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

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**ABSTRACT**

The rapid increase of the elderly population and chronic diseases have augmented disability in today's world. This situation 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. Nowadays, artificial intelligence techniques have been applied to improve the performance of these technologies. This article shows 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 Falls Efficacy Scale (FES). Three ML algorithms were applied K-Nearest Neighbors (KNN), Decision tree, and Support Vector Machine (SVM). Results show the accuracy of classification over 95%, 99%, and 89%, respectively, and validate the correlation between qualitative scales and biomechanical responses in balance training. This classifier poses as an innovative tool to help professionals adjust and improve 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 around the world have some type of disability. Being a growing figure, attributed to the aging of the population and the increase in chronic diseases (“OMS | Discapacidad y rehabilitación,” n.d.). Where, balance and postural control are some of the main skills affected by aging, neuromotor diseases, or traumas at the motor level.

On the other hand, the diagnosis, training, and balance rehabilitation processes use evaluation methodologies 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, their result tends to be subjective and depends on the experience of the evaluator.

In order to obtain a more efficient and reliable process, novel training programs have been generated (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 to 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 help to clarify the impact that robotics brings to this type of task and mitigate 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), Electroencephalogram (EEG)(Venkata Phanikrishna, Jaya Prakash, & Suchismitha, 2021), and COP to classify, monitor, and assist training and rehabilitation programs to improve the user's performance.

Based on state of the art and current trends in intelligence and machine learning algorithms. This article presents the development of an automatic classification system for IPAQ and FES, utilizing 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, FES, and even detect the characteristics of the surface on which the training is carried out (stable and unstable surface), through the quantitative analysis of signals typical of COP of a user and anthropometric measurements.

This article deals mainly with the development of the classifier system. Starting with the selection and processing of the features extracted from the stabilometry signals and anthropometric measurements. 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 are effective in high dimensional space tasks, even in cases where the number of dimensions is greater than the number of samples, KNN as a non-parametric method is helpful in tasks where decision boundaries are not regular, and decision trees are perfect to handle multi-output problems (Pedregosa et al., 2011). Finally, the precision, F1-score, and recall results of the three techniques used are presented.

## MATERIALS AND METHODS

For the design of the physical activity classifier, the database described in (Santos & Duarte, 2016), was used, this database consists of information from 1930 tests performed by 163 subjects. For data capture, the participants maintained a stationary standing position for 60s in four different situations: eyes open or closed while standing on a stable or unstable surface. Each condition was tested three times. The experimental setup is shown in Fig. 1.

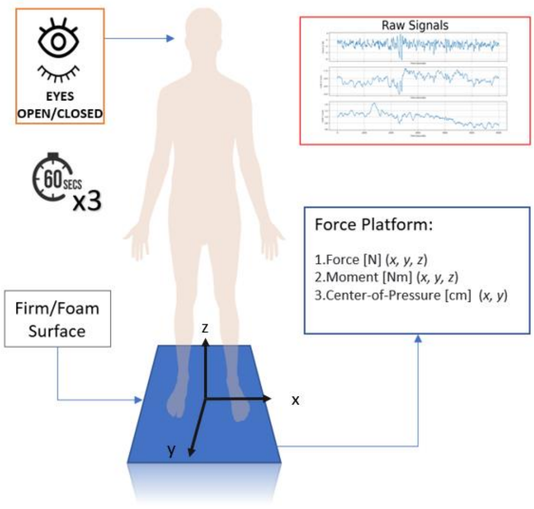



**Figure 1**. Experimental Setup

Through a force platform 8 different signals are captured:

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 the following qualitative evaluations of physical activity indices and balance of the participants:

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

The classifier only includes the 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 process 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). Since it is not known whether the acquisition instruments do not have a constant calibration for each test, the mean signal level of each sample is eliminated by subtracting a polynomial of degree six that models the behavior of each signal. Fig. 2 shows the process described above using the data from the force on the Y-axis.

