Validation of an IMU-Based Gait Analysis Method for Assessment of Fall Risk Against Traditional Methods

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***Abstract*—Falls are a severe problem in older adults, often resulting in severe consequences such as injuries or loss of consciousness. It is crucial to screen fall risk in order to prescribe appropriate therapies that can potentially prevent falls. Identifying individuals who have experienced falls in the past, commonly known as fallers, is used to evaluate fall risk, as a prior fall indicates a higher likelihood of future falls. The methods that have the most support from evidence are Gait Speed (GS) and Time Up and Go (TUG), which use specific cut-off values to evaluate the fall risk. There have been proposals for alternative methods that use wearable sensor technology to improve fall risk assessment. Although these technological alternatives are promising, further research is necessary to validate their use in clinical settings. In this study, we propose a method for identifying fallers based on a Support Vector Machine (SVM) classifier. The inputs for the classifier are the gait parameters obtained from a 30-minute walk recorded using an Inertial Measurement Unit (IMU) placed at the foot of patients. We validated our proposed method using a sample of 157 patients aged over 70 years. Our findings indicate significant differences ($p<0.05$) in stride speed, clearance, angular velocity, acceleration, and coefficient of variability among steps between fallers and non-fallers. The proposed method demonstrates the its potential to classify fallers with an accuracy of 79.6%, slightly outperforming the GS method which provides an accuracy of 77.0%, and also overcomes its dependency on the cut-off speed to determine fallers. This method could be valuable in detecting fallers during long-term monitoring that does not require periodic evaluations in a clinical setting.**

***Index Terms*—Fall risk assessment, retrospective falls, SFRT, older adults, gait spatio-temporal parameters, inertial measurement units, IMU.**

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I. Introduction

THE current world population is aging with approximately 12% of individuals being elderly adults (age>60 years) at present [1]. It is projected that this percentage will rise to 22% by the year 2050.

Aging is associated with an increased prevalence of chronic diseases, functional decline, and dependency. Therefore, the focus of healthcare management for this population is shifting from solely treating diseases to maintaining functional abilities, thereby enhancing the overall well-being of older adults [2]. In this context, the concept of frailty has gained considerable attention.

Frailty, a syndrome characterized by weakness that is closely linked to aging, affects more than 7% of older adults [3]. It is particularly alarming that this prevalence significantly increases to 25% in individuals aged 85 years and older.

Frailty represents a physiological decline and heightened vulnerability to stressors [3]. It is an extreme scenario in which the typical age-related decline becomes dysregulated [4]. Frailty is associated with undesirable consequences such as falls, which can result in fractures, head injuries, or even fatalities [5].

Consequently, it is crucial to assess frailty and fall risk in order for physicians to prescribe appropriate interventions to prevent the adverse outcomes of falls. This assessment generally involves an evaluation of the functional abilities of older patients [6]. Identifying those at risk of falling, commonly known as fallers, can also serve as an indicator of fall risk [7].

Functional evaluation methods include the assessment of gait, balance, and strength, which are directly related to the functional capacity and frailty status of patients [6]. Among these methods, the Gait Speed test [8] and the Time Up and Go (TUG) test [9] are the most widely recommended assessments for evaluating fall risk [6].

The recent efforts in this field are focused on the development and validation of Sensor-based Fall Risk Testing (SFRT) techniques. These SFRT methods aim to provide objective measurements and functional testing outside of the clinical setting. Consequently, SFRT alternatives have the potential to more accurately reflect the everyday motor behavior and are highly appealing to clinicians [10].

SFRT methods rely on technological sensing solutions. Portable sensors, such as inertial sensors or plantar pressure insoles, possess the potential to assess fall risk [11], [12], [13]. They are frequently used due to their non-interference with patient movements, affordability, easy of use, and suitability for any environment [14]. Portable sensors enable the estimation of reliable gait parameter measurements [15].

In the identification of fallers, Inertial Measurement Units (IMUs) are the most commonly used portable sensors. IMU measurements are frequently recorded during functional evaluation tests [16], [17], activities of daily living (ADL) [18], [19] or gait assessments [20], [21], [22], [23], [24].

For functional evaluation tests, such as sit-to-stand or balance assessments, IMU measurements improve the classification between fallers and non-fallers [16], [17]. In the monitoring of ADL, acceleration measurements in a Naive Bayes classifier achieve a 61% sensitivity and a 67% specificity in screening fallers [18]. Similar results are obtained with the Non-Dominant Hand Grip Strength, TUG, and GS tests. Studies focused on gait use IMU signals to identify fallers, achieving a 73.4% accuracy using Random Forests [20] and 57% with Neural Networks [22].

IMU signals are also used to estimate spatio-temporal or qualitative gait parameters, which are applied in the identification of fallers. Gait quality metrics, such as the number of steps and their regularity, have been used as predictors in Logistic Regression (LR), providing a 71.6% accuracy [23]. Spatio-temporal parameters predict falls with a 47% sensitivity and a 47% specificity using LR [21], and a 59% accuracy with Support Vector Machine (SVM) classifiers [24]. Deep learning approaches could improve the accuracy reported by traditional machine learning methods. Long short-term memory (LSTM) Neural Networks, utilizing sequential gait parameters to evaluate 76 subjects achieve a 92.1% accuracy in this case [25].

Existing fall risk evaluation alternatives are limited in their application and validation. Classical methods are commonly performed during consultations or in nursing homes, and their outcomes may be influenced by the presence of clinicians, known as the "white-coat effect". These approaches are well-known to influence patient behavior. Moreover, the GS and TUG tests rely on the establishment of cut-off values to identify fallers and there is no consensus on the optimal values [26].

On another note, the interpretability and validation of existing SFRT proposals is limited. This interpretability is crucial for gaining the trust of physicians in utilizing these technological proposals. The most accurate proposals involve time and frequency-domain features extracted from IMU measurements [20]. However, frequency-domain parameters are not directly interpretable in relation to the health status of patients, making their results difficult to understand [27].

Future technological proposals should incorporate explainable metrics to ensure the interpretability of classifiers [28]. Spatio-temporal gait parameters, which are widely used and well-established in gait research, can be related to falls [12], [13], [27], [29]. Spatio-temporal gait parameters obtained from pressure insoles have been found to enhance the IMU-based identification of fallers, achieving an 84% accuracy [30]. However, studies that utilize spatio-temporal gait parameters estimated from IMUs to predict falls using interpretable methods have shown improved classification, with a 59% accuracy [24]. Deep Learning approaches are promising to outperform these results, as in [25]. However, the reported results are validated in only 16 individuals, needing further research to obtain conclusive findings. Moreover, Deep Learning methods are opaque in their analysis of the trained model's features, making them less appealing for their use by clinicians.

To classify fallers using gait parameters, the identification of significant features is crucial [14], [21]. In a previous study [13], we analyzed the most significant gait parameters measured from inertial sensors to discriminate between fallers and non-fallers. Based on this analysis, the study highlighted both significant and non-significant gait parameters in faller identification. The most relevant parameters identified for assessing fall risk are related to stability, trunk movements, and physical activity. However, there is no consensus regarding spatio-temporal gait parameters, such as gait speed, stride length, and stride time. This lack of agreement stems from variability in the methodology among studies, leading to inconsistencies in their evaluation. Consequently, further studies analyzing the relationship between gait parameters and falls in older adults are required.

