Index of Physical activity and Fall Efficacy scale classification through biomechanical signals and Machine Learning.

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ABSTRACT

The rapid increase in the elderly population and chronic diseases has increased disability worldwide. This has led researchers and engineers to create tools and technologies that allow health caregivers, physical trainers, and health policymakers to understand, measure, and treat people with disabilities. In addition, artificial intelligence techniques have been used to improve the performance of these technologies. This article presents the development of a novel classifier that utilizes machine learning (ML) algorithms and biomechanical signals to predict a subject's International Physical Activity Questionnaire (IPAQ) and Fall Efficacy Scale (FES) scores. Three ML algorithms were applied: K-nearest neighbors (KNN), decision tree, and support vector machine (SVM). The results showed classification accuracies of over 95%, 99%, and 89%, respectively, and validated the correlation between qualitative scales and biomechanical responses in balance training. This classifier is an innovative tool that helps professionals adjust and improve their physical training programs.

Keywords: Postural Sway; Physical Activity; Support Vector Machine; K-Nearest Neighbors; Decision Tree.

INTRODUCTION

According to the World Health Organization (WHO), more than one billion people worldwide have some type of disability. This is a growing figure, attributed to the aging of the population and the increase in chronic diseases ("OMS | Discapacidad y rehabilitación," n.d.). Balance and postural control are among the main skills affected by aging, neuromotor diseases, and trauma at the motor level.

However, diagnosis, training, and balance rehabilitation processes use evaluation methodologies that are usually based on qualitative tests. Tests such as the Berg Balance Scale (Brouwer, Kal, van der Kamp, & Houdijk, 2019), IPAQ (Craig et al., 2003), and FES (Hauer et al., 2010) are applied by specialized personnel. Nonetheless, the results tend to be subjective and depend on the evaluators' experience.

Novel training programs have been developed to obtain more efficient and reliable processes (Betker, Szturm, & Moussavi, 2005; Fitzgerald, Trakarnratanakul, Dunne, Smyth, & Caulfield, 2008; Van Diest, Lamoth, Stegenga, Verkerke, & Postema, 2013), including assistive robotics technologies (Kharboutly et al., 2015; Patanè & Cappa, 2011; Rastegarpanah, Saadat, Borboni, & Stolkin, 2017; Schouten, Boonstra, Nieuwenhuis, Campfens, & Van Der Kooij, 2011). However, the benefits, advantages, and disadvantages of these tools for physical training and rehabilitation procedures are not yet clear (Gui, Tan, Liu, & Zhang, 2020; Jakob et al., 2018; Zhang et al., 2017). Due to this, (Agarwal & Deshpande, 2019; Franceschini et al., 2020; Rodgers et al., 2019; Stinear, Lang, Zeiler, & Byblow, 2020; Yozbatiran & Francisco, 2019) support the idea of the need for better procedures and protocols, which helps to clarify the impact that robotics brings to this type of task and mitigates the problem of subjectivity in these procedures.

In recent years, various artificial intelligence and machine learning techniques have been implemented in topics related to the classification of levels of physical activity and activities of daily living (Pires, Garcia, Pombo, Flórez-Revuelta, & Spinsante, 2017), detection of falls (Sun, Hsieh, & Sosnoff, 2019; Yang & Gao, 2020), autonomous training, execution of tasks without the supervision of an expert (Jiao, Wu, Bie, Umek, & Kos, 2018), detection of emotions when executing physical exercises (Rincon, Costa, Carrascosa, Novais, & Julian, 2019), and methodologies of assisted training with haptic feedback (Bao, Klatt, Whitney, Sienko, & Wiens, 2019a). Recently, these applications have used direct measurements such as electrocardiogram (ECG) signals(Allam, Samantray, & Ari, 2020; Patro, Jaya Prakash, Jayamanmadha Rao, & Rajesh Kumar, 2020; Prakash & Ari, 2019b, 2019a), electroencephalograms (EEG)(Venkata Phanikrishna, Jaya Prakash, & Suchismitha, 2021), and COP to classify, monitor, and assist training and rehabilitation programs to improve user performance.

