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A systematic review on fall detection systems for elderly healthcare

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Abstract

To ensure healthy lives and promoting well-being for all in the society at all ages is one of the goals of United Nations. Specially, health of elderly people plays an important factor in productivity and prosperity of any country. According to reports, there will be over two billion elderly people worldwide by 2050. Most of elderly people live independently and need some system to protect them from any kind of fall. As old people are highly susceptible to fall due to weak body structure as well as some external conditions, researchers from academia and industries are developing fall detections systems (FDS) or devices to prevent them from fall. Hence, this paper majorly aims to review the papers on fall detection systems (FDS) to protect elderly people from any kind of fall. Papers selected for this study spans from 2017- 2023. FDS will be helpful to sustain the health of elderly persons. In view of strengthening research in this domain, this study gives an integrated and a critical review of work done in this area for both wearable, non-wearable systems and hybrid systems with research directions as the advent of new technologies like deep learning, computer vision, Internet of Things (IoT) and big data may improve the existing approaches/ systems.

Keywords Fall Detection systems · Elderly Healthcare · Machine learning · IoT · Segmentation · Wearable · Non-wearable · Sensors

1 Introduction

Each and every country all over the world is encountering an increase in population of elderly people. As per World Health Organization (WHO), by 2030, one in six people on the earth will be 60 or older [1]. Moreover, there will be twice as many people worldwide who are 60 years of age or older in 2050. Ageing occurs biologically as a result

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of the accumulation of several kinds of cellular and molecular damage over time. It leads to weakening physical and mental abilities of older people. Consequently, elderly people suffer from health related problems and keeping the people healthy is major concern of all countries. Elderly people become more prone to falls due weak muscular structure and other factors whose severity frequently necessitates medical treatment. WHO estimates that 30% of persons over 65 experience one or more accidental falls each year, and that incidence rises to 50% for those over 80. Due to this large number of fall incidents, various methods described below have been developed to detect a number of falls, prevent and protect senior people. [2, 3].

- **Fall detection**: Fall detection [4, 5] leads to methods which detect the happening of fall. The systems operate on the principle of pattern recognition. In case of a sudden change in the pattern, it works on human activity recognition like walking, sitting, standing and notices sudden changes in the body sensor parameters and observes the particular deviation as fall.
- **Fall prevention:** Fall prevention is one aspect in elderly healthcare [2]. The falls can be prevented by avoiding risks thereby making home safer, going for regular health checkups and right exercises, wearing comfortable clothing. It also involves generating warning signals in case of possible fall to mitigate the falling risks.
- **Fall protection:** Fall protection [6–8] deals with arranging on time medical services. Elderly can be protected from fall by doing for regular medical checkups. The home environment should be safe like to avoid slippery floors of bathrooms, a bath mat should be used to increase the grip, grab bars should be installed along with stairs, a mobility aid like a simple cane stick can protect from possible fall. Moreover, in case of fall, the medical emergency services should be informed on time and proper care should be taken.

Abbreviations used in the paper are shown in Table 1. The following are the contributions made in the manuscript:

- The manuscript has chosen to review articles related to Fall detection systems for elderly people. Moreover, this paper has chosen a study of latest papers ranging from 2017–2023 in literature of fall detection systems to prevent elders from falls.
- A critical analysis of the recent articles is done as mentioned in the Table 2, 3, 4, 5 and 6.

Table 1 List of Abbreviations and Acronyms

Abbreviations	Description
FDS	Fall Detection Systems
IoT	Internet of Things
SVM	Support vector machine
LSTM	Long Short-Term Memory networks
HAR	Human Activity Recognition
FPS	Fall Prevention Systems
FDAFPS	Fall Detection and Prevention System
CNN	Convolution Neural Network

Table 2 Review of various methods for Camera-based fall detection

Author	Year	Dataset	Purpose	Methodology	Result
Miguel et al. [42]	2017	53 videos were collected from a laboratory and a house	An accurate detection system	Foreground Segmentation/ background subtraction is used to extract subject from images Noise present in the data is reduced using Kalman filter. This filter is also employed to trace periodic changes of different human actions KNN approach is applied to classify subject's current state	Sensitivity: 96% Specificity: 96.9%
Soni et al. [43]	2019	UR Fall Dataset (publicly available[77]	Automatic fall detection for indoor environment	GMM based background subtraction is done for detection of movement of a person Important geometric features are extracted to distinguish fall from other actions of daily life using Support vector machine (SVM)	Sensitivity: 98.15% Specificity: 97.10%
Lezzar et al. [17]	2020	one public Fallen Person Dataset (FPDS) [78], and the second created locally	Improved Camera-based fall detection method	Fall, daily actions, and occlusion are distinguished by employing SVM Features are extracted by a Yolov3	Sensitivity = 100% Precision = 93.94% for FPDS data set
Kosarava et al [79]	2021	Video Data set [77] and (ImViA) [80]]	Simple fall control system	Support vector machine, decision tree and random forest were used as classification models	Accuracy: 100% on both data sets
Keskes et al. [81]	2021	Data collected by using RGB-D camera Publicly available data sets: TST Fall detection dataset v2, NTU RGB-D, and Fallfree dataset[82–84]	Accurate and Robust fall detection system	Spatial Temporal Graph Convolutional Networks (ST-GCN) using skeletal data was used	Accuracy: 100% on TST v2 Dataset 97.3% on Fallfree Dataset 92.1% on NTU RGB-D Dataset

