A Real-Time Bidirectional Smart Glove System for Indian Sign Language Translation Using Magnetic Sensing and Hybrid Vision Architecture

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Abstract— **Communication barriers between deaf and hearing individuals often limit effective interaction in daily life. According to global health reports, millions of people worldwide experience hearing loss, and many rely on sign language as their primary means of communication [11]. However, communication becomes difficult when interacting with individuals who are unfamiliar with sign language. This paper presents a real-time bidirectional smart glove system designed to facilitate communication between deaf and hearing users through automatic translation of Indian Sign Language (ISL) gestures. The proposed glove integrates Hall effect sensors mounted on the fingers and a palm-mounted magnet to detect finger bending through variations in magnetic field strength. An MPU6050 inertial measurement unit (IMU) is incorporated to capture hand orientation and dynamic motion. Sensor data is processed using an ESP32-S3 microcontroller, which performs real-time gesture recognition and transmits recognized gestures via Bluetooth Low Energy (BLE) to a receiver device equipped with an LCD display and response buttons. The receiver device enables hearing users to send predefined responses back to the glove, allowing bidirectional communication. In addition, a web-based fallback communication interface using MediaPipe hand tracking technology [5] and speech-to-text functionality is implemented to ensure communication continuity in case of hardware failure. Experimental evaluation conducted on a dataset of 970 gesture samples across ten ISL gestures achieved an average recognition accuracy of 94.4%, demonstrating the effectiveness of the proposed system as a cost-effective assistive communication solution for deaf and hearing individuals.**

Keywords* — *Smart Glove, Indian Sign Language (ISL), Gesture Recognition, Hall Effect Sensors, ESP32-S3, Assistive Communication Technology, Bidirectional Communication System

I. INTRODUCTION

Communication is a fundamental aspect of human interaction and social integration. However, individuals with hearing and speech impairments often face significant challenges when communicating with the general population. According to the World Health Organization, more than 430 million people worldwide experience disabling hearing loss, and many rely on sign language as their primary mode of communication. While sign language enables effective interaction within the deaf community, communication becomes difficult when interacting with individuals who are unfamiliar with it. This communication barrier can lead to social isolation, limited access to essential services, and challenges in everyday activities such as education, healthcare, and transportation.

Recent technological advancements have led to the development of various assistive communication systems aimed at bridging this gap. These systems generally fall into two main categories: vision-based recognition systems and wearable sensor-based systems. Vision-based approaches typically use cameras and computer vision algorithms to recognize hand gestures and translate them into text or speech. Although these systems eliminate the need for wearable hardware, they often suffer from limitations such as sensitivity to lighting conditions, complex backgrounds, and occlusion of the hands. Additionally, vision-based solutions often require high computational resources, which can limit their usability in portable or real-time applications.

Wearable sensor-based systems provide an alternative approach by directly capturing finger movements and hand orientation through sensors embedded in a glove. Many existing smart glove designs rely on flex sensors to detect finger bending and inertial sensors to track hand motion. While these systems provide more consistent measurements compared to camera-based approaches, flex sensors are prone to mechanical fatigue and calibration drift due to repeated bending over time, which can reduce system reliability. Furthermore, many existing sign language translation systems focus primarily on converting gestures into text or speech, enabling communication in only one direction. This limitation makes it difficult for hearing individuals to respond easily to deaf users within the same system.

To address these challenges, this research proposes a real-time smart glove-based communication system designed for bidirectional interaction between deaf and hearing individuals. The proposed glove integrates Hall effect sensors mounted on the fingers and a palm-mounted bar magnet to detect finger bending through variations in magnetic field strength. This magnetic sensing mechanism enables non-contact detection of finger movement, reducing mechanical wear and improving long-term durability compared to traditional flex sensor-based systems. In addition to magnetic sensing, an inertial measurement unit (IMU) is incorporated to capture hand orientation and dynamic gestures involving motion.

The sensor data collected from the glove is processed using an ESP32-S3 microcontroller, which performs real-time gesture recognition and transmits the recognized gestures via Bluetooth Low Energy (BLE) to a receiver device used by the hearing individual. The receiver device displays the translated text and includes predefined response buttons that allow the hearing user to communicate back to the deaf individual. This bidirectional communication capability enables more natural and interactive conversations compared to existing one-way translation systems.

