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1232: HUMAN-CENTRIC MULTIMEDIA ANALYSIS

# A review on fall detection systems in bathrooms: challenges and opportunities

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## Abstract

The share of the aged population over and above 65 years increased from 6% in 1990 to 9% in 2019. The percentage of the aged population might increase further to 16% by 2050. Due to socio-demographic changes and nuclear family setups, elder people live alone and encounter many issues at home, especially falls, while doing their daily activities. The probability of a fall inside the bathroom is higher than a fall inside the living place due to specific hazards. Various research works have been proposed to monitor people from falls (fall detection systems -FADE) inside the home environment. However, those systems do not concentrate much on fall detection inside the bathrooms (FADEB). Alternatively, we witness certain smart gadgets for the safety of the elders inside the bathroom, which prevents them from a fall by assisting. However, these gadgets are not designed in a way to report the fall. To overview the FADEB systems, electronic databases such as PubMed, Web of Science (WoS), Scopus, Google Scholar, and DBLP were used to fetch the research works published from 2007 to 2023. The FADEB papers are filtered out and critically reviewed in terms of implementation details concerning data collection, feature extraction, and classification. The specific challenges related to FADEB are quoted that need to be addressed in the near future to monitor the falls inside the bathroom.

**Keywords** Fall detection · Fall prevention · Fall risk assessment · Smart bathrooms · Smart gadgets · Toilets · Bathrooms · Restrooms

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## 1 Introduction

The elderly population over and above 60 years of age is increasing multi-fold, which will continue increasing for the next 20 years [1]. In 2020, it was 727 million, which is expected to be in triple fold by the year 2050 [2]. The increase in the population of aged people has raised the average life expectancy to 73.2 years as of 2021 [3]. The longer life of an aged person brings more opportunities for them, their families, and societies in terms of education, economy, etc. The extent of these opportunities and contributions highly depends on the aged person's health. If a person lives longer with good health, she/ he will be independent and be able to carry out their activities, which greatly favors the family and community. The socio-demographic shifts and the preference for nuclear families create a situation for elderly persons to live alone [4]. These situations may create more accidents in elderly persons, such as falls, exposure to heat, smoke, fire, and electric shock, which could cause a severe threat to their health [5].

Among these accidents, falls are common and result in catastrophic consequences that include pain, loss of independence, poor quality of life, and even death if unnoticed for a more extended period [6]. The National Institute of Aging (NIA) estimates that one out of every three elderly individuals reports a fall at least once a year, of which 20% have serious consequences [7]. In addition, it reports that the bathrooms/ restrooms are considered to be the riskiest places at home vis-à-vis fall-related injury and death. 80% of the fall and their related injuries happen in the bathroom, and 33% of these incidents demand hospital admission [8]. The research works [9, 10] have also proven that the falls inside the bathroom are twice as likely as other fall events. It is also reported in a survey [11] that the bathroom is the most dangerous room for a fall. In addition, the research work by [12] has reported that the significant causes of a fall inside the bathroom are slippery surfaces, cluttered floors/environments, absence of support rails, and improper illumination [13, 14]. Depending upon the nature of the fall-related injury, the elderly persons might be bedridden, and as a consequence, the hospital expenses would also be more [15]. These implications of falls and their related injuries will negatively impact their family and community.

The problem of falls in the bathroom/ restroom has attracted more researchers and industries to provide bathroom safety gadgets and even smart bathrooms, primarily through smart devices[16]. Smart bathrooms are one such idea that exploded from the smart homes that can help the elders and their families become happier and healthier. As per NIA, many research industries have investigated smart gadgets used to ensure the safety of elderly people by preventing them from falling. However, these devices are intended to provide confidence to the elders to carry out their daily activities independently, thereby improving their quality of life. Though these smart gadgets are available at low cost and help the elderly person independently, no guarantee that falls will not occur. Even if the bathrooms are equipped with smart gadgets, a specific fall detection (FADE) system is required to report the fall to the caretakers or family members once the fall occurs. Several FADE systems have been proposed to detect falls, mainly in the living room, bedroom, halls, etc., as quoted in the review papers [17–19]. Some research works have also discussed the perspective of activity recognition in the bathrooms, such as bathing, washing hands, etc., as reported in [19], but they do not handle the falls. Few papers have been proposed for fall detection in the bathroom (FADEB). In the current scenario, the need for FADEB is high for the welfare of the elders. Thus this paper presents a systematic review of FADE systems in the bathroom (FADEB) and its implementation with the following contributions.

- Data Collection - Categorizes the FADEB concerning the sensor used to collect the data with its advantages and limitations.
- Pre-processing and Feature Extraction - Introduces a critical review of FADEB to the feature extracted for recognition.
- Classification - Categorizes the FADEB systems in terms of classification used to classify the activities.
- Shortcomings of the FADEB systems in various aspects and terms of implementation and subjects involved for the experimentation.
- Prospectus of future scope and improvements of FADEB, which other researchers can implement.

The remaining section of this paper is organized as follows. Section 2 discusses the search strategy/ selection criteria of research papers for the systematic review. Section 3 presents the fall detection systems categorized based on the type of sensor used for data collection and analysis with the features extracted for classification. Section 4 discusses the scope for future enhancements from the problems listed in Section 3, and finally, Section 5 concludes the paper.

## 2 Search Strategy/ Selection Criteria

Recently since the year 2007, researchers have shown interest in the fall detection (FADE) system to monitor elders, especially from falls. To overview the methodologies proposed for FADEB, electronic databases such as PubMed, Web of Science (WoS), Scopus and, Google Scholar, DBLP were used to fetch the research works published from 2007 to 2023. Sample keywords such as “Fall Detection Systems", “Fall Detection," “Fall at Bathrooms," “Elderly Fall detection system," “Elderly monitoring system in the bathroom," etc. are used to extract the papers. The articles included in this systematic review are downloaded from January 2023 to August 2023 (updated after 1st round of review) as per the following conditions

1. Open access article
2. Accessible by the institution
3. Full-length original articles between the years 2007 and 2023
4. Papers published only in English
5. Articles that presented the keywords defined by the search string on the abstract or title
6. Articles that presented the methodology for studying fall events such as fall detection, prevention, and risk assessment.

Around 2022, research papers related to the search query were extracted, and 1996 were retained after removing the duplicate entries. 53 review papers on FADE systems were screened. A total of 1943 articles deal with FADE systems. Further, the articles that do not contain the keywords such as bathroom/ toilet/ restrooms are removed (1924 articles). Finally, 19 research articles were included in the systematic study of FADEB. The detailed analysis of the PRISMA model involved in selecting the research article for this systematic review is shown in Fig. 1. In addition to these 17 articles, only 1 article that deals with faint detection in a home environment is also considered for the systematic review as it trades with the elderly person.