Based on the state-of-the-art and current trends in intelligence and machine learning algorithms, this article presents the development of an automatic classification system for the IPAQ and FES that utilizes postural sway signals from an existing database (Santos & Duarte, 2016) and machine learning. The hypothesis proposes that it is possible to determine the level of IPAQ and FES and even detect the characteristics of the surface on which the training is carried out (stable and unstable surfaces) through the quantitative analysis of signals typical of the COP of a user and anthropometric measurements.

This study primarily focuses on the development of a classifier system. The features extracted from stabilometric signals and anthropometric measurements were selected and processed. Continuing with the design and choice of optimal parameters of the classifiers commonly used in balance evaluation tasks, KNN (Ahmed, Mehmood, Nadeem, Mehmood, & Rizwan, 2017; Liang, Liu, Li, & Zhao, 2019), decision trees (Leu, Ko, Lin, Susanto, & Yu, 2017) , and SVM (Bao et al., 2019a) using concurrent algorithms. The selected algorithms present several advantages. For instance, SVM is effective in high-dimensional space tasks, even in cases where the number of dimensions is greater than the number of samples. KNN is a non-parametric method that is helpful in tasks where decision boundaries are not regular, and decision trees are perfect for handling multi-output problems (Pedregosa et al., 2011). Finally, the precision, F1-score, and recall results of the three techniques are presented.

MATERIALS AND METHODS

For the design of the physical activity classifier, the database described by (Santos & Duarte, 2016), which consisted of information from 1,930 tests performed by 163 subjects, was used. For data capture, the participants maintained a stationary standing position for 60 s in four different situations: eyes open or closed, while standing on a stable or unstable surface. Each condition was tested in triplicates. The experimental setup is illustrated in Fig. 1.

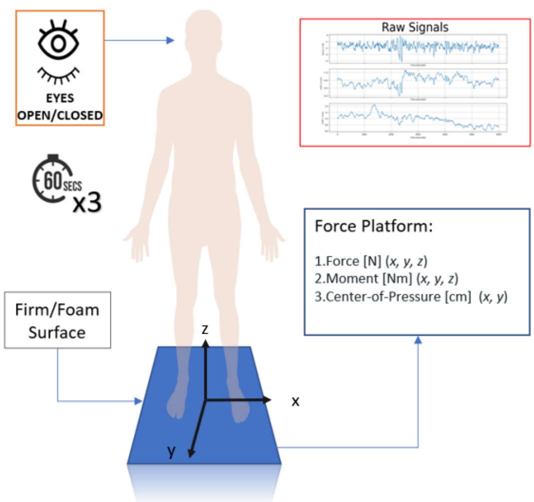


Figure 1. Experimental Setup

Eight different signals were captured through a force platform:

1. Force [N] (*x, y, z*)
2. Moment [Nm] (*x, y, z*)
3. Center-of-Pressure [cm] (*x,y*)

The database includes the results of qualitative evaluations of physical activity indices and participant balance.

- Short Falls Efficacy Scale International
- International Physical Activity
- Trail Making Test
- Mini Balance Evaluation Systems Tests

The classifier only included information corresponding to healthy subjects who did not report any type of disability or disease according to the information provided by the researchers.

Signal processing and filtering

The signals were filtered and processed before the extraction and selection of relevant features. A fifth-order Butterworth type low pass filter was applied with a cutoff frequency equal to 5 Hz according to (Doyle, Hsiao-Wecksler, Ragan, & Rosengren, 2007; Paillard & Noé, 2015). Because it is not known whether the acquisition instruments have a constant calibration for each test, the mean signal level of each sample was eliminated by subtracting a polynomial of degree six, which models the behavior of each signal. Fig. 2 shows the process described above using data from the force on the Y-axis.

