Deep Learning for Computer Vision based Activity Recognition and Fall Detection of the Elderly: a Systematic Review

F. Xavier Gaya-Morey^{1,2,3*†}, Cristina Manresa-Yee^{1,2,3†} and José M. Buades-Rubio^{1,2,3†}

¹Group of Computer Graphics, Computer Vision and AI (UGIVIA), Universitat de les Illes Balears (UIB), Carretera de Valldemossa, km 7.5, Palma, 07122, Illes Balears, Spain.

²Research Institute of Health Sciences (IUNICS), Universitat de les Illes Balears (UIB), Carretera de Valldemossa, km 7.5, Palma, 07122, Illes Balears, Spain.

³Department of Mathematics and Computer Science, Universitat de les Illes Balears (UIB), Carretera de Valldemossa, km 7.5, Palma, 07122, Illes Balears, Spain.

*Corresponding author(s). E-mail(s): francesc-xavier.gaya@uib.es; Contributing authors: cristina.manresa@uib.es; josemaria.buades@uib.es; †These authors contributed equally to this work.

Abstract

As the percentage of elderly people in developed countries increases worldwide, the healthcare of this collective is a worrying matter, especially if it includes the preservation of their autonomy. In this direction, many studies are being published on Ambient Assisted Living (AAL) systems, which help to reduce the preoccupations raised by the independent living of the elderly. In this study, a systematic review of the literature is presented on fall detection and Human Activity Recognition (HAR) for the elderly, as the two main tasks to solve to guarantee the safety of elderly people living alone. To address the current tendency to perform these two tasks, the review focuses on the use of Deep Learning (DL) based approaches on computer vision data. In addition, different collections of data like DL models, datasets or hardware (e.g. depth or thermal cameras) are gathered from the reviewed studies and provided for reference in future studies. Strengths

and weaknesses of existing approaches are also discussed and, based on them, our recommendations for future works are provided.

Keywords: Human activity recognition, Fall detection, Ambient assisted living, Deep learning, Computer vision, Elderly

1 Introduction

While global population continues to grow at a fast rate, life expectancy is also increasing rapidly, especially in developed countries. According to Bloom and Luca [1], life expectancy in China and India has risen by nearly 30 years since 1950. In most developed countries, a 20% of the population is aged 60+, and will rise to more than 30% in the next four decades.

For this reason, problems related with elderly¹ care are becoming more frequent and preoccupying, since more people need to be cared about. One of the most common dangerous situations this collective has to face is when a fall occurs. The World Health Organization states some worrying and eye-opening facts on this matter, like that falls are the second leading cause of unintentional injury deaths worldwide, that each year an estimated 684,000 individuals die from falls globally and that 37.3 million falls that are severe enough to require medical attention occur each year, among others [2]. In addition to the harm caused to the elderly when a fall occurs, there are also economic costs associated with their treatment, which added up in 2010 to "between 0.85% and 1.5% of the total health care expenditures within the USA, Australia, EU15 and the United Kingdom" [3].

Automatic detection of the falls of the elderly is possible through data collected from wearable or environmental devices, such as accelerometers, gyroscopes, cameras, etc. Not only detection of falls, but also activity recognition is feasible, which can be of use for multiple purposes: from automatic life-logging [4] to finding habits to diagnose illnesses based on the omission or repetition of basic tasks [5].

From the data perspective for fall detection and Human Activity Recognition (HAR) tasks, vision data from different types of camera is in increasingly use due to its multiple advantages over wearable devices or other sensors: detection of multiple events simultaneously, suitability for multiple subjects, environments and tasks, ease of installation and use, possibility of verifying the data visually, etc. [6].

From the algorithmic perspective, Deep Learning (DL) has pushed the limits of what was possible in the domain of digital image processing according to Walsh et al. [7], becoming the state of the art in many different areas. In recent years, multiple DL architectures have been designed and tested for computer vision tasks, posing the question of which one to use for HAR and fall detection of the older people.

In this work, we perform a Systematic Literature Review (SLR) on DL based HAR and fall detection from vision data for the elderly care. The review process is based

¹In this work, the term "elderly" has been used to refer to people over 65 years old, for it is the most extended term for referring to them in the field of Computer Science. However, in other fields the preferred term can differ, as in the Psychology field, where the most used term is "older adults".

on the guidelines for performing an SLR in Software Engineering by Kitchenham and Charters [8], which offer great guidance over the methodology, structure and good practices. The document is structured as follows: firstly, the background of the study is approached, offering the insight of previous reviews on the topic and the definition of the main concepts; secondly, the review questions are enumerated; next, the review methods are explained in detail (data sources, search strategy, study selection, quality assessment and data extraction); then, the resulting list of studies is analyzed in detail to offer the information needed to answer the review questions; to follow up, in the discussion, the review questions are answered and the different discoveries are discussed; finally, the extracted conclusions of the SLR are presented.

2 Summary of previous reviews

Mining the literature, we find several reviews which address fall detection and HAR, focusing on different aspects or limiting the studies to use some kind of data. However, most of them (apart from [9]) do not follow a systematic and rigorous method, which could lead to the introduction of bias due to researchers' previous knowledge and opinions [8]. This fact supports the need of performing the current systematic review on the topic, based on a predefined search strategy in order to be thorough and fair.

In this section, relevant reviews and surveys of the last ten years are analyzed and synthesized. The most relevant ones are summarized in Table 1, however, none of them covers exactly the topics reviewed in this work.

A review about activity pattern monitoring using depth sensors is carried out in [10], exploring this kind of visual data as a substitute of RGB video or images to preserve the privacy of the older adults. Studies are grouped by the type of computing technique used (among which DL can be found) and also used datasets are analyzed.

A systematic review on datasets used for HAR and fall detection is performed in [9], resulting in an extensive list of over 700 datasets of multiple modalities (video, joints, inertial measurement units, etc.). Multiple taxonomies are created to group the datasets in different ways: by population groups of interest, by data type, by creation purpose, etc. From all of them, only four contain elderly people.

In [11], a review on DL based fall detection systems is performed. It offers a good understanding on how DL is used for this specific task, analyzing different types of falls, listing popular fall detection datasets, explaining common metrics for evaluation and reviewing different works on this field, along with different architectures. Vision data types included are RGB, depth and thermal. The main drawback of this review related to this systematic work is the specificity of the reviewed task, which leads to a lack of relevant studies.

A broader number of tasks are reviewed in [12], detecting not only falls, but also other useful information by studying different kinds of data extracted from the video sequences: body shape change, posture, 3D head motion, spatial-temporal, gait and skeleton. The raw input for all techniques are still RGB, depth and thermal data. In this case, techniques are not restricted to be based on DL, but also traditional computer vision techniques are reviewed, meaning that many of the works will fall out of the scope of the present systematic review, focused on the DL usage.

Table 1 Previous reviews on similar topics.

Title	Task/s	Ref.	Year
In-Home Older Adults' Activity Pattern Monitoring Using Depth Sensors: A Review	Fall detection, HAR	[10]	2022
Human Movement Datasets: An Interdisciplinary Scoping Review	Fall detection, HAR, other	[9]	2022
Vision-based human fall detection systems using deep learning: A review	Fall detection	[11]	2022
Human fall detection and activity monitoring: a comparative analysis of vision-based methods for classification and detection techniques	Fall detection, HAR, other	[12]	2022
Comprehensive Review of Vision-Based Fall Detection Systems	Fall detection	[13]	2021
A review on video-based active and assisted living technologies for automated lifelogging	Fall detection, HAR, Physiological signals	[4]	2020
A review of state-of-the-art techniques for abnormal human activity recognition	Fall detection, HAR	[14]	2019
ViFa: an analytical framework for vision-based fall detection in a surveillance environment	Fall detection	[15]	2019
Vision-based patient monitoring: a comprehensive review of algorithms and technologies	Fall detection, HAR, other	[16]	2018

Fall detection was already reviewed in [13], where not only DL techniques were included, in contrast to the aforementioned work [11]. In this case, only works published in the previous 5 years are reviewed. The most commonly used processing steps for this task are described and analyzed, along with ML models, datasets, metrics and tracking techniques. Comparatives are also performed between different works using the same datasets. The majority of reviewed works use RGB and depth data, even though a work using IR data is also included.

A review on fall detection, HAR and physiological signals analysis for Ambient Assisted Living (AAL) systems is performed in [4]. The search is done on Google Scholar, between years 2015-2020 (both included) and the search keywords are provided. This review focuses on analyzing and describing different works found on the field, rather than on comparing results or establishing a taxonomy. In addition, privacy and user acceptance from the different studies are also taken into account.

In [14], the review is centered on abnormal human activity recognition, which as anomaly detection, refers to rarely occurring activities or non-conforming patterns in data, including, among others, fall detection. The work offers a classification of the reviewed studies according to the number of users targeted at once, the number of dimensions of the visual data (2D or 3D) and the type of features used: handcrafted or DL based; it also offers useful tables gathering related studies, and different figures extracted from them, to illustrate how they perform abnormal HAR.

Table 2 Comparison of previous reviews with ours. By columns, important aspects taken into account in this review, and whether they are addressed or not by each review. From left to right: if the review is systematic; focuses on the exploration of DL solutions; targets elderly people as the users of the system; centers on the use of vision data; explores the Fall Detection and the Human Activity Recognition tasks; explores the use of RGB, depth or infrared data; takes privacy as a critical concern; describes the hardware used in the found studies; and if it studies the deployment of the FD and HAR systems in real environments.

	tic		Focus	3	Ta	sk		Data	,		AAL	
	Systematic	DL	Elderly	Vision	FD	HAR	RGB	Depth	IR	Privacy	Hardware	Deployment
Momin et al. [10]	X	X	1	1	1	1	X	1	X	1	X	Х
Olugbade et al. [9]	✓	X	Х	X	X	X	✓	/	✓	X	X	X
Alam et al. [11]	Х	1	/	1	1	X	1	/	1	1	X	X
Rastogi and Singh [12]	Х	X	/	/	1	/	1	/	/	X	X	Х
Gutiérrez et al. [13]	Х	X	/	/	1	X	1	/	/	X	X	Х
Climent-Pérez et al. [4]	X	X	/	/	1	/	1	/	/	1	X	X
Dhiman and Vishwakarma [14]	X	X	/	1	1	X	1	1	Х	Х	X	X
Ezatzadeh and Keyvanpour [15]	X	X	/	/	1	X	1	/	Х	Х	X	X
Sathyanarayana et al.[16]	Х	X	/	1	1	/	1	/	1	1	X	Х
This study	1	1	1	✓	✓	✓	1	✓	✓	1	✓	✓

An analytical framework (ViFa) for comparing different fall detection methods is proposed in [15]. First, different classifications of the methods are proposed, based on the input data (monocular, multi-camera or depth), the kind of features (shape, head motion, etc.) and the classification type (thresholds or learnt model). Then different criteria are proposed for evaluating the categorized methods, and finally a qualitative evaluation is performed based on these criteria. Among the criteria, typical metrics like accuracy can be found, but also less frequent ones, like the system implementation cost, real-time execution capabilities and resistance to occlusions and overlapping.

Many different patient monitoring tasks are reviewed in [16]: fall and sleep apnea detection, and sleep, epilepsy, breathing, facial expression, vital signs and activity monitoring. Even sub-tasks like pain or depression detection are included. For each task, the used data, technologies and techniques are analyzed and discussed, which offers a good overall picture of patient monitoring algorithms and techniques, at the cost of not diving into further details for any particular task.

As observed, different aspects of the subject matter addressed in this work have already been reviewed in previous studies. However, there are distinctive differences that underscore the necessity of the current work. Table 2 sheds light upon this by displaying the pivotal aspects considered in the current review, along with whether they are addressed or not in the aforementioned reviews.

As shown, the only prior review that centered on the study of DL techniques was conducted by [11], who did not include HAR in their research, and hence their review lacks almost half of the studies analyzed in this work. Conversely, the remaining reviews encompassed also techniques based on the utilization of handcrafted features or classical vision approaches. By focusing exclusively on DL-based solutions, our objective is to identify, categorize, and elucidate the entire spectrum of works built for

fall detection and HAR. Furthermore, there are discernible differences in the approach when dealing with DL, such as the importance of the training dataset, architecture, and kind of features extracted and employed. These distinctions are accounted for as we establish a taxonomy of the identified techniques and delve into their explanations in detail.

Another noticeable aspect is that HAR was reviewed in less than a half of the reviews, being the fall detection task the main focus of these. Additionally, in many cases, these tasks were not the sole focus of the review: as mentioned earlier, [16] reviewed various patient monitoring tasks, including sleep apnea detection, and epilepsy, breathing and vital signs monitoring among others. Similarly, [14] covered other abnormal activities alongside fall detection. Due to the broader scope of these reviews, they did not uncover as many studies as this study did in relation to the specific tasks of fall detection and HAR in the elderly. Furthermore, their analysis did not delve as deeply into the intricacies of these tasks.

On the other hand, only a limited number of reviews explored the application of the reviewed systems within Ambient Assisted Living (AAL) systems, along with the associated implications. Privacy was a major concern only in four reviews. None of the reviews thoroughly examined the hardware employed, beyond mentioning the prevalent use of the Kinect camera. Additionally, the effective deployment of fall detection or HAR systems was not extensively explored in any of the reviews. Conversely, we attributed great importance to these three aspects, which play a major role in facilitating the transference to society.

Finally, it is imperative to highlight that, apart from [9], none of the previous reviews followed a systematic review process. By adhering rigorously to the systematic review methodology as outlined by [8], our work distinguishes itself by ensuring a robust and unbiased selection and analysis of relevant studies. As part of our systematic review methodology, we conducted a thorough search across various databases, employing well-defined search strings aligned with our research questions. We carefully assessed the quality of each study and applied strict exclusion criteria to ensure the inclusion of only the most relevant and high-quality literature in our review. This systematic process aims to minimize any potential bias and ensures that our review is based on a well-rounded selection of literature.

3 Review Questions

The review questions of this work are presented in Table 3. Questions RQ1 and RQ2 are the primary review questions, while the remaining are secondary ones.

In RQ1, the question posed is about the DL technique used to recognize the activities or detect the fall of an elderly person, while the secondary questions are about the details of the different aspects when carrying out the task: the kind of data (RGB, depth, thermal, etc.), the used architecture (CNN, RNN, etc.), and the dataset. The reason behind this question is to be able to list the most common characteristics of DL based methods for HAR and fall detection on the elderly, so as to make easier and faster the developing of new methods for these tasks.

Table 3 Primary and secondary research questions used for this SLR.

