Fall Risk Assessment Using Gait Analysis and Wearable Sensors: A Machine Learning Approach

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***Abstract*— Falls among older adults are a leading cause of injury and mortality, necessitating accurate and timely fall risk assessment to enable preventive interventions.This study presents a novel framework for fall detection in elderly individuals using wearable sensors and machine learning techniques. Data collected of 71 participants, including accelerometer readings from the lower back, were analyzed using four segmentation algorithms to identify key gait events. In order to discriminate fallers from non-fallers, a time and frequency-domain features were extracted associate with Principal Component Analysis (PCA) to reduce feature dimensionality while retaining 99% of the data's variance. A comparison of machine learning models revealed that K-Nearest Neighbors (KNN) achieved the highest accuracy (89.7%) and computational efficiency.**

***Index Terms*— Gait analysis ,Fall detection, Inertial sensor, Machine learning, segmentation algorithm.**

I. Introduction :

FAlls are a leading cause of injury and mortality among older adults, particularly those with chronic conditions or impaired mobility. Identifying individuals at risk of falling is critical to preventing falls and reducing associated healthcare burdens [1]. Gait analysis, facilitated by wearable sensors, has emerged as a non-invasive and effective means of assessing fall risk in various populations. Recent advancements in sensor technology and machine learning have enabled the development of systems that can capture subtle gait changes, offering potential for real-time monitoring and prediction of falls.

Traditional methods for fall risk assessment often rely on clinical evaluations, such as the Timed Up and Go (TUG) test or gait assessments conducted under controlled environments [2]–[4]. While these approaches provide valuable insights, they are often time-intensive, resource-heavy, and limited in their capacity to detect dynamic gait changes during daily activities. However, wearable sensors, such as accelerometers and gyroscopes, provide an alternative by enabling continuous monitoring and producing comprehensive datasets that reflect individual gait variations.

Despite this progress, several challenges remain. Many systems and studies employ multiple sensors, which can be obtrusive and impractical for daily use. Moreover, deep learning techniques, while powerful, often require significant computational resources, limiting their applicability in real-time or resource-constrained settings. Addressing these limitations, this study leverages the Long Term Movement Monitoring (LTMM) database [5], a publicly available dataset containing accelerometer and gyroscope signals from older adults, to develop a practical and efficient fall detection system. By combining advanced segmentation algorithms, feature extraction, dimensionality reduction, and machine learning classifiers, we aim to achieve a balance between accuracy, computational efficiency, and real-world usability.

The remainder of the paper is structured as follows: Section 2 offers an overview and recent developments in the area. Subsequently, Section 3 clarifies the proposed method and the material requirements. Section 4 presents the results and discussion, and the paper concludes with a summary and future work.

II. Related Work

Numerous studies have explored fall detection systems using various sensor placements and machine learning algorithms, particularly in the context of gait analysis [6]. For instance, Chen et al. employed an accelerometer placed at L3–L5 during the Timed Up and Go (TUG) test, using wavelet transformation and a stacked autoencoder network, achieving an impressive 94.1% accuracy [7]. Qui et al. used five sensors across five different tests with an SVM classifier, reaching 89.4% accuracy [8]. Similarly, Rivolta et al. used a single accelerometer on the chest during the Tinetti test, achieving 89% accuracy with an artificial neural network (ANN) [9]. Gietzelt et al. collected one-week walking data from elderly individuals with dementia, employing decision trees for classification, and achieved an accuracy of 88.5% [10]. Meanwhile, Yu et al. used an accelerometer during the TUG test, integrating demographic information with the Short Form Berg Balance Scale, and reached 84% accuracy [11].

Some studies have focused on the placement of accelerometers to optimize fall detection. Greene et al. explored the use of five Shimmer sensors during three activities, showing 87.58%

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accuracy in men and 78.11% in women, indicating gender-specific performance differences [12]. Similarly, Howcroft et al. [13] employed four tri-axial accelerometers placed on the left and right shank, head, and pelvis, along with pressure-sensing insoles, achieving 84% accuracy using a multi-layer perceptron neural network. Similä et al. focused on two accelerometers located in the lower back (L3-L5) and the right hip, achieving accuracies between 69% and 79% during tasks such as the Berg Balance Scale and Timed Up and Go tests [14]. Doheny et al. [15] utilized two Shimmer tri-axial accelerometers positioned on the lateral right thigh and sternum, achieving an overall accuracy of 74.4% for fall classification during sit-to-stand tasks . Bautmans et al. [16] analyzed data from a single accelerometer placed in the pelvis and reported 77% accuracy while focusing on step time asymmetry and muscle force indicators.

