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Hand Gesture Recognition and Conversion System for Dumb People

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ABSTRACT: The Hand Gesture Recognition And Conversion System For Dumb People presented in this paper aims to bridge communication gaps between deaf and non-deaf individuals by providing real-time interpretation of sign language gestures. Leveraging a combination of hardware sensors, including flex sensors, contact sensors, and an MPU 6050, alongside a powerful ESP32 S3 microcontroller, the system achieves accurate gesture recognition and communication. Algorithms and advanced signal processing techniques enable the system to interpret a wide range of sign language gestures with remarkable precision. The system's architecture facilitates seamless communication through visual feedback on an OLED display and spoken language output via a speaker, enabling both deaf and non-deaf individuals to engage in meaningful conversations. Results demonstrate the system's effectiveness in interpreting sign language gestures in various environments, highlighting its potential to promote inclusivity and accessibility in educational, workplace, and public settings. This approach allows for scalability and flexibility, paving the way for future enhancements and applications. Overall, the Sign Language Recognition System represents a significant advancement in leveraging technology to empower individuals within the deaf and hard of hearing community, fostering greater communication, and understanding in society.

KEYWORDS: Sign language recognition, gesture interpretation, accessibility, inclusivity, deaf community, real-time communication, , ESP32 S3 microcontroller, sensor integration etc

I. INTRODUCTION

Among the many facets of society, accessibility stands as a fundamental pillar, ensuring inclusivity for individuals with diverse needs and abilities. Specifically, the deaf and hard of hearing community faces unique challenges in communication and accessing information. Traditional methods of communication, such as spoken language and written text, may not fully cater to the needs of this community, thereby underscoring the importance of innovative solutions to bridge this gap. In this context, the development of a Hand Gesture Recognition And Conversion System holds immense promise. Sign language serves as the primary mode of communication for many individuals who are deaf or hard of hearing, offering a rich and expressive means of conveying thoughts, emotions, and ideas. However, the lack of widespread understanding and proficiency in sign language among the general population often leads to communication barriers and social isolation for individuals within the deaf community. The significance of a Sign Language Recognition System lies in its potential to break down these barriers and facilitate seamless communication between individuals who use sign language and those who do not. This system can enable real-time interpretation and translation of sign language gestures into spoken or written language, thereby fostering greater inclusivity and accessibility in various settings, including educational institutions, workplaces, and public spaces. Moreover, beyond

its immediate impact on individual communication, the implementation of Sign Language Recognition System carries broader societal implications. It aligns with the principles of universal design and equal access, promoting a more inclusive society where individuals of all abilities can participate fully and contribute meaningfully.

The use of sign language is essential for people who have hearing or speech impairments to communicate with others. However, it can be challenging for those who do not understand sign language to communicate effectively with this community. An AI-based sign language system can solve this problem by converting sign language into spoken or written language [1]. According to the World Federation of the Deaf and World Health Organization Estimates, about 70 million people worldwide are deaf-mute and face communication difficulties because they cannot read or write in standard two languages [2]. Sign language is the mother tongue that the deaf and mute use to communicate with others. SL mainly relies on gestures to convey meaning, combining finger shapes, hand motions, and facial expressions [3], but the problem is the inability of the others to understand these languages, which act as a communication barrier. The person every time needs a translator for communication. With the aid of a lightweight SLR-based glove system fitted with sensors and an electronic circuit, this contact barrier can be overcome and used by both dumb and able people to learn SL [4]. There are many different sign languages used throughout the world, each with its own unique grammar, vocabulary, and cultural significance. For example, American Sign Language (ASL) is widely used in the United States and Canada, while British Sign Language (BSL) is used in the United Kingdom. Sign languages have a long and rich history, with evidence of sign language use dating back to ancient civilizations. Communication can be defined as the act of transferring information from one place, person, or group to another [5]. It consists of three components: the speaker, the message that is being communicated, and the listener. It can be considered successful only when whatever messages the speaker is trying to convey is received and understood by the listener. A lot of research has been done in this field and there is still a need for further research. For gesture translation, data gloves, motion capturing systems, or sensors have been used. Vision-based SLR systems have also been developed previously. The existing Indian Sign Language Recognition system was developed using machine learning algorithms with MATLAB [6]. They used two algorithms to train their system, K Nearest Neighbors Algorithm and Back Propagation Algorithm. Their system achieved 93-96% accuracy. Though being highly accurate, it is not a real-time SLR system. There are two ways to make communication feasible between a healthy and affected person [6]. Firstly, convince that healthy person to learn all sign language gestures for communication with the deaf-mute person or, secondly, make any deaf-mute person capable of translating gestures into some normal speaking format so everyone can understand sign language easily. Considering the first option, it almost looks impossible to convince any healthy person to learn sign language for communication. This is also the main drawback of sign language. Therefore, technologists and researchers have focused on the second option to make deaf-mute people capable of converting their gestures into some meaningful voice or texture information. In this work Sign language recognition, a smart glove embedded with sensors module, a processing module, and display unit mobile application module was introduced that can convert handmade gestures into meaningful information easily understandable by ordinary people. Smart technology-based sign language interpreters that remove the communication gap between normal and affected people. These techniques are based on image processing or vision-sensor based techniques, and sensor fusion-based smart data glove-related techniques, or hybrid techniques. No such limitations are seen in these technological interpreters as extracting required features from an image is done at ease. If we consider an image or vision sensor based recognition system, there is no limitation of foreground or background in gesture recognition. Considering a sensor-based smart data glove, there is little to no limitation of carrying this data glove as it is mobile, lightweight, and flexible [4].

