Int. J. Adv. Res. Sci. Technol. Volume 14, Issue 08, 2025, pp.1630-1633.

IJARST

International Journal of Advanced Research in Science and Technology

https://doi.org/10.62226/ijarst20252574

ISSN 2319 – 1783 (Print)

ISSN 2320 – 1126 (Online)

Gesture-Based Silent Communication System for Military and Defense Applications

Nahid Parween[1], Aqsa Equbal[2] and Syeda Shira Moin[3]

Aligarh Muslim University, Aligarh, Uttar Pradesh, India[1,2,3]

shira.moin@zhcet.ac.in

ARTICLE INFO

Article history:

Received 02 Aug 2025

Accepted 12 Aug 2025

Available online 14 Aug 2025

Keywords:

Gesture recognition, machine learning, silent communication.

ABSTRACT

This paper presents a novel gesture recognition glove system designed for silent communication in military and defense scenarios. Adapted from a sign language translator, the system enables users to transmit predefined commands using hand gestures. Equipped with flex sensors, the glove captures finger positions, which are processed using a machine learning model to classify gestures. Output is conveyed using wireless transmission to a remote receiver. This system offers a reliable mode of communication in high-risk environments.

Introduction:

In high-risk environments such as military and defense operations, the ability to communicate discreetly and effectively is critical to both mission success and personnel safety. Traditional communication methods—verbal commands, hand signals, or radio communication—are often impractical or even dangerous in stealth-based scenarios where silence and non-detection are vital. This underscores the need for an intuitive, low-profile, and silent communication alternative that can function reliably in dynamic field conditions.

Gesture-based communication offers a promising solution, especially when integrated with wearable electronics. Recent advances in embedded systems, flexible sensors, and machine learning have enabled the development of gloves capable of recognizing hand gestures and converting them into machine-interpretable signals. While many such systems have been designed for assisting speech- or hearing-impaired individuals through sign language translation, their utility in military or tactical domains remains largely unexplored.

This research presents a gesture-based silent communication system, a glove-based wearable solution designed specifically for defense personnel. The system uses flex sensors to capture hand gestures, which are then classified using a machine learning model deployed on a microcontroller. Recognized commands are wirelessly transmitted via long-range LoRa module to a receiver unit, which can provide either visual, audio, or haptic output depending on the operational context.

By combining real-time gesture recognition with long-range encrypted wireless transmission, this system enables secret communication without speech or visible cues. The proposed solution is lightweight, field-deployable, and does not rely on external devices such as smartphones or screens, making it ideal for low-visibility and high-mobility situations encountered in modern military settings.

Related Work:

Silent and gesture-based communication systems have received increasing attention, especially in the domains of assistive technology and military operations. Various approaches have been proposed to design wearable devices that can capture human gestures and translate them into meaningful commands. This section reviews key contributions in the field and highlights the motivation for our proposed work.

Stasi et al. (2013) presented a comprehensive glove-based system for silent communication in military contexts. Their design integrated bend sensors and accelerometers to capture hand state, orientation, and motion. A Support Vector Machine (SVM) classifier implemented on an Android platform was used to interpret predefined commands, which were then transmitted wirelessly and displayed on a heads-up display (HUD) mounted on ballistic eyewear. While the system demonstrated reliability in controlled conditions, it required analog comparator circuits and user-specific calibration, adding complexity and reducing portability.

Arakeri et al. (2014) proposed a gesture recognition system for human-computer interaction using flex sensors and accelerometers. The system utilized an Arduino microcontroller for data acquisition and applied rule-based logic for gesture interpretation. Though not designed for military use, this work demonstrated the feasibility of building simple gesture-based systems with minimal hardware. However, the absence of machine learning limited its adaptability and accuracy across users.

Jin et al. (2012) explored a wearable inertial sensing system for full-body motion capture and recognition. The system employed multiple inertial measurement units (IMUs) and probabilistic models to recognize complex gestures. While effective in high-resolution motion tracking, the bulkiness and high processing demands of the system rendered it impractical for lightweight, mission-specific applications such as military field communication.

