Learning and Nonlinear Models - Journal of the Brazilian Society on Computational Intelligence (SBIC), Vol. 23, Iss. 2, pp. 4–10, 2025
https://doi.org/10.21528/lnlm-vol23-no2-art1

THE USAGE OF STABILOMETRIC INFORMATION TO AUTOMATICALLY PREDICT BALANCE EVALUATION SCORES

Nathan H. C. Zebendo, Jonathan N. Gois, Diego R. G. Gonzalez
Federal Center for Technological Education Celso Suckow da Fonseca (CEFET/RJ), Nova Friburgo, RJ, Brazil.
nathan.zebendo@aluno.cefet-rj.br, {jonathan.gois, diego.gonzalez}@cefet-rj.br

Wesley L. Passos, Gabriel M. Araujo, Amaro A. de Lima
Federal Center for Technological Education Celso Suckow da Fonseca (CEFET/RJ), Nova Iguaçu, RJ, Brazil.
{wesley.passos, gabriel.araujo, amaro.lima}@cefet-rj.br

Resumo – Este trabalho apresenta uma proposta de estimar automaticamente as notas de teste de equilíbrio postural e de seus subsistemas através de resultados de estabilometria. Estes resultados são obtidos com o uso de uma plataforma de força que captura a variação de posicionamento do centro de pressão da pessoa no decorrer do tempo. Já as notas de teste de equilíbrio postural são realizadas por profissionais da área de saúde habilitados e compreendem a avaliação de vários subsistemas que separadamente podem fornecer diagnósticos específicos e combinados podem compor um método de avaliação completo, denominado MINI-BESTest. O diagnóstico precoce possibilita a identificação do risco de quedas devido ao avanço da idade ou por doenças limitantes relacionadas. Utilizando uma abordagem hierárquica, que possibilita a automatização do processo e a redução da subjetividade da avaliação, é possível estimar a nota do MINI-BESTest e do seu subsistema de Controle Postural Reativo com uma precisão de, respectivamente, 17% e 20% maior do que o estado da arte.

Palavras-chave – Estabilometria, plataforma de força, MINI-BESTest, árvores aleatórias, regressão por vetores de suporte.

Abstract – This paper proposes automatically estimating postural balance test scores and their subsystems using stabilometry results. These results are obtained using a force platform that captures the variation in the person's center of pressure position over time. On the other hand, postural balance test scores are conducted by qualified health professionals and comprise the assessment of various subsystems that can provide specific diagnoses separately and, when combined, can form a comprehensive assessment method called the MINI-BESTest. Early diagnosis makes it possible to identify the risk of falls due to advancing age or related limiting illnesses. Using a hierarchical approach, which makes it possible to automate the process and reduce the subjectivity of the assessment, it is possible to estimate the MINI-BESTest score and its Reactive Postural Control subsystem with an accuracy of, respectively, 17% and 20% higher than the state-of-the-art.

Keywords – Stabilometry, force platform, MINI-BESTest, random forest, support vector regression.

1. INTRODUCTION

The ability to stand and perform different tasks in an upright posture is one of the primary skills at any age for an individual with healthy postural balance [1]. Postural balance involves the coordination of the sensory and motor systems in stabilizing the body's center of mass in the face of external or internal disturbances without falling [2–4]. However, various factors can impact balance or the ability to perform tasks requiring precise body movements. These include age, a sedentary lifestyle, and diseases affecting the visual, vestibular, or somatosensory systems [1, 5], as well as neurological disorders such as Parkinson's disease [6]. Falls are a leading cause of death worldwide, particularly among the elderly population. In Brazil, data from 2000 to 2019 indicate a concerning upward trend, with 135,209 deaths from falls among individuals aged 60 and older [7]. Therefore, in a population with a growing number of elderly individuals, developing functional clinical assessments to predict fall risk becomes important [3].

Two primary methodologies for assessing postural balance are instrumental techniques and clinical assessment scales [8–10]. Stabilometry, the most widely used instrumental technique, assesses oscillations in the center of pressure (COP) position of an individual in the orthostatic posture, as measured by a force platform [5, 11, 12]. This method assesses how the human body maintains its posture and balance in response to different sensory stimuli, usually in measurements of up to 60 s. Changes in COP oscillations, both in the area and speed of oscillation, have the potential to help detect and diagnose deficiencies in the systems involved in maintaining balance, such as the central and peripheral nervous systems or the musculoskeletal system, as well as assessing the risk of falls [11, 13]. However, as postural oscillations involve these different physiological systems, interpreting these measurements requires other information about the individual. As a result, there is often no clarity about the cause of changes in balance [3, 5].