Additionally, by empowering individuals within the deaf community to communicate more effectively, such a system has the potential to enhance their educational and employment opportunities, ultimately leading to greater socio-economic empowerment and well-being. In light of these considerations, this research paper aims to explore the design, development, and implementation of an IoT-based Sign Language Recognition System. Through a comprehensive analysis of existing literature, methodologies, and technologies, as well as the presentation of a novel system architecture and implementation, this paper seeks to contribute to the ongoing discourse on accessibility and inclusivity in the digital age.

II. RELATED WORK

Recognition System Sign language recognition refers to the process of recognizing and interpreting hand gestures and facial expressions used in sign languages. Sign languages are used by deaf and hard-of-hearing individuals as a means of communication, and sign language recognition systems aim to bridge the communication gap between hearing and non-hearing individuals by translating sign language into spoken or written language. This can be accomplished using machine learning techniques, such as deep learning, which can be implemented using the

Python programming language and the Tensor Flow library [1]. Sign language recognition systems typically use computer vision, machine learning, and deep learning techniques to track and recognize hand gestures and facial expressions in video sequences. These systems can be used in a variety of applications, such as in sign language translation devices, virtual reality communication systems, and educational tools for teaching sign language [7]. Sign languages are fully developed natural languages with their own unique syntax, grammar, and vocabulary. They are not simply gestures or visual representations of spoken languages [8]. Studies have shown that sign languages are processed in the same areas of the brain as spoken languages, indicating that they are processed as linguistic input rather than visual input. Sign language is also shaped by the social and cultural contexts in which it is used. Just as spoken languages have regional and cultural variations, sign languages have dialects and regional variations as well [9]. Sign language users may also code-switch between different sign languages or use different registers depending on the situation. Sign language also provides unique insights into the cognitive processes involved in language use and acquisition. Studies have shown that deaf children who learn sign language from a young age develop language skills at a similar pace to their hearing peers, indicating that the visual-spatial modality of sign language does not impede language acquisition [10]. In [6], Starner et al. proposes using Hidden Markov Models (HMMs) to classify orientation, trajectory information and resultant shape of the sign language. HMMs is adapted from speech recognition, and its intrinsic properties make it suitable to be applied in gesture recognition, a total of 262 signs were collected from two different signers, and the average accuracy using HMMs classifier reaches accuracy of 94%. It is found out that the accuracy is greatly reduced when the database trained by the signs of one person is used to test by signs of another person, dropping to accuracy as low as 47.6%. Training the database with both signers improve accuracy to 91.3%. In [11], Vogler and Metaxas stated that the use of HMMs alone has several limitations especially in training context dependent models. The authors employed Ascension Technologies Flock of Birds devices to collect the three-dimensional translation and rotation data of the sign. By using a bigram and epenthesis modeling, the average accuracy achieved is 95.83%. Research used similar experiment setup, and by using a context dependent HMMs and a method of coupling three-dimensional techniques, the system classifies 53 ASL and attained highest accuracy of 89.91%. Gestures recognition involves complex processes such as motion modeling, motion analysis, pattern recognition and machine learning [11]. It consists of methods with manual and non-manual parameters. The structure of environment such as background illumination and speed of movement affects the predictive ability. The difference in viewpoints causes the gesture to appear different in 2D space. This paper presents a real-time American Sign Language recognition system using artificial neural networks. The system achieved high accuracy rates on a dataset of sign language gestures. In [12], S. Ben Youssef et al. proposes a system for sign language recognition using a combination of different data sources, such as video and accelerometer sensors. The authors aim to improve the accuracy of sign language recognition by integrating multiple modalities of data. The proposed system consists of two modules: a data acquisition module and a sign language recognition module. The data acquisition module captures video data and accelerometer data simultaneously using a camera