

Dual-Function Smart Wearable Glove for Early Parkinson's Diagnosis and Post-Fracture Motor Recovery Monitoring

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Abstract: Early detection of Parkinson's disease and proper monitoring of hand movement after fractures are important for improving patient treatment and recovery. In many cases, doctors rely on visual observation and periodic checkups, which may not provide continuous and accurate information. To address this gap, a dual-function smart wearable glove detects early signs of Parkinson's disease and monitors hand rehabilitation after fractures. The proposed glove uses the XIAO NRF52840 Sense microcontroller. Two force-sensitive resistors (FSRs) are placed on the index finger and thumb to measure grip strength, which is an important indicator of hand function. A MEMS motion sensor captures hand movements, tremors, and motion patterns. For Parkinson's detection, users perform a spiral drawing task, and the system processes the collected sensor data using a deep learning model trained with Edge Impulse. The model classifies the user's condition into Non-Parkinson, Stage 1 (Moderate), and Stage 2 (Severe). For post-fracture rehabilitation, the glove continuously records grip force and motion data over time to track improvements in hand coordination and control. An RFID reader and ESP32 module store patient identity and test results, enabling continuous monitoring and personalized assessment. The developed dual-function glove is low-cost, portable, and easy to use, making it suitable for both clinical and home-based monitoring. It provides an objective method for neurological screening and rehabilitation tracking, helping doctors and patients with early diagnosis and recovery evaluation.

Keywords: Wearable Glove; Parkinson's Disease Detection; Hand Rehabilitation Monitoring; Xiao Nrf52840 Sense; Force-Sensitive Resistors; MEMS Sensor; Spiral Drawing Test.

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1. Introduction

Neurological disorders and musculoskeletal injuries are major causes of long-term disability and reduced quality of life worldwide [18]. Among neurological conditions, Parkinson's disease (PD) is one of the most prevalent neurodegenerative disorders, affecting more than 10 million people globally, with its prevalence expected to increase significantly in the coming decades. Progressive motor impairments, including tremors, bradykinesia, rigidity, and loss of fine motor control, characterize PD. Early detection of these symptoms is crucial for effective treatment and slowing disease progression [19]. However, current clinical diagnosis primarily relies on subjective assessments such as the Unified Parkinson's Disease Rating Scale (UPDRS), which depends heavily on clinician expertise and periodic observation, leading to delayed diagnosis and limited continuous monitoring. Similarly, patients recovering from hand fractures or upper-limb injuries require continuous monitoring of grip strength, motion coordination, and neuromuscular control to ensure effective rehabilitation [20]. Conventional rehabilitation assessment methods are typically based on periodic physiotherapy sessions, manual measurements, and patient self-reporting, which lack objectivity and real-time tracking [29]. The lack of continuous quantitative monitoring tools often leads to inconsistent recovery outcomes and delayed identification of rehabilitation stagnation. Recent advances in wearable sensing technologies and embedded machine learning have opened new possibilities for objective, continuous motor-function assessment. Sensors such as inertial measurement units (IMUs) and force-sensitive resistors (FSRs) show promise for capturing motion and grip-force data for clinical analysis [21]. However, most existing wearable systems are designed for a single purpose, such as tremor detection, gesture recognition, or rehabilitation monitoring, and lack an integrated framework capable of addressing both neurological diagnosis and post-injury recovery within a unified platform [22].

To address these limitations, this paper proposes a dual-function smart wearable glove for early Parkinson's disease detection and post-fracture motor rehabilitation monitoring [23]. The proposed system integrates multimodal sensors, including FSRs for grip-force measurement and a MEMS-based IMU for motion tracking, combined with embedded machine learning techniques for automated classification of motor impairments. The glove provides continuous, objective, and quantitative assessment of hand motor performance, enabling early neurological screening and personalized rehabilitation tracking [24]. In this work, researchers investigate multiple machine learning and deep learning models to accurately classify motor impairment patterns from multimodal sensor data [25]. Traditional machine learning algorithms such as Random Forest serve as baseline classifiers because of their robustness and ability to handle nonlinear relationships in extracted grip-force and motion features. Deep learning models, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), are also explored to learn complex spatial and temporal patterns from sensor signals automatically. CNN models identify tremor signatures and motion irregularities from transformed sensor representations [26]. At the same time, RNN-based architectures such as Long Short-Term Memory (LSTM) networks capture temporal dependencies in continuous hand-movement sequences. Researchers evaluate these models using accuracy, precision, recall, and F1-score, and select the model with the highest accuracy and computational efficiency for deployment on the XIAO NRF52840 Sense microcontroller [27]. The main contributions of this work include designing a low-cost wearable glove for dual clinical applications, implementing embedded machine learning for motor-function classification, and evaluating grip- and motion-based biomarkers for Parkinson's detection and rehabilitation monitoring [28].

