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An architectural framework of elderly healthcare monitoring and tracking through wearable sensor technologies

Abeer Alsadoon[1,2,3] · Ghazi Al-Naymat[4,5] · Oday D. Jerew[3]

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Abstract
The growing elderly population in smart home environments necessitates increased remote medical support and frequent doctor visits. To address this need, wearable sensor technology plays a crucial role in designing effective healthcare systems for the elderly, facilitating human–machine interaction. However, wearable technology has not been implemented accurately in monitoring various vital healthcare parameters of elders because of inaccurate monitoring. In addition, healthcare providers encounter issues regarding the acceptability of healthcare parameter monitoring and secure data communication within the context of elderly care in smart home environments. Therefore, this research is dedicated to investigating the accuracy of wearable sensors in monitoring healthcare parameters and ensuring secure data transmission. An architectural framework is introduced, outlining the critical components of a comprehensive system, including Sensing, Data storage, and Data communication (SDD) for the monitoring process. These vital components highlight the system's functionality and introduce elements for monitoring and tracking various healthcare parameters through wearable sensors. The collected data is subsequently communicated to healthcare providers to enhance the well-being of elderly individuals. The SDD taxonomy guides the implementation of wearable sensor technology through environmental and body sensors. The proposed system demonstrates the accuracy enhancement of healthcare parameter monitoring and tracking through smart sensors. This study evaluates state-of-the-art articles on monitoring and tracking healthcare parameters through wearable sensors. In conclusion, this study underscores the importance of delineating the SSD taxonomy by classifying the system's major components, contributing to the analysis and resolution of existing challenges. It emphasizes the efficiency of remote monitoring techniques in enhancing healthcare services for the elderly in smart home environments.

Keywords Wearable sensing devices · Cloud computing · Sensors · Artificial intelligence · Elderly healthcare

Extended author information available on the last page of the article

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1 Introduction

The elderly in smart home environments always require more remote medical support; they also need to visit doctors frequently [1]. The implementation of wearable sensors helps to design suitable healthcare systems for the elderly in smart homes [3]. It has been identified that the human and machine interface increased vividly [6]. In this way, smart sensors are used for monitoring vital healthcare parameters of the elderly in smart homes [12]. Elderly healthcare is maintained in the context of home-oriented health monitoring systems, monitoring of the elderly, and remote medical [19]. Elderly healthcare monitoring is the systematic and continuous tracking, assessment, and management of the health and well-being of elderly individuals.

Furthermore, smart sensor technology is employed to offer assistance and alleviate discomfort for the elders. Thus, it is essential to design robust sensor-based healthcare monitoring and tracking [71]. Therefore, the research aimed to monitor and track vital healthcare parameters for maintaining elderly care [11]. Also, monitor and track the situation of elderly people in the smart home environment. This can be done through wearable sensor technology accurately attached to the elderly by using various intelligent sensors that monitor and analyze their activities such as heartbeat, etcetera [15]. The components of the system are sensing data storage and data communication [7]. These components are important for wearable sensor technology for elderly care [67].

To define the issue of certain research domains, wearable sensor technology is implemented by remote monitoring techniques for people [22]. The particular technology is applied in the domain of elderly care to monitor and track healthcare parameters [90]. The limitation of the technology is identified as inaccurate monitoring of various healthcare parameters [24]. Other limitations of wearable sensors include the intrusive nature and potential user discomfort. In practice, the choice of wearable sensors depends on the specific application and user comfort considerations. The proposed taxonomy aims to implement wearable sensors for healthcare parameter monitoring [34]. Moreover, the smart sensors monitor and further track the vital parameters for maintaining elderly care [88].

Towards that, SDD (Sensing, Data storage, Data communication) taxonomy is used so that wearable technology and monitoring techniques can be accurately combined in elderly care [54]. In this taxonomy, we followed a similar methodology used in [91] and [92], which has been very useful and helpful in healthcare.

The research focuses on analyzing and evaluating the latest literature on wearable sensor technology and monitoring and tracking techniques used for monitoring and tracking various healthcare parameters from the elderly's body [35]. Also, the feasible monitoring of healthcare parameters improved the wearable technology system towards providing robust and sophisticated services to the elderly living in smart home environments [62, 72]. Moreover, classifying various major components helps analyze and evaluate solutions to existing problems [37]. The detailed system is quite crucial in the elderly care domain. This is because remote monitoring techniques are more efficient than other healthcare techniques [56].

There is a limitation in the current solution, which could have provided real-time healthcare monitoring and tracking frequently [69]. The detailed model improved the problems identified in the existing solution by implementing a robust SDD taxonomy that helps regularly and frequently monitor and track elderly healthcare parameters in the smart home environment [57]. Further, SDD taxonomy helps in sensing various healthcare parameters, sensed data classification on the required criteria, and communication of various classified and analyzed data to the respective healthcare provider to achieve high accuracy and healthcare security for elderly people in the smart home environment [45].

The research project is structured into distinct sections. Section 2 commences with a literature review, where numerous papers are gathered, and relevant components are identified. Sections 3 and 4 also offer an advanced solution by utilizing the system components. Section 5 introduces a proposed model that enhances the state-of-the-art solution using algorithms and diagrams. Section 6 evaluates and validates the system, while Section 7 verifies the proposed system. Finally, Section 8 and 9 delve into discussing the research findings and presenting the conclusions, respectively.

2 Literature review

The other researchers have used fewer components in their taxonomy, such as one or two, but three central components are used in this research. Further, our proposed SDD taxonomy aims to help researchers improve healthcare monitoring of various healthcare parameters through wearable sensors. The research has focused on proposed techniques and algorithms that can be used to improve the accuracy of monitoring and tracking various healthcare parameters of the elderly in the smart home environment. The methods and tools suitable for the research domain can be deployed to improve the monitoring accuracy of healthcare parameters in the healthcare industry. The literature review section is divided into three major sections based on the SDD taxonomy: sensing various healthcare parameters using wearable sensors, storing sensed data using monitoring techniques, and communicating healthcare data.

Robot-integrated smart home (RiSH) has been proposed for improving the security of elderly people in smart homes and monitoring various healthcare parameters through wearable sensors [70]. They proposed a solution to resolve the existing problem by using RiSH, a robotics-based system that improved the safety of elderly people in smart homes. The result reveals that the overall accuracy of healthcare parameters detection has achieved 80% [13]. In the words of [4], accelerometer sensors are used for accurately sensing walking and movement-related motions. An improvement of 78.69% has been achieved by implementing the proposed machine learning algorithm in comparing the existing solution [76]. Also, the elderly walking is monitored to improve the healthcare of elderly people. This solution provides a special prototype that develops and reflects in the health care of the human. The Optical flow feedback convolution neural network for improving elderly posture recognition was proposed by [64]. The features that are identified in the system are machine learning models, motion detection, and recognition. Further, the results reveal that the current ratio has achieved 82.7% accuracy. Constrained Markov Decision Process (CMPD), Adaptive Learning Algorithm introduced towards optimizing the energy consumption in intra and beyond networks while communicating the monitored healthcare data, proposed by [1]. The intelligent algorithm has proven to achieve a 100% throughput improvement in various power consumption budgets [55]. The current solution is much more valuable because of its advancement than the other available solutions and has achieved all the promised results. BAN logic model and mutual authentication have been detailed for improving patient health and the precision medical field [83]. The current solution is valuable because it solves two major problems. First, it increases the productivity of the medical field, and second, it increases the network's lifespan by minimizing energy consumption [58]. The proposed solution has increased the network's life and the production of healthcare monitoring.

An established machine learning-based accelerometer used to monitor the walking parameters for improving the healthcare of elderly people was introduced by [63]. Further, inertial motion units and accelerometer signals are used for communicating the accelerometer data [61]. It provided vital information about the elderly walking, i.e., age and surface information. Moreover, the precision achieved 95.2%. Machine learning algorithm-based robust wearable sensors to monitor the healthcare parameters for improving the health of elderly people in the smart home environment was proposed by [38]. Towards that, robust biomedical sensors and wearable inertial sensors are equipped for domestic monitoring [36]. Even though data storage and high operational costs remain issues in the proposed system, the equipped sensors achieved an accuracy of (mean ± std = 0.99 ± 0.01). The proposed activity testing algorithm aimed to present an activity testing algorithm towards improving the healthcare of the elderly in smart homes with feasible activity prediction [10]. Recurrent neural networks are used for encoding sequential time information [59]. The detailed solution has achieved a mean accuracy of 99.52% during the sensor-based features based on Recurrent Neural Network (RNN). Other machine learning and deep learning algorithms were proposed to monitor various activities performed by the elderly in smart homes [32]. The convolutional neural network-based (CNN) algorithms have improved the classification accuracy of activity recognition. The CNN layers achieved a classification accuracy of 90.9%, even with the limited number of sensors [53].

Big data analytics have been detailed in managing healthcare data using Internet of Things (IoT) devices [5, 95]. Further, the sleep disorder factors are monitored through robust wearable sensors. The cloud layer accurately manages, analyzes, and stores the monitored data [8]. The proposed system monitored the air quality index prediction with 93.3% accuracy. The engine based on the formal concept analysis was proposed to provide real-time cognitive assistance [66]. The formal concept analysis proposed analysis system has been used to improve activity recognition accuracy. The results reveal that the data repetition error has been 100% detected [2]. Heterogeneous features are selected using the J48 decision tree model. Snowball sampling and Partial Least Square SEM (PLS-SEM) were proposed for analyzing the healthcare data in the smart home environment [31]. The system has improved while analyzing the healthcare data with a rate of ~ 89.67% from the current solution. Smart homes are highly advanced and provide cognitive assistance to elderly people. The Optimal Relay Placement Algorithm (ORPA) was used to increase the radio signal's obstacle-overcoming capability and find the best location to place the relays in an environment [50]. This research proposed a capable greedy algorithm ORPA that was used to calculate the best location for relay placement. Further, an improvement of 79.89% has been achieved in the current solution [16].

Established Smartphone applications and Wearable Sensors for Smart Healthcare Monitoring Systems (SW-SHMS) towards dynamic access control to healthcare data and provide better treatment to the patient [87]. The research helped in overcoming the security flaws by proposing a mutual trust-based model in the healthcare environment. The centric positioning techniques have achieved localization accuracy [18].

The Support Vector Machine-based classifier was proposed for managing monitored healthcare data [68]. The nodes above a threshold are chosen to be cluster nodes, and by using body sensors, patient health-related monitoring processes are performed [20]. Further, the energy efficiency of the SVM-based classifier has increased, along with the accuracy of 89.65% compared to the existing data management system [77]. The mobile phone-based algorithm was proposed for improving the gait speed estimation accuracy using machine learning algorithm-based wearable sensors [44, 78]. BioStampRC sensors were used for posterior directions [21]. Furthermore, the BioStampRC sensors accurately estimated the gait speed at 98.7%. The machine learning algorithm-based wearable sensors were introduced for identifying the diagnosis of the elderly. The feasibility of diagnosis monitoring has been achieved through the robust wearable sensors worn by the elderly living in the smart home environment [42, 96, 101]. The monitored data is further communicated to the healthcare provider in the context of the healthcare industry [25]. The belt-worn IMU has measured the angular velocity and acceleration with an accuracy of 98.01%. Activity recognition and lightweight algorithms were introduced to achieve high accuracy while recognizing elderly activities [52]. The codebook is used for feature representation, and sequences are converted into a feature representation with an accuracy of 89.89% [26]. Although latency has been identified in the proposed activity monitoring of the elderly in the context of the healthcare industry, the sensors are adequately used for measuring acceleration forces.

A depth sensor-based approach is proposed for monitoring and detecting the healthcare of elderly people [33]. The fall detection algorithm is used to detect the person through the robust Kinect sensors. The movement of the elderly is detected, monitored, and evaluated through the Y or Z coordinates [28]. The proposed solution gains an accuracy of 86.83%. Enhanced the health and living in their homes with the Unified Theory of Acceptance and Use of Technology (UTAUT) Framework to provide better management and online healthcare treatment [30]. Smart homes use smart devices to provide protection and healthy living for elderly people. It provides the security of elderly people has been improved by 81.4%. According to [13], the human body's activity is detected and enhanced with the help of a smartwatch or other devices. The Forward–Backward algorithm, the Diffie-Hellman algorithm, is used for solving the issue of the sitting-related problem by implementing sensor-based devices such as Smartwatches, etc. An improvement of 89.56% has been identified compared with the existing solution [41]. Smart intelligent and multimodal systems were implemented to solve the security issue of smart home healthcare systems. The controlling home appliances used radio frequency-based home automation to control all home appliances [39, 97, 104]. Wireless Bluetooth technology provides remote access from PC control appliances, which helps in feasible data communication [43]. Advanced processing and machine learning algorithms have been introduced to accurately process the monitored data [47, 98, 100]. The W3C semantic sensors are ontology and are used for observation in smart IoT environments to complete some tasks. The proposed algorithm achieved an accuracy of 89.76%.

Wearable sensors are feasible for tracking various healthcare parameters [17, 102]. More precisely, the proposed system aimed at implementing wearable sensors to monitor sleep timing to predict migraine attacks [40] better. Further, Quadratic discriminant analysis (QDA) achieved 84.1% accuracy than the existing solution [29]. Moreover, the classifiers achieved an accuracy of 91.2%, a sensitivity of 99.6%, and a specificity of 90.0%. Further, a Long Short-Term Memory (LSTM) network and wearable sensor were presented to provide feasible human activity recognition [14]. The proposed deep convolutional network and machine learning application help to monitor the data through robust wearable sensors [60]. It provides the testing time reduced by 38% through the backpropagation algorithm. Moreover, the results improved by 8% than the current solution classifying running speed conditions using a single wearable sensor in the context of elderly in smart homes [80]. The wearable sensors and feature extraction algorithm are used for accurate monitoring of speed conditions [74]. Moreover, MATLAB software and wearable sensors are equipped for monitoring the healthcare parameters of the elderly body [48]. The segmentation method achieved five-stride (97.49 ($\pm$4.57) %) with the greatest classification accuracy.

