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Adaptive Domain-Adversarial Multi-Instance Learning for Wearable-Sensor-Based Parkinson's Disease Severity Assessment

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***Abstract*—Wearable sensors combined with machine learning provide an effective solution for assessing Parkinson's Disease (PD) severity. However, time-series data from wearable sensors often lack window-level labels for PD severity, resulting in weak supervision, which introduces the challenge of label noise. Additionally, patient variability causes distributional discrepancies, further complicating the learning process. To address these issues, we propose Adaptive Domain-Adversarial Multi-Instance Learning (ADAMIL), which combines and refines Multiple-Instance Learning (MIL) with domain-adversarial techniques. We improve traditional MIL by incorporating self-attention mechanisms and learnable positional encoding, enabling ADAMIL to capture temporal dependencies more effectively, thus making it better suited for mitigating label noise in weakly supervised time-series data. Furthermore, ADAMIL refines domain-adversarial learning to autonomously align latent distributions, ensuring robust domain-invariant feature learning without relying on predefined labels. Experimental results show that ADAMIL achieves 85.29% accuracy and 80.57% F1-score in fine-grained PD severity classification, outperforming existing methods. Notably, this performance is achieved using only a single wrist-worn sensor, underscoring its potential for practical use in clinical and home settings. The code is available at https://github.com/xzxzy12345XZY/ADAMIL.**

***Index Terms*—Parkinson's Disease, Domain-Adversarial Learning, Multi-Instance Learning, Wearable Sensors.**

I. INTRODUCTION

Parkinson's Disease (PD) is a common neurodegenerative disorder characterized by a combination of motor and non-motor symptoms, such as tremors, bradykinesia, rigidity, and sleep disturbances [1]. It is the second most prevalent neurodegenerative disease, affecting 2-3% of individuals over the age of 65 [2]. Although there is currently no cure for PD, early diagnosis and timely intervention are crucial for alleviating symptoms and slowing disease progression [3].

Traditionally, The diagnosis of Parkinson's Disease (PD) primarily relies on the Movement Disorder Society's revised Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [4], a widely recognized clinical assessment tool that is quite time-consuming. Additionally, PD diagnosis using specialized imaging techniques like PET and MRI involves high costs. Recently, methods combining wearable technology with machine learning have shown significant potential for the quantitative assessment of PD [5]–[10]. Machine learning models like Support Vector Machines (SVM) and LightGBM (LGBM), and deep learning models such as CNN-LSTM (CNNLSTM) and LSTM-CNN (LSTMCNN), have achieved some success in early PD detection and classification of motor symptom severity [11]–[13]. However, the practical application of models for Parkinson's Disease (PD) severity assessment based on wearable sensor data faces two major challenges: label noise and distributional differences [14], [15].

In evaluating Parkinson's Disease (PD) using sensor data, label noise remains a significant challenge. Most existing methods use a sliding window to segment time-series data, assigning uniform, coarse-grained labels to each segment (see Fig. 1a). This ignores the dynamic nature of PD symptoms, resulting in mismatched instances and labels, thereby introducing substantial noise [15]. As shown in Fig. 1a, not every segment consistently reflects the severity level, which exacerbates label inconsistency.

To address this issue, the Multiple-Instance Learning (MIL) has been introduced. In the MIL, a patient's activity session is treated as a 'bag' that contains multiple sliding window instances, with the label for the bag representing the overall severity of the session. The advantage of this approach is that it does not require precise labeling for each individual instance but instead uses bag-level labels to guide the learning process, thereby effectively handling weak supervision and label uncertainty.

