

Article

Parkinson's Disease Classification Using Machine Learning and Wrist Rigidity Measurements from an Active Orthosis

Adriano Alves Pereira ^{1,2}, Daniel Hilário da Silva ^{1,3,*}, Caio Tonus Ribeiro ¹, Caroline Valentini de Queiroz ¹,
Luanne Cardoso Mendes ¹, Leandro Rodrigues da Silva Souza ^{1,4}, Selma Terezinha Milagre ¹,
Adriano de Oliveira Andrade ¹ and Carlos Dias Maciel ²

- ¹ Postgraduate Program in Biomedical Engineering, Faculty of Electrical Engineering, Federal University of Uberlândia, Uberlândia 38400-902, MG, Brazil; adriano.pereira@ufu.br (A.A.P.); caiot@ufu.br (C.T.R.); caroline.valentini@ufu.br (C.V.d.Q.); luanneccmendes@ufu.br (L.C.M.); leandro.souza@ifgoiano.edu.br (L.R.d.S.S.); selma.milagre@ufu.br (S.T.M.); adriano@ufu.br (A.d.O.A.)
 - ² Faculty of Engineering and Sciences (Guaratinguetá Campus), Department of Electrical Engineering, State University of São Paulo Júlio de Mesquita Filho (UNESP), Guaratinguetá 12516-410, SP, Brazil; carlos.maciell@unesp.br
 - ³ Federal Institute of Education, Science, and Technology Goiano (IF Goiano), Department of Computer Science (Campus Cristalina), Cristalina 73850-000, GO, Brazil
 - ⁴ Federal Institute of Education, Science, and Technology Goiano (IF Goiano), Department of Computer Science (Campus Rio Verde), Rio Verde 75901-980, GO, Brazil
- * Correspondence: daniel.hilario@ifgoiano.edu.br

Abstract

Background: Rigidity is a cardinal symptom of Parkinson's Disease (PD), yet its clinical evaluation remains largely subjective and susceptible to errors. This study introduces an innovative method for objectively classifying individuals with PD by combining an active wrist orthosis with Machine Learning (ML) models. **Methods:** The orthosis, equipped with current and force sensors, recorded biomechanical signals during passive wrist flexion and extension, from which twelve quantitative features were extracted. Data were collected from 30 participants (15 with PD and 15 Healthy Controls). Nineteen supervised ML algorithms were systematically evaluated through feature selection, cross-validation, and hyperparameter tuning. **Results:** Using all twelve features, QDA achieved an accuracy of 0.889 and sensitivity of 1.000, followed by GPC (0.778) and LDA (0.778). After applying feature selection with the Correlation-based Feature Subset to reduce redundancy, Extra Trees reached 0.833 accuracy, while both QDA and GPC maintained accuracies of 0.778. This consistency across models, even with a reduced feature set, highlights the robustness of the extracted biomarkers. **Conclusions:** These findings confirm that wrist rigidity signals provide discriminative quantitative information between PD patients and HC and are able to support PD classification, combining engineering innovation with clinical practice that highlights the potential of integrating wearable devices and ML as a personalized healthcare in PD.



Academic Editor: Lei Shu

Received: 29 October 2025

Revised: 15 December 2025

Accepted: 16 December 2025

Published: 19 December 2025

Copyright: © 2025 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Keywords: biomarkers; classification; computer vision; machine learning; Parkinson's disease; rigidity; wrist orthosis

1. Introduction

Parkinson's Disease (PD) is a neurodegenerative condition affecting approximately 10 million people worldwide, making it the second most common neurodegenerative disorder after Alzheimer's Disease [1,2]. Characterized by both motor and non-motor

symptoms, the prevalence and impact of PD doubled from 1990 to 2015, driven by increasing longevity [3]. The four cardinal motor signs and symptoms are resting tremor, muscle rigidity, akinesia or bradykinesia, and postural instability, often summarized by the acronym TRAP [4]. Despite advancements, the diagnosis of PD remains predominantly clinical, based on medical history and physical examination, which makes it susceptible to subjectivity and inaccuracies [4,5].

The societal impact of this condition is rapidly increasing. According to [6] PD has shown a fastest growing in terms of prevalence and disability. Between 1990 and 2021, the number of affected individuals increased 274% worldwide [6], a trend likely to accelerate with the aging population, which is the main risk factor for the disease [7]. This rising prevalence highlights the urgent need for more accurate and objective clinical tools to manage the disease effectively.

Among the motor symptoms, rigidity is a central feature of PD, affecting over 83% to 89% of diagnosed individuals [8,9]. It is defined as an increased resistance to passive joint movement, maintaining a constant degree of resistance regardless of the angular position, which poses a significant diagnostic challenge. Rigidity can be of the “lead pipe” or “cogwheel” type [8]. Rigidity is influenced by both neural and non-neural components [9]. The clinical assessment of this symptom contributes to the high error rates in PD diagnosis, ranging from 15% to 24%. Despite using advanced neuroimaging and other tests, diagnostic mistakes still occur, emphasizing the need for more objective methods to evaluate key motor signs like rigidity [10,11].

Currently, the most objective clinical assessment available is performed using the semi-quantitative Movement Disorder Society-Unified Parkinson’s Disease Rating Scale [12]. Although this scale is the gold standard, it is inherently subjective and can lead to diagnostic errors in up to 20% of cases [9,13].

While rigidity can affect the entire body, its impact on the upper limbs, especially the wrist, is particularly disabling. The wrist joint plays a vital role in many daily activities such as eating, writing, and opening doors. Therefore, wrist rigidity can greatly reduce a person’s functional ability and independence, directly affecting their quality of life [14,15]. As a result, accurately measuring wrist rigidity is more than just a technical task; it is crucial for developing targeted treatments and improving patient outcomes.

Due to the limitations of subjective assessment, there is an increasing effort to develop objective and quantitative methods for evaluating rigidity.

In the study conducted by [16], eight individuals diagnosed with Parkinson’s Disease, aged 53.6 ± 5.7 years, responsive to levodopa and undergoing Deep Brain Stimulation (DBS), were evaluated. The control group consisted of young adults aged 30.9 ± 4.8 years. The authors employed a palm-worn orthosis to quantify rigidity, called the Bionics Institute Rigidity Device (BiRD). This device uses a motor to induce flexion of the third finger at the metacarpophalangeal joint, and integrated sensors record measurements during flexion and extension. Rigidity was characterized using the slope of the force–displacement curve (Force Rate) and the total area under this curve (Work). Their findings demonstrated that both parameters successfully distinguished individuals with PD from the control group.

Similarly, [17] conducted a study with seven individuals with PD (67 ± 11 years) and fourteen healthy adults (25 ± 2 years) participated. A wrist wearable orthosis, called PDMeter, was used to automatically perform wrist flexion and extension while participants were instructed to avoid voluntary muscle contraction to isolate rigidity. The rigidity was quantified through linear regression of the torque–angle curve. The results indicated that the parameter derived from the orthosis reliably differentiated the PD group from the healthy group.

Other approaches include robotic exoskeletons, such as the KINARM, along with inertial sensors, electromyography, myotonometry, and elastography, all of which aim for increased precision and reproducibility [18].

In [19] was conducted a Scoping Review on the assessment of wrist stiffness in Parkinson's disease. The aim of the study was to identify current methods for assessing wrist stiffness and its stage of development. One of the methods analyzed was motion capture assessment. Nine articles were found on this topic [20–28]. Among the nine articles, three required a professional to perform the extension and flexion movements [25–27], and two articles used the same device [20,23]. Thus, only five devices in the articles found performed the extension and flexion movement in the wrist automatically [21–24,28], and none of these articles associated the wrist orthosis with machine learning, confirming the scarcity of research on the subject.

Our study incorporates elements from the research conducted by [16,23]. Data collection and certain signal characteristics were informed by [16] and applied to a wrist orthosis to compare rigidity between individuals with Parkinson's disease (PD) and healthy controls. To enhance the interpretation of results regarding rigidity and movement, we expanded both the number and type of features used by [16,23]. Unlike [16,23,29], in addition to statistical analysis, we employed machine learning techniques to evaluate whether the selected features could successfully classify the PD and healthy groups. While several studies utilize wrist orthoses in conjunction with statistical analysis or machine learning, these devices are generally implemented to control wrist movements in assistive technology. However, studies assessing or quantitatively measuring rigidity remain scarce. The objective of this research is to develop a tool that provides objective measurements to assist healthcare professionals in diagnosing rigidity and that complements the MDS-UPDRS, particularly in its assessment of rigidity.

The use of Machine Learning (ML) models is essential for transforming this objective data into clinically useful information. Using the PyCaret library [30,31] in Python 3.10, several ML algorithms, such as the Extra Trees Classifier (ETC), Gradient Boosting Classifier (GBC), and K-Neighbors Classifier (KNN), have been employed for classification to distinguish between individuals with PD and healthy controls (HC). Techniques such as feature selection and hyperparameter optimization are applied to enhance the performance of the models.

In this context, this study presents a proof-of-concept for the development and validation of an instrumented wrist orthosis as an innovative tool for objectively measuring rigidity. This orthosis, developed at the Center for Innovation and Health Technology Assessment (NIATS) at Federal University of Uberlândia (UFU), incorporates a linear servomotor with current and force sensors. Along with computer vision tools, the orthosis enables the analysis of the forces required to perform passive wrist flexion and extension movements, providing detailed biomechanical metrics.

Having established the need for objective methods, this paper outlines our proposed solution that fills this critical gap. We propose a custom-designed wrist orthosis combined with ML to accurately distinguish individuals with PD from healthy controls. The following sections detail our methodology. Section 2 describes our comprehensive methodology, from data collection to model development, including the application of feature selection techniques. Section 3 presents the main classification results. Section 4 presents the Related Works. The results are interpreted and discussed in Section 5, while introducing directions for future works and addresses the limitations of the present study. Finally, Section 6 provides the study's conclusions.

This approach improves the scientific understanding of rigidity as a biomechanical biomarker and establishes the groundwork for AI-assisted tools designed to support clinicians in the diagnostic assessment of PD.

2. Materials and Methods

This section explains the methodology used to classify individuals with PD based on biomechanical data. We first introduce the instrumented wrist orthosis developed for this study, then describe the dataset, the preprocessing steps for the wrist rigidity signals, and the ML techniques employed.

2.1. The Orthosis

The core of our methodology is a custom-developed active wrist orthosis created at the NIATS laboratory (UFU) for the objective quantification of rigidity in PD with the patent BR1020140232826. The device serves as an objective tool to overcome the limitations of subjective scales, such as the MDS-UPDRS.

Weighing 850 g, the system is actuated by a Faulhaber DC linear servomotor LM 2070-080-11 (Faulhaber, Schönaich, Germany) managed by a high-precision controller MCLM 3006 S RS (Faulhaber, Schönaich, Germany). The operating principle involves the motor performing passive wrist flexion and extension movements on the participant. Rigidity is quantified by measuring the motor's current consumption, which is proportional to the resistive force exerted by the wrist. The details of this device are shown in Figure 1.

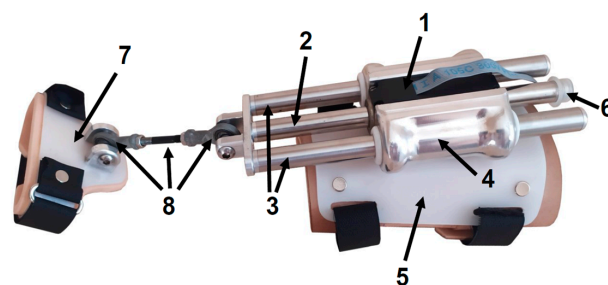


Figure 1. Active wrist orthosis. (1) Actuator, (2) Actuator's cylindrical shaft, (3) Auxiliary cylindrical shafts, (4) Actuator casing, (5) Forearm attachment structure, (6) Safety displacement limiter, (7) Hand coupling structure, (8) Spherical joints.

Figure 2 depicts the experimental setup, showing the active wrist orthosis fitted to a volunteer's forearm and hand. The wrist is positioned at its maximum range of passive motion, illustrating full extension (a) and full flexion (b) as captured during the data acquisition protocol.

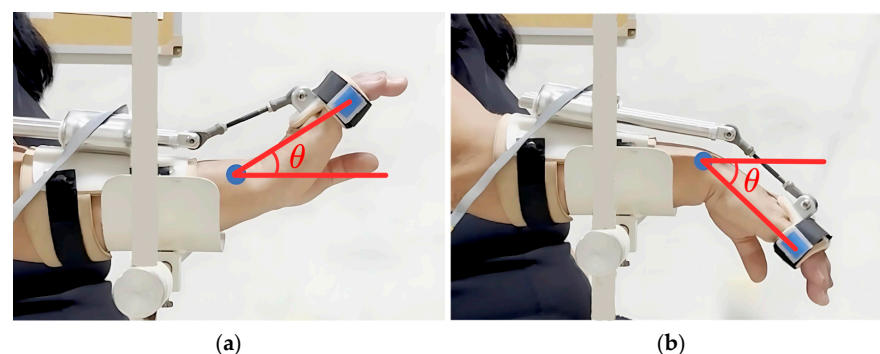


Figure 2. Experimental setup of the active wrist orthosis positioned at maximum amplitude angles during: (a) extension and (b) flexion movements. The colored markers indicate the anatomical reference points used for motion tracking.

