Analysis of Waist and Wrist Positioning Wearable Machine Learning Models to Detect Falls

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Falls are a widespread issue affecting people worldwide, regardless of their social status. Falls lead to physical, psychological, and economic consequences. Experts are developing solutions for this problem, given the high frequency of falls among the elderly. This study presents various ML models, which can predict human falls using signals of a wearable sensor located on the wrist or the waist. By extracting the mean, standard deviation, and range, we were able to train and evaluate various machine learning models considering accelerometers and gyroscopes as sensors. The combination of these characteristics and sensors resulted in the RF waist model achieving the most favorable metrics, achieving an accuracy rate of 97.22%.

Introduction: Over time, our bodies undergo a natural weakening process, leading to diminished physical well-being. This progression introduces novel challenges and obstacles for older adults, necessitating heightened vigilance. However, not everyone can sustain a constant state of awareness. Consequently, the elderly demographic is witnessing a rising incidence of falls. As each year elapses, individuals aged 60 and above find themselves increasingly vulnerable to experiencing falls [1].

Among the elderly population, falls occur abruptly and with alarming frequency. According to the findings in [2], approximately 30% of individuals aged 65 or above experience a fall at least once annually, and this percentage rises to 50% for those over 80 years old. The ubiquity of falls has garnered worldwide attention due to its substantial consequences for individuals and governments alike. As a result, researchers are tirelessly pursuing solutions to enhance the overall quality of life for those impacted by this concern.

According to [3], the detection of falls involves intricate pattern recognition, which varies from one individual to another. Falls can be described as the unintended interruption of one's activities on the ground, floor, or a lower surface [1]. Shockingly, an estimated 684,000 fatal falls occur annually, with a notable 80% of these incidents concentrated in low- and middle-income countries [1].

As mentioned in [4], the majority of falls occur in a forward, backward, or sideways manner. Notably, when a fall occurs alongside a loss of consciousness, the body suffers greater impact; since there is no impact absorption by the human and the body hits the ground directly. Numerous factors can elevate the likelihood of a fall occurrence. The natural aging process does impact senior citizens more. These factors can be categorized into two distinct groups: intrinsic and extrinsic [4, 5].

Intrinsic factors can be defined as those dependent on the individual, such as dizziness, lightheadedness, and a low muscle mass percentage. Extrinsic factors can be characterized as external to the elderly individual. These can be encountered in everyday situations, such as inappropriate footwear, damaged sidewalks, stairs, and others [5].

Serious injuries resulting from falls can encompass various consequences, including traumatic brain injuries, concussions, hemorrhages, and cuts [5]. Roughly one out of every three adults residing in their homes encounters a fall annually [6]. [1] highlights that several factors can contribute to an individual's vulnerability to falls, like age, gender, and overall health standing out as significant influences.

Falls serve as a significant cause of hospital admissions and stand as the leading contributor to mortality among individuals aged 65 and above [4]. The consequences of falls, as mentioned in [4,5], include both physical and psychological damage, like the fear of suffering a new fall. [4] underscores the substantial financial implications linked to such occurrences. Economic consequences ensuing after a fall are also of significance. Medical bills can become substantial, particularly if an individual needs to purchase medical equipment, undergo rehabilitation, and undergo medical evaluations.

Related works: To establish a benchmark for the results obtained in this study, 12 pertinent works were selected by searching into five repositories (IEEE Xplore, CAPES, EBSCO, ScienceDirect, and Google Scholar). A complete list of related works and open datasets can be found in the following document[1]. These studies focused on fall detection employing wearable sensors and machine learning (ML) models to categorize sensor data. The articles were written in English and published between 2014 and 2022. Authors had the flexibility to opt for various sensors, such as accelerometers, gyroscope, magnetometer, and barometer; but authors mostly used the accelerometer and gyroscope. In addition to wearable sensors, authors also had the option to utilize sensors embedded in smartphones.

