SPORT TK-EuroAmerican Journal of Sport Sciences

https://revistas.um.es/sportk Online ISSN: 2340-8812
Received: **15/01/2023.** Accepted: **30/03/2023.** Published: **24/06/2023**

Fall risk detection mechanism in the elderly, based on electromyographic signals, through the use of artificial intelligence

Leónidas Arias-Poblete[1], Sebastián Álvarez-Arangua[1], Daniel Jerez-Mayorga[1,2], Claudio Chamorro[1], Paloma Ferrero-Hernández[3], Gerson Ferrari[4,5], Claudio Farías-Valenzuela[6*]

[1] Exercise and Rehabilitation Sciences Institute, School of Physical Therapy, Faculty of Rehabilitation Sciences, Universidad Andres Bello, Santiago, 7591538, Chile.

[2] Strength & Conditioning Laboratory, CTS-642 Research Group, Department Physical Education and Sports, Faculty of Sport Sciences, University of Granada, Granada, Spain.

[3] Facultad de Educación y Cultura, Universidad SEK, Santiago 7520318, Chile.

[4] Facultad de Ciencias de la Salud, Universidad Autónoma de Chile, Providencia 7500912, Chile.

[5] Sciences of Physical Activity, Sports and Health School, University of Santiago of Chile (USACH), Santiago 9170022, Chile.

[6] Instituto del Deporte, Universidad de Las Américas, Santiago 9170022, Chile.

* Correspondence: Claudio Farías-Valenzuela; cfaria46@edu.udla.cl

ABSTRACT

Introduction: The tests used to classify older adults at risk of falls are questioned in literature. Tools from the field of artificial intelligence are an alternative to classify older adults more precisely. **Objective:** To identify the risk of falls in the elderly through electromyographic signals of the lower limb, using tools from the field of artificial intelligence. **Methods:** A descriptive study design was used. The unit of analysis was made up of 32 older adults (16 with and 16 without risk of falls). The electrical activity of the lower limb muscles was recorded during the functional walking gesture. The cycles obtained were divided into training and validation sets, and then from the amplitude variable, select attributes using the Weka software. Finally, the Support Vector Machines (SVM) classifier was implemented. **Results:** A classifier of two classes (elderly adults with and without risk of falls) based on SVM was built, whose performance was: Kappa index 0.97 (almost perfect agreement strength), sensitivity 97%, specificity 100%. **Conclusions:** The SVM artificial intelligence technique applied to the analysis of lower limb electromyographic signals during walking can be considered a precision tool of diagnostic, monitoring and follow-up for older adults with and without risk of falls.

KEYWORDS: Older adults; Fall risk; Gait; Electromyography; Support vector machines

1. INTRODUCTION

A frequent problem in the growing population of older adults are falls, which can be defined as the occurrence of an involuntary event that inadvertently causes the patient to reach the ground or to a lower level than where they were (González et al., 2001). The global prevalence of falls in the elderly is 26.5%, where the highest prevalence rate is related to the continents of Oceania and America with 34.4% and 27.9% respectively (Salari et al., 2022). These events generally occur during locomotion, that is, in dynamic or postural transition conditions that involve single-leg support and weight transfer (Yack & Berger, 1993). It has been reported that there is a direct relationship between age and the probability of falling (Tinetti & Williams, 1997), which leads to the need of understanding that other variables are correlated with this event, in order to guide public policies towards those conditions that increase this possibility, even more if we consider that in Chile the tests used to classify older adults at risk of falls are: Timed up and Go (TUG) and single-leg station (López et al., 2010), whose variability cut-off points and poor psychometric properties question its usefulness (Beauchet et al., 2011; González et al., 2001; Rydwik et al., 2011; Schoene et al., 2013).

In this context, studies have found that the main cause of falls was stumbling (59%) for both men and women, followed by slipping (25%), and that these occurred mainly in winter and autumn, with a percentage of 34% and 25%, respectively. On the other hand, it is estimated that between 62% and 70% of falls occur during locomotion (Berg et al., 1997; Cali & Kiel, 1995; Norton et al., 1997), establishing that there are certain characteristics in the gait pattern that may be related to fall events. Several researchers have searched for the existence of this relationship (Kyrdalen et al., 2019; MacAulay et al., 2022; Menz et al., 2003; Ronthal, 2019), where it has been reported that older adults that are more likely to fall present a slower gait and with irregularities in their cadence compared to older adults with less probability of falling. In a prospective study carried out in female older adults, it was found that some sensorimotor aspects such as decrease in visual acuity, quadriceps strength, vestibular performance, tactile sensation, vibratory sensation, reaction time and balance are predictors of alterations in space parameters of marching. In addition, it was reported that the women who fell two or more times during the study period presented a significant increase in the stance phase during a gait cycle and a significantly lower and variable cadence than those women who fell only once or did not fall (Lord et al., 1996).

When evaluating the role of the musculature in the event of a fall, it has been studied that sarcopenia is a characteristic of biological aging, which represents the progressive loss of mass, quality and strength of skeletal muscle (Bijlsma et al., 2013; Yeung et al. al., 2019). In this context, its serious consequences on the health status of older adults involve loss of functionality, dependency, and falls (Landi et al., 2012; Lauretani et al., 2003). If studies based on the prediction of skeletal appendicular muscle mass are considered in anthropometric measurements of older adults, it is possible to establish that one of the research focuses is muscle; however, only structural aspects are considered (Lera et al., 2014). In this line, if we consider that muscle tissue plays a role in the event of falling (Yeung et al., 2019), it is important to evaluate different dimensions of this element, establishing its function as the focus of study in the present investigation. Under this paradigm, electromyography (EMG) allows us to evaluate the electrophysiological activity of the muscle under different conditions, including dynamic activities such as walking (Agostini et al., 2010; Frigo & Crenna, 2009; Papagiannis et al., 2019), gesture that, according to the aforehead mentioned, represents more than 60% of the instances in which an older adult falls (Cali & Kiel, 1995; Norton et al., 1997).

The early identification of the risk of falls in the elderly population offers the opportunity for its prevention, therefore, the search for new techniques that allow users to be classified efficiently at risk of falls would optimize the process. In this context, tools from the field of artificial intelligence such as neural networks (NN) have been used to establish differences between classes of data (Kriegeskorte & Golan, 2019); however, other techniques derived from the Artificial intelligence such as SVM have been currently proven to be a powerful tool for data learning and solving classification and regression problems with a superior classification performance (Wang et al., 2022). Unlike NN, SVM find an optimal separation hyperplane that provides superior generalization capability, especially when the dimension of the input data is high and the number of observations available for model development or training is limited (Zavaljevski et al., 2002). Considering the aforementioned background, this research proposes using SVM for the automatic recognition of the condition of older adults with and without risk of falls. That tool uses as a substrate the attributes derived from the statistical properties of the EMG signal, which was collected from the electrical activity of the lower limb muscles, under a functional context such as walking. The aim of this study was to identify the risk of falls in older adults through electromyographic signals of the lower limb, using tools from the field of artificial intelligence.

