RESEARCH PAPER

MEDIGLOVE: A SMART REHABILITATION GLOVES WITH MYOELECTRIC GESTURE RECOGNITION

G.Senbagavalli [1*], Tabassum Ara AF [2], Bharath Kumar Narahari [3], Kinny Garg [4]

[1*] Associate Professor, Department of Electronics and Communication Engineering, AMC Engineering College, Bengaluru, Karnataka-560083, India. Email: shenbab4u@gmail.com

[2]Student in Master of Technology, Department of Electronics and Communication Engineering, AMC Engineering College, Bengaluru, Karnataka-560083, India. Email: tabu047@gmail.com

[3] Master of Science in Mechanical Engineering, Opto Mechanical Engineer Email: bharath859@gmail.com

[4]Associate Professor, Department of Electronics and Communication Engineering, AMC Engineering College, Bengaluru, Karnataka-560083, India. Email: kinnygarg25@gmail.com

***Corresponding Author:** G.Senbagavalli, Associate Professor, Department of Electronics and Communication Engineering, AMC Engineering College, Bengaluru, Karnataka-560083, India. Email: shenbab4u@gmail.com, Phone:91-8722401462

Abstract: Hand motor impairments caused by stroke, injury, or neurological disorders require long-term rehabilitation, which is often repetitive, monotonous, and resource-intensive. To address these challenges, this paper presents MediGlove, a smart rehabilitation glove that integrates sensor-based motion tracking, gamified therapy, and gesture-based Internet of Things (IoT) control to enhance patient engagement and functional recovery. The proposed system supports dual functionality, including interactive rehabilitation through a Unity-based gaming environment, gesture-controlled operation of smart appliances using a relay module and functional recovery of patient is analyzed using Machine learning models such as random forest, support vector machine etc,. Experimental results demonstrate accurate motion tracking, system latency below 100 ms, and reliable mode switching without interference. The solution is cost-effective, portable, and user-centric, promoting improved motivation, independence, and remote therapy monitoring. MediGlove shows strong potential as an efficient, technology-driven rehabilitation tool suitable for both clinical and home-based applications.

Keywords: Internet of Things, Sensors, Remote monitoring, Gestures, Machine learning Models
How to cite this article: Senbagavalli G, Tabassum Ara AF, Narahari BK, Garg K. MediGlove: A Smart Rehabilitation Gloves with Myoelectric Gesture Recognition. Int J Drug Deliv Technol. 2026;16(63s):1668-1678. DOI: 10.25258/ijddt.16.63s.170

INTRODUCTION

Hand motor impairments resulting from neurological disorders such as stroke, Parkinson's disease, cerebral palsy, and traumatic injuries significantly affect an individual's ability to perform daily activities(5,8,11,16). These impairments reduce dexterity, coordination, and muscular strength, thereby limiting independence and overall quality of life(5). Rehabilitation therapy plays a vital role in restoring motor function; however, conventional rehabilitation methods primarily rely on repetitive exercises conducted under the supervision of trained physiotherapists. Although effective, these approaches are often time-consuming, monotonous, and require continuous clinical support, making them less accessible, especially in remote and resource-constrained environments.

With the rapid advancement of technology, there has been increasing interest in developing smart rehabilitation systems that leverage wearable devices, embedded systems, and Internet of Things (IoT) technologies. These systems enable real-time monitoring of hand movements, provide immediate feedback, and facilitate remote rehabilitation. By reducing dependency on constant clinical supervision, such solutions improve accessibility and convenience for patients while supporting efficient therapy management.

Several research studies have proposed wearable smart glove systems for hand rehabilitation. These systems typically incorporate flex sensors and inertial measurement units (IMUs), such as accelerometers, to accurately capture finger bending and wrist motion(12-15). The collected data is processed using microcontrollers to analyze movement patterns and evaluate patient performance. Furthermore, wireless communication technologies are often integrated to transmit data to healthcare professionals, enabling remote monitoring and assessment. This approach supports the growing trend of tele-rehabilitation and enhances continuity of care.

Another important development in this domain is the integration of gamification into rehabilitation systems(7,19). Traditional therapy exercises can become repetitive and lead to decreased patient motivation and adherence over time. To address this limitation, researchers have incorporated interactive gaming platforms, such as Unity-based environments, into rehabilitation systems. These gamified solutions provide visual feedback, challenges, and rewards, transforming routine exercises into engaging activities. As a result, patient participation and consistency are significantly improved, leading to better rehabilitation outcomes.

In addition to therapeutic applications, some smart glove systems extend their functionality to include gesture-based control of external devices(20). By recognizing predefined hand gestures, these systems enable users to control home appliances such as lights and fans. This feature enhances the practical utility of rehabilitation devices by allowing patients to apply regained motor skills in real-world scenarios, thereby promoting independence and confidence.

Despite these advancements, existing rehabilitation systems face several challenges. Many solutions focus primarily on motion tracking without offering comprehensive feedback or user-friendly interfaces. Additionally, factors such as sensor inaccuracies, calibration requirements, limited gesture recognition capabilities(16-18), and high implementation costsrestrict their widespread adoption. Moreover, most existing systems lack full integration of rehabilitation, gamification, and IoT-based control within a single platform.

