Detection of Arm Swing Limitations in Simulated Parkinson's Disease Gait Conditions: A Pilot Study

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Keywords: Wearables, Gait, Machine Learning, Accelerometer, Gyroscope.

Abstract: Human gait is a biomechanical process vital to health, with abnormalities often linked to neurological disorders like Parkinson's disease (PD). In PD patients, arm swing during walking becomes asymmetric and reduced in amplitude, providing a potential biomarker for early diagnosis and monitoring disease progression. This pilot study focuses on detecting variations in arm swing amplitude and asymmetry using data collected from smartwatches worn by 24 participants under different gait conditions. Participants walked while carrying progressively heavier loads (0 kg, 2 kg, and 4 kg) to simulate restricted arm swing. Machine learning models were developed to classify these conditions using accelerometer and gyroscope data. Results showed that the K-Nearest Neighbours algorithm performed best, achieving up to 94.3% accuracy. Although the models effectively distinguished between load and no-load conditions, it was difficult to differentiate between different load levels. These findings highlight the potential of wearable devices for PD gait analysis, though further refinement and testing with PD patients are needed for clinical application.

1 INTRODUCTION

Human gait is the biomechanical process of locomotion, characterized by the coordinated, rhythmic alternation of weight-bearing between the lower limbs, enabling forward movement while maintaining an upright posture. Although the walking process is unique to everyone, commonalities exist that enable the definition of a characteristic and standardized pattern for normal human gait (Braune & Fischer, 1987).

During gait, the central nervous system generates oscillation of the arms to stabilise gait, regain balance and reduce energy expenditure. Due to the close relationship between arm swing and gait, it is common for gait estimations, such as step counting, to be derived by monitoring arm swing movements (Meyns et al., 2013).

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Detection of Arm Swing Limitations in Simulated Parkinson's Disease Gait Conditions: A Pilot Study.
DOI: 10.5220/0013231600003911

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 2: HEALTHINF*, pages 1029-1036
ISBN: 978-989-758-731-3; ISSN: 2184-4305

Gait biomechanics is fundamental to health, as various diseases can disrupt the mechanical interactions involved, leading to impaired movement, instability, or mobility limitations. Many gait abnormalities arise involuntarily and are primarily linked to neurological, musculoskeletal, or systemic disorders, further impacting an individual's functional capacity (Cicirelli et al., 2022).

Festinating gait, characterized by an accelerated and unsteady walking pattern with short, rapid steps that seem to propel the individual forward, is one of the most common motor symptoms observed in patients with Parkinson's Disease (PD).

PD is a progressive neurodegenerative disorder that affects the central nervous system, resulting in both motor and non-motor symptoms. The condition arises when dopamine-producing neurons in the brain become deficient, leading to impaired motor control and other systemic effects (Wirdefeldt et al., 2011).

Symptoms of PD usually manifest gradually, with a barely perceptible tremor in one hand often being the initial sign in most cases. While tremors are common, the disorder may also cause muscle stiffness and reduced movement. The movements become reduced in amplitude, speed, and symmetry, leading to increased fatigue and the adoption of compensatory postures to maintain balance (Morris et al., 2001).

These motor symptoms affect not only gait in the lower limbs but also arm swing. Therefore, in PD patients, the arm swing has a lower amplitude, cadence and step width during gait. In addition, the PD usually manifests with more pronounced effects on one side of the body., which causes the effects on gait to be reflected asymmetrically, both in the legs and in the arm swing (Djaldetti et al., 2006). Individuals with PD demonstrated significantly greater asymmetry in arm swing compared to those without gait pathology (Lewek et al., 2010).

Based on this premise, the present case study was designed. The objective is to develop a restricted arm swing classifier focused on detecting variations in amplitude and asymmetry using machine learning models. To achieve this, an experiment was conducted in which participants wore a smartwatch and were subjected to progressively restricted gait conditions, from least to most constrained, to simulate different levels of restricted arm swing.

Under these restrictions, the braking speed of arm swing is expected to be affected in a manner that can be detected by the smartwatch. To simulate this effect, different loads (0 kg, 2 kg, and 4 kg) were used during various gait measurements. As the load increases, a reduction in the swing angle is anticipated, recreating similar conditions to the movement restrictions experienced by PD patients.

The asymmetry in arm swing may serve as a valuable biomarker for the early diagnosis of PD and for monitoring disease progression in its initial stages.