The Balance Evaluation Systems Test (BESTest) [14], one of the evaluation scales, is a comprehensive tool that evaluates balance. It utilizes a series of standardized tests to measure an individual's ability to maintain balance under various conditions, thus helping to discriminate between different types of balance disorders [3]. The BESTest includes a questionnaire comprising 27 tasks across six subsystems involved in postural balance: Anticipatory Postural Adjustments (APA), Reactive Postural Control (RPC), Sensory Orientation (SO), and Dynamic Gait (DG), Biomechanical Constraints (BC) and Stability Limits (SL), totaling 108 score points. However, the main limitations of the BESTest include the need for a qualified professional to administer the assessment and the extensive time required to complete the test [3]. A shorter variant, the Mini-Balance Evaluation Systems Test (MINI-BESTest), reduces execution time by assessing only four subsystems: APA, RPC, SO, and DG. It consists of 14 items and scores on a scale from 0 to 28 [15, 16]. The MINI-BESTest yields results comparable to the BESTest and may more effectively identify patients with Parkinson's disease [14]. Although the tests yield a numerical result, factors such as the professionals' experience and the conditions in which they are conducted can subjectively influence the outcome.

Given the advantages of the MINI-BESTest in detecting changes in postural balance and its associated subsystems, one proposed alternative to address some of its limitations is the automatic prediction of MINI-BESTest scores using stabilometry data [17]. By inputting stabilometric variables into a regression model, it is possible to estimate the overall MINI-BESTest score and the scores of its subtests: APA, RPC, SO, and DG. However, selecting the most appropriate stabilometric variables and choosing the most reproducible regression models remain areas that require further investigation. This study aims to propose an automated methodology to support qualified professionals in postural assessment. By utilizing stabilometric data, this approach predicts both the overall MINI-BESTest score and the scores of its subtests. Additionally, the work introduces a methodology for feature extraction to enhance the accuracy of these predictions.

The following sections of this paper are organized as follows: Section 2 presents the works on stabiliometric evaluation using machine learning techniques; then, Section 3 presents the methodology proposed in this work; the results obtained by the proposed method and the comparison with the state-of-the-art are available in Section 4; finally, the conclusions are set out in Section 5.

2 RELATED WORKS

Increasing the ability to assess fall risk, particularly in vulnerable populations such as the elderly, is fundamental for preventing serious injuries and improving quality of life. Recent studies have explored various technological approaches, including machine learning and analysis of the COP trajectories, to enhance the accuracy of postural balance assessments and fall risk predictions.

In [18], the authors explored applying six machine learning algorithms to predict falls in a balance test using a database of 163 participants. The study highlighted that all models successfully classified participants into fall-risk groups, demonstrating the effectiveness of these tools in the early identification of individuals at risk. Numerical evidence of the relationship between balance control subsystems is provided, paving the way for the use of machine learning to analyze these relationships in more detail. It is worth noticing that the results presented in this reference could not be directly compared to the ones of the present research, since they address different problems.

The authors of [19] used machine learning algorithms to classify the risk of falls based on posturographic parameters. The study, which included 215 participants, highlights the relevance of data-driven approaches in improving fall prevention strategies. Similarly to [18], the material is focused on estimating the risk of falls, reaching up to 77% of accuracy, which can not be compared to the results of the present work.

The article [20] advanced the field by combining machine learning techniques with analysis of variables in the time domain and entropy, using a public COP database. The authors combined a partial least squares discriminant analysis classifier with the nonlinear dynamics of COP time series. Although it proved effective for classifying age-related postural oscillations reaching an accuracy of 88% for eyes opened standing on a compliant surface, there is the limitation of not exploring other methodologies.