From Fig. 1, it is apparent that most research and review papers deal with only general FADE systems and not the FADEB. To highlight the detailed publication count year on year, the FADE, FADEB, and review paper on FADE systems are shown in Fig. 2, despite enough reviews (53 review papers) available for fall detection systems (FADE) in a home

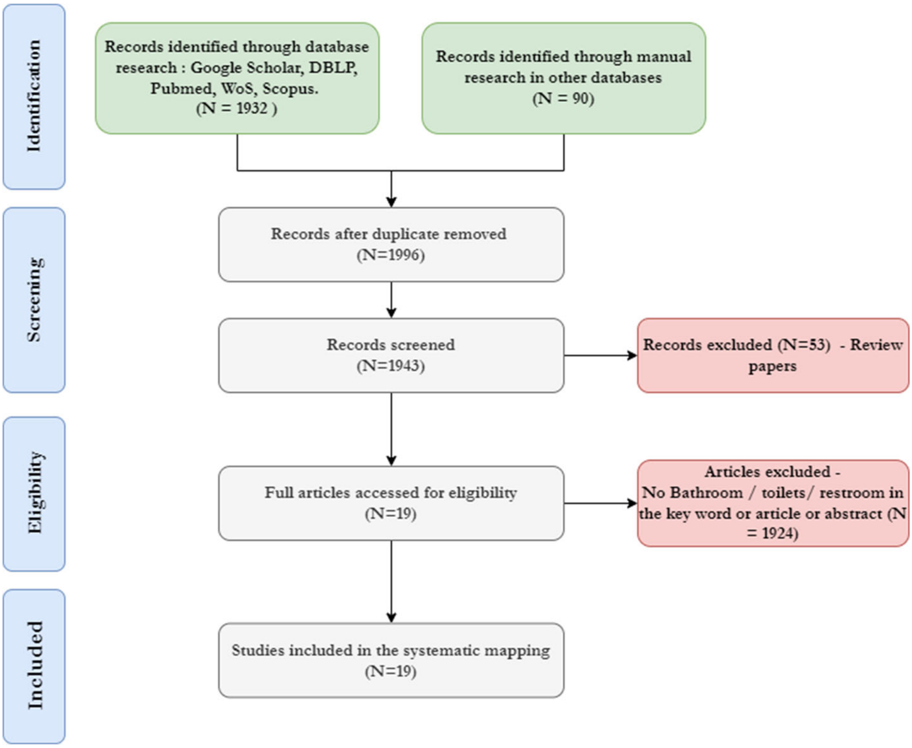


**Fig. 1** Flowchart of PRISMA standard used in the selection of research article for systematic review

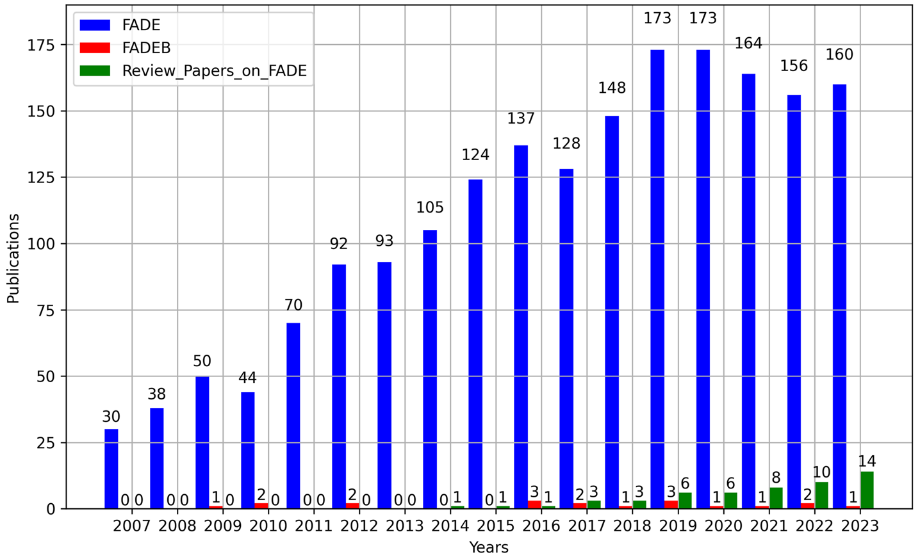


**Fig. 2** Research works on FADE/ FADEB systems published from 2007 to 2023

environment. To the best of our knowledge, no specific critical review paper deals with the FADE system in the bathroom, toilet, or restroom (FADEB), and this will be the first paper for such a critical review.

Moreover, the research works published for FADE systems are thoroughly analyzed for future scope and enhancements. About 23.19% of published FADE systems have reported the researchers to concentrate on FADEB, 35.94% work to propose FADE systems at night, 8.87% on fall risk assessment, and 32.00% on fall prevention systems. From these observations, it is evident that the researcher needs a critical understanding of what the FADEB systems are up to in the current research. These two main factors have motivated a lot to go into the review of FADEB.

## 3 Fall detection systems in bathrooms/ toilets (FADEB)

In the last decade, there has been enormous effort taken by researchers and industries to develop various FADE systems. It has been categorized generally into indoor and outdoor environments. Specifically, the indoors have been further categorized into the hall, kitchen, bathroom, pathway, etc., as shown in Fig. 3.

In the last decade, various researchers have proposed FADE systems for the well-being of elders through ambient models, vision systems, and wearable devices to monitor the elders inside the home, as quoted in various research works [17, 18]. In addition, specific industries have also launched automatic fall detection systems using wearable devices in the smart home environment, as reported in [20]. These FADE systems and commercial products have shown promising results indoors, especially in the living room. However, these systems are

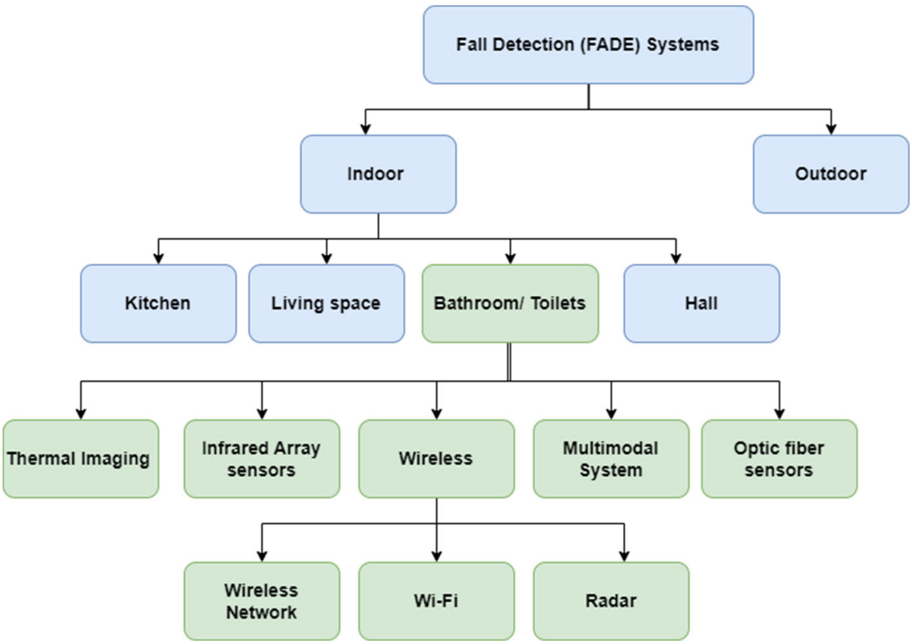


**Fig. 3** Categorization of Fall Detection (FADE) Systems

not suitable to be installed in the bathrooms. Wearing smartwatches or devices or holding a phone while peeing creates discomfort for the elders, and most of the time, the elders may forget to carry or wear the devices [21]. In the case of vision systems, it may intrude on the privacy of the elders as it is not primarily considered indoors and is best suitable for the outdoor environment. Finally, ambient sensors with waterproofing are more expensive to install and maintain. Thus, the fall detection system for bathrooms/ restrooms/ toilets is still an open and challenging problem for researchers. In the case of FADEB, only a few research works have evolved during the last decade, and the works are categorized as shown in Fig. 3. The Green shade of Fig. 3 refers to the implementation analysis of FADEB systems. A critical analysis has been made on the implementation of FADEB systems which is categorized into three phases such as sensor details (data collection), pre-processing, feature extraction, and classification with its merits and demerits. The taxonomy of the critical review is highlighted in Fig. 4.

### 3.1 Data collection - sensor details

The data collected in the FADEB systems have been implemented using ambient non-intrusive sensors such as Thermal image cameras, Infrared sensor arrays, and wireless devices. Mostly the sensor/ devices used are non-intrusive as intrusive devices cannot be used inside the bathroom for data collection while peeing, etc., The detailed information on data collection concerning sensors details, Number of sensors, Position sensitivity (Pos. Sen.) of the sensor, fall types, environments, subjects involved in the experimentation, fall events and non-fall events are highlighted in Table 1. During the experimentation, the fall types considered are Real-time, Simulated, and Semi-simulated which are represented as R, S, and SS respectively.

