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Embedded IoT-Based Smart Assistive Glove System for Real-Time Gesture Recognition and Emergency Alerts

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Abstract- Communication is a daily struggle for people with speech and hearing impairments whenever the person across from them does not know sign language, and that struggle turns serious in an emergency, when getting help depends on being understood right away. Vision-based recognition, wearable sensing, and sensor-fusion methods have each moved sign lan-guage interpretation forward, but every one runs into the same problems: heavy computation, poor portability, slow response, or privacy loss. This paper works through these gesture recognition approaches, weighing what each does well against where it falls short, and looks at how embedded machine learning and edge computing are changing what a wearable device can do. One gap keeps showing up across the literature: almost none of these communication-focused systems build in real emergency support, and the few that try rarely fit how a nonverbal or hearing-impaired person would want to trigger one. Building on that gap, this paper proposes EchoHand, an IoT-enabled glove pairing flex sensors, a six-axis IMU, and an ESP32 microcontroller to recognize gestures and produce speech or text output, while reusing that pipeline to send a location-aware alert when needed. It closes by covering the practical hurdles this design faces and where it goes next.

Keywords: Assistive Technology, Internet of Things, Ges-ture Recognition, Smart Wearables, Sensor Fusion, Embedded Machine Learning, TinyML, Edge Computing, Emergency Alert Systems, Sign Language Recognition.

I. INTRODUCTION

Effective communication is basic to human interaction, yet people with speech and hearing impairments still run into real obstacles when trying to express themselves, especially around others who do not know sign language. Sign language is a rich and capable medium, but it only works when the other person understands it, and trained interpreters are not always around. This gap turns dangerous in an emergency, where the inability to communicate distress quickly can have serious con-sequences [7], [16]. Studies on communication breakdown in time-critical settings such as emergency departments confirm that this is not a hypothetical concern: delays caused purely by a communication barrier measurably affect outcomes for the people involved [16].

Researchers have tried several ways to close this gap over the years. The earliest efforts leaned on vision-based systems, using cameras and image processing to interpret gestures [2]. These systems produced encouraging results, but they carry real baggage: performance drops with poor lighting, background clutter throws off recognition, and the computation involved is substantial [2]. Continuous video monitoring also raises obvious privacy concerns and limits how portable a sys-tem can be, since a fixed or body-mounted camera constrains where and how the user can be understood.

To work around these issues, later research turned to wear-able, sensor-based solutions, with smart gloves fitted with flex sensors becoming a common choice for capturing finger movement. These designs are more portable and do not depend on ambient conditions the way cameras do. Even so, many of them fall short on recognizing a full range of sign vocabulary, keep translation speed low, and add mechanical complexity [27]. Bringing in inertial measurement units (IMUs) and sensor-fusion techniques has helped close some of that gap by capturing both static hand poses and the dynamics of movement together, rather than treating a gesture as a single frozen shape.

At the same time, progress in embedded machine learning, and TinyML specifically, has made it possible to process sensor data directly on a microcontroller instead of sending it to the cloud. That shift from cloud-based to edge-based computation cuts latency, makes the system more responsive, and keeps user data local [23]. Still, most systems in this space stop at communication and leave user safety as an afterthought, as though the two needs belong to separate product categories entirely.

On the other side of the field, IoT-based emergency alert systems already handle personal safety well, using GPS track-ing, SMS alerts, and panic buttons, but the literature keeps pointing to a need for systems built specifically around the communication needs of people with disabilities, not bolted onto a generic safety product [4].

Taken together, this points to an unmet need: a single system that handles both communication and safety rather than treating them as separate problems. Looking across the literature, there is a clear gap around integrated, real-time, portable solutions that address both constraints at once. Wear-able hand-gesture interfaces, built on sensor fusion, embedded intelligence, and wireless communication, look like the most promising direction for closing that gap [14]. The remainder of this paper surveys the relevant technical approaches, identifies the specific gaps they leave open, proposes EchoHand as a response to those gaps, and discusses the practical challenges and future directions that follow from that proposal.

II. RELATED WORK

This section reviews the main technical approaches to gesture and sign-language recognition, along with the state of IoT-based safety systems, to establish where EchoHand fits.

A. Vision-Based Gesture Recognition

Camera-based recognition was the starting point for most work in this area. Early surveys frame the problem as one of extracting hand shape, pose, and motion trajectories from image sequences and mapping them to gesture classes [20]. Subsequent work extended this into full sign-language analysis pipelines covering both manual and non-manual cues [19], and broader human-activity recognition surveys have since folded gesture recognition into the wider vision-based sensing literature [8]. More recent structured reviews of vision-based hand-gesture systems report steady accuracy gains from deep convolutional and transformer-based models as datasets and compute budgets have grown [10].

