Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 21 No. 14 (2025) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v21i14.56687

PAPER

On the Application of DeepLabCut for the Assessment of Spiral and Sinusoidal Patterns in Individuals with Parkinson's Disease

José Renato Munari Nardo[1], Daniel Hilário da Silva[1,2] (✉), Caio Tonus Ribeiro[1,3], Adriano Alves Pereira[1], Luanne Cardoso Mendes[1], Adriano de Oliveira Andrade[1]

[1]Federal University of Uberlandia, Uberlandia, Brazil

[2]Science and Technology of Goiás, Cristalina Campus, Goiás, Brazil

[3]President Antônio Carlos College of Uberlandia, Uberlandia, Brazil

daniel.hilario@ifgoiano.edu.br

ABSTRACT

Early diagnosis of Parkinson's disease (PD) is a clinical challenge due to the non-specific nature of the initial motor symptoms (MS) and the limitations of traditional diagnostic methods. Hand-drawn tasks, such as Archimedes' spiral, have emerged as potential tools for assessing motor impairment. This study aimed to employ computer vision and machine learning (ML) techniques, with an emphasis on the use of DeepLabCut (DLC), to analyze drawing patterns of individuals with PD and healthy controls. Twenty individuals (10 with PD and 10 healthy controls), matched for age and gender, participated in the study. Each participant completed 12 manual drawings, totaling 240 samples recorded on video. The recordings were processed in DLC to extract spatial coordinates, and the resulting signals were preprocessed and normalized. Eighty-five variables related to amplitude, frequency, entropy, statistical properties, and displacement were extracted. For classification, attribute selection techniques and 14 supervised ML algorithms were applied, using cross-validation (CV) for performance evaluation. The ML models applied to the drawing patterns demonstrated high classification ability, with an accuracy of approximately 93%. The Extra Trees Classifier (ETC) showed the highest performance, reaching an AUC of 0.98, followed by K-Neighbors with an AUC of 0.97. Attribute selection contributed to performance optimization, and CV strategies ensured the robustness of the results. These findings highlight the potential of DLC and ML as a non-invasive tool for early detection and monitoring of motor impairment in Parkinson's disease.

KEYWORDS

Parkinson's disease (PD), assistive technology, computer vision, DeepLabCut, machine learning (ML)

Nardo, J. R. M., da Silva, D. H., Ribeiro, C. T., Pereira, A. A., Mendes, L. C., Andrade, A. D. O. (2025). On the Application of DeepLabCut for the Assessment of Spiral and Sinusoidal Patterns in Individuals with Parkinson's Disease. *International Journal of Online and Biomedical Engineering (iJOE)*, 21(14), pp. 38–57. https://doi.org/10.3991/ijoe.v21i14.56687

Article submitted 2025-05-17. Revision uploaded 2025-08-27. Final acceptance 2025-09-08.

1 INTRODUCTION

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by the degeneration of dopaminergic neurons within the substantia nigra and the subsequent accumulation of misfolded α-synuclein, which forms intracellular inclusions known as Lewy bodies. The pathogenesis of PD is multifactorial, encompassing genetic predispositions, environmental exposures, age-related changes, and aberrant protein aggregation, among other contributing factors. Epidemiological studies have estimated that approximately 6.1 million individuals globally are afflicted with PD and that therapeutic interventions, such as levodopa, have substantially improved the quality of life for many patients [1], [2].

1.1 State of the art

The diagnostic process for PD is inherently complex and fraught with uncertainty. A multitude of factors, including advancing age, sex (with men exhibiting a higher susceptibility to the disease), comorbid conditions, and a lower body mass index, may predispose individuals to PD [3], [4]. Moreover, genetic factors are integral to the disease's etiology; several genetic mutations have been implicated, including those affecting the gene encoding α-synuclein. Age remains the most significant risk factor for PD, with its incidence increasing as individuals age, particularly after the sixth decade of life. Motor symptoms (MS) represent the most observed initial manifestations of the disease and encompass a constellation of cardinal features that define its clinical presentation [2].

A resting tremor is a hallmark motor symptom, often presented as a tremor that diminishes during voluntary movement. The tremors most frequently affect the hands, legs, and fingers. Bradykinesia, or the slowness of voluntary movement, is another characteristic feature, manifesting as difficulties in performing tasks, executing repetitive motions, and experiencing a generalized sense of lethargy. The primary MS of PD includes tremors, rigidity, bradykinesia/akinesia, and postural instability. Non-MS are equally prevalent, including dysautonomia, excessive daytime somnolence, neuroleptic sensitivity, mood disturbances, and cognitive dysfunction [5], [6].

Rigidity, characterized by an increase in muscle tone and resistance to passive movement, is a frequent symptom of PD. This muscular stiffness is typically symmetrical, affecting opposing muscle groups equally, and it can lead to significant discomfort, pain, and mobility challenges. Achieving an accurate diagnosis of PD requires a thorough evaluation of the patient's clinical history, identification of asymmetric motor signs, and the exclusion of alternative diagnoses. Despite these efforts, diagnostic errors remain commonplace, with misdiagnosis rates ranging between 15% and 24%. Essential tremor and secondary forms of parkinsonism are among the most frequently encountered misdiagnoses. Diagnostic precision can be enhanced through a combination of tests, including genetic screenings, drug challenge tests, clinical neurophysiological assessments, autonomic function evaluations, olfactory testing, and advanced neuroimaging techniques. However, even with these diagnostic tools, errors persist [1], [2].

Due to the impact of motor impairments on the ability of PD patients to perform tasks such as drawing or writing, studies utilizing the Archimedes spiral have been extensively conducted. These experiments are a staple in the diagnostic process for neurodegenerative disorders, widely employed by neurologists and psychiatrists worldwide [7]. Over time, these spiral and drawing assessments have evolved, integrating advanced technologies such as digital tablets [8] and machine learning (ML) techniques [7]. To better address the challenges of diagnosing the hallmark MS—tremor, rigidity, and bradykinesia—innovative solutions leveraging ML have emerged, offering more precise diagnostic tools.

The utilization of ML methods to discern patterns within datasets of PD patients has already been undertaken. In recent years, the volume of scholarly publications addressing the integration of ML in the context of PD has seen significant growth. Previous investigations have critically analyzed the role of ML in the diagnostic process of PD, with an emphasis on motor symptoms, largely relying on the analysis of kinematic sensor data [9], [10].

Beyond PD, recent advances have demonstrated the potential of ML across different biomedical domains. For example, [11] applied ML techniques to breast cancer detection, while [12] proposed a Swin Transformer-based segmentation framework for Alzheimer's disease, both achieving high accuracy in extracting complex clinical patterns. These studies reinforce the versatility of ML in supporting diagnosis and monitoring in healthcare. Computer vision-based tools have seen widespread adoption across various domains, with the technique undergoing significant evolution in recent years, driven by advancements in computational processing power. At present, markerless computer vision tools such as DeepLabCut (DLC) [13] are at the forefront. This sophisticated tool empowers users to train neural networks to accurately track targeted objects or body parts from video footage or still images. By integrating DLC with a custom experimental protocol developed and rigorously tested by the authors, researchers can precisely capture and analyze movements during the drawing process. The acquired data is subsequently processed through a specialized code developed by the authors, utilizing the PyCaret library. This tool enables the concurrent training and evaluation of numerous ML algorithms, facilitating the extraction of valuable data from two distinct groups [14], [15].

