Fall Risk Prediction Using Instrumented Footwear in Institutionalized Older Adults

Huanghe Zhang*, Chuanyan Wu*, Yulong Huang, Rui Song, Damiano Zanotto, Sunil K. Agrawal

***Abstract*— This study presents a novel framework that utilizes instrumented footwear to predict fall risk in institutionalized older adults by leveraging stride-to-stride gait data. The older adults are categorized into fallers and non-fallers using three distinct criteria: retrospective fall history, prospective fall occurrence, and a combination of both retrospective and prospective data. Three types of data collected from N=95 institutionalized older adults are analyzed: traditional timed mobility tests, gait data collected from a validated electronic walkway, and gait data collected with instrumented footwear developed by our team. The importance of each type of data is assessed using a brute-force search method, through which the optimal features are selected. AdaBoost algorithms are then utilized to develop predictive models based on the selected features. The models are evaluated using leave-one-out cross-validation and 10-fold cross-validation. The results show that models using gait data from the instrumented footwear outperformed those based on traditional tests and walkway data, with area under the receiver operating characteristic curve (AUC) values for predicting prospective falls being 0.47, 0.66, and 0.80, respectively. The sensitivity of the models increases when they are trained using both past and future falls data, rather than relying solely on past or future falls data. This study demonstrates the potential of instrumented footwear for fall risk assessment in elderly individuals. The findings provide valuable insights for fall prevention and care, highlighting the superior predictive capabilities of the developed system compared to traditional methods.**

***Index Terms*— Fall Risk Assessment, Instrumented Footwear, Machine Learning**

This work was supported in part by the National Key R&D Program of China under Grant 2023YFB4706104, in part by the Shandong Excellent Young Scientists Fund Program (Overseas) under Grant 2024HWYQ-019, and in part by the Columbia-Coulter Translational Research Partnership under Grant UR008231. *(Corresponding author: Sunil K. Agrawal.)*

H. Zhang (e-mail: zhanghuanghe@sdu.edu.cn) and R. Song are with the Center for Robotics, School of Control Science and Engineering, Shandong University, Jinan, Shandong, China.

C. Wu (e-mail: chuanyan_wu@163.com) is with the Center for Robotics, School of Control Science and Engineering, Shandong University and the School of Intelligent Engineering, Shandong Management University, Jinan, Shandong, China.

Y. Huang (e-mail: heuedu@163.com) is with the College of Intelligent Systems Science and Engineering, Harbin Engineering University, Harbin 150001, China.

D. Zanotto (e-mail: damiano.zanotto@stevens.edu) is with the Department of Mechanical Engineering, Stevens Institute of Technology, Hoboken, New Jersey, United States.

S. K. Agrawal (e-mail: sunil.agrawal@columbia.edu) is with the Department of Mechanical Engineering, Columbia University, New York, United States.

*These authors contributed equally to this work.

I. Introduction

FALLS are serious and costly events among old adults. In 2020, according to the Centers for Disease Control and Prevention [1], 3 million falls in older adults have been recorded by emergency departments and caused approximately $50 billion in direct medical costs. This economic burden of falls will reach $100 billion by 2030. In addition, falls among adults aged 65 or older caused over 36,000 deaths in 2020, making it the leading cause of injury death in this population. Thus, assessing fall risk is crucial for older adults. More than just identifying those at risk, effective fall risk assessments are integral to initiating targeted prevention strategies, such as exercise-based therapies. These interventions are proven to substantially reduce the incidence of falls and enhance the health and quality of life for this population [2], [3].

The traditional fall risk assessment is based on clinical observations and timed mobility tests, such as the five times sit to stand test (FTSST) [4], the Timed Up and Go (TUG) test [5], and the 6-Minute Walk Test (6MWT) [6]. While these tests are quick and easy to administer, their outcomes are subjective (i.e., clinical observations) and cannot effectively predict falls in older adults (i.e., timed mobility tests) if used alone [7]. Therefore, quantitative gait analysis, which has higher diagnostic power than clinical observations, has been proposed for fall risk assessment [8]. Research has shown that gait parameters such as stride length, stride velocity, stride time, swing time, and double support time are correlated with an increased risk of falls [9]. Additionally, the stride-to-stride fluctuations, called gait variability, in these gait parameters might represent a more robust indicator of falling than average gait metrics [10], [11]. Increased stride variability can be viewed as gait instability or poor balance [9], [11], and therefore results in more likelihood of falling. For these reasons, a simple and effective fall risk prediction system typically includes two parts: 1) an accurate gait parameters estimation system and 2) an accurate fall risk prediction model based on gait data [12].

Fall risk prediction systems typically employ three categories of sensor technologies: camera sensors [13], infrared sensors [14], and wearable sensors [12] to measure gait parameters. However, camera sensors and infrared sensors tend to be costly and come with privacy concerns due to their audiovisual recording capabilities and the requirement for users to be within range of the stationary system [15]. To address these limitations, wearable sensor-based systems for fall risk prediction have emerged as a cost-effective and

This article has been accepted for publication in IEEE Transactions on Neural Systems and Rehabilitation Engineering. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2024.3510300

portable alternative. Notably, among these wearable sensors, instrumented footwear equipped with pressure sensors [16]–[18] and inertial sensors [19], [20] are particularly favored for prolonged monitoring, given their unobtrusive nature and ergonomic design. Gait events, including initial contact, mid-stance, and last contact, can be accurately identified through the data collected by inertial sensors [21] or pressure sensors [22]. Subsequently, temporal gait parameters such as stride time, swing time, and double support time can be directly computed utilizing these precisely detected gait events. On the other hand, spatial gait parameters like stride length are determined by initially eliminating the influence of gravity from the accelerometer readings of the inertial sensor. This process is then followed by a double integration performed between successive mid-stance phases, commonly known as the ‘foot displacement method’ in the literature [21], [23]. In order to obtain drift-free gait parameters, zero velocity update and velocity drift compensation are typically included in the implementation [21], [23].

After obtaining accurate gait parameters, the next step is to create a fall risk prediction model. Leveraging the power of machine learning, many scholars have proposed effective models based on gait data [24]–[26]. For instance, Greene et al. [27] developed logistic regression models to predict fall risk among older adults, achieving a mean accuracy of 76.8%. However, this method required additional input information, including ’Return time’ from the TUG test, as well as the participant’s height and weight. The logistic regression classifier was also investigated in [16], where a series of candidate classifiers, such as support vector machine, k-nearest neighbor, decision tree, random forest, and AdaBoost, were tested. Notably, AdaBoost achieved the best results with an accuracy of 87.5% solely utilizing plantar pressure information. It is important to note, however, that the fall risk in this study relied on clinical test scores rather than actual recorded instances of historical falls. The utilization of random forest was also reported in [28], employing a wearable sensor attached to the sternum for assessing fall risk. However, the model’s performance evaluation did not incorporate cross-validation, introducing uncertainty regarding its generalization capabilities. This limitation was also observed in [29], where Long Short-Term Memory (LSTM) neural networks were proposed. Most importantly, these models were validated only on retrospective fall history, not on prospective fall occurrences.

The two primary limitations of retrospective assessments are potential memory inaccuracies regarding past falls and alterations in gait resulting from previous falls [30]. To address these limitations, Paterson et al. [19] and Schwesig et al. [20] implemented logistic regression models to predict prospective fall risk in older adults. Nonetheless, the performance of these models was modest, achieving prediction success rates of 67% and 66%, respectively. Furthermore, Howcroft et al. [31] explored the use of neural networks, naïve Bayesian, and support vector machine classifiers for predicting fall risk, but the highest accuracy achieved was only 57%. Additionally, Ye et al. developed and validated an XGBoost-based fall risk prediction model using electronic health records from older adults, predicting 58.01% of falls within the first 30 days and 54.93% of falls between 30–60 days in the following year [32]. Dormosh et al. explored the use of unstructured clinical notes alongside structured data to predict falls in older adults, employing natural language processing and machine learning. Their combined model, which integrated both structured variables and topics from unstructured notes, achieved an AUC of 0.718, demonstrating the potential of unstructured notes in enhancing fall prediction models [33]

Fig. 1: The instrumented footwear (i.e., *SoleSound*) used in this study [34]. (A) The logic unit is attached to the heel, and the ultrasonic sensor is mounted on the medial side of the footwear, although it was not used in this study. (B) The locations of the four piezoresistive force sensors and the 9-DOF IMU.

