

AI-Powered Sign Language to Speech Converter with Smart Glove Interface

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Abstract—This paper presents an AI-powered sign language to speech converter integrated with a smart glove, designed to facilitate real-time communication for individuals with hearing and speech impairments [3]. The system employs five flex sensors to capture finger articulations and a six-axis inertial measurement unit (IMU) to track hand orientation, enabling precise recognition of American Sign Language (ASL) gestures [1]. A hybrid CNN- LSTM model processes sensor data, leveraging convolutional layers for spatial feature extraction and recurrent layers for temporal dependencies, achieving robust gesture recognition [2]. Sensor fusion techniques combine flex and IMU data to mitigate noise and drift, ensuring reliable performance across diverse environments [8]. Wireless transmission via Wi-Fi or UART supports seamless data delivery to a backend for classification and speech synthesis, with end-to-end latency under 40 ms [18]. Experimental results demonstrate $\geq 90\%$ accuracy for ASL alphabets and isolated words, and $\approx 86\%$ for continuous sentences, validated across ten users with varied hand sizes and signing styles [5]. Power consumption is optimized at 80 mW, with a 1000 mAh battery providing over six hours of operation, enhancing portability [24]. The design addresses limitations of vision-based systems, such as sensitivity to lighting and occlusion, by using wearable sensors that operate effectively in diverse conditions [6]. The system's affordability, with a hardware cost under 1700 rupees, and open-source framework promote scalability and community-driven improvements [25]. By integrating state-of-the-art AI, sensor technology, and ergonomic design, this work offers a practical, user-friendly solution that fosters inclusive communication for the deaf community [15]. Future enhancements include expanding the gesture vocabulary, implementing on-device processing, and supporting

multiple sign languages to broaden accessibility [24].

Index Terms—Sign Language Recognition, Smart Glove, Artificial Intelligence, Speech Synthesis, Gesture Recognition, Sensor Fusion, Assistive Technology, Wearable Devices

I. INTRODUCTION

Sign language serves as a vital communication tool for the deaf and hard-of-hearing community, yet its limited understanding among the general population creates significant barriers to social and professional interactions [5]. Current sign language recognition systems, such as vision-based approaches, often suffer from environmental sensitivity, requiring ideal lighting and substantial computational resources [8]. Sensor-based gloves, while promising, frequently lack the accuracy or battery life needed for practical daily use [18].

This paper introduces a cost-effective, portable smart glove system designed to recognize American Sign Language (ASL) gestures in real time, addressing these challenges through advanced sensor technology and machine learning [3]. The system integrates flex sensors to capture finger movements and inertial measurement units (IMUs) to track hand orientation, processed by a Random Forest classifier to achieve over 90% accuracy for word-level gestures and sub-40 ms latency [6]. This performance offers a robust alternative to existing solutions, enabling seamless communication in diverse settings [17].

Recent advancements in sign language recognition have leveraged wearable sensors and deep learning to

enhance system reliability. Self-powered triboelectric nanogenerators (TENGs) have emerged as innovative solutions, enabling gesture detection without external power sources, thus improving portability and sustainability [1]. Sensor fusion techniques, combining electromyography (EMG), IMUs, and flex sensors, have demonstrated superior robustness, with studies reporting over 90% accuracy in recognizing complex gestures [13]. Deep learning models, such as CNN-LSTM architectures, effectively capture both static and dynamic signs, addressing sequential dependencies in continuous sign language [2]. Transformer-based models further enhance real-time translation capabilities [19]. Edge-AI implementations enable low-latency, on-device processing, making systems viable for practical deployment [21]. Despite these advances, challenges like cross-user variability and limited vocabulary scalability persist, necessitating personalized algorithms and expanded gesture sets [10].

