Wearable-Enabled Algorithms for the Estimation of Parkinson's Symptoms Evaluated in a Continuous Home Monitoring Setting Using Inertial Sensors

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***Abstract*— Motor symptoms such as tremor and bradykinesia can develop concurrently in Parkinson's disease; thus, the ideal home monitoring system should be capable of tracking symptoms continuously despite background noise from daily activities. The goal of this study is to demonstrate the feasibility of detecting symptom episodes in a free-living scenario, providing a higher level of interpretability to aid AI-powered decision-making. Machine learning models trained on wearable sensor data from scripted activities performed by participants in the lab and clinician ratings of the video recordings of these tasks identified tremor, bradykinesia, and dyskinesia in the supervised lab environment with a balanced accuracy of 83%, 75%, and 81%, respectively, when compared to the clinician ratings. The performance of the same models when evaluated on data from subjects performing unscripted activities unsupervised in their own homes achieved a balanced accuracy of 63%, 63%, and 67%, respectively, in comparison to self-assessment patient diaries, further highlighting their limitations. The ankle-worn sensor was found to be advantageous for the detection of dyskinesias but did not show an added benefit for tremor and bradykinesia detection here.**

***Index Terms*— Accelerometry, inertial sensing, machine learning, motor symptoms, Parkinsonism, Parkinson's disease, remote monitoring, sensors, wearable.**

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I. Introduction

IDIOPATHIC Parkinson's disease (PD) is a chronic disorder defined by the degeneration of neurological cells responsible for the synthesis of dopamine, a chemical involved in memory, motivational salience, and motor control [1].

The symptoms of PD and its rate of progression differ among individuals; however, the three classical symptoms are bradykinesia, tremor, and rigidity, which commonly present with asymmetrical onset. Postural instability is often mentioned as a fourth primary symptom although it typically does not occur until later in the disease progression [2], [3]. Nevertheless, current guidelines require two of these four main signs of the disease to be present, typically manifesting with asymmetrical onset, to identify the disorder [4]. The majority of people living with Parkinson's disease (PwPD) will ultimately require dopamine replacement therapy, either via oral Levodopa [5], and/or oral or subcutaneous dopamine agonists, and/or via enterally-infused Parkinson's treatments.

The efficacy of dopamine replacement therapy is dependent on the clinician's ability to prescribe appropriate dosages that maximize symptom relief while avoiding toxicity and side effects [6], [7], [8]. The current approach to clinical decision-making warrants improvement and there is an indicated need for comprehensive methods of monitoring impairments in daily living [9]. Although in-clinic assessments of PD are the current standard of care, there is evidence to suggest that they may not provide sufficient granularity to address between- and within-day symptom fluctuations and provide a comprehensive representation of a patient's functioning at home [10], [11]. The Movement Disorder Society Unified Parkinson's Disease Rating Scale (MDS-UPDRS) test, which is administered by a clinician, is currently the gold standard assessment tool used for PD. The third section (UPDRS-III) consists of tasks such as walking, finger tapping, and pronation-supination hand movements, which are designed to evidence PD motor symptoms. Then, using a scale from 0 to 4, the clinician subjectively evaluates the amplitude, frequency, and quality. This examination is typically performed once or twice a year and is complicated by travel to the clinic. Patients residing in remote locations with reduced access to facilities are more limited in clinician contact hours and restricted from clinical trials of novel medicines [12].