The typical pipeline in this category acquires gesture data through a camera, applies classical or learned image-processing steps to isolate the hand region, and then passes the result through a classifier such as a convolutional net-work or a hidden Markov model before producing a text or speech output. This pipeline can recognize a large and expressive gesture vocabulary and does not require the user to wear any hardware at all, which is a genuine advantage for adoption. Despite this progress, the core limitations that motivated the shift away from vision-only systems have not gone away: performance is sensitive to lighting and occlusion, the computational load of running deep models on video is high, continuous camera capture is inherently privacy-invasive for the user and bystanders alike, and the system is tied to wherever the camera happens to be mounted, which works against portability and against emergency use in an unplanned location.

B. Wearable Sensor-Based Systems

Flex-sensor gloves address the portability and privacy prob-lems directly by measuring finger curvature instead of imaging the hand. Continuous finger-gesture recognition using flex sensors has been shown to work well for discrete gesture classes with comparatively simple hardware [9]. Fiber-based sensing has also been explored, with auxetic-interlaced yarn sensors paired with a neural network to translate sign gestures into output [27]. More recent designs integrate flex and motion sensors together on the same glove with an AI backend for real-time assistive communication [30], and multi-sensor fusion gloves have been built specifically for human-robot interaction rather than person-to-person communication [13]. Data-glove systems combining multimodal fusion algorithms, such as FI-HGR, report improved robustness over single-modality sensing [28].

These wearable designs typically place one flex sensor per finger to track curvature, route the resulting analog or digital signal to a microcontroller for real-time processing, and map the sensed gesture to a predefined linguistic output. Compared with vision-based systems, this class of device is independent of ambient lighting, tolerant of cluttered backgrounds, and naturally more private because no image of the user or their surroundings is ever captured. The tradeoff is that finger cur-vature alone struggles to disambiguate gestures that share hand shape but differ in orientation or motion, and the vocabulary a purely flex-sensor glove can support is finite unless additional sensing is added, which is where IMUs come in.

C. IMU-Based and Sensor-Fusion Approaches

Accelerometer-based recognition was one of the first at-tempts to capture gesture dynamics rather than static pose, using dynamic time warping and similar techniques to classify motion trajectories [3]. Later work paired a single six-axis IMU with a recurrent neural network to recognize hand gestures from motion data alone, without any camera or flex sensor [5]. Direct comparisons between RGB-D vision and IMU-based recognition in human-robot interaction settings suggest that IMUs hold up well against vision systems while avoiding their lighting and privacy drawbacks [21].

Wearable rings using multi-finger gesture recognition through supervised learning show that even minimal, ring-scale IMU hardware can support usable classification [17], and continuous, in-definite gesture-recognition systems built around directional and shape-based arm movement demonstrate that IMU-driven recognition scales beyond just finger-level gestures [12]. Com-bining flex sensors with an IMU, rather than choosing one or the other, is the direction most current smart-glove designs are converging on, since finger curvature and hand orientation capture complementary information: the former tells the sys-tem how the fingers are bent, and the latter tells it how the hand as a whole is moving through space, which is exactly the distinction needed to separate gestures that would otherwise look identical to a flex sensor alone.

D. Embedded Machine Learning and Edge Computing

Running gesture-classification models on the sensing device itself, rather than streaming data to a phone or cloud server, is central to making wearable systems fast and private. Reviews of machine learning for microcontroller-class hardware lay out the constraints this imposes on model size, memory footprint, and inference latency [22]. TinyML surveys describe the broader toolchain and deployment patterns that make on-device inference practical for battery-powered wearables [1], and systematic reviews focused on ultra-low-power AI for large-scale IoT deployments echo the same emphasis on power efficiency as the binding constraint [23]. Some work has pushed further into biologically-inspired computation, using spiking neural networks to mimic frequency-domain analysis for power-efficient gesture sensing at the edge [6].

Across this body of work, the pattern is consistent: edge inference trades some model capacity for latency, privacy, and battery life, which is exactly the tradeoff a wearable assistive device needs to make. A microcontroller such as the ESP32 cannot run the large transformer-based models increasingly common in vision-based recognition, but it can comfortably run a lightweight classifier over flex-sensor and IMU features, and doing so removes the round trip to a phone or server that would otherwise add tens to hundreds of milliseconds of latency to every gesture, latency that matters a great deal when the gesture in question is a call for help.

