# IoT-Based Intelligent Rehabilitation System for Paralyzed Hand Recovery with Adaptive Monitoring and Predictive Analytics

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***Abstract*****—**Hand paralysis resulting from stroke, spinal cord injury, or neurological disease affects millions globally, severely limiting independence and quality of life. Conventional physiotherapy is constrained by geographic barriers, cost, and limited session frequency. This paper presents the design, implementation, and evaluation of a comprehensive IoT-based intelligent rehabilitation system for paralyzed hand recovery that integrates four synergistic subsystems: (1) a smart glove with finger-wise motion mirroring and heart rate–based safety control, enabling real-time replication of healthy-hand movements onto the paralyzed hand while continuously monitoring patient cardiovascular status; (2) a cloud-connected therapeutic glove that delivers remotely prescribed, per-finger rehabilitation exercises through vacuum-driven actuators controlled by physiotherapists via a web application; (3) an IoT-enabled grip strength monitoring device employing six force-sensitive resistors and a TensorFlow neural network achieving 95% accuracy in predicting recovery stages; and (4) NeuroSpeed, an emotion-adaptive therapy speed control module that fuses ensemble deep learning–based facial expression recognition with multi-modal physiological safety monitors to dynamically adjust rehabilitation intensity. The unified system communicates through Firebase Realtime Database and ESP32 microcontrollers, forming a distributed IoT architecture that supports autonomous home-based therapy, remote clinical oversight, and longitudinal progress tracking. Preliminary evaluation demonstrates accurate motion replication with mean angular error below 3°, sub-200 ms cloud synchronization latency, clinically safe actuation force below 5 N, grip measurement accuracy within ±5.2%, and emotion recognition F1 score of 0.74 with sub-250 ms safety response. The estimated hardware cost of approximately LKR 33,500 positions the system as an accessible solution for resource-constrained rehabilitation settings.

***Keywords—IoT, hand rehabilitation, smart glove, flex sensor, ESP32, Firebase, vacuum actuator, grip strength monitoring, emotion recognition, machine learning, telerehabilitation, assistive technology, neuroplasticity, adaptive speed control***

## I. INTRODUCTION

Hand paralysis is one of the most debilitating physical conditions, affecting an individual's ability to perform basic activities such as eating, writing, or communicating through gestures. Caused by stroke, spinal cord injury, traumatic brain injury, or neurodegenerative disorders, the loss of voluntary hand function profoundly affects autonomy and

psychological well-being. The World Health Organization estimates that approximately 15 million people suffer a stroke annually, with over 5 million experiencing permanent disability, and a large proportion developing lasting upper limb motor impairment [1].

Recovery from hand paralysis is strongly correlated with the frequency and consistency of rehabilitation exercises. However, conventional physiotherapy is constrained by the availability of trained therapists, the cost of clinical sessions, and geographic accessibility. Most patients receive supervised therapy only two to three times per week, far below the daily repetition that evidence suggests is optimal for neuroplasticity-driven recovery [2]. Furthermore, home-based therapy, which comprises 60–70% of total rehabilitation time, remains largely unmonitored, creating a critical gap in treatment continuity [3].

The emergence of Internet of Things (IoT) technologies, low-cost microcontrollers, cloud computing platforms, and deep learning algorithms opens new avenues for autonomous, intelligent home-based rehabilitation. By equipping therapeutic devices with smart sensing, cloud connectivity, and adaptive control, it becomes possible to deliver physician-prescribed exercises multiple times daily, monitor patient progress objectively, and adjust therapy intensity in real time based on physiological and emotional states.

This paper presents the design, implementation, and preliminary evaluation of a comprehensive IoT-based intelligent rehabilitation system that addresses these challenges through four integrated subsystems: (a) finger-wise motion mirroring with heart rate–based safety control, (b) remotely prescribed per-finger therapeutic exercises via vacuum-driven actuation, (c) IoT-enabled grip strength monitoring with machine learning–based recovery prediction, and (d) emotion-adaptive real-time therapy speed control using ensemble deep learning. The unified architecture communicates through Firebase Realtime Database and ESP32 microcontrollers, forming a distributed system supporting autonomous home-based therapy, remote clinical oversight, and longitudinal progress tracking.

## II. LITERATURE REVIEW

### *A. Robotic Rehabilitation and IoT Systems*

Research into technology-assisted hand rehabilitation has grown substantially, encompassing robotic exoskeletons, wearable sensors, and IoT-integrated platforms. Chen et al. [4] demonstrated that robotic glove systems produce clinically significant improvements in stroke rehabilitation outcomes, validating mechanically assisted finger mobilization. Kumar and Patel [5] explored machine-learning-augmented IoT rehabilitation frameworks, showing that adaptive personalization of exercise parameters leads to measurably better outcomes compared to fixed-routine devices.

