Internet of Things and Cloud Activity Monitoring Systems for Elderly Healthcare

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Abstract According to the World Health Organization, people aged 60 years and above globally will be 2 billion in 2050 by increasing from its present 841 million populaces. With the recent advances in smart healthcare systems that make treatment available for all, it is expected that longevity becomes the norm for humans. Providing a convenient platform for elderly patients has therefore become the attraction of various researchers from different fields, and this makes the smart healthcare system become a point of desirability for many. The advancement in information technology especially in the area of Internet of Things (IoT), cloud computing, and wearable devices has helped bring healthcare nearer to the rural areas and improve elderly care globally. Ambient Assisted Living (AAL) makes it possible to incorporate emerging technology into our everyday activities. Therefore, this chapter explains the important role of IoT and Cloud activity monitoring systems for elderly healthcare in medicine to reduce caregivers' needs and help the aged live an active life. Also, proposes a framework of an intelligent IoT and cloud activity monitoring system for elderly healthcare using a wearable body sensor network. The suggested system educates and warns healthcare workers in real-time about changes in the health status of aged patients in order to recommend preventative steps that can save lives. The proposed system can accommodate any number of wearable sensors devices and a

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huge number of applications. The platform also enables remote health monitoring, and real-time monitoring, thus reduce the workload on the medical personnel. IoT and cloud activity monitoring system is a quick and rapid way of monitoring, and diagnosis of elderly patients by depriving them of diffusion of the infection to others.

Keywords Internet of Things · Elderly patient · Activity monitoring · Cloud computing · Smart healthcare system

1 Introduction

The constant aged of the world's population places greater strain on society and welfare systems, making it critical to develop better programs and inventions capable of treating medical problems associated with old age. E-Health provides initiatives to assist seniors in living longer in their homes, as well as innovative services to help pay for specific treatment or recuperation. Population aging is a visible phenomenon with significant social and economic implications. Over 70-year-olds will increase in number from 64 million in 2010 to 122 million in 2060 [1]. To address the problems that these phenomena has produced, the concept of Ambient Assisted Living (AAL) has been elevated as a target solution to healthcare, describing a network that is interconnected, context-aware, ubiquitous, customizable, responsive, and anticipative.

The ProActive Ageing initiative ("Prolonging ACTIVE life for an active and stable AGEING") offers web services for the successful (re) integration of older people into societal and operational life, for the enhancement of an elderly person's self-well-being and freedom through continuous learning and knowledge exchange, and for the delivery of structured training programs for structured workers [2]. According to the Internet of Things Technology Initiative (AIOTI), 110 European provinces have defined Active and Safe old age as a target for intelligent expertise [3, 4]. The AAL Joint solutions built health monitoring (HM) as a significant group of use cases established in European projects FP6 and FP7, with other thematic areas being behavior tracking, mobility associate, fitness instructor, grocery, and diet planner, socializing with Smart TV [5]. IoT has always been the crucial information technology for building such use cases because of its ability to upgrade real-world things and merge them into the Cloud [6]. Despite the limitations of IoT devices' storage and processing capabilities in comparison to continuously increasing criteria for the amount of device-generated data and their decision theory, cloud computing is emerging as a very appealing alternative solution with the potential to provide omnipresent, accessible, on-demand network access to a shared configuration database [7].

Apart from communicating and exchanging data between health professionals, cloud computing is widely used in many other areas of healthcare, including medical imaging (storage, exchanging, and processing), public health and patient self-management, hospital management and clinical information systems, and preparing, coordinating, or reviewing therapeutic interventions (Statistical analysis, text analysis, or medical trials) [8].

IoT devices, such as satellites, may have applications in the healthcare industry for Heart rate monitors, blood sugar supervises, and endoscopic capsules [9–11]. Sensors, actuators, and other mobile technologies are used devices in the therapeutic business will revolutionize it, especially during pandemic outbreaks [12, 13]. The Internet of Medical Things (IoMT) is a linked network of smart healthcare devices that accept data from internet communications networks and transmit it to healthcare information systems [14, 15]. Currently, 3.7 million therapeutic devices are in use that are linked to and monitored by various areas of the body in order to offer medical alerts [16, 17].

These IoMT networks communicate to public cloud such as Google Cloud Technology, Microsoft Azure Cloud, Amazon Web Services, and others bespoke network services in order to collect storage and analytics data. Patients with lingering or long-term illnesses can benefit from remote medical monitoring using IoT services. These systems can track and monitor patients who use embedded sensor equipment in medical centers.

They can transmit the fitness data across to their doctor. Medical gadgets that can be coupled or launched as IoT technology include infusion pumps that link to analytical monitors and hospital beds with sensors for monitoring patients' health status. Items like "Smart" objects with various sensors and actuators that are completely equipped to operate in their respective surroundings, as well as incorporated communication infrastructure to link with any imaginable alternative, assist the Internet of Things (IoT) in reaching its full potential. As shown in Fig. 1, the most common usage of IoT for old persons is activity monitoring.

The IoT is a large-scale machine deployment, such as machine type communication (MTC), that conducts sensing and actuation activities with little or no human participation. The number of Internet-connected items is predicted to outweigh the world's population. The number of linked health devices is fast expanding [18], as the IoT is concerned with the realism of connecting specific physical commodities to the internet. In addition, healthcare is the largest target market for IoT, with pulse rate tracking being the most advantageous use [19]. Simple devices like glucose meters and heart rate monitors, as well as IoT systems that feed data into more complicated technologies, might be used to create emergency alarm systems and remote medical monitoring systems.

This chapter presents (1) the integration of devices into an IoT- driven remote healthcare system and (2) the utilization of an IoT-based platform to track the health of older patients.

The rest of this chapter is organized as follows: Sect. 2 discusses deployment of IoT in elderly monitoring scheme. Section 3 has a detailed discussion of applications of IoT and Cloud computing in elderly monitoring systems. Section 4 presents the ICEAMS framework for activities monitoring of the elderly patient. Section 5 presents a practical case of ICEAMS for monitoring elderly people, and finally Sect. 6 concluded the chapter and presents future direction for the chapter.