In this study, the instrumented footwear named *SoleSound*, a pair of sandals equipped with piezo-resistive sensors, inertial measurement units (IMU), and ultrasonic sensors, is used to predict fall risk. This fully portable system can measure a rich set of gait parameters, including cadence, stride time, swing time, single/double support time, symmetry ratios, stride length, stride velocity, stride width, foot-ground clearance, foot trajectory, and ankle plantar-dorsiflexion angle. The accuracy and precision of these gait parameters have been validated against ground truth in both young, healthy adults [34] and institutionalized older adults [35]. In our previous work, we have extensively focused on developing regression models to accurately estimate spatiotemporal gait parameters [36]–[40], center of pressure trajectories [41], [42], dynamic margin of stability [43], and hip joint angle [44]. In this study, our goal is to leverage AdaBoost to enhance the accuracy and performance of the instrumented footwear in predicting fall risk. A total of N=95 older adults are classified into fallers and non-fallers using three distinct criteria: retrospective fall history, prospective fall occurrence, and a combination of both retrospective and prospective data. *To the best of the authors’ knowledge, this study represents a pioneering effort in the field of fall risk prediction using wearable sensors by integrating both retrospective fall history and prospective fall occurrence.* The main contributions of this paper include 1) identification of effective gait parameters for fall risk prediction; 2) development of an AdaBoost-based fall risk prediction model; 3) validation of the proposed models both on retrospective and prospective fall data.

II. Material and Methods

TABLE I: Subject Information (SD = Standard Deviation)

	Type I (retrospective fall history)		Type II (prospective fall occurrence)		Type III (Type I $\vee$ Type II)	
	Faller (N=16)	Non-Faller (N=79)	Faller (N=15)	Non-Faller (N=80)	Faller (N=21)	Non-Faller (N=74)
Age, years (mean $\pm$ SD)	83.9 $\pm$ 7.8	84.6 $\pm$ 8.1	85.1 $\pm$ 6.7	84.3 $\pm$ 8.3	84.4 $\pm$ 6.9	84.5 $\pm$ 8.4
Female,%	14, 87.5%	53, 67.1%	11, 73.3%	56, 70.0%	17, 81.0%	50, 67.6%
Weight, kg (mean $\pm$ SD)	64.4 $\pm$ 17.8	68.3 $\pm$ 16.9	60.2 $\pm$ 17.8	69.1 $\pm$ 16.6	64.4 $\pm$ 18.6	68.6 $\pm$ 16.5
Height, cm (mean $\pm$ SD)	161.6 $\pm$ 8.3	164.2 $\pm$ 9.3	162.6 $\pm$ 9.3	163.9 $\pm$ 9.2	162.7 $\pm$ 8.2	164.0 $\pm$ 9.4
TUG, s (mean $\pm$ SD)	24.3 $\pm$ 12.4	21.4 $\pm$ 13.7	24.4 $\pm$ 14.5	21.4 $\pm$ 13.3	24.9 $\pm$ 14.0	21.0 $\pm$ 13.3
6MWT, m (mean $\pm$ SD)	206.6 $\pm$ 87.9	229.2 $\pm$ 85.7	204.3 $\pm$ 89.0	229.3 $\pm$ 85.5	206.3 $\pm$ 95.0	230.8 $\pm$ 83.2
FTSST, s (mean $\pm$ SD)	21.0 $\pm$ 11.3	18.9 $\pm$ 13.2	21.1 $\pm$ 9.8	18.9 $\pm$ 13.4	21.4 $\pm$ 11.1	18.6 $\pm$ 13.3

A. System Description

SoleSound [34], a fully portable instrumented footwear system (Figure 1), was developed at the Columbia University Robotics and Rehabilitation Laboratory. *SoleSound* includes two foot modules and a data logger. Each foot module consists of four piezoresistive force sensors, a nine-degrees-of-freedom (9-DOF) IMU (Yost Labs Inc., Portsmouth, OH), and a logic unit. The foot module also includes an ultrasonic sensor attached to the medial side of the footwear, though it was not used in this study, as shown in Figure 1-A. The force sensors are strategically positioned beneath the distal phalanx, the head of the first metatarsal, the head of the fifth metatarsal, and the calcaneus. The IMU is centrally embedded along the midline of the foot module, below the tarsometatarsal articulations, as shown in Figure 1-B.

The foot module collects foot pressure and kinematic data through a microcontroller (32-bit ARM Cortex-M4) powered by a compact 400 mAh Li-Po battery. Both the microcontroller and battery are housed in a custom plastic enclosure attached to the heel. The collected data is sampled at a rate of 500 Hz and wirelessly transmitted via UDP over a local IEEE 802.11n WLAN to a single-board computer running the data logger software. Simultaneously, the data is sent to a graphical user interface implemented in Matlab (The MathWorks, Natick, MA, USA) at a frequency of 50 Hz for visualization purposes.

B. Experimental Protocol

Ninety-five institutionalized older adults wearing appropriate sizes of *SoleSound* volunteered for the TUG, FTSST, and 6MWT in their living places under the supervision of a physical therapist. The older adults were recruited from five long-term care facilities in the New York metropolitan area. The Columbia University Institutional Review Board approved the experimental protocol and all participants provided informed consent. Gait parameters were simultaneously collected by the *SoleSound* and a validated electronic walkway, a 6-meter-long instrumented walkway (Zeno Walkway, Protokinetics LLC, Havertown, PA, USA). The instrumented walkway was located in the middle of a 25-meter-long course. A custom-made wireless board operating at 500 Hz was used to synchronize the two systems.

Research has shown that a history of falls is one of the strongest predictors of future falls [45], especially for older adults who have sustained an injurious fall [46]. Therefore, participants were categorized as fallers[1] if they had experienced at least one fall in the six months preceding the tests (Type I), reported at least one fall during the six-month following the tests (Type II), or experienced at least one fall extending from the previous six months into the six-month follow-up period (Type III). Their information is reported in Table I. Participants' fall histories were checked by their primary care doctors, who had access to their medical records. These data were periodically reviewed and updated for accuracy up to six months after the end of the test.

[1]Similar to [30], this study labels fallers as having fall risk and non-fallers as having no fall risk.

C. Fall Risk Prediction Using AdaBoost

In our research, we collected data from three different sources: timed mobility tests (i.e., TUG, FTSST, and 6MWT), gait data collected from the instrumented walkway during the 6MWT, and gait data collected from the instrumented footwear during the 6MWT. It is important to note that while the walkway data are confined to the length of the 6-meter mat, the instrumented footwear captures detailed gait data across the full 25-meter course, providing a richer and more extensive dataset. We first analyzed the importance of each type of data and selected the optimal features using a brute-force search method [47] (i.e., by testing all possible combinations). AUC, which refers to the area under the Receiver Operating Characteristic (ROC) curve, was selected to compare different classifiers [47]. The AUC value ranges from 0 to 1, where an AUC of 0.5 indicates that the model's predictive ability is no better than random guessing, while an AUC closer to 1 signifies that the model effectively distinguishes between positive and negative classes. After obtaining the optimal features, we constructed AdaBoost models for fall risk prediction under the three defined conditions (i.e., Type I, Type II, and Type III), Figure 2.

