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Computational Solutions for Human Falls Classification

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ABSTRACT In the last two decades, studies about using technology for automatic detection of human falls increased considerably. The automatic detection of falls allows for quicker aid that is key to increasing the chances of treatment and mitigating the consequences of falls. However, each type of fall has its specificities and determining the correct type of fall can help treat the person who has fallen. Although it is essential to use computational methods to classify falls, there are few studies about that in the literature, especially compared to the studies that propose solutions for fall detection. In this sense, we execute a systematic literature review (SLR) using the (Kitchenham et al., 2009) method to investigate the computational solutions used to classify the different types of falls. We performed a search on Scopus, Web of Science, and PubMed scientific databases looking for computational methods to fall classification in their papers. We use the grounded theory methodology for a more detailed qualitative analysis of the papers. As a result of our search, we selected a total of 36 studies for our review and found two different computational methods for classifying falls. Related to the steps used in each method, we found fourteen different types of sensors, four different techniques for background and foreground extraction of videos, twenty-one techniques for feature extraction, and seven different fall classification strategies. Finally, we also identified fifty-one different types of falls. In conclusion, we believe that the methods and techniques analyzed in our study can help developers to create new and better systems for classification, detection, and prevention of falls and falls database. Besides, we identified gaps that can be explored in future research related to the automatic classification of falls.

INDEX TERMS Automated falls, classification algorithms, e-health, falls, falls classification, types of falls.

I. INTRODUCTION

Falls are the main cause of morbidity, disability, and increased utilization of health care among the older adults [2] population. According to the World Health Organization (WHO) [3], falls are the leading cause of serious injury in the elderly, reaching as much as 28-35% of people over the age of 65 and over 32-42% of people over 70 years of age. Fall is defined as "an event in which a person inadvertently comes to rest on the ground, floor, or lower-level" [4]. It is crucial to immediately detect the situation when a fall occurs because these accidents usually lead to more severe illness or even death. Early detection of falls is essential for rescuing injured people from danger and getting help as quickly as possible [5]. For Mubashir *et al.* [6], the demand for surveillance systems, especially for fall detection, has increased in the health sector with the rapid growth of the older adult population in the world. It has become relevant then to develop intelligent surveillance systems that can automatically monitor and detect falls.

Several fall detection devices and fall risk assessment and prevention systems have been developed to enable older adults or those with chronic diseases to live safely and independently at home. According to Abdelhedi *et al.* [7], a fall detection system is one or more system that sends an alert in response to a fall. A miniaturized fall detection device seeks

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to improve the accuracy of fall detection, having a minimal impact on the user's daily life (e.g., apple watch series 4). Moreover, a fall risk assessment system is one or more systems capable of identifying the risk of a person falling based on sensory data and well-defined measures [8], [9].

Falls may be due to intrinsic causes (such as pre-existing diseases) or extrinsic causes (such as slippery environments) and may have specific characteristics that impact the reliability of fall prevention and fall detection solutions [9]. Therefore, works that seek to provide these computational solutions usually classify or categorize types of falls according to the characteristics observed about it, for example, the direction of the fall, the place where the fall occurred, the speed of the fall, the final position, or even the post-fall movement. According to Mubashir *et al.* [6], we should be considering different scenarios when identifying different types of falls: walking or standing falls, falls with supports (e.g., stairs), falls during sleep or lying in bed, and falls when sitting in a chair.

It is also interesting to note that some fall characteristics also exist in daily actions, for example, a squat also demonstrates a rapid downward movement. Moreover, each fall has specificities that may be related to the profile of the person [10], [11] and to the health status of the patient when the fall occurred, for example, some falls may correlate with specific diseases [12]. Besides, there are types of falls that are more dangerous and deserve more attention [13]. For example, falls to the sides may be more likely to cause fractures in frail older adults [14], [15].

Thus, it is important to not only develop solutions for fall prevention and fall detection but also to classify its types according to characteristics observed for each fall. Using known computational methods to classify human falls may be advantageous for developing better fall detection applications, fall risk assessment systems, and fall prevention solutions capable of identifying specificities and even possible causes of falls, as in Makhlouf *et al.* [16]. These methods should have steps and techniques for each of these steps well-defined to allow replicability. These methods can also aid in building fall databases to be used in experiments aimed at new automatic fall detection and prevention solutions and assist in the faster identification of better treatment for each specific type of fall.

Therefore, we execute a Systematic Literature Review (SLR) and find studies from 2006 to 2021 with methods for classifying human falls aided by computational technologies. Moreover, we analyze how these methods work. As a result, we found thirty-six studies that use fall classification methods. Based on these studies, two different types of methods with three or four activities are identified. These methods have as main activities: Sensing, Background and Foreground Extraction (exclusively for methods based on Video Technologies), Feature Extraction, and Execution of the Fall Classification Strategy. Also, we found three types of technologies used by these studies and 51 different types of falls covered by the selected studies. Each kind of fall is related to an observed characteristic of each fall. Finally, we find out open questions about fall classification not treated by these studies and challenges that require further research.

II. RESEARCH METHODOLOGY

We based our Systematic Literature Review (SLR) on the method proposed by Brereton *et al.* [17] and Kitchenham *et al.* [1]. This method is the most used for developing SLRs in the software engineering area and has three activities: Planning, Execution (or conducting), and Presentation (or documentation). Each activity has a series of specific tasks for SLR development. Figure 1 illustrates the process adopted in this study.

During the SLR planning, we define the research questions and the search strategy and generate the protocol that guides the execution. This protocol is constructed and validated interactively. In our case, we created several versions of this protocol and submitted it to the evaluation of specialists until obtaining the final version. This document contains the general objective of the review, the search strategy, the research questions, the papers' eligibility criteria, the quality assessment criteria of the selected literature, and the list of data that we want to extract from the selected literature.

In the conducting phase, we execute the search strategy and apply the eligibility criteria for selecting the papers. After this, we verify the quality criteria of the selected studies and extract and synthesize the data.

Finally, in the presentation phase, we generate the report and discuss the results. This paper presents our report, and it contains the results of the SLR and the discussion about them. This work follows the model of the Preferred Reporting Items for Systematic Reviews and Meta-Analyzes (PRISMA) [19] that suggests the discussion of the results based on the research questions.

A. PLANNING

This section presents the research questions, the search strategy, the query string, and the eligibility criteria.

