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PREDICTING PARKINSON'S DISEASE CLINICAL STAGES WITH EXTREME LEARNING MACHINE ON CENTER OF PRESSURE DATA

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Abstract. Parkinson's disease (PD) is a progressive disorder that affects body movement, with postural instability contributing to fall risk. This study applies machine learning to assess whether postural sway features derived from center-of-pressure (COP) data can differentiate PD stages classified by the Hoehn and Yahr (H&Y) system. COP data from 32 PD patients (mean age 65.5 years, mean disease duration 7.4 years) were collected during bipedal balancing on stable and unstable surfaces with eyes open and closed. Thirteen time-domain features were extracted, and an extreme learning machine (ELM) was trained to predict PD stages based on four metrics: accuracy, recall, precision, and F1-score. The features were evaluated across nine cases with selective removal of specific COP variables. Results showed high classification accuracy across all cases (over 80%), with Instance 3 achieving the highest accuracy (91.7%) by excluding "mean velocity" in both sway directions under stable and unstable conditions. These findings suggest that COP-based postural sway measurements can effectively indicate PD progression, with specific variables reflecting distinct physiological mechanisms in postural control.

Keywords. Balance, Postural control, Posturography, Parkinsonism, Hoehn and Yahr, Extreme Learning Machine.

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1. Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder that significantly increases disability and mortality rates with advancing age. This condition primarily results from the degeneration of dopamine-producing neurons in the substantia nigra pars compacta (SNpc) [7], leading to dopamine deficiency in the nigrostriatal pathway. This deficiency manifests in motor symptoms such as tremors, rigidity, bradykinesia, postural instability, hypomimia, micrographia, festination, shuffling gait, dysarthria, and dystonia [7, 26]. The "TRAP" mnemonic-tremor, rigidity, akinesia, and postural instability-serves as an early assessment tool in the differential diagnosis of PD [12]. Classifying PD's clinical stages, such as with the Hoehn and Yahr (H&Y) scale, helps evaluate the extent of a patient's disability, grading PD severity on a 1–5 scale [16]. Stages 1–3 indicate mild disability, allowing independent living, while stages 4 and 5 reflect severe disability and reduced quality of life [16, 33].

Postural instability, a primary motor symptom of PD, leads to falls and loss of independence, becoming especially critical in later stages [26, 19]. Early postural instability, within three years of PD diagnosis or before age 60, is a significant diagnostic marker [2]. Identifying and monitoring postural instability early is essential to reduce the economic and emotional burden on patients and healthcare systems [26]. However, subtle early-stage postural sway in PD (e.g., H&Y stage 1) is challenging to detect visually, and PD diagnoses are often missed due to nonspecific symptoms [23]. A practical approach to assessing postural control involves measuring postural instability through center-of-pressure (COP)

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data obtained from force platforms. These platforms provide posturographic data on ground reaction forces and moments, represented as COP motions [10], which reflect neuromuscular control over the body's center of mass [10] and the myoelectric activities involved in maintaining balance [13, 29, 34, 20].

Accurate measuring instruments, such as force platforms, can detect postural control issues in PD patients with mild symptoms, making COP-based postural sway variables a valuable biomarker of PD progression [23, 3, 4]. While postural impairment is often analyzed through posturography, postural sway features-such as time-domain, frequency-domain, and time-frequency measures-are used to evaluate postural control [10, 30, 31]. Previous studies indicate that time-domain features are particularly effective in distinguishing PD patients from healthy older adults [11]. In this study, we focus on time-domain features that estimate COP displacement or velocity from stabilograms, as these parameters are thought to correlate with different physiological control mechanisms [9].

However, comparing outcomes across studies can be challenging due to the distinct physiological mechanisms reflected in various sway measures. For example, COP velocity measures the average speed of COP trajectory, playing a role in modulating myoelectric activity with feedback control [2, 24]. Sample entropy (SamEn), which measures the regularity of COP trajectory, reflects the complexity of quiet standing postural control and irregular neuromuscular control strategies [1, 14]. Identifying effective COP measures to differentiate PD clinical stages can be enhanced through machine learning techniques, such as support vector machines (SVM), random forests (RF), k-nearest neighbors (KNN), and neural networks, which have been used in medical research [36, 18]. In this study, we utilize an "extreme learning machine" (ELM), a feedforward neural network introduced by Huang et al. [17], chosen for its fast learning speed, efficient convergence, robust generalization, and ease of implementation [5].

In summary, the current study aims to identify postural sway measures, based on COP variables, that differentiate PD motor symptom stages using the H&Y system. By focusing on standard COP-based time-domain variables and analyzing them with an ELM model, we aim to enhance the evaluation of postural instability across PD stages.

2. Materials and Methods

2.1. **Secondary data analysis.** The dataset used in this study consists of center-of-pressure (COP) displacement data from 32 idiopathic PD patients (mean age 65.5 ± 10.4 years; mean disease duration 7.4 ± 4.6 years) [8]. The participants, comprising 8 females and 24 males, were recruited from local communities and were on a stable dose of levodopa (L-dopa) for at least one month before data collection. They self-reported having no vestibular, visual, or somatosensory impairments, nor any additional neurological or physical dysfunctions beyond Parkinson's disease. Table 1 summarizes the participant characteristics: age ranged from 44 to 81 years, height from 151.5 to 184.0 cm, body mass from 53.3 to 95.6 kg, BMI from 17.5 to 31.5 kg/m^2, disease duration from 1 to 19 years, daily L-dopa equivalent dose from 100 to 2,100 mg, and Hoehn and Yahr (H&Y) scale scores from 1 to 4. Data were gathered at the Biomechanics and Motor Control Laboratory of the Federal University of ABC, Brazil. The study protocol was approved by the local ethics committee, and all participants provided written informed consent before data collection [8].

