Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 22 No. 4 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v22i04.59523

PAPER

The Role of Artificial Intelligence and Machine Learning in Balance Classification Using Center of Pressure – A Comprehensive Review

Wittaya Duangnga[1], **Nattadon Pannucharoenwong**[1](✉), **Phadungsak Rattanadecho**[1], **Wachirathorn Janchomphu**[2], **Suphasit Panvichien**[3]

[1]Thammasat University, Pathum Thani, Thailand

[2]Rajamangala University of Technology Tawan-ok, Chanthaburi, Thailand

[3]King's College London, WC2R 2LS, United Kingdom

pnattado@engr.tu.ac.th

ABSTRACT

Balance control is essential for safe daily activities, and impaired postural stability is strongly associated with fall risk, particularly in older adults. This systematic review examined the performance of artificial intelligence (AI) and machine learning (ML) methods for balance classification using Center of Pressure (CoP) data. Following PRISMA guidelines, 47 studies published between 2015 and 2025 were included. Force-platform-based post-urography remained the predominant sensing modality, while wearable technologies increasingly enabled assessment beyond laboratory environments. Support vector machine (SVM) was the most frequently used algorithm, followed by neural network (NN)-based models. Deep learning (DL) architectures, including convolutional neural networks (CNN) and long short-term memory networks (LSTM), achieved high classification accuracy by capturing complex balance patterns. Traditional ML models also demonstrated strong performance with lower computational demands and greater interpretability, supporting clinical feasibility. However, class imbalance remains a key limitation, often reducing sensitivity in high-risk groups. Future studies should prioritize robust and clinically deployable models for reliable real-world balance assessment and personalized rehabilitation.

KEYWORDS

balance classification, center of pressure (CoP), insoles, force plate, artificial intelligence (AI)

1 INTRODUCTION

Balance control is among the most basic human abilities for daily living. Maintaining body balance requires the integration of several systems functions, including the nervous, muscular, and sensory systems [1]–[3]. Balance impairment or loss of balance can greatly diminish quality of life and increase the risk of dangerous accidents or lead to cause of death, especially falls in the elderly [4], [5].

Duangnga, W., Pannucharoenwong, N., Rattanadecho, P., Janchomphu, W., Panvichien, S. (2026). The Role of Artificial Intelligence and Machine Learning in Balance Classification Using Center of Pressure – A Comprehensive Review. *International Journal of Online and Biomedical Engineering (iJOE)*, 22(4), pp. 4–25. https://doi.org/10.3991/ijoe.v22i04.59523

Article submitted 2025-11-06. Revision uploaded 2026-01-13. Final acceptance 2026-01-14.

At the present, various types of technologies are employed to assess balance performance. A force platform is considered the gold standard for quantitative stability assessment in a laboratory environment [6], [7]. This equipment can evaluate ground reaction forces and determine the position of CoP, presenting the movement of the body's center of mass while standing [8]. CoP data contains a variety of parameters that can be used in stability analysis, such as total displacement, sway area, mean velocity, and standard deviation of the movement [8]–[11].

In the medical field, AI and ML are widely and significantly utilized, especially in diagnosis, treatment prediction, and supported clinical decision-making [12]–[18]. In the field of balance assessment, the current study has shown that ML application can efficiently explore CoP data and classify balance ability levels. The study [19] demonstrated that AI can accurately assess balance control subsystems using 224 features extracted from CoP data to map them to assessment scores provided by physical therapists. In 2024, the study [20] used ML and explainable AI methods to classify fall risk in community-dwelling older adults using posturographic parameters.

Although a growing body of research has applied AI/ML techniques to CoP data for balance classification, a structured and up-to-date synthesis of the current state of this field is still lacking. Previous studies have shown that AI/ML-based approaches can achieve high classification accuracy, often exceeding 90%, in identifying balance impairments related to pathological conditions such as diabetes and Parkinson's disease, as well as in fall risk assessment [21]–[25]. Nevertheless, important limitations remain with respect to practical and clinical deployment [26], [27]. In particular, many reported models demonstrate a clear imbalance between accuracy and sensitivity, with reduced recall in high-risk groups due to class imbalance, where sensitivity values as low have been reported [20], [28]. In addition, the reliable classification of mid-level balance conditions remains challenging because of substantial feature overlap between normal and at risk populations, which increases the likelihood of misclassification compared with clearly distinct conditions [24], [29]. These issues are further intensified by the gap between laboratory-based experimental protocols and real-world applications, as most existing models rely on static standing tasks under highly controlled conditions. Which do not adequately reflect dynamic balance demands in daily activities [29]–[31]. Therefore, a comprehensive review is required to systematically examine the AI/ML models used for CoP-based balance classification, analyze their methodological characteristics and performance outcomes, and identify current challenges and future research directions. This review aims to provide an accessible and application-oriented overview to support researchers, system developers, and practitioners in the effective design and implementation of AI/ML-enabled balance assessment systems.

2 METHODOLOGY OF REVIEW

2.1 Research problem

In the light of the pivotal role and functions of AI/ML in the modern era. It has been applied in various medical fileds, including medical imaging analysis, clinical outcome prediction, and rehabilitation technologies. Consequently, it is essential to systematically analyze previous studies to compile the effectiveness of AI/ML. To guide the direction of the current review, a specific research equation to define as, "What is the effectiveness of AI/ML-based center of pressure (CoP) analysis in balance classification?"

2.2 Search strategy

A comprehensive review was conducted using the keywords "center of pressure," "CoP," "balance classification," "balance," "postural control," "postural sway," "sway," "force plate," "foot pressure," "pressure sensor," "IMU," "artificial intelligence," and "machine learning," and using search strategies were "AND" and "OR." To evaluate current trends, an article published in the period from January 2015 to August 2025 was included in this review.

2.3 Eligible article and article selection

The study selection followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [32], [33]. Electronic database searches yielded 4,344 records from IEEE (n = 1,223), PubMed (n = 1,598), ScienceDirect (n = 47), Scopus (n = 101), SpringerLink (n = 1,267), and ResearchGate (n = 98), with two additional articles identified through manual searching. All records were screened based on titles and abstracts, during which duplicate entries were removed and predefined inclusion criteria were applied, resulting in the exclusion of 4,299 records. The remaining 47 articles were assessed in full text for eligibility.

Eligible studies were read in full and included if they were published in English between January 2015 and August 2025, employed CoP measurement devices such as force platforms, pressure mats, pressure-sensitive insoles, balance boards, or comparable systems, and utilized artificial intelligence (AI) or machine learning (ML) techniques for CoP data analysis. Studies were further required to focus on balance classification, assessment, or diagnostic applications using CoP data, involve human participants or human-derived CoP datasets, and report quantitative AI/ML performance outcomes, including accuracy, sensitivity, specificity, area under the curve (AUC), or related evaluation metrics. Following full-text evaluation, all 47 articles satisfied the eligibility criteria and were included in the final qualitative synthesis. The overall study selection process is summarized in the PRISMA flow diagram. (see Figure 1)

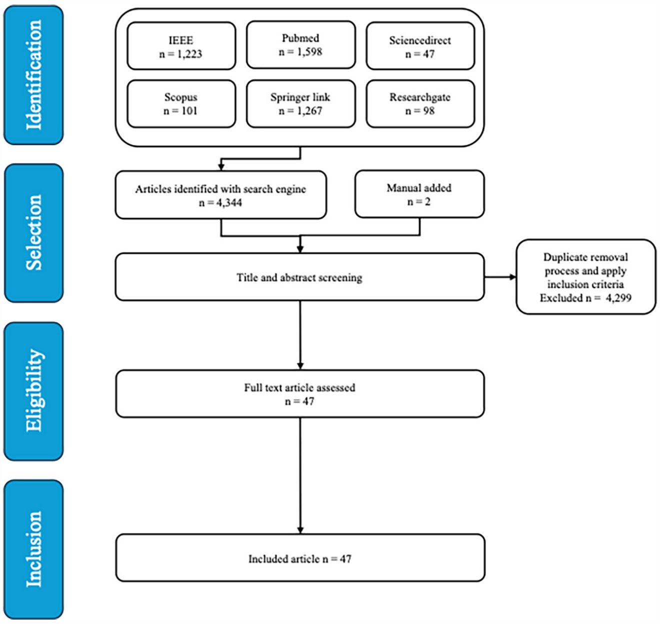

Fig. 1. PRISMA flow diagram

2.4 Data extraction

After including an article, the data required for synthesis were collected from each article. The data extracted for this review includes first author (year), population, sample size, assessment devices, AI/ML approach, and effectiveness outcome.