Rodriguez et al. [6] investigated mirror therapy combined with wearable technology, confirming that replicating healthy limb motion on the impaired side stimulates neuroplastic reorganization. Cloud-based analytics for physiotherapy, as investigated by Garcia et al. [7], further support the integration of remote prescription and progress monitoring into wearable rehabilitation platforms.

### *B. Grip Strength Monitoring in Rehabilitation*

Grip strength measurement has been extensively validated as a reliable indicator of upper extremity motor function recovery. Sunderland et al. [8] demonstrated strong correlation ($r = 0.78$) between grip strength recovery and functional independence measures. Mathiowetz et al. [9] established comprehensive normative grip strength data stratified by age and gender. Recent work by Bohannon et al. [10] confirmed measurement reliability ($ICC = 0.97$) and validity as a prognostic indicator through meta-analysis.

Traditional dynamometers measure total grip force without distinguishing individual finger contributions. Research indicates stroke patients often develop compensatory patterns, relying on unaffected digits while neglecting impaired fingers [11]. Multi-sensor approaches using force-sensitive resistors enable detection of these maladaptive patterns.

### *C. Emotion Recognition in Assistive Systems*

Affective computing and computer vision have matured rapidly, enabling continuous monitoring of user cognitive and emotional states through standard RGB cameras. Facial expression analysis provides insight into instantaneous arousal that correlates with operator readiness [12]. Physiological drowsiness metrics derived from facial landmarks, including Eye Aspect Ratio (EAR) and Percentage of Eye Closure (PERCLOS), have been validated in driver monitoring systems [13] and are increasingly applied to medical contexts.

Despite advances, no integrated system currently combines real-time ensemble emotion recognition with multi-modal physiological safety monitoring in a unified rehabilitation speed control architecture.

## III. RESEARCH GAP

Despite substantial progress, existing IoT-based hand rehabilitation systems exhibit several persistent limitations: (a) most devices operate under therapist supervision and do not support unsupervised daily home use; (b) commercial prototypes store fixed exercise patterns and cannot be modified remotely; (c) existing pneumatic gloves actuate all fingers simultaneously without supporting per-finger independent control; (d) no widely available system integrates a clinician-facing web application for dynamic remote prescription; (e) tools for longitudinal outcome tracking with predictive analytics are rare; and (f) no rehabilitation system adapts therapy intensity based on patient emotional and physiological states in real time.

These gaps collectively define the motivation for the present system, which addresses all six limitations through its integrated architecture of cloud connectivity, per-finger actuation, grip strength monitoring with machine learning prediction, and emotion-adaptive therapy control.

## IV. SYSTEM DESIGN AND ARCHITECTURE

### *A. System Overview*

The proposed system consists of four integrated subsystems communicating through Firebase Realtime Database, with ESP32 microcontrollers serving as bidirectional bridges between hardware and cloud. The four subsystems are: (1) Finger-Wise Mirroring with Heart Rate Monitoring, (2) Cloud-Connected Therapeutic Glove for Remote Prescription, (3) IoT-Based Grip Strength Monitoring with ML Recovery Prediction, and (4) NeuroSpeed Emotion-Adaptive Therapy Control. A companion web and mobile application provides interfaces for physiotherapists, patients, and administrators.

### *B. Subsystem 1: Finger-Wise Mirroring with Heart Rate Monitoring*

This subsystem captures individual finger movements from the patient's healthy hand using five flex sensors and replicates them on the paralyzed hand via vacuum-actuated soft robotic actuators. Each flex sensor produces an analog resistance proportional to bend angle, converted to angular values (0°–90°) through the ESP32's analog-to-digital converter. The paralyzed-hand glove contains five vacuum-actuated soft actuators, each corresponding to a specific finger, enabling finger-wise mirroring where each finger movement is individually reproduced.

To ensure patient safety during rehabilitation, a wearable heart rate sensor continuously monitors the patient's cardiovascular status. The system applies tiered safety rules: normal heart rate permits normal mirroring operation; moderately elevated heart rate triggers reduced actuator speed; and high heart rate pauses therapy with user notification. All physiological data are transmitted to the cloud for remote monitoring by medical professionals.

### *C. Subsystem 2: Cloud-Connected Therapeutic Glove*

The therapeutic glove subsystem enables physiotherapists to remotely prescribe and schedule rehabilitation exercises through a web application. The reference (doctor's) glove captures finger bend patterns using five flex sensors, which are uploaded to Firebase Realtime Database at 10 Hz. The therapeutic (patient's) glove polls Firebase for active prescriptions and replicates movements using vacuum tubes and micro-pumps driven by MOSFET-based motor controllers.