TABLE III: Model Performance Comparison for Fine-Grained PD Severity Assessment

HC vs. Mild vs. Moderate vs. Severe in Private Dataset																	
Num	Activity Name	LGBM[11]				CNNLSTM[12]				LSTMCNN[13]				Ours			
		Acc	Pre	Rec	F1	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1
1	FingerTap	54.55	54.67	39.03	39.58	48.48	36.72	27.78	20.96	48.48	28.74	33.33	28.41	**66.67**	**66.29**	**68.19**	**66.36**
2	HandOpen	66.67	61.01	50.00	50.98	48.48	36.72	31.25	25.96	54.55	56.71	37.92	38.21	**66.67**	**69.52**	**61.39**	**63.67**
3	WristRotation	63.64	58.33	46.25	45.60	69.70	38.53	47.22	41.96	72.73	61.04	52.22	49.17	**69.70**	**67.08**	**66.53**	**66.62**
4	RHandFlip	54.55	27.84	37.78	31.77	48.48	24.54	36.67	29.11	51.52	24.18	38.33	29.57	**69.70**	**73.27**	**67.64**	**68.87**
5	LHandFlip	66.67	64.42	46.67	46.63	63.64	52.50	46.11	45.25	66.67	86.01	51.25	55.03	**72.73**	**74.05**	**62.36**	**65.65**
6	FingerNoseL	65.52	39.58	40.62	37.65	51.72	37.50	33.33	29.17	51.72	28.78	33.48	30.78	**65.52**	**69.09**	**72.32**	**70.00**
7	FingerNoseR	63.64	76.50	48.47	52.50	60.61	42.45	43.33	41.87	69.70	51.67	52.78	51.32	**75.76**	**88.47**	**65.42**	**68.78**
8	HandRaise	46.88	11.72	25.00	15.96	50.00	27.50	36.88	29.17	56.25	63.39	40.62	39.66	**68.75**	**67.95**	**65.42**	**64.58**
9	WalkBack	45.45	11.36	25.00	15.62	54.55	62.50	41.25	40.95	54.55	62.50	41.25	40.95	**78.79**	**89.38**	**71.53**	**76.30**
10	SitStand	56.67	29.00	33.33	28.66	63.33	80.61	51.88	56.13	53.33	26.04	48.21	33.77	**76.67**	**81.61**	**76.98**	**77.85**
11	DrinkWater	61.76	46.27	49.48	47.14	73.53	66.00	53.47	53.04	76.47	66.67	59.72	60.20	**85.29**	**94.05**	**74.72**	**80.57**
12	PickUpThings	57.14	43.71	45.83	41.22	60.71	29.76	35.71	31.90	64.29	50.89	49.26	47.74	**82.14**	**90.55**	**75.30**	**80.97**
13	Sit	65.52	36.16	44.44	38.77	62.07	47.29	54.17	50.31	44.83	35.71	27.78	20.00	**65.52**	**69.55**	**68.33**	**68.78**
14	Stand	55.56	28.78	34.72	30.83	48.15	36.54	37.50	32.46	44.44	57.81	48.61	46.21	**74.07**	**79.55**	**65.97**	**69.59**
15	ArmSwing	61.54	55.73	49.62	50.00	57.69	37.50	36.11	32.05	57.69	29.97	37.63	33.33	**73.08**	**81.25**	**67.87**	**71.31**
16	DrawingSpirals	62.50	31.29	40.06	35.09	54.17	28.12	33.81	30.44	62.50	68.75	65.91	66.20	**70.83**	**86.46**	**69.60**	**71.38**

TABLE IV: Model Performance Comparison for PD vs. DD Classification

PD vs. DD in PADS [32]																	
Num	Activity Name	LGBM[11]				CNNLSTM[12]				LSTMCNN[13]				Ours			
		Acc	Pre	Rec	F1	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1	Acc	Pre	Rec	F1
1	Relaxed1	70.41	35.20	50.00	41.32	72.45	69.75	55.45	53.04	71.43	85.57	51.72	44.90	**80.61**	**82.74**	**69.24**	**71.70**
2	Relaxed2	72.45	73.67	54.45	50.81	74.49	71.12	60.89	61.45	77.55	73.28	70.06	71.21	**78.57**	**74.29**	**73.79**	**74.02**
3	RelaxedTask1	76.53	78.07	62.34	63.19	71.43	69.12	52.72	47.71	76.53	81.53	61.34	61.69	**76.53**	**71.79**	**69.34**	**70.26**
4	RelaxedTask2	76.53	87.50	60.34	60.00	70.41	35.20	50.00	41.32	72.45	73.67	54.45	50.81	**77.55**	**73.59**	**69.07**	**70.47**
5	StretchHold	71.13	61.02	52.12	47.61	77.32	87.91	60.71	60.77	74.23	86.70	55.36	52.01	**81.44**	**78.36**	**74.22**	**75.75**
6	LiftHold	71.13	35.57	50.00	41.57	71.13	35.57	50.00	41.57	75.26	75.14	59.27	59.07	**80.41**	**77.16**	**72.44**	**74.06**
7	HoldWeight	70.41	35.20	50.00	41.32	75.51	74.29	61.62	62.31	73.47	68.42	60.17	60.61	**78.57**	**74.43**	**75.79**	**75.01**
8	PointFinger	73.47	70.41	58.17	57.56	70.41	35.20	50.00	41.32	74.49	71.12	60.89	61.45	**78.57**	**76.11**	**68.79**	**70.61**
9	DrinkGlas	70.41	35.20	50.00	41.32	77.55	74.80	67.07	68.75	77.55	75.82	66.07	67.76	**80.61**	**77.81**	**73.24**	**74.82**
10	CrossArms	71.43	64.84	54.72	52.36	75.51	71.24	64.62	65.91	74.49	74.72	58.9	58.35	**80.61**	**79.51**	**71.24**	**73.41**
11	TouchIndex	71.13	35.57	50.00	41.57	72.16	69.50	52.85	48.17	73.20	86.32	53.57	48.74	**77.32**	**73.21**	**67.08**	**68.65**
12	TouchNose	73.20	68.33	56.75	55.66	74.23	68.86	60.66	61.34	77.32	73.21	67.08	68.65	**81.44**	**79.06**	**73.16**	**75.09**
13	Entrainment1	73.20	86.32	53.57	48.74	71.13	35.57	50.00	41.57	76.29	70.97	69.54	70.15	**80.41**	**82.19**	**68.19**	**70.62**
14	Entrainment2	74.23	76.96	56.42	54.36	71.13	35.57	50.00	41.57	74.23	72.94	57.48	56.42	**77.32**	**72.35**	**70.26**	**71.10**