#### 3.1.1 Thermal image camera/sensors

A thermal image camera emits infrared energy termed heat signature at the place where it was installed. Analyzing the thermal image's heat map/ signature data, the activities can be identified and classified [22, 23]. Kido et al. in the year 2009, [24] installed the thermal image sensor for the process of fall detection inside the bathroom. The sensor was placed at a specific height, and the toilet seat was at 0.4m for the subjects to sit on. Additional fall markers were placed on the floor at five different locations aside from the toilet seat 0.4m away for the data related to the person's activities. Similarly, Wong et al. [25] have

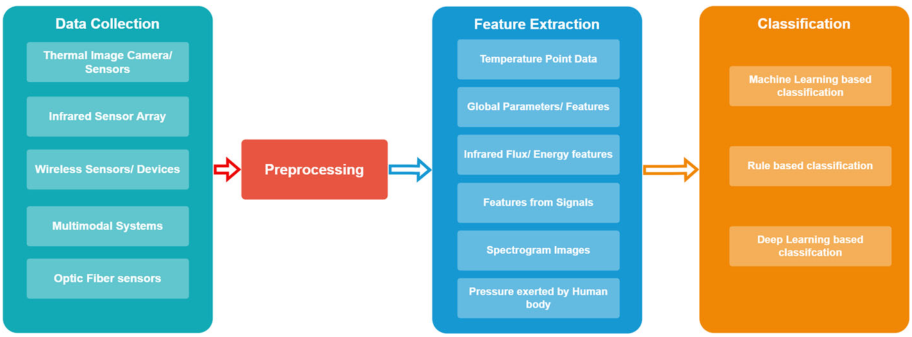


**Fig. 4** Taxonomy of critical review on Fall Detection Systems in Bathrooms/ restrooms (FADEB)

**Table 1** Data Collection - Sensor Details of the FADEB systems

| Res. work | Sensor details | # of sensors | Pos. Sen. | Fall Type | Environment | Subjects | Fall Events | Non-Fall Events |
|---|---|---|---|---|---|---|---|---|
| **Thermal Image sensor/ camera** | | | | | | | | |
| Kido et al. [24] | TP-L0260EN | 1 | ✓ | S | Demo toilet | Males - 10 | 60 | 20 |
| Wong et al. [25] | Thermo vision A-20M | 1 | × | R | Apartment | Female - 1 | Faint | Non-Faint |
| Shirogan et al. [26] | TP-H0260AN | 4 | ✓ | S | Demo toilet | 8 adults | 14 | 14 |
| **Infrared sensor array** | | | | | | | | |
| Popescu et al. [28] | Panasonic Motion sensors | 8 | ✓ | SS | Laboratory | 2 Stunt actors | 42 | 15 |
| Sixsmith et al. [29] | pyroelectric array | 1 | × | S | Laboratory | Trained Actress | 14 | 30 |
| **Wireless Devices** | | | | | | | | |
| Khin et al. [31] | BLE112 chipset + 2dBi/ 5dBi Antenna | 2 | ✓ | S | Bathroom (3m x 3m) | NM | Fall duration of 20 - 25 min. | NM |
| Cheng et al. [32] | Beagle Bone Black with Zig-Bee + XBee Cape and Series Pro 2B antenna | 1 | NA | S | Bathroom (1.95m x 3.1m) | Small and Large Objects | - | |
| Wang et al. [34] | Desktop + Laptops with NIC + CSITool. | 1 set | ✓ | S | 6m x 6m square room | Male - 12, Female - 5 | 150 | 200 |
| Zhang et al. [35] | Two laptops with Intel 5300 NIC | 1 set | ✓ | S | Bathtub | 1 | 2 | 1 |
| Duan et al. [36] | Wireless router + Laptop + Wi-Fi NIC card + CSI | 1 set | × | S | Home bathroom | 5 | NM[1] | NM |
| Tsuchiyama et al. [37] | Broadband horn antenna | 1 | ✓ | S | House toilet | 3 | NM | NM |

**Table 1** continued

| Res. work | Sensor details | # of sensors | Pos. Sen. | Fall Type | Environment | Subjects | Fall Events | Non-Fall Events |
|---|---|---|---|---|---|---|---|---|
| Saho et al. [38] | Doppler radar | 1 | ✓ | S | Restroom | 21 young men | Normal Bathroom actions | No Fall |
| Dobashi et al. [39] | Ultrasonic sensor UD-330 | 1 | ✓ | S | Bathroom | 3 | 2 | 1 |
| Huang et al. [40] | Ultrasonic sensor array | 1 | ✓ | S | 10’ x 10’ room | NM | NM | NM |
| Multimodal Systems | | | | | | | | |
| Makhlouf et al. [41] | Photoelectric + Accelerometer | Sp.[2] | × | S | Entire house | NM | NM | NM |
| Daher et al. [42] | Sensing Floor | 1 | × | R | Bathroom | 6 | 34 | 337 |
| Optical Fiber sensors | | | | | | | | |
| Nishiyama et al. [43] | Laser + photo diode attached to a rubber mats | Sp. | ✓ | S | Bathroom | 2 | NM | NM |
| Feng et al. [44] | Fiber sensor and cable | Sp. | × | S | Bathroom | 8 | NM | 3 |

[1] Not mentioned
[2] Specific to experimentation

illustrated the simple faint detection technique using a thermal imaging camera. The camera is positioned at 230cm height and 10 degrees from the horizontal axis of the site area. The system utilized the height and width of each frame of the thermal image for the extraction of features and classification. Shirogane et al. [26] have utilized the thermal camera for fall detection by investigating the camera position at multiple places during the experimentation. Four sensors were installed at four environmental locations to identify the normal and falling postures. The research works [24–26] generate a thermal image as data for the process of activity recognition in the bathroom using feature extraction and classification phase.

#### 3.1.2 Infrared sensor array

In general, an infrared sensor array uses an arrangement of the thermopile sensor array concerning the field of view. Each thermopile element of the infrared sensor contains the temperature value. Different sensors may be placed at various locations in the experimentation area to analyze the height and shape of the human body to monitor their activities. The infrared sensor array systems are utilized in the FADE systems as it is the most cost-effective and efficient in detecting fall [27]. Popescu et al. [28] have presented a vertical passive infrared sensors (PIR) array (VAMPIR) system that uses a vertical array of multiple PIR sensors. This system uses the advantage of the cost of PIR to form an inexpensive way of detecting a fall using the infrared signature. Four sets of two PIR sensors were arranged on vertical support 1 foot apart. The installed sensors have a filter that allows only infrared light with a 10-micrometer wavelength to reduce the effect of non-targeted sources. Sixsmith et al. [29] have presented a SIMBAD (Smart Inactivity Monitor using Array-based Detectors) using a low-cost, array-based passive sensor technology based on the use of pyroelectric infrared (IR) detector arrays. The SIMBAD is a prototype developed for fall detection. He et al. [30] proposed a non-invasive fall detector for bathrooms using a micro-electromechanical systems pyroelectric IR sensor (MEMS PIR) to produce the IR signature (pulse data) for activity recognition. Research works [28, 29] generate a 1-dimensional infrared signature (pulse data) for the process of activity recognition in FADEB.