2. METHODS

2.1. Design

This study presents a descriptive cross-sectional study design.

2.2. Participants

The participating subjects were 32 older adults, 16 at risk of falls (mean age 71 years, ± 2.73) and 16 without risk of falls (mean age 72 years, ± 2.24), who lived in the community and they were enrolled in a public health center in the Metropolitan Region, Santiago of Chile. The inclusion criteria were having between 65 and 79 years old at the time of the evaluation, having an independent gait and a normal body mass index (under 24.9). The exclusion criteria consisted of presenting a recent history of musculoskeletal injuries such as fractures or sprains in an interval time of 1 year prior to the study, or residual anomalies from fractures or sprains in the past (declared by the user and/or detected by the evaluator), exhibiting uncorrected visual function disorders, vestibular health conditions, obesity, malnutrition, using of technical aids for walking (cane, walker, among others). Based on the above, the elements that differentiated the group without risk of falls from the subjects with risk of falls, is that the latter had altered static and dynamic balance, that is, they presented ≤4 seconds in the single-leg station and ≥15 seconds in the TUG (López et al., 2010). Additionally, to be classified in this group, they had to have a history of falls in the last year. Both the study protocol and the informed consent were approved by the research ethics committee of the Metropolitan University of Educational Sciences (UMCE), complying with the requirements and ethical protocols for research on human beings established in Law 20,120.

2.3. Data acquisition systems

Electromyographic activity was recorded by Delsys equipment, Bagnoli-16 EMG System, which was connected to a National Instrument acquisition card (NI USB-6259), which allowed the analog-digital conversion of the recorded data. Additionally, a synchronizer was used for the connection of the pressure sensor (Figure 1), which contributes to detect the beginning and end of each gait cycle (Frigo & Crenna, 2009), sending a signal during heel contact. The collection was carried out as follows: signal amplification (x1000), filtered (20-450 Hz) and sampled at 2 kHz.

Figure 1. Experimental setup for data recording

2.4. Measurement protocol

Each participant was asked to attend with comfortable clothes (shorts and t-shirt). Before carrying out the test, they had to read and accept the informed consent, which briefly explained what the study consisted of and its possible risks. Subsequently, each participant was prepared, proceeding to the location of the 7 electrodes for electromyographic data collection, the pressure sensor to be able to define the beginning of each gait cycle and the anchoring system at the thorax level, where the module that connects the electrodes to the electromyograph was located. The surface electrodes were placed according to the recommendations of the SENIAM (SENIAM., 2020) in the following muscles: gluteus medius, rectus femoris, vastus medialis, biceps femoris, tibialis anterior, gastrocnemius lateralis, and soleus. It is important to note that each muscle was registered only in the dominant lower limb. On the other hand, each of these corresponds to a channel within the electromyograph that was the same for all measurements. In addition, an additional channel was used for the pressure sensor. The choice of these muscles was decided in accordance with the recommendation of the literature (Frigo & Crenna, 2009), which states that an electromyographic gait study will be more valid if at least one muscle is evaluated both anteriorly and posteriorly of the thigh as of the leg, as well as muscles involved in the hip such as the gluteus medius. Finally, the walking test consisted of walking in a straight line for a distance of 10 meters on a flat surface, where the instructions to the participants were as follows:

- Remain standing in the area marked as the start of the walking test.
- Walk as normal as possible, as you usually do.
- Start with the dominant foot.

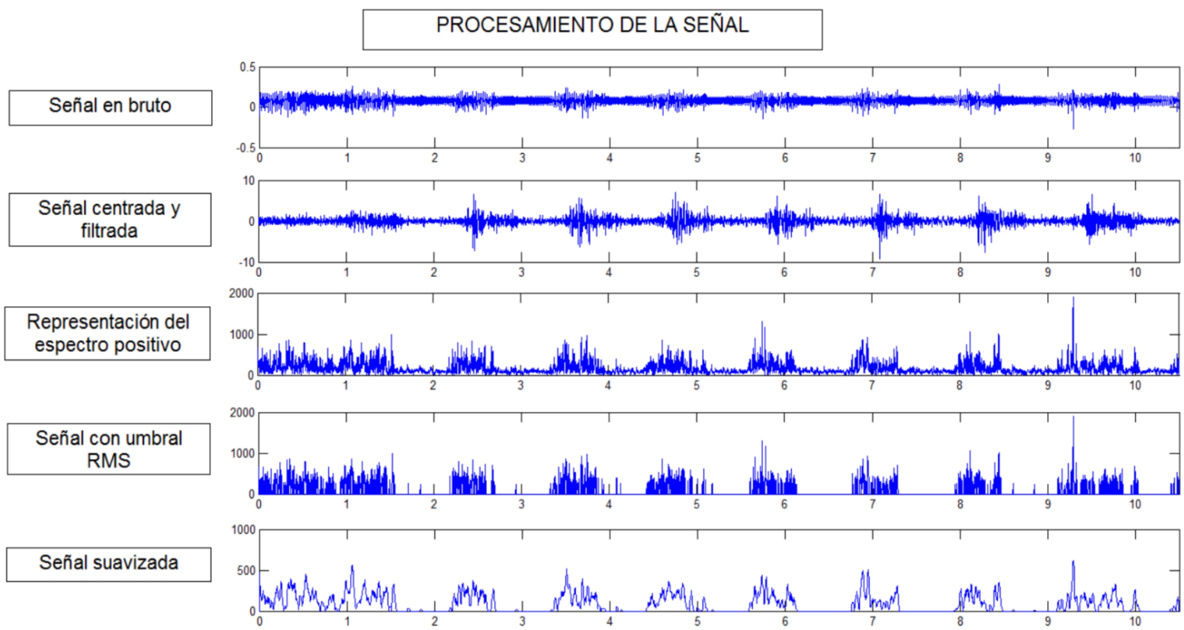
Four records were made, the first of these was an adaptation test, while the other three were valid.