Human activity monitoring data is accurately assessed through the predicted mean vote (PMV) index [23]. They introduced personal thermal comfort assessment using optimization techniques to improve human fall detection accuracy. It provides the sensors' accuracy of $\pm$2% for humidity and $\pm$0.5 $\circ$C for air temperature [27]. A model presented SmartFall towards improving the fall detection of the elderly in smart homes [46, 75]. They used SmartFall to identify the falls of the elderly in smart homes and communication of monitored data through wearable technology-based smartwatches. The real-time fallen data is detected accurately [49]. The missed fall is presented as false positives (FPs) that reduce the chances of time consumption in the system [51]. The improvement can be achieved through Nexus 5X smart phone with 1.8 GHz hexa-core processor, which is used as a data communication tool in the detailed solution [85]. A practical solution WISE system for adequate healthcare monitoring of elderly people was introduced by [9]. The proposed solution Wearable IoTcloud-baSed hEalth monitoring system (WISE), improved the performance of healthcare monitoring through the accelerometer sensors. The smartphone-based accelerometer sensor provided an accelerometer rate with an accuracy of 98.6%. A one-class support vector machine to define typical movement patterns was introduced by [53]. The wearable sensors have been used for monitoring the accelerometer rate and gyroscopic rate of the object through robust sensors. iNEMO inertial module was used as the inertial sensor to measure the velocity of the object [84]. The research has achieved an overall accuracy of 90%. However, future work shall focus on examining the impact of gait data [86].

The limitation of the range of sensors remains in the system [70]. The limitation of computational sources is identified in the research, but the improvement can be seen in the future work of the research [4]. The system has the limitation of inaccurate moving object identification that causes errors [64, 65]. The system has identified that the process needs extreme expert supervision for smooth completion, but the Lagrangian approach facilitates the transformation of the problem to provide an easy solution [1]. A minor limitation has occurred due to the involvement of many external factors. The limitation of the system is that features were not extracted accurately [63]. Data storage remains an issue, and high computational costs are the drawbacks of this system [38]. Their system has identified that gyroscopic data was not collected with precision and accuracy due to a lack of adaptability [10]. The proposed solution has identified the lack of identity approximation, but the improvement can be achieved by applying a sparse auto-encoder in the optimum feature location [32]. In [93], they analyze the shared requirements of elderly and disabled individuals, after which we assess a variety of IoT applications capable of delivering the necessary assistance. In [66], the system's limitation is that the features are not shared accurately. In [31], the major limitation identified in the proposed system is that the objects are not presented geometrically. The limitations of complexity and complicated processes are placed in the system [50]. The requirement of keen observation and expert supervision remains a major limitation in the research [87]. The limitation of high complexity in the monitoring processes is identified in the proposed solution [68]. Inadequate device location has been notified as the limitation of the proposed solution, but the noticeable improvement is identified through gait walking speed estimation during the over-ground ambulation [44]. Moreover, the temporal phases are not identified adequately due to the high error rate in the system [42]. However, latency has been identified in the proposed activity monitoring of the elderly in the context of the healthcare industry [52]. Nonetheless, the proposed sensor-based system does not accurately monitor the direction of movements [33]. Sometimes, technical issues occur in the system due to inaccurate sensing, but smart device performance is increased with the help of smart technologies using IoT [30, 99]. The system's limitation of inaccurate data communication remains, but sensors use Visual recognition-enabled devices to monitor body language [13]. In their system, data communication is found to be less secure due to inaccurate networking, but the Arduino prototyping board can be used to see which devices are working or not [39]. The limitation of limited interaction between humans and robots has been identified, but improvement could be seen through data processing services [47]. In [71], the system has identified that the inaccurate recognition of various healthcare parameters remains a limitation. The limitation in [14] is this system's motion detection difficulty. The limited storage capacity and inaccurate running condition monitoring have not been performed accurately [80]. The high latency was identified when extracting the sensed data [23]. The complexity was identified at the time of data extraction [46]. Limited memory, Storage capacity, and computing capacity are not performed accurately [9]. Limited sensor information and sample size prevented the work to accurate [53]. In [103], the aim was to help the elderly choose suitable physical activity and healthcare monitoring devices.

Towards monitoring and tracking various healthcare parameters from elderly people, monitoring techniques are used with the different methods described in the literature review section. It has been identified that literature number 2 of week 1 was the most accurate and relevant to the research domain. This literature includes the Hidden Markov Model (HMM) and the healthcare parameter monitoring technique to monitor elderly people's healthcare. The system consists of various components, i.e., the diffie-hellman algorithm, smartwatches, and binary images. In Fig. 1, the architecture for elderly assisted living in healthcare using wearable sensor technologies is provided. However, Fig. 2 shows the state-of-the-art solution.

3 Proposed Framework

The current cutting-edge solution is hindered by issues such as unreliable monitoring, insufficient recognition of activities, inaccurate data synchronization, and imprecise data classification. In order to address these shortcomings, an enhanced solution has been developed, incorporating components that enhance the precision of healthcare parameter

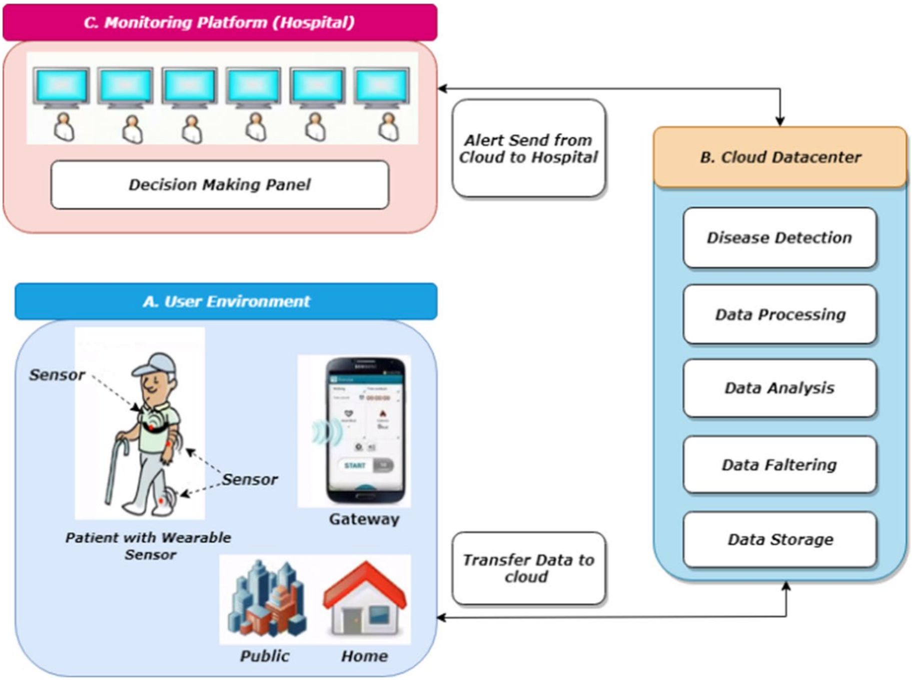

Fig. 1 Architecture for elderly assisted living in healthcare using wearable sensor technologies

monitoring and tracking through the utilization of smart wearable sensor technology. Figure 3 depicts the proposed architectural framework and the new added features.

4 Framework Components

The Sensing, Data storage, and Data communication (SDD) taxonomy was conducted to review current wearable sensor technologies and knowledge. In this taxonomy, we followed the same structure as [91] and [92]. Further, healthcare monitoring and tracking are evaluated in the background of elderly assisted living. Towards that, SDD taxonomy is conducted where sensing, data storage, and data communication help to sense and track the vital healthcare data for maintaining the health of the elderly living. Moreover, the evaluation, validation, and advancement of the system are going to be treated in this report.

In the report, 150 research articles have been reviewed and considered. Further, we identified that only 30 articles met the research domain requirements. There are some principles and standards that need to be focused on. In this research, wearable sensor technology is described in the context of elderly assisted living because it helps monitor and track vital healthcare parameters. Moreover, the research introduced a robust methodology to maintain the health of elderly people.

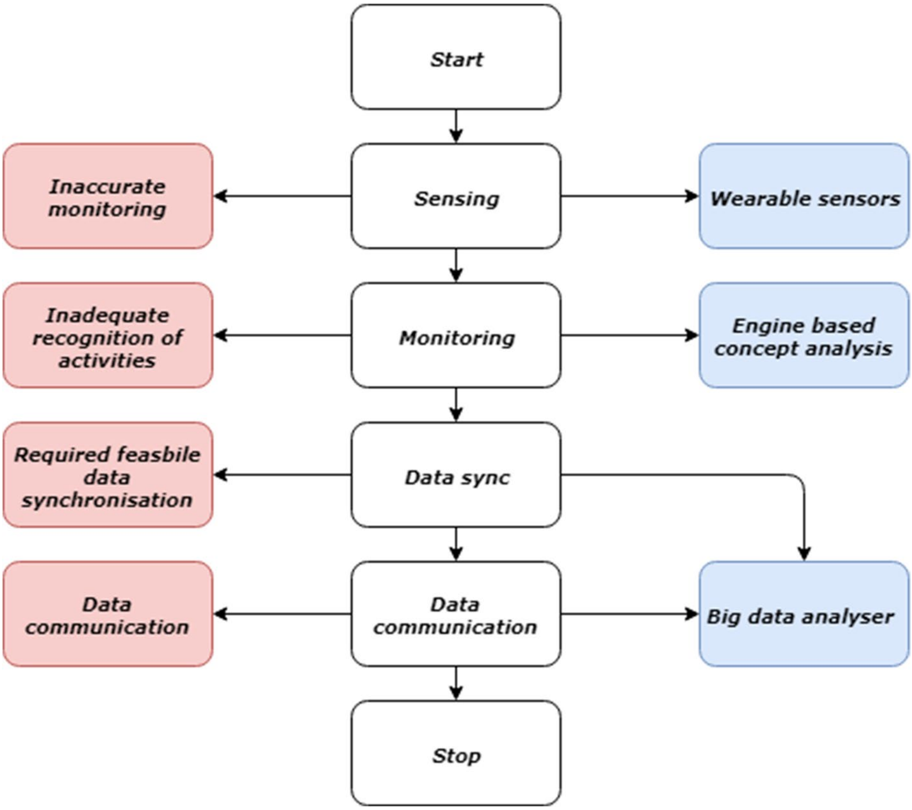

Fig. 2 The State-of-art solution

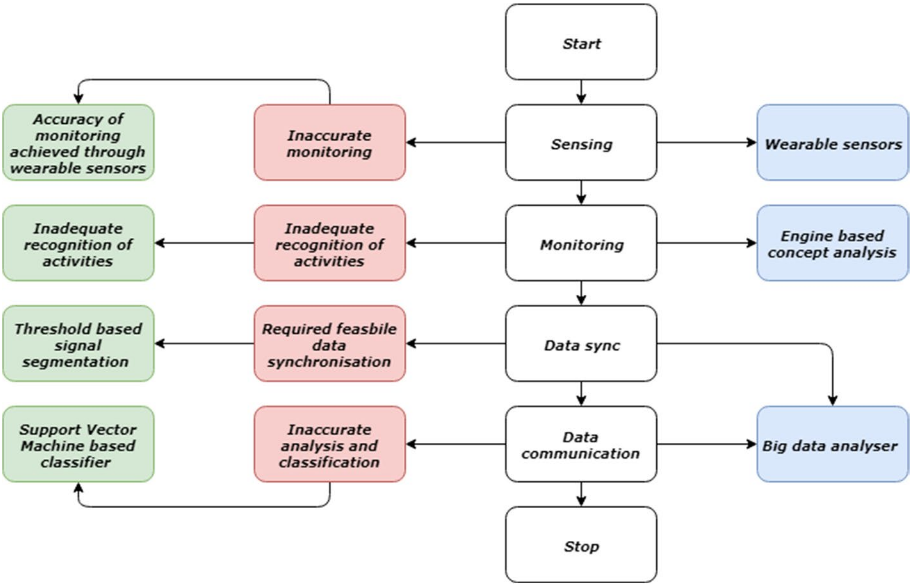

Fig. 3 The proposed solution. Green rectangles show the added components

By going through the literature review, considerable knowledge and ideas were gathered. Consequently, to improve the remote monitoring and tracking of essential parameters of elderly people in the healthcare industry, comprehensive insight is required to be prepared. Three major facts that are needed to be considered in the research are as follows –

- Provide the major parameters that assist the elderly in maintaining health and regular diagnosis.
- What are the ways through which the relevant data can be collected and merged in this research?
- How can tracking and monitoring healthcare parameters improve elderly assisted living?

Subsequently, considering these three facts, wearable sensor technologies are classified for healthcare monitoring and tracking vital information within the healthcare industry.

4.1 Taxonomy for Healthcare Monitoring and Tracking

Initially, the first factor used in the SDD taxonomy is sensing. Through the sensing or tracking stage, healthcare-related vital information is sensed through wearable sensor technologies. Moreover, Artificial Intelligence (AI) technologies are used for collecting physiological data. The sensed data is essential because it would help to provide elderly assisted living. The components and sub-components of sensing are presented in Table 1. In addition, the sensed data stored in the cloud, known as electronic healthcare data, is based on machine learning technology. This sensed healthcare data could be retrieved and communicated at any time. Once the data is stored, it can be further transmitted to the healthcare provider or elderly assistant. Hence, the feasible sensing and tracking of vital healthcare parameters can improve assisted elderly living. All three components of

SDD taxonomy is further sub-classified along with their respective example or instances in Fig. 4. It can be further seen that these components are interrelated to each other. The instances in Table I underline the importance of particular factors in a certain domain.

In Fig. 4, all three major SDD taxonomy components are proposed. Further, all components interact with each other in a way to get a better understanding of the research domain. The remaining portion contains the evaluation, verification, and classification of the introduced SDD taxonomy. Further, these aspects are calculated in the classification of the system. More precisely, Fig. 4 represents the classes and sub-classes of the SDD taxonomy.

