Parkinson's Disease Detection Through Inertial Signals and Posture Insights

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Abstract: In the development of deep learning systems aimed at detecting Parkinson's Disease (PD) using inertial sensors, some aspects could be essential to refine tremor detection methodologies in realistic scenarios. This work analyses the effect of the subjects' posture during tremor recordings and the required amount of data to assess a proper PD detection in a Leave-One-Subject-Out Cross-Validation (LOSO CV) scenario. We propose a deep learning architecture that learns a PD biomarker from accelerometer signals to classify subjects between healthy and PD patients. This study uses the PD-BioStampRC21 dataset, containing accelerometer recordings from healthy and PD participants equipped with five inertial sensors. An increment of performance was obtained when using sitting windows compared to using lying windows for Fast Fourier Transform (FFT) input signal domain. Moreover, using 5 minutes per subject could be sufficient to properly evaluate the PD status of a patient without losing performance, reaching a window-level accuracy of 77.71 ± 1.07 % and a user-level accuracy of 87.10 ± 11.80 %. Furthermore, a knowledge transfer could be performed when training the system with sitting instances and testing with lying examples, indicating that the sitting activity contains valuable information that allows an effective generalization to lying instances.

1 INTRODUCTION

Biometrics research has experienced substantial expansion in recent years, particularly finding increased applications in the healthcare sector. The scope of healthcare biometrics extends beyond controlling access to electronic medical records and patient identification; it encompasses medical decision support tools designed for patient care. These tools extract biomarkers that define patient health, contributing to illness detection, analysis of medication response, and the management of chronic conditions such as Parkinson's Disease (PD).

PD is a neurodegenerative disorder characterized by motor impairments like tremor, bradykinesia, rigidity, and postural instability (Jankovic, 2008). These impairments impact various motor functions, including planning, programming, sequencing, movement initiation, and execution (José, 1995).

Deep learning algorithms have being employed for human motion recognition to model physical activities using wearables or cameras (Manuel Gil-Martin, San-Segundo, Fernandez-Martinez, & Ferreiros-Lopez, 2020, 2021; Gil-Martín, San-Segundo, Fernández-Martínez, & de Córdoba, 2020; Zhang et al., 2017). Consequently, these technologies can also be utilized to model tremor movements associated with PD.

This work proposes a PD detection system based on a deep learning architecture that allows analyzing the effect of the subject's posture performed while recording the motion from inertial signals. Additionally, this analyzes the recording time required from each subject to evaluate the tremor and distinguish between healthy people and PD patients. The primary contributions of this research are as follows:

- Analysis of the inertial signal domain and sensors for PD detection.
- Assessment of different postures to detect PD based on tremor symptom.
- Study of the required recording time to test a patient and obtain an accurate detection.

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- Analysis of knowledge transfer for training and testing the PD detection system using different postures.

This paper is organized as follows. Section 2 reviews the literature of PD detection using inertial sensors. Section 3 reviews the material and methods used in this study, including a description of the dataset, the signal processing, the deep neural network, and the evaluation methodology. Section 4 describes the experiments and the obtained results. Finally, section 5 summarizes the main conclusions of the paper.

2 RELATED WORKS

Several researchers have explored the application of machine learning for detecting motor symptoms associated with PD through the use of wearable sensors (Channa, Ifrim, Popescu, & Popescu, 2021; Lang et al., 2019). However, there remain several factors that could enhance PD detection systems in real-world scenarios that could benefit the patients.

Concerning the extraction of features from inertial signals, different features have used proposed in previous works for PD detection based on tremor. Most of these features are based on measurements in the time domain (such as mean, range, or cross-correlation) (Cole, Roy, De Luca, Nawab, & Ieee, 2010; Garcia-Magarino, Medrano, Plaza, & Olivan, 2016), in the frequency domain (such as dominant frequency, energy content in a particular band, or signal entropy) (Rigas et al., 2012), or a combination of both domains (Dai, Zhang, & Lueth, 2015). Moreover, other previous works have concluded that features traditionally used for speech processing (e.g., frequency analysis using the Mel scale, cepstral coefficients) are also effective in classifying human motion from accelerometer data (San-Segundo, Manuel Montero, Barra-Chicote, Fernandez, & Manuel Pardo, 2016; San-Segundo, Navarro-Hellin, Torres-Sanchez, Hodgins, & De la Torre, 2019; Vanrell, Milone, & Rufiner, 2018).