The measurement procedures are detailed in de Oliveira et al. [8]. Before testing, all participants refrained from taking Parkinson's medication for at least 12 hours. Each participant completed four balancing conditions: standing on a rigid surface with open eyes, on a rigid surface with closed eyes, on an unstable surface with open eyes, and an unstable surface with closed eyes. Each condition lasted 30 seconds and was repeated three times, with the order randomized across participants. For the rigid surface trials, participants stood directly on a 40 × 60 cm force platform (OPT400600-1000; AMTI, Watertown, MA, USA). Participants stood on a 6-cm-high foam pad (Balance Pad Elite, Airex AG, Switzerland) for the unstable surface trials atop the force platform.

TABLE 1. The characteristics of the participants

Subject ID	Gender	Age (years)	Height (cm)	Weight (kg)	BMI (kg/m^2)	Disease duration (years)	L-dopa equivalent units (mg/day)	H&Y scale
1	Male	46	171	61.5	21.0	8	600	2
2	Female	53	170	62.6	21.6	4	275	1
3	Female	44	157	53.3	21.6	14	665	2
4	Male	50	176	73.6	23.8	5	2100	2
5	Male	53	167	77.2	27.7	14	950	2
6	Male	53	178	55.3	17.5	8	500	2
7	Male	57	173.5	57.7	19.2	4	1000	2
8	Male	60	179	92.5	28.9	5	750	3
9	Male	61	180	68.7	21.2	10	800	2
10	Male	62	166.5	57.4	20.7	7	610	2
11	Male	62	177	95.6	30.5	5	1100	2
12	Male	69	165	76.5	28.1	1	770	2
13	Male	69	182	71.2	21.5	4	550	2
14	Male	70	162	71.8	27.4	4	500	2
15	Male	71	179	72.8	22.7	2	400	2
16	Male	73	168	79.0	28.0	3	400	2
17	Male	74	165	62.2	22.9	12	750	2
18	Male	76	167	65.4	23.4	11	500	2
19	Female	77	151.5	60.2	26.2	15	100	2
20	Male	77	184	83.0	24.5	13	366	2
21	Female	78	165	70.8	26.0	6	700	2
22	Female	53	155	57.6	24.0	5	664	3
23	Male	60	175	77.1	25.2	7	900	3
24	Male	65	168	89.0	31.5	15	766	3
25	Male	66	168	60.0	21.3	8	1000	3
26	Male	68	169	68.9	24.1	19	1664	3
27	Male	68	161	63.9	24.7	4	300	3
28	Male	74	179	94.6	29.5	3	250	3
29	Female	78	158	64.8	25.9	3	500	3
30	Male	81	154.5	65.7	27.5	4	866	3
31	Female	82	160	72.1	28.1	5	300	3
32	Female	66	168	87.0	30.8	10	600	4
Mean		**65.5**	**168.7**	**70.9**	**24.9**	**7.4**	**693.6**	
SD		**10.4**	**8.6**	**11.7**	**3.6**	**4.6**	**399.6**	

Participants stood barefoot, keeping as still as possible with arms at their sides, focusing on a 5-cm black target positioned on a wall 3 meters away at eye level. For closed-eye trials, participants initially looked at the target with their eyes open to find a stable posture, then closed their eyes for the prosecution. For all trials, they stood with feet positioned at a 20-degree angle and heels spaced 10 cm apart, as illustrated in Duarte et al. [10]. After each trial, participants were assisted in stepping off the platform and given a one-minute rest before the subsequent trial.

The center-of-pressure (COP) signals for both anteroposterior (ap) and mediolateral (ml) directions were calculated using a standard formula [32] and smoothed with a 10 Hz, fourth-order, zero-lag low-pass Butterworth filter [8]. Figure 1 displays example stabilograms from a female PD patient at H&Y stage 1, illustrating the postural sway displacements observed while maintaining balance.