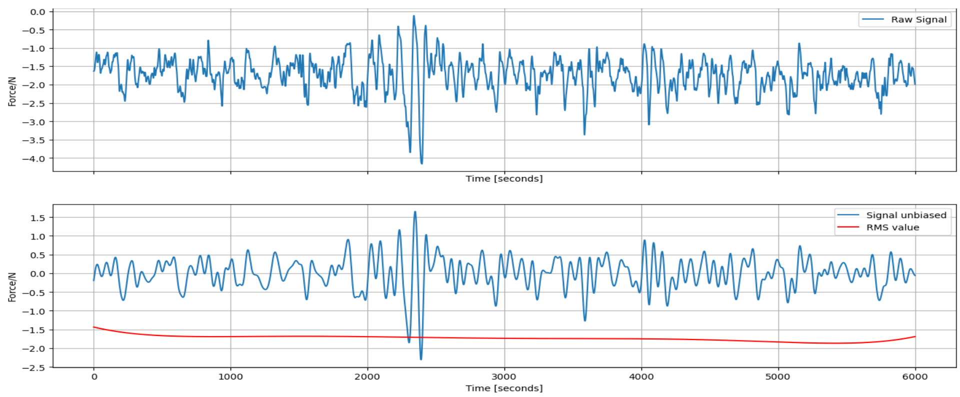


Figure 2. Signal processing

Feature selection

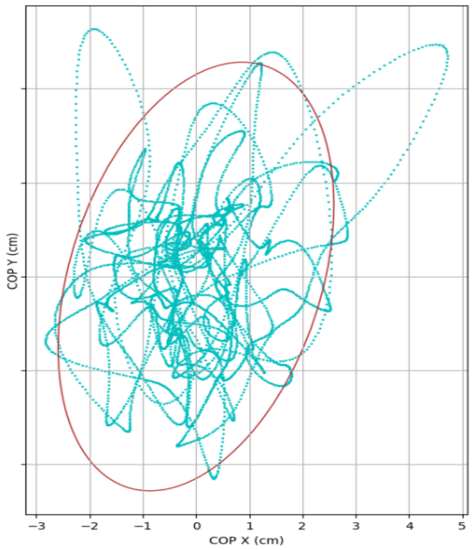
The features extracted from the signals were obtained from the categories listed in Table 1. These are some of the most common methods for analyzing the COP behavior of individuals (Brouwer et al., 2019; Doyle et al., 2007; Yamamoto et al., 2015). Kinematic and statistical estimators of each of the database signals and anthropometric measurements of the test subjects were applied.

A total of 85 features, usually determined using postural control and stabilometry analyzers(Paillard & Noé, 2015; Yamamoto et al., 2015), were extracted by combining the categories listed in Table 1. The measurements included the maximum displacement, maximum frequency, mean amplitude, area of the COP, maximum length in each axis of excursion, maximum force in each axis, root mean square in each axis of displacement, and mean displacement angle. Anthropometric variables directly involved in the various balance mechanisms of the human body were incorporated: body mass index, weight, foot length, and height.

Table 1. Feature extraction categories

Kinematic Estimator	Statistical estimator	Anthropometric measures
1. 95% confidence ellipse 2. Length of total displacement 3. Root mean square of the COP 4. Frequency 5. Velocity gradient COP 6. Maximum displacement per-axis 7. Angle	8. Mean 9. Median 10. Fashion 11. Standard deviation 12. Maximum 13. Minimum 14. Variance	15. Body Mass Index (BMI) 16. Height 17. Weight 18. Foot length

Figure 3. 95% confidence ellipse area



Values within the 95% confidence ellipse area were used to eliminate abnormal disturbance values during data capture. This estimator was calculated as described (Doyle et al., 2007); and thetime, angles and maximum amplitudes corresponding to the area described by the subject's movement were extracted (Fig. 3).

Physical activity index classifier

To determine the IPAQ, FES, and surface of the experiment, the data were filtered, scaled, and normalized using only healthy subjects (without any reported disease). In total, 648 observations with 85 features were used. Eighty% of the data was used for the training process, and the remaining 20% was used for algorithm validation. Data from the participants were used either in the training or testing sets.

The techniques selected to design the classifier were KNN, decision trees, and SVM. These algorithms are supervised classification techniques that are typically used for state or outcome prediction problems based on known and correlated data or features.

Classification techniques were implemented in Python using the scikit-learn tool (Li & Phung, 2014). For their validation and evaluation, the F1-score, precision, and recall of each algorithm (Bao, Klatt, Whitney, Sienko, & Wiens, 2019b) were evaluated.

$$F1\text{-}Score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \qquad (1)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (2)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (3)$$

Statistical analyses using ANOVA, F-values, and p-values were performed to select the most relevant features for each algorithm. These show the statistical significance of independent versus dependent variables and are commonly used in problems where the input data are numeric and the output variable is categorical.