Recent reviews have highlighted a growing body of research focused on video-only approaches for PD detection, particularly through the analysis of motor tasks such as finger tapping [16]. These methods typically rely on markerless pose estimation frameworks (e.g., OpenPose, MediaPipe, MMPose) to automatically track finger and hand movements from video recordings. From these trajectories, features such as amplitude, speed, fatigue, and rhythm are extracted and used to train ML models for binary classification (PD vs. healthy control) or multiclass prediction aligned with UPDRS severity scores.

Importantly, recent studies emphasize the shift from handcrafted feature engineering toward deep neural networks and ensemble methods, which show higher robustness but still face challenges related to dataset imbalance and limited availability of benchmark data.

Furthermore, the latest video-based PD systems increasingly integrate advanced architectures, including convolutional and transformer-based models, achieving performance levels that rival traditional sensor-based approaches [17]. Collectively, these works underscore the transition toward fully automated, noninvasive, and scalable PD assessment frameworks, highlighting video analysis as one of the most promising frontiers in the field.

1.2 Research objectives and hypotheses

At present, there is a gap in the literature regarding the explicit evaluation of DLC for analyzing hand-drawn tasks in PD. Building on this, the present study is guided by the following research questions: whether features extracted from spiral and sinusoidal drawings through DLC can accurately differentiate individuals with PD from healthy controls, which ML algorithms provide the most reliable performance for this classification task, and whether feature selection (FS) techniques contribute to improving classification accuracy.

Accordingly, we hypothesize that the features obtained using DLC from spiral and sinusoidal drawings contain discriminative information between PD patients and healthy controls, and that supervised ML models, particularly when combined with attribute selection, will achieve high classification accuracy.

In line with these hypotheses, this study introduces the use of DLC combined with ML algorithms to evaluate spiral and sinusoidal drawings of people with PD. It exploits various techniques throughout the model training process by using the PyCaret library. Additionally, it highlights the key characteristics that play a critical role in enabling the most effective models to make accurate classification decisions.

2 MATERIALS AND METHODS

This section outlines the dataset utilized, the preprocessing procedures implemented, and the ML methods employed. The aim is to comprehensively explain the methodology used to classify PD through features extracted from drawing patterns, detailing each step from data acquisition to model performance evaluation.

2.1 Dataset

This study utilized a dataset comprising features derived from two distinct participant groups: individuals diagnosed with PD and healthy controls (HC). Both groups consisted of 10 participants, matched for age and sex to minimize demographic differences. Before participation, all individuals underwent preliminary evaluations to ensure the eligibility criteria for participants as follows: a confirmed diagnosis of PD performed by a neurologist or geriatrician; being aged between 40 and 100 years old; taking PD medication; having a mild to moderate stage of PD (Hoehn and Yahr levels I, II, and III) [18]; and have a Mini Mental State Examination score greater than [19].

The data collection process followed the protocol presented in [14]. The study received ethical approval from the Research Ethics Committee of the Federal University of Uberlândia under CAAE number 43229921.8.0000.5152. All participants provided written informed consent before taking part in the study. To ensure a robust dataset, each participant was required to perform the drawing task 12 times using their dominant hand. All individuals in the PD group completed the task while under the effect of their medication (ON state). This decision aimed to minimize variability due to motor fluctuations, providing more standardized conditions across participants. Although performing the task during the ON state may reduce the visibility of some motor impairments that are more pronounced in the OFF state, it ensures greater consistency in the collected data. The final dataset consists of 240 recorded samples of drawing patterns from 10 individuals diagnosed with PD and 10 HC. Table 1 provides detailed information about the participants.

Table 1. Clinical and demographic variables

Item	Healthy Individuals	PD Individuals	Total
Recording Number	120	120	240
Gender Male	4	4	8
Gender Female	6	6	12
UPDRS-III	–	20.5 ± 16.81	–
H&Y	–	1 ± 0.84	–
Age (years)	57 ± 6.50	60.5 ± 6.78	–

Note: UPDRS-III: Unified PD Rating Scale-Part III; H&Y: Hoehn & Yahr.

2.2 Data acquisition

The video recordings were captured using a smartphone with a resolution of 3840×2160 pixels and a frame rate of 30 frames per second. Post-processing involved editing the videos to eliminate irrelevant sections, such as the video track before and after the drawing process starts and finishes, that include the middle section between the last spiral and the first sinus wave drawings, such as the audio track, and compressing the resolution to 1920×1080 pixels, while maintaining the original frame rate of 30 FPS.

The video compression (made with Capcut Software) process ensures compatibility with less powerful machines, such as machines that do not include a dedicated graphics card with at least 6 Gb of RAM memory. After recording and editing, videos were processed in DLC to extract pixels X and Y positions for further analysis as shown in Figure 1.

The initial high resolution was chosen to capture subtle details of hand movements with optimal precision. The subsequent downscaling to 1920×1080 pixels preserved essential movement information while balancing data quality and computational efficiency. This trade-off ensured that the dataset remained accessible for processing on standard hardware without compromising the reliability of movement feature extraction.

Position data was processed for ten participants from each group (PD and HC). Data was organized into two folders: one for PD participants and another for matched HC participants. The data was then prepared for processing in the classification framework as shown in Figure 2. These samples were treated as independent records, each containing unique features related to drawing dynamics, as presented in Table A1. Initially available in CSV format, the dataset generated by processing the Raw data from DLC underwent a careful curation process. Irrelevant columns, such as metadata (e.g., “ID”), were excluded from streamlining the dataset for analysis, also aiming to reduce the risk of overfitting.

After preprocessing, the final dataset comprised a total of 240 records with 85 numerical variables (refer to Table A1), which included drawing-related features, participant demographics (e.g., “Age”), and the target variable indicating group status (PD or HC). The dataset was thoroughly checked for missing values, and no inconsistencies were found, ensuring the reliability of the subsequent analyses.

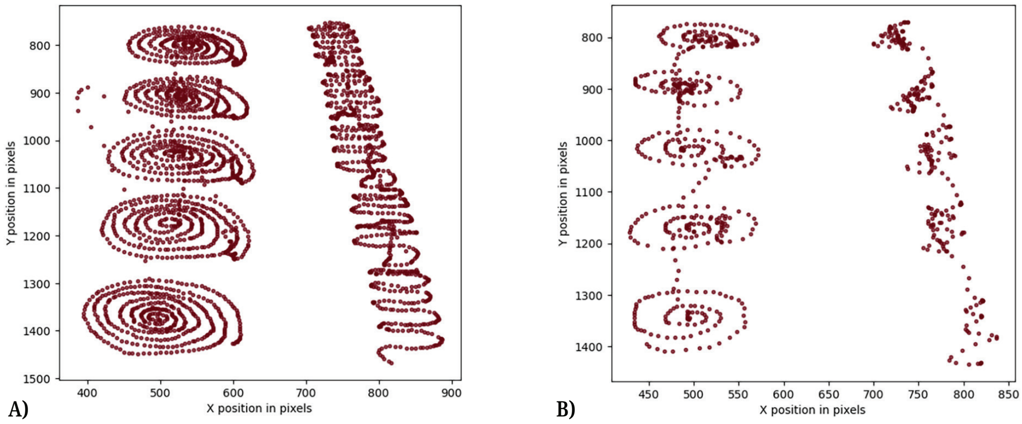

Fig. 1. X and Y pixel positional data: A) Data from an individual of the Healthy Group, B) Data from an individual of the PD Group

Python's standard libraries were utilized to facilitate the data processing workflow during the data preprocessing stage. The features were normalized using a Z-score transformation, ensuring a zero mean and unit variance. This approach, as described by [20], was applied to address the varied scales of the features extracted from the drawing patterns. Since the dataset contains variables with different scales, it is necessary to apply normalization techniques to ensure consistency. This process allows all features to contribute equally during the training of ML models, preventing those with larger scales from dominating the learning process [21]. Each participant contributed with multiple drawing samples, to ensure more samples of variance among drawings, allowing for a better comprehension of the voluntary patterns.

