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OmniSign: An Intelligent Wearable System for Bidirectional Indian Sign Language Communication

Om Dudhe¹, Sarthak Warhade², Atwika Dhongde³, Arnavi Kadu⁴, Om Mokalkar⁵, R. M. Gharat⁶

Students, Department of Electronics Engineering, Dr. Panjabrao Deshmukh Polytechnic, Amravati,
Maharashtra, India¹⁻⁵

I/C HOD, Department of Electronics of Engineering, Dr. Panjabrao Deshmukh Polytechnic, Amravati,
Maharashtra, India⁶

ABSTRACT: Communication barriers between Indian Sign Language (ISL) users and people unfamiliar with sign language highlight the need for accessible assistive technologies. A Government of India publication issued in December 2024 reported a World Health Organization (WHO) estimate of approximately 63 million people in India with significant auditory impairment. This estimate highlights the scale of hearing-related challenges but does not represent the number of ISL users. This paper presents OmniSign: An Intelligent Wearable System for Bidirectional Indian Sign Language Communication, integrating dual sensory gloves with an Android application. Each glove incorporates five resistive flex sensors, an MPU6050 inertial measurement unit (IMU), and an ESP32 microcontroller to capture finger-bending and hand-motion data. The collected sensor data are transmitted to the application through Bluetooth Low Energy (BLE) for processing and gesture recognition. In the sign-to-communication direction, recognized gestures are presented as text and voice output. In the reverse direction, speech or typed text is processed and matched with corresponding pre-recorded ISL videos for visual communication. The system follows an offline-first approach, enabling core communication functions to operate without continuous internet connectivity. By combining wearable sensing, wireless communication, gesture recognition, and ISL video output, OmniSign aims to provide a practical communication bridge between ISL users and non-signers.

KEYWORDS: Indian Sign Language, Smart Gloves, Flex Sensors, MPU6050, ESP32, Gesture Recognition, Assistive Communication, Bluetooth Low Energy, Android Application, Bidirectional Communication

I. INTRODUCTION

According to the Government of India's National Programme for Prevention and Control of Deafness, approximately 29.97 lakh people were screened for deafness during the 2024–25 financial year, compared with approximately 16.76 lakh in 2023–24. These figures demonstrate the scale of hearing-screening activities in India, although they do not represent the total number of people with hearing impairment. The need for accessible communication technologies remains important, particularly for interactions between Indian Sign Language (ISL) users and people unfamiliar with sign language.

To understand communication challenges at the user level, our team conducted a primary survey at Shri Bulidan Rathi Mukbadhir Vidyalaya, Amravati, involving 100 participants. The survey examined their commonly used communication methods, difficulties when interacting with non-ISL users, and views on technology-assisted communication. The responses indicated that The survey will examine commonly used communication methods, difficulties when interacting with non-ISL users, and the potential usefulness of technology-assisted communication. The findings will be analysed to identify user needs and guide the development of OmniSign. These findings helped our team identify communication requirements relevant to the development of OmniSign.

Existing communication methods can create difficulties when people who use Indian Sign Language interact with people who do not understand it. A practical solution must support communication in both directions: converting signed gestures into understandable text or speech, and converting spoken or typed messages into visual ISL content. The

challenge is to integrate these functions into a portable system that combines wearable sensing, wireless communication, and mobile application processing.

To address the identified communication challenges, this paper proposes OmniSign: An Intelligent Wearable System for Bidirectional Indian Sign Language Communication. The system integrates two sensory gloves with an Android application. Each glove uses five resistive flex sensors, one MPU6050 inertial measurement unit (IMU), and one ESP32 microcontroller to capture finger-bending and hand-motion data. The sensor data are transmitted to the application through Bluetooth Low Energy (BLE) for processing and gesture recognition. In one direction, recognized gestures are presented as text and voice. In the reverse direction, spoken or typed input is processed and matched with corresponding pre-recorded ISL videos. The system follows an offline-first design, with the aim of supporting communication without continuous internet connectivity.