As for tremor detection algorithms, previous works have used a wide variety of machine learning algorithms, such as decision trees (Garcia-Magarino et al., 2016), random forests, hidden Markov models (Rigas et al., 2012), and neural networks (Hathaliya et al., 2022). For example a previous work (Hathaliya et al., 2022) used a deep learning architecture to model tremor obtaining a 92.4% of accuracy using 6.4-second windows of raw samples using a single sensor on the left anterior forearm. However, the data distribution used in this work seems to simulate a too optimistic scenario since data from the same subjects were included in both training and testing subsets and no distinction between physical activities was performed. In addition, there exists a lack of a study of the amount of data required to properly assess unseen patients' PD status.

Literature which mixes physical activity and PD assessment is predominantly focused on investigating whether an individual's likelihood of developing PD is influenced by the extent of their physical activity. Notably, prior studies have yielded insights suggesting a correlation between higher levels of physical activity and a lower incidence of PD, particularly among women, with findings underscoring the importance of these results in strategic planning for interventions aimed at PD prevention (Portugal et al., 2023). While the literature has extensively explored the link between overall physical activity and PD risk, a noticeable gap exists in research focused on determining the specific types of physical activities during which PD detection is most discernible. Unlike general physical activity assessments, postures offer a unique perspective, as they involve more fixed positions where tremors could become distinctly noticeable, and other movements are less likely to mask tremor signals in acceleration data.

This work proposes the use of a deep network for both feature learning and tremor detection in a realistic scenario and aims to analyse the effect of different factors to develop a proper PD detection system, such as the subjects' posture or the test time required per subject, rather than focusing solely on obtaining the best detection performance. The selection of an appropriate type and amount of data collection could improve the overall assessment during medical visits.

3 MATERIALS AND METHODS

This section includes information about the dataset used in this work, the signal processing applied, and the deep neural network used in the PD detection system and the followed evaluation methodology.

3.1 Dataset

The PD-BioStampRC21 dataset (Adams et al., 2021; Adams et al., 2017) comprises tri-axial accelerometer data obtained from five wearable sensors, encompassing participants with both

Parkinson's disease (PD) and healthy controls. The data collection utilized lightweight MC 10 BioStamp RC sensors, with each participant wearing five sensors affixed to specific body parts—chest, left anterior thigh, right anterior thigh, left anterior forearm, and right anterior forearm, as depicted in Figure 1. The samples were acquired at a sampling rate of 31.25 Hz. The dataset encompasses recordings from 34 subjects: 17 healthy controls and 17 PD participants. Upon analysis, it was observed that some sensors from control participants with IDs 007, 014, and 060 had missing data, prompting their exclusion from the study.

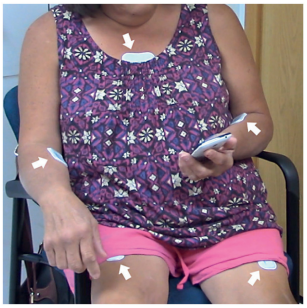

Figure 1: A study participant wearing the sensors at five different locations on the chest and each limb (Adams et al., 2017).

3.2 Signal Pre-Processing

In this work, we used the information from each inertial sensor isolated or from all together using two possible input formats to feed the deep neural networks: Raw data and Fast Fourier Transform (FFT) magnitude coefficients. Moreover, we analysed the amount of data from each user that we need to properly assess his PD status: 1, 5, 10, and 15 minutes for each participant along with their status in order to feed the classification system.

Initially, the recordings were segmented into overlapping windows, with a shift equal to half the window size between consecutive windows. All windows from each participant were labelled as either healthy control or PD based on the respective participant's health status. The classification system then categorizes each window as either belonging to a healthy control or a person with PD. In this work, we evaluated the classification performance when considering a window size of 3.2 seconds corresponding to 100 time samples. We obtained the best classification performance using this window size over this dataset in preliminary studies.