1) Feature Extraction: The set of candidate input features for the fall risk prediction model encompasses outcomes from traditional mobility tests (i.e., TUG, 6MWT, and FTSST). Additionally, it includes the mean and coefficient of variation (CV) for stride length (SL), stride velocity (SV), swing time (SW), double support time (DS), and stride time (ST) during the 6MWT [35].

2) Feature Selection: The feature selection process is depicted in Figure 3, and can also be summarized as follows:

(1) Split the dataset into training set and test set.

(2) Define an empty feature combination list to store all possible feature combinations. For each possible feature combination size (from 1 to N, where N is the total number of features), use an iterative method to generate all possible feature combinations.

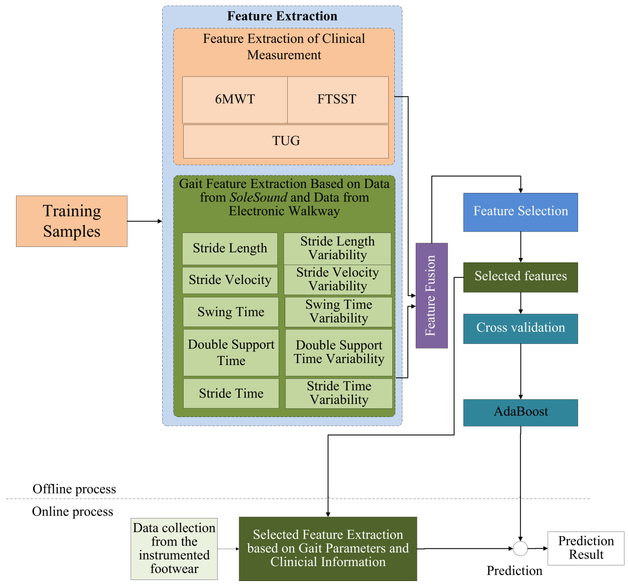


Fig. 2: The flowchart of the system. The electronic walkway incorporates a grid of pressure sensors, uniformly spaced at 1.27 cm intervals and embedded within a thin mat, enabling precise estimation of spatial and temporal gait parameters.

(3) For each feature combination, train a classifier model on the training dataset, then evaluate its performance by calculating the AUC value on the test dataset.

(4) During each iteration, compare the AUC value with the current best AUC value. If the new AUC value is higher, update the best AUC value and record the current feature combination.

if AUC $\geq$ AUC_Best: AUC_Best = AUC

(5) Select the feature combination with the best AUC value among all feature combinations as the final selection.

3) AdaBoost Classifier: The AdaBoost (Adaptive Boosting) classifier is a popular machine learning algorithm used for binary classification problems [47]. It is an ensemble method that combines multiple weak classifiers to create a strong classifier. Studies have shown that AdaBoost offers significant advantages in handling imbalanced data, enhancing model robustness, and improving classification performance [47], [48]. AdaBoost has also been reported to outperform other machine learning models, such as support vector machines, k-nearest neighbors, decision trees, and random forests in fall risk prediction [16]. Therefore, we selected AdaBoost to build the prediction model in this study.

We developed three models named Adacon, Adawalk, and Adafootwear, using different sources of gait data. Adacon utilized conventional features derived from the outcomes of the TUG, 6MWT, and FTSST. Adawalk was based on gait features obtained from the 6-meter-long instrumented walkway. Notably, Adafootwear used comprehensive gait data collected from the instrumented footwear, which covered the entire course of the 6MWT, not just the limited 6-meter walkway.

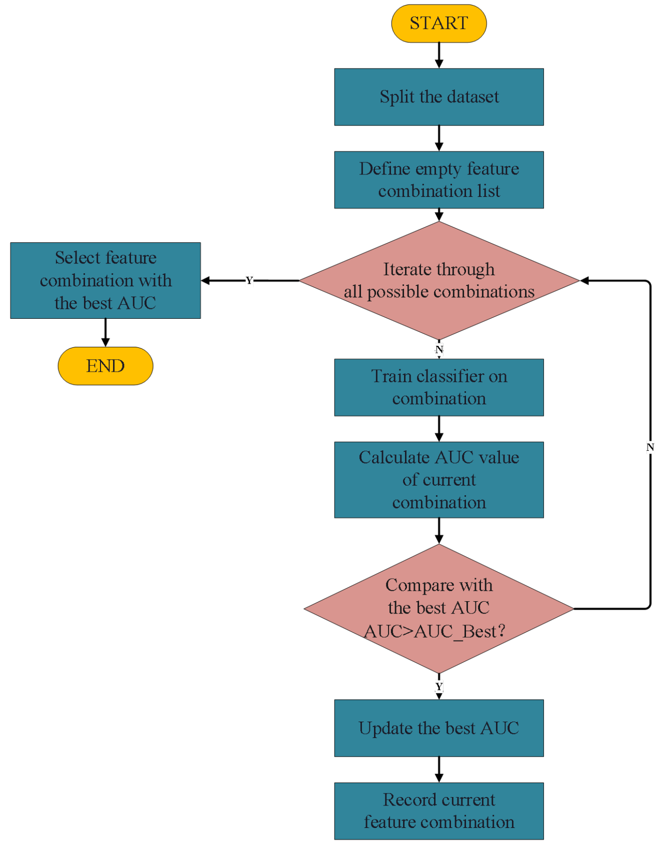


Fig. 3: The flowchart of feature selection. The dataset is split into a training set and a test set. A brute-force search method is then used to evaluate every possible feature combination. For each combination, the classifier is trained on the training set and its performance is assessed on the test set, measured by the AUC value. The feature combination that yields the highest AUC is selected as the optimal set, thereby ensuring maximum predictive accuracy.

D. Model Training and Evaluation

Leave-one-out cross-validation (LOOCV) was used to evaluate the unbiased performance of the proposed models [49]. LOOCV involves training the model on all but one sample and testing it on the left-out sample. This process is repeated for each sample in the dataset. LOOCV helps assess how well the model generalizes to unseen data. To assess the statistical significance of performance differences among the three models (i.e., Adacon, Adawalk, and Adafootwear), we also conducted 10-fold cross-validation. In this process, we performed a single 10-fold cross-validation. For each of the 10 folds, we used nine folds to train all three models (i.e., Adacon, Adawalk, and Adafootwear), and the remaining fold was used to test their performance. This process was repeated 10 times, once for each fold being the test set. The results from each fold were then aggregated to provide a robust comparison of the models' performances and to assess statistical significance.

The true positive rate (TPR), false positive rate (FPR), ROC curve, and AUC were selected as error metrics [47]. TPR, also referred to as sensitivity or recall, measures the proportion

This article has been accepted for publication in IEEE Transactions on Neural Systems and Rehabilitation Engineering. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2024.3510300

of actual positives correctly identified by the model. It is calculated as the ratio of true positives (TP, where an older adult is correctly classified as a faller when they are indeed a faller) to the sum of TP and false negatives (FN, where an older adult is incorrectly classified as a non-faller when they are actually a faller). The formula is as follows:

$$TPR = \frac{TP}{TP + FN} \tag{1}$$

FPR represents the proportion of actual negatives that were incorrectly classified as positives. It is calculated as the ratio of false positives (FP, where an older adult is incorrectly classified as a faller when they are actually a non-faller) to the sum of FP and true negatives (TN, where an older adult is correctly classified as a non-faller when they are indeed a non-faller). The formula is as follows:

$$FPR = \frac{FP}{FP + TN} \tag{2}$$

The ROC curve plots TPR against FPR at various classification thresholds, making it a widely used tool for evaluating binary classifiers.

E. Statistical Analysis

Two-way repeated-measures ANOVA was used to identify significant effects of the data source (Adacon, Adawalk, and Adafootwear) and classification criteria (Type I, Type II, and Type III), as well as potential interactions between these two factors. The AUC value was chosen as the dependent variable, as it is commonly used to compare classifiers [47]. When significant effects were found ($\alpha < 0.05$), post-hoc comparisons were conducted using the Bonferroni-Holm correction, as appropriate. All statistical analysis was carried out in SPSS v28 (IBM Corporation, Armonk, NY).

