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IoT-Enabled Sensor Glove for Communication and Health Monitoring in Paralysed Patients †

Angshuman Khan, Uttam Narendra Thakur and Sikta Mandal *

University of Engineering & Management, Jaipur 303807, Rajasthan, India; email1@email.com (A.K.); email2@email.com (U.N.T.)
* Correspondence: angshuman.khan@uem.edu.in or angshumankhan2910@gmail.com
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Abstract

Due to their limited mobility and vocal limitations, paralysed individuals frequently struggle with communication and health monitoring. This work introduces an Internet of Things (IoT)-based system that combines continuous health monitoring with a sensor-based smart glove to enhance patient care. The glove detects falls, sends emergency messages via hand gestures, and monitors vital indicators, including SpO_2, heart rate, and body temperature. The smart glove uses Arduino and ESP8266 modules with MPU6050, MAX30100, LM35, and flex sensors for these functions. MPU6050 detects falls precisely, while MAX30100 and flex sensors measure gestures, SpO_2, heart rate, and body temperature. The flex sensor interprets hand motions as emergency alerts sent via Wi-Fi to a cloud platform for remote monitoring. The experimental results confirmed the superiority and validated the efficacy of the suggested module. Scalability, data logging, and real-time access are guaranteed by IoT integration. The actual test cases were predicted using a Support Vector Machine, achieving an average accuracy of 81.98%. The suggested module is affordable, non-invasive, easy to use, and appropriate for clinical and residential use. The system meets the essential needs of disabled people, enhancing both their quality of life and carer connectivity. Advanced machine learning for dynamic gesture detection and telemedicine integration is a potential future improvement.

Keywords: Internet of Things (IOT); smart glove; sensors; gesture recognition; health monitoring; support vector machine

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1. Introduction

The IoT-based healthcare system for paralysis patients with paralysis introduces an innovative solution to transform the care and rehabilitation experience for individuals with paralysis [1]. Paralysis impairs muscle movement in parts or all of the body and poses serious challenges regarding mobility, independence, and overall quality of life [2]. Unfortunately, traditional healthcare methods often fall short—especially in remote or underserved regions—where continuous care, physical therapy, and access to specialised rehabilitation are limited [3]. With recent technological progress, the Internet of Things (IoT) has emerged as a game-changer in the healthcare sector. IoT enables real-time health monitoring, remote medical support, and personalised treatment through interconnected smart devices [3]. These devices, equipped with sensors and linked via communication networks and cloud platforms, can continuously gather and analyse patient data [2]. It allows for the remote tracking of vital signs, muscle responses, and rehabilitation progress—helping healthcare providers deliver more effective and timely interventions [2]. Such systems improve patient outcomes and reduce the burden on caregivers and medical staff. At the heart of this system is a patient monitoring setup, where sensors continuously collect physiological data. These sensors are directly attached to the patient and are responsible for detecting and transmitting real-time information. The complete system includes sensor networks, display modules, wireless communication units, and various supporting technologies that provide comprehensive, round-the-clock care.

The motivation of this work stems from the communication and health-monitoring challenges faced by paralysed individuals due to their limited mobility and vocal impairments. These limitations make it difficult for them to convey emergencies, receive timely medical assistance, and maintain continuous health tracking. By integrating IoT technology with a smart glove capable of monitoring vital signs, detecting falls, and sending emergency alerts through simple hand gestures, the system aims to provide an affordable, non-invasive, and user-friendly solution that enhances patient safety, quality of life, and caregiver connectivity in both clinical and home settings.

The main contributions of this research are mentioned below.

- Development of an IoT-based smart glove system that integrates continuous health monitoring and gesture-based emergency communication for paralysed individuals.
- Implement multiple sensors with Arduino and ESP8266 for fall detection, SpO_2, heart rate, body temperature measurement, and gesture recognition.
- Real-time data transmission to a cloud platform for remote monitoring, ensuring scalability, data logging, and accessibility.
- Application of a Support Vector Machine (SVM) model for gesture prediction, achieving an average accuracy.
- Deliver an affordable, user-friendly solution suitable for clinical and home environments, improving patient quality of life and caregiver connectivity.