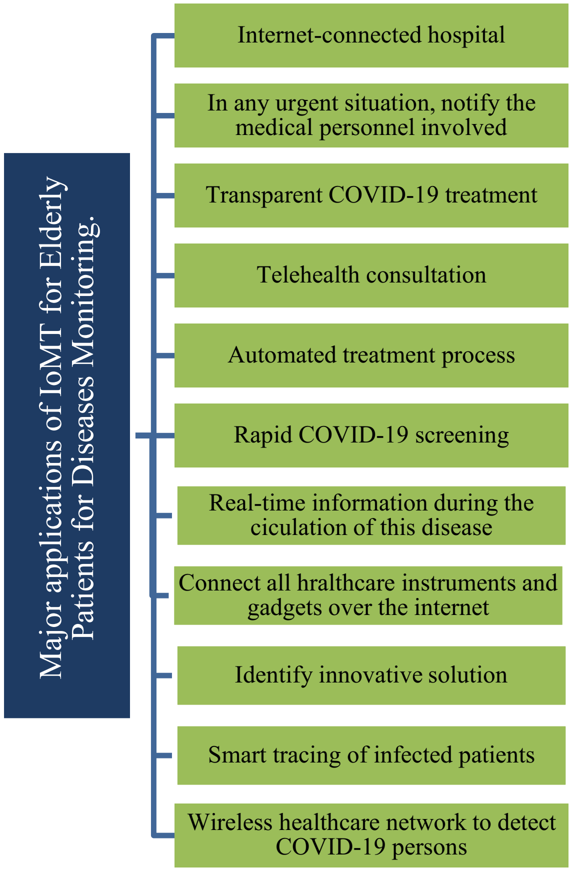

Fig. 1 Major application of IoT for elderly patients for diseases monitoring

2 Application of Internet of Things in Elderly Activity Monitoring Systems

2.1 IoT Operations

The latest breakthroughs in IoT, wearable sensors, and telecommunication technologies have made human living smarter in the age of universal computing, allowing smart healthcare services to be delivered [9, 10, 20]. The IoT has the ability to completely change the medical industry. Patients, medical staff, and carers, as well as monitoring devices are all connected by software and ICT technologies [9].

The healthcare sector in most emerging countries is facing severe economic issues, owing to the expanding number of reliable and high-quality services necessary for the aged. Elderly persons require extra care and attention because even a little illness or injury can result in irreversible damage [21].

According to the results of a poll performed by the United States of Elderly, 90% of elderly inhabitants want to be able to dwell in their own residences [22]. Many older persons choose to age in their own homes, according to recent studies [23], but they need caretakers or medical professionals to pay attention to them and keep an eye on or assist them. As a result, developing new tools and technology to assist elder individuals in aging in place is critical [24].

Increases technical advancements have resulted in an increase in lifespan breakthroughs the share of old individuals has grown in recent years. Age-related frailty, chronic diseases, and disabilities are all difficulties that these elderly persons must cope with on a daily basis. Recently, there has been a surge in interest in establishing aged care services based on cutting-edge technology with the goal of allowing seniors to live independently. The IoT has been established as a cutting-edge concept for linking real and virtual items in order to improve services, and it has the potential to significantly improve remote geriatric monitoring. Several recent initiatives have been made to address elderly care needs using IoT-based solutions [21].

There is a growing need for unique technology that can deliver effective remote geriatric monitoring services. To this goal, a variety of current disciplines should be used to serve the needs of the aged, taking into account their limits in everyday life. IoT, as a promising paradigm, has the capacity to provide such essential services to the elderly [25]. The IoT is a cutting-edge technology that combines sensor development, data gathering, network resources and services required, database administration, and information processing are all examples of data computing, and other disciplines to enable objects (e.g., entity, individuals) having distinct identities in order to communicate to a central server and build local connections [9]. IoT-enabled systems' connection allows entities to communicate and combine data to get a more thorough understanding of their functioning as well as the features of their surroundings, allowing them to provide more advanced services that are sophisticated and effective. One of the primary advantages of IoT application is that they enable continuous (i.e., 24/7) remote monitoring systems, which help to raise people's standard of living [26].

By linking items and people, the IoT has the capability to fundamentally influence numerous human characteristics existence. The system architecture may be partitioned into three levels depending on the characteristics and functionalists of IoT-enabled systems (data collecting, communication, and exploration), as stated by various academics. The architecture of an IoT-enabled system, on the other hand, may be redefined in terms of its use cases. As illustrated in Fig. 2, the system in our situation is defined as follows in order to meet the needs of elderly monitoring:

Perception layer: This is the first stratum and the one closest to the individual being tracked. The core objective of the insight level is to acquire necessary data from the client, as well as communication with upper levels. The perception layer, as shown in Fig. 2, may be classified into two parts: the body area network (BAN) and fixed/mobile sensors in the vicinity. The BAN may be seen as a web of vital signs peripherals (e.g., chest belts, infusion pumps, and blood stress monitors) or sensing gadgets (e.g., smartwatches, fitness trackers, and smart headwear) that gather user data. Medical data such as vital symbols (e.g., rate of heartbeat and rate of breathing),

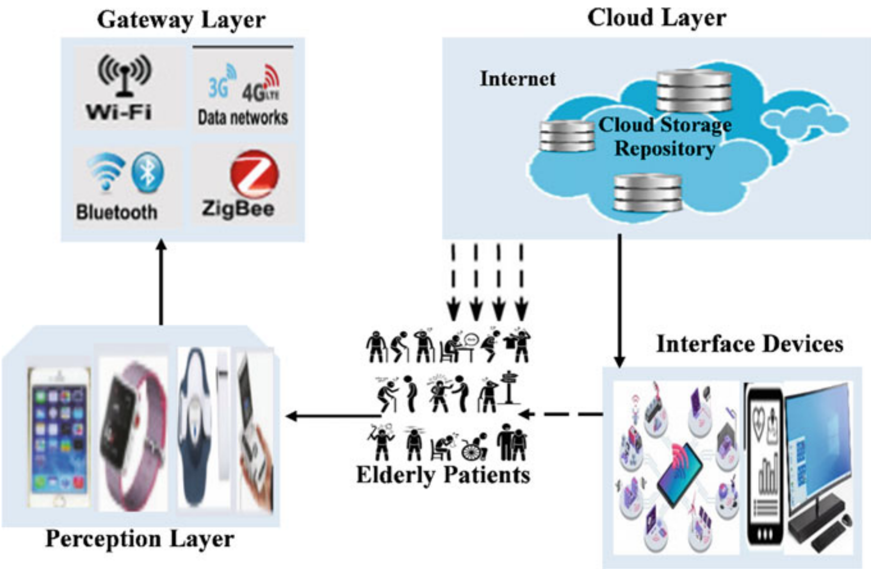

Fig. 2 A multi-layer IoT-based elderly monitoring system architecture

these devices record blood sugar levels, galvanic skin responses (GSR), and location information like position, exercise habits, and rest amount. The second type consists of fixed contexts sensors, which are commonly seen in residences and other public locations (e.g., surveillance camera, Smart TV, etc.). Environmental elements are also detected and responded to using mobile context sensors. This section includes a wide range of robotics.