E. Sign Language and Communication-Focused Systems

A separate thread of work looks at the communication output side rather than just gesture classification. Surveys of wearable interfaces and algorithms for hand-gesture recog-nition frame the design space in terms of sensor modality, recognition algorithm, and output channel together [14], while more recent surveys of vision-based hand-gesture recogni-tion track how the field has moved toward transformer and large-model approaches [15]. On the output side, AI has been used to generate Indian Sign Language from natural speech and text, effectively running the translation problem in the opposite direction from a glove-based system [29], and wearable "intelligent throat" devices have been devel-oped to help stroke patients with dysarthria produce natural speech, showing that the same wearable-plus-edge-AI pattern extends to other communication impairments [25]. Vision-and-wearable combinations have also been tested for daily gesture recognition in human-robot interaction settings, suggesting hybrid sensing is a viable middle ground where a device can tolerate the added complexity [11].

F. IoT-Based Emergency Alert and Safety Systems

Emergency alert systems have developed largely on a sep-arate track from communication-assistance devices. Wearable safety and security devices built on IoT technology typically combine GPS, a panic trigger, and a wireless alert mechanism to notify a contact or authority [24], and the SafeHer system applies the same pattern specifically to women's personal safety [26]. Purpose-built systems for people with hearing and visual impairment address emergency alerting directly, using non-auditory and non-visual cues to signal danger [7]. IoT-based frameworks aimed at improving emergency com-munication for people with disabilities argue explicitly for personalization, noting that a generic panic button does not account for how a nonverbal or hearing-impaired user would actually need to interact with the system [4]. Older reviews of assistive technology for hearing and speech disorders reinforce the same point from a different angle, noting that most tools in this broader category were never designed with emergency use in mind to begin with [18].

What stands out across this section is a fairly clean divi-sion of labor in the literature: one line of research focuses on recognizing and translating gestures, and a separate line focuses on emergency alerting, with very little work sitting at the intersection of both.

G. Comparative Summary of Existing Categories

Table II-G summarizes the four broad categories surveyed above against the criteria a real-world assistive device needs to satisfy. Vision-based systems score well on gesture vo-cabulary size but poorly on portability and privacy. Sensor-based wearables invert that tradeoff, gaining portability and privacy at the cost of a smaller, more rigid gesture set unless sensor fusion is applied. Sensor-fusion systems narrow that gap but add hardware and processing complexity. Standalone IoT safety devices solve the emergency side cleanly but were never designed to carry communication content at all.

Table I
Comparative Overview Of Gesture Recognition And Assistive Wearable Categories

Category	Strength	Limitation	Emergency Support
Vision-based	Rich gesture vocabulary	Lighting and privacy dependent	Generally not ad-dressed
Flex-sensor glove	Portable and private	Limited dynamic gestures	Generally not ad-dressed
Sensor fusion	Improved recognition	Increased sys-tem complexity	Limited
IoT safety wearable	Reliable alert-ing	Limited communication support	Core function

III. RESEARCH GAP

Pulling the sections above together, three gaps recur across the literature:

- **Communication and safety are treated as separate problems**. Gesture-recognition systems, whether vision-based, flex-sensor, or IMU-based, are built to translate a gesture into text or speech and stop there. Emergency-alert wearables solve a different problem, sending a location and a signal, but offer no way to specify what the emergency actually is [24], [26]. A user wearing both a communication glove and a separate panic-button device would still need two pieces of hardware, two habits, and two failure points to be fully served.

- **On-device processing is underused in communication-focused designs**. Much of the flex-sensor and IMU literature still assumes a companion phone or external processor for classification [5], [27], even though TinyML research shows this is no longer strictly necessary on hardware like the ESP32 [1], [22]. Depending on an external device for the core recognition step reintroduces exactly the latency and connectivity dependence that edge computing is meant to remove.
- **Personalization for disability-specific emergency needs is rarely built in**. Where emergency systems do exist for this population, the literature explicitly flags a lack of personalization to how a nonverbal user would actually trigger and describe an emergency [4], rather than press-ing a generic panic button that carries no context about what kind of help is needed.

Taken together, these three gaps describe a fairly specific unmet requirement: a wearable that recognizes gestures on-device, uses that recognition pipeline for everyday communication, and reuses the same pipeline, rather than a separate always-idle button, to detect and describe an emergency. No single system reviewed above satisfies all three points at once. EchoHand is proposed as a direct response to this requirement.