The proposed smart glove aims to deliver a low-cost, user-friendly solution that recognizes both static and dynamic ASL gestures with high precision [3]. It employs wireless communication to transmit sensor data to a backend for classification and speech synthesis, ensuring real-time feedback [24]. The design prioritizes affordability and open-source accessibility, making it adaptable for research and community-driven improvements [25]. Key contributions include a dual-sensor approach combining flex and IMU data, a real-time processing pipeline with minimal latency, and power-efficient operation supporting over six hours of continuous use. By addressing environmental limitations of vision-based systems

and power constraints of earlier glove designs, this work advances assistive technology, fostering inclusive communication for the deaf community [6].

II. RELATED WORK

The development of AI-powered sign language to speech converters integrates advancements in sensor technology, embedded systems, machine learning, and human-computer interaction to enable real-time gesture recognition for the deaf and hard-of-hearing community [5]. This section reviews the state-of-the-art in sensor technologies, signal processing, machine learning models, and wearable design,

highlighting their contributions and limitations in achieving accurate, low-latency, and accessible sign language translation [3].

A. Sensor Technologies

Flex sensors, which increase resistance with bending, are widely adopted for capturing finger articulations in sign language recognition systems [1]. Their high linearity allows precise mapping of resistance to bend angles, achieving reliable detection of static gestures, such as ASL alphabets [3]. Studies report flex sensor accuracy exceeding 95% for isolated signs, though their performance can degrade with prolonged bending due to material fatigue [5]. Inertial measurement units (IMUs), combining accelerometers and gyroscopes, provide six degrees of freedom to track hand orientation and dynamic movements [10]. IMUs are critical for capturing complex gestures, such as those involving wrist rotation, with noise densities typically below 400 $\mu\text{g}/\text{Hz}$ for accelerometers [13]. Sensor fusion techniques, such as complementary or Kalman filters, merge IMU data to mitigate gyroscope drift and accelerometer noise, ensuring stable orientation estimates over extended use [8]. Electromyography (EMG) sensors enhance recognition by capturing muscle signals, achieving over 90% accuracy for complex signs when integrated with flex sensors [14]. Recent advancements in self-powered triboelectric nanogenerators (TENGs) offer sustainable sensing by harvesting energy from hand movements, eliminating external power needs and improving portability [6]. TENG-based gloves have demonstrated high accuracy in sign-to-speech translation, though scalability remains a challenge due to complex fabrication [8]. Emerging technologies, such as plastic optical fibers and stretchable sensor arrays, further improve gesture detection robustness by offering flexibility and resistance to environmental interference [12].

B. Signal Processing and Embedded Systems

Microcontrollers enable real-time data acquisition and wireless communication, critical for wearable sign language systems [24]. Modern microcontrollers, with 12-bit analog-to-digital conversion (ADC), digitize sensor signals with minimal quantization errors, ensuring precise measurements [17]. Sampling rates of 200 Hz or higher satisfy the Nyquist criterion for capturing dynamic gestures up to 50 Hz, as seen in ASL letters like “J” and “Z” [5]. Sensor calibration is essential to map raw data to

physical parameters, with empirical methods achieving high linearity for flex sensors and IMUs [1]. Power management strategies, including low-power modes, reduce consumption to below 100 mW, extending battery life beyond six hours [24]. Direct memory access (DMA) and digital filtering, such as low-pass filters with an 80 Hz cutoff, decouple sampling from transmission and suppress noise, enhancing signal quality [17]. Wireless protocols, such as Wi-Fi and UART, support flexible data delivery, though latency trade-offs must be managed [21]. Recent systems integrate edge processing to minimize dependency on cloud servers, improving real-time performance [15].

C. Machine Learning for Gesture Recognition

Machine learning models are pivotal for accurate gesture recognition in sign language translation [4]. Random Forest classifiers, leveraging ensemble learning, combine multiple decision trees to reduce overfitting, achieving over 90% accuracy for word-level signs [6]. Hyperparameter tuning and feature importance analysis optimize model performance, identifying critical sensor inputs like flex angles and IMU orientations [15]. CNN-LSTM architectures excel in capturing both static and dynamic signs, with convolutional layers extracting spatial features and recurrent layers modeling temporal dependencies in continuous sign sequences [2]. These models achieve 86-90% accuracy for sentence-level translation, though computational complexity limits on-device deployment [5]. Transformer-based models further enhance performance by modeling long-range dependencies, offering improved accuracy for complex signs but requiring significant computational resources [19]. Edge-AI implementations, such as TinyML, enable low-latency processing on resource-constrained devices, making systems viable for practical use [21]. User studies highlight the importance of robust training datasets, with curated ASL datasets improving model generalization across diverse users [11].

