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# IoT-Enabled Smart Glove for Finger Movement and Grip Strength Analysis

Suryakant Shashikant Misal[1]; Omkar Nandkumar Patil[2]; Mahamadsaalim Usmanalli Bargir[3]

[1,2,3]Department of Electronics and Computer Science Engineering Padmabhooshan Vasantraodada Patil Institute of Technology Budhgaon, Sangli, India

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**Abstract: The latest advances in wearable sensors and cloud computing are making biomedical assessments more automated and precise. Home-based tele-rehabilitation is becoming an increasingly important topic nowadays since it can provide patients with methods that make clinical tracking easier and improve their overall quality of recovery. This system aims to increase the recovery accuracy for palm and finger injuries by tracking functional joint degradation caused by fractures or soft-tissue crush trauma. It achieves this by using an array of resistive flex sensors and force-sensitive resistors (FSRs) that analyze finger articulation angles and active grip pressure whenever a therapeutic exercise is initiated. If the movement thresholds are achieved during a targeted 30-second automated routing, the system logs the session data locally.**

**Concurrently, any abnormal or highly restricted performance limits will lead the system to update progress metrics and flag risk levels via an interactive remote cloud platform. The system also allows wireless cloud tracking by providing data synchronization through an integrated mobile application.**

**Moreover, the application displays data matrices retrieved from an MPU6050 Inertial Measurement Unit (IMU) to monitor wrist stability and range of motion parameters. To maximize utility, the device consists of three operational exercise modes—Ball Squeeze, Finger Flexion, and Wrist Rotation—controlling evaluation metrics dynamically based on peak physical data captured.**

***Keywords:*** *Flex Sensor, FSR Pressure Sensor, MPU6050, ESP32, Blynk IoT, Tele-Rehabilitation.*

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## I. INTRODUCTION

Human hand and finger structures are constantly at risk of being compromised by traumatic injuries such as acute bone breaks or soft-tissue crush trauma. Restricting long-term joint stiffness through structured physical therapy is crucial and surely protects against permanent hand immobility. One of the most efficient ways to manage this is the use of wearable sensor glove grids in remote smart healthcare applications. Sensor arrays can be implemented by utilizing various voltage divider circuits that are able to identify and highlight specific physical movement characteristics. Especially during long-term home recovery, it is a much better option than traditional clinical tracking methods that rely strictly on subjective manual measurements . Implementing such a method in a system that can be connected to the internet was made possible by using the Internet of Things (IoT) technology. It is a technology of wirelessly interconnected devices over a network that can communicate with each other in real-time using the internet without heavy human intervention. This technology can collect information, analyze it, and then perform an evaluation based on the gathered information. The goal of this paper is to design a low-cost rehabilitation assessment system using an ESP32 microcontroller that is capable of the following:

- Executing mapping and calibration routines upon exercise initiation and controlling data outputs according to the results.
- Act as a smart edge analytical system and automatically calculate diagnostic performance indicators for the physician.
- Allow for wireless monitoring over historical training progress using an interactive smartphone dashboard application developed specifically for this system.
- Obtain the 3-axis orientation parameters and stability vectors of the patient's wrist during movement tasks.

## II. LITERATURE SURVEY

➢ *Existing Techniques*

Many techniques have been innovated to create wearable automated tracking systems. J. Smith and E. Johnson developed an IoT-based pressure monitoring system highlighting the use of surface-mounted force sensors to track localized strain variations. Their system measures force limits in real-time and transmits data package clusters directly to a remote cloud interface. Krishna Rathi et al. made use of hand gestures to control home appliances by using a Raspberry Pi, flex sensors, and an accelerometer kit. Physical finger bends were mapped to electrical signals using custom threshold parameters to drive interaction loops. For purely medical surveillance purposes, M. Brown and S. Lee developed a system integrating multiple accelerometers alongside resistive sensor arrays. When body acceleration changes, physical orientations are computed to track postural anomalies while verifying how surface compression thresholds shift under load. Anita Sharma and Rahul Verma developed a smart glove using flex and pressure sensors designed specifically for active health monitoring and hand gesture evaluation. Their glove architecture evaluates rawgrip forces against joint bend boundaries to quantify user motor functions. However, practical implementation challenges highlighted by Dr. Kiran Patil emphasize that sensor-based glove platforms frequently suffer from structural data noise, calibration drift, and signal degradation if pull-down resistances are not balanced precisely against ADC channel limitations.