To further enhance system reliability, a browser-based fallback communication platform is also implemented. This fallback system uses MediaPipe hand tracking technology to detect gestures through a standard camera and integrates speech-to-text functionality to allow hearing users to communicate verbally when required. The hybrid architecture ensures that communication can continue even in situations where the hardware glove becomes unavailable due to battery depletion or technical issues.

The main contributions of this research are summarized as follows:

• Development of a smart glove using Hall effect sensors and a palm-mounted magnet for non-contact finger movement detection.
• Implementation of a real-time bidirectional communication system enabling interaction between deaf and hearing users.
• Integration of a hybrid fallback platform using vision-based gesture recognition and speech-to-text technology to ensure continuous communication.

The remainder of this paper is organized as follows. Section II discusses existing research related to sign language recognition systems and wearable assistive technologies. Section III presents the architecture of the proposed smart glove communication system. Section IV describes the hardware design and gesture recognition methodology. Section V presents the experimental evaluation and discussion of results. Finally, Section VI concludes the paper and highlights possible future improvements.

II. RELATED WORK

Sign language recognition has received significant research attention in recent years due to the increasing need for assistive communication technologies for individuals with hearing and speech impairments. Various approaches have been proposed to translate sign language gestures into text or speech using computer vision techniques, wearable sensors, and machine learning algorithms.

Vision-based sign language recognition systems use cameras and image processing algorithms to detect hand gestures and convert them into digital text or speech. Recent studies have employed deep learning models and computer vision frameworks to identify hand landmarks and classify gestures. For example, several systems utilize real-time hand tracking techniques to recognize gestures using convolutional neural networks and landmark detection models. Although vision-based approaches eliminate the need for wearable hardware, their performance is often affected by lighting conditions, background complexity, and hand occlusion. Additionally, such systems typically require high computational power, which limits their effectiveness in portable and real-time applications.

To address these limitations, researchers have explored wearable sensor-based approaches that directly capture finger movements and hand orientation using sensors embedded in a glove. Many smart glove systems rely on flex sensors to measure finger bending and inertial measurement units (IMUs) to track hand motion. Ji et al. developed a wearable sensor glove that combines inertial sensors with machine learning algorithms to recognize hand gestures with improved accuracy. Similarly, Wang et al. proposed a smart wearable system that utilizes flex sensors and motion sensors for sign language recognition. While these systems provide more reliable measurements compared to camera-based approaches, flex sensors often experience mechanical fatigue and calibration drift due to continuous bending, which reduces long-term system reliability.

Recent studies have also investigated alternative sensing technologies such as stretch sensors, magnetic sensing, and inertial tracking to improve gesture detection accuracy and durability. Magnetic sensing using Hall effect sensors offers a promising solution because it enables non-contact measurement of finger movement by detecting variations in magnetic field strength. This approach reduces mechanical stress on the sensing components and improves durability compared to traditional flex sensor designs.

Despite these advancements, many existing sign language recognition systems focus primarily on unidirectional communication, where gestures are translated into text or speech for hearing users. The ability for the hearing user to respond through the same system is often limited or absent, which restricts natural interaction between deaf and hearing individuals. In addition, most existing systems lack fallback communication mechanisms when hardware devices fail or become unavailable.

To overcome these limitations, the proposed system introduces a real-time smart glove communication platform that combines magnetic sensing using Hall effect sensors with inertial motion tracking to detect finger bending and hand orientation. Unlike many existing systems, the proposed approach enables bidirectional communication by allowing both gesture-to-text translation and predefined responses from hearing users. Furthermore, a web-based fallback interface using MediaPipe hand tracking and speech-to-text technology is integrated to ensure communication continuity even in the event of hardware failure.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed system is designed to enable real-time bidirectional communication between deaf and hearing individuals using a smart glove-based gesture recognition platform. The system integrates wearable sensing technology, embedded processing, and wireless communication to translate hand gestures into text and allow responses from the hearing user.