Next, for each window, we analysed time and frequency domain signals as inputs for a deep neural network, incorporating two distinct preprocessing approaches based on the signal domain. For Raw data, the original signal suffered no preprocessing, and the inputs for the deep neural network consisted directly of the time samples encompassed within each window. For the FFT, the inputs comprised the coefficients of the FFT magnitude. These coefficients were computed in advance for each analysis window, representing the spectrum from 0 Hz to 15.625 HZ (half of the sampling frequency in the PD-BioStampRC21 dataset). We decided to compute this input format because the energy in tremor motion mostly concentrates in low frequencies (M. Gil-Martin, Montero, & San-Segundo, 2019). This paper analyses and compares both alternatives for tremor modelling and detection.

In addition, this work is focused on analysing the effect of the posture performed during the motion recording in order to study which activity is better to detect the tremor and generalize to new recordings. We labelled the 3.2-second windows as ‘lying’ or ‘sitting’ using the information from the chest and thigh sensors (Adams et al., 2017). For each window, we determined the dominant axis for each sensor (the axis direction along which the mean acceleration was largest) and labelled the window considering the orientation and location of the sensors.

3.3 Deep Learning Architecture

The deep learning architecture used in this study is a Convolutional Neural Network (CNN) consisting of two main components: a feature learning subnet and a classification subnet. The first subnet acquires insights from raw data or FFT magnitude coefficients extracted from inertial signals through two convolutional layers (32 kernels of dimensions (1, 5)) and two max-pooling layers (kernels of dimensions (1, 2)). The second subnet uses fully connected layers to categorize the learned features into the predicted classes: a healthy person or a PD patient. Dropout layers (0.3) were incorporated after max-pooling and fully connected layers to prevent overfitting during training. The final layer employes a SoftMax activation function to provide predictions for each class in every analysis frame, while intermediate layers used ReLU to mitigate the gradient vanishing effect. Categorical cross-entropy serves as the loss metric, and the Adaptive Moment Estimation (Adam) optimizer dynamically adjusted the learning rate during training. The deep learning structure was trained during 30 epochs and a batch size of 100. Figure 2 illustrates the architecture

utilized in this study for modelling and classifying analysis windows as either belonging to a healthy person or a PD patient.

As depicted in the figure, the inputs of the CNN are structured in a 2D matrix with dimensions N x M. N represented the number of input signals, which is 3 when utilizing a single sensor (X, Y, and Z signals) or 15 when incorporating all five sensors available in the dataset (3 x 5). M denotes the number of analysed samples from each sensor signal, depending on the signal domain in each experiment. When using raw data as input, M is equal to the size of the analysis window (100). However, in the frequency domain, M represents the number of FFT coefficients obtained from each window, equating to half the window size (50).

3.4 Evaluation Methodology

In this work, a specific data distribution has been used to create the most realistic scenario for a PD detection system: the Leave-One-Subject-Out (LOSO) Cross Validation (CV) strategy.

This strategy is a specific type of K-fold CV where the system is evaluated with the data from one subject and is trained with the data from the rest of the K-1 subjects. In this case, the process is repeated several times leaving a different subject for testing and the results are also the average of the partial results obtained for all repetitions.

This strategy avoids using recordings from the same subjects in both training and testing subsets, which pursues a more realistic scenario where a new unseen patient's data will be modelled without using data from that subject. LOSO CV allows generalizing to new, unseen subjects, while capturing a wide variability of tremor motions from the training subjects.

As evaluation metric, we used accuracy, which defines the ratio between the number of correctly classified examples and the number of total examples. This way, for a classification problem with N testing examples and C classes, accuracy is defined in Equation (1).

$$\text{Accuracy} = \frac{1}{N}\sum_{i=1}^{C} P_{ii} \quad (1)$$

In addition, we used confidence intervals, which include plausible values for a specific metric, to show assure a significant difference between results of two experiments (when their confidence intervals do not overlap). Equation (2) represents the computation of confidence intervals attached to a specific metric value and N samples when the confidence level is 95%.

$$CI(95\%) = \pm 1.96\sqrt{\frac{\text{metric} \times (100 - \text{metric})}{N}} \quad (2)$$

In this study, we characterized PD tremor at the window level, as the input examples for the deep neural architecture were based on windows. Nonetheless, we also presented performance at the user level, where the prediction for an individual was determined by the mode of predictions across all the windows associated with that subject. This methodology enables the incorporation of information from all windows into a unified prediction, offering a more holistic perspective from a medical standpoint. Such an approach facilitates the identification of overarching health patterns instead of solely concentrating on the existence or non-existence of tremors during short time intervals, thereby mitigating the potential for incomplete or inaccurate assessments.