4.1.1 Sensing

This section contains two sub-classes of sensing main components: wearable sensors and cloud data. In addition, their functionality includes sensing, tracking, and monitoring. The classes and sub-classes are provided in Table 1 and Fig. 5 correlated to each other with their instances. Detailed data classes and sub-classes are measured towards addressing the requirement in the SDD taxonomy for feasible classification and specification of each type of data deployed in the research review.

4.1.2 Data storage

In the way to manage and store the data, various data classifiers are used, which help to classify the healthcare data sensed through the wearable sensors. In the same way, wearable sensors and activity recognition are used for accurate storage analysis of the elderly monitoring results (Fig. 6). Support vector machine (SVM) and engine-based concept analysis are applied for further analysis.

4.1.3 Data communication

Once the data is sensed and stored, the healthcare data is communicated through classification, data analysis, and healthcare surveillance (Fig. 7). The healthcare provider and elderly can retrieve the data through the security claim. Figure 7 provides the flowchart of the data communication and its main classes and sub-classes.

Table 1 Main Attributes & Common Instances of the Sensing, Data Storage, and Data Communication

Factor/Class	Main Attributes	Common Instances
Sensing	Input	Various healthcare parameters
Wearable sensors	Sensors	Sensing, tracking, monitoring
Cloud	Environment	Storing, communication
Data storage	Process	Fog layer, IoT, monitored data
Elderly monitoring	Analysis	Wearable sensors, Activity recognition
Storage analysis	Data synchronization	Support vector machine, engine-based concept analysis
Data communication	System	Wireless data, lightweight algorithms, big data analyser
Classification	Data processing	Support Vector Machine-based classifier, CNN, BackPropagation (BP)
Data analysis	Analysis	Activity information, disease information, vital parameters
Healthcare surveillance	Setting	Software, Hardware, classifiers, Smart sensors

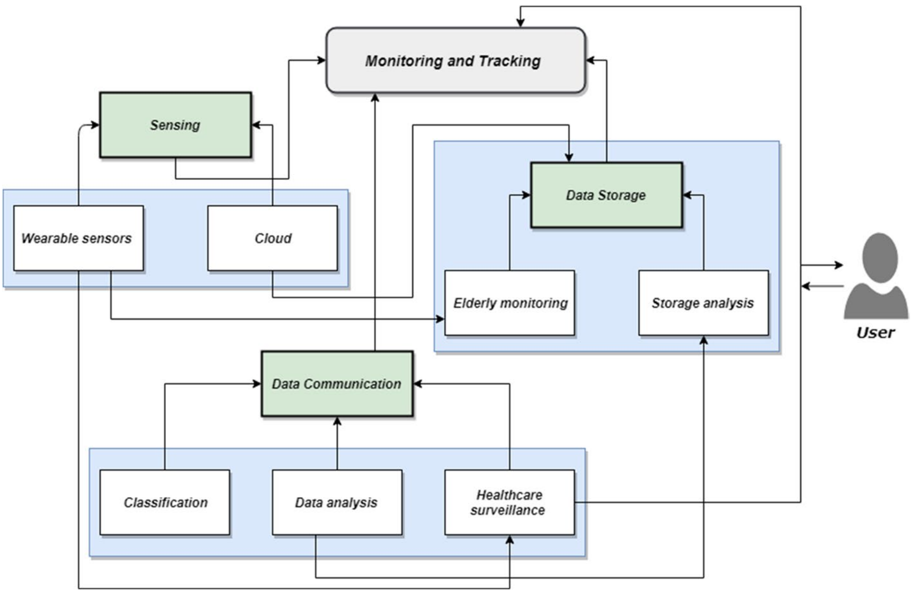

Fig. 4 The three factors of Monitoring and Tracking taxonomy (i.e., Sensing, Data Storage, and Data communication)

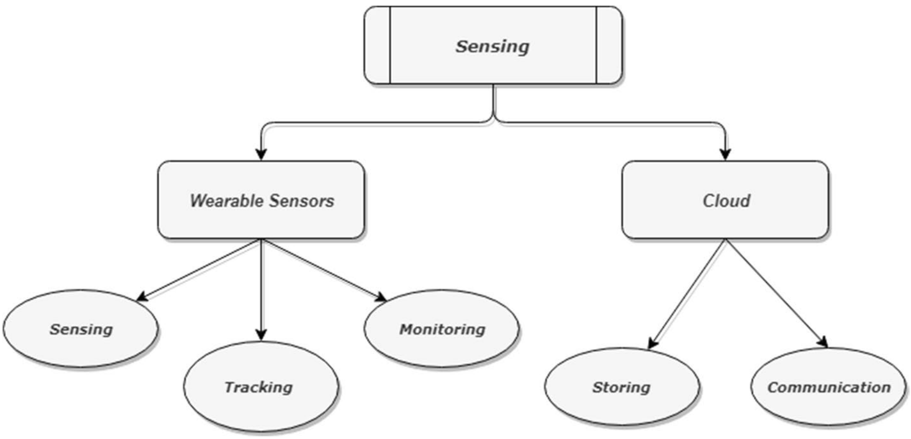

Fig. 5 Main attributes and instances of Sensing

4.2 Purpose of the Proposed Framework

4.2.1 Sensing

The aim of considering sensing as part of elderly assistance is to carry out what data needs to be sensed to improve elderly health. In other words, sensing, tracking, and monitoring are aimed in this section. Furthermore, the data is collected and communicated to the cloud environment to maintain sensed data security.

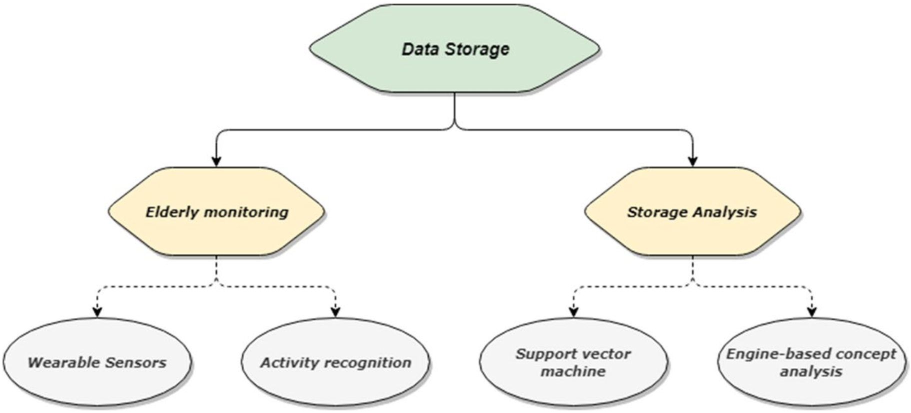

Fig. 6 Main attributes and instances of Data Storage

4.2.2 Data storage

Wireless sensor networks are used to manage and store the data. This section stores data such as activity recognition, various healthcare data, and wearable sensor-based data. Furthermore, the data is stored in the cloud using feasible wireless communication networks. All the sub-classes of data storage are mentioned in Fig. 3.

4.2.3 Data communication

The sensed data is communicated to respected healthcare providers using the lightweight algorithm and big data analyzers. The sub-classes are divided into classification, data

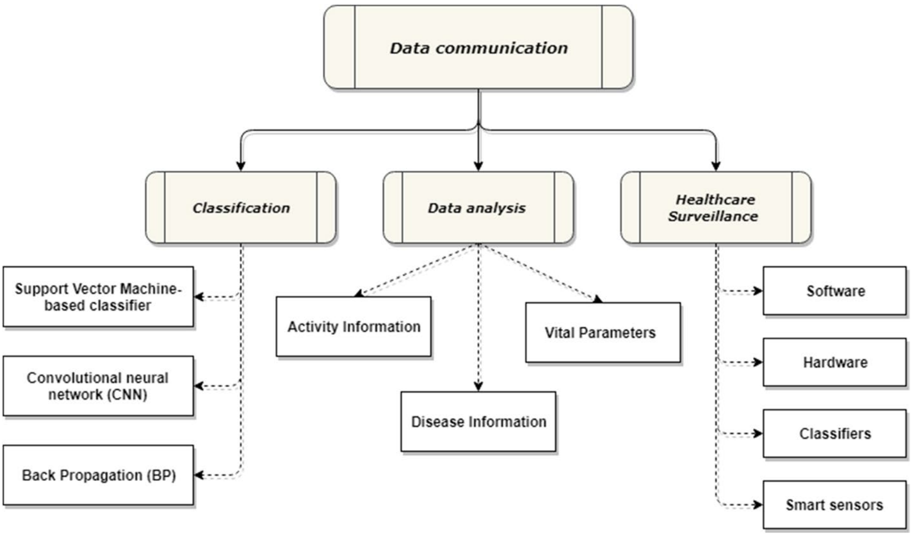

Fig. 7 Main attributes and instances of Data Communication

analysis, and healthcare surveillance. In addition, the data is communicated to healthcare providers using a support vector machine-based classifier and convolution neural network.

5 Framework Classification

Around 130 results or journals have been evaluated and analyzed in the research. Of 130 results, 30 journals have been finalized to conduct the research in the given research domain. Further, for getting detailed and established information about the research, only journals published in 2018–2019 were considered. More precisely, Q1 and Q2 level journals as these journals are more precise and contain detailed and established information about the research. The journals are only collected on the basis of activity recognition and monitoring techniques. All 30 journals are classified and evaluated in the below section based on the proposed taxonomy and its useful components for constructing this research. Thus, the classification is prepared on 30 selected journals. In Table 2, various components are evaluated based on the proposed taxonomy and its components that are useful in obtaining detailed information about the research in the context of elderly care.

In Table 3: the classification and evaluation are done based on sensing components and various parameters that provide detailed information about the sensors that can be deployed for elderly care.

In Table 4, the systems are classified in the background of various techniques and methods that are used for providing data storage to the data sensed and monitored through the various smart sensors.

Table 5 presents the evaluation of various parameters in the context of data communication to the research healthcare and security provider for improving and maintaining the elderly people care in the background of smart homes environment.

5.1 Sensing

Various journals are aimed at the sensing component and utilization of this component in their research works. The sub-components, such as wearable sensors and clouds, are essential for the research.

1. Wearable sensor: In [5], they stated that the feasible healthcare tracking and monitoring of healthcare parameters are achieved by implementing an Ensemble machine learning algorithm within the system. Also, it helps monitor the healthcare parameters in a real-time environment and allows communication with the respective healthcare professionals.
2. Cloud: After sensing the healthcare parameters, the sensed data is Communicated and stored in the cloud environment. Towards that, an Optical flow feedback convolution neural network has been implemented for accurate healthcare data communication and storage [64].

5.2 Data storage

The data storage component is essential because it must be stored securely and efficiently before communicating the healthcare-sensed data. Towards that, the data storage

Table 2 Classification Of The Systems Based On The Proposed Sdd Taxonomy

Ref. No	Monitoring and Tracking techniques	Sensing		Data storage		Data communication		
		Wearable sensors	*Cloud*	*Elderly monitoring*	*Storage analysis*	*Classification*	*Data analysis*	*Healthcare surveillance*
[31]	Unified Theory of Acceptance	Real time sensing	Storing	Activity recognition	Support vector machine	Support Vector Machine-based classifier	Vital parameters	Smart sensors
[13]	Diffie-Hellman algorithm	Human monitoring	Storing	Activity recognition	Multi-dimensional Scaling	Forward–Backward algorithm	Human robot interaction	Smart watches
[39]	Secured RF Based Wireless Home Automation	Remote Sensing	Communication	IOTE fall system	Cross-validation	Machine learning algorithm	Mean-shift Algorithm	Video surveillance
[6]	Ensemble machine learning algorithm	Tracking and monitoring	Data Storing	Fall detection recognition	K-fold cross-validation	Ensemble learning algorithm	Splitter technique	Accelerometer sensor
[47]	Semantics-based platform	Human Sensing	Data Storing	Activity recognition	Support vector machine	Action Executor	Task generating service	IoRT (internet of robotics things)
[70]	Robot-integrated smart home (RiSH)	Human position tracking	Communication and storing	Activity recognition	Two-level application	Multi-sensor fusions	Dynamic Bayesian Network	Wearable motion sensors
[64]	Optical flow feedback convolution neural network	Motion detection	Communication and storing	Intelligent fall detection	Cross-validation	Rule-based filters	Feature feedback mechanism	Activity sensors and 3DCNN
[5]	Big data analytics	Sleep monitoring	Data Storing	Health monitoring	Cloud computing	Obtrusive sleep apnea	Scikit-learn 0.18.0	Wireless sensors networks
[66]	Engine based on the formal concept analysis	Accurate activity sensing	Data Storing	Activity recognition	Graph searching algorithm	Depth First Search (DFS) algorithm	Formal Concept Analysis	Smart devices and Motion sensor
[31]	Snowball sampling, Partial Least Square SEM (PLS-SEM)	Healthcare monitoring system	Communication and storing	Self-capabilities of elderly person	Support vector machine	Back Propagation	Dimension identification	Smart sensors

Table 2 (continued)

Ref. No	Monitoring and Tracking techniques	Sensing		Data storage		Data communication		
		Wearable sensors	*Cloud*	*Elderly monitoring*	*Storage analysis*	*Classification*	*Data analysis*	*Healthcare surveillance*
[1]	Constrained Markov Decision process (CMPD)	Healthcare monitoring system	Data Storing	Health monitoring	Lagrangianapproach	Intelligent Adaptive Learning Algorithm	Constrained Markov Decision process	Wireless Body Area Network
[50, 81]	Optimal Relay Placement Algorithm (ORPA)	Home health monitoring	Communication and storing	Indoor health monitoring system	Support Vector Machine	Optimal Relay Placement Algorithm	Disease information	Smart sensors
[87]	Smart-phone app and Wearable Sensors for Smart Healthcare Monitoring System	Real-time monitoring	Data Storing	Health monitoring	Cross-validation	Conventional Neural Network	Vital health parameters	Wireless sensor networks
[68]	Support vector machine-based classifier	Human monitoring	Communication and storing	Health monitoring	Wireless channel information	Support vector machine-based classifier	K-nearest neighbor	K-mean and C-band
[83]	Robust and anonymous patient monitoring system	Patient monitoring system	Data Storing	Health monitoring	Support Vector Machine	Support vector machine-based classifier	Password authentication	Sensor Nodes and AVISPA software
[17]	Wearable sensors for early detection system	Healthcare monitoring	Communication and storing	Migraine attack recognition	Machine learning	Electroencephalography	Linear discriminant analysis	Biosignals and sensors
[14]	Long Short-Term Memory (LSTM) Network	Patient monitoring system	Data Storing	Human activity recognition	Radial basis function (RBF) hidden nodes	BackPropagation (BP)	Disease Analysis	Wearable sensors and Sensor signals