The primary objective of this study is to assess the effectiveness of a comprehensive set of gait parameters in distinguishing between fallers and non-fallers using machine learning. Specifically, we evaluate the use of classical shallow machine learning methods in order to ensure the interpretability of the proposed approach. To achieve this, this work examines the most significant gait parameters and their correlation with past falls. These gait parameters are obtained from an IMU positioned at the foot of patients during unrestricted walking. The focus is on spatio-temporal gait parameters, combined with the maximum and minimum values derived from inertial measurements. This allows for the interpretation of inertial parameters in terms of foot rotation speed and accelerations at different gait phases. We compare the proposed approach, based on relevant spatio-temporal and inertial gait parameters, with the outcomes of two functional evaluation tests commonly used to detect fallers: the

GS and TUG tests. These tests serve as the baseline since they are the most recommended approaches functional and fall risk evaluation [6].

This work is organized as follows: Section II describes the data used in the development of this work, the gait parameters extracted from the IMU recordings, the fall risk assessment approaches evaluated, and the metrics used to evaluate them; Section III details the results in the identification of fallers; section IV discusses these results and finally, Section V summarizes the main remarks obtained from this work.

II. Materials and Methods

A. Subjects

The validation of the proposed method will utilize patient data from the GSTRIDE database [31], [32]. This dataset consists of anthropometric characteristics, frailty, and functional metrics of $n = 163$ older adults with the assessment of their health status. The data includes information from to 45 men and 118 women, ranging in age from 70 and 98 y.o.. These individuals exhibit variations in their functional and cognitive capacities. Additionally, the dataset includes experimental inertial measurements captured during a walking test performed by the patients.

A total of 157 patients in the database included all the necessary information for evaluating the fall risk assessment methods. These participants were divided into two groups: fallers ($n = 81$, including 64 women and 17 men, with an age of 84.2 ± 5.5 y.o., mass of 62.4 ± 13.1 kg and height of 1.52 ± 0.08 m) and non-fallers ($n = 76$, including 51 women and 25 men, with an average age of 80.8 ± 6.4 y.o., mass of 65.7 ± 12.7 kg, and height of 1.62 ± 0.10 m). The classification was based on the occurrence of severe falls in the year preceding the tests, following the critieria established for fall prevention management in [6]. Severe falls are defined as those resulting in adverse consequences such as injuries or loss of consciousness.

B. Functional Tests

The functional tests evaluated in this study are the 4-meter Gait Speed test and the TUG test. In the 4-meter test, physicians record the time taken and the average speed of a patient walking a distance of 4 m [8]. An additional meter is added at the beginning and end of the test to exclude the influence of initial acceleration and final deceleration on the calculated speed. The TUG test involves standing up from a seated position, performing a walking speed test with a 180 ° turn, and then sitting back down, all without utilizing the arms [9]. These two classical tests are employed as a baseline in this study due to their extensive use in clinical settings.

C. Gait Parameters

As an alternative to the classical tests (GS and TUG), we propose a gait analysis method using foot-mounted IMUs. One IMU was placed on one foot of the patients while they walked on different environments and surfaces at their chosen speed. The IMU was fixed to the upper part of the shoe to ensure that it did not move relative to the foot. We used elastic straps around

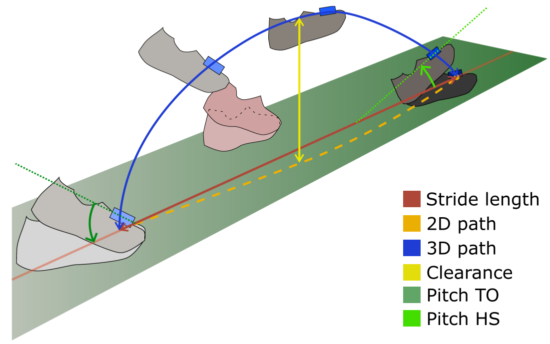

Fig. 1. Spatial gait parameters. The red shoe represents the left foot, and the gray-black shoe depicts the motion of the right foot during the gait cycle. It is important to note that we assume that the pitch angle of the IMU is comparable to the angle of the foot in relation to the floor.

the device, encircling the foot at the sole and securing them in the heel area. The IMU Y-axis pointed to the front, the Z-axis upwards and X-axis to the medial or lateral of the body, depending on its placement on the left or right foot. For a more detailed description of the acquisition protocol, see [31]. The duration of the walking test ranged from 15 to 30 minutes, with an average duration of 21.4 ± 7.1 minutes.

Different IMUs were used for simultaneous tests. In some cases, the IMUs were from different manufacturers but had similar technical characteristics. However, previous studies proved that the spatio-temporal estimation results do not differ significantly when different IMUs are used, so it did not affect the results [33]. Most of the IMUs used were specifically developed for this study with an iNEMO inertial module (LSM6DSRX, STMicroelectronics, CH). These IMUs were developed within the framework of the GSTRIDE project by Rey Juan Carlos University, Infanta SofÃia University Hospital, and the Spanish National Research Council. Additionally, when necessary, we recorded the tests with a commercial IMU (Physilog 6S, GaitUp, CH). In this case, only the raw data was recorded, but the processing algorithms for gait parameter estimation were the same as in the other IMUs.

We estimate the spatio-temporal parameters and the potentially relevant signal peaks from the IMU recordings. We process the gait recordings with the INS-ZUPT algorithm detailed in [34], which detects the gait phases. Based on the detected gait phases, this algorithm provides the spatial parameters shown in Fig. 1 and two temporal magnitudes. The estimated spatio-temporal parameters are as follows:

- Stride length: straight distance between successive contact points of the same foot on the floor.
- Stride velocity: stride length divided by the gait cycle time or time spent in a single stride.
- 2D path: length of the foot trajectory projected on the horizontal plane divided by the stride length.
- 3D path: length of the three-dimensional trajectory divided by the stride length.
- Clearance: elevation of the foot during the swing phase.
- Percentage of time in the gait phases detected (swing, loading, and pushing): percentage of time during which

the foot is in the different gait phases, divided by the gait cycle time.

- Pitch angle in the heel strike (HS) and toe-off (TO) events: foot angle relative to the floor in HS and TO events.

These parameters are explained in detail in the data descriptor in [31].

D. Feature Selection

To ensure methodological precision, we exclude mathematically interrelated parameters. Since stride time, stride length, and their respective velocities are closely intertwined, our feature analysis focuses solely on stride length and its velocity. We do not consider cadence, which is the reciprocal of stride velocity, in our evaluation. Additionally, we selectively include the duration percentage of three out of the four gait phases (swing, loading, and pushing), as the remaining portion of the gait cycle corresponds to the foot-flat phase.

Furthermore, we estimate the maximum and minimum values of the acceleration and gyroscope Euclidean norms magnitudes in the detected gait phases. To not oversimplify the analysis, we divide the swing phase into three sub-phases. We separately study the elevation of the foot from the end of the pushing phase, its forward movement, and its descent until the loading phase begins. Visually, we observe that the elevation and descent of the foot occur in the first and last quarter of the swing phase, respectively, so we divide the swing phase accordingly. Finally, we also examine the motion variation recorded in the foot-flat phase in terms of the standard deviation of the acceleration and angular velocity Euclidean norms magnitudes.

