Internet of Things 8 (2019) 100124

Contents lists available at ScienceDirect

Internet of Things

journal homepage: www.elsevier.com/locate/iot

Review article

Practical fall detection based on IoT technologies: A survey

Nassim Mozaffari[c], Javad Rezazadeh[b,c], Reza Farahbakhsh[a,*], Samaneh Yazdani[c], Kumbesan Sandrasegaran[b]

[a] Institut Mines-Télécom, Télécom SudParis, France
[b] University of Technology Sydney, Sydney, Australia
[c] Islamic Azad University, North Tehran Branch, Iran

ARTICLE INFO

Article history:
Received 15 May 2019
Revised 8 October 2019
Accepted 8 October 2019
Available online 15 October 2019

Keywords:
Internet of Things (IoT)
Fall Prediction
Fall Prevention
Fall Detection
Machine Learning

ABSTRACT

Fall is the second incident that leads to death over the world. Fall event happens to numerous groups of people consist of elderly, babies and also younger people. Admittedly, fall-related research must be considered as one of the most important aspects of a healthy lifestyle. For this reason, Internet of Things(IoT) is the emerging technology and a powerful candidate to develop fall diagnosis system. In this paper, we have discussed the three stages of fall as Prediction, Prevention, and Detection. We have illustrated Edge, Fog, and Cloud layers as IoT layers to develop a fall diagnosis system. At the end of the paper, we have considered the challenges of fall diagnosis systems and suggested future aspects.

1. Introduction

Fall is one of the unpleasant events in daily life that declines human health [1]. Fall indicates that the body loses its balance and brings dramatic changes to body acceleration, and happens to the elderly [2,3], patients [4–6], athletes [7], workers [8–10] and even healthy people [11,12]. World Health Organization (WHO) provides statistical analysis for falls in the world. Falling is the second incident that leads to death and the greatest number of fatal falls are related to the elderly who are more than 65 years. 37.3 million falls happen each year which lead to severe injuries and care needs. WHO emphasizes prioritizing fall-related research must be considered for health fields (http://www.who.int).

According to the Centers for Disease Control and Prevention (CDC) (https://www.cdc.gov/), consequences of fall are shown in Fig. 1. Fear of falling reduces self-confidence and increases dependence on others. Therefore, the Independence of Individuals decreased and himself/herself cannot live alone. Fractures and disabilities are the result of falling that reduced each activity, even more, some injuries can lead to death. Elderly people need permanent care when the injury severity is high and it costs a lot. CDC has reported the average hospital cost for a fall injury is over $30,000.

Experiments have been conducted to reduce consequences of fall and increase the quality of elderly life more than a decade [2,13–15]. There are several factors that affect fall events. Fig. 2 shows some of those factors. The factors are classified into two categorize, intrinsic [16] and extrinsic. We have studied age, lack of balance, and reaction time delay as intrinsic factors and stairs, slip, and lack of equipment as extrinsic factors in this paper.

The different directions of possible daily living fall events shown in Table 1. Fall types consist of forward/backward fall, lateral (right/left) fall, and straight fall [17–20]. When a fall event happens, body acceleration changes suddenly. Toward a

* Corresponding author.
E-mail addresses: n.mozaffari@iau-tnb.ac.ir (N. Mozaffari), rezazadeh@ieee.org (J. Rezazadeh), reza.farahbakhsh@it-sudparis.eu (R. Farahbakhsh), samaneh.yazdani@gmail.com (S. Yazdani), Kumbesan.Sandrasegaran@uts.edu.au (K. Sandrasegaran).

https://doi.org/10.1016/j.iot.2019.100124
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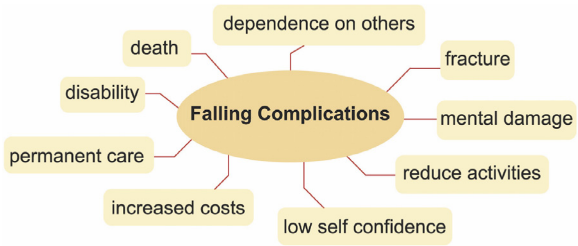

Fig. 1. Falling Complications.

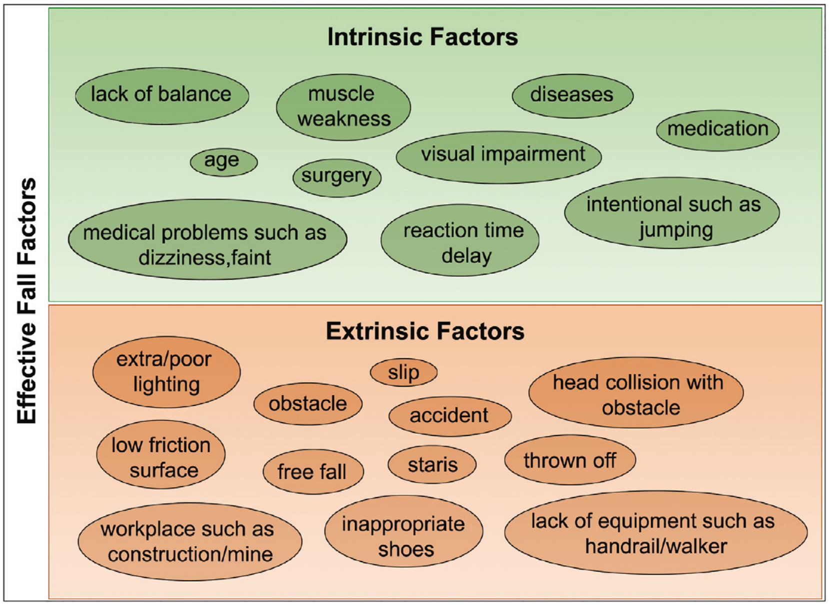

Fig. 2. Influential Factors leading to a Fall.

Table 1
Different direction of fall for potential daily living fall.