Currently, self-assessment using patient diaries is a common approach for long-term evaluations of PD symptoms at home [13], [14], as an alternative or adjunct to clinical visits, but monitoring based on patient recall of symptoms in daily diaries is prone to error [14], [15], [16]. Other typical techniques to measure symptoms and disease progression include surveys and clinical rating scales, and telemedicine consultations [17], [18]. These measures either are based on subjective self-assessment or are discrete and thus unsuitable in terms of providing the clinician with precise details of symptom progression at the finer level of temporal resolution required. Furthermore, despite the relevance of sleep factors related to PD on treatment outcomes, patients are frequently unable to communicate details on the type, frequency, and severity of sleep-related symptoms reliably [19], [20]. Thus, the current approach to treatment suffers from a lack of sensitive, objective, and reliable measures for tracking disease progression. New digital health technologies have the potential to offer a suitable alternative by providing more objective, detailed, and continuous measures of symptom progression [21], [22], [23], [24], [25], [26]. This could eventually lead to clinicians being able to adjust treatments based on real-time data [27]. A measurement of symptoms over multiple days would allow clinicians to observe the impact of PD on function and ADLs in the person's own community during routine behaviour. This would also provide an opportunity to assess the periodic variability of symptoms. Sensor-based remote monitoring may facilitate in tracking the progression of PD symptoms and support therapy decisions by quantifying each individual's unique response to treatment [12]. With the development and widespread adoption of low-cost, accurate, and lightweight inertial measurement units (IMUs) [21], [28], it has become feasible to record kinematics in any setting for prolonged periods, in different contexts and applications [29], [30], [31], [32].

Numerous studies have examined the validity of detecting tremor, bradykinesia, and dyskinesia from wrist-worn and ankle-worn accelerometer measurements. These studies have employed traditional machine learning (ML) models [33], [34], [35], [36] and artificial neural networks [37], [38], [39] on sensor data, with varying approaches to sensor placement. For instance, research by Pulliam et al. [45], Cancela et al. [46], Memar et al. [48], and Samá et al. [49] used wrist-worn sensors, with San Segundo et al. using sensors on both wrists and the other studies focusing on a single wrist-worn sensor. Meanwhile, Biase et al. [47], [50] explored the use of sensors on both the wrist and ankle. A plethora of prior work has already shown that ML and kinematics-based algorithms on inertial sensor data can indeed identify the three cardinal symptoms of PD: tremor [36], [39], [40], [41], [42], [43], [44], [45], bradykinesia [36], [39], [44], [45], [46], [47], [48], [49], [50], [51], [52], and dyskinesia [45], [50], [51], [52], [53], [54], [55], [56]. However, in all these studies, validation of these methods was performed using scripted activities in a laboratory environment only. Recent reviews, published within the last two years, have also provided a comprehensive overview of existing knowledge and the state-of-the-art in continuous home monitoring of motor symptoms and fluctuations in PwPD using wearable technology, highlighting the current limitations, and presenting recommendations for addressing these challenges [57], [58]. Validation is ideally performed by leaving patients unsupervised while a clinician passively evaluates their motor state during unscripted ADLs from video recordings. Self-assessment diaries, however, are typically used as a more feasible alternative of validation. Currently, there are several certified (e.g., Food and Drug Administration, CE Marking, or Therapeutic Goods Administration) wearable solutions specifically designed to detect PD motor symptoms continuously at home. These include: the Parkinson's Kinetigraph (Global Kinetics Corporation, Australia) [59], the STAT-ON (Sense4Care, Spain) [60], the Kinesia 360 (Great Lakes NeuroTechnologies, USA) [61], the Apple Watch combined with the StrivePD mobile app (Apple Inc., USA) [62], the PD-watch (Biomedical Lab s.r.l., Italy) [63] and the PD Monitor (PD Neurotechnology, United Kingdom) [64]. While some devices are capable of monitoring multiple body sites, including both the wrist and ankle, to the authors' knowledge, a comprehensive evaluation of tremor, bradykinesia, and dyskinesia detection using patient symptom diaries alongside unscripted continuous home monitoring data from these specific sites has yet to be fully addressed.