II. LITERATURE REVIEW

1. Saeed et al. (2022) presents “A Systematic Review on Systems-Based Sensory Gloves for Sign Language Pattern Recognition: An Update From 2017 to 2022” evaluating 115 papers to analyze wearable gesture interfaces utilizing flex, pressure, and IMU sensors. The findings reveal a significant bias where 76% of research is restricted to single-handed signs, 95% targets isolated gestures, and 46% operates purely on static configurations. Unlike existing localized designs that achieve high accuracy on small vocabularies, this study highlights critical research gaps across the entire field, such as a complete disregard for non-manual grammatical components like facial expressions and the lack of a universal rule framework. Prior data glove-based approaches have failed to provide the scale and multi-modal configuration required for functional daily communication[1].

2. Oliveira et al. (2019) introduces “The VirtualSign Channel for the Communication Between Deaf and Hearing Users,” a bidirectional translation framework utilizing a 3D avatar for text-to-sign translation and a hybrid setup of Kinect v2 and data gloves for sign-to-text translation. Testing Portuguese Sign Language with 14-flexion sensor 5DT Ultra gloves and 9-spatial sensor IFG gloves on a 100-word dataset yielded a superior top-two accuracy of 70% for the flexion model, whereas the gyroscope-based glove dropped to 18% due to palm orientation variations. Unlike prior hybrid methods that struggled with high computational overhead and strict field-of-vision dependencies, this configuration prioritizes localized real-time translation in academic environments. However, the system faces structural limitations, including an inability to process simultaneous state triggers smoothly and an absence of facial expression capture[2].

3. van der Merwe et al. (2021) explores “Automated Sign Language Alphabet Detection,” focusing on data acquisition through a finger-tracking glove embedded with resistive flex sensors and routed via an Arduino Leonardo to a multi-layer Artificial Neural Network (ANN). The system applies feature vector normalization to balance angular variations and successfully recognized six static South African Sign Language (SASL) signs with 96% accuracy. Unlike conventional vision approaches that suffer from complex background and ambient lighting sensitivities, this design introduces a direct mapping alternative that captures finger deflections reliably. Prior research on sensor-based gloves showed high precision, but this specific setup remains constrained by a small lexicon, single-hand focus, trial-and-error network parameter tuning, and a tethered USB connection that hinders spatial portability[3].

4. Wajahat et al. (2024) presents “Development of AI-Enabled Sign Language Predicting Glove Using 3-D Printed Triboelectric Sensors,” focusing on self-powered smart interfaces that integrate flexible contact separation mode triboelectric nanogenerators (TEENG) onto a Showa glove base. Finger motions generate voltage spikes read by an Arduino Uno, which are processed using an LSTM model to achieve 99% training and validation accuracy for characters A–J. Unlike existing wearable systems that rely on heavy, expensive, or rigid commercial components, this configuration leverages low-cost, flexible, 3D-printed energy-harvesting materials. Prior works have achieved successful gesture classification, but this system faces material limitations where alternative GRU models overfit, and spatial CNN architectures confuse highly similar finger configurations like letters “i” and “j”[4].

5. Begum et al. (2024) describes an “AI-Based Sensory Glove System to Recognize Bengali Sign Language (BaSL)” integrating five 4.5-inch resistive flex sensors and a wrist MPU6050 IMU managed by an Arduino Nano and a Raspberry Pi 3B edge processor. Evaluating 41 dynamic Bengali words, the system achieved a superior user-independent average accuracy of 94.73% using a combined CNN-LSTM architecture compared to 90.34% from a

standalone CNN. Unlike traditional vision systems affected by complex backgrounds and occlusions, this design provides portable and user-independent gesture capture. However, prior deep learning glove designs often overlook edge processing constraints, and this specific setup encounters high processing latency exceeding 4 seconds for complex gestures alongside single-hand lexicon restrictions[5].