2.2. Participant Selection, Workflow, and Dataset

The participant selection process was conducted in two main phases.

Phase 1: Recruitment and Initial Screening

The experimental group consisted of individuals with a confirmed clinical diagnosis of PD, as determined by an expert neurologist. The healthy control HC group, composed of volunteers with no history of neurological diseases.

Phase 2: Application of Eligibility Criteria and Matching

All potential participants were screened against predefined inclusion and exclusion criteria, based on established protocols [32,33]. The primary inclusion criterion for the PD group was a formal clinical diagnosis. Exclusion criteria for all participants included the presence of any other neurological condition, joint disease, or any painful condition that could affect movement. Following the screening, the final groups were formed by matching participants from each group by age and sex to minimize demographic confounding variables.

Following approval from the Research Ethics Committee of the Federal University of Uberlândia under the CAAE number 84004924.1.0000.5152, we recruited 30 participants who provided written informed consent. The groups consisted of 15 individuals with PD (GPD) matched by age and sex with the group of 15 Healthy Control (HC) individuals (GHC). Because the aim of the study was to distinguish GPD from GHC, the GPD group was not stratified by Parkinson's Disease stages. Furthermore, the sample size was insufficient to allow for a meaningful subdivision of GPD according to disease stage.

In accordance with the protocol approved, specific Parkinson's Disease clinical scales were not administered to the HC. The inclusion criteria for these participants were strictly based on the confirmed absence of neurological or orthopedic history; therefore, such clinical data were not collected. Participant demographics are detailed in Table 1.

Table 1. Clinical and demographic variables. Age and MDS-UPDRS Part III scores are presented as mean $\pm$ standard deviation, and gender as counts.

Item	HC	PD	Total
Gender Male	8	8	16
Gender Female	7	7	14
MDS-UPDRS Part III (Motor) ¹	-	20.90 $\pm$ 9.70	-
Age (years)	62.07 $\pm$ 5.68	62.00 $\pm$ 5.21	-
Total	15	15	30

¹ Part III: Motor Examination (3.1–3.18).

An instrumented orthosis performed a predefined motor protocol on each participant's wrist to collect biomechanical and video data. The protocol involved passive, sequential flexion–extension movements in the sagittal plane, organized into three sets of 10 repetitions, with a 2 min rest interval between each set, producing three distinct sets of data for each participant. All measures were used by the classifiers, totaling 45 measures for each group. The volunteer is initially positioned in a chair with forearm support. Before the orthosis is fitted, a passive wrist joint stretching protocol is performed, simulating the movements that will later be actively performed by the device. This stage consists of 30 s of wrist flexion followed by 30 s of wrist extension. Data was collected during the “OFF” medication state of the GPD.

The orthosis was attached to the individual's forearm with standardized positioning, 6 cm from the ulnar styloid process, taking into account individual anatomical varia-

tions. This positioning criterion follows the recommendations of [34], aiming to ensure proper biomechanical alignment and the reproducibility of measurements taken during the analysis.

In healthy individuals, the orthosis was placed on the dominant hand. In individuals with PD, the orthosis was placed on the most affected limb, as identified by the expert neurologist based on clinical history and the MDS-UPDRS Part III scores (specifically Item 3.3–Rigidity). According to ref. [35], no method of assessing Parkinson’s Disease can replace clinical analysis, reinforcing that the use of objective or subjective tools is complementary. Thus, as the positioning of the orthosis should be performed a priori, in relation to the experiment, the MDS-UPDRS scale was used to determine the most affected side [36,37].

During data collection, participants were instructed not to resist or react voluntarily to the orthosis’s movement, allowing the mechanical system to act freely on the joint [13]. Before data collection, participants were familiarized with the orthosis to refrain from exerting any voluntary force during flexion and extension movements. Data collection was performed after the researchers had verified that the participant was already familiar with the orthosis. Joint rigidity was measured by the force applied by the motor during flexion and extension movements, assuming that the greater the force required to move the joint, the greater the observed rigidity.

The orthosis’s internal sensors recorded quantitative biomechanical data, including electrical current, time, and linear displacement during wrist flexion and extension, recorded at a sampling rate of 166,67 Hz. Simultaneously, the wrist movement was filmed by a camera positioned at a 90-degree angle to the movement. Video recording was recorded at a frame rate of 60 Hz, to enable the extraction of the wrist’s angular variation over time. Due to the difference in sampling rate and frame rate, the video data was interpolated to increase the frame rate from 60 Hz to 166.67 Hz, using the spline function in MATLAB R2025b. The angular variation in the wrist movement was estimated using the Kinovea® 2025.1.1 software by means of two markers, as shown in Figure 2.

The methodology was divided into three stages. The first stage is Data Collection, which involves acquiring biomechanical signals using the instrumented wrist orthosis, synchronized with video recordings of the movements. Next, during the Data Modeling and Evaluation stage, the features extracted from the signals were organized and analyzed under two conditions: one using the complete set of predictors and another after applying the CFS technique to reduce redundancy. Finally, in the third stage, the processed datasets were submitted to 19 different Machine Learning algorithms to train and evaluate models capable of classifying individuals based on the features. This study followed the steps shown in Figure 3.

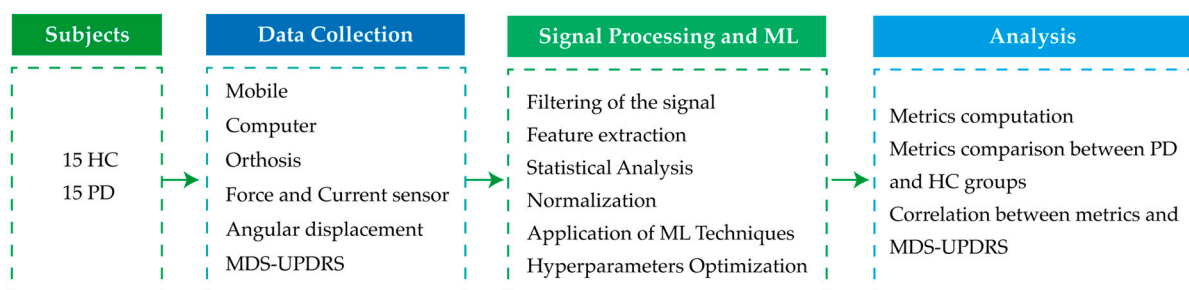


Figure 3. Schematic diagram of the complete experimental workflow. The process ranges from subject recruitment to acquisition with the active orthosis to the final analysis.

To ensure a systematic and reproducible analysis, this study followed a structured four-stage experimental workflow, as illustrated in Figure 3. The schematic diagram of the entire process is described as follows:

- (1) Subjects—15 HC and 15 PD participated in the research;
- (2) Data Collection—the collection of data is made in this stage using mobile, computer, wrist orthosis, and MDS-UPDRS;
- (3) Signal Processing and ML—the signal is filtered, and the features are extracted, and is applied to statistical analysis, normalization, ML techniques, and hyperparameter optimization;
- (4) Analysis—the results from the signal processing are analyzed to compute metrics, to compare PD and HC groups, and to compute the correlation between metrics and MDS-UPDRS score.

2.3. Preprocessing Signals and Feature Definition

The signals were band-pass-filtered between 1 and 16 Hz to remove low- and high-frequency artifacts [38]. For the removal of linear trends, the value of filtered signal was subtracted from its mean, the resulting signal was normalized using the z-score technique. The equation for the z-score is given by Equation (1):

$$R = \frac{x_i - \mu}{\sigma} \quad (1)$$

where

$X = \{x_1, x_2, \dots, x_i\}$ — x_i is the i th element

μ —mean of the signal

σ —standard deviation

R was used to calculate the features.

The z-score is a widely used technique in machine learning as it eliminates bias from feature values and standardizes data variance, thereby preventing features with larger scales from dominating the learning process [39]. Table 2 presents the 12 biomechanical features derived from the orthosis signals used as inputs for the classification models.

Table 2. Variables used in the experiment.

Features	Equation	Description
MAV	$MAV = \frac{1}{N} \sum_{i=1}^N x_i $ where N—number of elements of X	Estimate the mean absolute value of the signal.
MAVSD	$MAVSD = \frac{1}{N-2} \sum_{i=1}^{N-2} x_{i+2} - x_i $	Estimate the mean absolute value of the second difference of the signal.
MAVFD	$MAVFD = \frac{1}{N-1} \sum_{i=1}^{N-1} x_{i+1} - x_i $	Estimate of the mean absolute value of the first difference of the signal.
PEAK	$PEAK = \max\{x_i\}_{i=1}^N$	Estimate the maximum value of the signal.
RANGE	$RANGE = \max\{x_i\}_{i=1}^N - \min\{x_i\}_{i=1}^N$	Amplitude of the signal.
STD	$STD = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2}$	Standard deviation of the signal.
FR_Extension	Force Rate: inclination coefficient of the curve during extension movement.	* Slope of the linear regression of force (N) vs. angle (degree) during extension movement.
FR_Flexion	Force Rate: inclination coefficient of the curve during flexion movement.	* Slope of the linear regression of force (N) vs. angle (degree) during flexion movement.

Table 2. Cont.

Features	Equation	Description
<i>C_Extension</i>	Area under the curve of current (A) vs. time (s) during extension movement.	Charge during extension movement.
<i>C_Flexion</i>	Area under the curve of current (A) vs. time (s) during flexion movement.	Charge during flexion movement.
<i>W_Extension</i>	Area under the curve of force (N) vs. displacement (m) during extension movement.	Work during extension movement.
<i>W_Flexion</i>	Area under the curve of force (N) vs. displacement (m) during flexion movement.	Work during flexion movement.

* The linear regression and the confidence interval were calculated using the MATLAB R2025b fitlm function.

The features, as shown in Table 2, were organized into three distinct categories: statistical (*RANGE*, *STD*) amplitude (*MAV*, *MAVSD*, *MAVFD* and *PEAK*), dynamic characteristics (*FR_Extension*, *FR_Flexion*, *C_Extension*, *C_Flexion*, *W_Extension* and *W_Flexion*) derived from the extension and flexion phases, and derived biomechanical parameters.

We used a multimodal data collection setup, combining signals from an active wrist orthosis with synchronized video recordings of passive wrist flexion and extension movements. Each participant completed three trials. For each trial, 12 features were extracted.

Outlier detection and removal were conducted according to Equations (2) and (3) [29].

$$Lower = Q1 - 1.5 * INTQ \quad (2)$$

$$Upper = Q3 + 1.5 * INTQ \quad (3)$$

where *INTQ* is the interquartile range (*Q3*–*Q1*); *Q3* is the third quartile; and *Q1* is the first quartile.

2.4. Data Split, Cross-Validation, Feature Selection, and Optimization

The dataset was divided into two subsets: a training set (80% of samples, *n* = 72) and a hold-out test set (20%, *n* = 18), a methodology supported by previous studies [2,32,33,40].

Each research participant performed the experimental protocol three times, and all measurements were used. Thus, to avoid data from the same individual being simultaneously in the test and training subsets, the partitioning of training and testing sets was performed strictly at the subject level, not the sample level. We employed a Stratified Group strategy (grouping by *Subject_ID*), which forces all 3 repetitions from any given participant to be allocated exclusively to the same subset. This guarantees that no data from a subject used in training ever appears in the test set. We employed a stratified group K-fold cross-validation protocol (*k* = 5) similar to that described in [33,41] for model development and tuning. This strategy was explicitly selected to ensure that the class distribution remained balanced across folds (stratification) while strictly maintaining subject independence (grouping) to prevent data leakage.

Furthermore, feature selection (FS) techniques were used in this study as part of our preprocessing pipeline to improve model efficiency and interpretability. The purpose of FS is to select a subset of the most informative predictors from the initial feature set. This step is essential not only for reducing computational load but also for enhancing classification accuracy by removing redundant or irrelevant variables [40,42,43].

Relying solely on default algorithm parameters can result in subpar performance; thus, a systematic search for the best configuration is essential for maximizing model accuracy

and generalization, a practice well-supported by the literature [2,33,44]. To unlock each classifier's full potential, we conducted a hyperparameter tuning stage using the 'tune_model' function, which applies a randomized search method by default [30,31]. Unlike the exhaustive Grid Search approach employed in related studies such as Rehman et al. (2019) [2], Randomized Search samples parameter settings from statistical distributions rather than a manually defined grid [45]. This strategy was adopted to enhance computational efficiency and minimize researcher bias in defining the search space. For each model, we evaluated 80 randomly sampled configurations ($n_iter = 80$) were evaluated using the fixed random seed ($session_id = 1245$) to ensure reproducibility. The resulting fine-tuned models were then used to generate final predictions by applying the function 'predict_model' on the unseen test set.

2.5. Statistical Analysis

A statistical analysis was performed to compare demographic, clinical (specifically, the MDS-UPDRS Part III motor score), and key biomechanical features between GHC and GPD, with a significance level set for all statistical tests at $\alpha = 0.05$. To compare the ages between GHC and GPD statistically, the Shapiro–Wilk test [46] (p -values = 0.2174 and 0.6898, respectively) was used to assess the normality of the data, indicating that age data in both groups followed a normal distribution. Therefore, Levene's test (p -value = 0.6695) was conducted to check for homogeneity of variances. The results showed that the variances could be considered equal. After performing Levene's test, Student's t -test was conducted.