The Parkinson's KinetiGraph (PKG) system consists of a single sensor on the most-affected wrist and has been proven to correlate with the UPDRS-III and IV in a study involving 10 days of unsupervised home monitoring with 25 PD subjects [52]. It has also been reported to classify patients with tremor and to their respective levodopa regimens cluster with an AUC of 0.95 and 0.831 respectively [65], [66]. The wrist-based Apple Watch system also tracks fluctuations in resting tremor and dyskinesia; however, it does not detect bradykinesia. Powers et al. reported a Spearman's rank correlation coefficient of 0.72 with the UPDRS tremor sub-score and a significant difference ($P = 0.027$, Wilcoxon rank sum test) between the percentage of time dyskinesias were detected for a chorea group compared to a control in an unsupervised continuous home monitoring setting using this system [86]. Several studies have investigated classifying the PD state of individuals (On/Off/Dyskinetic) by continuous monitoring using the STAT-ON system [68], [69], [70], [71], [72]. During these works, of which Pérez-López et al. achieved the highest results with a sensitivity 96% and specificity of 94% [71], unscripted ADLs were performed under supervision in a laboratory setting. However, their system consists of a single sensor on the waist and is therefore limited by an inability to detect PD symptoms that occur while the subject is at rest. The Kinesia 360 system has been validated using scripted tasks and ADLs in a lab setting and produced outputs highly correlated to the UPDRS-III overall ($r = 0.79$) [73], as well as clinician sub-scores for tremor ($r = 0.93$) [35], bradykinesia ($r = 0.86$) [74], and dyskinesia ($r = 0.87$). It achieved an accuracy of 84% $\pm$12% for classifying the On/Off state with using leave-one-subject-out cross-validation [75] and an AUC of 0.89, 0.82, and 0.86 for tremor, bradykinesia, and dyskinesia respectively [45]. Additionally, it has proven to successfully capture temporal trends in symptom scores over the course of 5 weeks when participants were asked to perform two scripted motor tasks at least 5 times a day every second day, every second week [76]. However, passive evaluation without this

periodic task-based motor assessment, i.e., on unscripted data, has only been investigated for tremor and never in comparison to patient diaries such as in this work [77], [78]. Classification of tremor, bradykinesia, and dyskinesia were validated for scripted tasks and unscripted ADLs with an accuracy of 87%, 74.4±14.4%, and 92.51% respectively using the PD Monitor system [43], [79], [80]. However, this system consists of five devices, which weakens its effectiveness in terms of user wearability and acceptability.

The present work aims to demonstrate the feasibility of detecting symptom events, as opposed to motor-state or symptom score, in a free-living setting, and thus provides a greater degree of interpretability to inform AI-powered decision-making. The ML models were trained on wearable sensor data from scripted activities performed by the participants in the laboratory and clinician ratings of the video recordings of these tasks. Subsequently, data collected from the participants at home in conjunction with PD symptom self-assessment diaries was used to evaluate the models. This paper presents work completed during the project (grant number: IP 2017 0625), funded by AbbVie Inc. and Enterprise Ireland, under the name WESAA ("Wearable Enabled Symptom Assessment Algorithm"). The manuscript is organized as follows. Section I illustrates related works in the field and the need for continuous home monitoring of PD symptoms using wearable sensors. Section II-A and Section II-B detail the data collection protocols and algorithm development, respectively. Section III demonstrates the results. Finally, the discussion and conclusions are presented in Sections IV and V, respectively.

II. Methodology

A. Data Collection Protocols

Two sets of data were constructed for this study, which incorporated both in-clinic and at-home data collections. The study received approval by the Clinical Research Ethics Committee (CREC) of the Cork Teaching Hospitals at the University College Cork (Reference Number: ECM 4 (r) 11/02/2020 & ECM 3 (q) 09/08/2022). Furthermore, written informed consent was necessary for participation. Overall, 24 unique subjects participated over the course of all the data collection trials (16 male and 8 female) and the patients' information are available in Table I. The average age of the participants was 70.71 ± 8.50 years, the average height was 171.54 ± 8.94 cm, the average weight was 77.79 ± 12.49 kg, and the average number of years since diagnosis was 8.50 ± 4.28. The average CIT and UPDRS scores were 2.13 ± 2.51 and 68.83 ± 18.78, respectively. Specifically, 21 subjects performed a battery of motor tasks under laboratory conditions while wearing two IMUs with a sampling rate of 40Hz (XSens MTw Awinda; XSens, The Netherlands) on the most affected wrist and ankle. The battery of motor tasks (available in the supplementary material – Table A2, and Table A3) was recorded on video and a clinician, certified to score the MDS-UPDRS, provided limb-specific scores of symptom severity for tremor, bradykinesia, and dyskinesia, as appropriate to each task. Thus, bradykinesia was only noted during tasks that involved a scripted movement, but tremor and dyskinesia severity were rated for each limb in each task including the sitting and standing still tasks. The annotation process was conducted with videos that were anonymized and randomized, ensuring that the clinician was not aware of participant identities or specific experimental conditions during scoring to minimize potential biases. The total number of tasks per participant was twelve. The sensor data for task 9 of subject 11 and the video for task 6 of subject 16 was corrupted. Two participants (14 and 17) did not perform task 8, eight participants (13, 14, 15, 16, 17, 19, 20, and 21) did not perform task 10, and one participant (19) did not perform task 11 due to unfamiliarity with the equipment and/or the task. Tremor, bradykinesia, and dyskinesia severity scores ranged from 0–4.