2 BACKGROUND

In recent years, numerous studies have investigated the potential of wearable devices for healthcare applications. Some research has concentrated on the development of specialized devices, like STAT-ON® (Rodríguez-Martín et al., 2019), while others have utilized commercially available devices to assess PD symptoms (Polvorinos-Fernández, et al., 2024; Sigcha et al., 2023). Wearable devices allow the definition of a wide range of digital biomarkers related to PD motor symptoms such as tremor, bradykinesia or gait disturbances (Polvorinos-Fernández, et al., 2024).

A study conducted by (Warmerdam et al., 2020) using a wrist-worn inertial sensor to compare the gait patterns of a healthy individual with those of a PD patient exhibiting gait impairments. The results revealed that the gait of the PD patients was non-cyclical, with numerous fluctuations and irregularities, in contrast to the healthy individual's gait, which displayed a repetitive and cyclical pattern.

(Takami et al., 2020) performed gait tests using a accelerometer measurement device with healthy individuals under varying conditions: normal gait, gait with one arm restricted, both arms restricted, and exaggerated arm swing in the Wernicke-Mann position. The results showed that, compared to normal gait, arm swing velocity significantly decreased when participants performed gait exercises with one arm restricted or with no arm movement.

(Siragy et al., 2020) studied how PD patients with and without arm swing restriction walked over different terrains. The arm-swing analysis revealed that PD patients appropriately reduced their step length as a compensatory mechanism for the restricted arm swing.

The need for advanced tools to improve the diagnosis and continuous monitoring PD is increasingly evident. The use of smart technologies for managing diseases like PD is gaining popularity, with wearable technologies standing out due to their low cost, long battery life, and non-invasive nature. These features make them ideal for developing continuous monitoring systems for PD.

In the case of gait observation, providing objective, gait-based measurements, wearable sensor systems allow clinicians to personalize rehabilitation, therapeutic, or pharmacological interventions to meet each patient’s specific needs. This personalized approach enhances treatment efficacy and contributes to more effective management of disease progression.

This pilot study presents a starting point for the identification of abnormal gait patterns in patients with PD. The proposed algorithm could be used for early detection of movement disorders, with a specific focus on analysing braking dynamics during gait, based on data collected from a wearable device.

3 MATERIALS AND METHODS

3.1 Data Collection

The data used in this study were collected during the BIOCLITE project, using a custom-designed m-health wearable application, which utilized smartwatches to track motor symptoms in PD patients.

Data were collected from a group of 24 volunteers, with a balanced gender distribution and ages ranging from 24 to 40 years, with no known gait pathology (Polvorinos-Fernández, et al., 2024). All participants were persons without known pathologies and performed the three specific activities outlined in the protocol of this work. Data collection covered a period of two days in which, in five to ten minutes interval, each participant performed the three proposed activities.

3.2 Acquisition Device

The BIOCLITE project use a commercial smartwatch for data collection. During each of the measurement sessions the smartwatch was worn on each patient's preferred wrist. This wearable device allows to collect movement signals in the time domain using its built-in inertial sensors. For this study, the accelerometer and gyroscope (along three axes) were used for data collection. The accelerometer measured in m/s^2, while the gyroscope measured in rad/s.

In this work, the smartwatch used for data collection has a dimension of 39.3×40.4×9.8 mm and a weight of 28.7g. The smartwatch is equipped with an LSM6DS0 package, which integrates a 3-axis digital gyroscope and a 3-axis digital accelerometer.

The sampling frequency is configured at 50 Hz. This frequency was chosen because it is well-suited for the analysis of human movement, which typically focuses on a frequency range of 0.8 to 1.5 Hz during normal and abnormal gait (Winter, 2009).

3.3 Experimental Protocol

During the data collection sessions, each participant performed a test under different conditions to approximate several gait conditions.

Each participant must walk in a straight line from the starting point to a marked point, wait for 3 seconds at that point, turn around to change the direction of movement, wait another 3 seconds and walk back to the starting point. Participants were instructed to perform the test at their preferred walking speed, repeating the process three times: once with no load, a second time carrying a 2 kg weight, and a third time carrying a 4 kg weight. This order was established to try to avoid fatigue affecting the participants, even though there was a rest period between each test.

For each participant and each performed test, a researcher was responsible for starting the recording of the data from the smartwatch, indicating to the participants the start of the test, logging the exact time at which the test had started, and, once the test had been completed, stopping the measurement. In this case, the activities were not recorded with a video camera due to patient privacy issues.