ID	Research Question
RQ1	Which DL techniques are used for human activity recognition and fall detection on elderly people?
RQ1.1	Which is the most used kind of data?
RQ1.2	Which are the most used architectures?
RQ1.3	Which are the most used datasets?
RQ2	How can these tasks be deployed successfully in a real environment?
RQ2.1	Which is the most used hardware (cameras, robots, etc.)?
RQ2.2	How is privacy of the elderly preserved?

In RQ2, the question is about the deployment of the different tasks in a real-case scenario, and the secondary questions focus on two important aspects to take into account in the deployment: the hardware to use and the privacy of the users. Works with an implementation in real environments, whether it is through the use of robots or a camera-based setup, are expected to be found among the selected studies, so it is desirable to know which are the most used cameras, robots and other hardware used in the deployment. Moreover, privacy is a particularly preoccupying aspect to take into account when dealing with users, and the most extended ways of coping with it are of interest for any researcher wanting a deployment of a HAR or fall detection system.

4 Review Methods

4.1 Data sources

For this systematic review, five data sources were selected: SCOPUS, Web of Science (WOS), IEEE Explore Digital Library, ACM Digital Library and PubMed.

SCOPUS and WOS were selected as generic digital libraries, which contain knowledge accross multiple areas, whereas the others were chosen for their more specialized content on a specific area: IEEE is more focused on engineering and technology, ACM is specialized on computer science and PubMed is centered on biomedical studies. This selection of databases, with studies from multiple areas, was made aiming to embrace the maximum amount of related content.

The distribution of studies found from each source is plotted in Figure 1. As shown, the majority of studies were collected from ACM and SCOPUS, while very few (only 108 of a total of 2222) come from PubMed.

4.2 Search strategy

Different query strings were built to match the syntax of each digital library, keeping the differences at a minimum while using the same synonyms for the different concepts searched. For each query string, the different concepts were connected using logical AND, while the synonyms for each concept where connected with logical OR. To

Number of publications by source

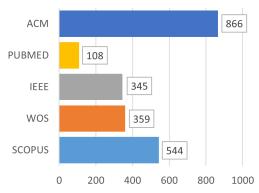


Fig. 1 Number of publications obtained from each database, before study selection (2222 in total).

cope with inflection of some keywords, the "*" operator was used after the root word, allowing any possible end of word.

For the SCOPUS library, the search was limited to only title, abstract or keywords, since the amount of results obtained otherwise was unfeasible, as well as the majority being poorly relevant. However, the whole text was searched for the remaining databases.

The main searched concepts, along with the employed list of synonyms, are the following:

- Task to perform (activity recognition or fall detection): "action recognition" OR "activit* recognition" OR "fall* detection" OR "behaviour recognition" OR "behaviour detection" OR "physical activity recognition"
- Ambient Assisted Living: "monitoring" OR "assist* living" OR "AAL" OR "smart home" OR "activit* of daily life" OR "activit* of daily living" OR "ADL"
- Target collective (elderly people): "elder*" OR "old* people" OR "senior"
- Kind of data used (Computer Vision): "vision" OR "rgb" OR "video" OR "image" OR "skeleton" OR "depth" OR "camera" OR "gesture"

Since Deep Learning has become popular recently, fewer related studies were found in the first considered years, as it can be seen in Figure 2. For this reason, the search was limited to only include studies published in the last 10 years. As shown, most studies found are from the last 5 years (from 2018 and on).

The results of study collection and duplicate removal can be seen in Figure 3. As shown, a total of 2222 studies were collected from the different sources using the aforementioned queries, of which 584 where detected as duplicates and removed, leaving a total of 1638 studies.

4.3 Study selection

After collecting the studies from the different sources, limiting by year and removing duplicates, exclusion criteria were applied to exclude non relevant studies. The exclusion criteria were:

Accumulated relevant publications by year

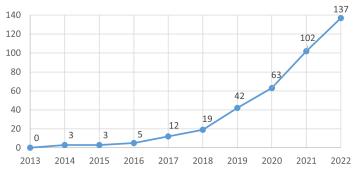


Fig. 2 Accumulated publications from 2013 to 2022 (both included) after study selection.

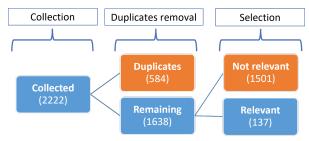


Fig. 3 Collected articles after each phase of the systematic search: collection from the different sources, duplicates removal and study selection, using inclusion and exclusion criteria.

- Deep Learning: studies not using DL were considered not relevant for this review. Including this concept in the exclusion criteria rather than in the query strings enabled to find more relevant studies, since there were many studies not referencing DL directly, but using the name of a specific model instead.
- Language: not in English or Spanish.
- Data type: data used is not either RGB, depth or IR. Both videos and images are included. Skeleton data is also included, but only if computed from the other three kinds of data. Studies where sensory data is used along with vision data are also include, allowing multimodal approaches.
- Availability: studies not accessible for different reasons: part of payed content (like book chapters), source website down or retracted content.
- Redundancy: in some cases, a journal article is published extending a work already presented in a conference. In these cases, the conference proceedings publications were omitted, since the journal article is an extension of the same work.
- Task: studies centered on different tasks than HAR or fall detection, like velocity estimation, gait trend, level of tiredness, etc. Studies which do not perform HAR or fall detection directly, but present a new dataset for these tasks are included.
- Target collective: studies which are not centered on elderly people were excluded. It is not enough to mention this collective as one of the beneficiaries of the work: the

study has to either use data of elderly people or have them in mind when designing the experiment.

- Works in progress: conference proceedings about works in progress, only containing the first stages of the study, were excluded. In most cases, they lacked the experimentation phase.
- Quality: publications with very poor quality (null reproducibility, very biased decisions, too small datasets, etc.) were excluded. More information about quality assessment in Section 4.4.

As seen in Figure 3, only 137 studies remain after applying the exclusion criteria, of which 82 are conference proceedings and 55 are journal articles. These studies will be presented in more detail, classified and compared in next sections.

4.4 Quality assessment

Since there is no agreed definition of study "quality", the proposed guidelines in [8] were followed, addressing mainly bias and validity of the studies as a measure of quality. Specifically, the following aspects were taken into account:

- **Reproducibility**. Whether the work can be replicated. This can be achieved by disclosing the dataset used or using external datasets, and by either publishing the used code for the model or giving enough details to recreate the model.
- Comparison with other works. Whether the obtained performance of the model is compared with the state of the art. Note that the comparison should be done in fair conditions, meaning that the models should be trained and tested on the same data, since bias can be introduced otherwise.
- Use of external datasets. By testing the model on external datasets, possible bias from the data can be removed and comparison with other models for the same task is easier. At the same time, other studies can use the results without needing to retrain the model on other data.

The aforementioned aspects were included in the list of fields in the data extraction phase (last 3 fields), which is addressed in Section 4.5. Moreover, these quality aspects were used also as exclusion criteria, as already mentioned in Section 4.3.

In addition to these aspects, the type of study, either conference proceedings or journal article, was also taken into account as a quality indicator, since journal articles tend to be longer and more mature. As already mentioned, there are more conference proceedings (82) than journal articles (55).

4.5 Data extraction and synthesis

From each study left after applying the exclusion criteria, different data were extracted in order to summarize the content and to establish taxonomies for various aspects of interest. All data were gathered in a table where, for each work, the following fields were extracted:

- Title
- Author/s

- Type (journal article or conference proceedings)
- Publication year
- Task (HAR or fall detection)
- Data type (RGB, depth, IR or skeleton)
- Auxiliary sensor data type (accelerometers, gyroscopes, etc.)
- Camera used
- Dataset (name of external dataset/s or "custom")
- DL model/s and task (skeleton joints estimation, feature extraction, classification, etc.)
- Other ML models or computer vision techniques used
- System integration in a robot (yes/no) and which one
- System integration in a framework (yes/no)
- How is privacy preserved? (depth or IR only, low resolution, etc.)
- Reproducible (yes/no)
- Test with external datasets
- Comparison with other approaches

The full list of relevant studies is shown in Tables 4 and 5, displaying only basic information of each one. The remaining information will be synthesized in Section 5 in the form of tables and plots, which allow to see the distribution of works by used data types, DL model family, dataset, etc. Aside from this information, especially relevant or interesting aspects of the works will also be summarized and relevant concepts will be addressed in more detail.

Table 4 Complete list of relevant studies analyzed in the current systematic review. The task of the studies can either be FD (fall detection), HAR (Human Action Recognition) or FD, HAR (both). CV data column refers to the type of computer vision data used to perform the task/s: RGB, D (depth) or IR (infrared). Data types are separated by a comma if the study requires all of them or by a slash if it only needs one of them (continued on next page).

Ref.	Year	Task	CV Data	Ref.	Year	Task	CV Data
[17]	2022	FD	RGB-D	[18]	2021	FD	RGB
[19]	2022	FD	RGB	[20]	2021	FD	RGB
[21]	2022	FD	RGB	[22]	2021	FD	RGB
[23]	2022	FD	RGB	[24]	2021	FD	RGB
[25]	2022	FD	D	[26]	2021	FD	RGB
[27]	2022	FD	RGB	[28]	2021	FD	RGB
[29]	2022	FD	RGB	[30]	2021	FD & HAR	IR
[31]	2022	FD	RGB	[32]	2021	FD & HAR	RGB
[33]	2022	FD	RGB	[34]	2021	FD & HAR	RGB
[35]	2022	FD	RGB/D/IR	[36]	2021	FD & HAR	RGB
[37]	2022	FD	RGB	[38]	2021	FD & HAR	RGB
[39]	2022	FD	RGB	[40]	2021	FD & HAR	RGB
[41]	2022	FD	RGB	[42]	2021	HAR	RGB
[43]	2022	FD	RGB	[44]	2021	HAR	D
[45]	2022	FD	RGB	[46]	2021	HAR	RGB
[47]	2022	FD	RGB	[48]	2021	HAR	RGB/D
[49]	2022	FD & HAR	RGB	[50]	2021	HAR	D
[51]	2022	FD & HAR	RGB	[52]	2021	HAR	RGB
[53]	2022	FD & HAR	RGB	[54]	2021	HAR	RGB/D
[55]	2022	FD & HAR	RGB	[56]	2021	HAR	D
[57]	2022	FD & HAR	RGB	[58]	2021	HAR	RGB
[59]	2022	FD & HAR	RGB	[60]	2021	HAR	D
[61]	2022	HAR	RGB	[62]	2021	HAR	D
[63]	2022	HAR	RGB	[64]	2021	HAR	RGB
[65]	2022	HAR	RGB	[66]	2021	HAR	IR
[<mark>67</mark>]	2022	HAR	D	[68]	2021	HAR	RGB
[69]	2022	HAR	RGB	[70]	2020	FD	RGB
[71]	2022	HAR	RGB-D	[72]	2020	FD	RGB
[73]	2022	HAR	RGB	[74]	2020	FD	RGB
[75]	2022	HAR	RGB	[76]	2020	FD	RGB-D
[77]	2022	HAR	RGB	[78]	2020	FD	RGB
[79]	2022	HAR	D	[80]	2020	FD	RGB
[81]	2022	HAR	RGB	[82]	2020	FD	RGB
[83]	2022	HAR	D	[84]	2020	FD	RGB
[85]	2022	HAR	RGB/D	[86]	2020	FD	RGB
[87]	2021	FD	RGB	[88]	2020	FD	RGB-D
[89]	2021	FD	RGB	[90]	2020	FD	RGB
[91]	2021	FD	RGB	[92]	2020	FD	RGB
[93]	2021	FD	RGB	[94]	2020	FD & HAR	RGB
[95]	2021	FD	RGB	[96]	2020	FD & HAR	IR
[97]	2021	FD	RGB	[98]	2020	HAR	RGB
[99]	2021	FD	RGB	[100]	2020	HAR	RGB-D
[101]	2021	FD	RGB	[102]	2020	HAR	RGB-D
[103]	2021	FD	RGB	[104]	2020	HAR	RGB
[105]	2021	FD	RGB/D	[106]	2020	HAR	RGB
[107]	2021	FD	RGB	[108]	2020	HAR	RGB
[109]	2021	FD	RGB	[110]	2020	HAR	RGB
[111]	2021	FD	RGB	[112]	2019	FD	RGB

Table 5 Complete list of relevant studies analyzed in the current systematic review. The task of the studies can either be FD (fall detection), HAR (Human Action Recognition) or FD, HAR (both). CV data column refers to the type of computer vision data used to perform the task/s: RGB, D (depth) or IR (infrared). Data types are separated by a comma if the study requires all of them or by a slash if it only needs one of them (continuation).

Ref.	Year	Task	CV Data	Ref.	Year	Task	CV Data
[113]	2019	FD	RGB	[114]	2019	HAR	D
[115]	2019	FD	RGB	[116]	2018	FD	RGB
[117]	2019	FD	RGB	[118]	2018	FD	RGB
[119]	2019	FD	RGB	[120]	2018	FD & HAR	IR
[121]	2019	FD	RGB	[122]	2018	FD & HAR	RGB
[123]	2019	FD	RGB, IR	[124]	2018	HAR	RGB
[125]	2019	FD	RGB	[126]	2018	HAR	RGB
[127]	2019	FD	RGB-D	[128]	2018	HAR	RGB
[129]	2019	FD	RGB	[130]	2017	FD	RGB
[131]	2019	FD	RGB	[132]	2017	FD	D
[133]	2019	FD	IR	[134]	2017	FD	IR
[135]	2019	FD	RGB	[136]	2017	FD & HAR	RGB-D
[137]	2019	HAR	D	[138]	2017	FD & HAR	RGB
[139]	2019	HAR	RGB	[140]	2017	HAR	RGB
[141]	2019	HAR	D	[142]	2017	HAR	D
[143]	2019	HAR	RGB	[144]	2016	FD	D
[145]	2019	HAR	RGB	[146]	2016	FD	RGB
[147]	2019	HAR	D	[148]	2014	FD	RGB
[149]	2019	HAR	RGB	[150]	2014	HAR	D
[151]	2019	HAR	RGB	[152]	2014	HAR	RGB-D
[153]	2019	HAR	RGB				

5 Results

In this section, tables and charts are provided to summarize the results of the review. To further improve the visualization and understanding of the information, different aspects are addressed separately and divided into subsections, corresponding to the related research questions. Note that primary research questions will be related to all sections targeting their secondary review questions.

5.1 RQ1: Fall detection and Human Activity Recognition

The two main tasks explored in the review are fall detection and Human Activity Recognition (HAR), treating fall detection as an especially important case of HAR. As shown in Figure 4, fall detection has been the most explored task in the last 10 years (86 studies in total), while there are a smaller number of studies dealing with HAR (69 studies in total). It can also be appreciated that it is quite rare to see studies dealing with both tasks at the same time: only 18 from a total of 137 studies (approximately a 13%).