The authors of [21] investigated the MINI-BESTest cut-off point for predicting the risk of falls using COP signals. The study revealed that COP measurement is a promising tool for estimating fall risk. Although the material originally estimated MINI-BESTest score reaching a poor correlation of 18% with the actual values, splitting the data using a cut-off point transformed the score regression estimation into a two-class classification, which significantly improved the performance. However, this differs from the present paper's experimental framework.

In [22], COP trajectories are mathematically modeled in order to classify elderly individuals with a history of falling. The estimated parameters showed that the COP trajectories of elderly individuals are more irregular, providing a potential basis for preventive interventions. It is classified with 88% of accuracy age-related and 77% fall-experienced subjects.

The study in [23] demonstrated how deep neural networks can be used to accurately predict fall risks using a public database containing signals captured from a force platform, highlighting the importance of network architectural simplicity and minimal complexity in such models. The results were presented under Fall Efficacy Scale (FES), which were separated into 3 classes reaching 99.9% of accuracy.

The authors of [17] implemented machine learning algorithms to assess balance control subsystems accurately. The study used a public database of human balance assessments to introduce new parameters that have been shown to improve the accuracy of balance control assessments. This is the only material that can be directly compared to our study, since it also estimates MINI-BESTest and subsystems scores by using regression analysis.

These studies highlight the increasing trend of applying machine learning methods and advanced data analysis to improve clinical trial prediction and fall risk assessment. All the references mentioned previously used the BDS dataset, which is publicly available, except for [19], which uses its own dataset related to fall risk in community-dwelling older adults, available upon request. Both datasets employed questionnaires in conjunction with qualitative tests for the subjects; no individual clinical tests were administered. Despite these advances, challenges such as the dependence on open databases and the need for more extensive clinical validation indicate areas for future research. Continued exploration and integration of new technologies, along with the development of more robust and accessible models, are essential for progressing the fields of fall prevention and rehabilitation.

3 METHODOLOGY

This section details the dataset used in this work, the features proposed for automatic evaluation, and the methodology used for this purpose.

3.1 DATASET

This study used the BDS (*Balance Data Set*) [24], a public dataset in which the postural oscillations of 163 volunteers (116 women) were measured, aged between 18 and 85 years, with a body mass between 44.0 Kg and 75.9 Kg, height between 1.40 m and 1.89 m and body mass index (BMI) ranging from 17.2 to 31.9 Kg/m^2. Among the test participants, 10% reported one or more physical limitations, including hearing, vestibular, visual, cognitive, or musculoskeletal deficits.

The experimental protocol involved standing on a force platform in the orthostatic position, with the feet oriented in a fixed place for 60 s. In total, data were collected in four experimental conditions: standing on a rigid or foam surface, with eyes open or closed. Each arrangement was repeated three times, totaling 12 measurements per volunteer.

Ground reaction forces, force moments, and COP displacement in the anterior-posterior (AP) and medial-lateral (ML) directions were recorded at a sampling frequency of 100 Hz using a force platform (OPT400600-1000; AMTI, Watertown, MA, USA) and an acquisition module (*Optima Signal Conditioner*, AMTI, Watertown, MA, USA). The signals were then filtered using a fourth-order Butterworth low-pass filter with a cut-off frequency of 10 Hz and no phase shift/delay in order to minimize unwanted noise and harmonics [25]. The database also contains individual identification questionnaires, anthropometric measurements, and the results of clinical balance tests, such as the MINI-BESTest.

Therefore, the dataset is made up of the identification of the test performed, subject information (weight, height, BMI, gender, foot size, nationality, skin color, years of schooling, preferred type of footwear, diseases, medications used, and disabilities), number of falls in the last 12 months, answers to the questionnaires *Falls Efficacy Scale-International* (FES-I) [26] and *International Physical Activity Questionnaire Short Version* (IPAQ) [27], the time spent attempting the test and the scores for the MINI-BESTest and its subtests (APA, RPC, SO, and DG), as well as the 12 stabilometric measurements per volunteer.

In addition, due to the limited number of volunteers and the number of tests carried out, it is important to note that the data set is unbalanced, with biases at the extremes of the evaluations.