This literature survey aims to review and analyze existing smart rehabilitation glove systems and related technologies. It focuses on identifying the techniques used, evaluating system performance, and highlighting the advantages and limitations of current approaches. By examining these aspects, the survey seeks to identify research gaps and provide direction for the development of more efficient, cost-effective, and user-friendly rehabilitation solutions.

In summary, the integration of wearable technology, real-time data processing, gamification, and IoT has the potential to transform traditional rehabilitation practices into more interactive and accessible systems. This study contributes to understanding current advancements and emphasizes the need for innovative solutions that enhance patient engagement, improve recovery outcomes, and support remote healthcare delivery.

LITERATURE SURVEY:

A literature survey on smart rehabilitation gloves focuses on recent advancements in wearable technology for hand motor recovery. Various research works involving sensor-based motion tracking, IoT-enabled systems, and gamified rehabilitation techniques are analyzed and compared. The study reviews multiple approaches such as flex sensor-based gloves, soft robotic rehabilitation devices, and gesture recognition systems, highlighting their methodologies, advantages, and limitations. Key factors such as accuracy, cost, usability, and real-time performance are examined across different models. The survey identifies existing challenges including limited adaptability, high cost of advanced systems, and lack of user engagement in traditional methods. Based on the analysis, future enhancements such as improved sensor integration, AI-based feedback systems, and remote monitoring capabilities are suggested. This literature survey provides a comprehensive understanding of current technologies and helps in identifying research gaps for developing efficient and user-friendly rehabilitation solutions.

Table 1: Comparative Study of various rehabilitation devices

Paper	Technique Used	Results	Advantages	Disadvantages
K.Cowell at.al[1]	Portable CT imaging, compact hardware	Faster diagnosis, reduced delay	On-site imaging, better survival, quick decisions	High cost, lower resolution, power issues.
R. Xu at.al[2]	FES, EEG monitoring	Improved motor recovery, cortical activity	Enhances plasticity, natural movement	Complex setup, calibration needed, limited for severe cases
R.Zhang at.al [3]	EEG-based BCI, Machine learning.	Personalized motor recovery	Adaptive rehab, active participation	Expensive, training required, noisy signals
M.Glassen at.al [4]	EEG, EMG analysis	Better neural-muscular understanding	Helps targeted therapy	Complex, not real-time, variable results

S. Rahman at.al [5]	AI, ML, Deep Learning	Improved prediction & therapy planning	Data-driven, better outcomes	Data dependency, ethical issues
Y.-A. Li at.al [6]	Robotic exoskeleton, EMG	Improved strength & mobility.	Consistent training, independence	Expensive, bulky, supervision needed
C.S.Choy at.al [7]	Virtual Reality, Motor Imagery	Better engagement & recovery.	Immersive, motivating	Motion sickness, costly
K.Cisek at.al [8]	AI, robotics, wearables review	Identified trends & gaps	Broad insights	No practical validation
M. Liu at.al [9]	Brain stimulation, EEG	Improved brain connectivity	Non-invasive, safe	Variable results, monitoring needed
K. J. Nolan at.al [10]	Robotic gait training.	Improved walking ability.	Adjustable intensity, faster recovery.	Expensive, expert required.

RESEARCH GAP:

From the literature survey, the following gaps are identified:

1) Lack of **Gamification** in many rehabilitation systems.
2) Limited **Patient Engagement and Motivation.**
3) **High cost and complexity** of advanced systems.
4) Absence of **dual functionality (rehab + real-life application).**
5) Limited **remote monitoring in basic systems.**
6) No integration of **IoT + gaming + motion tracking together.**

These gaps highlight the need for a cost-effective, interactive, and multifunctional system, which is addressed by MediGlove.

PROPOSED SYSTEM:

The proposed MediGlove system adopts a systematic and modular methodology to design and develop a smart rehabilitation glove for post-stroke hand recovery. The methodology integrates sensing, processing, communication, and application layers to ensure accurate motion tracking, real-time response, and user-friendly interaction as shown in figure 1. The overall system workflow follows a sequential pipeline consisting of data acquisition, signal conditioning, feature extraction, gesture recognition, communication, application integration, and feedback monitoring.

A. System Architecture Overview

The MediGlove is a wearable embedded system comprising five flex sensors and a tri-axis accelerometer interfaced with a microcontroller. The system operates in two functional modes: rehabilitation mode and IoT control mode. In rehabilitation mode, hand movements are mapped to a Unity-based gaming environment, whereas in IoT mode, recognized gestures are used to control external appliances via a relay module. The architecture ensures seamless switching between both modes without interference as per flow diagram in the given figure2