In more advanced techniques, Nait et al. [17] used raw acceleration signals with deep learning, achieving a moderate 0.75 AUC , while Caby et al. used ten accelerometers placed on various body locations and achieved 95% accuracy using machine learning classifiers, though this approach was quite obtrusive and limited to low-risk subjects [18]. Marschollek et al. employed a single waist-mounted accelerometer to assess various tasks, including Timed Up and Go, kinetic energy measurements, and 20-meter walks. Their studies reported accuracies ranging from 65% to 90%, depending on the specific task and features analyzed. They highlighted the trade-offs between sensitivity and specificity, with sensitivity scores ranging from 39% to 74% and specificity reaching up to 100% in certain cases [19]. Can Tunca employed LSTM networks trained in spatio-temporal features derived from inertial sensors, achieving 92.1% accuracy, showing the potential of deep learning for gait-based fall detection [20]. Buisseret et al. combined an accelerometer and gyrometer during a 6-minute walk, using CNN-based deep learning but reported 81% accuracy and 62.5% sensitivity, indicating low sensitivity [21]. Meanwhile, Sabri Altunkaya achieved 82.2% accuracy and 82.9% sensitivity using a single accelerometer and the 17 most important features of those weighted for K = 20 nearest neighbors, highlighting the feasibility of single sensor solutions in clinical applications [22].

III. Material and Method:

The methodology adopted in this study is depicted in Figure 1, focusing on two essential aspects of gait analysis: the segmentation of the gait cycle and its subsequent classification. Initially, a comparative evaluation of various segmentation algorithms is conducted. These algorithms are designed to break down complex gait data into smaller, more interpretable segments, facilitating the identification of key gait events. Following this, machine learning algorithms are employed to classify these events into two categories: fall and non-fall.

A. Segmentation Methods

The analysis of human gait requires precise methods for extracting and interpreting the information contained in motion signals. Gait segmentation is one of the key steps in gait

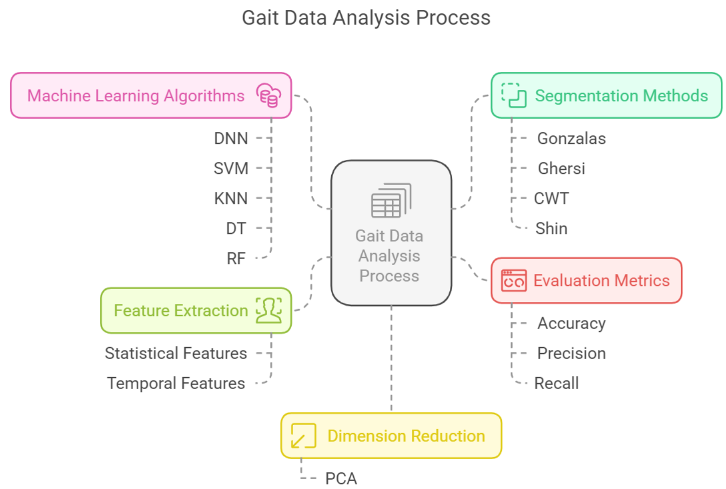


Fig. 1: Flow chart of the used methodology.

analysis, and requires an accurate detection of two key events: Initial Contact (IC) and Final Contact (FC).

The initial contact (IC) refers to the moment the heel first touches the ground during gait, signifying the beginning of the stance phase, which is the portion of the gait cycle when the foot remains in contact with the ground. In contrast, the final contact (FC) denotes the conclusion of the stance phase and the onset of the swing phase, during which the foot lifts off the ground and moves forward [23].

In this work, four gait cycle segmentation algorithms reported in the literature were used for a comparative analysis:

1) Algorithm of Gonzalez: The algorithm operates by first identifying zones linked to the occurrence of an IC event and subsequently pinpointing the corresponding peak. To determine these zones, the method detects zero crossings from positive to negative in the filtered anteroposterior acceleration signal. Once the zones and their time intervals are established, local maxima are identified in the raw signal. A series of heuristic rules are then applied to accurately associate the peak with the IC event. After the IC is identified, the process initiates a search for the contralateral FC within the raw vertical acceleration signal [24].