Forward/ Backward	Fall forward/backward while walking/running caused by obstacle, slip/flat surface Fall forward/backward while going down stairs/going up stairs Fall forward/backward while sitting to standing/standing to sitting Fall forward/backward while getting in/out of a car Fall forward/backward while bending to the floor to put shoes/pick something up
Lateral Right/Left	Fall lateral while walking/running caused by obstacle, slip/flat surface Fall lateral while sleeping on a bed Fall lateral while ridding a cycle Fall lateral while sitting on a chair
Straight	Fall straight while sitting to standing/standing to sitting

better understanding of the mechanism of a fall event, changes of body acceleration shown in Fig. 3, [21] and phases of a fall event explained by the following.

- *Pre-impact phase*

This phase is a few milliseconds and happens right before fall to the ground, and called lead-time. As a result, balancing, body acceleration and weight reduced. After then the body falls to the ground. At the prediction stage, researchers have gained 700 milliseconds as the maximum time for pre-impact fall prediction [22].

- *Impact phase*

Collision moment is when the body's acceleration changes rapidly and suddenly, and the body falls to the ground and can do severe damage.

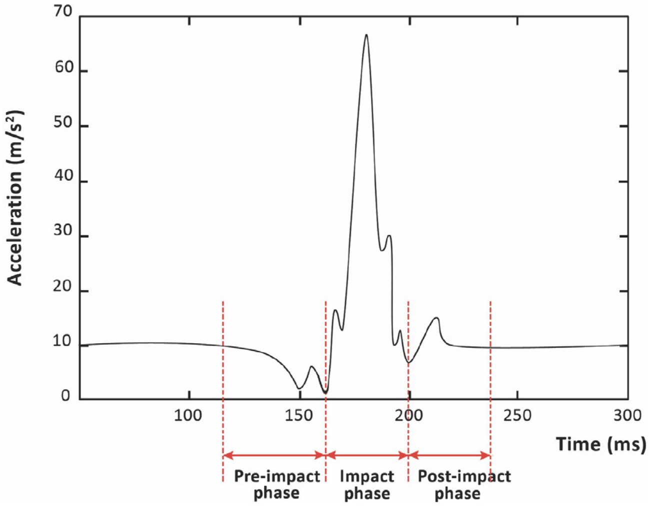

Fig. 3. A normal fall event acceleration.

- *Post-impact phase*

Changes of body acceleration are small in this phase, and the person is in a state of shock. In each phase, fall events can be detected and informed to caregivers and doctors by communication channels, and also the risk of serious injuries can be avoided.

Internet of Things (IoT) is a candidate to solve fall challenges [23,24]. IoT provides smart sensors [25], communication channels [26], processing, and storage capabilities and three layers of Edge [27], Fog [28], and Cloud [29,30] that can be used as IoT layers in order to develop fall diagnosis systems. IoT also has strong capabilities to process and store massive data and also provides services for end users and other layers [31]. Both Edge and Fog can serve to detect falls. Edge processes information and it is close to the location of sensors, devices, and users, but Fog is close to the local network and infrastructure.

Previous studies focused on different aspects of fall and presented a review of fall detection. Experiments have been conducted in every aspect of fall diagnosis system. [32–35]. There are several methods to diagnose fall, therefore, in this paper, we have presented literature on previous works and after then we have discussed Prediction, Prevention, and Detection as three stages of fall. We provided IoT components such as edge, fog, and cloud layers and finally discussed challenges and solutions.

Toward that end, this paper presents a review of the existing studies related to the Fall event topic. In Section 2 we discussed normal sensors and smart sensors and IoT expectation of smart sensors. Next, we focused on each Fall stage and IoT layer. We discussed the cons and pros of IoT layers for fall diagnosis systems and then we provided a scenario in Section 3. In Section 4 we proposed challenges and future works to detect Fall, and finally, we discussed the conclusion in Section 5.

2. On sensors

Sensors are one of the closest components to the user's location which are distributed in a smart environment. Healthcare systems need sensors to gather accurate information. We discussed sensors on e-health in this section.

2.1. Sensors on e-health

Table 2 shows the sensors, that help prevent, predict and detect falls (In this section, we just used the word of Detection as an abbreviation). As shown in Table 2 the sensors are classified into three groups, Motion sensors, Physiological sensors, and Environmental sensors. In Motion sensors group, the accelerometer is the main sensor to detect fall by changing of body acceleration [36]. The accelerometer is an electrical component which measures acceleration (The rate of change of velocity of an object with respect to time, G or $\frac{m}{s^2}$) in three axes x, y, and z. There is a probability of a fall event when the body acceleration increases than the fall threshold value. So it is a simple way to detect fall using an accelerometer and fall threshold value. And the gyroscope is a mechanical component which measures angular velocity (Motion around x, y, and z-axes). Gyroscope measures orientation in pitch, roll, and yaw, and detects fall forward/backward or left/right. And Magnetometer measures geomagnetic field to detect the direction of a fall event.

Physiological sensors measure vital signs of the body [37]. Typically, in a fall event, vital signs changed rapidly because of shock after fall. A probability of a fall event can be confirmed, by monitor the physiological changes. Electrocardiography

Table 2
Classification of sensors technologies used for fall stages.

