Evaluation of the Performance of Wearables' Inertial Sensors for the Diagnosis of Resting Tremor in Parkinson's Disease

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Keywords: Motor Symptoms, Wearables, Accelerometer, Gyroscope, Machine Learning.

Abstract: Currently, objective monitoring of resting tremor in Parkinson's disease (PD) involves wearable devices and machine learning. Smartwatches may present an affordable method for remote and unintrusive tremor monitoring. However, the development of optimized systems is necessary to perform accurate monitoring in free-living settings. In this study, the potential of inertial sensors to detect resting tremors is evaluated. A smartwatch was placed on the wrist of six subjects with PD during the execution of MDS-UPDRS motor tasks. Data were collected over eight weeks from triaxial accelerometer and gyroscope simultaneously and used to implement machine learning algorithms to detect resting tremor. The best performance (accuracy 97.0% in tremor detection) was achieved using accelerometer data analysed with a Random Forest classifier, while the gyroscope showed lower performance (93.0%). The results indicates that the use of the accelerometer in commercial smartwatches can offer effective results for detecting resting tremors, while reducing computational workload. These results show opportunities for the development of robust free-living tremor monitoring systems using commodity devices and algorithms using a single sensor.

1 INTRODUCTION

Parkinson's disease is a neurodegenerative disease affecting the central nervous system, leading to motor and non-motor manifestations. PD occurs when neurons do not produce enough of the chemical "dopamine" (Wirdefeldt, Adami, Cole, Trichopoulos, & Mandel, 2011).

Globally, 7–10 million individuals are currently affected by PD, with an upward trend in recent years. PD is rare before the age of 50 and exhibits a greater

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Polvorinos-Fernández, C., Sigcha, L., Pereira de Pablo, L., Borzí, L., Cardoso, P., Costa, N., Costa, S., López, J., de Arcas, G. and Pavón, I.
Evaluation of the Performance of Wearables' Inertial Sensors for the Diagnosis of Resting Tremor in Parkinson's Disease.
DOI: 10.5220/0012571600003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 2*, pages 820-827
ISBN: 978-989-758-688-0; ISSN: 2184-4305

prevalence among men compared to women. The incidence of PD increases with age, affecting around 1% of the population aged 60 or older (Rocca, 2018).

The development of the disease over time is dependent on the person who suffers from it. During the disease, patients progress through different stages, associated with the severity of the symptoms and physical disability caused. Currently, the diagnosis and monitoring of the disease is conducted by a medical specialist who assesses a series of exercises performed by the patients using standardized guidelines (Bhidayasiri & Martinez-Martin, 2017).

Among the motor symptoms in PD, the most common and diagnostically distinct motor symptoms is tremor (Halli-Tierney, Luker, & Carroll, 2020). Tremor can be defined as an involuntary oscillatory movement of parts of the human body, such as in the hands or feet. There are different types of tremors associated with PD, classified as resting tremor, that presents when patients are relaxed; and action tremor, which occurs when holding a position against gravity or during any voluntary movement (Gironell, 2018).

The frequency range in which this type of tremor manifest is in the range of 3.5-7 Hz (Salarian, et al., 2003), while common human movements are usually found in the 0-20 Hz band (Mannini, Intille, Rosenberger, Sabatini, & Haskell, 2013).

Currently, levodopa is the principal drug used to treat PD actively (LeWitt, 2008). It acts by converting to dopamine in the brain and works vigorously on controlling tremors in patients.

The subjective nature of motor assessment based in observation techniques and the sporadic follow-up commonly performed in clinical settings hinders the implementation of precise therapies. For this reason, the need of tools to improve the diagnosis and continuous monitoring is still required.

The use of smart technologies for diseases such as PD is currently on the rise. Wearable technologies, stand out for their low cost, battery life, non-invasiveness, can bring an excellent technological support to implement monitoring systems for PD.

The use of inertial sensors such as accelerometers and gyroscopes included in wearable devices with an appropriate processing of these data and a subsequent implementation of artificial intelligence algorithms can be a promising alternative for the monitoring of motor symptoms in PD in free-living conditions.

In this work, it has been evaluated which of the inertial sensors integrated in a smartwatch, accelerometer or gyroscope, could provide better performance in terms of accuracy for the classification of tremor in PD patients using machine learning models. The dataset (Sigcha, et al., 2023) used contains weekly records from several Parkinson's disease patients during various planned activities, while they were wearing a smartwatch.

