**Abstract**

Background: The diagnosis of Parkinson's disease (PD), which has a slow neurodegenerative course, is still primarily clinical and is prone to error and delay. Because motor symptoms develop slowly, objective measures must be used for early detection and ongoing observation.

The purpose of our study is to develop and test a novel SmartGlove sensor and machine learning (ML) techniques in order to assess PD motor symptoms objectively and data-drivenly.

Methods: Participants performing standardized motor tasks provided high-rate data to the SmartGlove system, which was enabled by an inertial sensor. Sensor data was used to derive comprehensive features. Statistical significance testing (T-Tests), ensemble learning frameworks (Random Forest), and dimension reduction techniques (PCA) were employed in a rigorous feature selection process to identify the best biomarkers for motor state discrimination before and after drug administration.

Key Findings: Clinical evaluations and system quantitative measures showed a strong correlation (r > 0.8). Non-linear and dynamic features, specifically the Lyapunov exponent, RMSSD, and sample entropy, were found to be significant predictors of motor symptoms typical of Parkinson's disease (PD) using a feature selection approach.

In conclusion, our suggested IoT and machine learning paradigm has a lot of promise for impartial, remote, ongoing Parkinson's disease observation. Our paradigm makes it possible to comprehend how symptoms change and how effective treatments are, which opens the door to customized treatment regimens and better patient outcomes.

**1. Introduction**

**1.1. Neurodegenerative Diseases**

Global health systems face a significant and growing challenge in the form of neurodegenerative diseases. These conditions cause severe motor and cognitive impairment and are characterized by a progressive disruption of the structure and function of neurons. As the world's population ages, neurodegenerative diseases like Parkinson's and Alzheimer's disease are becoming more common. These conditions have a significant negative impact on patients' quality of life and are becoming more and more expensive. Innovative methods of early detection, assessment, and treatment are required for these difficult disorders.

**1.2. Parkinson's Disease**

A common neurodegenerative disease that primarily affects the motor system is Parkinson's disease (PD). Tremor, bradykinesia (slow movement), rigidity, and postural instability are classic clinical presentations. Non-motor symptoms like mood disorders, sleep disorders, and cognitive impairment are frequently present as well. Since there are no particular biological tests that can result in an early diagnosis, PD diagnosis primarily depends on clinical evaluation, despite the fact that the condition's symptom profile is complex. As a result, slow symptom progression leads to misdiagnosis or delay, which leads to ineffective treatment, poor patient outcomes, and a lower quality of life (Jankovic, 2008).

**1.3. IoT and ML in Parkinson's Disease**

The early detection and monitoring of Parkinson's disease (PD) could be greatly aided by recent technological advancements, particularly in the fields of machine learning (ML) and the internet of things (IoT). IoT sensors such as smartwatches, wearable health monitors, and others allow continuous and non-intrusive monitoring of motor activities, tremor frequencies, and gait abnormalities in real-time. These tools enable an evaluation of a patient's health while they are engaging in their regular activities and continue to gather large amounts of data outside of the typical clinical settings. One can more accurately identify early indicators of Parkinson's disease and enable early interventions by using machine learning techniques on this data (Javaid et al., 2022; Li et al., 2024). For example, ML algorithms can analyze speech patterns, motor skills, and other non-motor symptoms and differentiate subtle patterns that could foretell the full-blown expression of the disease.

**1.4. State of the Art and Our Contribution**

The pursuit of accurate, quantitative, and real-time measurement of Parkinson's disease (PD) motor symptoms has been the prime interest of computational neurology. It is rich in the current state-of-the-art research that utilizes diverse sensor modalities and machine learning (ML) methodologies. Pioneering work has validated the potential of smartphone sensor-derived composite scores, like the mobile Parkinson Disease Score (mPDS), that highly correlate to the conventional standards, such as the MDS-UPDRS, and that are capable of tracking intraday symptom variation as well as response to therapy (Zhan et al., 2018). In the same line, smartphone-enabled active tests as well as passive monitoring during clinical trial protocols have been shown to be realistic, reliable, and highly sensible, usually uncovering abnormalities even among those patients rated as normal on specific items of the UPDRS during the clinic evaluation (Lipsmeier et al., 2018).