3.2 FEATURE EXTRACTION

COP recordings are traditionally used by researchers to assess the output of the postural control system [28], as the displacement of the COP at the limits of stability and its magnitude are associated with the risk of falls [5, 11, 12]. Several parameters derived from raw COP data, in both the time and frequency domains, have been employed to evaluate overall balance performance [3, 28]. Based on previous studies [5, 11, 28–31], typically used parameters were extracted from the COP displacement measurements in the ML and AP directions, COP_x and COP_y, respectively. As the position of the feet on the platform varies between tests and individuals, the linear trend (linear fitting) was removed from the data in both directions. From the COP_x and COP_y signals, the variance, entropy, kurtosis, asymmetry (*skewness*), RMS (*Root Mean Square*), amplitude, crest factor, impulse factor, kurtosis factor, mean velocity and mean of the resulting velocity (COP_{vel}) were calculated. Another characteristic selected from the displacement pattern of the center of pressure was the elliptical area that involves most of the COP's displacement on the force platform (COP_{area}). In addition to the temporal characteristics, the parameters in the frequency domain were extracted: mean frequency (COP_{freq}) and maximum power, 50% and 95% percentiles of the power spectral density (PSD). The parameters extracted from the COP were carefully selected to provide a representative characterization of the phenomenon under investigation, according to the regressors evaluated. Additional data representations were also tested, but they did not prove to be relevant.

3.3 PROPOSED MODEL

Following a similar experimental structure to that adopted in [17], an extract from the BDS dataset was used, consisting of 1,896 measurements from 158 volunteers, with all the measurements from the 5 volunteers whose collection had been incomplete having been suppressed. Following the same experimental reasoning aims to allow a direct comparison between the state-of-the-art and the proposal presented in the text.

The COP_x and COP_y variables from the 12 measurements of each volunteer were concatenated to form a time series, from which the characteristics presented in Section 3.2 were extracted, 12 of which were temporal, one geometric (area traveled), four spectral and four anthropometric, making up a vector of 12 characteristics for each user.

To predict the MINI-BESTest scores, two regression models [32] were used with a supervised statistical learning method, taking as inputs the extracted characteristics and also the anthropometric data corresponding to each individual, such as age, weight, height, and gender. The supervised learning regression used was the Random Forest (RF) [33] and Support Vector Regression (SVR) [34].

Learning and Nonlinear Models - Journal of the Brazilian Society on Computational Intelligence (SBIC), Vol. 23, Iss. 2, pp. 4–10, 2025
https://doi.org/10.21528/lnlm-vol23-no2-art1

Observing that the lowest MINI-BESTest scores are from elderly volunteers and/or those with some physical or cognitive limitation or illness, a specific model for predicting these scores can bring greater reliability to the model.

Therefore, the proposal of this work is a hierarchical classification approach based on two steps (Fig. 1):

1. Stratification: with the training data and a reduced set of features (anthropometric features, COP_{area}, COP_{vel}, and COP_{freq}), a separation into two groups is proposed using the unsupervised k-means method. In this step, two training groups are generated, Training A and Training B, and the centroids are associated with each of them. The separation was made into just two groups to avoid compromising the generalizability of the model found, as splitting the dataset reduces the number of training samples.

2. Classification: in the classification stage, the data segregated from the previous stage is used to train two different models: Regressor A and Regressor B, where Regressor can be RF or SVR. Since these models deal with a smaller sample space of individuals, they were proposed to achieve a better fit in the regression.

As the amount of data in the training stage is small, this work proposes the use of the K-fold cross-validation method [33] to reduce the risk of overfitting and ensure the generalization of the proposed model.