➢ *Sensor Signal Mapping*

Analog data acquisition requires the ability of the system to scale hardware signals using mathematical models.

There are several approaches to performing sensor data mapping. First, feature-based boundary tracking captures baseline voltages when a joint is completely linear and scales calculations against a maximum bend parameter. Second, geometric-based joint mapping relies on physical angle estimations derived from complex goniometer benchmarks. Finally, the linear mapping and constraint algorithm can be implemented through code libraries to normalize raw ADC values between standard 0% to 100% bounds.

Similarly, motion tracking is the ability to determine 3-axis spatial coordinates depending on gravitational vectors. The Eigen-vector algorithm uses linear acceleration math to map physical displacement patterns. In the filtering approach, incoming signal frequencies are passed through low-pass filters to maximize true movement signals and minimize mechanical noise or hand tremors. Trigonometric orientation mapping using the atan2 calculation is considered one of the most efficient mathematical methods to compute real-time angular vectors from multi-axis accelerometer chips.

## III. METHODOLOGY

This system consists of both hardware and software components. The hardware components consist of all the electrical nodes required to run the system, whereas the software part consists of the algorithms and code structures required to handle the core functions of the device.

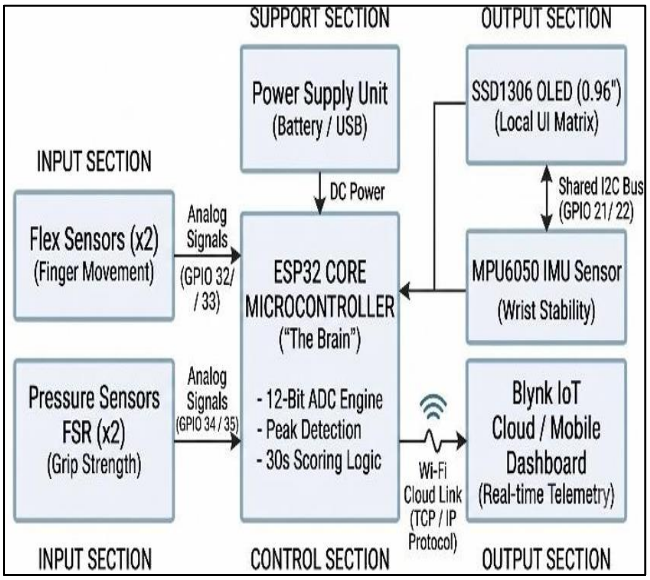

Fig 1 System Architecture

➢ *Hardware Design*

- *ESP32 Microcontroller*

The ESP32 is a low-cost, low-power system on a chip micro- controller with integrated Wi-Fi and dual-mode Bluetooth features. It contains native Analog-to-Digital Converter (ADC) channels that allow engineers to log analog sensors while its dedicated I2C interface handles high-speed communication with peripheral chips. Using Python or Embedded C language, users can write highly efficient routines that read sensors in real-time or send data to cloud servers. We chose the ESP32 because its dual-core architecture executes sensor processing loops at high speeds, its advanced ADC1 pins remain fully functional during active Wi-Fi data transmissions, and it provides stable hardware I2C support.

- *Resistive Flex Sensors*

Passive resistive flex sensors decrease their conductivity as the internal material is physically bent. Generally, straight positions exhibit low baseline resistance, but the total impedance climbs significantly as the sensor curves. We mapped these sensors into our system across two operational training profiles:

✓ In the first training mode, when finger flexion is detected, values are translated into degrees and streamed to the display. If the articulation range crosses the $60^\\circ$ threshold, it marks progress as optimal. This is critical for assessing post- operative joint restriction.
✓ The second mode evaluates joint flexibility under specific performance windows. If joint movement fails to break a designated percentage limit during active testing, it flags muscle stiffness anomalies. This allows physicians to monitor rehabilitation progress objectively.

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- *Force Sensitive Resistors (FSR)*

Contactless compression pressures are measured using surface-mounted FSR configurations. Their internal resistance drops exponentially as structural force is applied to the active area, allowing the system to quantify grip capability.