Table 2 (continued)

Author	Year	Dataset	Purpose	Methodology	Result
Shu & shu [85]	2021	Data set created	Low cost Fall monitoring	Calculation of velocities and accelerations for fall is done Relevance Vector Machine (RVM) is taken for classification Each color channel (red, green, and blue) from each image is used to obtain Histogram of Oriented Gradients features Data matrix is made linear with Principal Component Analysis (PCA)	Held-out accuracy : 89% Training accuracy: 94%
Zhao et al. [86]	2022	Publicly available data et: NTU[82], UP- Fall[87] & UR-Fall [77]	Accurate and light weight Fall detection system	Skeleton information is extracted using OpenPose and used to recognize fall Spatial information is used by the adaptive graph convolution module A multi-scale temporal convolution network is employed to fully get temporal contextual details Finally, recognition score is computed using softmax function	Accuracy: 94.5% on NTU data set Accuracy: 98.85% on UP-Fall data set Accuracy: 97% on UR data set

Table 2 (continued)

Author	Year	Dataset	Purpose	Methodology	Result
Inturi et al. [88]	2023	Publicly available data set: UP-Fall[75]	A fall and activity detection system based on accurate keypoint detection	Human joint points are extracted using AlphaPose model CNN is applied to analyze keypoints using spatial correlation and These keypoints are inferred to be the joint points of the subject Long short-term memory (LSTM) is employed to protect long-term dependencies	Accuracy: 98.59% Sensitivity: 94.37% Specificity: 98.96%
Jiangjiao et al. [89]	2022	Publicly available data set: UR[77] and Le2i [90] Self created data set	Improved fall detection system	YOLOv3 for object identification and Multi-stage Pose Estimation Network for finding ekypoints are employed Sliding window is used to divide to keypoints in frames to obtain dynamic features An adaptive keypoint attention module is employed to improve LSTM	Accuracy: 99.73% on UR data set Accuracy: 99.62% on Le2i data set Accuracy: 94.74% on self created data set
Lian et al. [91]	2023	Publicly available data set: UR[77], Le2i [90], and RFDS[91]	Robust fall detection system	Weakly supervised learning-based dual-modal network is used A deep multiple instance learning framework is used to learn the fall events using weak labels	Accuracy: 98.4% on UR data set Accuracy: 99.0% on Le2i data set Accuracy: 97.2% on RFDS data set

Table 3 Pros-Cons of the various methods for Camera-based fall detection

Reference	Pros	Cons
[42]	• After fall is found, designed system shows images. To prevent any damage by third party, images can be modified.	• It was designed for daylight situations; hence certain light and ambient conditions can affect the quality of an image as well as gives more variance with time. • Expensive camera were used to cover night time images may also worsen the quality of an image. • As elderly people have various kinds of movement patterns due to different health conditions and mix of different age, nature of an observed subject must also be focused. • Fall detection algorithms may get affected by any walking aids if they are in between subject and camera.
[43]	• Better detection rate as compared to state of art methods	• Although static camera's location was taken to minimize the occlusion, but in real world occlusion may occur.
[17]	• Improved camera-based fall detection systems • Occlusions detection is done.	• Study was fall detection in dark. • RGB cameras used could not detect objects in dark.
[79]	• Computationally efficient without compromising accuracy	• Occlusions were not taken care of.
[81]	• Skeletal data is taken which has an edge over RGB data due to being invariant to illumination and different backgrounds. • A trajectory of human motion using w ith a few joint positions are used by taking skeletal sequence. • Low computational volume	• Partial and total occlusion scenarios were not taken care of. • Chosen fall datasets is unrepresentative of real lif.e • Performance was not evaluated for an occlusion-robustness.
[85]	• Highly accurate, less expensive and multi-camera equipped fall detection system • Fall detection capable to cover long distant objects, capturing images in presence of furniture/ people/animals in the same area	• Fall data set taken under study was limited as well as less diverse. • Shadow from humans was not considered in videos.
[86]	• Light weight FDS • More Accurate • Subgraph-based deep learning method	• Skeleton information was not used for representation of falls. • Approach did not play any role in fall events.
[88]	• Accurate keypoints detection using AlphaPose as compared to OpenPose • Computationally less complex due to use of a single camera-based system and RGB images	• Keypoint detection had not considered the issue of shadows which may result in wrong detection of keypoints. • Occlusion was also not taken care of in proposed method.
[89]	• Improved performance in terms of accuracy	• Takes more execution time • Temporal features were not taken care of in proposed FDS.
[91]	• Less execution time • No requirement of fine-grained annotations	• Workload of data annotation is increased. • Occlusion is also not taken care of in proposed method.