First, we specified four **research questions** for this SLR, as follows:

1) What are the computational methods used to classify falls?
2) What are the techniques used in each activity of these methods?
3) What are the advantages of using fall classification methods?
4) Which types of falls are classified by these methods?

We analyzed and discussed the answers to these questions in Section IV.

The **search strategy** of this SLR consists of two phases. In the first phase, we utilized a query string to search papers in public scientific studies databases. In the second phase, we performed a manual procedure, known as snowballing, to analyze the citations (snowballing forward) and references (snowballing backward) of the articles previously selected in the first phase. Snowballing is used to complement the

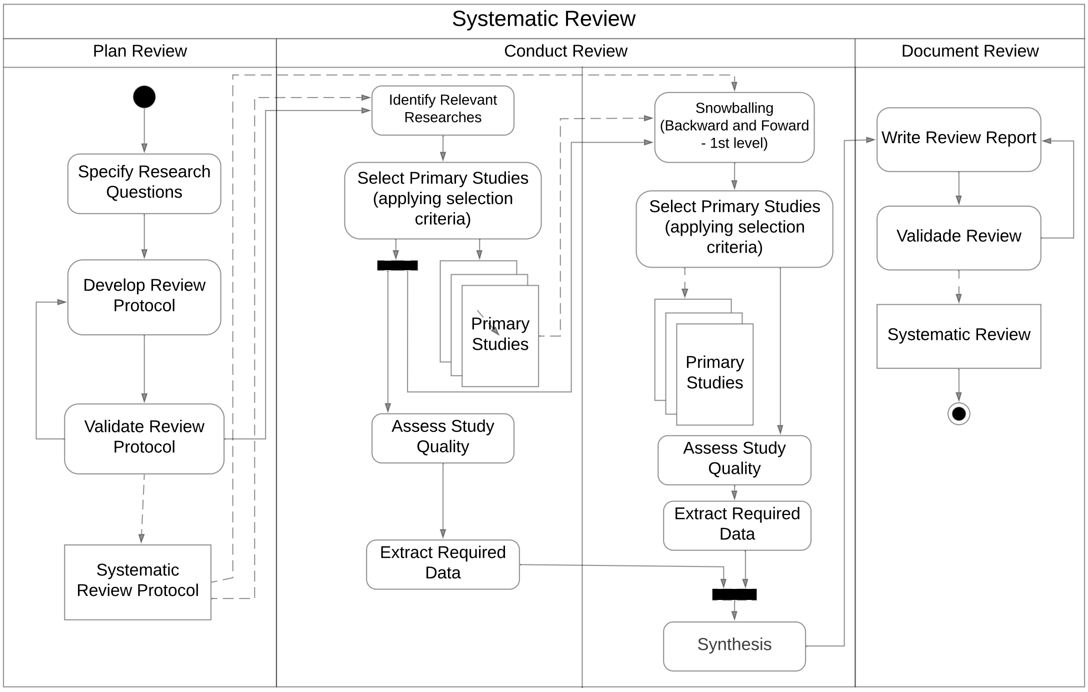


FIGURE 1. Systematic Review Process (Adapted from Brereton [17] and Wohlin *et al.* [18]).

search procedure in the public databases, making the literature search coverage more complete. These two initial phases were executed from April to May 2018.

We chose the databases SCOPUS and Web of Science for the first phase of the literature search. According to Archambault *et al.* [20], and Aghaei Chadegani *et al.* [21], which are the most relevant search databases for Computer Science, aggregating works of several other relevant databases for the area of Computing and related.

In April 2021, we executed a new search phase. In this phase, we made a new search on the Scopus database, considering articles after 2018, and we added a new database, PubMed [22], a well-known literature database for research in the medical literature. In PubMed, we do not restrict the search date.

For the generation of the **query string**, we used the PICO approach that was created for systematic reviews in medical research areas, but which is also widely used in Software Engineering research [19], [23]. This method separates the question into four aspects: Population of interest (Population), Intervention, Comparison, and Outcome of interest. The Population represents the types of studies we want to address in the research. The Intervention corresponds to what characteristic we want to find in studies on our Population. The Comparison is related to the control group used in the experiments carried out in our population studies. Finally, the Outcome of interest corresponds to the information we want to find in our population studies. Table 1 shows the elements identified for each component of the PICO approach, according to the research questions presented previously.

TABLE 1. Identified elements of the PICO approach.

Aspect	Identified Element
Population	Papers about human fall in the e-health research area and related (e.g., Telemedicine)
Intervention	Classification indicators
Comparison	Not applied in this research
Outcome interest	Techniques, Methods and Technologies

In general, systematic literature reviews in the Software Engineering area are exploratory studies designed to characterize a specific research line. In this case, these SLRs do not use a control group, and we do not use any term for Comparison. However, some authors consider that the lack of this item of the PICO approach is a quasi-systematic review [24], [25].

We evaluated several query strings with the help of three experts until we obtained the final version presented in Textbox 1. These specialists also evaluated the protocol generated during the planning phase.

Textbox 1. Query String

("Fall" OR "Falls" OR "Human Falling" OR "Falling Human" OR "Falls in*" OR "Accidental falls") AND ("Smart Health" OR "E-health" OR "Ambient Assisted Living" OR "AAL" OR "Tele-healthcare" OR "Telemedicine" OR "Healthcare") AND (classifi* OR detect* OR identifi* OR "recognition") AND ("Technique" OR "Approach" OR "Model" OR "Procedure" OR "Method" OR "Process" OR "Technology")

The papers resulting from our search had their bibliographic references in .bibtex format extracted from the databases. The data was then organized and stored as PDF files by Mendeley[1] software, which was also used to manage the execution of the selected activity.

For the selection of the most relevant studies, it is necessary to define exclusion and inclusion criteria (called **eligibility criteria**) that can be replicated by other researchers [1]. In this SLR, the exclusion criteria operate in sequential order similar to an Access Control List (ACL) as in Sanndhu and Samarati [26]. Thus, when we found a match on the list, we performed the exclusion action and did not check any other criterion.

We defined the following exclusion criteria for this SLR:

- Non-English papers (E1);
- Non-articles, Non-conference papers, Non-book chapters (E2);
- Papers with less than five pages (short paper) (E3);
- Secondary studies (e.g., literature review) (E4);
- Papers that do not present the falls classification (E5); and
- Papers that do not use computational technology to classification, detection or recognition of human falls (E6).