2. Literature Review

Simone and Kamper [1] investigated design considerations for wearable monitors to measure finger posture, demonstrating early use of bend sensors for finger-joint tracking. Their prototype showed the promise of wearable finger sensing but was bulky and lacked force/grip measurement. This work motivates lightweight, multi-sensor glove designs that combine posture and grip sensing for clinical use. Oung et al. [2] reviewed technologies for assessing motor disorders in Parkinson's disease, covering wearable sensors, EMG, EEG, imaging, and multimodal approaches. The review highlighted broad potential but noted limited real-time, portable solutions optimized for continuous screening. Their analysis underscores the need for compact, real-time wearables that integrate multiple sensor modalities. Goschenhofer et al. [3] applied deep learning to wearable sensor data for Parkinson's severity monitoring, using CNN/LSTM and transfer learning on time-series signals. The approach achieved strong classification but required large, labelled datasets and heavy computation. This shows the value of ML pipelines yet stresses the need for lightweight, Edge-optimized models for on-device inference. Gil-Martin et al. [4] proposed a CNN model using FFT-transformed drawing movement inputs to detect Parkinson's-related motor irregularities. Their method performs well on controlled drawing tests but generalizes poorly to unconstrained hand activities. This highlights the importance of combining drawing tests with full-hand kinematics in wearable devices. Han et al. [5] evaluated conductive gloves using silver-nylon yarn to sense finger movements, proving textile-based sensing is feasible for flexible wearables. However, precision and finger coverage were limited, reducing suitability for detailed motor assessment. The results motivate hybrid sensor layouts (FSRs + IMU) to improve accuracy across fingers.

Lin et al. [6] designed a modular data glove using 9-axis inertial measurement units (IMUs) mounted at each finger joint, combined with a sensor fusion algorithm to compute static and dynamic range-of-motion parameters. The modular architecture improved maintainability, since a damaged IMU module could be replaced without redesigning the entire glove. However, the system required careful placement calibration at each joint, and cumulative IMU drift during extended use remained a

limitation. This work highlights the value of modular, replaceable sensor units and reinforces the need for periodic recalibration in multi-IMU glove designs. Hazman et al. [7] implemented a smart glove with a 3-axis IMU (MPU6050) and Arduino for hand movement monitoring, offering a low-cost portable solution. IMU drift and reduced accuracy during rapid gestures were major drawbacks. This highlights the need to combine IMU data with complementary sensors (e.g., FSRs) and apply drift compensation for reliable motion tracking. Chen et al. [8] introduced a lobster-inspired hybrid soft-rigid robotic glove for hand rehabilitation driven by sEMG signals, improving adaptive assistance and force output. The design was promising but remained at an early experimental stage without extensive clinical validation. This suggests integrating assistive actuation with validated sensing for closed-loop rehab. Oess et al. [9] developed and validated a low-cost instrumented glove for hand function assessment, systematically testing multiple bend-sensor types for signal stability and comparing sensor-derived joint angles against traditional goniometry. The glove demonstrated high repeatability during activities-of-daily-living tasks and was validated in patients with cervical spinal cord injury. Its main limitation was a reliance on flexible bend sensors alone, without complementary grip-force or inertial data to capture broader motor performance. This underscores the benefit of pairing validated bend-sensing with additional force and motion modalities for richer clinical assessment.