2) Algorithm of Ghersi: This algorithm suggests modeling the acceleration signal as a modified triangle wave through the dynamic time warping (DTW) method, rather than depending on pre-trained acceleration models or searching for a fundamental component of acceleration to identify regions of interest for IC events. In this model, local maxima of the triangle wave serve as estimates of IC, while local minima provide rough approximations of FC. Upon detection of IC and FC events, a correction for omitted or superfluous steps is initiated, followed by an optimization phase to achieve the definitive segmentation of the gait cycle [25].

3) Continuous Wavelet Transform (CWT) Algorithm: After linear detrending and low-pass filtering to clean up the acceleration signal, the pre-processed signal is integrated using a trapezoidal rule, then differentiated by cwt using an estimated wavelet scale and a first-order Gaussian wavelet. A search for local minima corresponding to the IC event is performed on the differentiated signal obtained, then the latter is differentiated again and the local maxima found is labeled as the FC event [26].

4) Algorithm of Shin: An adaptive step length estimation algorithm is proposed, beginning with the application of a sliding window summation technique to reduce data noise. This is followed by the differential acceleration method, which efficiently removes the effects of gravity. Once the signal is processed and refined, the zero-crossing method is utilized to identify the transition point from negative to positive, marking the Initial Contact (IC) event. This algorithm is designed to enhance step detection accuracy. [27].

B. Features Extraction

Feature extraction is crucial in the analysis of human gait, as it allows key information embedded in motion signals to be quantified and represented. Table 1 presents the various categories of features used in our study. Seven commonly used statistical features (mean, signal energy, standard deviation, skewness, maximum, and minimum values) are selected to help identify trends or patterns in walking, as well as any irregularities. Additionally, spatio-temporal features (such as cadence, step duration, etc.) are included to describe the dynamic relationship between a person's movement through space and the synchronization of their actions.

C. Dimensionality reduction

In our study, Principal Component Analysis (PCA) is applied as a dimensionality reduction technique to simplify and reduce the number of features used in the analysis [28].

PCA works by transforming the original set of correlated variables into a smaller set of uncorrelated variables, called principal components, which capture the most significant variance in the data. By focusing on the components that explain the largest proportion of variance, it can reduce the dataset's complexity while preserving the majority of essential information.

D. Classification

Several machine learning algorithms were implemented and evaluated in our study for benchmarking purposes. These included Support Vector Machine (SVM), Decision Tree (DT), Decision Tree enhanced with AdaBoost, Random Forest (RF), Random Forest combined with AdaBoost, K-Nearest Neighbors (KNN), Gaussian Naive Bayes (GNB), and Deep Neural Network (DNN). Each algorithm possesses unique strengths that help us identify the most effective model for our task. A systematic evaluation was performed to assess their effectiveness and precision in identifying patterns and anomalies within gait data.

IV. Results and Discussion:

This study utilizes the Long Term Movement Monitoring (LTMM) database from PhysioNet [5], which contains three-axis accelerometer and gyroscope data collected from the lower backs of 71 subjects. Table II provides an overview of the demographic and functional performance indicators available in the LTMM database. The dataset comprises information gathered from 71 community-dwelling older adults, with an average age of 78.36 ± 4.71 years (range 65–87 years). Participants were categorized into two groups, fallers and non-fallers, based on self-reported falls over the previous year. Those who reported two or more falls were designated as fallers, while all others were classified as non-fallers.

In terms of hardware, the dataset includes accelerometer and gyroscope signals collected using a belt equipped with a lightweight sensor (DynaPort, 87 × 45 × 14 mm, 74 g). This sensor, worn on the participants' lower backs, contains a triaxial accelerometer and gyroscope, enabling precise and comprehensive measurement of walking activity.

Although the LTMM database contains data collected in both real-life and laboratory environments, for our study, only data generated in the laboratory were used. This choice was made to leverage the controlled environment of the laboratory, which allows for standardization and reproducibility of measurements and enhanced sensor accuracy. In this setting, participants walked at a comfortable, self-selected pace, providing a more accurate representation of their natural gait.

Participants engaged in their usual daily activities without specific instructions or alterations to their routines, allowing for the observation of naturally varying gait patterns. Despite the lack of a standardized walking structure, parameters derived from accelerometer data were found to be associated with fall status, both retrospectively and prospectively. These findings indicate that the extracted features may serve as objective indicators of fall risk.

A. Segmentation methods results

This section presents the results obtained from applying four segmentation algorithms to the LTMM database. Our objective was to detect two key gait events: initial contact (IC) and final contact (FC). Figure 2 illustrates these events as identified by each algorithm, providing a comparative view of their detection accuracy and consistency.