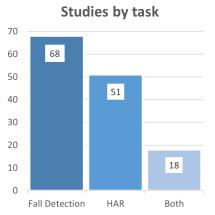
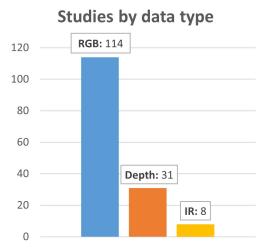


Fig. 4 Distribution of studies by target task: fall detection, HAR or both.

5.2 RQ1.1: Input data type

From the collected studies, 3 types of vision data have been considered: RGB, depth and infrared (IR). The number of occurrences of these can be observed in Figure 5. It was found that the RGB data are the most extended for fall detection and HAR on the elderly (114 studies), followed by depth data (31 studies), and finally by IR data (8 studies).



 ${f Fig.~5}$ Distribution of studies by data type used. Note that more than one data type was used in some studies.

There has also been found a notable number of studies which extract skeleton joints from the vision data to later use them to detect falls or to recognize different activities. More precisely, a 44% of the studies used skeleton joints estimation to perform classification, while only a 56% did not, and so the skeleton joints extraction seems to be a very extended practice.

In some studies, along with vision data, sensor data is used to further improve the results of the system, by using different models or strategies to perform the classification and then fusing the results. Five types of sensor data have been found in the review: Inertial Measurement Unit (IMU)², audio, barometer, luminosity and radar. The studies using these sensors can be seen in Table 6, which add up to a total of only 11 studies using multimodal data. Note that barometers, radars and luminosity data are always used together with an IMU.

Table 6 Non computer vision data found in the collected studies, together with the studies using them. Note that they have to be used together with computer vision data in order to be included in the review.

Sensor	Ref.	Year	Authors
IMU	[19]	2022	Meraikhi and Al-Rajab
	[89]	2021	Galvão et al.
	[63]	2022	Lin et al.
	[71]	2022	Ouyang et al.
	[99]	2021	Divya and Sri
	[78]	2020	Serpa et al.
	[86]	2020	Lv et al.
	[31]	2022	Aarthi and Juliet
	[77]	2022	Islam et al.
Audio	[137]	2019	Siriwardhana et al.
	[58]	2020	Iksan et al.
Barometer	[86]	2020	Lv et al.
Luminosity	[99]	2021	Divya and Sri
Radar	[71]	2022	Ouyang et al.

5.3 RQ1.2: DL models

Table 7 summarizes all DL models used to perform the tasks of fall detection and HAR. These models are not always used standalone, but for different specific tasks: skeleton joints estimation, optical flow computation, feature extraction, etc. The type of input data used by the models also differs and needs, in many cases, the computation of a specific type of features. This is reflected in Figure 6, where a taxonomy of the DL models used in the found studies according to different aspects is displayed.

 $^{^2}$ Studies not specifying the use of an IMU but using accelerometers and gyroscopes have also been included in this group.

Table 7 Complete list of DL models used in the reviewed studies. The first two columns refer to the models' reference and name, while the last three refer to their usage in the reviewed studies: task/s they are used for, input data they are feed with and the number of studies of the review in which they are found. FD is used for Fall Detection, OF for Optical Flow and OD for Object Detection, for brevity. Different models belonging to the same family (a.k.a. later improvements of the same model) have been grouped; this is the case for R-CNN, LSTM, YOLO, VGG, ResNet, RNN, CNN and GCN models.

	Model		Studies	
Ref.	Name	Task	Input data	N
[154]	OpenPose	2D Skeleton	RGB Image	23
[155]	AlphaPose	2D Skeleton	RGB Image	9
[156]	MediaPipe	2D Skeleton	RGB Image	4
[157]	PoseNet	2D Skeleton	RGB Image	2
[158]	STN	3D Skeleton	RGB-D Image	1
[159]	OpenNI	3D Skeleton	Depth Image	1
[160]	DeeperCut	2D Skeleton	RGB Image	1
[161]	RMPE	2D Skeleton	RGB Image	1
[162]	PoseFlow	2D Skeleton	RGB Image	1
[163]	Baidu AI	2D Skeleton	RGB Image	1
[164]	MobileNet	2D Skeleton, HAR, FD	RGB Image	4
[165]	DeepHAR	2D Skeleton, HAR, FD	RGB Image	1
[166]	C3D	Features	RGB Video	1
[167]	DCF-Net	Features	RGB Image	1
[168]	GoogLeNet	Features	RGB Image	1
[169]	PCA-Net	Features	RGB Image	1
[170]	PWC-Net	Features (OF)	RGB Video	1
[171]	Slowfast	Features	RGB Video	1
[172]	SqueezeNet	Features	RGB Image	1
[173]	LiteFlowNet	Features (OF)	RGB Video	1
[174]	InceptionV3	Features, HAR	RGB or Depth Image	2
[175]	R-CNN	Features (OD), FD	RGB Image	8
[176]	CNN	Features, HAR, FD	Image, Video or features	56
[177]	LSTM	Features, HAR, FD	Skel. sequence or Video features	25
[178]	YOLO	Features (OD), HAR, FD	RGB Image	14
[179]	VGG	Features, HAR, FD	RGB or Depth Image	11
[180]	ResNet	Features, HAR, FD	RGB or Depth Image or Skel. Pose	9
[181]	RNN	Features, HAR, FD	Skel. sequence or Video features	7
[182]	GCN	Features, HAR, FD	Skel. sequence or Video features	7
[183]	GRU	Features, HAR, FD	Skel. sequence or Video features	6
[184]	I3D	Features, HAR, FD	RGB Video	4
[185]	SOM	HAR	Skeleton Pose	2
[186]	AIA	HAR	Video features and Bound. Boxes	1
[187]	Transformer	HAR	IR image (8x8)	1
[188]	Glimpse Clouds	HAR	Skeleton sequence	1
[189]	iCAN	HAR	Bounding Boxes sequence	1
[190]	Autoencoder	FD	Different features	2
[190]	GAN	FD	Different features	2
[191]	DeepFall	FD	RGB, Depth or IR Video	1
[192]	DBN	FD	Different features	1
[29]	FallNet	FD	RGB Video	1
[29]	Siamese CNNs	FD	RGB or Optical Flow Video	1
[194]	Sep-TCN	FD	Skeleton sequence	1
	MLP	HAR, FD	Different features	1 5
[196]		l '		о 2
[197]	AlexNet	HAR, FD	Feature image	2 1
[53]	ARFD-Net	HAR, FD	Skeleton sequence	1

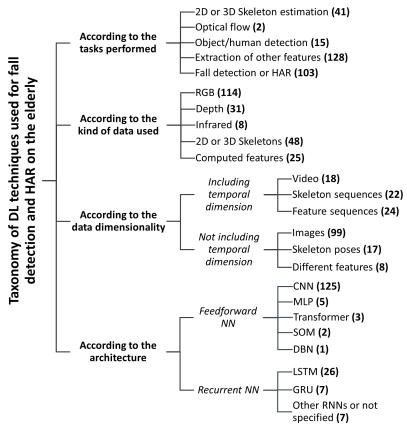


Fig. 6 Taxonomy of the DL techniques used in the found studies. The number of studies where each category was used is displayed in bold. Note that multiple models were used in many studies, and hence the same study can be counted in more than one category.

As already mentioned in section 5.2, there is a great amount of studies using skeleton joints as features for fall detection and HAR, and to estimate these joints, different DL models are used. The two most used models are: OpenPose [154] and AlphaPose [155]. OpenPose is based on a non-parametric representation (which they refer to as Part Affinity Fields) to find all skeleton joints from all humans in the image at once, while AlphaPose performs first human detection and then predicts the skeleton joints for each one. From both, the first one is more used than the second one (23 vs. 9 studies), although the second one is more recent. Once the skeleton joints have been extracted, many different models are used for fall detection and HAR using these data:

• Recurrent Networks: the Long-Short Term Memory (LSTM) [177] and the Gated Recurrent Unit (GRU) [183] are the most used ones, although others can also be found (grouped in the table as RNN).

- **Graph-Based Network:** only one has been found: the Graph-Convolutional Network (GCN) [182], which treats the skeletons as a graph, rather than as a sequence.
- Convolutional Networks: many are used, like VGG-16 or VGG-19 [179], MobileNet [164] or AlexNet [197].

There are two models used for optical flow estimation among the studies: PWC-Net [170] and LiteFlowNet [173], and two used for object (or human) detection: R-CNN [175] and YOLO [178]. It is much more frequent the use of object detection (22 studies) than the optical flow computation (2 studies). Object detection has been found to be used with different purposes in the studies:

- To obtain a sequence of bounding boxes for the objects in the scene, which can be used as features in next steps.
- To trigger later computation of fall detection or HAR upon detection of human presence, saving computation time.
- To perform background subtraction, in order to reduce the complexity of the data by focusing on the target person.
- To get features from the humans in the scene, like the height-to-width ratio, which are then used for fall detection or HAR in further steps.

DL computed features other than skeleton joints, optical flow and object/human bounding boxes are mainly computed through convolutional models like VGG-16 or VGG-19 [179], ResNet [180] or InceptionV3 [174], only to mention a few. Non DL-based features are also used in the reviewed studies, although less frequently. Among them we can find: HOG (Histograms of Oriented Gradients), HOF (Histograms of Optical Flow), LBP (Local Binary Patterns) and the use of BOVW (Bag of Visual Words). After obtaining the different kinds of features, multiple DL models are used to perform classification. However, at this stage it is also frequent to use non-deep machine learning models like the Support Vector Machine, or even rule-based classification on simple features like the height-to-width ratio or the spine angle.

From the reviewed studies, there are some which treat the fall detection task as a normal/abnormal classification task, by modeling normal activities and treating the falls as abnormal data. To do so, feature extraction is first performed (either by using pre-trained models to extract spatio-temporal features from video/image or by using estimated skeleton joints) and then a model is trained to fit the *normal* activities. In [144] and [150], Self Organizing Maps (SOM) are used to model normal activities from simple skeletal data; a Support Vector Data Description (SVDD) is used in [116] and the MPED-RNN network is used in [26] also on skeletal data; DeepFall [192] is used in [35] with different data modalities (RGB, depth and IR); an Autoencoder is used in [123] and [45] after obtaining spatio-temporal features using other nets; and Generative Adversarial Networks (GANs) [191] are used in [18] and [37], using the discriminator as the normal/abnormal classifier.

5.4 RQ1.3: Datasets

From the reviewed studies, a list of used datasets for activity recognition and fall detection has been collected. The list of datasets is summarized in Table 8. Only publicly available datasets have been included, aiming at providing a list that can be used for future works on the area. In cases where datasets do not have an official acronym, a custom one has been used. The column "Elderly" refers to whether the dataset contains samples with elderly people, "Falls" refers to whether at least one of the classes is for the falling activity and "Samples" refers to the number of samples found in the dataset, whether they are images or videos (note that the length of the videos can differ greatly). The list has been ordered by the number of studies in this review using each dataset (in descending order) and then by year (also descending order).

From the results, the following common characteristics can be observed for the different aspects:

- Elderly: most datasets do not include elderly people in the samples (only an 11% do).
- Falls: most include falls as a class (57% of the datasets).
- **Type:** almost all of them offer the samples in video format and not as images (86% vs. 14%).
- Data types: the RGB images/videos are always provided and, in many cases, also depth frames and skeleton joints are also provided (in 48% and 38% of the datasets respectively). The remaining data types are more rarely found: inertial data is only provided in 13% of the datasets, while IR data and MHV (Motion History Volumes) only in two and one datasets respectively.
- **Samples:** the number of samples differs greatly between datasets, varying from less than 50 to more than 50,000.
- Classes: the number of classes also varies greatly: from 2 classes (usually fall and not fall) to 700 in the Kinetics 700-2020 dataset [198]. Note that the datasets which offer that amount of classes are most likely not focused on AAL, but rather on the activity recognition task.
- Studies: half of the datasets are only used in one study, while only 4 are used in more than 10 studies.

Table 8 Complete list of publicly available datasets used in the reviewed studies, with their basic specifications. Columns Eld., Cl. and N refer to the presence of elderly people in the datasets, number of classes and number of the reviewed studies in which they appear respectively.

Ref.	Dataset	Eld.	Falls	Type	Data types	Samples	Cl.	N
[199]	URFD	No	Yes	Video	RGB-D, Skel., IMU	140	2	34
[200]	MultiCam	No	Yes	Video	RGB	192	2	16
[201]	UP-FALL	No	Yes	Video	RGB, IR, IMU	561	11	15
[202]	NTU RGB+D	No	Yes	Video	RGB-D, Skel.	56880	60	13
[136]	FDD-Adhikari	No	No	Image	RGB-D	21499	5	8
[203]	Le2i	No	Yes	Video	RGB	222	2	6
[204]	FDD-Charfi	No	Yes	Video	RGB	250	2	6
[205]	CAD-60	No	No	Video	RGB-D	720	12	4
[100]	PRECIS HAR	No	Yes	Video	RGB-D	800	16	3
[206]	UTD-MHAD	No	No	Video	RGB-D, Skel., IMU	861	27	3
[207]	MSRDailyActivity3D	No	No	Video	RGB-D, Skel.	320	16	3
[208]	HMDB51	No	Yes	Video	RGB	6766	51	3
[209]	KTH	No	No	Video	RGB	2391	6	3
[210]	ETRIActivity3D	Yes	Yes	Video	RGB-D, Skel.	112620	55	2
[125]	FPDS	No	Yes	Image	RGB	2064	2	2
[211]	NTU RGB $+$ D 120	No	Yes	Video	RGB-D, Skel.	114480	120	2
[114]	ToyotaSmartHome	Yes	No	Video	RGB-D, Skel.	16115	31	2
[212]	HQFSD	Yes	Yes	Video	RGB	55	2	2
[213]	UWA3DII	No	Yes	Video	RGB-D, Skel.	120	30	2
[214]	FDD-TST	No	Yes	Video	RGB-D, Skel., IMU	132	8	2
[215]	N-UCLA	No	No	Video	RGB-D, Skel.	100	10	2
[216]	CAD-120	No	No	Video	RGB-D	1200	10	2
[217]	UCF101	No	No	Video	RGB	13320	101	2
[218]	UTKinect-Action3D	No	No	Video	RGB-D, Skel.	200	10	2
[29]	FallAction	No	Yes	Video	RGB	2000	20	1
[33]	VWFP	No	Yes	Image	RGB	6071	2	1
[35]	MUVIM	Yes	Yes	Video	RGB-D, IR, IMU	244	2	1
[219]	FPDS-Elderly	Yes	Yes	Image	RGB	413	2	1
[54]	KIST SynADL	No	Yes	Video	RGB-D, Skel.	462200	55	1
[198]	Kinetics 700-2020	No	Yes	Video	RGB	647907	700	1
[94]	ALMOND	No	Yes	Video	RGB	7565	22	1
[220]	C-MHAD	No	Yes	Video	RGB, IMU	120	7	1
[221]	FDD-Chen	No	Yes	Video	RGB	30	2	1
[222]	OOPS	No	Yes	Video	RGB	20338	2	1
[223]	Kinetics 600	No	Yes	Video	RGB	495547	600	1
[128]	NAD	No	No	Video	RGB	84	7	1
[224]	YTBF	No	Yes	Video	RGB-D, Skel.	606	2	1
[225]	PKU-MMD	No	Yes	Video	RGB-D, Skel.	21545	51	1
[226]	Kinetics 400	No	No	Video	RGB	306245	400	1
[227]	KARD	No	No	Video	RGB-D, Skel.	540	18	1
[228]	V-COCO	No	No	Image	RGB	10346	25	1
[229]	MMU	No	Yes	Video	RGB	51	2	1
[230]	DMLSmartActions	No	Yes	Video	RGB-D, Skel.	932	12	1
[231]	Florence3D	No	No	Video	RGB-D, Skel.	215	9	1
[232]	$ACT4^2$	No	Yes	Video	RGB-D, Skel.	6844	14	1
[233]	BIT-interaction	No	No	Video	RGB	400	8	1
[234]	Stanford40	No	No	Image	RGB	9532	40	1
[235]	IXMAS	No	No	Video	RGB, MHV	330	11	1