Rashid and Hasan [10] surveyed wearable technologies for hand-joint monitoring in rehabilitation, categorizing existing devices into flex-sensor, accelerometer, vision, Hall-effect, stretch-sensor, and magnetic-sensor-based approaches. The review found that flex-sensor and IMU-based gloves offered the best balance of cost, wearability, and joint-angle accuracy, while vision-based systems, though highly precise, were impractical for continuous home use. The authors noted a lack of standardized evaluation protocols across studies, limiting direct comparison between devices. This points to the need to combine flex-sensor and IMU modalities within a single glove design and adopt standardized validation procedures. Yang et al. [11] designed a portable, glove-controlled hand exoskeleton for bilateral rehabilitation, in which a flex-sensor-equipped sensing glove on the less-affected hand drives an exoskeleton on the affected hand, supported by a virtual-reality game to encourage repeated practice. The system improved patient engagement and enabled home-based bilateral training, but relied on a single flex sensor per finger without grip-force or tremor-related measurements. This suggests an opportunity to extend sensing-glove-driven rehabilitation systems with grip-force and motion-tracking sensors for more comprehensive recovery monitoring. Sigcha et al. [12] used smartwatch IMU sensors with CNN and Random Forest methods to detect bradykinesia, enabling unobtrusive monitoring. The study was constrained to early-stage datasets and lacked full UPDRS coverage. This points to the benefit of combining wrist wearables with finger/hand sensors for richer diagnostic signals. Zhu et al. [13] proposed a soft-actuated wearable glove with strain sensors and hybrid PID control for rehabilitation and grasp assistance. While adaptive, the structure was complex and limited in finger abduction support.

The work suggests balancing mechanical complexity with functional coverage in rehab glove designs. Rastegari et al. [14] demonstrated Parkinson's detection using passive wrist accelerometer monitoring and SVM classification, offering low-burden continuous assessment. Limitations included short-duration datasets and sensitivity to windowing choices. This reinforces the need for long-term datasets and robust feature extraction in wearable diagnostic systems. Zha et al. [15] developed a wearable rehabilitation wristband for patients recovering from distal radius fractures, using three thin-film pressure sensors to detect wrist rehabilitation actions such as flexion/extension and radial/ulnar deviation, classified through an autoencoder and support vector machine. The system reliably recognized rehabilitation exercises and addressed poor patient compliance during home-based recovery. Still, it was limited to wrist-level pressure sensing without finger-level grip or tremor data. This reinforces the relevance of combining pressure-based wrist monitoring with finger-level grip-force and motion sensing for a more complete post-fracture assessment. Dontha et al. [16] designed embroidered FSR-based wearable sensors interfaced via Bluetooth and ESP32 for touch-based applications, showing low-cost scalability. The sensors were limited to low-force ranges (<5 N), making them unsuitable for higher-force rehabilitation tasks. This points to selecting FSRs or alternatives with an appropriate force range for clinical use. Kabir et al. [17] performed a systematic review of 35 hand-rehabilitation devices, analysing EMG control and assistive technologies, and found wide variability in device frameworks and evaluation standards. The review calls for standardized benchmarks and clinical validation protocols—an important guideline for developing deployable rehabilitation gloves.

3. Proposed System

The proposed system is an intelligent wearable glove designed to objectively assess hand motor performance using multimodal sensing and embedded analytics. The glove integrates Force Sensitive Resistors (FSRs), a 9-axis MEMS IMU, and an RFID module to capture comprehensive physiological and motion-related signals. Together, these sensors measure grip strength, force stability, tremor characteristics, hand orientation, and overall movement patterns. Integrating heterogeneous sensing elements enables high-resolution monitoring of fine motor impairments that are difficult to detect through traditional visual observation. The system uses the XIAO NRF52840 Sense microcontroller to acquire data at high sampling rates and perform real-time signal conditioning. The system applies filters such as Butterworth and Kalman smoothing to remove noise and stabilize measurement accuracy. From the conditioned data, the system extracts clinically relevant features, including RMS acceleration, tremor frequency components, grip stability metrics, jerk magnitude, and trajectory deviation parameters. These

processed features are used as input to a lightweight neural network model deployed through Edge Impulse. The optimized model operates entirely on the microcontroller, enabling fast, on-device inference without requiring cloud computation (Figure 1).