Furthermore, to explore the relationships among the 12 features, a correlation analysis was performed. The resulting correlation matrix was displayed as a heatmap and used as a preliminary step to reduce multicollinearity before the feature selection process.

The performance of each classifier was quantified using standard metrics calculated from the confusion matrix outcomes: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) [42]. Metrics for performance, Accuracy, Precision, Sensitivity, Specificity, F-score and MCC (Equations (4)–(9), respectively), were computed for each classifier [44,47–49].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (6)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (7)$$

$$F - \text{Score} = 2 * \frac{(\text{Precision} * \text{Sensitivity})}{(\text{Precision} + \text{Sensitivity})} \quad (8)$$

$$\text{MCC} = \frac{TN * TP - FN * FP}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (9)$$

Multiple linear correlation was used to verify the correlation between the calculated GPD characteristics and the MDS-UPDRS Part III.

2.6. Framework for ML Classification Modeling

We developed a supervised ML pipeline to classify participants based on the orthosis data. The 12 biomechanical features served as predictor variables, while the Status (PD or HC) was the response variable.

To ensure a comprehensive and unbiased evaluation, we adopted a multi-model approach inspired by established literature [50–52]. This initial pool of algorithms included:

Ada Boost Classifier (ADA), CatBoost Classifier (CATBOOST), Decision Tree Classifier (DTC), Dummy Classifier (DUMMY), Extra Trees Classifier (ET), Extreme Gradient Boosting (XGBoost), Gaussian Process Classifier (GPC), Gradient Boosting Classifier (GBC), K-Neighbors Classifier (KNN), Light Gradient Boosting Machine (LGBM), Linear Discriminant Analysis (LDA), Logistic Regression (LR), MLP Classifier (MLP), Naïve Bayes (NB), Quadratic Discriminant Analysis (QDA), Random Forest (RF) Classifier, Ridge Classifier (RIDGE), Support Vector Machine with a Linear Kernel (SVM), and Support Vector Machine with a Radial Kernel (RBFSVM).

A comprehensive set of classification algorithms from the PyCaret and Scikit-learn libraries was systematically assessed. The whole pipeline was built in Python 3.10, as illustrated in Figure 4.

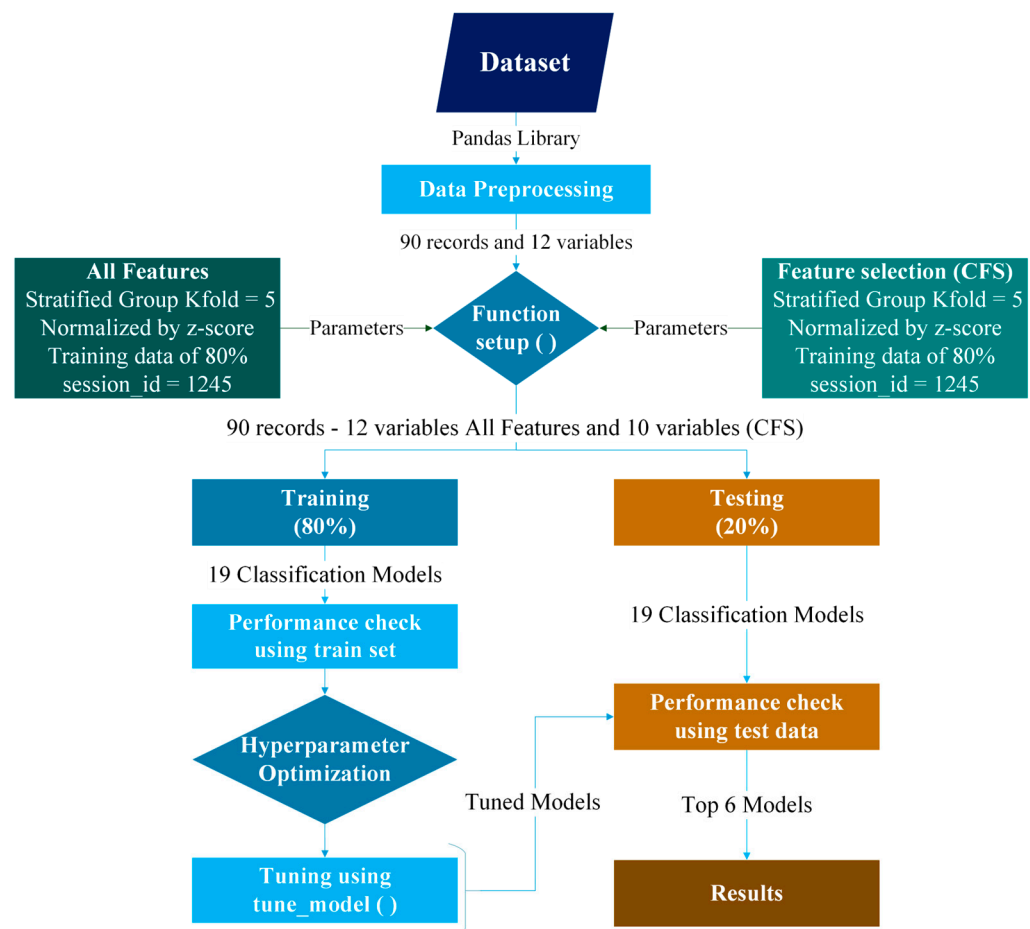


Figure 4. Framework for ML modeling for PD classification.

This diverse selection of models, combined with a feature selection technique, enabled a robust comparison, using the Accuracy metric, to find the most effective model for our specific dataset. The methodology described was applied, resulting in the outcomes presented in the next section.

3. Results

In this section, we present the performance results of the ML models in classifying individuals with PD based on the biomechanical data from the active wrist orthosis.

3.1. Sample Characterization and Typical Biomechanical Signals

The boxplots in Figure 5 indicate that the median and dispersion of ages are similar between groups, with no evidence of extreme outliers. Subsequently, a Student's *t*-test was

performed to assess whether a statistically significant difference existed between the mean ages of the two groups. The resulting p -value of 0.9735 confirms the absence of statistically significant differences in mean age between groups.

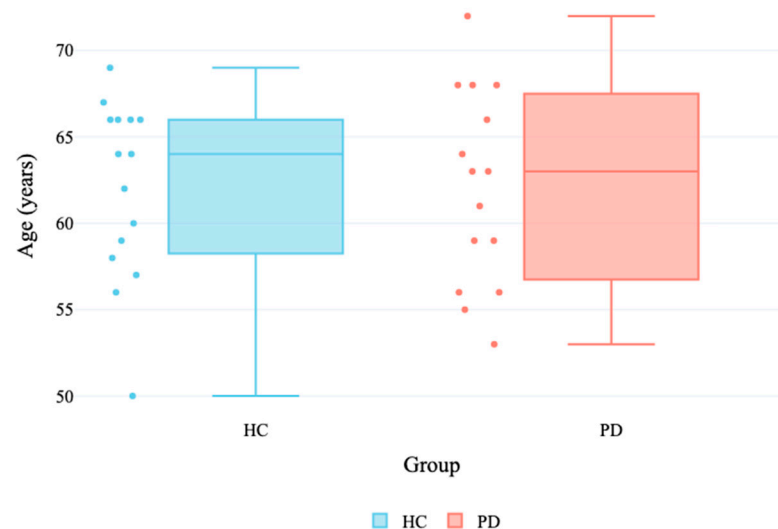


Figure 5. Boxplots of participants' ages in the control and Parkinson's Disease groups.

Figures 6–8 illustrate the typical signals from GHC (left column) and GPD (right column).

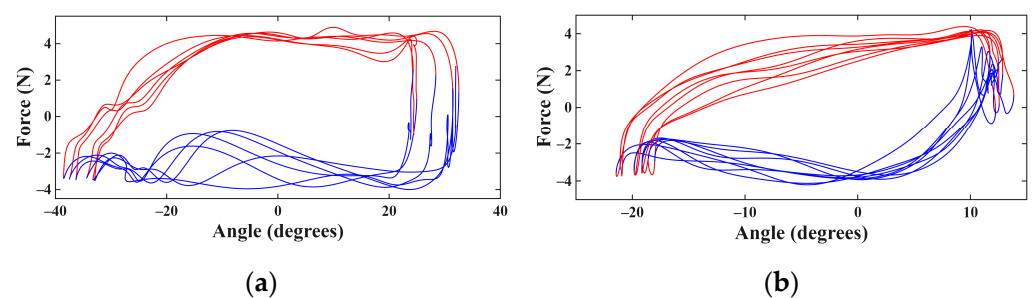


Figure 6. Typical signals presented by each group. GHC: left and GPD: right. (a,b)—Force vs. angle: Red—extension movement. Blue—flexion movement.

Before applying ML models, a correlation analysis was conducted to explore the relationships among the 12 biomechanical features. The resulting correlation matrix is displayed as a heatmap in Figure 9, highlighting the features with high correlation. This multicollinearity indicates redundant information and underscores the importance of the subsequent feature selection step for creating more robust and interpretable models.

3.2. Results of Classification Models for All Features

For each classification model, we used the pipeline outlined in Table 3.

The other parameters for the setup function were kept at the default settings. A standard seed was used to ensure the experiment's reproducibility and consistent results.

Subsequently, a systematic hyperparameter optimization was performed for all evaluated algorithms, using the `tune_model` function, the optimization was conducted for all classifiers using the pipeline shown in Table 4.

The objective function was defined as F1 (`optimize = 'F1'`), as it balances precision and sensitivity [2,40]. Additionally, the parameter `choose_better = True` ensured that the tuned model would only replace the baseline when presenting an improvement in the metric, thereby preserving comparability and mitigating risks of performance degradation. Finally, after optimization, the six best models were applied to the test data using the `predict_model`

function. This final step consolidated the evaluation of the classification models, enabling the identification of those with the most significant predictive potential in the context of this study.

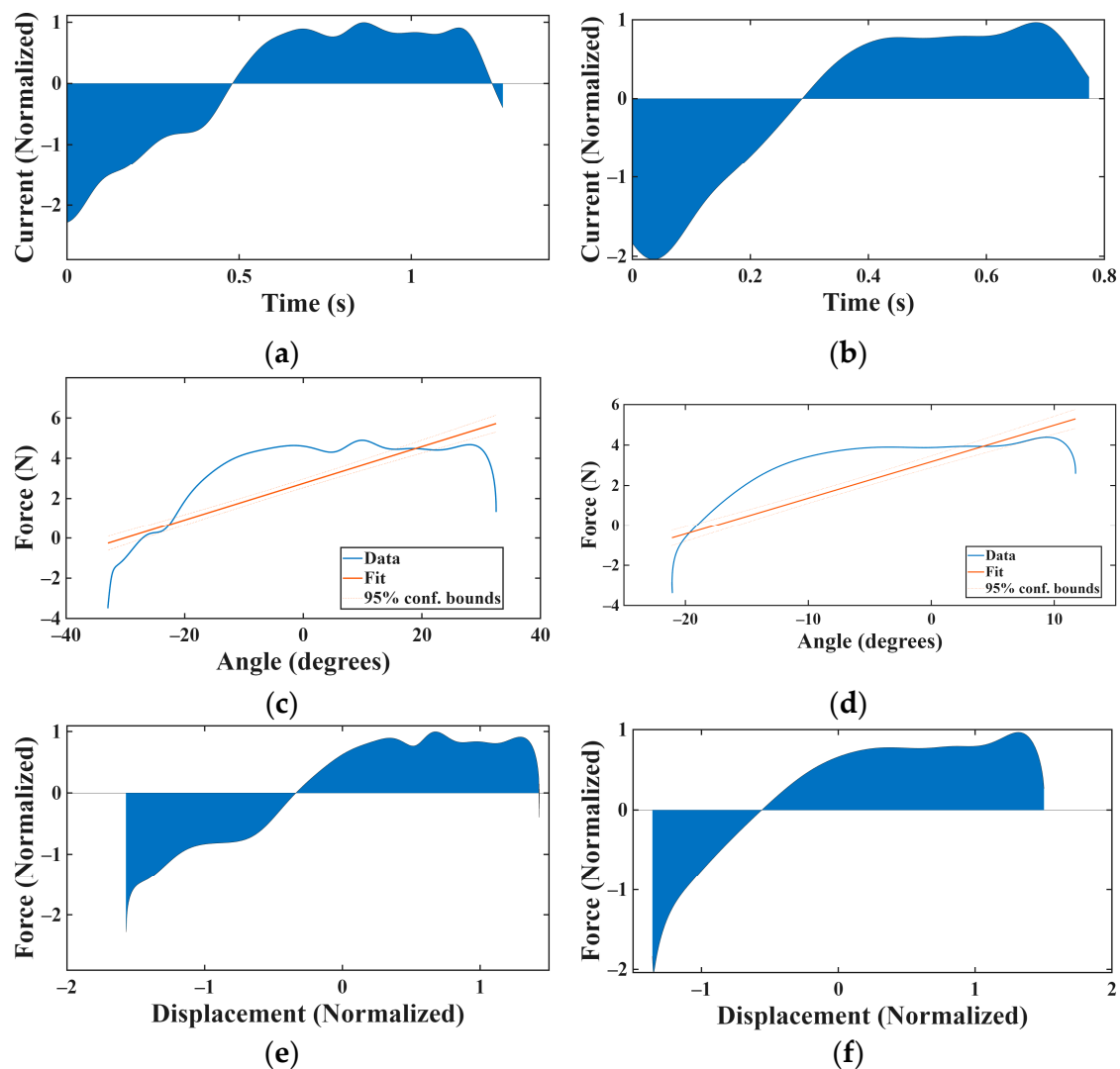


Figure 7. Typical extension signals presented by each group. GHC: left and GPD: right. (a,b)—the blue area represents the Charge (C) during the extension movement. (c,d)—the slope of the line (red) represents the Force Rate (FR) during the extension movement. (e,f)—the blue area represents the Work (W) during the extension movement.