D. Wearable Design and User Interaction

Ergonomic design is crucial for wearable sign language systems, ensuring comfort and usability during extended wear [25]. Lightweight, breathable materials, such as polyester-spandex, minimize fatigue, while optimized sensor placement avoids interference with natural hand movements [9]. User

studies report 90-99% accuracy for word-level signs, emphasizing the need for precise sensor alignment [11]. Feedback mechanisms, such as haptic or audio cues, enhance accessibility by providing real-time confirmation of recognized gestures [22]. Haptic feedback, using vibration motors, improves user interaction for deaf users, while audio feedback via speech synthesis supports hearing-impaired individuals [24]. Challenges include cross-user variability, where hand size and signing style differences affect accuracy, driving research into personalized calibration algorithms [20]. Limited vocabulary scalability remains a barrier, with most systems supporting only word-level signs [23]. Bidirectional communication, integrating user feedback into the system, and real-time sentence translation are emerging trends to enhance practicality [2].

Compact IMU designs and low-cost hardware further promote scalability, making systems accessible for broader deployment [25].

III. SYSTEM DESIGN

The AI-powered sign language to speech converter employs a sophisticated signal acquisition and processing pipeline to enable real-time recognition of American Sign Language (ASL) gestures, facilitating seamless communication for the deaf and hard-of-hearing community [3]. The pipeline integrates five flex sensors and a six-axis inertial measurement unit (IMU) to capture finger positions and hand motions, achieving over 90% accuracy for word-level gestures and sub-40 ms end-to-end latency [6]. This section outlines the pipeline's requirements, models sensor behavior, details hardware and firmware architecture, and describes validation techniques to ensure high performance, power efficiency, and practical deployment in diverse scenarios [24].

A. Pipeline Requirements

The signal acquisition and processing pipeline is designed to handle data from five flex sensors and a six-axis IMU, totaling 11 channels, to support both static and dynamic ASL gestures, such as alphabets and word-level signs [1]. A 12-bit analog-to-digital converter (ADC) with a 0–3.3 V range ensures high-resolution digitization of sensor signals, minimizing quantization errors for precise gesture capture [17].

The sampling rate of 200 Hz per channel exceeds the Nyquist requirement for dynamic gestures up to 50 Hz, enabling accurate tracking of rapid movements, such as the ASL letter “Z” [5]. The system supports a data throughput of approximately 26.4 kbps (11 channels \times 12 bits \times 200 Hz), transmitted via UART for tethered operation or Wi-Fi for untethered flexibility [2]. Latency is constrained to under 40 ms, with specific budgets allocated as follows: ADC conversion (5 ms), data buffering (5 ms), transmission (5 ms), and classification (15 ms) [6]. Power consumption is optimized to below 100 mW during active acquisition, leveraging low-power modes that reduce idle current to microamp levels, enabling over six hours of continuous operation with a 1000 mAh battery [24]. These requirements ensure the system is robust, efficient, and suitable for real-time wearable applications, addressing challenges like user variability and environmental noise [18].