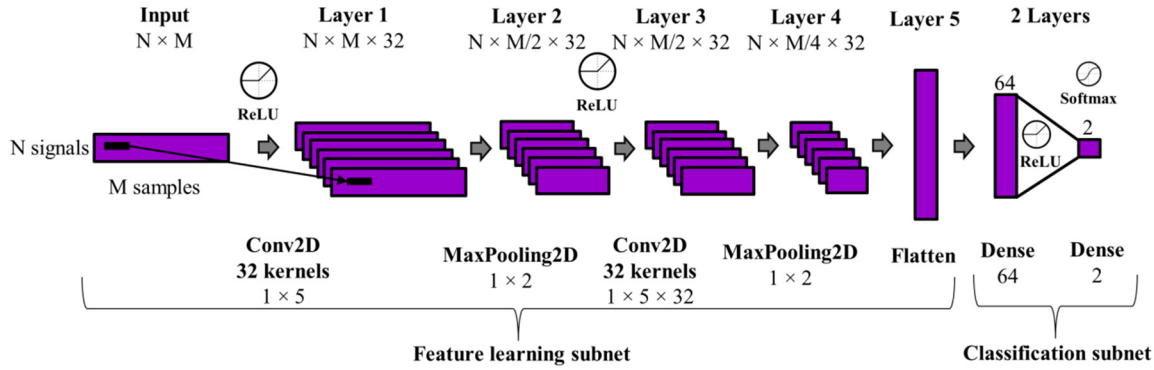

Figure 2: Convolutional Neural Network Architecture for PD detection where N denotes the number of input signals (3 or 15) and M denotes the number of samples for each analysis window or example (100 or 50).

4 RESULTS AND DISCUSSION

This section contains details about the experiments performed in this work, including results and discussion about the posture performed, the required time for testing a subject and the possibility of training and testing the system using recordings from different postures.

4.1 Posture Insights

Regarding the posture insights, we decided to evaluate the PD detection performance of the system when using Lying and Sitting activities windows and different sensors separately. Moreover, we analysed the effect of the signal domain (Raw or FFT) over this detection. Figure 3 shows a comparison of performance at window-level when using 15 minutes per subject for different input signal domains, performed activity, and sensor(s).

We observed a significant increment of performance when using signals in the frequency domain for most of the sensors when using each of the activities. An increase in visibility of PD tremor may be attributed to its intensified presence in the frequency domain. Information regarding the energy associated with the tremor frequency (between 3–9 Hz (Deuschl, Fietzek, Klebe, & Volkmann, 2003; M. Gil-Martin et al., 2019)) and its harmonics can be observed in the spectrum of the X, Y, and Z signals recorded by the inertial sensor. Consequently, using a CNN with FFT magnitude coefficients as inputs has proven to achieve superior results when compared to employing raw data samples directly.

Comparing the activities performed while recording the data, we observed an increment of performance when using sitting windows compared to using lying windows for both input signal domains (employing the same amount of data, i.e. 15 minutes per subject for these experiments). Sitting activity emerges as a potentially more helpful setting for detecting PD tremor using inertial sensors. This may be attributed to the muscle engagement necessary for maintaining an upright sitting position, making tremors more pronounced, compared to a relaxed lying posture. Furthermore, the sitting posture offers a consistent and distinctive structure across various subjects. Individuals tend to sustain relatively fixed sitting positions, ensuring a uniform and easily recognizable posture. In contrast, lying down introduces, especially during sleeping, postural changes, leading to significant alterations in the representations along the x, y, and z axes of inertial sensors. The standardization of sitting posture stands in contrast to the variability in lying posture, where alterations in body orientation during sleep could hinder the maintenance of consistent sensor data representations. When using 15 minutes per subject, we obtained a maximum performance of 73.92 ± 0.65 % employing the FFT of sitting activity and all the sensors, compared to 60.39 ± 0.73 % when using the lying activity in the same setup.

Moreover, the exploration of isolated sensors, both in the upper and lower limbs, presents a promising avenue for the creation of biomarkers associated with tremors manifesting in distinct parts of the body. This nuanced analysis allows for a more granular understanding of the tremor patterns specific to each limb, potentially leading to the development of targeted biomarkers. Such biomarkers could offer valuable insights into the severity and characteristics of tremors across different body regions, as the Unified Parkinson's Disease Rating Scale (UPDRS) assessment. Figure 3 also informs that chest sensor is the most informative location to detect PD but the rest sensors also achieve reasonable performance for the classification task. However, since we obtained better performance with all the sensors, we decided to use all of them for the rest of experiments of this study.