To ensure the evaluation of accurately detected steps and avoid miscalculations, we limit the steps studied. We only consider strides with a length larger than 0.15 m, and 2D and 3D paths lower than 150% and 180% times the step length, respectively.

Our analysis focuses exclusively on straight strides. For each patient, we calculate the average and coefficient of variation (CV) of the gait parameters (Section II-C) in the straight strides. For the analysis of the motion variation in the foot-flat phase, we only study its average. This results in a total of 20 spatio-temporal gait parameters and 30 parameters of the acceleration and gyroscope norms.

The most relevant gait parameters calculated serve as predictors for the classification of fallers. To determine these relevant parameters, we perform a significance analysis for each predictor using a chi-square test [35]. Only these features with a p-value (p) lower than 0.05 ($p < 0.05$) in the significance analysis to differentiate fallers are included in the study.

We also eliminate highly correlated features to avoid redundancy between input pairs [36]. The maximum allowed Pearson's correlation coefficient between features is set at $C = 0.9$. For each group of correlated features, we select the one that yields the lowest p-value.

E. Data Analysis

We investigated the performance of eight machine learning classifiers in identifying fallers, using the selected features. We identify fallers by the classification as either fallers or non-fallers. The machine learning classifiers include SVMs with three different kernels (Gaussian, polynomial, and linear), Random Forest, K-nearest Neighbors, Multilayer Perceptron, Linear Discriminant Analysis, and Logistic Regressor (see Table II in Appendix A). The SVM with a linear kernel was chosen for the further analysis due to its highest classification accuracy.

Consequently, the selected features are used as inputs for an SVM classifier [37]. SVMs search for the maximum separation between the two groups of patients. The decision function of these classifiers is the separation hyperplane that maximizes the separation of the two populations.

Regarding the hyperparameters of the SVM, the predictor variables were standardized prior to model training by using their average and standard deviation. Furthermore, a grid-search was performed to optimize the *Kernel Scale* and the *Regularization Parameter*. For the Kernel Scale, we utilise the Matlab optimizer with the Regularization Parameter set at 1, resulting in an average of 2.56 ± 0.02 across all test sets. To assess the Kernel Scale, we examine five values around the optimal value when the Regularization Parameter is fixed: 0.1, 2, 2.5, 3, 10, focusing on the optimal value and utilizing a logarithmic scale. Similarly, a logarithmic scale was employed for the Regularization Parameter, with the values 0.01, 0.1, 1, 10 and 100 being evaluated.

We compare the gait-based approach with the GS and TUG tests, taking into consideration the dependency of the last on the chosen cut-off values. The 4-meter GS test and the TUG test are commonly used with specific cut-off values to distinguish between fallers and non-fallers. Patients with a gait speed lower than 0.8 m/s in the GS test and a TUG time greater than 15 s are identified as fallers, as these are the commonly accepted cut-off values [6].

We thoroughly analyze the limitations of the traditional methods, GS and TUG, associated with their cut-off values. There is no consensus on the optimal cut-off values for identifying fallers [26]. Therefore, we examine the impact of different cut-off values on the accuracy of faller identification. To do so, we analyze the classification accuracy using other frequently used cut-off values. For the GS test, the cut-off values range between 0.6 and 1 m/s, and in the TUG test, the cut-off values are around 15 s.

F. Evaluation of Methods

To assess the identification of fallers using SVMs, it is necessary to divide the data into training and testing sets. This allow us to measure the SVM's ability to generalize by evaluating its classification metrics on the test set. Since the dataset only includes 157 patients, we evaluate all of them in different test sets. To do that, we employ a k-fold cross-validation approach, randomizing the order of the patients to create 10 different sets of test data. For each set, the SVM is trained on 90% of the patients and tested on the remaining 10%. This process is repeated 10 times, ensuring that all patients' measurement are included in the evaluation. Consequently, the metrics explained in the following are provided as an average and standard deviation of the results obtained for the ten iterations.

We comprehensively evaluate the performance of the proposed gait analysis-based method, the GS test, and the TUG test with four classification metrics. In the identification of fallers (positive, P), accurately identifying both fallers (true positives, TP) and non-fallers (true negative, TN) is crucial. Therefore, we measure the accuracy of the provided classifications (1) [38]. Misclassifying non-fallers as fallers (false positives, FP) would result in prescribing physical therapy to a patient with an undetermined health status. Conversely, misclassifying fallers as non-fallers (false negatives, FN) would lead to a lack of treatment for a patient in need of care. The latter scenario has the potential for a fall to occur, which is the undesirable consequence we aim to prevent. To analyze these sources of errors, we examine the rate of correctly identified fallers among all the actual fallers, known as sensitivity (2), and the F1-score (3), which represents the rate of correctly identified fallers among all identified fallers.

$$\text{acc } (\%) = \frac{TP + TN}{P + N} 100 \tag{1}$$

$$\text{sens } (\%) = \frac{TP}{TP + FN} 100 \tag{2}$$

$$\text{F1 } (\%) = \frac{2\ TP}{2\ TP + FP + FN} 100 \tag{3}$$

III. Results

A. Gait Parameters Analysis

The correlation analysis eliminates gait parameters that exhibit linear dependence. For the explanation of these parameters, see Section II-C. Additionally, Fig. 1 provides a visual representation of these spatial parameters. Among the spatio-temporal gait parameters, the stride velocity demonstrates a strong high correlation with both the mean stride length ($C = 0.95$) and the percentage of time in the swing phase ($C = 0.93$). Furthermore, CV for both the 2D and 3D path length shows a high correlation ($C = 0.94$). Consequently, we exclude the mean stride length, the mean percentage of time in the swing phase, and the CV of the 2D path for further analysis.

The three parameters extracted from the norms of the IMU signals that we eliminate are as follows: the mean maximum of angular velocity in the final part of the swing is correlated with the mean maximum of angular velocity in the pushing phase ($C = 0.98$); the CV of the maximum acceleration in the pushing phase is highly correlated with the CV of the maximum acceleration in the final part of the swing ($C = 0.97$); and the mean maximum acceleration in the pushing phase, which is correlated with the mean of the maximum acceleration in the final part of the swing phase ($C = 0.98$).

The chi-square analysis finds 16 features significantly different ($p < 0.05$) between fallers and non-fallers. Fig. 2 shows the p-value obtained for the non-correlated features. The mean stride velocity, clearance, and maximum angular velocity in pushing distinguish fallers most effectively, see the explanation of gait parameters in Section II-C. The CV of stride velocity and maximum angular velocity while pushing may distinguish both populations. The parameters of the percentage of time in the gait phases and stride length, referred to the average time in each of them, and their variability, are relevant for identifying fallers. The rotation angle of the foot also differs between fallers and non-fallers, with the Pitch CV in the Heel Strike being determinant. In the case of the maxima and minima of IMU signals, the average values of metrics differ more than their variability, and the most relevant features correspond to the gait phases of the foot stance. In the loading phase, the mean maximum angular velocity and acceleration as well as the minimum acceleration, are different between fallers and non-fallers. In pushing, the mean maximum angular velocity and its CV also differ between fallers and non-fallers. Finally, the mean minimum angular velocity and the CV of the maximum and minimum angular velocity in the third sub-phase of swing are relevant for identifying fallers.