In addition to smartphones, specific PD symptoms have been targeted with special-purpose sensors. Quantification of bradykinesia, the PD hallmark, has been achieved successfully with gyrosensors during tapping tests, demonstrating strong correlations with clinical ratings (Kim et al., 2010). Tremor measurement has been automated with body-worn accelerometers combined with Hidden Markov Models, classifying tremor type and severity reliably (Rigas et al.). Moreover, inertial sensors have been used to detect and classify complex gait disorders such as Freezing of Gait (FOG) reliably (Djuric-Jovicic et al., 2014). Even speech has been targeted in the remote monitoring paradigm, where off-the-shelf speech tests analyzed with signal analysis combined with regression models are capable of tracking PD progression with clinically helpful accuracy (Tsanas et al., 2010). Notably, incorporation of the resulting objective measures into standard care has been shown to improve significantly the resulting clinical outcomes, including the UPDRS as well as quality-of-life scores (Farzanehfar et al., 2018).

Latest advances still investigate the integration of sensor data and advanced ML. Research has looked into the integration of speech signals along with ensemble classifiers such as AdaBoost (Bukhari and Ogudo, 2024) as well as the processing of gait as well as tremor data obtained from off-the-shelf wearable devices. Still missing, though, is an integrative, high-fidelity method for tracking the subtle kinematics of hand movement—a key domain for the measurement of bradykinesia as well as tremor—beyond controlled smartphone tasks.

This work contributes to this vibrant body of research through the proposal of a unifying methodology grounded in a bespoke SmartGlove system that would allow in-depth analysis of hand movement. Our contribution is tripartite:

* Innovation and pilot use of the SmartGlove, a sensor- rich tool to capture high-accuracy, multi-parameter kinematic output of the hand.
* Construction of a holistic, multiple-component feature selection framework that goes beyond single technologies by integrating statistical significance (t-tests), ensemble learning (Random Forest), and analysis of variance (PCA) to pick the most discriminating, non-redundant biomarkers.
* The recognition of essential attributes—especially non-linear dynamics and spectral traits—that are notably proficient in differentiating motor states in Parkinson's Disease patients both prior to and following medication, offers an enhanced array of digital biomarkers for prospective diagnostic and monitoring applications.

By emphasizing the rich data space of hand kinematics and adopting a rigorous, multi-faceted analytical framework, this research hopes to improve the accuracy and completeness of objective PD evaluation.

Briefly stated, the key innovation of this work lies in the combination of a specially crafted data-capture device with an upper-level analytical framework. Contrast this with previous work, which has employed repurposed consumer devices or targeted a very limited set of symptoms, and our specially developed SmartGlove presents a previously unmatched, high-fidelity view of hand motion's rich kinematics. Coupled with our multi-modal feature choice methodology, this system doesn't merely replicate clinical scores but uncovers a novel class of physiologically enlightening biomarkers—specifically in the non-linear dynamic range—that are hidden under conventional analysis. This end-to-end machine learning model is a significant advancement toward precise, data-based neurology from correlation against clinical scales to the detection of underlying digital biomarkers for Parkinson's disease.

**1.5. Structure of Paper**

The remainder of this paper follows this organization: Section 2 outlines the materials and methods utilized with a detailed description of the system architecture of the SmartGlove system, the process of data acquisition related to individual exercises of the hands, and the overall feature extraction process. Section 3 details the multi-faceted feature choice strategy and the composite scoring system used to determine the best biomarkers. Section 4 presents the results of the analytical work with a particular interest in the crucial features and the effectiveness of the choice of methods. Finally, Section 5 discusses implications of the research results, points out limitations of the study, and suggests directions of future research.

**2. Materials and Methods**

This chapter presents the technical setup used for data acquisition, the methods used for recovering kinematic data, and the complete methodology used for deriving features that define the motor symptoms of Parkinson's Disease (PD).

**2.1. SmartGlove System and Sources of Data**

The system of interest here as a primary data source is the SmartGlove system, a specially developed wearable system that has been created with the intent of telemonitoring motor symptoms of PD patients. It has been created with the support of the Operational Program of the Epirus Region 2014-2020 and ESPA 2014-2020 with a view of increasing innovative health and biotechnology solutions.

The system of SmartGlove has three primary subsystems:

1. Textile Glove: Made of durable, biocompatible materials, the glove has conductive areas on the palm and fingers that aid movement recognition. It is sweat-resistant and can be washed. It is also expected to last longer than 10 years.

2. System on Chip (SoC): The central processing unit encompasses a low-energy microcontroller that incorporates a Bluetooth 5.0 module, facilitating wireless data communication while utilizing minimal energy resources (with a typical operational range of 10-100 meters, contingent upon the surrounding environment).