Gateway Layer: The gateway layer accepts sensual information through mobile and wireless methods from the sensor node (such as Bluetooth, 6LoWPAN, and Zigbee) and transfers it to the Cloud layer for processing. In Fig. 2, the layer is separated into two clusters. The first is for fixed access points that transmit data indoors and are put in senior homes. The mobile access point is the second type, which is utilized for outside purposes. A smartphone is an excellent example of a data transmission and processing mobile access point.

The **Cloud layer**: In the data center, this is a distant layer. As seen in Fig. 2 the layer is divided into several divisions. Incoming data is stored in data centers before being analyzed using the Cloud's great computing capacity. Reasoning [27], machine learning algorithms [28], pattern recognition approaches [29], and other data analysis techniques are used. In order to successfully respond to the requirements of the elderly, decisions and reactions are made based on the results. These backend apps are capable of detecting lifestyle patterns in the elderly, like Mild Cognitive Impairment (MCI) [30], as well as anticipate chronic and acute disorders, such as blood glucose concentration prediction for a diabetic [10]. End-users, such as the monitored individual, their caregivers, and medical professionals, can be provided with a variety of apps and services, like a mobile user application, to communicate the outcomes.

2.2 IoT and Elderly Monitoring Systems

Meeting the needs of the elderly is one of the most important uses of IoT-based distant surveillance systems. On one side, senior fragility makes people more sensitive to a number of illnesses (severe and lingering), deficiencies (e.g., graphic, physical, and verbal), and limitations (e.g., poor memory) and, on either hand, raises the risk of being unaware on the other (e.g., computer illiteracy). As a result of disregarding the need of senior care, an increase in old dependency or the requirement for them to reside in a treatment facility may ensue. In this situation, IoT-based distant sensor observing can help resolve the aforementioned concerns, reduce the repercussions, and allow seniors to live freely. Given the projected high growth of the elderly population in the near future, major investments in innovative senior care concepts and technologies, such as the IoT are required. A number of methods have been offered to fulfill the standards of the aged by compensating for deficiencies or avoiding the unavoidable effects.

2.2.1 Health Monitoring

Due to aging's fragility and sensitivity to viral infections (e.g., acute and chronic ailments), monitoring system becomes the most significant aspect of aging remote monitoring. Remote health monitoring raises the standard of care to elderly's quality of life by identifying and alerting caretakers in the case of an emergency, as well as reducing nursing and hospital visits, and hence healthcare costs. In 2011, older people accounted for more than a one-third of all clinic charges and visits in the United States, according to a research conducted by the Agency for Healthcare Research and Quality (AHRQ) [31]. As a result, providing remote health monitoring services at home is critical to improving care services and lowering hospital expenditures and stays for the elderly. Besides, as the world's potential supporting ratio declines, a large number of older citizens may confront a future with a restricted quantity of care and supportive services.

The improvements are then applied based on sensor feedback, and a customized workout regimen is proposed without the requirement for direct human supervision. Acceptance of new technology is typically difficult, especially when the system's target users are the elderly. This reduced the use of traditional equipment (e.g., television) in various health monitoring techniques to provide more user-friendly services for old folks. In this context, Spin-sante and Gambi [32] propose a remote patient monitoring system related to digital television that incorporates a range of wire-free medical devices (e.g., oximeter, breathing tester, and glycaemia meter). Macis and colleagues worked on the HEREiAM programme [33], it explains how a

TV-based system may give greater aid and support to the elderly. The project uses a TV set at home to provide a variety of services to solve remote healthcare technology acceptability as well as other challenges such as security and social communication [34].

Another indicator that represents the health status of the elderly is daily activity. Physical activity, eating (meal frequency and length), sleeping, and other activities are only a few of them. Several efforts have been taken to this end, leveraging various techniques and sensory data to offer activity monitoring for the aged. Kasteren and colleagues [35] discuss a system (created as part of the CARE project) that tracks and recognizes older people's activity levels using wireless sensors and recognition mode.

2.2.2 Nutrition Monitoring

Malnutrition is a common aging problem that may be handled, whether it is caused by a deficit (undernutrition), excess (overnutrition), or a lack of appropriate nutrition. The elderly are more likely to suffer from malnutrition [36, 37]. Malnutrition has been linked to a number of health problems in the elderly, including cardiovascular and cerebrovascular disease, osteoporosis, and diabetes [10]. Nutrition monitoring, particularly weight and nutrition tracking, along with health tracking via IoT-based wearable sensors, are critical to enhancing people's health and well-being of senior citizens.

Various approaches and systems have previously been offered in this area. ChefMyself is a nutrition-related monitoring app that presents a methodology to help older people track their food intake [38]. It provides remote nutrition monitoring, including weight tracking (through cordless scales), diet tracking, a recipe repository, and grocery and cooking aid for the aged are all available via a Cloud-based connection. It also provides access to social networking sites to encourage the elderly to engage in more social activities.

Added method, DIET4Elders Sanchez et al. [39], shows a scheme (hardware and software) for monitoring, advising, and providing facilities for day-to-day events connected to senior people's dining habits in order to avoid malnutrition. The following are the three tiers of their suggested system: (1) Surveillance Module contains relevant data from everyday experiences, Evaluation and Appraisal Layer extracts information [40] and expertise about daily self-feeding, and Support Service Layer provides additional information (including interactions) from medical sources professionals and caretakers.

A wearable IoT-based gadget called eButton [41, 42] has been devised for those with specific requirements, such as the elderly, to accomplish multi-function remote monitoring. The eButton gadget uses a pictorial sensor on the patient chest to track his or her nutrition. Based on earlier models of food forms, the food volume is also approximated from the photos. The collected data, when combined with supplemental data (e.g., meal information), displays the user's daily nutrition and calories. In addition, the gadget provides services for tracking physical activity, such as sedentary occurrences and daily calorie consumption.

2.2.3 Safety Monitoring

One of the most pressing concerns in the lives of the elderly is security. As people age, they develop impairments, frailty, and forgetfulness, making it necessary to monitor their safety in order to live independently. An actual tracking system, on either hand, is capable of identifying risky circumstances can offer aged users with a sense of security as well as knowledge of their status for family who may not be there. In this field, several strategies and efforts to address remote safety monitoring of elderly people have been described. The most important ones are included in the following sections, which cover various phases of sensor watching in day-to-day undertakings. As an effect of illnesses or restrictions brought on by age, as well as visual and physical problems, elderly people are more likely than younger people to fall. Falls can cause serious injury or even death [43].