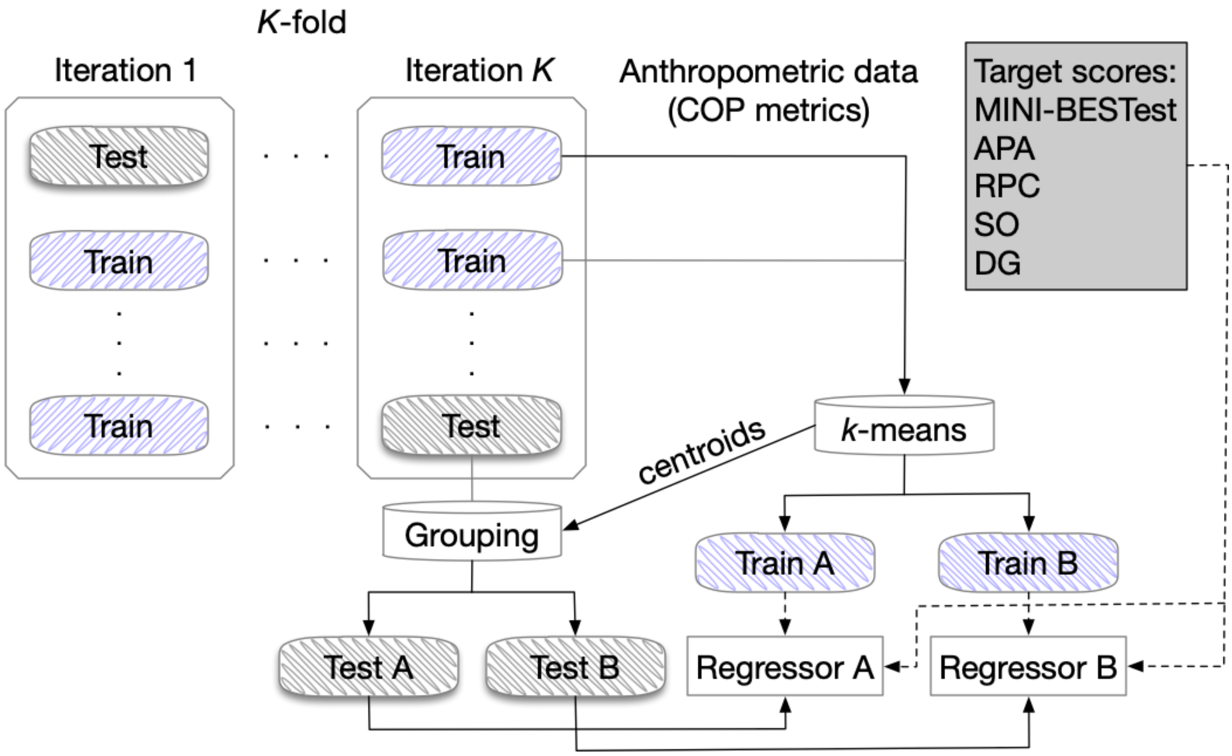

Figure 1: Data stratification model applied to the training and test vectors.

Initially, the data was separated into K distinct groups. The training stage was conducted with $K - 1$ groups, and the test stage was carried out with one of these groups. Each iteration rotates which group is in the test stage and which is in the training stage.

The study presented applies RF and SVR regressors to the p-dimensional feature vector of the data from 9 folds in order to train models that estimate the results of the MINI-BESTest, APA, RPC, SO, and DG. Once the models have been trained, the test is carried out on the remaining fold. However, machine learning techniques require the optimization of the hyperparameters of the algorithms used. Therefore, the optimal hyperparameter search used the *Grid Search* algorithm, which tests all the preconfigured parameters and returns the set that performed best, as well as the trained grid. The hyperparameters evaluated for SVR were ϵ=$\{0.1;0.2;...;0.9\}$, which defines a margin of tolerance within which prediction errors are not penalized, allowing the model to ignore small deviations and focus on capturing the overall trend of the data; kernel functions linear, polynomial, RBF (radial basis function), and sigmoidal; for RF regressor the functions Mean Squared Error (MSE) and Mean Absolute Error (MAE) were the criterion to measure the quality of split; and maximum number of features as p, $\sqrt{p}$ and $\log_2 p$.

The system proposed in this work consists of evaluating the complexity of data representation in order to use a single model. In this way, the data was separated into k=2 clusters using an unsupervised machine learning algorithm called k-means. The data was divided into clusters A and B, whose centroids (vectors representing the center of the clusters) are used to decide which cluster a given (unknown) test belongs to. Different RF and SVR regression models are generated for each cluster, and the test vector under analysis is applied to the associated model.