3.Sensors: The glove contains a multi-modal sensor suite:

* Flex sensors to measure finger bending.
* Contact sensors to detect finger-to-palm interaction.
* A 9-axis Inertial Measurement Unit (IMU), composed of a 3-axis accelerometer, 3-axis gyroscope, and 3-axis magnetometer, to identify hands' orientation and movement. IMU has outputs of up to a sampling rate of 100 Hz and a resolution of 16 bits.

The system is supplemented with a power management circuitry developed for lithium-polymer batteries, as well as with flash memory used for transient storage of data. The SmartGlove complies with the IEC 60601-1 medical electrical apparatus safety standard, thus ensuring reliability for medical applications.

The SmartGlove sends data via Bluetooth to the mobPark mobile app supporting Android 6.0+ as well as iOS 11+. The app acts as an intermediary providing the possibility of managing the profile of the users, providing screen-level cues of exercises, as well as capturing sensor data at a sampling rate of 100 Hz. Then the captured data gets securely sent via an encrypted HTTPS connection to a centralized cloud platform like AWS or Azure for storage, processing, and analyzing purposes with a consideration of the General Data Protection Regulation (GDPR).

**2.2. Data Collection Exercises**

Data recording was at a sampling rate of 100 Hz, selected to efficiently capture tremor frequencies from 4 to 6 Hz and also captures bradykinesia. Measurements were obtained before and after medication administration (i.e., Levodopa) as a means of investigating therapeutic action. Four carefully designed motor tasks were incorporated into the experiment as described next:

* Exercise 1 (Postural Stability): Patient sits with their hands resting on their legs with palms facing upwards and counts from 1 to 10. It checks postural stability and resting tremor.
* Exercise 2 (Coordination): The patient stands with their hands at shoulder height and counts to ten while attempting to touch their index fingers together. It is intended to assess tremor and coordination when standing for a long time.
* Exercise 3 (Finger Tapping Speed): With their palm flat, the participant taps their index finger back and forth against their thumb, then quickly returns to the starting position ten times. It is a traditional metric used to evaluate bradykinesia and motor speed.
* Exercise 4 (Hand Speed of Closing and Opening): For ten repetitions, the patient continuously makes a fist with an open palm and returns to an open position as quickly as they can. It checks for bradykinesia and hand rigidity.

**2.3. Feature Extraction**

Numerous features were taken from the raw sensor data (accelerometer, gyroscope, magnetometer) for each exercise in order to quantitatively describe the motor symptoms of Parkinson's disease. These features were computed using 50% overlap (50 samples, 0.5 seconds) and sliding windows of 100 samples (1 second). These features extracted are as follows:

* Statistical Properties: These characteristics provide a succinct explanation of the signal's variation and distribution. The following properties were calculated: Skewness, Kurtosis, Quartile Deviation, Mean, Standard Deviation, Variance, Minimum, Maximum, Range, Median, and Interquartile Range (IQR).
* Energy Characteristics: These metrics assess the signal's intensity and degree of activity. Signal Magnitude Area (SMA), Root Mean Square (RMS), Total Energy, and Logarithmic Energy are among the features that were extracted. • Spectral features are taken into consideration by frequency-domain features.
* Frequency-Domain Features: These are essential for detecting tremors and take into account the signal's spectral characteristics. Included are the following features: Dominant Frequency, Spectral Flatness, Spectral Flux, Spectral Variability, Spectral Entropy, Spectral Centroid, Spectral Spread, and Spectral Roll-on(85%).
* Dynamic and Nonlinear Features: These characteristics specify the signal's temporal fluctuations, complexity, and predictability. The following characteristics are taken into consideration: Mean Absolute Deviation (MAD), Root Mean Square of Successive Differences (RMSSD), Higuchi Fractal Dimension, Lyapunov Exponent, and Sample Entropy.

Since each feature includes specific aspects of motor impairment typical of the disease, such as tremor regularity, movement amplitude, and signal complexity, the selection of features was driven by a large body of literature on PD analysis.