Dedicated fall detection approaches have been proposed to alleviate such problems. Fall detection technologies can be split into two groups, according to Igual et al. [44]: Remote monitoring devices and situationally systems. Wearable sensors are divided into two types on the sensory level: cellphones and small sensors put on a band or cloth. For some users, wearing sensors instead of being continually filmed by cameras in context-aware systems provides a more pleasant user experience. When a fall is detected, Technologies including a 3D accelerometer, gyroscope, and magnetometer are utilized to evaluate a patient's sudden positioning and orientation changes situations, evaluate the data, and execute additional operations (e.g., show warnings). Smartphone-based techniques are presented by Fang et al. [45], Sposaro and Tyson [46] and Habib et al. [47], while wearable sensor-based techniques are presented by Habib et al. [47], Cheng [48] and Odunmbaku [49].

Context-aware methods, on either hand, are being designed to measure collapses using optical sensors. Context-aware systems have limitations as compared to wearable sensors, such as geographic coverage of mounted cameras or disquiet for certain elder individuals who feel continually observed. Context-aware systems, on the other hand, provide a number of benefits for the examined individual, including eradicating the necessity to wear the device all of the time and lowering the risk of overlooking to convey the sensors. In this vein, [50, 51] have suggested two important fall detection projects, which employ a complexity camera and an automaton vision system, separately, to detect falls.

Moreover, as part of a comprehensive geriatric monitoring strategy employing ocular sensors, the FEARLESS scheme targets to monitor ageing individuals without the need of wearable sensors [52]. Elderly people are constantly monitored by a system that collects records from 3D depth sensors (such as Kinect), lenses as well as speakers and sends it to a computer [53]. In addition, a comprehensive fall detection system is suggested [54], which employs a number of approaches to identify persons and their activity. When an emergency happens (for example, a fall), the system sends the data to the server, which analyzes it and delivers necessary notices and outcomes via application procedures (for example, healthcare/medical professionals' cellphones) [55].

3 Application of Internet of Things and Cloud Computing in Elderly Activity Monitoring Systems

3.1 The Role of IoT and Cloud Computing in Elderly Activity Monitoring Systems

The nation's well-being and the livelihood of its citizens are inextricably links and solely depends on the healthcare services and the medical information technology of such nations. To move a step forward in healthcare services, the utilization of cloud computing (CC) and the IoT has really changed the modern medicine in developed nations. Due to the various merits of cloud computing like virtualization, efficiency, high reliability and scalability have helped smart healthcare to change the prospects of healthcare industries. The development of a high-efficiency medical monitoring and management systems, cost reduction, and the building of a public cloud in a hospital to promote resource sharing are some other importance of cloud computing in the healthcare sectors. Medical information transmission, tracking, and intelligent patient monitoring can be achieved using the RFID and other acoustic electromagnetic sensors in smart healthcare system [56–58]. The use of modern healthcare technology and Internet has really support the healthcare sectors to realize real-time patient monitoring system, safe and efficient medical management system. Internet integration with cloud computing has open up new potential for medical system for real-time patient monitoring and management even in social domains, thanks to the rapid growth of the Internet [59, 60].

The two worlds of cloud and IoT have evolved in their own ways. However, a number of common advantages have been identified in the literature, which can be used to forecast the future. On the one hand, the IoT can take advantage of cloud computing's nearly limitless capacity and resources to compensate for technical limitations. CC, in particular, can be an effective option for managing Internet services as well as the composition and use of things or data applications. CC, on the other hand, can benefit from the IoT by expanding its reach to deal with things in the real world in a more distributed and dynamic manner, as well as deliver new services in a wide range of real-world scenarios.

By definition, the IoT involves a huge number of data sources, generates huge amount of both unstructured and structured data with the following three primary characteristics: volume, velocity, and variety. As a result, huge amounts of data must be collected, processed, visualized, archived, shared, and searched. The data generated by IoT can be effectively managed by the cloud, thus created the most convenient and cost-effective ways of dealing with such data [61] because it provides practically unlimited and on-demand storage capacity at a cheap cost. Sharing of such huge data with third parties becomes easier with this integration and new potential for data aggregation, integration [62].

Because of platform flexibility, operational compatibility, and on-demand service delivery, cloud computing has the ability to realize data integration and interoperation for pervasive health monitoring [63, 64]. Cloud databases have been presented as a means of providing users with transparent and safe access to heterogeneous databases and platforms. CC platforms can help elderly activity monitoring systems improve system interoperability in a cost-effective manner. Developing a monitoring system combining these two technologies has been proved efficient in providing healthcare facilities in remote areas in helping caregivers and physicians to provide quality healthcare services to the elderly patients. The CC is used as a supportive technology in an IoT-based system in terms of computational capability, storage, resource utilization, and reduced energy consumption. Also, the cloud has been a favorite of IoT-based system by enhancing service deliveries globally and deliver unspeakable services in a distributed and dynamic manner. The IoT-based cloud framework can still be extended in the smart environment for the development and application of new service delivery.

3.2 IoT and Cloud Challenges in Elderly Activity Monitoring Systems

The IoT connects and communicates with billions of devices and sensors, allowing us to provide knowledge that helps us in our everyday lives. CC, on either hand, provides internet connectivity that is on-demand, easy, and expandable, letting users to share computer resources and, as a result, allowing for dynamic data integration from a variety of source. Various challenges that are associated with the implementation of IoT in healthcare systems can be overcome by the integration of CC with the IoT. This will address the concerns of IoT implementation in medical sectors. The various resources provided by the CC can be of merits to the IoT-based system, while the Cloud can acquire greater visibility in order to enhance its constraints in a more flexible and dispersed approach with physical objects.

The Cloud-based IoT approach has been successfully integrated in an aging activity monitoring system may face several challenges. Some of the issues are as follows:

Security and privacy: Data may be transported from the real world to the Cloud using cloud-based IoT. The major challenge in the implementation of cloud in IoT-based system is the authorization guidelines and regulations for clients to gain access to sensitive information on the platforms. This is very critical for protecting users' identity, especially when data quality is necessary, and sensitive medical information are on transit [65]. Furthermore, when key IoT applications migrate to the

Cloud, problems developed due to a lack of trust in the service provider, information about service level agreements (SLAs), and data placement [66, 67]. Multitenancy can potentially lead to the leakage of sensitive data. Furthermore, due to the processing power limits imposed by IoT items, digital signatures cannot be used for anything [65]. New concerns require extra care; for example, the distributed system is vulnerable to SQL injection, session hijacking, cross-site scripting, and side-channel attacks. Critical issues like session hijacking and virtual server exit are also possibilities for an issue [68].