It was noted that all studies used signals monitored by accelerometers. Several studies also incorporated a gyroscope and the magnetometer is only present in 2 of them. Figure 1 displays a pie chart depicting the distribution of the ML algorithms employed in the relevant works. Notably, the Support Vector Machine (SVM) stands out as the most frequently used algorithm, having a total of 11 (28%) implementations among the related works selected. In this paper, we used the SVM, k-NN and RF to perform fall classification due to their popularity.

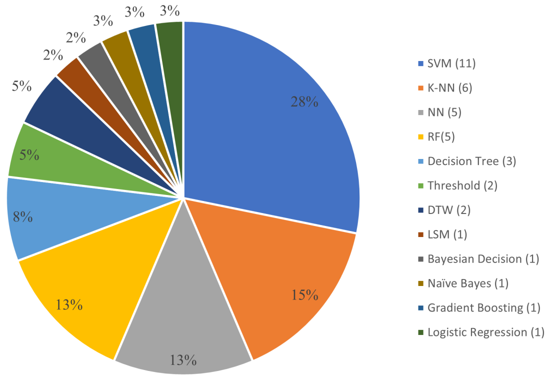

Fig. 1. Methodologies and algorithms employed in the relevant studies.

Given that fall detection systems handle time series data, authors had the flexibility to select diverse statistical features to more accurately portray falls and Activities of Daily Living (ADL). Authors can opt for basic statistical features, including mean, median, and standard deviation, but authors can use more complex features, for instance, the Fast Fourier Transform coefficients seen in three studies.

To facilitate a comparison between the results of the related works and the findings presented in this paper, it is essential to take into account the following metrics for evaluating the model's performance: accuracy, sensitivity, and specificity. [8] defines the accuracy as the model's ability to predict correctly, the sensitivity is the model's ability to predict falls correctly and the specificity is the model's ability to predict ADL correctly. As mentioned before the SVM is the most used classical ML algorithm within the related works. Among the SVM applications, the best results were 99.94% accuracy, 99.05% sensitivity, and 99.95% specificity [8]. For the k-NN algorithm the best results were 99.65% accuracy, 100% sensitivity, and 99.29% specificity [8]. [7] reported a 85.86% accuracy for the SVM model and a 90.10% for the RF model, both trained with waist data.

Open datasets: The necessity to select a dataset for training and testing the ML models was evident. A thorough search yielded a discovery of nine open datasets. These datasets span from 2014, to the most recent one, published in 2021. Each of these datasets was fashioned utilizing wearable sensors or harnessed the embedded sensors of smartphones. For example, the MobiFall dataset was created employing an accelerometer and gyroscope embedded within a Samsung Galaxy S3 smartphone, whereas the UniMiB SHAR solely relied on the accelerometer embedded within the Samsung Galaxy Nexus I9250.

All identified datasets uniformly employ the accelerometer as a sensor. The gyroscope is present in all datasets except for one. Due to its power consumption, the magnetometer is less commonly used than the other two sensors, featured in 5 datasets . The FallAllD [7] dataset stands as the sole one employing a barometer to capture body height. The number of

[1] http://bit.ly/teddy-ordonez-literature-and-open-datasets

participants engaged in the simulation of ADL and falls ranges from 8 to 38 individuals, with a majority being young adults.

Given our objective of categorizing data into two classes—ADL and Falls—datasets must encompass diverse examples for each category. For instance, prevalent ADL captured in the datasets encompass activities like walking, jogging, sitting down, and squatting. However, it's noteworthy that the DOFDA dataset documented only 5 distinct types of ADL.

Volunteers also participated in recording falls, with the freedom to choose the type of fall they felt comfortable simulating [7]. A variety of fall types were taken into account, including forward, backward, and side falls. Fall classifications should encompass aspects like rotation and recovery following impact [7]. Despite the possibility of users getting back on their feet post-fall, accurate fall identification remains crucial due to the potential occurrence of internal injuries that might go unnoticed by the user [7].