6. Marin et al. (2025) proposes the “Real-Time Sign Language-to-Speech Translation System With AI-Powered Wearable Technology,” introducing a cyber-physical prototype called "SignSpeak" that embeds five SpectraFlex bend sensors and an MPU6050 spatial tracker into a wearable glove. An Arduino Mega streams data to a host PC running a TensorFlow deep neural network, classifying 29 gesture classes with 94.7% accuracy and a low end-to-end response delay of 112 ms. Unlike costly commercial glasses or camera-based setups that lack daily portability, this affordable model provides rapid real-time speech synthesis. Prior research on assistive communication devices has remained technocentric and cost-prohibitive, whereas this prototype lowers access barriers but remains limited by single-glove tracking, measurement drift during sharp movements, and per-user calibration requirements[6].

7. Chen et al. (2026) presents “Real-Time Sign Language Interpretation via Customized Sign Language Gloves and Motion Retrieval” integrating flex sensors, a 9-axis IMU, and fingertip pressure sensors to capture finger deflections, quaternions, and body contacts. The system bypasses heavy neural processing by implementing a lightweight motion retrieval algorithm utilizing k-d trees and an Online Lazy Neighborhood Graph (OLNG) to interpret 300 words with 92% accuracy in under 7 ms on an Intel N100 processor. Unlike traditional deep networks requiring massive datasets and heavy edge computing resources, this approach needs only a single sample per gesture. However, prior glove designs face spatial mapping issues, and this setup is limited by an inability to resolve lateral finger spacing or track absolute positions relative to the head[7].

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10. Shenoy et al. (2022) presents “Design and Validation of an IMU Based Full Hand Kinematic Measurement System” developing a Hand Kinematics Measurement System (HKMS) integrating 16 BNO055 IMU sensors and 6 microcontrollers configured in a master-slave topology. The hardware architecture streams 15-joint orientation quaternions in real time at 100 Hz via Wi-Fi or USB to execute kinematic range of motion (ROM) and principal component synergy analysis. Unlike conventional commercial data gloves that obstruct the palmar surface and decrease hand dexterity by 29%, or optical trackers restricted by lab setups and line-of-sight blockages, this design completely eliminates palmar strapping to preserve natural dexterity. Prior works often output data at low sampling rates or rely on intensive host-side filtering, whereas this architecture offloads sensor fusion to onboard processors to simplify reproduction, though it encounters minor orientation drift during rapid, continuous, and repetitive joint rotations at high speeds exceeding 240°/s[10].

11. DelPreto et al. (2022) presents “A Wearable Smart Glove and Its Application of Pose and Gesture Detection to Sign Language Classification” creating a self-contained smart wearable system utilizing an off-the-shelf conductive knit glove sensorized with a loop-weaved network of 16 resistive strain channels and a 3-axis accelerometer. The

system embeds a pre-trained long short-term memory (LSTM) neural network directly onto an STM32H7 microcontroller to perform dynamic time-series classification of 24 ASL signs at 5 Hz with 96.3% segmented example accuracy. Unlike high-fidelity virtual reality gloves that demand intricate custom fabrication and expensive external host processing, this low-profile model optimizes accessibility by processing signals and running predictions entirely on-board. Prior research focused strictly on isolated static frames, but this multi-modal structure accommodates timing variations via data augmentation, though it experiences minor response latencies due to fabric hysteresis and faces brief false-positive overlaps during initial movement phases[11].

III. METHODOLOGY

Titel: "OmniSign: An Intelligent Wearable System for Bidirectional Indian Sign Language Communication"