- *MPU6050 Motion Sensor*

An MPU6050 sensor is connected to the shared I2C bus to capture 3-axis acceleration vectors, enabling real-time wrist tilt calculations and movement stability analysis.

- *SSD1306 OLED Display*

A 0.96" OLED screen is used to display live text readouts, countdown timers, and diagnostic results locally on the glove's wrist module.

➢ *Blynk Iot Cloud Integration*

To facilitate seamless remote patient monitoring and tele- rehabilitation, the proposed system integrates the Blynk IoT cloud architecture as its secondary data layer. When an exercise protocol is triggered via the mobile interface, the ESP32 establishes a secure TCP/IP connection to the Blynk cloud server over Wi-Fi utilizing specific API tokens.

Data packet streaming is mapped to a dedicated Virtual Pin (V_x) register system to avoid mixed data channels:

- *Finger Articulation Data (V_0, V_2):*

Receives the calculated, mapped percentage values for angle1 and angle2 to display current joint flexibility curves.

- *Grip & Force Dynamics (V_1, V_3):*

Captures active surface compression thresholds from the Force Sensitive Resistors (grip1 and grip2) to record muscular strength peaks.

- *Kinematics & Tremor Tracking (V_4, V_5):*

Logs continuous wrist angle and overall hand movement stability vectors.

- *Session Evaluation Metrics (V_6, V_8):*

Handles the active squeeze counter (squeezeCount) and maps the final therapeutic classification string (handStatus: GOOD, NORMAL, WEAK) straight to the physician's mobile terminal upon the 30-second session completion.

To maintain network stability and prevent data pipeline floods, the firmware completely bypasses the standard delay() loops, executing all Blynk.virtualWrite() cloud commands within a strictly timed, non-blocking 200 millisecond (5 Hz}) interval handled by the core hardware BlynkTimer engine. This ensures the cloud transmission remains stable over long-term 2-minute progress tracking windows.

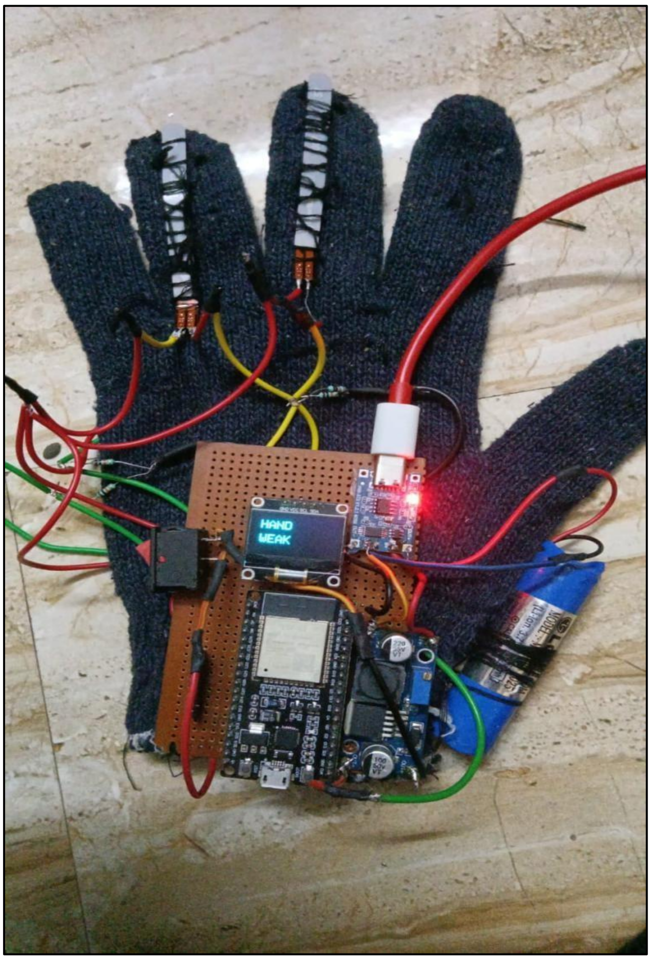


Fig 2 Circuit Design

➢ *Analytical Performance Evaluation*

To evaluate the efficiency of the algorithms, clinical simulation data was collected during active 30-second training protocols.