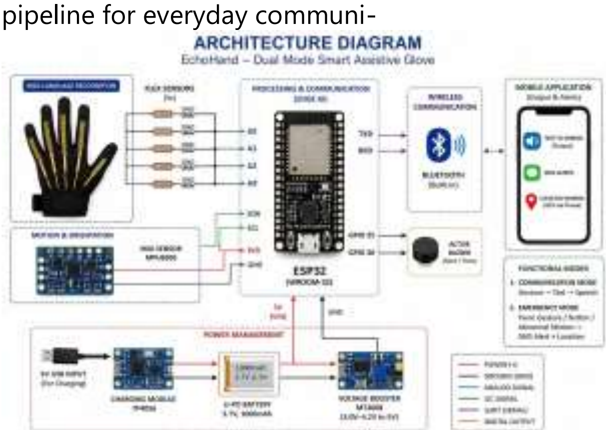

Fig. 1. Overall architecture of the proposed EchoHand assistive framework. The system integrates flex sensors, an IMU, an ESP32 microcontroller, Bluetooth communication, and emergency alert functionality within a single wearable platform.

IV. PROPOSED ECHOHAND FRAMEWORK

EchoHand is presented here as a system-level design rather than a fully validated deployment, consistent with the review scope of this paper. The framework is organized into four layers: sensing, processing, communication output, and emer-gency alerting, with a fifth cross-cutting layer that governs how the device switches between its two operating modes.

A. Sensing Layer

Each finger carries a flex sensor to capture curvature, following the same principle used in prior flex-sensor gloves [9], [30]. A six-axis IMU (accelerometer and gyroscope) is mounted on the back of the hand to capture orientation and motion dynamics, addressing the ambiguity that flex sensors alone cannot resolve [5], [21]. Combining the two sensor types follows the sensor-fusion pattern shown to outperform either modality alone [13], [28].

B. Processing Layer

An ESP32 microcontroller reads the flex-sensor and IMU data and runs a lightweight, pre-trained classifier on-device to map sensor patterns to gesture classes. Keeping inference local follows the TinyML pattern for microcontroller-class hardware [22], [23], avoiding the latency and privacy cost of sending raw sensor data off the glove. The ESP32 was chosen specifically because it packs Wi-Fi and Bluetooth radios onto the same chip as the processor, which removes the need for a separate communication module and keeps the bill of materials, and therefore the final device cost, low.

C. Communication Output Layer

Recognized gestures are converted to text and/or synthe-sized speech, delivered either through a small onboard display and speaker or forwarded to a paired smartphone app over Bluetooth. This mirrors the output stage used in prior glove-based translation systems [27], [30], but keeps the recognition step itself on the glove rather than the phone, so that commu-nication remains functional even when no phone is paired or nearby.

D. Emergency Alert Layer

A specific, reserved gesture (or a physical panic switch as a fallback) triggers the emergency path instead of the normal communication path. On trigger, the ESP32 uses its Wi-Fi/Bluetooth link, paired with a GPS module or a connected phone's location, to send an SMS or app notification containing the user's location and a short pre-set message to a designated contact, following the alerting pattern used in existing IoT safety devices [24], [26] but routed through the same gesture-recognition pipeline used for everyday commu-nication, rather than a separate always-idle panic button. This is the specific design response to the personalization gap noted in Section III [4].

E. Functional Modes and Mode Switching

The device operates in one of two functional modes at any given time. In communication mode, the default state, recognized gestures are routed to the text-to-speech and Bluetooth output path described above. In emergency mode, triggered either by the reserved panic gesture, a physical button, or an abnormal-motion signature detected by the IMU (such as a sudden fall), the ESP32 instead drives an onboard active buzzer for immediate local alerting and simultaneously dispatches an SMS alert with GPS-derived location data to the designated contact. Because both modes share the same sens-ing and processing hardware, switching between them costs nothing in terms of additional components, and the transition itself takes place in software, which keeps the device's power and space budget close to that of a communication-only glove while adding a safety function that would otherwise require a second wearable entirely.

V. COMPARATIVE DISCUSSION

Table II lines up the major approaches covered in Section II against the criteria that matter most for an everyday assistive device: portability, latency, privacy exposure, and whether emergency alerting is built in at all.

The pattern in Table II is what motivates the proposed design: sensor-fusion gloves already solve portability, latency, and privacy well, and IoT safety wearables already solve emergency alerting well, but almost nothing in the reviewed literature does both at once from a single device with a shared recognition pipeline. EchoHand's contribution is therefore less about inventing a new sensing modality and more about closing the integration gap between two mature but previously separate lines of work.