Sensors	Types of sensors	Types of signal	Description (metric to measure)	Wearable/ Ambient
Motion	Accelerometer	Body movement	Main wearable sensor that measures body acceleration [44]	Wearable
	Gyroscope	Angular rotation	Measures orientation in pitch, roll and yaw [45]	Wearable
	Magnetometer	Geomagnetic field	Detect the direction of fallen body	Wearable
	Gravity	Earth's gravity	Measures acceleration effect of Earth's gravity on body	Wearable
	GPS	Coordinates	Determine the fall location	Wearable
Physiological	Electrocardiography (ECG)	Electrical signals	Measures electrical function signals of the heart [46]	wearable
	Photoplethysmography(PPG)	Blood flow	Measures the concentration of blood dissolved oxygen	wearable
	Spirometer Sensor	Lung volumes and lung capacity	Measures respiratory changes, expiration and lung volume	wearable
	Galvanic Skin Response Sensors (GSR)	Electrical skin resistance	Measures reaction skin changes, stress and skin humidity [47]	wearable
	Pedometer Sensors	Steps	Measures steps for motion patterns	wearable
	Blood Pressure Sensors	Blood pressure	Measures systolic, diastolic and mean arterial pressure [48]	wearable
	Blood Oxygen Sensors	Blood oxygen	Measure pulse rates and blood oxygen saturation level	wearable
	Electrooculography (EOG)	Corneoretinal standing potential (Electrooculogram)	Detect visual impairment [49]	wearable
	Temperature Sensors	Heat/coldness energy	Measure body temperatures [50]	wearable
Environmental sensors	Voice detection	Human-voice signals Voice/noise/vibration	Determine acoustic, noise and used for help ask [51,52]	ambient
	Microphone Array sensor	Voice/noise/vibration	detect the sound of body collision with the ground [53–56]	Wearable/ ambient
	Humidity Sensors	Humidity	Measures body humidity	wearable
	Light Sensors	Light intensity	Measures light intensity and body movement on surfaces	ambient
	Ultrasonic Sensors	Proximity between objects	Detect distance between body and floor by sending a pulse	Wearable/ ambient
	RFID Tags	Radio frequency	Detect person collision to the floor	Wearable/ ambient
	Barometer	Pressure between objects	Measures contact pressure between body and floor [57]	Wearable/ ambient
	Inclinometer Sensors	Gradient	Measures gradient between body and floor	Wearable
	Altimeter Sensors	Height	Measures body height	wearable
	SenseCam	Video stream/ posture	Record fall event [58–60]	Wearable
	Camera	Video stream/ posture	Detect indoor fall [43,60,61]	ambient
	WiFi	radio signal	Detect indoor fall by radio signal [62]	ambient

is the method which records electrical signals generated by the heart's muscle and it shows the heart's status in different situations [38]. Photoplethysmography is the process of monitoring the blood volume changes. A spirometer is a diagnostic device to monitor the lung volume and airflow. Galvanic skin response is a feature that shows electrical characteristics of the skin by human sympathetic nervous system responses. Blood pressure is shown by systolic for the highest pressure and diastolic for the lowest pressure and it is vital to life. Even more, sensors are able to monitor oxygen saturation in the blood. Electrooculography is a method that measures eye movement by the resting potential of the retina. Physiological signs can be detected easily like body temperature or as mentioned above can be detected more complex.

Smart environments utilize a set of smart environmental sensors to detect fall by voice, changes light intensity and proximity between body and floor. In [39], the authors provided WiFi as a sensor to detect fall by the effect of radio signals from the physical environment. Vision-based sensors are also classified into the Environmental group. By processing output signals from RGB cameras [40] and 3D cameras as video streams [41–43] and processing color or thermal postures, a fall event can be detected.

2.2. Locations of sensors

Previous studies have conducted on the location of sensors [63]. Each sensor is installed in a predefined location such as the waist, chest, hand, arm, thigh, and pocket of a shirt and trouser as body position [64]. Bed, floor, walls or event objects like a tap or handhold are environmental positions. There are integrated sensors that locate in a platform like a smartphone [65–70] and smartwatch [71,72]. The sensors interact with each other by Wifi, Bluetooth [73–75], ZigBee [76,77], and other

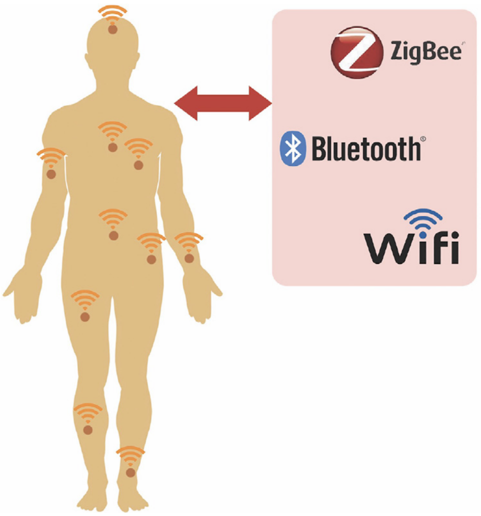

Fig. 4. Potential location in a body for placement of sensors and the main communication channels.

communication channels [78,79]. Fig. 4 shows potential location on a body to place sensors and the main communication channels.

2.3. Smart sensors

Common sensors only carry out sensing tasks such as wireless sensor networks [80], but IoT needs smart sensors [81]. A smart sensor is a tiny unit that has transducers, amplifiers and a microprocessor which process inputs and then transfer output through wireless communication [82]. One or set of logically connected smart sensors locate on Edge layer of IoT architecture.

IoT expectation from smart sensors:

– Integration logically: They are very tiny and a large number of them is distributed throughout the environment such as indoor navigation system [83], crowdsourcing and Sensing for Indoor Localization [84], underwater acoustic sensor [85] and mobile sensors [86,87]. They are logically connected with each other, to overcome low power, performance, and storage, so data is combined and provide more precise information about situations.
– Edge computing: Smart sensors are supported by tiny software and they process data by a learned model in real-time, so the bandwidth of the communication channel is consumed less in order to transfer limited data to the other layers like middle-ware technologies for cloud of things [88]
– Energy efficiency: Smart sensors can survive many years by using low energy consumption [89]. They can use energy harvesting such as heat energy for recharging. Therefore distributed smart sensors are the main components of E-health monitoring systems especially fall diagnosis systems that discussed in the following.

3. On fall detection

3.1. Fall stages

IoT-based healthcare monitoring technology plays a key role in improving people's lives [90]. According to Delahoz and Labrador [33] one of the most important healthcare problems of elderly who live alone, and workers [91] who work in construction and mine is fall events, that cause bones to fracture, loss of independence and even death. Therefore, in this section, we discussed three stages of diagnosis fall event based on IoT, consist of Prediction, Prevention, and Detection respectively as shown in Fig. 5.

