important to provide a brief overview of the system's implementation. Our project is a pure IoT-based solution that focuses on two main modules: the Gesture Detection Module and the Health Monitoring Module. The Gesture Detection Module enables intuitive interaction with the system by recognizing and interpreting user gestures. It utilizes sensors and IoT devices to capture and process gesture data in real-time, providing seamless and responsive user experiences. The Health Monitoring Module utilizes IoT-enabled wearable devices to gather and analyze essential health parameters, including heart rate, blood pressure, and body temperature. It establishes a seamless connection between the devices and the system, allowing for continuous monitoring and proactive health management. The forthcoming use case diagrams, will provide a comprehensive visual representation of the functionalities and interactions within these modules.

Algorithm 2 : Algorithm for the Health Monitoring System

```
1. Initialize the heartbeat sensor, buzzer, and temperature sensor

2. Enter the main loop function. Void main()

3. //To measure the Heartbeat
   HEART_BEAT_MONITOR ( ):
   a. Reset the heartbeat count.
   b. Clear the LCD display.
   c. Start measuring the heartbeat for 5 seconds.
      If heartbeat_value < 100 :
        count = count + 1
      // wait till heart beat goes above the threshold value
   d. heartbeat_value = heartbeat_value * 12
   e. If heartbeat_value > 90 :
      Trigger an alert buzzer.
      Trigger an emergency message.
   f. end If
   g. end If
```

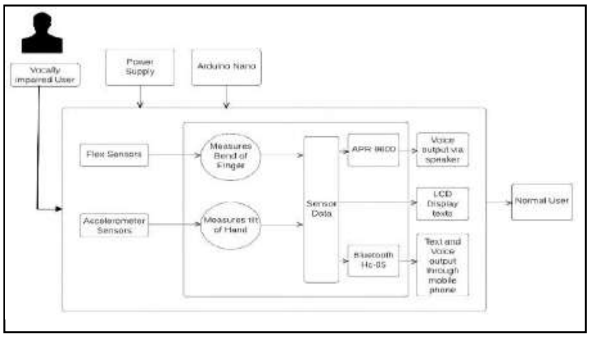

Fig 3: Use case diagram for gesture recognition module

In this use case diagram, the primary actor is the Vocally-Impaired User, who interacts with the smart glove to perform various functions. The use cases are as follows: Convert Sign Language: The User performs sign language, which is detected by the flex sensors and accelerometer in the smart glove. The glove then converts this data to both voice and text output using the APR module and speaker output and LCD display. Display Output: The translated sign language output is displayed on the LCD display as text, providing the User with an immediate way to see the translation. Voice Output: The translated sign language output is produced as voice output using the speaker output interface. Bluetooth Output: The smart glove can connect to a mobile device through Bluetooth to allow for transmitting the translated data to a mobile device. This use case diagram provides a clear visual representation of the various functions of the smart glove and how they work together to convert sign language gestures into both voice and text output, without relying on machine learning. The use case diagram presents the functions of a smart glove for converting sign language gestures into voice and text output. The user performs sign language gestures, which are recognized by the smart glove through its sensors and algorithms. The recognized gestures are then converted into voice output allowing non sign language users to understand the message audibly.

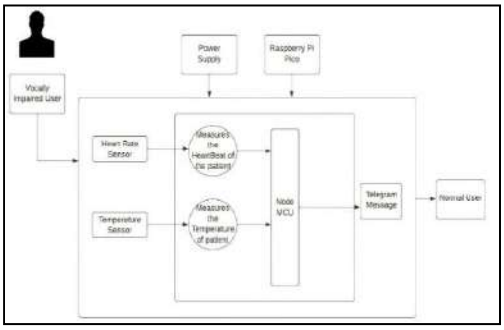

Fig 4: Use case diagram for health monitoring module.

The above diagram illustrates the main use cases for the health monitoring project. The user is the primary actor in the system.

The first two use cases are to measure the heart rate and temperature, respectively. These readings are then checked against the predefined threshold values to ensure that they are within safe limits. If the readings exceed the threshold values, then a telegram message is sent to the caretaker using the Node MCU module. The use cases involve processing the data using the Raspberry Pi Pico microcontroller. Finally, the last use case involves comparing the readings with the threshold values and sending a telegram message to the caretaker in case of any abnormalities and sounding a buzzer.

4. Results And Discussion

Our MEMS based hand glove gives us output in three different ways one of the output will be heard from the speaker via APR Module, the other one will be projected on the LCD Display, the last one will be shown in the mobile application via the Bluetooth module.