2 BACKGROUND

Currently, the most used method for the assessment of PD is the Movement Disorders Society's review of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS) (Goetz, et al., 2008). Motor symptoms are evaluated in the part III of this guide on a scale of 0 to 4, with 0 assigned to the non-existence of symptoms and 4 the label for the most severe value.

Despite this scale is widely used, the evaluation can be subjective by the physician and depends on his or her perception at the time, which may vary from one neurologist to another. This, together with the fact that patients make very occasional visits to the clinic, has led many authors to study the possibility of remote and objective symptom monitoring.

Therefore, in recent years, numerous studies have evaluated the possibility of using wearable devices for healthcare applications. Some studies have focused on the development of specific devices, while others have used commercial devices for the evaluation of PD pathologies (Sigcha, et al., 2023).

Regardless of how the monitoring has been approached, MEMS (Micro Electronic Mechanical Systems) type sensors have been used due to their small size and low cost. The most common sensors used in motor symptom monitoring are the accelerometer and the gyroscope. A study conducted by (San-Segundo, et al., 2020) used accelerometers to compare tremor detection in free-living conditions and in the laboratory environment, achieving a 10% and 5% error. (López-Blanco, et al., 2019) conducted one year of monitoring using a smartwatch that collected data from a gyroscope yielded a Spearman coefficient between the mean of the resting tremor scores and smartwatch measurements was 0.81.

The combination of accelerometer and gyroscope data for tremor detection was evaluated in (Sun, et al., 2021), where a watch integrating both sensors was developed, achieving an accuracy of over 94%.

Despite the progress in tremor monitoring, previous studies have not focused on evaluating which inertial sensor (accelerometer or gyroscope) can provide more information to assess this symptom. This paper will to study the potential of inertial sensors in a commercial smartwatch to detect restring tremor and evaluate which dataset, the one collected from the accelerometer or the one obtained from the gyroscope, could provide more useful information.

3 MATERIALS AND METHODS

3.1 Data Collection

The data used in this study were collected during the TECAPARK project (TECAPARK, n.d.), using a proprietary m-health application named Monipar (Sigcha, et al., 2023). A consumer-grade smartwatch and a smartphone were used to monitor motor symptoms in PD patients. The Monipar dataset contains weekly records from Parkinson's disease patients during planned activities, including standardized exercises and resting periods for their upper limbs, while they were wearing a smartwatch.

Data was collected from 6 PD patients (3 males/3 females, 64.2 ± 8.2 years). These subjects were in early stages of the disease according to the Hoehn and Yahr scale (Hoehn & Yahr, 1998) (H&Y = 1).

Three participants did not present tremors while the other three presented tremors. A trained specialist evaluated tremor according to MDS-UPDRS 3.17, assigning score from 0 (no tremor) to 2 (mild tremor).

The data collection was conducted over 8 weeks, and, during the study, all patients maintained their usual medication regimen.

To perform tasks such as signal labeling, preprocessing and feature extraction, MATLAB software (R2017a) was employed. For the evaluation and the training of the models, Python (3.6), and the libraries Pandas, and Scikit learn were chosen.

3.2 Acquisition Device (Smartwatch)

A consumer-grade smartwatch was used as the data acquisition device during the measurement sessions and was placed on the wrist of the most affected side.

The wearable device was used to collect vibration signals in the time domain using the bult-in inertial sensors (accelerometer and gyroscope) in three axes. In the case of the accelerometer, in m/s^2, and, for the gyroscope, in rad/s.

In this study, a smartwatch with dimensions of 46.6×51.8×12.9 mm and a weight of 32.5g was used, with WearOs® as the operating system. This smartwatch is equipped with an LSM6DS3 type package, which includes a 3-axis digital gyroscope and a 3-axis digital accelerometer. The triaxial accelerometer has a maximum measurement amplitude of ±2 g, while the triaxial gyroscope has a measurement range of ±2000 dps.

The smartwatch was set to record data at a sampling rate of 50 Hz. This frequency has been established as it is appropriate for the analysis of human movement, as common human movements are usually found in the 0-20 Hz band, while it also allows recording the typical PD tremors in the range of 3.5-7 Hz (Salarian, et al., 2003).

3.3 Experimental Protocol

In each measurement session, each patient performed 8 exercises designed to assess the motor status, including resting periods between exercises. These exercises were conducted using Monipar application, which guides the user through exercises by displaying the tasks to be performed on the mobile screen.