2. Existing Works

The literature review for an IoT-based healthcare system for paralysis patients with paralysis explores the wide range of technological innovations and research efforts that focus on improving rehabilitation and patient care using IoT. These studies provide insight into the current landscape and highlight the opportunities and limitations that guide the development of more effective and accessible systems. This review brings together various works that have contributed to the understanding and advancement of IoT applications in healthcare, particularly for individuals with paralysis. An intelligent rehabilitation glove enhanced by IoT technology to assist patients recovering hand function has been introduced in [4]. The glove has integrated sensors and actuators that monitor therapeutic movements and deliver personalised exercise regimens. The study highlights the glove's potential to improve engagement, track recovery trends, and support individualised therapy. The practicality of using wearable devices for home-based hand rehabilitation, especially in stroke survivors, is suggested in [5]. The system used motion sensors and interactive software to guide and evaluate therapeutic exercises. Results showed that patients found the devices easy to use and comfortable. The work in [6] focused on how technology can enhance patient motivation during stroke rehabilitation. The study looked at tools such as wearable devices, virtual reality platforms, and mobile apps designed to increase patient engagement. This work offered real-time feedback, gamified experiences, and tailored exercise plans, making rehabilitation more interactive and enjoyable, thus improving therapy compliance. The broader trends of IoT applications in stroke rehabilitation have been discussed in [7]. It details how wearable sensors and smart systems enable the real-time tracking of vital signs and therapy progress. In [8], a soft robotic glove was developed to help patients regain hand mobility. Built with flexible materials and actuators, the glove supported passive and active hand movements. It offered adaptable support aligned with the patient's therapy needs, promoting muscle strength and movement coordination. The work [9] examined the acceptance and usability of wearable and robotic rehabilitation technologies. The findings revealed that successful integration of these devices depends not only on their technical capabilities but also on user experience—ease of use, comfort, and affordability were significant factors influencing long-term adoption. Another work in [10] developed a prototype smart glove to support dexterous hand rehabilitation. The glove integrated actuators and motion sensors to guide patients through hand exercises with real-time feedback. Clinical trials indicated improvements in hand strength and coordination, suggesting strong potential for use in therapy routines. An IoT-based rehabilitation system that allowed real-time tracking of patient vitals, movement patterns, and therapy results has been proposed in [11]. The system leveraged cloud computing and wearable devices to enable remote patient monitoring, empowering healthcare providers to make informed, timely decisions regarding patient care. A personalised IoT rehabilitation system that targeted upper limb movement in patients was suggested in [12]. With wearable sensors and actuators, the system offered real-time feedback and therapy adjustments tailored to each user. The work in [13] explored how wearable IoT devices could support stroke rehabilitation outside hospital environments. Their research demonstrated that real-time monitoring of vital signs and therapy progress allows for early detection of issues, timely intervention, and better patient outcomes.

Current IoT-based rehabilitation systems for paralysis patients with paralysis show promise but face several limitations. Most studies are short-term, with small and non-diverse samples, limiting generalizability. Personalisation is often static, with little real-time adaptation to patient progress, and usability factors like comfort, affordability, and long-term adherence are underexplored. Critical aspects such as energy efficiency, data privacy, interoperability with clinical systems, and cost-effectiveness are rarely addressed. Additionally, there is limited focus on multimodal sensing, algorithm transparency, and deployment in low-resource settings, along with a lack of open datasets for reproducibility.

Gaps in multimodal sensing, algorithm transparency, and deployment in low-resource settings further limit their scalability and inclusivity. Addressing these issues requires more robust, adaptive, and accessible solutions supported by standardised evaluation protocols and open datasets.

The prime novelty points of this work include:

- Integration of fall detection, vital sign monitoring, and gesture-based emergency alerts into a single IoT-enabled smart glove.
- Multi-sensor fusion (MPU6050, MAX30100, LM35, flex sensors) for comprehensive, real-time health and safety tracking.
- Cloud-based remote monitoring with data logging for scalability and continuous caregiver access.
- Application of SVM for dynamic gesture recognition with reasonable accuracy.
- Low-cost, non-invasive, and portable design suitable for clinical and home use.

3. Proposed Model

The experimental apparatus comprises a glove outfitted with various sensors, including flex sensors, inertial measurement units (IMUs), and pressure sensors, intended to record finger flexion, wrist orientation, and additional motion attributes. These sensors produce signals that correlate to physical movements, which are subsequently directed through an interface circuit for signal conditioning. This phase guarantees noise attenuation, appropriate scaling, and analog-to-digital conversion as required, facilitating precise and accurate data capture. The processed sensor data is gathered using a microcontroller or data collection unit, which organizes and transmits the values to a linked computer for subsequent analysis. A simple schematic of the proposed model is shown in Figure 1.