Table 2 (continued)

Ref. No	Monitoring and Tracking techniques	Sensing		Data storage		Data communication		
		Wearable sensors	*Cloud*	*Elderly monitoring*	*Storage analysis*	*Classification*	*Data analysis*	*Healthcare surveillance*
[80]	Correlation-based feature selection algorithm	Healthcare monitoring	Data Storing	Health monitoring	Feature extraction algorithm	Low pass Butterworth	Machine learning	MATLAB software and wearable sensors
[63]	Machine learning algorithms based on signals	Patient monitoring system	Data Storing and tracking	Healthcare monitoring	Inertial measurement units	Support vector machine-based classifier	Mean-shift Algorithm	Accelerometer signals and wearable inertial sensor
[38]	Smart Sensing Architecture	Domestic monitoring	Data Storing	Healthcare monitoring	Zephyr Bioharness 3.0 (BH3)	Taidoc TD4277	Open Service Gateway Initiative	Biomedical sensors
[10]	Wearable sensor-based activity prediction system	Elderly health monitoring	Data Storing and tracking	Activity prediction for elderly care	Hidden Markov Model	Recurrent neural networks	Activity prediction system	Wearable sensors
[32]	Deep learning algorithm	Patient monitoring system	Data Storing and tracking	Human activity recognition	Support Vector Machine	Convolutional neural network	Deep Boltzmann Machine	Mobile and wearable sensors
[44]	Mobile phone-based algorithm	Healthcare monitoring	Data Storing	Healthcare monitoring	Estimating walking speed	BioStampRC Investigator Application	Vector magnitude	BioStampRC sensors
[42]	Machine learning algorithm	Patient monitoring system	Data Storing and tracking	Healthcare monitoring	Davies-Bouldin Index	Root Mean Square	Belt-worn inertial measurement unit	Wearable sensors
[52]	Light-weight algorithm	Healthcare monitoring	Data Storing	Sensor-based activity recognition	Feature learning approach	Advanced Message Queuing Protocol	Google NEXUS 5X	Smartphones and sensors
[33]	Depth sensor-based approach	Assistive living monitoring	Data Storing and tracking	Fall detection recognition	Fall detection algorithm	Support vector machine-based classifier	V-disparity map	Non-invasive sensors

Table 2 (continued)

Ref. No	Monitoring and Tracking techniques	Sensing		Data storage		Data communication		
		Wearable sensors	*Cloud*	*Elderly monitoring*	*Storage analysis*	*Classification*	*Data analysis*	*Healthcare surveillance*
[23]	Personal Thermal Comfort Assessment	Human activity monitoring	Monitoring and tracking	Human activity recognition	Support Vector Machine	Predicted Percentage of Dissatisfied index	Hot wire anemometer	Wearable sensors
[46]	Smartfall: a smartwatch-based fall detection system	Human monitoring	Monitoring and tracking	Fall detection recognition	Recurrent neural network	Support vector machine-based classifier	Naive Bayes	Smartwatch and Nexus 5X smartphone
[9]	Wearable IoTcloud-baSed-hEalth monitoring system (WISE)	Health monitoring	Monitoring and tracking	Activity recognition	Engine based concept analysis	Light weight algorithms	Dynamic time warping algorithm	Mobile and wearable sensors
[53]	One-class support vector machine (OCSVM)	Human activity monitoring	Monitoring and tracking	Human activity recognition	3D linear acceleration	Cross-validated baseline data	Event detection algorithm	Wearable sensors

Table 3 Classification Of Systems On The Background Of Sensing Components

Ref. No	Specific Tools	Effective key attribute	Performance of assets				Monitoring and Tracking Accuracy	
			Fall and motion detection	Motion perdition	Human monitoring	Standard Deviation	High	Low
[31]	• Smart Sensors • Actuators	Multi-dimensional Scaling	Absolute impossible	Precise	Inadequate	9.8%		✓
[13]	• Microsoft Kinect • Smart watches	Human robot interaction	Very low	Imprecise	Inadequate	1.9%	✓	
[39]	• Multi nodal • Smartphone	Mean-shift Algorithm	Moderate	Precise	Moderate	4.3%	✓	
[6]	• Tunslip6 • 6LawPAN	Splitter technique	Moderate	Precise	Inadequate	8.6%		✓
[47]	• Ontology • Internet of things	Task generating service	Very low	Precise	Moderate	5.3%	✓	
[70]	• Dynamic Bayesian Network • Home service robot	Dynamic Bayesian Network	Moderate	Imprecise	Inadequate	8.94%		✓
[64]	• Convolutional neural network • Optical flow	Feature feedback mechanism	Absolute impossible	Precise	Moderate	1.84%	✓	
[5]	• Fog computing • Cloud computing	Scikit-learn 0.18.0	Moderate	Imprecise	Inadequate	6.04%		✓
[66]	• Smart devices • Wireless sensors	Formal Concept Analysis	Very low	Imprecise	Inadequate	7.8%		✓
[31]	• Smart sensors • IoT devices	Dimension identification	Moderate	Precise	Moderate	3.1%	✓	
[1]	• Wireless Body Area Network • Sensor	Constrained Markov Decision process	Moderate	Precise	Moderate	1.9%	✓	
[50]	• Wireless sensor • Wearable sensor	Disease information	High	Precise	Moderate	4.3%		✓

Table 3 (continued)

Ref. No	Specific Tools	Effective key attribute	Performance of assets				Monitoring and Tracking Accuracy	
			Fall and motion detection	Motion perdition	Human monitoring	Standard Deviation	High	Low
[87]	• Sensor network • Internet of things	Vital health parameters	Very low	Imprecise	Moderate	3.6%	✓	
[68]	• Sensor Nodes • Cluster Heads	K-nearest neighbor	Very low	Precise	Inadequate	9.8%		✓
[83]	• Sensor Nodes • AVISPA software	Support Vector Machine	Moderate	Precise	Inadequate	8.94%		✓
[17]	• Motion sensors • Visual sensors	Linear discriminant analysis	Absolute impossible	Imprecise	Inadequate	7.1%		✓
[14]	• Sensor signals • Neural network	Extreme learning machine (ELM)	Very low	Imprecise	Moderate	4.9%		✓
[80]	• MATLAB software • Wearable sensors	Davies-Bouldin Index	High	Imprecise	Moderate	1.9%	✓	
[63]	• Inertial motion unit (IMU) • Accelerometer signals	Mean-shift Algorithm	Moderate	Precise	Moderate	4.3%	✓	
[38]	• Biomedical sensors • Wearable sensors	Open Service Gateway Initiative	Moderate	Precise	Moderate	3.6%	✓	
[10]	• Wearable sensors • Recurrent Neural Network	Activity prediction system	High	Precise	Inadequate	8.5%		✓
[32]	• Deep Autoencoder • Sparse Coding	Deep Boltzmann Machine	Absolute impossible	Imprecise	Inadequate	6.5%		✓
[44]	• Machine learning • Wearable sensors	Vector magnitude	Moderate	Precise	Moderate	3.8%	✓	
[42]	• Wearable sensors • Feature extraction	Belt-worn inertial measurement unit	High	Imprecise	Moderate	4.8%		✓

Table 3 (continued)

Ref. No	Specific Tools	Effective key attribute	Performance of assets				Monitoring and Tracking Accuracy	
			Fall and motion detection	Motion perdition	Human monitoring	Standard Deviation	High	Low
[52]	• Wearable sensors • CloudLet	Google NEXUS 5X	Absolute impossible	Precise	Moderate	1.5%	✓	
[33]	• Non-invasive sensors • Video cameras	V-disparity map	High	Imprecise	Inadequate	6.5%		✓
[23]	• Machine learning • Wearable sensing	Hot wire anemometer	Very low	Imprecise	Moderate	3.6%	✓	
[46]	• Smartwatch • Deep learning	Naive Bayes	Moderate	Imprecise	Inadequate	9.2%		✓
[9]	• Cloud computing • WISE-Cloud	Dynamic time warping algorithm	Moderate	Imprecise	Moderate	2.7%	✓	
[53]	• Wearable sensors • (3D) linear accelerations	Event detection algorithm	Absolute impossible	Precise	Moderate	1.9%	✓	

Table 4 Classification Of The Systems Based On Data Storage Components

Ref. No	Types of Wireless devices	Effective algorithm used	Quality of this work		Elderly assistive living of Monitoring and tracking		Improvement Attained (in %)
			High	Low	Wearable sensor data	False positive rate	
[32]	Wearable Accessories	Unified Theory of Acceptance	✓		Accurate	0.005	90%
[13]	Smartwatch and Nexus 5X smartphone	Diffie-Hellman algorithm	✓		Accurate	0.000	98.6%
[39]	Mobile and wearable sensors	Fuzzy inference system		✓	Inaccurate	0.057	64.6%
[6]	Wearable sensors	Ensemble machine learning algorithm	✓		Accurate	0.003	75.3%
[47]	Smartwatches	Semantics-based platform	✓		Accurate	0.002	86.83%
[70]	Video surveillance	Robot-integrated smart home (RiSH)	✓		Accurate	0.002	87.1%
[64]	Accelerometer sensor	Optical flow feedback convolution neural network		✓	Inaccurate	0.054	60.1%
[5]	IoRT (internet of robotics things)	Big data analytics	✓		Accurate	0.003	98.7%
[66]	Wearable motion sensors	Engine based on the formal concept analysis	✓		Accurate	0.006	90.7%
[31]	Activity sensors and 3DCNN	Snowball sampling, Partial Least Square SEM (PLS-SEM)		✓	Inaccurate	0.046	69.98%
[1]	Wireless sensors networks	Constrained Markov Decision Process (CMPD)	✓		Accurate	0.000	83.1%
[50]	Smart devices and Motion sensor	Optimal Relay Placement Algorithm (ORPA)		✓	Inaccurate	0.046	55.2%
[87]	Smart sensors	Smart-phone app and Wearable Sensors for Smart Healthcare Monitoring System		✓	Inaccurate	0.033	65.7%
[68]	Wireless Body Area Network	Support vector machine-based classifier	✓		Accurate	0.000	80.6%
[83]	Smart sensors	Robust and anonymous patient monitoring system		✓	Inaccurate	0.041	49.8%
[17]	Wireless sensor networks	Wearable sensors for early detection system	✓		Accurate	0.000	79.9%
[14]	K-mean and C-band	Long Short-Term Memory (LSTM) Network		✓	Inaccurate	0.022	54.1%
[80]	Sensor Nodes and AVISPA software	Correlation-based feature selection algorithm		✓	Inaccurate	0.017	46.35%
[63]	Biosignals and sensors	Machine learning algorithms based on signals	✓		Accurate	0.000	83.90%
[38]	Wearable sensors and Sensor signals	Smart Sensing Architecture	✓		Accurate	0.002	91.56%

Table 4 (continued)

Ref. No	Types of Wireless devices	Effective algorithm used	Quality of this work		Elderly assistive living of Monitoring and tracking		Improvement Attained (in %)
			High	Low	Wearable sensor data	False positive rate	
[10]	MATLAB software and wearable sensors	Wearable sensor-based activity prediction system	✓		Accurate	0.001	85.33%
[32]	Accelerometer signals and wearable inertial sensor	Deep learning algorithm		✓	Inaccurate	0.031	65.5%
[44]	Biomedical sensors	Mobile phone-based algorithm	✓		Accurate	0.001	75.43%
[42]	Wearable sensors	Machine learning algorithm		✓	Inaccurate	0.051	53.1%
[52]	Mobile and wearable sensors	Light-weight algorithm		✓	Inaccurate	0.018	49.7%
[33]	BioStampRCsensors	Depth sensor-based approach	✓		Accurate	0.002	94.3%
[23]	Wearable sensors	Personal Thermal Comfort Assessment		✓	Inaccurate	0.035	49.4%
[46]	Smartphones and sensors	Smartfall: a smartwatch-based fall detection system	✓		Accurate	0.001	91.87%
[9]	Non-invasive sensors	Wearable IoTcloud-baSedhEalth monitoring system (WISE)		✓	Inaccurate	0.033	39.21%
[53]	Wearable sensors	One-class support vector machine (OCSVM)		✓	Inaccurate	0.046	48.11%

Table 5 Classification Of The Systems In The Context Of Data Communication Components

Ref. No	Study Criteria	Vulnerabilitty description	Performance of assets			Activity recognition		
			Person body tracking speed	Sensor based Human monitoring	Error rate [1–10]	Classifier used	False positive rate	Accuracy
[31]	Real-time sensing	• Sometimes Technical issues occur • Time consuming	High	Accurate	~0.1	Support Vector Machine-based classifier	Inadequate	99.1%
[13]	Human monitoring	• The direction of movements is not accurately monitored	Medium	Semi Accurate	~3.2	J48	Moderate	78.5%
[39]	Remote Sensing	• Some systems have critical problems that are not able to solve	High	Accurate	~0.3	Support Vector Machine-based classifier	Moderate	89.1%
[6]	Tracking and monitoring	• High latency while extracting the sensed data	High	Accurate	~1.0	Naïve Bayes	Inadequate	96.5%
[47]	Human Sensing	• Computational costs high in this process	Medium	Semi Accurate	~2.1	Dynamic Bayesian	Moderate	56.2%
[70]	Human position tracking	• Inaccurate voice recognition • Limited range of sensors	High	Accurate	~0.2	J48	Inadequate	98.2%
[64]	Motion detection	• The moving objects are not accurately identified	Low	Inaccurate	~6.3	Scikit-learn 0.18.0	Moderate	48.2%
[5]	Sleep monitoring	• Some systems have not relied on IoT • High cost is required	High	Accurate	~0.6	J48	Moderate	89.2%
[66]	Accurate activity sensing	• Node location is inaccurate • Features are not accurately shared	Low	Inaccurate	~5.3	Naïve Bayes	Inadequate	46.1%