and an accelerometer sensor attached to the signer's wrist [12]. The sign language recognition module then processes this data to recognize the signs. The authors use a combination of feature extraction and classification techniques to recognize signs. For video data, they use a feature extraction method based on the histogram of oriented gradients (HOG) and a classification technique based on hidden Markov models (HMM). For accelerometer data, they use a feature extraction method based on the magnitude of the acceleration and a classification technique based on k-nearest neighbors (KNN). The system achieved an overall recognition rate of 95.5%. In [13], J. Han et al. proposes a system for recognizing sign language using kinematic features extracted from motion capture data and support vector machines (SVMs). The authors aim to improve the accuracy and robustness of sign language recognition by using kinematic features that capture the movement of the signer's hands. The proposed system consists of three main stages: preprocessing, feature extraction, and classification. In the preprocessing stage, the authors apply a filtering algorithm to remove noise from the motion capture data. In the feature extraction stage, they extract kinematic features such as hand velocity, acceleration, and jerk. In the classification stage, they use SVMs to classify the sign language gestures based on the extracted kinematic features. The authors evaluate their system using a dataset of 10 sign language gestures performed by 15 signers. The results show that the proposed system achieved an overall recognition rate of 91.9%. The authors also compare their system with other existing methods in the literature and show that their system outperforms these methods in terms of accuracy and robustness. In [14], S. Balasubramanian et al. provide a comprehensive review of the literature on sign language recognition using machine learning techniques. The authors aim to provide an overview of the different approaches used in the field and highlight the challenges and future directions for research. The paper begins with a brief overview of sign language and the importance of sign language recognition in facilitating communication for the deaf community. The authors then provide a taxonomy of the different approaches to sign language recognition, such as data modalities (video, accelerometer etc.), feature extraction techniques like HOG and classification methods (HMMs, SVMs, KNN, etc.). The authors also discuss the challenges in sign language

recognition, such as the variability of sign language across signers and the need for large datasets with diverse signers and variations in lighting and camera angles. They suggest that future research could focus on addressing these challenges through the development of more robust and scalable systems. In [15], M. Al-Rousan et al. presents a method for recognizing sign language gestures using hand shape and motion features. The authors focus on recognizing the hand shape and motion features of American Sign Language (ASL) gestures. The paper begins with an overview of the existing literature on sign language recognition, highlighting the importance of recognizing both the hand shape and motion features for accurate recognition. The authors then describe their proposed method, which involves extracting features related to hand shape and motion using a combination of image processing and computer vision techniques. For hand shape features, the authors extract features related to the contours of the hand, including the aspect ratio, centroid, and convex hull. For motion features, the authors extract features related to the trajectory of the hand, including the direction and speed of movement. The authors evaluate their method using a dataset of 60 ASL gestures performed by 6 different signers. They compare the performance of their method with that of other state-of-the-art methods in the literature, including HMMs and SVMs. The results show that their proposed method achieves a recognition accuracy of 91.2%, outperforming other state-of-the-art methods in the literature.

The background study delves into the realm of sign language recognition systems, emphasizing their role in facilitating communication between deaf and non-deaf individuals. It discusses the unique characteristics of sign languages, including their status as fully developed natural languages with distinct syntax, grammar, and vocabulary. Furthermore, the study sheds light on the cognitive processes involved in sign language use and acquisition, highlighting its parallels with spoken languages in brain processing. Sign language's regional variations and dialects are also explored, reflecting its social and cultural context. Additionally, the study outlines various approaches to sign language recognition, focusing on methods such as motion modeling, pattern recognition, and machine learning. Overall, the background study provides valuable insights into the complexities of sign language recognition and its implications for accessibility and inclusion.