Prediction

Prediction stage intends to predict a fall event before it by exploring previous records and real-time records of signals [92]. Prediction stage discovers abnormal fall patterns by realizing irregular signals. The signals are physical and physiological signs and video streams and postures which are gathered by sensors then are transferred to Fog and Cloud layer of an IoT healthcare architecture [93]. Cloud is suggested for Prediction stage because of its powerful capabilities and strengths. There is a Computation Centre in Cloud that utilizes complex learning algorithms to discover abnormal patterns and fall risks [94] by processing signals. Fog is suggested to predict a fall event, by processing real-time signals, just a few milliseconds before it. Each signal has several features, for example, a physical signal like a gait consists of size, direction and

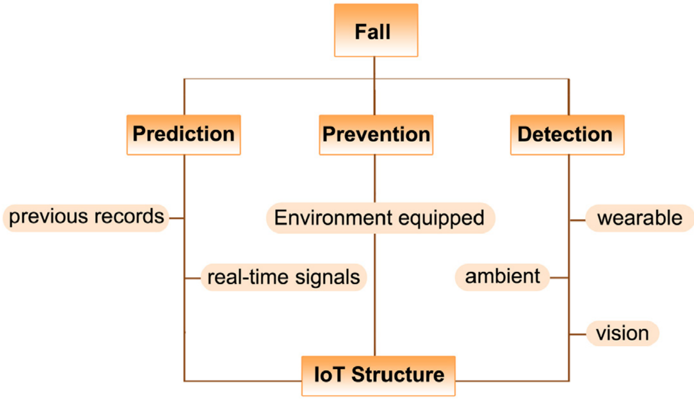

Fig. 5. Fall diagnosis stages.

Table 3
Samples of measured features in prediction systems.

Signals	Measured features
Physical (Motion) Signal	Single leg standing time features [97]
	Acceleration time series [92]
	Dual task gait and single task gait [98]
Physiological Signal	Gait analysis by Electromyography (EMG) and Electroencephalography (EEG) [99]
	Foot pressure in the big toe, the metatarsal and the heel [100]
Video/posture	Sum of the y-axis and the x-axis direction histograms pixels [101]
	Motion-pose geometric descriptor in histograms-based representation [102]

velocity and a physiological signal like electrocardiography (ECG) consists of time, rate and intensity and a visual signal like a body posture consists of histograms pixel. Fall risks are diagnosed based on changes in the signal's features, some previous studies about fall risks summarized in Table 3. So warning alarms are produced to inform the probability of a fall event after observing sudden changes in the features. Prediction stage is essential for IoT-based fall diagnosis systems for the following features:

- Emergency assistance: Emergency assistance is accessible as soon as possible when different types of fall events happen.
- Comprehensive personal profile: Cloud layers are employed to create a comprehensive personal profile of health conditions, they provide strong capabilities and services.
- Pattern extraction: To discover fall patterns in patients, athletes, and workers. Pattern extraction can be generalized to a person who hasn't any records and has been recently monitored.
- Improving decision making: Fall patterns can serve as an input for Healthcare Decision Support System, and help doctors and managers to improve their decisions.
- Fall risks: To discover fall risks in different situations. Discovering fall risks is necessary to construct a smart home [95], smart hospital, smart construction, smart gym, and smart city [96] based on IoT in order to prevent fall events, as discussed in next.

Prevention

Prevention stage intends to provide IoT-based solutions that improves physical, physiological and environmental conditions to prevent fall events [103]. Typically prevention systems are provided based on fall risks factors as shown in Fig. 6. Fall risks factors are classified into personal and environmental factors [104]. Personal fall risks include physical and physiological and mental factors. Muscle weakness and disease are the main reasons for fall events and both them improved by treatment and exercise. The mental status and fear of falling that is strongly related to fall experience, is solved by enhancing mental and environmental security of life. Environmental fall risks are classified into indoor and outdoor. Edge layer of IoT architecture is suggested for reducing environmental fall risks. We suggested Edge Node includes smart sensors and devices equip the environment. For example, in an IoT-based smart bathroom [105], the authors designed the concept for IoT implementation by integrating wireless smart sensors, such as leak detection sensor, voice detection sensor, and water flow sensors. According to [106,107] the security of indoor and outdoor personal life improved by using wearable airbag which opens a few milliseconds before fall events. Furthermore, wearable [108] and robot [109] and help walking assistance robot [110,111] are suggested for both indoor and outdoor. In [111] the authors developed a walking aid robot to assist elderly. In another study [112] the authors provided a smart IoT-handrail that is useful to prevent fall events by gathering data about elderly walking speed. Prevention stage is essential for IoT-based fall diagnosis systems for the following features:

Integration and aggregation: Edge layer can integrate heterogeneous sensors and devices based on IoT protocols.

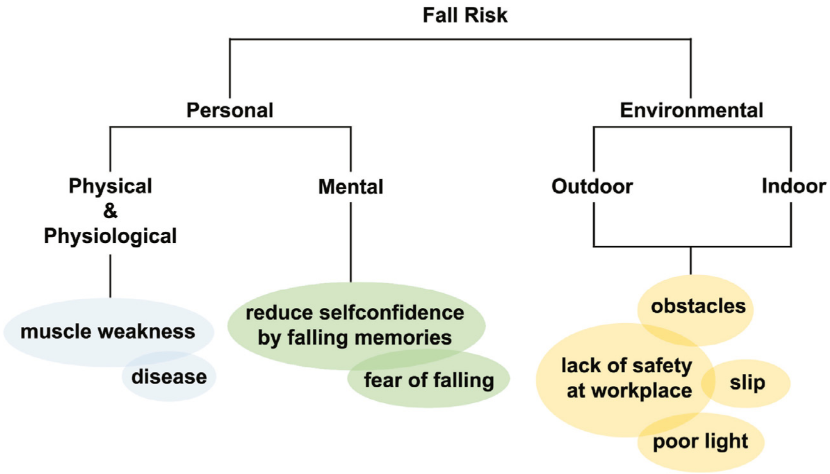

Fig. 6. Major risks in a fall, used for developing prevention systems.