2.3 Signal preprocessing

The signals collected and processed by DLC were organized into a JSON file consisting of three columns: time (in milliseconds), displacement on the x-axis, and displacement on the y-axis. Preprocessing was conducted using The R Project for Statistical Computing [22] to remove any information that wasn't of interest. The displacement signals were filtered using a 4th-order passband Butterworth filter with cutoff frequencies between 1 and 16 Hz, the typical filtering range for movement analysis [23]. Features were then calculated for each axis (x and y) and type of drawing (sinusoids or spirals), considering the amplitude of the signal, its frequency spectrum, entropy, statistical properties, and displacement. A comprehensive list of the extracted features and their descriptions is provided in Appendix A (refer to Table A1). Here we summarize the main feature categories.

The features within the amplitude category are derived from time-domain calculations and represent the magnitude of signal oscillations. These oscillations reflect the extent of movement in the object's placement during the data collection process [24]. Features classified under the frequency category refer to the rate of occurrence of oscillatory components within the signal over time when extracted in the time domain or to specific frequency components associated with the spectral distribution of signal energy when derived through frequency-domain transformations, such as the Fourier Transform [24]. Entropy, a measure of system disorder, provides valuable insights into system complexity, quantifying the uncertainty present within the analyzed sample window [24]. Statistical metrics are used to evaluate patterns of data distribution and dispersion. Displacement features, on the other hand, are extracted to assess the overall behavior of the object's movement throughout the experiment.

Data was then organized in a table comprised of 84 features: 21 for each axis and type of drawing (spirals or sinusoids), plus additional columns of the participant's age and group (1 for the PD and 0 for the HC), comprising 85 features (see Appendix and refer to Table A1) used for the classification stage and the target variable, group, denoting the individual's condition in the dataset.

2.4 Data split, cross-validation, and feature selection techniques

Following the examination of all models on the training dataset, cross-validation (CV) was employed with a different number of folds to analyze which one presented the best results. Our models underwent rigorous testing on various subsets of the data [14], [25]. The data was split into two subsets, training data and testing data, with proportions of 80% and 20%, respectively, as described in [20], similar to the division observed in the study of datasets from patients with PD [20], [26]. This is important to ensure that the algorithm was trained and tested on different datasets, removing any bias carried from the previous stage. The training set was used to train the models and evaluate their performance using CV. The chosen strategy was k-fold, with a fold number going from two to ten folders. The tests were done to ensure robustness in the evaluation process. After the test with the folders was complete, it was possible to verify that the optimal number of folders for our training dataset was six folders. Conversely, the test dataset was used to verify the model's generalization on unseen data.

The feature selection process was initially applied to the 84 features of the dataset to create a more compact and efficient model. Two FS techniques were employed: Remove_Multicollinearity, which eliminates features exhibiting high correlations to reduce redundancy and improve model interpretability [20], and the FS module from the PyCaret library, which uses a classical selection approach with the LightGBM estimator [27].

These FS methods were integrated into the classification workflows to generate refined subsets of features; each tested with different classification algorithms. The objective of applying these techniques was to identify the optimal number of features by evaluating their contribution to enhancing the accuracy of the classifiers. The FS process is outlined in Figure 2.

In this study, FS was applied as a preprocessing step in the data analysis pipeline to identify the most relevant features of the problem. FS offers several benefits, including reducing the time required for future data collection, enhancing the understanding of disease mechanisms, decreasing computational costs, and maintaining or even improving model performance [28]. Proper identification of key variables during the FS process can significantly enhance the accuracy of classification algorithms [28], [29].

2.5 Classification framework

In this study, we employed 14 supervised ML algorithms, widely cited in the literature [15], [30], to classify PD using the PyCaret library. The framework utilized 240 records and 85 numerical features that were standardized (zero mean and unit variance) as predictors, with the disease status (PD or HC) as the target variable. The implementation was done in Python, employing libraries such as Scikit-learn and PyCaret to streamline the process. The complete workflow, encompassing dataset preparation, splitting, processing, and result analysis, is presented in Figure 2 that illustrates the process for analyzing a dataset comprising patients with PD and healthy subjects. In this setup, two distinct processing pipelines were designed for comparative purposes.

The training process initially involved a diverse set of algorithms, including AdaBoost Classifier (ADA), Decision Tree Classifier (DTC), Dummy Classifier (DUMMY), Extra Trees Classifier (ETC), Gradient Boosting Classifier (GBC), K-Nearest Neighbors Classifier (KNN), Light Gradient Boosting Machine (LIGHTGBM), Linear Discriminant Analysis (LDA), Logistic Regression (LR), Naïve Bayes (NB), Quadratic Discriminant Analysis (QDA), Random Forest Classifier (RF), Ridge Classifier (RIDGE), and Support Vector Machine with a Linear Kernel (SVM).

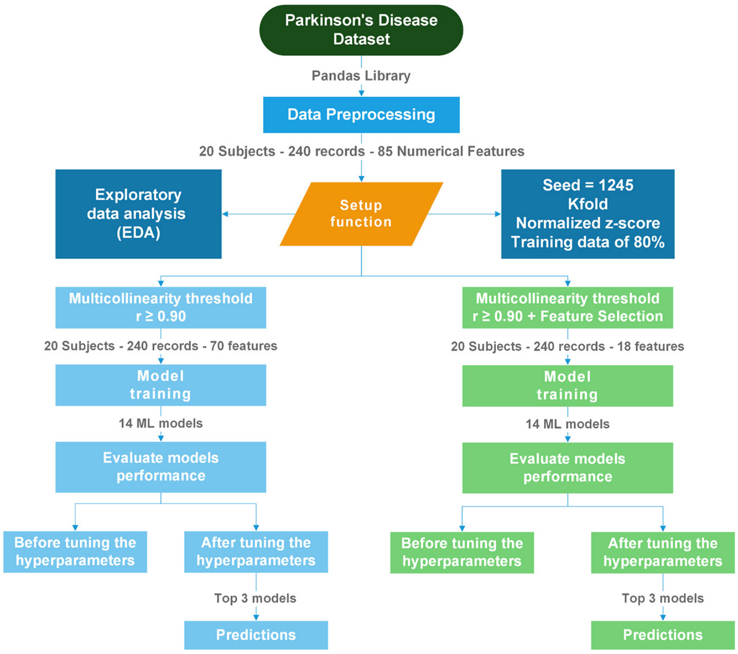

Fig. 2. Framework for classification of drawing patterns

In one of the processing flows, dimensionality reduction was performed solely by eliminating highly correlated variables, using a multicollinearity threshold of $r \geq 0.90$, which resulted in a subset of 70 features. In contrast, the alternative flow combined removing highly correlated variables with an FS step, aiming to identify the most relevant attributes for the problem, reducing the feature set to only 18 variables. The remainder of the pipeline followed the same procedure.

3 RESULTS

Using our code to work with the PyCaret library, it was possible to test several trials to achieve the best performance with the ML algorithms. The number of folds tested was from 2 to 10, and the best result was achieved with 6 folds for the tests involving FS and seven without using FS. After tuning the function, which is a basic function of the PyCaret library to force the ML algorithms to retry the optimal weights, the main test with FS could reach a mean precision of 86.46% for the ten best models. Table 2 shows the performance of each ML technique in the 6-fold trial with FS.