The University of Rzeszow Fall Detection (URFD) [199] is the most used dataset (34 studies), followed by MultiCam [200] (16 studies), UP-FALL [201] (15 studies) and NTU RGB+D [202] (13 studies). The remaining datasets were used less than 10 times, with approximately half of the datasets being used in only one study. URFD is focused on the fall detection problem, thus offering only 2 classes: fall and ADL, offers 70 different sequences from 2 perspectives (140 samples in total) and good variety of data modalities: RGB, depth, skeleton joints and inertial data. MultiCam does not offer that many data types (only RGB video), but rather focuses on multiple perspectives for the different sequences: 24 in total, each one from 8 perspectives (192 samples), also with only 2 classes: fall or confounding event. In the UP-FALL dataset, data for 17 subjects, 11 activities and 2 perspectives (561 samples) can be found, allowing both HAR and fall detection, since falls are one of the classes. It offers RGB video, infrared images and inertial data. NTU RGB+D offers many more samples: a total of 56880 from 40 subjects performing 60 activities, using different perspectives, heights and distances for the cameras. Since the dataset is recorded using Kinect cameras, it contains RGB video, depth images and skeleton joints. There exists also an extended version of this dataset: the NTU RGB+D 120 dataset [211], which extends it by adding 60 more classes. It is only used in two of the reviewed studies.

Although the vast majority of the datasets are obtained by the deployment of cameras in a real environment, some of them are obtained through a simulation. More specifically, [33] and [54] offer synthetic images and videos respectively, rather than real ones. Even though it is easier and cheaper to obtain a large dataset this way, the suitability of it for a deployment in a real environment may be compromised.

Some of the reviewed studies did not use datasets in the provided list, but rather worked with a custom made one. In Figure 7 it can be observed the proportion of studies using either a custom dataset, an external one or both. As shown, only 19 studies offer evaluation on both a custom and an external dataset, while it is more frequent to offer it only on an external dataset (77 studies) rather than only on a custom one (41 studies).

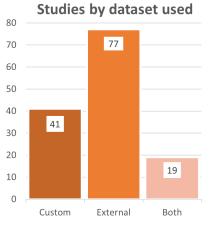


Fig. 7 Distribution of studies by dataset used

5.5 RQ2: Framework integration

In fifteen of the reviewed articles, a framework to integrate the HAR or fall detection task in a real environment was designed, attending to different aspects: security, use of cloud services, client-server configuration, network communications, IoT devices, etc. Next, we briefly describe the proposed frameworks.

In [61], a custom robot is proposed to integrate the HAR task in the environment, along with other ones like language processing to enable chatbot functionalities. In [94], a camera system is used instead to get the visual data and send it to a central server to perform all computation, and then notifications, reports and alerts are sent to a "guardian". In [46], activity recognition results along with recorded video data are sent to a developed mobile application, which is used to monitor the users of the system. In [140], an application implementing the Head-Toes-Knees-Shoulders (HTKS) game is built to assess cognitive dysfunctions, and a graphical interface is developed to visualize scores, charts and other information about the game. [23] centers on the fall detection task, establishing different phases: data acquisition through a camera system, computation on a central server and alert to a control center if a fall is detected, in charge of organizing a suitable response. In [99], a Docker-based system is proposed to control the flow between the different programs which participate in the fall detection task, distributing the amount of resources and regulating the communications. Docker is also used in [103], where the NAO robot is proposed for the data acquisition and interaction with the user to prevent falling situations. In [75], recorded video is processed and recognized activities are forwarded through a gateway to notify doctors or relatives or to update a graphical interface for monitoring the users. Similarly, in [58] the recordings are sent to a cloud server, which performs the HAR task and updates a mobile application. In [55], an intermediate step between the recording and the DL computation is added, to preprocess the video data and reduce the consumed bandwidth, which is also the case of [57]. In [126], the Pepper robot is used to deploy the system for its good acceptance among elderly people, and to recognize different exercises while interacting with the user. In [39], the system transfers the recording to a computer for human inspection when an abnormal state (fall) is detected. In [85], the proposed framework integrates the recognition of different activities in the monitoring system, and communicates with a control module which will use the results with different purposes, like triggering an alarm, and finally a similar framework is proposed in [47], where only cameras are deployed in the environment, which send the recordings to the cloud for fall detection and then warning alarms are triggered when a fall occurs.

5.6 RQ2.1: Hardware

To answer the review question **RQ2.1**, a list containing the hardware used in the reviewed studies (when available) has been made and is displayed in Table 9. Only hardware related to special cameras (thermal and depth) and to robots has been taken into account, since there is large variability in the common RGB cameras and in the hardware used for computation. Moreover, hardware information relative to datasets not created in the reviewed studies has been skipped.

Table 9 Hardware (special cameras and robots) used in the collected studies.

Type	Model	Brand	Ref.	Year	Authors
Depth Camera	Kinect (or v2)	Microsoft	[136]	2017	Adhikari et al.
			[137]	2019	Siriwardhana et al.
			[150]	2014	Jalal et al.
			[105]	2021	Li and Chen
			[147]	2019	Saini et al.
			[79]	2022	Guerra et al.
			[114]	2019	Das et al.
Depth Camera	Astra (or Pro)	Orbbec	[100]	2020	Popescu et al.
			[35]	2022	Denkovski et al.
			[62]	2021	Lumetzberger et al.
Depth Camera	XtionLive	ASUS	[144]	2016	Parisi and Wermter
Depth Camera	Horizon LiDAR	Livox	[56]	2021	Tu et al.
Thermal Camera	MLX90640	Melexis	[30]	2021	Rezaei et al.
			[96]	2020	Tateno et al.
Thermal Camera	FLIR E60	iTherml	[120]	2018	Akula et al.
Thermal Camera	FLIR ONE	iTherml	[35]	2022	Denkovski et al.
Thermal Camera	PI450	Optris	[123]	2019	Ma et al.
Thermal Camera	GRID-EYE	Panasonic	[134]	2017	Fan et al.
Thermal Camera	AMG8831	Panasonic	[66]	2021	Badarch et al.
Thermal Camera	HTPA32x32d	Heimann Sensor	[133]	2019	Rafferty et al.
Robot	Pepper	Aldebaran URG	[143]	2019	Nan et al.
			[126]	2018	Costa et al.
			[110]	2020	Lang et al.
Robot	NAO	Aldebaran URG	[144]	2016	Parisi and Wermter
			[103]	2021	Killian et al.
Robot	LOLA	Custom made	[125]	2019	Maldonado-Bascón et a
Robot	Dori	Custom made	[61]	2022	Kim et al.

To retrieve depth video, the most used camera is the Microsoft Kinect, followed by the Orbbec Astra. This may be due to the fact that they include both RGB and depth camera (based on IR camera), allowing 3D skeleton joint computation with sufficiently accurate results.

There is less consensus in the use of thermal cameras, where many different models of camera are used. There are also a lot of differences in the data retrieved, because of the sensors sensitivity to temperature, distance and resolution.

Only 7 studies have been found deploying HAR or fall detection on an AAL system using a robot, 3 of them using the Pepper robot, 2 using the NAO robot and the remaining using custom-made robots.

5.7 RQ2.2: Privacy protection

Not all studies lead with the privacy concerns when deploying a HAR or fall detection system in an AAL system. However, the solution can be found in the used data type selection, since some of them preserve the privacy better than others.

In Figure 8, the different privacy protection methods are shown, integrating the use of a less intrusive data type among them. As seen, from a total of 137 reviewed

studies, 61 do not cope with privacy concerns at all, using unmodified RGB video or images which show the elderly users of the system.

Studies by privacy protection method 50 61 40 30 22 10 7 Depth only RGB with privacy protection Skeleton from RGB None

Fig. 8 Distribution of studies by method used to preserve privacy. The total gives 138 studies because in [35] either depth or thermal data can be used.

There are 3 special cases where RGB data was used but including some kind of privacy protection: in [123], an IR camera is used to detect the face region of the frames and remove it from the RGB frames; in [124], blurring of the frames is performed before further recognition; and in [18], the RGB frames are modified in such a way that the person can not be identified, but fall detection can still be applied with good results. Despite this special cases, the most extended way of preserving the privacy of the users when using RGB cameras is skeleton joints estimation as the data used for classification. This is the case of 45 studies, which makes it the most extended privacy protection technique among all observed.

Another valid approach to preserve privacy is to avoid RGB cameras at all, either by using only thermal or depth cameras. This is the case of a total of 29 studies, from which the majority of the studies work with depth rather than with infrared data (22 vs. 7 studies).

6 Discussion

In Figure 9, the search process along with the main results found from the reviewed studies are briefly summarized. In this section, the found results are used to answer the review questions and the main strengths and weaknesses of the studies are discussed. A list of our recommendations based on our findings is also disclosed for use in future works.

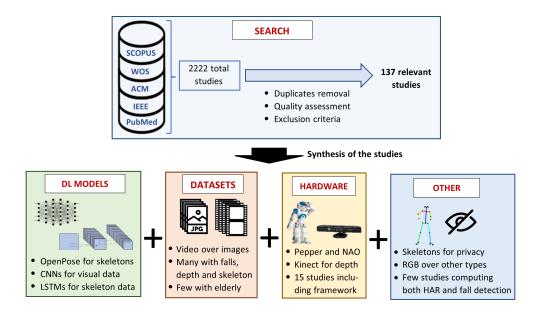


Fig. 9 Summary of the search process and found results.

6.1 RQ1: Which DL techniques are used for human activity recognition and fall detection on elderly people?

Even though fall detection could be understood as a special case of HAR, the findings show that the most frequent is to address this tasks separately: only 18 out of 137 studies (see Figure 4) cope with the two tasks. This can be due to the importance of the fall detection compared to the other activities (e.g. walking, getting up, etc.), which leads to an unbalanced problem if not dealt with separately.

To answer the RQ1.1, the most extended vision data type is RGB by far, as already seen in Figure 5. This may have to do with the ease of obtaining a common camera compared to a special one, equipped with either depth or infrared sensors, and other associated benefits, like a lower cost or the possibility to check data visually in an easier way. Infrared are the least used kind of cameras. They tend to be placed on the ceiling (top-down perspective) and to use very low resolutions, which enables the use of simpler (fewer layers) CNN models [30] [120] [133] and even of non-convolutionals like the LSTM [66] [96] [134], GRU [134] and Transformer [66]. Depth cameras are more extended than IR ones, but they are more used to extract skeleton joints than to perform fall detection and HAR directly on depth images/video.

Most extended architectures, related with RQ1.2, were shown in Section 5.3 and summarized in Table 7. Moreover, a taxonomy according to different aspects of the DL models was displayed in 6. Clearly, the most extended architectures are CNNs, and are used for many different tasks in the reviewed studies: skeleton joints estimation (most frequent models are OpenPose [154] and AlphaPose [155]), optical flow computation (PWC-Net [170] and LiteFlowNet [173]), object detection (R-CNN [175] and YOLO

[178]), extraction of spatial features (like in [97] or [45]), or directly to detect falls or recognize activities from images (like in [117], [52] or [98]), from video (like in [102] or [81]) or even from skeletal data (like in [42] or [51]). The other preferred architecture, from our findings, are RNNs, which are mostly used to work with skeletal data (like in [158] or [23]), but can also be found after CNNs, so that CNNs extract spatial features from each frame, and RNNs deal with the sequence of spatial features (like in [80] or [118]). Among the RNNs, the preferred model is the LSTM by far, followed by GRU, as seen in Table 7.

Another critical point when performing the fall detection and HAR tasks using DL is the dataset to learn from (RQ1.3), and the first decision to take is whether to use an already existing dataset or to create a custom one. Using only an external one can affect to the applicability of the technique to specific situations or environments, but it has the advantage of allowing comparison of different methods on the same data, while using only a custom one has the opposite effects. In Figure 7, the proportion of each type was already shown, and 41 can be observed to use only a custom dataset. The main inconvenient associated with this fact is the external validity of the findings, since no other state-of-the-art methods are evaluated on the same data for comparison. Moreover, in most reviewed studies where the only evaluation was done on a custom dataset, data was not made publicly available and very poor details were disclosed about them, thus reducing in great measure the reliability of the obtained results. From our perspective, to prove the well-functioning of the developed system, these studies should include an evaluation on external datasets.

By taking a deep look to Table 8, we think that the most used datasets are, in general, not the most suitable for the fall detection and HAR for the elderly people. First of all, because they do not contain elderly people at all, which we think is crucial to guarantee good results in a real deployment. In this aspect, the ETRIActivity3D [210], ToyotaSmartHome [114], HQFSD [212], MUVIM [35] and FPDS-Elderly [219] datasets would better fit, although the HQFSD dataset could be excluded for being synthetic. Another argument to not consider the most extended datasets is the number of samples, which we find too poor for the DL models to properly generalize. The two most used datasets consist of less than 200 samples, while approximately half of the used dataset contain less than 1,000. Instead, we think that datasets like the ETRIActivity3D, NTU RGB+D (or NTU RGB+D 120) or ToyotaSmartHome, which all offer more tan 10,000 samples, would bring better generalization results. A last note we want to remark on the dataset choosing step is that it is preferable for a dataset to be constructed for ADL than for general HAR. For instance, Kinetics (400, 600 or 700) or UCF101 would not be suitable for the tasks we consider, because they consist of videos collected from the Internet and may contain cuts and irrelevant activities.