The mean values for each gait parameter were calculated for both fallers and nonfallers, including cadence, step duration (SD), stride duration (SdD), double support duration (DSD), single support duration (SSD), stance phase duration (StPD), swing phase duration (SwPD) and gait symmetry. The result obtained is shown in table III.

The selection of the most appropriate algorithm depends on the specific objectives and priorities of the study. The Gonzalez algorithm provides a balanced approach by effectively distinguishing between fallers and non-fallers, particularly in cadence and symmetry. However, its limited sensitivity to subtle variations in gait phases, such as single- and double-stance durations, makes it better suited for applications prioritizing simplicity and general reliability. In contrast, the Ghersi

TABLE I: Features and corresponding equations used for gait analysis.

Description	Equation	Details
Mean: For each gait cycle, a mean value is computed using the following equation.	$\mu_i = \frac{1}{IC_{i+1} - IC_i} \sum_{j=IC_i}^{IC_{i+1}-1} a_j$	• a_j: Acceleration at time j between IC_i (initial contact) and IC_{i+1} • $IC_{i+1} - IC_i$: Number of data points in the gait cycle
Energy of a signal: Is the energy present in the acceleration signal, which can provide insights into the intensity of movement during walking	$E_i = \sum_{j=IC_i}^{IC_{i+1}} a_j^2$	• Sum of squared acceleration values within a gait cycle
Standard Deviation: For each gait cycle, the standard deviation is calculated using this equation:	$\sigma_i = \sqrt{\frac{1}{IC_{i+1} - IC_i} \sum_{j=IC_i}^{IC_{i+1}-1} (a_j - \mu_i)^2}$	• μ_i: Mean acceleration of the gait cycle
Variance: For each cycle is computed to quantify the degree of spread in gait using the following equation:	$\sigma_i^2 = \frac{1}{IC_{i+1} - IC_i} \sum_{j=IC_i}^{IC_{i+1}-1} (a_j - \mu_i)^2$	• Measures spread around the mean
Skewness: Quantifies the asymmetry of a probability distribution for each gait cycle according to the equation	$\frac{\frac{1}{IC_{i+1}-IC_i} \sum_{j=IC_i}^{IC_{i+1}-1} (a_j - \mu_i)^3}{\left(\sigma_i^2\right)^{3/2}}$	• Quantifies asymmetry of the acceleration distribution
Maximum/Minimum Value: Compute the highest or lowest value of each cycle using the following equation:	$\max(a_{IC_i}, \ldots, a_{IC_{i+1}})$ / $\min(a_{IC_i}, \ldots, a_{IC_{i+1}})$	• Peak positive/negative acceleration in the cycle
Cadence: Defined as the number of steps taken per unit of time (1 minute) for each segment (a gait cycle)	$\frac{60}{IC_{i+1} - IC_i}$	• Steps per minute (assumes IC timestamps in seconds)
Stride Duration: Is the time taken for a complete gait cycle, from Initial contact to the next one of the same foot	$SD_i = IC_{i+1} - IC_i$	• Time for one full gait cycle (heel strike to heel strike)
Step Duration: The time taken for a single step, from initial contact of one foot to initial contact of the opposite foot	$StD_i = IC_{R,i+1} - IC_{L,i}$	• Time between left and right foot initial contacts
Single Support Duration: Refers to the phase of a gait cycle in which a single foot makes contact with the ground, while the opposing foot is elevated.	$SSD_i = IC_i - FC_i$	• Time with only one foot in contact with the ground
Double Support Duration: Is the period during a gait cycle when both feet are in contact with the ground simultaneously.	$DSD_i = FC_{L,i} - IC_{R,i}$	• Time with both feet on the ground
Swing Phase Duration: Indicates the time during which a foot remains in the air.	$SwD_i = \frac{100 \times (IC_{i+1} - FC_i)}{SD_i}$	• Percentage of cycle with foot airborne
Stance Phase Duration: Indicates the time during which a foot remains in contact with the ground	$StD_i = \frac{100 \times (FC_i - IC_i)}{SD_i}$	• Percentage of cycle with foot grounded
Symmetry: Is quantitatively measured by evaluating the difference between right and left foot support times, normalized by their average:	$Sym = \frac{StD_{R,i} - StD_{L,i}}{\frac{1}{2}(StD_{R,i} + StD_{L,i})}$	• Compares left/right step durations
Step Length: The step length is estimated using the Weinberg formula	$SL = K \sqrt[4]{A_{\max} - A_{\min}}$	• Weinberg formula for step length estimation • K: User-specific scaling constant

