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Signox: Sensor-Based Lexical Mapping for Bi-directional Sign Language Transduction

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Abstract
Effective communication is fundamental to social participation; however, individuals who rely on sign language often encounter barriers due to the limited proficiency of the general population in sign-based interaction. This paper presents Signox, a sensor-based lexical mapping framework for bi-directional sign language transduction. The system employs flex sensors embedded within a wearable glove to capture fine-grained finger movements, which are processed using an ATmega328P microcontroller for accurate gesture interpretation [1]. The recognized gestures are converted into corresponding textual and synthesized speech outputs through an integrated display and audio module with multilingual adaptability [2]. Furthermore, the proposed system supports voice-to-sign transduction by converting spoken input into text using a speech recognition unit and mapping it to appropriate sign language representations displayed visually [3]. This framework is implemented as a streamlined embedded system to maintain stable functionality and high efficiency. The Signox framework establishes a scalable and inclusive solution for accessible communication across diverse educational, healthcare, and public service environments [4].

Keywords: *Sign Language, Speech Transduction, Wearable Technology, Bi-Directional Communication, Multilingual Translation, Accessibility*

1. Introduction

1.1. Context and Motivation

Sign language is a complex visual–gestural communication system that serves as the primary linguistic medium for individuals who rely on non-verbal communication. Similar to spoken languages, sign languages evolve naturally within their respective communities and develop independently of dominant regional spoken languages [6]. Each sign language possesses a distinct grammatical structure, vocabulary, and syntactic framework, unified by the common feature of visual perception. Sign languages vary globally, with well-known examples including American Sign Language (ASL), British Sign Language (BSL), Australian Sign Language (Auslan), French Sign Language (FSL), and Indian Sign Language (ISL), all of which possess distinct linguistic characteristics [7]. Fig. 1 illustrates the distribution and origin of major sign languages. Communication is essential for expressing thoughts, emotions, and intentions; however, individuals who depend on sign language often encounter difficulties in environments where sign communication is not widely understood [8]. This limitation creates significant barriers in social, educational, and professional interactions, leading to reduced accessibility and participation. Addressing this challenge requires innovative technological solutions capable of enabling effective interaction between sign language users and the general population [9].

1.2. Problem Statement and Research Gap

Existing assistive approaches, such as human interpreters and text- based communication tools, provide partial solutions to this communication gap. However, these methods are often constrained by

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availability, cost, and lack of real-time adaptability. Recent advances in gesture recognition and speech processing have enabled automated systems that translate hand gestures into text or speech, improving communication efficiency [10]. Despite these developments, most existing systems focus primarily on one-directional translation, either converting sign language into speech or speech into text, without supporting reciprocal interaction. A notable research gap persists in the development of a unified bidirectional communication framework that facilitates real-time translation between sign language and spoken language in both directions.

1.3.Objectives and Significance of the Study

This study proposes a sensor-based assistive communication system designed to enable bi-directional translation between sign language and spoken language. The system aims to convert hand gestures into audible speech and textual output while also transforming spoken input into visually displayed sign language representations.

This study aims to achieve accurate gesture recognition with multilingual adaptability and user-friendly interaction by integrating sensor-based detection, speech recognition, and visual sign mapping to enhance inclusive communication in educational, healthcare, and public service environments.

1.4.Organization and Structure

This paper focuses on designing and implementing a sensor-driven two-way communication framework capable of translating sign language into speech and converting spoken language into sign representations. The proposed approach focuses on gesture detection, voice processing, and visual sign representation to establish an effective communication bridge between users and non-sign language speakers. The remainder of this paper is organized as follows: Section 2 reviews related work in gesture recognition and assistive communication systems; Section 3 presents the design of the proposed system architecture along with the methodology used in this work. Section 4 describes the hardware and software implementation of the system. Section 5 discusses the experimental results and their analysis. Section 6 highlights the challenges and limitations, while Section 7 concludes the study and suggests directions for future research.