Table 5 (continued)

Ref. No	Study Criteria	Vulnerabilitty description	Performance of assets			Activity recognition		
			Person body tracking speed	Sensor based Human monitoring	Error rate [1–10]	Classifier used	False positive rate	Accuracy
[31]	Healthcare monitoring system	• Objects are not presented geometrically	High	Accurate	~0.4	Support Vector Machine-based classifier	Moderate	93.7%
[1]	Healthcare monitoring system	• The process needs extreme expert supervision for smooth completion	Low	Inaccurate	~8.1	Scikit-learn 0.18.0	Moderate	49.1%
[50]	Home health monitoring	• The process is complex and complicated	Low	Semi Accurate	~5.2	Naïve Bayes	Moderate	56.1%
[87]	Real-time monitoring	• In this process, high skilled employees • Complexity in the procedure	Low	Inaccurate	~4.3	K-nearest neighbor	Moderate	47.8%
[68]	Human monitoring	• Computational cost is high • Some drawbacks which make the process a bit difficult	High	Accurate	~0.3	Support Vector Machine-based classifier	Inadequate	91.6%
[83, 89]	Patient monitoring system	• The process might contain some minor errors due to external environmental factors	High	Accurate	~0.5	Support Vector Machine-based classifier	Inadequate	82.6%
[17]	Healthcare monitoring	• High computation and setup cost • The features are not accurately identified	Low	Inaccurate	~4.9	Naïve Bayes	Inadequate	44.2%

Table 5 (continued)

Ref. No	Study Criteria	Vulnerabilitty description	Performance of assets			Activity recognition		
			Person body tracking speed	Sensor based Human monitoring	Error rate [1–10]	Classifier used	False positive rate	Accuracy
[14]	Patient monitoring system	• The convolutional neural networks cannot be used directly	Low	Inaccurate	~8.3	Scikit-learn 0.18.0	Moderate	37.56%
[80]	Healthcare monitoring	• Not applicable for feature classification	High	Accurate	~0.2	K-nearest neighbor	Moderate	92.0%
[63]	Patient monitoring system	• The features are not extracted effectively	Medium	Semi Accurate	~3.3	Support Vector Machine-based classifier	Moderate	65.7%
[38]	Domestic monitoring	• Overlaps are not accurately measured	High	Accurate	~0.3	Hot wire anemometer	Moderate	89.5%
[10]	Elderly health monitoring	• Features are not extracted accurately • Data storage remains an issue	High	Accurate	~0.1	Scikit-learn 0.18.0	Inadequate	95.3%
[32]	Patient monitoring system	• Inaccurate prediction might be seen due to a lack of gyroscopic accuracy	High	Accurate	~2.8	Naïve Bayes	Inadequate	88.2%
[44]	Healthcare monitoring	• Gyroscopic data is not collected with precision and accuracy due to lack of adaptability	Low	Inaccurate	~6.3	Support Vector Machine-based classifier	Moderate	41.3%
[42]	Patient monitoring system	• Innate feature representation is less accurate	Medium	Accurate	~0.5	Google NEXUS 5X	Moderate	78.4%

Table 5 (continued)

Ref. No	Study Criteria	Vulnerabilitty description	Performance of assets			Activity recognition		
			Person body tracking speed	Sensor based Human monitoring	Error rate [1–10]	Classifier used	False positive rate	Accuracy
[52]	Healthcare monitoring	• Lack of identity approximation	High	Accurate	~0.4	V-disparity map	Moderate	81.6%
[33]	Assistive living monitoring	• Limited low and band-pass filtration	Medium	Semi Accurate	~4.3	Hot wire anemometer	Inadequate	56.3%
[23]	Human activity monitoring	• Inadequate cut-off frequency	High	Accurate	~0.3	Naive Bayes	Moderate	86.1%
[46]	Human monitoring	• The temporal phases are not identified adequately	Low	Semi Accurate	~4.3	Google NEXUS 5X	Inadequate	59.3%
[9]	Health monitoring	• Latency in the proposed activity recognition approach	High	Accurate	~0.14	Support Vector Machine-based classifier	Moderate	88.6%
[53]	Human activity monitoring	• Precision needs to be improved in the process	Medium	Semi Accurate	~5.3	Naïve Bayes	Moderate	61.3%

component is sub-devices into two different sub-components, i.e., elderly monitoring and storage analysis.

1. Elderly monitoring: Elderly monitoring has been aimed in the research to identify the vital healthcare parameters for communicating with the healthcare provider. Big data analytics introduces health monitoring [5, 94]. Moreover, fall detection and human activity recognition are accurately performed through a One-class support vector machine (OCSVM) [53].
2. Storage analysis: After monitoring elderly healthcare parameters, the storage is accurately analyzed for managing extensive healthcare-related data. Towards that, Multidimensional Scaling and K-fold cross-validation type storage managers are used to manage the healthcare system data [13].

5.3 Data communication

In the previous two system components, healthcare data is tracked, monitored, and stored in a cloud environment to maintain healthcare data security and accessibility. Moreover, data communication is divided into three sub-components: classification, data analysis, and healthcare surveillance.

1. Classification: A Support Vector Machine-based classifier is introduced for the feasible classification of various healthcare data within the healthcare management system. In addition, classification is performed for accurate healthcare data segregation [31].
2. Data analysis: Rule-based filters are used for feasible healthcare data analysis. Data analysis is required because various types of vital healthcare parameters are sensed through the sensors. Thus, it needs to be analyzed on a regular basis for feasible healthcare data management [64].
3. Healthcare surveillance: In order to provide accurate healthcare surveillance to elderly people in the healthcare data management system, Sensor Nodes and AVISPA software are found to be the most reliable and precise. This is because it helps to improve healthcare data management accessibility; thus, healthcare providers and patients can access the data at any time [83].

Thus, the overall classification is performed to provide generic criteria for evaluating all 30 journals in the context of SDD taxonomy components. The healthcare data is accurately tracked and monitored using smart wearable sensors and evaluating sensing, data management, and data communication components.

6 System Components Validation And Evaluation

While determining various relevant factors of the wearable sensing techniques, the component that adds value to the system needs to be evaluated and validated. The value-added components are crucial for evaluating and validating the research domain's context. Meanwhile, all the publications used in the system use certain evaluation and validation models.

For instance, most literature is aimed at wearable sensing technology for monitoring and tracking healthcare parameters in elderly care. This is because monitoring and tracking healthcare parameters is important; thus, the accuracy and efficiency of the monitoring need to be high. Table 6 lists all validation and evaluation of health care monitoring and tracking techniques with their mathematical Formula.

Many works of literature that are used in the research have contained limited or less information that makes the dataset incomplete. The uncompleted dataset can be stated as a single dataset. Moreover, the literature has not been verified for the complex and varied datasets. Thus, the single dataset validation has not been giving assurance for the system's performance on efficient levels due to the inability and inaccuracy to monitor and track the healthcare parameters of the elderly. The inaccurate healthcare monitoring leads to inadequate communication of healthcare parameters to healthcare professionals. Hence, the system must validate and evaluate the monitoring, tracking, and communication of data.

Monitoring and tracking sensors' performance is also important in evaluating and validating the system. Thus, the monitoring and tracking of various healthcare parameters need to be done on a regular basis to attain high accuracy. The sensing devices are required to be performed up to the prospect and provide the possible result to the system.

It has been identified that there are numerous literature journals where the evaluation of the system has not been performed through experiments and simulation. Further, the conceptual recommendation of the papers is stated through the numerical analysis of the model. Moreover, the research literature has not provided information on the background of real-time environments.

7 System verification

7.1 Description

The components used in the proposed system need to be evaluated due to their importance. In the same way, quantitative and qualitative methods are implemented in a mannered way toward evaluating the mechanisms. Moreover, the numerical analysis method is used to analyze the system. The proposed feasible system has solved the issue of inaccurate healthcare monitoring. In addition, the component existence can be compared with the proposed SDD taxonomy. The occurrence is presented in a percentage formation.

7.2 System identification

Towards evaluating the SDD taxonomy, a teat of overlap is conducted because it provides the occurrence of components and sub-components in the literature. The occurrence can be provided in the numerical value for more detailed information about the component occurrences. Moreover, sensing of healthcare parameters, monitoring, and tracking identified the component's time in the literature.

Table 6 Validation And Evaluation Of Health Care Monitoring And Tracking Techniques

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[31]	Unified Theory of Acceptance Software-defined networking	Activity recognition	Sensor data processing module	It detects and identifies the problem	To calculating goodness of fit (GoF) through- $GoF = \sqrt{(averageAVE) \times (average - R^2)}$ GoF – for the validity test, R AVE – square root of the of the diagonal attributes	Physiological signals Real-time monitoring system	The security of elderly people has been improved by 81.4%
[13]	Signal segmentation Cross-validation	Activity recognition	Activity recognition techniques and Kinect	Rotational features of body are measured	For calculating mean vector and covariance matrix by using- $b_j(x_t) = N\left(x_t \vert \mu_j, \sum_j \times (1)\right)$ $b_j(x_t)$ – is set of N numbers Initial value is represent by j	Human robot interaction Information assurance and security	Visual recognition is used by sensors enabled devices to monitor body languages
[39]	Encoder, decoder full integrated circuit	IOTE fall system	Arduino prototyping board	Encoding and decoding minimize interference and noise	For calculating weighted probability density distribution by- $m(x) = \frac{\sum_{x_i \in N(x)} K(x_i - x) x_i}{\sum_{x_i \in N(x)} K(x_i - x)}$ Where N(x) represents neighborhood of x $\sum_{x_i \in N(x)} K\left(x_i - x\right) x_i$ represent the mean-shift algorithms	Sensing Platforms and Data Flows Data Aggregation	Smart intelligent and multi-modal system solves the security issue of home
[6]	Features extraction Wireless body area networks	Fall detection recognition	Machine learning algorithm	Detects falls and distinguishes ADLs efficiently	The equation of signal magnitude area (SMA) performed as- $SMA = \frac{1}{w} \sum_{i=1}^{w} \left(\vert x_i \vert + \vert y_i \vert + \vert z_i \vert \right)$ Where W represent the window length X_i, Y_i and Z_i represents the acceleration signal of axis	BigML data analysis Tunslip6 Data Aggregation	In this analyse three subjects between age 40 to 60 year, mass 68.7 to 84.6 kg and height from 1.64 to 1.79 m

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[47]	Context-aware systems Ontology	Activity recognition	IoRT (internet of robotics things)	Data collection and transmission	For calculating deviation used root-mean-square performed as- $D_i = \sqrt{\frac{1}{\lvert\alpha\rvert}\sum_{\forall\alpha_j\in\alpha}\left(\overline{\varphi_j} - \frac{1}{N_{ij}}\sigma_{ij}\right)^2}$ Di is activity recognition of IoT N_{ij} is total data collection	Data processing service Task generating service	It increases intelligence; connectivity and it increase safety
[70]	Human position tracking Activity tracking	Activity recognition	User activity and motion recognition through motions sensors	The path created for fall detection is highly feasible	The optimal Lagrange multiplier L calculated as- $\lambda^{n+1} = \lambda^n + \epsilon\left(E_{\pi^*_{\lambda^n}} - E\right)$ λ^{n+1} = represents the optimal Lagrange multiplier L Where $\lambda^n + \epsilon$ represents the user activity motion	Inertial measurement unit (IMU) Dynamic Bayesian Network	The result reveals that the overall accuracy of fall detection has achieved 80% accuracy
[64]	Rule-based filters Feature feedback mechanism	Intelligent fall detection	Optical flow feedback convolutional neural network	Improved the accuracy of posture recognition	The Gaussian kernel to calculate current estimate used equation is- $K\left(x_i - x\right) = e^{-c\lVert x_i - x\rVert}$ $K(x_i - x)$ represents the value of intelligent fall detection value Where e and x are the motion capturing of the body	Real-home situation Physiological signals	The results reveal the current ratio has achieved 82.7% accuracy
[5]	Big data analytics Sleep monitoring	Health monitoring	Big data analyser, data manager, web application	Data has accurately managed	To incresing biomedicine used pridiction model to calcuating the accurate esitimated values- $pi = + \frac{1}{1+e^{-fi(x)}}$ Pi represent the accurate calculation and x_i is the big analyser application where the e and x are physiological parameters	Obtrusive sleep apnea Physiological parameters	The result reveals that the parameter monitoring is highly accurate and monitoring prediction with 93.3% accuracy

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[66]	Engine based on the formal concept analysis	Activity recognition	Depth First Search (DFS) algorithm	Improved the accuracy of activity recognition	The equation that calculate Bayesian decision value by using- $R = \left(p\left(BG \dashv \middle\vert \vec{x}^{(t)}\right)\right) / \left(p\left(FG \dashv \middle\vert \vec{x}^{(t)}\right)\right)$ R – is Activity recognition and FG is first Depth first search (DFS) Algorithm based on recognition	Bayesian network Two-step prediction model	The results reveal that the data repetition error has been 100% detected
[31]	Dimension identification Original tam constructs	Self-capabilities of elderly person	Partial Least Square Structural Equation Modelling (PLS-SEM) algorithm	Improved the smart living for elderly person	To calculate each time slot of queue length by using- $q^{n+1} = \min(q^n + x_l^n - x_B^n, B)$ q^{n+1} = queue length calculation $\min(q^n + x_l^n - x_B^n, B)$ algorithm of PLSEM	Behavioural intention Real-time monitoring system	The proposed system has provided high accuracy while monitoring the elderly objects
[1]	Wireless Body Area Network Remote Health monitoring	Health monitoring	Constrained Markov Decision process and Decision Making	Intelligent algorithm has proven to achieve a 100%	To calculate the sensor node energy consumption rate by using given formula- $u^n = x_B^n - k \bullet P_s\left(h_1^n\right)$ P_s represents the power consumption in nodes of sensors x_B^n represents the queued packed data	Intelligent Adaptive Learning Lagrangian approach	The intelligent transmission algorithm has proven to be advanced than the greedy scheme and other algorithms
[50]	Radio Propagation model Relay placement strategy	Indoor health monitoring system	Optimal Relay Placement Algorithm	Increase the obstacle overcoming capability of the radio signals	The Lagrangian approch by using formula- $J_{\pi,\lambda} = \liminf_{N \to \infty} \frac{1}{N} E\left(\sum_{n=0}^{N} u^n(s^n, x^n; \lambda)\right)^n$ Lagrangian approach is represented by $J_{\pi,\lambda}$ Whereas 1/N is the optimal Relay placement algorithms	Performance evaluation Optimal relay placement	It calculation of the best location to place the relay in a WSN health monitoring environment