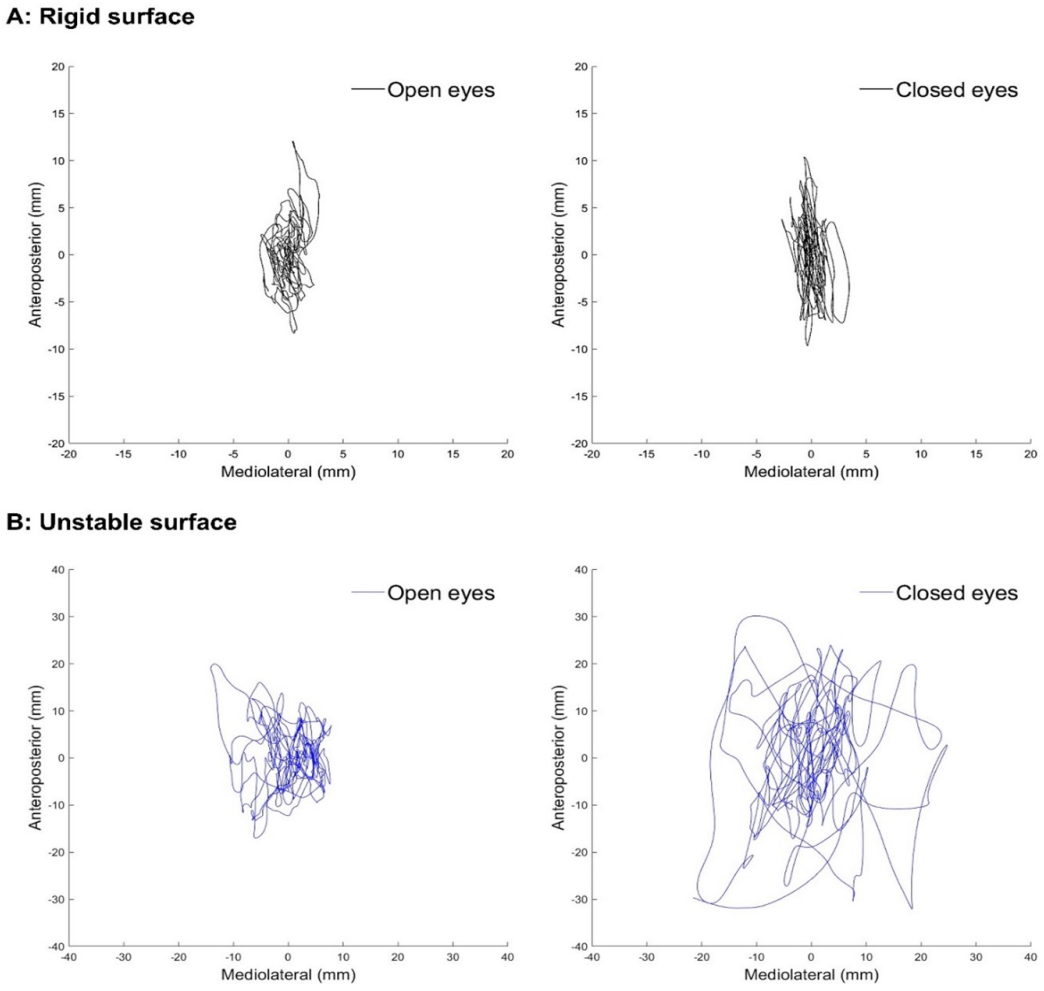


FIGURE 1. Stabilogram examples of bipedal balancing on (A) a rigid surface and (B) an unstable surface, with both open and closed eyes. Note: The COP data shown were obtained from a female PD patient at H&Y stage 1.

3. COP-BASED VARIABLE COMPUTATION

Two time-domain COP-based variables were calculated to assess postural control ability using a custom MATLAB™ program (MathWorks, Inc., Natick, MA). First, five variables were computed individually for the anteroposterior (COP_{ap}) and mediolateral (COP_{ml}) directions: amplitude displacement (AmpDis) as a measure of COP displacement distance [10], mean velocity (MV) for average COP trajectory speed [10], sample entropy (SamEn) as a measure of COP trajectory regularity [1], standard deviation (SD) for COP displacement variability [10], and root mean square (RMS) to quantify COP trajectory amplitude [10]. Second, three variables were derived from combined COP_{ap} and COP_{ml} signals: total sway displacement (TSD) indicating COP displacement frequency, total mean velocity (TMV) for overall COP trajectory velocity [10], and 95% ellipse area (95%EllipseArea) representing COP trajectory dispersion within 95% of the sway area [9]. A total of thirteen COP-based variables were computed per balancing trial for each participant. Each variable was calculated three times, and the average values were used in subsequent classification analyses.

3.1. **Classification models.** For H&Y classification, the inertial Mann forward-backward splitting algorithm developed by Peeyada et al. [27], based on the extreme learning machine (ELM) framework [17], was employed to train the model and determine the optimal output weight-the hidden layer, consisting of 250 nodes, processed input features using sigmoid activation functions. The training dataset included 32 cases, each labeled according to four stages of the Hoehn and Yahr (H&Y) scale [16]: stage 1 representing unilateral involvement with minimal or no functional disability; stage 2 indicating bilateral or midline involvement without balance impairment; stage 3 signifying bilateral disease with mild to moderate disability and impaired postural reflexes, though still physically independent; and stage 4 indicating bilateral disease with severe disability and impaired postural reflexes while remaining physically independent. The dataset was split into training and testing sets in a 70:30 ratio for machine learning implementation. Each case in the dataset included a sample identifier, 13 variables, and four conditions, as detailed in Table 2.

TABLE 2. Overview of the 13 variables with four balancing conditions for each case.