Table 4 Contribution made by authors in the field of fall detection using wearable sensors

Author	Dataset	Purpose	Methodology	Result	Pros	Cons
Diana Yacchirema [55], 2018	SisFall public available data set	Automatic activation and notification of alerts in case of fault 3D-axis accelerometer embedded into a 6LowPAN device for data collection	IOT and Big data	Accuracy = 91, 67% and Precision = 93, 75%	Detects three types of fall: forward, backward and lateral Smart IoT gateway for sending notifications	Error rate of 8% in fall identification
Kai-Chun Liu [58], 2018	SisFall public data set and one data created	Impact of sampling rate on energy savings Minimum sampling rate that maintains high performance	SVM, decision tree, naïve bayes, KNN	For sampling rates of 11.6 and 5.8 Hz, Accuracy > = 98% and 97% accuracy respectively	Effects of sampling rate from 200 to 128 are experimented using four machine learning methods	Different classification models performs best at different sampling rate
Luca Palmerini et al. [48], 2020	143 fall recordings from 40 subjects from the FARSEEING repository	Multiphase fall model features are more effective than conventional features Analysis of acceleration signals received by inertial sensor	Support vector machines along with multiphase fall model features	Sensitivity > 80%, a false alarm rate per hour = 0.56, and F-measure = 64.6%	Good impact of feature extraction from a multiphase fall model	More time in data acquisition for multiphase feature extraction
Kai-Chun Liu [59], 2020	494 falls from data acquisition and Sisfall dataset	Impact of window sizes on fall detection accuracy Segmentation approaches, sliding windows and impact-defined windows, are explored	SVM, KNN, Regression Tree, Naïve bayes	Accuracy > 94%	Comparison and effectiveness of sliding windows and impact defied windows as per the changes in window sizes	Difference in performance is very less (within 1%)
Mustafa Sahin Turan et al. [92], 2021	1600 fall trials	Use of wearable motion sensors for finding fall direction Comparison of classification algorithms	Eight machine learning classifiers	Accuracy > 96.2%	Multiclass classification indicating one out of four fall directions	Time taken by best performing algorithm is highest

Table 4 (continued)

Author	Dataset	Purpose	Methodology	Result	Pros	Cons
Marvi Waheed [61], 2021	SisFall and UP-Fall Detection	Data loss in Wearable Sensors	Deep learning	Accuracy > =97%	Effectiveness in fall detection in case of noisy data using Bidirectional Long Short-Term Memory (BiLSTM)	Comparison with Feature selection techniques is not done
Qian et al. [93], 2022	Data collection done	NB-IoT along with MEMS Microelectro-mechanical-systems	Mutilevel Threshold Algorithms	Accuracy = 94.88%, Sensitivity = 95.25%, Specificity = 94.5%	-portable and low-power fall detection system -multilevel threshold fall detection algorithm	Noise handling from sensor generated data is not discussed
Le et al. [65], 2022	MobileAct 2.0 and UP-Fall datasets	Time and frequency based Feature extraction along with Hjorth parameters	Classification algorithms: SVM, k-NN, ANN, J48, and RF	For MobileAct 2.0 dataset: F1-Score 95.23% (falls), 99.11% (non-falls), For UP-Fall datasets: 96.16% (falls), 99.90% (non-falls)	Enhanced performance due to effective feature selection	Performance is evaluated on two datasets
Butt [60], 2023	Fall data from Kaggle and UFRD dataset	Machine learning approaches Comparison of performance of LSTM and CNN-transfer learning	LSTM and CNN-transfer learning	Accuracy: LSTM = 88% CNN = 98%	Effectiveness of Deep learning is discussed in fall detection	Comparatively Longer training time
Kulurkar [94], 2023	Real time data collection	low-cost wearable sensing devices from Apache Flink and MbientLab	short-term with a long memory network architecture	95.87% accuracy	Energy consumption of wearable device is taken into consideration	Model is trained on small data size

Table 5 Summary of various sensors and devices suggested in different studies

Author, year	Sensor	Device	Methodology
Amir mehmood, 2019 [95]	Shimmer wearable sensors	Waist band with shimmer sensor and adjustable elastic strap	Mahalanobis distance is used to measure similarity between two patterns to find fall probability
Kimaya Desai, 2020 [40]	Accelerometer, Gyroscope	belt	ML- Logistic Regression
Luca palmerini, 2020 [48]	Inertial sensor attached on smartphone	Smartphone fixed with belt worn on lower back	SVM, KNN, Naïve bayes, random forests, and Logistic regression
Al Nahin et al. [96]	3 d axis accelerometer embedded into a 6LowPAN device	Accelerometer based	Decision tree
Kai Chun Liu, 2018 [58]	Accelerometer embedded in an Opal sensor	NA	KNN, Naïve bayes, Decision Tree, SVM
Mohammad Mehedi Hassan [56]	Gyroscopes, accelerometers, and orientation sensors	Smartphones'	Hybrid framework for CNN-LSTM-Based deep learning
Samad Barri Khojasteh et al. [97]	Accelerometer	wrist-worn 3DACC on a smart wristband	Genetic Algorithms (GA) and Simulated Annealing (SA) for Threshold Optimization
Qian et al. [93]	MEMS sensor	Wristband having sensor	Multilevel threshold algorithm
Honore [98]	Smartphone in built pedometer virtual sensor	Smartphone	Threshold-based accelerometer algorithm
Semwal [99]	Inertial measurement unit (IMU) sensor present in smartphone	smartphone	4 deep learning models, viz. CNN, LSTM, gated recurrent unit (GRU), CNN + LSTM
Chunhua [100]	thermopile IR array sensor and MEMS PIR sensor	Ambient sensor	three-layer BP neural network