We defined the following inclusion criterion for this SLR:

- Studies with experiments that have more than one type of fall (I1).
- Studies with computational methods for falls classification (I2).

B. CONDUCTING

In this phase, first, we executed a search with the query string from April to May 2018 in databases of academic papers and with the search filters referring to the exclusion criteria E1 and E2, which could be applied directly in the search engines the databases. We found 1163 articles for analysis. Using the Mendeley tool, we identified 297 duplicate papers or did not consider them because they did not have a title, abstract, or author. From the remaining 866 articles, we excluded 817, according to the exclusion criteria based on the dynamic reading of the papers, focusing on the title, abstract, and the most relevant parts of these papers. Then, from the 49 remaining papers, after evaluating the first inclusion criterion, we select 45 papers.

Following the Conducting phase steps, we execute a detailed reading of the articles to correctly apply the second inclusion criterion. However, to increase the research coverage, we opted to use the 45 articles remaining from the exclusion criteria and the first inclusion criterion as the source of the snowballing process. After the snowballing process, we executed a detailed reading of these papers and evaluated the second inclusion criterion.

To apply the snowballing technique, we identified the citations of the articles using Google Scholar, as suggested in Wohlin *et al.* [18]. Altogether, we found 2819 papers from citations of the 45 studies afore selected and another 1249 papers from the references, totaling 4068 papers for analysis. Using the Mendeley tool, we excluded 23 duplicate articles. From the remaining 4045 studies, we excluded 4008 papers, according to the exclusion criteria based on the dynamic reading of the papers, focusing on the title, abstract, and the most relevant parts of these papers, obtaining 37 studies. From these, we selected 36 papers after the first inclusion criterion assessment.

Finally, we read the 82 selected studies, and we found 30 articles that fulfill the second inclusion criterion.

In April 2021, we executed a new search in the academic databases, including the PubMed Database, and we found a new set of 1454 papers (552 from SCOPUS and 902 from PubMed). Using the Mendeley tool, we identified 967 duplicate papers or did not consider them because they did not have a title, abstract, or author. We identified that many studies found in PubMed had already been found in the search performed until 2018 in the SCOPUS and Web of Science databases. In PubMed, we did not use a time filter, and then, for this reason, we found a large number of duplicate papers. From the remaining 487 articles, we excluded 474, according to the exclusion criteria based on the dynamic reading of the papers, focusing on the title, abstract, and the most relevant parts of these papers. Finally, from the 13 left, we selected 6 papers after the first and the second inclusion criterion evaluation.

To conclude the selection, we extracted data from the 36 selected articles (i.e., the 30 articles found in the literature search carried out in 2018 and the other 6 articles added after the complementary literature search carried out in 2021) and assessed the quality of the papers. The quality assessment was based on well-defined criteria, as suggested by Kitchenham *et al.* [1]. Our goal is to evaluate the potential of the selected studies to contribute to the answers to the research questions. Then, for this SLR, we chose two quality assessment criteria, that are:

A Level of detailing of the fall classification method from the study; and

B Presence of different types of falls addressed in the study results.

For our review, two researchers who used an online form generated in Google forms performed the data extraction and the quality assessment. The form containing the information to be extracted from each paper can be seen at the link https://bityli.com/Y730w.

In Table 2, we show the scores for the answers of each quality criterion specified for this SLR. The first criterion indicates if the study presents a detailed fall classification method, which is a set of replicable and sequential activities that must be performed by the computational solution to classify falls. This criterion is directly correlated to the first and second research questions and weighs higher in our evaluation. The second criterion assesses if the evaluation procedure results in each study consider the different types of falls. By "different types of falls addressed in the study results", we mean results of the studies (possibly from

[1]Mendeley - https://www.mendeley.com/

TABLE 2. Quality assessment criteria scores.

#	Criteria	Score	Weight
1	Level of details of the fall classification method from the study	(+3) The paper presents a detailed method for falls classification. (+2) The paper has a method for falls classification, but does not detail it. (+1) The paper use falls classification of another study.	2
2	Presence of different types of falls addressed in the study results	(+4) The paper evaluates all fall types separately. (+3) The paper evaluates most types of falls separately. (+2) The paper evaluates some fall types. (+1) The paper evaluates only if there was a fall or not. (+0) There is no evaluation in the study.	1

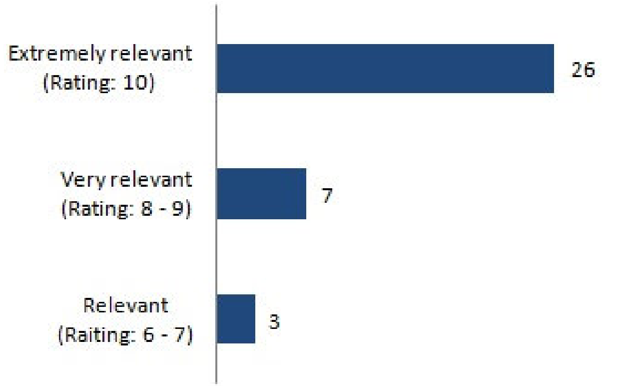


FIGURE 2. Analysis of the quality assessment criteria.

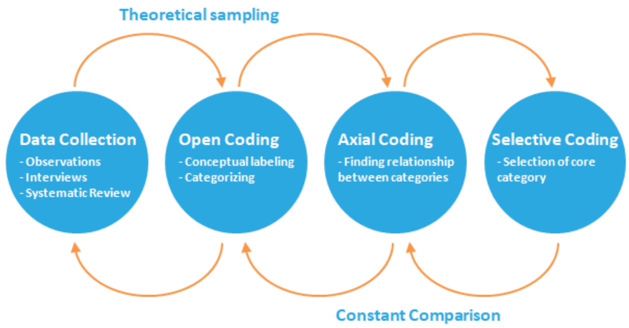


FIGURE 3. Data analysis procedure of the grounded theory method (adapted from Cho [28]).

experiments) that indicate not only that a fall has occurred but also something that characterizes the fall. This fall characterization, for example, indicates the direction of the fall (front, back, left, or right), the place where the fall occurred (kitchen, bathroom, living room), whether the fall was due to a slide, whether the fall was slow, or fast.

Figure 2 illustrates the distribution of the sum of the quality assessment criteria values multiplied by their weights for the 36 papers selected for this SLR.