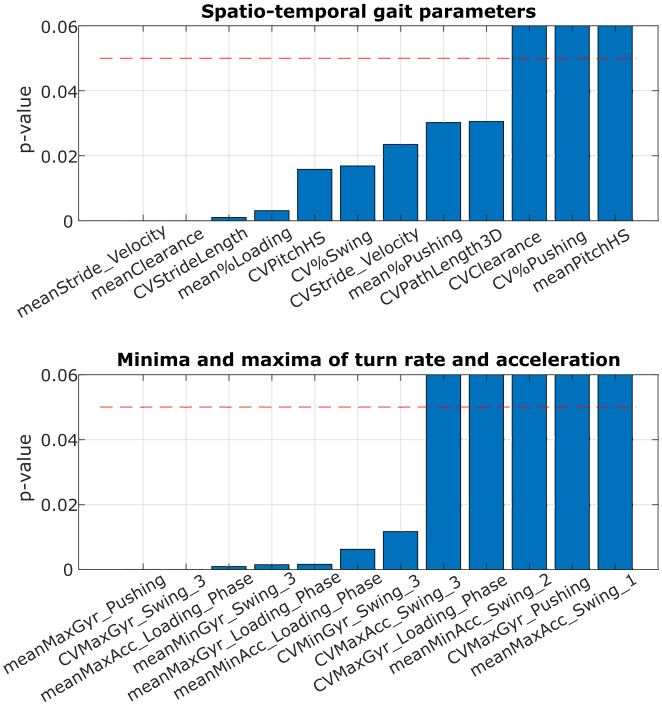

Fig. 2. Outcome of the significance analysis of the twelve most significant and non-correlated parameters. The bars represent the p-value of the spatio-temporal gait parameters (top) and those derived from the gyroscope and accelerometer measurements, ordered by their level of significance. Gait parameters with a significance level of $p > 0.05$ are not displayed. The red dashed line indicates the threshold of $p < 0.05$, which was established to include relevant features.

We analyze the selected features through the visualization of their boxplots in Fig. 3. These boxplots depict the distribution of features in terms of their median, 25th and 75th percentiles. We visualize the boxplots of each feature, differentiating between fallers and non-fallers. Notches are included in the boxplots to provide a visual representation of the statistical significance between the two populations. When notches of a particular feature for fallers and non-fallers do not overlap, it means that the medians of these groups exhibit a significant difference at the 5% significance level.

The boxplots in Fig. 3 present the 16 parameters normalized. According to these boxplots, fallers walk at a slower stride

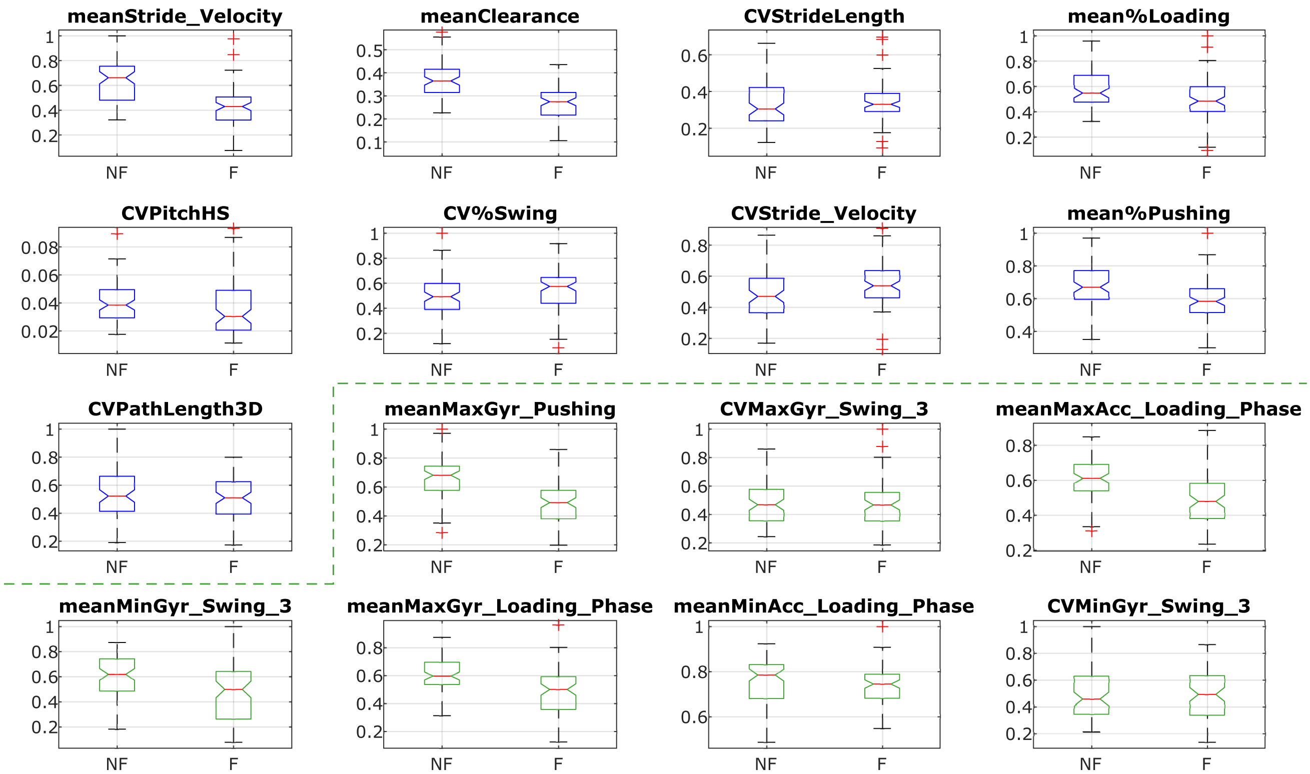

Fig. 3. Boxplots of the features selected for the differentiation between non-fallers (NF) and fallers (F). The spatio-temporal parameters are depicted in blue, while the maximum and minimum of the signals are represented in green. All features are normalized based on their maximum value.

velocity, maintain their feet closer to the floor, present a lower time in the loading and pushing phases, lower variation of the pitch angle in heel strike, and their steps are more variable in terms of stride length, percentage of time in swing, stride velocity and 3D path length. Fallers also present lower maximum angular velocity in pushing and loading, lower mean maxima and minima acceleration in loading, lower mean minima angular velocity in swing, and higher CV of the minima and lower mean maxima of angular velocity in the last part of the swing.

B. Gait Speed Analysis

The stride velocity is the most discriminative gait parameter. The stride velocity is highly related to the gait speed measured in the 4-meter GS test, commonly used in clinics. For that reason, we study whether it is possible to simplify the detection of fallers with this unique parameter. The most straightforward simplification consists of applying a cut-off value to separate fallers from non-fallers, as is done in the TUG or GS tests. We analyze the speed of patients during the free walk to study this possible application of a cut-off and present.