3 RESULTS OF REVIEW

This section presents and examines the findings of the literature review so that they relate to the objective in the current study.

3.1 General characteristics of studies

The temporal distribution of the included studies showed a clear increasing trend over the reviewed period from 2015 to 2025 (see Figure 2). Following the PRISMA-based selection process, 47 eligible studies were identified and included in the present review. The key characteristics of each included study are summarized in Table 1. Among the included studies, the majority were journal articles (n = 38), while conference proceedings accounted for a smaller proportion (n = 9) (see Figure 3). It should be noted that publications in 2025 represent a partial year up to the time of the literature search.

Table 1. Summary of eligible study characteristics

Study	Population	Sample Size	Assessment Device	Artificial Intelligence/ ML Approach
[24]	Healthy, diabetic, or neurologically	Not reported	Wii Balance Board	Random forest (RF) Logistic regression (LR) Naive Bayes (NB) Gradient boosting (GB) K-nearest neighbors (KNN) Local Interpretable Model-agnostic Explanations (LIME) Shapley Additive exPlanations (SHAP)
[27]	Healthy	163	Force platform	Artificial neural network (ANN)
[19]	Dataset from Human Balance Evaluation Database	Not presented	Force platform	PCPDD
[34]	Dataset	163	Posturography	ANN
[35]	Normal and Neurological condition	475	Force platform	LR support vector machine (SVM)
[36]	Older adults	Not reported	Not specified	Decision tree (DT) RF KNN SHAP

(Continued)

Table 1. Summary of eligible study characteristics *(Continued)*

Study	Population	Sample Size	Assessment Device	Artificial Intelligence/ ML Approach
[37]	Healthy adults	53	Triaxial inertial sensor	Least-Square Boosting (LSBoost) Bootstrap Aggregation (Bagging) SVM ANN Gaussian Process (GP)
[20]	Community-dwelling older adults	215	Tracker-based posturography	Ensemble Bagging Method NB SHAP
[38]	Healthy males	30	Insole system	Bidirectional Long Short-Term Memory (Bi-LSTM)
[26]	7–8 participants		Smart insoles	ANN Long Short-Term Memory (LSTM), Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM)
[39]	Adult males	25	Pedar-X insole	Feedforward Artificial Neural Network Long Short-Term Memory (LSTM)
[40]	Diabetics and healthy	Not reported	Smart insole, plantar surface	Classifier (no mention found)
[41]	Not reported		IMU	ANN
[42]	Parkinson’s disease	32	Force plate/pressure sensors	RF NN NB SVM DT KNN
[43]	Healthy	5	IMU	LSTM
[44]	Healthy	163	Force platform	KNN DT SVM
[45]	Stroke patients	185	Pressure-sensitive mat	Light Gradient-Boosting Machine Multilayer Perceptron (MLP)
[46]	Vestibular dysfunction	238	Force platform	GB Bagging LR ANN SVM MLP
[47]	Diabetic patients	Not reported	Wii Balance Board	NB KNN ANN DT
[48]	Santos and Duarte dataset	163	Force platform	GB ANN
[49]	Elderly	30	Smart Floor Pressure Sensor	SVM Regression

(Continued)

Table 1. Summary of eligible study characteristics *(Continued)*

Study	Population	Sample Size	Assessment Device	Artificial Intelligence/ ML Approach
[23]	Elderly	76	Force platform	DT
[50]	Elderly	209	Force platform	Hidden Markov Model Regression (HMMR)
[51]	Healthy young adults	40	Force platform	SVM Light Gradient-Boosting Machine LR
[28]	Parkinson's disease	69	Force platform	DT NB LR ANN SVM Bagging AdaBoost
[30]	Elderly	84	Wii Balance Board	Ranking Forest
[31]	Athletes	25	Force platform	LR SVM NB Ranking Forest
[52]	Elderly	75	Force platform	DT
[53]	Parkinson's disease and healthy	60	Force platform	HMMR
[54]	Elderly	51	Wii Balance Board	SVM KNN
[21]	Diabetic patients	104	Force platform	KNN
[55]	Parkinson's disease	60	Force platform	ANN
[56]	Inner ear balance disorder	60	Force platform	SVM RF KNN
[57]	Parkinson's disease	42	Force platform	DT NB RF
[58]	Elderly	Not reported	Force platform	Competitive Neural Network
[59]	Healthy	61	Force platform	Gaussian Mixture Model
[29]	Healthy young	14	Force platform	CNN SVM DT LR
[60]	Adults	67	Force platform	LR
[61]	Balance deficits	16	IMU	SVM
[62]	Healthy	17,541	Pressure sensor	ANN
[25]	Elderly	55	Motion capture	CNN

(Continued)

Table 1. Summary of eligible study characteristics *(Continued)*

Study	Population	Sample Size	Assessment Device	Artificial Intelligence/ ML Approach
[63]	Adults	163	Force platform	LR Linear Discriminant Analysis (LDA) KNN DT NB SVM
[64]	Participants with balance concerns	10	IMU	CNN
[22]	Cerebrovascular	53	IMU	SVM
[65]	Elderly	103	Wii Balance Board	LR SVM Generalized Additive Model (GAM) Regression Tree Regression
[66]	Healthy Adult	5	IMU	ANN CNN RF SVM
[67]	Normal foot and flat foot	11	Insole	ANN

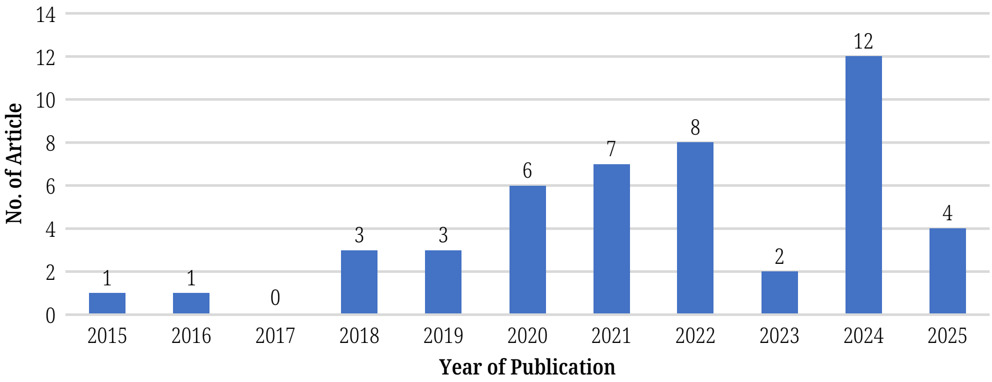

Fig. 2. Annual distribution of included articles

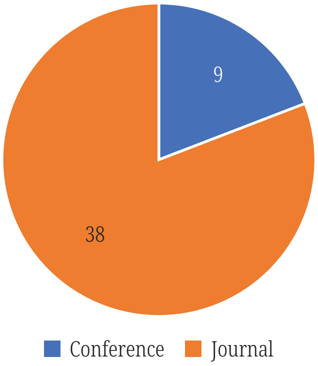

Fig. 3. Publication type of included articles

3.2 Assessment device/sensor type

The reviewed studies employed a variety of assessment devices for balance evaluation, with force-platform-based post-urography being the most widely used modality (n = 22; refer to Table 2). This was followed by wearable and consumer-level devices, including the Wii Balance Board (n = 5), and the IMUs (n = 5) reflecting increasing interest in portable and low-cost assessment systems. Smart insole-based systems such as instrumented insoles and Pedar-X were reported in a smaller number of studies (n = 5). While pressure-sensitive platforms, including pressure mats and smart floors, were less frequently adopted (n = 3). Additional devices categorized as others were reported sporadically across studies (n = 4). Overall, laboratory-grade force platforms remain the dominant measurement tool. Although emerging trends indicate a gradual shift toward wearable and accessible sensing technologies.