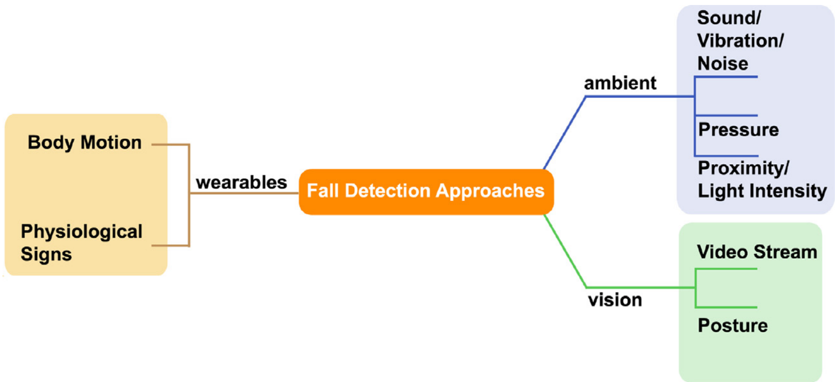

Fig. 7. Three major Fall detection approaches.

Security: security increased by developing a smart home, gym, and construction [113].
Reducing fall risks: Reducing fall injuries as a result of reducing fall risks.

Detection

The Detection stage is essential because there is always a probability of a fall event even if the prevention stage is implemented properly. Detection stage intends to detect a fall event after it. Fall detection approaches include wearable [114,115], ambient and vision approach [32] shown in Fig. 7. The wearable approach is classified into physical (body motion) and physiological signs. The ambient approach is classified into sound/vibration/noise and pressure and proximity/light intensity and the vision approach is classified into video stream and posture. In the past decades, different types of research have conducted on the three approaches [33–35,116].

Fall detection based on changes in body acceleration is one of the most common detection ways. Many types of research have done by the accelerometer and combination of accelerometer and gyroscope and magnetometer for better performance [75]. Fall acceleration is higher than the acceleration of walking and standing and sitting but is lower than the acceleration of jumping and cycling, so fall acceleration is checked by the threshold algorithm [73] and if there is a probability of a fall event, falling is confirmed by machine learning algorithms [117,118] such as support vector machine [119], naive Bayes, decision tree [120], neural network [121], and k-nearest neighbor [122,123]. After detection a fall, a GPS shows the location of event [65,124]. When a fall event happened, physiological signs [125,126] change suddenly, so using physiological sensors increased the accuracy of fall detection, based on heart rate [127,128], Electrocardiography(ECG), temperature, humidity [122], and so on. In a smart environment such as smart home [129,130] and smart hospital, falling can be detected by environmental sensors [131] such as voice detection, microphone array sensor, light sensor, RFID tags, and barometer. There is the ever increasing number of research on the video stream and body posture that represents the power of them in fall detection. Fig. 8 shows how different sensors help detect fall events in three approaches. Advantages and disadvantages in different fall detection approaches shown in Table 4.

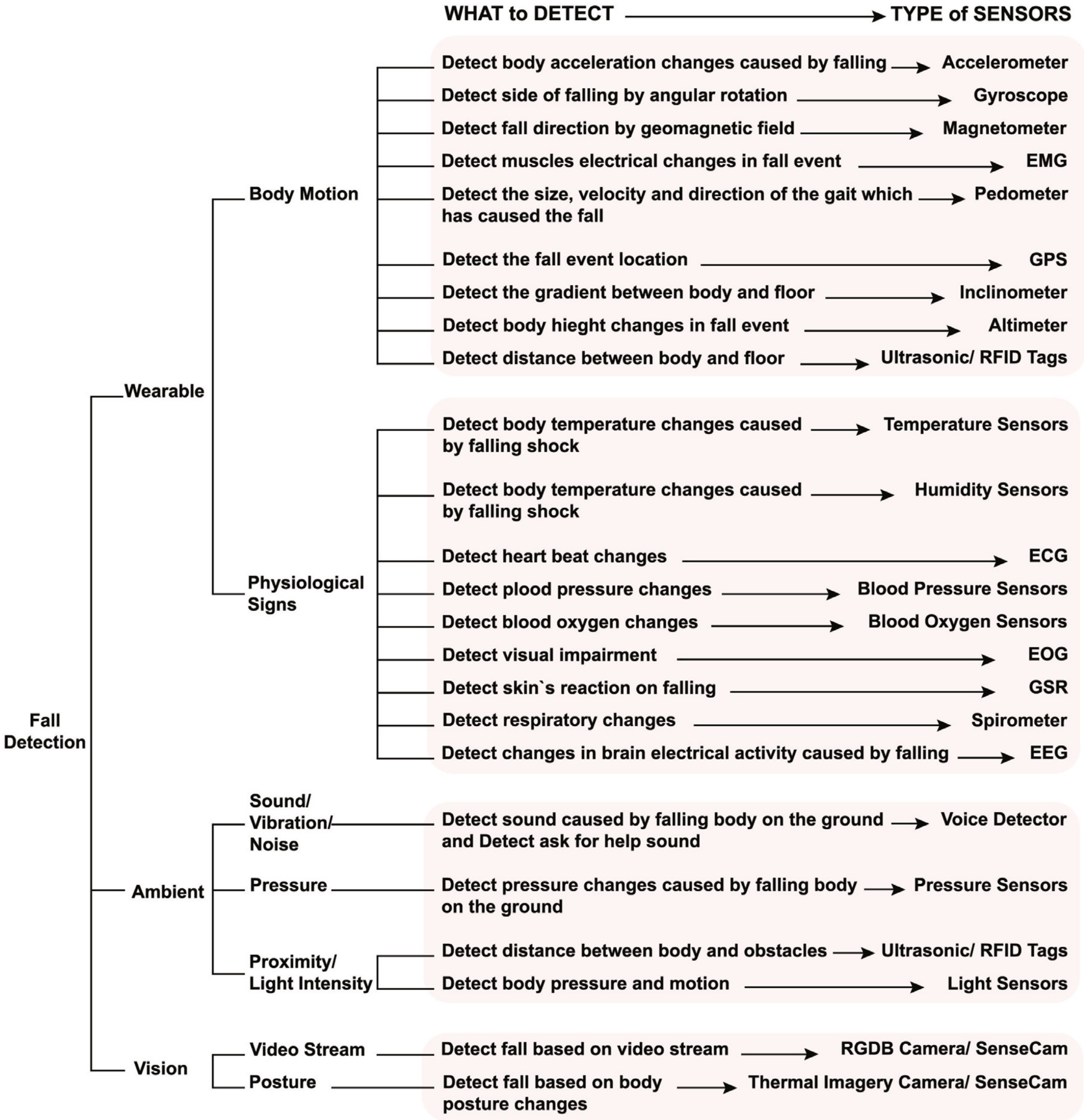

Fig. 8. How can a Fall be detected?.