C. SYNTHESIS AND THE GROUNDED THEORY

We arranged the extracted data in a Google sheet. We synthesized the data based on quantitative and qualitative analyses to get the results we present in the next section. For the qualitative analysis, we used the grounded theory (GT) methodology [27]. According to Corbin and Strauss [27], the GT is a specific methodology developed for building theory from data, but the grounded theory can be used in a more generic sense to denote theoretical constructs derived from qualitative analysis of data.

In general, GT has the following steps: planning, data collection, coding, and reporting [27]. In the planning step, we identify the area of interest and the research question. In our case, the area of interest is "Computational classification of human falls", and the research question is: "What are the computational methods used to classify falls? Furthermore, how do these methods work?". After the planning step, we collected the data, which is necessary to answer the research question. For our analysis, we used the data obtained during the data extraction phase of the systematic review.

The coding step is the main stage of the GT. According to Corbin and Strauss [27], in this step, we extract concepts (codes) from the raw data and correlate them hierarchically until we obtain a central concept (or code). In this research, we would like to obtain and relate concepts that characterize the methods used to classify falls. The coding step involves three tasks: open, axial, and selective coding. As presented in Figure 3, the coding step has two unique characteristics: theoretical sampling and constant comparative analysis [28]. Theoretical sampling is the step of collecting data for comparative evaluation, which means insight from initial data collection, and analysis leads to subsequent data collection and analysis. Constant comparative is an iterative activity of concurrent data collection and analysis. The Results of the Coding phase are presented in Section III.

D. THREATS TO VALIDITY

This systematic literature review focused on identifying computational solutions for the classification of human falls. Therefore, it is possible to have papers in the medical literature about fall classification not selected by this review because they do not use computational technologies for classification. It would be then interesting for future work to identify how the medical literature treats the classification of falls and to use that to propose new computational methods.

It is also possible that there are relevant studies related to this SLR that we could not find because: (i) the study sources are not indexed by the databases used in this review, and (ii) the query string does not cover the studies that we needed. However, to mitigate these threats, we used relevant electronic databases [20], [21] similar to many systematic research and reviews in the field covered by this SLR. Besides, several attempts were made to construct the final version of the query string. Moreover, we used the snowballing strategy [18] to increase the coverage of articles and possible inconsistency of the query string.

TABLE 3. List of selected papers by technology.

Technology	Paper selected
AAL	[29] [30]
Video	[31] [32] [33] [34] [35] [36] [37] [38] [39] [40]
Wearable	[41] [42] [43] [44] [45] [46] [47] [48] [49] [50] [4] [51] [52] [53] [54] [55] [56] [57]
AAL and Wearable	[58] [16]
Video and Wearable	[59] [60] [61]
AAL, Video and Wearables	[62]

III. RESULTS

In this SLR, we selected 36 papers to answer the defined research questions. These studies were published between 2006 and 2021. Table 3 shows the list of studies selected by the type of hardware used in the studies.

A. FALL CLASSIFICATION METHODS

We use the codification process in the GT methodology to analyze the fall classification methods and their techniques.

Firstly, in open coding, we check the data to understand the essence of ''what is'' expresses [27]. We inspect the data extracted from the papers using the extraction form, as done in Carvalho *et al.* [63]. Then, a conceptual name (code) is created to represent our understanding. Codes consist of an entire word, phrase, or paragraph. Table 4 presents some examples of codes. We use the QDA Miner Lite tool to aid open coding, as done in [64].

We created 61 codes divided into five categories: Sensors, Hardware limitations, Background and Foreground Extraction (BFE) techniques, Feature extraction techniques, and classification techniques. We extracted these categories from the articles themselves while we refined the codes. Table 5 presents the identified codes divided by categories. To facilitate the analysis, we identified the types of technology associated with each code.

The sensors category contains the kind of hardware used for the sensing of the raw data. The hardware limitation category presents the hardware limitations related to the device used to obtain the raw data. The BFE techniques category comprises image preprocessing techniques to remove background and foreground to determine the form to be tracked in the video, allowing feature extraction. These techniques are exclusively related to video technologies. The feature extraction techniques category contains the techniques used to extract features from the raw data. Finally, the classification techniques category contains the techniques used for fall classification.

Next, we correlated the open coding categories with the sequence of activities executed for falls classification in the selected papers (Axial coding step). With this, we identified that the fall classification solutions follow the method of Figure 4a when using wearables or AAL sensors, and the method of Figure 4b when using video sensors.

Figure 5 shows the representation of axial coding. It presents the relationships between the code categories from open coding and the activities of the fall classification methods. Lastly, according to Corbin and Strauss [27], when

TABLE 4. Examples of codes from open coding.

Code	Text segments from the extracted data
Dynamic Time Warping	"Dynamic Time Warping aligns two time series in such a way that some distance measure is minimized (usually the Euclidean distance is used). Optimal alignment (minimum distance warp path) is obtained by allowing the assignment of multiple successive values of one time series to a single value of the other time series...." [41] "We also collect segmented data streams generated by falls with various falling directions to build the anchoring data streams for the later DTW distance calculations. . . " [30]
Fall classification strategy based on thresholds	"The threshold was determined by considering accelerations in SVM (Signal Magnitude Vector) and in the x-, y-, and z-axes, whereas falls and stumbles were simulated. . . " [46]

all categories can be related to a core category, it means the researcher is doing selective coding. Selective coding is the final step of Grounded Theory and consists of linking categories around a core category and refining the resulting theoretical construction. As shown in the figure, this core category is the ''Falls Classification Methods'' in our research.

B. ACTIVITIES AND TECHNIQUES OF FALL CLASSIFICATION METHODS

This section describes the activities of the fall classification methods and the techniques used in the selected studies for each activity.

The sensing activity involves obtaining and storing the raw data that will be processed to generate the features. Associated with the sensing activity are the categories of sensors and hardware limitations. Ambient assisted living (AAL) environment sensors [16], [29], [30], [58], [62] obtain continuous data from specific locations that vary when there is a movement within that space. The presence sensors are used in conjunction with other types of technology sensors and fulfill the function of determining only the location of the individual in a specific room within that AAL. In contrast, the other AAL sensors obtain the data used to determine the type of movement, for example, the type of fall.