Table 1 Sign Languages and Origin

Sign Language	Region	Alphabet	Origin	Related Languages
ASL	United States and Canada	One-handed alphabet	Developed from French Sign Language (FSL)	Related to FSL
BSL	United Kingdom	Two-handed alphabet	Developed independently	Related to Auslan and NZSL (BANZSL family)
Auslan	Australia	Two-handed alphabet	Evolved from BSL and Irish Sign Language (ISL)	Related to BSL and NZSL (BANZSL family)
FSL	France	One-handed alphabet	Developed independently	Influenced ASL
ISL	India	Two-handed alphabet	Developed independently	Unique to India

2. Literature Review

The development of assistive communication technologies for individuals with speech and hearing impairments has gained significant research attention, particularly in the domain of sign language interaction. This section reviews existing vision-based, sensor-based, and hybrid approaches, highlighting their advantages, limitations, and the need for an efficient bi-directional communication system (Fig. 2) [11].

2.1.Vision-Based Sign Language Recognition

Vision-based systems utilize cameras and deep learning algorithms to interpret hand gestures. Yang and Lee proposed a hierarchical framework employing Conditional Random Fields (CRF) and BoostMap embedding, focusing on hand shape, motion, and spatial location, achieving recognition rates of 83% for signs and 78% for fingerspelling [12]. Rekha et al. implemented a skin color-based segmentation technique followed by Principal Curvature-Based Region (PCBR) detection and wavelet packet decomposition, achieving an accuracy of 91.3% using a Support Vector Machine (SVM) classifier [13]. Despite these promising results, vision-based systems are highly sensitive to lighting conditions, background complexity, and occlusion.

They also demand high computational power and extensive training datasets, making real-time deployment challenging in practical environments [14].

2.2.Sensor-Based Gesture Recognition

To overcome the limitations of vision-based methods, researchers have explored wearable sensor-based technologies. These systems employ flex sensors, accelerometers, and gyroscopes to directly capture hand and finger movements [15]. Sensor-based approaches are less affected by environmental factors such as lighting and background noise and enable faster real-time processing with lower computational overhead [16]. However, existing sensor-based systems often lack multilingual support and are limited in adaptability due to rigid hardware configurations. Furthermore, the absence of integrated feedback mechanisms reduces their effectiveness for seamless two-way communication [17].

2.3.Hybrid Models and AI Integration

Recent studies indicate that combining vision-based and sensor-based data can significantly enhance recognition accuracy and robustness. Monir et al. utilized Microsoft Kinect's skeletal tracking to extract vectors and angular features for posture recognition using priority- based matching matrices [18]. The integration of Artificial Intelligence (AI) and edge computing platforms such as Raspberry Pi further improves recognition accuracy and real-time performance. Edge AI enables on-device inference, reducing dependency on cloud computing and ensuring low-latency operation, which is essential for assistive communication systems [19].

2.4.Speech Synthesis for Multilingual Accessibility

Text-to-speech (TTS) technology plays a vital role in enabling real- time verbal communication from recognized sign gestures. Several studies have integrated speech synthesis modules into gesture recognition systems to convert text outputs into audible speech [20]. However, most existing implementations support only a limited number of languages and lack bidirectional translation capabilities. Additionally, many systems rely on complex hardware configurations, which limits portability and user convenience [21]. Recent developments have focused on integrating speech recognition with sign mapping to enable bidirectional communication between sign language users and speakers in real-time. Nevertheless, challenges remain in achieving high translation accuracy, natural voice synthesis, and seamless language switching within compact and portable system architectures.