2.5. Signal processing systems

The processing was carried out with the MatLab© software version 7.10.0, through the following protocol:

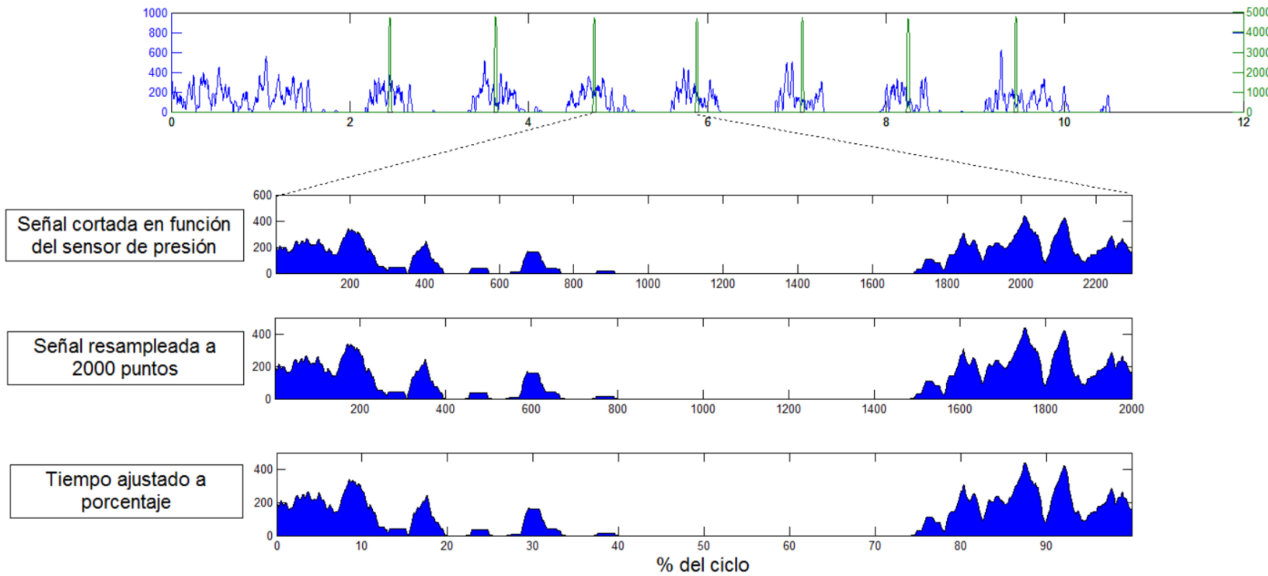
The first thing that was done to all the signals was filtering by Independent Component Analysis (ICA) using the FastICA 7 algorithm. Subsequently, the Hilbert transformation was applied, representing only the positive spectrum of the signal. Then, the Root Mean Square (RMS) of each signal was obtained, establishing the muscle activation threshold with said value (Tapia et al., 2017). Finally, smoothing with a moving average was applied, with the objective of leveling the amplitude peaks (Figure 2).

Figure 2. Initial processing of the electromyographic signal



Next, each of the EMG signals was cut according to the spikes generated by the pressure sensor, in order to obtain gait cycles independently. Once the cycles were established, they were resampled to 2000 points, with the objective of representing each data set as a coefficient (expressed as a percentage) relative to the reference value of the march gesture, which ranges from 0 to 100% (Figure 3).

Figure 3. Identification of gait cycles



**Note: In the upper portion of the image, the green vertical line represents the spike generated by the pressure sensor, whose function is to delimit each of the cycles of the functional gesture gait.*

2.5.1. Obtaining training and validation data sets

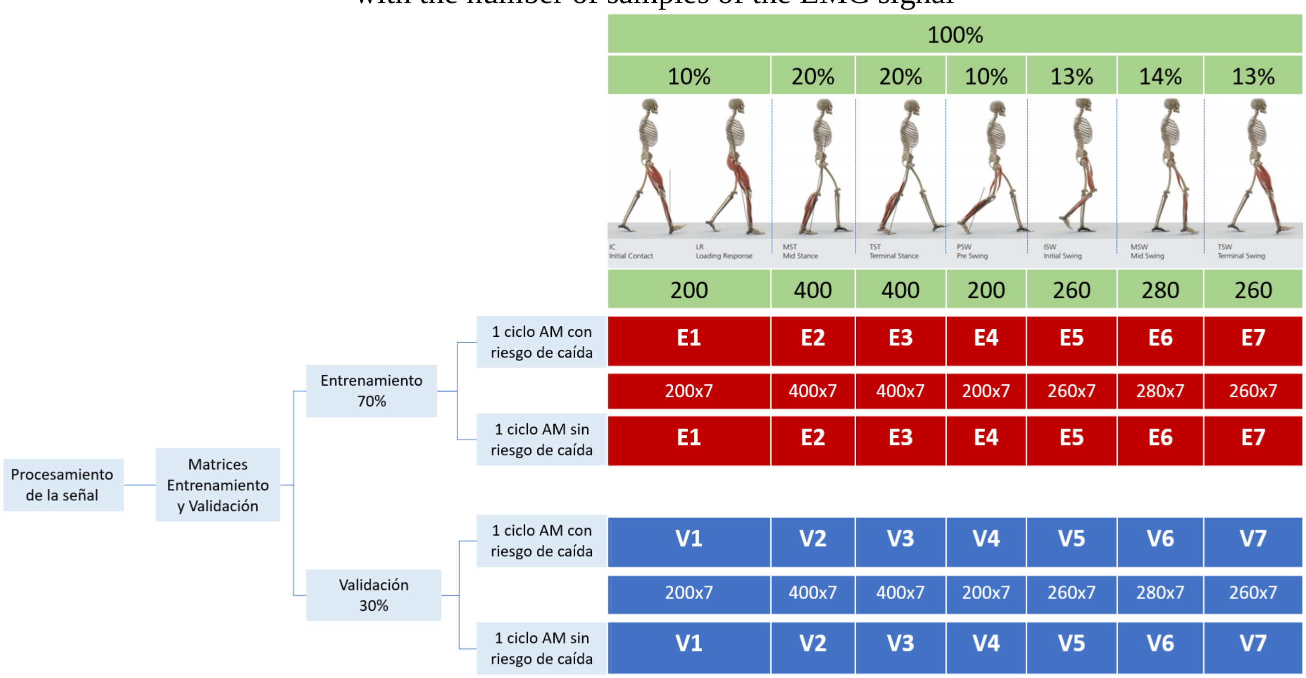
Although seven cycles were obtained in each record, the first and last ones were eliminated as they were considered to be acceleration and deceleration respectively, only the central cycles were used for the present study (five cycles per record). Once at this stage we proceeded as follows:

- Considering that three valid records were made per participant, the 15 cycles obtained were averaged, generating only one representative cycle for each subject under study.
- If we consider that the study participants were 32, 16 cycles were obtained for the group with risk of falls and 16 cycles for the group without risk of falls.
- The representative cycles of the 32 participants were divided into two data sets, training (70%) and validation (30%); therefore, the data set called training was made up of 22 cycles (11 for subjects at risk of falls and 11 for subjects without risk of falls). While the validation data set was made up of 10 cycles (5 of subjects with risk of falls and 5 of subjects without risk of falls).