#### 3.1.3 Wireless sensors/ devices

The wireless sensor/ devices have been implemented in the FADEB research as it has advantages such as low cost, contactless, non-light influence, and less privacy, etc. This section categorizes the wireless devices into Wireless sensor networks, Wi-Fi-based, radar-based, etc., and the detailed analysis is depicted as follows.
**Wireless Sensor Network (WSN)** The network consists of a spatially distributed sensor with one or more base stations (sink nodes) to monitor the activities in real-time. WSNs are mostly implemented to monitor activities such as temperature, vibration, or motion, etc., In an elderly monitoring application, the sink may communicate with the end-user via direct communications such as the Internet to report the fall and non-fall events. Khin et al. [31] have proposed a simple methodology using a WSN to detect the indoor falls. Two parallel layers of sensor nodes at different heights are deployed for monitoring fall and non-fall activities. The research work by [32] has developed a cost-effective fall detection and intervention system named FaDIS using a WSN. This work utilizes the WiFi-dependent assistive robotic system developed and deployed previously in the research work [33] to communicate with the XBEE modules to detect falls and other activities. The system has been implemented in a real-scale AAL environment. The sensory communication in terms of 1-dimensional data generated

between the transmitter and receiver nodes of the research works [31, 32] has been used to recognize the falls in the bathroom

**Wi-Fi Devices** Recently, the Wi-Fi-based FADE systems have become more prevalent [45]. These systems are highly utilized in indoor localization, positioning, and fall detection systems, and it has also been integrated with the bathroom. Wang et al. [34] have proposed a ToiFall, a prototype for syncope detection in the toilet environment. The system uses Laptops with NICs as sender and receiver Channel state information (CSI) tools developed by [46] on all three computers to transmit and receive CSI packets. Later, Zhang et al. [35] extended the work of [34] using commodity Wi-Fi devices to estimate the danger pose in bathrooms. This system used two laptops equipped with Intel 5300 NIC to transmit and receive Wi-Fi signals. The other laptop has been used for the server to store and process the CSI data collected at a rate of 20Hz on channel 40 in a 5-GHz band for a couple of hours on six different days. The above-reported papers on Wi-Fi-based FADE systems have certain limitations, such as environmental noise removal and moderate detection rate. Duan et al. [36] has proposed WiBFall - a Wi-Fi-based fall detection model for bathroom environments to overcome the issues. The system uses a wireless router as the transmitter and a portable computer terminal as a receiver. The portable computer is equipped with an 802.11 NIC card for data communication. In addition, the open-source CSI tool is installed on the receiving end device for real-time CSI data collection. In this phase of data collection, the CSI data also known as channel properties of a communication link has been used to determine the activities in a bathroom. The CSI information describes how the signal propagates from the transmitter to the receiver.

**Radar/ Radio sensor** The radar or the radio sensor system exploits the vital signs or characteristics of the Doppler signatures to analyze different features for identifying falls. Tsuchiyama et al. [37] have introduced a system that uses an ultra-wideband (UWB) radio sensor system to detect accidents inside the toilets. The UWB sensor was attached to the backside of the toilet seat lid, and various movements and states in the toilet were detected. A broadband horn antenna with a length of 4.9 cm and its opening is a rectangle with a height of 3.9 cm and a width of 3.2 cm. Installing the antenna on the back side of the toilet seat lid does not enter the user's sight in the toilet room and does not feel uncomfortable. Saho et al. [38] presented a radar-based remote measurement system with a Doppler radar mounted on the restroom ceiling and the wall. The system uses 24GHz continuous-wave radars with a $\pm 14^{\circ}$ plane directivity mounted to the wall. The radars were installed above 2.2m and 0.3 m behind the participant. The radar or radio sensors generate an analog signal to a specific device to recognize the activities.

**Ultrasonic sensor** The ultrasonic sensors use the 40Khz and 8 pulses signal waveform behaving as a receiver and transmitter to send the signal to a wireless device for event monitoring. The activity is monitored by measuring the time the signal takes to reach the reflector targets, the source sensors, and their relative distance. In FADEB systems, the sensors are positioned to array on top (ceiling), floor, or wall of the room. The threshold signal is analyzed to identify the activity as standing, sitting, or falling. The research work by Dobashi et al. [39] has proposed such a sensing system for detecting bather's fall for the benefit of Japanese people. The Ultrasound sensors are installed on the bathroom ceiling, which measures the distance between the sensor and a bather-implemented in a bathroom of 2200mm x 950 mm x 1400 mm (height x length x depth). On change in the distance, the system reports it as a fall. Huang et al. [40] introduced an automatic FADEB system using an array of ultrasonic wave transducers connected to a field-programmable gate array (FPGA) processor. Eight monitoring devices are installed on the wall during experimentation to monitor a person's activity inside a bathroom. The measure of distance between the sensor and an object within the shape of the ultrasonic wave up to a maximum distance of 254 inches and restricted to be used only in 10x10 room.

### 3.1.4 Multi-modal system

Recently, sensor fusions of heterogeneous devices have produced promising results in FADE systems [47]. The multi-modal system combines the 1-dimensional sensor data with 2-dimensional images sometimes for better recognition of activities. Multi-modal sensor fusion is highly used in smartphone sensor data with ambient sensors to improve the performance of the FADE systems. For the FADEB systems, Makhlouf et al. [41] have proposed a multi-modal system in an intelligent habitat to detect the fall of an older adult in the hall, kitchen, and bathroom. This methodology detects falls using the photoelectric sensors installed in the house and the accelerometer tied up with the older adult. The system has been simulated using Perinet. Daher et al. [42] have adopted a smartphone-based fall detection technique into a smart tile named INRIA-Nancy, i.e., tri-axial accelerometer and force sensors were concealed under intelligent smart tiles. This sensing floor consists of 104 tiles, each of 60*60 cm. This system originated primarily to avoid the false alarm rate between the lying down and fall posture. Tiles support a real-time process that ensures communication with their neighbors and any agent laid on them using ZigBee wireless technology. The force sensor used in the system permits detecting elders' falls, locating and tracking, and recognizing activities such as walking, standing, sitting, lying down, falling, transitions between them, etc. The sensor fusion has been performed between force sensor measurement and the accelerometer sensor decision to provide satisfactory results.

### 3.1.5 Optic fiber sensors

Optic fiber sensor cables are primarily used in communication systems as they are reliable for data transmission even if at a high cost [48]. These sensors have recently been integrated into FADE systems as they resist corrosion, electromagnetic inference, and waterproofing. The optic sensors generate an electric pulse on the bearing load of humans over the mat or the sensor fused in the ground area of activity recognition. Due to this nature, specific techniques have utilized the optical fiber sensors for bathroom FADE systems. Nishiyama et al. [43] has introduced a smart mat (thin mat) on the floor designed for human activity monitoring, especially in the bathroom. This mat uses a hetero-care fiber optic nerve sensor to detect activity on sensing pressure on human activities. The novel hetero-core optic fiber nerve sensor used in the system is sensitive to the bending action of the hetero-core position. Its fiber transmission line is unaffected by external circumstances and is lightweight and resistant to corrosion and electromagnetic inference. Feng et al. [44] have proposed a similar novel floor pressure imaging system using a smart floor embedded with pressure-sensitive fiber sensors for pressure imaging and prototype, respectively. This system is low-cost, unobtrusive, and waterproof. The smart floor prototype is tessellated with 7 x 7 grids of fiber sensors, and each grid is approximately 0.35 x 0.5 $m^2$, and thus, the dimension of the floor pressure image is 7 x 7. This system is highly interested in floor pressure imaging because it can sensitively detect the pressure imposed on its fiber cable while remaining robust to environmental noises.

#### 3.1.6 Audio based system

Kaur et al. [49] proposed a non-wearable, non-intrusive fall detection system for the bathroom using an autonomous mobile robot equipped with a microphone. This system utilizes the ambient sound recorded in the user's home and develops a solution based on a Transformer architecture. The proposed architecture takes noisy sound from the bathroom and classifies it into a fall/non-fall event.

### 3.2 Pre-processing

The pre-processing is highly required for machine learning-oriented tasks such as feature engineering/ selection and classification, especially in activity recognition as it involves human subjects for experimentation [21]. Noise may incur more error rates in the FADEB systems. Thus, the following section briefs about the FADEB systems that involve the pre-processing of signals/Images collected during data collection. Among all the FADEB, only limited systems have utilized a pre-processing module, as most of the system uses commercial devices for data collection that are not noise-prone.