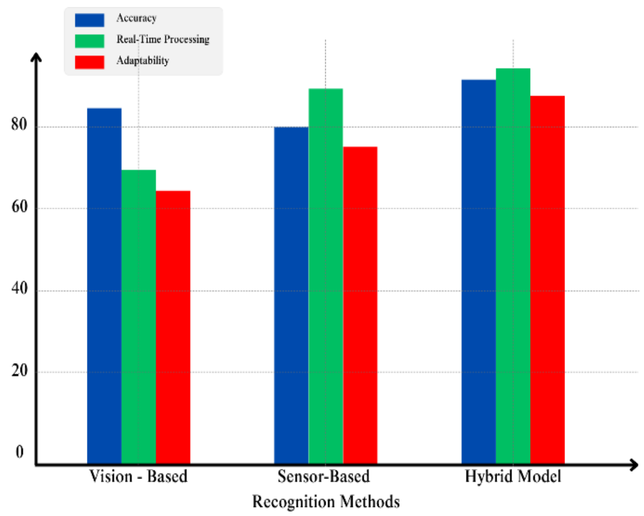

Figure 2 Data for Vision Based, Sensor Based and Hybrid Approaches

3. Proposed Methodology and System Design

3.1.System Architecture of the Smart Sign Glove

The proposed Signox system is designed as a bi-directional assistive communication platform that enables interaction between sign language users and spoken language users. The system translates hand gestures into text and speech (Phase 1) and converts spoken input into text along with the corresponding sign language display (Phase 2). It integrates flex sensors, an ATmega328P microcontroller, a DFPlayer Mini, an SD card, a speech recognition module, and display units to achieve real- time multimodal communication [22]. The system architecture consists of four major functional layers: input layer (data acquisition), processing and power management, communication and storage, and output layer (text, audio, and sign visualization).

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3.1.1. Input Layer (Data Acquisition)

The input layer is responsible for acquiring both gesture-based and voice-based inputs. Flex sensors are mounted on each finger of the glove to capture finger bending movements and convert them into electrical signals [23]. These sensors operate by varying their resistance according to finger displacement, enabling accurate measurement of gesture patterns [24]. In Phase 2 operation, a speech recognition module captures spoken input from a conversational partner and converts it into digital text for processing [25]. This dual-input mechanism allows the system to support two-way communication. The acquired sensor and speech data are transmitted to the ATmega328P microcontroller, which serves as the central processing unit. The controller interprets the incoming data and maps them to predefined gesture and speech patterns stored in its memory [26]. Noise filtering and calibration techniques are applied to eliminate minor fluctuations caused by unintended movements and environmental disturbances [22]. This integrated input framework ensures accurate recognition of both hand gestures and spoken commands, forming the foundation of the bi-directional translation process [23].

3.1.2. Processing and Power Management

The processing and power management layer handles gesture recognition, speech processing, and stable power distribution across all components. The ATmega328P microcontroller continuously analyzes flex sensor signals and speech input to determine the corresponding command or sign [24]. Once a valid input is identified, the controller triggers the appropriate output in the form of text display, speech synthesis, or sign visualization. A library of predefined commands is embedded within the controller program, enabling efficient translation and fast system response [25]. Power regulation is achieved using a 12V, 1A adapter as the primary power source, while an LM2596 DC-to-DC step-down converter provides regulated voltage levels required by various modules [26]. This ensures reliable operation and protects system components from voltage fluctuations [22]. A dedicated mode-selection switch is used to switch between multiple operational and language options, allowing the system to support flexible and multilingual user interaction [23].

3.1.3. Communication and Storage

The communication and storage layer manages data exchange between system modules and retrieves appropriate translation outputs. The DFPlayer Mini generates speech output by playing pre-recorded audio files stored on an SD card [24]. Individual audio files are mapped to distinct gestures or the translated voice input [25]. The SD card functions as the primary storage unit, maintaining a database of gesture-to-speech and speech-to-sign mappings [26]. When an input is recognized, the microcontroller sends commands to the DFPlayer Mini to retrieve and play the associated audio output [22]. The system supports scalability and customization, allowing additional gestures and languages to be incorporated by updating the stored files and modifying code parameters [23]. This modular structure enhances accessibility for users with diverse linguistic requirements [24].

3.1.4. Output Layer (Text and Audio Feedback)

The output layer provides multimodal feedback through text, speech, and sign representation. An LCD module displays the recognized gesture as text and presents converted speech input for user comprehension [25]. This visual feedback is particularly beneficial in noisy environments where audio output may not be practical [26]. For verbal communication, the DFPlayer Mini retrieves the corresponding audio file from the SD card and plays it through a speaker, enabling real-time conversion of gestures into audible speech [22]. In Phase 2 operation, spoken input is converted into text and displayed along with the corresponding sign language representation, allowing sign language users to understand verbal communication effectively [23]. This dual-output mechanism enhances communication efficiency and inclusivity by supporting both gesture-to-speech and speech-to-sign translation within a unified system [24]. The overall methodology is illustrated in the flow diagram shown in Fig. 3.