Condition	Variable	Description	Mean	SD	CV (%)	Min	Max
RC	RC1	COPap_AmpDis	22.1	8.9	40.0	8.6	45.2
	RC2	COPml_AmpDis	6.8	4.0	58.9	3.0	19.5
	RC3	COPap_MV	11.6	7.9	67.6	4.6	44.4
	RC4	COPml_MV	5.5	5.8	105.2	1.3	28.0
	RC5	COPap_SamEn	2.1	0.6	29.5	1.2	3.6
	RC6	COPml_SamEn	1.2	0.5	46.0	0.5	2.6
	RC7	COPap_SD	4.0	1.6	39.0	1.5	9.2
	RC8	COPml_SD	1.2	0.6	52.9	0.5	2.9
	RC9	COPap_RMS	4.0	1.6	39.0	1.5	9.2
	RC10	COPml_RMS	1.2	0.6	52.9	0.5	2.9
	RC11	COP_TSD	10430.9	4079.8	39.1	3842.3	23650.0
	RC12	COP_TMV	13.9	10.0	71.5	5.7	51.1
	RC13	COP_95%EllipseArea	91.8	79.5	86.6	12.3	321.4
RO	RO1	COPap_AmpDis	18.2	6.2	33.8	9.3	33.3
	RO2	COPml_AmpDis	6.3	3.1	48.8	2.7	17.7
	RO3	COPap_MV	8.9	5.7	63.7	4.2	35.1
	RO4	COPml_MV	4.7	3.8	80.2	1.3	17.6
	RO5	COPap_SamEn	1.8	0.4	23.1	1.3	2.8
	RO6	COPml_SamEn	1.1	0.5	39.4	0.5	2.4
	RO7	COPap_SD	3.6	1.3	36.5	1.7	6.8
	RO8	COPml_SD	1.1	0.5	46.5	0.5	3.0
	RO9	COPap_RMS	3.6	1.3	36.5	1.7	6.8
	RO10	COPml_RMS	1.1	0.5	46.5	0.5	3.0
	RO11	COP_TSD	9473.6	3319.1	35.0	4669.9	1745.9
	RO12	COP_TMV	11.0	6.8	62.1	4.9	39.7
	RO13	COP_95%EllipseArea	75.6	54.3	71.9	18.6	226.7

Condition	Variable	Description	Mean	SD	CV (%)	Min	Max
UC	UC1	COPap_AmpDis	58.9	14.1	24.0	36.7	89.3
	UC2	COPml_AmpDis	30.8	17.0	55.1	3.8	79.6
	UC3	COPap_MV	30.0	11.5	38.2	17.5	65.4
	UC4	COPml_MV	12.5	8.0	63.5	1.3	35.0
	UC5	COPap_SamEn	2.3	0.5	21.8	1.4	3.5
	UC6	COPml_SamEn	1.3	0.6	43.6	0.2	2.4
	UC7	COPap_SD	10.9	2.4	21.9	6.5	15.4
	UC8	COPml_SD	5.8	3.1	53.6	0.7	14.8
	UC9	COPap_RMS	10.9	2.4	21.9	6.5	15.4
	UC10	COPml_RMS	5.8	3.1	53.6	0.7	14.8
	UC11	COP_TSD	32053.1	8952.8	27.9	18621.6	55325.6
	UC12	COP_TMV	35.0	14.1	40.4	18.2	80.6
	UC13	COP_95%EllipseArea	1249.1	911.6	73.0	66.9	4187.0
UO	UO1	COPap_AmpDis	40.0	10.6	26.5	23.3	67.4
	UO2	COPml_AmpDis	22.1	12.5	56.4	2.2	57.0
	UO3	COPap_MV	18.4	8.0	43.2	7.6	46.6
	UO4	COPml_MV	9.0	6.4	71.5	1.0	28.7
	UO5	COPap_SamEn	1.8	0.5	25.9	1.0	3.2
	UO6	COPml_SamEn	1.1	0.5	48.1	0.2	2.1
	UO7	COPap_SD	7.5	2.0	26.3	4.5	12.4
	UO8	COPml_SD	4.3	2.4	55.1	0.5	10.7
	UO9	COPap_RMS	7.5	2.0	26.3	4.5	12.4
	UO10	COPml_RMS	4.3	2.4	55.1	0.5	10.7
	UO11	COP_TSD	22463.5	7253.7	32.3	11710.0	38373.4
	UO12	COP_TMV	22.2	10.7	48.1	8.7	59.7
	UO13	COP_95%EllipseArea	646.1	523.5	81.0	36.4	2063.9

Note: RC = balancing on a rigid surface with closed eyes; RO = balancing on a rigid surface with open eyes; UC = balancing on an unstable surface with closed eyes; UO = balancing on an unstable surface with open eyes; CV = coefficient of variation (%); and SD = standard deviation.

In this study, the effectiveness of machine learning techniques is evaluated using four metrics: Accuracy, Recall, Precision, and F1-score. Accuracy measures the algorithm's ability to classify cases into their respective categories. Recall (or sensitivity) indicates the proportion of instances from a particular class that are correctly identified. Precision assesses the reliability of optimistic predictions made by the algorithm. Finally, the F1-score, the harmonic mean of precision and recall, provides an overall performance rating. The definitions and formulations of these four metrics are as follows [17]:

$$\text{Accuracy (\%)} = \frac{TP + TN}{TP + FP + TN + FN} \times 100, \tag{1}$$

$$\text{Precision (\%)} = \frac{TP}{TP + FP} \times 100, \tag{2}$$

$$\text{Recall (\%)} = \frac{TP}{TP + FN} \times 100, \tag{3}$$

$$\text{F1-score (\%)} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \times 100. \tag{4}$$