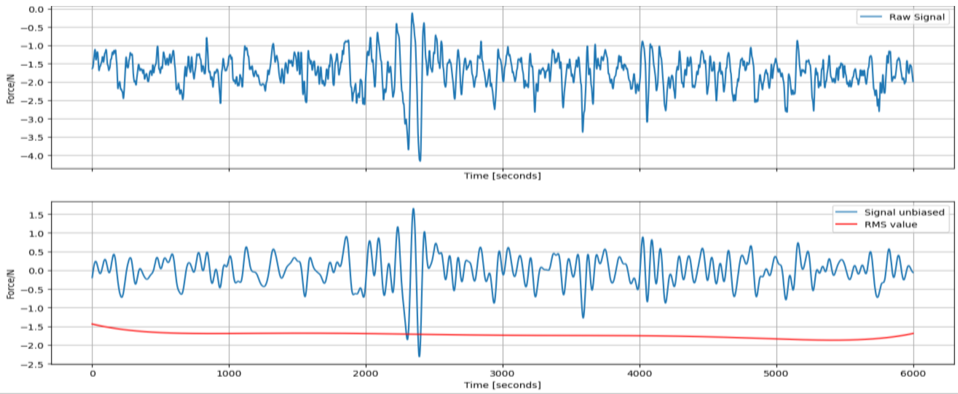



**Figure 2.** Signal processing

## Features selection

The features extracted from the signals were obtained from the categories stated in Table I. These are some of the most recurrent to analyze the behavior of the COP of an individual

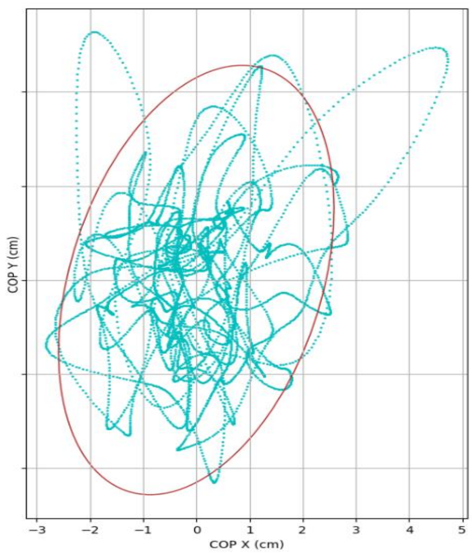
(Brouwer et al., 2019; Doyle et al., 2007; Yamamoto et al., 2015). Kinematic and statistical estimators to each of the database signals were applied as well as anthropometric measurements of the test subject.

A total of 85 features, usually determined in the postural control and stabilometry analyzes(Paillard & Noé, 2015; Yamamoto et al., 2015), were extracted by combining the categories stated in table 1. Measurements such as maximum displacement, maximum frequency, mean amplitude, area of the COP, the maximum length in each axis of excursion, maximum force in each axis, root mean square in each axis of displacement, and mean displacement angle. In turn, anthropometric variables directly involved with the various balance mechanisms of the human body were incorporated: body mass index, weight, foot length, and height of the individuals.

**Table 1.** feature extraction categories

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

Values within the 95% confidence ellipse area were used to eliminate abnormal values product of disturbances during data capture. The calculation of this estimator was performed as



described (Doyle et al., 2007); at the same time, angle and maximum amplitudes corresponding to the area described by the subject's movement were extracted. Fig. 3.

**Figure 3**. 95% confidence ellipse area

**Physical activity index classifier**

To determine the IPAQ, FES, and the surface of the experiment, the data were filtered, scaled, and normalized, using only healthy subjects (without any reported disease). A total of 648 observations with 85 features were used. 80% of the data were for the training process, and the remaining 20% for algorithm validation. Data from participants were used either in the training or testing set only.

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

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

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

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

On the other hand, statistical analysis using ANOVA, F-value, and p-value were implemented to select the most relevant features for each algorithm. These show the statistical significance of the independent versus dependent variables, and they are commonly used in problems where the input data is numeric and the output variable is categorical.

## Classification algorithms

The classification algorithms selected to determine the desired outputs were KNN, Decision Trees, and SVM. The operating parameters of each one are presented in Table 2.