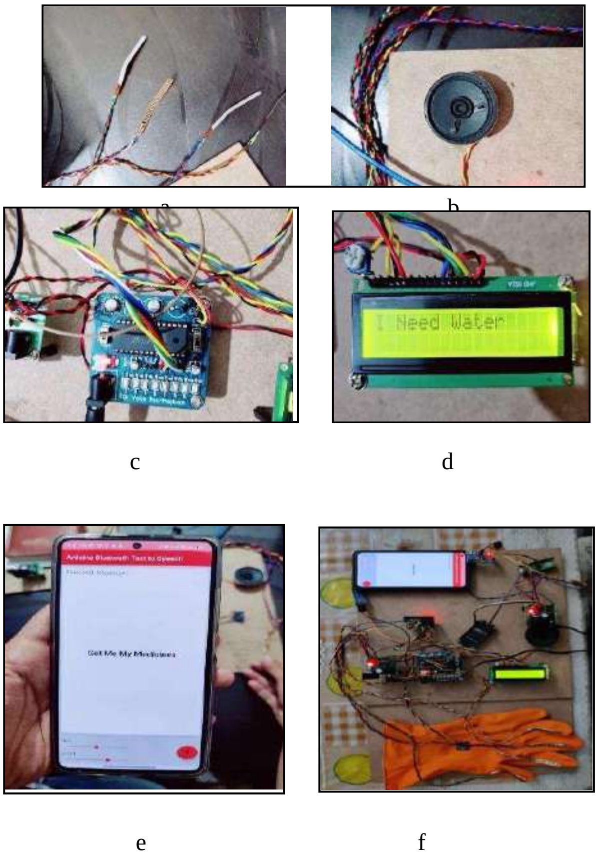

Fig 5: Photos of the model (a) Flex Sensor; (b) Speaker; (c) APR Module; (d) LCD Display; (e) Mobile Output; (f) Final Model

Figure 5(a) shows the flex sensor, which is a wearable device that measures the degree of bending of the user's fingers. This sensor is critical for detecting and recognizing hand gestures, as it provides real-time information about the user's hand movement. Figure 5(b) shows the speaker, which is used to provide audio feedback to the user based on the recognized hand gesture. An APR module has also been used, as shown in Fig 5(c), which is responsible for processing the data obtained from the flex sensor and providing the necessary information to the system. Figure 5(d) shows the LCD display, which is used to display the recognized hand gesture and other relevant information to the user. Figure 5(e) depicts the mobile output, which is used to send the recognized hand gesture to a mobile device for further processing or interaction. Finally, in Fig 5(f), the final model of the hand gesture recognition system can be seen, which integrates all of the components mentioned above.

5. Conclusion

The proposed smart glove system aims to offer a more intuitive and efficient means of communication for individuals who face challenges in speaking or expressing themselves, such as those who are deaf or mute. These gloves are equipped with sensors and electronic components capable of detecting hand gestures and finger movements. The captured gestures are then translated into speech or text, which can be conveyed through a connected device like a smartphone or speaker. By leveraging this technology, the existing communication gap between the general public and individuals who are deaf or mute can be significantly reduced, enabling enhanced and smoother interactions. Apart from serving as a communication tool, the suggested technology holds the potential to provide additional benefits to the deaf and mute communities, further improving their overall experience. For instance, this system has the capability to monitor and identify any unusual health concerns, thereby providing timely indications for emergency care personnel. This feature plays a crucial role in ensuring that individuals within these communities receive prompt and appropriate medical attention when needed. In order to maximize accessibility, the smart gloves are intentionally designed to be user-friendly and created in a manner that allows effortless wearing and utilization by individuals of all backgrounds. The Arduino Nano and Raspberry Pico, functioning as the system's central processing unit, offer a user-friendly experience and seamless configurability, eliminating the need for extensive software code modifications. One of the main advantages of the proposed system is its ability to function independently in everyday life, which significantly contributes to its appeal and market value. In conclusion, the suggested smart glove system designed for individuals with speech impairments has the potential to bring substantial benefits to the deaf, mute, and other individuals facing communication challenges. By offering a more intuitive and effective means of communication, the system holds the potential to greatly reduce the communication barrier between these communities and the general public. Moreover, it may provide additional advantages, such as facilitating emergency assistance notifications and monitoring for any irregular health conditions.

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