The video sensors [32]–[38], [40], [59]–[62], in general, can be divided into four types of approaches, using video 2D, 3D, Infrared or based on the variation of luminosity or colors. In all cases, the general idea is to identify a region of interest of the video that contains the human body, and when this region varies, we identify an occurrence of falls. Finally, all wearable approaches [4], [16], [41]–[62], [65]–[69] uses accelerometer to derive from the raw data that is used to identify and classify the fall. However, many of the works also used other sensors like gyroscope, magnetometer, barometer, which are used as an altimeter, ECG and even heart rate sensors, used to identify the heart rate at the time of a fall.

We found some hardware limitations directly related to the sensing of the approaches that use video or wearable. The similarity between various human postures, the occlusion caused by objects in front of the individual, and the limited memory are the hardware limitations identified for video

TABLE 5. Codes identified in the open coding step.

Category	Codes
Sensors	(AAL) Ambient Sensors; (AAL) Presence Sensors; (AAL) RFID Tags; (Video) ATC Video Sensors;(Video) Infrared; (Video) Microsoft Kinect; (Video) Video Camera 2D and 3D; (Wearable) ECG; (Wearable) Smart IR Tags; (Wearable) with accelerometer; (Wearable) with accelerometer and gyroscope; (Wearable) with accelerometer, gyroscope and magnetometer; (Wearable) with accelerometer, gyroscope, magnetometer and altimeter; (Wearable) with Accelerometer and Heart Rate Sensor.
Hardware limitations	(Video) Human Posture Similarity; (Video) Occlusion; (Video) Video limited memory; (Wearable) Location of the sensor; (Wearable) Poor processing power and limited battery.
BFE techniques	Reference background; Gaussian mixture and weighted subtraction; Gaussian mixture; Window regression layer.
Feature extraction techniques	(Ambient Sensors) Gaussian-like probability density; (RFID Tags/Smart IR Tags) Dynamic Time Warping; (AAL) Raw data from presence sensor; (ATC Video) Point-cloud compromised; (Microsoft Kinect) Region Proposal Network and Fast Region-based Convolutional Network; (Microsoft Kinect) V-disparity; (Video 2D or 3D) α-β-γ filter; (Video 2D or 3D) Bayesian Segmentation; (Video 2D or 3D) Change in the human shape; (Video 2D or 3D) R-transform; (Video 2D or 3D) R-transform and Generalized discriminant analysis; (Video 2D or 3D) R-transform and Principal component analysis and Independent component analysis; (Video) Raw data from 2D or 3D video; (Wearable with Accelerometer and Gyroscope and Magnetometer and Altimeter) PDR algorithm; (Wearable with Accelerometer) Discrete wavelet transform; (Wearable with Accelerometer) Median filter & Low pass filter & Elliptical infinite impulse response filter; (Wearable) Raw data from accelerometer; (Wearable) Raw data from accelerometer and gyroscope; (Wearable) Raw data from accelerometer, gyroscope and magnetometer; (Wearable) Raw data from accelerometer and Heart Rate Sensor; (Wearable) Raw data from accelerometer, gyroscope, magnetometer and altimeter.
Classification techniques	(AAL/Video/Wearable/Wearable and AAL/Wearable and Video) Based on thresholds; (Video/Wearable) Pattern Recognition; (AAL/Video/Wearable) Based on thresholds and Pattern Recognition; (Video/Wearable) Based on logic inferences; (Wearable and AAL) Based on a Specific Grammar-Feature-Based; (Wearable) Based on a Specific Sequence of Classifiers; (Wearable) Multiple-Phases Features Pattern Recognition.

approaches. Finally, the limited battery of the devices, the low processing power, and the amount of storage of the equipment are the most common restrictions for the wearables. Besides, the location of the wearable in the body also influences the measurement. Most papers that treat this subject indicate that the results are best when the device is on the chest or the waist of the person.

The BFE activity separates the region of interest from the rest of the video. This activity is part of the video preprocessing and later affects feature extraction. The BFE techniques category is associated with this activity. Each BFE technique represents the video as points with values that vary among them. This variation may, for example, be obtained by checking the variation of the pixel sets that delimit specific regions of the image, as in the Gaussian mixing technique used in [35], [36], [38].

The feature extraction activity involves features generation from raw data or preprocessed data. These features will be used to detect and classify falls. Each feature extraction techniques category is associated with the feature extraction activity. Each feature extraction technique combines raw or preprocessed values to generate more representative (features). For example, a feature extraction technique for a solution using with accelerometer device can generate the Signal Magnitude Vector (SMV) feature [16], [43], [46], [47], [52]–[54], [69]. The SMV is generated by combining the values obtained for each axis during an accelerometer measurement and follows the formula:

$$SMV(t_i) = \sqrt{{A_x}^2(t_i) + {A_y}^2(t_i) + {A_z}^2(t_i)} \tag{1}$$

where t_i indicates the measurement in time i, and A_x, A_y, and A_z are the accelerometer values from axis x, y, and z. The SMV feature can generate other features, like standard deviation, or can be used alone by the classification strategies. We found 67 different features, as presented in Table 6, separated by the type of hardware. Note that some features are associated with more than one kind of device.

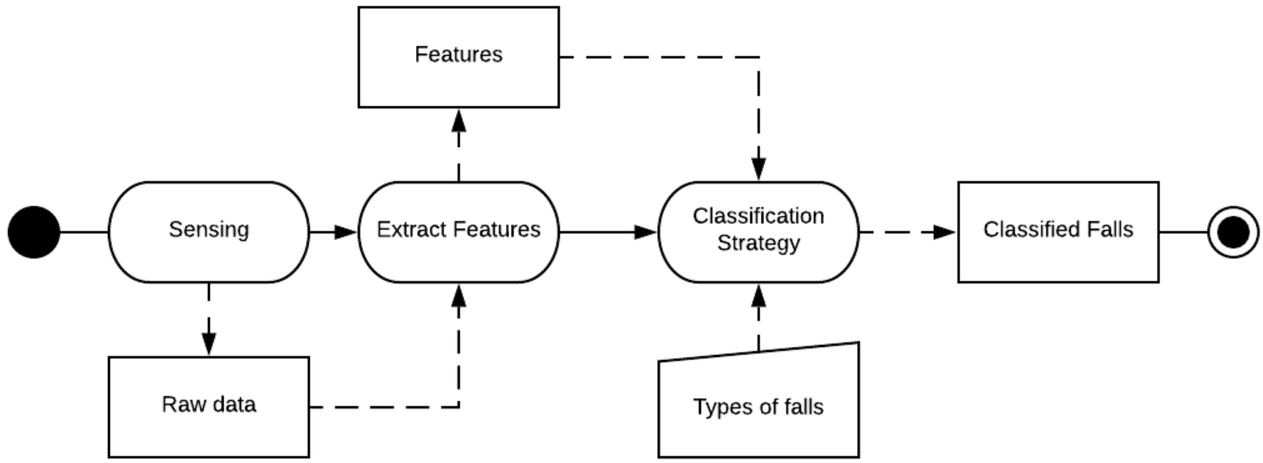
In the last activity, the classification strategies are executed, including the application of pattern recognition techniques. Note in Figure 4 that the types of falls are inputs to the activity, so they are predetermined.