Table 2. Six-fold FS trial ML performance

Algorithm	Accuracy Before Tuning (%)	Accuracy After Tuning (%)
ET	92.19	93.75
RF	90.10	87.50
GBC	86.98	91.67
LIGHTGBM	85.94	83.33
KNN	82.81	93.75
ADA	82.81	85.42
QDA	80.73	89.58
DT	79.69	77.08
NB	75.00	81.77
LR	73.44	79.17
Average (%)	**82.81**	**86.46**
STD (%)	**6.06**	**5.94**

Note: STD: Standard Deviation; ET: Extra Trees Classifier; RF: Random Forest Classifier; GBC: Gradient Boost Classifier; LIGHTGBM: Light Gradient Boosting Machine; KNN: K Neighbors Classifier; ADA: AdaBoost Classifier; QDA: Quadratic Discriminant Analysis; DT: Decision Tree Classifier; NB: Naive Bayes; LR: Logistic Regression.

Table 3 presents the results of the test without using FS. The ideal number of folds for this scenario was seven folds. On the one hand, it is possible to see that the average is slightly better than the test with FS after the tuning function was applied; on the other hand, the standard deviation was higher, which suggests more variation among ML algorithms. The average before the tuned model was worse than the test with FS; the standard deviation was a little higher than the FS test; still not a great difference if compared to the after-tuning model function.

Table 3. Six-fold: No FS trial ML performance

Algorithm	Accuracy Before Tuning (%)	Accuracy After Tuning (%)
GBC	90.06	93.75
ET	87.45	89.58
ADA	84.37	89.58
LIGHTGBM	82.77	85.42
RF	82.26	88.75
KNN	81.24	91.67
LR	79.72	70.83
RIDGE	78.61	72.92
LDA	76.53	70.83
DT	73.43	77.08
Average (%)	**81.75**	**87.09**
STD (%)	**4.95**	**9.12**

In this study, one of the main goals was to identify which features of the best algorithms for both tests with and without FS were considered more relevant to determining their actions. Figures 3 and 4 show the results for the best model for the FS test and the no FS test.

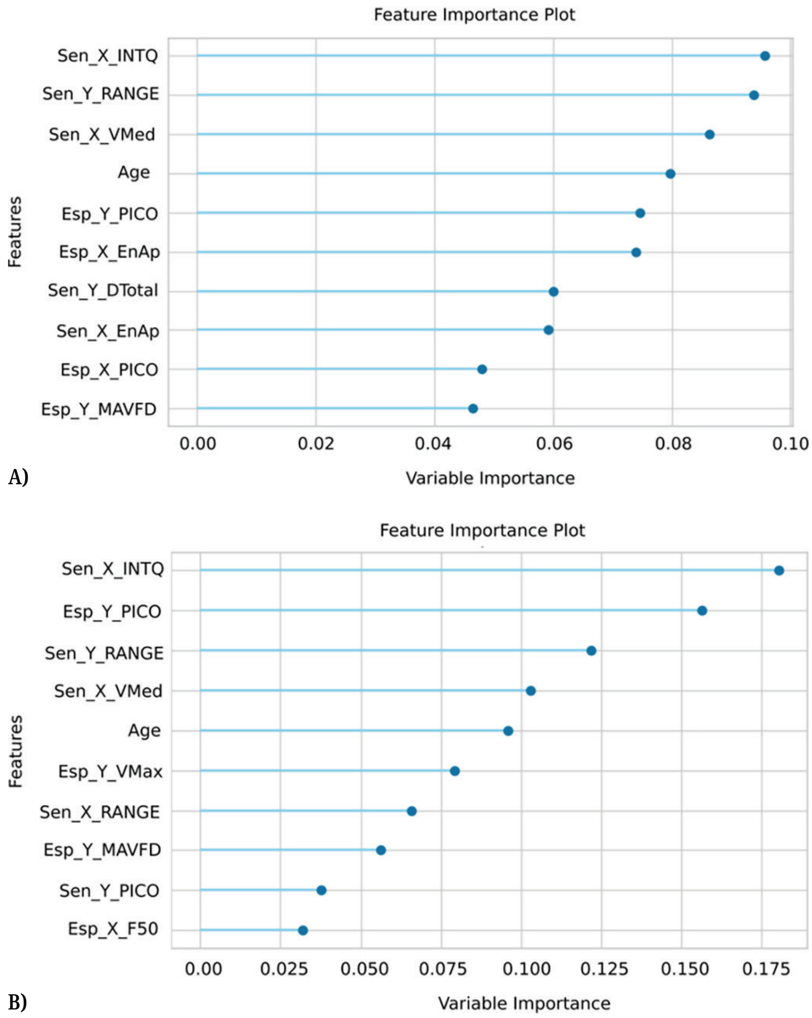

Fig. 3. (A) The feature importance plot for the best algorithm (ET classifier) on the six-fold trial after applying the tune model function and using FS (B) The feature importance plot for the best algorithm (GBC classifier) on the seven-fold trial after the tune model function was applied without using FS

Note: The names of the features include "Sen" for the sine drawings and "Esp" for the spirals; "X" and "Y" correspond to the axes of movement; and the other components are described in Table A1.

The Area Under the ROC Curve (AUC) is a commonly utilized measure to assess the effectiveness of binary classification models. The Receiver Operating Characteristic (ROC) curve depicts the relationship between the True Positive Rate (TPR) and the False Positive Rate (FPR) across different threshold values. An AUC score nearing 1 reflects outstanding discriminatory power, whereas an AUC of around 0.5 indicates performance similar to random chance [31].

In Figure 4, the AUC results for the two top-performing ML models in this study are presented. The highest-performing model, the Extra Trees Classifier, achieves an AUC of 0.98, closely followed by the K-Neighbors Classifier with an AUC of 0.97. These results highlight the models' strong ability to differentiate between classes, with AUC values approaching the ideal score of 1.