III. Results

The mean and CV for ST, SW, DS, SL, and SV measured by the instrumented walkway (i.e., Reference) and the instrumented footwear (i.e., *SoleSound*) during the 6MWT are reported in Table II.

TABLE II: Comparison of gait features measured by the instrumented walkway (i.e., Reference) and the instrumented footwear (i.e., *SoleSound*). The walkway data are confined to the length of the 6-meter mat, whereas the *SoleSound* collects data across the full 25-meter course throughout the entire 6MWT.

Type I	Faller (N=16)		Non-faller (N=79)	
	Reference	SoleSound	Reference	SoleSound
ST, s	1.30 ± 0.26	1.31 ± 0.26	1.27 ± 0.23	1.27 ± 0.22
SW, s	0.38 ± 0.04	0.38 ± 0.05	0.39 ± 0.06	0.40 ± 0.07
DS, s	0.27 ± 0.11	0.27 ± 0.10	0.24 ± 0.08	0.23 ± 0.06
SL, m	0.79 ± 0.23	0.82 ± 0.22	0.86 ± 0.25	0.91 ± 0.26
SV, m/s	0.65 ± 0.27	0.67 ± 0.25	0.70 ± 0.25	0.74 ± 0.26
cv_{ST}%	6.61 ± 3.22	7.26 ± 2.78	5.82 ± 2.37	6.54 ± 3.04
cv_{SW}%	10.20 ± 4.42	11.45 ± 4.31	11.04 ± 6.08	11.78 ± 7.55
cv_{DS}%	13.45 ± 3.59	14.19 ± 5.87	14.14 ± 4.88	14.58 ± 8.12
cv_{SL}%	9.11 ± 4.13	12.51 ± 4.14	9.28 ± 4.75	13.07 ± 6.04
cv_{SV}%	10.76 ± 3.75	14.21 ± 4.54	11.28 ± 4.93	14.51 ± 6.13
Type II	Faller (N=15)		Non-faller (N=80)	
ST, s	1.22 ± 0.21	1.24 ± 0.22	1.29 ± 0.23	1.29 ± 0.23
SW, s	0.37 ± 0.06	0.38 ± 0.06	0.39 ± 0.06	0.40 ± 0.06
DS, s	0.24 ± 0.07	0.23 ± 0.06	0.25 ± 0.09	0.24 ± 0.07
SL, m	0.76 ± 0.26	0.80 ± 0.25	0.87 ± 0.24	0.91 ± 0.25
SV, m/s	0.64 ± 0.27	0.67 ± 0.26	0.70 ± 0.25	0.74 ± 0.26
cv_{ST}%	7.46 ± 3.87	8.99 ± 4.98	5.67 ± 2.11	6.22 ± 2.25
cv_{SW}%	11.88 ± 6.13	15.33 ±12.80	10.72 ± 5.79	11.05 ± 5.28
cv_{DS}%	14.01 ± 3.86	14.39 ± 5.92	14.03 ± 4.83	14.54 ± 8.09
cv_{SL}%	11.25 ± 6.23	15.22 ± 6.55	8.87 ± 4.21	12.56 ± 5.53
cv_{SV}%	12.65 ± 5.63	16.33 ± 5.90	10.92 ± 4.54	14.10 ± 5.83
Type III	Faller (N=21)		Non-faller (N=74)	
ST, s	1.26 ± 0.25	1.27 ± 0.26	1.28 ± 0.23	1.28 ± 0.22
SW, s	0.37 ± 0.06	0.38 ± 0.06	0.40 ± 0.06	0.40 ± 0.07
DS, s	0.26 ± 0.10	0.25 ± 0.09	0.24 ± 0.08	0.24 ± 0.06
SL, m	0.77 ± 0.25	0.81 ± 0.25	0.87 ± 0.24	0.92 ± 0.25
SV, m/s	0.65 ± 0.29	0.67 ± 0.27	0.71 ± 0.24	0.74 ± 0.25
cv_{ST}%	6.98 ± 3.42	8.99 ± 4.42	5.66 ± 2.16	6.20 ± 2.29
cv_{SW}%	10.87 ± 5.43	15.33 ±11.13	10.91 ± 5.97	11.07 ± 5.37
cv_{DS}%	13.69 ± 3.47	14.39 ± 5.46	14.12 ± 4.98	14.56 ± 8.33
cv_{SL}%	10.26 ± 5.65	15.22 ± 6.09	8.96 ± 4.30	12.68 ± 5.66
cv_{SV}%	12.03 ± 5.15	16.33 ± 5.59	10.96 ± 4.62	14.19 ± 5.95

A. Feature Selection

Utilizing the feature selection methodology outlined in Section-II, models were constructed based on traditional measurement methods. The feature selection process involved evaluating the importance and relevance of various features for fall risk prediction. The resulting scores for the Top-5 selected features are presented in Table III.

These AUC values highlight the significance of each feature selected for the fall risk prediction models, which are based on traditional measurement methods. Higher scores denote a stronger link between the feature and fall risk, leading to a more precise and efficient prediction process, thereby enhancing the clinical utility of the models. It is important to note that the specific features and their scores listed in Table III are derived from the feature selection algorithm used in this study (i.e., Section-II-C). By testing all feature combinations, Table III reveals that solely including the FTSST outcome results in AUC values of 0.53, 0.47, and 0.53 under three different conditions, respectively. Subsequently, FTSST was incorporated into the development of the ”Adacon” prediction model, emphasizing its role in assessing mobility and balance.

Furthermore, employing the same feature selection methodology, models were constructed based on gait measurements from an instrumented walkway. The AUC scores for the Top-5 selected features are presented in Table IV. Our analysis reveals distinct optimal feature combinations for each condition: the combination of CV_{DS} and CV_{SV} yields the best result (AUC=0.69) for Type I; CV_{DS}, CV_{SW}, and ST for Type II (AUC=0.66); and CV_{DS}, CV_{SW}, SW, and ST for Type III (AUC=0.77). Consequently, the ’Adawalk’ model, specifically designed to evaluate gait dynamics on an instrumented walkway, incorporates these tailored gait metrics under each distinct type condition, thereby enhancing its predictive capacity for fall risk.

Applying the same feature selection methodology, additional models were developed based on gait measurements from instrumented footwear, as detailed in Table V. Our results reveal that for Type I conditions, the optimal feature combination—CV_{DS}, CV_{ST}, CV_{SL}, CV_{SV}, SW, and

TABLE III: The feature selection result of conventional measurements

	Features	AUC		Features	AUC		Features	AUC
Type I	FTSST	0.53	Type II	FTSST	0.47	Type III	FTSST	0.53
	TUG	0.47		TUG	0.47		FTSST, TUG	0.51
	FTSST, TUG	0.43		6MWT	0.39		TUG	0.47
	FTSST, 6MWT	0.38		FTSST, 6MWT	0.34		FTSST, TUG, 6MWT	0.40
	TUG, 6MWT	0.37		FTSST, TUG	0.34		TUG, 6MWT	0.39

TABLE IV: The feature selection result of gait measurements from the walkway

	Features	AUC
Type I	CV_{DS}, CV_{SV}	0.69
	CV_{DS}, CV_{SV}, ST	0.68
	CV_{DS}, CV_{ST}, ST, SW	0.68
	CV_{SW}, CV_{SV}, CV_{ST}, SW	0.68
	DS, ST, SW	0.68
Type II	CV_{DS}, CV_{SW}, ST	0.66
	CV_{DS}, CV_{SW}	0.63
	CV_{DS}	0.62
	CV_{DS}, CV_{SL}	0.61
	CV_{DS}, CV_{SW}, CV_{ST}, SL	0.61
Type III	CV_{DS}, CV_{SW}, SW, ST	0.77
	CV_{DS}, CV_{SW}, SW, ST, SV	0.75
	CV_{DS}, CV_{SW}, CV_{SV}, SW, ST, DS	0.74
	CV_{DS}, CV_{SW}, SW, ST, DS	0.73
	CV_{DS}, CV_{SW}, CV_{ST}, SW, ST	0.73