Only two cycles were obtained from each data set. For example, for training, one representative cycle of the group with risk of falls and another representative of the group without risk of falls were obtained. For such purposes, the 11 cycles of the group with and without risk of falls were averaged, as appropriate. Subsequently, each cycle was subdivided according to the phases (support and oscillation) and sub-phases of the gait proposed by Jacquelin Perry (2010): Response to the Load (E1), Medium Support (E2), Final Support (E3), Previous Oscillation (E4), Initial Oscillation (E5), Medium

Oscillation (E6) and Final Oscillation (E7), which from now on will be called stages. Although Perry (2010) proposes an Initial Contact stage (0-2% of the cycle), this was not considered in the present data analysis, since the Charge Response stage (0-10%) contains the previous. Therefore, the stages E1, E2, E3, E4, E5, E6 and E7 were obtained for the representative cycle of older adults with risk of falls, as well as for the representative cycle of older adults without risk of falls in both the group training, as well as the validation group. The extension of each stage results from the proportional relationship between the total number of samples in the cycle, which is 2000, and the percentage extension of each stage, therefore, stage E1 has 200 samples, E2 400, and so on. In the *nxm* matrix nomenclature, it is possible to establish that *n* varies according to the stage of the gait cycle that is being evaluated; however, *m* is 7, since it is the number of muscles that were evaluated. Therefore, each stage is constituted as shown in Figure 4.

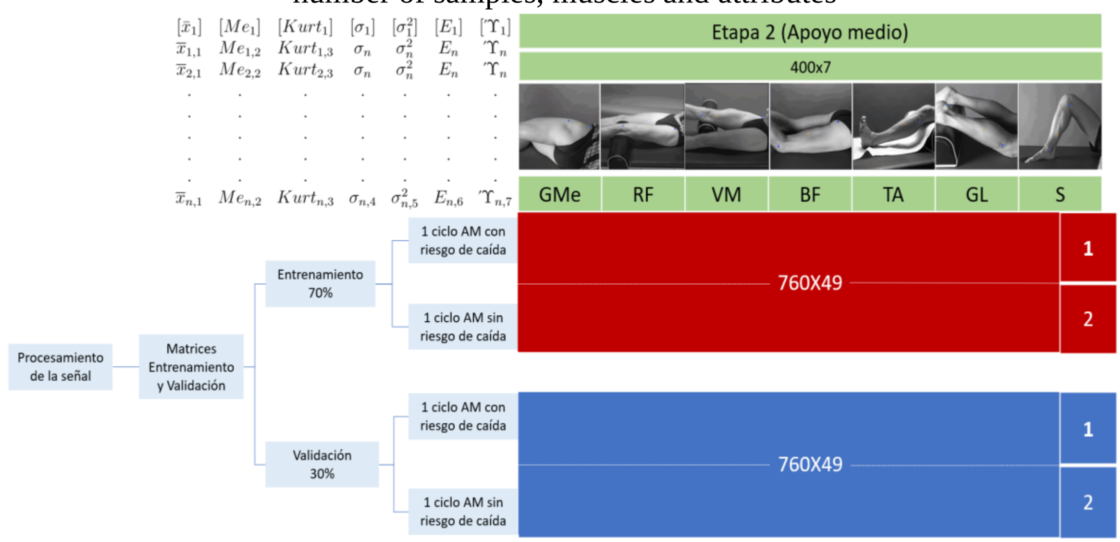
Figure 4. Representation of the stages into which the gait cycle was divided and its correspondence with the number of samples of the EMG signal



**Note: The letters E and V refer to the training and validation groups respectively, while the numbers that accompany each letter (E and V) relate to the stages of the gait cycle.*

Considering that the input variable of the electromyographic signal in the time domain was the amplitude, and from this the characteristics or attributes were extracted: Mean, Median, Kurtosis, Standard Deviation, Variance, Energy and Skew, we proceeded with the processing of each stage. For example, for stage 2 (E2 - medium support), the attributes of the amplitude variable were calculated for each muscle, with a mobile window of 20 points, where, according to what was previously indicated, the attributes studied were 7, so thus, each muscle was transformed into a *nx7* array. Then stage E2 became a 380x49 matrix, where 380 is the number of points in the stage, minus the size of the moving window, while 49 is the result of the number of muscles times the number of attributes. Subsequently, we proceeded to concatenate the matrices of the group without risk of falls, with its simile of the group with risk of falls, both for the training data set and for the validation data set. Example: stage E2 of the group with risk of falls from training, was concatenated with stage E2 of the group without risk of falls from the same data set, configuring a 760x49 matrix. Additionally, a column containing 380 rows with numbers 1 and 380 rows with numbers 2 was added. This step aimed to differentiate the data classes of the groups without and with risk of falls, respectively. In matrix nomenclature and in terms of processing, this action is expressed in Figure 5.

Figure 5. Analysis in matrix nomenclature, of the conversion of the E2 stage, according to the number of samples, muscles and attributes

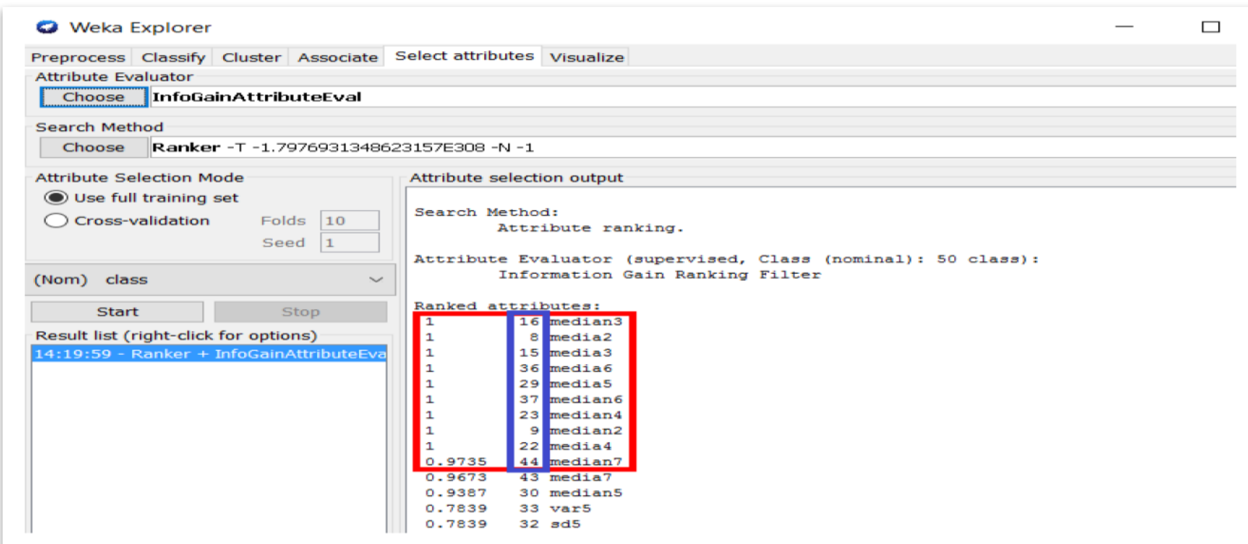


**Note: The nomenclature associated with the muscles is associated with the following: GMe (Gluteus Medius), RF (Rectus Femoris), VM (Vastus Medialis), BF (Biceps Femoris), TA (Anterior Tibial), GL (Lateral Gastrocnemius), S (Soleus).*