We identify seven types of fall classification techniques. The most common is the use of thresholds, and, in these cases, characteristic values, known as thresholds, are defined for certain phases of the movement of the fall. By exceeding these thresholds, the fall can be identified and, more specifically, the type of fall.

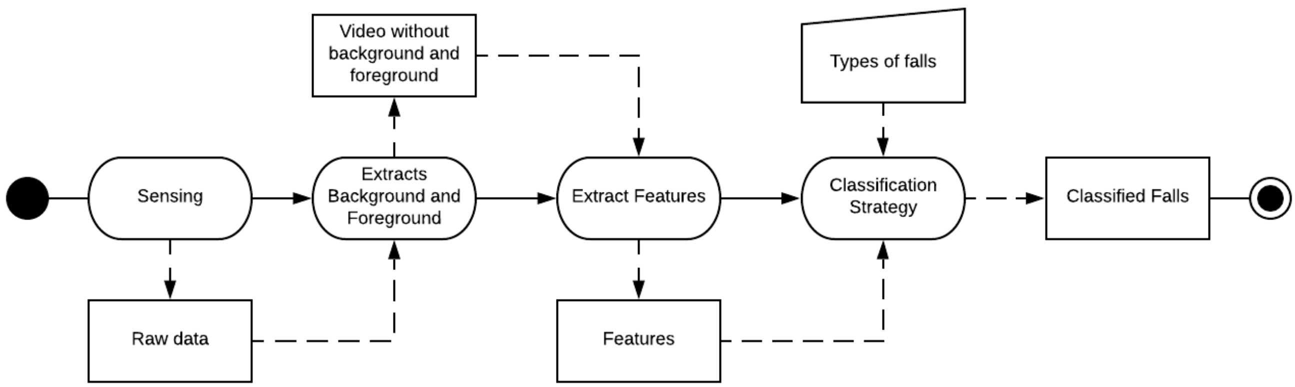
These thresholds are drawn from previous studies or determined by applying a pattern recognition technique employed to a training group. This training group consists of data obtained from fall experiments, explicitly performed for a study, or collected from public falls databases.

Another type of fall classification technique usually found in the papers are pattern recognition algorithms, in one or multiple phases [50], to classify falls based on a training set. With the algorithm trained, this event is classified according to the class whose values of the features more closely resemble when a new fall occurs. Some approaches use both thresholds and pattern recognition algorithms to detect and classify falls, rather than pattern recognition algorithms used only to identify thresholds.

Figure 6 presents the pattern recognition algorithms and how many of the studies selected uses each algorithm. It is worth mentioning that some studies contain more than one of these algorithms. We can see that Artificial Neural Network (ANN), k-Nearest Neighbors (KNN), and Support Vector Machines (SVM) are the most used algorithms. We believe this happens because they can sort data quickly and produce better results than other algorithms. However, the average training time of these algorithms is higher than others, like



(a) Classification method for wearable and AAL approaches.



(b) Classification method for video approaches.

FIGURE 4. Fall classification methods.

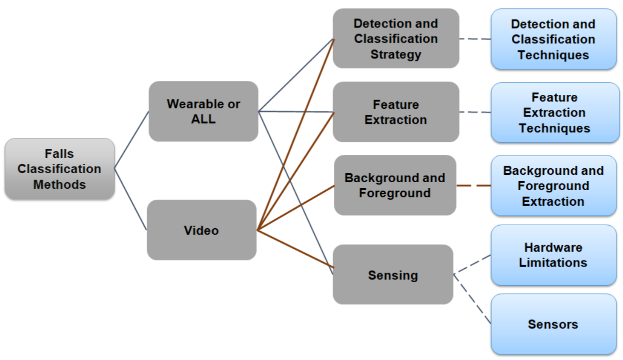


FIGURE 5. Axial and selective coding representation.

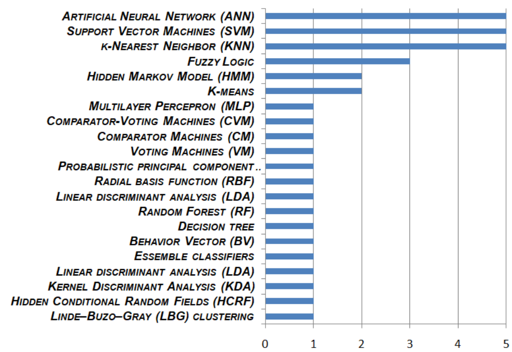


FIGURE 6. Recognition pattern algorithms.

tree-based algorithms. It is worth noting that there was a similar prevalence of ANN, SVM, and KNN algorithms in wearable-based and video-based systems studies. However, most of the other algorithms were used by the studies from video-based systems.

The studies [40], [47] and [62] use a set of rules of fuzzy inferences to detect and classify falls. They apply inference rules according to the value assumed by the features. This strategy is similar to the use of thresholds, but, in their case, some sets of values are related to the occurrence of the same type of fall, depending on the rules of inference formulated.

In short, we observed that the thresholds strategy is more common in systems that use wearable sensors and smartphones to obtain data. In contrast, there is a prevalence of strategies based on logical inferences and pattern recognition algorithms in video-based systems.