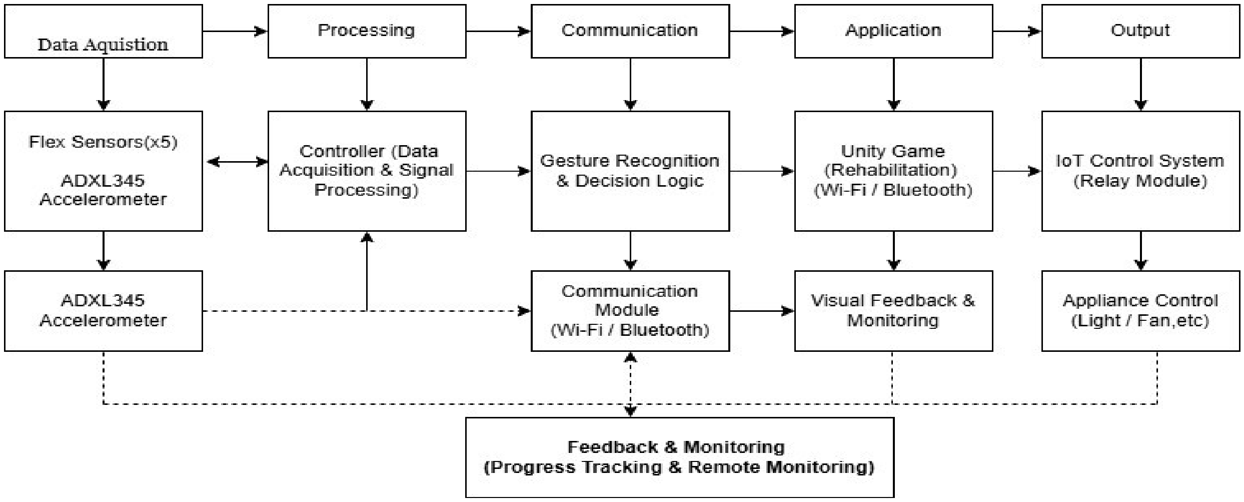

Figure 1: System Architecture of MediGlove System

B. Data Acquisition

The data acquisition module captures real-time hand movement using embedded sensors. Five flex sensors are positioned along each finger to measure bending by detecting resistance variations. The accelerometer measures acceleration and orientation along X, Y, and Z axes, enabling wrist motion tracking. The sensors continuously generate electrical signals proportional to finger flexion and hand movement, which are sampled by the microcontroller through its analog-to-digital conversion (ADC) channels. Continuous sampling ensures real-time monitoring and responsiveness of the system.

C. Signal Processing and Calibration

Raw sensor data is often affected by noise, drift, and environmental variations. Therefore, signal conditioning techniques such as filtering and smoothing are applied to enhance data quality. Normalization is performed to scale sensor values into a uniform range, ensuring consistency across different users. A calibration process is implemented to adapt the system to individual hand sizes and motion ranges, thereby improving personalization and accuracy. Feature extraction techniques are then applied to derive meaningful parameters such as finger bending angles, motion trajectories, and tilt orientation.

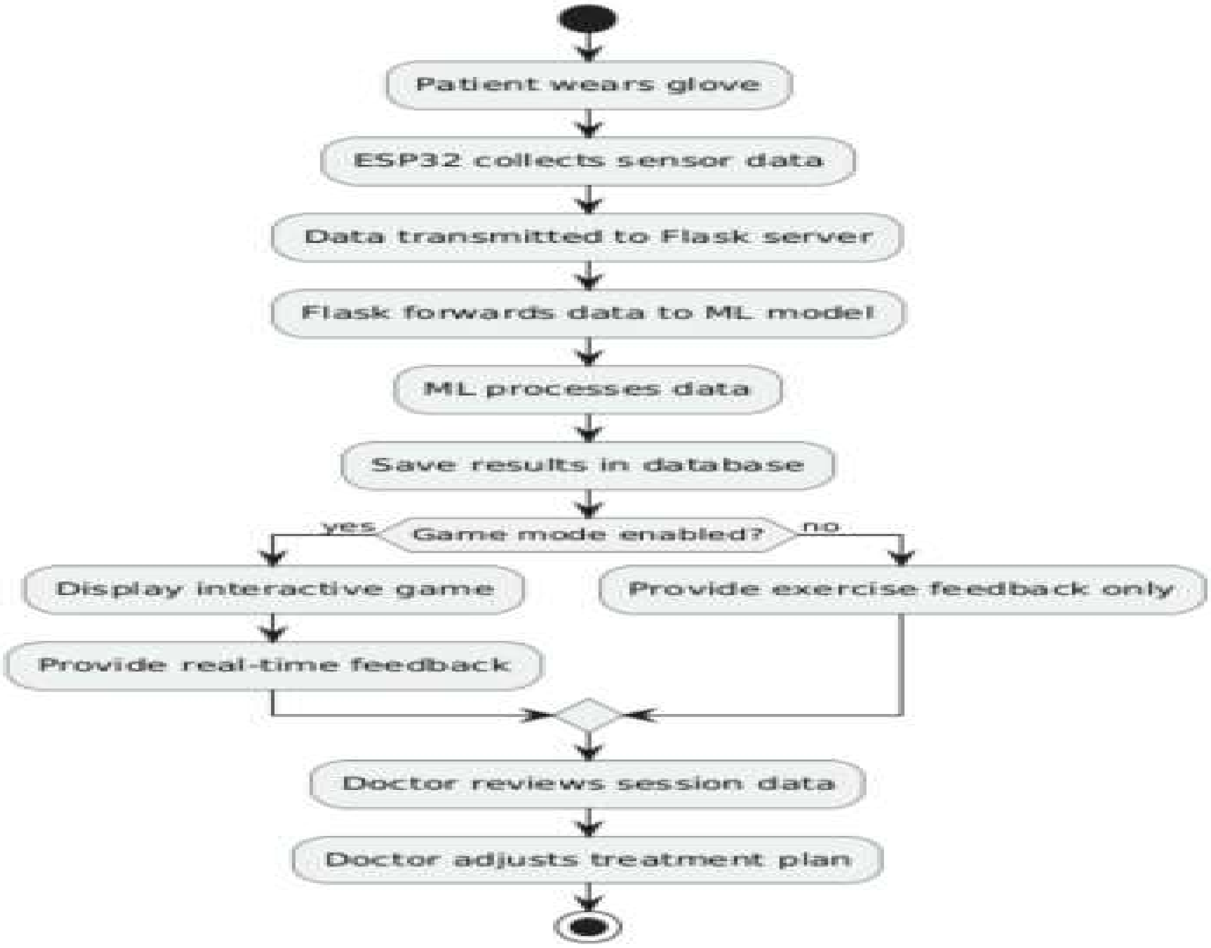

Figure 2: Methodology of proposed MediGlove System.