4 RESULTS

Table 1 shows the MAE results for MINI-BESTest, APA, RPC, SO, and DG of the proposed method with RF and SVR regressor separated by cluster, A and B, as well as calculating the weighted average performance to generate a single value and be able to compare it with pure RF and SVR (without using *k*-means) and with Ren *et al.* [17]. Initially comparing the performance of the pure RF and SVR regressor, clearly the RF overcomes SVR in all cases, but it could not outperform Ren *et al.* [17] in RPC and DG cases. A preliminary analysis of the data showed that two groups of samples were separated by the median system evaluation score. The clusters resulting from *k*-means are not related to the median but tend to relate to the input samples spatially. This fact becomes more evident when it is observed that the groupings divided the data by approximately 50% in all occurrences, with variations of up to 47.5% for grouping A and 52.5% for B. Numerically, the proposed method outperforms the state-of-the-art when estimating the MINI-BESTest, APA, RPC and SO results, achieving MAEs of 2.27, 0.69, 0.95 and 0.60, representing an improvement in performance of approximately 17%, 20%, 2% and 6%, respectively. It is worth noting that the proposed method obtained the best performance for MINI-BESTest, RPC, and SO with SVR, and for APA with RF regressor. In the case of DG, performance worsened by approximately 7% since the proposed method with SVR obtained an MAE of 1.05 and Ren *et al.* [17] obtained 0.98. Analyzing group A with RF and with SVR, the former only outperformed the latter in RPC, and considering the same regressor separation for group B, the former was successful in MINI-BESTest, APA, and DG. For both the pure SVR and clusters A and B, the optimal hyperparameters were a sigmoidal kernel and $\epsilon = 0.9$. Also, for the pure RF regressor and clusters A and B, the applied hyperparameters were the MSE function as split criterion kernel and p as the maximum number of features.

Table 1: Results MAE of the proposed method, group A (Grp A), B (Grp. B) and weighted mean (WM), with RF (w/RF) and with SVR (w/SVR) compared to Ren *et al.* [17] and pure RF and SVR for the cases of MINI-BEST (M-B), APA, RPC, SO and DG

Method	M-B	APA	RPC	SO	DG
Ren *et al.* [17]	2.66	0.83	0.97	0.64	**0.98**
RF	2.44	0.74	0.97	0.63	1.15
Proposed (WM) w/RF	2.32	**0.69**	0.97	0.66	1.09
Grp. A w/RF	2.13	0.62	0.90	0.57	1.07
Grp. B w/RF	2.49	0.76	1.03	0.74	1.11
SVR	3.48	1.16	0.97	0.72	1.39
Proposed (WM) w/SVR	**2.27**	0.71	**0.95**	**0.60**	1.05
Grp. A w/SVR	1.98	0.61	0.94	0.50	0.92
Grp. B w/SVR	2.54	0.79	0.96	0.68	1.18

The results corroborate the idea proposed in the methodology of not treating the data as if it belonged to a single group, clearly showing the numerical superiority of the proposed technique, especially in the case of the MINI-BESTest. This concept seems to be quite coherent since the data set represents real tests carried out with humans of various age groups and conditions, who fill in the most varied scales in the balance tests, and a single group is possibly incapable of explaining the subtleties of the different cases. Another point to note is that although the methodology only used 2 clusters due to the limited set of 158 volunteers, in a possible expansion of the data set, the methodology would be extensible by increasing the number of clusters.

5 CONCLUSIONS AND FUTURE WORKS

Assessing postural balance requires a specialized professional to analyze data measured on force platforms, which takes time. This article proposed an automated assessment system that uses machine learning to help professionals in order to reduce assessment time and mitigate possible assessor bias.

The idea consisted of capturing data measured on strength platforms, extracting characteristics, separating the data into two possible groupings, and training SVR models dependent on these groupings. When a new measurement is tested, its characteristics will first be extracted; then, according to its proximity to the centroid of each grouping, it will be applied to the corresponding model, generating its output, which can estimate both the MINI-BESTest result and the APA, RPC, SO, and DG subsystems. All are associated with different models/tasks.

The performance of the proposed system was very encouraging since it was able to outperform the state-of-the-art MAE for MINI-BESTest by 17%, and for the subsystem RPC by 20%, also obtaining better MAEs for the APA and SO subsystems, and only doing worse for DG. However, as the data is limited, clinical validation is needed to really prove the method's effectiveness.

Score prediction can enhance diagnostic clarity for professionals and mitigate biases in patient assessment. Furthermore, automated evaluation contributes to a more efficient prioritization and diagnostic workflow. Nonetheless, expert clinical judgment remains indispensable and should be integrated with automated methods to ensure accurate and reliable outcomes.