2.5.2. Attribute analysis in Weka software

The analysis of the matrices for the training and validation data set was performed in the Weka 3.6 software (Hall, 2009). In the first place, a selection of attributes was carried out, with the objective of avoiding the addition of irrelevant parameters for the classification, a procedure that was carried out in the following way: each stage of the training was subjected to an attribute selector, which for the present investigation was InfoGainAttributeEval. Then, the search method was chosen: Ranker. Subsequently, heuristically, the first 10 attributes (according to ranking) were chosen for each of the stages. An example of the visual interface offered by Weka, which allowed choosing the number of previously declared attributes, is presented in figure 6, where the selection of attributes from stage 1 of the training data set is observed. The 10 selected attributes can be clearly visualized, since they are demarcated in a red box. Within this demarcation, it can be seen to which muscles they belong, since if we consider that the attributes 1-7, 8-14, 15-21, 22-28, 29-35, 36-42, 43-49 (blue box) correspond to the gluteus medius, biceps femoris, gastrocnemius lateral, soleus, rectus femoris, vastus medialis and tibialis anterior muscles respectively. Then, we can ponder which muscle contributes the most to class differentiation and additionally, with what attribute it contributes to such differentiation. It is important to mention that this process was only carried out in the training data set, since the selection of attributes in the validation set was carried out based on what was previously obtained.

Figure 6. Visual interface of attribute selection in WEKA



Once the attributes of each stage were selected, both from the training and validation data sets, the SVM-based classifier was implemented. In the context of evaluating its performance, the confusion matrix was used, which, through a contingency table, allowed statistical measures such as the Kappa index, sensitivity and specificity to be extracted. Finally, SVM was compared with other classifiers (NaiveBayes, J48, Hyper-Pipes and ConjunctiveRule), using the same training and validation sets, whose statistical comparison measures were those mentioned in the previous point.

3. RESULTS

The presentation of the results was divided into three items:

- Contribution of the attributes and muscles to the differentiation of older adults with and without risk of falls.
- Performance of the SVM classifier.
- Comparison of the SVM classifier with other supervised learning modalities.

The above has the objective of analyzing the potential of the results in detail, considering the various aspects that could contribute to replicating this fall risk prediction methodology.

3.1. Contribution of attributes and muscles to the differentiation of older adults with and without risk of falls

In order to classify the electrophysiological signals from older adults with risk of falls and those without risk of falls, the attributes that differentiate both classes were identified. Considering these elements, the 10 attributes (according to ranking) evaluated in each of the stages of the gait cycle are the following (Table 1):

Table 1. Differentiating attributes of older adults with and without risk of falls

Selection of attributes						
Support phase				**Wing phase**		
E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**
16 *Me*	15 $\bar{X}$	15 $\bar{X}$	1 $\bar{X}$	1 $\bar{X}$	4 σ	1 $\bar{X}$
22 $\bar{X}$	30 *Me*	16 *Me*	20 *E*	44 *Me*	27 *E*	23 *Me*
15 $\bar{X}$	27 *E*	27 *E*	26 σ^2	5 σ^2	26 σ^2	2 *Me*
36 $\bar{X}$	6 *E*	18 σ	22 $\bar{X}$	22 $\bar{X}$	44 *Me*	37 *Me*
8 $\bar{X}$	16 *Me*	5 σ^2	27 *E*	23 *Me*	23 *Me*	29 $\bar{X}$
44 *Me*	23 *Me*	23 *Me*	23 *Me*	4 σ	1 $\bar{X}$	22 $\bar{X}$
23 *Me*	36 $\bar{X}$	22 $\bar{X}$	25 σ	43 $\bar{X}$	9 *Me*	8 $\bar{X}$
9 *Me*	22 $\bar{X}$	26 σ^2	16 *Me*	27 *E*	43 $\bar{X}$	6 *E*
29 $\bar{X}$	26 σ^2	25 σ	15 $\bar{X}$	6 *E*	22	5 σ^2
37 *Me*	25 σ	12 σ^2	6 *E*	2 *Me*	2 *Me*	43 $\bar{X}$

**Note: The symbols and letters indicated in the table represent the following: $\bar{X}$:Mean; Me: Median; Kurt: Kurtosis; σ: Standard Deviation; σ^2: Variance; E: Energy; Y: Skew.*

Table 1 shows that for the support phase (stages E1, E2, E3 and E4), the percentage contribution of each of the attributes is the following: mean 32.5%, median 30%, energy 15%, variance 12.5%, standard deviation 10%, kurtosis 0% and skew 0%. Percentages resulting from the relationship established between the number of times an attribute is repeated *100, divided by the total number of attributes of the support phase, which in this case are 40. Example: the attribute called average is repeated 13 times during the support phase, therefore its percentage contribution would be $\frac{13*100}{40} =$ 32,5%.

By carrying out a similar analysis in the oscillation phase (stages E5, E6 and E7), it can be seeing that the percentage contribution of each of the attributes is the following: mean 36.66%, median 33.33%, energy 13, 33%, variance 10%, standard deviation 6.66%, kurtosis 0% and skew 0%. Percentages resulting from the relationship established between the number of times an attribute is repeated *100, divided by the total number of attributes of the oscillation phase, which in this case are 30.

If the mean and median attributes are considered, which are the ones that weigh the most in differentiating the classes of older adults with and without risk of falls, it can be seeing that the soleus and gastrocnemius muscles are the ones that contribute the most in this individualization of conditions raised, since on the one hand, the average attribute of the soleus (expressed in Table 2 as 22 average) is manifested in the 4 stages of the stance phase, while the median (expressed in Table 2 as 23 median), does so in the same number and type of stages. On the other hand, the gastrocnemius muscle has the same behavior in terms of its contribution. It is important to point out that both muscles not only contribute with the mean and median attributes, but also with the energy, variance and standard deviation attributes, with the soleus muscle being the one that stands out the most within this condition. Regarding the oscillation phase, it can be seen that the soleus, gluteus medius and tibialis anterior are the muscles that contribute the most to the identification of older adults at risk of falls compared to older adults without risk of falls, since the median attribute of the soleus manifests itself in the 3 stages of the oscillation phase, while the median does so in the same number and type of stages. On the other hand, the mean and median attributes of the gluteus medius (expressed in Table 1 as 1 mean and 2 median respectively) are expressed in the 3 stages of the oscillation phase. Finally, the mean and median of the tibialis anterior (43 mean and 44 median), manifest in 3 and 2 stages of the oscillation phase respectively. It is important to note that the gluteus medius is the only muscle that contributes with 5 different attributes to the differentiation of the classes.