D. Gesture Recognition Mechanism

Gesture recognition is achieved using a rule-based classification approach. Predefined gesture patterns are created based on combinations of finger bending and wrist orientation. The processed sensor data is compared against these predefined thresholds to identify gestures. If the input matches a stored pattern, a corresponding action is triggered; otherwise, the system continues monitoring. This approach ensures low computational complexity and real-time performance suitable for embedded systems.

E. Communication Module

The microcontroller facilitates wireless communication using built-in Wi-Fi and Bluetooth capabilities. Sensor data is transmitted in real time to external applications such as the Unity interface or IoT devices. Communication protocols such as HTTP, MQTT, or serial communication are employed depending on the application requirements. The system is designed to maintain low latency (less than 100 ms), ensuring smooth and responsive interaction.

F. Application Integration

The MediGlove system integrates with a Unity-based rehabilitation platform that converts physical movements into interactive gaming tasks. The gamification strategy includes levels, scoring mechanisms, and visual feedback to motivate users and enhance engagement. The system also supports IoT-based control, where recognized gestures are mapped to appliance operations. For example, specific hand gestures can be used to turn lights ON/OFF or control fan speed via a relay module. This dual functionality enhances both therapeutic effectiveness and practical usability.

G. Output Execution

Based on recognized gestures, the system generates outputs in two forms. In rehabilitation mode, outputs are visual responses within the game environment, including movement tracking and performance feedback. In IoT mode, outputs are electrical control signals sent to the relay module for appliance operation. This ensures real-time interaction between user input and system response.

H. Feedback and Remote Monitoring

Feedback is a crucial component of the rehabilitation process. The system provides real-time visual feedback through the application interface, allowing users to correct their movements. Additionally, performance data is recorded and can be transmitted to healthcare professionals for remote monitoring. This enables continuous assessment of patient progress and supports tele-rehabilitation.

I. Implementation and Validation

The implementation process involves hardware setup, sensor calibration, firmware development using Embedded C/C++, Utility application development, and system integration. The sequence diagram shows the functional sequence of proposed system as illustrated in figure.3. The system is tested through functional, performance, and user testing. Experimental results demonstrate accurate motion tracking, reliable gesture recognition, and low system latency, validating the effectiveness of the proposed methodology.

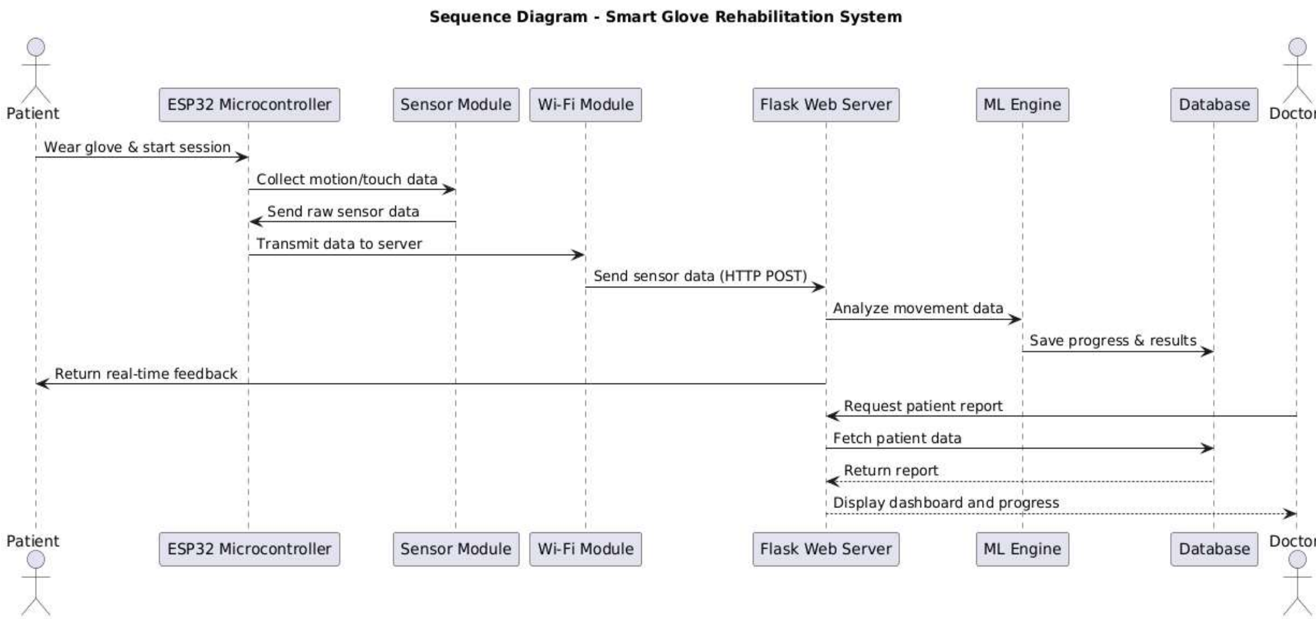

Figure 3: Sequence diagram of proposed MediGlove system

Comparison of Results

A comparison of the reviewed systems shows that:

1) Machine learning-based gloves provide higher accuracy.
2) IoT-based systems enable remote monitoring.
3) VR and robotic gloves improve interaction.
4) Most systems lack combined features.