Wong et al. [25] have acquired the thermal image camera as an RGB image and converted it into a binary image. The noise filtering removes noises, followed by morphological closing and hole filling to extract the absolute features. Wang et al. [34] extract the amplitude of CSI data by calculating the modulus of the CSI complex and then apply a 10-order Butterworth filter with a cutoff frequency of 40Hz on each row to remove the high-frequency noise. A centralization approach is also applied to remove static environmental components. It is also observed that CSI variance is sensitive to environmental changes, and thus variance-based method has also been implemented for movement segmentation. Zhang et al. [35] has performed amplitude and phase extraction, phase calibration, and Low-frequency information extraction. In the amplitude and phase extraction, amplitude and phase shift information are extracted from raw CSI data to avoid multi-reflection in an indoor environment. The phase information cannot be used directly due to the random noise caused by hardware imperfection and uncoordinated delay between transmitter and receiver. The phase calibration has been performed as given in [50]. In the low-frequency information extraction phase, the unnecessary high-frequency signals are filtered out using a fast Fourier transform (FFT). utilized the Butterworth high pass filter with a cutoff frequency of 30Hz to remove the zero-doppler frequency components, especially the echoes from static objects such as walls and toilet seats [38]. Kaur et al. [49] samples at a rate of 16 kHz, and converts raw audio to a 1-dimensional vector. In case of unequal size, the authors have padded with zero values.

### 3.3 Feature extraction

Feature extraction plays a vital role in any of the activity recognition processes [51]. The extraction of significant and vital features improves the recognition system's performance. This section briefly highlights the features extracted from 1-dimensional time series, quantitative, and 2-dimensional image data collected in the previous FADEB implementation. The detailed feature extraction analysis, pre-processing, dimensionality reduction, number (#) of feature extracted, and the feature type are highlighted in Table 2. The ✓ represents the phase of pre-processing and × represents vice-versa in the pre-processing column of Table 2.

**Table 2** Detailed analysis of features extracted by FADEB systems

| Res. work | Pre-proces. | Dimensionality Reduction | Feature Extracted | # of features | Feature Type |
|---|---|---|---|---|---|
| **Temperature-Point data** | | | | | |
| Kido et al. [24] | × | 2256 to 81 data points | Temperature data points | 81 | 1-d Vector data |
| Shirogan et al. [26] | × | 2256 to 552 data points | Temperature data points | 552 (l=23, w=24) | 2-d Quant. data |
| **Global Parameters/ Features** | | | | | |
| Wong et al. [25] | ✓ | Summing of 2-d pixels to numerical values | $H_p$,$H_c$,$W_p$,$W_c$ | 4 | Quant. data |
| Dobashi et al. [39] | × | × | Bathers height and Change in height inclination | 2 | Quant. data |
| Huang et al. [40] | × | × | Distance between the sensor and object | 1 | Quant. data |
| **Infrared Plux/ Energy features** | | | | | |
| Popescu et al. [28] | ✓ | × | 4 signals of 1-d time series data | 4 | Time series data |
| Sixsmith et al. [29] | × | × | Elliptical contour gradient | 16 x 16 | 2-d Quant. data |
| **Features from signals** | | | | | |
| Wang et al. [34] | ✓ | × | CSI Matrix | 96 features | Quant. data |
| Zhang et al. [35] | ✓ | ✓ | raw CSI data | 119324309863 | 1-d time series data |
| Khin et al. [31] | × | × | $\mu$ of RSSI in a window size | Depends on Window size | Quant. data |

**Table 2** continued

| Res. work | Pre-proces. | Dimensionality Reduction | Feature Extracted | # of features | Feature Type |
|---|---|---|---|---|---|
| Duan et al. [36] | ✓ | × | 1-d CSI sequence reconstructed to Frequency energy diagram | Duration of the activity | 2-d Quant. data |
| Tsuchiyama et al. [37] | × | × | Distance between RF signal and Objects | 3 distances | Quant. data |
| Cheng et al. [32] | × | × | Dimension of Laser Light | 5 | Quant. data |
| **Spectrogram Images** | | | | | |
| Saho et al. [38] | × | × | Spectrogram Image (Short Fourier Transform) | size of 168 x 218 x No of signals collected | 2-d Quant. data |
| **Multimodal features** | | | | | |
| Makhlouf et al. [41] | × | × | 3-d Accelerometer and Photo-electric sensor pressure | Duration of Activity | Time series and Quant. data |
| **Pressure exerted by Human body** | | | | | |
| Daher et al. [42] | × | × | Load force exerted in smart tiles | 5 x 11 | Quant. data |
| Nishiyama et al. [43] | × | × | db of hetero-core fiber sensor | depends on the object/subject pressure | Quant. data |
| Feng et al. [44] | × | × | Histogram of Floor pressure image | Distance between the histogram images | Quant. data |

#### 3.3.1 Temperature-point data

The thermal image consists of 47 * 48 = 2256 temperature-point data obtained at 3 Hz intervals. To reduce the data analysis, Kido et al. [24] have reduced the data points into 9*9=81 areas, where the average temperature of each area was determined with a discrimination rate for the fall detection. Among the 81 areas of data points, certain independent variables have been assigned for the discrimination. In this method, the discrimination rate is analyzed automatically by the SPSS tool to identify the normal and fall patterns. Shirogane et al. [26] have reduced the 2256 data points of a thermal image into 552 points of 23 x 24 (length x width). Then the discriminant formula has been extended from [24] in which four necessary independent variables are considered for discrimination. In this method, the discriminant formula completely depends on the behavior of the four subjects involved in the experimentation.

#### 3.3.2 Global parameters/ features

Wong et al. [25] extracted four global features $H_p$, $H_c$, $W_p$, $W_c$ that highly depend on the height and width of the person in the previous and current thermal images. $H_p$, $H_c$ is a human's height in the previous and current images. $W_p$, $W_c$ is the human's width in the previous and current image, respectively. In this approach, the pixel contents in each column and row are summed up from the pre-processed thermal binary image to identify the $H_p$, $H_c$, $W_p$, and $W_c$ to form a statistical classification model. Dobashi et al. [39] et al. utilize the ultrasound sensor with a status identification system to identify the bather's status. The height of the bather's head as the global feature has been used to determine the status as a standstill, sit, or tumbled. This global feature has been further extended as a degree of change (DC) metric using the least square metric to identify the bathers' frequent movement. Similarly, Huang et al. [40] measures the distance between the sensor and an object within the range of an ultrasonic wave. When an object is detected in the field of active sensor, it locates the distance within one inch of resolution for the activity recognition.

#### 3.3.3 Infrared plux/ energy features

Popescu et al. [28] utilize the differential voltage induced by the VAMPIR sensor energy on the movement/ reflection of human bodies. The positive voltage will be induced on the sensing left surface of the human body, and the negative voltage on the sensing right surface. In this method, the authors have used 8 different sensors from the VAMPIR array to process the person's behavior concomitantly. In another view, Sixsmith et al. [29] utilize an elliptical gradient contour tracking system to identify and track an elliptical target (human body) using the sensory array. The system can track targets exhibiting positive and negative contrast with the background and provides real-time estimates of target position, velocity, and shape/size.

#### 3.3.4 Features from signals

Wang et al. [34] have constructed the CSI matrix from the receiver and transmitter systems to reflect the textures of human movements. 15x15 Gabor filters of eight scales and six orientations have been applied for texture feature extraction. In addition, for each convoluted CSI matrix image, mean and standard deviation are extracted to form 6x8x2=96 features. Similarly, Zhang et al. [35] have extracted static features for activity recognition utilizing background subtraction to difference the reception antennas on each subcarrier, normalization of CSI data onto a value in a range of [0,1], and anomaly detection. In the case of danger detection, the dynamic dominant CSI features have been extracted using sliding window difference, normalization, and smoothing processes for classifying the danger and normal poses.