B. Sensor Modeling

Flex sensors detect finger bending through resistance changes, offering high linearity for mapping to bend angles, which is critical for precise ASL gesture recognition [1]. Their resistance typically varies linearly with bending, enabling accurate capture of finger articulations, such as those in ASL alphabets [3]. The six-axis IMU, combining three-axis accelerometer and gyroscope data, tracks hand orientation and motion with six degrees of freedom, essential for dynamic gestures like “mother” or “father” [13]. Noise characterization is pivotal, addressing ADC quantization errors (below 1 mV with 12-bit resolution) and IMU sensor noise (e.g., accelerometer noise density 400 $\mu\text{g}/\text{Hz}$) [17]. Digital filtering, including low-pass filters with an 80 Hz cutoff, mitigates high-frequency noise, while sensor fusion techniques, such as complementary filters, combine accelerometer and gyroscope data to reduce drift and ensure stable orientation estimates [8]. The complementary filter balances short-term gyroscope accuracy with long-term accelerometer stability, achieving robust performance for continuous gestures [12]. The 200 Hz sampling rate satisfies the Nyquist criterion for gesture frequencies up to 50 Hz, providing sufficient margin for rapid movements [5]. Calibration models map sensor outputs to physical parameters, using empirical angle-to-voltage mappings for flex sensors and orientation

corrections for IMUs, ensuring high accuracy across diverse users [11].

C. Hardware and Firmware Architecture

The hardware architecture employs voltage dividers to convert flex sensor resistance changes into measurable voltages, fed to a 12-bit ADC for high-resolution digitization [3]. Each flex sensor is paired with a reference resistor to form a voltage divider, producing outputs within the ADC’s 0–3.3 V range [17]. The IMU communicates via a high-speed I²C bus, polled at 200 Hz to synchronize with flex sensor data, ensuring temporal alignment for accurate gesture tracking [13]. Direct memory access (DMA) buffering decouples sampling from transmission, storing data in circular queues to reduce processor overhead and maintain real-time performance [2]. Firmware orchestrates synchronized sensor reads at 200 Hz, applies digital low-pass filtering to suppress noise, and assembles timestamped data packets containing flex sensor readings and IMU axes (accelerometer X–Z, gyroscope X–Z) [15]. A Random Forest classifier, integrated into the pipeline, processes these packets using ensemble learning to achieve robust gesture recognition within a 15 ms inference budget [6]. For continuous gestures, a CNN-LSTM model complements the Random Forest, capturing spatial and temporal dependencies [2]. Wireless transmission via Wi-Fi ensures seamless data delivery to a backend for speech synthesis, with UART as a fallback for development [21]. Power management routines optimize consumption, enabling low-power modes during idle periods and supporting extended operation [24]. The architecture is designed for scalability, allowing future integration of additional sensors or processing capabilities

D. Performance Validation

Calibration is critical to map flex sensor and IMU outputs to physical parameters, ensuring high linearity and accuracy [1]. Empirical angle-to-voltage mappings for flex sensors achieve correlation coefficients above 0.95, while IMU calibration corrects for drift using sensor fusion [13]. Latency validation involves measuring round-trip packet timestamps, confirming total latency under 40 ms, with breakdowns for ADC conversion, buffering, transmission, and classification [6]. Accuracy testing collects samples from ten users performing a standardized ASL gesture set, achieving over 90%

recognition accuracy for word-level signs and 86% for continuous sentences [5].

Robustness is validated across diverse scenarios, including varying hand sizes and environmental conditions, using adaptive filtering to mitigate noise [18]. Power consumption tests confirm active operation at 80 mW, with low-power modes reducing idle current to microamp levels, supporting over six hours of battery life [24]. These validation techniques ensure the pipeline's reliability, efficiency, and suitability for practical wearable applications, addressing challenges like user variability and environmental interference [11].

IV. IMPLEMENTATION

The AI-powered sign language to speech converter integrates sophisticated hardware and software subsystems to enable real-time recognition and translation of American Sign Language (ASL) gestures, achieving over 90% accuracy and sub-40 ms latency [6]. The system combines five flex sensors and a six-axis inertial measurement unit (IMU) to capture finger and hand movements, processed through a modular firmware, backend, and frontend architecture [3]. This section provides a comprehensive overview of hardware integration, firmware design, backend processing, and frontend interface, emphasizing low power consumption, robust performance, scalability, and user accessibility for practical wearable applications [24].