Table 2: Accuracy of Machine learning-based gloves

Machine Learning Models	Accuracy
Random forest	0.92
SVM	0.89
Naïve Bayes	0.87

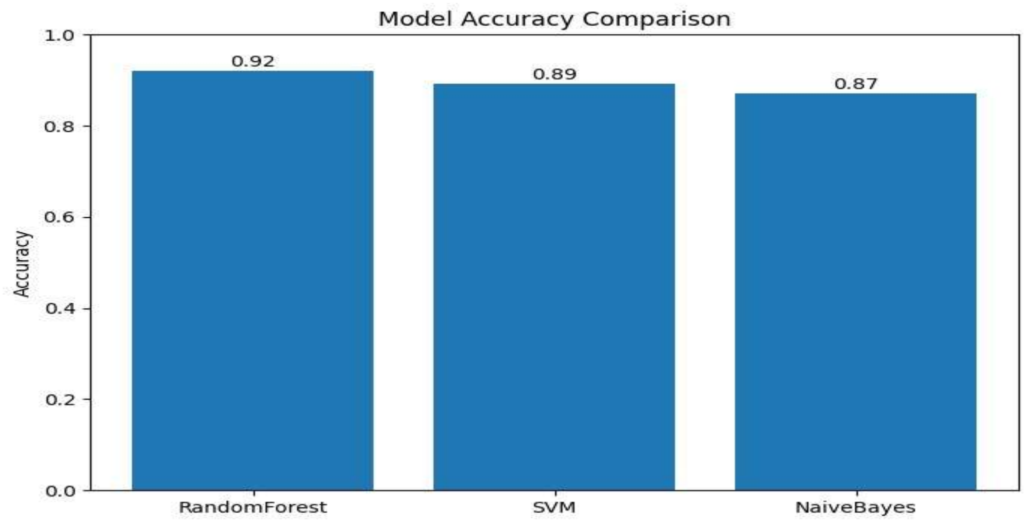

Figure 4: Accuracy comparison with machine learning models

Accuracy of proposed system is calculated in Naïve Bayes, Random forest and Support Vector Machine learning models as illustrated in figures 4-7 using the equation(1).

$$Accuracy = \frac{TP + TN}{TP + FP + FN + FP} \quad (1)$$

Where TP= True Positives, TN=True Negative FP=False Positive, FN=False Negative

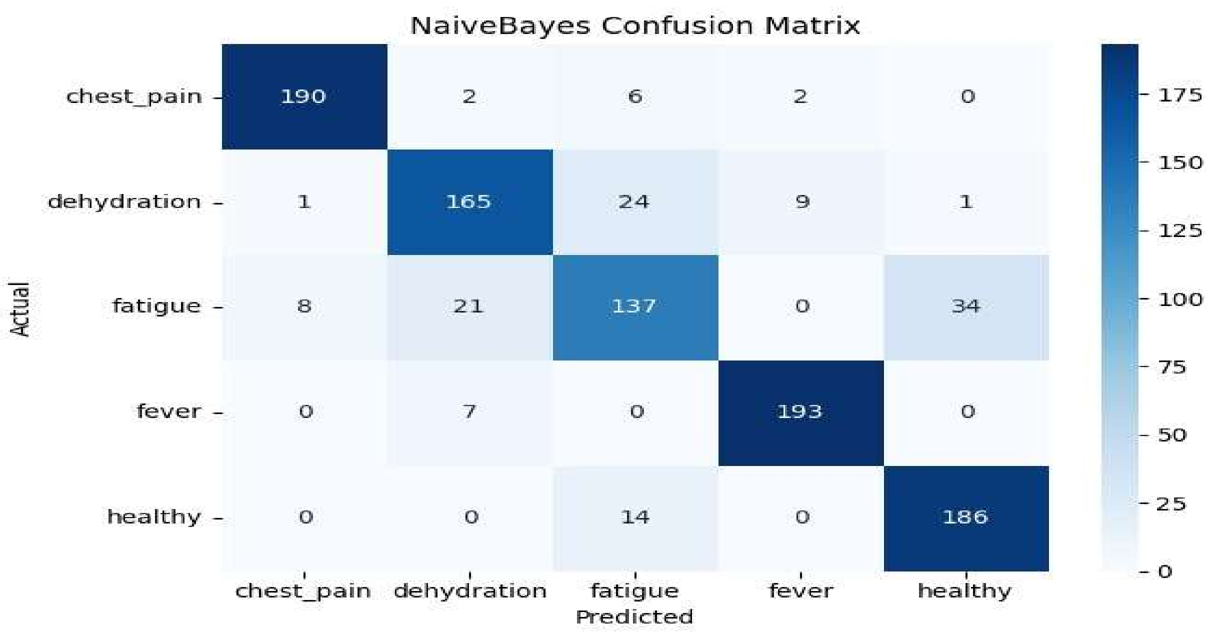

Figure 5: Accuracy comparison of Naïve Bayes model during different health conditions(Chest pain, dehydration, fatigue, fever and healthy) of patient