TABLE II: LTMM database's information

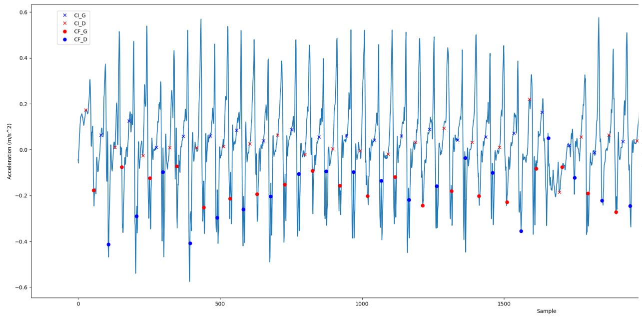
	No-Fallers	Fallers
Number of subjects (N)	39	32
Age (years)	78.77 ± 4.39	77.86 ± 5.09
Gender (% female)	64.10	65.62
Height (m)	1.64 ± 0.06	1.61 ± 0.09
Weight (kg)	72.02 ± 13.36	71.94 ± 12.29
Body mass index (kg/m2)	26.63 ± 3.99	27.86 ± 3.66
Years of education	14.39 ± 3.18	15.20 ± 3.48
Minimum mental state examination	28.47 ± 1.22	28.10 ± 1.58
Number of falls in past 6 months	0.15 ± 0.36	2.56 ± 2.23
Number of false steps in past year	0.82 ± 1.75	18.5 ± 52.43
Walking speed (m/s)	1.19 ± 0.24	0.97 ± 0.30

algorithm demonstrates robust and consistent performance across multiple parameters with minimal variability, making it ideal for applications requiring stable and reliable results across different datasets, despite its slightly reduced sensitivity to larger differences in certain metrics, such as cadence. On the other hand, the Shin algorithm is highly sensitive to gait variability, as it highlights pronounced differences in cadence and stance durations. However, the increased variability in its results can affect robustness, restricting its suitability to applications focused on detecting subtle gait abnormalities in high-risk populations. Finally, the CWT algorithm is effective in identifying critical variations in gait parameters, such as double- and single-stance durations, which are essential for analyzing stability.Nevertheless, its higher variability, particularly among fallers, reduces its reliability, limiting its application to phase-specific gait analysis and the detection of dynamic instabilities.

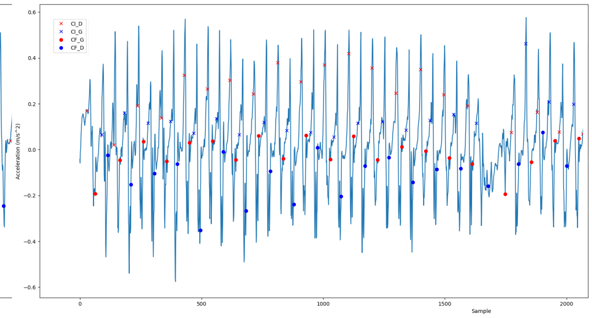
Considering that the main objective of this study is to develop a real-time fall prediction system in a short time frame, the Gonzalez algorithm was selected. Its balance of simplicity, efficiency, and reliability makes it a good fit for this application.

B. Classificaion results

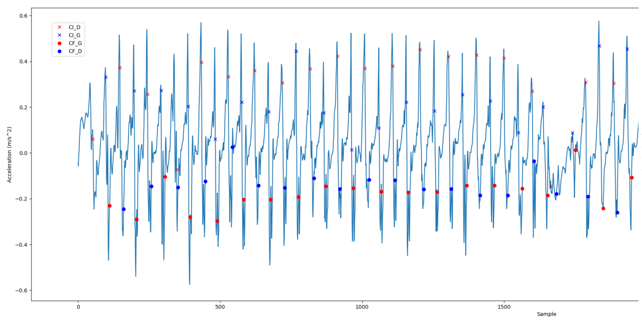
In order to proceed with classification, the extracted features were first standardized to ensure consistency in all parameters. The dataset were then split into three distinct subsets: one for