The measurement track was a straight corridor where the point of departure and return was marked with a cross on the ground. The straight section is 30 metres long, and the corridor is more than 5 metres wide, which allowed the measurement session to be carried out without any problems.

For each participant and activity, a new file was created. Therefore, considering that there were 24 participants and 3 different activities, a total of 72 data files were obtained.

3.4 Data Labelling

For data labelling, the name of the files generated with the custom-designed m-health smartwatch application was essential. This name identifies which device was used (this information is not valid for this study given that all the performed tests were carried out with the same device) together with the date on which it was created and the exact time at which the recording was started.

Based on this date and time, each of the records was assigned a person label (1 to 24) and an activity label (1 for no load gait, 2 for 2 kg gait and 3 for 4 kg gait), correlating with the manual registration made by the person in charge of the trials, who takes notes of which person carried out each activity as well as the starting time. These labels were then reviewed by viewing each file to ensure that they matched and contained valid data records.

Figure 1 shows the distribution of data collected according to the activity label. It can be observed that the distribution is homogeneous among the 3 gait conditions. The slight differences observed between activities can be attributed to the fact that participants were allowed to choose the speed at which they performed each test. Consequently, variations in walking speed among participants resulted in differences in the number of samples collected, as the sampling rate is the same for all the subjects. The activity with the highest number of samples is the one related to walking without loads.

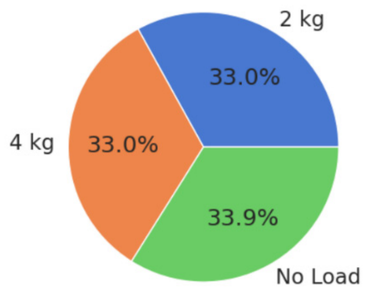

Figure 1: Distribution of data collected according to the activity label.

3.5 Algorithmic Approach

This paper presents machine learning models designed to predict the level of hand movement constraint (free, 2 kg or 4 kg) using data from accelerometer and gyroscope. The development of these models followed the schema shown in Figure 2.

To train and evaluate the proposed models, the signal obtained from the smartwatch must be processed to get better results.

First, the valid parts of each of the records were selected, as the periods from the start of the recording until the person starts walking, the standing period before and after the turn, the turn itself, and the period from the end of the activity until the end of the recording were not used. As a result, since there are two gait periods for each record (outward and return), the final database of 144 valid records was defined.

On this basis, this study was performed using two different databases. On the one hand, the accelerometer and gyroscope signals from each of the 3 axes were used independently (6 signals in total). On the other hand, the signal obtained from each of the three axes of each sensor was combined into one by means of Euclidean Norm according to equations 1 and 2 (2 signals in total). This is since the inertial sensors embedded in the wearable device can have a random orientation, so this combination has been performed to avoid errors. In addition, during the experimental phase, the participants placed the smartwatch in different ways and the orientation of the watch is different for the left and the right hand.

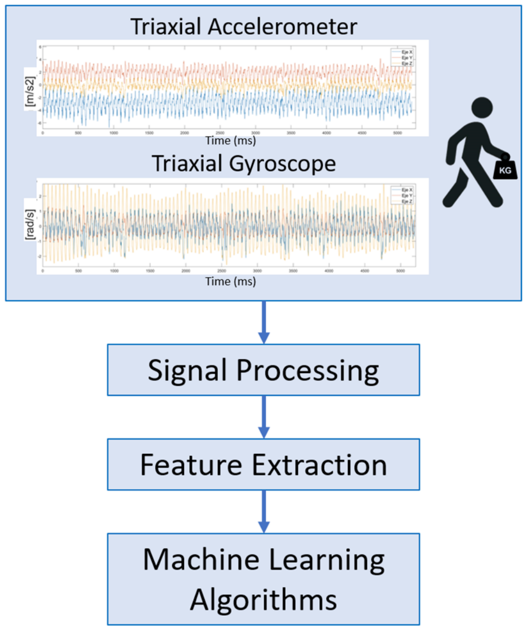

Figure 2: Algorithm approach diagram.

$$Accel = \sqrt{accel_x^2 + accel_y^2 + accel_z^2} \quad (1)$$

$$Gyro = \sqrt{gyro_x^2 + gyro_y^2 + gyro_z^2} \quad (2)$$

After calculating the Eucliden norm, the following steps to be explained apply both to the 3 axes separately and to the combination of these. The signal was filtered using a 3-order Butterworth band-pass filter in the frequency range between 0.5 and 10 Hz. This range is appropriate for human activity recognition, in particular, human gait (Winter, 2009).