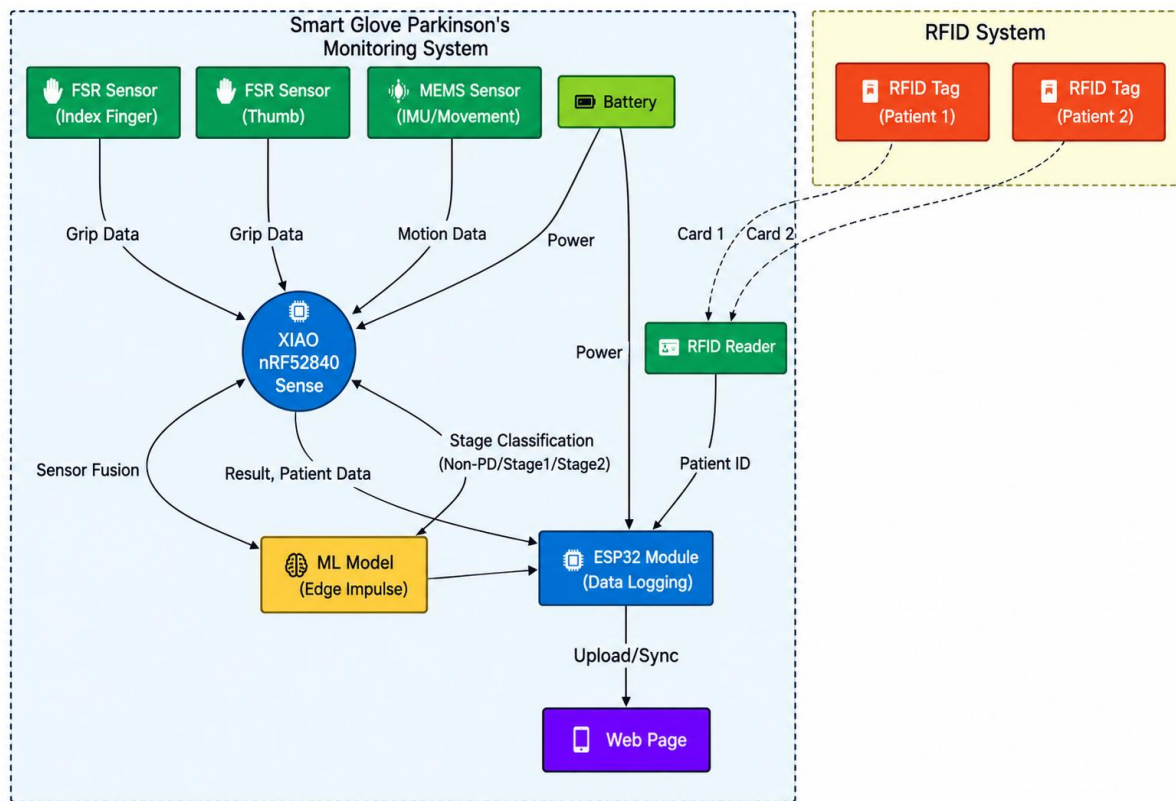


Figure 1: Proposed system block diagram

An ESP32 communication module establishes wireless connectivity and securely transmits sensor data to a cloud platform using Wi-Fi and MQTT. The cloud system stores the data, performs long-term trend analysis, and provides clinicians with continuous access to patient performance metrics. A dedicated dashboard visualizes real-time hand motion trajectories, tremor graphs, grip-force curves, and recovery progression trends. Automated alerts notify clinicians when the system detects abnormal patterns or stagnation, enabling timely intervention. By combining embedded sensing, signal processing, machine learning, and IoT connectivity in a compact, low-cost glove, the proposed system offers a scalable alternative to laboratory-grade assessment tools. It delivers objective, quantitative, and repeatable measurements that support both clinical evaluation and continuous home-based monitoring. This integrated approach eliminates the need for multiple separate devices and offers a comprehensive platform for assessing neurological and orthopedic motor impairments.

4. Methodology

The methodology for developing the proposed wearable glove follows a structured, multi-stage workflow to ensure accurate motor-function assessment and reliable long-term monitoring. The entire process is divided into three major phases: (A) multimodal sensor data acquisition and preprocessing, (B) feature extraction and embedded machine learning deployment, and (C) Data communication and clinical data visualization. Each phase supports high-fidelity signal capture, efficient real-time processing, and seamless integration with cloud-based monitoring systems for neurological and rehabilitation applications.