Classification algorithms

The classification algorithms selected to determine the desired outputs were the KNN, decision trees, and SVM. The operating parameters are listed in Table 2.

Table 2. Classification parameters

Algorithm	Parameters	Output
KNN	• K=1 • Search algorithm ='kd_tree' • distance =Manhattan distance	IPAQ
	• K=3 • Search algorithm ='kd_tree' • distance=Manhattan distance	FES/ Surface
Decision trees	• Search criteria =entropy • Max Depth=30 • Random state=32	IPAQ/ FES/ Surface
SVM	• Penalty parameters (C=110.1) • Kernel='rbf' • Decision function shape=one vs one	IPAQ/ FES/ Surface

The parameter K of the KNN estimator was evaluated by studying the resulting precision according to the variation of K during 100 epochs. Fig. 4, green margin represents the standard deviation of the accuracy for a certain number of neighbors (K). The Manhattan distance parameter showed better results compared to the traditional Euclidean distance parameter because this measure works best with larger data.

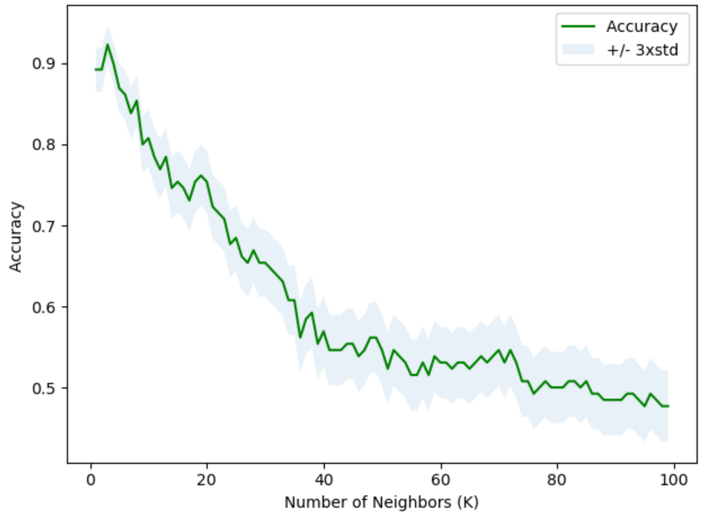


Figure 4. Best K for KNN and standard deviation accuracy

The search criterion for the decision tree was entropy as it aimed to eliminate the heterogeneity of the elements located in each section of the tree. A search depth of 30 was used because of the large number of extracted features.

Similar to the KNN algorithm, the SVM estimator is constructed as a multiclass estimator, evaluating various combinations of parameters by employing a random search with the RandomizedSearchCV library (Li & Phung, 2014). The penalty parameters (C), kernel, and weight of the characteristics were found through random optimization according to ("3.2. Tuning the hyper-parameters of an estimator — scikit-learn 0.24.1 documentation," n.d.).

RESULTS AND DISCUSSION

The following results were obtained by applying different ML techniques to the test set. The designed classifier was first evaluated by considering 85 extracted features. Using (2), the results obtained are shown in Table 3. To improve the results, the search for the main features using ANOVA was implemented according to the dependent variable studied, IPAQ (High, Low, and Moderate) and FES (High Concern, Medium Concern, and Low Concern).

Table 3. Precision Before Choosing Main Features

Algorithm	**Precision Before Feature Importance**		
	IPAQ	FES	Surface
KNN	0.87	0.84	0.98
Decision Tree	1.00	0.97	0.99
SVM	0.77	0.73	0.97

The biomechanical variables reflected by the COP showed acceptable statistical significance when evaluating the IPAQ and type of surface; however, in the evaluation of the FES, the anthropometric features of the individual showed greater significance than the biomechanical variables. This validates the initial hypothesis regarding the possibility of classifying individuals according to quantitative variables. The Main 5 features of each outcome are listed in Table 4.