**Table 2.** Classification parameters

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

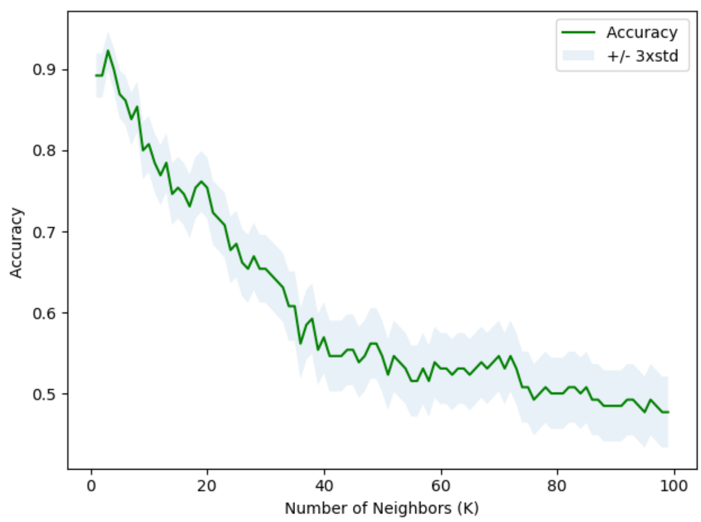


**Figure 4.** Best K for KNN and standard deviation accuracy

The search criteria for the decision tree was entropy since it aims to eliminate the heterogeneity of the elements that are located in each section of the tree. A search depth of 30 was used due to the large number of features extracted.

As in the KNN algorithm, the SVM estimator was constructed as a multiclass one, evaluating various combinations of parameters 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 extracted from applying the different ML techniques to the testing set. The evaluation of the designed classifier was firstly carried out considering the 85 features extracted. Using (2), the results obtained are shown in Table 3, to try 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), 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 evaluating IPAQ and the type of Surface, however, in the evaluation of the FES the anthropometric features of the individual showed greater significance compared to the biomechanical variables. This validates the initial hypothesis of the possibility of classifying an individual according to quantitative variables. The Main 5 features for each outcome are shown 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 found for each outcome, the precision of the classifier was again evaluated for each technique. Table 5 shows 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 allowed to improve the average precision of the KNN classifiers from 89.6% to 95.6% and SVM from 83.3% to 89.3%, considering their performance estimating IPAQ, FES, and Surface.

The Decision Tree registered an increase in the prediction of the FES, however, it registered a slight decrease when predicting the surface of the experiment. This suggests that the algorithm needs all the 85 extracted features to be able to achieve the highest precision.

Finally, (2) and (3) were replaced in (1) to the evaluation of the F1-Score. Performance results of the classifier are shown in Table 6 and the average performance of the classifiers throughout the different validations of the IPAQ, FES, and Surface 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 idea of using COP as a direct measurement of the physical activity status. In addition, these results over 95% are comparable with other studies that applied direct measures of the human being 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 IPAQ and FES.

Of note, these results are comparable with the study of Liao et al.(Liao, Wu, Wei, Chou, & Chang, 2021), where they used the same database selected for this article to the analysis of COP signals by using decision tree and empirical mode decomposition to predict falls among older adults. Therefore, this supports ML and COP measures to classify physical activity conditions.

Finally, The biomechanical variables extracted from the COP showed a direct correlation with the type of surface where the standing experiment was performed. Although this was a predictable result, it served to corroborate the design of the classifiers and highlight the ability of these techniques to find correlations in features where they are difficult to observe with the naked eye, even by highly trained personnel (therapists, physiatrists, trainers, etc. others). The main limitation with the classifier developed is related to the database. Although the data recollection is stated in the study protocol (Santos & Duarte, 2016), it may have biases and confounders that may affect the data's generalizability to other populations.

## CONCLUSION

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

For its part, This system shows the possibility of using similar solutions to support the processes of diagnosis and evaluation of physical activity by specialized personnel. The integration of this classifier to the assistive robotics system for balance training presented in (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.

Future works intend to compile a database of healthy subjects during the execution of dynamic exercises (eg Limits of stability, reaching exercises), to find the correlation of the variables extracted by the classifier and the performance of the user in certain balance training. This would help evaluators to adjust or validate procedures in clinical settings.

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