TABLE V: The feature selection result of gait measurements from the instrumented footwear

	Features	AUC
Type I	CV_{DS}, CV_{ST}, CV_{SL}, CV_{SV}, SW, SV	0.81
	CV_{ST}, CV_{SL}, SW, SV, SL	0.78
	CV_{DS}, CV_{ST}, CV_{SL}, SW, SV	0.78
	CV_{ST}, CV_{SL}, CV_{SV}, SW, SV	0.77
	CV_{SL}, SW, ST, SV	0.76
Type II	CV_{ST}, CV_{SW}, CV_{SL}, CV_{SV}, SL, SV	0.80
	CV_{ST}, CV_{SL}, CV_{SV}, SV	0.76
	CV_{ST}, CV_{SL}, CV_{SV}, SL	0.76
	CV_{ST}, CV_{SL}, CV_{SV}, ST, SL, SV	0.76
	CV_{ST}, CV_{SL}, CV_{SV}	0.75
Type III	CV_{ST}, CV_{SL}, SW, ST, SL, SV	0.77
	CV_{ST}, CV_{SL}, SW, ST, SL, SV, DS	0.73
	CV_{ST}, CV_{SL}, CV_{SV}, SW, ST, SL	0.71
	CV_{ST}, CV_{SL}, SW, SL, SV, DS	0.71
	CV_{ST}, CV_{SL}, CV_{SW}, SW, SL, SV	0.71

SV—achieves an AUC of 0.81; for Type II, the combination of CV_{ST}, CV_{SW}, CV_{SL}, CV_{SV}, SL, and SV (AUC=0.80); and for Type III, CV_{ST}, CV_{SL}, SW, ST, SL, and SV (AUC=0.77). Thus, the 'Adafootwear' model, specifically designed for assessing gait dynamics via instrumented footwear, incorporates these tailored gait metrics for each distinct condition, further enhancing its predictive capability for fall risk.

TABLE VI: AUC values for Adacon, Adawalk, and Adafootwear using 10-fold cross-validation

Model	Type I	Type II	Type III
Adacon	0.57	0.56	0.54
Adawalk	0.61	0.57	0.71
Adafootwear	0.70	0.70	0.76

TABLE VII: p-values of the two-way repeated-measures ANOVA (DS = data source, CC = classification criteria, ns = not significant)

	DS	CC	DS$*$CC
AUC	< 0.05	ns	ns

TABLE VIII: Adjusted p-values from the post-hoc analyses following one-way repeated-measures ANOVA. The Bonferroni-Holm method was used to adjust for multiple pairwise comparisons across the different AdaBoost classifiers.

	Adacon/ Adawalk	Adacon/ Adafootwear	Adawalk/ Adafootwear
AUC	ns	< 0.05	ns

B. Performance Evaluation

The AUC values for Adacon, Adawalk, and Adafootwear using 10-fold cross-validation are presented in Table VI. The results of the repeated-measures ANOVA are shown in Table VII, and the post-hoc analyses are reported in Table VIII. In summary, there was no interaction between the data source and the classification criteria. Although no significant effect was observed for the classification criteria, AUC values improved notably when combining past fall data with future fall data for both Adawalk (from 0.57 to 0.71) and Adafootwear (from 0.70 to 0.76), as shown in Table VI. Additionally, the data source significantly influenced the predictive ability of the AdaBoost classifiers. A separate one-way repeated-measures ANOVA (Table VIII) indicated that Adafootwear significantly outperformed Adacon, but not Adawalk. This might be due to the unbalanced nature of our dataset.

The ROC curves for Adacon, Adawalk, and Adafootwear under three type conditions using LOOCV are shown in Figure 4, Figure 5, and Figure 6, respectively. The confusion matrices using LOOCV for Adacon, Adawalk, and Adafootwear are shown in Figure 7, Figure 8, and Figure 9, respectively. In summary, the ROC curves obtained from the Adafootwear were closer to the top left corner for all three conditions (i.e., Type I, II, and III) compared to Adacon and Adawalk, indicating a lower FPR at higher sensitivity. The performance of models trained using gait data was better than those trained on traditional timed mobility test outcomes. Adafootwear demonstrated superior performance compared to Adawalk, indicating that models trained with data from the instrumented footwear outperformed those based on data from the instrumented walkway. Moreover, the sensitivity (i.e., TPR) of the models increases when they are trained using both past and future falls data, rather than relying solely on past or future falls data.

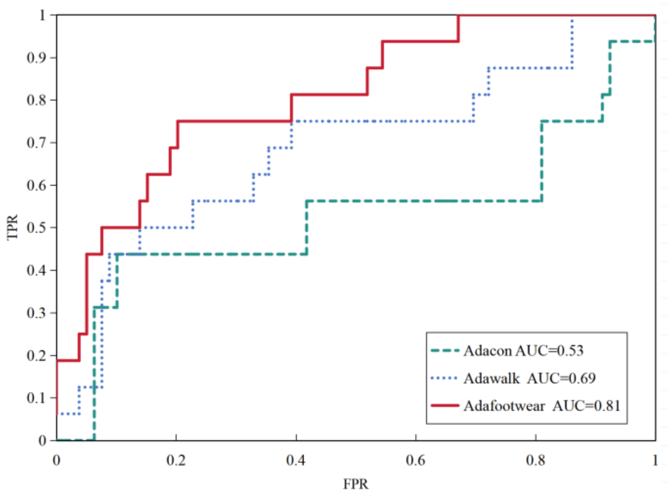


Fig. 4: ROC curves for Adacon, Adawalk, and Adafootwear under Type I condition using LOOCV (TPR = true positive rate, FPR = false positive rate).

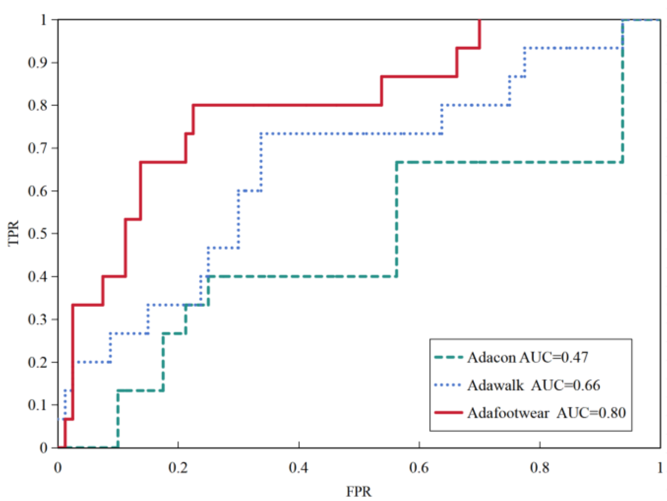


Fig. 5: ROC curves for Adacon, Adawalk, and Adafootwear under Type II condition using LOOCV.

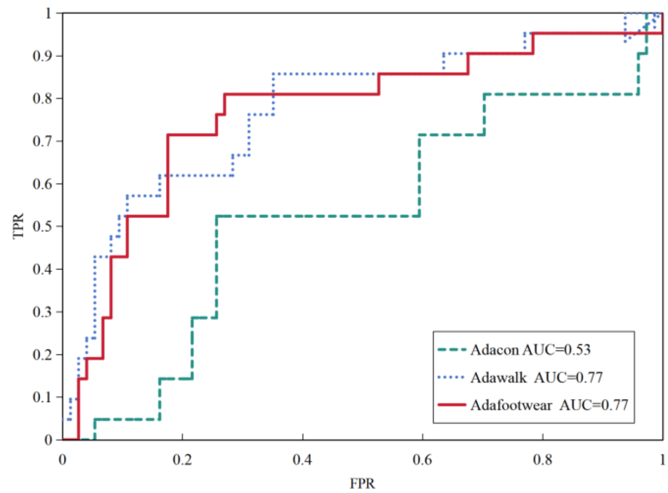


Fig. 6: ROC curves for Adacon, Adawalk, and Adafootwear under Type III condition using LOOCV.