Table 2. Summary of assessment devices or sensor types

Assessment Devices	No. of Study	Study
Force Platform/Force Plate/ Posturography	22	[19]; [27]; [35]; [44]; [46]; [48]; [23]; [50]; [51]; [28]; [31]; [52]; [53]; [21]; [55]; [56]; [57]; [58]; [59]; [29]; [63]
Wii Balance Board	5	[24]; [47]; [30]; [54]; [65]
IMU	5	[43]; [61]; [64]; [22]; [66]
Smart Insoles/Insole System/ Pedar-X	5	[38]; [26]; [39]; [40]; [67]
Pressure Mat/Pressure-Sensitive/ Smart Floor	3	[45]; [42]; [49]
Others	4	[41]; [37]; [20]; [25]

3.3 AI/ML approach

The literature review demonstrates extensive use of AI and ML algorithms for balance assessment, with diverse model architectures reported (refer to Table 3). SVM was the most frequently employed approach (n = 17), followed by ANN/NN (n = 13). LR (n = 11) and DT models (n = 10) were also commonly adopted, primarily due to their computational simplicity and interpretability. KNN (n = 9) was applied less frequently, while ensemble learning methods, including RF and boosting-based techniques, were introduced to enhance classification robustness and predictive stability. Although less prevalent, deep learning (DL) models such as CNN and LSTM networks were increasingly reported for modeling complex spatiotemporal balance data. Overall, conventional ML methods remain predominant, with a clear trend toward ensemble and DL approaches in recent studies.

Table 3. Summary of AI/ML approach

AI/ML Algorithm	No. of Study	Study	Primary Application
SVM	17	[35]; [37]; [42]; [44]; [46]; [49]; [51]; [28]; [54]; [56]; [29]; [25]; [61]; [63]; [22]; [65]; [66]	Classification of postural sway or balance disorders
ANN/NN	13	[27]; [34]; [37]; [26]; [41]; [42]; [47]; [48]; [28]; [55]; [62]; [66]; [67]	Identify sway patterns, predict postural control

(Continued)

Table 3. Summary of AI/ML approach *(Continued)*

AI/ML Algorithm	No. of Study	Study	Primary Application
LR	11	[24]; [35]; [46]; [42]; [51]; [28]; [53]; [29]; [60]; [63]; [65]	Analyze predictive factors and classify balance impairment
DT	10	[36]; [42]; [44]; [47]; [23]; [28]; [52]; [57]; [29]; [63]	Easy-to-understand data classification Use in combination with boosting
KNN	9	[24]; [36]; [42]; [44]; [47];[54]; [21]; [56]; [63]	Identify balance impairment classification from CoP or sway data
NB	8	[20]; [42]; [47]; [28]; [31]; [56]; [57]; [63]	It is used to classify basic data with a large number of features
RF	7	[24]; [36]; [42]; [46]; [56]; [57]; [66]	Classifying multiple groups and increasing accuracy
GB/LGBM	5	[24]; [45]; [46]; [48]; [51]	Increase the efficiency of balancing classification and prediction
LSTM/Bi-LSTM/CNN-LSTM	4	[38]; [26]; [39]; [43]	Analytic time series such as CoP trajectory, insole pressure
Bagging/Boosting/Ensemble Methods	4	[37]; [20]; [46]; [28]	Increase model stability by combining data from multiple classifiers
CNN	4	[29]; [64]; [26]; [66]	Process spatial patterns from CoP images or pressure maps
HMM	2	[50]; [53]	Analyze the temporal transition of the balance
Gaussian Process/Gaussian Mixture Model (GMM)	2	[37]; [59]	Evaluate the distribution of the balancing signal
LDA	1	[63]	Reduce dimensions and classify the balance group

3.4 AI/ML performance

According to Table 4, balance assessment models can be broadly classified into two categories: DL and ML approaches. DL models are well suited for high-dimensional and temporally continuous data such as CoP trajectories. ANN has reported classification accuracies up to 99% for balance pathology detection, with coefficients of determination (R^2) reaching 0.987 and high reliability in CoP path length prediction (ICC 0.91–0.94). CNN has achieved 95–99% accuracy in age-related postural control classification and up to 94.7% accuracy in environmental condition recognition. Recurrent models, including LSTM and Bi-LSTM, have demonstrated strong temporal modeling capability with correlation coefficients of 0.90–0.99 for CoP trajectory prediction and 0.92–0.99 for CoG trajectory estimation, accompanied by low prediction error. MLP models have achieved AUC values of 0.78–0.82 in predicting impaired functional outcomes.

ML models remain effective for targeted diagnostic and screening tasks. KNN has achieved accuracies up to 97–98% in diabetic neuropathy screening. SVM has reported fall risk classification accuracies as 96.49% and Berg Balance Scale (BBS) prediction accuracies between 88.0% and 93.2%. DT and RF models have shown robust performance, with DT achieving F1 scores of 0.97–1.00 in predicting physical activity and fear of falling indices and RF achieving accuracies up to 96.65% in health status classification. LR has demonstrated moderate to strong discriminative ability (AUC 0.66–0.83) and high correlation in stability index prediction (r 0.943–0.983). HMMR, when applied to combined anterior-posterior and mediolateral CoP data, has delivered classification accuracies up to 98.5%.

Overall, DL models, particularly ANN and CNN, consistently achieve higher performance in complex balance assessment tasks, often approaching 99% accuracy. Nevertheless, ML models such as KNN and SVM remain highly competitive for fall-risk screening and disease-specific classification, offering advantages in interpretability and computational efficiency suitable for real-time and resource-limited applications.

Table 4. AI/ML performance

Study	Task Type	Models	Performance
[24]	Classification	RF	Accuracy 0.9665, Precision 0.966, Recall 0.966, F1-score 0.966, AUC 0.9948
		KNN	Accuracy 0.9732, Precision 0.972, Recall 0.973, F1-score 0.973, AUC 0.9875
		GB	Accuracy 0.9615, Precision 0.961, Recall 0.962, F1-score 0.961, AUC 0.9882
		LR	Accuracy 0.9464, Precision 0.946, Recall 0.946, F1-score 0.946, AUC 0.8956
[27]	Regression	ANN	Training $R^2 = 0.99998$, Testing $R^2 = 0.93509$, Overall $R^2 = 0.98697$, $MSE = 0.0711$
[19]	Regression	PCPDD (RF)	Minimum MAE Mini-BESTest 2.658
[34]	Classification	ANN	Accuracy 0.99, Sensitivity 0.99, Specificity 0.89
[35]	Classification	LR	Accuracy 0.727, Precision 0.722, Recall 0.813, F1-score 0.765
		SVM	Accuracy 0.655, Precision 0.615, Recall 1.000, F1-score 0.762
[36]	Classification	DT	Accuracy 0.51–0.76, Sensitivity 0.51–0.76, Specificity 0.77–0.91, Precision 0.53–0.76, F1-score 0.51–0.76
		RF	Accuracy 0.62–0.84, Sensitivity 0.62–0.83, Specificity 0.83–0.94, Precision 0.62–0.84, F1-score 0.62–0.83
		KNN	Accuracy 0.71–0.88, Sensitivity 0.69–0.87, Specificity 0.87–0.95, Precision 0.70–0.87, F1-score 0.69–0.87
[37]	Regression	LSBoost	ρ 0.86–0.87, ICC 0.89–0.92, CV 36%
		Bagging	ρ 0.88–0.89, ICC 0.91–0.93, CV 30%
		ANN	ρ 0.89–0.90, ICC 0.91–0.94, CV 30%
		SVM	ρ 0.89–0.90, ICC 0.90–0.94, CV 31%
[20]	Classification	Bagging method	Accuracy 0.58–0.74, Sensitivity 0.40–0.86, Specificity 0.64–0.75, AUC 0.49–0.85
		NB	Accuracy 0.60–0.78, Sensitivity 0.40–0.86, Specificity 0.66–0.76, AUC 0.63–0.89
		Easy Ensemble	Accuracy 0.60–0.77, Sensitivity 0.40–0.86, Specificity 0.60–0.75, AUC 0.63–0.90
[38]	Regression	Bi-LSTM	Correlation 0.92–0.99, rRMSE 2.10–14.24%

(Continued)