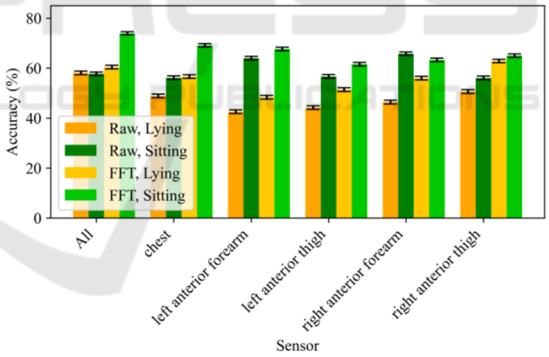

Figure 3: Accuracy at window-level using 15 minutes per subject depending on the input signal domain, the activity performed while recording the tremor and the sensor(s) used.

4.2 Required Time for Testing a Subject

Concerning the test time used from each subject to build a proper PD detection biomarker, we decided to analyse how much we could reduce the test time used from each subject without losing significant performance. We analysed 1, 5, 10, and 15 minutes from each subject for testing the system. We kept the 15 minutes per subject for training the system

(which corresponds to 465 minutes considering the remaining 31 subjects).

Figure 4 shows a comparison of performance at window-level when using 15 minutes per subject for training for different input signal domains and activity performed during recording when evaluating unseen subjects using different amount of data (1, 5, 10 and 15 minutes). Figure 5 shows the same comparison of performance at user-level. These figures show that using 5 minutes from each subject at testing stage would be enough to properly assess unseen subjects' PD status (accuracies of 77.71 ± 1.07 % at window-level and 87.10 ± 11.80 % at user-level using the FFT while sitting). Despite of the fact that assessing 1 minute could be sufficient (accuracies of 74.72 ± 2.52 % at window-level and 70.97 ± 15.98 % at user-level using the FFT while sitting) since there is no significant difference between both results, using 5 minutes could offer a more robust solution since 1 minute could be a short interval during a patient could not manifest a PD tremor.

Clinical visits intended to assess the progression of PD are often constrained by their brevity, making it challenging to draw conclusive and accurate insights into PD detection. Contrary to this common limitation, the findings presented in this paper underscore a notable advance: 5 minutes of recording proves sufficient for achieving a robust PD detection. The results indicate that extending the recording time from a new subject beyond this threshold does not yield discernible improvements in classification performance. This revelation challenges the conventional notion of requiring long recording periods, emphasizing the capability of a concise data collection approach for accurate PD detection.

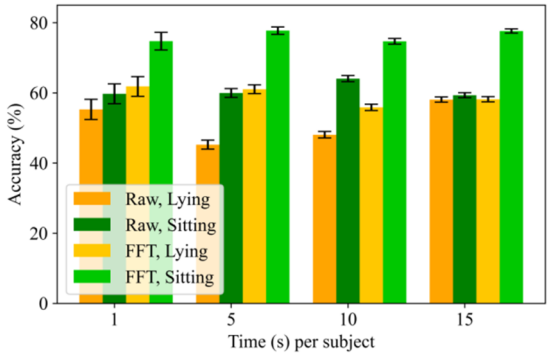

Figure 4: Accuracy at window-level using 15 minutes per subject for training depending on the input signal domain, the activity performed and the time per subject used for testing.

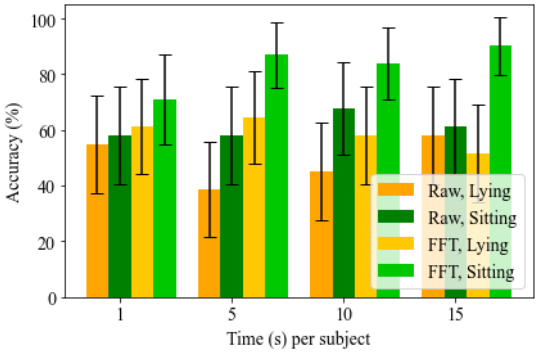

Figure 5: Accuracy at user-level using 15 minutes per subject for training depending on the input signal domain, the activity performed and the time per subject used for testing.