Additionally, a confusion matrix is presented to show the relationship between actual and predicted classes: TP (True Positive) for correctly classified cases, TN (True Negative) for correctly identified negatives, FP (False Positive) for incorrect classifications marked as positive, and FN(False Negative) for incorrect classifications marked as negative. The multi-class cross-entropy loss is used in multi-class classification as follows: where y^j is 0 or 1, indicating whether the class label j is the correct classification, and $\hat{y}^j$ is a probability of a class y^j, and N is the number of scalar values in the model output.

$$\text{Loss} = -\frac{1}{N}\sum_{j=1}^{N} y^j \log(\hat{y}^j) \tag{5}$$

The training dataset was divided into nine scenarios based on two types of time-domain COP-based variables, with a maximum training limit of 1,000 iterations. In Instance 2–6, individual variables were calculated for both COPap and COPml directions. Furthermore, variable removal was performed for both COPap (related to ankle muscle control) and COPml (related to hip and trunk muscle control) [15], considering both stable and unstable surfaces to assess postural control [6].

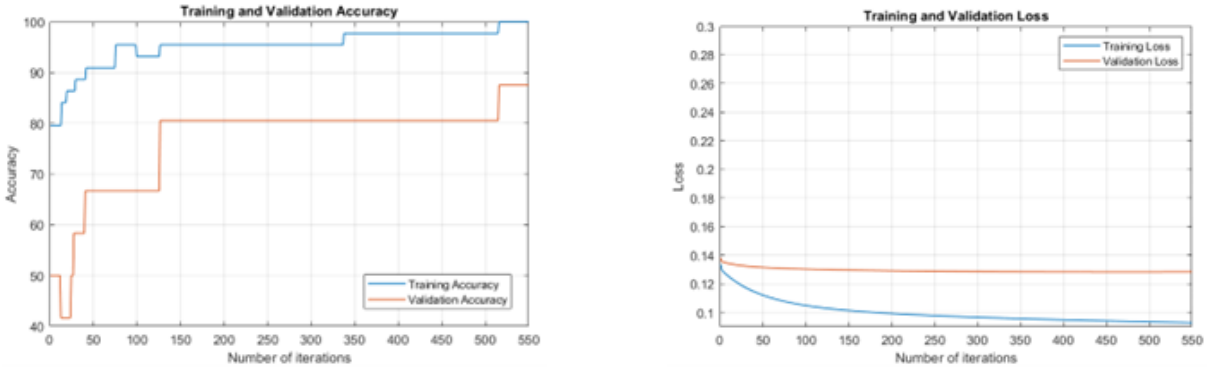
Instance	Variables Removed
1	All data
2	RC1, RC2, RO1, RO2, UC1, UC2, UO1, UO2 were removed
3	RC3, RC4, RO3, RO4, UC3, UC4, UO3, UO4 were removed
4	RC5, RC6, RO5, RO6, UC5, UC6, UO5, UO6 were removed
5	RC7, RC8, RO7, RO8, UC7, UC8, UO7, UO8 were removed
6	RC9, RC10, RO9, RO10, UC9, UC10, UO9, UO10 were removed
7	RC11, RO11, UC11, UO11 were removed
8	RC12, RO12, UC12, UO12 were removed
9	RC13, RO13, UC13, UO13 were removed

3.2. **Results.** Table 3 presents the results obtained for the classifiers, detailing Training Time, Precision, Recall, F1-score, and Accuracy for individual Parkinson's cases when specific COP-based variables are selectively excluded. Overall, all cases achieved high accuracy levels, exceeding 80%. Notably, Instance 3 reached the highest accuracy of 91.7% when the variable "mean velocity" (MV) was excluded from the COP_{ap} and COP_{ml} directions. Additionally, training and validation loss and training accuracy indicate no overfitting in the data, as illustrated for Instance 1-3 in Figure 2, Instance 4-6 in Figure 3, and Instance 7-9 in Figure 4.

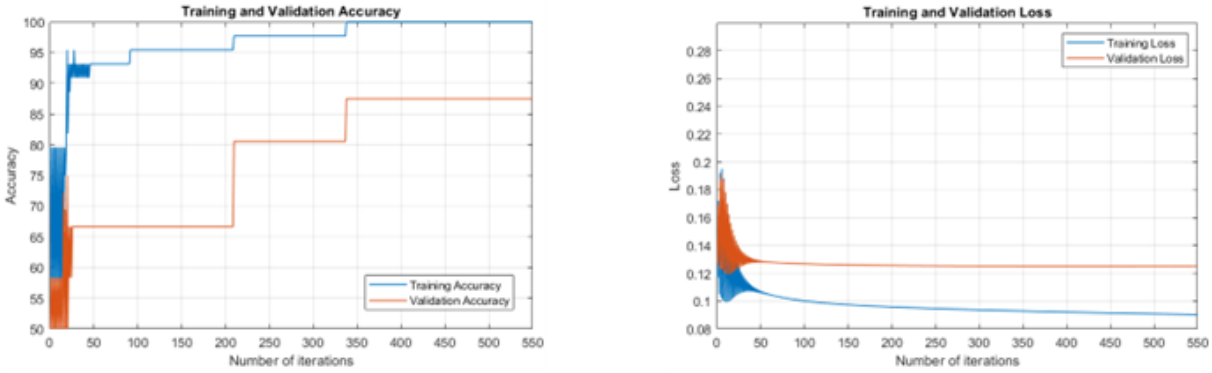
TABLE 3. The performance in training Parkinson's data of all cases.