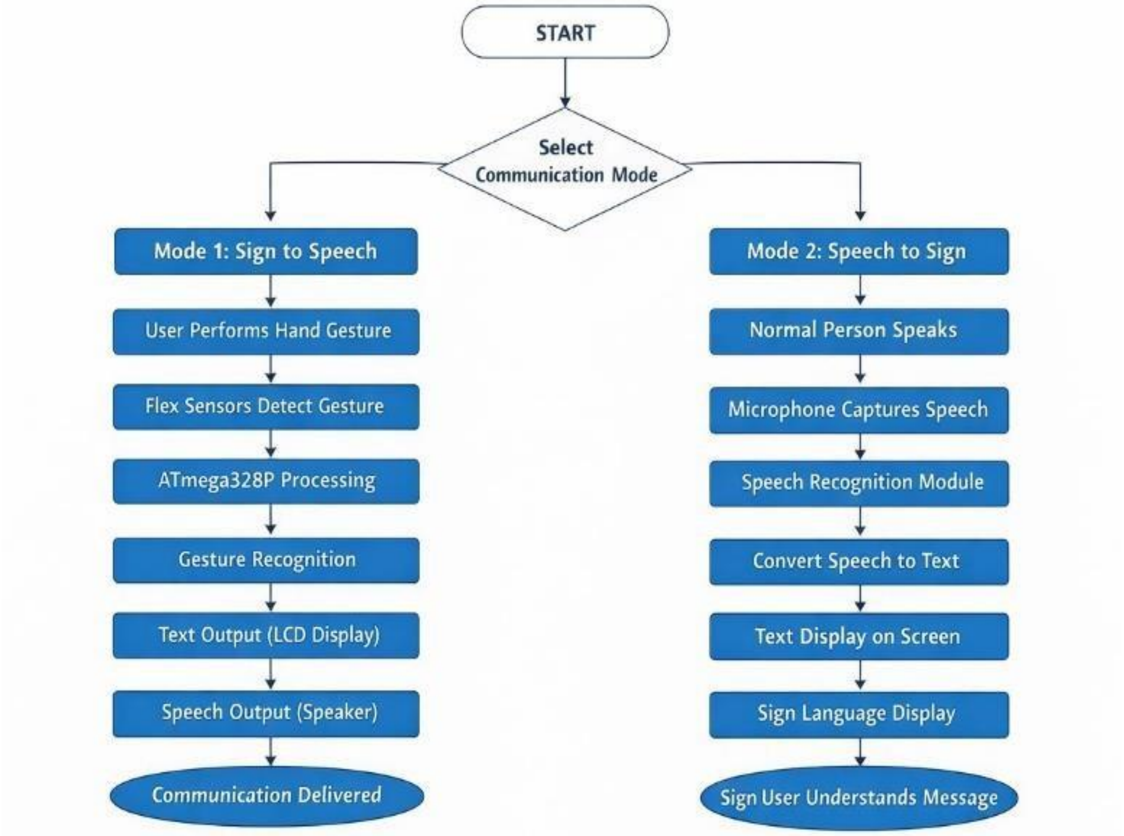

Figure 3 **Flow Diagram of System Design**

4. Implementation

In Signox , flex sensors are used to capture and monitor finger bending movements. The sensors vary their electrical resistance according to the amount of bend, and this change is translated into voltage signals that are interpreted by the microcontroller to detect particular gestures [27]. These sensors provide high accuracy and fast response time, ensuring precise gesture interpretation [28]. Their low power consumption enhances system efficiency, allowing prolonged operation without excessive energy usage [29]. In addition, their flexibility, low weight, and durability make them suitable for continuous use, providing both comfort and dependable performance over time [30]. Consistent sensor performance allows accurate and seamless gesture detection, contributing significantly to the functionality of the glove [31]. The DFPlayer Mini module is responsible for storing and playing pre-recorded audio responses corresponding to recognized gestures. It obtains control signals from the microcontroller and accesses the required audio file from the SD card, which is then played through the speaker [32]. Due to its compact form factor, efficient power consumption, and high- quality audio output without requiring an external decoder, it is appropriate for embedded system integration [33]. By supporting MP3 and WAV file formats, the system delivers consistent audio output and facilitates real-time voice generation corresponding to translated sign language gestures [34]. The ATmega328P microcontroller serves as the core processing unit of the smart sign language glove. The system reads voltage variations produced by the flex sensors, analyzes the data, and associates it with stored gesture patterns in memory [35]. Based on the recognized gesture, the controller sends commands to the DFPlayer Mini for audio playback and updates the LCD with the corresponding textual output [36]. Due to its minimal power requirement, rapid processing, and availability of several I/O pins, the device can effectively integrate sensors and peripherals, resulting in a responsive sign language translation system [37]. To facilitate multilingual communication, a 3-pole terminal switch is used to toggle between different language modes for audio output [38]. By toggling between preset language options, the device ensures flexibility and adaptability in diverse communication environments [39]. Its reliable switching mechanism, stable electrical connectivity, and minimal power consumption enhance overall system usability and durability [40]. The speaker is responsible for delivering audible output by playing the pre-recorded voice responses corresponding to the recognized gestures [41]. It ensures that translated sign language is clearly communicated to surrounding listeners [42]. Its efficiency is characterized by clear sound reproduction, low power usage, and compatibility with the DFPlayer Mini, making the system user-friendly and effective for real-time interaction [43].