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[87]	Cloud Data-center Smart-phone app	Health monitoring	Access control rule se	Secure user interaction with the healthcare data	For calculating the predicted samples accuracy used formula is- $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ TP represent the Total pulse rate of Accuracy detect the total number of the frequency of the health monitoring devices	Ambient assisted living Real-time monitoring	The communicating parties and reducing the security flaws in the network to minimum
[68]	Choice of cluster heads Threshold value	Health monitoring	K-nearest neighbor	Energy efficient SVM-based classifier with increased	To calculating current sequence in average position through- $\overline{\varphi_j} = \frac{1}{\#\alpha_j}\sum_{k=1}^{\lvert\alpha\rvert} k,$ φ_j denoted the average position k-nearest neighbor $\frac{1}{\#\alpha_j}$ is the support vector machine classifier increased	Data aggregation Data classification and Monitoring	In this finding the CH at minimum distance from the base station
[83]	WSN setup in a field Energy model Ambient	Health monitoring	Ambient patient health monitoring	Increased patient health monitoring productivity and network lifespan	To calculate the long term average power consumption as- $E = \limsup_{N\to\infty} \frac{1}{N} E\left[\sum_{n=1}^{N} c^n\left(h_B^n, \pi(s^n)\right) \lvert s^0\right]$ Long term average is denoted by power consumption of monitoring and productivity where $\frac{1}{N}$ is patient health	Patient registration Monitoring phase Real-time monitoring system	The research has increased the life of the network and also the production of the healthcare monitoring
[17]	Migraine attack recognition Electroencephalography signals	Migraine attack recognition	Quadratic discriminant analysis (QDA) classifier	Detect the migration phases with the accuracy of 66%	The single hidden-layer neural network used hidden nodes for calculating output of the network- $\sum_{i=1}^{M} \beta_i f\left(W_i \bullet X_j + b_j\right) = o_j$ F represents the frequency of the hidden-layer network and W_i is the quadratic discriminant analysis	Epileptic seizures prediction Real-home situation	The classifiers achieved accuracy 91.2%, sensitivity 99.6%, and specificity 90.0%

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[14]	Feature extraction Deep Convolutional Network	Human activity recognition	Long Short-Term Memory (LSTM) Network	Outclassed the deep non-recurrent network by 6%	To estimate performace classification accuracy by using F-measures formula- $F_1 = \sum_i 2^* \omega_i \frac{precision_i \bullet recall_i}{precision_i + recall_i}$ where wi = ni /N represents proportion of samples of the ith class ith class samples denoted by N	Extreme Learning Machine Real-time monitoring	The testing time reduced by 38% through the back propagation algorithm
[80]	MATLAB software Accelerometer signals	Health monitoring	Feature extraction algorithm	Achieved five-stride (97.49 (±4.57)%) with greatest classification accuracy	The possible activity labels probability provided by using given formula- $p(c/p) = arg\max_{c=C} exp \frac{exp(p^{L-1} w^L + b^L)}{\sum_{k=1}^{NC} exp(p^{L-1} w^k)}$ Possible activity labels probability denoted by $p(c/p)$ Arg-max represent the human activity recognition	Stride segmentation Accelerometer signal segmentation	The ability to lower down the computation load than the existing feature sets i.e. (0.0041 (±0.0002) s)
[63, 79]	Inertial motion unit Accelerometer signals	Healthcare monitoring	Area under the curve (AUC)	Provided performance metrics i.e. achieved AUC = 0.97 and 0.96	To measure the magnitude of the acceleration vector by using Euclidean norm- $\|\vec{r}\|_2 = \sqrt{r_x^2 + r_y^2 + r_z^2}$ acceleration magnitude is denoted by $\|\vec{r}\|$ where the Euclidean norm represents the R	Data classification and Monitoring Physiological signals	The elderly walking i.e. age information, surface information. Moreover, the precision achieved 95.2%

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[38]	Open Service Gateway Initiative Biomedical sensors	Healthcare monitoring	Zephyr Bio-harness 3.0 (BH3)	Achieved accuracy of (mean ± std = 0.99 ± 0.01)	In sliding window to calculate the difference b/w min and max resultant acceleration- $\Delta S = \lVert S_{max} - S_{min} \rVert_2$ ΔS represent sliding window angle frequency Where maximum frequency denoted by S_{max} and S_{min} represent denoted by the S_{min}	Data pre-processing Real-home situation	Monitored mean, diastolic and systolic heart rate and blood pressure with the rage i.e. HR: 40 ÷ 199 bpm
[10]	ECG sensors Numerous signals	Activity prediction for elderly care	Hidden Markov Model (HMM)	Mean prediction rate of 89.98% has been achieved	For the estimation of sequence modeling used formula is- $I_t = \beta\left(W_{PI}P_t + W_{HI}H_{t-1} + b_I\right)$ Where W denotes the weight matrix, B is the bias vectors Logistic Sigmoid function represents by β	Sequencing modeling Physiological signals	Achieved the mean accuracy of 99.52% during the sensor based features
[32]	Deep Boltzmann Machine Sparse auto-encoder	Human activity recognition	Convolutional Neural Network Layers	Despite the high performance and accuracy is achieved 95.1% accuracy	The benifical output provided by convolutional operation is represent as- $C_i^{1,j} = \alpha\left(b_j^l + \sum_{m=1}^{M} w_m^{l,j} x_{i+m-1}^{l-1,j}\right)$ Where L denotes index layer σ is activation function and bias term is represented by feature map	Wireless sensor data mining Handling complex activities	Achieved classification accuracy of 90.9% even at the limited number of sensors

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[44]	Feature extraction Gait speed estimation	Healthcare monitoring	BioStampRC Investigator Application	Accuracy of estimating the gait speed at 98.7%	To calculating average accuracy for data balancing the used formula is- $Averageaccuracy = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{(TP+FP)_i}$ Average accuracy is the Bio stamp average accuracy TP is the total speed of sensor nodes	Estimating walking speed Gyro and accelerometer	The wearable sensors have resulted the accuracy of 98.7% and evaluate Speed ranging from 0.7 to 1.7 m/s
[42]	Wearable sensor signal processing Inertial measurement unit	Healthcare monitoring	Wearable sensor based mood induction	Achieved the accuracy of 81% and specificity of 88%	The human monitoring speed calculated by using given formula- $Speed = \frac{D_c - D_p}{t_c - t_p}$ Speed represent the human monitoring speed Where D_t and D_v are the healthcare wearable sensor data	Inertial Measurement Unit Davies-Bouldin Index	The statics reveal that the overall accuracy achieved 81%
[52]	RabbitMQ Advanced Message Queuing Protocol	Sensor-based activity recognition	Google NEXUS 5X (smartphone)	Measured acceleration forces, angular velocity	The irregular movements of distance by using- $D = \sqrt{\left((y-y)^2 + (x-x)^2\right)}$ D represent the irregular movements of data Where Y and x are the angular velocity	Data integration Codebook	The smartphone and codebook is used that provide accuracy of 87.1%

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[33]	Non-invasive sensors Fall detection algorithm	Fall detection recognition	Fall detection algorithm	Body motion gets evaluated through the Y or Z coordinate	To calculate the distance b/w floor and any joint the used formula is- $Height(H) = \frac{\lvert Ax+By+Cz+D \rvert}{(A^2+B^2+C^2)}$ x, y, and z are the joint coordinates A, B and C are the value of coordinates D represents the height	Fall confirmation Velocity monitoring	The proposed solution improving the security of elderly person in the smart home environment and gain accuracy of 86.83%
[23]	Logistic regression and Optimization technique	Human activity recognition	Optimization technique and Hot wire anemometer	Accurately monitor the air velocity with the accuracy of ±4%	To calculate particular precision, precision and accuracy through- $Recall = Sensitivity = \frac{TP}{(TP+FN)}$ $Precision = TP/(TP + FP)$ TP an d FP are the precision accuracy	Personal Thermal Comfort Assessment Physiological signals	The accuracy of sensors have achieved accuracy of ±2% for humidity and ±0.5 ◦C for air temperature
[46]	Feature selection Naive Bayes	Fall detection recognition	Nexus 5X smartphone	The notch data is collected with the accuracy 93.45%	The matrix of state transition probability calculate as- $a_{ij} = P(q_{t+1} = s_j \mid q_t = s_i)$ A_{ij} denotes the value of state transition where P is the collected accuracy of threshold q and s are the detection recognition	Threshold detection Predicting falls	The research achieved 94.6% accuracy by using Support Vector Machine (SVM) for decision making

Table 6 (continued)

Ref. No	Clinical Context	Study Criteria	Validation and Evaluation Criteria		Mathematical Formula	Validation and evaluation ofdata sets	Results
			Input	Output			
[9]	ECG monitoring Accelerometer sensors	Activity recognition	Wearable IoT-cloud-baSed-hEalth monitoring system	Achieved improvement of 4.58%	To calculating the Sound separation and localization used formula- $X_i(k) = \sum_{j=1}^{Ns} H_i(k)S_j(k) + N_i(k)$ $X_i(k)$ Represents the calculation of sound and localization data $\sum_{j=1}^{Ns} H_i$ is the wearable data activity recognition	Real-time personal health Physiological signals	The accuracy of proposed solution achieved 98.6% through the accelerometer sensors
[53]	(3D) linear accelerations Cross-validated baseline data	Human activity recognition	Single-subject boundary thresholds	Achieved the range of 0.1–0.8 with the average value of 0.4 (0.3)%	To estimate decision function used equation is support vector performed as- $y(x) = sign\left[\sum_{k=1}^{N} \alpha_k y_k K(x_k, x) + b\right]$ $y(x)$ represents the decision function of equation X and y are the data of SVM Where b is the cross validated baseline	Cross-validated baseline data Data classification and monitoring	The research has achieved overall accuracy of 90% and Gait trial data were achieved 0.5 (0.4)% and 17.7 (17.1)%

7.3 Completeness

While ensuring the system's completeness, evaluation of the major components and sub-components in the state-of-art. In this way, 30 journals were presented with the quality of Q1 and Q2 type journals. In this way, several journals have been aimed at healthcare parameter sensing and monitoring techniques in the context of smart home environments and elderly care. Figure 8 presents the percentage of component and sub-component occurrence with the proper demonstration. Table 7 lists all term frequencies used in the 30 publications.

Figure 8 details the evaluation and analysis of various components and sub-components. The existing SDD taxonomy can be disciplined in the data classified and fog layer context. It has also been identified that the existence of these components is the least. Also, the components are the least overlapped in the system. More precisely, if the SDD taxonomy is not applicable, then the taxonomy shall be penalized in the context of the elderly healthcare environment.

8 Discussion

8.1 Justification

In this section, a discussion is going to be undertaken on which care components are to be discussed that are rarely discussed in the research literature. To provide the importance of certain components, instances are figured out from the literature connected to the components in the SDD (Sensing, Data Storage, and Data communication) taxonomy and its standards. The discussion section also highlights the value of evaluating various taxonomy components.

8.2 Sub-factor of each component

1.1.1.**Sensing – Cloud:** In the various literature that is reviewed in the research, most literature has discussed wearable sensor technology and detailed the sensors in their pieces of literature. Yet, the cloud has not been discussed in the research in the context of

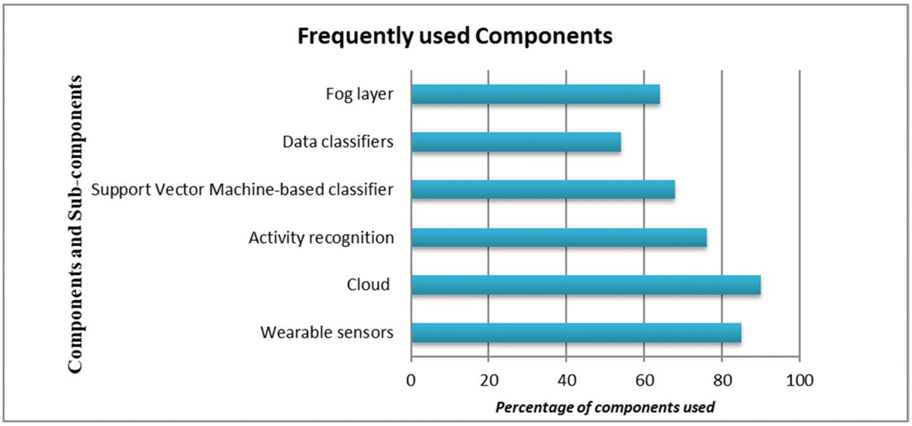

Fig. 8 Occurrence of the classes and components in the analysed literature, i.e., 90% is the occurrence rate of cloud components

Table 7 Term Frequency For 30 Publications

Term	Frequency	Term	Frequency	Term	Frequency
Data Collection	65	Ontology	58	Position tracking	49
Activity recognition	50	Body activity recognition	85	Health `monitoring	115
Microsoft Kinect	16	Quality of life	28	Activity prediction	95
Accelerometer sensor	28	Behavioral intention	22	Wireless sensor networks	72
Ambient assisted living	102	Real-time monitoring	52	Support vector machine	54
Wearable motion sensors	62	Remote Health monitoring	28	Human activity tracking	98
Social Internet of Things [73]	35	Human robot interaction	42	Internet of things gateway	48

healthcare parameter tracking and monitoring. Cloud technology helps to communicate and monitor healthcare data with the respective medical professionals. Though the researchers have not discussed it, only two pieces of literature detailed the cloud.