Its domain-adversarial component autonomously aligns latent distributions, ensuring robust, domain-invariant feature learning without predefined labels. Experimental results show that ADAMIL outperforms existing methods in both fine-grained PD severity assessment and PD vs. DD classification, confirming its effectiveness.

Notably, ADAMIL achieves these results using only a single wrist-worn sensor, underscoring its efficiency, practicality, and suitability for applications in both clinical and home use. This highlights the practical viability and scalability of such methods in real-world scenarios, particularly in contexts where ease of deployment, cost-effectiveness, and minimal hardware requirements are critical. Future work will enhance the MIL component by incorporating domain-specific prior knowledge and automate the selection of latent distributions (K), improving adaptability and minimizing manual tuning for broader real-world applications.

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Medical Signals Augmentation for Parkinson's Disease Diagnosis in Low-Resource Settings Across Time, Activity and Patients

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***Abstract*—Automated Parkinson's diagnosis(PD) through wearable intelligence technologies has achieved considerable results, but its application in the wild environment presents challenges due to small on-state samples and sparse distribution across time, activity patterns, and subjects. To tackle these challenges, this study proposes a novel data augmentation model to improve PD recognition results in the wild. Our model utilizes a three-level augmentation strategy across different times, patterns, and subjects. Specifically, we apply temporal-level augmentation and aggregation to learn distinct representations, while using pattern/subject-level combinations and augmentations to generate additional samples. As a result, this augmentation approach not only facilitates the acquisition of diverse representations for symptoms but also addresses challenges such as missing data and small sample sizes, which are common for medical data in a free-living environments. This proposed model has applied to a real Parkinson's Disease (PD) dataset collected in low-resource settings, where it achieves impressive accuracy in the fine-grained classification of PD severity (mild, moderate, severe). In conclusion, this study contributes to more accurate PD self-diagnosis in real-world environments, thereby enabling remote drug intervention guidance from doctors.**

***Index Terms*—Parkinson's disease, free-living environment, data augmentation, contrastive learning, representation learning, dimensionality reduction**

I. Introduction

As a common neurodegenerative disorder, Parkinson's disease(PD) [28] significantly reduces the patient's quality of life. The clinical diagnosis of PD relies on three main clinical diagnostic features(including tremors, dyskinesia and bradykinesia), and is often assisted by neurological symptoms such as dementia, fatigue, and insomnia. Early detection and fine-grained classification of PD can offer earlier and more accurate drug interventions that delay the overall process of the disease. Currently, MDS-UPDRS [1] is widely used as a clinical tool for assessing Parkinson's disease. It gives detailed criteria on how to do assessments for PD from the aspects of mood, daily activities, and motor tasks, but is limited by poor temporal resolution and subjective decisions. Therefore, digital measurement techniques have been explored for more accurate remote monitoring [2], [3] of PD patients. These techniques collected accelerometer and gyroscope data from the inertial measurement units(IMU), and extracted hand-crafted features or automatically learned features for pattern recognition by using machine learning algorithms. They are widely applied in recognizing different PD symptoms(such as resting tremor [4], gait disturbance [5], [6] and fine-motor fluctuations [7]), which evaluate the possibility to detect PD states or motor symptoms by using data from IMU. But most of them focused on symptom detection through specific activities and failed in the wild environment since data collection, annotation, processing and analysis are all more complex than in a clinically controlled setting.