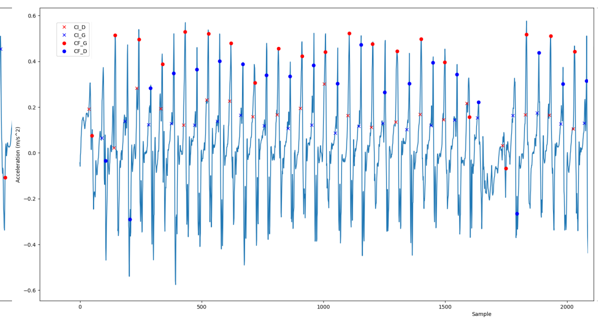
(a) Shin



(b) CWT



(c) Ghersi



(d) Gonzalez

Fig. 2: IC and FC events as identified by each algorithm: (a) Shin, (b) CWT, (c) Ghersi, and (d) Gonzalez

TABLE III: Mean value of each gait parameter for the each segmentation algorithm

Parameters	**Category**	**Gonzalez**	**Ghersi**	**Shin**	**CWT**
Cadence (step/mn)	Fallers	103.80 ± 11.41	105.18 ± 12.4	128.83 ± 30.17	104.3 ± 11.05
	Non-fallers	114 ± 9.14	114.24 ± 11.7	122.91 ± 11.1	112.61 ± 9.44
SD	Fallers	0.59 ± 0.097	0.58 ± 0.08	0.52 ± 0.0	0.59 ± 0.08
	Non-fallers	0.545 ± 0.073	0.53 ± 0.05	0.51 ± 0.03	0.548 ± 0.052
SdD	Fallers	1.202 ± 0.21	1.16 ± 0.16	1.043 ± 0.09	1.19 ± 0.15
	Non-fallers	1.129 ± 0.33	1.05 ± 0.07	1.031 ± 0.07	1.08 ± 0.1
DSD	Fallers	0.079 ± 0.031	0.104 ± 0.04	0.25 ± 0.04	0.29 ± 0.51
	Non-fallers	0.085 ± 0.037	0.1 ± 0.03	0.26 ± 0.02	0.14 ± 0.66
SSD	Fallers	0.52 ± 0.087	0.46 ± 0.08	0.26 ± 0.03	0.88 ± 0.54
	Non-fallers	0.4599 ± 0.084	0.42 ± 0.05	0.25 ± 0.03	0.69 ± 0.69
StPD	Fallers	0.56 ± 0.026	0.599 ± 0.04	0.74 ± 0.02	0.27 ± 0.4
	Non-fallers	0.58 ±0.038	0.595 ± 0.03	0.75 ± 0.01	0.37 ± 0.54
SwPD	Fallers	0.43 ± 0.026	0.4 ± 0.03	0.26 ± 0.03	0.72 ± 0.4
	Non-fallers	0.42 ± 0.038	0.405 ± 0.03	0.24 ± 0.01	0.62 ± 0.54
Symmetry	Fallers	0.9571 ± 0.024	0.95 ± 0.03	/	0.96 ± 0.05
	Non-fallers	0.9579 ± 0.085	0.97 ± 0.03	/	0.96 ± 0.033

training, one for evaluation, and one for testing, as detailed in Table IV. Subsequently, Principal Component Analysis (PCA) was employed as a dimensionality reduction technique for the feature set. To preserve at least 99% of the total variance, it was determined that 10 principal components were necessary, as illustrated in Figure 3.

TABLE IV: Data distribution of all features

Subsets	Percentage (%)	Cycle number
Training	70	2112
Validation	10	302
Test	20	604

This preprocessing step ensured that the data were optimized for classification while retaining the most significant features necessary to differentiate between fallers and non-fallers. To determine the optimal configurations for each classification model, an extensive hyperparameter search was conducted using the **GridSearchCV** method. The resulting best hyperparameters for each model are detailed in TableV.

Based on these configurations, the models' performance was evaluated using several metrics: Precision, Recall, F1-score, Accuracy, and ROC-AUC score.

The ROC-AUC-score represents the area under the Receiver Operating Characteristic (ROC) curve. while the formulas for the other metrics are as follows:

$$\textbf{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{1}$$

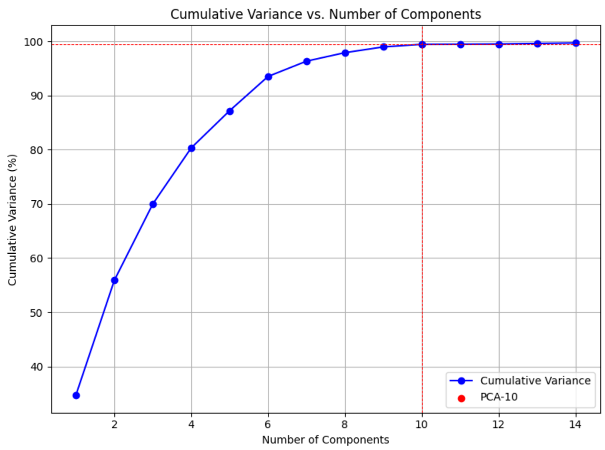


Fig. 3: Cumulative Variance vs.Number of Components

$$\textbf{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2}$$

$$\textbf{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\textbf{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Where : TP refers to True Positives, the correctly predicted positive samples. TN refers to True Negatives, the correctly predicted negative samples. FP refers to False Positives, the negative samples incorrectly predicted as positive. And FN refers to False Negatives, the positive samples incorrectly predicted as negative.