The LCD module visually presents the recognized gesture by displaying the corresponding textual output [44]. This feature is especially beneficial in environments where audio output may not be sufficient or for users who prefer visual confirmation [45]. With minimal power requirements, fast response, and clear text display, the device offers improved accessibility and user- friendly operation [46]. In Phase 2, the Signox system is enhanced to support reverse communication by converting spoken language into textual and visual sign output. A microphone module is integrated to capture voice input from users, which is processed using Python-based speech recognition techniques [47]. The captured audio signals are converted into text, enabling accurate recognition of spoken words [48]. The recognized text is then mapped to corresponding sign language representations stored in the system database [49]. These sign representations are displayed on the LCD screen in text or symbolic sign images, allowing individuals with hearing or speech limitations to understand spoken communication visually [50]. This bidirectional communication approach enables both gesture-to-speech and speech-to-sign translation, making the system inclusive and interactive [51]. Efficient data processing and synchronization between voice input, text generation, and visual display are achieved using optimized Python algorithms and real-time signal processing techniques [52]. Noise filtering and error-handling mechanisms are incorporated to improve recognition accuracy and reduce misinterpretation caused by background disturbances [53]. The Phase 2 implementation transforms the glove into a two-way communication bridge rather than a one- directional assistive device [54]. Python is adopted as the core programming language owing to its flexibility, user-friendly syntax, and the availability of various speech processing libraries. It ensures efficient mapping of sensor inputs and voice data to predefined gesture and text outputs while maintaining real-time system responsiveness [55]. The integration of hardware and Python-based software results in a smooth, reliable, and user-friendly communication system [56].

5. Results and Discussion

The performance of the Signox system was evaluated for both Phase 1 (gesture-to-text and speech translation) and Phase 2 (voice-to-text and sign display). The flex sensors demonstrated reliable detection of finger movements, and the ATmega328P microcontroller processed the sensor data in real time with minimal latency, enabling accurate gesture recognition and output generation (Fig. 4) [35].

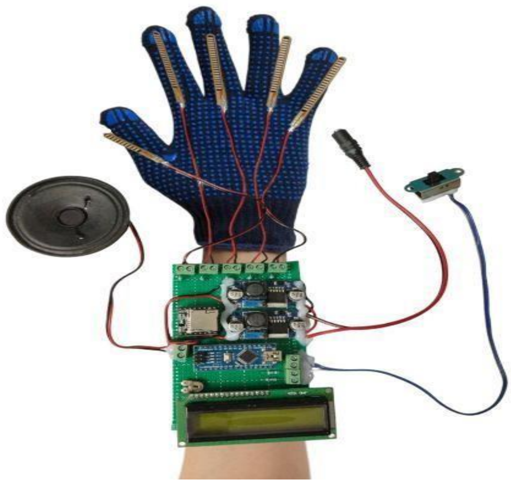

Figure 4 Sensor-Based Sign Language to Speech System (Digital Design) – Phase 1

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The system successfully identified predefined hand gestures and mapped them to corresponding text and audio outputs using the DFPlayer Mini module [36]. The average response time for gesture recognition and output generation was approximately 1.2 seconds, which ensured smooth and efficient communication between users [37]. The LCD provided clear visual feedback by displaying the recognized gesture and selected language mode, while the DFPlayer Mini retrieved and played the appropriate pre-recorded audio files from the SD card without observable errors (Fig. 5) [38]. Phase 2 evaluation confirmed that the system could effectively convert spoken input into text using Python-based speech recognition techniques [39]. The identified text was mapped to its relevant sign language representation and presented on the LCD, allowing spoken communication to be interpreted visually (Fig. 6) [40]. This bidirectional communication capability,