The proposal to adopt groupings in order to deal with the greater complexity and possibly different nature of the data proved to be very effective. However, an investigation into the importance of the characteristics used could reduce the dimensionality of the input vector and increase the efficiency of the regressor. The study of other regression techniques and artificial expansion of the data set could be interesting future steps. Moreover, practical validation involving patients and healthcare professionals is critical to guide the development of effective new techniques.

REFERENCES

[1] N. Van Humbeeck, R. Kliegl and R. T. Krampe. "Lifespan changes in postural control". *Scientific Reports*, vol. 13, no. 1, pp. 541, 2023.

[2] F. B. Horak. "Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls?" *Age and ageing*, vol. 35, no. suppl_2, pp. ii7–ii11, 2006.

[3] M. Mancini and F. B. Horak. "The relevance of clinical balance assessment tools to differentiate balance deficits". *European journal of physical and rehabilitation medicine*, vol. 46, no. 2, pp. 239, 2010.

[4] A. S. Pollock, B. R. Durward, P. J. Rowe and J. P. Paul. "What is balance?" *Clinical rehabilitation*, vol. 14, no. 4, pp. 402–406, 2000.

[5] J. E. Visser, M. G. Carpenter, H. van der Kooij and B. R. Bloem. "The clinical utility of posturography". *Clinical Neurophysiology*, vol. 119, no. 11, pp. 2424–2436, 2008.

[6] J.-H. Park, Y.-J. Kang and F. B. Horak. "What is wrong with balance in Parkinson's disease?" *Journal of movement disorders*, vol. 8, no. 3, pp. 109, 2015.

[7] I. C. M. Gonçalves. "Análise da tendência de mortalidade por quedas em idosos, no Brasil, no período de 2000-2019". 2022.

[8] S.-H. Park. "Tools for assessing fall risk in the elderly: A systematic review and meta-analysis". *Aging Clinical and Experimental Research*, vol. 30, no. 1, pp. 1–16, April 2017.

[9] N. Banker, C. Gough and S. Gordon. "Classification of balance assessment technology: A scoping review of systematic reviews". *Studies in Health Technology and Informatics*, vol. 268, pp. 45–59, March 2020.

[10] L. Abou, J. Peters, E. Wong, R. Akers, M. S. Dossou, J. J. Sosnoff and L. A. Rice. "Gait and balance assessments using smartphone applications in Parkinson's disease: A systematic review". *Journal of Medical Systems*, vol. 45, no. 9, pp. 87, August 2021.

[11] F. Quijoux, A. Nicolaï, I. Chairi, I. Bargiotas, D. Ricard, A. Yelnik, L. Oudre, F. Bertin-Hugault, P.-P. Vidal, N. Vayatis *et al.*. "A review of center of pressure (COP) variables to quantify standing balance in elderly people: Algorithms and open-access code". *Physiological reports*, vol. 9, no. 22, pp. e15067, 2021.

[12] S. B. Richmond, B. W. Fling, H. Lee and D. S. Peterson. "The assessment of center of mass and center of pressure during quiet stance: Current applications and future directions". *Journal of biomechanics*, vol. 123, pp. 110485, 2021.

[13] F.-Y. Liao, C.-C. Wu, Y.-C. Wei, L.-W. Chou, K.-M. Chang *et al.*. "Analysis of center of pressure signals by using decision tree and empirical mode decomposition to predict falls among older adults". *Journal of healthcare engineering*, vol. 2021, 2021.

[14] F. B. Horak, D. M. Wrisley and J. Frank. "The balance evaluation systems test (BESTest) to differentiate balance deficits". *Physical therapy*, vol. 89, no. 5, pp. 484–498, 2009.

[15] F. Franchignoni, F. Horak, M. Godi, A. Nardone and A. Giordano. "Using psychometric techniques to improve the Balance Evaluation System's Test: the mini-BESTest". *Journal of rehabilitation medicine: official journal of the UEMS European Board of Physical and Rehabilitation Medicine*, vol. 42, no. 4, pp. 323, 2010.

[16] L. King and F. Horak. "On the mini-BESTest: scoring and the reporting of total scores". *Physical therapy*, vol. 93, no. 4, pp. 571–575, 2013.