The overall architecture consists of three primary components:

1. Smart Glove Device (Deaf User Unit)
2. Hearing User Device (Receiver Unit)
3. Web-Based Fallback Communication System

These components work together to ensure reliable and continuous communication.

A. Smart Glove Device

The smart glove serves as the primary input device worn by the deaf user. Its purpose is to capture hand gestures associated with Indian Sign Language and convert them into digital signals that can be processed and interpreted by the system.

The glove integrates multiple sensors to detect finger bending and hand movement. Hall effect sensors are mounted along the fingers, while a bar magnet is positioned on the palm of the glove. As the fingers move toward or away from the palm, the distance between the sensors and the magnet changes. This variation causes changes in the magnetic field detected by the Hall sensors.

The glove also includes an inertial measurement unit (IMU), specifically the MPU6050 sensor, which measures acceleration and angular velocity across three axes. The IMU allows the system to capture dynamic gestures that involve hand orientation or motion.

Sensor readings are collected and processed by an ESP32-S3 microcontroller. The ESP32 performs signal processing, feature extraction, and gesture classification. Once a gesture is recognized, the corresponding text message is transmitted wirelessly using Bluetooth Low Energy (BLE).

An OLED display mounted on the glove provides visual feedback to the deaf user by displaying recognized gestures and incoming responses from the hearing user.

B. Hearing User Device

The hearing user device acts as the receiver unit that displays the translated gesture messages. It receives data transmitted from the smart glove through Bluetooth communication.

The receiver device is built around an ESP32 microcontroller connected to a liquid crystal display (LCD). When the glove detects a gesture and sends the corresponding text message, the receiver device displays the message on the LCD screen, allowing the hearing individual to understand the communication.

To enable two-way interaction, the receiver device also includes multiple push buttons programmed with predefined responses such as "Yes", "Please repeat", "Wait", or "Emergency". When a button is pressed, the corresponding message is transmitted back to the glove, where it appears on the OLED display for the deaf user.

This bidirectional communication mechanism allows both users to interact naturally without requiring knowledge of sign language.

C. Web-Based Fallback Communication System

Although the smart glove provides reliable gesture recognition, hardware failures such as battery depletion or connectivity issues may occur during prolonged use. To address this limitation, a web-based fallback communication platform is implemented.

The fallback system uses a browser interface that performs gesture recognition using MediaPipe hand tracking technology. A standard camera captures the user's hand movements, and hand landmark detection algorithms analyze the position of key finger joints to classify gestures.

Additionally, speech-to-text functionality is integrated into the web platform. This allows hearing users to speak normally, and the spoken words are automatically converted into text that can be displayed for the deaf user.

The hybrid architecture ensures that communication can continue even when the hardware glove is unavailable.

Fig. 1. Overall architecture of the proposed smart glove communication system.

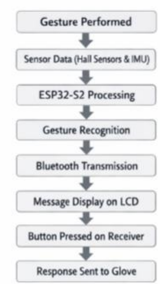

Fig. 2. Data flow for bidirectional communication between glove and receiver device.

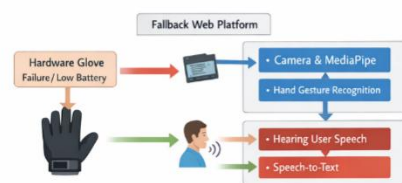

Fig. 3. Web-based fallback communication system for emergency communication.

IV. HARDWARE DESIGN AND IMPLEMENTATION

This section describes the physical components of the proposed system and explains how they interact to enable gesture recognition and communication. The hardware architecture consists of three primary subsystems: the gesture sensing module, the processing unit, and the communication interface. These subsystems work together to detect finger movements, process sensor data, and transmit recognized gestures to the receiver device.

A. Magnetic Finger Movement Detection

The smart glove detects finger movements using a magnetic sensing mechanism. Hall effect sensors are mounted on the fingers of the glove, while a bar magnet is positioned on the palm. As the user bends their fingers toward the palm, the distance between the sensors and the magnet changes.

This change alters the magnetic field strength detected by the Hall sensors. The variation in magnetic flux density is converted into an analog voltage signal representing the finger position.