After adjusting the signal to the desired frequency range, it was segmented into 128-sample windows (2.56 seconds) with a 50% overlap. For the 144 records, 2454 windows were generated. This combination of windowing and overlapping is suitable for different PD motor symptoms analysis (Patel et al., 2009; Sigcha et al., 2021). As the data is divided by records and each one corresponds to a different participant and activity, dividing each of these records into windows did not create a problem regarding labelling, as all the windows had the same labels associated with their source records.

Then, the signal was converted to the frequency domain using the Fast Fourier Transform (FFT). This was because it is expected that the dominant frequencies of braking during walking will allow a correct differentiation between individuals walking freely and those carrying varying weights., so bringing the data into the frequency domain can be a key aspect to obtain good results. Since the sampling frequency is defined as 50 Hz, the maximum frequency for which data is available is 25 Hz (higher than the usual frequency of human movement). In this case, 65 spectral lines were calculated using the FFT, each with a bandwidth of approximately 0.38 Hz.

For this work, the extracted features correspond to the amplitude of each of the 65 spectral lines of each signal. For the database formed by the original signals in 3 axes, and for 2 sensors (accelerometer and gyroscope), we will have 390 features. In the database composed of the Euclidean signal of accelerometer and gyroscope, 130 features will be calculated. In both databases, all the proposed features were calculated for the 2454 defined windows.

After the feature extraction process, machine learning models were developed, trained, validated, and analysed with the two databases independently to evaluate their performance and effectiveness in addressing the study objectives. For the training and testing of the models, the windows defined for 21 of the 24 participants were divided into 60% training and 40% test, using Hold Out Validation. The 3 remaining participants (randomly selected) were used to validate the trained models, with the aim of testing the reliability of the models on data never seen before.

For this work, the variable to be predicted is the one corresponding to the activity category, related to whether, during the walk, the person was walking without load (label 0), with 2 kg (label 1) or with 4 kg (label 2). Since the target variable is categorical, classification models were employed. The models used in this study include Gradient Boosting (GB), AdaBoost (ADAB), K-Nearest Neighbours (KNN), Random Forest (RF), and Decision Tree (DT). The models were evaluated using accuracy, recall, specificity, precision, and F1-score metrics.

4 EXPERIMENTS AND RESULTS

This section presents the results obtained from the study, which involved conducting various experiments with different datasets. Section 4.1 details the results derived from the 3-axis signals of the accelerometer and gyroscope. Section 4.2 presents the findings based on the Euclidean norm of the combined signals from both sensors. In each section, the model with the best performance was identified, and validation of this model was carried out using data from three randomly selected subjects.

4.1 Results of the Training Models Using the 3-Axis Database

The classification models proposed in Section 3.5 were implemented and trained using the dataset of 390 features extracted from the frequency domain for each triaxial signal of accelerometer and gyroscope.

First, it will be determined which of the models proposed is the one that offers the best performance. Figure 3 show the metrics obtained for each trained machine learning model using the testing data.

It is noteworthy that recall values are high across all models. This indicates that the models effectively identify most of the true positive cases, i.e. the models are less likely to miss relevant cases, which makes them suitable for tasks where it is a priority to capture all positive cases, such as in medical diagnosis, of possible application in this study.

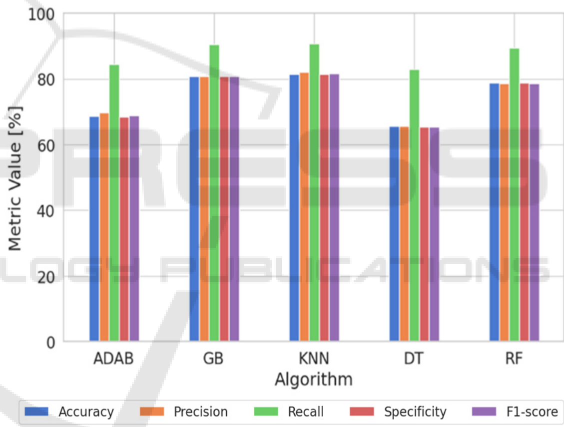

Figure 3: Metrics comparison for the proposed algorithm using 3-axial accelerometer and gyroscope test data.

The analysis revealed that the KNN algorithm demonstrated the best performance among the evaluated models., with an accuracy of 81.5 %, a precision of 82.0 %, a recall of 90.8 %, a specificity of 81.4 % and a F1-score of 81.6 %. On the opposite side, the worst model is the DT with 69.4 %, 69.3 %, 84.8 %, 69.2 % and 69.1 % in respective metrics. Table 1 shows in detail the metrics obtained with the test dataset for the best model.