Different kinds of sensing methods can be used for sensing various healthcare parameters from elderly people. Sensing, tracking, and monitoring methods are included in the literature. Yet, it has been noticed that cloud and its common instances were not included in the literature. Hence, the passage of these methods is not required and should not be considered. Nonetheless, the literature section discusses the components of Sensing, tracking, and monitoring.

2.2.2. **Data storage – Storage analysis:** It has been identified so far that the literature has not included storage analysis in their research. Even though it has been noticed that the data storage has been detailed by various researchers in their literature, data synchronization in the storage analysis is important for the research because it helps get information about the healthcare data that needs to be stored in the external storage sources. After all, only 1 article has detailed information about storage analysis, but it is to be considered that the storage analysis should be discussed more in the research as it helps to manipulate the healthcare data.

Various data storage processes are not detailed in the research so far, such as Support vector machine, engine-based concept analysis, etc. Moreover, these components have not been discussed and are not required to be because of their low weightage in the research domain. Yet, elderly monitoring and its components are discussed more in the research publication due to its high reliability.

3.3.3. **Data communication – Classification:** It can be concluded that almost every researcher has included data communication in their research and literature. Yet, the classification components have not been discussed in detail. So far, only 1 research paper has provided information about classification and its components. Yet, it has been identified that classification plays a crucial role in healthcare data synchronization that helps manage healthcare data with accuracy and efficiency.

Support Vector Machine-based classifier, CNN, and Backpropagation (BP) are the types of classification that have been least included in the literature. Only 1 publication out of 30 journals discussed classification and the term data classifiers. Thus, it can be stated that these terms are the least reliable and capable of improving the research.

The conclusion of this section includes various processes and ways. In other words, sensing healthcare parameters and monitoring data through the cloud environment, data storage through the analysis of available or required storage, and healthcare data communication through classifying data using classifiers. These components are essential for improving elderly healthcare, which the research needs to detail.

8.3 Describing the few publications

In this research, 30 publications included information about sensing, but only 2 articles included a discussion about the cloud. In [31], they proposed cloud-based smart devices that help communicate the healthcare data sensed through the various wearable sensor technologies. In [47], they stated that cloud storage and communication could be used for communicating healthcare data for regular monitoring and tracking of data. Thus, the cloud is used as a tool for healthcare data sensing.

1. **Data storage – Storage analysis:** All 30 journal papers that are included in the research discussed data storage, but it has been identified that only 1 journal has provided information about storage analysis. Towards that discussed storage analysis using cloud computing to manage extensive healthcare data. Storage analysis is also helpful for effective healthcare data communication [9].
2. **Data communication – Classification:** The data classification includes a Support Vector Machine-based classifier, CNN, and backpropagation (BP). These terms are included in only one publication, i.e. [14], introduced data classifiers for classifying healthcare data and communicating it with the respective healthcare professionals.

In the research, various kinds of literature were selected that have aimed at data communication, but the classification component was found to be the least. Although there are multiple classifiers for classifying healthcare data, the publications and researchers do not discuss these sub-components.

The fewer occurrences of selected components and sub-components in the discussion section revealed that cloud, storage analysis, and classification have no primary role in apprising monitoring and tracking healthcare parameters for improving elderly healthcare management in the context of the healthcare industry.

9 Conclusion

The research focused on cultivating a model for Health care Monitoring and Tracking through Wearable Sensor Technologies in the context of Elderly Assisted Living. Moreover, it eliminated the issues and limitations of the currently used literature and publications. In addition, the proposed taxonomy (SDD) tested the system in the context of monitoring and tracking accuracy and effectiveness while communicating the sensed data within the healthcare industry. The finding of the system is indicated through the combination of numerous wearable sensors and devices for healthcare parameter monitoring. Further, communication of monitored data through data communication methods is accurate and capable of using feasible tracking and communication of data through a cloud environment. Yet, the system's limitations are imprecise monitoring of healthcare parameters, and healthcare data has not been classified accurately in the research and least reliable. On the other hand, the models have not been tested and verified as of now, leading the research to be aimed at the future direction. The future direction of the research shall aim to test and verify the model in a real-time environment; this can identify the usability and applicability of the system. Moreover, the system should be able to detect numerous tools for categorizing the tracked and monitored vital information.

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Declarations

Conflicts of interest No Conflicts of interest for this work.

References

1. Zang W, Miao F, Gravina R, Sun F, Fortino G, Li Y (2019) CMDP-based intelligent transmission for wireless body area network in remote health monitoring. Neural Comput Appl 10(2):1–9
2. Yang X, Tian Y (2017) Super normal vector for human activity recognition with depth cameras. IEEE Trans Pattern Anal Mach Intell 39(5):1028–1039
3. Yang X, Shah SA, Ren A, Fan D, Zhao N, Zheng S, Zhao W, Wang W, Soh PJ, Abbasi QH (2018) S-band sensing-based motion assessment framework for cerebellar dysfunction patients. IEEE Sens J 7(1):1–15
4. Yacchirema D, de Puga JS, Palau C, Esteve M (2019) Fall detection system for elderly people using IoT and ensemble machine learning algorithm. Pers Ubiquit Comput 10(5):1–17
5. Yacchirema DC, Sarabia-Jácome D, Palau CE, Esteve M (2018) A smart system for sleep monitoring by integrating IoT with big data analytics. IEEE Access 6(2):35988–36001
6. Xia M, Zhang Y, Zhang C (2018) A TAM-based approach to explore the effect of online experience on destination image: a smartphone user's perspective. J Destin Mark Manag 8(5):259–270
7. Woo MW, Lee J, Park K (2018) A reliable IoT system for personal healthcare devices. Futur Gener Comput Syst 78(8):626–640
8. Willy RW (2018) Innovations and pitfalls in the use of wearable devices in the prevention and rehabilitation of running related injuries. Phys Ther Sport 29(7):26–33
9. Wan J, Al-awlaqi MA, Li M, O'Grady M, Gu X, Wang J, Cao N (2018) Wearable IoT enabled real-time health monitoring system. EURASIP J Wirel Commun Netw 2018(1):298
10. Uddin MZ (2019) A wearable sensor-based activity prediction system to facilitate edge computing in smart healthcare system. J Parallel Distrib Comput 123(44):46–53
11. Thompson WR (2017) Worldwide survey of fitness trends for 2018: the CREP edition. ACSM's Health Fitness J 21(6):10–19
12. Thapliyal H, Nath RK, Mohanty SP (2018) Smart home environment for mild cognitive impairment population: solutions to improve care and quality of life. IEEE Consum Electron Mag 7(1):68–76
13. Tariq M, Majeed H, Beg MO, Khan FA, Derhab A (2019) Accurate detection of sitting posture activities in a secure IoT based assisted living environment. Futur Gener Comput Syst 92(9):745–757
14. Sun J, Fu Y, Li S, He J, Xu C, Tan L (2018) Sequential human activity recognition based on deep convolutional network and extreme learning machine using wearable sensors. J Sensors 12(8):2011–2018
15. Sodhro AH, Chen L, Sekhari A, Ouzrout Y, Wu W (2018) Energy efficiency comparison between data rate control and transmission power control algorithms for wireless body sensor networks. Int J Distrib Sens Netw 14(1):1550147717750030
16. Simoens P, Dragone M, Saffiotti A (2018) The internet of robotic things: a review of concept, added value and applications. Int J Adv Rob Syst 15(1):1729881418759424
17. Siirtola P, Koskimäki H, Mönttinen H, Röning J (2018) Using sleep time data from wearable sensors for early detection of migraine attacks. Sensors 18(5):1374
18. Siirtola P, Koskimäki H, Röning J (2016) Personal models for eHealth-improving user-dependent human activity recognition models using noise injection. In 2016 IEEE Symp Series Comput Intell (SSCI) 18(4):1–7
19. Shirali-Shahreza S, Ganjali Y (2018) Protecting home user devices with an SDN-based firewall. IEEE Trans Consum Electron 64(1):92–100

20. Shirahama K, Grzegorzek M (2017) On the generality of codebook approach for sensor-based human activity recognition. Electronics 6(2):44
21. Sendra S, Parra L, Lloret J, Tomás J (2018) Smart system for children's chronic illness monitoring. Information Fusion 40(9):76–86
22. Santoyo-Ramón J, Casilari E, Cano-García J (2018) Analysis of a smartphone-based architecture with multiple mobility sensors for fall detection with supervised learning. Sensors 18(4):1155
23. Salamone F, Belussi L, Currò C, Danza L, Ghellere M, Guazzi G, Lenzi B, Megale V, Meroni I (2018) Integrated method for personal thermal comfort assessment and optimization through users' feedback, IoT and machine learning: a case study. Sensors 18(5):1602
24. Roselin J, Latha P, Benitta S (2017) Maximizing the wireless sensor networks lifetime through energy efficient connected coverage. Ad Hoc Netw 62(2):1–10
25. Reichherzer T, Satterfield S, Belitsos J, Chudzynski J, Watson L (2016) An agent-based architecture for sensor data collection and reasoning in smart home environments for independent living. Can Conf Artif Intell Springer 24(4):15–20
26. Radu V, Lane ND, Bhattacharya S, Mascolo C, Marina MK, Kawsar F (2016) Towards multimodal deep learning for activity recognition on mobile devices. In Proc 2016 ACM Int Joint Conf Pervasive Ubiquit Comput: Adjunct 18(6):185–188
27. Pham M, Mengistu Y, Do H, Sheng W (2018) Delivering home healthcare through a cloud-based smart home environment (CoSHE). Futur Gener Comput Syst 81(24):129–140
28. Pease SG, Trueman R, Davies C, Grosberg J, Yau KH, Kaur N, Conway P, West A (2018) An intelligent real-time cyber-physical toolset for energy and process prediction and optimisation in the future industrial internet of things. Futur Gener Comput Syst 79(21):815–829
29. Palumbo F, La Rosa D, Ferro E, Bacciu D, Gallicchio C, Micheli A, Chessa S, Vozzi F, Parodi O (2017) Reliability and human factors in ambient assisted living environments. J Reliab Intell Environ 3(3):139–157
30. Pal D, Funilkul S, Charoenkitkarn N, Kanthamanon P (2018) Internet-of-things and smart homes for elderly healthcare: an end user perspective. IEEE Access 6(1):10483–10496
31. Pal D, Funilkul S, Vanijja V, Papasratorn B (2018) Analyzing the elderly users' adoption of smarthome services. IEEE Access 6(4):51238–51252
32. Nweke HF, Teh YW, Al-Garadi MA, Alo UR (2018) Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: state of the art and research challenges. Expert Syst Appl 105(14):233–261
33. Nizam Y, Mohd MNH, Jamil MMA (2017) Human fall detection from depth images using position and velocity of subject. Procedia Comput Sci 137(24):131–137
34. Nizam Y, Mohd M, Jamil M (2018) Development of a user-adaptable human fall detection based on fall risk levels using depth sensor. Sensors 18(7):2260
35. Navarro J, Vidaña-Vila E, Alsina-Pagès R, Hervás M (2018) Real-time distributed architecture for remote acoustic elderly monitoring in residential-scale ambient assisted living scenarios. Sensors 18(8):2492
36. Moummadi K, Abidar R, Medromi H, Ziani A (2018) Secured remote control of greenhouse based on wireless sensor network and multi agent systems. In Int Conf Adv Intell Syst Sustain Dev Springer 25(8):427–439
37. Moraes J, Rocha M, Vasconcelos G, VasconcelosFilho J, de Albuquerque V, Alexandria A (2018) Advances in photopletysmography signal analysis for biomedical applications. Sensors 18(6):1894
38. Monteriù A, Prist M, Frontoni E, Longhi S, Pietroni F, Casaccia S, Scalise L, Cenci A, Romeo L, Berta R, Pescosolido L, Orlandi G, Revel GM (2018) A smart sensing architecture for domestic monitoring: methodological approach and experimental validation. Sensors 18(7):2310
39. Monowar MI, Shakil SR, Kafi AH, Rhaman MK (2019) Framework of an intelligent, multi nodal and secured RF based wireless home automation system for multifunctional devices. Wireless Pers Commun 8(3):1–16
40. Min W, Cui H, Rao H, Li Z, Yao L (2018) Detection of human falls on furniture using scene analysis based on deep learning and activity characteristics. IEEE Access 6(3):9324–9335
41. McGinnis RS, McGinnis EW, Hruschak J, Lopez-Duran NL, Fitzgerald K, Rosenblum KL, Muzik M (2018) Wearable sensors and machine learning diagnose anxiety and depression in young children. In 2018 IEEE EMBS Int Conf Biomed Health Inform (BHI) 41(9):410–413
42. McGinnis RS, McGinnis EW, Hruschak J, Lopez-Duran NL, Fitzgerald K, Rosenblum KL, Muzik M (2019) Rapid detection of internalizing diagnosis in young children enabled by wearable sensors and machine learning. PLoS ONE 14(1):e0210267
43. McGinnis RS, Cain SM, Davidson SP, Vitali RV, McLean SG, Perkins NC (2017) Inertial sensor and cluster analysis for discriminating agility run technique and quantifying changes across load. Biomed Signal Process Control 32(11):150–156