Some studies also use specific strategies to detect falls. Li [58] proposes a specific grammar based on

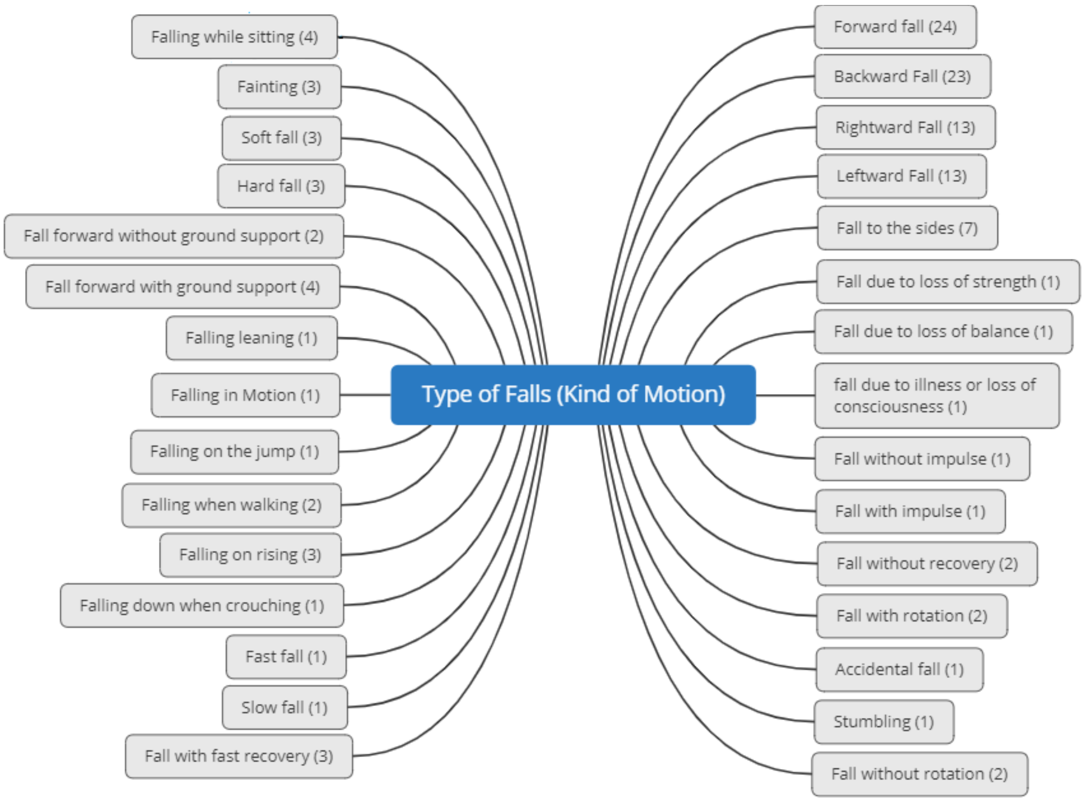


FIGURE 7. Types of falls identified for the category: Kind of Motion.

features. This approach detects a particular type of fall by combining the grammar elements in some ways. In He and Li [54], classifiers are generated based on features extracted from wearable data, which, when combined in specific sequences, correspond to particular types of falls.

C. TYPES OF FALLS

In our systematic review, we identified a total of 51 different types of falls. According to Yu [70], falls are related to movement performed and position and are divided into four major categories: falls from standing, falls from sitting, falls from lying, and falls from standing on a support (e.g., a ladder). However, we found other categories of types of falls in Makhlouf *et al.* [16], which classifies falls into three different types of cardiac problems (bradycardia, tachycardia, and cardiac arrest), and according to where they occurred (e.g., bathroom, kitchen, room, living room). In addition, Saha *et al.* [57] and Gulati and Kaur [62] show falls related to cardiac and respiratory problems.

Therefore, we decided to categorize the types of falls into four categories: falls related to health issues, location, the position of the person, and the kind of motion. Figure 7 shows the types of falls for the category Kind of Motion, and Figure 8 presents the types of falls for another three categories. The number next to each type of fall in the figure informs the number of articles in which the type of fall was mentioned.

TABLE 6. Features used for fall classification strategy.

Type	Features
AAL	Mean value, Variance, Location, Euclidean distance.
Video	3D Silhouette, 2D Silhouette, ID position, Centroid, Color, Binary map, 3D Depth image, Position, Speed, Acceleration of the centre of gravity, Orientation, Length, Distance of joint of human skeleton, Angle of joint of human skeleton, Velocity of joint of human skeleton, Shape aspect ratio, Height, Human motion velocity, Distance to object.
Wearable	Tilt angles, Signal magnitude vector, Acceleration magnitude, Angular velocity, Direction, Euclidean norm, Motion angle, Euclidean distance, Square root of the square of the gyroscope values, Square root of the square of the magnetometer values, Wavelet acceleration, Heart rate.

The categories kind of motion and the position include the same types of falls presented by Yu [70], but they have more examples of falls that use elements related to the movement performed (direction of fall, rotation, speed, severity) and the position before or after the fall. Finally, it is worth noting that the most used falls in the studied literature are related to the direction of movement (Forward, Backward, Leftward, and Rightward), as can be seen in Figure 7.

D. PROFILE OF THE EXPERIMENT PARTICIPANTS

In general, to evaluate the proposed approaches for classifying falls, the studies use falls from databases or experiments generated by each research. Most of these papers present a profile of the experiment participants and, with this, it is possible to get more information about the approaches. We identified that 19 of the articles present quantity and some profiles of the participants.

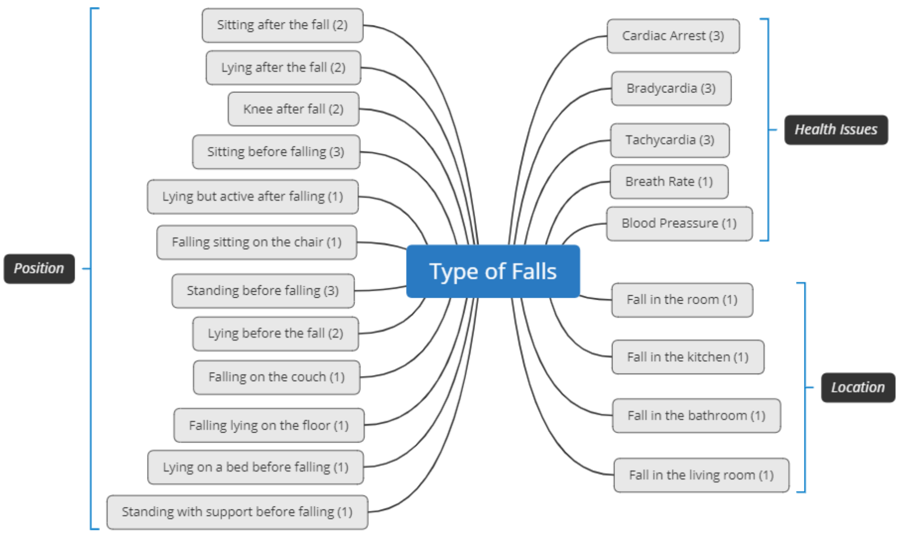


FIGURE 8. Types of falls identified for the categories: Health Issues, Location and Position.