IV. Discussion

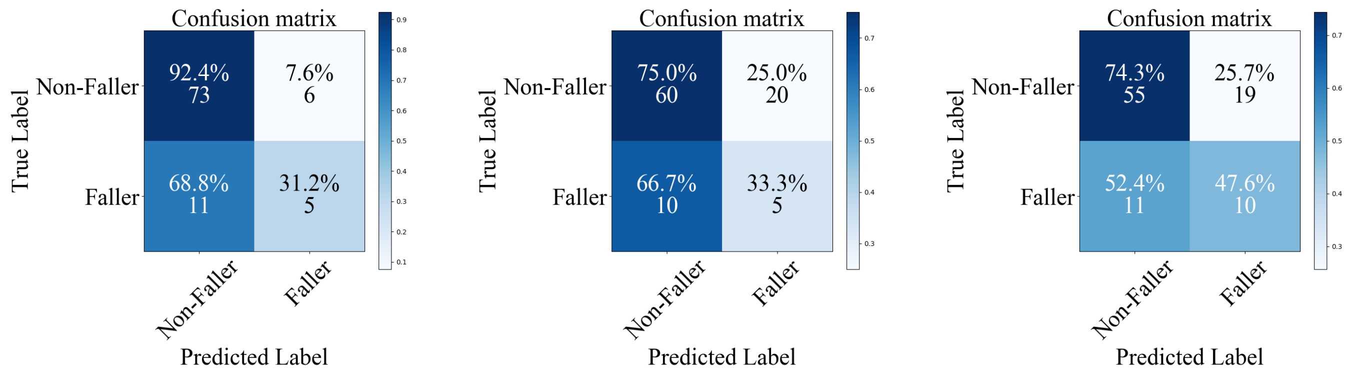
While wearable sensors are widely used to assess fall risk in older adults, most studies rely on retrospective fall history [8], [30]. A significant limitation of these studies is the alteration in gait due to past falls [30]. Older adults, often influenced by an inherent fear of falling, typically exhibit reduced stride velocity, decreased stride length, and extended double support duration [10]. While these gait alterations significantly impact the models predicting fall risk, their correlation with future falls remains uncertain [10], [30]. Our results highlight this limitation: when the fall risk prediction model, trained solely on retrospective fall data, is applied to a cohort of older adults at risk of future falls but without prior fall history (six participants in our study), its predictive accuracy drops to zero. Unlike models trained only on prospective fall data [19], [20], [31], to the best of the authors' knowledge, this study is the first to integrate both types of data in constructing a fall risk prediction model using wearable sensors. This approach has led to an improvement in the model's sensitivity.

Traditionally, fall risk prediction has relied on timed mobility tests, such as FTSST, TUG, and 6MWT. However, their efficacy in predicting fall risk is limited, with AUC values not exceeding 0.53, which is nearly equivalent to a random guess. This limitation is corroborated by prior research [7] indicating that TUG scores do not significantly predict fall occurrences. Additionally, the determination of a precise cutoff value for the TUG score presents a persistent challenge, with proposed thresholds ranging from greater than 12 seconds [1] to over 15 seconds [50]. Remarkably, in our study, the average TUG score for individuals who did not fall was 21 seconds, substantially above the often-recommended cutoff of 15 seconds.

Unlike the reference system, a 6-meter-long instrumented walkway, our instrumented footwear allows for a detailed gait evaluation across a larger number of strides. Particularly in the case of the 6MWT, usually conducted on a 25m or 30m straight-line course much larger than 6m [6], [35], using instrumented walkway results in collecting only a small portion of strides (in our study, this value is 24%), leaving a large number of strides unused. For this reason, the mean and variability of gait parameters estimated by the instrumented footwear are more trustworthy than those derived from the instrumented walkway. Therefore, the Adafootwear model demonstrated superior performance compared to the adawalk model in predicting fall risk in older adults.

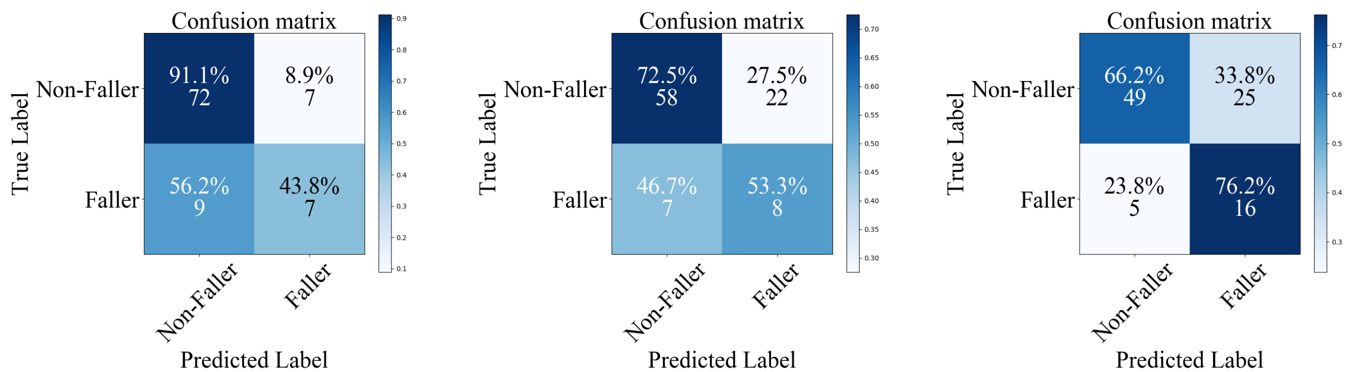
Due to AdaBoost's superior robustness and ability to handle non-linear relationships compared to logistic regression, our Adafootwear model demonstrated enhanced performance when compared to previous studies utilizing logistic regression models [19], [20]. As the primary objective of this study is to establish the potential utility of instrumented footwear for predicting fall risk in the everyday environments of older adults, we intentionally excluded outcomes from the TUG, 6MWT, and FTSST as input features for our prediction model. Despite evidence suggesting the potential benefits of incorporating TUG scores into logistic regression models [27], our focus

This article has been accepted for publication in IEEE Transactions on Neural Systems and Rehabilitation Engineering. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TNSRE.2024.3510300



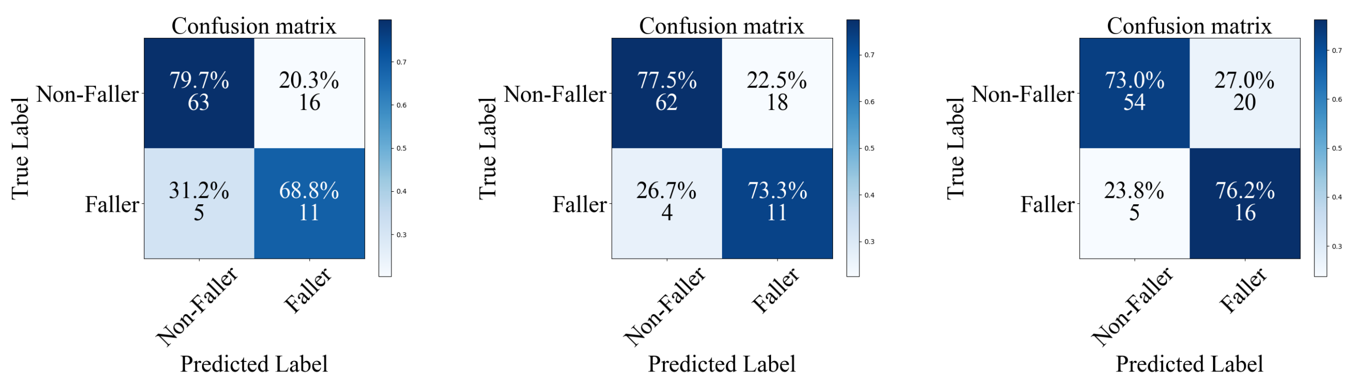
(a) Type I (b) Type II (c) Type III

Fig. 7: Confusion matrices for Adacon.