Patient data is collected using portable devices and sensors. Medical facilities must be adequately protected so that patients can use their smartphones to receive health status updates. The implementation of a smart healthcare system opens up the possibility of expanding healthcare to the entire population. The implementation of an intelligent healthcare system can minimize the time it takes for patients to see doctors or the time it takes for diagnosis results to come back. This also allows for immediate access to medical care and services. The scalability of a smart healthcare system must be taken seriously in order to retain confidence between patients and medical experts, and this will save quality time. It is the primary issue, and obtaining information from end-users through illegal companies is not only inappropriate, but also poses a risk to the personal safety of medical data. The key issue with the smart healthcare system's introduction and adoption is security and privacy. Security is required in various layers of the IoT-based system like in cloud, fog, and system as a result of the integration of these layers [69].

Performance: High bandwidth is required to transfer the huge volumes of data sent to the internet by IoT devices. As an aftermath, acquiring appropriate network performance to transfer data to cloud infrastructures is a major concern; unfortunately, broadband development is not keeping up with storage and compute progress [70]. In a variety of contexts, great reactivity is required for service and data provision [68]. This is due to the fact that timeliness can be altered by unforeseen events, and real-time applications are highly dependent on performance efficiency [71].

Big data: With several specialists predicting that Data Mining would outnumber 50 billion connected devices by 2020, it's vital to focus on the transportation, accessing, retention, and analysis of the huge volumes of data. Indeed, it is clear that the IoT will be one of the key sources of big data due to the recent technological development in smart healthcare systems. The Cloud can permit long-term preservation of the data produced by IoT and allow complex analysis on such data [72]. Because the application's whole performance is strongly based on the features of this data management service, analysis of the huge data produced is a serious concern. Finding the ideal data management system that will enable the cloud to handle massive volumes of data remains a big difficulty [73]. Information security is extremely important, not only because of the influence it has on quality of service, but also because of security issues on the devices that are connected to cloud services [74].

Heterogeneity: One of the major challenges encounter in cloud-based IoT system is choosing the best from variety of devices, software products, and other resources that might be employed for new or advanced applications in healthcare system.

Cloud systems have heterogeneity difficulties; for example, most Cloud services have proprietary interfaces, permitting resource integration dependent on individual providers [75]. Likewise, when end-users adopt multi-Cloud solutions, the heterogeneity problem may intensify, as services would rely on many providers to improve application performance and robustness [72].

Because of the heterogeneity that exists within IoT-based systems during data processing, data formatting, and data clearing, it is challenging to process medical data. In a smart healthcare system for patient monitoring, enabling a network to link with numerous sensors is an example problem. When data is moved to another system for processing or analysis, heterogeneity must be present for this to happen. As you progress through the fog layer, you'll encounter many nodes, clusters, switches, and other devices that are required for data processing and communication [76]. In order to communicate with end-users using IoT-based devices and sensors, heterogeneity is a key element to consider when creating architecture that allows for numerous device monitoring [77].

Legal Issues: In recent research on specific applications, legal considerations have played a large role. Service providers, for example, must comply with a variety of international regulations. Users, on the other hand, should contribute to the data collecting effort [61]. There is no standard guide and regulations for computing the protocols and interfaces for various products and services in a smart healthcare system. A dedicated agency is needed to handle this problem, and standards should be put in place to standardize the healthcare system. This will help with data dissimilarity and achieving real-time reaction. Communication protocol, data aggregation interfaces, system interfaces, and gateway interfaces should all be seriously addressed for proper standardization [78].

3.3 IoT and Cloud for Improving Elderly Healthcare

The problems of security, low performance, privacy, and reliability issues associated with IoT are due to the limited processing power and storage capacity. These challenges must improve the performance of IoT-based system and the healthcare sectors will be able to enjoy the benefits of using this platform. The combinations of both IoT and cloud has brought effective solution to address these problems. The IoT also expands the boundaries in which the cloud works with real-world items in a more dispersed manner, as well as enabling innovative services for billions of devices in a variety of real-world situations [79]. Furthermore, the Cloud simplifies the use of apps and services for end-users while lowering the cost of doing so. The Cloud also streamlines IoT data collection and processing, allowing for rapid, low-cost setup and incorporation for sophisticated data processing and utilization [80]. The advantages of incorporating IoT into the cloud for elderly monitoring are as follows.

The Cloud-based IoT paradigm has two important features: application and data exchange. IoT can be used to transmit ubiquitous applications, and automation can be used to simplify low-cost data distribution and gathering. Using built-in apps and bespoke gateways, the Cloud is a practical and cost-efficient option for connecting, managing, and tracking anything [81]. The accessibilities of quick Interactive surveillance and remote object management, and also data actual accessibility, are made possible by systems. Though the Cloud can considerably enhance and facilitate IoT interconnectivity, it does have drawbacks in several areas. The move of huge data from IoT to the cloud can create practical restrictions of such data to be moved to the cloud storage device [82, 83].

The Internet of Everything (IoE) collects billions of devices and sensors that create new opportunities with various medical threats [10]. The world is fast advancing toward the IoE domain, with billions of people talking among each other, as well as a range of data being gathered. The Cloud-based IoT technique expands the Cloud through IoT devices, allowing the Cloud to operate with a variety of real-world situations and resulting in the production of new innovations in medical sectors [72]. The devices, protocols, and technologies that make up the IoT are diverse. As a result, achieving dependability, scalability, compatibility, safety, accessibility, and effectiveness can be difficult. The majority of these concerns are resolved when IoT is integrated into the cloud [84]. Other benefits include ease of use and access, as well as inexpensive deployment costs [85, 86].

The IoT comprises a vast number of data sources that create a vast volume of semi-structured or unstructured data [87] since it may be utilized on billions of devices. Big Data has three qualities [88]: diversity like the data type, velocity such as data generation frequency, and the data size which is the volume. The cloud is the most appropriate and cost-effective options of dealing with the huge amount of data generated by IoT-based system. It also opens up new possibilities for data integration, aggregation, and sharing with others [9, 10]. Acquired data is transported to nodes with high capabilities due to IoT devices that have limited processing capabilities that make the data processing to be more complicated and sometimes impossible to process this huge data. The IoT generated data will be transported to where aggregation and processing takes place. Yet, without a suitable underlying infrastructure, achieving scalability remains a difficulty. The Cloud provided a virtual computing capabilities and an on-demand usage paradigm [10]. In order to improve income and decrease hazards at a cheaper cost, predictive techniques and data-driven policy making can be included into the IoT [9].