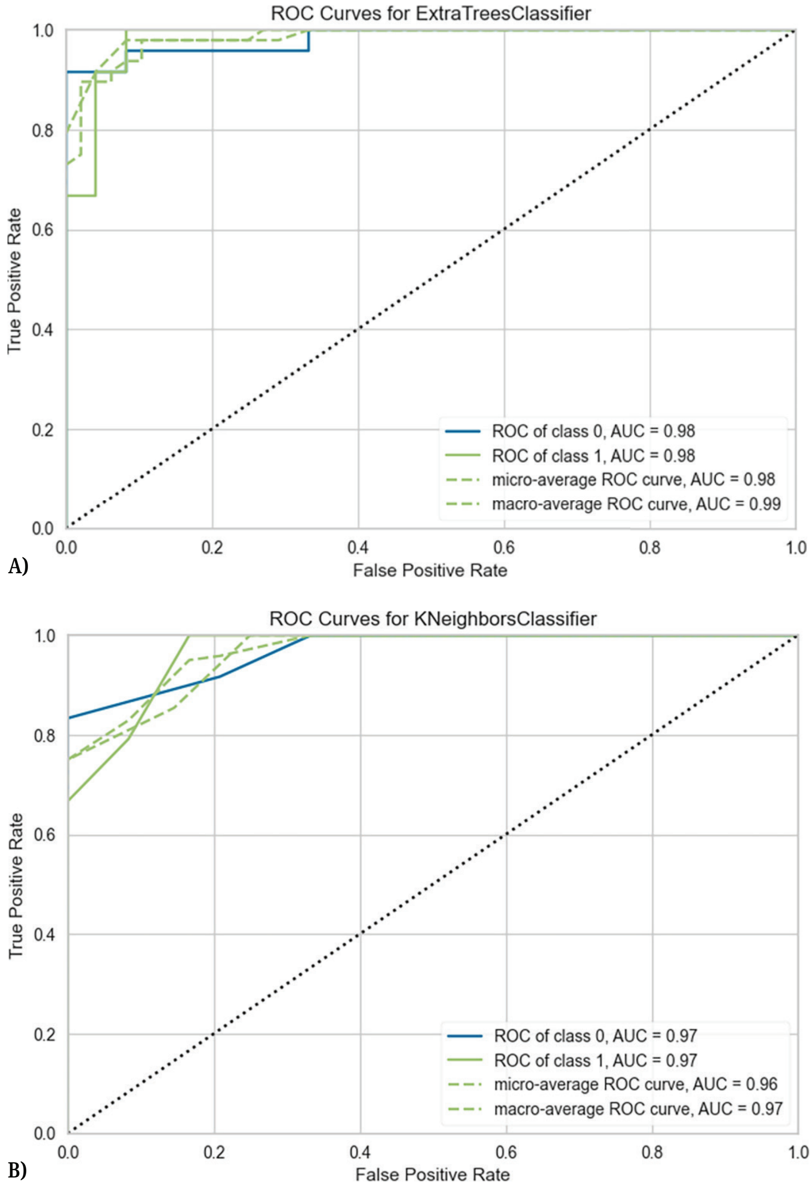

Fig. 4. (A) ROC Curve for ETC model using feature selection; (B) ROC Curve for K-neighbors Classifier model using feature selection

4 DISCUSSION

This study demonstrates the effectiveness of ML models in analyzing video-based handwriting movements for PD detection. Unlike previous studies that rely on static images, we employed DLC for feature extraction from videos, followed by data processing in RStudio and ML analysis in Python using the PyCaret library.

4.1 Interpretation of results

To acquire data using the DLC software, first it was necessary to train the algorithm. To do the training we employed approximately 16 video recordings, each generating 40 images to pretrain the neural network. The images were selected according to the software's default parameters and subsequently trained over 400,000 iterations. This relatively modest number of images and reduced iterations is facilitated by the DLC's pre-trained network, which employs a diverse array of ML methodologies and datasets to fine-tune the neural network architecture [13], [32].

The data was extracted from two distinct sets of drawings, each comprising five consecutive spiral drawings followed by five sequential sinusoidal wave illustrations [33]. By utilizing the specifically trained neural network mentioned above, it was possible to attain an accuracy exceeding 97% in tracking the pen tip, adhering to the protocol delineated in prior research [14].

This automated setup ensured an optimized workflow, enhancing reproducibility and minimizing data leakage risks. The PyCaret library facilitated an efficient pipeline for model training and evaluation, allowing for the comparison of 14 default ML models. The process involved creating, optimizing, and validating the models using the following functions: create_model(), tune_model(), and predict_model() [27], [34]. This systematic approach allowed for the identification of the most effective classification techniques for PD detection. Among the tested models, ET, KNN, and GBC emerged as the top performers, achieving the highest AUC and accuracy scores across different trials.

The Extra Trees model, achieving an AUC of 0.98 and an accuracy of 93.75% after hyperparameter tuning with FS, demonstrated the strongest discriminatory power. Its ensemble-based structure effectively captured non-linear relationships within the extracted kinetic features, making it a robust choice for PD classification. The KNN model, with an AUC of 0.97 and an identical accuracy of 93.75%, also performed exceptionally well, benefiting from its proximity-based classification, which identifies localized feature distributions within the dataset.

Similarly, the GBC showed a significant improvement with feature selection, reaching an AUC of 0.98 and an accuracy of 91.67%, supporting the effectiveness of boosting techniques in medical data classification. Notably, in the trial without FS, the GBC model achieved the highest accuracy of 93.75%, followed by KNN at 91.67% and ET at 89.58%, reinforcing the robustness of these methods in different feature configurations.

The study further confirmed that FS significantly improved model performance, demonstrating that selecting the most relevant variables enhances interpretability while reducing computational complexity. The average accuracy across all models increased from 83.33% to 86.46% with FS, and the standard deviation decreased from 9.47% to 5.94%, highlighting its positive impact. Additionally, key movement features related to pen trajectory, velocity fluctuations, and pressure variations played a crucial role in distinguishing PD patients from the control group.

By systematically integrating automated model selection, feature engineering, and optimization, this study presents a reproducible and efficient pipeline for PD detection, laying the groundwork for future clinical applications. The feature importance graph in Figure 3 depicts the significant contributors to the ML model's classification of PD patients using drawing characteristics collected from their drawings. Specifically, the features are 'Sen_X_INTQ,' 'Sen_Y_RANGE,' 'Sen_X_VMED,' 'AGE,' and 'Esp_Y_PICO.' Those features are the top five determinants for both models to achieve high accuracy results.

4.2 Comparison with existing literature

The detection of PD through handwriting and drawing analysis has been widely studied using various ML and deep learning approaches. Several studies have investigated different methodological strategies, including feature extraction, transfer learning, and deep neural networks, often relying on specialized equipment, such as digitizing tablets, to acquire high-precision data. In contrast, our approach employed only images extracted from video recordings, eliminating the need for additional specialized devices. This methodological simplification enhances accessibility and potential real-world application while still achieving robust classification performance.

In literature, there are studies that utilize spiral drawings to detect disease markers. These studies employ various approaches to analyze spiral drawings. For instance, in [33], [35], researchers use an image of a hand-drawn spiral alongside sinusoidal wave drawings, extracting measures such as drawing speed, smoothness, and tightness. In other studies, instead of relying on static images, researchers use digitized drawings and extract relevant data from them.

Studies such [35], [36] demonstrate the potential to analyze spiral drawings and extract patterns and characteristics that differentiate healthy individuals from PD patients. These studies suggest that it is possible not only to distinguish between the two groups but also to identify differences between more and less affected arms in PD patients. In [36], it was shown that the PD group had an average drawing time nearly twice as long as that of the healthy group. Additionally, the PD group exhibited a radial error of 5.2 pixels, compared to 2.6 pixels in the healthy group. The study also measured the hemispherical pressure ratio between the right and left arms, with the PD group showing a value of 0.82, while the healthy participants had a value of 0.92.

Studies like [8], [37] utilized digital tools to capture the movement involved in spiral drawing. They employed a tablet and a pen with sensors capable of detecting acceleration and pressure. Using these technologies, they were able to extract data from the drawings. In [8] it was demonstrated that PD subjects could be distinguished from healthy individuals based on drawing accelerations. The study found that the healthy group exhibited accelerations below 0.05 points in most scenarios, while the PD group reached acceleration peaks of 0.25 points. In [37], the researchers created five markers and concluded that PD patients drew more slowly, with their drawings having less magnitude and appearing lighter than those of the healthy participants.

The two other studies investigating the use of ML for PD detection take distinct approaches. Using images of spiral drawings, which were then processed using CNN algorithms [33]. This approach achieved an accuracy of 93.3%, an average recall of 94%, and an average precision of 93.5%, with an F1 score of 93.94%. The confusion matrix, based on 30 images, revealed 13 true positives, 15 true negatives, 2 false positives (from the healthy group), and 0 false negatives. The [38] study, on the other hand, employed four different algorithms, each with a unique approach. The ML models in this study reached a maximum precision of 75%. It was found that the RF and the Support Vector Classifier performed optimally, while the KNN classifier achieved only 33% precision, and LR reached 66%. Despite variations in precision, the overall accuracy of the models produced better results: LR and RF achieved 91.6% accuracy, the Support Vector Classifier attained 75%, and the KNN classifier reached only 50%.