4.1. Sensor Data Acquisition and Preprocessing

The first phase involves continuously acquiring motion and grip-force signals from the 9-axis MEMS IMU and the Force Sensitive Resistors (FSRs). The IMU records tri-axial acceleration, angular velocity, and magnetic orientation at 100 Hz, enabling detailed capture of tremor amplitudes, movement speed, and trajectory deviations. The FSR sensors placed on the thumb and index finger measure dynamic grip-pressure variations, providing insight into force consistency, fatigue, and stability during motor activity. The sensor outputs are synchronized using timestamp alignment to ensure temporal accuracy

across modalities. To improve signal reliability, the raw data undergo a preprocessing pipeline that includes noise reduction and drift compensation. A Butterworth filter removes high-frequency noise without distorting primary movement characteristics, while a Kalman filter stabilizes orientation readings by correcting drift over time. The pre-processed and calibrated signals ensure that subsequent analytical stages operate on clean, high-quality input data.

4.2. Feature Extraction and Machine Learning Integration

After preprocessing, the system extracts time-domain, frequency-domain, and statistical features to characterize the user's motor performance. Time-domain features such as RMS acceleration, jerk magnitude, peak-to-peak motion, and grip-force variability quantify motion smoothness and fine-motor stability. Frequency-domain features derived using the Fast Fourier Transform (FFT) identify dominant tremor frequencies and spectral energy distribution, which are clinically significant for detecting Parkinsonian patterns. Researchers compute additional trajectory deviation and smoothness metrics from IMU orientation data to evaluate irregularities during hand movement tasks. These extracted features serve as input to a lightweight neural network model developed using the Edge Impulse platform. The model is trained on labeled datasets representing various motor conditions and then optimized through quantization and memory compression for deployment on the XIAO NRF52840 Sense microcontroller. This enables real-time, on-device inference with minimal latency and low computational overhead, allowing the system to function reliably even in low-connectivity environments.

4.3. Data Transmission and Clinical Visualization

The final phase integrates wireless communication and remote monitoring capabilities. The ESP32 communication module transmits processed data and classification results to a cloud server via Wi-Fi and MQTT, ensuring secure, efficient data transfer. The cloud backend stores the incoming data and supports longitudinal tracking of patient performance across multiple sessions. A dedicated clinical dashboard provides real-time visualization, including motion trajectories, tremor frequency graphs, grip-force plots, and recovery trends over extended periods. Automated alerts notify clinicians of abnormal variations, stagnation in progress, or deviations from expected recovery patterns. This IoT-enabled visualization infrastructure allows healthcare professionals to remotely assess patient status and make evidence-based adjustments to treatment plans, significantly improving diagnostic accuracy and rehabilitation outcomes.

4.4. Hardware Implementation

The hardware implementation of the proposed intelligent wearable glove is structured into three major subsystems:

Multimodal Sensor Layer: The wearable glove incorporates an Inertial Measurement Unit (IMU) and multiple Force Sensitive Resistors (FSRs) to capture motion dynamics and grip-force variations. The IMU provides tri-axial acceleration, angular velocity, and orientation information through a high-precision accelerometer and gyroscope, enabling real-time assessment of tremors, instability, and motor task smoothness. The FSRs are positioned on the fingertips and palm regions to measure distributed pressure profiles during gripping and fine-motor activities. All sensors interface via I²C and analog channels, maintaining a consistent sampling frequency of 100 Hz. The sensors are mounted on a flexible, lightweight substrate to preserve comfort and allow natural hand articulation (Figure 2).

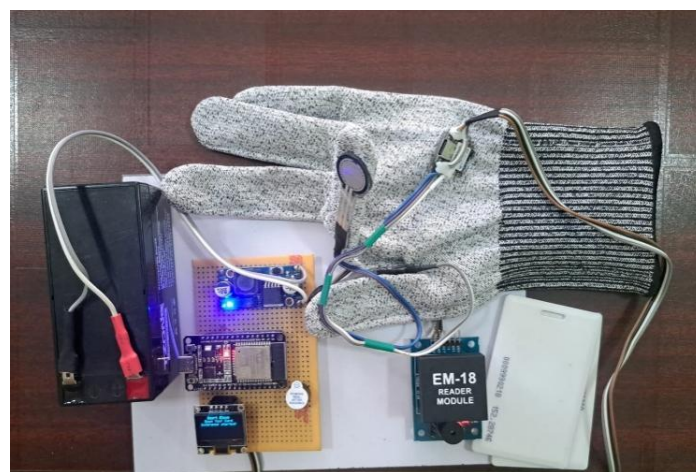


Figure 2: The design prototype of the glove technology that integrates sensors, microcontroller, RFID reader module, and communication module