Instance	Training Time (s)	Precision	Recall	F1-score	Accuracy
1	0.514	85.0	85.4	85.2	87.5
2	0.615	85.0	85.4	85.2	87.5
3	0.595	91.7	91.7	91.7	91.7
4	0.588	85.0	85.4	85.2	87.5
5	0.604	85.0	85.4	85.2	87.5
6	0.587	85.0	85.4	85.2	87.5
7	0.646	85.0	85.4	85.2	87.5
8	0.581	85.0	85.4	85.2	87.5
9	0.620	85.0	85.4	85.2	87.5

Instance 1



Instance 2



Instance 3

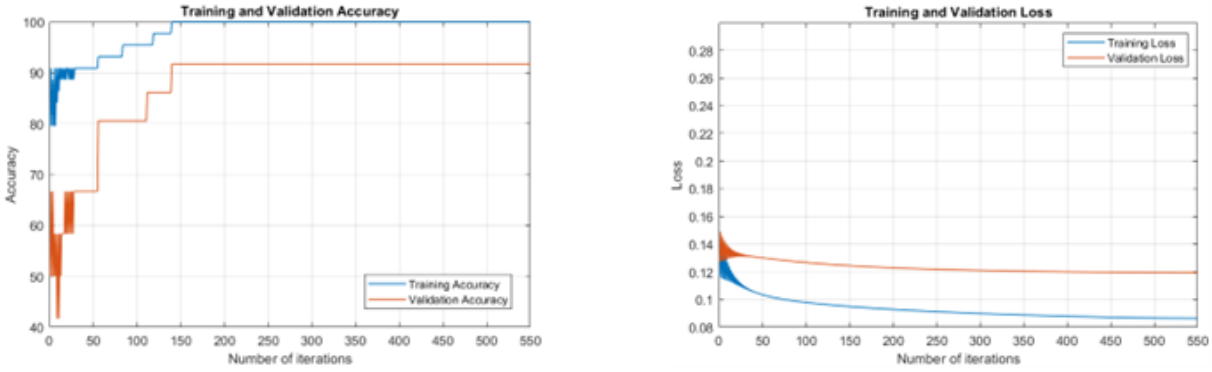
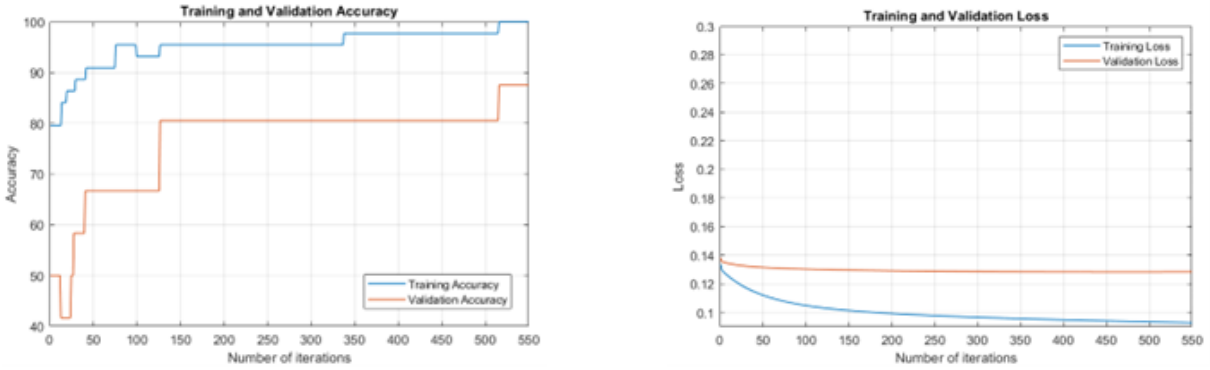


FIGURE 2. Graphs of training and validation loss alongside training accuracy of Instance 1, Instance 2, and Instance 3.

Instance 4



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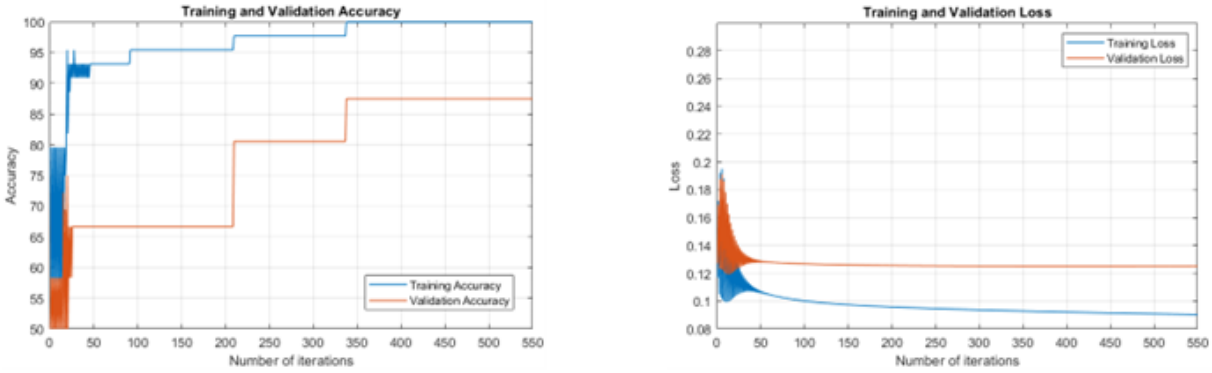