Table 6 Analysis of Hybrid (Ccombination of wearable and non wearable) FDS

Reference	Year	Dataset	Methodology	Result	Pros	Cons
[56]	2019	MobiAct dataset	Hybrid Deep CNN-LSTM-Based	Accuracy > = 96.75%	mobile-enabled fall detection	Data set from only Accelerometer is considered
[72]	2021	Self data collection 225 related to ADL and 180 related to fall	Backpropagation neural network algorithm	Accuracy = 96.3%, specificity of 96.4%, Sensitivity of 95.5%	Reduction in response time	Comparison with other approaches and datasets is lacking
[70]	2019	Data captured through video and accelerometer	cloud-network-edge architecture	Accuracy = 96.67% Recall = 96.67% Precision = 98.39% and F1-score = 97.52%	Efficient in terms of accuracy	High computation time
[76]	2023	UP-Fall detection dataset[87]	A multi-level feature fusion technique is designed A multi-head CNN with attention module is employed Attention Module Convolutional LSTM is used to deal with temporal features	Accuracy: 97.9& when Camera 2 and wearable sensor were used Accuracy: 96.49% when Camera 1 and wearable sensor were used Accuracy: 94.9% when camera 1 & camera 2 and wearable sensor were used	Efficiency of IHAR system is increased	A lot of resources are needed to train and infer results Not suitable for the use cases such edge computing or TinyML
[101]	2020	Self created data set	Employs a combination of YOLO-V3 and Lite-FlowNet)	Accuracy: 93.74%	Less expensive solution A mobile application	Approach must be validated on standard data set as well
[102]	2022	UP-Fall dataset[87] DMLSmartActions dataset Combined dataset	Deep learning algorithms: CNN, LSTM, ResNet and others	Accuracy(CNN): 98.55% on Up-Fall dataset Accuracy(CNN): 86.97% on DMLSmartActions Accuracy (CNN): 92.86% on combined data set	Data set having inertial as well as video sensor	Comparison with recent approaches not given

- Studies related to fall detection using wearable, non- wearable devices and hybrid have been considered for this manuscript with future research directions.
- A systematic approach for doing review is done using PRISMA.

Remaining paper is organized into 7 sections. Second section illustrates related work of review papers done by academicians for FDS and FPS. Section 3 gives the procedure adopted for doing this review. Fourth, fifth and sixth section sections depict an intensive review of research papers pertaining to non-wearable, wearable and hybrid (fusion) FDS based on IoT, big data and cloud computing respectively. Section 7 gives future research directions for fall detection systems. Lastly, Section 8 concludes the paper.

2 Related work

Various researchers have done studies on fall detection and prevention systems (FDAPS) [3, 9–12] using various technologies. Mooyeon et al. in [3] have discussed how fall can be prevented using various applications. These applications deploy many technologies such as video systems, virtual reality, artificial intelligence and Internet of things (IoT) using wearable/non wearable devices, big data, virtual reality and others. They discussed how fall can be reduced using these preventive methods. However, they have not given detailed description of fall detection systems. Authors in [9] have overviewed fall detection as well as fall prevention systems on various parameters such as data sets, algorithms used, placement of sensors and age. However, their work lacks those papers where deep learning algorithms were used. Marion, et al. in [10] discussed various issues faced by researchers in designing FDAPS. Further, they also discussed the difficulties such as digital divide, social stigma, setting threshold, entourage and others faced by elderly people in adopting new technological applications to avoid falls. But, a systematic review was lacking in their paper. Odasso, et al. of [11] have given various ways and invention strategies to prevent fall. But they have not included the study of fall detection systems. Another study done by Emily [12] revealed that fall can be reduced by minimizing the risk of fall. They also exposed that how common invention ways such as supportive footwear, eyeglass and education are not very much effective for fall prevention. Recently, Torres-Guzman et al. [12] have gone through 44 papers and revealed that most of FDAPS are using smartphone and threshold- based monitoring system. Their study did not cover the FDS comprising wearable andf non wearable FDS. Alam et al. [13] has studied various papers related to only vision based fall detection and Ramachandran eta l. [14] have given an overview of fall detection systems using wearable devices.

Majority of the reviews done by researchers have got more papers of FDS as compared to fall prevention systems (FPS) [3, 9–12, 15]. Therefore, this paper has chosen to review literature on FDS, three types of solutions have been studied in the literature of FDS. One is wearable devices, another is non wearable devices and third is hybrid systems. Hence this paper has chosen to review articles related to FDS ranging from 2017–2023 in literature of fall detection systems to prevent elders from falls.

3 Proposed procedure of systematic review

A review presented under this study makes use of Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [9, 16] technique during selection of papers. The chosen approach for review comprises of identifying the papers for writing review, selecting papers based on its suitability and finally including the leftover papers for analysis. PRISMA technique is mainly divided into the following steps:

1. Identification

   In the beginning, around 35000 results from 2010 -2023 are obtained using the strings “fall detection “ or “fall prevention” from academic library of Google scholar and IEEE-explore. However, result set obtained was compressed by refining search by employing multi-strings. 342 publications were set apart from databases. In first stage of PRISMA, 41 duplicate records obtained from both libraries are removed.
2. Screening

   During screening process, the some articles are also removed due to the following reasons:

   - 47 articles were removed due to Survey articles
   - 29 articles were eliminated because of unavailability of articles from search engines
   - 107 articles before 2016 were not considered.
   - 92 articles not using machine learning/deep learning methods or not reported results are also not reviewed.
3. Inclusion

   After screening process, critical analysis of 26 papers is included in this review. The detailed analysis of these papers is given in Sections 4, 5 and 6.