6.2 RQ2: How can these tasks be deployed successfully in a real environment?

A list of studies including fall detection and HAR in a framework has been given in Section 5.5: a total of 15 studies. In these studies, the most common is to use a deployment of cameras of different types to collect the data and send it to a central server to then compute fall detection and HAR.

Answering RQ2.1, the camera used differs greatly in the case of recording RGB video, but to record depth data, there is a clear preference for the Microsoft Kinect (7 studies) and the Orbbec Astra (3 studies) cameras, as already shown in Table 9. On the other hand, there is not a clear preference for thermal recording, since only one camera is used in more than one study: Melaxis MLX90640. Therefore, there is a great variability regarding the images taken with the different cameras: a very broad range of resolutions (from 8×8 images with the Panasonic GRID-EYE [134] to 1440 \times 1080 with the iTherml FLIR ONE [35]), different maximum distances and even different sensitivity to temperature.

Also in reference to RQ2.1, the most used robots are Pepper and NAO, both from Aldebaran URG. The two robots include different RGB cameras, microphones, speakers and other sensors to interact with users in a more human manner. It is even possible to incorporate new kinds of camera, as shown in [144], where an ASUS XtionLive is located on the head of the robot to enable depth vision. However, most probably these two robots are the most extended due to their totally reprogrammable interface, since it enables to change the software used for the different tasks in order to better fit different situations.

Another important aspect when deploying a fall detection or HAR system in a real environment is the privacy of the users (RQ2.2), which is a major concern in many of the reviewed studies, while it is not for many others: as already mentioned in Section 5.7, almost half (61 of 137) of the reviewed studies do not take into account the privacy preservation of the users, either leaving it for future work or directly omitting it. From our point of view and having observed the different ways of coping with privacy protection, it is not an aspect to be skipped or postponed for later, since the main solutions consist on changing the kind of data used, and thus change radically the possible solutions. The most straightforward approach is using depth or infrared imaging, which will guarantee that the users are not recognized in any phase of the recognition process. However, since this is a very limiting method, a trade-off between no privacy protection and no RGB recording can be to allow RGB recording only in the first step of recognition, avoiding the storage of these data and instead storing (if needed) anonymized features. These kinds of features can be either modified RGB recordings with privacy protection (like in [123], [124] and [18]), which allow to store (and thus, check) footage of real cases but keeping privacy; skeleton joints (the most extended approach, being used in 44% of the studies, as seen in Section 5.2), which is, at the same time, a very efficient way to greatly reduce the amount of data to process; or spatio-temporal features, obtained using different DL models, with the inconvenient of not being human-interpretable.

6.3 Strengths and weaknesses of the reviewed studies

Having reviewed the 137 relevant studies and answered the review questions, in this subsection we discuss the main strengths and weaknesses we have observed, which we think can be of use to know at the time of working in new studies on the topic.

We have found many benefits in the use of skeleton joints: using them instead of raw image or video data allows a great reduction in the data size, at the same time of offering user anonymization and still being able to obtain good results in fall detection and HAR. In addition, there is an increasing number of ways to obtain human skeletons from RGB or depth data: only in the reviewed studies, 12 different DL models to estimate skeleton joints from image or video data were found (shown in Table 7).

The major strength of studies using only depth or infrared data is the privacy protection they offer, because there is not RGB footage recorded at any time of the system pipeline. However, the major weaknesses of these studies are two: having less data to perform detection or recognition (more notable in the case of IR recordings, where the resolution tends to be much lower) and having less understandable data, which can bring some problems when the system needs to be manually checked when errors occur.

From among the reviewed studies, there are 18 which perform both tasks: fall detection and HAR (refer to Figure 4), which we think is of remarkable importance, because when performing HAR on elderly people, it will most possibly be desirable to be able to also detect accidental falls. An important note on this is that although fall detection can be integrated as another class when performing HAR, it should be computed separately, because it is critical. For this reason, most studies including fall detection perform it in a different way than the recognition of the other classes.

Since fall detection and HAR for the elderly are tasks aiming to help this collective in an AAL, studies which offer a framework for deploying the system in a real environment are of especial interest. This is the case of 15 studies, listed in Section 5.5.

Even though the major part of the reviewed studies include an evaluation on existing datasets for fall detection and HAR, there are 41 which only perform it on new custom datasets (shown in Figure 7), which limits the reliability of the results when there is not comparison with other existing techniques or models. On the other hand, 19 of the studies still make use of a custom dataset, but also offer an evaluation on external datasets, getting the best out of both: specialization on the custom data and comparison with other approaches.

From the data perspective, we have observed two frequent weaknesses: the number of samples of the datasets used, and the lack of elderly people in these datasets. As shown in Table 8, the two most used datasets contain less than two hundred samples which seems too few when using DL to perform the tasks of fall detection and HAR. Moreover, in the same table it can be seen that, in the majority of the datasets (89%), elderly people do not participate in the samples, which can bring problems at the deployment phase, since they are the target users of the system.

6.4 Recommendations for future studies on the topic

Based on the results of this SLR, we list a series of especially important facts, to our understanding, which should be taken into account when performing a new study on the topic.

First of all, it is important to assess user's privacy. As seen, the way to protect privacy will most probably affect to the kind of data to use, going from using RGB data to either modified RGB, depth, IR or skeleton data, which prevent the identification of the users in the footage. For this reason, we recommend to consider it as a key aspect from the beginning.

To evaluate the proposed model, a publicly available dataset should be used, to enable comparison with other existing models or techniques. The most extended ones for fall detection are URFD [199] and MultiCam [200], while for HAR are UP-FALL [201] and NTU RGB+D [202]. Instead of the mentioned datasets, however, we encourage the use of ETRIActivity3D [210] or ToyotaSmartHome [114], which offer a much larger collection of video samples and include elderly people in the data. Both datasets can be used for HAR, while only ETRIActivity3D includes falls in the dataset, and both offer different perspectives from many elderly users, many classes (at least 30) and also various modalities, including RGB, depth and skeleton joints.

If a custom dataset is provided, we recommend to make it publicly available for different reasons: it can be of use in future studies, by either directly using it or merging it with other ones to form a larger dataset; it will increase the reliability of the experiments on it, by making them replicable; and it will enable comparison of the proposed model or technique with newer ones. To collect the custom dataset, the most common is to use a Microsoft Kinect camera if depth or skeleton data are desired, while there is no common agreement for infrared recordings.

When deploying the system in a real environment, according to the reviewed studies, the most usual is to build a camera setup in the environment, which records the data and sends it to a central server to perform the different tasks. It is also the most affordable option, depending on the kind of camera, resolution and processing it is needed by the system. Nevertheless, in case it is preferred to use an assistive robot, both the NEO and the Pepper robots are viable solutions that have been used in 5 of the reviewed studies. Their main advantage is to incorporate cameras, speakers, microphones and other required components, at the same time of offering many customizable options, which can make them able to adapt to different projects and environments.

7 Conclusions

In this work, an SLR on fall detection and Human Activity Recognition (HAR) for the elderly has been performed. The study has focused on addressing two primary review questions related to the implementation of deep learning techniques for these tasks, using computer vision data, specifically looking at the various DL architectures, datasets, and data types employed. Furthermore, the study examined the deployment of these techniques in real-world environments, considering the hardware used and the privacy of the users. The findings provide valuable insights into the effective implementation of deep learning techniques for fall detection and human activity recognition in elderly care.

We reviewed 137 relevant studies and structured the main findings to make the available evidence more accessible to readers and researchers. The main results of this work can be of especial interest for future studies on this topic given the rising importance and prominence of AAL and DL techniques. Our main contributions are a summary of the existent methods (Tables 4 and 5), the datasets used in the reviewed studies which are publicly available (Table 8), the DL models used along with basic

information (Table 7), the depth and thermal cameras and the robots used in the different studies (Table 9), and a list of the studies integrating the system in a framework (Section 5.5).

Although privacy is a common concern when deploying camera-based systems, many of the reviewed studies do not cope with it at all (45% to be precise, as seen in Figure 8), and more studies assessing elderly users' perception and preferences regarding this aspect need to be done. The most extended privacy protection method, whether if it is chosen bearing the privacy factor in mind or not, is the use of skeleton joints estimation as data for fall detection and HAR, being used in 44% of the studies. Other common methods include avoiding RGB recordings, using instead depth or IR only cameras.

A great variety of DL architectures have been found in the reviewed studies, but the vast majority are convolutional or recurrent. They are used in different steps of the fall detection and HAR tasks, like skeleton joints estimation, optical flow computation or spatio-temporal features extraction only to mention a few. Convolution-based networks seem to be the preferred ones for many of the mentioned tasks, like Open-Pose [154] for skeleton joints estimation, as shown in Table 7. However, to cope with skeletal data, RNNs like the LSTM [177] take the lead.

DL based methods rely on big amounts of data to perform satisfactorily and to generalize properly, and so we think that the most extended datasets for fall detection like URFD [199] or MultiCam [200] with under two hundred samples are not enough, which is also the case of many others of the datasets used in the reviewed studies. Another important feature the datasets targeting elderly people should have is, precisely, to include elderly people in the data, which does not happen in the vast majority of the datasets. With these two factors in mind, the ETRIActivity3D [210] dataset seems to be the most appropriate one for the fall detection task, while this one along with the ToyotaSmartHome [114] dataset seem the best options for the HAR task.

Future work on the topic could include diving deeper into specific DL architectures, to review the main differences and contributions of the studies, and even offer an evaluation comparison on different datasets.

Declarations

Funding. Grant PID2019-104829RA-I00 funded by MCIN/AEI/10.13039/501100011033, project EXPLainable Artificial INtelligence systems for health and well-beING (EXPLAINING). Grant PID2022-136779OB-C32 funded by MCIN/AEI/10.13039/501100011033 and by ERDF A way of making Europe, project Playful Experiences with Interactive Social Agents and Robots (PLEISAR): Social Learning and Intergenerational Communication. F. X. Gaya-Morey was supported by an FPU scholarship from the Ministry of European Funds, University and Culture of the Government of the Balearic Islands.

Competing interests. The authors have no competing interests to declare that are relevant to the content of this article.

Authors' contributions. F.Xavier Gaya-Morey: Conceptualization, Methodology, Validation, Investigation, Writing - Original Draft, Writing - Review & Editing Preparation, Visualization.

Cristina Manresa-Yee: Conceptualization, Methodology, Writing - Review & Editing Preparation, Supervision, Project administration, Funding acquisition.

Jose M. Buades-Rubio: Conceptualization, Methodology, Writing - Review & Editing Preparation, Supervision, Project administration, Funding acquisition.

Ethical and informed consent for data used. This article does not contain any studies with human participants or animals performed by any of the authors.

Data availability and access. All relevant data for the study can be found, structured and organized in the form of tables, throughout this document. No additional data were generated.

References

- [1] Bloom, D.E., Luca, D.L.: Chapter 1 the global demography of aging: Facts, explanations, future. vol. 1, pp. 3–56. North-Holland (2016)
- [2] WHO: World Health Organization fact sheets: Falls. https://www.who.int/en/news-room/fact-sheets/detail/falls (2021)
- [3] Heinrich, S., Rapp, K., Rissmann, U., Becker, C., König, H.-H.: Cost of falls in old age: a systematic review. Osteoporosis International **21**, 891–902 (2010)
- [4] Climent-Pérez, P., Spinsante, S., Mihailidis, A., Florez-Revuelta, F.: A review on video-based active and assisted living technologies for automated lifelogging. Expert Systems with Applications 139 (2020)
- [5] Khodabandehloo, E., Riboni, D., Alimohammadi, A.: Healthxai: Collaborative and explainable ai for supporting early diagnosis of cognitive decline. Future Generation Computer Systems 116, 168–189 (2021)
- [6] Nizam, Y., Jamil, M.M.A.: Classification of daily life activities for human fall detection: A systematic review of the techniques and approaches. Studies in Systems, Decision and Control 273, 137–179 (2020)
- [7] Walsh, J., O' Mahony, N., Campbell, S., Carvalho, A., Krpalkova, L., Velasco-Hernandez, G., Harapanahalli, S., Riordan, D.: Deep learning vs. traditional computer vision. (2019)
- [8] Kitchenham, B., Charters, S.: Guidelines for performing systematic literature reviews in software engineering 2 (2007)
- [9] Olugbade, T., Bieńkiewicz, M., Barbareschi, G., D'amato, V., Oneto, L., Camurri, A., Holloway, C., Björkman, M., Keller, P., Clayton, M., Williams, A.C.D.C., Gold, N., Becchio, C., Bardy, B., Bianchi-Berthouze, N.: Human

- movement datasets: An interdisciplinary scoping review. ACM Comput. Surv. **55** (2022)
- [10] Momin, M.S., Sufian, A., Barman, D., Dutta, P., Dong, M., Leo, M.: In-home older adults' activity pattern monitoring using depth sensors: A review. Sensors **22** (2022)
- [11] Alam, E., Sufian, A., Dutta, P., Leo, M.: Vision-based human fall detection systems using deep learning: A review. Computers in Biology and Medicine 146, 105626 (2022)
- [12] Rastogi, S., Singh, J.: Human fall detection and activity monitoring: a comparative analysis of vision-based methods for classification and detection techniques. Soft Computing 26, 3679–3701 (2022)
- [13] Gutiérrez, J., Rodríguez, V., Martin, S.: Comprehensive review of vision-based fall detection systems. Sensors **21**(3) (2021)
- [14] Dhiman, C., Vishwakarma, D.K.: A review of state-of-the-art techniques for abnormal human activity recognition. Engineering Applications of Artificial Intelligence 77, 21–45 (2019)
- [15] Ezatzadeh, S., Keyvanpour, M.R.: Vifa: an analytical framework for vision-based fall detection in a surveillance environment. Multimedia Tools and Applications **78**, 25515–25537 (2019)
- [16] Sathyanarayana, S., Satzoda, R.K., Sathyanarayana, S., Thambipillai, S.: Vision-based patient monitoring: a comprehensive review of algorithms and technologies. Journal of Ambient Intelligence and Humanized Computing 9, 225–251 (2018)
- [17] Li, S., Man, C., Shen, A., Guan, Z., Mao, W., Luo, S., Zhang, R., Yu, H.: A fall detection network by 2d/3d spatio-temporal joint models with tensor compression on edge. ACM Trans. Embed. Comput. Syst. 21 (2022)
- [18] Liu, J., Tan, R., Han, G., Sun, N., Kwong, S.: Privacy-preserving in-home fall detection using visual shielding sensing and private information-embedding. IEEE Transactions on Multimedia 23, 3684–3699 (2021)
- [19] Meraikhi, S.A., Al-Rajab, M.: A multimodal approach of machine and deep learnings to enhance the fall of elderly people. Journal of Information Technology Management 14, 168–184 (2022)
- [20] Zherdev, D., Zherdeva, L., Agapov, S., Sapozhnikov, A., Nikonorov, A., Chaplygin, S.: Producing synthetic dataset for human fall detection in ar/vr environments. Applied Sciences (Switzerland) 11 (2021)