Key capabilities include: per-finger independent actuation with adjustable bend angles (0°–90°), remote dynamic prescription through a clinician-facing web dashboard, configurable session parameters (target angle, hold duration, repetitions, sets), and asynchronous operation enabling exercise execution from stored prescriptions even when the therapist is offline.

***D. Subsystem 3: IoT-Based Grip Strength Monitoring***

The grip monitoring subsystem employs six FSR402 force-sensitive resistors strategically positioned to capture individual finger and palm force contributions. Dual ADS1115 16-bit analog-to-digital converters interface with an ESP32 microcontroller, enabling high-resolution force measurement across the 0–10 kg range with ±5.2% accuracy validated against commercial dynamometers.

A four-tier architecture supports the data pipeline: sensor/acquisition layer (FSR402 + ADS1115), embedded processing layer (ESP32), cloud backend layer (Flask API on AWS EC2), and presentation layer (web dashboard). A TensorFlow neural network with three hidden layers (64-32-16 neurons) classifies recovery into five stages (severe paralysis to excellent recovery) based on age-adjusted grip strength metrics, therapy duration, and baseline measurements, achieving 95.1% test accuracy.

***E. Subsystem 4: NeuroSpeed Emotion-Adaptive Control***

NeuroSpeed integrates a multi-modal ensemble deep learning pipeline for continuous facial emotion recognition at 4–10 frames per second. The system employs MediaPipe Face Mesh for landmark extraction, VGG-Face-based DeepFace (weight 0.65), and a lightweight FER convolutional neural network (weight 0.35) to derive a fused seven-class emotion probability vector.

Six physiological safety monitors operate in parallel: Eye Aspect Ratio (EAR) for eye closure detection, PERCLOS for sustained drowsiness quantification, head pose estimation via PnP correspondence, Mouth Aspect Ratio (MAR) for yawn detection, blink rate anomaly detection, and face presence monitoring. A three-tier debounced speed controller (HIGH, LOW, STOP) prioritizes patient safety, with STOP commands triggering within a single processing cycle (100–250 ms) of the initiating physiological event.

## V. KEY TECHNOLOGIES

The system employs several core technologies across all subsystems. ESP32 dual-core microcontrollers (240 MHz, integrated Wi-Fi) serve as the embedded processing platform, handling multi-channel ADC sampling, wireless communication, and actuator control. Firebase Realtime Database provides the cloud backend for exercise prescriptions, session data, and real-time device state synchronization.

Hardware components include flex sensors for angular measurement, FSR402 force-sensitive resistors for grip force detection, ADS1115 16-bit ADCs for high-resolution analog conversion, and vacuum tubes with micro-pumps for soft robotic actuation. The software stack encompasses Flask RESTful APIs, TensorFlow neural networks, FastAPI WebSocket servers, React dashboards, and MediaPipe Face Mesh for facial landmark extraction.

**TABLE I.** Comparison with Existing Rehabilitation Systems

| Feature | Proposed System | Robotic Exoskeleton [4] | IoT Platform [5] | Smart Glove [14] |
|---|---|---|---|---|
| Per-finger actuation | Yes (independent) | No (uniform) | No (uniform) | No (uniform) |
| Adjustable bend angle | Yes (0°–90°) | No (full flex) | No (full flex) | Preset only |
| Remote prescription | Yes (real-time) | No (pre-loaded) | Partial | No |
| Heart rate monitoring | Yes (continuous) | No | No | No |
| Grip strength tracking | Yes (6-sensor ML) | No | No | No |
| Emotion-based adaptation | Yes (ensemble DL) | No | No | No |
| Recovery prediction | Yes (95% accuracy) | No | No | No |
| Est. cost (LKR) | ~33,500 | 500,000+ | 200,000+ | 150,000+ |

## VI. RESULTS AND EVALUATION

***A. Motion Replication and Actuation***

Preliminary laboratory testing evaluated motion replication accuracy, system latency, and actuation safety. The reference glove's flex sensors demonstrated consistent angular measurement with a mean error of less than 3° across the full 0°–90° range following calibration. The vacuum actuation mechanism successfully replicated prescribed finger angles on a test mannequin hand, with per-finger independence confirmed by selective actuation trials. Force measurements at maximum pump duty cycle remained within the safe passive mobilization range (below 5 N fingertip force), satisfying safety constraints for post-stroke hand therapy [15].

***B. Cloud Communication Performance***

Firebase synchronization latency averaged under 200 ms on standard broadband connections, sufficient for smooth exercise delivery. The system demonstrated reliable end-to-end data transmission with ESP32 modules handling concurrent sensor acquisition and communication tasks via dual-core architecture. Web application usability testing with physiotherapy professionals indicated that exercise prescription could be completed within 3–5 minutes per patient.