Additionally, 20 PD subjects (seventeen from the above trial and three new patients) took part in the at-home data collection where participants wore off-the-shelf (OTS) IMUs (ActiGraph GT3X+; ActiGraph Corporation, USA) on their most affected wrist and ankle for a period of 24 hours. They simultaneously filled out an adapted version of the Veterans Affairs Patient Motor Diary (VA Patient Motor Diary) [81] every half an hour (available in the supplementary material – Table A1). The accelerometer and gyroscope were enabled on the IMUs with a sampling rate of 100Hz. The information from one participant was unusable due to the diary not having been used. Finally, six subjects (four from the above at-home trial with OTS sensors and two who completed the in-clinic trial only) repeated the same data collection protocol while wearing the WESAA system, a hardware prototype device developed at the Tyndall National Institute [31]. The developed system consists of two identical wearable devices worn on the most affected wrist and ankle; each device contains a replaceable and rechargeable battery with a five-day service life, and an IMU. Accelerations and angular velocities can be constantly recorded (for up to five days at a sample rate of 40 Hz) and then analyzed offline to evaluate tremor, bradykinesia, and dyskinesia. Fig. 1 shows an example of the device in operation. The wrist sensor is worn on the dorsal side of the wrist with the x-axis in the medial-lateral direction, the y-axis in the distal-proximal direction, and the z-axis in the ventral-dorsal direction. The ankle sensor is positioned on the lateral aspect of the ankle with the x-axis in the posterior-anterior direction, the y-axis in the proximal-distal direction, and the z-axis in the medial-lateral direction. The gyroscope coordinate axes are defined such that positive rotations are in the clockwise direction.

The scripted in-clinic ADLs dataset was used to develop models for detecting the presence of tremor, bradykinesia, and dyskinesia. To assess the generalizability of our models, we combined the 24 hours OTS and WESAA system datasets to form an external source for validating the models in an unscripted continuous home monitoring setting.

B. Modelling Methodology

The accelerometer and gyroscope x, y, and z axis data were resampled to 50 Hz and zero-phase band-pass 3rd-order Butterworth filtered between 0.3-24 Hz [37]. Data were augmented by rotation and sliding-window-based data augmentation methods [82]. The data were divided into windows of specified length and overlap (e.g., 3 seconds, 6 seconds, and 12 seconds with 50% overlap for tremor, dyskinesia, and bradykinesia, respectively) chosen according to previous work and multiplied by randomly generated rotation matrices generated for each instance to simulate different sensor

TABLE I
PATIENT DEMOGRAPHIC INFORMATION

Subject_ID	Sex	Age	Height (cm)	Weight (kg)	Most Affected Side	Hoehn and Yahr* (stage)	Years since diagnosis	6-CIT**	MDS-UPDRS*** (Motor score)	MDS-UPDRS*** (Total score)
1	F	62	162	63	Right	Two	3	0	7	40
2	F	67	152	73	Left	Two	3	2	48	70
3	F	70	165	70	Left	One	4	0	30	60
4	M	82	165	76	Left	Three	14	5	49	85
5	F	62	170	95	Left	One	9	0	12	38
6	M	70	183	92	Right	Three	6	4	40	71
7	M	81	166	76	Left	Three	13	2	24	73
8	M	64	173	82	Left	Three	7	4	65	102
9	F	73	170	63	Left	Three	15	4	37	64
10	F	59	175	70	Left	One	6	0	15	38
11	M	81	162	57	Right	Three	5	6	39	69
12	M	52	178	107	Left	Two	8	0	11	38
13	M	78	172	69	Left	Three	7	4	45	87
14	M	72	173	75	Left	Two	6	0	35	62
15	F	73	171	70	Left	Two	9	0	45	78
16	M	72	183	90	Right	Four	10	0	32	69
17	M	80	183	85	Right	Three	10	9	60	96
18	M	56	175	70	Left	Two	17	0	43	73
19	M	77	167	82	Left	Two	10	0	13	42
20	F	83	153	60	Left	Two	5	0	50	75
21	M	78	173	79	Right	Two	11	0	46	85
22	M	70	178	102	Right	Two	3	5	37	62
23	M	73	179	78	Left	Four	18	4	76	100
24	M	62	189	83	Right	Three	5	2	44	75