- [21] Chen, P.-C., Chang, C.-H., Chan, Y.-W., Tasi, Y.-T., Chu, W.C.: An approach to real-time fall detection based on openpose and lstm, pp. 1573–1578 (2022)
- [22] Feng, X., Jiang, W.: Research on human fall detection based on tiny-yolov3 algorithm, pp. 1326–1330. Association for Computing Machinery, New York, NY, USA (2021)
- [23] Anwary, A.R., Rahman, M.A., Muzahid, A.J.M., Ashraf, A.W.U., Patwary, M., Hussain, A.: Deep learning enabled fall detection exploiting gait analysis. Annu Int Conf IEEE Eng Med Biol Soc 2022, 4683–4686 (2022)
- [24] Xie, L., Yang, Y., Zeyu, F., Naqvi, S.M.: Skeleton-based fall events classification with data fusion. Institute of Electrical and Electronics Engineers Inc., Karlsruhe, Germany (2021)
- [25] Fayad, M., Hachani, M.-Y., Mostefaoui, A., Chouali, S., Yahiaoui, R.: Elderly fall detection: A lightweight kinect based deep learning approach, pp. 89–95. Association for Computing Machinery, New York, NY, USA (2022)
- [26] Fatima, M., Yousaf, M.H., Yasin, A., Velastin, S.A.: Unsupervised fall detection approach using human skeletons, pp. 1–6 (2021)
- [27] Lau, X.L., Connie, T., Goh, M.K.O., Lau, S.H.: Fall detection and motion analysis using visual approaches. International Journal of Technology 13, 1173–1182 (2022)
- [28] Berlin, S.J., John, M.: Vision based human fall detection with siamese convolutional neural networks. Journal of Ambient Intelligence and Humanized Computing (2021)
- [29] Nigam, N., Dutta, T., Verma, D.: Fall-perceived action recognition of persons with neurological disorders using semantic supervision. IEEE Transactions on Cognitive and Developmental Systems, 1 (2022)
- [30] Rezaei, A.M., Stevens, M.C., Argha, A., Mascheroni, A., Puiatti, A., Lovell, N.H.: An unobtrusive fall detection system using low resolution thermal sensors and convolutional neural networks, pp. 6949–6952 (2021)
- [31] Aarthi, M.S., Juliet, S.: Intelligent fall detection system based on sensor and image data for elderly monitoring, pp. 1259–1265 (2022)
- [32] Fernando, Y.P.N., Gunasekara, K.D.B., Sirikumara, K.P., Galappaththi, U.E., Thilakarathna, T., Kasthurirathna, D.: Computer vision based privacy protected fall detection and behavior monitoring system for the care of the elderly, vol. 2021-September, pp. 1–7. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2021)

- [33] Carrara, F., Pasco, L., Gennaro, C., Falchi, F.: Learning to detect fallen people in virtual worlds, pp. 126–130. Association for Computing Machinery, New York, NY, USA (2022)
- [34] Tseng, H.-T., Hsieh, C.-C., Hsu, T.-Y.: Elder action recognition based on convolutional neural network and long short-term memory, pp. 1–2 (2021)
- [35] Denkovski, S., Khan, S.S., Malamis, B., Moon, S.Y., Ye, B., Mihailidis, A.: Multi visual modality fall detection dataset. IEEE Access 10, 106422–106435 (2022)
- [36] Ramirez, H., Velastin, S.A., Meza, I., Fabregas, E., Makris, D., Farias, G.: Fall detection and activity recognition using human skeleton features. IEEE Access 9, 33532–33542 (2021)
- [37] Galvão, Y.M., Portela, L., Barros, P., Araújo Fagundes, R.A., Fernandes, B.J.T.: Onefall-gan: A one-class gan framework applied to fall detection. Engineering Science and Technology, an International Journal (2022)
- [38] Wang, X., Talavera, E., Karastoyanova, D., Azzopardi, G.: Fall detection and recognition from egocentric visual data: A case study. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 12661 LNCS, 431–443 (2021)
- [39] Zheng, H., Liu, Y., Wu, X., Zhang, Y.: Realization of elderly fall integration monitoring system based on alphapose and yolov4, pp. 604–620. Institute of Electrical and Electronics Engineers Inc., Hangzhou, China (2022)
- [40] Hasib, R., Khan, K.N., Yu, M., Khan, M.S.: Vision-based human posture classification and fall detection using convolutional neural network, pp. 74–79 (2021)
- [41] Zahan, S., Hassan, G.M., Mian, A.: Sdfa: Structure aware discriminative feature aggregation for efficient human fall detection in video. IEEE Transactions on Industrial Informatics, 1–9 (2022)
- [42] Giannakos, I., Mathe, E., Spyrou, E., Mylonas, P.: A study on the effect of occlusion in human activity recognition, pp. 473–482. Association for Computing Machinery, New York, NY, USA (2021)
- [43] Rajalaxmi, R.R., Gothai, E., Suganth, V., Vignesh, S., Varun, T.: Vision based fall detection using optimized convolutional neural network, pp. 1–6. Institute of Electrical and Electronics Engineers Inc., Coimbatore, India (2022)
- [44] Wang, J., Yang, W.: Action recognition based on cross spatial temporal graph convolution. Association for Computing Machinery, New York, NY, USA (2021)
- [45] Anitha, G., Priya, S.B.: Vision based real time monitoring system for elderly fall

- event detection using deep learning. Computer Systems Science and Engineering 42, 87–103 (2022)
- [46] Awal, M.I., Iksan, L.H., Fhamy, R.Z., Basuki, D.K., Sukaridhoto, S., Wada, K.: Action recognition with spatiotemporal analysis and support vector machine for elderly monitoring system, pp. 470–475. Institute of Electrical and Electronics Engineers Inc., Surabaya, Indonesia (2021)
- [47] Zhang, Y., Zheng, X., Liang, W., Zhang, S., Yuan, X.: Visual surveillance for human fall detection in healthcare iot. IEEE Multimedia 29, 36–46 (2022)
- [48] Byeon, Y.-H., Kim, D., Lee, J., Kwak, K.-C.: Body and hand-object roi-based behavior recognition using deep learning. Sensors **21**, 1–23 (2021)
- [49] Inturi, A.R., Manikandan, V.M., Garrapally, V.: A novel vision-based fall detection scheme using keypoints of human skeleton with long short-term memory network. Arabian Journal for Science and Engineering (2022)
- [50] Budisteanu, E.-A., Mocanu, I.G.: Combining supervised and unsupervised learning algorithms for human activity recognition. SENSORS **21** (2021)
- [51] Suarez, J.J.P., Orillaza, N., Naval, P.: Afar: A real-time vision-based activity monitoring and fall detection framework using 1d convolutional neural networks, pp. 555–559. Association for Computing Machinery, New York, NY, USA (2022)
- [52] Sivakumar, M., Iswarya, E., Malusha, K., Priyadharshini, T.Y.: Computer vision based wellness analysis of geriatrics, pp. 1762–1765. Institute of Electrical and Electronics Engineers Inc., Coimbatore, India (2021)
- [53] Yadav, S.K., Luthra, A., Tiwari, K., Pandey, H.M., Akbar, S.A.: Arfdnet: An efficient activity recognition & fall detection system using latent feature pooling. Knowledge-Based Systems 239 (2022)
- [54] Hwang, H., Jang, C., Park, G., Cho, J., Kim, I.-J.: Eldersim: A synthetic data generation platform for human action recognition in eldercare applications. IEEE Access, 1 (2021)
- [55] Rajavel, R., Ravichandran, S.K., Harimoorthy, K., Nagappan, P., Gobichettipalayam, K.R.: Iot-based smart healthcare video surveillance system using edge computing. Journal of Ambient Intelligence and Humanized Computing 13, 3195–3207 (2022)
- [56] Tu, L., Ouyang, X., Zhou, J., He, Y., Xing, G.: Feddl: Federated learning via dynamic layer sharing for human activity recognition, pp. 15–28. Association for Computing Machinery, New York, NY, USA (2021)

- [57] Wang, B., Wu, X., Gong, M., Zhao, J., Sun, Y.: Lightweight network based real-time anomaly detection method for caregiving at home, pp. 1323–1328. Institute of Electrical and Electronics Engineers Inc., Hangzhou, China (2022)
- [58] Iksan, L.H., Awal, M.I., Fhamy, R.Z., Pratama, A.A., Basuki, D.K., Sukaridhoto, S.: Implementation of cloud based action recognition backend platform, pp. 1–6 (2021)
- [59] Xie, L., Sun, Y., Chambers, J.A., Naqvi, S.M.: Privacy preserving multi-class fall classification based on cascaded learning and noisy labels handling, pp. 1–6. Institute of Electrical and Electronics Engineers Inc., Linköping, Sweden (2022)
- [60] Tianming, Z., Pengbiao, Z., Peng, X., Bintao, W.: Multi-stream cnn-lstm network with partition strategy for human action recognition, pp. 431–435. Association for Computing Machinery, New York, NY, USA (2021)
- [61] Kim, J.-W., Choi, Y.-L., Jeong, S.-H., Han, J.: A care robot with ethical sensing system for older adults at home. Sensors (Basel) **22**, 7515 (2022)
- [62] Lumetzberger, J., Raoofpour, A., Kampel, M.: Privacy preserving getup detection, pp. 234–243. Association for Computing Machinery, New York, NY, USA (2021)
- [63] Lin, F., Wang, Z., Zhao, H., Qiu, S., Shi, X., Wu, L., Gravina, R., Fortino, G.: Adaptive multi-modal fusion framework for activity monitoring of people with mobility disability. IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS 26, 4314–4324 (2022)
- [64] Nambissan, G.S., Mahajan, P., Sharma, S., Gupta, N.: The variegated applications of deep learning techniques in human activity recognition, pp. 223–233. Association for Computing Machinery, New York, NY, USA (2021)
- [65] He, J., Xiang, M., Zhao, X.: An elderly indoor behavior recognition method based on improved slowfast network, vol. 2216. IOP Publishing Ltd, San Francisco, CA, USA (2022)
- [66] Badarch, L., Gochoo, M., Batnasan, G., Alnajjar, F., Tan, T.-H.: Ultra-low resolution infrared sensor-based wireless sensor network for privacy-preserved recognition of daily activities of living. Institute of Electrical and Electronics Engineers Inc., Boston, MA, USA (2021)
- [67] Patsch, C., Zakour, M., Chaudhari, R.: Automatic recognition of human activities combining model-based ai and machine learning, pp. 15–22. SCITEPRESS, Setubal, Portugal (2022)
- [68] Tan, T.-H., Hus, J.-H., Liu, S.-H., Huang, Y.-F., Gochoo, M.: Using direct acyclic graphs to enhance skeleton-based action recognition with a linear-map

- convolution neural network. Sensors 21 (2021)
- [69] Zhang, C., Yang, X.: Bed-leaving action recognition based on yolov3 and alphapose, pp. 117–123. Association for Computing Machinery, New York, NY, USA (2022)
- [70] Mobsite, S., Alaoui, N., Boulmalf, M.: A framework for elders fall detection using deep learning, pp. 69–74 (2020)
- [71] Ouyang, X., Shuai, X., Zhou, J., Shi, I.W., Xie, Z., Xing, G., Huang, J.: Cosmo: Contrastive fusion learning with small data for multimodal human activity recognition, pp. 324–337. Association for Computing Machinery, New York, NY, USA (2022)
- [72] Han, K., Yang, Q., Huang, Z.: A two-stage fall recognition algorithm based on human posture features. Sensors (Switzerland) 20, 1–21 (2020)
- [73] Prasad, S.K., Ko, Y.-B.: Deep learning based human activity recognition with improved accuracy, vol. 2022-October, pp. 1492–1495. IEEE Computer Society, Jeju Island, Republic of Korea (2022)
- [74] Chiang, J.W.H., Zhang, L.: Deep learning-based fall detection, vol. 12, pp. 891–898. WORLD SCIENTIFIC PUBL CO PTE LTD, Singapore (2020)
- [75] Achirei, S.-D., Heghea, M.-C., Lupu, R.-G., Manta, V.-I.: Human activity recognition for assisted living based on scene understanding. Applied Sciences (Switzerland) 12 (2022)
- [76] Khraief, C., Benzarti, F., Amiri, H.: Elderly fall detection based on multi-stream deep convolutional networks. Multimedia Tools and Applications 79, 19537– 19560 (2020)
- [77] Islam, M.M., Nooruddin, S., Karray, F.: Multimodal human activity recognition for smart healthcare applications, vol. 2022-October, pp. 196–203. Institute of Electrical and Electronics Engineers Inc., Prague, Czech Republic (2022)
- [78] Serpa, Y.R., Nogueira, M.B., Neto, P.P.M., Rodrigues, M.A.F.: Evaluating pose estimation as a solution to the fall detection problem, pp. 1–7. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2020)
- [79] Guerra, B.M.V., Schmid, M., Beltrami, G., Ramat, S.: Neural networks for automatic posture recognition in ambient-assisted living. Sensors **22** (2022)
- [80] Berardini, D., Moccia, S., Migliorelli, L., Pacifici, I., Massimo, P.D., Paolanti, M., Frontoni, E.: Fall detection for elderly-people monitoring using learned features and recurrent neural networks. Experimental Results 1 (2020)