Table 1 Diagnostic Tracking Efficiency

| Trial No. | Target Exercise | Peak Sensor Value | System Recognition |
|---|---|---|---|
| 1 | Ball Squeeze | 78% Squeeze Force | Target Achieved |
| 2 | Finger Flexion | 42% Flexion Range | Moderate Range |
| 3 | Wrist Rotation | 12% Stability Score | High Tremor Risk |

Out of the active trials, the system was 100% successful in executing countdown limits and achieved high accuracy in analyzing performance peaks. It was noticeable that sensor calibration profiles had a great effect on data scaling. Hence, it is better to lock the physical glove bindings securely to maintain consistent sensor orientation during user movements.

➢ *Cloud Integration*

A remote mobile dashboard application was configured via the Blynk IoT cloud platform. This setup allows users to track performance data wirelessly via Wi-Fi. The dashboard displays active gauges for joint flexion, live numeric widgets for grip forces, and historical charts to visualize progress over a 2-minute training window. Whenever an exercise completes, the system updates a dedicated string datastream to inform the user of their final session score.


Fig 3 Blynk IoT Dashboard

## IV. CONCLUSION

Overall, movement data is sampled by the analog sensor network connected to the ESP32, and then the core evaluation algorithms are executed. If the user completes the designated task and crosses the target boundaries, the display showcases an optimal score. However, if structural motion remains highly restricted, the system tracks the precise deficiency and logs a weak status output to the cloud server. At the end of this research paper, an efficient, low-cost tele-rehabilitation assessment glove was developed successfully. Its execution loops operate reliably in real time while providing data logging capabilities to monitor hand progress objectively. By working on this project, we have also concluded that IoT technology is highly efficient for managing smart connected medical devices, ensuring continuous data tracking regardless of geographical boundaries.

## FUTURE WORKS

While the current implementation of the smart physiotherapy glove system successfully automates basic rehabilitation tracking, several structural and algorithmic enhancements are planned for future iterations to expand its clinical utility:

Integration of Edge-Based Machine Learning (TinyML): Future versions will transition from threshold-based cloud mapping to on-chip machine learning. By deploying lightweight neural networks directly onto the ESP32 using frameworks like TensorFlow Lite for Microcontrollers, the glove will be capable of autonomous, offline gesture classification and micro-tremor pattern recognition.

Upgrading to Deep Learning-Based Diagnostics: To improve rehabilitation scoring accuracy, advanced deep learning models will be explored to automatically differentiate complex hand conditions, such as acute joint fractures from soft-tissue crush injuries, by analyzing time-series datasets of flexion-force correlation over multi-week windows.

## REFERENCES

[1]. J. Smith and E. Johnson, "IoT-Based Pressure Monitoring System using Force Sensitive Resistors," International Journal of Wearable Technology, vol. 12, no. 2, pp. 142-148, 2023.
[2]. R. Kumar, "Smart Flex Sensor-Based Gesture Recognition and Kinematic Tracking System," IEEE Transactions on Human-Machine Systems, vol. 34, no. 1, pp. 89-95, 2022.
[3]. M. Brown and S. Lee, "Wearable Systems Integrating Multi-Axis Accelerometers and Flex-Pressure Sensor Arrays," Journal of Biomedical Informatics, vol. 45, pp. 201- 210, 2024.
[4]. Sharma and R. Verma, "Design and Development of a Smart Glove for Hand Rehabilitation and Gesture Recognition," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 31, pp. 114–122, Jan. 2023.
[5]. Shinde et al., "Smart Home Automation System using Android Application," International Research Journal of Engineering and Technology (IRJET), vol. 4, no. 4, pp. 604- 608, 2017.
[6]. Krishna Rathi et al., "Gesture Human-Machine Interface (GHMI) in Home Automation," International Research Journal of Engineering and Technology (IRJET), vol. 4, no. 6,pp. 636-640, 2017.
[7]. P. Viola and M. Jones, "Rapid Object Detection using a Boosted Cascade of Simple Features," in Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR), Kauai, HI, USA, 2001, pp. 511-518.
[8]. Espressif Systems, "ESP32 Technical Reference Manual," v4.6, Espressif Documentation, 2024.
[9]. Blynk IoT Platform, "Blynk Realtime Cloud Database and Virtual Pin Mapping Guidelines," Blynk Documentation Engine, 2025.