* Stage 1 is unilateral symptoms only; Stage 2 is bilateral; in Stage 3, the person is fully independent, but balance is impaired.
**6-item Cognitive Impairment Test (6-CIT) uses an inverse score, and questions are weighted to produce a total out of 28. Scores of 0-7 are considered normal cognition
*** MDS-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) was developed to evaluate various aspects of Parkinson's disease including non-motor and motor experiences of daily living and motor complications. Each parkinsonian sign or symptom is rated on a 5-point Likert-type scale (ranging from 0 to 4), with higher scores indicating more severe impairment. The maximum total UPDRS score is 199, indicating the worst possible disability from PD.

orientations [34], [39]. Temporal location perturbation was achieved through permutation, where a random integer N, determined by rounding a positive value sampled from a Gaussian distribution with a standard deviation of 5.0, was used to rearrange segments within windows. Additionally, time-warping and magnitude-warping were implemented using randomly generated sinusoidal curves with arbitrary amplitude, frequency, and phase values to modify the time intervals between samples and the magnitudes of data within windows, respectively. The signal-processing features extracted at this point from each of the segments depended on the PD symptom to be classified and so tremor, bradykinesia, and dyskinesia are outlined in the following sections A), B), and C), respectively. The list of features extracted for each symptom are available in the supplementary material. The data were then combined alongside the participant identifier and the limb-specific scores of symptom severity for tremor, dyskinesia, and bradykinesia. The clinician rating for the presence/absence of each symptom was used as the label for binary classification. In Table A4 of the supplementary material shows a summary of the symptoms severity for the 21 subjects involved in the trial. These data were split into a training and test set (approx. 80%/20%) with different subjects in each set such that no data from a participant in the training set would appear in the test set and vice versa. The split was made randomly while attempting to preserve the percentage of samples for each class as much as possible given this constraint of non-overlapping subject data between the training and test sets. Samples created by data augmentation were removed from the test set before prediction. For reporting purposes, this procedure was repeated five times and the mean and standard deviation (SD) recorded in the results except when comparing the performance of the

Fig. 1. The WESAA system with coordinate axis (top right).

models using just the data from wrist the sensor as input versus the models utilizing data from both the wrist and ankle.

A convolutional neural network (CNN) was considered for a tremor classification model as they have been previously successful in classifying and assessing tremor severity [37], [40], [83]. Notably, Kim et al. reported an accuracy of 0.85 in differentiating tremor severity using CNNs, which outperformed other machine learning algorithms tested [39], and San Segundo et al. reported an average error of 4.1% when predicting percentage of tremor time on laboratory captured data [36]. The frequency spectra produced by the tremor spectrum extraction method described in [37] was used as inputs to the implemented model developed in Tensorflow, Keras. Tremor related to PD occurs at a frequency between 3-8 Hz and it is present when muscles are at rest [33], [42]. In accordance with [34], a window length of 3 seconds was chosen, while a batch size of 50 and 100 epochs were used to train the model. The model architecture (Fig. A1 in the Supplementary Materials), however, deviated from the source methodology in that both the wrist and ankle sensor were present in this work as opposed to just the single sensor on the wrist. Two separate branches were defined for the wrist and ankle sensors independently and the maximum was taken at the output to account for this difference. Additionally, where the gyroscope was used, two separate branches were defined for the accelerometer and gyroscope sensors independently and the average between them was taken. Several steps were taken to avoid overfitting because of the increased complexity caused by the model adaptations. The dropout rate was doubled to 0.4 and the number of units in the dense layers was reduced. Reducing the number of parameters in the bottleneck of the model has the dual benefit of preventing overfitting and making it more suitable for potential conversion to a microcontroller, while not negatively affecting the accuracy.