Khin et al. [31] have analyzed the received signal strength indicators (RSSI) of each pair of sensor nodes deployed indoors to monitor human activities. The authors have investigated various network configurations for the installation of devices by measuring the signal strength of human presence in the environmental setup. Duan et al., [36] reconstructed the CSI amplitude data with the feature characterization method, also known as feature reconstruction using [52]. This process has reconstructed the one-dimensional time series CSI data into a two-dimensional frequency diagram. Later the Butterworth filtering was applied as a post-processing filtering method to improve the classification performance.

Tsuchiyama et al. [37] utilize the UWB sensor to generate signals in range profile to identify the presence of human subjects inside the bathroom. These signals are monitored at three different places, and the fluctuation ratio of all these signals based on threshold has been used to identify the behavioral change of a person. Cheng et al. [32] have extracted the laser light features on the presence of humans inside the toilet. This system has five different laser lights. On the movement of a human, each light will be turned on to activate the impulse for recognition of activities.

Kaur et al. [49] utilize log mel spectrograms, raw audios, and a novel set of features for audio, termed “Diff” features for the recognition of activities.

#### 3.3.5 Spectrogram images

Saho et al. [38] utilized the short-time Fourier transforms (STFT) to convert the received antenna (wireless) signals to spectrogram images (time-velocity-power distribution images).

#### 3.3.6 Multimodal features

Makhlouf et al. [41] integrate the 9-axis accelerometer signal obtained from the accelerometer device placed on the belt to track the person’s activity, such as standing, sitting, walking, etc. Then the photoelectric sensor pressure obtained from the door handle, wash basin tap, etc. has been used to analyze the door’s opening/ closing, etc. In this method, these two features are combined to analyze a person’s activity.

#### 3.3.7 Pressure exerted by human body

Daher et al. [42] measure the load forces exerted on the floor that can be used to determine the posture of the monitoring person. This approach collected the pressure amount, pressure duration on a smart tile and the tiles’ proximity for classification. Nischiyama et al. [43] also collect pressure monitoring by detecting changes in optical loss of the hetero-core sensors available with the smart bathroom mats. The changes in the decibels (dB) and time response of the hetero-care sensors have been applied with a relative algorithm for classification. Alternatively, Feng et al. [44] have identified the floor pressure imaging of the fiber optic cable in the presence of a human. The imaging has been projected, and the corresponding histogram has been identified with a distance measure to classify the events.

### 3.4 Classification

Classification, also called activity recognition, results in activities based on the features collected from the data sources. The classification process is mostly supervised and can be done through machine learning, deep learning, or graphical models. The FADEB systems additionally involve rule-based classification where the threshold or rules are inferred from the training process to recognize the activities. The performance of activity recognition is measured only through the results of the classification task in terms of Accuracy (Acc.), precision (Prec.), recall (Rec.), and F1 score (F1). The detailed report on performance analysis of FADEB systems concerning the classifiers is shown in Table 3.

#### 3.4.1 Machine learning based classification

In the machine learning-based classification, most of the FADEB system involves a supervised learning mechanism in which the training data is targeted with a class label. Zhang et al. [35] utilizes a one-class support vector machine (SVM) to classify danger and non-danger positions from the static and dynamic features collected during the process. Wang et al. [34] utilize SVM and ResNet for the classification of fall and non-fall events prescribed by the CSI features extracted. Popescu et al. [28] utilize the graphical model - Hidden Markov Model (HMM) to classify the activities inferred by the signal generated from the VAMPIR array. The ROC curve has been inferred from the data observed during experimentation. He et al. [30] used a Backpropagation neural network to classify the event as non-fall and fall events.

#### 3.4.2 Rule based classification

The Rule-based classification classifies the activity into a normal and falls based on the threshold or rules inferred by the system. Kido et al. [24] have proposed a rule-based classification in which the discriminant ratio is calculated based on certain independent variables of the temperature data point. The resultant value is identified to be a fall if the discriminant ratio of $Z < 1.2655$ else a normal activity. Shirogane et al. [26] extends the inference rule of [24] by reducing the independent variables of the temperature data point and inferred the discriminant ratio as $Z < 0$ to be normal else fall. Khin et al. [31] also induce the rule-based classification based on the inequality that arises with $\mu$ of the RSSI value in sliding window size. The presence and absence of humans are identified based on comparing two consecutive window sizes using the inequality rules.

Tsuchiyama et al. [37] have also proposed a rule-based classifier to classify the state as normal/dangerous by checking the fluctuations of a person's height using three different distance measures of the sensor. Cheng et al. [32] favor a rule-based classification. This method uses the number of instructions executed by the XBBBEE to infer the rules. Dobashi et al. [39] have utilized a similar rule-based method to classify the accident and normal behavior using the height and change in the height inclination of the human body. Research work by Feng et al. [44] has compared the histogram of pressure images using a Euclidean distance to infer the activity as normal and fall. Wong et al. [25] have utilized the complex rules from the height and width of the person to classify the activity. Similarly, Huang et al. [40] also utilize the change in the height and clock time as a rule to classify the images. Sixsmith et al. [29], another rule-based classification mechanism classifies the activity based on the pressure exerted in a 16x16 pyroelectric array. Makhlouf et al. [41] infer two rules one for the accelerometer signal and the other for the photoelectric sensor placed on the door

**Table 3** Performance Analysis of FADEB systems

| Res. work | Classifier | Performance Analysis | Remarks/ Future Scope |
|---|---|---|---|
| **Rule based classification** | | | |
| Kido et al. [24] | Rule-based | Acc. 97.5% | Applicable to specific independent variable data points. Lowest discrimination rate. Asymmetric motion patterns into fall discrimination data by adding time-series elements to the FADEB. |
| Wong et al. [25] | Rule-based | Acc. on Poor lighting 96.15% and Indoor 86.19% | Applicable for a specific environment. To be executed for multi-residents and animals |
| Shirogan et al. [26] | Rule-based | Acc. 97.8% | Lowest discrimination rate @ 60.2%. Fall posture is planned to recognize the entire human body |
| Sixsmith et al. [29] | Rule-based | Prec. 66.19%, Rec. 79.82%, Acc. 77.27% | Tested with a prototype |
| Khin et al. [31] | Rule-based | Not Applicable | Inequality rules has been framed from the training data |
| Cheng et al. [32] | Rule-based | Not Applicable | Only feasibility analysis has been conducted |
| Tsuchiyama et al. [37] | Rule-based | Acc. 95.5% | Error rate $< 0.8$. To involve subjects of various ages, especially the elders |
| Dobashi et al. [39] | Rule-based | Acc. 100% | Rule is not given for the recognition and to experiment the person with different physique. |
| Huang et al. [40] | Rule-based | Not Applicable | Only prototype has been deployed and planned to make it user-friendly |
| Makhlouf et al. [41] | Rule-based | Not applicable | Only timestamp of fall has been identified based on fused data |
| Nishiyama et al. [43] | Rule-based | Not Applicable | Only prototype has been deployed |
| Feng et al. [44] | Rule-based | Prec. 97.6%, Acc. 97.667 % | Implementation is costlier and planned to distinguish the pets and humans |

**Table 3** continued

| Res. work | Classifier | Performance Analysis | Remarks/ Future Scope |
|---|---|---|---|
| Daher et al. [42] | Rule-based | Sensitivity >90% | Less Privacy. |
| **Machine Learning based classification** | | | |
| Zhang et al. [35] | 1-class SVM | Prec. 83.61% Rec. 96.23% F1 89.47% Computation Time 5.20s | Less amount of activity has been considered for experimentation |
| Popescu et al. [28] | HMM | Not Applicable | Only ROC Curve inferred, to investigate with multiple sensors |
| Wang et al. [34] | SVM | Prec. 98.0% Rec. 98.7% Acc. 98.6% | Toilet normal activities hasn't been categorized |
| He et al. [30] | BP | Prec. 94.5%, Rec. 90.94%, Acc. 92.81%, F1-92.66% | Infrastructure is robust and not feasible to implement at low cost. |
| **Deep Learning based classification** | | | |
| Duan et al. [36] | CNN | Acc. 99.63% | Accuracy improvised due to post-processing by Butterworth filter |
| Wang et al. [34] | ResNet | Prec. 98.0% Rec. 100.0% Acc. 99.1% | Toilet normal activities hasn't been categorized |
| Saho et al. [38] | CNN | Acc. 95.6±2.28% | Only young people participated with limited of 8 behaviours |
| | LSTM | Acc. 83.2±3.93% | |
| Kaur et al. [49] | Transformer + MLP | Acc. 86.73% | Requires an autonomous robot for the recognition |

handle for the activity classification. Similarly, Nishiyama et al. [43] and Daher et al. [42] discover the rule for classification using a threshold value of the feature extracted during the training phase.