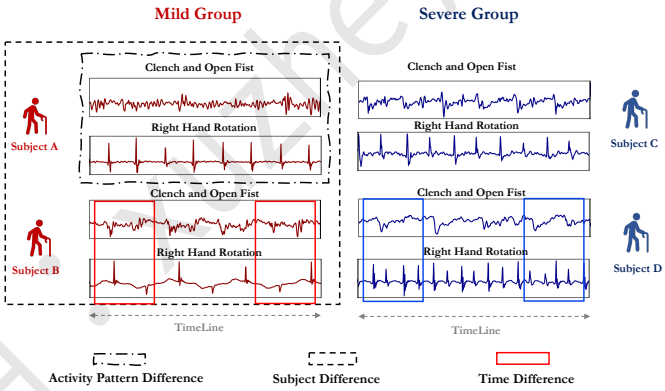

Fig. 1. Example of the signal variety across activity patterns, time, and subject.

Automated PD diagnosis in a wild environment [8] faces many challenges such as small on-state samples, individual differences, sparse distribution symptoms, and environmental influences, because of the continuous and unobtrusively data collection. In the real life experiment, most data from PD patients are in an ON state instead of an OFF state. Meanwhile,

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Leveraging Multi-Sensor Data and Domain Adaptation for Improved Parkinson's Disease Assessment

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***Abstract*—Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by motor symptoms such as tremors, rigidity, and bradykinesia. Accurate and early diagnosis is crucial for effective management and treatment. Some quantitative studies have combined wearable technology with machine learning methods, demonstrating a high potential for practical application. However, these studies mostly use single-location, single-sensor data collected from PD patients in clinical settings, neglecting the diversity of PD symptoms and the real-world application scenarios in free-living environments. This paper proposes an auxiliary diagnosis framework for PD based on multi-location, multi-sensor fusion, and unsupervised domain adaptation. The multi-location, multi-sensor fusion can mitigate the asymmetry of Parkinson's symptoms, while unsupervised domain adaptation helps transfer in-hospital data to free-living environments without the need for manual labeling of the free-living data. Additionally, this paper designs a multi-head attention mechanism that focuses the disease classifier on sensors with strong feature discrimination and good distribution alignment. This experiment relies on wearable sensor data from 60 PD patients and 12 healthy controls, achieving an impressive accuracy of 90.46%, a precision of 88.28%, a recall of 88.09%, and an F1-score of 88.14%.**

***Index Terms*—Parkinson's disease, free-living environments, Wearable Technology, multi-sensor fusion, unsupervised domain adaptation.**

I. Introduction

Parkinson's disease (PD) is one of the rapidly increasing neurodegenerative disorders worldwide [1]. Between 1990 and 2015, the prevalence of PD doubled, exceeding 6 million cases. Primarily attributed to aging, this figure is anticipated to double once more, surpassing 12 million by 2040 [2]. PD is typified by the gradual depletion of dopaminergic neurons in the midbrain, leading to a range of motor and non-motor dysfunctions [3]. Motor symptoms encompass bradykinesia, rigidity, resting tremor, micrographia, and various speech impairments, among others [4]. Non-motor symptoms comprise depression, sleep disorders, language impairment, and other manifestations [5]. Ensuring precise and timely identification of PD is paramount, as it furnishes critical insights essential for effectively mitigating its advancement.

Currently, PD diagnosis by neurologists typically relies on physical examination-related clinical scales, such as the Movement Disorder Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS), which entails substantial time and labor investment [6]. Additionally, clinical scale scores obtained in this manner are subject to external environmental factors and the expertise of neurologists, introducing significant subjectivity into the assessment [7] [8].

Recently, most studies claim that inertial sensors can quantify certain motor symptoms in PD using data from accelerometers, gyroscopes, and magnetometers [9]–[13]. However, these studies [14]–[17] are limited to using single-location, single-sensor setups to assist in the assessment of PD symptoms. Patients with PD often present with unilateral motor symptoms that eventually spread to the other side [18]. Therefore, using a single sensor on a single body location to detect PD symptoms would overlook the diversity and asymmetry of PD onset.

PD exhibits heterogeneity in symptom presentation and progression [19]. Specifically, this heterogeneity refers to significant differences among patients in terms of symptom types, severity, and the rate of disease progression. This results in variations in data distribution between different patients. In recent years, unsupervised domain adaptation (UDA) techniques have been explored to bridge the domain gap between different environments. UDA methods can be broadly classified into mapping-based approaches, such as Maximum

TABLE VI
DETAILED RESULTS OF THE PROPOSED FRAMEWORK FOR PD SEVERITY CLASSIFICATION IN DIFFERENT USER GROUPS: HEALTHY CONTROLS, MILD, MODERATE, AND SEVERE PD