Figure 5 **Prototype Back View – Phase 1**

significantly enhanced the usability of the system by allowing interaction between both gesture-based and voice-based users [41]. Small deviations in sensor readings were observed during testing, mainly caused by unintentional hand motion and environmental disturbances [42]. Despite this, the system maintained stable overall performance. The implementation of filtering and noise reduction techniques improved recognition accuracy and minimized misinterpretation of gestures and voice inputs [43]. The power management subsystem operated reliably, providing stable voltage to all components throughout testing [44]. The LM2596 DC-DC step-down converter effectively regulated power distribution and prevented voltage fluctuations that could degrade system performance [45]. No overheating or unexpected shutdowns were observed during continuous operation, indicating stable and safe system behavior [46]. The 3-pole terminal switch enabled seamless switching between different language modes, ensuring flexibility and adaptability in multilingual communication scenarios (Fig. 7) [47]. Overall, the

Figure 6 **Prototype Front View – Phase 1**

Signox system demonstrated high accuracy, stability, and responsiveness in both Phase 1 and Phase 2 (Fig. 8) operations. The combined results confirm that the system functions as a two- way communication bridge rather than a single-direction assistive device, providing meaningful and reliable interaction for individuals with speech and hearing challenges [48]. Further improvements can be achieved by incorporating advanced filtering algorithms and adaptive calibration methods to enhance recognition accuracy under varying environmental and user

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conditions [49]. Despite these limitations, the experimental results validate the feasibility and effectiveness of the proposed Signox system as a practical and inclusive communication solution [50].