Table 4. Statistical significance of biomechanical features

Outcome	**Number of Feature importance**	**Main 5 Biomechanical Features**	***p*-value**
IPAQ	53	Variance of Moment in Z	0.000427
		Variance of Moment in X	0.00105
		RMS of Moment in Z	0.00164
		Standard deviation of Moment in Z	0.001648
		Standard deviation of Moment in X	0.00204
FES	34	Maximum Frequency in Z	0.044
		Average Force in X	0.05735
		X-Force Mode	0.06471
		Maximum frequency in X	0.06472
		Variance of Force in X	0.069
Surface	48	COP displacement in Y	6.91e-156
		COP length in Y	6.53e-146
		Standard deviation COP in Y	2.611e-145
		RMS COP in Y	2.611e-145
		COP length in X	1.742e-144

Once the most relevant features were identified for each outcome, the precision of the classifier was re-evaluated for each technique. Table 5 lists the precision after the feature-importance procedure.

Table 5. Precision of classifiers after choice of main features

Algorithm	**Precision After feature Importance**		
	IPAQ	FES	Surface
KNN	0.97	0.92	0.98
Decision Tree	1.00	1.00	0.97
SVM	0.85	0.84	0.99

The results obtained suggest that the procedure of choice and optimization of parameters for each estimator improved the average precision of the KNN classifiers from 89.6% to 95.6% and that of the SVM from 83.3% to 89.3%, considering their performance in estimating the IPAQ, FES, and Surface.

The decision tree registered an increase in FES prediction; however, it registered a slight decrease when predicting the surface of the experiment. This suggests that the algorithm requires all 85 extracted features to achieve the highest precision.

Finally, (2) and (3) were replaced in (1) to evaluate the F1-Score. The performance results of the classifier are listed in Table 6, and the average performance of the classifiers throughout the different validations of the IPAQ, FES, and Surface are listed in Table 7.

Table 6. Results of F1 score and Recall of each classifier.

Algorithm	F1 Score and Recall After feature Importance					
	IPAQ		FES		Surface	
	F1 score	recall	F1 score	recall	F1 score	recall
KNN	0.97	0.97	0.91	0.90	0.98	0.98
Decision Tree	1.00	1.00	1.00	1.00	0.97	0.97
SVM	0.84	0.83	0.81	0.81	0.99	0.99

Table 7. Average performance of classifiers

Average Performance (IPAQ, FES, Surface)	KNN	Decision Tree	SVM
Precision	95.6%	99%	89.3%
F1-score	95.3%	99%	88%
Recall	95%	99%	87.6%

The average results support the use of COP as a direct measure of physical activity status. In addition, these results (over 95 %) are comparable to those of other studies that applied direct measures of human beings, such as ECG (Allam et al., 2020; Prakash & Ari, 2019b) and EEG(Venkata Phanikrishna et al., 2021), and applied similar ML techniques with similar average results. Although the tests did not present greater complexity to the participants, and the extracted signals did not show easily identifiable patterns of behavior, the classification algorithms achieved a high average performance when classifying the various states of the IPAQ and FES.

Of note, these results are comparable with those of Liao et al.(Liao, Wu, Wei, Chou, & Chang, 2021), who used the same database selected for this article to analyze COP signals using a decision tree and empirical mode decomposition to predict falls among older adults. This supports the use of ML and COP measures for classifying physical activity conditions.

Finally, the biomechanical variables extracted from the COP were directly correlated with the type of surface on which the standing experiments were performed. Although this was a predictable result, it corroborated the design of the classifiers and highlighted the ability of these techniques to identify correlations in features that are difficult to observe with the naked eye, even by highly trained personnel (therapists, physiatrists, trainers, etc.).

The main limitation of the proposed classifier is related to the database. Although data recollection was stated in the study protocol (Santos & Duarte, 2016), there may be biases and confounders that affect the generalizability of the data to other populations.

CONCLUSION

The designed classifier uses the COP to classify the IPAQ and FES of subjects with a high accuracy of over 95.6%. In addition, a correlation between the qualitative assessment scales (IPAQ and FES) and the features of the biomechanical behavior of the human body was found using the feature importance process. Thus, the high F1 score, recall, and precision of the designed algorithms validated the application of these techniques to predict the IPAQ, FES, and Surface. Moreover, this classifier is an innovative tool to support diagnosis, assessment, and physical training processes through a direct measure of the COP.