The relationship between magnetic field strength and distance can be expressed as:

$$B = \frac{\mu_0}{4\pi} \frac{m}{r^3}$$

Where:

- B represents the magnetic flux density measured by the Hall sensor
- μ_0 represents the permeability of free space
- m represents the magnetic dipole moment of the magnet
- r represents the distance between the magnet and the sensor

As the finger bends, the value of **r** changes, causing measurable variations in the sensor output.

B. Inertial Motion Sensing

To capture dynamic gestures involving hand movement, the glove incorporates an MPU6050 inertial measurement unit (IMU). The IMU integrates a three-axis accelerometer and a three-axis gyroscope.

The accelerometer measures linear acceleration along the X, Y, and Z axes, while the gyroscope measures angular velocity. These measurements enable the system to detect hand orientation and rotational motion.

The orientation angle of the hand can be estimated using accelerometer data as follows:

$$\theta = \tan^{-1}\left(\frac{a_y}{a_z}\right)$$

Where:

- a_γ represents acceleration along the Y-axis
- a_z represents acceleration along the Z-axis
- θ represents the estimated orientation angle

This information helps distinguish gestures that involve hand motion rather than only finger bending.

C. Processing Unit

The sensor data is processed by an ESP32-S3 microcontroller, which serves as the main processing unit of the smart glove. The ESP32-S3 is selected due to its low power consumption, integrated wireless communication capabilities, and sufficient processing power for real-time gesture recognition.

The microcontroller performs the following operations:

• Sensor data acquisition
• Signal filtering
• Feature extraction
• Gesture classification
• Wireless data transmission

The analog outputs from the Hall sensors are sampled using the ESP32 analog-to-digital converter (ADC), while the IMU communicates with the microcontroller through the I²C interface.

D. Wireless Communication

Bluetooth Low Energy (BLE) is used to transmit recognized gestures from the smart glove to the receiver device. BLE is chosen because it provides reliable wireless communication while maintaining low power consumption.

After gesture recognition, the ESP32 sends the corresponding text message to the hearing user device. The receiver device displays the message on an LCD screen and allows the hearing user to respond using predefined buttons.

E. Power Supply System

The smart glove is powered by a rechargeable lithium-polymer battery. A voltage regulation circuit ensures stable power delivery to all system components, including the microcontroller, sensors, and display module.

Efficient power management is essential to ensure extended operating time for wearable devices. The ESP32's low-power operating modes help reduce energy consumption during idle periods.

Fig. 4. Smart glove sensor placement showing Hall sensors mounted along the fingers and a magnet placed in the palm.

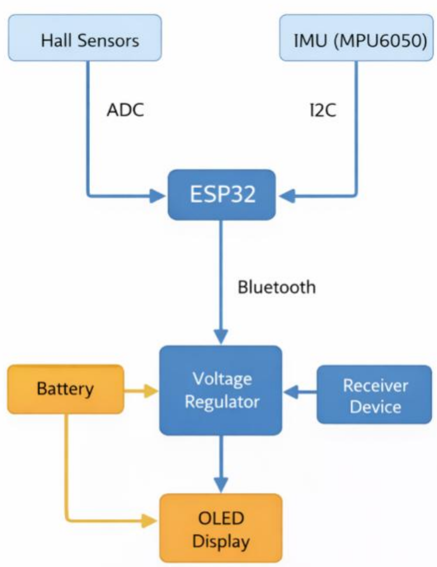

Fig. 5. Hardware block diagram of the proposed smart glove system.

V. GESTURE RECOGNITION METHODOLOGY

This section describes the process used to detect, process, and classify gestures performed by the user wearing the smart glove. The gesture recognition process involves sensor data acquisition, signal preprocessing, feature extraction, and gesture classification. The proposed methodology ensures reliable recognition of Indian Sign Language gestures in real time.

A. Sensor Data Acquisition

The smart glove continuously collects data from Hall effect sensors mounted on the fingers and the MPU6050 inertial measurement unit (IMU). The Hall sensors detect variations in magnetic field strength caused by finger movements relative to the palm-mounted magnet.