Fig. 4 depicts the distribution of patients with respect to the gait speed measured in the GS test and during the free walk. In the free walk gait speed, fallers walk at a similar speed to that during the GS test, possibly because they cannot walk faster at all. However, not all non-fallers walk at the same gait speed as in the GS test. Most non-fallers (80%) walk at a gait speed faster than 0.8 m/s in the GS test, as shown in Fig. 4 (top). Conversely,

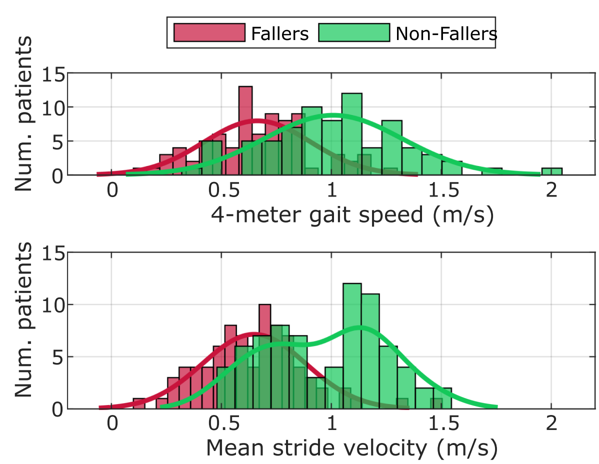

Fig. 4. Distribution of the fallers and non-fallers populations, based on their gait speed in the 4-meter GS test (top) and the free walk test (bottom).

in the long-duration test, non-fallers can be divided into two main groups of patients who walk at a gait speed higher or lower than 0.9 m/s (see Fig. 4, bottom).

C. Detection of Fallers

The proposed method utilizes an SVM model to discern fallers by analyzing significant gait parameters. Only the sixteen gait parameters, which exhibit statistical significance ($p < 0.05$) in

TABLE I
CLASSIFICATION METRICS OBTAINED BY THE THREE METHODS IN THE IDENTIFICATION OF FALLERS AND NON-FALLERS

	GS	TUG	Gait Param. - SVMI
acc (%)	77.0 ± 9.1	66.5 ± 14.1	79.7 ± 8.5
sens (%)	75.3 ± 14.9	52.5 ± 16.3	78.0 ± 15.5
F1 (%)	76.3 ± 9.1	61.1 ± 14.4	80.1 ± 9.3

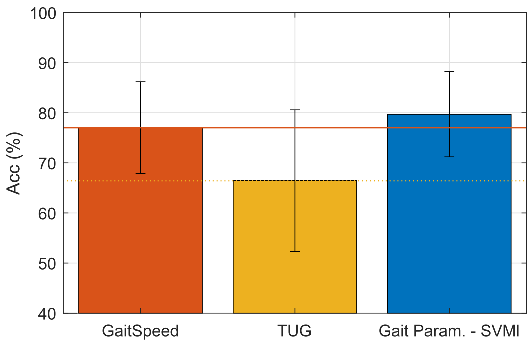

Fig. 5. Mean and standard deviation of the classification accuracy achieved in distinguishing fallers and non-fallers using the GS and TUG test, as well as employing the gait analysis parameters with the SVM classifier.

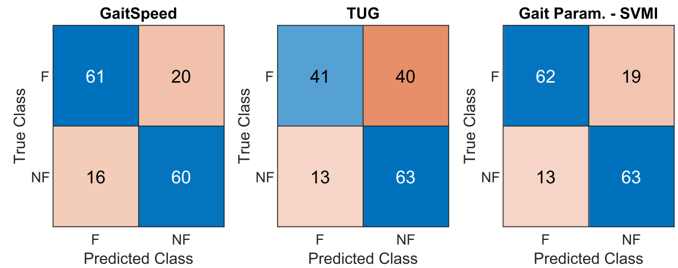

Fig. 6. Confusion matrices of the classification of fallers (F) and non-fallers (NF) using the 4-metre GS test, TUG time, and SVM analysis based on gait parameters.

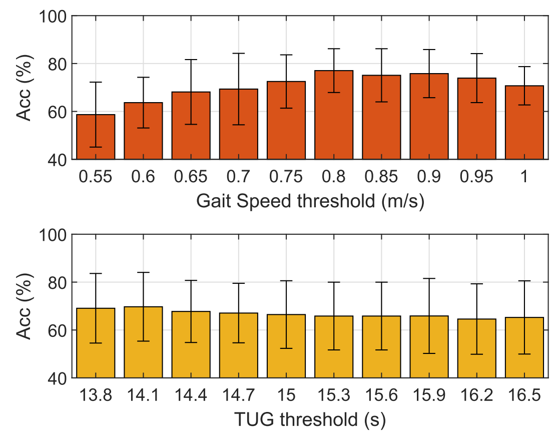

Fig. 7. Accuracy of the GS and TUG classical methods to detect fallers using the commonly applied the cut-off values.

differentiating between fallers and non-fallers are employed as predictors.

In relation to the hyperparameters of the SVM, the predictors are standardized and the optimized hyperparameters are determined based on the results obtained from the grid search. For a comprehensive overview of the grid-search outcomes, refer to Tables III and IV in Appendix B. The Kernel Scale set to 2.5 and the Regularization Parameter set to 1 demonstrate the highest accuracy in the validation datasets, thus making them the optimal hyperparameters. Consequently, these values are the ones employed in the subsequent analysis.

Fig. 5 shows the average accuracy of the SVM using the optimized hyperparameters for the ten test sets. The results of this proposal are shown in comparison to that of the GS and TUG tests. The error bars show the standard deviation of the error for the ten test sets. The proposed SVM-based classification, incorporating gait parameters, exhibits slight superior performance to the functional tests. The SVM achieves an accuracy of 79.7%, which is comparable to the accuracy achieved with the GS and TUG tests, namely 77.0% and 66.5%, respectively.

Table I presents the classification metrics of the faller identification methods. In addition to the accuracy, the proposed method demonstrated increased sensitivity and F1-score metrics. The SVM with gait parameters outperforms the TUG test by achieving higher average values and reduced variability in its classification metrics. Our proposal means an improvement of 50% in the sensitivity, and 30% in the F1-score compared to the TUG test. Compared to the GS test, the SVM classification metrics are slightly higher. The proposed method shows a 4% increase in sensitivity and F1-score metrics. While the improvement in metrics in comparison with GS is minor, it is noteworthy due to the advantages of the proposed method, which does not rely on the selection of a threshold value.

The confusion matrices in Fig. 6 illustrate the classification between fallers and non-fallers using the different approaches. Consistent with the metrics in Table I, the proposed gait analysis method shows an increase in correctly identifying fallers and non-fallers. The improvement is particularly significant when compared to the TUG test. The confusion matrix in the center of Fig. 6 highlights that misidentification of fallers is the main source errors in the TUG test. As previously discussed, misidentifying non-fallers is an undesirable outcome, as it would result in patients not receiving necessary treatment. Neither the GS nor the proposed method has this limitation, with the latter offering the advantage of not depending on threshold values.

As stated in Section II-E, the metrics provided by the GS and TUG tests rely on established cut-off values. In this work, we set the cut-off values for gait speed and TUG time to the recommended values [6]. To investigate the dependency on these values, we present accuracy results applying frequently used cut-off values from previous literature in Fig. 7.

Fig. 7 demonstrates the dependency of classification accuracy on the cut-off values. For the population under study, the optimal cut-off values are determined to be 0.8 m/s for the GS test and 14.1 s for the TUG test. With these values, the maximum classification accuracy using the TUG test is 69.4%, while the GS test achieves a maximum accuracy of 77.0%. However, values of 1.0 m/s or 15 s decrease the classification accuracy by approximately 5%.