Mitra and Acharya (2007) conducted a foundational survey on gesture recognition, comparing vision-based and sensor-based systems. Their study covered various classification methods, including Hidden Markov Models, SVMs, and neural networks, while also identifying challenges like variability in gestures, real-time processing constraints, and environmental occlusion. This survey provided a theoretical basis for future developments in gesture-based systems.

Singh and Sharma (2020) developed a smart glove aimed at facilitating silent communication for the speech-impaired. Their prototype used five flex sensors and an MPU6050 accelerometer, with data processed on an Arduino and transmitted via Bluetooth to a mobile app. Although similar in structure to our system, their approach lacked machine learning, relying instead on hardcoded thresholds for gesture classification, and was not adapted for high-stakes environments such as defence operations.

Kumar et al. (2021) proposed a low-cost smart glove for sign language recognition using flex sensors and a neural network implemented in Python. The system effectively translated gestures into text and speech. However, it required an external computer for processing, limiting its mobility and real-time applicability in embedded or field conditions.

In summary, existing literature offers a range of wearable gesture recognition systems, mostly focused on assistive or civilian applications. Military-specific systems often involve complex hardware setups or depend on external computing platforms. In contrast, our proposed system employs a lightweight, embedded SVM-based classification model that runs inference directly on the microcontroller, enabling efficient, real-time silent communication for defense scenarios without requiring external devices.

Proposed System:

We propose a wearable, Arduino-based smart glove system designed specifically for silent communication in military and defense scenarios. The system enables discreet gesture-based messaging using a combination of embedded sensors and machine learning classification. It provides real-time communication without the need for spoken commands or visible hand signals, making it suitable for secret operations or environments with communication restrictions.

The glove is embedded with five flex sensors (one on each finger) that detect finger bending. The sensor readings are processed in real-time by an onboard Arduino Mega 2560 microcontroller. The gesture data is normalized using a precomputed scaler and passed through a Support Vector Machine (SVM) classifier trained offline. The resulting classification identifies the intended command or phrase associated with the gesture.

Once a gesture is recognized, the corresponding command is sent wirelessly to a remote receiver using a long-range LoRa module. At the receiver end, the message can be delivered in different ways depending on the situation — it might be shown on a small screen, played as audio through a speaker or earpiece, or simply indicated by a vibration. This flexibility allows the system to adapt to a variety of field conditions, whether it's a silent operation where sound must be avoided or a more open environment where spoken or visual messages are appropriate.

Our system differs from prior approaches by enabling lightweight, fully embedded machine learning inference without reliance on external platforms or rule-based logic. The trained SVM model is implemented as simplified C code, allowing efficient real-time classification on the Arduino hardware. This architecture enhances portability, reduces latency, and ensures secure, low-profile operation in field conditions.

System Architecture:

The proposed Gesture-Based Silent Communication System is designed as a compact, wearable solution capable of real-time gesture recognition and secure command transmission in operational environments. The architecture comprises two main subsystems: (1) the wearable transmitter glove and (2) the portable receiver module. The system is developed to function autonomously in the field without dependence on external computational resources.

1. Transmitter Unit (Glove Module)

The transmitter is a glove embedded with multiple sensors and a microcontroller that performs gesture acquisition, processing, classification, and wireless transmission as shown in Fig 1.

1.1. Sensing Layer

Five flex Sensors are positioned along each finger. These resistive sensors capture finger-bending patterns corresponding to specific hand gestures.

1.2. Processing and Classification

- Microcontroller (Arduino Mega 2560): Reads analog/digital input from sensors and preprocesses data.
- Embedded SVM Model: A pre-trained Support Vector Machine model is deployed directly on the microcontroller using simplified logic to classify the input pattern into one of the predefined gesture classes.
- Real-Time Inference: The model performs classification with low latency (<100 ms), enabling near-instant feedback.

1.3. Communication Module

- LoRa Transceiver: Selected for its long-range (2–10 km), low-power, and encrypted communication capabilities. It transmits the classified gesture as an encoded command to the receiver unit.
- Encryption Layer (Optional): AES-based encryption is implemented to ensure secure transmission of sensitive gesture commands.