44. McGinnis RS, Mahadevan N, Moon Y, Seagers K, Sheth N, Wright JA Jr, DiCristofaro S, Silva I, Jortberg E, Ceruolo M, Pindado JA, Sosnoff J, Ghaffari R, Patel S (2017) A machine learning approach for gait speed estimation using skin-mounted wearable sensors: from healthy controls to individuals with multiple sclerosis. PLoS ONE 12(6):e0178366
45. McGinnis EW, McGinnis RS, Hruschak J, Bilek E, Ip K, Morlen D, Lawler J, Lopez-Duran NL, Fitzgerald K, Rosenblum KL, Muzik M (2018) Wearable sensors detect childhood internalizing disorders during mood induction task. PLoS ONE 13(4):e0195598
46. Mauldin T, Canby M, Metsis V, Ngu A, Rivera C (2018) Smartfall: a smartwatch-based fall detection system using deep learning. Sensors 18(10):3363
47. Mahieu C, Ongenae F, De Backere F, Bonte P, De Turck F, Simoens P (2019) Semantics-based platform for context-aware and personalized robot interaction in the internet of robotic things. J Syst Softw 149(35):138–157
48. Luo M, Wang Z, Ke K, Cao B, Zhai Y, Zhou X (2018) Human metabolic rate and thermal comfort in buildings: the problem and challenge. Build Environ 131(22):44–52
49. Lobato FMF, de Resende DCO, do Nascimento RP, Siqueira ALC, Jacob AFL, de Santana AL (2017) Multimodal low-invasive system for sleep quality monitoring and improvement. Beyond Internet Things Springer 14(6):223–242
50. Li Y, Chen CS, Chi K, Zhang J (2018) Two-tiered relay node placement for WSN-based home health monitoring system. Peer-to-Peer Netw App 45(12):1–15
51. Kumari S, Khan MK, Li X, Wu F (2016) Design of a user anonymous password authentication scheme without smart card. Int J Commun Syst 29(3):441–458
52. Köping L, Shirahama K, Grzegorzek M (2018) A general framework for sensor-based human activity recognition. Comput Biol Med 95(14):248–260
53. Kobsar D, Ferber R (2018) Wearable sensor data to track subject-specific movement patterns related to clinical outcomes using a machine learning approach. Sensors 18(9):2828
54. Kim J, Zhou Y, Schiavon S, Raftery P, Brager G (2018) Personal comfort models: predicting individuals' thermal preference using occupant heating and cooling behavior and machine learning. Build Environ 129(11):96–106
55. Khojasteh S, Villar J, Chira C, González V, de la Cal E (2018) Improving fall detection using an on-wrist wearable accelerometer. Sensors 18(5):1350
56. Khan FA, Haldar NAH, Ali A, Iftikhar M, Zia TA, Zomaya AY (2017) A continuous change detection mechanism to identify anomalies in ECG signals for WBAN-based healthcare environments. IEEE Access 5(2):13531–13544
57. Kanan R, Elhassan O, Bensalem R (2018) An IoT-based autonomous system for workers' safety in construction sites with real-time alarming, monitoring, and positioning strategies. Autom Constr 88(14):73–86
58. Kahng M, Andrews PY, Kalro A, Chau DHP (2018) Activis: visual exploration of industry-scale deep neural network models. IEEE Trans Visual Comput Graphics 24(1):88–97
59 Janidarmian M, Roshan Fekr A, Radecka K, Zilic Z (2017) A comprehensive analysis on wearable acceleration sensors in human activity recognition. Sensors 17(3):529
60. Jalloul N (2018) Wearable sensors for the monitoring of movement disorders. Biomed J 41(4):249–253
61. Igelström H, Åsenlöf P, Emtner M, Lindberg E (2017) Improvement in obstructive sleep apnea after a tailored behavioural sleep medicine intervention targeting healthy eating and physical activity: a randomised controlled trial. Sleep and Breathing 10:1–9
62. Hu L, Peng C, Evans S, Peng T, Liu Y, Tang R, Tiwari A (2017) Minimising the machining energy consumption of a machine tool by sequencing the features of a part. Energy 121(11):292–305
63. Hu B, Dixon PC, Jacobs JV, Dennerlein JT, Schiffman JM (2018) Machine learning algorithms based on signals from a single wearable inertial sensor can detect surface-and age-related differences in walking. J Biomech 71(9):37–42
64. Hsieh YZ, Jeng YL (2018) Development of home intelligent fall detection IoT system based on feedback optical flow convolutional neural network. IEEE Access 6(2):6048–6057
65. Hassan MM, Uddin MZ, Mohamed A, Almogren A (2018) A robust human activity recognition system using smartphone sensors and deep learning. Futur Gener Comput Syst 81(9):307–313
66. Hao J, Bouzouane A, Bouchard B, Gaboury S (2018) Activity inference engine for real-time cognitive assistance in smart environments. J Ambient Intell Humaniz Comput 9(3):679–698
67. Haladjian J, Haug J, Nüske S, Bruegge B (2018) A wearable sensor system for lameness detection in dairy cattle. Multimodal Technol Interaction 2(2):27
68. Haider D, Ren A, Fan D, Zhao N, Yang X, Shah SA, Hu F, Abbasi QH (2019) An efficient monitoring of eclamptic seizures in wireless sensors networks. Comput Electr Eng 75(22):16–30

69. Fujiwara K, Miyajima M, Yamakawa T, Abe E, Suzuki Y, Sawada Y, Kano M, Maehara T, Ohta K, Sasai-Sakuma T, Sasano T, Matsuura M, Matsushima E (2016) Epileptic seizure prediction based on multivariate statistical process control of heart rate variability features. IEEE Trans Biomed Eng 63(6):1321–1332
70. Do HM, Pham M, Sheng W, Yang D, Liu M (2018) RiSH: a robot-integrated smart home for elderly care. Robot Auton Syst 101(24):74–92
71. Dixon PC, Schütte KH, Vanwanseele B, Jacobs JV, Dennerlein JT, Schiffman JM (2018) Gait adaptations of older adults on an uneven brick surface can be predicted by age-related physiological changes in strength. Gait Posture 61(12):257–262
72. de Oliveira Júnior WG, de Oliveira JM, Munoz R, de Albuquerque VHC (2018) A proposal for internet of smart home things based on bci system to aid patients with amyotrophic lateral sclerosis. Neural Comput App 9(1):1–11
73. De Maio C, Fenza G, Loia V, Orciuoli F (2017) Unfolding social content evolution along time and semantics. Futur Gener Comput Syst 66(9):146–159
74. De Maio C, Fenza G, Loia V, Parente M (2016) Time aware knowledge extraction for microblog summarization on twitter. Information Fusion 28(4):60–74
75. Cippitelli E, Fioranelli F, Gambi E, Spinsante S (2017) Radar and RGB-depth sensors for fall detection: a review. IEEE Sens J 17(12):3585–3604
76. Chaccour K, Darazi R, El Hassani AH, Andrès E (2017) From fall detection to fall prevention: a generic classification of fall-related systems. IEEE Sens J 17(3):812–822
77. Cao L, Wang Y, Zhang B, Jin Q, Vasilakos AV (2018) GCHAR: an efficient group-based context—Aware human activity recognition on smartphone. J Parallel Distrib Comput 118(14):67–80
78. Camps J, Samà A, Martín M, Rodríguez-Martín D, Pérez-López C, Alcaine S, Mestre B, Prats A, Crespo MC, Cabestany J, Bayés A, Català A (2017) Deep learning for detecting freezing of gait episodes in parkinson's disease based on accelerometers. In Int Work-Conference Artif Neural Netw Springer 92(18):344–355
79. Benson LC, Clermont CA, Bošnjak E, Ferber R (2018) The use of wearable devices for walking and running gait analysis outside of the lab: a systematic review. Gait Posture 9(1):45–55
80. Benson LC, Clermont CA, Osis ST, Kobsar D, Ferber R (2018) Classifying running speed conditions using a single wearable sensor: optimal segmentation and feature extraction methods. J Biomech 71(11):94–99
81. Bagaa M, Chelli A, Djenouri D, Taleb T, Balasingham I, Kansanen K (2017) Optimal placement of relay nodes over limited positions in wireless sensor networks. IEEE Trans Wireless Commun 16(4):2205–2219
82. Amin R, Biswas GP (2016) A secure light weight scheme for user authentication and key agreement in multi-gateway based wireless sensor networks. Ad Hoc Netw 36(14):58–80
83. Amin R, Islam SH, Biswas GP, Khan MK, Kumar N (2018) A robust and anonymous patient monitoring system using wireless medical sensor networks. Futur Gener Comput Syst 80(4):483–495
84. Alvear-Sandoval RF, Figueiras-Vidal AR (2018) On building ensembles of stacked denoising auto-encoding classifiers and their further improvement. Information Fusion 39(10):41–52
85. Al-Taee MA, Al-Nuaimy W, Muhsin ZJ, Al-Ataby A (2017) Robot assistant in management of diabetes in children based on the internet of things. IEEE Internet Things J 4(2):437–445
86. Alsina-Pagès R, Navarro J, Alías F, Hervás M (2017) homesound: real-time audio event detection based on high performance computing for behaviour and surveillance remote monitoring. Sensors 17(4):854
87. Al-khafajiy M, Baker T, Chalmers C, Asim M, Kolivand H, Fahim M, Waraich A (2019) Remote health monitoring of elderly through wearable sensors. Multimed Tools App 10(4):1–26
88. Alfano FRDA, Olesen BW, Palella BI (2017) Povl ole fanger's impact ten years later. Energy and Buildings 152(24):243–249
89. Adapa A, Nah FFH, Hall RH, Siau K, Smith SN (2018) Factors influencing the adoption of smart wearable devices. Int J Human-Comput Inter 34(5):399–409
90. Abtoy A, Touhafi A, Tahiri A (2018) Ambient assisted living system's models and architectures: a survey of the state of the art. J King Saud Univ-Comput Inf Sci 23(1):201–210
91 Alsadoon A, Al-Naymat G, Alsadoon OH, Prasad PWC (2021) DDV: A taxonomy for deep learning methods in detecting prostate cancer. Neural Process Lett 53(4):2665–2685. https://doi.org/10.1007/s11063-021-10485-y
92. Shah B, Alsadoon A, Prasad PWC, Al-Naymat G, Beg A (2021) DPV: a taxonomy for utilizing deep learning as a prediction technique for various types of cancers detection. Multimed Tools App 80(14):21339–21361. https://doi.org/10.1007/s11042-021-10769-4
93. Perez AJ, Siddiqui F, Zeadally S, Lane D (2023) A review of IoT systems to enable independence for the elderly and disabled individuals. Internet of Things (Netherlands) 21 https://doi.org/10.1016/j.iot.2022.100653

94. Chaudhary A, Mishra R, Gupta HP, Shukla KK (2023) Jointly prediction of activities, locations, and starting times for isolated elderly people. IEEE J Biomed Health Inform 27(5):2288–2295. https://doi.org/10.1109/JBHI.2021.3121296
95. Tamilselvi T, Lakshmi D, Lavanya R, Revathi K (2023) Digital companion for elders in tracking health and intelligent recommendation support using deep learning. Int J Recent Innov Trends Comput Commun 11(3):145–152. https://doi.org/10.17762/ijritcc.v11i3.6331
96. Shaik T, Tao X, Higgins N, Li L, Gururajan R, Zhou X, Acharya UR (2023) Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. Wiley Interdiscip Rev 13(2):e1485. https://doi.org/10.1002/widm.1485
97. Lach E, Szewczenko A, Chuchnowska I, Bursiewicz N, Benek I, Widzisz-Pronobis S, Bal D, Elsner K, Sanigórska M, Sutor M, Włodarz J (2023) The problem of monitoring the psycho-physical condition of seniors during proposed activities in urban space. Sensors 23(3):1602. https://doi.org/10.3390/s23031602
98. Babu DV, Ramya S (2023) Wearable Device based Fall Prediction and Alert Mechanism for Aged People using IoT Technolog. Proceedings of the 3rd International Conference on Artificial Intelligence and Smart Energy, ICAIS 2023: 51-56. https://doi.org/10.1109/ICAIS56108.2023.10073853
99. Saile KND, Navatha K (2022) Smart IoT devices for the elderly and people with disabilities. Advanced Healthcare Systems: Empowering Physicians with IoT-Enabled Technol 101-114. https://doi.org/10.1002/9781119769293.ch8
100. Shilpa Aarthi M, Juliet S. (2022) Intelligent Fall Detection System based on Sensor and Image data for Elderly Monitoring. 4th International Conference on Inventive Research in Computing Applications, ICIRCA 2022 - Proceedings 1259-1265. https://doi.org/10.1109/ICIRCA54612.2022.9985734
101. Awotunde JB, Ajagbe SA, Florez H (2022) Internet of things with wearable devices and artificial intelligence for elderly uninterrupted healthcare monitoring systems. Commun Comput Inform Sci 1643 CCIS, 278-291
102. Foukarakis M, Adami I, Ntoa S, Koutras G, Kutsuras T, Stefanakis N, Partarakis N, Ioannidi D, Zabulis X, Stephanidis C (2022) An integrated approach to support health monitoring of older adults. Commun Comput Inform Sci 1654 CCIS 427-435. https://doi.org/10.1007/978-3-031-19679-9_54
103. Teixeira E, Fonseca H, Diniz-Sousa F, Veras L, Boppre G, Oliveira J, Pinto D, Alves AJ, Barbosa A, Mendes R, Marques-Aleixo I (2021) Wearable devices for physical activity and healthcare monitoring in elderly people: A critical review. Geriatrics (Switzerland) 6(2):38. https://doi.org/10.3390/geriatrics6020038
104. Kiruthika V, Krishna GGR, Karthik G, Xavier XB, Sankaran KS, Kavitha BC (2021) Smart Wearable Device for Blind and Elderly People. 2021 International Conference on Computational Performance Evaluation, ComPE 199-203. https://doi.org/10.1109/ComPE53109.2021.9752340

Authors and Affiliations

Abeer Alsadoon[1,2,3] · **Ghazi Al-Naymat**[4,5] · **Oday D. Jerew**[3]

✉ Abeer Alsadoon
alsadoon.abeer@gmail.com

[1] School of Computing Mathematics and Engineering, Charles Sturt University (CSU), Bathurst, Australia

[2] School of Computer Data and Mathematical Sciences, Western Sydney University (WSU), Sydney, Australia

[3] Asia Pacific International College (APIC), Sydney, Australia

[4] College of Engineering and Information Technology, Ajman University, Ajman, UAE

[5] Artificial Intelligence Research Center (AIRC), Ajman University, Ajman, UAE