(a) Type I (b) Type II (c) Type III

Fig. 8: Confusion matrices for Adawalk



(a) Type I (b) Type II (c) Type III

Fig. 9: Confusion matrices for Adafoowear.

was on evaluating the standalone effectiveness of instrumented footwear. Benefiting from the extensive stride data collected in this study, our Adafootwear model demonstrated superior performance compared to classical machine learning models, such as neural networks, naive Bayesian, and SVM, even when incorporating additional inertial information from the head and pelvis [31]. This suggests that relying solely on gait information calculated from a 7.62-meter course [31] may not be sufficient. Notably, Tunca et al. [29] introduced a deep learning risk prediction model that achieved an impressive accuracy of 92.1%. However, the evaluation of the model's performance did not include cross-validation, casting doubts on its generalization capabilities. Furthermore, the validation of these models was exclusively based on retrospective data, which does not confirm their predictive reliability in real-world scenarios where prospective data is crucial. This limitation significantly restricts their practical applicability in predicting future events based on new, unseen data. Most importantly, the proposed AdaFootwear achieved an AUC of 0.80, outperforming the XGBoost model [32] and the natural language processing approach [33], both of which rely on electronic health records. This further demonstrates that gait data are highly correlated with future falls.

Despite the promising performance of our model, there are some limitations to consider. The inclusion of prospective falls data introduces considerable complexity, as the characteristics of prospective falls differ from those of retrospective falls. The features needed to predict prospective falls may not be fully recognized or utilized by the model, and the increased data volume and uncertainty make it more challenging to accurately predict 'no fall' cases. While this added complexity is essential for improving fall risk prediction, it may reduce the model's generalization performance in certain scenarios. Future research could focus on optimizing the balance between model complexity and predictive accuracy, particularly in handling both future and historical fall data more effectively. Additionally, this study predominantly utilized the AdaBoost algorithm for constructing predictive models. Future investigations will expand the methodological approach by comparing AdaBoost with other machine learning algorithms, such as support vector machines and artificial neural networks. Furthermore, the potential application of deep learning models will be explored to assess their efficacy in enhancing the accuracy of the instrumented footwear designed for fall risk prediction.

V. Conclusion

This study presented a novel approach using instrumented footwear for fall risk prediction in institutionalized older adults. The findings highlight the importance of gait data in identifying potential fall risks. The performance of the model developed based on the gait data collected from the instrumented footwear was better than those of models using traditional data and data from the instrumented walkway. By integrating both retrospective fall history and prospective fall occurrence, the sensitivity of the model increases.

This research contributes to the field of fall risk assessment in the elderly, providing valuable insights for fall prevention and care. However, further enhancements are needed to optimize the predictive accuracy of fall risk prediction models by exploring more advanced feature extraction techniques and machine learning algorithms. Future studies may also explore the integration of multiple models to further improve the accuracy and reliability of fall risk prediction systems.

VI. Acknowledgments

The authors would like to thank Dr. Enrique Jinete and the staff at Healing Therapeutics, LLC for their help with recruiting, scheduling, and administering the functional assessment tests to the study participants.

VII. Disclosure

The author reports no conflicts of interest in this work.

References

[1] CDC, "CDC supports communities," Tech. Rep., 9 2022. [Online]. Available: https://www.cdc.gov/falls/pdf/CDC-DIP_Ata-Glance_Falls_508.pdf
[2] L. D. Gillespie, M. C. Robertson, W. J. Gillespie, C. Sherrington, S. Gates, L. Clemson, and S. E. Lamb, "Interventions for preventing falls in older people living in the community," *Cochrane database of systematic reviews*, no. 9, 2012.
[3] H.-M. Noh, H. J. Song, Y. S. Park, J. Han, and Y. K. Roh, "Fall predictors beyond fall risk assessment tool items for acute hospitalized older adults: a matched case–control study," *Scientific reports*, vol. 11, no. 1, p. 1503, 2021.
[4] A. Tiedemann, H. Shimada, C. Sherrington, S. Murray, and S. Lord, "The comparative ability of eight functional mobility tests for predicting falls in community-dwelling older people," *Age and ageing*, vol. 37, no. 4, pp. 430–435, 2008.
[5] D. Podsiadlo and S. Richardson, "The timed "up & go": a test of basic functional mobility for frail elderly persons," *Journal of the American geriatrics Society*, vol. 39, no. 2, pp. 142–148, 1991.
[6] P. L. Enright, "The six-minute walk test," *Respiratory care*, vol. 48, no. 8, pp. 783–785, 2003.
[7] E. Barry, R. Galvin, C. Keogh, F. Horgan, and T. Fahey, "Is the timed up and go test a useful predictor of risk of falls in community dwelling older adults: a systematic review and meta-analysis," *BMC geriatrics*, vol. 14, no. 1, pp. 1–14, 2014.
[8] L. Montesinos, R. Castaldo, and L. Pecchia, "Wearable inertial sensors for fall risk assessment and prediction in older adults: A systematic review and meta-analysis," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 26, no. 3, pp. 573–582, 2018.
[9] J. Verghese, R. Holtzer, R. B. Lipton, and C. Wang, "Quantitative gait markers and incident fall risk in older adults," *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences*, vol. 64, no. 8, pp. 896–901, 2009.
[10] B. E. Maki, "Gait changes in older adults: predictors of falls or indicators of fear?" *Journal of the American geriatrics society*, vol. 45, no. 3, pp. 313–320, 1997.
[11] J. M. Hausdorff, "Gait variability: methods, modeling and meaning," *Journal of neuroengineering and rehabilitation*, vol. 2, no. 1, pp. 1–9, 2005.
[12] R. Rajagopalan, I. Litvan, and T.-P. Jung, "Fall prediction and prevention systems: recent trends, challenges, and future research directions," *Sensors*, vol. 17, no. 11, p. 2509, 2017.
[13] A. Dubois, T. Bihl, and J.-P. Bresciani, "Identifying fall risk predictors by monitoring daily activities at home using a depth sensor coupled to machine learning algorithms," *Sensors*, vol. 21, no. 6, p. 1957, 2021.
[14] W.-H. Chen and H.-P. Ma, "A fall detection system based on infrared array sensors with tracking capability for the elderly at home," in *2015 17th International Conference on E-health Networking, Application & Services (HealthCom)*. IEEE, Conference Proceedings, pp. 428–434.
[15] P. Glover-Kapfer, C. A. Soto-Navarro, and O. R. Wearn, "Camera-trapping version 3.0: current constraints and future priorities for development," *Remote Sensing in Ecology and Conservation*, vol. 5, no. 3, pp. 209–223, 2019.
[16] Z. Song, J. Ou, L. Shu, G. Hu, S. Wu, X. Xu, and Z. Chen, "Fall risk assessment for the elderly based on weak foot features of wearable plantar pressure," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 30, pp. 1060–1070, 2022.
[17] E. Anzai, D. Ren, L. Cazenille, N. Aubert-Kato, J. Tripette, and Y. Ohta, "Random forest algorithms to classify frailty and falling history in seniors using plantar pressure measurement insoles: a large-scale feasibility study," *BMC geriatrics*, vol. 22, no. 1, pp. 1–16, 2022.
[18] J. Howcroft, J. Kofman, and E. D. Lemaire, "Prospective fall-risk prediction models for older adults based on wearable sensors," *IEEE transactions on neural systems and rehabilitation engineering*, vol. 25, no. 10, pp. 1812–1820, 2017.
[19] K. Paterson, K. Hill, and N. Lythgo, "Stride dynamics, gait variability and prospective falls risk in active community dwelling older women," *Gait & posture*, vol. 33, no. 2, pp. 251–255, 2011.
[20] 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," *Clinical rehabilitation*, vol. 27, no. 2, pp. 183–190, 2013.