Table II
Comparison of Gesture Recognition Approaches

Approach	Portab-ility	Latency	Privacy	Emergency Alert
Vision-based	Low	Medium – High	Low	Not present
Flex-sensor glove	High	Low	High	Not present
IMU-based	High	Low	High	Not present
Sensor fusion (flex + IMU)	High	Low	High	Rare
IoT safety wearable	High	Low	High	Built in
EchoHand (proposed)	High	Low	High	Built in

VI. CHALLENGES AND LIMITATIONS

Even with a clear design direction, an integrated system like EchoHand inherits practical challenges from every category it draws on, and a few new ones from combining them.

A. Gesture Accuracy and Variability

Hand size, gesture execution speed, and user-specific move-ment habits all introduce variation into the raw sensor stream, and this variation can cause a classifier trained on one set of users to misclassify gestures from another. Because EchoHand reuses its gesture classifier for the emergency path as well as for everyday communication, misclassification is not just an inconvenience here; a missed panic gesture or a false-triggered alert both carry real consequences, which raises the bar for classifier reliability compared with a communication-only device.

B. Gesture Vocabulary and Sensor Drift

Flex sensors and IMUs are both prone to drift and calibra-tion error over time, and a predefined gesture vocabulary is, by construction, finite. Expanding that vocabulary to cover more of a given sign language requires a larger training dataset and a more capable model, which works against the memory and compute budget of a microcontroller-class device such as the ESP32.

C. Connectivity Dependence for Alerting

The emergency-alert path depends on GPS acquisition and either a cellular/SMS link or a paired smartphone's connec-tivity. In areas with weak signal, an alert can be delayed or fail to send altogether, which is precisely the situation in which an emergency communication tool is needed most. Any deployment of EchoHand would need a documented fallback behavior, such as local buzzer alerting, for exactly this case.

D. Hardware and Power Constraints

Combining flex sensors, an IMU, on-device inference, wire-less alerting, and a rechargeable power supply on one wearable creates real pressure on battery life and physical size. Keeping the classifier lightweight enough for the ESP32 and keeping continuous IMU sampling power-efficient are competing goals that any prototype will need to balance empirically rather than by design alone.

E. User Adaptability and Cost

Any gesture-based system asks something of its user: con-sistent, learnable gestures and, typically, an onboarding period. Combined with the added bill of materials for GPS and wireless alerting hardware, this raises both the learning curve and the unit cost relative to a communication-only glove, both of which affect real-world adoption regardless of how well the underlying sensing performs.

VII. FUTURE DIRECTIONS

Several directions follow naturally from the challenges above and from the system-level scope of this paper.

Dataset collection and empirical validation is the most im-mediate next step: building the physical prototype, collecting a gesture dataset from real users with varying hand sizes, and benchmarking classifier accuracy and inference latency on the ESP32 itself rather than in simulation.

Expanded gesture vocabulary and multilingual output would broaden EchoHand's reach beyond a fixed sign set and a single spoken-language output, which matters for adoption across different regions and sign-language dialects.

Automatic emergency detection could supplement the reserved-gesture and panic-button triggers already in the de-sign with IMU-based fall detection or other abnormal-motion cues, reducing reliance on the user being able to perform a deliberate gesture at the moment of an emergency.

Field testing of the alerting path end to end, including GPS acquisition time and SMS delivery reliability in low-signal areas, is necessary before the emergency layer can be trusted in practice rather than assumed to work.

Hardware miniaturization, using more compact flexible sensors and a smaller board layout, would improve wearability and long-term comfort, which is ultimately what determines whether a device like this gets worn consistently enough to be useful in an actual emergency.

VIII. CONCLUSION

This review looked across vision-based, flex-sensor, IMU-based, and sensor-fusion gesture recognition methods, along-side the current state of embedded machine learning and IoT-based emergency alerting, and found a consistent gap: communication assistance and safety features are almost al-ways built as separate products rather than one integrated device. EchoHand is proposed as a way to close that gap, using an ESP32-based sensing and processing pipeline that handles both everyday gesture-to-speech communication and emergency alerting through the same hardware and the same recognition logic, switching between a communication mode and an emergency mode entirely in software. The challenges discussed in Section VI, particularly around gesture reliability and connectivity-dependent alerting, and the directions out-lined in Section VII define a concrete path from the system-level design presented here toward a validated, field-tested prototype, which is the necessary next stage before a system like this would be ready for real-world assistive use.

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