Considering that even simulated falls can potentially lead to injuries, the authors of multiple datasets, including explicitly state that they employed mattresses or mats to prevent harm to volunteers participating in fall simulations. It's crucial to acknowledge that the utilization of mats can alter sensor readings due to the impact-softening effect, resulting in different acceleration peak values. However, in contrast, FallAllD opted not to use any form of mattress to minimize fall impact. A comprehensive overview of the previously discussed datasets is available in Table 1.

This is why we opted to utilize the accelerometer and gyroscope data from the FallAllD dataset [7] to train, validate, and test the selected ML models. The FallAllD dataset [7] stands as a cutting-edge dataset encompassing 44 ADL and 35 falls, marking it as the dataset with the largest number of simulations among all the datasets explored in this study. This dataset was formulated with the collaborative effort of 15 volunteers. FallAllD encompasses readings from the accelerometer, gyroscope, magnetometer, and barometer [7], rendering it the most comprehensive and authentic dataset among the available open datasets.

Table 1: datasets summary.

ID	Dataset Name	Sensors	# of volunteers	ADLs/Falls
1	KFall	A, G & M	32	21/15
2	SisFall	A & G	38	19/15
3	Up-Fall	A & G	17	6/5
4	UMAFall	A, G & M	17	8/3
5	MobiFall*	A & G	24	9/4
6	UniMiB SHAR *	A	30	9/8
7	DOFDA	A, G, & M	8	5/13
8	Erciyes University [8]	A, G, M	14	16/20
9	FallAllD [7]	A, G, M & B	15	44/35

A = Accelerometer, G = Gyroscope, M = Magnetometer and B = Barometer.
* Smartphone built-in sensors

FallAllD analysis: As outlined in reference [7], FallAllD was meticulously recorded following a consistent pattern for each trial conducted by volunteers. Data from the accelerometer, gyroscope, magnetometer, and barometer were integrated to construct the FallAllD dataset, as previously indicated. For a more comprehensive understanding of the sensor specifications and data sampling, kindly refer to [7]. The array of sensors was positioned across three distinct regions of the volunteer's body: neck, wrist, and waist [7].

For the FallAllD dataset, the authors consciously adhered to a consistent simulation pattern, stipulating that both ADL, and falls should be recorded over a duration of 20 seconds [7]. This approach ensured uniform data recording regardless of the specific movement being captured. In regard to ADL, cyclic and transitory ADL were encompassed. For example, cyclic ADL like walking and jogging were executed repeatedly over the 20-second time frame. Transitory ADL, in contrast, refers to actions that conclude with the volunteer adopting a particular posture, like sitting down on a chair [7].

Volunteers engaged in various types of falls, encompassing scenarios where the starting position was inactive (sitting, lying, or standing still) and in motion (jogging, walking, or attempting to lay down) [7]. They used protective gear including helmets, knee pads, jackets, and back protection, while not using mattresses for cushioning [7]. Falls were systematically explored in multiple directions: forward, backward, sideways, and syncope. Notably, falls with subsequent recovery were also categorized as falls, considering the potential for internal injuries. For reference, Figure 2 offers an illustration of a graph depicting accelerometer and gyroscope data following a forward fall with recovery.

In the provided illustration, the volunteer initiated walking and approximately by the 9th second, a forward fall was simulated. This

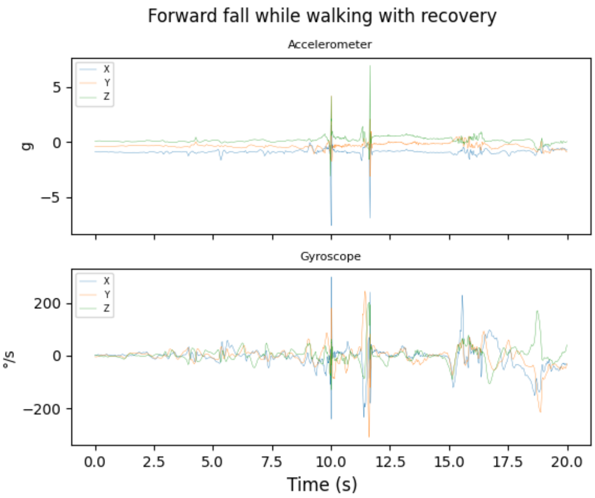

Fig. 2. Graph representing a forward fall with recovery.