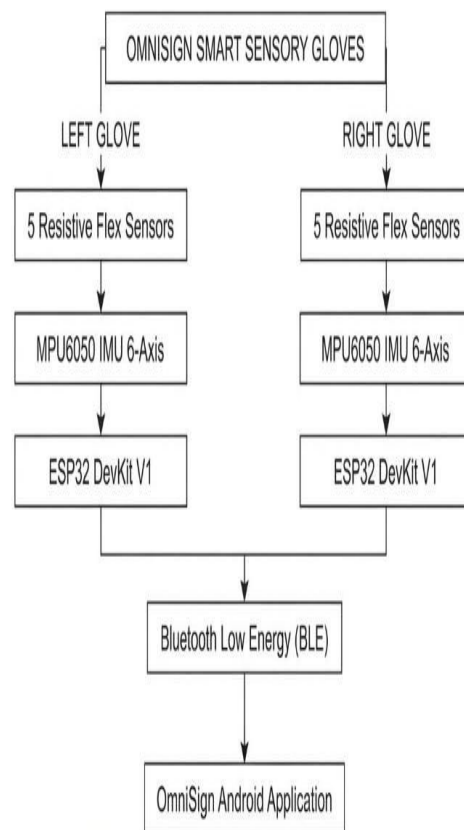


Fig.1. Hardware architecture of the OmniSign smart sensory gloves

Figure 1: Software Architecture of the OmniSign Android Application

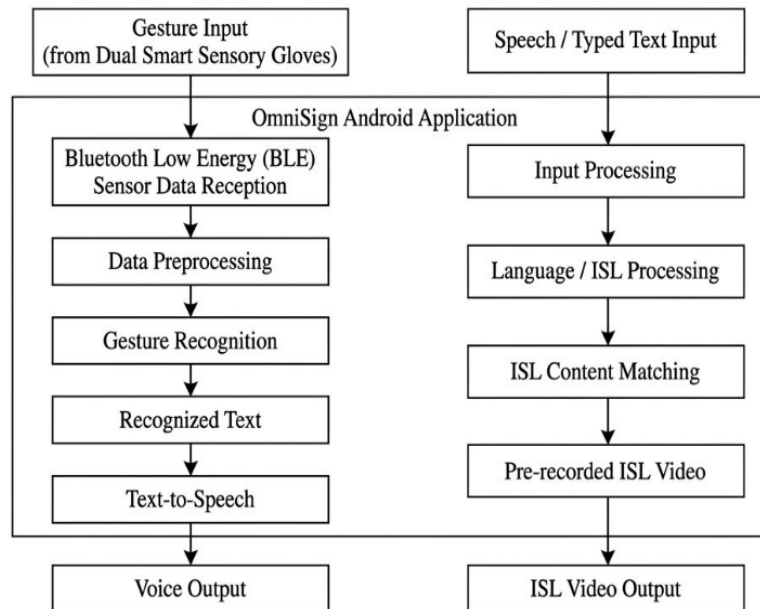


Fig.2 Software architecture of the OmniSign Android application

The proposed methodology follows a sequential data flow in which physical hand movements are first converted into sensor signals, transmitted to the mobile application, processed for gesture interpretation, and finally converted into an appropriate communication output. The complete methodology is divided into hardware-side sensing and software-side processing.

A. Hardware Methodology

As illustrated in Fig. 1, the hardware stage begins with the acquisition of finger and hand-motion signals from both gloves. When a user performs a sign, the bending of each finger produces corresponding changes in the electrical response of the resistive flex sensors. At the same time, the MPU6050 captures the motion of the hand through its accelerometer and gyroscope measurements. Thus, the system obtains complementary information representing finger configuration and hand movement.

The sensor signals from each glove are acquired by its ESP32 DevKit V1. The ESP32 organizes the acquired measurements into data packets for wireless transmission. The data from the left and right gloves are then communicated to the Android application through Bluetooth Low Energy (BLE). This process converts the physical hand movement into a digital sensor-data stream that can be processed by the software system.

B. Software Methodology

The software stage begins when the Android application receives the sensor stream through BLE, as shown in Fig. 2. The received data are first prepared for recognition through preprocessing so that the sensor measurements can be used consistently by the recognition module. The processed data are then analysed to determine the corresponding gesture and generate its textual representation.