4 Framework for IoT and Cloud in Elderly Activity Monitoring Systems

The architecture of the IoT-Cloud Elderly Activity Monitoring System (ICEAMS) is a difficult task, and several solutions were investigated. One of the key problems facing IoT's reality in developing smart personalized healthcare systems is data collecting and integration from different IoT devices. Because IoT devices collect complex and dynamic data on medical evaluation, monitoring, and therapy plans, and predictions in healthcare, appraising or incorporating a large amount of data is difficult. Data aggregation from individual device data sources is a critical issue that requires immediate attention. As a result, it'll be fascinating to discover which IoT sensors boost the performance of intelligent systems that gather a variety of disease indications. As a result, it would be critical to look into whether there was any other background data that could help the model perform better. Furthermore, more research is needed to determine the quality of the properties chosen from each biomarker.

Evaluation, treatment planning, and prediction are other important aspects of IoT implementation for elderly activity monitoring systems. These are needed to create a system capable of switching among web and local storage categorization algorithms with little processing time while actually providing and onward patient information care. This chapter lays out the framework for ICEAMS, a system that monitors the health of elderly people via a network of wearable sensors. Body temperature and pulse, for example, aid in the collection of physiological pointers. Because of the sensitive data acquired from these embedded devices, it will be uploaded straight to the public cloud sensor nodes' limited computing and storage capabilities, as well as to prevent utilizing a smartphone as a sensor module.

The ICEAMS employs cellphones and wearable sensors to watch seniors in real time, resulting in increased medical productivity by providing a more efficient and effective healthcare network with home-based supervision. The main goal of the ICEAMS is to track clinical data collected from the elderly's wearable device, create a data record in the cloud server, as well as then make this data available to registered healthcare practitioners and clinicians at any time. The process is made up of three layers that work together to achieve the system's goals. For example, in the older person's layers, each layer has its own standards and methods, but the most important components are that the devices, as well as the pathways, should be able to link to cloud services to store patient data. Figure 3 depicts the system's primary layers.

4.1 Elderly Patients' Layer (Wearable Devices)

The patient's body is equipped with a wearable monitor and smartphone sensors to collect clinical data. There are many different types of healthcare sensors accessible today. These sensors calculate vital indicators like intensity of oxygen in the blood, temperature, pulse rate, blood glucose, and SPo2 [89]. It's critical to keep track of these warning sign in the patient's body because any suspicious data could lead to an infection. A drop in the human body's oxygen supply, for example, causes sleep apnea, which can lead to death. Unusual blood pressure can lead to kidney illness or diabetes, and should be monitored in elderly patients. The sensitive information is transferred to the patient's mobile app through Bluetooth and then to a database server. In addition, sensors can calculate and deliver data on a daily basis without the need for patient intervention (IoT), boosting the efficiency of interface design and making it more convenient.

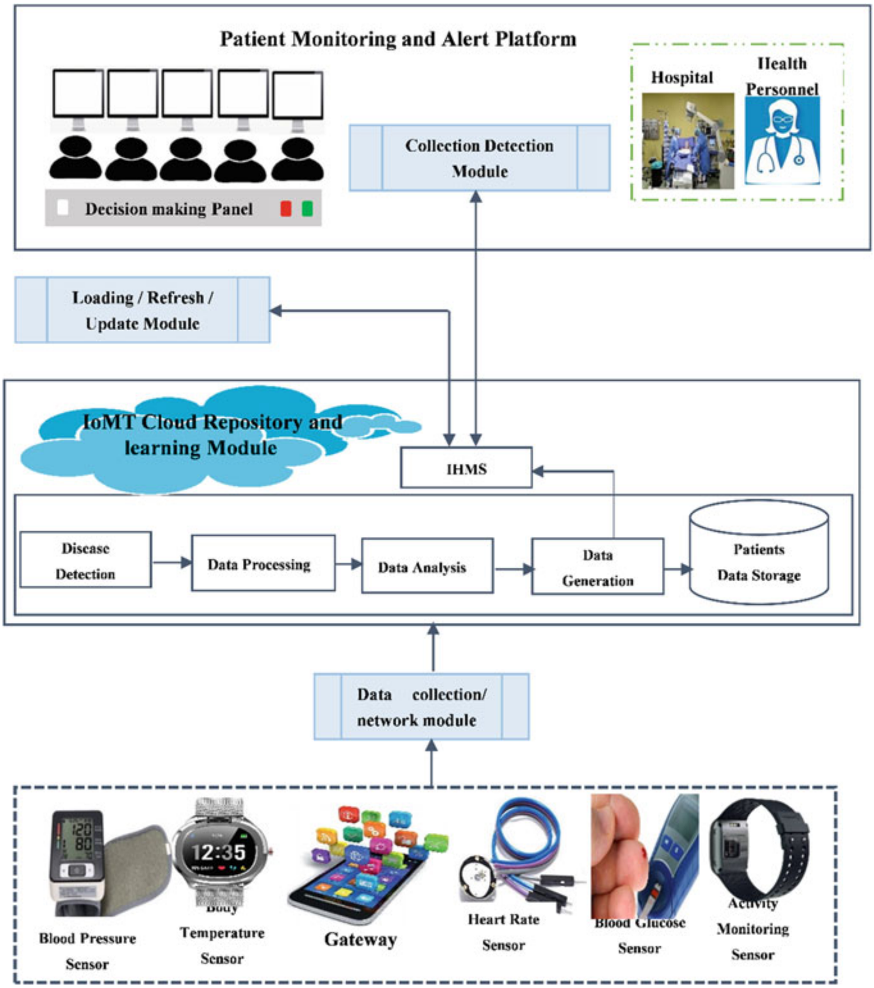

Fig. 3 High-level overview of CI-WBSN system framework

4.2 IoT-Cloud-Based (Data Layer)

The cloud is a network place where data is stored and processed. Patient data can be processed in the cloud and then made available for medical review through the network. As a consequence, all records will be gathered and disseminated in the cloud in order to identify any problem in medical data, and irregular disparities in patient records will be categorized based on the patient's condition and disease. All papers will be transmitted to the patient's and/or doctor's website, the emergency room, or both, depending on the patient's circumstance. Hence, the IoT web encourages collaboration and data transmission through its platform, which allows healthcare professionals to save client records, analyses, and diagnostics so that other specialists may immediately read information related to shared interests. It displays patient records in real-time updates and speedier medications.