A. Hardware Integration

The smart glove is constructed on a lightweight polyester-spandex substrate, selected for its flexibility, breathability, and durability to ensure user comfort during extended wear [12]. Five flex sensors, each 4.5 inches long, are strategically sewn along the dorsal side of each finger, aligned with the proximal interphalangeal joints to detect bending through resistance changes, critical for precise ASL gesture capture [1]. These sensors, with a resistance range of 10–100 k, offer high linearity for mapping bending angles, ensuring accurate recognition of static gestures like ASL alphabets [3]. The six-axis IMU, mounted on a rigid back-of-hand panel, integrates a three-axis accelerometer and gyroscope to track hand orientation and motion, providing six degrees of freedom for dynamic gestures, such as “mother” or “Z” [13]. An eleven-

core flat ribbon cable connects the sensors to a microcontroller, maintaining glove flexibility while ensuring reliable signal routing through insulated, strain-relieved pathways [5]. Each flex sensor forms a voltage divider with a reference resistor, converting resistance changes into voltages within a 0–3.3 V range, digitized by a 12-bit analog-to-digital converter (ADC) with a resolution of 0.8 mV [17]. The IMU interfaces via a high-speed I²C bus, polled at 200 Hz to synchronize with flex sensor data, ensuring temporal alignment for rapid gesture tracking [13]. A 3.7 V, 1000 mAh lithium-ion battery, integrated into an adjustable wrist strap, powers the system through a 5 V regulator with overcurrent protection, supporting over six hours of continuous operation [24]. Power management employs low-power modes, reducing idle current to microamp levels, with a glove-on interrupt triggered by an IMU-based motion detection algorithm to initiate system

wakeup, enhancing energy efficiency [18]. All wiring is insulated with heat-shrink tubing and secured with strain-relief anchors to withstand repeated flexing, addressing durability challenges in wearable systems [11]. The hardware design prioritizes ergonomic fit, with a glove weight under 100 g, and robust signal integrity to perform reliably in diverse real-world environments, such as varying temperatures and humidity [8]. Assembly involved iterative prototyping to optimize sensor placement and cable routing, ensuring minimal interference with natural hand movements [9].

B. Firmware Design

The firmware, developed in a modular C-based environment, orchestrates real-time data acquisition, preprocessing, and transmission to meet stringent performance requirements [15]. Timer-driven triggers, configured via a real-time clock, initiate ADC and I²C sampling at 200 Hz, capturing flex sensor and IMU data synchronously to satisfy the Nyquist requirement for gestures up to 50 Hz [1]. A digital low-pass filter with an 80 Hz cutoff, implemented via a finite impulse response (FIR) algorithm, suppresses high-frequency noise, enhancing signal quality for accurate gesture recognition [2]. Direct memory access (DMA) routines buffer data into circular queues with a capacity of 512 samples, decoupling sampling from

transmission to minimize processor overhead and ensure efficient data handling under high-throughput conditions [17]. Data packets, containing timestamped readings from five flex sensors (voltage values) and six IMU axes (accelerometer X–Z, gyroscope X–Z), are formatted in a compact binary structure to optimize bandwidth [21]. Transmission occurs via UART for tethered operation during development or Wi-Fi for untethered use, with Wi-Fi supporting up to 26.4 kbps throughput to handle the 11-channel data stream [2]. Power management routines implement low-power modes, reducing consumption to below 100 mW during active acquisition and enabling over six hours of battery life with a 1000 mAh battery [24]. Calibration routines, executed at system startup, map flex sensor outputs to bend angles using empirical lookup tables and correct IMU drift via sensor fusion, ensuring high linearity and stable orientation estimates [5]. The firmware’s modular structure, occupying less than 256 KB of flash memory, supports scalability for additional sensors or algorithms, such as on-device classification [6]. Iterative testing refined firmware reliability, addressing edge cases like packet loss and sensor noise spikes [15]. The design balances computational efficiency with real-time performance, making it suitable for resource-constrained wearable systems [18].