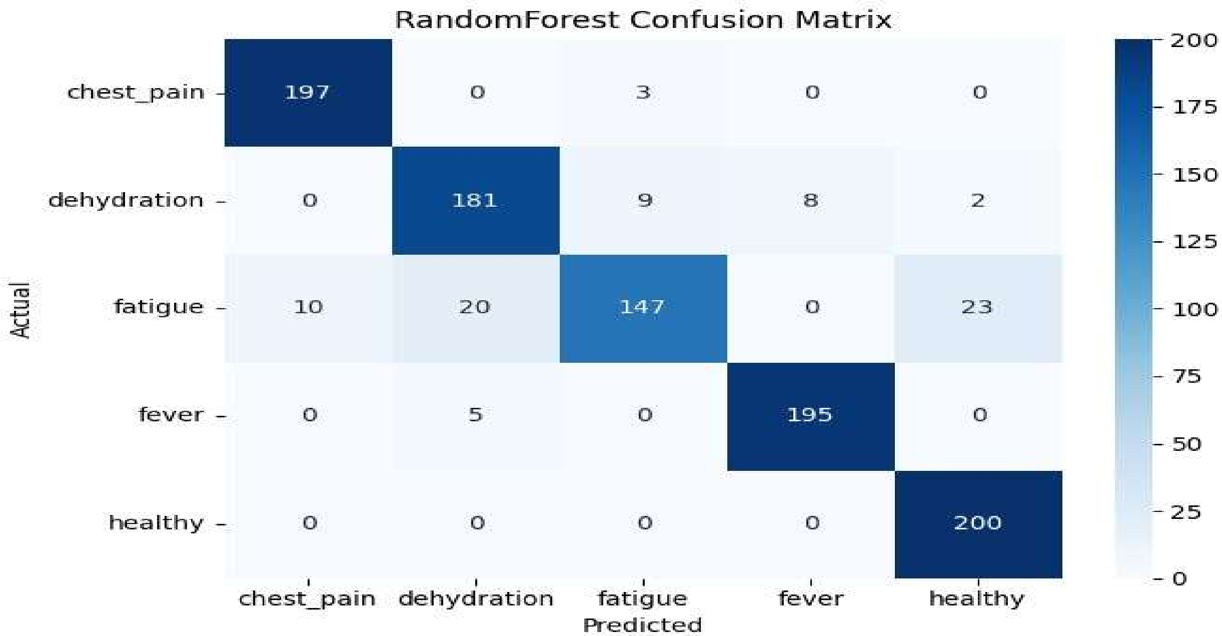

Figure 6: Accuracy comparison of Random Forest model during different health conditions(Chest pain, dehydration, fatigue, fever and healthy) of patient

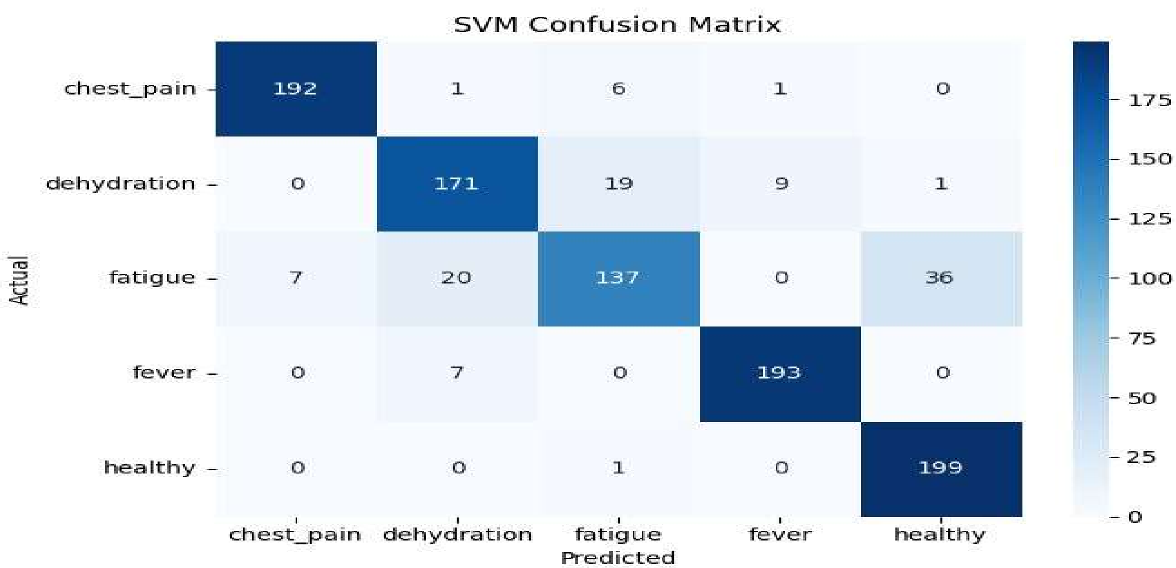

Figure 7: Accuracy comparison of Support Vector Machine model during different health conditions(Chest pain, dehydration, fatigue, fever and healthy) of patient.