Upon transfer, the data is subjected to preprocessing, encompassing normalisation to eliminate scale discrepancies, extracting pertinent statistical and temporal aspects, and, if required, reducing dimensionality to improve computing performance. The curated dataset is subsequently provided to a Support Vector Machine (SVM) classifier designed to differentiate between various gestures or movements. The system generates gesture labels instantaneously, which can be exhibited, archived, or utilised for the operation of external devices such as robotic arms or virtual reality interfaces. The process includes a calibration phase before actual trials, followed by performance evaluation utilising accuracy measures, confusion matrices, and real-time tests to ascertain the reliability and responsiveness of the system.

The sensor workflow of the proposed model is depicted in Figure 2. This work has three main components: preprocessing, feature extraction, and classifier optimisation. First, the raw sensor data from flex sensors, accelerometers, and gyroscopes should be preprocessed for consistency and noise reduction. This involves normalising all readings—either scaling them to a range between 0 and 1 or applying z-score normalisation—and using a low-pass filter, such as a Butterworth or moving average filter, to remove high-frequency noise. Continuous data streams should then be segmented into fixed-size windows, for example, 200 ms per segment with 50% overlap, ensuring uniform input length for feature extraction.

Figure 1. Simple schematic of the proposed model.

From each window, a set of discriminative features should be extracted. For flex sensors, this includes the mean, variance, and slope of bend angle changes. Accelerometer data can contribute statistical measures such as mean and standard deviation, and derived metrics like signal magnitude area (SMA), pitch, and roll. Gyroscope data should provide angular velocity measures, including mean, standard deviation, and signal energy. Optionally, frequency-domain features such as the magnitudes of the first 5–10 FFT coefficients can be included to capture gesture dynamics, resulting in a final feature vector of around 30–50 features per gesture.

The SVM should be configured with an RBF kernel to handle the nonlinear patterns typical in gesture data. Initial hyperparameters can include a penalty parameter L = 10 for balanced margin control, with *k* set to "scale" for automatic kernel width adjustment. If the gesture dataset is imbalanced, a `balanced` class weight setting can help improve performance across classes. A one-vs-one multi-class strategy is recommended for sign language gestures. Model training should use a 70–15–15 split for training, validation, and testing, combined with 5-fold cross-validation to fine-tune L and k within ranges such as L = {0.1, 1, 10, 100} and *k* = {0.001, 0.01, 0.1, 1}.

Finally, for deployment, the trained SVM model can be exported as a '.pkl' file using scikit-learn and integrated into either the glove's microcontroller or a connected smartphone application. The preprocessing pipeline must be replicated precisely during deployment to ensure consistency between training and inference. This approach offers a lightweight yet powerful recognition system well-suited for real-time sign language interpretation.

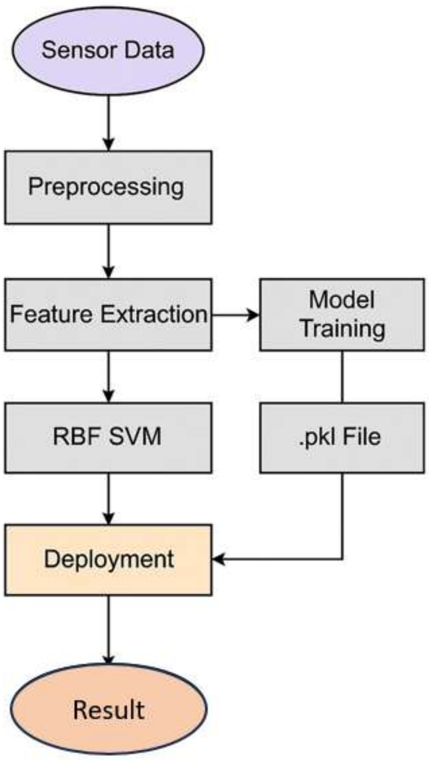

Figure 2. The sensing workflow of the proposed model.