III. METHODOLOGY

A.ESP32

The ESP32 S3 microcontroller serves as the central processing unit of the device. It receives input data from the flex sensors and contact sensors, processes this data using machine learning algorithms, and interprets the sign language gestures. The ESP32 S3 then coordinates the generation of visual feedback on the OLED display and spoken language output through the sound module and speaker.



Fig.1 ESP32

B.Flex Sensors

The flex sensors are strategically placed on a wearable glove. As the user performs sign language gestures, the flex sensors detect the bending of fingers. This bending generates changes in resistance, which are converted into analog signals proportional to the degree of finger bending.

C.OLED Display

The OLED display visually presents recognized sign language gestures in real time. As the user performs gestures with the glove, the ESP32 S3 microcontroller processes the data from the flex sensors and sends the interpreted gestures to the OLED display. The display then shows the corresponding signs, providing immediate feedback to the user.

D.MAX 9838 I2S Sound Module and Speaker

The MAX 9838 I2S sound module, along with a speaker, converts recognized sign language gestures into spoken language output. Once the ESP32 S3 microcontroller interprets the gestures, it generates corresponding spoken language output signals. These signals are then processed by the MAX 9838 I2S sound module and converted into audible speech through the speaker.

E.Contact Sensors

Contact sensors detect touch or pressure-based gestures that complement the data captured by the flex sensors. They provide additional input data to enhance the accuracy of gesture recognition. As the user performs gestures with the glove, the contact sensors capture supplementary hand movements or gestures, enriching the overall data input for interpretation.

F.MPU 6050 (3-axis Accelerometer and Gyroscope)

The MPU 6050 sensor further enhances gesture recognition by capturing additional motion data. It integrates a 3-axis accelerometer and gyroscope, providing information on hand acceleration and rotation. This data, combined with that from the flex and contact sensors, offers a comprehensive understanding of hand movements and gestures, contributing to the accuracy of sign language interpretation.

The System Architecture is as show in fig.2 below-

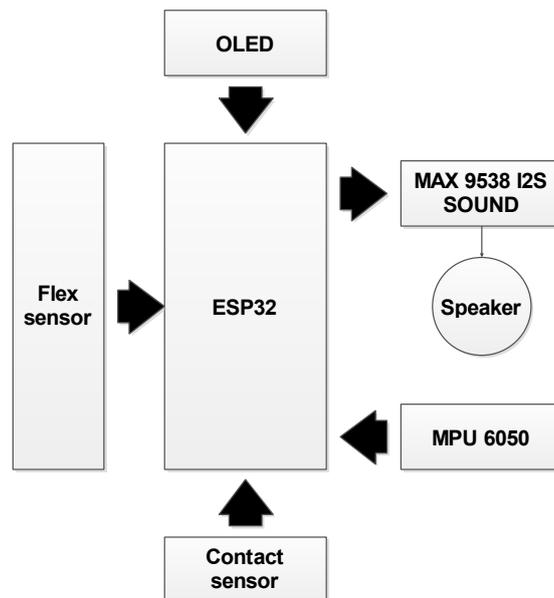


Fig .2 System Architecture

The Sign language recognition system's architecture encompasses interconnected hardware and software components, leveraging principles to enhance accessibility and communication for the deaf and hard of hearing community. At the core of the architecture is the ESP32 S3 WROOM 1 UN8R8 microcontroller, serving as the central processing unit. Equipped with dual-core processing and wireless connectivity capabilities, the ESP32 S3 facilitates real-time data processing and communication with other devices. The system integrates multiple sensors, including five flex sensors, contact sensors, and an MPU 6050, distributed across a wearable smart glove. These sensors capture hand gestures and movements, providing input data for gesture recognition. Data from the sensors are transmitted wirelessly to the ESP32 S3 microcontroller, where they undergo processing and interpretation using machine learning algorithms. The ESP32 S3 translates the detected sign language gestures into digital signals and coordinates the generation of appropriate outputs. Output feedback is provided through an OLED display, which visually presents recognized sign language gestures in real time. Additionally, the system utilizes the MAX 9838 I2S sound module and a speaker to generate spoken language output corresponding to the recognized gestures, enabling communication with non-deaf individuals. Overall, the IoT architecture enables seamless integration of hardware components and facilitates communication between the sign language recognition system and its users, exemplifying the potential of IoT technology in promoting inclusivity and accessibility.