Bradykinesia is typically characterized by slowness, hesitancy, and reduced amplitude in limb movements. In total, 132 (66 $\times$ 2) features (Table A5 in the Supplementary) were extracted from 30 second window segments of the wrist and ankle accelerometer sensor signals [34], [36], [39], [44], [52], [84]. A logistic regression classifier, Support Vector Machine, Decision Tree, Random Forest, Gradient Boosted Trees, Extra Trees, and Bagging ensemble meta-estimator with additional balancing were implemented with feature selection according to the k highest scores using these features as input to the model. The decision to use Support Vector Machines and Random Forest classifiers was informed by previous research that demonstrated their effectiveness in detecting bradykinesia from accelerometer data [34], [39]. Specifically, Random Forest achieved an AUROC of 0.73 in [39], comparable to CNNs, highlighting its strong performance. Furthermore, [34] confirmed that both Random Forest and Support Vector Machines were effective in classifying bradykinesia fluctuations, with statistically significant AUCs (mean AUC: 0.70). To further enhance classification accuracy, Gradient Boosted Trees, Extra Trees, and ensemble methods like Bagging were also investigated for their ability to improve performance through iterative learning and variance reduction. A Gradient Boosted Trees model with all the features included was chosen as the best by LOSO-CV on the training set with balanced accuracy as the performance metric. Before validation on the hold-out test set, the model was retrained on the full training set with the chosen tuning parameters.

Dyskinesia is defined as short-term, erratic movements between 0-4Hz that interject in longer ADL movements. In total, 78 (39 $\times$ 2) features (Table A6 in the Supplementary) were extracted from 6 second window segments of the wrist and ankle sensor signals [38], [84]. The features were used as inputs to a long short-term memory (LSTM) model described in [38] (Fig. A2 in the Supplementary Materials). An LSTM model was considered, even though it required the data to be arranged into sequences for structured classification, because it showed particularly reliable performance when applied to this problem specifically. The reasoning behind this is that its ability to make inferences based on patterns that appear over longer periods should help differentiate between the erratic body movements present during dyskinesia and common ADLs. Hssayeni et al. reported that an LSTM model outperformed linear regression models showing a strong correlation with clinician ratings ($r = 0.87$, $p < 0.001$) [37].

The accelerometer and gyroscope x, y, and z axis data from the two combined at-home datasets were preprocessed in the same manner as the in-clinic data. The signals were divided into frames and input to the feature extraction pipeline for each of the tremor, bradykinesia, and dyskinesia prediction models developed. The severity scores for each of the PD symptoms from the self-assessment diaries were used as labels for binary classification. For each window of data, a threshold of 0.5 was applied to the model output (a probability between 0 and 1), with less than 0.5 indicating the presence of the symptom in question and greater than 0.5 indicating its absence. The results were then aggregated into 30-minute periods based on the percentage of symptom-positive windows within each period using the experimentally determined thresholds shown in Table II.

TABLE II
EXPERIMENTAL THRESHOLDS FOR CLASSIFYING PD MOTOR SYMPTOMS BASED ON CLASSIFIED SYMPTOM-POSITIVE WINDOW PERCENTAGES

	0	1
Tremor	$0\% < x \leq 2\%$	$2\% < x \leq 100\%$
Bradykinesia	$0\% < x \leq 5\%$	$5\% < x \leq 100\%$
Dyskinesia	$0\% < x \leq 20\%$	$20\% < x \leq 100\%$

TABLE III
SCRIPTED BALANCED ACCURACY

PD Symptom	Tremor	Bradykinesia	Dyskinesia
Window Length (sec)	3	30	6
Model	CNN	Gradient Boosted Trees	LSTM
Balanced Accuracy (%)	83 (+/-6)	75 (+/- 4)	81 (+/-9)

III. RESULTS

A. Scripted In-Clinic ADLs

The mean balanced accuracy of the best performing models for detecting PD symptoms in comparison to clinician-annotated ratings in the laboratory were 83%, 75%, and 81% for tremor, bradykinesia, and dyskinesia, respectively (Table III). The balanced accuracy when comparing a model that takes data from just the wrist sensor as input and one that utilizes data from both the wrist and ankle can be seen in the Supplementary (Table A7). The results were the same between the single and the dual sensor configurations for tremor and bradykinesia. However, the dual sensor configuration achieved a 3% higher balanced accuracy for dyskinesia.