It can be noticed that there is a trend towards classification performance. For the identification of no-load gait, related to the movement without loads, the specificity, recall, precision and f1-score metrics have a high performance, between 88,01 % to 98,42%. On the other hand, for observations related to loaded movement, these metrics are relatively lower, with values from 74,22% to 87,19 %. However, the overall accuracy of the 3 categories is 81.51 %, which is quite high, considering that we are working with a not very extensive database.

Table 1: Metrics obtained for KNN algorithm for the 3-axis test dataset.

[%]	No Load	2 kg	4 kg
Accuracy		81,5	
Precision	96,6	74,2	75,2
Recall	88,0	75,5	80,8
Specificity	98,4	87,2	86,8
F1-score	92,1	74,9	77,9

Once the best model has been determined, it will be used for validation with the 3 randomly selected subject data. The confusion matrix, shown in Figure 4, will be used for this purpose.

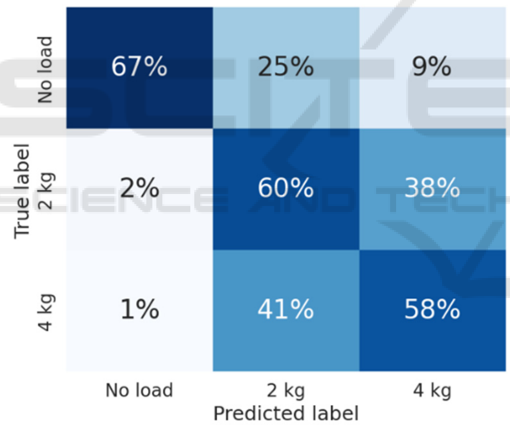

Figure 4: Normalized Confusion Matrix for the 3-axis validation dataset.

It can be observed that the differentiation between walking with loads and without loads can be done relatively easily. Moreover, the algorithm is more wrong predicting that it is loaded when it is free (34%) than in interpreting that it is free when it is loaded (3%). However, distinguishing between label 1 (2 kg load) and label 2 (4 kg load) is a challenging task. The model misclassifies label 1 as 2 38% of the windows and label 2 as 1 in 41% of cases.

4.2 Results of the Training Models Using the Combined Signal Database

In this section we will present the study proposed in the previous section using a different database, the one composed of the triaxial accelerometer and gyroscope signals combined using the Euclidean standard. In comparison with the previous case, it will be moved from dealing with a signal of 6 different channels to one with only 2.

Figure 5 shows the metrics obtained with the test dataset associated to the trained models. It can be noticed that the values obtained are higher than those obtained in the previous section. While in section 4.1 the results were between 65% and 90%, those calculated with the database of the combined signals have obtained values between 72% and 98%.

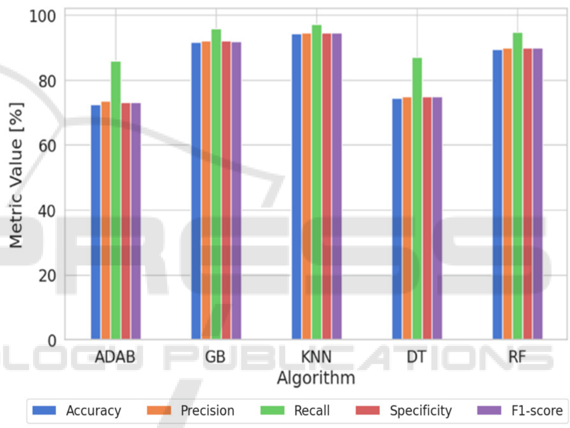

Figure 5: Metrics comparison for the proposed algorithm using combined accelerometer and gyroscope test data.

Again, the best performing model is the KNN algorithm. The worst performer, meanwhile, is the ADAB algorithm. Table 1 shows in detail the metrics obtained for the best model with the test dataset.

Table 2: Metrics obtained for KNN algorithm for the combined signal test dataset.

[%]	No Load	2 kg	4 kg
Accuracy		94,30	
Precision	99,63	91,50	92,28
Recall	99,83	95,34	96,15
Specificity	99,26	92,72	91,32
F1-score	99,44	92,11	91,79

The trend continues to be that label 1 is the one with the best metrics, i.e. the one that is most accurately identified. Accuracy, recall, specificity and F1 score all have values around 99%. These metrics for labels 2 and 3, corresponding to loaded gait, are around 92%. The accuracy is around 94%, higher than in the previous case.