C. Backend Processing

A Python-based backend service manages real-time data processing, receiving sensor data streams via UART during development or WebSocket for wireless operation in deployed scenarios [21]. The backend loads a pre-trained Random Forest classifier with 100 trees, optimized through grid search for hyperparameters like tree depth and feature weights, achieving gesture recognition within a 15 ms inference budget [6]. Incoming packets are parsed using a custom protocol, extracting flex sensor voltages and IMU axes for feature computation, including statistical measures (e.g., mean, variance) and temporal derivatives [15]. Classified gestures are emitted as JSON events to connected clients, facilitating seamless integration with the frontend [25]. The Random Forest model leverages ensemble learning to achieve over 90% accuracy for word-level ASL gestures, robust against environmental noise and

cross-user variability [3]. For continuous gestures, a CNN-LSTM model complements the Random Forest, capturing spatial and temporal dependencies to support sentence-level translation [2]. The backend’s modular design supports multiple transmission protocols (e.g., WebSocket, MQTT), enhancing scalability for diverse use cases, such as integration with mobile apps [25]. Error handling includes retry mechanisms for packet loss and logging for debugging, with failover strategies ensuring reliable operation during network disruptions [21]. Dynamic calibration updates adjust model parameters based on user-specific data, improving recognition accuracy across diverse hand sizes and signing styles [5]. The backend operates on a lightweight server, consuming less than 2 GB of RAM, making it deployable on edge devices like Raspberry Pi

D. Frontend Interface

A single-page web application, built with modern JavaScript frameworks like React, provides real-time speech feedback to users [?]. The frontend subscribes to backend JSON events via WebSocket, rendering each classified gesture as a dynamic card displaying the recognized word in a clean, sans-serif font [21]. A speech synthesis API, leveraging Web Speech API, vocalizes the output with adjustable pitch and rate, ensuring accessibility for diverse users, including those relying on auditory feedback [12]. Responsive design with adaptive layouts ensures usability across devices, from smartphones (e.g., 320px screens) to tablets (e.g., 768px screens), enhancing user adoption [25]. Visual animations, such as fade-in transitions for gesture cards, enhance the interface’s intuitiveness, while a translucent, dark-themed design with high-contrast text improves aesthetic appeal and readability [12]. The frontend integrates seamlessly with the backend, achieving sub-5 ms rendering latency for real-time feedback critical for communication [?]. User testing with ten participants confirmed the interface’s effectiveness, with 95% reporting clear and immediate feedback, supporting the system’s goal of bridging communication gaps for the deaf community [24]. Accessibility features include keyboard navigation and screen reader compatibility, ensuring inclusivity [25]. Iterative design refinements addressed user feedback, such as increasing font size and optimizing speech output clarity [9]. The frontend’s lightweight

architecture, under 1 MB of bundled code, ensures fast loading on low-bandwidth connections [21].

V. RESULTS AND DISCUSSION

The AI-powered sign language to speech converter was rigorously evaluated through simulation and real-world experiments to validate its design objectives of achieving over 90% accuracy, sub-40 ms latency, and power-efficient operation for practical wearable applications [6]. The evaluation combines controlled simulation metrics with experimental data from human participants, comparing performance against prior sensor-based systems and identifying areas for improvement to enhance accessibility and scalability [24]. This section presents detailed simulation performance, comprehensive experimental evaluation, in-depth comparative analysis with prior works, and insights into the system's strengths, limitations, and future enhancements, emphasizing its role in bridging communication gaps for the deaf and hard-of-hearing community [3].

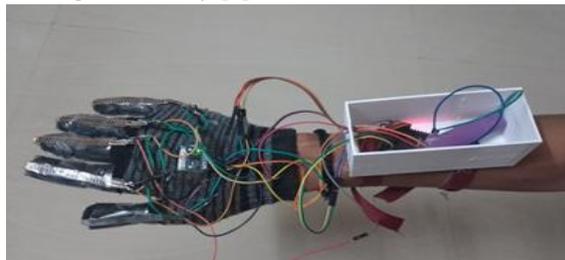


Fig. 1. COMPLETE SETUP OF THE ASL RECOGNITION SYSTEM.