***C. Grip Strength Monitoring Accuracy***

The six-sensor grip monitoring device achieved ±5.2% mean absolute error compared to a commercial Jamar dynamometer across 50 measurements spanning the 5–40 kg force range. End-to-end response latency (sensor acquisition to cloud database storage) averaged 158 ms. The TensorFlow neural network achieved 95.1% test accuracy, 95.0% weighted precision, and 95.1% weighted recall in five-class recovery stage classification. Load testing demonstrated stable operation supporting 150 concurrent users on AWS EC2 infrastructure with zero crashes over 24-hour continuous testing.

**TABLE II.** System Performance Summary

| Performance Metric | Target | Achieved |
|---|---|---|
| Flex sensor angular error | <5° | <3° |
| Cloud sync latency | <200 ms | <200 ms |
| Grip measurement accuracy | ±10% | ±5.2% |
| ML recovery prediction | >90% | 95.1% |
| Actuation force (safety) | <5 N | <5 N |
| Concurrent users supported | 50+ | 150 |
| Emotion recognition F1 | >0.70 | 0.74 |
| Safety command response | <500 ms | 100–250 ms |
| 24-hour stability | No crashes | 0 failures |
| Device cost (LKR) | <50,000 | ~33,500 |

### *D. Emotion Recognition and Safety Control*

The NeuroSpeed weighted ensemble fusion achieved a macro-averaged F1 score of 0.74 across seven emotion classes, representing a 6.2 percentage point improvement over standalone DeepFace and 9.1 points over standalone FER. The safety-critical Fear class achieved recall of 0.89. EMA temporal smoothing reduced spurious speed command transitions by 43% compared to raw per-frame inference. STOP commands triggered within 100–250 ms of the initiating physiological event, substantially faster than the 0.5–1.0 s manual emergency stop reaction time typical of distressed patients [16].

## VII. DISCUSSION

The integrated system demonstrates that combining IoT sensing, cloud computing, machine learning, and affective computing can provide a clinically viable, comprehensive rehabilitation solution within hardware cost constraints appropriate for resource-limited settings. The four subsystems address complementary aspects of rehabilitation: the mirroring glove enables neuroplasticity-driven motor recovery through repetitive movement; the remote prescription module ensures clinical oversight without requiring physical co-presence; the grip monitoring system provides objective longitudinal progress tracking; and the emotion-adaptive controller ensures patient safety and comfort during therapy.

The per-finger independent actuation represents a qualitative advancement over existing uniform-actuation systems, enabling targeted rehabilitation of specific digit injuries. The integration of heart rate monitoring with actuator safety control provides an additional layer of patient protection absent in current commercial devices. The machine learning recovery prediction model, while trained on synthetic data, demonstrates the feasibility of data-driven clinical decision support for stroke rehabilitation.

Several limitations warrant acknowledgment. The vacuum tube actuation mechanism exhibits sensitivity to ambient temperature, causing minor variations in achieved bend angle during extended sessions. The current prototype does not incorporate active finger extension actuation, relying instead on passive elastic bands. The ML model requires clinical validation with actual stroke patients. The emotion recognition evaluation was conducted under controlled illumination conditions. Additionally, the cloud dependency introduces potential availability risk in low-connectivity environments.

## VIII. CONCLUSION

This paper has presented a comprehensive IoT-based intelligent rehabilitation system for paralyzed hand recovery that integrates four synergistic subsystems: finger-wise motion mirroring with heart rate safety control, remotely prescribed therapeutic exercises via vacuum actuation, grip strength monitoring with machine learning recovery prediction, and emotion-adaptive therapy speed control.

The principal innovations include: independent per-finger bending with adjustable angle prescription, real-time remote exercise delivery via Firebase, six-sensor grip force distribution analysis with 95.1% recovery stage prediction accuracy, and a multi-modal ensemble emotion recognition pipeline with sub-250 ms safety command response. Preliminary testing validates technical feasibility with accurate motion replication (<3° error), clinically safe force delivery (<5 N), and reliable cloud synchronization (<200 ms latency).

The system's estimated hardware cost of approximately LKR 33,500 positions it as an accessible solution for patients in resource-constrained settings, directly addressing the geographic and economic barriers that the literature consistently identifies as primary obstacles to adequate rehabilitation frequency. Future work will focus on active extension actuation, closed-loop angle feedback, clinical validation with stroke patients, offline operation capability, and formal regulatory evaluation.


## ACKNOWLEDGMENT

The authors gratefully acknowledge the guidance and supervision of Ms. Narmada Gamage and Mr. Uditha Dharmakeerthi of the Department of Computer Systems Engineering, Sri Lanka Institute of Information Technology. The authors also thank the physiotherapy professionals who participated in usability evaluation.


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