Instance 6

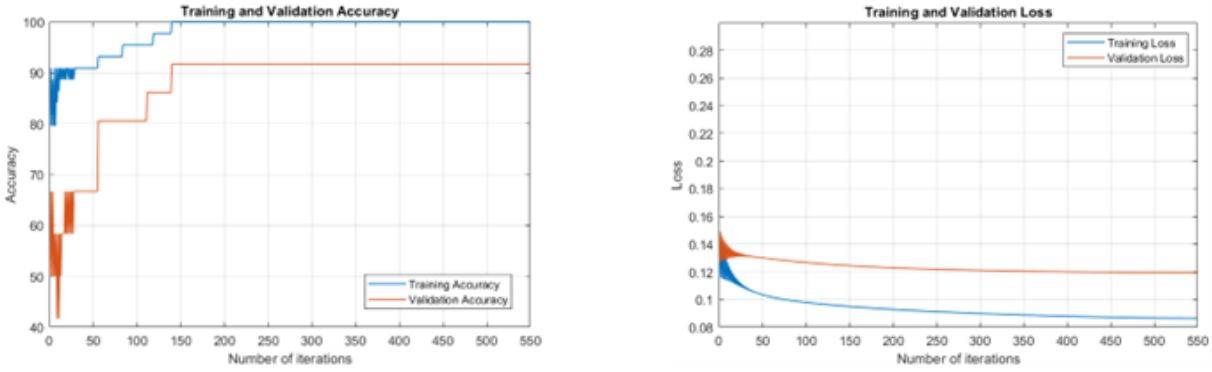
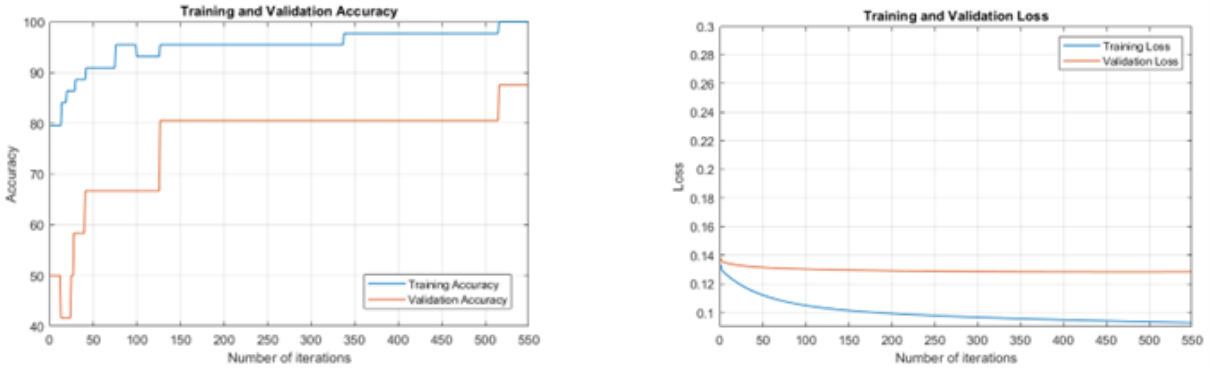
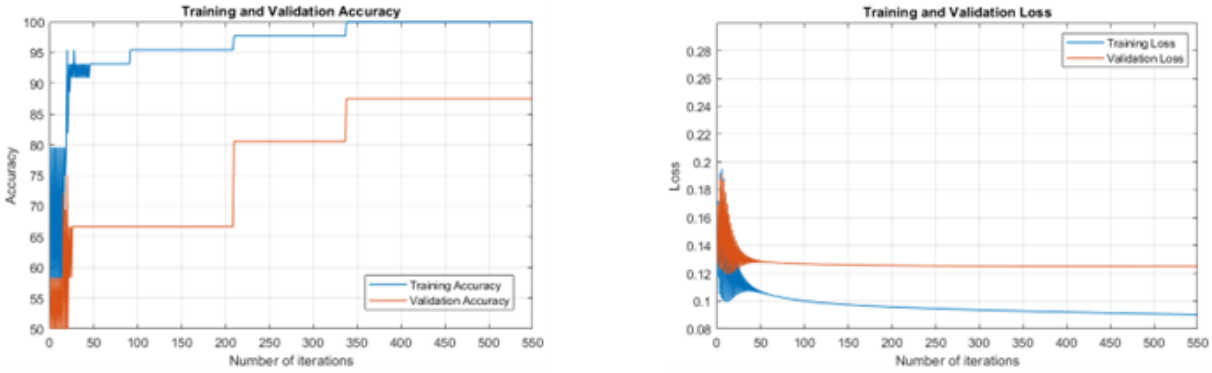


FIGURE 3. Graphs of training and validation loss alongside training accuracy of Instance 4, Instance 5, and Instance 6.