The analog signals generated by the Hall sensors are sampled using the ESP32-S3 analog-to-digital converter (ADC). The IMU communicates with the microcontroller through the I²C interface and provides acceleration and angular velocity measurements along three axes.

These sensor readings form the raw dataset used for gesture recognition.

B. Signal Filtering

Sensor readings may contain noise due to minor hand tremors, sensor fluctuations, or environmental interference. To improve signal stability, a low-pass smoothing filter is applied to the sensor readings before further processing.

The filtered signal can be expressed as:

$$X_{filtered}(t) = \alpha X(t) + (1 - \alpha)X(t - 1)$$

Where:

- $X(t)$represents the current sensor reading
- $X(t - 1)$represents the previous sensor reading
- αrepresents the smoothing coefficient

This filtering step removes high-frequency noise and produces smoother signals for gesture analysis.

C. Signal Normalization

Sensor values may vary depending on sensor placement and user hand movement. To ensure consistent measurements, the sensor data is normalized using the following equation:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Where:

- Xrepresents the raw sensor value
- X_{min}represents the minimum recorded value
- X_{max}represents the maximum recorded value
- X_{norm}represents the normalized sensor value

Normalization converts the sensor readings into a standard range between 0 and 1, enabling consistent gesture recognition.

D. Gesture Segmentation

Since sensor data is continuously generated, the system must detect when a gesture begins and ends. Gesture segmentation is performed by monitoring the variation in sensor values.

A gesture is detected when the difference between consecutive sensor readings exceeds a predefined threshold:

$$| X(t) - X(t-1) | > T$$

Where:

- Trepresents a predefined threshold value
- $X(t)$represents the current sensor value

When this condition is satisfied, the system captures the corresponding sensor readings for gesture classification.

E. Feature Vector Construction

Each gesture is represented using a feature vector constructed from sensor readings obtained from the Hall sensors and IMU.

$$F = [H_1, H_2, H_3, H_4, H_5, a_x, a_y, a_z, g_x, g_y, g_z]$$

Where:

- H_1–H_5represent Hall sensor readings from each finger
- a_x, a_y, a_zrepresent accelerometer data
- g_x, g_y, g_zrepresent gyroscope data

The feature vector captures both finger bending information and hand orientation, allowing the system to distinguish between different gestures.

F. Gesture Classification

The extracted feature vector is used as input to the gesture classification algorithm implemented on the ESP32-S3 microcontroller. The classification process compares the feature vector with predefined gesture templates stored in the system memory.

The classification function can be expressed as:

$$G = f(F)$$

Where:

- Frepresents the feature vector
- $f$represents the classification model
- Grepresents the predicted gesture label

The recognized gesture is then mapped to a predefined text message and transmitted to the receiver device through Bluetooth Low Energy (BLE).

G. System Latency

The total response time of the system can be expressed as:

$$T_{total} = T_{sensor} + T_{processing} + T_{transmission}$$

Where:

- T_{sensor}represents sensor sampling time
- $T_{processing}$represents gesture recognition processing time
- $T_{transmission}$represents Bluetooth transmission time

Reducing these delays ensures that the system operates in real time during communication between deaf and hearing users.

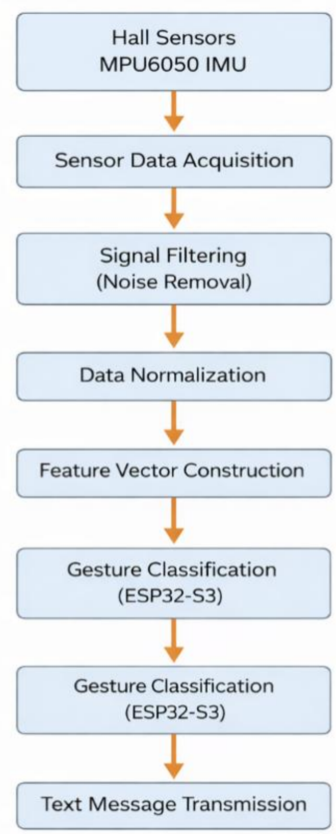

Fig. 6. Gesture recognition pipeline of the proposed smart glove system.