Table 4. AI/ML performance *(Continued)*

Study	Task Type	Models	Performance
[26]	Regression	ANN	RMSE 177–200 N
		LSTM	RMSE 156–189 N
		CNN-LSTM	RMSE 172–179 N
[39]	Regression	ANN	Correlation 0.93–0.99, RMSE 0.018–0.065, rRMSE 5.7–12.5%
		LSTM	Correlation 0.95–0.99, RMSE 0.001–0.062, rRMSE 5.1–9.8%
[40]	Classification	Distance AB (threshold-based)	Sensitivity 0.98, Specificity 0.93, AUC 0.99
		Distance BC (threshold-based)	Sensitivity 0.88, Specificity 0.97, AUC 0.94
		Ratio Ra (BC/AB)	Sensitivity 0.95, Specificity 0.97, AUC 0.99
		Balance Index (BI)	Sensitivity 0.68, Specificity 0.97, AUC 0.85
[41]	Regression	ANN	Correlation 0.85–0.99
[42]	Classification	RF	Accuracy 0.75–0.81, FNR 0.10–0.23, F1-score 0.80–0.83, Precision 0.83–0.87
		NN	Accuracy 0.72–0.79, FNR 0.21–0.25, F1-score 0.75–0.80, Precision 0.80–0.85
		NB	Accuracy 0.73–0.78, FNR 0.21–0.23, F1-score 0.77–0.80, Precision 0.77–0.80
		SVM	Accuracy 0.70–0.72, FNR 0.23–0.29, F1-score 0.69–0.80, Precision 0.67–0.71
		DT	Accuracy 0.69–0.70, FNR 0.29–0.39, F1-score 0.60–0.69, Precision 0.69–0.71
		KNN	Accuracy 0.64–0.69, FNR 0.30–0.39, F1-score 0.60–0.69, Precision 0.69
[43]	Regression	LSTM	NRMSE (AP) 0.04–0.08, NRMSE (ML) 0.22–0.29, Jaccard (AP) 0.87–0.96, Jaccard (ML) 0.39–0.80
[44]	Classification	KNN	Precision 0.92–0.98, Recall 0.90–0.98, F1-score 0.91–0.98
		DT	Precision 0.97–1.00, Recall 0.97–1.00, F1-score 0.97–1.00
		SVM	Precision 0.84–0.99, Recall 0.81–0.99, F1-score 0.81–0.99
[45]	Classification	Light Gradient-Boosting Machine (LGBM)	AUC 0.75–0.80
		MLP	AUC 0.78–0.82
[46]	Classification	GB	AUC 0.84–0.95, Recall 0.77–0.91
		Bagging Classifier	AUC 0.82–0.90, Recall 0.75–0.89
		RF	AUC 0.80–0.88, Recall 0.74–0.88
		LR	AUC 0.77–0.93, Recall 0.71–0.85
		MLP	AUC 0.70–0.82, Recall 0.66–0.80
		SVM	AUC 0.78–0.84, Recall 0.69–0.79

(Continued)

Table 4. AI/ML performance *(Continued)*

Study	Task Type	Models	Performance
[47]	Classification	NB	Accuracy 0.67, Sensitivity 0.56, Precision 0.63, AUC 0.60
		KNN	Accuracy 0.51–0.87, Sensitivity 0.61–0.94, Precision 0.61–0.88, AUC 0.59–0.92
		NN	Accuracy 0.60–0.76, Sensitivity 0.77–0.94, Precision 0.65–0.81, AUC 0.54–0.85
		DT	Accuracy 0.83, Sensitivity 0.78, Precision 0.78, AUC 0.50
[48]	Classification	Gradient Boosting (XGBoost)	Accuracy 0.71–0.74, Recall 0.56–0.78, Precision 0.67–0.83, F1-score 0.67–0.72
		ANN	Accuracy 0.72, Recall 0.72, Precision 0.69, F1-score 0.71
[49]	Classification	SVM	Accuracy 0.74–0.82
		LR	Accuracy 0.30
	Regression	Support Vector Regression (SVR)	RMSE 0.53–0.98
		LR	RMSE 0.80–1.30
[23]	Classification	DT	Accuracy 0.84–0.85, Sensitivity 0.83–0.85, Specificity 0.84–0.86
[50]	Classification	Machine-learning PS score	Sensitivity 0.736, Specificity 0.628, AUC 0.66
		Machine-learning PS score	Sensitivity 0.642, Specificity 0.598, AUC 0.64
[51]	Classification	SVM	Accuracy 0.8125–0.8959, F1-score 0.8029–0.8936
		LGBM	Accuracy 0.8194–0.8750, F1-score 0.8194–0.8750
		LR	Accuracy 0.8236–0.8889, F1-score 0.8252–0.8919
[28]	Classification	DT	Accuracy 0.82–0.88, AUC 0.61–0.83, Sensitivity 0.30–0.57, Precision 0.50–0.75, F1-score 0.35–0.63, Specificity 0.94–0.96
		NB	Accuracy 0.82, AUC 0.70, Sensitivity 0.27, Precision 0.50, F1-score 0.35, Specificity 0.94
		LR	Accuracy 0.70, AUC 0.48, Sensitivity 0.10, Precision 0.10, F1-score 0.10, Specificity 0.84
		ANN	Accuracy 0.80, AUC 0.55, Sensitivity 0.00, Precision 0.00, Specificity 0.98
		SVM	Accuracy 0.82, AUC 0.46, Sensitivity 0.00, Precision 0.00, Specificity 1.00
		Bagging ID3 (best model)	Accuracy 0.88, AUC 0.83, Sensitivity 0.57, Precision 0.75, F1-score 0.63, Specificity 0.96
[30]	Classification	Ranking Forest	AUC 0.75
[31]	Classification	Ranking Forest	Sensitivity 0.95, Specificity 0.35
		NB	Sensitivity 0.85, Specificity 0.40
[52]	Classification	DT	Accuracy 0.66–0.94, AUC 0.76

(Continued)

Table 4. AI/ML performance *(Continued)*

Study	Task Type	Models	Performance
[53]	Classification	Hidden Markov Model Regression; HMMR (AP direction)	Accuracy 0.852
		HMMR (ML direction)	Accuracy 0.942
		HMMR (AP + ML)	Accuracy 0.985
[54]	Classification	SVM	Accuracy 0.9649–0.0402
		KNN	Accuracy 0.9572–0.0148
[21]	Classification	KNN	Accuracy 0.83–0.98, Sensitivity 0.94–1.00, Specificity 0.94–0.97
[55]	Regression	ANN	No classification metrics report
[56]	Classification	KNN	Accuracy 0.73–0.883, Sensitivity 0.80–0.933, Specificity 0.60–0.833, F1-score 0.78–0.89
		NB	Accuracy 0.85–0.867, Sensitivity 0.867–0.90, Specificity 0.833, F1-score 0.85–0.87
		SVM	Accuracy 0.833–0.85, Sensitivity 0.867–0.90, Specificity 0.80, F1-score 0.84–0.86
		RF	Accuracy 0.80, Sensitivity 0.833, Specificity 0.767, F1-score 0.81
[57]	Classification	DT	Accuracy 0.80, Sensitivity 0.89, Specificity 0.63, AUC 0.77
		NB	Accuracy 0.73, Sensitivity 0.86, Specificity 0.50, AUC 0.71
		RF	Accuracy 0.75, Sensitivity 0.82, Specificity 0.63, AUC 0.84
[58]	Modeling/ clustering	Competitive Neural Network	No classification metrics reported
[59]	Classification	GMM-based Sway Index	Sensitivity 0.875–0.909, Specificity 0.824–0.843, AUC 0.90–0.91
[29]	Classification	CNN	Accuracy 0.947–0.013, Precision 0.949–0.011, Recall 0.948–0.011, F1-score 0.947–0.014
		SVM	Accuracy 0.875–0.036, Precision 0.872–0.036, Recall 0.870–0.036, F1-score 0.870–0.036
		DT	Accuracy 0.787–0.057, Precision 0.788–0.056, Recall 0.786–0.056, F1-score 0.786–0.056
		LR	Accuracy 0.628–0.073, Precision 0.627–0.109, Recall 0.628–0.107, F1-score 0.623–0.109
[60]	Classification	LR	AUC 0.66–0.83
[61]	Classification	SVM	Accuracy 0.643–0.820, F1-score 0.64–0.81
[62]	Classification	ANN	Accuracy 0.905, Precision 0.908, Recall 0.905, F1-score 0.906, AUC 0.93–0.99
	Regression	ANN	R^2 0.922
[25]	Classification	CNN	Accuracy 0.95–0.99, Sensitivity 0.96–1.00, Specificity 0.88–0.98, PPV 0.95–0.99, NPV 0.91–1.00, Kappa 0.88–0.97

(Continued)