4 Elderly healthcare using non-wearable FDS

A great deal of work is being done by researchers to detect falls of elderly people using non-wearable fall detection systems. The following sub sections summarize contribution made in directions of non-wearable devices, its effectiveness, and shortcomings of these systems.

4.1 Contribution for non- wearable fall detection systems

These systems make use of cameras and various sensors like acoustic, environmental, and infrared sensors. Review of these different FDS made by rsearchers is given below.

- **Camera-based fall detection**

Multiple cameras [4], a single camera, a 2D [17, 18] cameras,3D time of flight camera, three-dimensional of images with depth data are all subcategories of camera-based systems [19, 20]. The multi-camera system rebuilds a 3D image, evaluates the person’s volume distribution along the vertical axis, and notify when the majority of the volume is close to the ground for a predetermined amount of time. This device is difficult to set up, takes lengthy calibration, and is ineffective when there are multiple people present or when one is partially blocked by furniture.

While time-of-flight cameras [19] are substantially more expensive and have lower lateral resolution than conventional 2D video cameras. In contrast to wearable and ambient-based detection systems, camera-based systems are still widely utilized because they provide various advantages in terms of robustness and the absence of human involvement after installation. These devices are typically charged by power outlets or may be with a backup power source (battery pack) [4].

Consequently, a thorough analysis of non-wearable systems is provided in the next paragraph. Research community has devised a number of camera-based methods to identify the fall. Table 2 and Table 3 gives detailed summary of work done by researchers along with pros and cons of each method.

- **Floor sensors/ambient sensors**

There are context-aware systems that use a variety of sensors, including piezoelectric, pressure [21], polymer, smart carpet, floor vibration sensors [22, 23] in addition to camera-based systems. The ambient sensor network was set up to lower healthcare expenditures. Health of human beings were monitored through periodic reporting, monitoring daily-life actions, and various notifications. In another research work, throughout the house, various sensors like magnetic contact, environmental, water, energy pressure, and passive infrared motion sensors were dispersed as part of the system [24].

When a subject walks on floor platforms or instrumented walkways, sensors were placed along them to calculate gait using pressure/force sensors as well as moment transducers [22, 25, 26]. Force platforms and pressure measurement systems are the two different categories of floor sensors [27, 28]. Although pressure sensors are able to find the centre of pressure. These are incapable to compute the applied force vector. It should be separated from force platforms. The pressure patterns under a foot can be measured using pressure measurement instruments, but the horizontal or shear parts of the applied forces cannot be utilized. The systems based on floor sensors analyzed the force exerted to the floor when walking. Latest advances in this direction, propounds that future falls as well as adverse incidents like physical functional decline [29–32] and fall risks [33, 34] in elderly healthcare can be forecasted by change in gait parameters.

Muheidat et al. [28] presented a context-aware and private real-time reporting aging in place system. They designed a cooperative cloudlet system in which closest cloudlet will receive the data from the sensors. Then, it will provide desired information in real time in least possible time. Experiments obtain that their model is able to give 95% sensitivity and 85% specificity for detecting falls.

Recently, Alharthi [35] studied characteristics of gait changeability. They analyzed gait intervals and found that these are accountable for various gait patterns in persons. Convolution neural network (CNN) was employed in their floor sensor system.

- **Acoustic sensors/infrared sensor**

The sound of falls can be measured by employing acoustic sensors. An acoustic fall detection system was designed by Khan et al. employing sound waves [36]. They extracted Mel-scale frequency cepstral coefficients features and applied support vector machine. Recently, Younis et al. proposed median deviated ternary patterns(features) to train SVM for classification of fall and non-fall incidents [37]. They evaluated performance of proposed approach on A3 fall 2.0 dataset [38] and the MSP-UET fall detection datasets and achieved an accuracy of 98% and 97%, respectively. Further, infrared sensors are also being used for fall detection of humans [39].

4.2 Effectiveness of non-wearable fall detection systems

Wearable devices like Tri-axial accelerometers need to be placed to the wrist or another body part, or sewn into the fabric of shoes or clothing, to monitor body inclination [40]. The acceleration of rotation is calculated by gyroscopes [41]. However, the main issue with this kind of technology is that elderly people frequently forget to wear them [17] and in the instance of a help button, it is worthless if the individual has fallen asleep. Additionally, these devices require batteries and an expensive 24-h monitoring staff in addition to a monthly subscription charge [42].

These issues can be well handled with vision-based systems [4, 5, 17, 42–44]. The fundamental benefit of computer vision systems is that no extra equipment needs to be worn by the user. From cameras, a lot of data may be gleaned, including position, motion, and the subject's movements. Therefore, a computer vision system not only provides information on falls but also on other daily actions like the taking of medications or the timing of meals and sleep [42].

4.3 Shortcomings of non-wearable systems

Camera based systems need an installation cost [17, 42]. These devices should be placed as well as positioned with care to take image / video of elderly person. This system also has a privacy concerns. Moreover, in case of theft, these cameras can be switched off or broken; it will lead to unavailability of data. As a person can move from one place to another place inside home, it necessitates multiple cameras to be installed with their capacity and backup.

Sound sensors [36] in vision based systems also can malfunction due to less battery, some perturbations and others. Infrared sensors [39] are influenced by hard articles like smoke, dust, and others. It is also works work for short distances and not able to capture data beyond that.