#### 3.4.3 Deep learning-based classification

Deep learning algorithms have emerged on a large scale because of their efficiency in classification without an exclusive feature engineering/ selection process. Recently, deep learning algorithms have played a significant role in activity recognition, especially in fall detection [53]. Duan et al. [36] introduced a neural network architecture based on a Convolutional neural network to classify two-dimensional CSI data. The network has ConvBatchNormalization, Conv2D, and ConvBatchNormalization concatenated with two ConvBatchNormalization layers. Then the layers are again concatenated to the GlobalAveragePooling layer and finally classified using the softmax classifier. Wang et al. [34] utilize ResNet, a one-dimensional model for the classification of fall and non-fall events prescribed by the CSI features extracted. Saho et al. [38] utilize both CNN and LSTM to infer exclusively the activities of fall and non-fall by analyzing the wall and ceiling radar spectrogram images. Kaur et al. [49] utilize the transformer encoder layer and a multi-layer perceptron to classify the events as fall and non-fall. The system has achieved an accuracy of 86.73%.

### 3.5 Critical comparisons

In addition to the above comparisons, specific effective and quantitative parameters listed in Table 4 are analyzed for the critical comparison of each FADEB system. Cost-effectiveness is significant for replicating the experimentation for future development. As the FADEB involves elderly persons' health care, the systems should be robust enough to noise and illumination. As vision systems are most sensitive to illumination and thus a detailed analysis of illumination is considered. Scalability is another component, as the elderly may have a large actuation area in / her house. The system needs to cover up his entire actuation area in this scenario. Installation of these systems may sometimes be complicated, and the particular system is easy enough to place in the experimentation environment. A water-resistant system is highly required as the systems are supposed to handle older adults with water inside the bathroom. Finally, the non-intrusiveness of the devices is highly important because the elders could not wear or take any device with them during the bathroom access or pee inside. Privacy awareness is the most critical factor; the monitoring is entirely inside the bathroom. No elders may prefer to record or capture any content that may intrude on their privacy. The detailed analyses of all these parameters are compared and are shown in Table 4. The tick mark represents the availability of that respective facility or the quantitative parameters of the system. The cross mark represents the vice versa of the tick mark.

In addition to the comparison of the effective and quantitative parameters of the existing FADEB systems, the factors that influence and facilitate the process of FADEB have been discussed in Table 5. The facilitating factors of FADEB systems are mostly the data that have been collected from the device/ system installed in the bathroom. In specific, each device/ system has certain data that provide more information regarding the activity which has been carried out inside the bathroom either in terms of image, signal or time series data, etc., In mean meantime, more influencing factors affect the performance of each FADEB system such as position sensitivity of the device, number of devices installed, ambient temperature,

**Table 4** Effective and Quantitative parameters of Fall Detection Systems in Bathrooms (FADEB)

| Research Work | Cost | Sensitive to Noise | Sensitive to illumination | Scalability | Installation Feasibility | Water Resistant | Non-Intrusive Device | Privacy aware |
|---|---|---|---|---|---|---|---|---|
| Kido et al. [24] | Low | × | Sometimes | × | ✓ | × | ✓ | ×(Elders wont trust) |
| Wong et al. [25] | Low | × | Sometimes | × | ✓ | × | ✓ | ✓ |
| Shirogan et al. [26] | Low | × | Sometimes | × | ✓ | × | ✓ | ×(Elders wont trust) |
| Popescu et al. [28] | Medium | × | × | × | × | ✓ | ✓ | ✓ |
| Sixsmith et al. [29] | Medium | × | × | × | × | ✓ | ✓ | ✓ |
| He et al. [30] | High | × | × | × | × | × | ✓ | ✓ |
| Khin et al. [31] | Medium | ✓ | × | × | × | × | ✓ | ✓ |
| Cheng et al. [32] | Medium | ✓ | × | × | × | × | ✓ | ✓ |
| Wang et al. [34] | High | ✓ | × | × | × | × | ✓ | ✓ |
| Zhang et al. [35] | High | ✓ | × | × | × | × | ✓ | ✓ |
| Duan et al. [36] | High | × | × | × | × | × | ✓ | ✓ |
| Tsuchiyama et al. [37] | Medium | ✓ | × | × | × | × | ✓ | ✓ |
| Saho et al. [38] | Medium | ✓ | × | × | × | × | ✓ | ✓ |
| Dobashi et al. [39] | High | ✓ | × | × | × | × | ✓ | ✓ |
| Huang et al. [40] | High | ✓ | × | × | ✓ | × | ✓ | ✓ |
| Makhlouf et al. [41] | High | × | ✓ | ✓ | × | × | ✓ | ✓ |
| Daher et al. [42] | High | × | × | × | × | ✓ | ✓ | ✓ |
| Nishiyama et al. [43] | High | × | × | × | × | × | ✓ | ✓ |
| Feng et al. [44] | High | × | × | × | × | × | ✓ | ✓ |
| Kaur et al. [49] | High | × | × | ✓ | × | × | ✓ | ✓ |

**Table 5** Factors that influence and facilitate the task of State-of-the-art Fall Detection Systems in Bathrooms (FADEB)

| Research Work | Facilitating factors of FADEB systems | Influencing factors of FADEB systems |
|---|---|---|
| Kido et al. [24] | Heat map of a thermal image camera | Position sensitivity of a thermal camera and Resistance to Ambience Temperature |
| Wong et al. [25] | Heat map of a thermal image camera | Position sensitive and Requirement of multiple devices that is costlier |
| Shirogan et al. [26] | Heat map of a thermal image camera | Position sensitive and Requirement of multiple devices that is costlier |
| Popescu et al. [28] | Analog data of PIR sensor Array | Requires to install multiple devices in 360 degrees to detect all the fall and non-fall activities |
| Sixsmith et al. [29] | Pyroelectric ceramic material | Pet and kids may distort the loads of ceramic material that leads to false alarms |
| He et al. [30] | MEMS sensor data with Edge device | High latency (response time is high) and less scalable |
| Khin et al. [31] | Changes in the received signal strength indicators of sensor nodes | Sensitive to the position of transmitter, receiver, and height of the person. Less chances to detect a person with mobility (wheel-chair) |
| Cheng et al. [32] | BeagleBone Black development platform serves as the sink node | Implementation is infeasible in real-time environment + costlier + High maintenance |
| Wang et al. [34] | Textures of CSI images | Sensitive to the device and transmission speed |
| Zhang et al. [35] | Static and dynamic features of CSI data | Computation time is costlier, requires high-end computer system to process the data |
| Duan et al. [36] | Time series CSI data | sensitive to noise and specific fall activities |
| Tsuchiyama et al. [37] | Respiratory data using ultra-wideband radio | prone to radio waves |
| Saho et al. [38] | Doppler radar data | Sensitive to the location of the device and motion features are not significant enough to implement in real-time |

**Table 5** continued

| Research Work | Facilitating factors of FADEB systems | Influencing factors of FADEB systems |
|---|---|---|
| Dobashi et al. [39] | Ultrasound sensors | Position sensitivity and prone to radiation |
| Huang et al. [40] | Ultrasonic wave transducers of FPGA array | sensitive to noise and signal |
| Makhlouf et al. [41] | Accelerometer and Photoelectric sensors of Petrinets | Not compatible to wear a belt that has three-dimensional accelerometer throughout the day + Battery lifetime of accelerometer device |
| Daher et al. [42] | Load exerted in the smart tile | Load similar to human such as Dog, objects such as gas cylinders, recognition of children, etc., |
| Nishiyama et al. [43] | Smart pressure sensing mats | costlier + Pet, object and kids Identification are infeasible |
| Feng et al. [44] | Pressure image on the smart floor | Objects such as bucket of water, stool, Partial lying of human and Pets |
| Kaur et al. [49] | Audio waves | Requires a high cost autonomous robot for the activity detection |

illumination, etc., The detailed specification of the facilitation factors and influencing factors of each FADEB system regarding the task has been listed in Table 5.