Table 4. AI/ML performance *(Continued)*

Study	Task Type	Models	Performance
[63]	Classification	LR	Accuracy 0.63–0.95, Precision 0.45–1.00, Sensitivity 0.11–1.00
		Linear Discriminant Analysis (LDA)	Accuracy 0.52–0.54, Precision 0.07–0.84, Sensitivity 0.11–0.55
		KNN	Accuracy 0.52–0.92, Precision 0.00–0.88, Sensitivity 0.00–1.00
		DT	Accuracy 0.58–0.84, Precision 0.25–0.90, Sensitivity 0.25–0.90
		NB	Accuracy 0.58–0.71, Precision 0.50–1.00, Sensitivity 0.11–1.00
		SVM	Accuracy 0.64–0.92, Precision 0.00–1.00, Sensitivity 0.00–1.00
[64]	Classification	CNN	Accuracy 0.55–0.57, AUC 0.77–0.8
[22]	Classification	SVM	Accuracy 0.880–0.932
[65]	Regression	LR	r 0.943–0.983
		SVM	r 0.891–0.968
		GAM Regression	r 0.786–0.865
		Regression Tree	r 0.943–0.983
[66]	Classification	ANN	Accuracy: 0.98, Precision: 0.97, Recall: 0.98, F1-score: 0.97
		CNN	Accuracy: 0.97, Precision: 0.96, Recall: 0.97, F1-score: 0.96
		RF	Accuracy: 0.96, Precision: 0.95, Recall: 0.96, F1-score: 0.95
		SVM	Accuracy: 0.90, Precision: 0.89, Recall: 0.90, F1-score: 0.89
[67]	Regression	ANN	RMSE: 1.03–10.31 N

Note: R^2; Coefficient of Determination, r; Correlation Coefficient, RMS; Root Mean Square, RMSE; Root Mean Square Error, MAE; Mean Absolute Error, CV; Cross Validation, ρ; Spearman's Rank Correlation Coefficient, ICC; Intraclass Correlation Coefficient, AUC; Area Under the Curve, NPV; Negative Predictive Value, PPV; Positive Predictive Value.

4 DISCUSSION

4.1 Assessment device with AI/ML approach for balance classification

According to the result of this review, the force platform is the most advanced balance assessment device, with 22 studies reflected, which improves the accuracy and performance of continuous balance measurement. As studied by [27], the force platform had high accuracy (R = 0.99998) for balance classification. This is consistent with a previous study [65], which reported that the AI/ML models applied with the force platform had high accuracy 0.786 to 0.983 under seven test conditions. Whereas Wii Balance Boards and Smart Insoles are showing upward popularity trends in balance assessment, the trends in smart balance assessment studies indicate a transition from laboratory-based systems to wearable devices [24], [30], [47], [54], [65]. The finding of [38] is that they reported the insoles combined with ML show a tendency to be an effective low-cost device for detecting balance deficits, balance assessment, and monitoring rehabilitation programs. Which is consistent with the study of [26], smart insoles applied with an AI/ML model improving balance evaluation. A wearable device such as Smart Insoles, IMUs, and Pressure Mats is capable of collected more continuous everyday balance data than a stationary such as a Force Platform.

Even though the Force Platform persists as the gold standard in terms of accuracy and resolution, its limitations in size, cost, and real-world application have sparked interest in the development of wearable devices that can be connected to AI systems to automatically analyze balance [62], [65].

4.2 AI/ML performance

ML model architectures, notably SVM, KNN, and DT, have consistently exhibited remarkable efficacy across a broad spectrum of classification tasks [22], [25], [44], [54]. Previous studies consistently report high discriminative performance when applied to clearly defined classification problems, such as age group differentiation or separation of individuals with pathological conditions from healthy controls [25]. For instance, KNN has achieved classification accuracies as high as 97.32% (refer to Table 4) when distinguishing healthy participants from individuals with neuropathy [24]. Similarly, DT-based models have reported accuracies ranging from 97% to 100% in classifying balance conditions, while the study by Mertes et al. demonstrated a classification accuracy of 95.72% in identifying individuals at risk of falling [54].

Although DL approaches, particularly CNN, have shown outstanding performance (95–99%), especially when applied to short-duration signals of approximately 2.5 seconds [25], [29], conventional ML models remain widely adopted in clinical settings. This preference is largely attributable to their superior interpretability and substantially lower computational requirements, which facilitate practical deployment in routine clinical environments [21], [24]. Notably, prior work has shown that SVM-based models can predict BBS scores with an accuracy of up to 93.2%, outperforming multilayer perceptron-based DL models while achieving processing speeds approximately 38 times faster [22]. Furthermore, SVM has been successfully applied to the classification of Parkinson's disease, reaching accuracies as high as 97% [25].

Despite these promising results, sensitivity for fall risk detection has been reported to vary widely across studies, ranging from near 0% to almost 100%, reflecting the influence of multiple methodological factors. Liang et al. [20] demonstrated that the choice of classification criteria substantially affects sensitivity, reporting higher discriminative performance (AUC 0.80–0.90) and sensitivity when Timed Up and Go (TUG) scores were used as grouping criteria, compared with models relying solely on fall history. This finding suggests that CoP parameters more directly reflect mobility-related impairments than fall occurrence behavior alone [20]. Conversely, the study [63] reported markedly low sensitivity values, in some cases approaching 0.00, largely attributable to severe class imbalance, where the number of fallers was substantially smaller than non-fallers. Under such conditions, models tend to favor the majority class to maintain overall accuracy, thereby compromising sensitivity for fall detection [63]. Additional evidence indicates that disease complexity and symptom heterogeneity may further influence model sensitivity [28], [30]. Feature engineering has also been identified as a critical determinant of model performance. Sarmah et al. demonstrated that incorporating demographic and anthropometric variables, including age, body mass index (BMI), and foot length, alongside CoP-derived features, resulted in a substantial improvement in sensitivity (e.g., from 40% to 59% in selected models) [34]. These findings are consistent with the work of [27], which highlighted age and educational level as significant contributors to balance control profiles [27]. Moreover, multiple studies have reported that mediolateral (ML) CoP features exhibit particularly high sensitivity for discriminating fall risk and neuropathological conditions [20], [43], [63]. Collectively, the performance of ML-based models in these studies may be conceptualized as a form of high-resolution digital magnification. [20], [24], [39], [44].

4.3 AI/ML application for balance classification

In the overview of application trends of earlier studies, the reviewed literature confirms that AI/ML techniques provide effective tools for balance classification using CoP data. Previous work has demonstrated that conventional ML models, particularly SVM, LR, and ANN, are well suited for balance impairment classification and fall-risk screening due to their robustness and computational efficiency [23], [35], [46], [55], [65].

During 2023–2025, the trend of using ensemble methods such as RF, GB, Bagging, and Boosting is likely to increase significantly, as they can combine the advantages of multiple types of algorithms to reduce model bias and variance, resulting in significantly higher accuracy and durability of results, especially when using data from complex stabilization devices such as force platforms or multi-position sensors. According to [24], they reported the assimilation of ensemble learning methods, including RF and GB, significantly improved the classification accuracy of postural balance patterns when compared to traditional classifiers. Similarly, the study [46] and [48] found that boosting-based models provided superior performance in identifying balance impairments, especially when applied to high-dimensional force platform datasets.

In the field of DL, the algorithms of LSTM and CNN-LSTM have received significant attention due to their potential to process time-series data from insole devices, IMUs, or pressure mats continuously and in accordance with daily balancing behaviors. Previous findings [26], [38], [39] reported that the LSTM model enables the system to capture sequential dependencies and temporal dynamics of balance signals more effectively than conventional ML algorithms. In the same way, the study [43] reported that hybrid LSTM networks using IMU and insole pressure data achieved higher sensitivity and specificity in detecting balance instability compared with traditional classifiers such as SVM and ANN [62]. These models are able to accurately detect pattern recognition of subtle movements such as body swing, CoP displacement, and perturbation response, allowing for better classification of sub-level balance defects than traditional statistical analysis [26], [38], [61], [62].

However, data processing from such devices often uses a variety of AI/ML techniques, such as SVM, ANN, RF, LSTM, and GB, to classify or predict a person's level of balance impairment. In addition, the application of ML techniques is capable of improving the balance assessment system to be able to discriminate balance impairment level more accurately. It also helps detect complex movement patterns that may not be observable with traditional clinical assessment. The Current study has focused on integrating AI/ML technology with wearable devices to develop personalized rehabilitation programs and assessments that can be applied both in the clinic and home.