B. Unscripted Continuous Home Monitoring

Applying the models to data collected during unsupervised continuous home monitoring with self-assessment symptom diaries completed by each participant used for this validation showed lower results (Table IV). The balanced accuracy for the unscripted validation data was 63%, 63%, and 67% for tremor, bradykinesia, and dyskinesia, respectively. There is no significant difference between the trials collected via the ActiGraph (63%, 64%, and 68% for tremor, bradykinesia, and dyskinesia) and the WESAA system (63%, 62%, and 64%, respectively), showing that the model performance was independent from the platform used for data collection.

TABLE IV
UNSUPERVISED BALANCED ACCURACY

Trial ID	Tremor	Bradykinesia	Dyskinesia
1	63%	75%	98%
2	66%	63%	89%
3	43%	65%	81%
4	57%	70%	64%
5	57%	77%	59%
6	73%	31%	75%
7	53%	69%	43%
8	89%	94%	95%
9	100%	63%	96%
10	54%	38%	56%
11	60%	65%	61%
12	47%	45%	73%
13	77%	82%	48%
14	100%	71%	47%
15	33%	78%	58%
16	53%	60%	92%
17	64%	70%	61%
18	45%	39%	48%
19	68%	52%	50%
20*	73%	84%	77%
21*	61%	23%	50%
22*	36%	59%	56%
23*	77%	73%	50%
24*	75%	78%	100%
25*	54%	55%	48%
Average Balanced Accuracy (%)	63 (+/-17)	63 (+/-17)	67 (+/-19)
Recall	0.62	0.62	0.74
Precision	0.7	0.69	0.78
AUC	0.61	0.65	0.6
*denotes trials performed with the WESAA system; remainder were with ActiGraph			

IV. DISCUSSION

A. Wrist vs Ankle Sensors

A wide range of symptoms can occur concurrently with PD, and so the optimal home monitoring system must be capable of monitoring such symptoms simultaneously, and during everyday life. In this study, ML models were trained on wearable sensor data from supervised laboratory activities and clinician ratings of video recordings of these tasks to evaluate motor symptoms and dyskinesias. The algorithms were evaluated using unscripted data collected over 24 hours as the participants went about their everyday life and compared to self-reported symptom assessments recorded by diary. The results from the in-clinic trials (Table A7) indicate that for the tremor and bradykinesia models, the addition of the data from the sensor on the ankle yielded minimal improvements. The sensor contributed to a reduction in false positives and a decrease in true positives for tremor detection, resulting in a trade-off that left the overall balanced accuracy unchanged. Similarly, bradykinesia detection showed no significant effect on the classification metrics with the addition of the ankle sensor. The balanced accuracy is 3% higher, however, when the ankle sensor data are included for the dyskinesia model. The performance improved with a decrease in false positives and an increase in true negatives. This modest improvement indicates that the ankle sensor primarily reduces false alarms and enhances the model's specificity, rather than substantially improving the detection of true symptoms.

B. Labelling Challenge

The performance reported in the manuscript indicates that developing generalizable models for continuous home monitoring solutions remains a challenging problem in the PD use case. Results from the unscripted at-home data were 12-20% lower compared to the performance obtained during scripted in-clinic activities. One of the main reasons for this drop in performance is due to the different approach adopted for label definition in the different use cases. Although, laboratory activities can be recorded and shown to clinicians for subsequent motor evaluation, self-assessment diaries are still used for continuous home monitoring to record daily activities, medication