3.2. Two-class classifier based on Support Vector Machines

Considering the training and validation groups, it was possible to build a classifier of two classes (older adults with risk of falls and without risk of falls) based on SVM, and in the context of evaluating their performance, statistical measures such as the Kappa index, sensitivity and specificity. This analysis was carried out for each of the phases of the gait cycle with their respective stages.

According to Table 2, it can be seen that the statistical measures that denote a decrease in the performance of the classifier are expressed in the final support stage (E3), particularly in sensitivity (87%) and in the Kappa index (0.85); however, despite the fact that the latter decreases below the value 1, it is still considered almost perfect according to the nomenclature of Landis & Koch (1977). Regarding the rest of the stages, the Kappa index is equal to 1, while the sensitivity and specificity are 100%.

Table 2. Performance Evaluation of the Support Vector Machine Classifier

	Gait cycle stages						
Statistical measure	E1	E2	E3	E4	E5	E6	E7
CCI (%)	100	100	92,76	100	100	100	100
ICI (%)	0	0	7,23	0	0	0	0
Kappa index	1	1	0,85	1	1	1	1
Sensitivity (%)	100	100	87	100	100	100	100
Specificity (%)	100	100	100	100	100	100	100

**Note: The acronyms CCI and ICI refer to the terms correctly classified instances and incorrectly classified instances, respectively.*

3.3. Comparison of the Support Vector Machine classifier with other supervised learning modalities

In order to evaluate the capacity of the SVM classifier, it was compared with the supervised learning modalities Naive-Bayes, J48, HyperPipes and ConjunctiveRule. Based on these elements, the analysis measures were: Kappa index, sensitivity and specificity.

In Table 3, it is established that all the classifiers present a weighted Kappa (KP) less than 1; however, the SVM classifier is the one that shows the best performance (KP=0.97), while in the second place is NaiveBayes (KP=0.84). It is important to note that if we analyze the classifiers by phase (support-oscillation), it can be seen that most of them decrease in value during the support phase (E1, E2, E3 and E4), especially in the medium support stages (E2) and final support (E3).

Table 3. Kappa Index Comparison for Classifiers: Support Vector Machine, NaiveBayes, J48, HyperPipes and ConjunctiveRule

	Gait cycle stages							
Classifiers	E1	E2	E3	E4	E5	E6	E7	KP
SVM	1	1	0,85	1	1	1	1	0,97
NaiveBayes	1	0,88	0,57	1	0,87	1	0,78	0,84
J48	0,83	0,71	0,58	0,93	1	1	1	0,83
HyperPipes	1	0,67	0,45	1	1	1	1	0,82
ConjunctiveRule	1	0,7	0,26	1	1	1	1	0,79

**Note: The weighted Kappa (KP) column refers to the contribution of each stage of the gait cycle to the total Kappa index.*

On the other hand, when evaluating the sensitivity of each classifier, it can be seen that the weighted sensitivity is over 90%, with a maximum of 97% (SVM) and a minimum of 93% (NaiveBayes). Additionally, it is possible to mention that the stage of the support phase that presents the lowest sensitivity is E3, with a range that goes from 87% to 71% (Table 4).

Table 4. Sensitivity Comparison for Classifiers: Support

Vector Machine, NaiveBayes, J48, HyperPipes and ConjunctiveRule

	Gait cycle stages							
Classifiers	E1	E2	E3	E4	E5	E6	E7	SP
SVM (%)	100	100	87	100	100	100	100	97
NaiveBayes (%)	100	100	77	100	100	100	82	93
J48 (%)	100	100	78	94	100	100	100	95
HyperPipes (%)	100	100	71	100	100	100	100	94
ConjunctiveRule (%)	100	100	77	100	100	100	100	95

**Note: The Weighted Sensitivity (SP) column refers to the contribution of each stage of the gait cycle to the total Sensitivity.*

In the context of evaluating the weighted specificity, it varies between 89% and 100% for the SVM and HyperPipes classifiers respectively. The stages of the gait cycle that express the lowest performance are E2 and E3, even reaching values below 70% (Table 5).

Table 5. Specificity Comparison for Classifiers: Support Vector Machine, NaiveBayes, J48, HyperPipes and ConjunctiveRule

	Gait cycle stages							
Classifiers	E1	E2	E3	E4	E5	E6	E7	EP
SVM	100%	100%	100%	100%	100%	100%	100%	100%
NaiveBayes	100%	88%	100%	100%	87%	100%	78%	92%
J48	83%	71%	88%	93%	100%	100%	100%	90%
HyperPipes	100%	67%	95%	100%	100%	100%	100%	89%
ConjunctiveRule	100%	70%	78%	100%	100%	100%	100%	91%

**Note: The Weighted Specificity (SP) column refers to the contribution of each stage of the gait cycle to the total specificity.*

4. DISCUSSION

Verification of the correctness of a rule is done by repeated comparison between the calculated, the observed results, and the development of a new basic rule, which can be done only by model searching that best fits the experiment. In most gait analyses, the application of both mechanical and statistical rules lacks the satisfaction of some required conditions. In the case of biomechanics, some values cannot be measured (for example, internal forces can only be estimated), due to the fact that the human body is not rigid, which is usually the assumption (De Groote & Falisse, 2021). Regarding statistics, each method was developed for a given experiment under certain conditions, therefore, the accuracy of the results is guaranteed only if the required conditions are given in accordance with the model of how the data was generated (Vapnik, 1995). In gait analysis, this model is a controversial point since the application of a statistical test of many different parameters without having any previous paradigm is incorrect, especially if we consider that the results of the tests are random values and some of them can be significant by chance. The aforementioned lack can be overcome by verifying the results, as is usually done, according to the basic rules of the sciences, where verification guarantees a lower error rate of any algorithm, regardless of whether it is statistical, mechanical or of some other kind (Hastie et al., 2009).

The evaluation of gait is legitimately a controversial topic, because the quality definition of this gesture is very subjective and depends on the context and the aim of the evaluation, especially if we associate it with the definition of an ideal gait pattern, which could vary markedly in different groups of patients. For example, a patient with an artificial limb will undoubtedly have to learn a different gait style compared to a patient with a calcaneal fracture. Some difficulties in finding general rules for gait evaluation may be caused by an effect that is well known in cognitive science, pattern recognition, and artificial intelligence, which is based on the fact that the information extracted from patterns depends on the point of view used. For example, analyzing the angular displacement of the knee in isolation can lead to completely different information than the observation of the entire gait pattern, even more if those variables that we are studying are not strongly related to the phenomenon to be investigated. This aspect was overcome in the present study, since the variables used come from muscle tissue, which, according to the literature, plays a relevant role in the event of falling (Landi et al., 2012), even more if we ponder that the musculature was evaluated in dynamic conditions such as walking, a gesture that represents a large percentage of the instances in which an older adult falls (Norton et al., 1997).