	Healthy Control			Mild			Moderate			Severe		
Test Group	**Pre**	**Rec**	**F1**	**Pre**	**Rec**	**F1**	**Pre**	**Rec**	**F1**	**Pre**	**Rec**	**F1**
Group1	98.47	100	99.23	100	98.60	99.30	99.01	100	99.50	99.41	100	99.70
Group2	100	100	100	100	95.18	97.53	98.91	100	99.45	88.14	100	93.69
Group3	100	100	100	75.39	92.62	83.12	14.74	0.03	0.05	92.52	100	96.12
Group4	100	99.19	99.59	98.18	97.16	97.67	100	96.68	98.31	93.20	100	96.48
Group5	89.64	100	94.54	97.31	96.97	94.60	100	96.97	98.46	90.42	95.41	92.85
Group6	100	100	100	91.30	100	95.45	100	76.46	86.66	96.75	89.03	92.73
Group7	94.08	100	96.95	69.71	80.22	74.60	0	0	0	95.00	87.77	91.24
Group8	100	92.94	96.34	92.85	100	96.29	100	80.91	89.45	93.26	96.07	94.65
Group9	100	100	100	94.17	97.01	95.57	91.57	84.41	87.85	100	100	100
Group10	100	100	100	81.94	95.78	88.32	100	96.99	98.47	77.96	42.55	55.06
Group11	98.10	99.36	98.72	91.94	100	95.80	100	77.85	87.54	100	97.34	98.65
Group12	98.03	100	99.00	68.68	75.69	72.01	0	0	0	84.26	100	91.46
Overall	98.19	99.29	98.69	88.45	94.10	90.85	75.35	67.52	70.47	92.57	92.34	91.88

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Modeling Parkinson's Disease Aided Diagnosis with Multi-Instance Learning: An Effective Approach to Mitigate Label Noise

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***Abstract*—An effective auxiliary diagnostic model for the severity of Parkinson's disease (PD) could help hospitals reduce their workload, particularly in nations or regions where medical resources are limited. However, a critical challenge persists that hampers the progress of such endeavors. Previous studies have employed label propagation techniques that assign uniform labels to all activity signal segments of a patient, neglecting the complex expression of PD symptoms, thereby introducing label noise. To confront this challenge, we have collected an extensive set of PD activity signals from a clinical setting and have proposed an efficient and robust framework for assessing PD severity. Specifically, we gathered wearable device data on 14 daily activities from 70 PD patients, based on the Unified Parkinson's Disease Rating Scale Part III. Our data analysis indicates that many segments within the activities were incorrectly labeled, significantly impairing the classification performance of the model. We introduced a novel framework based on Multi-Instance Learning with a Re-weighted Discriminative Instance Mapping (RDIM) to model PD auxiliary diagnosis, aiming to eliminate the impact of label noise present in the data. The results demonstrate that our framework achieves an accuracy of 80.88% in classifying the severity of PD, effectively addressing the label noise caused by coarse-grained label propagation.**

***Index Terms*—Parkinson's Disease, Multi-Instance Learning, Wearable Devices, Label Noise, Inexact Supervision**

I. Introduction

Parkinson's Disease (PD) is currently the second most prevalent neurodegenerative disorder, primarily characterized by symptoms such as tremors, bradykinesia, and gait freezing. These manifestations severely impair the quality of life of patients. Numerous studies suggest that appropriate treatments can slow down the progression of the disease. physicians often assess patients using the Unified Parkinson's Disease Rating Scale (UPDRS) [1].

In medical practice, physicians primarily rely on a patient's clinical symptoms and patient's recollection of their medical history and propose treatment recommendations. This estimation of PD is time-consuming and complex, and relies on the subjective experience of the physician.

With the rapid advancement of the Internet of Things (IoT) [2]–[5] and Cyber-Physical Systems (CPS) [6], there has been a growing focus on the assessment of Parkinson's Disease (PD) in recent literature [7]–[11]. The deployment of wearable sensors to monitor and assess PD through analysis of patient movements has become a significant area of investigation. For instance, prior research has predominantly concentrated on detecting discrete symptoms, such as tremor, bradykinesia [12]–[16], and gait freezing [17]–[19]. While these studies have contributed valuable insights into the severity of individual PD symptoms, they have not provided a holistic evaluation of the patient's overall disease stage. This limitation stems from the fact that the comprehensive assessment of PD severity, as stipulated by the Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS), necessitates the observation of a spectrum of symptoms manifested across various activities. Existing research has largely been restricted to the examination of isolated symptoms or singular activities, hence not capturing the full spectrum of activities and symptoms required for an all-encompassing assessment of the disease's progression.

Despite the promising potential of machine learning in diagnosing and treating PD, there exists a significant gap in the current research regarding the assessment of PD

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