4.3 Transfer Knowledge Between Postures

In the pursuit of refining the robustness and generalizability of a PD detection system, this work also explored the idea of training the system with data collected in a lying posture and subsequently testing it with recordings from a sitting posture, and vice versa. This way, we could inspect the capacity of generalization across distinct postures by knowledge transferring between lying and sitting postures.

Figure 6 shows a comparison of performance when using lying and sitting activities to train the system (X axis) and to evaluate it (legend). In these experiments, 15 minutes per subject were used for training and 5 minutes per subject were used for testing. In this figure, the columns of the same colours are directly comparable because the testing data are exactly the same. As a general comment, we can say that there is not huge degradation in performance. That means that the tremor appears in the limbs involuntarily in different positions, but there are significant differences. This way, we could observe that when training a system with lying and testing with sitting (green columns of left bars) the performance drops compared to the scenario of also training with sitting data (green columns of right bars) for both input signal domains. This aspect reflects that lying activity does not incorporate sufficient information to generalize to sitting instances. However, training a system with sitting and testing with lying (yellow columns of right bars) the performance remains similar compared to the scenario of also training with lying data (yellow columns of left bars). This aspect reveals that sitting activity incorporates valuable information to generalize to lying instances.

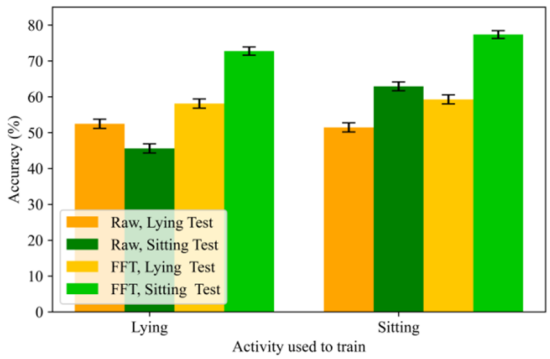

Figure 6: Accuracy at window-level using 15 minutes per subject for training and 5 minutes per subject for testing depending on the input signal domain, the activities performed during training (X axis) and testing (legend).

5 CONCLUSIONS

A broad data analysis in realistic scenarios is necessary when detecting PD through a deep learning system using inertial sensors to highlight key factors to the refinement of tremor detection. This work uses the PD-BioStampRC21 dataset including healthy control and PD participants wearing five inertial sensors to make an exhaustive study concerning the posture performed during the data collection.

Ensuring an appropriate distribution of data is crucial in PD detection to prevent data overlap between training and testing subsets and create systems that could generalize to unseen subjects. The LOSO CV technique emerges as a robust solution, achieving model generalizability.

Sitting activity becomes a crucial recording setting for detecting PD tremor using inertial sensors. The standardization of sitting activity among different subjects compared to lying activity, especially during sleeping, could benefit the tremor detection for unseen subjects. The proposed system obtained an accuracy of 73.92 ± 0.65 % when using 15 minutes per subject from all sensors and the FFT of sitting activity compared to 60.39 ± 0.73 % when using lying activity.

Concerning the required amount of data from a testing subject, we observed that using 5 minutes while sitting could be sufficient to provide a robust solution. This way, it is not necessary to record a large amount of data from a patient to properly assess his PD status.

When training a system with lying and testing with sitting, there is a significant decrease in performance compared to training and testing with sitting data. This suggests that lying activity lacks sufficient information to generalize to sitting instances. However, when training with sitting and testing with lying, the performance remains similar to the scenario of training with lying data. This indicates that sitting activity contains valuable information that allows for effective generalization to lying instances.

As future work, there is potential for further refinement in the data analysis. More specifically, enhancing the selection of windows characterized by high energy levels could prove helpful in identifying examples where tremors are more noticeable, thereby enhancing the overall performance of PD detection. Moreover, the creation of a regression system capable of precisely estimating UPDRS scores could provide valuable insights into the disease progression. The incorporation of these aspects could contribute to the development of more effective diagnostic and monitoring tools for PD.

Regarding the limitations of this study, it is relevant to remark that the PD detection proposed is based on motion symptoms. Although these symptoms appear in many patients, they do not appear with the same intensity. The system proposed can be completed with other AI-based system extracting information from other signals like EEG.

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