IV. Discussion

The primary finding of this work is the demonstration that gait parameters have the capacity to be used to distinguish fallers from non-fallers, surpassing the performance of traditional clinical methods. These results are consistent with previous investigations that differentiate fallers from non-fallers based on data of gait kinematic parameters. However, the predictive parameters utilized in this work offer the added advantage of being interpretable. Consequently, this study demonstrates that incorporating gait spatio-temporal parameters of the motion of feet (such as mean stride velocity, clearance, percentage of time in loading and pushing and CV of stride velocity, stride length, pitch in heel strike, percentage of time in swing and 3D path length) as well as the maximum and minimum acceleration and angular velocity (including mean maximum angular velocity in pushing and loading, maximum and minimum acceleration in loading, minimum angular velocity in the third sub-phase of swing, and CV of maximum and minimum angular velocity in the last sub-phase of swing) slightly improves the identification of fallers compared to the commonly used clinical tests, both GS and TUG. Moreover, this approach overcomes the reliance on establishing specific thresholds, which are associated with clinical tests, to differentiate between fallers and non-fallers.

The spatio-temporal parameters of the foot define the gait pattern exhibited by fallers (see Fig. 3). Consistent with previous literature, the findings indicate that fallers tend to walk at a slower stride velocity and maintain their feet closer to the ground, resulting in a lower mean clearance in comparison to non-fallers [39]. Furthermore, fallers spend a significantly smaller percentage of the the gait cycle duration in the loading and pushing gait phases. A closer examination of the relationship between the percentage of time in the loading and pushing phases reveals that fallers also exhibit a shorter period in swing, indicating a longer period of contact with the ground in comparison to non-fallers. Consequently, in addition to the slower speed during the foot motion, fallers' reduced stride velocity can be attributed in part to an increased duration of foot-ground contact. Additionally, the study demonstrates that gait variability in terms of stride length and stride velocity is associated with, which is coherent with previous research [12]. Notably, fallers show a higher CV in terms of percentage time in the swing phase, as well as stride velocity and length, indicating a more irregular gait pattern in comparison to non-fallers.

The study examines the gait patterns of fallers by analyzing spatio-temporal gait parameters and kinematic measures of the feet during gait. The results show that fallers exhibit lower maximum angular velocity in the pushing and loading phases (see Fig. 3), indicating slower foot rotation. This is consistent with the fact that fallers spend less time in these phases and therefore perform less foot rotation during gait. Fallers also exhibit smaller minimum angular velocity in the third sub-phase of swing, indicating reduced foot rotation compared to non-fallers. In addition, fallers show lower maximum and minimum acceleration in the loading phase, suggesting a smaller range of accelerations and slower movement compared to non-fallers. Moreover, non-fallers display increased CV in maximum and minimum angular velocity in the last sub-phase of swing, reflecting the greater variability in the inertial parameters. This greater variability was also observed in the spatio-temporal parameters.

The identification of gait parameters that significantly differ in fallers and non-fallers enables a more effective differentiation between these two populations than relying solely on average walking speed. While walking speed measured in short tests such as the GS test is commonly used to distinguish fallers from non-fallers, this speed is not a reliable measure for separating fallers in longer, free walking tests. As depicted in Fig. 4, non-fallers generally show faster walking speed in the GS test compared to fallers. However, in the 30-minute test, non-fallers can be further categorized into two groups: one that walks at a similar speed to fallers and another that walks at a faster pace. Applying the commonly recommended threshold of 0.8 m/s gait speed, the number of patients identified as fallers increases by more than 50%, from 16 to 25 patients. Therefore, the speed threshold used in the GS test cannot be applied to the 30-minute test for distinguishing fallers from non-fallers. Consequently, the gait pattern parameters identified in this study (slower speed, longer foot flat phase, greater variability, reduced and slower foot rotation, and decreased acceleration compared to non-fallers) provide valuable and essential information for identifying fallers.

The proposed method of fall risk assessment, based on the significantly different gait parameters in fallers is comparable to clinical assessment methods. The accuracy in distinguishing fallers from non-fallers using the GS test and the gait analysis classification is comparable, as depicted in Fig. 5). Notably, the method proposed in this study demonstrates greater accuracy than the classical methods. Moreover, the sensitivity increases with the gait analysis, resulting in fewer fallers being misclassified as non-fallers compared to both the TUG and gait speed tests, as shown in Fig. 6. Sensitivity is particularly relevant in faller identification methods, as the objective is to minimize the misclassification of fallers. Interestingly, all the evaluated metrics - accuracy, sensitivity, and F1-score - improve with the proposed method.

Furthermore, the proposed approach also overcomes the dependence of classical assessment methods on cut-off values to differentiate fallers and non-fallers. We examine the dependency of the GS and TUG tests on the commonly used cut-off values for faller identification, as presented in Fig. 7. For the patients analyzed in this study, the GS of 0.8 m/s and TUG time of 14.1 s provide the highest accuracy. However, there exists a 20% accuracy variation between the best and worst accuracy results of the TUG, depending on the chosen cut-off. Thus, the selection of an optimal cut-off value is crucial to obtain an accurate faller identification.

We compare our proposal with the optimal cut-off value for the GS but a different one for the TUG test. Regarding the TUG, the recommended cut-off does not correspond to the optimal value for the dataset used. However, the difference between this recommended cut-off and the optimal value is only 3.2%. Therefore, the discussion derived from this study remains equally valid. Conversely, for the comparison with the GS test, we use the optimal cut-off for gait speed. Given that the proposed method proposed slightly increases the classification metrics, we prove that the gait analysis parameters serve as a viable alternative to the primary test used.

Another advantage of the proposed approach is that the gait recording is performed without the presence of a supervising physician. This offers two significant benefits when conducting tests. First, it eliminates bias in test results associated with patients' motivation (or lack of thereof) to perform the test under observation, commonly known as the white coat effect. Second, tests can be carried out using IMUs without the need for hospital visits since no instructions on how to walk are necessary. Consequently, patients can be assessed over long periods without the inconvenience of visiting a clinic.

To the best of the authors' knowledge, this is one of the first studies that proposes a method for classifying fallers based on explainable and widely known gait parameters obtained from a single IMU on the foot. While the combination of acceleration and spatio-temporal parameters has been shown to be suitable for identifying fallers [30], the spatio-temporal parameters were obtained from pressure-sensing insoles. Kelly et al. identified accelerometry time and frequency-domain features from IMUs on the hip to identify fallers [18]. They also demonstrated that accelerometry features improve the detection of fallers when evaluated using metrics from TUG, GS, and Non-Dominant Hand Grip Strength functional tests. However, acceleration features are not easily interpretable and do not provide information about the gait pattern of fallers. Recent research has focused on the use of spatio-temporal parameters, which are widely used and well-established in gait research and provide interpretable information. Although gait spatio-temporal parameters have been used to predict falls, these studies have analyzed a small number of patients (71 in [24]). In contrast to previous research, this study uses spatio-temporal parameters to classify fallers based on their higher risk of falling and their classification can be used, with the aim of detecting future fallers. In the near future, it would be of interest to analyze these parameters in relation to the incidence of subsequent falls.

The main limitation of this study is the number of volunteers analyzed. While the number of volunteers is higher than in previous research and sufficient to demonstrate that the proposed method can achieve higher accuracy in identifying fallers compared to classical methods, it would be advisable to analyze the proposal with a larger population.