The study [39] utilized deep learning models, specifically VGG19, InceptionV3, ResNet50v2, and DenseNet169, to classify hand-drawn spirals obtained through a structured data collection process. The authors achieved a high accuracy rate, with InceptionV3 reaching 89% accuracy and a receiver operating characteristic (ROC) curve value of 95%. However, their dataset consisted of 102 spiral drawings, likely obtained under controlled conditions using dedicated digitizing equipment.

Our study, despite relying solely on video-based image acquisition, demonstrated comparable classification performance, underscoring the robustness of our approach.

Similarly, the study [40] introduced histograms of oriented gradients (HOG) to analyze sinusoidal and spiral handwriting patterns, using a dataset comprising 20 PD patients and 20 healthy controls. Their approach combined HOG descriptors with ML classifiers, including random forest, k-nearest neighbor, and support vector machines, achieving an accuracy of 83.1% in identifying tremors in sinusoidal patterns. The authors relied on digital tablets to capture high-resolution handwriting signals, whereas our study extracted features from video images without the need for such specialized hardware, maintaining a comparable level of accuracy.

Another notable study [41] explored the diagnosis of PD using off-line Archimedean spiral images, proposing a novel distance-based feature extraction method. Their dataset, collected at a specialized movement disorders center, consisted of handwriting samples from 37 PD patients and 38 healthy individuals. Participants used conventional ink pens on pre-printed templates placed over a digitizing tablet, allowing for immediate full visual feedback. Their method achieved an accuracy of up to 81.66% using support vector machines. In contrast, our approach bypasses the need for printed templates and digitizing hardware, relying instead on video-based feature extraction, thereby broadening its applicability.

The study [42] employed Fourier domain analysis to transform hand-drawn spiral images into frequency-based features. Their dataset consisted of spirals drawn by both PD patients and healthy individuals, captured using digital tablets. While their Fourier-based approach achieved 81.5% accuracy, their best-performing deep learning model (VGG16) reached 95.4% accuracy. Our approach, while not directly comparable in methodology, similarly achieved high accuracy levels while relying solely on images extracted from videos, demonstrating that a simplified data acquisition process can still yield competitive results.

Additionally, the study [43] proposed a handwriting-based PD prediction approach incorporating a cosine annealing scheduler with deep transfer learning. Using the NIATS dataset, which includes handwriting samples collected under controlled conditions, they evaluated multiple deep learning models, with VGG19 achieving the highest accuracy of 96.67%. Although their approach is highly effective, it depends on structured handwriting data obtained under specific conditions, whereas our method achieves strong classification performance without requiring controlled handwriting acquisition.

Finally, the study [44] introduced a deep transfer learning model for PD detection, optimizing FS using a genetic algorithm and employing KNN for classification. Their approach achieved an accuracy above 95%, with a precision of 98% and an AUC of 0.90. However, like other studies, they relied on structured handwriting data, likely collected under controlled conditions with specialized hardware. Our method, despite utilizing only images extracted from video recordings, reaches comparable performance levels, reinforcing the efficacy of video-based feature extraction for PD detection.

Overall, the comparison of these studies highlights the effectiveness of our methodology in detecting PD without the use of specialized acquisition hardware. While many existing approaches achieve high accuracy through controlled data collection using digitizing tablets or pre-structured handwriting tasks, our method demonstrates that video-based image extraction can serve as a viable alternative. This not only expands the accessibility of PD detection technologies but also suggests that real-world implementations requiring minimal equipment may be feasible.

4.3 Study limitations

This study has several limitations. First, the data was sourced from a single population, which may introduce bias related to patient demographics, handwriting styles, and recording conditions, affecting the generalizability. Future studies should use data from multiple centers and diverse demographics for a broader representation of handwriting variations in PD patients.

Another limitation is feature representation. While DLC accurately tracked the pen tip, some subtle motions may not have been captured. The pipeline, involving Python for DLC, R for preprocessing, and Python (PyCaret) for analysis, may not be suitable for real-time healthcare deployment.

Lastly, the study used traditional ML models, but future research could explore deep learning architectures for handwriting analysis to assess potential advantages.

4.4 Future work

Future research should focus on expanding the dataset with a larger sample size and more diverse handwriting styles. Integrating multimodal data, such as combining handwriting video analysis with sensor-based motion tracking (e.g., accelerometers, gyroscopes), could improve PD detection by capturing movement irregularities not fully detectable through handwriting alone.

Another promising direction is combining medical video or image analysis with other biomarkers, like voice and gait analysis [45], [46]. Multi-biomarker approaches can enhance PD classification by offering a more comprehensive view of disease progression and improving diagnostic accuracy and early detection.

In addition, the development of a cloud-based platform for remote monitoring and diagnostic support, as proposed in [21], represents an important next step. Such a platform would enable real-time data streaming, integration of multiple biomarkers, and remote clinical supervision, thereby extending the applicability of the proposed method. This evolution would not only align the system with the growing demand for e-health solutions but also make it scalable for broader clinical use.

Finally, developing real-time diagnostic tools for clinical use is crucial, due to the time necessary to process the data being longer than 30 minutes. Optimizing the system for real-time motion tracking and classification would make PD diagnosis faster and more accessible.

5 CONCLUSION

In this study, we explored the application of ML techniques to analyze drawing signals obtained through DLC in PD patients. Using the PyCaret low-code ML library in Python and incorporating R for signal preprocessing, we evaluated 14 classification models with default configurations. The top-performing models for classifying patient status demonstrated impressive accuracy, with the three best models achieving results between 89.58% and 93.75% using the "Remove Multicollinearity" technique. Similarly, when employing the classic FS method available in PyCaret with the LightGBM estimator, three other models achieved accuracy ranging from 91.67% to 93.75%. This comparison underlines the effectiveness of FS in refining predictive performance. To ensure robust evaluation, we analyzed the dataset with fold numbers varying from $k = 2$ to $k = 10$, identifying $k = 6$ as yielding the most reliable results. Notably, the KNN model demonstrated an improvement in accuracy from 82.81% on the training data to 93.75% on the testing data, reflecting a variation of 10.94% and showcasing its adaptability and precision. These findings emphasize the practicality and potential of tools like DLC and PyCaret in leveraging ML for clinical applications. Even with relatively simple configurations, the models demonstrated remarkable performance in classifying patients with PD. In summary, this study contributes to the growing body of research on biomedical AI applications by demonstrating the feasibility of handwriting motion analysis for PD detection. The proposed framework serves as a foundation for further development, with the potential to assist clinicians in early diagnosis and disease monitoring, ultimately improving patient care and quality of life.

6 ACKNOWLEDGMENTS

The present work was carried out with the support of the National Council for Scientific and Technological Development (444437/2024-0, 442150/2023-7, and 405365/2023-3), Coordination for the Improvement of Higher Education Personnel (CAPES), and the Foundation for Research Support of the State of Minas Gerais (FAPEMIG APQ-05015-24). AOA (302942/2022-0) is a fellow of CNPq.