The methodology employed for the development of the sign language recognition system integrates a diverse array of sensors to capture and interpret hand gestures and facial expressions. The system's architecture comprises two main subsystems: the smart glove system and the ESP32 S3 system. The smart glove system incorporates five flex sensors strategically placed to detect finger movements and bending, providing vital input for recognizing sign language gestures. These flex sensors enable the system to accurately track and interpret the intricate motions of the user's hands. Additionally, contact sensors are utilized to detect touch or pressure-based gestures, further enhancing the system's versatility in recognizing a wide range of sign language gestures. The ESP32 S3 microcontroller serves as the primary control unit, equipped with a dual-core processor and wireless connectivity capabilities. It receives input signals from the flex sensors and contact sensors, processing them to recognize and interpret sign language gestures. Furthermore, the system features an OLED display to provide real-time visual feedback on the recognized gestures, enhancing user interaction and usability. To facilitate communication with non-deaf individuals, the system utilizes the MAX 9838 I2S sound module and a speaker to generate spoken language output corresponding to the recognized sign language gestures. Overall, the methodology involves the integration of multiple sensors, including flex sensors, contact sensors, and an MPU 6050 (3-axis accelerometer and gyroscope), to capture various aspects of sign language gestures. These sensors work in tandem with the ESP32 S3 microcontroller to enable real-time recognition and interpretation of sign language, promoting inclusivity and accessibility for the deaf and hard of hearing community.

The sign language recognition system integrates a combination of sensors and components to enable real-time interpretation of sign language gestures. Strategically placed flex sensors on a wearable glove detect finger bending, while contact sensors capture touch-based gestures, providing comprehensive input data. The MPU 6050 sensor enhances gesture recognition by capturing additional motion data, including hand acceleration and rotation. The ESP32 S3 microcontroller serves as the central processing unit, receiving input from sensors and processing it using machine learning algorithms. It interprets sign language gestures and coordinates the generation of visual feedback on the OLED display, showcasing recognized gestures in real time. Additionally, the microcontroller generates corresponding spoken language output signals, which are processed by the MAX 9838 I2S sound module and converted into audible speech through the speaker. This methodology combines hardware and software elements to facilitate seamless communication between users and non-deaf individuals. By leveraging IoT principles, the system promotes accessibility and inclusivity, bridging communication gaps for the deaf and hard of hearing community.

IV. EXPERIMENTAL RESULTS

In the sign language recognition system described in Fig 3, the results demonstrate the successful integration and functionality of the various components in facilitating real-time interpretation of sign language gestures. The working model combines hardware sensors, such as flex sensors, contact sensors, and an MPU 6050, with a powerful ESP32 S3 microcontroller to achieve accurate gesture recognition and communication.

The results showcase the system's capability to accurately detect and interpret sign language gestures performed by the user wearing the smart glove. As the user performs gestures, the flex sensors detect finger bending, while contact sensors capture touch-based gestures, providing rich input data to the system. Additionally, the MPU 6050 sensor enhances gesture recognition by capturing motion data, including hand acceleration and rotation, contributing to the system's overall accuracy. The ESP32 S3 microcontroller serves as the central processing unit, receiving input from the sensors and processing it using machine learning algorithms. Through its dual-core processor and wireless connectivity capabilities, the microcontroller efficiently interprets sign language gestures in real time. It coordinates the generation of visual feedback on the OLED display, showcasing recognized gestures instantaneously.