V. Conclusion

This study validates a method for evaluating fall risk based on gait parameters. Initially, we first examined the spatio-temporal gait parameters and identified sixteen parameters that significantly differ between fallers and non-fallers. These parameters define a gait pattern characterized by slow speed, angular velocity, acceleration, clearance, and variability of pitch angle, as well as high variability in the stride length and in the gait phases duration. Notably, the most significant parameter, stride speed, is found differed from the speed measured in clinical settings. In the GS tests (4-meter), most non-fallers walked at a faster pace compared to the free walk long tests (30 minutes).

TABLE II
Accuracy Percentage of the Eight Analyzed Methods

Algorithm	Accuracy (%)
SVM Gaussian kernel	66.9 ± 9.8
SVM linear kernel	79.7 ± 8.5
SVM polynomial kernel	68.9 ± 9.7
Random Forest	70.8 ± 9.6
K-nearest Neighbor	69.6 ± 12.4
Multilayer Perceptron	72.0 ± 6.5
Linear Discriminant Analysis	76.4 ± 10.6
Logistic Regressor	71.3 ± 7.6

TABLE III
Average and Standard Deviation Accuracy (%) for Ten Validation Sets

	Accuracy (%) for each Kernel Scale value				
R.P.	0.1	2	2.5	3	10
0.01	74.4 ± 10.9	68.8 ± 12.3	66.7 ± 11.7	57.4 ± 19.5	39.7 ± 5.9
0.1	72.3 ± 8.7	70.8 ± 11.0	70.9 ± 11.0	70.9 ± 12.5	52.5 ± 16.8
1	72.3 ± 8.7	74.4 ± 11.8	$\mathbf{75.1 \pm 9.1}$	74.43 ± 10.3	70.9 ± 10.9
10	72.3 ± 8.7	72.9 ± 11.7	72.9 ± 11.7	73.7 ± 11.8	75.1 ± 9.1
100	70.9 ± 11.9	72.3 ± 8.7	72.3 ± 8.7	72.3 ± 8.7	74.4 ± 10.9

Columns separate the Kernel Scale value and rows separate the Regularization Parameter (R.P.) values.

The fall risk evaluation method proposed in this study is comparable to the standard approach used to evaluate the fall risk in older adults. Our proposed method can identify fallers with similar or higher accuracy, sensitivity, and F1-score compared to the GS and TUG tests. Additionally, it overcomes the reliance on cut-off values used to identify fallers in the GS and TUG tests.

Future research should explore the analysis of gait parameters from both feet instead of just one. Moreover, since machine learning algorithms only provide a classification output distinguishing fallers from non-fallers, incorporating additional information could yield more comprehensive results. Finally, it would be valuable to investigate whether integrating the outcomes of faller identification outcomes into real-time fall detection systems could enhance their performance.

Appendix

A. Classifiers Comparison

Table II shows the accuracy provided by the classifiers analyzed before the validation with the traditional methods.

B. Hyperparameters Optimization

The hyperparameters are optimized by dividing one training set into ten subsets and iteratively using one of these subsets to validate the hyperparameters evaluated in each combination. The metric to be optimized is the average accuracy and its standard deviation for the ten subsets independently evaluated. The average accuracy for each combination of Kernel Scale and Regularization Parameter is shown in Table III, where the most accurate values for each subset are marked with bold letters.

In Table III, the optimal hyperparameters configuration is Kernel Scale set to 2.5 and Regularization Parameter equal to 1. These hyperparameter values provide the highest accuracy with the lowest standard deviation, which is $75.14 \pm 9.14\%$.

Fixing the Kernel Scale and the Regularization Parameter to 10, the accuracy reported is quite similar. However, the classifier

TABLE IV
ACCURACY IN PERCENTAGE IN EACH TRAIN-VALIDATION DATA SPLIT FOR THE EVALUATED REGULARIZATION PARAMETER VALUES

	Accuracy (%) in each Train-Validation split										
Reg. Param.	1	2	3	4	5	6	7	8	9	10	Avg.±STD
0.01	64.3	**92.9**	57.1	57.1	66.7	**71.4**	71.4	71.4	50.0	64.3	66.7 ± 11.7
0.1	71.4	85.7	**71.4**	57.1	80.0	64.3	**78.6**	78.6	50.0	71.4	70.9 ± 11.0
1	**78.6**	78.6	64.3	**71.4**	80.0	64.3	**78.6**	**78.6**	**64.3**	**92.9**	**75.1 ± 9.1**
10	71.4	78.6	64.3	71.4	**86.7**	57.1	**78.6**	71.4	57.1	**92.9**	72.9 ± 11.7
100	71.4	78.6	64.3	71.4	80.0	57.1	**78.6**	71.4	**64.3**	85.7	72.3 ± 8.7

Columns separate the validation sub-sets and rows separate the Regularization Parameter (R.P.) values. The last column shows the average (Avg.) and standard deviation (STD) of the accuracy.

obtains high variations in accuracy for this Kernel Scale value (see column for Kernel Scale equal to 10 compared to the column for Kernel Scale equal to 2.5). This variation makes the classifier less stable, so we select the previous hyperparameters configuration.

Furthermore, we assess the impact of the Regularization Parameter selected individually for each validation sub-set. To do so, we fix the Kernel Scale to 2.5 since the initial optimization of the parameter also yields this optimal value. The accuracy percentage for each subset is displayed in Table IV, where the most accurate values for each subset are indicated with bold letters.

Table IV demonstrates that the Regularization Parameter equal to 1 is the most suitable one for the majority of subsets. This value offers the highest accuracy with the lowest variation among the ten subsets. Due to the consistent results, we set the Regularization Parameter to 1 and maintain the Kernel Scale at 2.5.

REFERENCES

[1] WHO, "Ageing and health," 2021. [Online]. Available: https://www.who.int/

[2] L. Rodriguez-Mañas, F. Rodríguez-Artalejo, and A. J. Sinclair, "The third transition: The clinical evolution oriented to the contemporary older patient," *J. Amer. Med. Directors Assoc.*, vol. 18, no. 1, pp. 8–9, 2017.

[3] L. P. Fried et al., "Frailty in older adults: Evidence for a phenotype," *Journals Gerontol. Ser. A, Biol. Sci. Med. Sci.*, vol. 56, no. 3, pp. M146–M157, 2001.

[4] L. P. Fried, A. A. Cohen, Q.-L. Xue, J. Walston, K. Bandeen-Roche, and R. Varadhan, "The physical frailty syndrome as a transition from homeostatic symphony to cacophony," *Nature Aging*, vol. 1, no. 1, pp. 36–46, 2021.

[5] W. H. Organization, *Integrated Care for Older People: Guidelines on Community-Level Interventions to Manage Declines in Intrinsic Capacity*, Geneva, Switzerland: World Health Organization, 2017.

[6] M. Montero-Odasso et al., "World guidelines for falls prevention and management for older adults: A global initiative," *Age Ageing*, vol. 51, no. 9, 2022, Art. no. afac205.

[7] P. Bet, P. C. Castro, and M. A. Ponti, "Fall detection and fall risk assessment in older person using wearable sensors: A systematic review," *Int. J. Med. Inform.*, vol. 130, 2019, Art. no. 103946.