Figure 7 Prototype in Working state – Phase 1

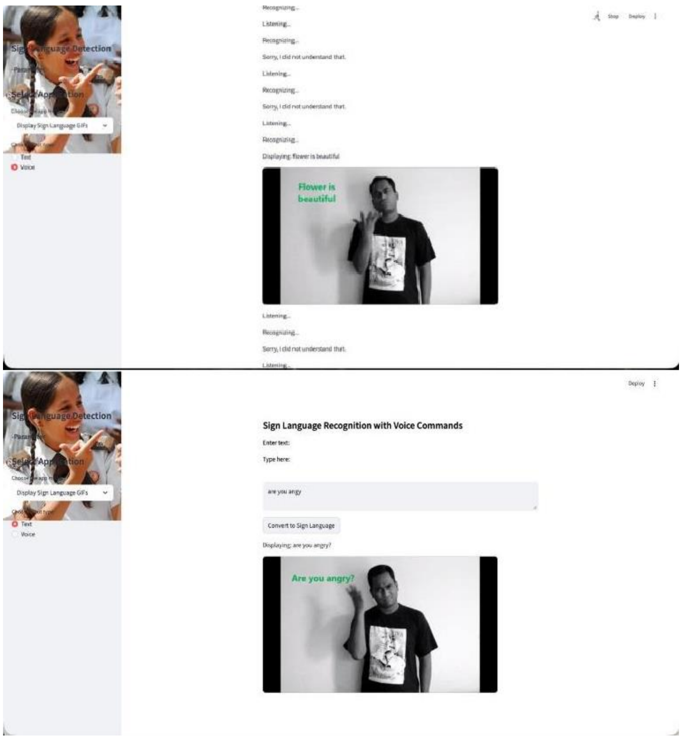

Figure 8 Sample Outputs – Phase 2

6. Challenges and Limitations

The Signox system, while demonstrating effective bidirectional communication through gesture-to-speech and voice-to-text translation, encounters several challenges and limitations that influence its performance and usability. One of the primary challenges is achieving high gesture recognition accuracy, as variations in hand size, finger flexibility, and movement patterns among users can affect sensor readings and require precise calibration of flex sensors for optimal performance [50]. Furthermore, the system relies on a predefined gesture vocabulary, limiting its ability to interpret a wider range of sign language expressions and dynamic gestures [51]. Another challenge involves multilingual audio storage and processing. Supporting multiple languages increases memory requirements and demands efficient SD card management and data compression techniques to optimize storage capacity [52]. Power consumption also remains a limitation, as prolonged operation requires regular battery recharging or an external power source, which may reduce portability and continuous usability [53] Response time is another important consideration, since simultaneous processing of multiple sensor and voice inputs may introduce minor delays in generating text and audio outputs. This necessitates further optimization in signal processing and microcontroller efficiency to ensure real-time communication [54]. Environmental factors such as ambient noise can affect the clarity of speaker output, while lighting conditions may impact the visibility and readability of the LCD display [55]. Hardware durability presents an additional limitation, as continuous bending of flex sensors over extended periods can lead to mechanical wear and reduced sensitivity, requiring periodic maintenance or replacement [56]. Moreover, user adaptation is required, since first-time users may need training to perform gestures consistently and accurately to reduce misinterpretation and improve recognition reliability [57]. Despite these limitations, several improvements can enhance system performance and practicality. Gesture recognition accuracy can be improved through the integration of machine learning algorithms that adapt to individual hand movement patterns and dynamically calibrate sensor thresholds [58]. Expanding the vocabulary of recognized gestures can be achieved by employing microcontrollers with higher processing capability and larger memory resources [59]. Efficient SD card management and compression methods can further optimize multilingual audio storage [60]. Portability can be improved by using rechargeable lithium-ion batteries with advanced power management systems to extend operational time [61]. Response time can be reduced by optimizing signal processing routines and computational efficiency within the control unit [62]. Environmental challenges can be mitigated through noise-cancellation techniques for clearer speaker output and by using high-contrast LCD or OLED displays to enhance readability under varying lighting conditions [63]. Improving sensor durability through the use of robust materials and protective coatings can extend hardware lifespan and maintain consistent performance [64]. Finally, incorporating a user-friendly interface with guided training sessions can help users quickly adapt to the system, improving gesture accuracy and minimizing errors [65]. With these refinements, the Signox system can become more reliable, user-friendly, and effective for real-world communication applications [66].

Figure 9 Conceptual Futuristic Wearable Model

Conclusion and Future Scope

The Signox framework offers a bidirectional communication solution that connects sign language users with people who depend on spoken language.. In its Phase 1, the system transforms hand gestures into text and voice output to support effective communication. In Phase 2, the system recognizes spoken words and converts them into text and sign language representations using holographic or visual display technology, thereby enabling individuals with hearing impairments to perceive spoken conversations in real time [67]. holographic display, which can visually project recognized speech as holographic text or sign representations. This will significantly improve accessibility and provide a more intuitive and immersive method of communication for users [68]. Additionally, incorporating advanced AI-powered speech recognition models will improve accuracy and reliability, particularly in noisy environments, ensuring smooth and uninterrupted interaction between users [69]. Future versions of the system can also support multilingual speech recognition and sign language translation, allowing Signox to be adopted globally and making it inclusive for users from different linguistic backgrounds [70]. Furthermore, replacing conventional displays with augmented reality (AR) interfaces can enhance portability and user comfort, enabling translated speech and sign representations to be viewed through AR glasses or mobile devices [71]. Enhancements in AI-driven gesture recognition algorithms will further improve adaptability by learning individual user gesture patterns, reducing calibration errors and increasing recognition accuracy over time [72]. The integration of flexible electronics and smart fabrics into the glove design can improve comfort, durability, and practicality for everyday use [73]. By combining real-time sign-to-speech translation with speech-to-sign and holographic visualization, Signox offers a dual-function communication framework that promotes inclusivity in education, workplaces, healthcare, and public environments [74]. These advancements will ensure that Signox continues to evolve as a powerful assistive technology like wrist watches shown in Fig. 9, fostering equal communication opportunities and eliminating barriers between individuals regardless of their hearing or speaking abilities [75].

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With ongoing innovation and the incorporation of technologies like artificial intelligence, augmented reality, and wearable devices, Signox moves closer to a future where communication barriers are minimized and inclusive communication becomes widely accessible [76].

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