In specific, each exercise belongs to the MDS-UPDRS part III. The exercises proposed are related to the amplitude of resting and postural tremor of the hands, movement of the hands towards the chest, finger tapping, hand movements, pronation-supination of the hands, getting up and gait.

Each exercise has a different duration (explanation plus execution); some take 15 seconds, while others may require 50 seconds. Furthermore, there is a 30-second break between exercises, making 7 minutes the approximate duration of each single measurement session. Furthermore, each patient's sessions were video recorded for subsequent labeling.

For the completion of this work, only the data related to resting tremor amplitude, assessed through section 3.17 of the MDS-UPDRS were used. In this task, the patient should sit quietly in a chair with hands resting on the armrest (not on the lap) and feet resting comfortably on the floor, for 10 seconds, without any other indication. Figure 1 shows the interface of the resting tremor exercise.

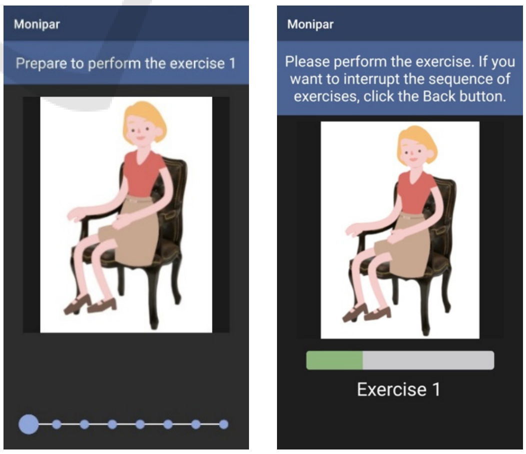

Figure 1: Exercise explanation in mobile application.

3.4 Data Labelling

For data labelling, Monipar automatic generated labels were used for each of the exercises. The sequence of exercises is numbered from 1 to 8 according to the order in which they are performed. The resting tremor exercise corresponds to label 1.

For tremor labeling, data were automatically labeled using thresholds according to magnitude analysis in the tremor band (3.5-7.5 Hz). Then, these labels were verified and corrected using video recordings for each test. Data was labeled according to the MDS-UPDRS section 3.17 guidelines. In specific, the following were assigned to the data: 0 (Normal) if no tremor is observed, 1 (Slight) if the maximum amplitude of the movement is less than 1 cm, 2 (Mild) if the maximum amplitude is between 1 and 3 cm, 3 (Moderate) if it is between 3, and 10 cm and as 4 (Severe) if it is greater than 10 cm.

Figure 2 shows the distribution of tremor labels. Only labels 0,1,2 are available, with 0 being the most common label, present in 78% of the data.

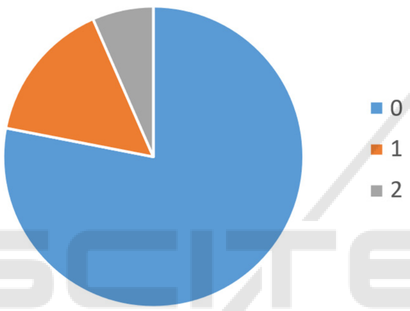

Figure 2: Observations distributed by tremor label.

In this paper, the tremor label was used in two ways. On the one hand, to classify among MDS-UPDRS scores. And on the other hand, to differentiate between the presence or not of tremor, so labels 1 and 2 will be grouped into a single label.

3.5 Algorithmic Approach

This paper presents machine learning models that predict the level of tremor amplitude using accelerometer and gyroscope data to identify which of them is more useful for prediction. This work was developed following the schema shown in Figure 3.

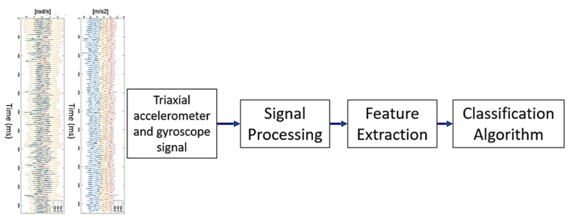

Figure 3: Algorithm development diagram.