Table 3. Hyperparameters of the pipeline for classification model implementation.

Parameter	Value
Target	'Group'
Train size	80%
Fold strategy	Stratified Group K-Fold
Fold groups	'Subject_ID'
Number of folds	5
Normalized	z-score
Seed	1245

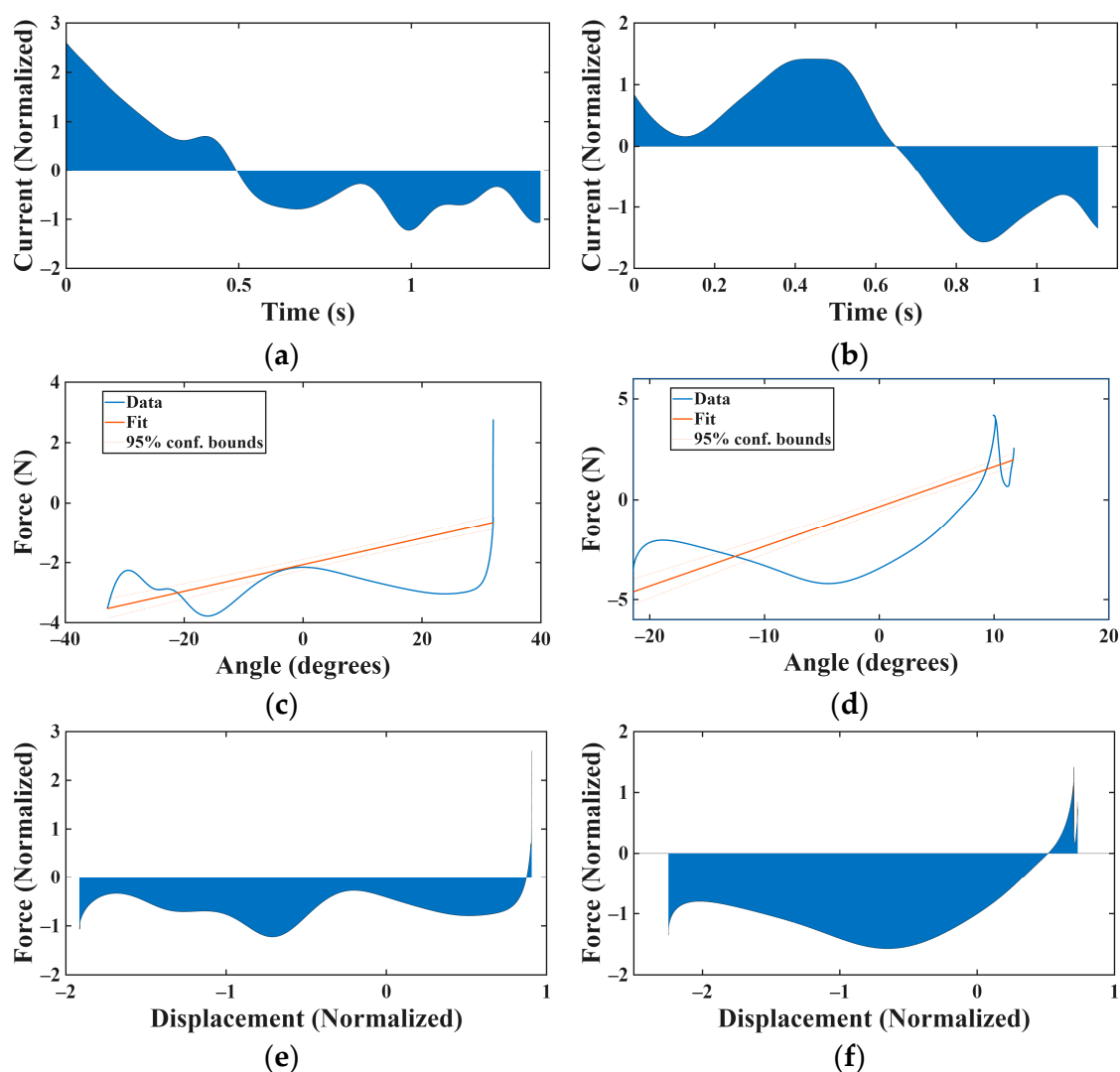


Figure 8. Typical flexion signals presented by each group. GHC: left and GPD: right. (a,b)—the blue area represents the Charge (C) during the flexion movement. (c,d)—the slope of the line (red) represents the Force Rate (FR) during the flexion movement. (e,f)—the blue area represents the Work (W) during the flexion movement.

Table 4. Hyperparameter for the models optimization process.

Hyperparameter Optimized	Value
Optimize	F1
Verbose	False
Samples number	n_iter = 80
Better	choose_better = True

After optimization, two models showed an improvement in mean accuracy. The KNN and RBFsVM models stood out with the most significant growth, increasing by 27.33% from 0.611 to 0.778. Subsequently, the RBFsVM model's performance evolved from 0.667 to 0.778, resulting in an 16.64% of gain. In contrast, QDA maintains an accuracy of 0.889. The remaining models (NB, LDA, and GPC) showed no change in their performance. Considering the set of six models, the overall mean accuracy showed no significant variation, maintaining a baseline of approximately 80%.

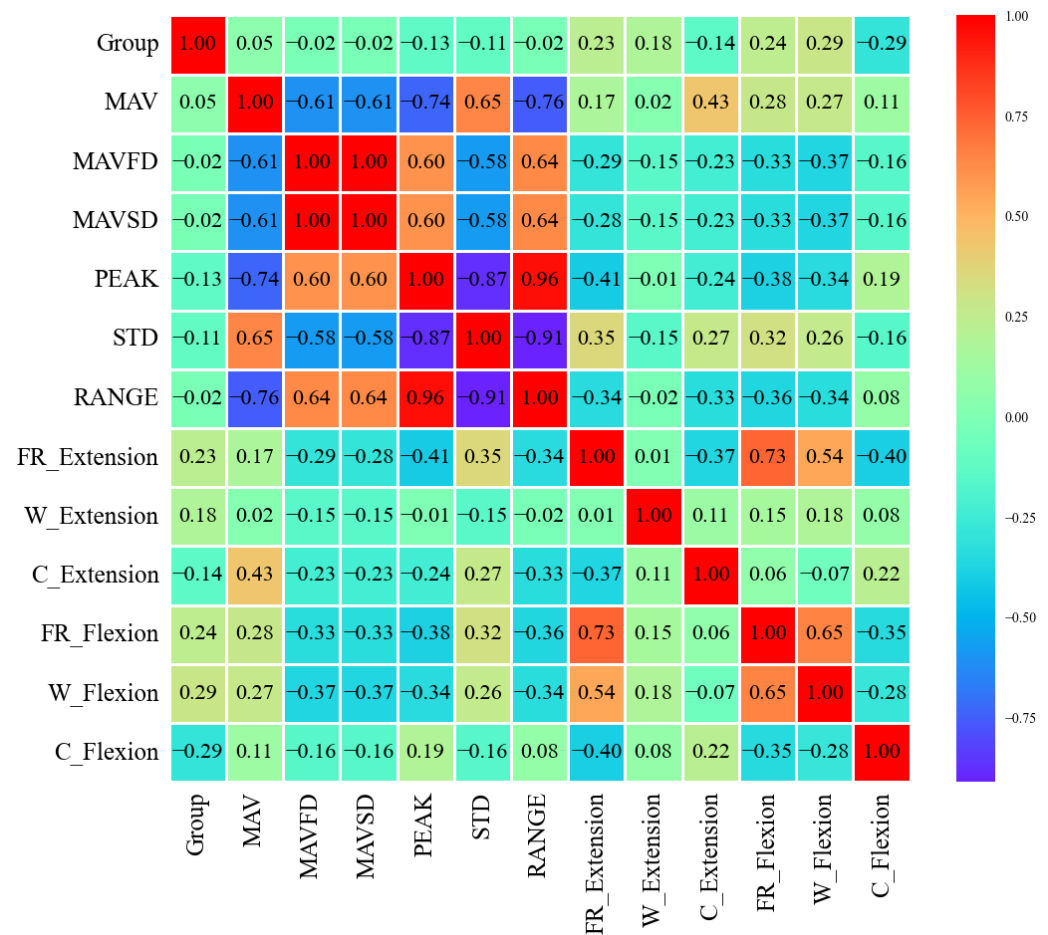


Figure 9. Heatmap of the correlation matrix for the 12 biomechanical features. Warmer colors (red) indicate a strong positive correlation, while cooler colors (blue) indicate a strong negative correlation. Values inside the cells represent the correlation coefficients.

3.3. Results of Classification Models After Applying a Feature Selection Technique

The method applied for feature selection was CFS, as defined in [2,40], which was used to select highly correlated features from the obtained signal, utilizing a threshold for the correlation coefficient $r \geq 0.96$. The correlation values of the removed variables ranged from 0.96 to 0.99, confirming the high level of correlation. In total, two variables were eliminated, and the final set of features, including those selected and those excluded, is detailed in Table 5, except for the target variable for the models, which is the group variable.

Table 5. Features removed and selected to be applied to ml models after the CFS technique.

Method	Features Removed	Features Selected
CFS	MAVFD and PEAK	MAV, MAVSD, RANGE, STD, FR_Extension, FR_Flexion, W_Extension, W_Flexion, C_Extension, C_Flexion
Number	2	10

All 19 classification models were subjected to the pipeline presented in Table 3, which included an additional step to remove multicollinearity using a correlation threshold of 0.95.

The results shown in Table 6a were obtained by running the algorithms with the default parameters from the PyCaret library, in Table 6b are presented the main performance metrics obtained for each classifier after the hyperparameters optimization. Evaluating the

19 models using the 10 selected features, after CFS, the ET, QDA, MLP, GPC, NB, and ADA algorithms achieved the best performance on the testing data without hyperparameter tuning as presented in Table 6c. After hyperparameters optimization and CFS, six classification models stood out for their performance improvements. Table 6d summarizes the resulting performance metrics for the top six models, enabling an identification of the most robust classifiers within this optimized feature space.

Table 6. Classification model results considering raw data (a), Top 6 Classification models after systematic hyperparameter optimization (b), Top 6 Classification models after CFS (c) and Top 6 Classification models after hyperparameter optimization and CFS (d).

Item	Model	All 19 Classification Models with Default Parameters						
		Acc	Sen	Spe	Pre	F1	AUC	MCC
(a)	QDA	0.889	1.000	0.778	0.818	0.900	0.852	0.798
	LDA	0.778	0.667	0.889	0.857	0.750	0.741	0.570
	GPC	0.778	0.556	1.000	1.000	0.714	0.790	0.620
	SVM	0.722	0.778	0.667	0.700	0.737	0.722	0.447
	ET	0.722	0.667	0.778	0.750	0.706	0.864	0.447
	GBC	0.722	0.667	0.778	0.750	0.706	0.728	0.447
	DT	0.722	0.556	0.889	0.833	0.667	0.722	0.471
	MLP	0.722	0.556	0.889	0.833	0.667	0.815	0.471
	NB	0.722	0.556	0.889	0.833	0.667	0.728	0.471
	LR	0.667	0.667	0.667	0.667	0.667	0.691	0.333
	RBFSVM	0.667	0.667	0.667	0.667	0.667	0.815	0.333
	RIDGE	0.667	0.667	0.667	0.667	0.667	0.667	0.333
	CATBOOST	0.667	0.556	0.778	0.714	0.625	0.815	0.342
	LIGHTGBM	0.667	0.556	0.778	0.714	0.625	0.741	0.342
	RF	0.667	0.556	0.778	0.714	0.625	0.778	0.342
	XGBOOST	0.667	0.556	0.778	0.714	0.625	0.778	0.342
	KNN	0.611	0.556	0.667	0.625	0.588	0.679	0.224
	ADA	0.611	0.444	0.778	0.667	0.533	0.704	0.236
	DUMMY	0.500	0.000	1.000	0.000	0.000	0.500	0.000
Item	Model	Top 6 Classification models after hyperparameter optimization						
(b)	QDA	0.889	1.000	0.778	0.818	0.900	0.852	0.798
	KNN	0.778	0.667	0.889	0.857	0.750	0.778	0.570
	RBFSVM	0.778	0.667	0.889	0.857	0.750	0.889	0.570
	GPC	0.778	0.556	1.000	1.000	0.714	0.790	0.620
	LDA	0.778	0.667	0.889	0.857	0.750	0.704	0.447
	NB	0.722	0.556	0.889	0.833	0.667	0.728	0.471
Item	Model	Top 6 Classification models after CFS						
(c)	ET	0.833	0.667	1.000	1.000	0.800	0.907	0.707
	DT	0.778	0.667	0.889	0.857	0.750	0.778	0.570
	QDA	0.778	0.667	0.889	0.857	0.750	0.802	0.570

Table 6. Cont.