Another topic of interest is the selection algorithms, which can be used to extract essential characteristics of some pathology, allowing a more precise diagnosis. In this context, the fact of analyzing a large number of attributes associated with a gesture or pattern could result in a better approach as opposed to inferential statistical analysis, which is limited to examining individual characteristics. Lai et al (2009), in their study on automatic recognition of the gait pattern exhibited in users with patellofemoral dysfunction (PFD) by means of SVM, based on kinematic and kinetic characteristics, found that the latter had 85.15% classification accuracy versus 74.07% of the first. On the other hand, if an attribute selector is used, the accuracy percentage for classifying subjects with patellofemoral pain syndrome increases even more, reaching 88.89%. If we compare these results with those obtained in the present study, it can be observed that the SVM tool can successfully classify people with and without risk of falls, showing superior performance in relation to other classifiers. This is supported by the high value of statistical measures such as the Kappa index, sensitivity and specificity, as shown in tables 3, 4 and 5, respectively. If we analyze the performance of the SVM classifier separately, it can be seen that the weighted sensitivity (97%), weighted specificity (100%) and weighted Kappa index (0.97) are higher when an attribute selector is applied compared to use all the attributes, since for example through this last condition the sensitivity values fell to 89%, which tells us that there are characteristics that are irrelevant in the classification process, where more than enhancing this process, they tend to hinder it. In this line, defining criteria to choose the number of attributes that are going to represent the differentiation between two classes, conditions the values obtained in the previously exposed statistical measures.

If we evaluate the attributes that characterize the stages of the gait cycle and therefore contribute to differentiating the classes, we can observe that each muscle contributes differently to this end. For example, when analyzing Table 1, it can be seen that in the support phase (with its corresponding stages), only 2 muscles, soleus and gastrocnemius, contribute with 67.5% of the attributes. While in the swing phase, gluteus medius and soleus contribute with 70% of the attributes. Confirming the trend evidenced in the support phase, regarding the contribution of the soleus in the differentiation of the classes; however, this time the gluteus medius is added, to the detriment of the gastrocnemius.

These elements are encouraging from multiple perspectives, first of all, in the stance phase the muscles that contribute the most to the differentiation of the classes (soleus and lateral gastrocnemius) are those that have a high kinematic correlation with the phase that is being evaluated. On the other hand, only two muscles in each phase contribute with over 60% of the identification of the classes; therefore, in the context of designing an automatic fall risk detection system, based on attributes derived from the statistics properties of EMG signal, it could be enough to analyze the soleus, gastrocnemius and gluteus medius muscles during the gait cycle, which is enhanced by the high values of sensitivity, specificity and Kappa index, obtained with the SVM classifier.

Finally, when evaluating the tests currently used in Chile to select older adults at risk of falls, we found the TUG and the single-leg station, whose thresholds are ≤4 seconds and ≥15 seconds, respectively (López et al., 2010); however, when consulting the available literature, it is noted that there are no cut-off points that can be recommended (Schoene et al., 2013). This situation suggests that the different cultural and anthropometric realities play an important role when it comes to establish dichotomous criteria, in the discrimination of older adults with and without risk of falls. If we focus on the TUG, a considerable overlapping of times is reported between older adults with and without risk of falls (Beauchet et al., 2011; González et al., 2001; Rydwik et al., 2011; Schoene et al. , 2013), a condition that was manifested in the present study, where in order to avoid this bias, 3 participants willing to collaborate had to be excluded, because they did not meet all the inclusion criteria to be classified within the group without risk of falls, although they presented a time of <15 seconds in the TUG test, but they had a history of falls in the last 6 months. These elements confirm that the arbitrariness in the selection of cut-off points relativizes an optimal classification of older adults, therefore, the choice of variables from muscle tissue could be a good alternative to distinguish between older adults at risk of falls and those without risk of falls.

Among the strengths of this research, the data processing methodology can be mentioned, since it contributes to the least possible loss of information. Moreover, it contributes to an adequate characterization of the attributes for each phase and stage of the gait cycle. When evaluating the weaknesses, these are mainly related to the reduced unit of analysis, an aspect that affects the formation of the training and validation groups for the construction of the classifier. Finally, it is important to point out that, although it is not feasible to have an electromyograph in each health center, the present data processing methodology could be used, adding an adequate sample size calculation (representative of older adults living in the community), to redefine the cut-off points of the tests used in the evaluation of falls risk, being able to establish a timely referral plan that prevents further functional deterioration of the elderly. This last aspect is of vital importance for the development of public health policies, which could determine a greater emphasis on the intervention of the event of falling by a qualified professional from the movement study area.

5. CONCLUSION

The SVM artificial intelligence technique, applied to the analysis of lower limb electromyographic signals during walking, can be considered as a precision tool for the diagnostic, monitoring and follow-up of older adults with and without risk of falls, which is based on the high values of their psychometric properties (sensitivity, specificity and Kappa index) at the time of classification.

6. REFERENCES

1. Agostini, V., Nascimbeni, A., Gaffuri, A., Imazio, P., Benedetti, M., & Knaflitz, M. (2010). Normative EMG activation patterns of school-age children during gait. *Gait & posture, 32*(3), 285-289.
2. Beauchet, O., Fantino, B., Allali, G., Muir, S., Montero-Odasso, M., & Annweiler, C. (2011). Timed Up and Go test and risk of falls in older adults: a systematic review. *The journal of nutrition, health & aging, 15*(10), 933-938.
3. Berg, W. P., Alessio, H. M., Mills, E. M., & Tong, C. (1997). Circumstances and consequences of falls in independent community-dwelling older adults. *Age and ageing, 26*(4), 261-268.
4. Bijlsma, A., Meskers, C., Ling, C., Narici, M., Kurrle, S., Cameron, I., Westendorp, R., & Maier, A. (2013). Defining sarcopenia: the impact of different diagnostic criteria on the prevalence of sarcopenia in a large middle aged cohort. *Age, 35*(3), 871-881.

