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 fall 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 (2009) [1] 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 falls 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]. When a fall occurs, it is crucial to immediately detect the situation, 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 and Shao (2013) [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. (2016) [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 to improve the accuracy of fall detection, having a
minimal impact on the daily life of the user (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 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 and Shao (2013) [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 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. (2018) [15]. 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 the classification of human fall 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 as well as challenges that require further research.

II. RESEARCH METHODOLOGY

We based our Systematic Literature Review (SLR) on the method proposed by Brereton et al. (2007) [17] and Kitchenham et al. (2009) [1]. This is the most used method 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 the 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 of 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-Analyses (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, and, in the second phase, we performed a manual procedure, known as snowballing, to analyze the citations (snowballing forward) and references...
FIGURE 1: Systematic Review Process (Adapted from Brereton (2007) [17] and Wohlin et al. (2014) [18]).

(snowballing backward) of the articles previously selected in the first phase. Snowballing is used to complement the 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. (2009) [20] and Aghaei et al. (2013) [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 the 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, which is also widely used in Software Engineering research [23] [19]. 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      | 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
The papers resulting from our search had their bibliographic references in .bib format extracted from the databases. The data was then organized and stored as PDF files by Mendeley 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 Sandhu and Samarati (1994) [26]. Thus, when we found a match on the list, we performed the exclusion action, and we 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 of the databases. We found 1163 articles for analysis and, using the Mendeley tool, we identified 297 either duplicate papers or we did not consider the papers 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, to correctly apply the second inclusion criterion, a detailed reading of the articles was needed. However, to increase the research coverage, we opted to use the 45 articles remaining from the application of the exclusion criteria and the first inclusion criterion as the source of the snowballing process. Just after the snowballing process, we did the 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. (2014) [18]. Altogether, we found 2819 papers from citations of the 45 studies aforeselected 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 either duplicate papers or we did not consider the papers 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, 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. (2009), [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, the data extraction and the quality assessment were performed by two researchers who used an online form generated in Google forms. The form containing the
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      |
|    |                                                                          | (+2) The paper has a method for falls classification, but does not detail it. |        |
|    |                                                                          | (+1) The paper uses falls classification of another study. |        |
| 2  | Presence of different types of falls addressed in the study results       | (+4) The paper evaluates all fall types separately. | 1      |
|    |                                                                          | (+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. |        |

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 has a higher weight 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 experiments) that indicate not only that a fall has occurred but also something that characterizes the fall. For example, 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.

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 did the data collection, 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 (2008) [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 studies 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.

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.

TABLE 3: List of selected papers by technology.

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

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. (2018) [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 create 61 codes, which were divided into five categories: Sensors, Hardware limitations, Background and Foreground Extraction (BFE) techniques, Feature extraction techniques, and classification techniques. These categories were extracted 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.

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 con-
TABLE 5: Codes identified in the open coding step.

| Category                  | Codes                                                                 |
|---------------------------|----------------------------------------------------------------------|
| Sensors                   | (AAL) Ambient Sensors; (AAL) Presence Sensors; (AAL) RFID Tags; (Video) AFT 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 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 tech.  | (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) ω-β-γ filter; (Video 2D or 3D) Bayesian Segmentation; (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 alimeter. |
| Classification tech.      | (AAL/Video/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. |

Continuous data from specific locations that vary when there is movement within that space. The presence sensors are used in conjunction with sensors of other types of technology and fulfill the function of determining only the location of the individual in a specific room within that AAL, while the other AAL sensors obtain the data that will be 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 [3], [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 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 treats 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], [50], [53], [69]. The SMV is generated by combining the values obtained for each axis during an accelerometer measurement and follows the formula:

\[
SMV(t_i) = \sqrt{A_x^2(t_i) + A_y^2(t_i) + A_z^2(t_i)}
\]

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 be used to 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
sequences, correspond to particular types of falls. From wearable data, which, when combined in specific ways, classifiers are generated based on features extracted from wearable sensors. In He and Li (2013) [54], this approach detects a particular type of fall by combining the grammar elements in some ways. In He and Li (2013) [54], some sets of values are related to the occurrence of the same type of fall, depending on the rules of inference formulated. 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 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 [47], [40], 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 (2011) [55] proposes a specific grammar based on features. This approach detects a particular type of fall by combining the grammar elements in some ways. In He and Li (2013) [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 (2008) [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 Makhlof et al. (2018) [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. (2018) [57] and Gulati and Kaur (2021) [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 4 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.

The categories kind of motion and the position include the same types of falls presents by Yu (2008) [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 the classification of 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 profile of the participants.

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., [49] [38] [52]) admit that there could be variations when they use their proposals with older adults, but, according to Karantonis et al. (2006) [40], 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 measurements of the sensors, but they do not show examples of how these characteristics affect the results.

IV. DISCUSSION

In this section, we discussed the SLR results and identified 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].

Makhlof et al. (2018) [16], Saha et al. (2018) [57] and Gulati and Kaur (2021) [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. However, most of them do not clarify why these are the categories that should be considered. We believe that, to build relevant databases, 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 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. 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. Finally, only Ponce and Martínez-Villaseñor (2020) [60] take into account how the falls database used is classified. We believe that is advantageous to use classification methods in existing falls datasets to classify them or assist the creation of new fall databases.
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 that 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 classification of falls. 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.

Finally, as one of the results of this study, we identified challenges and open questions in the SLR selected papers that can be addressed in future work, which 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.

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