7 REFERENCES

[1] V. Cabreira and J. Massano, "Parkinson's disease: Clinical review and update," *Acta Med Port*, vol. 32, no. 10, pp. 661–670, 2019. https://doi.org/10.20344/amp.11978

[2] M. J. Armstrong and M. S. Okun, "Diagnosis and treatment of parkinson disease: A review," *JAMA*, vol. 323, no. 6, pp. 548–560, 2020. https://doi.org/10.1001/jama.2019.22360

[3] E. Ray Dorsey *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.*, vol. 17, no. 11, pp. 939–953, 2018. https://doi.org/10.1016/S1474-4422(18)30295-3

[4] S. Cerri, L. Mus, and F. Blandini, "Parkinson's disease in Women and men: What's the difference?" *Journal of Parkinson's Disease*, vol. 9, no. 3, pp. 501–515, 2019. https://doi.org/10.3233/JPD-191683

[5] D. W. Dickson, "Neuropathology of Parkinson disease," *Parkinsonism Relat. Disord.*, vol. 46, pp. S30–S33, 2018. https://doi.org/10.1016/j.parkreldis.2017.07.033

[6] J. Jankovic, "Parkinson's disease: Clinical features and diagnosis," *J. Neurol. Neurosurg. Psychiatry*, vol. 79, no. 4, pp. 368–376, 2008. https://doi.org/10.1136/jnnp.2007.131045

[7] S. Nõmm, S. Zarembo, K. Medijainen, P. Taba, and A. Toomela, "Deep CNN based classification of the archimedes spiral drawing tests to support diagnostics of the Parkinson's disease," *IFAC-PapersOnLine*, vol. 53, no. 5, pp. 260–264, 2020. https://doi.org/10.1016/j.ifacol.2021.04.185

[8] M. E. Isenkul, B. E. Sakar, and B. E. S. Olcay Kursun, "Improved spiral test using digitized graphics tablet for monitoring Parkinson's disease," in *The 2nd International Conference on E-Health and TeleMedicine-ICEHTM 2014*, Istanbul, Turkey, 2014, pp. 171–175. https://doi.org/10.13140/RG.2.1.1898.6005

[9] J. Mei, C. Desrosiers, and J. Frasnelli, "Machine learning for the diagnosis of Parkinson's disease: A review of literature," *Frontiers in Aging* Neuroscience, vol. 13, 2021. https://doi.org/10.3389/fnagi.2021.633752

[10] M. A. Islam, M. Z. H. Majumder, M. A. Hussein, K. M. Hossain, and M. S. Miah, "A review of machine learning and deep learning algorithms for Parkinson's disease detection using handwriting and voice datasets," *Heliyon*, vol. 10, no. 3, 2024. https://doi.org/10.1016/j.heliyon.2024.e25469

[11] M. M. AL-Nawashi, O. M. AL-Hazaimeh, and M. Kh. Khazaaleh, "New approach for breast cancer detection-based machine learning technique," *Applied Computer Science*, vol. 20, no. 1, 2024. https://doi.org/10.35784/acs-2024-01

[12] N. Gharaibeh, A. A. Abu-Ein, O. M. Al-hazaimeh, K. M. O. Nahar, W. A. Abu-Ain, and M. M. Al-Nawashi, "Swin transformer-based segmentation and multi-scale feature pyramid fusion module for alzheimer's disease with machine learning," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 19, no. 4, pp. 22–50, 2023. https://doi.org/10.3991/ijoe.v19i04.37677

[13] A. Mathis *et al.*, "DeepLabCut: Markerless pose estimation of user-defined body parts with deep learning," *Nat, Neurosci.*, vol. 21, no. 9, pp. 1281–1289, 2018. https://doi.org/10.1038/s41593-018-0209-y

[14] J. Renato *et al.*, "An experimental protocol for video recording with a smartphone for use in a pre-trained neural network," in *XV Simpósio de Engenharia Biomédica (XV SEB)*, Uberlândia, MG, Brasil, 2023. https://doi.org/10.5281/zenodo.10157450

[15] D. Hilário da Silva *et al.*, "A low-code machine learning library in Python applied to classify and interpret data of patients with Parkinson's disease using voice records," in *XV Simpósio de Engenharia Biomédica (XV SEB)*, Uberlândia, MG, Brasil, 2023. https://doi.org/10.5281/zenodo.10162024

[16] J. Amo-Salas, A. Olivares-Gil, Á. García-Bustillo, D. García-García, Á. Arnaiz-González, and E. Cubo, "Computer vision for Parkinson's disease evaluation: A survey on finger tapping," *Healthcare*, vol. 12, no. 4, p. 439, 2024. https://doi.org/10.3390/healthcare12040439

[17] D. Deng *et al.*, "Interpretable video-based tracking and quantification of parkinsonism clinical motor states," *NPJ Parkinson's Dis.*, vol. 10, no. 1, p. 122, 2024. https://doi.org/10.1038/s41531-024-00742-x

[18] E. Ballatori, F. Roila, B. Ruggeri, A. A. Bruno, S. Tiberti, and F. di Orio, "The uniscale assessment of quality of life: Applications to oncology," in *Handbook of Disease Burdens and Quality of Life Measures*, V. R. Preedy and R. R. Watson, Eds., Springer, New York, NY, 2010, pp. 179–194. https://doi.org/10.1007/978-0-387-78665-0_10

[19] M. F. Folstein, S. E. Folstein, and P. R. Mchugh, "'Mini-mental state' examination," *APA PsycTests*, 1975. https://doi.org/10.1037/t07757-000

[20] R. Z. U. Rehman, S. Del Din, Y. Guan, A. J. Yarnall, J. Q. Shi, and L. Rochester, "Selecting clinically relevant gait characteristics for classification of early Parkinson's disease: A comprehensive machine learning approach," *Sci. Rep.*, vol. 9, no. 1, 2019. https://doi.org/10.1038/s41598-019-53656-7

[21] I. Tougui, A. Jilbab, and J. El Mhamdi, "Machine learning smart system for Parkinson disease classification using the voice as a biomarker," *Healthc. Inform. Res.*, vol. 28, no. 3, pp. 210–221, 2022. https://doi.org/10.4258/hir.2022.28.3.210

[22] "R: A language and environment for statistical computing." [Online]. Available: https://cran.r-project.org/

[23] V. de Lima Gonçalves *et al.*, "A hybrid linear discriminant analysis and genetic algorithm to create a linear model of aging when performing motor tasks through inertial sensors positioned on the hand and forearm," *Biomed. Eng. Online*, vol. 22, no. 1, p. 98, 2023. https://doi.org/10.1186/s12938-023-01161-4

[24] S. Gruss *et al.*, "Pain intensity recognition rates via biopotential feature patterns with support vector machines," *PLoS ONE*, vol. 10, no. 10, p. e0140330, 2015. https://doi.org/10.1371/journal.pone.0140330

[25] G. Deuschl, M. Lauk, and J. Timmer, "Tremor classification and tremor time series analysis," *Chaos: An Interdisciplinary Journal of Nonlinear Science*, vol. 5, no. 1, pp. 48–51, 1995. https://doi.org/10.1063/1.166084

[26] A. Yasar, I. Saritas, M. A. Sahman, and A. C. Cinar, "Classification of Parkinson disease data with artificial neural networks," *IOP Conference Series: Materials Science and Engineering*, RUDN University, Moscow, Russian Federation, vol. 675, 2019. https://doi.org/10.1088/1757-899X/675/1/012031

[27] A. Moez, "PyCaret: An open source, low-code machine learning library in Python." Accessed: Apr. 5, 2025. [Online]. Available: https://pycaret.gitbook.io/docs

[28] Z. Karapinar Senturk, "Early diagnosis of Parkinson's disease using machine learning algorithms," *Med. Hypotheses*, vol. 138, 2020. https://doi.org/10.1016/j.mehy.2020.109603

[29] D. Jain and V. Singh, "Feature selection and classification systems for chronic disease prediction: A review," *Egyptian Informatics Journal*, vol. 19, no. 1, pp. 179–189, 2018. https://doi.org/10.1016/j.eij.2018.03.002

[30] I. Karabayir, S. M. Goldman, S. Pappu, and O. Akbilgic, "Gradient boosting for Parkinson's disease diagnosis from voice recordings," *BMC Med. Inform. Decis. Mak.*, vol. 20, no. 1, 2020. https://doi.org/10.1186/s12911-020-01250-7