To train and evaluate the proposed models, the signal obtained from the smartwatch has been processed. First, 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). 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, the computational load during training and prediction can be reduced.

$$Accel = \sqrt{accel_x^2 + accel_y^2 + accel_z^2} \tag{1}$$

$$Gyro = \sqrt{gyro_x^2 + gyro_y^2 + gyro_z^2} \tag{2}$$

After calculating the Eucliden norm the signal was filtered using a Butterworth band-pass filter of order 3 to select the signal between 0.5 and 10 Hz. This frequency range is suitable for human activity recognition and relevant for the tremor present in PD (Khan, Hammerla, Mellor, & Plötz, 2016).

Following, signal segmentation was performed using 128-sample windows (2.56 seconds) using 50% overlap. A total of 5158 windows have been defined. This combination of segmentation and overlapping is recommended for PD tremor analysis (Patel, et al., 2009) using inertial sensors.

To establish the tremor amplitude label in each of the windows, if the label is repeated for more than half of the observations in each window, the assigned value will be that label. If this does not occur, such windows will be excluded.

Finally, the signal was transformed to the frequency domain using the Fast Fourier Transform (FFT), since it has been shown (Ahlrichs & Samà, 2014) that the signal in the frequency domain could be representative to evaluate the tremor.

Both time and frequency domain features will be obtained. The time variables are the easiest to obtain since do not entail a very high computational cost; however, they do not lead to very robust conclusions due to their difficult interpretation in this domain in view of the tremors associated with human movement. Nevertheless, the frequency variables allow an improvement in the detection of the tremors despite being more computationally complex to acquire due to the need to calculate the FFT.

For each domain, the same type of features was obtained. The Table 1 shows the extracted features with a brief explanation of each of them. The database used will be composed of 18 characteristics, 9 from the time domain and 9 from the frequency domain.

Table 1: Features extracted from the filtered accelerometer and gyroscope signals in each domain.

Feature	Description
Standard Deviation	Returns the standard deviation of the signals in each domain.
Mean	Calculates the median value of all the measurements.
Median	Finds the median value of the filtered signals in each domain.
Percentile 25	The 25th percentile of the input data for each domain signal slice.
Percentile 75	The 75th percentile of the input data for each domain signal slice.
Skewness	Asymmetry of the filtered signals in each domain.
Max	Finds the maximum of the values for each window in each domain.
Min	Finds the minimum of the values for each window in each domain.
Entropy	Returns the entropy of the filtered signals in each domain.

To these 18 features, those obtained from the FFT of the signal must be added. In this case, 65 additional features were obtained. So, a total of 83 features were calculated for each of the 5158 defined windows.

For the development of machine learning models, the database was divided using Hold Out Validation. In this case, 80% (4126 windows) of the data for algorithm training and 20% (1032 windows) for algorithm validation. Although all measurements were collected during the same task, since human movement, especially PD, is different from one to another, the train-test distribution has been randomized among the entire dataset.

As the target variable is categorical, the models proposed are classification models. In this study, the following models are proposed: Gradient Boosting (XGB), AdaBoost (ADAB), KNeighbours (KNN), Random Forest (RF), Logistic Regression (LR) and Decision Tree (TREE). Evaluation of the models was performed using accuracy, sensitivity, specificity, precision and F1-score metrics.

4 EXPERIMENTS AND RESULTS

This section presents the results obtained in the present study. Multiple experiments were conducted to evaluate and determine which sensors provide the best performance. Section 4.1 presents the results related to the evaluation using a binary classification between tremor and non-tremor, obtaining the best sensor with the results of the best model obtained. Section 4.2 presents the results using the classification of the tremor level thresholds according to the MDS-UPDRS scale and establishing the best sensor and model obtained.

4.1 Results of the Training of Binary Models

The proposed classification models shown in Section 3.5 were implemented and trained using the set of features extracted from the time and frequency domains for each triaxial signal. In specific, two different sets of features were extracted to each inertial sensor (accelerometer and gyroscope).

In this case, as an unbalanced database is used, metrics such as accuracy or precision, which measure the proportion of correct predictions out of the total number of predictions, can be misleading as they provide a very high percentage of correct predictions, but they could be only correct predictions of no tremor. Thus, the study has focused on analyzing the F1-score, because this metric combines precision and recall using their harmonic mean, so a maximum F1-score implies maximizing both precision and recall simultaneously. Figure 4 show the training results obtained, as reflected in the F1-score for each of the models for the accelerometer and the gyroscope.