IMPLEMENTATION RESULTS

The experimental results of the proposed MediGlove system as shown in figure.8 demonstrate its effectiveness in accurately capturing hand movements and translating them into meaningful outputs for both rehabilitation and IoT control applications. The system integrates flex sensors and an ADXL345 accelerometer with an ESP32 microcontroller to ensure precise motion tracking and real-time data processing. During testing, the flex sensors showed consistent and reliable variation in resistance corresponding to finger bending, enabling accurate detection of different hand gestures. The accelerometer further enhanced motion tracking by providing stable orientation and movement data across three axes. Calibration techniques significantly reduced sensor errors, improving overall system accuracy.

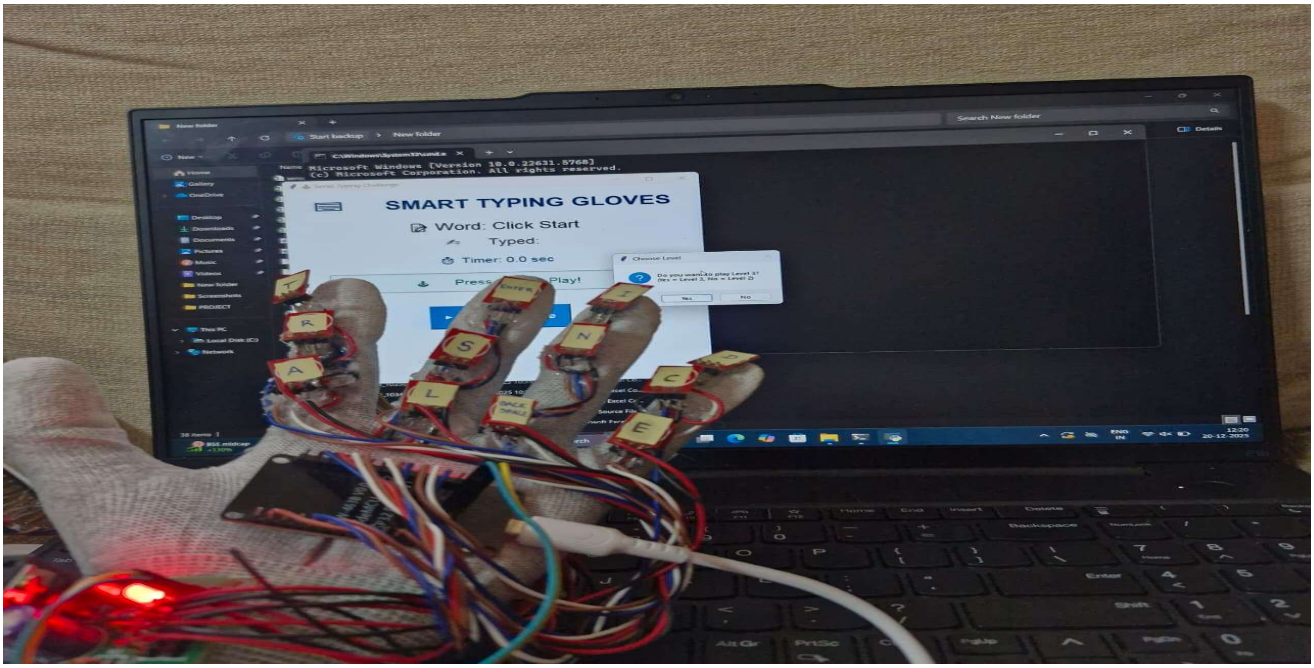

Figure 8: Implementation of proposed Mediglove System

The gesture recognition module achieved high accuracy in identifying predefined gestures, with minimal misclassification observed during repeated trials. The demonstrated efficient real-time processing capability and maintained stable wireless communication, ensuring smooth data transmission between the glove and the application. Latency testing confirmed that the system response time remained below 100 milliseconds, enabling near real-time interaction, which is essential for both rehabilitation exercises and IoT control.

In the rehabilitation mode, the Unity-based application successfully mapped hand movements to interactive game actions, providing a smooth and engaging user experience. Users were able to perform exercises effectively, and the gamified environment increased motivation and participation. In IoT control mode, the system reliably executed appliance control operations such as ON/OFF switching based on recognized gestures, with high responsiveness and accuracy.

Integration testing verified that all hardware and software components worked cohesively as a unified system. Communication between sensors, microcontroller, and application remained stable with no significant data loss. Reliability testing under continuous operation confirmed that the system maintained consistent performance without failure, while safety testing ensured that there was no overheating and all components were safe for user interaction.

User acceptance testing indicated that the glove is comfortable for prolonged use and easy to operate. Feedback from users highlighted the system's usability, responsiveness, and effectiveness in assisting rehabilitation. However, certain limitations were observed, including a limited number of test users, controlled testing conditions, and the need for further evaluation under long-term usage scenarios.

Overall, the results validate that the MediGlove system achieves high accuracy, low latency, and reliable performance. The integration of wearable sensing technology with IoT and gamification provides a promising and practical solution for modern hand rehabilitation and smart control applications.

CONCLUSION

In this paper, a comprehensive review of existing smart glove-based rehabilitation systems has been presented, focusing on the integration of wearable sensors, Internet of Things (IoT), and gesture recognition technologies for hand motor recovery. The surveyed studies demonstrate that flex sensors, accelerometers, and utilized to capture and analyze hand movements with reasonable accuracy and efficiency. Additionally, the incorporation of wireless communication enables real-time monitoring and supports remote rehabilitation, making these systems suitable for home-based therapy.