This system shows the possibility of using similar solutions to support the diagnosis and evaluation of physical activity by specialized personnel. The integration of this classifier with the assistive robotics system for balance training presented by (Rivera, Abril, Niño-Suarez, Avilés, & Castillo-Castañeda, 2021), is intended to mitigate the problem of subjectivity present in balance evaluation systems, allowing them to adjust the assistance parameters of the robotic platform according to the user's performance.

In future studies we intend to compile a database of healthy subjects during the execution of dynamic exercises (e.g., limits of stability and reaching exercises) to determine the correlation between the variables extracted by the classifier and the performance of the user in certain balance training. This will help evaluators adjust or validate procedures in clinical settings.

REFERENCES

3.2. Tuning the hyper-parameters of an estimator — scikit-learn 0.24.1 documentation. (n.d.). Retrieved February 19, 2021, from https://scikit-learn.org/stable/modules/grid_search.html#exhausting-the-resources

Agarwal, P., & Deshpande, A. D. (2019). A Framework for Adaptation of Training Task, Assistance and Feedback for Optimizing Motor (Re)-Learning With a Robotic Exoskeleton. *IEEE Robotics and Automation Letters*, *4*(2), 808–815. https://doi.org/10.1109/LRA.2019.2891431

Ahmed, M., Mehmood, N., Nadeem, A., Mehmood, A., & Rizwan, K. (2017). Fall detection system for the elderly based on the classification of shimmer sensor prototype data. *Healthcare Informatics Research*, *23*(3), 147–158. https://doi.org/10.4258/hir.2017.23.3.147

Allam, J. P., Samantray, S., & Ari, S. (2020). SpEC: A system for patient specific ECG beat classification using deep residual network. *Biocybernetics and Biomedical Engineering*, *Vol. 40*(4), 1446–1457. https://doi.org/10.1016/J.BBE.2020.08.001

Bao, T., Klatt, B. N., Whitney, S. L., Sienko, K. H., & Wiens, J. (2019a). Automatically Evaluating Balance: A Machine Learning Approach. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *27*(2), 179–186. https://doi.org/10.1109/TNSRE.2019.2891000

Bao, T., Klatt, B. N., Whitney, S. L., Sienko, K. H., & Wiens, J. (2019b). Automatically Evaluating Balance: A Machine Learning Approach. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. https://doi.org/10.1109/TNSRE.2019.2891000

Betker, A. L., Szturm, T., & Moussavi, Z. (2005). Development of an Interactive Motivating Tool for Rehabilitation Movements. In *2005 IEEE Engineering in Medicine and Biology 27th Annual Conference*. https://doi.org/10.1109/IEMBS.2005.1616090

Brouwer, R., Kal, E., van der Kamp, J., & Houdijk, H. (2019). Validation of the stabilometer balance test: Bridging the gap between clinical and research based balance control assessments for stroke patients. *Gait and Posture*, *67*(June 2018), 77–84. https://doi.org/10.1016/j.gaitpost.2018.09.025

Craig, C. L., Marshall, A. L., Sjöström, M., Bauman, A. E., Booth, M. L., Ainsworth, B. E., … Oja, P. (2003). International physical activity questionnaire: 12-Country reliability and validity. *Medicine and Science in Sports and Exercise*. https://doi.org/10.1249/01.MSS.0000078924.61453.FB

Doyle, R. J., Hsiao-Wecksler, E. T., Ragan, B. G., & Rosengren, K. S. (2007). Generalizability of center of pressure measures of quiet standing. *Gait and Posture*, *25*(2), 166–171. https://doi.org/10.1016/j.gaitpost.2006.03.004

Fitzgerald, D., Trakarnratanakul, N., Dunne, L., Smyth, B., & Caulfield, B. (2008). Development and user evaluation of a virtual rehabilitation system for wobble board balance training. In *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. https://doi.org/10.1109/IEMBS.2008.4650134

Franceschini, M., Mazzoleni, S., Goffredo, M., Pournajaf, S., Galafate, D., Criscuolo, S., … Posteraro, F. (2020). Upper limb robot-assisted rehabilitation versus physical therapy on subacute stroke patients: A follow-up study. *Journal of Bodywork and Movement Therapies*, *24*(1), 194–198. https://doi.org/10.1016/j.jbmt.2019.03.016