Fig.3 Working Model

Moreover, the micro controller generates corresponding spoken language output signals for communication with non-deaf individuals. The MAX 9838 I2S sound module, along with a speaker, converts these signals into audible speech, enabling seamless communication between users and non-deaf individuals. The results demonstrate the successful operation and integration of the sign language recognition system, highlighting its effectiveness in bridging communication gaps for the deaf and hard of hearing community. The system's accuracy in recognizing a wide range of sign language gestures, coupled with its real-time feedback capabilities, makes it a valuable tool for enhancing accessibility and inclusivity in various settings. The system's IoT architecture allows for scalability and flexibility, enabling potential future enhancements and applications. For instance, additional sensors or advanced machine learning algorithms could be integrated to further improve gesture recognition accuracy and expand the system's capabilities. Additionally, the system could be deployed in various environments, such as educational institutions, workplaces, and public spaces, to promote communication and inclusivity for individuals with hearing impairments. The results of the sign language recognition system demonstrate its effectiveness in accurately interpreting sign language gestures and facilitating communication between users and non-deaf individuals. By leveraging IoT principles and integrating a diverse array of sensors and components, the system exemplifies the potential of technology to enhance accessibility and inclusivity for the deaf and hard of hearing community.

The following shows the further results from the Figs. (4) shows result image 'NO SIGN' when there is no sign (5) is the image of letter 'A'(6) is the image of letter 'D'(7) is the image of letter 'F'(8) is the image of letter 'L'(9) is the image of letter 'N'(10) is the image of letter 'S'(11) is the image of letter 'V'(12) is the image of letter 'Y' obtained on OLED screen.