(c)	GPC	0.778	0.556	1.000	1.000	0.714	0.778	0.620
	NB	0.778	0.556	1.000	1.000	0.714	0.790	0.620
	RF	0.778	0.556	1.000	1.000	0.714	0.802	0.620
Item	Model	Top 6 Classification models after hyperparameter optimization and CFS						
(d)	QDA	0.778	0.667	0.889	0.857	0.750	0.802	0.570
	RBFSVM	0.778	0.667	0.889	0.857	0.750	0.864	0.570
	GPC	0.778	0.556	1.000	1.000	0.714	0.778	0.620
	KNN	0.778	0.667	0.889	0.857	0.750	0.778	0.570
	NB	0.778	0.556	1.000	1.000	0.714	0.765	0.620
	ADA	0.778	0.667	0.889	0.857	0.750	0.728	0.570

Acc—Mean of Accuracy; Sen—Mean of Sensitivity; Spe—Mean of Specificity, Pre—Mean of Precision, F1—F-score (%), AUC—Area Under the Curve [0,1] *; and MCC—Matthews Correlation Coefficient [−1, 1] *. *—interval of values.

Following the initial analysis using the features selected by the CFS technique, hyperparameter optimization was performed to refine the performance of the classifiers. For this stage, the same optimization pipeline detailed in Table 4 was employed, maintaining methodological standardization and ensuring a direct and equitable comparison with the results previously obtained for the complete feature set. In a manner analogous to the previous analysis, all models were optimized using the reduced feature set and subsequently applied to the test data for final evaluation.

The QDA maintained the highest accuracy at 0.778, confirming its robustness across both before and after the FS technique. The RBFSVM also improved, reaching 0.778 accuracy with a precision of 0.857. KNN also achieved an accuracy of 0.778 with a precision of 0.857 on the test set, representing one of the most significant relative gains compared to its baseline. GPC and NB achieved comparable results, with accuracies of 0.778, underscoring the positive impact of the optimization process on classifier performance, as shown in Figure 10.

Impact of the Optimization after the technique of CFS on Mean Accuracy - The Top 6 Models

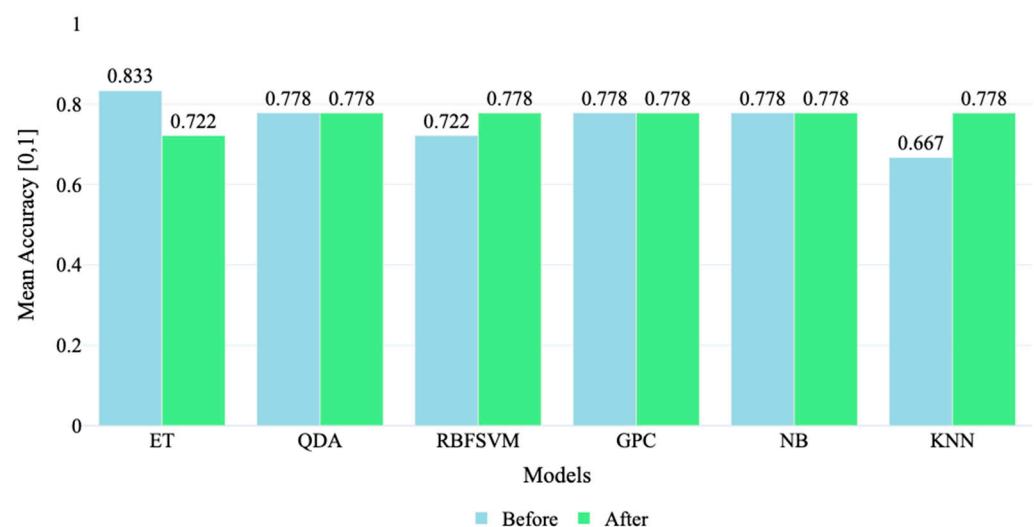


Figure 10. Impact of CFS Optimization on Mean Accuracy of the Top 6 Models.

Figure 11 presents the confusion matrices of the three best performing models—the QDA, KNN, and RBFSVM—which served as the basis for the calculation of the metrics

reported in Table 6b. These results highlight the classifiers' ability to consistently distinguish GPD from GHC in the test set, reinforcing the robustness of the applied framework process.

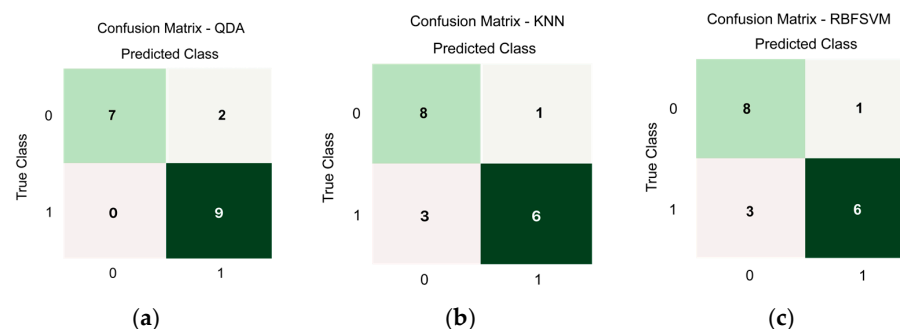


Figure 11. Confusion matrices of the QDA (a), KNN (b), and RBFSVM (c) models on the test set after CFS feature selection.

Figures 12 and 13 present the feature importance analyses for the ADA and CATBOOST classification models, respectively. It is important to note that the RBFSVM algorithm does not provide a native mechanism for estimating feature importance, as it relies on kernel functions, which prevents a direct assessment of the most influential variables.

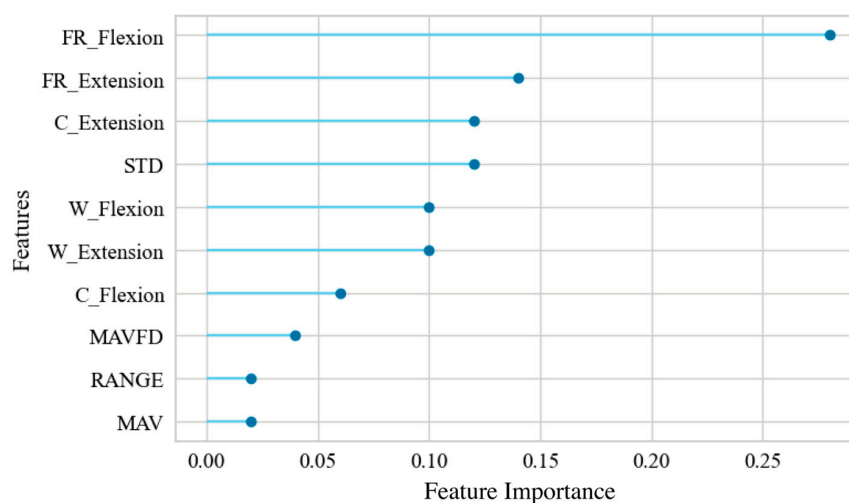


Figure 12. Feature importance of the ADA model after CFS feature selection.

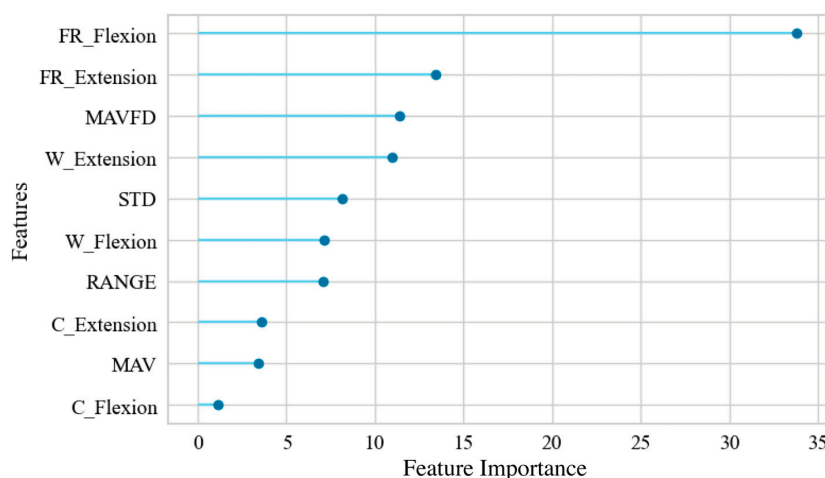


Figure 13. Feature importance of the CATBOOST model after CFS feature selection.

Therefore, the analysis was restricted to models capable of internally generating these estimates. In this context, ADA and CATBOOST were selected as representative algorithms. Notably, both models achieved performance metrics on the independent test set after optimization, reaching an accuracy of 0.778 and 0.700, respectively, and a precision of 0.857 for ADA. These results provide further insight into the contribution of specific biomechanical features to the classification task, enhancing the interpretability of the proposed approach.

3.4. Comparative Analysis of Model Accuracy Before and After Feature Selection

Figure 14 compares the average accuracy of the six top-performing classification models before the optimization process using the pipeline shown in Table 4, under two conditions: using the complete feature set and after applying the CFS feature selection technique.

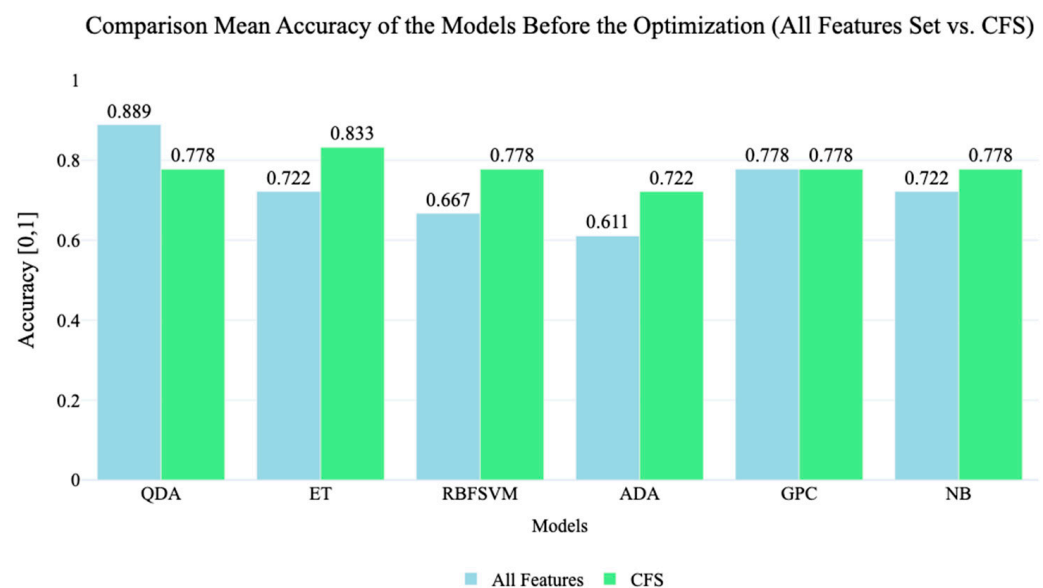


Figure 14. Comparative Analysis of Accuracy before the optimization: All features x CFS.

The accuracy of the QDA model, which initially performed best without hyperparameter optimization on the full feature set, decreased from 0.889 to 0.778, while GPC showed a constant result after feature reduction. In contrast, the ET improved from 0.722 to 0.833, RBFSVM from 0.667 to 0.778, ADA from 0.611 to 0.722, and NB from 0.722 to 0.778, showing significant gains in accuracy.

3.5. Robustness and Generalization Analysis

To assess the stability of the proposed solution and ensure that the reported performance was not an artifact of a specific data partition, a comprehensive robustness analysis was conducted. We evaluated the impact of varying the training set size (50–90%) and the internal validation strategy on the model's generalization performance. Figures 15 and 16 show how test accuracy changed for the Top 6 performing models, applied to All Features, before and after hyperparameter optimization.

Complementarily, Figure 17 presents the distribution of test accuracy across the 5-fold cross-validation scenarios. The compact boxplots, particularly at the chosen 80% training split, indicate low variance among the variances, confirming that the models are learning robust patterns rather than overfitting to specific data subsets.

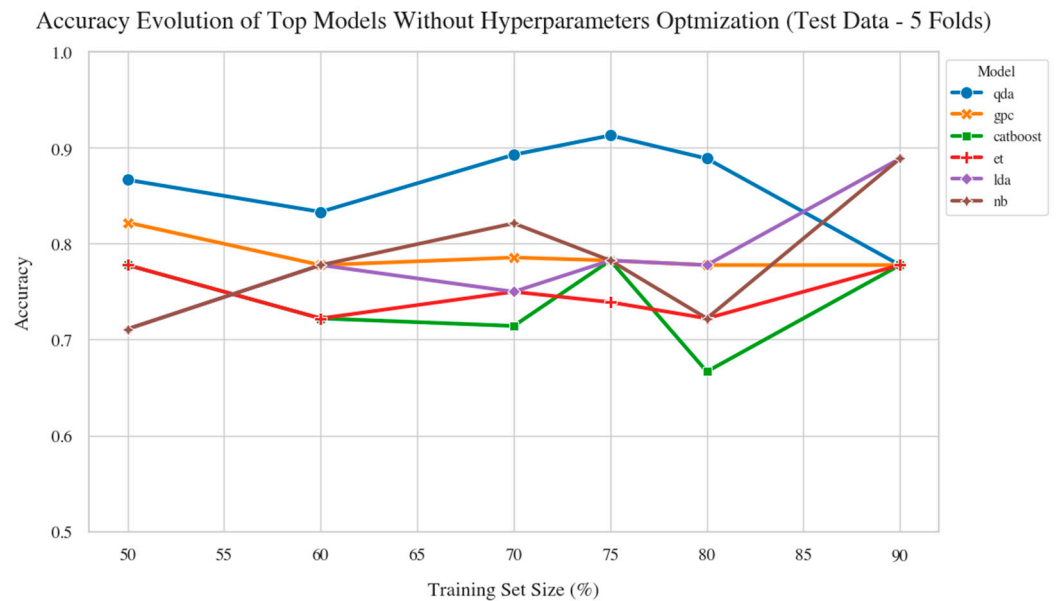


Figure 15. Test accuracy evolution of the Top 6 models across varying training set sizes (50% to 90%) using Stratified Group K-Fold ($k = 5$) for All Features without optimization considering the test data.