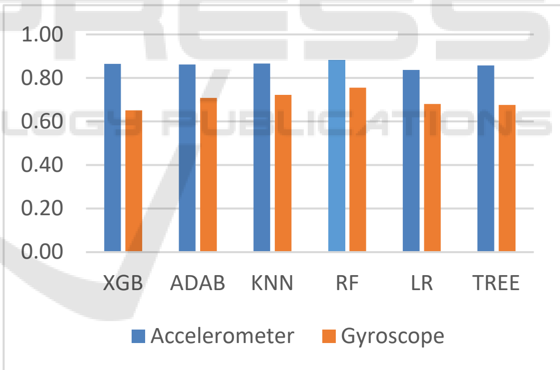

Figure 4: F1-score comparison for each algorithm using accelerometer and gyroscope data.

From the observation of figures 4, it is evident that results obtained from the data provided by the accelerometer suppose a better performance of the prediction model over those achieved through the gyroscope. The average F1-score value of the models trained with the accelerometer data was 0.86 while that obtained with the gyroscope dataset is 0.70.

However, to determine which is the best classification model obtained, all calculated metrics were considered. Table 2 and Table 3 show the training results for each of the models.

Among all the machine learning algorithms implemented, it is observed that the Random Forest algorithm offers the best metrics, and in particular the balance of sensitivity and specificity is highlighted.

Table 2: Metrics obtained for each machine learning algorithm from accelerometer data.

	Accuracy	Sensitivity	Specificity	Precision	F1-score
XGB	0,94	0,86	0,96	0,87	0,87
ADAB	0,94	0,87	0,96	0,86	0,86
KNN	0,94	0,86	0,97	0,88	0,87
RF	0,95	0,87	0,97	0,90	0,88
LR	0,93	0,81	0,97	0,87	0,84
TREE	0,94	0,86	0,96	0,86	0,86

Table 3: Metrics obtained for each machine learning algorithm from gyroscope data.

	Accuracy	Sensitivity	Specificity	Precision	F1-score
XGB	0,88	0,51	0,99	0,92	0,65
ADAB	0,89	0,61	0,97	0,84	0,71
KNN	0,90	0,61	0,98	0,89	0,72
RF	0,90	0,68	0,97	0,86	0,76
LR	0,88	0,57	0,97	0,85	0,68
TREE	0,86	0,68	0,90	0,67	0,68

The test data, 20% of the total dataset, has been evaluated with the best model, Random Forest, to identify which of the two dataset yields better results. The metrics are shown in Table 4 while the related normalized confusion matrices are shown in Figure 5.

Table 4: Metrics associated with Random Forest algorithm for accelerometer and gyroscope for test set.

[%]	Accelerometer	Gyroscope
Accuracy	96.98	92.99
Sensitivity	91.06	75.07
Specificity	98.56	97.70
Precision	94.38	89.54
F1-score	92.69	81.67

It can be appreciated that both inertial sensors have above 75% in all the metrics that were considered. However, there are notable differences based on the selected inertial sensor. For all these metrics, the accelerometer database shows better performance than the gyroscope. While both sensors obtain quite similar specificity values, significant differences are shown in the other metrics, with the most significant difference in sensitivity, where the accelerometer provides a value of 91% while the gyroscope obtains a value of 75%.

It is noteworthy that the gyroscope data produces an error of 25% predicting no tremor when it is tremor. 91.06% sensitivity and 98.56% specificity for the data provided by the accelerometer indicate a very high accuracy rate in the prediction of resting tremors.

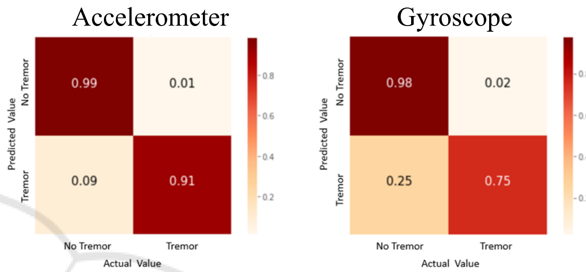

Figure 5: Confusion matrices for accelerometer and gyroscope for test set.

4.2 Results of the Training of Multiclass Models

This experiment will approach the lines of resting tremor prediction in a more qualitative way, leaving behind binary classification. It has sought to evaluate the performance of the algorithms by faithfully predicting the tremor label assigned by the MDS-UPDRS scale, using multiple classification.

In this case, the model that has been proposed is the one that has achieved the best results in the binary classification model. The Table 5 shows the metrics obtained from the model trained using the data from the different data sources.