Embedded Processing and Computation Layer: An ESP32 microcontroller drives the system, selected for its dual-core processing capability, high clock speed, integrated Wi-Fi, and suitability for embedded AI applications. The microcontroller handles real-time data acquisition, applies digital signal processing filters, extracts features, and performs inference using the quantized neural network model generated in Edge Impulse. The neural network is stored locally in the microcontroller’s flash memory, enabling low-latency prediction without reliance on external computing resources. The ADC channels process the FSR inputs, while I²C communication retrieves IMU data. Firmware routines manage synchronized buffering, Butterworth and Kalman filtering, and optimized computational pipelines to ensure consistent performance even under constrained power conditions.

Wireless Communication and Power Management Layer: The ESP32’s integrated Wi-Fi module enables seamless transmission of sensor data, extracted features, and classification outputs to the cloud dashboard via MQTT for low-latency communication. A 3.7 V lithium-ion battery powers the glove and connects to a TP4056 charging module and a regulated 3.3 V power supply. Power optimization techniques, including deep-sleep cycles and controlled sensor sampling, maximize operational duration. A compact PCB layout integrates the power circuitry, microcontroller, and sensor interfaces efficiently. The PCB is mounted on the dorsal side of the glove to avoid restricting finger movement, while flexible ribbon cables connect the sensors to maintain ergonomic comfort and mechanical durability. The overall hardware configuration ensures a lightweight, robust, and portable design suitable for extended clinical monitoring, rehabilitation applications, and remote assessment scenarios.

4.5. System Architecture

The proposed wearable glove system architecture integrates multimodal sensing, data acquisition, signal processing, and local visualization into a compact, standalone device for monitoring hand motor function. The architecture consists of three main modules: (1) Sensor and Data Acquisition, (2) Embedded Processing and Signal Analysis, and (3) Local Monitoring and Visualization. Each module is optimized to provide accurate, real-time measurement of grip strength, motion, and fine-motor coordination during rehabilitation tasks (Figure 3).

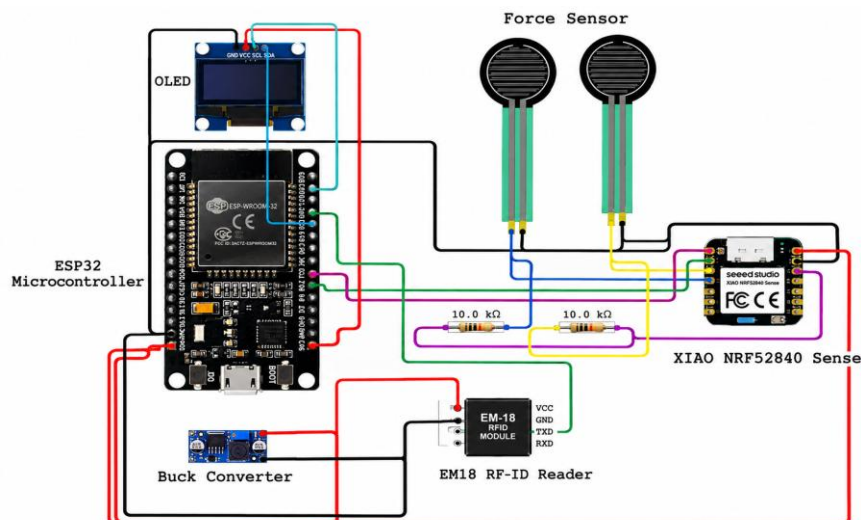


Figure 3: Circuit diagram of the proposed system

Sensor and Data Acquisition: The glove integrates a 9-axis MEMS Inertial Measurement Unit (IMU) and Force Sensitive Resistors (FSRs) on the thumb, index finger, and palm. The IMU measures tri-axial acceleration, angular velocity, and orientation to capture hand motion patterns, tremors, and trajectory deviations. The FSRs detect grip force, pressure distribution, and stability during gripping and functional tasks. Sensor signals are sampled at 100 Hz and synchronized to maintain temporal accuracy across modalities. To improve signal quality, Butterworth filtering removes high-frequency noise and a Kalman filter compensates for drift, providing reliable input for further analysis.