[21] A. Rampp, J. Barth, S. Schülein, K.-G. Gaßmann, J. Klucken, and B. M. Eskofier, "Inertial sensor-based stride parameter calculation from gait sequences in geriatric patients," *IEEE transactions on biomedical engineering*, vol. 62, no. 4, pp. 1089–1097, 2014.

[22] J. M. Hausdorff, Z. Ladin, and J. Y. Wei, "Footswitch system for measurement of the temporal parameters of gait," *Journal of biomechanics*, vol. 28, no. 3, pp. 347–351, 1995.

[23] B. Mariani, C. Hoskovec, S. Rochat, C. Büla, J. Penders, and K. Aminian, "3d gait assessment in young and elderly subjects using foot-worn inertial sensors," *Journal of biomechanics*, vol. 43, no. 15, pp. 2999–3006, 2010.

[24] A. Ramachandran and A. Karuppiah, "A survey on recent advances in wearable fall detection systems," *BioMed research international*, vol. 2020, no. 1, p. 2167160, 2020.

[25] S. Usmani, A. Saboor, M. Haris, M. A. Khan, and H. Park, "Latest research trends in fall detection and prevention using machine learning: A systematic review," *Sensors*, vol. 21, no. 15, p. 5134, 2021.

[26] X. Wang, J. Ellul, and G. Azzopardi, "Elderly fall detection systems: A literature survey," *Frontiers in Robotics and AI*, vol. 7, p. 71, 2020.

[27] B. R. Greene, A. O'Donovan, R. Romero-Ortuno, L. Cogan, C. N. Scanaill, and R. A. Kenny, "Quantitative falls risk assessment using the timed up and go test," *IEEE Transactions on biomedical Engineering*, vol. 57, no. 12, pp. 2918–2926, 2010.

[28] T. E. Lockhart, R. Soangra, H. Yoon, T. Wu, C. W. Frames, R. Weaver, and K. A. Roberto, "Prediction of fall risk among community-dwelling older adults using a wearable system," *Scientific reports*, vol. 11, no. 1, p. 20976, 2021.

[29] 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 journal of biomedical and health informatics*, vol. 24, no. 7, pp. 1994–2005, 2019.

[30] J. Howcroft, J. Kofman, and E. D. Lemaire, "Review of fall risk assessment in geriatric populations using inertial sensors," *Journal of neuroengineering and rehabilitation*, vol. 10, pp. 1–12, 2013.

[31] N. Eichler, S. Raz, A. Toledano-Shubi, D. Livne, I. Shimshoni, and H. Hel-Or, "Automatic and efficient fall risk assessment based on machine learning," *Sensors*, vol. 22, no. 4, p. 1557, 2022.

[32] C. Ye, J. Li, S. Hao, M. Liu, H. Jin, L. Zheng, M. Xia, B. Jin, C. Zhu, S. T. Alfreds *et al.*, "Identification of elders at higher risk for fall with statewide electronic health records and a machine learning algorithm," *International journal of medical informatics*, vol. 137, p. 104105, 2020.

[33] N. Dormosh, M. C. Schut, M. W. Heymans, O. Maarsingh, J. Bouman, N. van der Velde, and A. Abu-Hanna, "Predicting future falls in older people using natural language processing of general practitioners' clinical notes," *Age and ageing*, vol. 52, no. 4, p. afad046, 2023.

[34] S. Minto, D. Zanotto, E. M. Boggs, G. Rosati, and S. K. Agrawal, "Validation of a footwear-based gait analysis system with action-related feedback," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 9, pp. 971–980, 2015.

[35] H. Zhang, T. T. H. Duong, A. K. Rao, P. Mazzoni, S. K. Agrawal, Y. Guo, and D. Zanotto, "Transductive learning models for accurate ambulatory gait analysis in elderly residents of assisted living facilities," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 124–134, 2022.

[36] H. Zhang, M. O. Tay, Z. Suar, M. Kurt, and D. Zanotto, "Regression models for estimating kinematic gait parameters with instrumented footwear." IEEE, Conference Proceedings, pp. 1169–1174.

[37] H. Zhang, Y. Guo, and D. Zanotto, "Accurate ambulatory gait analysis in walking and running using machine learning models," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 1, pp. 191–202, 2019.

[38] H. Zhang, Z. Chen, D. Zanotto, and Y. Guo, "Robot-assisted and wearable sensor-mediated autonomous gait analysis §." IEEE, Conference Proceedings, pp. 6795–6802.

[39] T. T. H. Duong, S. Goldman, H. Zhang, R. Salazar, S. Beenders, K. M. Cornett, J. M. Bain, J. Montes, and D. Zanotto, "Validation of insole-based gait analysis system in young children with a neurodevelopmental disorder and autism traits." IEEE, Conference Proceedings, pp. 715–720.

[40] H. Zhang, C. Wu, Y. Huang, X. Li, X. Ma, R. Song, and S. K. Agrawal, "2d deep convolutional neural networks for estimating stride length and velocity in institutionalized older adults," *IEEE Sensors Journal*, 2024.

[41] H. Zhang, D. Zanotto, and S. K. Agrawal, "Estimating cop trajectories and kinematic gait parameters in walking and running using instrumented insoles," *IEEE Robotics and Automation Letters*, vol. 2, no. 4, pp. 2159–2165, 2017.

[42] T. T. Duong, D. Uher, S. D. Young, R. Farooquee, A. Druffner, A. Pasternak, C. Kanner, M. Fragala-Pinkham, J. Montes, and D. Zanotto, "Accurate cop trajectory estimation in healthy and pathological gait using multimodal instrumented insoles and deep learning models," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 4801–4811, 2023.

[43] Z. Chen, H. Zhang, A. Zaferiou, D. Zanotto, and Y. Guo, "Mobile robot assisted gait monitoring and dynamic margin of stability estimation," vol. 4, no. 2, 2022, Journal Article, pp. 460–471.

[44] T. T. H. Duong, H. Zhang, T. S. Lynch, and D. Zanotto, "Improving the accuracy of wearable sensors for human locomotion tracking using phase-locked regression models." IEEE, Conference Proceedings, pp. 145–150.

[45] S. Deandrea, E. Lucenteforte, F. Bravi, R. Foschi, C. La Vecchia, and E. Negri, "Risk factors for falls in community-dwelling older people: a systematic review and meta-analysis," *Epidemiology*, vol. 21, no. 5, pp. 658–668, 2010.

[46] P. Pohl, E. Nordin, A. Lundquist, U. Bergström, and L. Lundin-Olsson, "Community-dwelling older people with an injurious fall are likely to sustain new injurious falls within 5 years-a prospective long-term follow-up study," *BMC geriatrics*, vol. 14, pp. 1–7, 2014.

[47] A. Géron, *Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow*. " O'Reilly Media, Inc.", 2022.

[48] J. Tang, A. Henderson, and P. Gardner, "Exploring adaboost and random forests machine learning approaches for infrared pathology on unbalanced data sets," *Analyst*, vol. 146, no. 19, pp. 5880–5891, 2021.

[49] S. Theodoridis and K. Koutroumbas, *Pattern recognition*. Elsevier, 2006.

[50] M. Montero-Odasso, N. Van Der Velde, F. C. Martin, M. Petrovic, M. P. Tan, J. Ryg, S. Aguilar-Navarro, N. B. Alexander, C. Becker, H. Blain *et al.*, "World guidelines for falls prevention and management for older adults: a global initiative," *Age and ageing*, vol. 51, no. 9, p. afac205, 2022.