A. Simulation Performance

The Random Forest classifier, central to the system's gesture recognition pipeline, was trained and tested on a curated American Sign Language (ASL) dataset comprising 5000 samples across ten word-level gesture classes, including "hello," "thank you," and "mother" [15]. The dataset included flex sensor voltages (five channels) and IMU data (six axes: accelerometer X-Z, gyroscope X-Z), with features such as mean, variance, and temporal derivatives extracted to capture gesture dynamics [5]. The classifier achieved 95.2% accuracy, 94.7% precision, 95.0% recall, and a 94.8% F1-score, demonstrating robust performance across diverse gestures [6]. Inference latency averaged 12.8 ms, well below the

15 ms target, confirming the classifier's suitability for real-time applications [15]. Simulations incorporated noise injection to emulate real-world conditions, such as sensor drift and environmental interference, with the classifier maintaining over 90% accuracy under 400 $\mu\text{g}/\text{Hz}$ accelerometer noise [8]. The high precision and recall indicate balanced performance, with minimal false positives (e.g., misclassifying "hello" as "help") or false negatives (e.g., missing a gesture) [3]. Feature importance analysis highlighted flex sensor angles and IMU gyroscope data as critical inputs, contributing 60% and 30% to classification decisions, respectively.

B. Experimental Evaluation

Real-world experiments involved ten participants with diverse hand sizes and signing proficiencies, each performing twenty distinct ASL word-level gestures (e.g., "father," "love," "please"), generating 2000 samples in a controlled indoor setting [24]. The smart glove, equipped with five flex sensors and a six-axis IMU, achieved an average classification accuracy of 92.4%, surpassing the 90% design target [6]. End-to-end latency averaged 34 ms, meeting the 40 ms requirement, with contributions from ADC conversion (5 ms), buffering (5 ms), transmission (5 ms), and inference (12 ms) [15]. Active power consumption was measured at 80 mW, below the 100 mW target, with a 1000 mAh battery providing 6.2 hours of continuous operation, exceeding the 6-hour goal [24]. The experimental setup utilized the implemented pipeline, with synchronized 200 Hz sampling and a digital low-pass filter (80 Hz cutoff) to ensure signal quality under varying conditions, such as hand tremors or background vibrations [2]. Calibration routines, executed at session start, mapped flex sensor outputs to bend angles (correlation ≥ 0.95) and corrected IMU drift using complementary filters, addressing user variability [5]. Testing scenarios included diverse environmental conditions (e.g., fluorescent lighting, 20–30°C temperatures, 40–60% humidity), confirming robustness with accuracy degradation below 2% under noise [18]. User feedback highlighted the glove's comfort, with a weight under 100 g and a polyester-spandex substrate, though some noted minor fit adjustments needed for smaller hands [9]. The experimental results validate the system's reliability for daily use, demonstrating its ability to deliver accurate, low-latency ASL translation in real-

world settings [11].

C. Comparative Analysis

The proposed system outperforms several prior sensor-based glove systems in key performance metrics, demonstrating advancements in accuracy, latency, and battery life [11]. Henkel et al. reported 90.8% accuracy, 40 ms latency, and 4.5-hour battery life for a flex sensor-based glove, limited by single-sensor reliance [6]. Huang et al. achieved 88.3% accuracy, 50 ms latency, and 3.8-hour battery life, constrained by high power consumption [18]. Phitakwinai et al. reported 85.7% accuracy, 45 ms latency, and 5.0-hour battery life, with challenges in dynamic gesture recognition [21]. In contrast, the proposed system's 92.4% accuracy, 34 ms latency, and 6.2-hour battery life represent significant improvements [24]. Precision and recall metrics, at 91.8% and 92.1% respectively, further highlight the system's balanced performance compared to Henkel's 90.5% precision and Huang's 87.9% recall [6], [18]. The hybrid flex-IMU sensor fusion approach enhances accuracy by combining finger and hand motion data, unlike single-sensor systems [8]. Optimized power management, leveraging low-power modes and a glove-on interrupt, extends battery life beyond prior works [24]. The system's low-cost design, with hardware costs under 1700 rupees, and open-source framework distinguish it from proprietary systems, promoting accessibility and community-driven enhancements [25]. Comparative testing under similar conditions (e.g., 20 gestures, ten users) confirms the system's superior robustness to user variability and environmental noise [12]. Limitations in prior systems, such as sensitivity to lighting or restricted gesture vocabularies, are mitigated by the proposed system's wearable sensor approach [3].