[31] T. A. Medeiros, R. G. Saraiva Junior, G. De Souza E Cassia, F. A. De Oliveira Nascimento, and J. L. A. De Carvalho, "Classification of 1p/19q status in low-grade gliomas: Experiments with radiomic features and ensemble-based machine learning methods," *Brazilian Archives of Biology and Technology*, vol. 66, 2023. https://doi.org/10.1590/1678-4324-2023230002

[32] T. Nath, A. Mathis, A. C. Chen, A. Patel, M. Bethge, and M. W. Mathis, "Using DeepLabCut for 3D markerless pose estimation across species and behaviors," *Nat. Protoc.*, vol. 14, no. 7, pp. 2152–2176, 2019. https://doi.org/10.1038/s41596-019-0176-0

[33] S. Chakraborty, S. Aich, E. Han, J. Park, and H. C. Kim, "Digital security global agenda for safe society!" in *The 22nd International Conference on Advanced Communications Technology (ICACT 2020)* Phoenix Park, Pyeongchang, Korea (South), 2020.

[34] G. Tolios, *Simplifying Machine Learning with PyCaret A Low-Code Approach for Beginners and Experts!* vol. 1, 1st ed. Victoria, BC, Canada: Leanpub book, 2022.

[35] R. Saunders-Pullman *et al.*, "Validity of spiral analysis in early Parkinson's disease," *Movement Disorders*, vol. 23, no. 4, pp. 531–537, 2008. https://doi.org/10.1002/mds.21874

[36] D. Surangsrirat and C. Thanawattano, "Android application for spiral analysis in Parkinson's disease," in *2012 Proceedings of IEEE Southeastcon*, Orlando, FL, USA, 2012, pp. 1–6. https://doi.org/10.1109/SECON.2012.6196943

[37] M. San Luciano *et al.*, "Digitized spiral drawing: A possible biomarker for early Parkinson's disease," *PLoS ONE*, vol. 11, no. 10, 2016. https://doi.org/10.1371/journal.pone.0162799

[38] M. Kamble, P. Shrivastava, and M. Jain, "Digitized spiral drawing classification for Parkinson's disease diagnosis," *Measurement: Sensors*, vol. 16, 2021. https://doi.org/10.1016/j.measen.2021.100047

[39] N. Farhah, "Utilizing deep learning models in an intelligent spiral drawing classification system for Parkinson's disease classification," *Front. Med. (Lausanne)*, vol. 11, 2024. https://doi.org/10.3389/fmed.2024.1453743

[40] J. P. Folador *et al.*, "On the use of histograms of oriented gradients for tremor detection from sinusoidal and spiral handwritten drawings of people with Parkinson's disease," *Med. Biol. Eng. Comput.*, vol. 59, no. 1, pp. 195–214, 2021. https://doi.org/10.1007/s11517-020-02303-9

[41] J. Das Gupta and B. Chanda, "Novel features for diagnosis of Parkinson's disease from off-line Archimedean spiral images," in *2019 IEEE 10th International Conference on Awareness Science and Technology (iCAST)*, IEEE, 2019, pp. 1–6. https://doi.org/10.1109/ICAwST.2019.8923159

[42] R. E. Desipio, “Parkinson’s disease automated hand tremor analysis from spiral images,” PhD Thesis, Virginia Tech, 2023.
[43] Y. Huang, K. Chaturvedi, A. A. Nayan, M. H. Hesamian, A. Braytee, and M. Prasad, “Early Parkinson’s disease diagnosis through hand-drawn spiral and wave analysis using deep learning techniques,” *Information (Switzerland)*, vol. 15, no. 4, p. 220, 2024. https://doi.org/10.3390/info15040220
[44] S. M. Abdullah *et al.*, “Deep transfer learning based Parkinson’s disease detection using optimized feature selection,” *IEEE Access*, vol. 11, pp. 3511–3524, 2023. https://doi.org/10.1109/ACCESS.2023.3233969
[45] D. H. da Silva, L. R. da Silva Souza, C. T. Ribeiro, and A. A. Pereira, “Application of open-source, low-code machine-learning library in Python to diagnose Parkinson’s disease using voice signal features,” *Brazilian Archives of Biology and Technology*, vol. 68, 2025. https://doi.org/10.1590/1678-4324-2025230860
[46] O. M. Beigi, L. R. Nóbrega, S. Houghten, A. Alves Pereira, and A. de Oliveira Andrade, “Freezing of gait in Parkinson’s disease: Classification using computational intelligence,” *BioSystems*, vol. 232, 2023. https://doi.org/10.1016/j.biosystems.2023.105006

8 APPENDIX A

Table A1. Features extracted from the gathered data

Group	Abbreviation	Description
Amplitude [23]	MAV	Mean Absolute Value
	MAVFD	Mean Absolute Value of the First Difference
	MAVSD	Mean Absolute Value of the Second Difference
	RMS	Root Mean Square
	PEAK	Maximum value of the vector, considering only positive values
	ZC	Zero Crossing
Frequency [23]	FMean	Mean Frequency
	FPeak	Frequency with the maximum power
	F50	Median Frequency
	F80	Sum of the power of frequencies below 80% of total energy
	P3.5_7.5	Power in frequency band 3.5–7.5 Hz
Entropy [23]	EnFuzzy	Fuzzy Entropy
	EnAp	Approximate entropy
Statistical [23]	VAR	Variance
	RANGE	Amplitude Range
	INTQ	Interquartile Range
	SKEW	Asymmetry
	KURTOSIS	Flattening of the curve
Displacement [23]	VMean	Mean Velocity
	VMax	Max Velocity
	DTotal	Total displacement

9 AUTHORS

José Renato Munari Nardo is a Mechanical Engineer and Master's researcher in Biomedical Engineering at the Federal University of Uberlândia, specializing in motion analysis, machine learning, and computer vision applied to health science. He has a professional experience in product design, FEA and CFD simulations, and a strong background in automotive engineering (E-mail: jose.munari@ufu.br).

Daniel Hilário da Silva is a student of the Postgraduate Program in Biomedical Engineering, at the Faculty of Electrical Engineering, Federal University of Uberlândia, and is working as a Lecturer at the Instituto Federal de Educação, Ciência e Tecnologia Goiano – Campus Cristalina, Goiás, Brazil (E-mail: daniel.hilario@ifgoiano.edu.br).

Caio Tonus Ribeiro is a Professor at the Presidente Antônio Carlos University and a student of the Postgraduate Program in Biomedical Engineering at the Faculty of Electrical Engineering, Federal University of Uberlândia, Brazil (E-mail: caiot@ufu.br).

Adriano Alves Pereira is a Professor in the Postgraduate Program in Biomedical Engineering at the Faculty of Electrical Engineering, Federal University of Uberlândia, Brazil (E-mail: adriano.pereira@ufu.br).

Luanne Cardoso Mendes is a Biomedical Engineer and Professor in the Faculty of Electrical Engineering at the Federal University of Uberlândia (UFU, Brazil). She is also part of the Postgraduate Program in Biomedical Engineering at UFU, conducting research on Parkinson's disease and related areas (E-mail: luannecmendes@ufu.br).

Adriano de Oliveira Andrade is an Electrical Engineer and Professor in the Faculty of Electrical Engineering at the Federal University of Uberlândia (UFU, Brazil). He also integrates the Postgraduate Program in Biomedical Engineering at UFU. His research focuses on the neuromuscular in the context of movement disorders (E-mail: adriano@ufu.br).