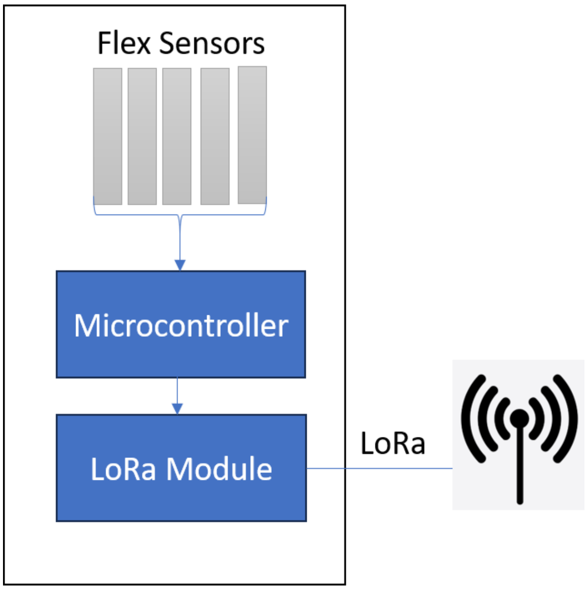

Fig 1: Block diagram of transmitter unit

2. Receiver Unit

The receiver unit is responsible for decrypting, interpreting, and conveying the received commands to the end-user in the desired format as illustrated in Fig 2.

2.1. LoRa Receiver

- Continuously listens for incoming messages from the transmitter glove.
- Matches received code to predefined commands (e.g., "Advance," "Enemy Spotted").

2.2. Output Interface

Depending on the mission requirements, the receiver may feature one or more of the following:

- Audio Output: A DFPlayer Mini or equivalent module plays pre-recorded voice clips corresponding to recognized commands via speaker or earpiece.

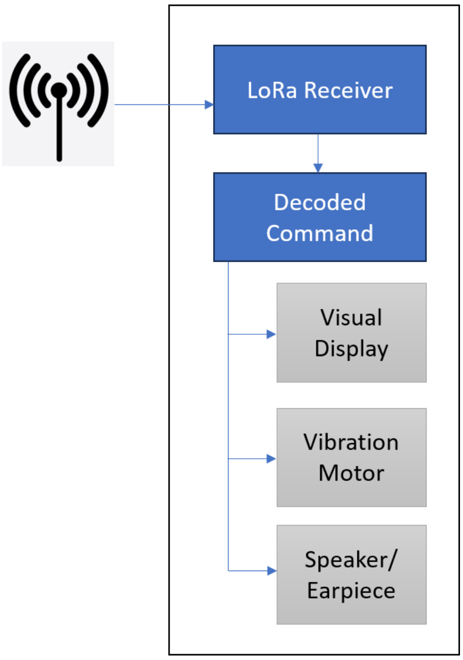

Fig 2: Block diagram of receiver unit

- Visual Display: A compact OLED or LCD screen can be used to show textual descriptions of gestures (optional).
- Haptic Feedback: A vibration motor provides tactile alerts, useful in silent or low-visibility operations.

Experimental Setup and Results

To evaluate the effectiveness of the proposed gesture-based silent communication system, two distinct datasets were used: one containing static hand gestures corresponding to the 26 alphabetic letters (A–Z), and another focused on a smaller set of mission-specific phrases intended for military use. Both datasets were collected using a glove embedded with five flex sensors, and each sample consisted of five analog sensor readings representing finger bend positions.

Fig 3: Glove setup used for data collection

1. Dataset Description

Letters Dataset:

The first dataset was designed to evaluate how well the system can recognize a wide variety of static hand gestures. It includes 26 gesture classes, each corresponding to a letter of the alphabet from A to Z. For each class, around 27 to 28 samples were collected, resulting in a total of over 700 gesture recordings. Each sample is made up of five values — one from each flex sensor — representing the degree of finger bending during the gesture. Although there were slight variations in the number of samples across classes, this imbalance was addressed using stratified sampling during model training. This dataset served as a benchmark to test the system's ability to handle a larger number of gesture categories reliably and accurately.