Gui, K., Tan, U.-X., Liu, H., & Zhang, D. (2020). Electromyography-Driven Progressive Assist-as-Needed Control for Lower Limb Exoskeleton. *IEEE Transactions on Medical Robotics and Bionics*, *2*(1), 50–58. https://doi.org/10.1109/tmrb.2020.2970222

Hauer, K., Yardley, L., Beyer, N., Kempen, G., Dias, N., Campbell, M., … Todd, C. (2010). Validation of the falls efficacy scale and falls efficacy scale international in geriatric patients with and without cognitive impairment: Results of self-report and interview-based questionnaires. *Gerontology*, *56*(2), 190–199. https://doi.org/10.1159/000236027

Jakob, I., Kollreider, A., Germanotta, M., Benetti, F., Cruciani, A., Padua, L., & Aprile, I. (2018). Robotic and Sensor Technology for Upper Limb Rehabilitation. *PM and R*, *10*(9), S189–S197. https://doi.org/10.1016/j.pmrj.2018.07.011

Jiao, L., Wu, H., Bie, R., Umek, A., & Kos, A. (2018). Multi-sensor Golf Swing Classification Using Deep CNN. In *Procedia Computer Science*. https://doi.org/10.1016/j.procs.2018.03.046

Kharboutly, H., Ma, J., Benali, A., Thoumie, P., Pasqui, V., & Bouzit, M. (2015). Design of multiple axis robotic platform for postural stability analysis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. https://doi.org/10.1109/TNSRE.2014.2329533

Leu, F. Y., Ko, C. Y., Lin, Y. C., Susanto, H., & Yu, H. C. (2017). Fall Detection and Motion Classification by Using Decision Tree on Mobile Phone. In *Smart Sensors Networks: Communication Technologies and Intelligent Applications* (pp. 205–237). Elsevier Inc. https://doi.org/10.1016/B978-0-12-809859-2.00013-9

Li, H., & Phung, D. (2014). Journal of Machine Learning Research: Preface. *Journal of Machine Learning Research*, *39*(2014), i–ii.

Liang, S., Liu, Y., Li, G., & Zhao, G. (2019). Elderly Fall Risk Prediction with Plantar Center of Force Using ConvLSTM Algorithm. In *2019 IEEE International Conference on Cyborg and Bionic Systems, CBS 2019* (pp. 36–41). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/CBS46900.2019.9114487

Liao, F.-Y., Wu, C.-C., Wei, Y.-C., Chou, L.-W., & Chang, K.-M. (2021). Analysis of Center of Pressure Signals by Using Decision Tree and Empirical Mode Decomposition to Predict Falls among Older Adults. *Journal of Healthcare Engineering*, *2021*, 1–10. https://doi.org/10.1155/2021/6252445

OMS | Discapacidad y rehabilitación. (n.d.). Retrieved June 17, 2020, from https://www.who.int/disabilities/es/

Paillard, T., & Noé, F. (2015). Techniques and Methods for Testing the Postural Function in Healthy and Pathological Subjects. *BioMed Research International*, *2015*. https://doi.org/10.1155/2015/891390

Patanè, F., & Cappa, P. (2011). A 3-DOF parallel robot with spherical motion for the rehabilitation and evaluation of balance performance. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. https://doi.org/10.1109/TNSRE.2010.2089535

Patro, K. K., Jaya Prakash, A., Jayamanmadha Rao, M., & Rajesh Kumar, P. (2020). An Efficient Optimized Feature Selection with Machine Learning Approach for ECG Biometric Recognition. *Https://Doi.Org/10.1080/03772063.2020.1725663*. https://doi.org/10.1080/03772063.2020.1725663

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., … Duchesnay, É. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*(85), 2825–2830. Retrieved from http://jmlr.org/papers/v12/pedregosa11a.html

Pires, I. M., Garcia, N. M., Pombo, N., Flórez-Revuelta, F., & Spinsante, S. (2017). Pattern recognition techniques for the identification of activities of daily living using mobile device accelerometer. *ArXiv*.