instance is marked by a significant peak in acceleration, registering an excess of -5g on the accelerometer's X-axis upon impact. Around the 12th second of the simulation, the volunteer recuperates and resumes walking following the fall. This scenario typifies how falls with subsequent recovery need to be classified as falls, considering the user's experience. All fall simulations adhered to this pattern: commencing with a pre-fall status, the fall simulation occurs around the 9th second of the recording.

As our intention is to integrate the most effective ML model into a microcontroller, aiming to develop a wearable device for detecting falls among the elderly, a strategic decision has been made to extract a 5-second segment from the 20-second recordings provided by volunteers in [7]. This 5-second window encapsulates the most pivotal phase of the simulation: the impact. Within this segment, the accelerometer and gyroscope data authentically mirror the characteristics of a fall. Following a thorough graphical analysis of every fall and ADL simulation in the dataset, we have chosen to extract data from the interval starting at the 7.5-second mark up to the 12.5-second mark. This range captures both the impact and a distinctive representation of ADL within the specified window. Notably, data extraction encompasses not only the impact phase but also the subsequent recovery phase when applicable [7]. The ML models were trained and evaluated based on the information extracted from this designated window.

Development: Upon completion of data analysis, the subsequent step entails extraction of the 5-second window and the necessary features to train and evaluate the ML models. We employed the Python programming language, using essential libraries like Pandas, Matplotlib, and Scikit-Learn. These libraries provided the essential functionalities for data manipulation and analysis, data visualization, and ML implementation, respectively. In FallAllD dataset, each simulation was meticulously annotated with information including subject ID, device type, activity ID, trial number, and sensor data [7]. Given our focus on crafting ML models for wearable devices, our emphasis rested on the wrist and waist devices. This selection was driven by the aim to design a wearable device that is ergonomic for older individuals, taking into consideration their common use of belts and watches. This strategy led us to apply a filter using Pandas, enabling the creation of a filtered dataset exclusively containing data from the aforementioned devices.

A condensed representation of the development process is presented in Figure 3. A more detailed description of each step of the development can be found below.

Having obtained the refined dataset, the next step involved implementing data manipulation procedures. Foremost, it was necessary to assign labels to each activity, categorizing them as either "Fall" or "ADL". As elucidated in [7], the activity ID provides the means to distinguish the nature of the data representation. To execute this categorization, we introduced a new column named "Fall". Herein, activities with an ID below 100 were assigned a value of 0, signifying ADL, while those exceeding 100 were assigned a value of 1 to denote falls. Furthermore, it's imperative to highlight that the data within the FallAllD dataset has been stored in a raw format following the sensor readings. Consequently, the

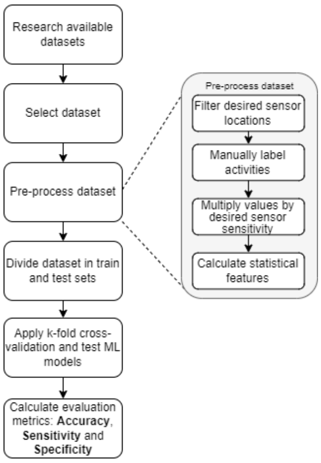

Fig. 3. Graphical representation of the development process.

values can be scaled by the sensor's sensitivity for compatibility reasons. Operating within a simulation environment, we scaled the accelerometer and gyroscope values by their respective sensitivities, which are 0.244 mg/LSB and 70 mdps/LSB.