[17] P. Ren, S. Huang, Y. Feng, J. Chen, Q. Wang, Y. Guo, Q. Yuan, D. Yao and D. Ma. "Assessment of balance control subsystems by artificial intelligence". *IEEE transactions on neural systems and rehabilitation engineering*, vol. 28, no. 3, pp. 658–668, 2020.

[18] J. Pennone, N. F. Aguero, D. M. Martini, L. Mochizuki and A. A. do Passo, Suaide. "Fall prediction in a quiet standing balance test via machine learning: Is it possible?" *PLoS One*, vol. 19, no. 4, pp. e0296355, 2024.

[19] H.-W. Liang, R. Ameri, S. Band, H.-S. Chen, S.-Y. Ho, B. Zaidan, K.-C. Chang and A. Chang. "Fall risk classification with posturographic parameters in community-dwelling older adults: a machine learning and explainable artificial intelligence approach". *Journal of NeuroEngineering and Rehabilitation*, vol. 21, pp. 15, 2024.

https://doi.org/10.21528/lnlm-vol23-no2-art1

[20] V. Alcan. "Enhancing age-related postural sway classification using partial least squares-discriminant analysis and hybrid feature set". *Neural Computing and Applications*, vol. 36, pp. 5621–5643, 2024.

[21] 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, no. 12, pp. 2133, 2022.

[22] Y. Tawaki, T. Nishimura and T. Murakami. "Classification of Older and Fall-Experienced Subjects by Postural Sway Data Using Mass Spring Damper Model". *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 40–49, 2021.

[23] M. Savadkoohi, T. Oladunni and L. A. Thompson. "Deep neural networks for human's fall-risk prediction using force-plate time series signal". *Expert Systems with Applications*, vol. 182, no. 15, pp. 115220, 2021.

[24] D. A. Santos and M. Duarte. "A public data set of human balance evaluations". *PeerJ*, vol. 4, pp. e2648, 2016.

[25] I. W. Selesnick and C. S. Burrus. "Generalized digital Butterworth filter design". *IEEE Transactions on signal processing*, vol. 46, no. 6, pp. 1688–1694, 1998.

[26] G. I. Kempen, L. Yardley, J. C. Van Haastregt, G. R. Zijlstra, N. Beyer, K. Hauer and C. Todd. "The Short FES-I: a shortened version of the falls efficacy scale-international to assess fear of falling". *Age and ageing*, vol. 37, no. 1, pp. 45–50, 2008.

[27] C. L. Craig, A. L. Marshall, M. Sjöström, A. E. Bauman, M. L. Booth, B. E. Ainsworth, M. Pratt, U. Ekelund, A. Yngve, J. F. Sallis *et al.*. "International physical activity questionnaire: 12-country reliability and validity". *Medicine & science in sports & exercise*, vol. 35, no. 8, pp. 1381–1395, 2003.

[28] T. Paillard and F. Noé. "Techniques and Methods for Testing the Postural Function in Healthy and Pathological Subjects". *BioMed Research International*, vol. 2015, pp. 891390, 2015.

[29] M. Duarte and S. M. Freitas. "Revisão sobre posturografia baseada em plataforma de força para avaliação do equilíbrio". *Brazilian Journal of Physical Therapy*, vol. 14, pp. 183–192, 2010.

[30] M. Duarte. "Comments on "Ellipse area calculations and their applicability in posturography"(Schubert and Kirchner, vol. 39, pages 518–522, 2014)". *Gait Posture*, vol. 41, no. 1, pp. 44–45, 2015.

[31] C. Maurer and R. J. Peterka. "A New Interpretation of Spontaneous Sway Measures Based on a Simple Model of Human Postural Control". *Journal of Neurophysiology*, vol. 93, no. 1, pp. 189–200, 2005.

[32] Y. S. Abu-Mostafa, M. Magdon-Ismail and H.-T. Lin. *Learning from data*, volume 4. AMLBook New York, 2012.

[33] G. James, D. Witten, T. Hastie and R. Tibshirani. *An introduction to statistical learning*, volume 112. Springer, 2013.

[34] M. Awad, R. Khanna, M. Awad and R. Khanna. "Support vector regression". *Efficient learning machines: Theories, concepts, and applications for engineers and system designers*, pp. 67–80, 2015.