Prakash, A. J., & Ari, S. (2019a). A system for automatic cardiac arrhythmia recognition using electrocardiogram signal. *Undefined*, 891–911. https://doi.org/10.1016/B978-0-08-102420-1.00042-X

Prakash, A. J., & Ari, S. (2019b). AAMI Standard Cardiac Arrhythmia Detection with Random Forest Using Mixed Features. *Undefined*. https://doi.org/10.1109/INDICON47234.2019.9030317

Rastegarpanah, A., Saadat, M., Borboni, A., & Stolkin, R. (2017). Application of a parallel robot in lower limb rehabilitation: A brief capability study. In *International Conference on Robotics and Automation for Humanitarian Applications, RAHA 2016 - Conference Proceedings*. https://doi.org/10.1109/RAHA.2016.7931865

Rincon, J. A., Costa, A., Carrascosa, C., Novais, P., & Julian, V. (2019). Emerald—exercise monitoring emotional assistant. *Sensors (Switzerland)*. https://doi.org/10.3390/s19081953

Rivera, O., Abril, J. D., Niño-Suarez, P. A., Avilés, O. F., & Castillo-Castañeda, E. (2021). Two dof robotic platform for balance rehabilitation tasks. In *Mechanisms and Machine Science*. https://doi.org/10.1007/978-3-030-60372-4_37

Rodgers, H., Bosomworth, H., Krebs, H. I., van Wijck, F., Howel, D., Wilson, N., … Shaw, L. (2019). Robot assisted training for the upper limb after stroke (RATULS): a multicentre randomised controlled trial. *The Lancet*, *394*(10192), 51–62. https://doi.org/10.1016/S0140-6736(19)31055-4

Santos, D. A., & Duarte, M. (2016). A public data set of human balance evaluations. *PeerJ*. https://doi.org/10.7717/peerj.2648

Schouten, A. C., Boonstra, T. A., Nieuwenhuis, F., Campfens, S. F., & Van Der Kooij, H. (2011). A bilateral ankle manipulator to investigate human balance control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. https://doi.org/10.1109/TNSRE.2011.2163644

Stinear, C. M., Lang, C. E., Zeiler, S., & Byblow, W. D. (2020). Advances and challenges in stroke rehabilitation. *The Lancet Neurology*, *19*(4), 348–360. https://doi.org/10.1016/S1474-4422(19)30415-6

Sun, R., Hsieh, K. L., & Sosnoff, J. J. (2019). Fall Risk Prediction in Multiple Sclerosis Using Postural Sway Measures: A Machine Learning Approach. *Scientific Reports*. https://doi.org/10.1038/s41598-019-52697-2

Van Diest, M., Lamoth, C. J., Stegenga, J., Verkerke, G. J., & Postema, K. (2013). Exergaming for balance training of elderly: State of the art and future developments. *Journal of NeuroEngineering and Rehabilitation*. https://doi.org/10.1186/1743-0003-10-101

Venkata Phanikrishna, B., Jaya Prakash, A., & Suchismitha, C. (2021). Deep Review of Machine Learning Techniques on Detection of Drowsiness Using EEG Signal. *Https://Doi.Org/10.1080/03772063.2021.1913070*. https://doi.org/10.1080/03772063.2021.1913070

Yamamoto, T., Smith, C. E., Suzuki, Y., Kiyono, K., Tanahashi, T., Sakoda, S., … Nomura, T. (2015). Universal and individual characteristics of postural sway during quiet standing in healthy young adults. *Physiological Reports*. https://doi.org/10.14814/phy2.12329

Yang, T., & Gao, X. (2020). Adaptive Neural Sliding-Mode Controller for Alternative Control Strategies in Lower Limb Rehabilitation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *28*(1), 238–247. https://doi.org/10.1109/TNSRE.2019.2946407

Yozbatiran, N., & Francisco, G. E. (2019). Robot-assisted Therapy for the Upper Limb after Cervical Spinal Cord Injury. *Physical Medicine and Rehabilitation Clinics of North America*, *30*(2), 367–384. https://doi.org/10.1016/j.pmr.2018.12.008

Zhang, M., Xie, S. Q., Li, X., Zhu, G., Meng, W., Huang, X., & Veale, A. J. (2017). Adaptive patient-cooperative control of a compliant ankle rehabilitation robot (CARR) with enhanced training safety. *IEEE Transactions on Industrial Electronics*, *65*(2), 1398–1407. https://doi.org/10.1109/TIE.2017.2733425