5. Cali, C. M., & Kiel, D. P. (1995). An epidemiologic study of fall-related fractures among institutionalized older people. *Journal of the American Geriatrics Society, 43*(12), 1336-1340.
6. De Groote, F., & Falisse, A. (2021). Perspective on musculoskeletal modelling and predictive simulations of human movement to assess the neuromechanics of gait. *Proceedings. Biological sciences*, *288*(1946), 20202432. https://doi.org/10.1098/rspb.2020.2432
7. Frigo, C., & Crenna, P. (2009). Multichannel SEMG in clinical gait analysis: a review and state-of-the-art. *Clinical Biomechanics*, *24*(3), 236-245.
8. González, G., Marín, P. P., & Pereira, G. (2001). Características de las caídas en el adulto mayor que vive en la comunidad. *Revista médica de Chile, 129*(9), 1021-1030.
9. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., & Witten, I. H. . (2009). The WEKA data mining software: an update. *ACM SIGKDD explorations, newsletter, 11(1), 10-18.*
10. Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: data mining, inference, and prediction.* Springer series in statistics. Springer New York.
11. Jacquelin Perry, M. (2010). *Gait analysis: normal and pathological function.* New Jersey: SLACK.
12. Kyrdalen, I. L., Thingstad, P., Sandvik, L., & Ormstad, H. (2019). Associations between gait speed and well-known fall risk factors among community-dwelling older adults. *Physiotherapy research international: the journal for researchers and clinicians in physical therapy*, *24*(1), e1743. https://doi.org/10.1002/pri.1743
13. Lai, D. T., Levinger, P., Begg, R. K., Gilleard, W. L., & Palaniswami, M. (2009). Automatic recognition of gait patterns exhibiting patellofemoral pain syndrome using a support vector machine approach. *IEEE Transactions on Information Technology in Biomedicine, 13*(5), 810-817.
14. Landi, F., Liperoti, R., Russo, A., Giovannini, S., Tosato, M., Capoluongo, E., Bernabei, R., & Onder, G. (2012). Sarcopenia as a risk factor for falls in elderly individuals: results from the ilSIRENTE study. *Clinical nutrition, 31*(5), 652-658.
15. Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 159-174.
16. Lauretani, F., Russo, C. R., Bandinelli, S., Bartali, B., Cavazzini, C., Di Iorio, A., Corsi, A. M., Rantanen, T., Guralnik, J. M., & Ferrucci, L. (2003). Age-associated changes in skeletal muscles and their effect on mobility: an operational diagnosis of sarcopenia. *Journal of applied physiology*, *95*(5), 1851-1860.
17. Lera, L., Albala, C., Ángel, B., Sánchez, H., Picrin, Y., Hormazabal, M. J., & Quiero, A. (2014). Anthropometric model for the prediction of appendicular skeletal muscle mass in Chilean older adults. *Nutrición Hospitalaria, 29*(3), 611-617.
18. López, R., Mancilla, E., Villalobos, A., & Herrera, P. (2010). *Manual de prevención de caídas en el adulto mayor.* Gobierno de Chile, Ministerio de salud.
19. Lord, S. R., Lloyd, D. G., & Keung Li, S. (1996). Sensori-motor function, gait patterns and falls in community-dwelling women. *Age and ageing, 25*(4), 292-299.
20. MacAulay, R. K., Boeve, A., D'Errico, L., Halpin, A., Szeles, D. M., & Wagner, M. T. (2022). Slower gait speed increases risk of falling in older adults with depression and cognitive complaints. *Psychology, health & medicine*, *27*(7), 1576–1581. https://doi.org/10.1080/13548506.2021.1903056
21. Menz, H. B., Lord, S. R., & Fitzpatrick, R. C. (2003). Acceleration patterns of the head and pelvis when walking are associated with risk of falling in community-dwelling older people. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *58*(5), M446-M452.

22. Norton, R., Campbell, A. J., Lee-Joe, T., Robinson, E., & Butler, M. (1997). Circumstances of falls resulting in hip fractures among older people. *Journal of the American Geriatrics Society, 45*(9), 1108-1112.
23. Papagiannis, G. I., Triantafyllou, A. I., Roumpelakis, I. M., Zampeli, F., Garyfallia Eleni, P., Koulouvaris, P., Papadopoulos, E. C., Papagelopoulos, P. J., & Babis, G. C. (2019). Methodology of surface electromyography in gait analysis: review of the literature. *Journal of medical engineering & technology*, *43*(1), 59–65. https://doi.org/10.1080/03091902.2019.1609610
24. Ronthal M. (2019). Gait Disorders and Falls in the Elderly. *The Medical clinics of North America*, *103*(2), 203–213. https://doi.org/10.1016/j.mcna.2018.10.010
25. Rydwik, E., Bergland, A., Forsén, L., & Frändin, K. (2011). Psychometric properties of timed up and go in elderly people: a systematic review. *Physical & Occupational Therapy in Geriatrics, 29*(2), 102-125.
26. Salari, N., Darvishi, N., Ahmadipanah, M., Shohaimi, S., & Mohammadi, M. (2022). Global prevalence of falls in the older adults: a comprehensive systematic review and meta-analysis. *Journal of orthopaedic surgery and research*, *17*(1), 334. https://doi.org/10.1186/s13018-022-03222-1
27. Schoene, D., Wu, S. M. S., Mikolaizak, A. S., Menant, J. C., Smith, S. T., Delbaere, K., & Lord, S. R. (2013). Discriminative ability and predictive validity of the timed Up and Go test in identifying older people who fall: systematic review and meta-analysis. *Journal of the American Geriatrics Society, 61*(2), 202-208.
28. SENIAM. (2020). *Surface ElectroMyoGraphy for the Non-Invasive Assessment of Muscles [Internet]. Enschede, Netherlands*. http://www.seniam.org.
29. Tinetti, M. E., & Williams, C. S. (1997). Falls, injuries due to falls, and the risk of admission to a nursing home. *New England journal of medicine*, *337*(18), 1279-1284.
30. Vapnik, V. N. (1995). *The nature of statistical learning.* Theory.
31. Wang, H., Shao, Y., Zhou, S., Zhang, C., & Xiu, N. (2022). Support Vector Machine Classifier via $L_{0/1}$ Soft-Margin Loss. *IEEE transactions on pattern analysis and machine intelligence*, *44*(10), 7253–7265. https://doi.org/10.1109/TPAMI.2021.3092177
32. Yack, H. J., & Berger, R. C. (1993). Dynamic stability in the elderly: identifying a possible measure. *Journal of gerontology, 48*(5), M225-M230.
33. Yeung, S. S. Y., Reijnierse, E. M., Pham, V. K., Trappenburg, M. C., Lim, W. K., Meskers, C. G. M., & Maier, A. B. (2019). Sarcopenia and its association with falls and fractures in older adults: A systematic review and meta-analysis. *Journal of cachexia, sarcopenia and muscle*, *10*(3), 485–500. https://doi.org/10.1002/jcsm.12411
34. Zavaljevski, N., Stevens, F. J., & Reifman, J. (2002). Support vector machines with selective kernel scaling for protein classification and identification of key amino acid positions. *Bioinformatics, 18*(5), 689-696.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received financial support from the General Research Directorate (DGI) of Andres Bello University, through the Biomedical and Clinical Sciences project.