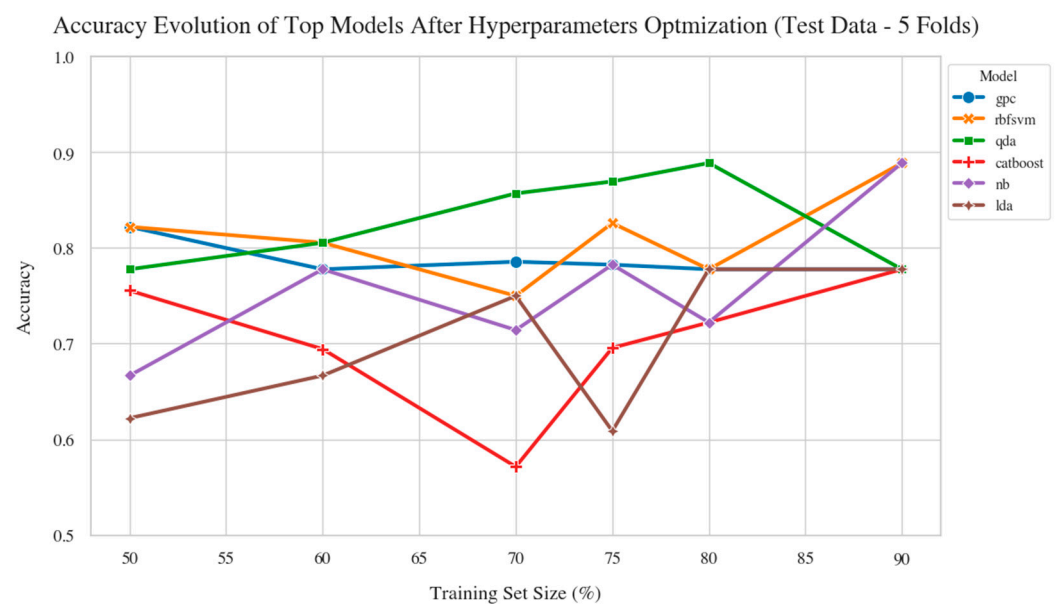


Figure 16. Test accuracy evolution of the Top 6 models across varying training set sizes (50% to 90%) using Stratified Group K-Fold ($k = 5$) for All Features after optimization considering the test data.

Beyond binary classification, it is crucial to understand how biomechanical characteristics relate to clinical severity. A complementary multiple linear regression analysis, using the 12 characteristics extracted from the GPD, demonstrated the ability to predict specific stiffness scores (item 3.3 of the MDS-UPDRS). The model achieved an coefficient of determination (R^2) of 0.682, indicating that biomechanical metrics explain approximately 68.2% of the variability observed in clinical scores, with a Mean Squared Error (RMSE) of 1.25 points.

Considering the results presented, the next section provides an interpretation of these findings and compares them with previously published studies.

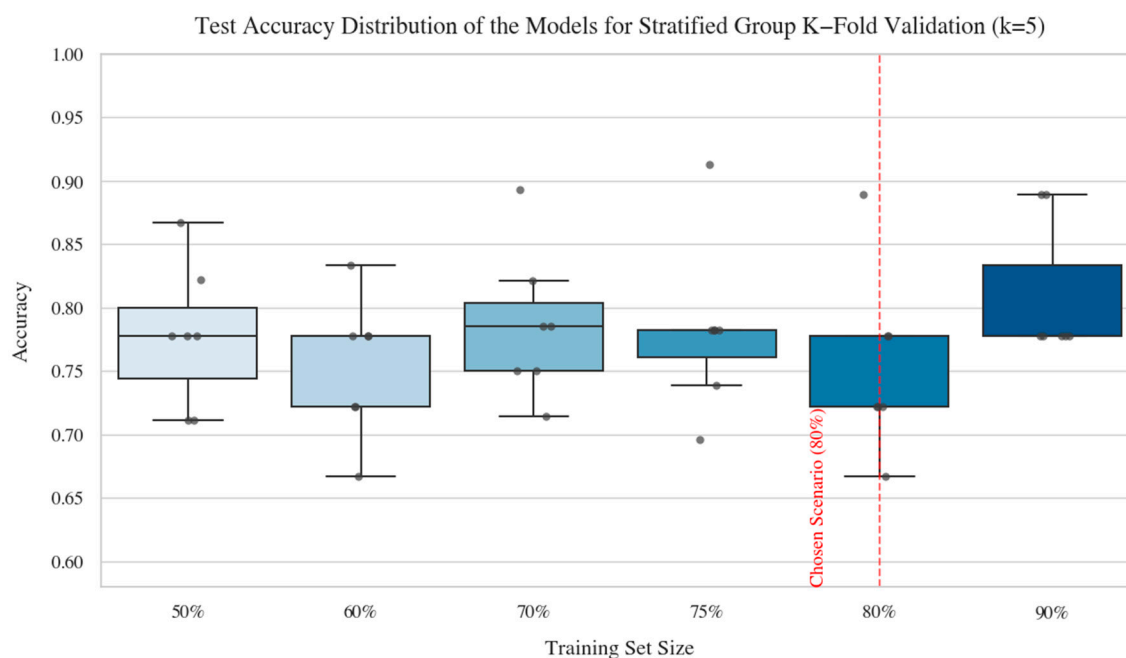


Figure 17. Distribution of test accuracy for the Top 6 models across training partitions (50% to 90%) using Stratified Group K-Fold ($k = 5$). The dashed line indicates the 80% scenario.

4. Related Works Section

There is significant growth in studies on PD, but current studies on objective methods for assessing rigidity, specifically wrist rigidity and biomechanical movements, are still few. Table 7 presents articles that evaluated wrist rigidity using biomechanical wrist data for rigidity assessment. Table 7 summarizes key quantitative methods for assessing wrist rigidity in PD. The comparison highlights three factors: (i) Measurement, (ii) Analysis Focus, and (iii) Wrist Movement.

Table 7. Comparison of related research on quantitative wrist rigidity assessment, highlighting methodological differences and research gaps.

Study	Measurement	Analysis Focus	Wrist Movement
Formica et al. (2012) [21]	Torque, displacement angle and Electromyography (EMG)	Statistical	Automatic
Powell et al. (2012) [22]	Torque, displacement angle and EMG	Statistical	Automatic
Raiano et al. (2020) [23]	Torque and displacement angle	Statistical	Automatic
Zito et al. (2018) [24]	Torque and displacement angle	Statistical	Automatic
Costa et al. (2015) [25]	Angular Speed	Statistical and sensitivity	A professional is needed to perform the flexion and extension movement.
Lopes et al. (2019) [26]	Angular Speed	Accuracy	A professional is needed to perform the flexion and extension movement.
Assis et al. (2016) [27]	Angular Speed	Polynomial mathematical model	A professional is needed to perform the flexion and extension movement.

Table 7. Cont.

Study	Measurement	Analysis Focus	Wrist Movement
MUTLU (2019) [28]	Force and displacement angle	Comparison between physician scores and scores on the scale used in the paper.	Automatic
Proposed study	Force and displacement angle	ML Classification (Stratified Group K-Fold)	Automatic

As shown in the final row of Table 7, our work extends these foundations by integrating a custom-built active wrist orthosis with a comprehensive ML framework. Additionally, the study employs a stratified group K-fold validation strategy on a balanced dataset to ensure robust and generalizable classification performance.

5. Discussion

5.1. Baseline Characteristics

Statistical analyses confirmed that the GPD and GHC were comparable in age, with Shapiro–Wilk and Levene’s tests indicating normal distribution and homogeneity of variances, respectively. Student’s *t*-test revealed no significant age difference between groups, ensuring that age-related effects did not confound subsequent analyses. After confirming group comparability, motor outcomes were evaluated.

5.2. Neurodegenerative Diseases

Neurodegenerative diseases (ND) are characterized by progressive deterioration of neurons. Currently, there is no cure for ND, only treatments to alleviate symptoms. Early diagnosis of ND is very important to allow intervention before ND sets in, as the progression of ND can be slowed when therapies are applied in the early stages of ND [53].

5.3. ML Discussion

This study used three repeated measures for each participant. Repeated measures are data collected several times from the same individual [17]. However, repeated measures are correlated with each other. Traditional statistical methods use indirect measures to circumvent this problem, but machine learning models can be modeled using repeated measures directly [17].

With this method, it is possible to build a model that incorporates repeated measures [17]. There are several types of repeated measures and data in the biomedical field, such as data collected by healthcare professionals and sensor data. Repeated measures are increasingly common in multivariate prediction research [54]. For this reason, one application for repeated measures in conjunction with machine learning to support early diagnosis of neurodegenerative diseases (ND), including PD, allows for early intervention in ND [53]. There is growing interest in applying ML to PD diagnosis. The metrics used in our research are the most widely used among researchers applying ML to PD diagnosis [45,55].

The initial modeling phase involved applying all classifiers to the complete set of 12 biomechanical features to establish a performance baseline. This approach yielded high classification accuracy, demonstrating the predictive potential of the raw data. Specifically, QDA achieved the highest performance with an accuracy of 0.889. Following hyperparameter optimization, models such as RBFSVM, KNN, GPC, and LDA also achieved competitive results, reaching an accuracy of 0.778. This result is very important and positive when compared with the clinical diagnosis, since in the clinical diagnosis, the accuracy is 73.8%

when performed by non-specialists, with the diagnostic accuracy being on average 79.6% when the PD diagnosis is performed by movement disorders specialists, and increases to 83.9% after monitoring the individual with PD [5].

While promising, these initial results were based on a feature set with known multicollinearity, as shown in the correlation heatmap in Figure 9, which could limit the model's generalizability and interpretability. This finding directly motivated the subsequent application of the CFS method [56].

To build more robust and parsimonious models, CFS was applied. The impact of this feature reduction on the performance of the top six models is illustrated in the comparative graph, Figure 14. The analysis reveals a notable shift in the best-performing algorithms: models sensitive to redundant features, such as QDA, saw a decrease in accuracy. In contrast, models as ET, ADA and NB, showed significant performance gains, with their accuracies rising to 0.833, 0.722 and 0.778, respectively. This outcome highlights a key finding: feature selection was crucial for filtering noise and allowing more robust algorithms to achieve high, stable performance, leading to a final set of models that are not only accurate but also less complex. These results corroborate the results of [57], who also obtained an improvement in the accuracy results of the classifiers when using the CFS method.

The top models after the CFS and hyperparameter optimization, especially QDA, GPC, and RBFSVM, achieved accuracies of 0.778 on the independent test set, with high specificity, precision, and F1-scores. These results highlight not only the strong discriminative ability of the proposed biomechanical biomarkers but also the robustness of the optimization process, which consistently enhanced predictive performance across various algorithms. The QDA model was the most accurate, while GPC and NB demonstrated exceptional specificity and precision, highlighting the importance of using different models when analyzing diverse clinical conditions, such as PD. In [58], the authors evaluated the fluctuations in the individual's vocal pattern for the diagnosis of PD, they found that ET had the highest accuracy, in agreement with our results.

Another important finding concerns the feature importance analysis, which revealed consistent patterns across different algorithms. Despite methodological differences between ADA and CATBOOST, both models consistently ranked Force Rate and Work features, such as *FR_Flexion*, *FR_Extension*, *W_Flexion* and *W_Extension* among the most influential variables. This convergence suggests that these biomechanical parameters are reliable markers of rigidity, capturing altered neuromuscular effort and movement dynamics in individuals with PD. Our result corroborates [16], where the authors also found that the characteristics Force Rate during flexion and Work during flexion were among those that had the greatest influence on the final model. These two characteristics were used to characterize stiffness. On the other hand, Charge did not play a role that substantially influenced the model of [16], as occurred in our research.

The agreement between tree-based methods with different learning strategies enhances the interpretability of the models and supports the clinical relevance of the proposed biomarkers.

Compared to other modalities studied in the literature, the present findings are especially significant. Several studies have focused on acoustic biomarkers, using sustained phonation and speech-based features to train ML models. For example, refs. [47,48] found that gradient boosting and support vector machines achieved over 80% accuracy in detecting PD from voice signals. Likewise, ref. [50] employed semi-supervised learning for dysphonic voice classification, confirming the predictive power of acoustic parameters. Although promising, these methods are naturally influenced by external factors, such as recording quality and comorbid vocal impairments, which can limit their generalizabil-

ity. In contrast, rigidity measurements directly assess a cardinal motor symptom of PD, providing a more specific and clinically relevant biomarker.