5 Elderly healthcare using wearable FDS

Falls suffered by elderly people may cause serious injuries. In that case, immediate medical assistance is required. As a fall may occur at any place, so the wearable devices or sensors are greatly beneficial for instant medical help. These devices present a cost effective and easy to use system to identify fall based scenarios from other daily activities. The most effective fall detection system use machine learning algorithms. There are different types of sensors that are used in wearable devices.

- Smart sensors

Although, there are many sensors available and used, however all fall detection system based on wearable devices use accelerometer, gyroscope in common [41].

- Accelerometer in wearable devices

Accelerometer is one of the most commonly used wearable sensor equipped in wide range of fall detection systems. It captures body movement accelerations in three orthogonal planes. These observation are related to a number of physical activities like step count, running, time spent in various physical activities, energy expenditure etc. Wearable devices like accelerometer have low accuracy sometimes while recording movements in adults as compared to younger people as the movement through walker can be slow. This also depends on the body part where sensor is placed. It can better capture if placed at hip location as compared to hand part. To avoid this limitation, researchers have used research grade accelerometer [Eduardo Teixeira]. Accelerometer offer several advantages like low weight, less cost, low power consumption, small size, easy to use, can be embedded on any device or can be mounted on different body parts.

- Gyroscopes

Another very popular sensor used for the purpose of fall detection is Gyroscope. Gyroscope is an inertial sensor which can measure the angular velocity and orientation of any object and are also known angular sensors. The angular velocity is measured as the deviation from the rotational angle of the object and depicted in degree per second. Gyroscope and accelerometer are used together as the directional movement is measured by accelerometer while any tilt or angular velocity is captured by gyroscope.

- Sensors embedded in smart phone

There are also studies that make use of sensors embedded in mobile phones [45–47]. Fall detection using smart devices are of added advantage. Luca palmerini et al. used inertial sensor embedded on smartphone or a dedicated system. Both types of systems were fixed and worn on the lower back. Smartphone was attached with a waist worn belt while the other system was attached to the skin with the help of medical tape [48].

The shortcoming of these systems is that there is whole dependency on the mobile phones. So, the concerned persons should always carry mobile phone with themselves and do remember to keep it charged as well. Moreover, another difficulty is that the required sensors are not always embedded with all kind of mobile phones. As a result, there may not be effective results out of such system.

There is lot of contribution from authors who conducted experimentation for elderly fall detection using wearable sensors. There is use of single sensor or multiple sensors in different proposed approaches. Study shows that utilizing signals from different sensors produce better and more accurate results. This survey presents different perspectives about the elderly fall detection viz. data sources, variety of sensors and wearable devices. This study will be helpful for the researchers who want to pursue work in elderly fall detection with a summarization of recent work pursued in the field and with categorization of the some of the points where further exploration can be advantageous. The work in the following subsections provides the literature review in order to investigate the present situation of elderly fall detection using wearable devices.

5.1 Contribution in the field of fall detection with wearable sensors

In terms of supporting elderly healthcare, an accurate detection of fall incident is absolutely essential to provide timely medical support. Numerous efforts have been put and identified in the field of fall detection using wearable sensors [14, 49, 50]. Table 4 depicts the contribution made by authors in the field of fall detection using wearable sensors along with pros and cons of each approach.

5.2 Fall detection using wearable sensors

Fall can be detected broadly in two ways using wearable sensors: one is by using threshold based systems and second is by means of machine learning based approaches.

5.2.1 Threshold-based wearable fall detection systems

Much work on fall detection has been proposed based on threshold based approach [103]. The application of threshold based approach has been proved useful in multiple aspects like identification of fall scenario and classification of type of falls and near fall conditions [51].

The threshold based method works on the principle that it detects a fall whenever the value of acceleration obtained from the accelerometer which may be embedded in a wearable device is out of the boundary value of the threshold. Although this method seems very simple, having less computational cost and complexity, however, the challenge is to figure out the appropriate value for the threshold to distinguish daily activities from the fall.

According to Kimaya Desai et al., a sudden gradual decrease and then a subsequent peak increase in the accelerometer value is considered as fall [40]. To get through sensor integral errors, authors proposed an effective sensor fusion module which utilizes upper and lower threshold values [52]. Fall detection system is implemented using differential piezoresistive pressure sensors embedded in a carpet using threshold based technique [53]

5.2.2 Machine learning-based wearable systems for fall detection

Although threshold based systems have been able to produce effective results in many studies. However, the approach could not produce correct result in some scenarios due to ambiguity in deciding the range of threshold. A number of machine learning approaches have been proposed and applied to observe the corresponding effectiveness. De quadros et al. proposed use of machine learning based approaches for identification of possible fall scenario from the data obtained from wearable sensors embedded on wrist wearable device [54]. A comparison between threshold based and machine learning approaches portray that machine learning approaches produce better result as compared with threshold based approaches. Figure 1 shows flow diagram for machine learning-based model building.