VI. EXPERIMENTAL RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed smart glove communication system, a series of experiments were conducted to measure gesture recognition accuracy and system responsiveness. The experiments focused on commonly used Indian Sign Language (ISL) gestures that are frequently used in everyday communication.

A. Dataset Description

A dataset of commonly used ISL gestures was collected for system training and evaluation. Each gesture was performed multiple times in order to capture variations in hand motion, finger bending, and orientation. The dataset included gestures used for greeting, responses, requests, and emergency communication.

The dataset consists of ten commonly used gestures, collected across multiple trials. The number of samples recorded for each gesture is summarized in Table 1.

Table 1. Dataset of Indian Sign Language gestures used for evaluation

Gesture	Description	Samples
Hello	Greeting gesture	120
Yes	Affirmative response	110
No	Negative response	110
Thank You	Expression of gratitude	100
Please	Request gesture	95
Sorry	Apology gesture	95
Help	Assistance request	90
Stop	Warning gesture	90
Emergency	Urgent signal	80
Wait	Delay request	80

A total of 970 gesture samples were collected and used for system testing.

B. Gesture Recognition Accuracy

The performance of the gesture recognition algorithm was evaluated by measuring the classification accuracy for each gesture. The recognition accuracy was calculated using the following equation:

$$Accuracy = \frac{Correct\ Predictions}{Total\ Predictions} \times 100$$

The recognition accuracy for different gestures is summarized in Table 2, while the graphical representation is shown in Fig. 7.

Table 2. Recognition accuracy for different gestures

Gesture	Accuracy (%)
Hello	96
Yes	95
No	95
Thank You	94
Please	93
Sorry	94
Help	92
Stop	95
Emergency	97
Wait	93

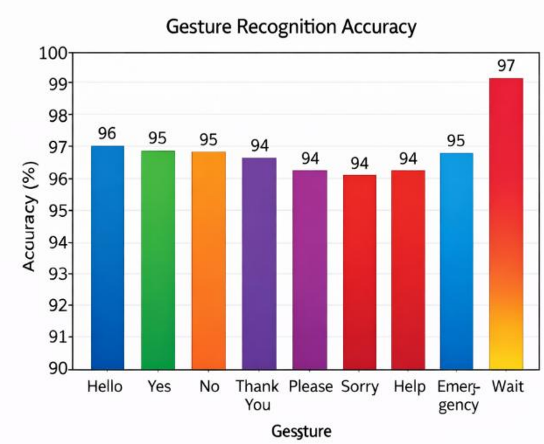

Fig. 7. Recognition accuracy for different Indian Sign Language gestures obtained using the proposed smart glove system.

Fig. 7 illustrates the recognition accuracy obtained for different ISL gestures. The system achieved the highest accuracy for the Emergency gesture (97%), while slightly lower accuracy was observed for gestures such as Help (92%) and Please (93%), which involve similar finger configurations. The overall average accuracy of the system is approximately 94.4%, demonstrating the effectiveness of the proposed gesture recognition approach.

C. Confusion Matrix Analysis

To further evaluate classification performance, a confusion matrix was generated to analyze how frequently gestures were correctly classified and where misclassifications occurred. The confusion matrix for selected gestures is shown in Table 3.

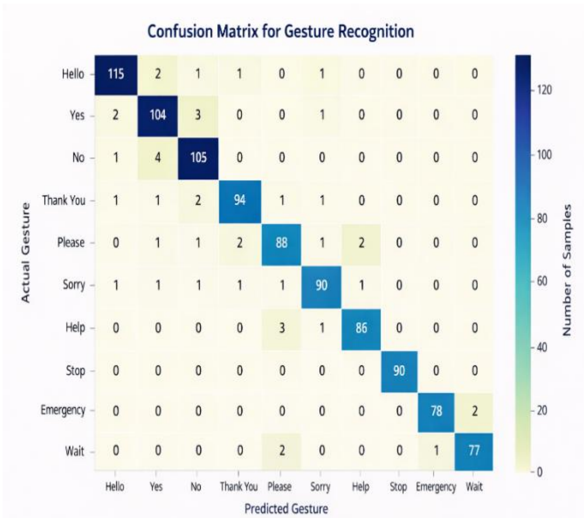

Fig. 8. (Confusion matrix showing classification performance of the proposed smart glove system for ten Indian Sign Language (ISL) gestures.