## 4 Scope for future enhancements

Various researchers have proposed specific techniques for detecting elders' falls in bathrooms/toilets using floor sensors, fiber optics, wireless/radar sensors, etc. However, specific challenges/ limitations of the state-of-the-art FADEB systems need to be addressed to improve the performance of FADE systems in toilets/bathrooms/restrooms, which can increase the market penetration of smart home systems.

**Optimal attachment of sensors/ devices** The state-of-the-art experimentations have been carried out by installing the devices/ sensors specific to their experimental setup. For instance, the research works [24, 25] have installed thermal image cameras at respective heights to track the activity of a human. The environment may change from one place to another place during the implementation. More investigation must be performed on placing the device/ sensors at an optimal position to improve the bathroom fall detection performance. Generic distance of height or positioning of sensors/devices may increase the commercialization of the research works; thereby, the falls inside the restrooms can be easily detected in a shorter duration.

**Benchmark Datasets** The existing research works have conducted the experimentation for a specific environment, and the collected data is not shared for replication by other researchers. There is no convincing benchmark dataset that could provide a golden standard for comparison and evaluation. It will be beneficial to improvise the performance of the existing systems in case of generating benchmark datasets in the area of FADEB systems. Real-time experiments can be conducted for a longer duration with diverse participants to generate a vast and balanced benchmark dataset.

**Real-time detection** The research works proposed on FADEB is completely an offline system (completely collected from the literature) and no system is completely online that detects falls in real-time. Now it's highly required to create a real-time system that can work online to deal with real-world scenarios.

**Privacy Protection** From the user's perspective, privacy is the major challenge for fall detection inside the bathroom, especially since the vision-based system can take part in the implementation. Though a thermal, Kinect camera can be used as an alternative measure to deal with depth images and skeleton data, many people don't prefer to use a camera inside the bathroom for monitoring, especially the elderly person. Security and privacy is therefore another topic that must be addressed in our opinion in cohesion with FADEB systems.

**Complex/ Asymmetric Activities** The research works have proposed a fall detection with simple normal and abnormal behaviors inside the bathrooms. There are no specific fall-like activities such as sitting, crawling, bending, searching under comfort, and cleaning the floor have been dealt with. It must be incorporated into the FADEB systems. Activity such as pulling down the pants and sitting in the comfort is sometimes considered as an anomaly, and that, too, in the case of elderly posture, is confirmed to be a fall. A more complex system must be modeled to classify the complex/ asymmetric activities.

**Subject at different ages** State-of-the-art mainly involves only young and healthy residents for experimentation, that too mostly male adults. There is an urgent need to deal with the wise scale of age people ranging from adult to elderly person. Research work [25] et al alone has experimented with a 70-year-old female lady who faints often. The other research works have been carried out in the controlled laboratory with the participants as their research lab students. The involvement of a wide scale of people may improve the commercialization aspect of the FADEB systems.

**Disabled/ Elderly people** As quoted in the previous scope, research works have considered only healthy young adults for experimentation. People with specific characteristics of high fall risks such as hemiplegic persons, stroke patients, or wheelchair users, must be considered for the experimentation. In particular, a wheelchair may hide/ block the sensor activity, which is placed on the floor for detecting a fall. Thermal cameras have to be tuned concerning the height of the bather to completely monitor their activities. A completely moderated structure of experimentation has to be carried out in this case.

**Unconstrained Monitoring** Mostly the falls are simulated by a healthy young adult subject and not in real-time by an elderly patient due to medical constraints. The young energetic may have a change in motion dynamics, which does not appear to be with an elderly person. As listed in Table 4, most of the experimentation considers only healthy and young adults. This proposed system may result in false alarms if implemented in real-time for the elderly restrooms.

**Performance Analysis (Effectiveness)** Activities considered in the state-of-the-art research work as listed in Table 1 have less duration (frames). The number of activities for the fall events considered in the experimentation is also less. In comparing the performance metrics of the existing works with Table 3 for these less data, the performance seems to be fair enough, however there is no specific/generalized machine/ deep learning algorithms have been implemented. The state-of-the-art has mostly discussed the deployment and inference of rules for the experimental setup. Proper performance analysis may inculcate novice researchers' research habits in FADE research. Moreover, the performance rate has more chances to be improved by providing a valuable/ efficient system to classify similar falls and non-fall events.

**Communication protocol** The research works proposed in Section 3 have no cause of communication effects and latency to report if the fall happens. Not a single research work deals with computation time except the research work by [35]. A proper communication protocol with efficient computation time for detecting falls to reduce the anxiety and fear of elders from further consequences of a fall is highly required for real-time implementation. In certain experiments, as quoted above, the falls are detected in an average time of 1.5 minutes [54]. These systems may have high chances of mortality to the elderly due to pain if they felt a severe bone fracture or other injuries.

**Device Invasiveness/ Intrusiveness** The state-of-the-art research works especially those that work with optical fiber, wi-fi devices, laser lights, and PIR sensor arrays have challenges with device invasiveness. They are not prone to water and dust. Smart mats (thins mats) proposed in [43, 44] have the option to short-circuit from the link if there is a heavy load of a human or water rolled over on it. More devices/ sensors can be investigated for FADEB systems that are not sensitive to noise, privacy intrusion, and security for elderly persons. In addition, the deployed system should be less costly in real-time implementation.

**Investigation on Deep/Machine Learning Models** The state-of-the-art works proposed in the literature deal mostly with the rule-based classifiers as detailed in Table 3. The rule-based system works perfectly for a numerical value and mathematical analysis for a certain experimental setup. It is not commonly applicable for the real-time implementation. Deep learning and machine learning models have evolved highly in the area of activity recognition systems, and it has provided promising results. More deep learning models, especially the transfer learning and pre-trained models need to be investigated to improve the performance in the case of 2-dimensional data. In the case of 1-dimensional feature representation self-attention mechanisms, pre-trained 1D models have to be investigated. For the machine learning-based models, an investigation has to be carefully carried out in the field of feature extraction and selection to improve the performance of activity recognition in FADEB systems.

**Zero/ No Luminance** Experimental setup of the state-of-the-art research works has been carried out in the controlled laboratory or the normal bathroom setup or apparatus. The concept of luminance doesn't take place in any of the FAEB systems proposed earlier. The systems should also be designed in a way that can work with or without proper luminance.

## 5 Conclusion

The motivation and background of this article are to list the open challenges and issues faced by the elders in an indoor smart / non-smart home environment. A specific fall detection system in the bathroom/ toilets has been analyzed as water is the most dangerous, which leads to slips and falls. Unnoticed falls and slips may lead to anxiety and fear, even leading to death. However, there are specific fall detection systems integrated into indoor home environments. This article implies the tremendous scope for the researchers involved in the interoperability aspect of smart homes and activity recognition, especially fall detection systems in bathrooms/ toilets.

**Data Availibility Statement** Data sharing not applicable to this article as no datasets were generated or analyzed during the current study

## Declarations

**Conflict of Interest** The authors declare that they have no conflict of interest.

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