Table 5: Comparison of the accuracy of each class for Random Forest (multiclass classification).

	Accelerometer			Gyroscope		
[%]	0	1	2	0	1	2
Accuracy		96.8			89.3	
Sensitivity	98.6	88.5	93.6	97.9	54.7	60.2
Specificity	98.6	88.5	93.6	97.9	54.7	60.2
Precision	97.9	88.9	100	93.7	64.6	75.5
F1-score	98.2	88.7	96.7	95.8	59.2	67.0

It can be noticed that the prediction of true resting tremors of amplitude according to MDS-UPDRS (scores 1 and 2) has a much higher hit rate with the accelerometer data than by the gyroscope. For the detection of no tremor (label 0), the values obtained by the accelerometer and the gyroscope are quite similar, however, it is again the dataset obtained from the accelerometer that provides the best results.

From the observation of Figure 6, for the gyroscope data, it is a difficult task to discern between tremor and no tremor. It makes an error of 36% predicting tremor 1 when it is really rest, and 38% predicting tremor 2 when it is tremor 1. This is not the case for the accelerometer, with very low percentages of error between predictions for no tremor and different level of tremor (11% and 6%, respectively).

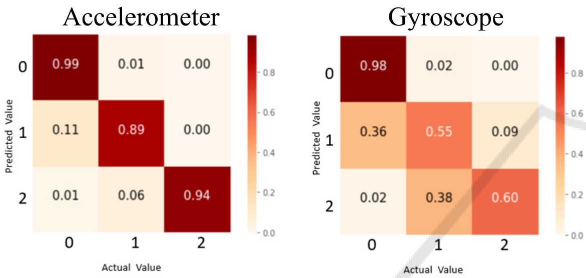

Figure 6: Confusion matrix for Random Forest model.

5 CONCLUSIONS

Monitoring PD individuals is crucial for precisely tracking their progression and treatments. This study seeks to optimize this process and aims to implement efficient algorithms to facilitate the monitoring.

With the rise of technology in recent decades, this study indicates that a commercial smartwatch can provide useful data to monitor resting tremor in PD in subjects. Several models for the prediction of resting tremor were implemented using data provided by inertial sensors embedded in a smartwatch during the performance of eight standardized exercises.

The results suggest that the use of the accelerometer as only inertial sensor can provide optimal results for prediction of resting tremor. The use of a single inertial sensor in wearables could help improve the battery performance and power consumption of the device, as well as reduce the computational load needed for data.

However, it should be noted that this study has certain limitations that need to be considered in future projects. It has been worked with 6 PD patients for 8 weeks, which may be a small sample. In addition, the database is unbalanced, with more than 75% of the samples from the same label. So, a larger number of measurement sessions would be necessary to increase the reliability of the study.

The binary prediction of PD resting tremor achieves its best hit rate using a Random Forest model with the accelerometer data, obtaining 91.06 % in the sensitivity metric and 98.56 % in the specificity metric. These results are remarkably satisfactory for the automatic detection of resting tremor, and are similar to those proposed in (Sun, et al., 2021) and (San-Segundo, et al., 2020), but with the advantage that it has been achieved using a single sensor.

To find a prediction that fits better the true level of resting tremor, an experiment has been conducted in which the Random Forest algorithm was trained for a multiple prediction that differentiates the resting tremor collected according to the MDS-UPDRS labelling guide. Based on the results, it is observed that, using the data provided by the accelerometer, it is possible to predict very reliably, with a sensitivity and specificity rate of 98.6% in no presence of resting tremor, 88.5 % for tremor with MDS-UPDRS score 1, and 93.6 % for resting tremor score 2, with the biggest challenge for the algorithm being the differentiation between no tremor and tremor score 1.

A multiclass classification gives a more specific idea of the severity of the disease, and in a future real-world application, would contribute to the clinician's understanding and follow-up of the patient's data.

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; and by “Ayudas para contratos predoctorales para la realización del doctorado con mención internacional en sus escuelas, facultad, centros e institutos de I+D+i”, funded by Programa Propio I+D+i 2022 from Universidad Politécnica de Madrid. The authors acknowledge to the Physical Education and Sports Science (PESS) department, the Health Research Institute (HRI), and the Data-Driven Computer Engineering (D2iCE) Group at University of Limerick, and the Instrumentation and Applied Acoustics Research Group (I2A2) at Universidad Politécnica de Madrid.

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