Embedded Processing and Signal Analysis: The ESP32 microcontroller serves as the core processing unit, handling real-time acquisition, filtering, and computation of key motion and force parameters. Time-domain features such as RMS acceleration, peak-to-peak motion, jerk, and grip-force variability quantify movement smoothness and stability. Frequency-

domain analysis using FFT detects tremor frequencies and characterizes motion irregularities. All computations run on-device, enabling immediate feedback without network or external computation dependencies.

Local Monitoring and Visualization: The system displays processed data on a local interface such as an OLED screen or PC dashboard. The interface presents graphical visualizations of hand-motion trajectories, grip-force trends, and tremor amplitudes to provide clear, immediate assessment of motor performance. The system supports longitudinal tracking by storing data locally for comparison across sessions, allowing clinicians and patients to monitor progress, identify irregularities, and adjust therapy as needed.

5. Results and Discussions

Researchers assessed the wearable glove system's performance using sensor data from controlled experiments. Researchers split the dataset into training and test subsets to objectively evaluate the algorithm's generalization capability. Researchers formulated the classification task as Parkinson's disease progression stage classification based on frequency-domain features calculated from grip force and motion signals. To assess the classification technique's efficiency, researchers designed and tested two types of artificial neural networks. The first was an LSTM, since this architecture can process time-dependent data. However, researchers processed the input time-series data through the Fast Fourier Transform, which significantly reduced temporal dependencies and limited the LSTM's ability to identify meaningful relationships between variables. This caused rather low classification results. The baseline model demonstrated an accuracy of 81.9%. A significant improvement is observed with the Dense Neural Network model. Treating the frequency features as separate inputs allowed the model better to capture correlations between the frequency features and disease progression. As a result, classification accuracy increased to 98.5%, along with improved validation loss. This emphasizes how important the choice of model architecture is, depending on the data. Researchers used confusion matrix analysis to assess classification performance across classes. This study showed the degree of accuracy achieved for each stage of Parkinson's disease and the areas of misclassification. Both classifiers performed well for the idle stage because it included no motion features, resulting in perfect accuracy. However, more differences emerged when classifying the active stages. The LSTM architecture showed significant confusion between Stage 1 and Stage 2 predictions, often mistaking the moderate tremor stage for a severe one (Table 1).

Table 1: Performance comparison of LSTM and dense neural network models

Metric	LSTM Model (Baseline)	Dense Neural Network (Final)
Accuracy	81.9%	98.5%
Validation Loss	0.57	0.05
Model Type	Recurrent Neural Network	Feedforward Neural Network
Feature Handling	Time-series data	Frequency-domain features
Suitability	Moderate performance	High accuracy and reliability

This may be because the algorithm relies on sequential training, which performs poorly when the dataset lacks temporal connections. Meanwhile, the Dense Neural Network minimized these errors by emphasizing frequency-related features unique to each stage. Clinically, fewer misclassifications have several positive effects. First, correctly identifying a healthy person means patients avoid undue stress or medical procedures. At the same time, an enhanced distinction between the two stages allows clinicians to develop more accurate treatment strategies. Preprocessing techniques such as noise reduction, normalization, and padding ensured dataset consistency. This process ensured all inputs had similar dimensions and reduced the effects of noise and gaps in the dataset. Another significant aspect of this research was running the trained model on the XIAO nRF52840 Sense microcontroller. Model quantization reduced the number of calculations while preserving high accuracy, enabling real-time predictions directly on the device. This feature avoided sending collected data to other systems and reduced latency. In addition to these benefits, the ESP32 module, along with RFID patient identification, enables collection of patient data for further monitoring. A web dashboard visualizes all collected information, helping medical specialists monitor disease progression. Traditional clinical analysis techniques cannot provide this information. Researchers collected the dataset from more than sixty participants, including both healthy individuals and patients at different stages of Parkinson's disease. Researchers selected participants across age groups to ensure diversity in motor activity and improve the model's generalizability (Table 2).