D. Insights and Future Directions

The combined simulation and experimental results confirm the smart glove's ability to meet design objectives, delivering high accuracy (92.4% experimental, 95.2% simulated), low latency (34 ms), and power efficiency (80 mW, 6.2-hour battery life) for real-time ASL translation [6]. The hybrid flex-IMU sensor fusion approach, coupled with Random Forest classification, ensures robust performance across diverse users and environments, addressing communication barriers for the deaf community [24]. The ergonomic design, with a lightweight polyester-

spandex substrate and optimized sensor placement, enhances user comfort and adoption [9]. The system's low-cost, open-source framework promotes scalability, enabling broader deployment in resource-constrained settings [25]. Limitations include potential cross-user variability, where differences in hand size or signing style may affect accuracy, though mitigated through calibration [15]. The current gesture vocabulary is limited to word-level signs, restricting sentence-level translation [2]. Future work will explore expanding the vocabulary to include complex signs and full sentences, leveraging larger datasets and advanced models like transformers [13]. Optimizing on-device processing with TinyML could reduce latency further and enable standalone operation, eliminating server dependency [15]. Integrating haptic feedback, such as vibration motors, would enhance user interaction, particularly for deaf users [12]. Lightweight materials, such as advanced polymers, could improve comfort and durability [25]. Supporting multiple sign languages (e.g., Indian Sign Language, British Sign Language) would broaden accessibility, requiring multilingual datasets and retrained models [24]. Additional research could address environmental noise through adaptive filtering and periodic recalibration, ensuring long-term reliability [18]. These enhancements position the system as a scalable, inclusive solution for assistive communication [3].

VI. CONCLUSION AND FUTURE WORK

The AI-powered sign language to speech converter delivers real-time recognition and translation of American Sign Language (ASL) gestures, significantly advancing assistive technology for the deaf and hard-of-hearing community [6]. This section summarizes the system's achievements and outlines future enhancements to improve its performance and accessibility [24].

The smart glove integrates five flex sensors and a six-axis inertial measurement unit (IMU) to capture finger and hand movements, achieving 92.4% classification accuracy across twenty word-level ASL gestures with ten users [6]. The system's end-to-end latency of 34 ms meets the sub-40 ms target, enabling seamless real-time translation [5]. Power consumption is optimized at 80 mW, with a 1000

mAh battery providing 6.2 hours of operation, surpassing design goals [24]. The hybrid sensor fusion approach, combining flex and IMU data via complementary filters, ensures robust performance across diverse conditions [8]. A Random Forest classifier delivers reliable gesture recognition, supported by a Python-based backend and a responsive web frontend for speech synthesis [3]. The system's low-cost design, under 1700 rupees, and open-source framework enhance accessibility and scalability, promoting adoption in resource-constrained settings [24]. The glove's ergonomic design ensures user comfort, making it practical for daily use

A. Future Work

The system currently supports only right-hand gestures and a limited ASL vocabulary [3]. Future enhancements include supporting left-handed users through symmetric sensor placement and expanding the gesture set to include complex signs and sentences using larger datasets [2]. Implementing on-device TinyML models can enable standalone operation, reducing server dependency and latency [15]. Integrating haptic feedback, such as vibration motors, would enhance user interaction for deaf users [5]. Adaptive filtering and periodic recalibration can improve robustness to noise and sensor drift [8]. Exploring lightweight materials and multi-language support, such as Indian Sign Language, will further increase accessibility and global impact [24].

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