Another critical research area involves gait analysis, which has been widely studied as a source of digital biomarkers for PD [2,59,60]. For example, systematically using ML on gait parameters and identifying clinically relevant features for early-stage classification, achieving performance similar to voice-based methods. These techniques benefit from capturing whole-body motor changes, but they also require larger and more complex data collection setups, which may not be practical in routine clinical settings. Compared to gait studies, the orthosis-based approach described here offers a more controlled, reproducible, and focused assessment of rigidity, with the added benefits of portability and suitability for outpatient or home use.

Multiple linear correlation resulted in an R^2 of 0.682, this suggests that the active orthosis captures not only the presence of the disease (classification) but also quantitative nuances of symptom severity, aligning with findings from similar study [16].

Taken together, these findings highlight the novel contribution of this study: using a wearable device to produce quantitative rigidity biomarkers that match the classification performance of well-established methods such as speech and gait analysis. By incorporating feature selection and systematic hyperparameter tuning, the methodology ensured consistent improvements across models, achieving performance levels comparable to those of state-of-the-art approaches.

Beyond its technical strengths, the proposed framework offers direct clinical relevance by addressing one of the most challenging aspects of Parkinson's Disease diagnosis: the subjectivity of rigidity assessment. As a result, this work not only demonstrates the potential of using orthosis-derived features for PD classification but also opens the door for broader use of objective, sensor-based tools in clinical neurology.

5.4. Future Work

Future work will focus on two main directions. The first targets the physical improvement of the active wrist orthosis. Immediate objectives include adding ergonomic features to boost user comfort and fit during assessments. This involves testing lighter materials, optimizing the device's shape for better weight distribution, and improving the forearm and hand-fastening systems.

These upgrades are vital for reducing participant effort, which is crucial for supporting long-term studies and potentially enabling the device to be used in home-based monitoring settings.

The second approach focuses on improving the system's software features and clinical applications. We plan to develop modules for automated report generation and real-time feedback, providing clinicians and patients with immediate, actionable information insights.

Longitudinal studies must be conducted to collect periodic measurements from a larger patient cohort over an extended period. This protocol will allow us to build a more robust database, capture the trajectory and fluctuations of rigidity over time, and systematically to analyze the impact of confounding variables. Such a dataset will be crucial for developing more precise and clinically generalizable predictive models.

5.5. Limitations of the Study

The findings of this study should be viewed with some limitations in mind. The main limitation is the small sample size, which could restrict the statistical power and how well our results apply to the larger population of people with PD. Although our validation method, including cross-validation and a hold-out test set, was meant to reduce overfitting,

confirming the results with a larger and more diverse group is needed. Additionally, this initial analysis did not consider potential confounding factors, like medication status or comorbidities, which are known to affect motor symptoms in PD.

Although all participants were assessed in the ‘OFF’ medication state to standardize the evaluation, the current sample size limited our ability to perform stratified analyses by specific disease stages or distinct motor phenotypes (e.g., tremor-dominant vs. akinetic-rigid). Consequently, the generalizability of the results to specific PD subgroups remains to be confirmed in larger cohorts.

The results of this study cannot be generalized. Our study was able to differentiate the PD group from the HC group. Future research should include groups with other neurological diseases with rigidity, aiming to generalize the method used.

6. Conclusions

This study presents a proof-of-concept demonstrating the feasibility and effectiveness of using ML models to classify individuals with PD based on wrist rigidity data collected by an active orthosis. The main goal was to address the limitations of subjective clinical assessments by developing an objective and quantitative diagnostic method. The method was validated using a K-fold strategy in stratified groups to ensure generalization, our results indicate strong performance in the classification task. Using all twelve rigidity-related features extracted from the orthosis, the QDA algorithm achieved the highest accuracy of 0.889, followed by LDA and GPC with an accuracy of 0.778 for all features without hyperparameter optimization, demonstrating significant discriminative ability. After applying feature selection with CFS to reduce redundancy, the ET model still achieved a high accuracy of 0.833, while QDA, GPC, and NB all reached 0.778. The consistency of these high-performance results, even with a reduced feature set, highlights the robustness of the biomechanical signals captured. Overall, the optimization process increased the average accuracy of the best models, further reinforcing the robustness of the biomechanical signals. These findings emphasize the potential of combining custom hardware with advanced ML techniques as a reliable diagnostic support tool for Parkinson’s Disease. The performance not only validates our methodology but also establishes it as a significant contribution to the field of motor assessment in PD. Unlike other ML approaches that rely on speech or gait data, directly measuring rigidity provides discriminative quantitative information between PD patients and HC and may serve as a tool to support PD classification, although further validation in larger and independent cohorts is required. This highlights the potential of our tool to support diagnosis and deliver objective metrics for tracking disease progression or response to treatment. In conclusion, combining an active wrist orthosis with ML models presents a strong method for objectively assessing PD, with the potential to improve diagnostic accuracy and support ongoing patient monitoring.

Author Contributions: Conceptualization, A.A.P., D.H.d.S. and C.T.R.; methodology, A.A.P., D.H.d.S., C.T.R., C.V.d.Q., L.C.M. and L.R.d.S.S.; software, A.A.P., D.H.d.S., C.T.R. and L.R.d.S.S.; validation, D.H.d.S., C.T.R. and L.R.d.S.S.; investigation, A.A.P., D.H.d.S., C.T.R., C.V.d.Q. and L.C.M.; resources, A.A.P., D.H.d.S., C.T.R., S.T.M. and C.V.d.Q.; data curation, A.A.P., D.H.d.S. and C.T.R.; writing—original draft preparation, D.H.d.S., A.A.P., C.T.R., L.C.M., L.R.d.S.S., STM and C.V.d.Q.; writing—review and editing, A.A.P., D.H.d.S., C.T.R., L.C.M., S.T.M. and L.R.d.S.S.; visualization, A.A.P., D.H.d.S., C.T.R., C.V.d.Q., L.C.M., L.R.d.S.S., A.d.O.A. and C.D.M.; supervision, A.A.P., A.d.O.A. and C.D.M.; project administration, A.A.P., A.d.O.A. and C.D.M.; funding acquisition, A.A.P., D.H.d.S., L.R.d.S.S., S.T.M., A.d.O.A. and C.D.M. All authors have read and agreed to the published version of the manuscript.

Funding: This work is sponsored by the National Council for Scientific and Technological Development (444437/2024-0, 442150/2023-7, 405365/2023-3, 302942/2022-0, 309525/2021-7 and

304389/2022-6), the Foundation for Research Support of the State of Minas Gerais (FAPEMIG APQ-05015-24) and the Coordination for Improvement of Higher Education Personnel.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the local ethics committee (CAAE84004924.1.0000.5152), approved on 4 November 2024.

Informed Consent Statement: Written informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are not publicly available due to privacy restrictions.

Acknowledgments: The present work was carried out with the support of the Ministry of Science, Technology, Innovation, and Communications (MCTIC); Federal Institute of Education, Science, and Technology Goiano (IF Goiano), National Council for Scientific and Technological Development, Coordination for the Improvement of Higher Education Personnel (CAPES), Foundation for Research Support of the State of Minas Gerais. AOA (302942/2022-0), AAP (309525/2021-7) and CDM (304389/2022-6) are CNPq fellows.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PD	Parkinson's Disease
HC	Healthy Control
GPD	Parkinson's Disease Group
GHC	Healthy Control Group
ML	Machine Learning
AI	Artificial Intelligence
CFS	Correlation-Based Feature Subset
MDS-UPDRS	Movement Disorder Society—Unified Parkinson's Disease Rating Scale
NIATS	Center for Innovation and Health Technology Assessment
MAV	Mean Absolute Value
MAVSD	Mean Absolute Value of the Second Difference
MAVFD	Mean Absolute Value of the First Difference
STD	Standard Deviation
FR	Force–Angle Slope
C	Electrical Charge
W	Work
AUC	Area Under the Curve
F1	F1-Score (harmonic mean of precision and sensitivity)
MCC	Matthews Correlation Coefficient
OFF	Medication withdrawal state in PD testing
CI	Confidence Interval
SE	Standard Error

References

1. Perez, C.; Roca, Y.C.; Naranjo, L.; Martin, J. Diagnosis and Tracking of Parkinson's Disease by using Automatically Extracted Acoustic Features. *J. Alzheimers Dis. Park.* **2016**, *6*, 1000260. [[CrossRef](#)]
2. Rehman, R.Z.U.; Del Din, S.; Guan, Y.; Yarnall, A.J.; Shi, J.Q.; Rochester, L. Selecting Clinically Relevant Gait Characteristics for Classification of Early Parkinson's Disease: A Comprehensive Machine Learning Approach. *Sci. Rep.* **2019**, *9*, 17269. [[CrossRef](#)] [[PubMed](#)]

3. Dorsey, E.R.; Elbaz, A.; Nichols, E.; Abbasi, N.; Abd-Allah, F.; Abdelalim, A.; Adsuar, J.C.; Ansha, M.G.; Brayne, C.; Choi, J.-Y.J.; et al. Global, regional, and national burden of Parkinson's disease, 1990–2016: A systematic analysis for the Global Burden of Disease Study 2016. *Lancet Neurol.* **2018**, *17*, 939–953. [\[CrossRef\]](#)
4. Jankovic, J. Parkinson's disease: Clinical features and diagnosis. *J. Neurol. Neurosurg. Psychiatry* **2008**, *79*, 368–376. [\[CrossRef\]](#)
5. Rizzo, G.; Copetti, M.; Arcuti, S.; Martino, D.; Fontana, A.; Logroscino, G. Accuracy of clinical diagnosis of Parkinson disease. *Neurology* **2016**, *86*, 566–576. [\[CrossRef\]](#)
6. Li, M.; Ye, X.; Huang, Z.; Ye, L.; Chen, C. Global burden of Parkinson's disease from 1990 to 2021: A population-based study. *BMJ Open* **2025**, *15*, e095610. [\[CrossRef\]](#)
7. Massano, J.; Bhatia, K.P. Clinical approach to Parkinson's disease: Features, diagnosis, and principles of management. *Cold Spring Harb. Perspect. Med.* **2012**, *2*, a008870. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Mak, M.K.Y.; Wong, E.C.Y.; Hui-Chan, C.W.Y. Quantitative measurement of trunk rigidity in parkinsonian patients. *J. Neurol.* **2007**, *254*, 202–209. [\[CrossRef\]](#)
9. Ferreira-Sánchez, M.d.R.; Moreno-Verdú, M.; Cano-de-la-Cuerda, R. Quantitative Measurement of Rigidity in Parkinson's Disease: A Systematic Review. *Sensors* **2020**, *20*, 880. [\[CrossRef\]](#)
10. Armstrong, M.J.; Okun, M.S. Diagnosis and Treatment of Parkinson Disease. *JAMA* **2020**, *323*, 548. [\[CrossRef\]](#)
11. Cabreira, V.; Massano, J. Doença de Parkinson: Revisão Clínica e Atualização. *Acta Med. Port.* **2019**, *32*, 661–670. [\[CrossRef\]](#)
12. Di Biase, L.; Summa, S.; Tosi, J.; Taffoni, F.; Marano, M.; Cascio Rizzo, A.; Vecchio, F.; Formica, D.; Di Lazzaro, V.; Di Pino, G.; et al. Quantitative Analysis of Bradykinesia and Rigidity in Parkinson's Disease. *Front. Neurol.* **2018**, *9*, 121. [\[CrossRef\]](#)
13. Sepehri, B.; Esteki, A.; Ebrahimi-Takamjani, E.; Shahidi, G.-A.; Khamseh, F.; Moinodin, M. Quantification of Rigidity in Parkinson's Disease. *Ann. Biomed. Eng.* **2007**, *35*, 2196–2203. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Bruder, A.M.; Taylor, N.F.; Dodd, K.J.; Shields, N. Physiotherapy intervention practice patterns used in rehabilitation after distal radial fracture. *Physiotherapy* **2013**, *99*, 233–240. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Mitsukane, M.; Sekiya, N.; Himei, S.; Oyama, K. Immediate Effects of Repetitive Wrist Extension on Grip Strength in Patients with Distal Radial Fracture. *Arch. Phys. Med. Rehabil.* **2015**, *96*, 862–868. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Perera, T.; Lee, W.L.; Jones, M.; Tan, J.L.; Proud, E.L.; Begg, A.; Sinclair, N.C.; Peppard, R.; McDermott, H.J. A palm-worn device to quantify rigidity in Parkinson's disease. *J. Neurosci. Methods* **2019**, *317*, 113–120. [\[CrossRef\]](#)
17. Lee, J.H.; Kang, D.R. From Traditional Statistical Methods to Machine and Deep Learning for Prediction Models. *Cardiovasc. Prev. Pharmacother.* **2020**, *2*, 50. [\[CrossRef\]](#)
18. Gaprielian, P.; Scott, S.H.; Lowrey, C.; Reid, S.; Pari, G.; Levy, R. Integrated robotics platform with haptic control differentiates subjects with Parkinson's disease from controls and quantifies the motor effects of levodopa. *J. Neuroeng. Rehabil.* **2019**, *16*, 124. [\[CrossRef\]](#)
19. Alves, C.M.; Rezende, A.R.; Marques, I.A.; Mendes, L.C.; de Sá, A.A.R.; Vieira, M.F.; Júnior, E.A.L.; Pereira, A.A.; Oliveira, F.H.M.; de Souza, L.P.S.; et al. Wrist Rigidity Evaluation in Parkinson's Disease: A Scoping Review. *Healthcare* **2022**, *10*, 2178. [\[CrossRef\]](#)
20. Raiano, L.; Di Pino, G.; Noccato, A.; Accoto, D.; Formica, D. Design of a Wearable Mechatronic Device to Measure the Wrist Rigidity in Parkinson's Disease Patients. In Proceedings of the 2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob), Enschede, The Netherlands, 26–29 August 2018; IEEE: New York, NY, USA, 2018; pp. 497–502. [\[CrossRef\]](#)
21. Formica, D.; Charles, S.K.; Zollo, L.; Guglielmelli, E.; Hogan, N.; Krebs, H.I. The passive stiffness of the wrist and forearm. *J. Neurophysiol.* **2012**, *108*, 1158–1166. [\[CrossRef\]](#)
22. Powell, D.; Threlkeld, A.J.; Fang, X.; Muthumani, A.; Xia, R. Amplitude- and velocity-dependency of rigidity measured at the wrist in Parkinson's disease. *Clin. Neurophysiol.* **2012**, *123*, 764–773. [\[CrossRef\]](#)
23. Raiano, L.; di Pino, G.; di Biase, L.; Tombini, M.; Tagliamonte, N.L.; Formica, D. PDMeter: A Wrist Wearable Device for an at-Home Assessment of the Parkinson's Disease Rigidity. *IEEE Trans. Neural Syst. Rehabil. Eng.* **2020**, *28*, 1325–1333. [\[CrossRef\]](#)
24. Zito, G.A.; Gerber, S.M.; Urwyler, P.; Shamsollahi, M.J.; Pal, N.; Benninger, D.; Nef, T. Development and Pilot Testing of a Novel Electromechanical Device to Measure Wrist Rigidity in Parkinson's Disease. In Proceedings of the 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 18–21 July 2018; IEEE: New York, NY, USA, 2018; pp. 4885–4888. [\[CrossRef\]](#)
25. Costa, P.; Rosas, M.J.; Vaz, R.; Cunha, J.P. Wrist rigidity assessment during Deep Brain Stimulation surgery. In Proceedings of the 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, Italy, 25–29 August 2015; IEEE: New York, NY, USA, 2015; pp. 3423–3426. [\[CrossRef\]](#)
26. Lopes, E.M.; Sevilla, A.; Vilas-Boas, M.D.C.; Choupina, H.M.P.; Nunes, D.P.; Rosas, M.J.; Oliveira, A.; Massano, J.; Vaz, R.; Cunha, J.P.S. iHandU: Towards the Validation of a Wrist Rigidity Estimation for Intraoperative DBS Electrode Position Optimization. In Proceedings of the 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER), San Francisco, CA, USA, 20–23 March 2019; IEEE: New York, NY, USA, 2019; pp. 449–452. [\[CrossRef\]](#)