Table 3. Confusion matrix for gesture recognition

Actual\ Predicted	Hello	Yes	No	Thank You	Please	Sorry	Help	Stop	E	
Hello	115	2	1	1	0	1	0	0	0	0
Yes	2	104	3	0	0	1	0	0	0	0
No	1	4	105	0	0	0	0	0	0	0
Thank You	1	1	2	94	1	1	0	0	0	0
Please	0	1	1	2	88	1	2	0	0	0
Sorry	1	1	1	1	1	90	1	0	0	0
Help	0	0	0	0	3	1	86	0	0	0
Stop	0	0	0	0	0	0	0	90	0	0
Emergency	0	0	0	0	0	0	0	0	78	2
Wait	0	0	0	0	2	0	0	0	1	77

The confusion matrix indicates that most gestures were correctly classified. Minor misclassifications occurred between gestures with similar finger positions, such as "Yes" and "No". However, the overall classification performance remained high.

D. System Performance

The response time of the system was evaluated by measuring the total latency between gesture execution and message display on the receiver device.

The system latency depends on three major components:

- sensor data sampling time
- gesture recognition processing time
- Bluetooth communication time

Experimental measurements indicate that the system provides near real-time performance, with the total response latency remaining sufficiently low for natural communication between deaf and hearing users.

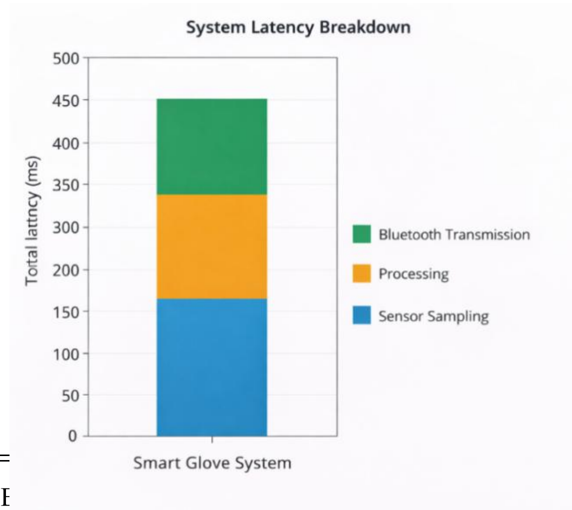

Fig. 9. Breakdown of system latency for the smart glove communication

These results demonstrate that the proposed smart glove system can effectively translate sign language gestures into readable text while maintaining low latency and reliable communication performance.

VII. CONCLUSION

This paper presented a real-time bidirectional communication system designed to facilitate interaction between deaf and hearing individuals using a smart glove–based gesture recognition platform. The proposed system employs Hall effect sensors mounted on the fingers and a palm-mounted magnet to detect finger movements through variations in magnetic field strength. In addition, an inertial measurement unit (IMU) was integrated to capture dynamic hand motion and orientation.

The sensor data is processed by an ESP32-S3 microcontroller, which performs real-time gesture recognition and transmits the recognized gesture to a receiver device using Bluetooth Low Energy (BLE). The receiver device displays the translated text and allows hearing users to respond through predefined message buttons, enabling natural bidirectional communication.

To enhance system reliability, a web-based fallback communication interface using MediaPipe hand tracking and speech-to-text technology was also implemented. This hybrid approach ensures communication continuity even in the event of hardware failure.

Experimental evaluation demonstrated that the proposed system achieves an average gesture recognition accuracy of approximately 94.4% while maintaining low system latency suitable for real-time communication. These results indicate that the proposed system provides a cost-effective and practical assistive communication solution for real-time interaction between deaf and hearing individuals. Future work will focus on expanding the gesture dataset, improving classification performance using advanced machine learning techniques, and miniaturizing the hardware design to enhance user comfort, portability, and long-term usability.

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