With the best model identified, it will be validated using data from the 3 randomly selected subjects. The confusion matrix, shown in Figure 5, will be utilized.

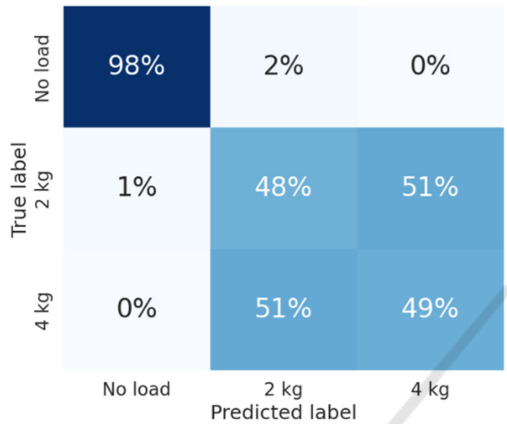

Figure 6: Normalized Confusion Matrix for the combined signal validation dataset.

In this case, the trend mentioned in the previous analysis becomes more pronounced as it is very accurate in identifying the unloaded gait with a 98% accuracy rate. On the other hand, when dealing with the loaded gait data, the predictions are not at all accurate, as it is only 50% correct to differentiate between 2 and 4 kg. In fact, it predicts as 4 kg when it is really 2 kg in 51% of the cases and the same happens in the opposite case, interpreting that it is 2 kg when it is really 4 kg.

5 CONCLUSIONS

This study developed and evaluated machine learning models for detecting arm swing constraints in simulated gait conditions, trying to be like the gait patterns of PD patients.

By utilizing accelerometer and gyroscope data from smartwatches, the machine learning models were able to classify participants walking under three conditions: no load, 2 kg load, and 4 kg load.

KNN model demonstrated the highest accuracy in both the 3-axis and Euclidean norm-based datasets, proving effective in distinguishing between loaded and unloaded gait patterns. However, while the models performed well in detecting the presence of a load, they encountered difficulties differentiating between the 2 kg and 4 kg weights, indicating that further refinement is needed for more nuanced classification. One possible explanation is that walking without a load, as opposed to carrying any load, induces significant changes in body posture, stride, and movement dynamics that can be effectively captured by the signals employed. However, when differentiating between loads, these differences may not be as pronounced.

Using the 3-axis dataset with the validation data set, it manages to differentiate the no load cases 67% of the time, the 2kg load cases 60% of the time and the 4kg load cases 58% of the time. For the combined signal dataset, on the other hand, this distribution changes, as the no load cases are matched 98% of the time while the 2 and 4 kg load cases are matched around 50% of the time.

This evaluation highlights the potential utility of each dataset employed in the analysis. The combined signal could be used to distinguish load and no-load cases while the 3-axial signal could be used to distinguish between different load situations.

It is important to acknowledge that this study has certain limitations that should be addressed in future research studies. The database consists of measurements from 24 healthy patients with no known gait pathology. In addition, no real PD patients have been involved, which would be interesting especially for the validation of the models.

Future work should focus on exploring the applicability of this type of test in PD patients to evaluate its practical utility, expanding the database by increasing the number of participants and incorporating diverse settings, such as varying loading conditions or extended durations, to study variability. Furthermore, it would be valuable to investigate additional machine learning algorithms, including traditional and recent advancements, such as deep learning, to enhance performance.

In practical implementation, several considerations must be addressed to transition this approach to real-world applications effectively. Smartwatches offer a non-intrusive platform for long-term monitoring; however, ensuring usability and fostering patient compliance remain crucial challenges. Validation of the system with PD patients across diverse daily living scenarios is necessary to establish model robustness and reliability under real-world conditions. Additionally, implementing secure and efficient data transmission mechanisms is essential to safeguard patient privacy and ensure reliability in remote monitoring applications.

Addressing these factors will significantly enhance the practical utility and scalability of this approach.

The findings of this study suggest that wearable sensor data combined with machine learning techniques offer valuable potential for gait analysis, with applications in the early diagnosis and monitoring of movement disorders such as PD.

ACKNOWLEDGEMENTS

This research has been possible thanks to the financing of the project BIOCLITE: PID2021-123708OB-I00, funded by MCIN/AEI/10.13039/501100011033/ FEDER, EU.

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