4.4 Limitation of AI/ML application

Nevertheless, the application of AI/ML techniques in the evaluation of each form of balance still has its own limitations. SVM is accurate but requires fine parameter adjustment and is not suitable for large data [35], [46]; LR is easy to understand but limited in analyzing nonlinear relationships [52], [60]; ANN requires a large amount of data and is difficult to interpret the results [27], [55]; RF and GB provide high accuracy but are resource-intensive and complex to customize [24, 48]; DT is easy to understand but unstable to slight changes in data [23], [57]; KNN is sensitive to noise, and performance decreases when the data is dimensional [44], [47]; while LSTM and CNN-LSTM are suitable for chronological data but require large data and complex calculations [26], [38], [43]. While NB is limited by the variable independence hypothesis [24], [28], HMM relies on statistical assumptions that may not cover actual locomotion behavior [50], [53]. However, the selection of appropriate techniques should be determined by the nature of the data. The purpose of the assessment and the balance between accuracy and the ability to interpret results in clinical terms.

5 CONCLUSION AND FUTURE WORK

Accumulating empirical evidence demonstrates both DL and conventional ML approaches are effective for balance assessment using CoP data, with their suitability depending on data characteristics and application context. DL models, particularly NN-based architectures, show strong capability in capturing complex and non-linear balance patterns, making them well suited for advanced analytical tasks and detailed postural characterization. For temporally structured balance signals, recurrent models provide clear advantages in modeling dynamic postural behavior. At the same time, conventional ML algorithms, especially SVM methods, remain widely adopted due to their computational efficiency, robustness, and ease of interpretation, which are essential for clinical screening and wearable implementations. Ensemble learning approaches have also emerged as promising solutions by improving model stability and reducing bias in heterogeneous datasets. Despite these advances, data imbalance continues to limit sensitivity in high-risk populations, highlighting the need for more robust training strategies.

From a clinical perspective, these findings highlight the feasibility of developing smart insole systems that integrate plantar pressure sensing with ML-based analytical approaches to support objective stratification of balance impairments in real-world contexts. Future research should focus on the extraction and validation of biomechanically meaningful features that capture key aspects of postural control as well as on the development of robust and generalizable models capable of accommodating interindividual variability and diverse usage conditions. In addition, longitudinal validation in clinical populations is required to confirm reliability, clinical relevance, and sensitivity to change. Such progress would enable smart insoles to advance beyond basic monitoring applications and function as practical, clinically relevant tools for fall risk assessment, decision support in balance-related care, and personalized rehabilitation programs and monitoring.

6 ACKNOWLEDGEMENT

This study is supported by the Thailand Science Research and Innovation (TSRI) Fundamental Fund, fiscal year 2026 (Contract No. TUFF56/2569). The authors would also like to express their gratitude to the authors and are also grateful to the Thammasat School of Engineering, Faculty of Engineering, Thammasat University, Department of Applied Science, Rajamangala University of Technology Tawan-ok, Chanthaburi Province, Thailand, and the Faculty of Medicine, King's College London, United Kingdom, for their valuable advice, corrections, and support of the staff members in this study.

7 REFERENCES

[1] S. Piriyayotha, A. Keawmalaitip, P. Muneesawang, and P. Lertsinthai, “ExercisePill: An exercise application for balance problems in the elderly,” *Int. J. Online Biomed. Eng.*, vol. 18, no. 4, pp. 79–93, 2022. https://doi.org/10.3991/ijoe.v18i04.27771

[2] F. B. Horak, C. L. Shupert, and A. Mirka, “Components of postural dyscontrol in the elderly: A review,” *Neurobiol. Aging*, vol. 10, no. 6, pp. 727–738, 1989. https://doi.org/10.1016/0197-4580(89)90010-9

[3] R. J. Peterka, “Sensorimotor integration in human postural control,” *J. Neurophysiol.*, vol. 88, no. 3, pp. 1097–1118, 2002. https://doi.org/10.1152/jn.2002.88.3.1097

[4] M. A. Ali, A. J. Hussain, and A. T. Sadiq, “Human fall down recognition using coordinates key points skeleton,” *Int. J. Online Biomed. Eng.*, vol. 18, no. 2, pp. 88–104, 2022. https://doi.org/10.3991/ijoe.v18i02.28017

[5] M. H. Habaebi, S. H. Yusoff, A. N. Ishak, M. R. Islam, J. Chebil, and A. Basahel, “Wearable smart phone sensor fall detection system,” *Int. J. Interact. Mob. Technol.*, vol. 16, no. 12, pp. 72–93, 2022. https://doi.org/10.3991/ijim.v16i12.30105

[6] L. Tesio, V. Rota, C. Chessa, and L. Perucca, “The 3D path of body centre of mass during adult human walking on force treadmill,” *J. Biomech.*, vol. 43, no. 5, pp. 938–944, 2010. https://doi.org/10.1016/j.jbiomech.2009.10.049

[7] B. Chen, P. Liu, F. Xiao, Z. Liu, and Y. Wang, “Review of the upright balance assessment based on the force plate,” *Int. J. Environ. Res. Public Health*, vol. 18, no. 5, p. 2696, 2021. https://doi.org/10.3390/ijerph18052696

[8] D. A. Winter, *Biomechanics and Motor Control of Human.* 4th ed. Hoboken, NJ, USA: Wiley, 2009. https://doi.org/10.1002/9780470549148

[9] F. Scoppa, R. Capra, M. Gallamini, and R. Shiffer, “Clinical stabilometry standardization: Basic definitions, acquisition interval, sampling frequency,” *Gait & Posture*, vol. 37, no. 2, pp. 290–292, 2013. https://doi.org/10.1016/j.gaitpost.2012.07.009

[10] R. M. Palmieri-Smith, C. Ingersoll, M. B. Stone, and B. A. Krause, “Center-of-pressure parameters used in the assessment of postural control,” *J. Sport Rehabil.*, vol. 11, no. 1, pp. 51–66, 2002. https://doi.org/10.1123/jsr.11.1.51

[11] V. Sanyod *et al.*, “IoT-based smart walking assistant for fall detection in the elderly,” *J. Online Biomed. Eng.*, vol. 21, no. 6, pp. 19–35, 2025. https://doi.org/10.3991/ijoe.v21i06.54443

[12] A. Rajkomar, J. Dean, and I. Kohane, “Machine learning in medicine,” *N. Engl. J. Med.*, vol. 380, no. 14, pp. 1347–1358, 2019. https://doi.org/10.1056/NEJMra1814259

[13] E. J. Topol, “High-performance medicine: The convergence of human and artificial intelligence,” *Nat. Med.*, vol. 25, no. 1, pp. 44–56, 2019. https://doi.org/10.1038/s41591-018-0300-7

[14] A. F. M. F. Ismail, M. F. M. Sam, K. A. Bakar, A. Ahamat, S. Adam, and M. I. Qureshi, “Artificial intelligence in healthcare business ecosystem,” *Int. J. Online Biomed. Eng.*, vol. 18, no. 9, pp. 100–114, 2022. https://doi.org/10.3991/ijoe.v18i09.32251

[15] H. Vega-Huerta *et al.*, “Convolutional neural networks on assembling classification models to detect melanoma skin cancer,” *Int. J. Online Biomed. Eng.*, vol. 18, no. 14, pp. 59–76, 2022. https://doi.org/10.3991/ijoe.v18i14.34435

[16] A. A. Siddique, J. Ferdouse, T. Habib, J. Mia, and M. S. Uddin, “Convolutional neural network modeling for eye disease recognition,” *Int. J. Online Biomed. Eng.*, vol. 18, no. 9, pp. 115–130, 2022. https://doi.org/10.3991/ijoe.v18i09.29847

[17] H. E. Villavicencio, J. Gamboa-Cruzado, J. López-Goycochea, and L. S. Soto, “The role of artificial intelligence in the diagnosis of neoplastic diseases: A systematic and bibliometric review,” *Int. J. Online Biomed. Eng.*, vol. 20, no. 4, pp. 43–68, 2024. https://doi.org/10.3991/ijoe.v20i04.45429

[18] K. Sindhu, A. N. Uday, S. J. Abhishek, and S. Anjali, "Gait analysis—A tool for medical inferences," *Int. J. Online Biomed. Eng.*, vol. 20, no. 6, pp. 153–166, 2024. https://doi.org/10.3991/ijoe.v20i06.45787