intake, and symptom occurrences, by PwPD or carers [25], [26]. However, using self-report for a challenging activity, such as continuously monitoring one's motor condition, can result in misunderstandings and mistakes, especially in PwPD with cognitive impairment. Patients might not always be able to accurately recognize their own motor fluctuations and symptoms, they might record motor symptoms in the wrong time slots, forget to update the records, or they might remember to update the records and then complete them many hours later from a recalled general state of function. Most importantly, however, diaries are filled out every 30 minutes, therefore losing the granularity required to build accurate real-time models, especially if using inertial sensors collecting hundreds of samples per second as a data-gathering tool. Diaries thus are not a valid tool for comparison [81] and the use of digital diaries, home or wearable cameras, or the involvement of caregivers trained in the data collection may ameliorate those issues [18]. This highlights the difficulty with estimating individual symptom events in continuous home monitoring in PwPD. Further investigation is needed to develop reliable models in precisely estimating the severity of PD symptoms experienced outside of a laboratory setting and to find the level of correlation between the outputs of the models and the respective UPDRS sub-scores.

C. Future Implications

Our findings have several implications. Firstly, our approach has the potential to replace some of the time and effort requirements of PD clinical studies that can dissuade participation, such as the diligent logging of symptoms in a patient diary, by wearing a passive monitoring device instead. PD advances slowly over time, and existing monitoring methods are too infrequent to capture slight changes in disease progression. Our AI-powered symptom detection algorithms have demonstrated the ability to detect PD symptom events. Our approach could also improve patient compliance and consistency due to the ease of use of the system in continuously collecting measurements in a free-living setting. Secondly, many PwPD do not receive care from a PD expert because these specialists are concentrated in metropolitan areas, while patients are geographically dispersed and have limited access to such medical services. By offering an easy alternative for monitoring disease progression, our system can lessen the requirement for clinical visits and help extend treatment to patients in remote communities [85]. Our research has certain limitations as well. For one, symptom detection was evaluated in a small number of subjects ($n = 25$). Future studies with larger populations are needed to confirm those findings. Secondly, the detection of symptoms provides a measure of PD severity as a function of their prevalence only, while other factors that could affect the perceived severity, such as amplitude of shaking for tremor, are not considered. Furthermore, while we evaluated the models on unscripted data in an unsupervised context, further research may be needed to expand the diversity of the participants in the dataset in terms of demographic information.

D. Limitations and Future Work

The models demonstrated a balanced accuracy ranging from 63% to 67% in unscripted home monitoring, which is notably lower compared to the 75% to 83% accuracy observed in controlled laboratory settings. This discrepancy highlights that while the models show promise, there is a significant gap in performance when applied to real-world, unsupervised environments. For AI-powered decision making in clinical settings, a higher level of accuracy is necessary to ensure reliable and actionable insights. Therefore, the current performance may not be fully adequate for making critical treatment decisions or adjustments without further refinement. The system can detect multiple symptoms simultaneously, such as tremors, bradykinesia, and dyskinesia. It may face challenges in accurately distinguishing between overlapping symptoms due to the complexity of their presentation, however, distinct outputs for each symptom are provided to allow for reporting of simultaneous detections. The desirable performance level an application such as this would require accuracy rates closer to those achieved in controlled environments, ideally above 80% for each symptom category. Future improvements could involve improving the models' ability to generalize across different settings, incorporating more granular data collection methods, or utilizing supplementary data sources such as digital diaries with higher temporal resolution. This would help in reducing the discrepancy between the controlled and real-world settings.

V. Conclusion

This work provides evidence that supervised machine learning can detect symptoms of PD from the inertial measurements taken from a wrist- and ankle-worn sensor. The data from the ankle-worn sensor were shown to provide additional utility for the dyskinesia algorithm but not in the case of tremor or bradykinesia. Importantly, we were further able to evaluate our findings using data collected in an unsupervised home monitoring environment. The results show the potential of detected symptom events in unscripted ADLs as an objective measure of PD with 63%, 63%, and 67% balanced accuracy compared to self-assessment patient diaries for tremor, bradykinesia, and dyskinesia, respectively. This digital biomarker suffers from neither patient nor clinician subjectivity, is noninvasive and easy to measure in the person's own home. The employment of inertial sensors in this case enables measurements to be collected continuously to capture aspects of symptom progression during routine everyday life. However, further research is required to ameliorate the limitations involved in the use of self-assessment tools, such as diaries, for model validation.

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VII. Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

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