4.3 Elderly Monitoring and Alert Platform (Hospital Layer)

The proposed system gives the medical doctor the opportunity of monitoring their patient in real-time using the information receive from the sensory data captured using various physiological devices. This can be done by study the data from cloud database which has been process by machine learning algorithm. The application gives the physicians update information about their patient conditions by replicates data and deleting all data in the IoMT server immediately it arrives to give real-time update on various signs. Therefore, making immediate decision in case of any emergency before the situation worsens.

The remaining components of a supported sensor network are mostly utilized for network pattern management and connections between device stages and their objects. In addition, domain-specific management within the computer system can be accessed and configured in the software program to access and configure similar device activities such active/inactive timestamps and sensing frequency. Domain-specific supervision, as a result, collaborates with both the public network and the component to install sensor network configuration and updates, as well as the component to inform/update the network's services about the new modifications. Similarly, the data analysis part of the cloud server exists, according to the services provided, to handle data processing tasks such as statistical analysis.

4.4 Elderly Monitoring and Alert Platform (Hospital Layer)

This framework allows the doctor to keep track of the information and sensory data of his or her patients. Physicians can study data from the program's cloud and take action based on it. This application replicates data in actual time by deleting all data from the IoMT server immediately it arrives, ensuring that physicians are up to date on the patient's condition and assisting paramedics in making an immediate decision in the event of an emergency before the situation worsens and hospital admission is avoided.

The remaining components of a supported sensor network are mostly utilized for network pattern management and connections between device stages and their objects. In addition, domain-specific management within the computer system can be accessed and configured in the software program to access and configure similar device activities such active/inactive timestamps and sensing frequency. Domain-specific supervision, as a result, collaborates with both the public network and the component to install sensor network configuration and updates, as well as the component to inform/update the network's services about the new modifications. Similarly, the data analysis part of the cloud server exists, according to the facilities provided, to handle data processing tasks such as statistical analysis.

4.5 The Gateway

This component is in charge of interfacing with patient devices that are used to diagnose patients' complaints and conduct initial data analysis. This component produces a description of the circumstances of patients who have been referred to healthcare. When an urgent condition is recognized, the Framework can also respond to indicators of irregularity by submitting a request for assistance (e.g., a demand for an assistant care provider) or an urgent request (e.g., a call for an ambulance).

5 The Practical Application of the Proposed Framework

5.1 Data Collection

IoT data should be acquired via IoT medical devices to observe the elderly's activities. The data obtained includes vital indicators like systolic and diastolic blood pressure, pulse rate, oxygen levels, sugar levels, and other physiological data detected by biomedical sensors distributed on the elderly's outfit or body using Body Area Network (BAN) and integrated devices in garments. A Personal Area Network (PAN) can also be used to monitor the elderly's behavioral changes and to respond to emergencies. The IoT devices continually detect and gather the data of health performance parameters in order to assess the operational technology for the aged. The extracted characteristics that keep track of your regular activities of human from MHEALTH dataset [20] were used for the proposed system, like old people's symptoms and body position connecting wireless body sensors. Devices on the chest, ankle, and wrist are utilized to track the different bodily parts moving.

The MHEALTH (Mobile HEALTH) dataset contains recordings of ten participants' body motion and vital signs while undertaking various physical activities. Sensors attached to the subject's chest, right wrist, and left ankle track the motion of various body components, including acceleration, rate of rotation, and magnetic field orientation. The sensor on the chest can also take 2-lead ECG readings, which can be utilized for basic cardiac monitoring, screening for various arrhythmias, or examining the effects of exercise on the ECG. The ECG data are recorded by sensors on the chest for heart rate monitoring [90, 91]. The dataset contains extracted features, with each subject being stored in its own log file: "MHEALTH subject SUBJECT

ID.log", which was then converted to "SUBJECT ID.CSV", with each record in the data file has the fields.

5.2 Data Preprocessing

For the data mining process, it is necessary to perform a data pretreatment step on the obtained IoT medical data to remove noise and inconsistencies. In addition, several feature selection strategies are used with the goal of reducing dimensions to make the classification portion of the senior monitoring system evaluation process easier. Since the dataset has performed feature selection on the IoMT-based data, the data preprocessing just concentrates on removing the noisy and inconsistencies in the data using rule-based method.

5.3 Prediction Algorithm for the Proposed Elderly Activity Monitoring System

The suggested system's goal is to label a recorded activity using the methods described in this chapter. Supervised machine learning algorithms were used, often known as classifiers, to achieve such labeling. The first stage is training, which involves using activities represented as features vectors and their labels to train the parameters of a given classifier. After that, the trained model is assessed by predicting the label of a specific assessment action in a way that is distinct from the training set.

For senior activity monitoring, a variety of classification methods have been investigated. However, there is no general classifier that surpasses all others when it comes to person identification [92]. KNN, NBNB, RFRF, Bayesian Networks, SVM, J48, Logistic Regression, Decision Tree, and ANN are among the most often used classifiers, hence, the proposed system used XGBooster classifier.

5.3.1 XGBoost Classifier

Chen and Guestrin [93] popularized XGBoost, a machine learning classifier that is both effective and scalable. The gradient enhancing decision tree first XGBoost ideal, which associations many decision trees in a boosting manner. Each new tree is created in order to lower the gradient boosting of the prior model's residual. Residual describes the differences between the real and expected values. The template has been trained until the quantity of decision trees defines the threshold. XGBoost follows the same notion of gradient boosting; to manage overfitting and enhance efficiency, it employs the quantity of spikes, training rate, subsampling ratio, and maximum tree depth are all variables to consider. Specifically, XGBoost optimizes the function goal, tree size, and scale of the weights, all of which are governed by typical variables for normalization. With many hyper-parameters, the XGBoost provides greater efficiency in a specific search space.

Gamma $\gamma \in (\theta, +\infty)$ denotes minimal loss reduction, which includes a split to render the partition on a tree's leaf node, according to the hyper-parameters. The minimum child weight $w_{\text{mc}} \in (\theta, +\infty)$ is defined as the minimum instance weight overall, implying that if the graph division stage yields a tree structure with the instance weight sum less than w_{mc}, the further partition will be discarded by the tree. The early stop algorithm works to find the optimum number of epochs that correspond to other hyper-parameters given. Finally, subsampling methods and $r_c \in (0, 1)$ column subsample ratio concepts were also provided by XGBoost in each tree. In the final step, to minimize the classification error, grid search is used to control the hyper-parameters.