[19] P. Ren *et al.*, "Assessment of balance control subsystems by artificial intelligence," *IEEE Trans. Neural. Syst. Rehabil. Eng.*, vol. 28, no. 3, pp. 658–668, 2020. https://doi.org/10.1109/TNSRE.2020.2966784

[20] H.-W. Liang *et al.*, "Fall risk classification with posturographic parameters in community-dwelling older adults: A machine learning and explainable artificial intelligence approach," *J. Neuroeng. Rehabil.*, vol. 21, no. 15, 2024. https://doi.org/10.1186/s12984-024-01310-3

[21] A. Mengarelli *et al.*, "A computer-aided screening solution for the identification of diabetic neuropathy from standing balance by leveraging multi-domain features," *IEEE Trans. Neural. Syst. Rehabil. Eng.*, vol. 32, pp. 2388–2397, 2024. https://doi.org/10.1109/TNSRE.2024.3419235

[22] Y. W. Kim, W. H. Cho, K. L. Joa, H. Y. Jung, and S. Lee, "A new auto-scoring algorithm for balance assessment with wearable IMU device based on nonlinear model," *J. Mech. Med. Biol.*, vol. 20, no. 10, 2020. https://doi.org/10.1142/S0219519420400114

[23] F.-Y. Liao, C.-C. Wu, Y.-C. Wei, L.-W. Chou, and K.-M. Chang, "Analysis of center of pressure signals by using decision tree and empirical model decomposition to predict falls among older adult," *J. Healthcare Eng.*, vol. 2021, 2021. https://doi.org/10.1155/2021/6252445

[24] S. R. Pandey, M. M. Oghaz, and J. G. Varghese, "Decoding diabetic neuropathy: Tap into postural sway for optimal feature detection based on machine learning approach," in *2024 International Conference on Inventive Computation Technologies (ICICT)*, Lalitpur, Nepal, 2024, pp. 1104–1111. https://doi.org/10.1109/ICICT60155.2024.10544768

[25] P. Lee, T.-B. Chen, S.-Y. Hsu, and C.-H. Liu, "Detection of postural control in young and elderly adults using deep and machine learning methods with joint–node plots," *Sensors*, vol. 21, no. 9, p. 3212, 2021. https://doi.org/10.3390/s21093212

[26] H. S. Choi, S. Yoon, J. Kim, H. Seo, and J. K. Choi, "Calibrating low-cost smart insole sensors with recurrent neural networks for accurate prediction of center of pressure," *Sensors*, vol. 24, p. 4765, 2024. https://doi.org/10.3390/s24154765

[27] M. F. Goethel, U. F. Ervilha, K. M. Becker, F. C. S. Parolini, and J. P. Vilas-Boas, "Development of a tool for comprehensive balance assessment based on artificial intelligence and anomaly detection," *Life*, vol. 15, p. 632, 2025. https://doi.org/10.3390/life15040632

[28] K. Barati, S. Behzadipur, M. Borushaki, and Z. Rahmati, "Classification of faller and non-faller parkinson's disease patients using wavelet-based multifractal spectrum of center of pressure signal," in *28th National and 6th International Iranian Conference on Biomedical Engineering (ICBME)*, Tehran, Iran, Islamic Republic, 2021, pp. 220–227. https://doi.org/10.1109/ICBME54433.2021.9750367

[29] V. Phan and H. Lee, "Deep learning: Predicting environments from short-time observations of postural balance," *IEEE Trans. Biomed. Eng.*, vol. 19, no. 11, pp. 3460–3471, 2022. https://doi.org/10.1109/TBME.2022.3170850

[30] J. Audiffren, I. Bargiotas, N. Vayatis, P.-P. Vidal, and D. Ricard, "A non linear scoring approach for evaluating balance: Classification of elderly as fallers and non-fallers," *PLoS ONE*, vol. 11, no. 12, 2016. https://doi.org/10.1371/journal.pone.0167456

[31] Y. Cheng *et al.*, "A novel classification method for balance differences in elite versus expert athletes based on composite multiscale complexity index and ranking forests," *PLoS ONE*, vol. 20, no. 1, 2025. https://doi.org/10.1371/journal.pone.0315454

[32] M. J. Page *et al.*, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," *BMJ*, vol. 372, no. 71, 2021. https://doi.org/10.1136/bmj.n160

[33] P. De-La-Cruz, R. Rojas-Coaquira, H. Vega-Huerta, J. Pérez-Quintanilla, and M. Lagos-Barzola, "A systematic review regarding the prediction of academic performance," *Comput. Sci.*, vol. 18, no. 2, pp. 1219–1231, 2022. https://doi.org/10.3844/jcssp.2022.1219.1231

[34] A. Sarmah *et al.*, "Framework for early detection and classification of balance pathologies using posturography and anthropometric variables," *Clin. Biomech.*, vol. 113, 2024. https://doi.org/10.1016/j.clinbiomech.2024.106214

[35] F. Rojas, I. K. Niazi, P. Maturana-Russel, and D. Taylor, "Exploring the potential of machine learning for the diagnosis of balance disorders based on centre of pressure analyses," *Sensors*, vol. 22, p. 9200, 2022. https://doi.org/10.3390/s22239200

[36] N. Rahimi *et al.*, "Distinguishing among standing postures with machine learning-based classification algorithms," *Exp. Brain Res.*, vol. 243, no. 3, 2024. https://doi.org/10.1007/s00221-024-06959-9

[37] K. Wantanajittikul, C. Wiboonsuntharangkoon, B. Chuatrakoon, and S. Kongsawasdi, "Application of machine learning to predict trajectory of the Center of Pressure (COP) path of postural sway using a triaxial inertial sensor," *Sci. World J.*, vol. 2022, 2022. https://doi.org/10.1155/2022/9483665

[38] J. Moon, D. Lee, H. Jung, A. Choi, and J. H. Mun, "Machine learning strategies for low-cost insole-based prediction of center of gravity during gait in healthy males," *Sensors*, vol. 22, p. 3499, 2022. https://doi.org/10.3390/s22093499

[39] A. Choi, H. Jung, K. Y. Lee, S. Lee, and J. H. Mun, "Machine learning approach to predict center of pressure trajectories in a complete gait cycle: A feedforward neural network vs. LSTM network," *Med. Biol. Eng. Comput.*, vol. 57, pp. 2693–2703, 2019. https://doi.org/10.1007/s11517-019-02056-0

[40] F. K. Fuss, A. M. Tan, and Y. Weizman, "Advanced dynamic centre of pressure diagnostics with smart insoles: Comparison of diabetic and healthy persons for diagnosing diabetic peripheral neuropathy," *Bioengineering*, vol. 11, p. 1241, 2024. https://doi.org/10.3390/bioengineering11121241

[41] I. J. Museck, D. L. Brinton, and J. C. Dean, "The use of wearable sensors and machine learning methods to estimate biomechanical characteristics during standing posture or locomotion: A systematic review," *Sensors*, vol. 24, p. 7280, 2024. https://doi.org/10.3390/s24227280

[42] R. Fadil, A. Huether, R. Brunnemer, and K. Tavakolian, "Early detection of Parkinson's disease using center of pressure data and machine learning," in *2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, 2021. https://doi.org/10.1109/EMBC46164.2021.9630451

[43] C.-C. Wu, Y.-J. Chen, C.-S. Hsu, Y.-T. Wen, and Y.-J. Lee, "Multiple inertial measurement unit combination and location for center of pressure prediction in gait," *Front. Bioeng. Biotechnol.*, vol. 8, 2020. https://doi.org/10.3389/fbioe.2020.566474

[44] O. Rivera, E. Castillo-Castaneda, O. F. Avilés, and R. Hernández, "Index of physical activity and fall efficacy scale classification through biomechanical signals and machine learning," *J. Eng. Res.*, vol. 11, no. 3A, pp. 91–102, 2022. https://doi.org/10.36909/jer.16527

[45] E.-T. Jeon, S.-H. Lee, M.-Y. Eun, and J.-M. Jung, "Center of pressure and machine learning-based gait score and clinical risk factors for predicting functional outcome in acute ischemic stroke," *Arch. Phys. Med. Rehabil.*, vol. 105, pp. 2277–2285, 2024. https://doi.org/10.1016/j.apmr.2024.08.006