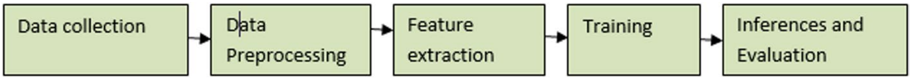

Fig. 1 Flow diagram for machine learning-based model building

Data collection For a fall detection system using wearable devices, the features are generally extracted from acceleration signals generated from accelerometer, pressure sensor or gyroscope. Most commonly used features which are simple as well as useful for fall detection are mean, standard deviation, tilt angles, sum vector magnitude etc. Static activities like sitting and standing etc. can be detected by means of mean value. At the same time, dynamic activities like running, walking, jumping etc. can be judged with the help of standard deviation. Signal magnitude area is also used to distinguish between static and dynamic activities. Other helpful features to identify static and dynamic activity are calculation of angles between ground and device in addition to the angle between device and gravitational vector. In the work done by Kimaya Desai et al., the data set consists of readings from accelerometer and gyroscope along the three coordinate axes. For identification of fall and no fall, readings from other daily activities like running, walking, bending, jogging and squatting has been considered. Time window average technique is used as the data from sensors belong to time series model. Diana Yacchirema et al. [55] used two accelerometers and one gyroscope for data collection and another is publicly available SisFall dataset for fall detection. The observations were gathered from 38 people. Out of these only observations for daily activity learning from 15 elderly people is considered further.

Data pre-processing Involves the processing and normalization of real time signals of human activity as extracted with the help of sensors. Since the sensors data is a sequence of samples, to analyze an activity, a windowing technique is applied. Different features like acceleration, slop value is computed from features generated across three axes. Mohammad Mehedi Hassan et al. calculated are 58 values for 20 statistical features computed for each window frame [56]. Majd Saleh et al. applied two segment feature extraction method. Also adopted an online method to consider the features with low computational cost [57].

Feature extraction For implementing fall detection system, the selection of distinctive features from the sensor data obtained proves fruitful. There are many features which have been considered by researchers. Authors performed fall detection using 54 features mainly focussing on time domain statistical features employed to standard deviation, mean, skewness of the three axes, and correlation coefficient between each pair of axes etc. [58, 59]. Another study was conducted on accelerometer data by extracting 44 features related to Hjorth parameter, frequency domain and time domain [60].

Training The model is created and trained on a large set of labelled data. This trained model is then used for testing the performance of proposed model. Different machine learning algorithms have been proposed and used for training the dataset received from the sensors and predicting the possibility of fall.

Wearable devices Authors have contributed in experimenting with use of wearable devices. There are two purposes to use multiple devices and used at different parts of the body. The purpose is to figure out the user convenience as well as to get the appropriate readings to access the correct prediction and assessment of fall.

Kimaya Desai et al. have suggested use of wearable belt for elderly people convenience. It consists of a battery, micro-controller and MPU6050 and GSM module. The motion sensors are placed at the front of the belt to capture the body orientation accurately.

Due to the necessity of timely intervention in case of elderly fall detection, there are fall detection devices available in the market. This can be in the form of smartphone based fall detection where inbuilt motion sensors try to distinguish the other physical activities from fall. Table 5 depicts the various sensors and devices suggested in different studies.

5.2.3 Effectiveness and adoption of wearable sensors and devices

- Fall detection systems using wearable devices are more popular as compared to camera based alternatives as these are low cost devices which does not interfere much with the privacy of the user.
- The sensors are also able to monitor changes in the activities of daily living. From violent or agitated movements that can be identified as some signal of abnormal activities happening to them like burglars etc.
- Other sensors like barometers, magnetometers, heart rate monitors, accelerometer and gyroscope are generally found in most fall detection system based on sensors [41].
- The activities related to daily living are discriminated or distinguished by various types of falls.(slips, trips, crashes, collapses etc.)
- There are no concerns of privacy issues while using devices embedded with sensor.

5.2.4 Shortcoming of wearable sensors and devices

Accelerometer and gyroscope are widely used in most of the research work for observation purpose. But, it has a slow response time while gyroscopes have a fast response time.

The disadvantage of smart phone based system is that the user is supposed to carry phone with him all day long. Second is the placement of smart phone based system. According to experimental settings, if the position of smart phone changes from chest pocket to pant pocket, it may not produce the same signals and the system may not perform well.

It is difficult to test these systems in real time environment with elderly people. The existing fall detection system mostly utilizes data collected from young adults as compared to the elderly people as the real time data from elderly people is not available.

As the training and test data used in machine learning algorithms is chosen from the same subject / person data. In actual scenarios, the subject will be different from the sample data. Most of the time, the performance degrades when system is tested and trained on different datasets. Some systems are not able to differentiate between the daily activities of living and fall incident. Sometimes, wearable devices produce false alarms of emergency and restrict user’s movements. The infrared sensors get impacted by temperature variation and lighting conditions. Battery life of wearable devices is also limited and needs to be recharged or changed which elderly people may forget to do.

5.2.5 Methodologies adapted for fall detection for wearable devices

Machine learning algorithms Various machine learning algorithms viz Support vector machine (SVM), k-Nearest Neighbor (k-NN), Naïve Bayes (NB), Regression tree have been widely applied in the current scenario.

Kai Chun Liu et al. applied in total, four machine learning algorithms to observe the performance of the proposed system. Majd Saleh et al. applied machine learning algorithm, Two SVM based fall detection algorithm is used to better achieve trade off among complexity and accuracy. The first SVM is of low computational cost and high sensitivity while the second one focuses more on accuracy.Activity of elders is captured through a 3 axial accelerometer [57]. Kimaya Desai et al. used Logistic regression predict the fall [40]. Diana Yacchirema et al. used decision tree model for fall detection [55]. Machine learning models are very powerful and effective in detection of fall cases however the performance lacks sometimes due to unbalanced and noisy nature of data obtained.