The papers [49] and [46] use falls or daily activities from adults over 60 years old, the main risk group. The others use experiments with adults, men, and women, between 19 and 57 years old, with most participants between 20 and 30 years old. Some of these authors (e.g., [38], [49], [52]) admit that there could be variations when they use their proposals with older adults, but, according to Karantonis *et al.* [46], experiments without the presence of older adults do not make the proposal unfeasible. Moreover, several studies have also identified the participants' height, weight, or body mass index. According to these studies, these characteristics may influence the sensors' measurements, but they do not show examples of how these characteristics affect the results.

IV. DISCUSSION

In this section, we discussed the SLR results and identify research gaps and challenges. This SLR aims to discover studies that present classifications of human falls supported by computational methods and how and why these studies use them. In this way, we found 36 studies that have a method to classify falls. In general, to evaluate such fall classification methods, the authors used experiments with data of different types of falls performed. Table 7 presents a summary of the answers to each Research Questions (RQs).

As shown in Table 7, we have identified two different types of computational methods used by the studies to classify falls, which differ mainly by the sensing technology used. We also identify techniques used in each activity of these methods. However, most of these methods are used only to improve the accuracy and precision of fall detection systems or systems to identify fall risk. However, they do not seek to identify the severity of these falls, thus prioritizing falls considered the most dangerous in the medical literature, such as lateral falls [14], [15].

Makhlouf *et al.* [16], Saha *et al.* [57] and Gulati and Kaur [62] are the exceptions that use fall types associated with diseases. There are still few studies that associate falls with specific health problems using computational technologies. In this sense, we believe that this type of relationship between falls and other health issues is a challenge that can be explored in future research.

As we mentioned before, these studies classified the types of falls in two categories based on the type of movement or based on the person's position before and after the fall.

TABLE 7. Summary of the Answers to the RQs.

Answers to the Research Questions
Research Question 1. What are the computational methods used to classify falls?
We identify two different methods used for fall classification. We found a method with three steps for solutions using AAL sensors or wearables: sensing, feature extraction, and execution of the classification strategy. Yet, the same activities are executed for video approaches, but before the feature extraction, there is one more activity: Background and Foreground Extraction.
Research Question 2. What are the techniques used in each activity of these methods?
This SLR identified four different techniques for background and foreground extraction of videos, twenty-one techniques for feature extraction, and seven different fall classification strategies. Also, we identify fourteen different types of sensors used by the selected studies, and five hardware limitations. The list of techniques is presented in Table 6 and detailed in the results section of this study.
Research Question 3. What are the advantages of using fall classification methods?
The studies intend to improve the precision and accuracy of systems, applications, or approaches of automatic detection of falls and recognize falls risk. The authors argue that different types of falls may behave considerably different from the data, and classifying each type of fall or group of types of falls allows greater accuracy in detecting falls. Besides, Makhlouf et al. (2018) [16], Saha et al. (2018) [57] and Gulati and Kaur (2021) [62] explore the advantages that identifying the type of fall can have in the best treatment of the patient.
Research Question 4. Which types of falls are classified by these methods?
All the way, we identified 51 types of falls. According to the literature, it is possible to categorize the types of falls as: falls related to the type of movement and falls related to the person's position before and after the fall movement. However, in our research, we found some works presenting types of falls that do not match into these categories. Therefore, we divide these types of falls into two other categories: falls location and falls related to health issues (See Figures 8 and 7).

However, most of them do not clarify why these are the categories that should be considered. To build relevant databases, we believe that it is important to understand the nature of the data and categorize it. Thus, another challenge that could be explored in future works should be to understand what makes the categories of the types of falls used in the literature relevant and if other relevant characteristics allow a better categorization of falls. In this sense, an exciting gap to be explored in future research is to identify, together with the literature of the health area and health professionals, if the types of falls presented by the works selected in this SLR are relevant to determine the severity of the fall event.

Moreover, the proposal of a classification method using sensor data obtained from fall events to identify new types of falls, for example, using grouping techniques such as clustering, could generate interesting future research. Some studies selected for this SLR utilize clustering techniques (e.g., the k-means algorithm), but these techniques were used to classify the falls according to the predefined types of falls.

Lastly, another open research topic is to use classification methods either in existing falls databases to classify them or to assist the creation of new falls databases. In our SLR, only the recent work of Ponce and Martínez-Villaseñor [60] take into account how falls database is classified.

V. CONCLUSION

Different types of falls can directly influence the quality and accuracy of fall detection and fall risk identification systems. Fall classification allows identifying particular problems and risks of specific types of falls. Furthermore, according to the medical literature, there is an inherent severity of each type of fall that is also important to consider. The detection and classification of falls can be done automatically using computer devices equipped with sensors capable of monitoring the movement of patients. Using a computational approach is mainly due to the agility in identifying the fall and the risks inherent to the type of fall the person suffered. So, the systematic literature review presented in this paper aimed to find automatic methods of fall classification in the literature as well as gaps for future research.

We utilized a two-step search strategy: a search using three academic article databases and a snowball strategy on the selected papers after searching the databases. Then, we found several computational fall classification solutions that, as we concluded, followed these two strategies. The differences between them are the sensors and activities employed. The first method is three-step, which is executed by wearables, and AAl approaches with the following activities: sensing, feature extraction, and falls classification strategy. The second method is four-step, which is executed by Video solutions with the same activities of the previous method plus a BFE activity. Besides, in this SLR, we also organized the types of falls found in the selected studies.

Moreover, we identified challenges and open questions in the SLR selected papers that can be addressed in future work and they are summarized as follows: (i) comparison of the techniques applied in each step of the methods and generation of a catalog to assist the development of new hardware and software solutions to falls detection and classification; (ii) a new approach for classifying falls that addresses the types of falls categorized in the medical literature and their inherent severity; and (iii) development of a solution, considering the methods and techniques identified in this study, to help classify and build new falls databases.

Lastly, considering the exploratory nature of our study, the comparison of the identified methods is beyond the scope of an SLR. Furthermore, the differences between the identified method types limits the possibility of comparing them, once the two types of methods identified in our study differ from each other due to the technology used (''Video'' or ''Wearable and AAL sensors'').

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