[8] R. W. Bohannon and Y.-C. Wang, "Four-meter gait speed: Normative values and reliability determined for adults participating in the nih toolbox study," *Arch. Phys. Med. Rehabil.*, vol. 100, no. 3, pp. 509–513, 2019.

[9] D. Podsiadlo and S. Richardson, "The timed 'up & go': A test of basic functional mobility for frail elderly persons," *J. Amer. Geriatrics Soc.*, vol. 39, no. 2, pp. 142–148, 1991.

[10] A. Mirelman, S. Shema, I. Maidan, and J. M. Hausdorff, "Gait," *Handbook Clin. Neurol.*, vol. 159, pp. 119–134, 2018.

[11] R. Sun and J. J. Sosnoff, "Novel sensing technology in fall risk assessment in older adults: A systematic review," *BMC Geriatrics*, vol. 18, pp. 1–10, 2018.

[12] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg, "Gait variability and fall risk in community-living older adults: A 1-year prospective study," *Arch. Phys. Med. Rehabil.*, vol. 82, no. 8, pp. 1050–1056, 2001.

[13] L. Ruiz-Ruiz, A. R. Jimenez, G. Garcia-Villamil, and F. Seco, "Detecting fall risk and frailty in elders with inertial motion sensors: A survey of significant gait parameters," *Sensors*, vol. 21, no. 20, 2021, Art. no. 6918.

[14] M. Chen et al., "A systematic review of wearable sensor-based technologies for fall risk assessment in older adults," *Sensors*, vol. 22, no. 18, 2022, Art. no. 6752.

[15] G. Vavasour, O. M. Giggins, J. Doyle, and D. Kelly, "How wearable sensors have been utilised to evaluate frailty in older adults: A systematic review," *J. Neuroengineering Rehabil.*, vol. 18, no. 1, pp. 1–20, 2021.

[16] N. Millor et al., "Gait velocity and chair sit-stand-sit performance improves current frailty-status identification," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 11, pp. 2018–2025, Nov. 2017.

[17] K. McManus, B. R. Greene, L. G. M. Ader, and B. Caulfield, "Development of data-driven metrics for balance impairment and fall risk assessment in older adults," *IEEE Trans. Biomed. Eng.*, vol. 69, no. 7, pp. 2324–2332, Jul. 2022.

[18] D. Kelly et al., "Improved screening of fall risk using free-living based accelerometer data," *J. Biomed. Inform.*, vol. 131, 2022, Art. no. 104116.

[19] P. R. Chakraborty and G. Sorwar, "A machine learning approach to identify fall risk for older adults," *Smart Health*, vol. 26, 2022, Art. no. 100303.

[20] D. Drover, J. Howcroft, J. Kofman, and E. D. Lemaire, "Faller classification in older adults using wearable sensors based on turn and straight-walking accelerometer-based features," *Sensors*, vol. 17, 2017, Art. no. 1321.

[21] R. Schwesig, D. Fischer, A. Lauenroth, S. Becker, and S. Leuchte, "Can falls be predicted with gait analytical and posturographic measurement systems? a prospective follow-up study in a nursing home population," *Clin. Rehabil.*, vol. 27, no. 2, pp. 183–190, 2013.

[22] J. Howcroft, J. Kofman, and E. D. Lemaire, "Prospective fall-risk prediction models for older adults based on wearable sensors," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 10, pp. 1812–1820, Oct. 2017.

[23] A. Weiss et al., "Does the evaluation of gait quality during daily life provide insight into fall risk? a novel approach using 3-day accelerometer recordings," *Neurorehabilitation Neural Repair*, vol. 27, no. 8, pp. 742–752, 2013.

[24] P. Aqueveque et al., "Predicting risk of falls in elderly using a single inertial measurement unit on the lower-back by estimating spatio-temporal gait parameters," in *2022 44th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, pp. 2390–2394.

[25] C. Tunca, G. Salur, and C. Ersoy, "Deep learning for fall risk assessment with inertial sensors: Utilizing domain knowledge in spatio-temporal gait parameters," *IEEE J. Biomed. Health Inform.*, vol. 24, no. 7, pp. 1994–2005, Jul. 2020.

[26] D. B. Jepsen et al., "Predicting falls in older adults: An umbrella review of instruments assessing gait, balance, and functional mobility," *BMC Geriatrics*, vol. 22, no. 1, pp. 1–27, 2022.

[27] I. Bargiotas et al., "Preventing falls: The use of machine learning for the prediction of future falls in individuals without history of fall," *J. Neurol.*, vol. 270, pp. 618–631, 2022.

[28] P. J. Phillips, C. A. Hahn, P. C. Fontana, D. A. Broniatowski, and M. A. Przybocki, "Four principles of explainable artificial intelligence," NIST Interagency/Internal Rep. (NISTIR), Nat. Inst. Stand. Technol., Gaithersburg, MD, USA, Tech. Rep., 2020.

[29] F. Petraglia, L. Scarcella, G. Pedrazzi, L. Brancato, R. Puers, and C. Costantino, "Inertial sensors versus standard systems in gait analysis: A systematic review and meta-analysis," *Eur. J. Phys. Rehabil. Med.*, vol. 55, no. 2, pp. 268–280, 2019.

[30] J. Howcroft, E. D. Lemaire, and J. Kofman, "Wearable-sensor-based classification models of faller status in older adults," *PLoS one*, vol. 11, 2016, Art. no. e0153240.

[31] S. García-de Villa et al., "A database with frailty, functional and inertial gait metrics for the research of fall causes in older adults," *Sci. Data*, vol. 10, no. 1, pp. 1–13, 2023.

[32] G. G.-V. Neira, "GSTRIDE: A database of frailty and functional assessments with inertial gait data from elderly fallers and non-fallers populations," *Zenodo*, Jul. 2022, doi: 10.5281/zenodo.6883292.

[33] G. García-Villamil, L. Ruiz, A. R. Jiménez, F. S. Granja, and M. C. Rodríguez-Sánchez, "Influence of IMU's measurement noise on the accuracy of stride-length estimation for gait analysis," in *Proc. CEUR Workshop Proc.*, 2021.

[34] L. Ruiz-Ruiz, F. Seco, A. Jiménez, S. Garcia, and J. J. García, "Evaluation of gait parameter estimation accuracy: A comparison between commercial IMU and optical capture motion system," in *2022 IEEE Int. Symp. Med. Meas. Appl.*, pp. 1–2.

[35] I. S. Thaseen and C. A. Kumar, "Intrusion detection model using fusion of chi-square feature selection and multi class svm," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 29, no. 4, pp. 462–472, 2017.

[36] R. Fisher, *Statistical Methods for Research Workers*, 13th ed. New York, NY, USA: Hafner, 1958.

[37] B. Schölkopf et al., *Learning With Kernels: Support Vector Machines, Regularization, Optimization, and Beyond*. Cambridge, MA, USA: MIT Press, 2002.

[38] A. Tharwat, "Classification assessment methods," *Appl. Comput. Informat.*, vol. 17, no. 1, pp. 168–192, 2020.

[39] M.-S. Kwon, Y.-R. Kwon, Y.-S. Park, and J.-W. Kim, "Comparison of gait patterns in elderly fallers and non-fallers," *Technol. Health Care*, vol. 26, no. S1, pp. 427–436, 2018.