Edge and Fog are suggested to detect fall events. Edge computes information and it is close to the sensors, devices, and users, but Fog is close to the local network and infrastructure. Edge is suggested to detect fall for the following features:

- Low latency, high security, and privacy because of the proximity to the sensors and users.
- To run lightweight algorithms.
- Only if the probability of a fall is detected, the data is transferred to Fog.
- Data in preprocessed format is transferred to other layers, instead of raw data.

Cons of Edge to detect fall:

- Fall is not detected definitively, because of low power computation.
- Storage is small-scale as micro storage.
- Consumption of energy and battery would be quickly.

Fog is suggested to detect fall for the following features:

- To run complex machine learning algorithms such as deep learning to detect fall.
- If Edge node has low energy, computation and data stream are not disconnected and data is directly transferred to Fog.

Table 4
Advantages and disadvantages in different fall detection approaches.

	Advantages	Disadvantages
Wearables	1. Individual monitor in all places and times	1. Wearing a permanent wearable is not pleasant for people
	2. Low cost	2. An unwanted impact on wearables can cause rapid changes and incorrect detection
Ambient	1. Non-contact monitoring	1. Generally all surfaces should be covered with these sensors
	2. Individual privacy	2. Easily exposed to noise
Vision	1. High accuracy	1. Dead spaces which is the result of the recording angle limited
		2. High cost

Table 5
Different machine learning techniques on fall detection approaches.

ML Technique	Classifier	The algorithm has been applied to these features	Supervised/ Unsupervised
Bayesian	Hidden Markov Model(GM-HMM)	Infrared Radiation Changes (IRC) [92]	Supervised
	Bayesian Network	Radio Frequency	Supervised
	Extended Kalman Filter	3D & 2D Images	Supervised
Decision Tree	Binary Type	Acceleration	Supervised
	Random Forest	Floor Vibration - Radio Frequency - Depth Images stream	Supervised
Instance Based	KNN	Audio Acceleration Thermal Image	Supervised
SVM	Support Vector Machine	Audio Acceleration [133] 3D Motion Representation - Depth Images stream - Radio Frequency - Extract Curvature Scale Space(CSS)	Supervised
	Multiple Kernel Learning Support Vector Machine	Acceleration	Supervised
	Linear Kernel	Floor Vibration	Supervised
	RBF Kernel	Floor Vibration	Supervised
	Non Linear	Acceleration	Supervised
Regression	Least Squares Method(LSM)	Audio	Supervised
	Logistic Regression(LR)	Acceleration & Air pressure	Supervised
Neural Network	Multi Layer Perceptron	Acceleration	Supervised
	Artificial Neural Network	Audio	Supervised
	Back Propagation	Acceleration	Supervised
	Convolutional Neural Networks	Video Stream	Supervised
	Extreme Learning Machine(ELM)	Acceleration Extract Curvature Scale Space(CSS)	Supervised

Most of the previous works carried out based on Detection systems and a smaller number of them are about Prediction and Prevention systems. We suggest that future research be conducted in combinations of systems for both predicting and discovering fall patterns. We suggest the system that is implemented on IoT layers as shown in Fig. 9.

Prediction stage is implemented on Fog layer to predict falls a few milliseconds before it and Cloud layer can predict a fall based on fall patterns. Prevention stage is developed on Edge layer for integration and synchronization sensors and devices. Detection stage is implemented on Edge because of proximity to the user and also on Fog layer because of power computation.

3.2. Learning from detection

We have discussed learning methods of fall stages and IoT layers in this subsection. Raw data should be changed to appropriate dataset by preprocessing. Data cleaning, data integration, data transformation, data reduction, and feature extraction are the main features of preprocessing. Fall is detected by techniques such as threshold fall value and machine learning.

The threshold technique is used when wearable sensors measure body acceleration in X, Y, and Z-axes and set a threshold value for fall acceleration. Body acceleration value is achieved by $\alpha = \sqrt{Ax^2 + Ay^2 + Az^2}$ and when the value of α increases than the fall threshold value, there is a probability of a fall event. Threshold methods have a lower accuracy but are used extensively because of low energy consumption and computational simplicity [132]. Fall threshold value is suggested for wearable accelerometer, gyroscope, and magnetometer in Edge layer.

Machine learning is used to get more accurate results. Machine learning is the domain of science that enables computers to search in data structures and obtains interesting information, which can create a model. They use training data to predict a problem and make optimal decisions. Machine learning techniques are categorized into supervised learning and unsupervised learning. Supervised learning is used more, to detect a fall in two steps which are training and validating. Table 5 shows some of the supervised algorithms in the previous studies. Some of machine learning algorithms have been used more in fall detection:

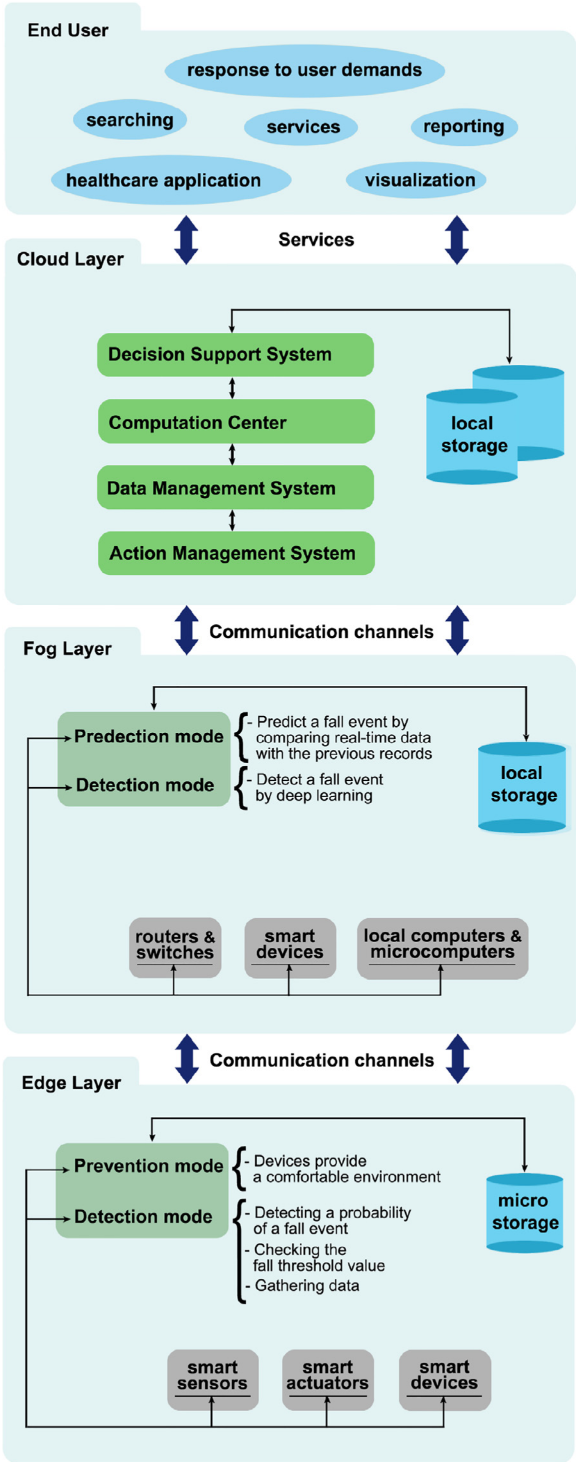

Fig. 9. Different aspects of Fall across IoT layers.

– Artificial Neural Network (ANN): This algorithm includes inputs, hidden layer, and outputs. The hidden layer may have several layers with the weighted neurons. In this algorithm learning is complex and unclear in a black-box of hidden layers and it does not show how a fall event has happened [134,135]. It has a high tolerant of heterogeneous data and provides a precise result, so it is suitable to detect fall especially on smart devices in Fog layer because it needs high power computation capabilities.

– Support Vector Machine (SVM) divides multidimensional data into two classes. SVM has less complexity on a small dataset with high dimensionality rather than ANN. It works well on unstructured data such as posture and it is suggested for Edge layer especially on postures of fall [133,136,137].
– Decision Tree classifies data into binary classes involving fall or non-fall (other activities) by answering predefined questions. In this algorithm learning is clear and easy to understand, so it is suitable for studying reasons of fall events, especially physical and physiological data that is used to discover fall patterns and risks [8,138].

For example the relationship between changes in blood pressure and fall or the relationship between blood oxygen level and fall.

– Naive Bayes: It is a simple algorithm with good performance and accuracy. It works with fewer memory and less time for training classifier. So it is suitable to run on Edge devices to detect falls directly [139].
– Deep Learning: IoT world includes millions of sensors that can produce data continuously as big data with velocity, volume, value, variety, and veracity [140]. To process a huge amount of data, a neural network with thousands or millions of hidden layers proposed as a deep learning method[141]. Deep learning works well with massive data. Deep learning, unlike normal machine learning techniques, doesn't need feature engineering. It takes a long time to train a huge amount of data but time to predict is small. And like a neural network, processing is in a black box and not easy to understand [142].

3.3. Research on IoT & fall detection

An E-health scenario based on IoT begins by sensing. Sensors gather physical, physiological and environmental data, then the data is processed by appropriate algorithms to predict, prevent and detect falls. We have proposed an IoT E-health scenario in a smart home, in this subsection. It is a choice to diagnose a fall for elderly. The scenario includes Edge, Fog, Cloud, and End User as shown in Fig. 9. In the following, we have clarified facets of the figure.

- Edge layer

Edge is the first layer of our scenario. Smart sensors, actuators, and devices as Edge Nodes are the main actors of this layer which gather physical, physiological and environmental data. They can serve as a static node such as a thermometer that located on the wall or a wearable node such as an accelerometer located on the body. The smart devices work in two modes in this layer, as Prevention mode and Detection mode. There is an Action Management that determines which devices work in Prevention mode and which of them work in Detection mode, and also determines which devices work or go to sleep for energy saving. In the Detection mode, sensors gather filtered signals. Preprocessing and processing data or Edge Computing is a substantial challenge in this mode. Data is compared with the fall threshold value and if a potential of a fall event is detected, data is transferred to Fog for fall confirmation. In Prevention mode devices provide a comfortable environment for the elderly before and after a fall event. For example, an IoT hand-rail help elderly to walk before a fall event and a wearable airbag prevents injuries after falling. Therefore the Edge layer output is a probability of a fall event that is transferred to Fog layer for confirmation, by communication channels as shown in Fig. 4. In Edge layer storage is micro-scale.

- Fog layer

Fog or Gateway is a bridge between Edge and Cloud which offers services on a smaller-scale than Cloud. Fog has benefits such as Low Latency, Scalability, Geographical Distribution, Flexibility, Heterogeneity, and Mobility Supports because of proximity to the End User [61]. Devices in Fog as Fog Nodes such as Arduino, PC Computer, routers, and switches are Static Gateways which installed in a room or such as Smartphone and Tablet as Wearable Gateways accompany elderly and support mobility. The devices work in two modes, Prediction mode, and Detection mode. In Fog, data is combined and analyzed for confirmation of a fall event. The more complex machine learning algorithms work in the Fog layer, Deep learning is suggested for analyzing because of speed. The action management provides two actions, local and general if a fall event detected. Local is notifications and orders to the actuators and devices in Edge layer to provide an appropriate environment such as balancing environment temperature. The general action is sending a notification to caregivers and doctors to inform them. Then the result is saved in local storage. Then for further computation and long-term storage, the results and information are transferred to Cloud by the communication channels.