The results are presented in Tables VI and VII. Table VIprovides an overview of the overall accuracy of the different algorithms, along with key performance indicators such as ROC curve and execution time. Table VII offers a more detailed analysis of the algorithms' performance, including precision, recall, and F1-score, specifically for classifying fallers and non-fallers.

The results, as detailed in the previous tables, highlight significant differences in the performance of various machine learning algorithms, reflecting trade-offs between accuracy, computational efficiency, and generalizability:

- **SVM** achieves a high training accuracy of 99.52% but shows a notable decrease in validation (87.90%) and test accuracy (87.6%). While this drop suggests slight overfitting, the model demonstrates robust fall prediction capabilities with a precision and recall of 91%.
- **KNN** exhibits competitive validation (88.54%) and test accuracy (89.7%), reflecting better generalization compared to SVM. It maintains balanced precision and recall (91% each) and stands out for its computational efficiency, requiring only 0.008 seconds to execute.
- **DT** shows the weakest performance among the evaluated models, with validation (79.62%) and test accuracy (77.2%) significantly lower than other algorithms. However, the addition of AdaBoost markedly improves its performance, increasing test accuracy to 85.8%. This improvement comes with a trade-off in execution time, which rises to 1.8 seconds.
- **RF and RF with AdaBoost** perform comparably to DT-AdaBoost, with test accuracies of 84.9%. While boosting marginally enhances their performance, the improvement appears to plateau, suggesting diminishing returns with these ensemble methods.
- **DNN** achieves a test accuracy of 89.4% and an ROC of 89%, comparable to KNN. However, its execution time of 29 seconds highlights the computational cost associated with deep learning, making it less practical for real-time applications unless computational resources are optimized.

TABLE V: Hyperparameters for the models used in this study.

Model	Hyperparameters
SVM	Kernel: RBF C parameter: 4 Gamma parameter: 1
KNN	Number of neighbors: 3
DT	Splitting criteria: Gini Maximum depth: 10 Minimum samples per leaf: 2 Minimum samples per split: 1
RF	Number of trees: 100 Maximum depth: 15 Splitting criteria: Gini Minimum samples per leaf: 2 Minimum samples per split: 1
DNN	**Layer 1: Dense** Units: 128 Activation: Relu **Layer 2: Dense** Units: 16 Activation: Relu **Layer 3: Dense** Units: 8 Activation: Relu **Layer 4: Dense** Units: 1 Activation: Sigmoid **Optimizer:** Adam **Learning rate:** 0.01 **Epochs:** 100 **Batch size:** 16

By analyzing precision, recall, and F1-score results:
Algorithms such as SVM, KNN, and DNN demonstrate balanced performance for both fall and no-fall classifications, achieving F1-scores of approximately 91% for falls. This indicates their reliability in detecting falls while minimizing false negatives. DT exhibits the lowest F1-scores (79% for falls and 76% for no-falls), highlighting its limitations when not enhanced with boosting techniques. Boosted models, such as DT-AdaBoost and RF-AdaBoost, show improved F1-scores (86%-87% for falls), showcasing the effectiveness of ensemble methods in enhancing sensitivity and specificity.
In terms of execution time and practicality:

TABLE VI: Performance Metrics of Different Algorithms

Algorithm	Training Accuracy [%]	Validation Accuracy [%]	Test Accuracy [%]	ROC [%]	Execution Time [s]
SVM	99.52	87.90	87.6	88	0.25
KNN	93.62	88.54	89.7	90	0.008
DT	94.43	79.62	77.2	78	0.05
DT with AdaBoost	100	86.62	85.8	86	1.8
RF	100	85.67	84.9	85	1.08
RF with AdaBoost	100	86.62	84.9	85	1.12
DNN	96.38	88.85	89.4	89	29