Given $X \in \mathbb{R}^{\text{n x d}}$ as training dataset with d features and n samples, XGBoost object function in tth is represented by

$$\text{Obj}^{(t)} \simeq \sum_{i-1}^{n} \left\{ \ell\left(y_i, \tilde{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right\} + \Omega(f_t), \tag{1}$$

$$g_i = \partial_{\tilde{y}(t-1)} \ell\left(y_i, \tilde{y}_i^{(t-1)}\right), h_i = \partial^2_{\tilde{y}(t-1)} \ell\left(y_i, \tilde{y}_i^{(t-1)}\right), \tag{2}$$

where the loss function ℓ is represented by the first gradient g_i, and, h_i is the second gradient of ℓ. To measure the complexity of the model, the regularization $\Omega(f_t) = \gamma T + \frac{1}{2}\varphi\varphi^2$ was used, where the number of leaf nodes is represented by T.

As demonstrated in Eq. (3), the logistic loss ℓ of the training loss measures how well the model fits on the training data,

$$\ell\left(y_i, \tilde{y}_i^{(t-1)}\right) = y_i \ln\left(1 + e^{-\tilde{y}_i}\right) + (1 - y_i) \ln\left(1 + e^{\tilde{y}_i}\right) \tag{3}$$

given the tth training sample $x_i \in \mathbb{R}^{\text{d}}$, assume that a XGBoost model of XGB contains K trees, the corresponding prediction $\tilde{y}_i$ is computed as

$$\tilde{y}_i = \sum_{k=1}^{k} F_k(x_i) \tag{4}$$

$$\text{s.t. } F_k \in \text{XGB}, \text{ where XGB} = \{F_1, F_2, F_3, \ldots, F_K\}. \tag{5}$$

R programming language was used to implement the proposed classifier and the evaluations were done using various performance metrics. The dataset with the relevant activity monitoring recognition was used with seamlessly incorporate all characteristics. The dataset contains 12 activities monitoring of elderly people.

Split the physical activities dataset vectors into two groups in a 70:30 ratio, randomly selecting 70% for training and 30% for testing. To train the classifier on the training set, use the XGBoost machine learning approach. For the 12 physical activities, the label index includes class labels like Climbing stairs, Cycling, Jogging, Frontal Elevation of Arms, Jump Front and Back, Lying down, Running, Sitting and Relaxing, Standing, waist bends Forward, Walking, Knees bending. All vectors that have the same values are added together and preserved. To determine the performance of the classifier, use the test dataset.

Table 1 displays the performance of the projected system using activity observing MHEALTH dataset using numerous metrics. The results obtained different metrics showed that the projected system is essential and relevant in elderly activity monitoring system for prediction and classification. The model has the highest predicted classification accuracy of 98.7%, which is excellent and may be used to forecast the elderly physical activities. For the sake of simplicity, the classification system generates results for the 12 physical activities designated as A1–A12.

To show how machine learning technique affects a classification on the activities monitoring on the dataset, Table 2 compares the proposed approach with several known approaches. Table 2 displays the cumulative performance measures for the proposed system and other models using the decreased MHEALTH dataset. The accuracy of the suggested approach is better than other approaches. The suggested elderly activities monitoring system, in general, has a 98.7% accuracy, which is 1.6% higher than the Multinomial Naïve Bayes with the second-highest accuracy. When equated to other techniques using the reduced MHEALTH dataset, the proposed approach performed better across all evaluation metrics. The proposed method's marginally higher accuracy is due to its robust feature selection and rule-based fitness calculation.

The proposed model differs from previous elderly activities monitoring classification models in that it uses a basic XGBoost estimate parameters that are appropriate for input to create its classification effectively and efficiently. Moreover, the model

Table 1 Proposed method evaluation

Activities	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)	ROC (%)
A1	95.4	96.2	96.8	95.7	95.3
A2	95.8	97.3	95.6	95.3	96.6
A3	97.3	97.6	97.3	98.4	98.1
A4	95.6	95.5	95.8	95.2	96.6
A5	98.2	97.8	98.4	98.8	99.3
A6	98.4	99.0	99.1	98.8	98.6
A7	96.7	97.3	97.1	96.9	96.6
A8	97.4	97.3	96.8	98.6	97.9
A9	98.3	98.8	98.7	98.5	98.8
A10	98.9	90.2	90.6	98.4	98.7
A11	96.4	96.5	96.8	96.2	96.7
A12	98.7	99.5	99.1	98.0	98.9

Table 2 Summary of performance comparison of accuracy of existing work

Technique	Dataset	Accuracy (%)
Random Forest [94]	UCI-HAR	60.0
CNN [95]	UCI-HAR	90.9
K-Means [94]	UCI-HAR	60.0
ANN [96]	UCI-HAR	91.4
CNN [97]	UCI-HAR	94.8
IBK [94]	UCI-HAR	90.0
SVM [98]	UCI-MHEALTH	65.4
Multinomial Naïve Bayes [20]	UCI-MHEALTH	97.1
CNN-pff [98]	UCI-MHEALTH	91.9
Naïve Bayes [94]	UCI-HAR	79.0
Proposed Model	UCI-MHEALTH	98.7

knows and examines high-level functionality, automatically decreases data dimensionality, and effectively portrays important features due to the reduced hidden layer. As a consequence, the proposed model is optimal for use in classification in healthcare industries with a vast amount of unlabeled and unstructured data, such as medical data.

6 Conclusions

Continuous population growth and corresponding increases in life expectancy, combined with worldwide infectious disease outbreaks in recent years, has prompted a quest for novel ways to make the most of limited resources. Automated illness monitoring, diagnosis, prediction, and treatment of patients provides not only quick data but also trustworthy service at a lower cost and correct outcomes from medical specialists. However, the healthcare system faces issues such as a lack of proper medical information, misdiagnosis, data treatment, and medical information transmission delays. To solve these identified problems this chapter proposed IoT-based cloud elderly monitoring system. The design integrates a deep learning mechanism to train the data using a XGBoost for classification of the capture data from the IoT devices. The data collected from different wearable sensors like body temperature, glucose sensors, heartbeat sensors, and chest were transmitted through IoT devices to the integrated cloud database. Deep learning was used to extract features from the patient capture data and the sensor signal is analyzed using XGBoost for the monitoring of the elderly activity. The proposed system can be widely used to monitor and diagnose patient physiological health situations globally using an internal network, hence, eliminating medical faults, reduce healthcare costs, minimize pressure on medical experts, enhancing patient satisfaction, and increase productivity in the healthcare system. The proposed model used XGBoost for the classification of the capture data using IoT-based devices and sensors from elderly activities, the result shown an improvement when compare with the recent state-of-the-art model.

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