- [81] Isoi, H., Takefusa, A., Nakada, H., Oguchi, M.: Performance of domain adaptation schemes in video action recognition using synthetic data, pp. 70–79. Association for Computing Machinery, New York, NY, USA (2022)
- [82] Romaissa, B.D., Mourad, O., Brahim, N., Yazid, B.: Fall detection using body geometry in video sequences, pp. 1–5 (2020)
- [83] Sun, H., Chen, Y.: Real-time elderly monitoring for senior safety by lightweight human action recognition, vol. 2022-May, pp. 1–6. IEEE Computer Society, Lincoln, NE, USA (2022)
- [84] Wang, X., Jia, K.: Human fall detection algorithm based on yolov3, pp. 50–54. Institute of Electrical and Electronics Engineers Inc., Beijing, China (2020)
- [85] Ji, Q.: The design of the lightweight smart home system and interaction experience of products for middle-aged and elderly users in smart cities. Comput Intell Neurosci 2022, 1279351 (2022)
- [86] Lv, X., Gao, Z., Yuan, C., Li, M., Chen, C.: Hybrid real-time fall detection system based on deep learning and multi-sensor fusion, pp. 386–391. Institute of Electrical and Electronics Engineers Inc., Shenzhen, China (2020)
- [87] Galvao, Y.M., Portela, L., Ferreira, J., Barros, P., Fagundes, O.A.D.A., Fernandes, B.J.T.: A framework for anomaly identification applied on fall detection. IEEE ACCESS 9, 77264–77274 (2021)
- [88] Kharazian, Z., Rahat, M., Fatemizadeh, E., Nasrabadi, A.M.: Increasing safety at smart elderly homes by human fall detection from video using transfer learning approaches, pp. 2774–2780. Research Publishing Services, Venice, Italy (2020)
- [89] Galvão, Y.M., Ferreira, J., Albuquerque, V.A., Barros, P., Fernandes, B.J.T.: A multimodal approach using deep learning for fall detection. Expert Systems with Applications **168** (2021)
- [90] Li, J., Xia, S.-T., Ding, Q.: Multi-level recognition on falls from activities of daily living, pp. 464–471. Association for Computing Machinery, New York, NY, USA (2020)
- [91] Kang, Y.-K., Kang, H.-Y., Kim, J.-B.: A study of fall detection system using context cognition method, pp. 79–83. Institute of Electrical and Electronics Engineers Inc., Ho Chi Minh City, Vietnam (2021)
- [92] Chen, Y., Li, W., Wang, L., Hu, J., Ye, M.: Vision-based fall event detection in complex background using attention guided bi-directional lstm. IEEE Access 8, 161337–161348 (2020)
- [93] Raj, A., Singh, D., Prakash, C.: Active human pose estimation for assisted living,

- pp. 110–116. Association for Computing Machinery, New York, NY, USA (2021)
- [94] Buzzelli, M., Albé, A., Ciocca, G.: A vision-based system for monitoring elderly people at home. Applied Sciences (Switzerland) 10 (2020)
- [95] Yang, Y., Ren, H., Li, C., Ding, C., Yu, H.: An edge-device based fast fall detection using spatio-temporal optical flow model, pp. 5067–5071. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2021)
- [96] Tateno, S., Meng, F., Qian, R., Li, T.: Human motion detection based on low resolution infrared array sensor, pp. 1016–1021 (2020)
- [97] Sultana, A., Deb, K., Dhar, P.K., Koshiba, T.: Classification of indoor human fall events using deep learning. Entropy (Basel) 23 (2021)
- [98] Tan, T.-H., Gochoo, M., Chen, H.-S., Liu, S.-H., Huang, Y.-F.: Activity recognition based on dcnn and kinect rgb images, pp. 1–4 (2020)
- [99] Divya, V., Sri, R.L.: Docker-based intelligent fall detection using edge-fog cloud infrastructure. IEEE Internet of Things Journal 8, 8133–8144 (2021)
- [100] Popescu, A.-C., Mocanu, I., Cramariuc, B.: Fusion mechanisms for human activity recognition using automated machine learning. IEEE ACCESS 8, 143996–144014 (2020)
- [101] Chen, Y., Du, R., Luo, K., Xiao, Y.: Fall detection system based on real-time pose estimation and svm, pp. 990–993. Institute of Electrical and Electronics Engineers Inc., Nanchang, China (2021)
- [102] Mathe, E., Tranou, A., Spyrou, E., Perantonis, S.: Human action recognition with deep learning techniques. Association for Computing Machinery, New York, NY, USA (2020)
- [103] Killian, L., Julien, M., Kevin, B., Maxime, L., Carolina, B., Mélanie, C., Nathalie, B., Sylvain, G., Sebastien, G.: Fall prevention and detection in smart homes using monocular cameras and an interactive social robot, pp. 7–12. Association for Computing Machinery, New York, NY, USA (2021)
- [104] Atikuzzaman, M., Rahman, T.R., Wazed, E., Hossain, M.P., Islam, M.Z.: Human activity recognition system from different poses with cnn, pp. 1–5. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2020)
- [105] Li, X., Chen, W.: Fall recognition algorithm for the elderly based on home service robot, pp. 329–335. Institute of Electrical and Electronics Engineers Inc., Zhengzhou, China (2021)
- [106] Gul, M.A., Yousaf, M.H., Nawaz, S., Rehman, Z.U., Kim, H.: Patient monitoring by abnormal human activity recognition based on cnn architecture. Electronics

- (Switzerland) 9, 1–14 (2020)
- [107] Ge, W., Luo, X., Tao, R., Shi, Y.: Human fall detection algorithm based on mixed attention mechanism, pp. 32–37. Association for Computing Machinery, New York, NY, USA (2021)
- [108] Jaouedi, N., Perales, F.J., Buades, J.M., Boujnah, N., Bouhlel, M.S.: Prediction of human activities based on a new structure of skeleton features and deep learning model. Sensors (Switzerland) **20**, 1–15 (2020)
- [109] Pita, M.S.U., Alon, A.S., Melo, P.M.B., Hernandez, R.M., Magboo, A.I.: Indoor human fall detection using data augmentation-assisted transfer learning in an aging population for smart homecare: A deep convolutional neural network approach, pp. 64–69. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2021)
- [110] Lang, X., Feng, Z., Yang, X.: Research on human-robot natural interaction algorithm based on body potential perception, pp. 260–264. Association for Computing Machinery, New York, NY, USA (2020)
- [111] Vaiyapuri, T., Lydia, E.L., Sikkandar, M.Y., Diaz, V.G., Pustokhina, I.V., Pustokhin, D.A.: Internet of things and deep learning enabled elderly fall detection model for smart homecare. IEEE Access 9, 113879–113888 (2021)
- [112] Wang, H., Gao, Z., Lin, W.: A fall detection system based on convolutional neural networks, pp. 242–246. Association for Computing Machinery, New York, NY, USA (2019)
- [113] Wang, F., Liu, J., Hu, G.D.: A novel indoor human fall detection method based on an end-to-end neural network and bagged tree classifier, pp. 384–389. Association for Computing Machinery, New York, NY, USA (2019)
- [114] Das, S., Dai, R., Koperski, M., Minciullo, L., Garattoni, L., Bremond, F., Francesca, G.: Toyota smarthome: Real-world activities of daily living, vol. 2019-October, pp. 833–842. Institute of Electrical and Electronics Engineers Inc., Seoul, Korea (South) (2019)
- [115] Brieva, J., Ponce, H., Moya-Albor, E., Martinez-Villasenor, L.: An intelligent human fall detection system using a vision-based strategy, pp. 1–5. Institute of Electrical and Electronics Engineers Inc., Los Alamitos, California, USA (2019)
- [116] Li, W., Tang, P., Jin, W., Hu, C., He, Z.: Accidental fall detection based on pose analysis and svdd, pp. 9244–9249 (2018)
- [117] Hassan, M.F.A., Hussain, A., Saad, M.H.M., Yusof, Y.: Convolution neural network-based action recognition for fall event detection. International Journal of Advanced Trends in Computer Science and Engineering 8 (2019)

- [118] Ge, C., Gu, I.Y.-H., Yang, J.: Co-saliency-enhanced deep recurrent convolutional networks for human fall detection in e-healthcare, pp. 1572–1575 (2018)
- [119] Mohamed, N.A., Zulkifley, M.A., Kamari, N.A.M.: Convolutional neural networks tracker with deterministic sampling for sudden fall detection, pp. 1–5. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2019)
- [120] Akula, A., Shah, A.K., Ghosh, R.: Deep learning approach for human action recognition in infrared images. Cognitive Systems Research **50**, 146–154 (2018)
- [121] Kumar, D., Ravikumar, A.K., Dharmalingam, V., Kafle, V.P.: Elderly health monitoring system with fall detection using multi-feature based person tracking, pp. 1–9. Institute of Electrical and Electronics Engineers Inc., Atlanta, GA, USA (2019)
- [122] Hsieh, Y.-Z., Jeng, Y.-L.: Development of home intelligent fall detection iot system based on feedback optical flow convolutional neural network. IEEE ACCESS 6, 6048–6057 (2018)
- [123] Ma, C., Shimada, A., Uchiyama, H., Nagahara, H., Taniguchi, R.-i.: Fall detection using optical level anonymous image sensing system. Optics and Laser Technology 110, 44–61 (2019)
- [124] Dimiccoli, M., Mar{i}n, J., Thomaz, E.: Mitigating bystander privacy concerns in egocentric activity recognition with deep learning and intentional image degradation. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 1 (2018)
- [125] Maldonado-Bascón, S., Iglesias-Iglesias, C., Martín-Martín, P., Lafuente-Arroyo, S.: Fallen people detection capabilities using assistive robot. Electronics (Switzerland) 8 (2019)
- [126] Costa, A., Martinez-Martin, E., Cazorla, M., Julian, V.: Pharos-physical assistant robot system. Sensors (Basel) 18 (2018)
- [127] Cameiro, S.A., Silva, G.P.D., Leite, G.V., Moreno, R., Guimaraes, S.J.F., Pedrini, H.: Multi-stream deep convolutional network using high-level features applied to fall detection in video sequences, vol. 2019-June, pp. 293–298. IEEE Computer Society, New York, NY, USA (2019)
- [128] Chen, Y., Yu, L., Ota, K., Dong, M.: Robust activity recognition for aging society. IEEE Journal of Biomedical and Health Informatics 22, 1754–1764 (2018)
- [129] Ferooz, F., Ashraf, M.A., Hussain, W., Butt, A.H., Khan, Y.D.: Person fall recognition by using deep learning: Convolutional neural networks and image category classification using bag of feature, pp. 1–6 (2019)

- [130] Ge, C., Gu, I.Y.-H., Yang, J.: Human fall detection using segment-level cnn features and sparse dictionary learning, pp. 1–6 (2017)
- [131] Safarzadeh, M., Alborzi, Y., Ardekany, A.N.: Real -time fall detection and alert system using pose estimation, pp. 508–511 (2019)
- [132] Hwang, S., Ahn, D., Park, H., Park, T.: Maximizing accuracy of fall detection and alert systems based on 3d convolutional neural network: Poster abstract, pp. 343–344. Association for Computing Machinery, New York, NY, USA (2017)
- [133] Rafferty, J., Medina-Quero, J., Quinn, S., Saunders, C., Ekerete, I., Nugent, C., Synnott, J., Garcia-Constantino, M.: Thermal vision based fall detection via logical and data driven processes, pp. 35–40. Institute of Electrical and Electronics Engineers Inc., Honolulu, HI, USA (2019)
- [134] Fan, X., Zhang, H., Leung, C., Shen, Z.: Robust unobtrusive fall detection using infrared array sensors, pp. 194–199 (2017)
- [135] Huang, Z., Liu, Y., Fang, Y., Horn, B.K.P.: Video-based fall detection for seniors with human pose estimation. Institute of Electrical and Electronics Engineers Inc., Boston, MA, USA (2019)
- [136] Adhikari, K., Bouchachia, H., Nait-Charif, H.: Activity recognition for indoor fall detection using convolutional neural network, pp. 81–84. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2017)
- [137] Siriwardhana, C., Madhuranga, D., Madushan, R., Gunasekera, K.: Classification of activities of daily living based on depth sequences and audio, pp. 278–283. Institute of Electrical and Electronics Engineers Inc., Kandy, Sri Lanka (2019)
- [138] Yu, M., Gong, L., Kollias, S.: Computer vision based fall detection by a convolutional neural network, pp. 416–420. Association for Computing Machinery, New York, NY, USA (2017)
- [139] Phyo, C.N., Zin, T.T., Tin, P.: Complex human-object interactions analyzer using a dcnn and svm hybrid approach. Applied Sciences (Switzerland) 9 (2019)
- [140] Gattupalli, S., Ebert, D., Papakostas, M., Makedon, F., Athitsos, V.: Cognilearn: A deep learning-based interface for cognitive behavior assessment, pp. 577–587. Association for Computing Machinery, New York, NY, USA (2017)
- [141] Phyo, C.N., Zin, T.T., Tin, P.: Deep learning for recognizing human activities using motions of skeletal joints. IEEE Transactions on Consumer Electronics 65, 243–252 (2019)
- [142] Neili, S., Gazzah, S., Yacoubi, M.A.E., Amara, N.E.B.: Human posture recognition approach based on convnets and svm classifier, pp. 1–6. Institute of

- Electrical and Electronics Engineers Inc., New York, NY, USA (2017)
- [143] Nan, M., Ghiță, A.S., Gavril, A.-F., Trascau, M., Sorici, A., Cramariuc, B., Florea, A.M.: Human action recognition for social robots, pp. 675–681 (2019)
- [144] Parisi, G.I., Wermter, S.: A neurocognitive robot assistant for robust event detection. Studies in Computational Intelligence **633**, 1–27 (2016)
- [145] Mehr, H.D., Polat, H.: Human activity recognition in smart home with deep learning approach, pp. 149–153. IEEE, New York, NY, USA (2019)
- [146] Wang, S., Chen, L., Zhou, Z., Sun, X., Dong, J.: Human fall detection in surveillance video based on pcanet. Multimedia Tools and Applications 75, 11603–11613 (2016)
- [147] Saini, R., Kumar, P., Kaur, B., Roy, P.P., Dogra, D.P., Santosh, K.C.: Kinect sensor-based interaction monitoring system using the blstm neural network in healthcare. International Journal of Machine Learning and Cybernetics 10, 2529–2540 (2019)
- [148] Feng, P., Yu, M., Naqvi, S.M., Chambers, J.A.: Deep learning for posture analysis in fall detection, pp. 12–17 (2014)
- [149] Jalal, A., Mahmood, M., Hasan, A.S.: Multi-features descriptors for human activity tracking and recognition in indoor-outdoor environments, pp. 371–376 (2019)
- [150] Jalal, A., Kamal, S., Kim, D.: Depth map-based human activity tracking and recognition using body joints features and self-organized map, pp. 1–6. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2014)
- [151] Ding, Q., Yang, F., Li, J., Wu, S., Zhao, B., Wang, Z., Xia, S.-T.: Rt-adi: Fast real-time video representation for multi-view human fall detection, pp. 13– 18. Institute of Electrical and Electronics Engineers Inc., New York, NY, USA (2019)
- [152] Iarlori, S., Ferracuti, F., Giantomassi, A., Longhi, S.: Rgb-d video monitoring system to assess the dementia disease state based on recurrent neural networks with parametric bias action recognition and dafs index evaluation. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 8548 LNCS, 156–163 (2014)
- [153] Priya, G.G.L., Jain, M., Santosh, K.C., Mouli, P.V.S.S.R.C.: Temporal superpixel based convolutional neural network (ts-cnn) for human activity recognition in unconstrained videos. Communications in Computer and Information Science 1035, 255–264 (2019)