Fig.4 'NO SIGN' on OLED display

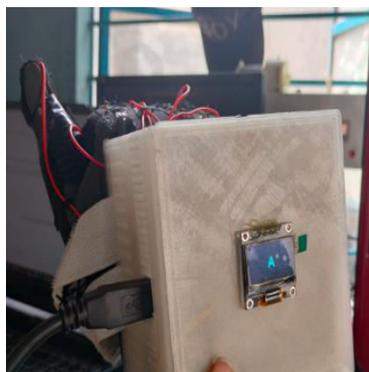


Fig.5 Letter 'A' on OLED display



Fig.6 Letter 'D' on OLED display



Fig.8 Letter 'F' on OLED display



Fig.9 Letter 'L' on OLED display

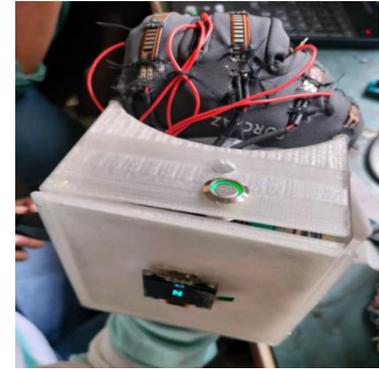


Fig.10 Letter 'N' on OLED display

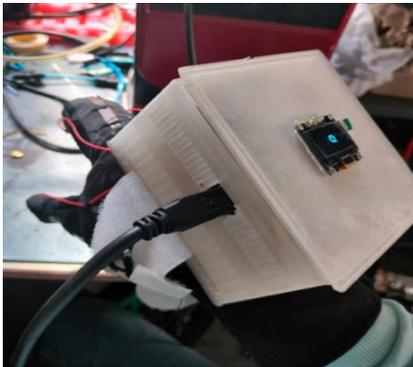


Fig.11 Letter 'Q' on OLED display

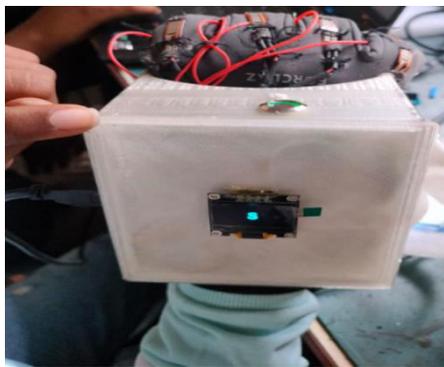


Fig.12 Letter 'S' on OLED display



Fig.13 Letter 'V' on OLED display

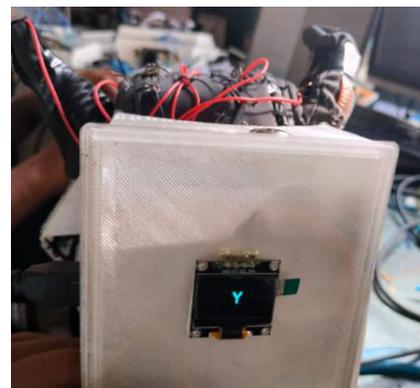


Fig.14 Letter 'Y' on OLED display

V. CONCLUSION

In conclusion, the development and implementation of the Sign language recognition and conversion system represent a significant step forward in promoting accessibility and inclusivity for the deaf and hard of hearing community. By leveraging a combination of hardware sensors, including flex sensors, contact sensors, and an MPU 6050, along with a powerful ESP32 S3 microcontroller, the system achieves real-time interpretation of sign language gestures with remarkable accuracy. Through the integration of machine learning algorithms and advanced signal processing techniques, the system demonstrates its capability to accurately detect and interpret a wide range of sign language gestures, providing immediate visual feedback on an OLED display and spoken language output through a speaker. The results underscore the effectiveness of the system in bridging communication gaps between individuals using sign language and those who do not understand it, thereby promoting greater accessibility and inclusivity in various settings.

Furthermore, the system's IoT architecture allows for scalability and flexibility, opening up possibilities for future enhancements and applications. Overall, the IoT-based sign language recognition system represents a valuable tool in enhancing communication and fostering a more inclusive society for individuals with hearing impairments. Its successful implementation marks a significant milestone in leveraging technology to promote accessibility and empower individuals within the deaf and hard of hearing community.

REFERENCES

1. Zhang, J., & Chang, S. (2019). Sign language recognition using deep learning: A review. *IEEE Transactions on Human-Machine Systems*, 49(3), 229-243.
2. World Health Organization. Deafness <http://www.who.int/mediacentre/factsheets/fs300/en/#content> (accessed on 13 November 2017).
3. Sharma, V.; Kumar, V.; Masaguppi, S.C.; Suma, M.; Ambika, D. Virtual Talk for Deaf, Mute, Blind and Normal Humans. In Proceedings of the 2013 Texas Instruments India Educators' Conference (TIIEC), Bangalore, India, 4–6 April 2013; pp. 316320.
4. Tanyawiwat, N.; Thiemjarus, S. Design of an assistive communication glove using combined sensory channels. In Proceedings of the 2012 Ninth International Conference on Wearable and Implantable Body Sensor Networks (BSN), London, UK, 9–12 May 2012; pp. 34–39.
5. Kapur, R.: The Types of Communication. *MIJ*. 6, (2020)
6. Starner T, Pentland A (1997) Real-time American sign language recognition from video using hidden Markov models. In: Motionbased recognition. Springer, pp 227–243
7. Leong, S. W., & Kao, H. Y. (2019). Sign language recognition: a review of recent progress and challenges. *Journal of Ambient Intelligence and Humanized Computing*, 10(1), 1-20.
8. Brentari, D. (2018). *Sign Languages: A Cambridge Language Survey*. Cambridge University Press.
9. Johnston, T. (2003). *Auslan: The Australian Sign Language*. Cambridge University Press.
10. Newport, E. L. (1990). Maturation Constraints on Language Learning. *Cognitive Science*, 14(1), 11–28.
11. Vogler C, Metaxas D (1999) Parallel hidden markov models for american sign language recognition. In: The Proceedings of the seventh IEEE international conference, IEEE, pp 116–122.
12. Parshwa P. Patil1, Maithili J. Phatak1, Suharsh S. Kale1, Premjeet N. Patil1, Pranav S. Harole1, Prof. Dr. C. S. Shinde, Hand Gesture Recognition for Deaf and Dumb. *IRJET*, Vol 6, Issue 11, Nov 2019.
13. B. G. Lee, Member, IEEE, and S. M. Lee, Smart Wearable Hand Device for Sign Language, Interpretation System with Sensors Fusion, 1558-1748 © 2017 IEEE.
14. Wang Jingqiu, Zhang Ting, An ARM-Based Embedded Gesture Recognition System Using a Data Glove, 978-1-4799-3708-0 © 2014 IEEE.
15. Danling Lu, Yuanlong Yu, and Huaping Liu, Gesture Recognition Using Data Glove: An Extreme Learning Machine Method, 978-1-5090-4364-4/16 © 2016 IEEE
16. Ji-Hwan Kim, Student Member, IEEE, Nguyen Duc Thang, Tae-Seong Kim, Member, IEEE, 3-D Hand Motion Tracking and Gesture Recognition Using a Data Glove 978-1-4244-4349-9/09 © 2009 IEEE.



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