[46] T. Kamogashir, C. Fujimoto, M. Kinoshita, Y. Kikkawa, T. Yamasob, and S. Iwasaki, "Prediction of vestibular dysfunction by applying machine learning algorithms to postural instability," *Front. Neurol.*, vol. 11, no. 7, 2020. https://doi.org/10.3389/fneur.2020.00007

[47] C. M. Villegas and D. C. Aqueveque, “Diagnosis of neuropathies in diabetic patients by applying machine learning,” *Ingeniare. Revista chilena de ingeniería*, vol. 29, no. 3, pp. 517–530, 2021. https://doi.org/10.4067/S0718-33052021000300517

[48] A. Montenegro, G. Sosa, N. Figuero, V. Vargas, and H. Franco, “Evaluation of stabilometry descriptors for human balance function classification using diagnostic and statokinesigram data,” *Biomed. Signal Process. Control*, vol. 84, 2023. https://doi.org/10.1016/j.bspc.2023.104861

[49] V. R. Chawan, M. Huber, N. Burns, and K. Daniel, “Person identification and tinetti score prediction using balance parameters: A machine learning approach to determine fall risk,” in *PETRA ’22: The 15th International Conference on PErvasive Technologies Related to Assistive Environments*, 2022. https://doi.org/10.1145/3529190.3529223

[50] K. E. Forth, K. L. Wirfel, S. D. Adams, N. J. Rianon, E. L. Aiden, and S. I. Madansingh, “A postural assessment utilizing machine learning prospectively identifies older adults at a high risk of falling,” *Front. Med.*, vol. 7, 2020. https://doi.org/10.3389/fmed.2020.591517

[51] X. Ning, Y. Kim, S. D. Min, X. Guo, and J. G. Ho, “Exploring achilles tendon vibration data classification for balance training: A wavelet-based machine learning approach,” *IEEE Access*, vol. 12, pp. 81783–81792, 2024. https://doi.org/10.1109/ACCESS.2024.3411010

[52] W.-Y. Liao, Y.-H. Chu, F.-Y. Liu, K.-M. Chang, and L.-W. Chou, “Cutoff point of mini-balance evaluation systems test scores for elderly estimated by center of pressure measurements by linear regression and decision tree classification,” *Life*, vol. 12, p. 2133, 2022. https://doi.org/10.3390/life12122133

[53] K. Safi, S. Mohammed, F. Attal, Y. Amirat, L. Oukhellou, and M. Khalil, “Automatic segmentation of stabilometric signals using hidden markov model regression,” *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 2, pp. 545–555, 2018. https://doi.org/10.1109/TASE.2016.2637165

[54] G. Mertes, G. Baldewijns, P.-J. Dingenen, T. Croonenborghs, and B. Vanrumste, “Automatic fall risk estimation using the Nintendo Wii balance board,” in *International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC)*, Lisbon, Portugal, 2015. https://doi.org/10.5220/0005208700750081

[55] Z. Rahmati, S. Behzadipour, A. C. Schouten, and G. Taghizadeh, “A postural control model to assess the improvement of balance rehabilitation in Parkinson’s disease,” in *2018 7th IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob)*, Enschede, Netherlands, 2018, pp. 1019–1024. https://doi.org/10.1109/BIOROB.2018.8487884

[56] H. Joutsijoki, J. Rasku, I. Pyykkö, and M. Juhol, “Classification of patients and controls based on stabilogram signal data,” *Intell. Data Anal.*, vol. 23, nos. 215–226, 2019. https://doi.org/10.3233/IDA-173704

[57] N. Pisani, M. Russo, M. C. Calabrese, F. D. Filippo, G. Cesarelli, and P. Barone, “Measurements of postural sway to classify freezing of gait in Parkinson’s disease,” in *2024 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)*, St. Albans, United Kingdom, 2024, pp. 154–159. https://doi.org/10.1109/MetroXRAINE62247.2024.10796311

[58] E. Araujo, G. E. F. Bentes, and R. Zangaro, “Body sway and global equilibrium condition of the elderly in quiet standing posture by using competitive neural networks,” *Appl. Soft. Comput.*, vol. 69, pp. 625–633, 2018. https://doi.org/10.1016/j.asoc.2018.05.004

[59] M. Ghahramani, H. Ismail, and R. Goecke, “A multidimensional approach to develop sway index using gaussian mixture model: A way of postural sway measurement and analysis in different age groups,” *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–11, 2021. https://doi.org/10.1109/TIM.2021.3107012

[60] C. Chou, S. H. Chou, Y. C. Chen, and C. J. Yang, “Using machine learning methods to detect physical conditions with postural balance,” *J. Ambient Intell. Humaniz. Comput.*, vol. 14, pp. 14499–14505, 2020. https://doi.org/10.1007/s12652-020-02261-y

[61] T. Bao, B. N. Klatt, S. L. Whitney, K. H. Sienko, and J. Wiens, "Automatically evaluating balance: A machine learning approach," *IEEE Trans. Neural. Syst. Rehabil. Eng.*, vol. 27, no. 2, pp. 179–186, 2019. https://doi.org/10.1109/TNSRE.2019.2891000

[62] J. Wu *et al.*, "Automated assessment of balance: A neural network approach based on large-scale balance function data," *Front. Public Health*, vol. 10, 2022. https://doi.org/10.3389/fpubh.2022.882811

[63] J. Pennone, N. F. Aguero, D. M. Martini, L. Mochizuki, and A. A. D. P. Suaide, "Fall prediction in a quiet standing balance test via machine learning: Is it possible?" *PLoS ONE*, vol. 20, no. 4, 2024. https://doi.org/10.1371/journal.pone.0296355

[64] F. Kamran *et al.*, "Automatically evaluating balance using machine learning and data from a single inertial measurement unit," *J. Neuroeng. Rehabil.*, vol. 18, no. 114, 2021. https://doi.org/10.1186/s12984-021-00894-4

[65] J.-W. Seo *et al.*, "Development and application of a stability index estimation algorithm based on machine learning for elderly balance ability diagnosis in daily life," *Bioengineering*, vol. 10, p. 943, 2023. https://doi.org/10.3390/bioengineering10080943

[66] M. F. Aqillah, W. A. Cahyadi, H. Mukhtar, S. Indriyanto, and S. Setiyadi, "Optimising real-time fall detection: A comparative study of machine learning algorithms using IMU sensor," in *The 2025 IEEE International Conference on Artificial Intelligence for Learning and Optimization (ICoAILO)*, 2025, pp. 13–18. https://doi.org/10.1109/ICoAILO66760.2025.11155939

[67] F. C. G. D. Zubiena, L. D'Alvia, D. O. M. A. Aeros, L. Liguori, and Z. D. Prete, "Design and development of a neural network based novel sensorized insole for ground reaction force and center of pressure estimation," in *Proceedings of the 2025 IEEE Medical Measurements & Applications (MeMeA)*, 2025, pp. 1–6. https://doi.org/10.1109/MeMeA65319.2025.11068028

8 AUTHORS

Mr. Wittaya Duangnga is a physiotherapist and a Ph.D. student in Medical Engineering at the Thammasat School of Engineering, Faculty of Engineering, Thammasat University, Pathum Thani, Thailand 12120. His area of interests focuses on Rehabilitation, Rehabilitation technology and innovation, and AI/ML in Rehabilitation (E-mail: wittaya.dua@dome.tu.ac.th).

Assoc. Prof. Dr. Nattadon Pannucharoenwong is with Thammasat University, Pathumthani, Thailand 12120. He is now with the Thammasat School of Engineering, Faculty of Engineering. His academic research interests focus on Mechanical Engineering and Medical Engineering (E-mail: pnattado@engr.tu.ac.th).

Prof. Dr. Phadungsak Rattanadecho is with the Thammasat University, Pathumthani, Thailand 12120. He is now with the Thammasat School of Engineering, Faculty of Engineering. His research is devoted on Mechanical Engineering and Medical Engineering.

Asst. Prof. Dr. Wachirathorn Janchomphu is with the Department of Applied Science, Rajamangala University of Technology Tawan-ok, Chanthaburi campus, Thailand 22210. Research interests focus on Information Technology, Artificial Intelligence, Remote Sensing and Geographic Information System (E-mail: wachirathorn_ja@rmutto.ac.th).

Mr. Suphasit Panvichien is with the Faculty of Medicine, King's College London, United Kingdom, has experience in Automotive engineering. He was interested in the area of Healthcare Technologies (Medical Robotics and Devices) and Biomedical Engineering.