For gesture-to-speech communication, the recognized text is passed to the text-to-speech stage, where it is converted into audible output. For the reverse communication path, the application accepts either speech or typed text. The input is processed and passed through the language/ISL processing stage to determine the appropriate sign-language content. The application then matches the processed input with its available ISL content and selects the corresponding pre-recorded ISL video for visual presentation.

IV. DISCUSSION

The proposed OmniSign framework combines wearable sensing and mobile software to address several limitations identified in existing sign-language recognition systems. The use of dual sensory gloves allows information from both hands to be captured, which is important for gestures involving coordinated bilateral hand movements. Combining resistive flex sensors with MPU6050-based motion sensing also provides two complementary forms of information: finger-bending patterns and hand-motion characteristics.

Another important aspect of the system is the separation of sensing and application-level processing. The ESP32 devices are responsible for sensor-data acquisition and wireless transmission, while the Android application handles the subsequent processing and communication functions. This architecture reduces the dependence on external desktop computers and supports a more portable system configuration. BLE further provides a wireless interface between the wearable hardware and the mobile application.

The bidirectional communication design extends the system beyond simple sign recognition. In the gesture-to-communication direction, recognized signs can be presented as text and voice, allowing an ISL user to communicate with a person who does not understand sign language. In the opposite direction, speech or typed text can be converted into corresponding pre-recorded ISL video content. This two-way approach addresses the communication process from both sides rather than treating sign recognition as an isolated classification task.

The offline-first design is also relevant for practical deployment because core processing resources and ISL video content can be maintained locally. However, the effectiveness of the complete system depends on factors such as sensor calibration, variations in hand position and glove fitting, sensor drift, the diversity of the gesture dataset, and the ability of the recognition model to generalize across different users and signing styles. These factors should therefore be evaluated experimentally before making claims about recognition accuracy or real-time performance.

Overall, OmniSign provides an integrated hardware–software framework that combines bilateral wearable sensing, wireless data acquisition, gesture recognition, and bidirectional ISL communication. The proposed architecture provides a foundation for experimental evaluation and further development of a practical wearable communication system.

V. CONCLUSION

OmniSign presents an integrated hardware–software framework for bidirectional Indian Sign Language communication. The proposed system combines dual sensory gloves equipped with resistive flex sensors, MPU6050 IMUs, and ESP32 microcontrollers to capture finger and hand movements, while Bluetooth Low Energy enables wireless communication with the Android application. The software processes the acquired sensor data for gesture recognition and provides text and voice output, while speech or typed input is converted into corresponding pre-recorded ISL video content.

By integrating bilateral wearable sensing, mobile processing, wireless communication, and two-way communication pathways, OmniSign provides a practical framework for reducing communication barriers between ISL users and non-ISL users. The offline-first design further supports operation without continuous dependence on internet connectivity.

The proposed system establishes a foundation for further experimental development of wearable ISL communication technologies. Future work will focus on expanding the gesture vocabulary, improving signer-independent recognition, evaluating continuous sign sequences, optimizing sensor calibration and robustness, and experimentally assessing recognition accuracy, response time, power consumption, and overall usability.