- [154] Cao, Z., Hidalgo Martinez, G., Simon, T., Wei, S., Sheikh, Y.A.: Openpose: Realtime multi-person 2d pose estimation using part affinity fields. IEEE Transactions on Pattern Analysis and Machine Intelligence (2019)
- [155] Fang, H.-S., Li, J., Tang, H., Xu, C., Zhu, H., Xiu, Y., Li, Y.-L., Lu, C.: Alphapose: Whole-body regional multi-person pose estimation and tracking in real-time. IEEE Transactions on Pattern Analysis and Machine Intelligence (2022)
- [156] Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., Zhang, F., Chang, C.-L., Yong, M.G., Lee, J., Chang, W.-T., Hua, W., Georg, M., Grundmann, M.: MediaPipe: A Framework for Building Perception Pipelines. arXiv (2019)
- [157] Papandreou, G., Zhu, T., Chen, L.-C., Gidaris, S., Tompson, J., Murphy, K.: Personlab: Person pose estimation and instance segmentation with a bottom-up, part-based, geometric embedding model. In: Computer Vision – ECCV 2018, pp. 282–299. Springer, Cham (2018)
- [158] Li, S., Man, C., Shen, A., Guan, Z., Mao, W., Luo, S., Zhang, R., Yu, H.: A fall detection network by 2d/3d spatio-temporal joint models with tensor compression on edge. ACM Trans. Embed. Comput. Syst. 21 (2022)
- [159] OpenNI: OpenNI library for Processing. https://code.google.com/archive/p/simple-openni/ (2011)
- [160] Insafutdinov, E., Pishchulin, L., Andres, B., Andriluka, M., Schieke, B.: Deepercut: A deeper, stronger, and faster multi-person pose estimation model. In: European Conference on Computer Vision (ECCV) (2016)
- [161] Fang, H.-S., Xie, S., Tai, Y.-W., Lu, C.: Rmpe: Regional multi-person pose estimation. In: 2017 IEEE International Conference on Computer Vision (ICCV), pp. 2353–2362 (2017)
- [162] Xiu, Y., Li, J., Wang, H., Fang, Y., Lu, C.: Pose flow: Efficient online pose tracking. In: BMVC (2018)
- [163] BaiduAI: Baidu AI: Human Body Analysis. https://intl.cloud.baidu.com/ product/body.html
- [164] Howard, A., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., Adam, H.: Mobilenets: Efficient convolutional neural networks for mobile vision applications (2017)
- [165] Luvizon, D.C., Picard, D., Tabia, H.: 2D/3D Pose Estimation and Action Recognition using Multitask Deep Learning. arXiv (2018)

- [166] Tran, D., Bourdev, L., Fergus, R., Torresani, L., Paluri, M.: Learning spatiotemporal features with 3d convolutional networks, pp. 4489–4497 (2015)
- [167] Wang, Q., Gao, J., Xing, J., Zhang, M., Hu, W.: DCFNet: Discriminant Correlation Filters Network for Visual Tracking. arXiv (2017)
- [168] Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Erhan, D., Vanhoucke, V., Rabinovich, A.: Going deeper with convolutions. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1–9 (2015)
- [169] Chan, T.-H., Jia, K., Gao, S., Lu, J., Zeng, Z., Ma, Y.: Pcanet: A simple deep learning baseline for image classification? IEEE Transactions on Image Processing 24(12), 5017–5032 (2015)
- [170] Sun, D., Yang, X., Liu, M.-Y., Kautz, J.: Pwc-net: Cnns for optical flow using pyramid, warping, and cost volume, pp. 8934–8943 (2018)
- [171] Feichtenhofer, C., Fan, H., Malik, J., He, K.: SlowFast Networks for Video Recognition. arXiv (2018)
- [172] Iandola, F., Han, S., Moskewicz, M., Ashraf, K., Dally, W., Keutzer, K.: Squeezenet: Alexnet-level accuracy with 50x fewer parameters and j0.5mb model size (2016)
- [173] Hui, T.-W., Tang, X., Loy, C.C.: LiteFlowNet: A Lightweight Convolutional Neural Network for Optical Flow Estimation (2018)
- [174] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z.: Rethinking the inception architecture for computer vision. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2818–2826 (2016)
- [175] Girshick, R., Donahue, J., Darrell, T., Malik, J.: Rich feature hierarchies for accurate object detection and semantic segmentation. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2013)
- [176] Fukushima, K.: Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. Biological Cybernetics 36(4), 193–202 (1980)
- [177] Hochreiter, S., Schmidhuber, J.: Long Short-Term Memory. Neural Computation 9(8), 1735–1780 (1997)
- [178] Redmon, J., Divvala, S., Girshick, R., Farhadi, A.: You only look once: Unified, real-time object detection, pp. 779–788 (2016)
- [179] Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale

- image recognition. arXiv 1409.1556 (2014)
- [180] He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770–778 (2016)
- [181] Elman, J.L.: Finding structure in time. Cognitive Science 14(2), 179–211 (1990)
- [182] Kipf, T.N., Welling, M.: Semi-Supervised Classification with Graph Convolutional Networks. arXiv (2016)
- [183] Cho, K., Merrienboer, B., Bahdanau, D., Bengio, Y.: On the properties of neural machine translation: Encoder-decoder approaches (2014)
- [184] Carreira, J., Zisserman, A.: Quo Vadis, Action Recognition? A New Model and the Kinetics Dataset. arXiv (2017)
- [185] Kohonen, T.: The self-organizing map. Proceedings of the IEEE **78**(9), 1464–1480 (1990)
- [186] Tang, J., Xia, J., Mu, X., Pang, B., Lu, C.: Asynchronous interaction aggregation for action detection. In: Computer Vision – ECCV 2020, pp. 71–87. Springer, Cham (2020)
- [187] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A., Kaiser, L., Polosukhin, I.: Attention is all you need (2017)
- [188] Baradel, F., Wolf, C., Mille, J., Taylor, G.: Glimpse clouds: Human activity recognition from unstructured feature points, pp. 469–478 (2018)
- [189] Gao, C., Zou, Y., Huang, J.-B.: iCAN: Instance-Centric Attention Network for Human-Object Interaction Detection. arXiv (2018)
- [190] Hinton, G.E., Salakhutdinov, R.R.: Reducing the dimensionality of data with neural networks. Science **313**(5786), 504–507 (2006)
- [191] Goodfellow, I.J., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y.: Generative Adversarial Networks. arXiv (2014)
- [192] Nogas, J., Khan, S., Mihailidis, A.: Deepfall: Non-invasive fall detection with deep spatio-temporal convolutional autoencoders. Journal of Healthcare Informatics Research 4 (2020)
- [193] Hinton, G.E.: Deep belief networks. Scholarpedia 4, 5947 (2009)
- [194] Koch, G.R.: Siamese neural networks for one-shot image recognition. (2015)
- [195] Hampiholi, B., Jarvers, C., Mader, W., Neumann, H.: Depthwise separable

- temporal convolutional network for action segmentation. In: 2020 International Conference on 3D Vision (3DV), pp. 633–641 (2020)
- [196] Rumelhart, D.E., Hinton, G.E., Williams, R.J.: Learning representations by back-propagating errors. nature **323**(6088), 533–536 (1986)
- [197] Krizhevsky, A., Sutskever, I., Hinton, G.E.: Imagenet classification with deep convolutional neural networks. Commun. ACM 60(6), 84–90 (2017) https://doi. org/10.1145/3065386
- [198] Smaira, L., Carreira, J., Noland, E., Clancy, E., Wu, A., Zisserman, A.: A Short Note on the Kinetics-700-2020 Human Action Dataset. arXiv (2020)
- [199] Kwolek, B., Kepski, M.: Human fall detection on embedded platform using depth maps and wireless accelerometer. Computer Methods and Programs in Biomedicine 117, 489–501 (2014)
- [200] Auvinet, E., Rougier, C., Meunier, J., St-Arnaud, A., Rousseau, J.: Multiple cameras fall data set (2011)
- [201] Martínez-Villaseñor, L., Ponce, H., Brieva, J., Moya-Albor, E., Núñez-Martínez, J., Peñafort-Asturiano, C.: Up-fall detection dataset: A multimodal approach. Sensors 19 (2019)
- [202] Shahroudy, A., Liu, J., Ng, T., Wang, G.: Ntu rgb+d: A large scale dataset for 3d human activity analysis. (2016)
- [203] Charfi, I., Miteran, J., Dubois, J., Atri, M., Tourki, R.: Optimized spatiotemporal descriptors for real-time fall detection: comparison of support vector machine and adaboost-based classification. Journal of Electronic Imaging 22, 41106 (2013)
- [204] Charfi, I., Miteran, J., Dubois, J., Atri, M., Tourki, R.: Definition and performance evaluation of a robust sym based fall detection solution, pp. 218–224 (2012)
- [205] Sung, J., Ponce, C., Selman, B., Saxena, A.: Unstructured human activity detection from rgbd images, pp. 842–849 (2012)
- [206] Chen, C., Jafari, R., Kehtarnavaz, N.: Utd-mhad: A multimodal dataset for human action recognition utilizing a depth camera and a wearable inertial sensor, pp. 168–172 (2015)
- [207] Wang, J., Liu, Z., Wu, Y., Yuan, J.: Mining actionlet ensemble for action recognition with depth cameras, pp. 1290–1297 (2012)
- [208] Kuehne, H., Jhuang, H., Garrote, E., Poggio, T., Serre, T.: Hmdb: A large video database for human motion recognition, pp. 2556–2563 (2011)

- [209] Schuldt, C., Laptev, I., Caputo, B.: Recognizing human actions: a local symapproach, vol. 3, pp. 32–363 (2004)
- [210] Jang, J., Kim, D., Park, C., Jang, M., Lee, J., Kim, D.: Etri-activity3d: A large-scale rgb-d dataset for robots to recognize daily activities of the elderly, pp. 10990–10997 (2020)
- [211] Liu, J., Shahroudy, A., Perez, M., Wang, G., Duan, L.-Y., Kot, A.: Ntu rgb+d 120: A large-scale benchmark for 3d human activity understanding. IEEE Transactions on Pattern Analysis and Machine Intelligence, 1–18 (2019)
- [212] Vanrumste, B., Debard, G., Croonenborghs, T., Mertes, G., Baldewijns, G.: Bridging the gap between real-life data and simulated data by providing a highly realistic fall dataset for evaluating camera-based fall detection algorithms. Healthcare Technology Letters 3 (2016)
- [213] Rahmani, H., Mahmood, A., Huynh, D., Mian, A.: Histogram of oriented principal components for cross-view action recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence 38, 2430–2443 (2016)
- [214] Gasparrini, S., Cippitelli, E., Gambi, E., Spinsante, S., Wåhslén, J., Orhan, I., Lindh, T.: Proposal and experimental evaluation of fall detection solution based on wearable and depth data fusion 399, 99–108 (2016)
- [215] wang, J., Nie, X., Xia, Y., Wu, Y., Zhu, S.: Cross-view action modeling, learning, and recognition. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2014)
- [216] Koppula, H., Gupta, R., Saxena, A.: Learning human activities and object affordances from rgb-d videos. The International Journal of Robotics Research 32 (2012)
- [217] Soomro, K., Zamir, A., Shah, M.: Ucf101: A dataset of 101 human actions classes from videos in the wild. CoRR (2012)
- [218] Xia, L., Chen, C.-C., Aggarwal, J.K.: View invariant human action recognition using histograms of 3d joints, pp. 20–27 (2012)
- [219] Maldonado-Bascón, S., Iglesias-Iglesias, C., Martín-Martín, P., Lafuente-Arroyo, S.: Elderly Dataset (2021)
- [220] Wei, H., Chopada, P., Kehtarnavaz, N.: C-mhad: Continuous multimodal human action dataset of simultaneous video and inertial sensing. Sensors **20** (2020)
- [221] Chen, Z.: Fall detection dataset (2019)
- [222] Epstein, D., Chen, B., Vondrick, C.: Oops! Predicting Unintentional Action in Video. arXiv (2019)

- [223] Carreira, J., Noland, E., Banki-Horvath, A., Hillier, C., Zisserman, A.: A Short Note about Kinetics-600. arXiv (2018)
- [224] Fan, Y., Levine, M., Gongjian, W., Qiu, S.: A deep neural network for real-time detection offalling humans in naturally occurring scenes. Neurocomputing 260 (2017)
- [225] Liu, C., Hu, Y., Li, Y., Song, S., Liu, J.: PKU-MMD: A Large Scale Benchmark for Continuous Multi-Modal Human Action Understanding. arXiv (2017)
- [226] Kay, W., Carreira, J., Simonyan, K., Zhang, B., Hillier, C., Vijayanarasimhan, S., Viola, F., Green, T., Back, T., Natsev, P., Suleyman, M., Zisserman, A.: The Kinetics Human Action Video Dataset. arXiv (2017)
- [227] Gaglio, S., Re, G.L., Morana, M.: Human activity recognition process using 3d posture data. IEEE Transactions on Human-Machine Systems 45, 586–597 (2015)
- [228] Gupta, S., Malik, J.: Visual Semantic Role Labeling. arXiv (2015)
- [229] Chua, J.-L., Chang, Y., Lim, W.: A simple vision-based fall detection technique for indoor video surveillance. Signal, Image and Video Processing 9 (2013)
- [230] Amiri, S.M., Pourazad, M.T., Nasiopoulos, P., Leung, V.C.M.: Non-intrusive human activity monitoring in a smart home environment, pp. 606–610 (2013)
- [231] Seidenari, L., Varano, V., Berretti, S., Bimbo, A.D., Pala, P.: Recognizing actions from depth cameras as weakly aligned multi-part bag-of-poses, pp. 479–485 (2013)
- [232] Cheng, Z., Qin, L., Ye, Y., Huang, Q., Tian, Q.: Human daily action analysis with multi-view and color-depth data, pp. 52–61. Springer, Berlin, Heidelberg (2012)
- [233] Kong, Y., Jia, Y., Fu, Y.: Learning human interaction by interactive phrases, pp. 300–313 (2012)
- [234] Yao, B., Jiang, X., Khosla, A., Lin, A., Guibas, L., Li, F.-F.: Human action recognition by learning bases of action attributes and parts, pp. 1331–1338 (2011)
- [235] Weinland, D., Ronfard, R., Boyer, E.: Free viewpoint action recognition using motion history volumes. Computer Vision and Image Understanding 104, 249– 257 (2006). Special Issue on Modeling People: Vision-based understanding of a person's shape, appearance, movement and behaviour