- Cloud layer

Cloud includes a Main Storage, a Healthcare Decision Support System, a Computation Centre, a Data Management System, and an Action Management System. Cloud can be located in a hospital. Computation Center processes data in two ways, first, individual's falling datasets are compared with the previous records to discover fall patterns, abnormal patterns, fall risks, and individual profile is completed more. Second, thousands of profile from different people is compared and analyzed with each other to discover universal fall patterns, abnormal patterns, and risks of fall, and also insights of falling is completed. The Action management system manages activities of the devices in Edge and Fog. Monitor system determines activities such as active or inactive sensors, energy for sensors and devices, aggregation and integration of devices. It focuses on discipline performance, selects the alternative device if there is a problem and forces the system to work according to predefined standards. It provides a comfortable environment by appropriate devices after a fall event. Therefore, Action Management selects devices and communication channels to work, aggregate and integrate sensors and devices and control all devices in layers. The Data Management System provides processing, analyzing, storing and notifying in the system. Cloud discovers insights on fall by aggregation and integration and sharing data. It provides inputs for the Decision Support System. Also, Data Management System controls streams of data in the system and determines which dataset is analyzed or transferred or stored. Storage in Cloud is long-term in a main storage. Cloud provides several services to users and a Decision Support System provides decisions based on information and patterns, healthcare application, searching, visualization, response to user demands, and reporting in real time. Therefore, the End User has a complete set of fall-related tools to monitor continuously. There are challenges in this scenario that some of them discussed in the next section.

4. Existing challenges and future research

This section highlights the existing challenges related to fall diagnosis systems based on IoT and provides ideas as solutions.

- *Fall diagnosis systems for different cases*

Studying other cases seems necessary, except for elderly, patients, and workers, in order to achieve a comprehensive insight of IoT-based fall detection. For example professional exercises, falling rock climbing, falling of sports competitors, babies and young children falls, and free fall, even more, other places with different scales and situations like a smart school and smart city.

- *Overlapping activities and multidimensional datasets*

In our daily lives, a fall overlaps complex activities like cycling, so it isn't as simple as a fall event during walking. Dataset from complex activities is multidimensional and has features that are dependent or independent with different scales and formats. An agreement seems necessary on a comprehensive fall multidimensional dataset.

- *IoT standardization for fall events*

An IoT architecture includes edge, fog, and cloud layers and supplies processing, storing, data managing, and decision-making of fall events. We suggested three stages for a fall diagnosis system that include prediction, prevention, and detection mode, and determines which layer is proper to each stage. Researches should be done to implement stages on each layer by using protocols, energy efficiency, and transfer methods between devices and layers, and specific learning methods for each layer. For example, a smartphone can work both on edge and fog as a device for fall detection.

- *Wearable computing*

Nowadays, a wearable processor like a smartwatch is too weak that may not be able to run complex learning algorithms, so data is transmitted to another device which is located in Fog. Powerful processors should be produced to detect fall by processing data and validating fall events in edge without needing other layers.

- *Integration logically*

Smart sensors consist of tiny microprocessors, noise filters, transducers, and amplifiers and they are more complex than normal sensors. Thousands or millions of them are distributed in IoT environment, they need to be integrated logically, in order to supply energy, communication with each other, extending sensors lifespan, and the lack of adequate processing and storage capabilities.

- *Sensors location*

Although many researches have conducted on sensors location, however, it is one of the challenging topics in the field of fall. Sensors location may be static or dynamic. For example, the implantable sensor that is static and inside the body is an emerging approach to monitoring. Protection of sensors from sudden impact, network connection, comfortable to wear, should be considered for both static and dynamic environment.

- *Personalization*

ML algorithms are getting advance in the direction of personalization, especially in e-health domain. The machines use all the background information to build a general learning model but they adapt the model based on the personal features of individuals. By this approach, we will come up with models that are designed based on the identified fall pattern of each person considering the personal characteristic of the person (e.g. age, weight, historical information, illness, etc.).

- *Prediction*

Prediction is a key to know when a fall event is going to happen. Abnormal gait, leg standing time, foot pressure and body histograms are the crucial features have been studied to predict fall events. Future research can investigate dizziness, epilepsy, hypertension, and cramp (muscle contraction). Understanding fall risks especially physiological fall risks are one of the most important components of the prediction system. Outputs from the prediction stage are used to develop smarter IoT-based environments.

- *Learning from fall*

We discussed algorithms on each fall stage and layer. But IoT produces big data from heterogeneous devices. Common machine learning algorithms are not adequate to analyze the huge amount of heterogeneous data. So deep learning is an integral part of IoT fall detection system. Integrating fall-related dataset from hospitals and clinics is necessary to supply deep learning input because there is not as large as a massive dataset, yet.

- *Action management*

Action management is a management system that organizes actions after detecting a fall event. The actions are categorized into local and general classes. The local actions send information and orders to the other smart devices and actuators in order to help the fallen person such as closing the tap, balancing temperature, and to determine the available amount of water in the bathtub. The general actions are notifications about the vital signs of fallen person and its situation that sent to caregivers and family and doctors.

- *Monitoring data flows*

There is a Data Management System to manage data in the Cloud. The system decides which data processed and which of them transferred to the next layer and also provided a dataset for Decision Support System. Therefore, monitoring the data flows in the system is a critical issue that should be investigated.

5. Conclusion

Fall is one of the main reasons for mental harm, lack of self-confidence, fractures, and even death. Fall event happens for the elderly, babies and young children, workers and other people. Cost of fall injuries treatment is over $30,000. Therefore fall-related research must be seriously considered in the field of health. Internet of Things(IoT) is an emerging technology that can develop a fall diagnosis system. A fall diagnosis system consists of three stages as Prediction, Prevention, and Detection. Internet of Things(IoT) has provided Edge, Fog, and Cloud as IoT layers in order to implement stages of fall diagnosis systems. For this purpose, IoT components involving smart sensors measure fall-related signals, and then machine learning algorithms detect fall events, and communication channels transfer information. All actions and data flows are controlled by IoT components. Therefore, in this paper we provided a scenario to clarify the concept of implementation of a fall diagnosis system on IoT layers and at the end we discussed challenges and ideas as solutions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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