Table 2: Class-wise performance comparison

Target Class	LSTM Accuracy	Dense Accuracy	Discussion
Idle	100%	100%	Both models accurately identified no-movement conditions
Normal	91.3%	100%	Dense model eliminated false positives seen in LSTM

Stage 1 (Moderate)	55.6%	92.9%	Significant improvement in early-stage detection
Stage 2 (Severe)	81.5%	100%	Dense model achieved perfect classification

The dataset was categorized into three primary classes: Non-Parkinson, Stage 1 (Moderate), and Stage 2 (Severe), along with an additional idle state representing no motion conditions. Data were collected in a controlled setup in which participants performed hand activities, including gripping and holding postures. Such actions were designed to capture all aspects of voluntary and involuntary actions affected by the disorder. The wearable glove captured data through sensors including the FSRs and IMUs. The sensors collected data at a sampling rate of 50 Hz and divided it into equally sized 5-second windows with 500 milliseconds of overlap to ensure consistent movement patterns. This method produced many data samples, which facilitated training and testing of the machine learning algorithms. Labels for each window were assigned according to the subject's clinical diagnosis, ensuring the information fed to the model was reliable. In addition to accuracy, precision, recall, and F1-score were computed to evaluate the model's robustness. Overall, the results show that the proposed solution performs better than conventional methods. The proposed solution's ability to integrate multi-sensor data collection, frequency-domain analysis, and machine learning into an effective framework for PD detection and diagnosis demonstrates the approach's efficiency. It suggests the approach can be used in practical healthcare settings, especially in resource-limited settings where more advanced and efficient ways to diagnose PD are needed. Despite these positive findings, the study has limitations. One limitation is the dataset size, which is limited, although it is more diverse than a clinical database. In addition, the experiments were conducted in controlled settings, which may not reflect real-world patient behavior.

6. Conclusion

In this paper, researchers designed a glove-based device that provides a promising tool for objective and accurate identification of the initial signs of Parkinson's disease and its later stages. Unlike conventional methods based on visual analysis and expert clinical experience, the proposed solution considers PD's physiological features, using force-sensitive resistors attached to the fingers and MEMS acceleration sensors to measure each finger's movement peculiarities. The glove therefore provides information about both grip and motion abnormalities, which are major symptoms of PD. The results show that the proposed solution performs well in diagnosing Parkinson's disease. When comparing the two models, the Dense Neural Network outperformed the LSTM model, achieving 98.5% accuracy, while the LSTM model scored only 81.9% correct predictions. The Dense model performed well because it used frequency-domain features. Because this model does not treat the data as a time series, it successfully analysed frequency-domain characteristics and found correlations between the examined features and disease stages. Another critical component of this study is deploying the trained model on the XIAO nRF52840 Sense microcontroller. The device will compute predictions locally, eliminating the need for an external system. In addition to saving precious time, this approach also provides greater privacy protection, a crucial factor for medical devices. The ability to analyse data in real time on a wearable, compact device makes the solution highly applicable to both clinical practice and remote health monitoring.

Furthermore, integrating patient identification using RFID technology, along with the ESP32 microcontroller's data-logging capabilities, further increases the solution's functionality. Recording patient data via the web-based dashboard allows medical staff to monitor disease progression and adjust the treatment regimen accordingly. Indeed, such a function becomes essential because Parkinson's disease is progressive and requires extended monitoring instead of a single assessment. Another critical point in this research is implementing real-time inference on the edge device. At the same time, it is necessary to discuss some limitations associated with this study. The problem is that the analysis data were gathered in a controlled environment, where patient behaviour may have been less variable. To improve prediction accuracy, the database size needs to increase, and the model should be tested under real-life conditions. Moreover, future enhancements will involve optimizing sensor placement and adding other physiological features. In conclusion, the proposed methodology is a promising solution for diagnosing Parkinson's disease and could serve as an effective alternative to existing treatment methods. The algorithm developed by the authors is reliable and applicable not only in the laboratory but also globally. This system is affordable and scalable, which explains its strong potential for practical use.

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Ethics and Consent Statement: This research adheres to ethical guidelines and obtains informed consent from all participants. Confidentiality measures were implemented to safeguard participant privacy.

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