Following these steps, we conducted basic statistical calculations to prepare the data for the training and testing of our ML models. In pursuit of comprehensive comparisons, we adopted similar features to those identified in [7]. We computed the mean, standard deviation, and range for each of the three axes corresponding to the sensors. As depicted in Figure 1, the three most prevalent ML models employed in related works were the Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and the Random Forest (RF). Consequently, we have opted to employ these same models, enabling a comparative analysis of the outcomes of this study with those of related works.

After calculating the necessary features, we divided the data into train and test sets using the *train_test_split* function from the Scikit-learn library. This function will aid in performing a split for train and test sets, setting 10% of the dataset aside for testing purposes. The remaining 90% were used to train and validate the models. We applied k-fold cross-validation, with k = 10, to further divide the training set into train and validation sets. This means that nine folds will be used to train and one fold to validate in one iteration. Repeating this process 10 times so this way every fold was used to validate the model, avoiding overfitting the models. With this partitioning, the dataset was divided into 70% for training, 20% for validation, and 10% for testing.

Results: As stated before, we trained the SVM, k-NN, and the RF models for waist and wrist devices using the accelerometer's and gyroscope's statistical features calculated before. We ended up having six different ML models, three for each location. For evaluation purposes, we calculated the accuracy (Acc), sensitivity (Se), and specificity (Sp) for each model [8]. These metrics can be defined by the following formulas, where TP, stands for True Positive, TN, True Negative, FP, False Positive and FN, False Negative:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} * 100 \quad (1)$$

$$Se = \frac{TP}{TP + FN} * 100 \quad (2)$$

$$Sp = \frac{TN}{TN + FP} * 100 \quad (3)$$

The outcomes obtained in this study are documented in Table 2 presented below. The best results for each location are highlighted in bold font.

Table 2: Results obtained.

Algorithm	Location	Acc (%)	Sp (%)	Se (%)
SVM	Waist	93.33	96.00	87.27
k-NN	Waist	83.33	91.45	68.25
RF	**Waist**	**97.22**	**98.42**	**96.15**
SVM	**Wrist**	**93.25**	**94.41**	**86.49**
k-NN	Wrist	87.71	91.5	63.46
RF	Wrist	92.86	94.23	86.36

The most effective ML model overall is the RF waist model, achieving an accuracy of 97.22%, a specificity of 98.42%, and a sensitivity of 96.15%. This model is as highly proficient as when compared to related studies, even outperforming some works. Notably, it's worth mentioning that this ML model exceeds the results outlined in [7], accomplishing a superior accuracy while utilizing the same model and features. Concerning the wrist, the SVM model demonstrated a marginally improved accuracy of 0.39% compared to the RF model. The RF model exhibited enhanced sensitivity in fall classification, leading to fewer FN (falls misclassified as ADL). Specifically, it demonstrated only **three** misclassified falls and **two** misclassified ADLs, whereas the SVM wrist model resulted in 12 misclassified falls and 5 misclassified ADL. The confusion matrix for the RF model is illustrated in Figure 4 below.

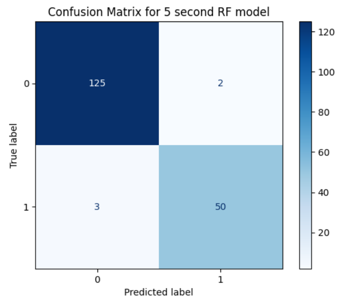

Fig. 4. Confusion matrix for RF waist model.

Conclusions: Falls represent a significant challenge for society, encompassing not only physical repercussions but also substantial economic and psychological impacts. The contemporary lifestyle often entails younger adults being preoccupied with work commitments away from home, leaving elderly individuals unsupervised.

In this work, we found that using an accelerometer and gyroscope located at the waist, instead of the wrist, it is possible to achieve better results. The RF model had an outstanding performance using only three features. It has a 97.22% accuracy, 98.42% specificity, and 96.15% sensitivity. We intend to integrate the top-performing ML classifier, namely the RF waist model, into a microcontroller. This integration aims to develop a wearable device with the capability to accurately detect falls.

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