Table 1Table of Characteristics for Movement Analysis in Parkinson's Disease

|  |  |  |  |
| --- | --- | --- | --- |
| **Category** | **Characteristics** | **Purpose** | **Clinical Significance** |
| Central Tendency | Mean, Median | Median Measures the central value of the signal | Detection of bradykinesia (slowed  movements) |
| Dispersion | Standard deviation, Variance, IQR, QD | Quantifies the spread of data | Identifies motion variability (e.g.  gravity, tremor) |
| Range | Minimum/Maximum value, Range | Records extreme values | Assessment of range of motion reduction  in patients with Parkinson's disease |
| Distribution Shape | Skewness, Kurtosis | Describes asymmetry/peakedness  of distribution | Correlation with irregular motor  patterns |
| Variability | Coefficient of Variation (CV), MAD,  RMSSD | Normalized measures of dispersion | Variability differentiation before  after the treatment |
| Energy | Total energy, Absolute Energy,  RMS | Measures signal intensity | Correlation with hypokinesia (reduced  motor energy) |
| Logarithmic Energy | Log Energy | Enhances subtle energy changes | Detection of small changes |
| Spectral | Spectral Entropy, Centroid | Analyzes frequency distribution | Localization of tremor and rhythmic  abnormality |
| Roll-off | 85% Roll-off | Frequency band where  85% of the power is concentrated | Characterization of tremor bandwidth |
| Dominant Frequency | Dominant Frequency | Identification of peak frequency | Detection of Parkinson's tremor (4-6Hz) |
| Spectral Shape | Flatness, Flux, Variability, Dispersion | Quantifies the stability of the  spectrum | Unstable tremors vs. rhythmic movements |
| Dynamics | Lyapunov Exponent, Sampling Entropy | Evaluates the chaos/regularity of the  system | Degeneration of motor control in  Parkinson's |
| Fractal | Dimension Higuchi | Measures the complexity of the signal | Loss of fine motor control |

**3. Feature Selection Methodology**

Feature selection is a critical step in developing accurate and interpretable machine learning (ML) models for Parkinson’s disease (PD) detection. In this study, a **multi-method scoring approach** was applied to identify the most informative features that differentiate between pre-medication and post-medication states. Instead of relying on a single method, three complementary techniques were employed, and their outputs were combined into a composite score.

**3.1 Multi-Method Scoring Approach**

For each feature, three independent scores were calculated:

* **Statistical Significance (Paired T-Test):**  
  A paired T-Test was performed between pre- and post-medication measurements. The score was defined as:

where ε prevents λ zero. A lower p-value corresponds to a higher score, indicating stronger statistical significance (Tukey, 1977).

* **Model-Based Importance (Random Forest):**  
  A Random Forest classifier was trained, and feature importance was derived from the mean decrease in Gini impurity across all trees in the ensemble (Patel et al., 2009).
* **Variance Contribution (PCA):**  
  Principal Component Analysis (PCA) was applied, and the importance of each feature was computed as the sum of the absolute loadings across all principal components, reflecting its overall contribution to data variance (Guyon & Elisseeff, 2003).

**3.2 Composite Score Calculation**

All three scores were normalized to the [0, 1] range. A final composite score was then computed as a weighted average:

Composite Score=(0.4×Score\_T−Test)+(0.3×Score\_RF)+(0.3×Score\_PCA)

This weighting scheme prioritizes statistical significance while also incorporating insights from model-based learning and variance-based analysis.

**3.3 Selection of Best Features**

Features were ranked according to their composite score, and the top-performing ones were selected for subsequent model development.

Representative high-ranking features included:

* **RMSSD** from the gyroscope during Exercise 2 (score: 0.663),
* **Lyapunov Exponent** (score: 0.644),
* **Higuchi Fractal Dimension** (score: 0.612).

These selected features served as the foundation for later predictive modeling and analysis, aiming to capture the most relevant motor signal characteristics associated with PD symptoms (Goetz et al., 2008; Chen et al., 2020).

Table 2 Top 20 features scored

|  |  |  |  |
| --- | --- | --- | --- |
| **Exercise** | **Sensor** | **Feature Name** | **Composite Score** |
| 2 | gyro | rmssd | 0.663 |
| 2 | gyro | lyapunov\_exponent | 0.644 |
| 2 | gyro | higuchi\_fractal\_dimension | 0.612 |
| 2 | gyro | range | 0.573 |
| 3 | acce | higuchi\_fractal\_dimension | 0.469 |
| 3 | gyro | max | 0.452 |
| 3 | acce | lyapunov\_exponent | 0.437 |
| 2 | gyro | spectral\_rolloff | 0.433 |
| 2 | acce | sample\_entropy | 0.422 |
| 0 | magn | lyapunov\_exponent | 0.406 |
| 0 | magn | spectral\_variability | 0.399 |
| 0 | magn | higuchi\_fractal\_dimension | 0.399 |
| 0 | magn | range | 0.381 |
| 3 | magn | rmssd | 0.376 |
| 0 | gyro | rmssd | 0.375 |
| 2 | gyro | std | 0.373 |
| 3 | acce | spectral\_flux | 0.367 |
| 1 | gyro | lyapunov\_exponent | 0.365 |
| 1 | gyro | rmssd | 0.361 |
| 1 | gyro | max | 0.358 |

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