TABLE VII: Detailed Performance Metrics for Classifying Falls and Non-Falls

Algorithm	Precision [%]		Recall [%]		F1-Score [%]	
	Fall	No-Fall	Fall	No-Fall	Fall	No-Fall
SVM	91	89	91	88	91	89
KNN	91	89	91	88	91	88
DT	74	81	83	71	79	76
DT-AdaBoost	86	85	88	83	87	84
RF	86	84	87	82	86	83
RF-AdaBoost	84	85	88	81	86	83
DNN	91	87	90	88	91	88

KNN is the fastest algorithm, with an execution time of just 0.008 seconds, making it highly suitable for real-time fall detection applications. SVM strikes a good balance between speed (0.25 seconds) and accuracy, making it another viable option for time-sensitive tasks. DNN, while highly accurate, demands significantly more computational resources, with an execution time of 29 seconds, which limits its practicality for real-time systems.

These results underline the importance of selecting classification models according to the computational constraints of the target application and the sensitivity required. For fall detection, it is crucial to minimize false negatives to avoid missing critical incidents, a criterion effectively met by KNN and SVM.

The findings of this study align with and extend existing research in fall risk assessment. Compared to [22], which also utilized the LTMM database and achieved 82% accuracy with 80% sensitivity and 84.2% specificity using twenty nearest neighbor (k=20), our approach achieves a higher test accuracy of 89.7% and competitive sensitivity through advanced dimensionality reduction techniques and optimized feature selection using three nearest neighbor (k=3). This highlights the efficacy of PCA in reducing data complexity without compromising predictive accuracy.

In contrast to studies such as [13] and [16], which placed accelerometers on the head and pelvis and achieved accuracies of 84% and 77.8%, the placement of an accelerometer in the lower back as is the case in the database used in our study allows the entire gait dynamic to be captured,ensuring broader applicability. Additionally, while [14] demonstrated high sensitivity (87.7%) with a dataset focused exclusively on female participants, our study ensures a balanced demographic representation, enhancing the generalizability of the results.

Similarly, deep learning approaches like those in [17] and [20], which achieved moderate AUC scores (0.63–0.96), often require significant computational resources, limiting their real-time applicability. In contrast, our use of KNN algorithm achieves an accuracy of 89.7% with a rapid execution time of 0.008 seconds, offers a practical alternative for real-time systems. These comparisons underscore the strengths of our approach in balancing accuracy, computational efficiency, and generalizability.

V. CONCLUSION AND FUTURE WORK

This study presents a comprehensive framework for fall risk assessment using gait analysis. Leveraging the Long Term Movement Monitoring (LTMM) database. An efficient and practical fall detection system was developed through the integration of advanced segmentation algorithms, robust feature extraction techniques, dimensionality reduction, and machine learning models. Our results demonstrate the effectiveness of the Gonzalez algorithm for segmenting gait cycles, achieving a balance of accuracy and simplicity well-suited for real-time applications.

Among the evaluated classifiers, K-Nearest Neighbors (KNN) emerged as the most practical model, achieving a test accuracy of 89.7% and an execution time of just 0.008 seconds. This highlights its suitability for real-time systems, particularly in resource-constrained environments. Support Vector Machine (SVM) also showed robust performance, offering a reliable alternative for applications requiring slightly higher computational resources. By comparison, deep learning models such as DNN provided competitive accuracy but were less feasible for real-time use due to their computational demands.

This study's approach emphasizes a balance between predictive accuracy, computational efficiency, and ease of deployment, addressing key limitations in existing fall detection systems. The use of PCA for dimensionality reduction not only enhanced computational efficiency but also maintained model accuracy, demonstrating the importance of optimizing feature sets for real-world applications.

While the findings are promising, further research is required to enhance the system's generalizability across diverse populations and activity conditions. Future work will explore integrating additional sensor modalities and optimizing deep learning models to improve both accuracy and computational feasibility. Additionally, validating the system in real-world clinical and home environments will be crucial to ensure its effectiveness and usability.

Ultimately, this study contributes to advancing fall detection systems by providing a framework that combines simplicity, efficiency, and accuracy. The proposed approach holds significant potential for improving the autonomy and safety of older adults, particularly in healthcare and community settings.

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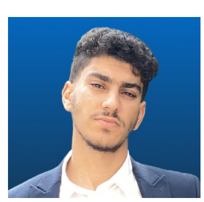

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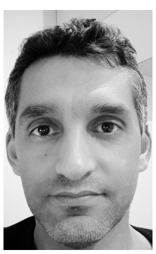

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