SVM is effective classification method but not suitable for handling large datasets due to training complexity. KNN is simple to implement distance based algorithm however, it faces issues while dealing with large dataset as it performs distance calculation from new point to each already existing point. Naive bays algorithm can handle large datasets and simple to implement. Variation in frequency distribution among training and test dataset degrades the performance.

Low power wireless sensors network To overcome the limitations of non wearable systems, wearable systems have been proposed, which usually employs low power inertial sensors like accelerometer and gyroscope typically attached to the body of the person for movement recognition when a fall takes place.

Deep learning algorithms Deep learning approaches are very popular now a days due to its capability to produce remarkable results. Deep learning methodology uses a large set of labelled data and neural network architecture that contain many layers [104]. It allows stacking of hidden layers to extract highly abstract features and make better re-use of learned features. Marvi Waheed et al. used deep learning for fall detection using wearable sensors [61]. Chen et al. also proposed use of deep learning on the data available by means of wearable sensors for slow fall detection [62]. Jain et al. presented a pre fall detection system to prevent the fall in order to mitigate the after effects of fall in elderly people. They applied deep learning for identification of pre fall detection [63]. An improved fall detection model in terms of accuracy was proposed by using whale optimization along with deep learning algorithm [64]. A comparison of deep learning algorithm using convolutional neural network and long short term memory is performed in comparison to machine learning algorithm on publicly available dataset [65]. Fall detection using range- Doppler radar based has been demonstrated using deep learning approach [66].

Deep learning algorithms achieve higher accuracy as compared to machine learning method or threshold based method. However, deep learning algorithms also require more data for training.

Artificial neural network The use of artificial neural network has been studied by Casilari-peraz and Francisco in possible fall detection. The study uses the data obtained from wearable devices for further investigation [67]. Luna-Perejon et al. also applied recurrent neural network for fall detection in case of wearable sensor devices [68]. Fall detection using CNN has been performed by using Wi-Fi-based CSI (Channel State Information) [69].

6 Elderly healthcare using hybrid FDS

These hybrid systems either using a combination of Internet of Things (IoT) [63], cloud computing and big data technologies or a combination of wearable and non-wearable systems.

Diana et al. applied smart IoT gateway, that enables the processing capabilities locally with the intention of reducing the processing time. Even in case of fall, the emergency alert notifications to healthcare professionals are sent through smart IoT gateway. It also sends information related to type of fall along with the location of house of the elderly person. Shahiduzzaman et al. projected the use of smart helmet for fall detection. Authors proposed a novel cloud-network-edge architecture for the possible outcome [70]. Pal et al. supported and presented the elderly healthcare by means of smart homes using Internet of things [71]. Ng et al. also researched and experimented to identify incidences of fall using IoT technology [72]. Deeppika et al. also proposed elderly healthcare application with the help of wearable and non-wearable sources using IoT application [73]. To increase the efficiency and accuracy of fall detection system, a hybrid approach has been proposed using the deep learning algorithms on visual input captured by camera [74]. Deep learning algorithms have been proposed on the images captured through CCTV camera to demonstrate their applicability in real time scenarios [75].

A multi model approach has also been proposed recently which considers visual data and sensor data to develop fusion architecture for human activity recognition. The visual data is analyzed using Convolution Block Attention Module while multi source sensor data is processed by using Convolutional Long Short Term Memory [76]. Summary of hybrid (a combination of wearable and non wearable) FDS with prons and cons is given in Table 6.

Open problems Although, the existing work proposed various solution approaches for effective fall detection and prevention. There are issues which need to be addressed in future research. There is a strong need for designing low-cost wearable sensing devices having less power consumption to increase battery life. The existing vision based approaches lack in maintaining privacy and coverage area. Effective techniques and algorithms need to be designed which takes care of real time management and support in case of fall detection. Transfer learning can be applied to boost performance to overcome issues of data unavailability.

7 Conclusion

Healthcare of human beings is one of the goals of all United Nations to provide happy, peaceful and prosperous life for sustainable development. Moreover, elderly healthcare is more challenging as older people suffers from a lot of health issues. Hence, this paper is focusing on falls happening in elderly people so that appropriate action can be taken before any mishap. In view of falls, a critical review of various recent studies is done for wearable as well as non-wearable fall detection systems. Paper is concluded with future research directions.

8 Future research directions for fall detection systems

Although, numerous approaches are proposed for detecting the fall for elderly healthcare using wearable as well as non-wearable devices. Still, there is a need to focus on given issues.

- Although wearable device-based fall detection systems can recognize the human activity without compromising the user's privacy but elderly people forgets to wear theses devices. Hence, privacy secure vision-based system should be designed.
- Context aware systems represent the fall detection systems that uses sensors placed in the areas such as pressure sensors, microphones and cameras. They have to be placed at different places. Hence when users leave the area, it is impossible to capture data. It leads to unavailability of data. Hence, robust fall detection systems should be designed.
- Fall may happen due to intrinsic (functional disability, balance impairments, vision. Muscle, etc.) as well as extrinsic factors. It needs to develop systems focusing on reducing extrinsic risk factors which are of major concern.
- There are a few FDS in which experiments are made on a large and intensive real-life dataset due to ethical reasons. Most FDS simulate fall like behavior in order to gather various cases of fall events. Hence, we need more effective and reliable FPS in real life settings.
- A few FDS have been designed to deal with occlusion. More FDS should be designed to take care of the same.

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