27. Assis, S.; Costa, P.; Rosas, M.J.; Vaz, R.; Cunha, J.P.S. An adaptive model approach for quantitative wrist rigidity evaluation during deep brain stimulation surgery. In Proceedings of the 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 16–20 August 2016; IEEE: New York, NY, USA, 2016; pp. 5809–5812. [\[CrossRef\]](#)
28. Mutlu, N.O.; Akbostanci, M.C.; Ari, F.; Karaarslan, F.T. Development of Methods to Detect Movement Disorders in Parkinson's Disease. In Proceedings of the 2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, 11–13 October 2019; IEEE: New York, NY, USA, 2019; pp. 1–7. [\[CrossRef\]](#)
29. Vinutha, H.P.; Poornima, B.; Sagar, B.M. *Detection of Outliers Using Interquartile Range Technique from Intrusion Dataset*; Springer: Berlin/Heidelberg, Germany, 2018; pp. 511–518. [\[CrossRef\]](#)
30. Ali, M. PyCaret: An Open Source, Low-Code Machine Learning Library in Python. Available online: <https://www.pycaret.org> (accessed on 28 January 2023).
31. Tolios, G. *Simplifying Machine Learning with PyCaret A Low-Code Approach for Beginners and Experts!* 1st ed.; Leanpub book: Victoria, BC, Canada, 2022; Volume 1.
32. Naranjo, L.; Pérez, C.J.; Campos-Roca, Y.; Martín, J. Addressing voice recording replications for Parkinson's disease detection. *Expert. Syst. Appl.* **2016**, *46*, 286–292. [\[CrossRef\]](#)
33. Tougui, I.; Jilbab, A.; El Mhamdi, J. Machine Learning Smart System for Parkinson Disease Classification Using the Voice as a Biomarker. *Healthc. Inform. Res.* **2022**, *28*, 210–221. [\[CrossRef\]](#)
34. Costa, S.C.; de Oliveira, A. *Avaliação Ergonômica de Uma Órtese Ativa de Punho Para a Reabilitação da Rigidez em Pessoas com a Doença de Parkinson*; Universidade Federal de Uberlândia: Uberlândia, Brazil, 2020.
35. Bhidayasiri, R.; Martinez-Martin, P. Clinical Assessments in Parkinson's Disease. *Int. Rev. Neurobiol.* **2017**, *132*, 129–182. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Van der Hoorn, A.; Burger, H.; Leenders, K.L.; de Jong, B.M. Handedness correlates with the dominant Parkinson side: A systematic review and meta-analysis. *Mov. Disord.* **2012**, *27*, 206–210. [\[CrossRef\]](#)
37. Barrett, M.J.; Wylie, S.A.; Harrison, M.B.; Wooten, G.F. Handedness and motor symptom asymmetry in Parkinson's disease. *J. Neurol. Neurosurg. Psychiatry* **2011**, *82*, 1122–1124. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Jeon, H.; Lee, W.; Park, H.; Lee, H.J.; Kim, S.K.; Kim, H.B.; Jeon, B.; Park, K.S. Automatic Classification of Tremor Severity in Parkinson's Disease Using a Wearable Device. *Sensors* **2017**, *17*, 2067. [\[CrossRef\]](#)
39. Kim, Y.-S.; Kim, M.K.; Fu, N.; Liu, J.; Wang, J.; Srebric, J. Investigating the impact of data normalization methods on predicting electricity consumption in a building using different artificial neural network models. *Sustain. Cities Soc.* **2025**, *118*, 105570. [\[CrossRef\]](#)
40. da Silva, D.H.; Ribeiro, C.T.; Souza, L.R.d.S.; Pereira, A.A. Application of Open-Source, Low-Code Machine-Learning Library in Python to Diagnose Parkinson's Disease Using Voice Signal Features. *Braz. Arch. Biol. Technol.* **2025**, *68*, e25230860. [\[CrossRef\]](#)
41. Rouvalis, A.; Tröger, J.; Steuer, J.; Arroyave, J.R.O.; Ruzs, J.; Pohjalainen, J.; Lindsay, H.; Möbius, B.; Klakow, D. Enhancing Detection of Parkinson-Induced Dysarthria with Cross-Lingual Transfer Learning. In *Lecture Notes in Computer Science*; Springer: Cham, Switzerland, 2026; pp. 218–234. [\[CrossRef\]](#)
42. Senturk, Z.K. Early diagnosis of Parkinson's disease using machine learning algorithms. *Med. Hypotheses* **2020**, *138*, 109603. [\[CrossRef\]](#)
43. Jain, D.; Singh, V. Feature selection and classification systems for chronic disease prediction: A review. *Egypt. Inform. J.* **2018**, *19*, 179–189. [\[CrossRef\]](#)
44. da Silva, D.H.; Ribeiro, C.T.; Souza, L.R.d.S.; Nardo, J.R.M.; Pereira, A.A. Exploring Essential Acoustic Features for Early Parkinson's Disease Classification: A Machine Learning Study. *Int. J. Online Biomed. Eng. (Ijoe)* **2025**, *21*, 98–120. [\[CrossRef\]](#)
45. Govindu, A.; Palwe, S. Early detection of Parkinson's disease using machine learning. *Procedia Comput. Sci.* **2023**, *218*, 249–261. [\[CrossRef\]](#)
46. Shapiro, S.S.; Wilk, M.B. An Analysis of Variance Test for Normality (Complete Samples). *Biometrika* **1965**, *52*, 591. [\[CrossRef\]](#)
47. Karabayir, I.; Goldman, S.M.; Pappu, S.; Akbilgic, O. Gradient boosting for Parkinson's disease diagnosis from voice recordings. *BMC Med. Inform. Decis. Mak.* **2020**, *20*, 228. [\[CrossRef\]](#)
48. Almeida, J.S.; Rebouças Filho, P.P.; Carneiro, T.; Wei, W.; Damaševičius, R.; Maskeliūnas, R.; de Albuquerque, V.H.C. Detecting Parkinson's disease with sustained phonation and speech signals using machine learning techniques. *Pattern Recognit. Lett.* **2019**, *125*, 55–62. [\[CrossRef\]](#)
49. Medeiros, T.A.; Saraiva, R.G.; Cassia, G.d.S.E.; Nascimento, F.A.d.O.; Carvalho, J.L.A.d. Classification of 1p/19q Status in Low-Grade Gliomas: Experiments with Radiomic Features and Ensemble-Based Machine Learning Methods. *Braz. Arch. Biol. Technol.* **2023**, *66*, e23230002. [\[CrossRef\]](#)
50. Bao, G.; Lin, M.; Sang, X.; Hou, Y.; Liu, Y.; Wu, Y. Classification of Dysphonic Voices in Parkinson's Disease with Semi-Supervised Competitive Learning Algorithm. *Biosensors* **2022**, *12*, 502. [\[CrossRef\]](#)

51. Özseven, T.; Özkorucu, Z.Ş. Optimization of Support Vector Machines for Prediction of Parkinson's Disease. *Meas. Sci. Rev.* **2023**, *23*, 1–10. [[CrossRef](#)]
52. Saeed, A.; Baber, J.; Abbas, M.Z.; Sajid, A.; Razzaq, H.; Khan, A.A. Improving the Imbalanced Data Accuracy Using CNN and ReLU. *IETI Trans. Data Anal. Forecast. (Itdaf)* **2024**, *2*, 50–58. [[CrossRef](#)]
53. Cascarano, A.; Mur-Petit, J.; Hernandez-Gonzalez, J.; Camacho, M.; de Toro Eadie, N.; Gkontra, P.; Chadeau-Hyam, M.; Vitrià, J.; Lekadir, K. Machine and deep learning for longitudinal biomedical data: A review of methods and applications. *Artif. Intell. Rev.* **2023**, *56*, 1711–1771. [[CrossRef](#)]
54. Plate, J.D.J.; van de Leur, R.R.; Leenen, L.P.H.; Hietbrink, F.; Peelen, L.M.; Eijkemans, M.J.C. Incorporating repeated measurements into prediction models in the critical care setting: A framework, systematic review and meta-analysis. *BMC Med. Res. Methodol.* **2019**, *19*, 199. [[CrossRef](#)]
55. Shokrpour, S.; Farid, A.M.; Abkenar, S.B.; Kashani, M.H.; Akbari, M.; Sarvzadeh, M. Machine learning for Parkinson's disease: A comprehensive review of datasets, algorithms, and challenges. *npj Parkinson's Dis.* **2025**, *11*, 187. [[CrossRef](#)] [[PubMed](#)]
56. Hall, M. *Correlation-Based Feature Selection for Discrete and Numeric Class Machine Learning*; University of Waikato: Hamilton, New Zealand, 2000.
57. Martinez-Eguiluz, M.; Arbelaiz, O.; Gurrutxaga, I.; Muguerza, J.; Perona, I.; Murueta-Goyena, A.; Acera, M.; Del Pino, R.; Tijero, B.; Gomez-Esteban, J.C.; et al. Diagnostic classification of Parkinson's disease based on non-motor manifestations and machine learning strategies. *Neural Comput. Appl.* **2023**, *35*, 5603–5617. [[CrossRef](#)]
58. Divya, J.; Radhakrishnan, P.; Pavithra, G.; Gopatoti, A.; Baburao, D.; Krishnamoorthy, R. Detection of Parkinson Disease using Machine Learning. In Proceedings of the 6th International Conference on Inventive Computation Technologies, ICICT 2023—Proceedings, Lalitpur, Nepal, 26–28 April 2023; pp. 53–57. [[CrossRef](#)]
59. Navita; Mittal, P.; Sharma, Y.K.; Rai, A.K.; Simaiya, S.; Lilhore, U.K.; Kumar, V. Gait-based Parkinson's disease diagnosis and severity classification using force sensors and machine learning. *Sci. Rep.* **2025**, *15*, 328. [[CrossRef](#)] [[PubMed](#)]
60. Li, W.; Chen, X.; Zhang, J.; Lu, J.; Zhang, C.; Bai, H.; Liang, J.; Wang, J.; Du, H.; Xue, G.; et al. Recognition of Freezing of Gait in Parkinson's Disease Based on Machine Vision. *Front. Aging Neurosci.* **2022**, *14*, 921081. [[CrossRef](#)]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.