REFERENCES

1. Z. R. Saeed, Z. B. Zainol, B. B. Zaidan, and A. H. Alamoodi, "A Systematic Review on Systems-Based Sensory Gloves for Sign Language Pattern Recognition: An Update From 2017 to 2022," *IEEE Access*, 2022, doi: 10.1109/ACCESS.2022.3219430.
2. T. Oliveira, N. Escudeiro, P. Escudeiro, E. Rocha, and F. M. Barbosa, "The VirtualSign Channel for the Communication Between Deaf and Hearing Users," *IEEE Revista Iberoamericana de Tecnologías del Aprendizaje*, Nov. 2019, doi: 10.1109/RITA.2019.2952270.
3. A. van der Merwe, E. N. Mambou, and T. G. Swart, "Automated Sign Language Alphabet Detection," in *Proceedings of 2021 IEEE AFRICON*, 2021, doi: 10.1109/AFRICON51333.2021.9570931.
4. M. Wajahat, A. Z. Kouzani, S. Y. Khoo, and M. A. P. Mahmud, "Development of AI-Enabled Sign Language Predicting Glove Using 3-D Printed Triboelectric Sensors," *IEEE Journal on Flexible Electronics*, June 2024, doi: 10.1109/JFLEX.2024.3419078 [HSaSSS.pdf].
5. H. Begum, O. Chowdhury, M. S. R. Hridoy, and M. M. Islam, "AI-Based Sensory Glove System to Recognize Bengali Sign Language (BaSL)," *IEEE Access*, 2024, doi: 10.1109/ACCESS.2024.3472498.
6. I. Marin, V. Babalian, and S. Slutu, "Real-Time Sign Language-to-Speech Translation System With AI-Powered Wearable Technology," *IEEE Access*, 2025, doi: 10.1109/ACCESS.2025.3602794.
7. C.-H. Chen, C.-Y. Yao, and S.-H. Hung, "Real-Time Sign Language Interpretation via Customized Sign Language Gloves and Motion Retrieval," *Sensors*, Aug. 2026, doi: 10.3390/s26154884.
8. S. Murali, K. R. Anandahari, A. Gopakumar, and K. S. Shaji, "Development of Sign Language using Flex Sensors," in *Proceedings of the 2020 International Conference on Smart Electronics and Communication (ICOSEC)*, 2020, doi: 10.1109/ICOSEC49089.2020.9215392.
9. S. Sharan, A. Kumar, S. K. Jha, and N. K. Singh, "GloveLingo: Enhancing Communication for the Hearing Impaired Through an Intelligent Indian Sign Language Glove Interface," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 2024, doi: 10.1109/TNSRE.2024.11241943.
10. O. A. Awosanmi, A. O. Balogun, and T. S. Ibiyemi, "Development of a Low-Cost Flex-Sensor and Machine Learning Based Sign Language Interpreter," *IEEE Journal of Biomedical and Health Informatics*, Apr. 2026, doi: 10.1109/JBHI.2026.11493897.
11. R. Rastgoo, K. Kiani, and S. Escalera, "Sign Language Recognition: A Deep Survey," *Expert Systems with Applications*, Feb. 2021, doi: 10.1016/j.eswa.2020.113794.
12. M. Lee and J. Bae, "Deep Learning Based Real-Time Recognition of Dynamic Finger Gestures Using a Data Glove," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.3039401.
13. M. Lee and J. Bae, "Real-Time Gesture Recognition in the View of Repeating Characteristics of Sign Languages," *IEEE Transactions on Industrial Informatics*, Dec. 2022, doi: 10.1109/TII.2022.3152214.
14. T. S. Dias, J. J. A. M. Júnior, and S. F. Pichorim, "An Instrumented Glove for Recognition of Brazilian Sign Language Alphabet," *IEEE Sensors Journal*, Feb. 2022, doi: 10.1109/JSEN.2021.3136790.
15. K. Aw, J. Budd, and T. Wilshaw-Sparkes, "Data Glove Using Soft and Stretchable Piezoresistive Sensors," *Micromachines*, Feb. 2022, doi: 10.3390/mi13030372.
16. J. Li, B. Liu, Y. Hu, J. Liu, X.-D. He, J. Yuan, and Q. Wu, "Plastic Optical Fiber Enabled Smart Glove for Machine Learning-Based Gesture Recognition," *IEEE Transactions on Industrial Electronics*, Apr. 2024, doi: 10.1109/TIE.2023.3277119.
17. E. Korzeniewska, M. Kania, and R. Zawiałak, "Textronic Glove Translating Polish Sign Language," *Sensors*, Sep. 2022, doi: 10.3390/s22186788.
18. B. G. Lee and S. M. Lee, "Smart Wearable Hand Device for Sign Language Interpretation System With Sensors Fusion," *IEEE Sensors Journal*, Feb. 2018, doi: 10.1109/JSEN.2017.2779466.



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