4. Results and Discussion

The glove uses built-in sensors to determine the wearer's temperature, heart rate, and hand gestures. Arduino is used to gather and communicate these sensor readings, after which Python is used to analyse the data for testing. The SVM classifier trains a machine learning model for data like gesture, heart rate, and temperature. Whether the condition is true or not is predicted by the result. A comparative analysis of SVM efficiency across different observation test cases for the proposed experiment is presented in Table 1. An efficiency of 83.33% is obtained in Test Case 1 with 44 true positives, 8 false positives, 7 false negatives, and 31 true negatives. With an efficiency of 81.65%, Test Case 2 displays 50 true negatives, 12 false positives, 8 false negatives, and 39 true positives. With an efficiency of 76.98%, Test Case 3 shows 45, 9, 10, and 46 as true positives, false positives, false negatives, and true negatives, respectively. Subsequent test cases show similar patterns. The calculated average efficiency for all situations is 81.98%.

Table 1. Comparative analysis of SVM efficiency on different observation test cases.

Observation/Test Case	True Positive	False Positive	False Negative	True Negative	Efficiency
1	44	8	7	31	83.33%
2	39	12	8	50	81.65%
3	45	9	10	46	82.73%
4	39	10	13	55	80.34%
5	59	14	11	42	80.16%
6	47	9	11	54	83.47%
7	45	10	8	38	82.18%

5. Comparison

The current work, designed for emergency hand gesture communication alongside vital sign monitoring, stands out from previous studies that primarily concentrated on a single functionality. Gesture-only systems, such as those by [14–16], and [18], achieved notably higher accuracies ranging from 88.97% to nearly 98%, owing to their optimization for dynamic sign language or gesture detection using dedicated sensors like flex sensors, IMUs, and textile-based capacitive sensors, often coupled with convolutional neural networks. In contrast, health-focused works like [17] and [19] emphasized rehabilitation or vital sign monitoring, prioritizing reliability and precision over classification accuracy, and did not attempt gesture-based interaction. While the current work reports a comparatively lower accuracy of 81.98%, this trade-off arises from the dual-purpose integration of gesture recognition and biomedical sensing, which introduces greater complexity and sensor noise. Unlike the specialized systems, it addresses a broader spectrum of user needs, making it more versatile for real-world emergency communication and health monitoring scenarios, though with some compromise in recognition performance.

Table 2. Comparative analysis of existing works and the proposed approach.

Works	Aim	Sensors Used	Algorithm/Classifier	Accuracy
[14]	To convert Bangla sign language to spoken Bangla text	Flex sensors, gyroscope, accelerometer	Convolutional neural network	88.97%
[15]	To capture and classify dynamic hand gestures	Flex sensors, force sensors, inertial measurement unit (IMU) sensor	Convolutional neural network	90%
[16]	To develop dynamic sign language gesture detection	Accelerometers, gyroscopes	DT, SVM, KNN, RF	~98%
[17]	To enhance and expedite the rehabilitation of hand motor skills after a brain stroke	Flexi-force sensors, flex sensors, MAX30100 sensor	NR	NR
[18]	To design a textile-based sensorized glove and an air-driven soft robotic glove	Capacitive textile sensors	LR, DT, KNN, MLP, XGB	93.45%
[19]	To develop a vital sign monitoring system	MPU6050, MAX30100, MLX9064	NR	NR
This work	To communicate emergency hand gestures and check vital signs,	MAX30100, LM35, flex sensors	SVM	81.98%

* NR: Not reported, DT: Decision tree, SVM: Support vector machine, KNN: K-nearest neighbor method, RF: Random Forest, LR: Logistic regression, MLP: Multi-layer perceptron, XGB: XG-Boost.

6. Conclusions

The integration of smart gloves with an IoT-based health monitoring system marks a significant advancement in assistive technology for paralysed patients. By translating hand gestures into speech through embedded sensors and a text-to-speech module, the system enables individuals with limited mobility and speech to communicate their needs more effectively, bridging the communication gap and restoring independence and dignity. In addition, it continuously tracks vital parameters such as heart rate, body temperature, and oxygen saturation, transmitting real-time data to healthcare providers via IoT platforms for prompt intervention. This dual functionality enhances patient safety, reduces the need for constant supervision, and improves the quality of care in both home and clinical environments.

Looking ahead, the system's adaptability supports future enhancements such as AI-driven gesture recognition, multilingual support, emotion detection, and advanced speech synthesis to expand accessibility and functionality. Integration with telemedicine platforms, predictive healthcare analytics, mobile alerts, and machine learning can enable faster emergency responses and proactive health management. Energy-efficient design, wireless charging, and patient-specific customisation make it a sustainable, inclusive solution with strong potential to transform assistive healthcare.

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