Phrase Dataset:

The second dataset was created with a more focused application in mind — facilitating silent communication in military and defense scenarios. It consists of four distinct gesture classes, each representing a specific phrase or command such as "Proceed," "Halt," "Enemy Ahead," and "All Clear." For each gesture, 27 samples were collected, making the dataset well-balanced and straightforward to work with. Like the first dataset, each sample includes five values from the flex sensors worn on the fingers. This smaller but purpose-driven dataset was ideal for training a lightweight and highly accurate model suitable for real-time deployment on a microcontroller.

2. Model Training and Evaluation

A Support Vector Machine (SVM) classifier with a linear kernel was trained separately on both datasets using Python's scikit-learn library. Prior to training, the input features were standardized using StandardScaler. A stratified 80-20 train-test split ensured fair class distribution across both sets.

Letters Dataset Result:

The model achieved an accuracy of 94%, with most classes demonstrating precision and recall scores above 0.90. A few letters with similar hand shapes (e.g., A vs. S) showed minor confusion. As shown in Table 1, the results confirm the model's capacity to distinguish a wide range of gestures reliably.

Phrase Dataset Result:

The classifier achieved 100% accuracy, with perfect scores across all evaluation metrics — precision, recall, and F1-score. The classification performance on the phrase dataset is shown in Table 2. Given the reduced complexity and clear distinction between command gestures, the model was not only highly accurate but also simple enough to be embedded.

	precision	recall	f1-score	support
A	0.75	0.60	0.67	5
B	1.00	1.00	1.00	6
C	0.83	1.00	0.91	5
D	0.86	1.00	0.92	6
E	0.86	1.00	0.92	6
F	1.00	1.00	1.00	6
G	1.00	1.00	1.00	6
H	1.00	0.83	0.91	6
I	1.00	1.00	1.00	6
J	1.00	1.00	1.00	5
K	1.00	0.80	0.89	5
L	1.00	1.00	1.00	6
M	1.00	0.80	0.89	5
N	1.00	1.00	1.00	5
O	1.00	0.67	0.80	6
P	1.00	1.00	1.00	6
Q	1.00	1.00	1.00	6
R	1.00	1.00	1.00	5
S	0.86	1.00	0.92	6
T	1.00	1.00	1.00	5
U	0.83	1.00	0.91	5
V	1.00	0.80	0.89	5
W	1.00	1.00	1.00	6
X	0.71	1.00	0.83	5
Y	1.00	1.00	1.00	6
Z	1.00	1.00	1.00	6

Table 1. Classification Report of Letters Dataset

	precision	recall	f1-score	support
Class 1	1.00	1.00	1.00	6
Class 2	1.00	1.00	1.00	5
Class 3	1.00	1.00	1.00	6
Class 4	1.00	1.00	1.00	6

Table 2. Classification Report of Phrase Dataset

3. Embedded Deployment on Arduino

While the 26-class SVM was used primarily for offline evaluation, the 4-class model trained on the phrase dataset was converted into Arduino-compatible logic. The trained model was translated into a set of nested conditional statements based on decision boundaries extracted from the SVM. This lightweight rule-based version was successfully deployed on an Arduino Mega 2560. Inference on the embedded system was performed in real-time, with average classification latency under 100 milliseconds. This demonstrated the feasibility of running machine learning-driven gesture recognition without external computing resources, ensuring full independence and operational readiness in the field.

Conclusion:

This study introduces a gesture-based silent communication system designed to support defense personnel in situations where verbal communication is not possible or safe. By using a glove embedded with five flex sensors, the system can accurately detect static hand gestures and interpret them using a lightweight SVM model running directly on a microcontroller. The recognized commands are transmitted wirelessly through a LoRa module to a receiver unit, which can provide visual, audio, or haptic feedback depending on the situation. The model achieved high accuracy on both letter-level and phrase-level datasets, highlighting the system's effectiveness and reliability.

Looking ahead, the system could be expanded to support more complex, dynamic gestures by adding motion sensors and temporal analysis. Communication security could be strengthened through data encryption, especially for sensitive defense use. There's also potential to reduce power consumption for longer field use and allow users to customize gesture-command mappings. With further development, this glove-based system could become a practical tool for silent, efficient communication in real-world military scenarios.

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