Instance 7



Instance 8



Instance 9

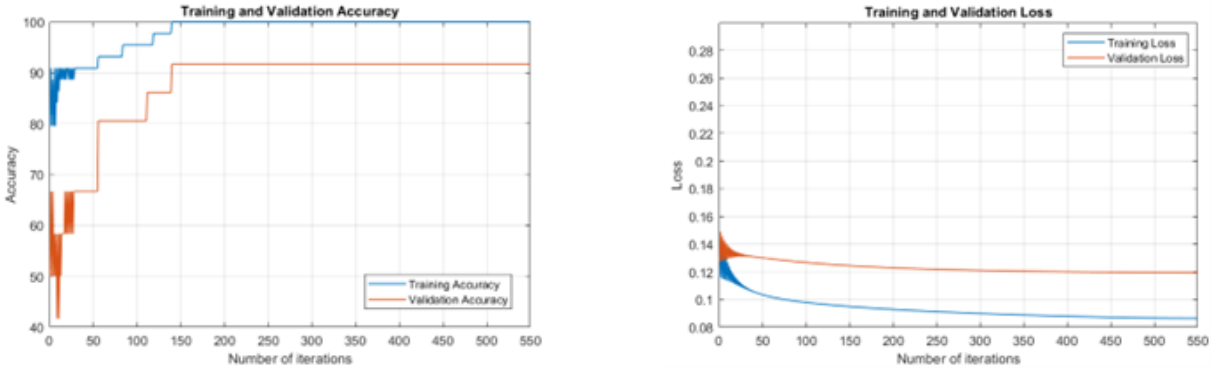


FIGURE 4. Graphs of training and validation loss alongside training accuracy of Instance 7, Instance 8, and Instance 9.

3.3. **Comparison of machine learning methods.** Table 4 presents a comparison of the highest accuracy achieved by various machine learning methods, including logistic regression kernel, boosted trees, support vector machines (SVM), k-nearest neighbors (KNN), and the method developed by Peeyada et al. [27].

3.4. **Discussion.** In this study, extreme learning machine (ELM) methods were used to identify which time-domain COP-based variables most effectively classify Parkinson's disease (PD) stages of motor symptoms according to the Hoehn and Yahr (H&Y) scale. Thirteen COP-based variables were tested

TABLE 4. Comparison of highest accuracy achieved by various machine learning methods on the Parkinson's Disease dataset.

Instance	Logistic Regression Kernel	Boosted Trees	SVM	KNN	Peeyada et al. [27]
1	78.1	59.4	81.2	75.0	87.5
2	81.2	59.4	81.2	75.0	87.5
3	75.0	59.4	84.4	75.0	91.7
4	75.0	59.4	81.2	71.9	87.5
5	78.1	59.4	81.2	75.0	87.5
6	78.1	59.4	81.2	75.0	87.5
7	78.1	59.4	81.2	75.0	87.5
8	78.1	59.4	81.2	75.0	87.5
9	78.1	59.4	84.4	75.0	87.5

across six cases, each with a subset of time-domain COP variables removed. Results indicate that applying machine learning to COP-based postural sway measures can accurately distinguish PD stages (¿ 80%) in all cases, highlighting posturography's sensitivity to balance control differences across H&Y stages in PD patients.

Although all time-domain COP features contribute to detecting balance impairment and differentiating H&Y stages, Instance 3, where"mean velocity" was excluded from individual COP directions, achieved the highest classification accuracy. This suggests that sway amplitude measures (e.g., sway range, path length, and area) are more robust predictors for PD stage differentiation than directional sway velocity measures. Typically, mean sway velocity is calculated by summing the distance between consecutive COP points over time for both anteroposterior and mediolateral components, indicating postural control efficiency, where lower velocities suggest better control [11]. However, in this study, Instance 3's "mean velocity" exclusion led to the highest predictive accuracy for PD stages, implying that sway velocity may be less sensitive to progressive postural instability in PD. Previous research supports this observation; for example, a 12-month study [21] showed that treatment for PD had minimal impact on sway velocity. Additionally, a survey of levodopa's effects on postural sway reported no significant difference between off- and on-levodopa conditions [3].

These findings suggest that time-domain COP features are valuable for assessing PD stages, as they reflect postural sway through metrics easily interpreted by displacement or velocity relative to the stabilogram's center [28]. For instance, COP path length quantifies two-dimensional displacement magnitude and indicates that shorter paths correlate with better stability [11]. The 95% ellipse area, covering the central sway area in both directions, further assesses postural stability, with smaller regions indicating better postural performance [11].

This study has limitations, including a small sample size that may affect generalizability. Also, postural sway abnormalities may appear in PD before clinical symptoms and levodopa treatment initiation [22, 35, 25]. Since these findings reflect postural assessment at a single time point in an off-levodopa condition, further research could identify which posturographic metrics are most responsive to rehabilitation.

4. CONCLUSIONS

These findings highlight the value of time-domain features derived from posturographic (COP) data in distinguishing motor dysfunction stages in individuals with PD. The study examined two categories of COP-based variables: those calculated independently for each sway direction (such as amplitude displacement, mean velocity, sample entropy, standard deviation, and root mean square) and those

derived from combined sway directions (including total sway displacement, total mean velocity, and 95% ellipse area). Overall, when combined with a machine learning approach, the proposed postural sway features show strong potential for clinical use in accurately predicting PD stages, achieving over 80% accuracy. Notably, excluding mean velocity parameters yielded the highest classification accuracy (91.7%) for distinguishing between PD stages.

Data Availability

The data are available upon reasonable request from the corresponding author.

Statements and Declarations

The authors declare that they have no conflicts of interest.

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