Furthermore, recent advancements highlight the importance of gamification and interactive platforms in improving patient engagement and motivation during rehabilitation exercises. Several studies emphasize that combining rehabilitation with virtual environments enhances user participation and consistency, ultimately contributing to better recovery outcomes. However, despite these improvements, many existing systems face limitations such as high cost, limited portability, dependency on clinical supervision, and constraints in gesture recognition accuracy.

Moreover, issues related to sensor calibration, data reliability, and scalability remain significant challenges in the development of efficient rehabilitation devices. The lack of personalized therapy solutions and limited integration with advanced technologies such as machine learning and cloud computing also indicate areas requiring further research.

In conclusion, although substantial progress has been made in the field of smart rehabilitation gloves, there is still a need for developing cost-effective, lightweight, and user-friendly systems that provide accurate motion tracking and enhanced user interaction. Future research should focus on improving sensor precision, expanding gesture recognition capabilities, and integrating intelligent algorithms to enable adaptive and personalized rehabilitation. Such advancements can significantly improve the effectiveness of therapy and enhance the quality of life for individuals with hand motor impairments.

SOURCE OF SUPPORT : None
CONFLICT OF INTEREST: None

REFERENCES:

[1] K. Cowell and T. Y. Pang, “Can We Miniaturize CT Technology for a Successful Mobile Stroke Unit Roll-Out?,” in *Proceedings of the 45th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2023.

[2] R. Xu and H. Zhang, “Symmetrical Contralaterally Controlled Functional Electrical Stimulation Enhanced Cortical Activity and Synchronization of Stroke Survivors,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, 2023.

[3] R. Zhang and C. Wang, “An Adaptive Brain-Computer Interface to Enhance Motor Recovery After Stroke,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, 2023.

[4] M. Glassen and G. Ames, “EEG Based Cortico-Muscular Connectivity During Standing Early Post Stroke,” in *Proceedings of the 45th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2023.

[5] S. Rahman and S. Sarker, “AI-Driven Stroke Rehabilitation Systems and Assessment: A Systematic Review,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, 2023.

[6] Y.-A. Li and Z.-J. Chen, “Exoskeleton-Assisted Sit-to-Stand Training Improves Lower-Limb Function through Modifications of Muscle Synergies in Subacute Stroke Survivors,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, 2023.

[7] C. S. Choy and S. L., “Virtual Reality Assisted Motor Imagery for Early Post-Stroke Recovery: A Review,” *IEEE Reviews in Biomedical Engineering*, 2023.

[8] K. Cisek and J. D. Kelleher, “Current Topics in Technology-Enabled Stroke Rehabilitation and Reintegration: A Scoping Review and Content Analysis,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, 2023.

[9] M. Liu and G. Xu, “Effects of Transcranial Direct Current Stimulation on EEG Power and Brain Functional Network in Stroke Patients,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. xxx–xxx, 2023.

[10] K. J. Nolan and G. R. Ames, “Intensity Modulated Exoskeleton Gait Training Post Stroke,” in *Proceedings of the 45th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2023.

[11] H. In, B. Kang, M. Sin, and K.-J. Cho,“Exo-Glove: A Wearable Robot for the Hand with a Soft Tendon Routing System,”IEEE Robotics & Automation Magazine, vol. 22, no. 1, pp. 97–105, Mar. 2015.

[12] S. Park, L. Bishop, and J. Stein,“A wearable gesture recognition system for rehabilitation using inertial sensors,”IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 24, no. 2, pp. 1–10, 2016.

[13] A. D. Marchal-Crespo and D. J. Reinkensmeyer,“Review of control strategies for robotic movement training after neurologic injury,”Journal of NeuroEngineering and Rehabilitation, vol. 6, no. 20, 2009.

[14] F. Cordella et al.,“Literature Review on Needs of Upper Limb Prosthesis Users,”Frontiers in Neuroscience, vol. 10, 2016.

[15] M. Ma and P. Ben-Tzvi,“RML Glove—An Exoskeleton Glove Mechanism With Haptic Feedback,”IEEE/ASME Transactions on Mechatronics, vol. 20, no. 2, pp. 641–652, Apr. 2015.

[16] J. L. Pons,“Rehabilitation Exoskeletal Robotics,”IEEE Engineering in Medicine and Biology Magazine, vol. 29, no. 3, pp. 57–63, 2010.

[17] S. Hussain, L. Xie, and S. Jamwal,“Adaptive robotic rehabilitation for hand function after stroke: A review,”IEEE Access, vol. 7, pp. 1–15, 2019.

[18] R. Riener, L. Lünenburger, and G. Colombo,“Human-centered robotics applied to gait training and rehabilitation,”Journal of Rehabilitation Research & Development, vol. 43, no. 5, pp. 679–694, 2006.

[19] N. Norouzi-Gheidari et al.,"Virtual reality for rehabilitation of upper extremity in stroke patients,"Journal of Stroke and Cerebrovascular Diseases, vol. 28, no. 1, pp. 1–12, 2019.

[20] A. Gupta, A. Kumar, and R. Singh,"IoT-Based Smart Wearable System for Hand Rehabilitation,"Procedia Computer Science, vol. 167, pp. 245–254, 2020.