Journal of Healthcare Engineering

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Review Article

The Internet of Things in Geriatric Healthcare

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There is a significant increase in the geriatric population across the globe. With the increase in the number of geriatric people and their associated health issues, the need for larger healthcare resources is inevitable. Because of this, healthcare service-providing industries are facing a severe challenge. However, technological advancement in recent years has enabled researchers to develop intelligent devices to deal with the scarcity of healthcare resources. In this regard, the Internet of things (IoT) technology has been a boon for healthcare services industries. It not only allows the monitoring of the health parameters of geriatric patients from a remote location but also lets them live an independent life in a cost-efficient way. The current paper provides up-to-date comprehensive knowledge of IoT-based technologies for geriatric healthcare applications. The study also discusses the current trends, issues, challenges, and future scope of research in the area of geriatric healthcare using IoT technology. Information provided in this paper will be helpful to develop futuristic solutions and provide efficient cost-effective healthcare services to the needy.

1. Introduction

The rapid advancements in clinical science and technologies have significantly increased the average life expectancy of humans across the globe [1]. This led to a substantial rise in the geriatric population. In 2015, the number of geriatric people was nearly equal to 8.5% of the world population and it was estimated that it will increase to 12% and 16.7% by the years 2030 and 2050, respectively [2]. As compared to other age groups, elderly persons are more prone to several health-related issues such as diabetes, hypertension, asthma, and chronic diseases. Hence, the elderly group of people needs the utmost attention in terms of medication, treatment, and care especially if they chose to live an independent life. The prime constraint in availing of a good healthcare service is its rising cost [3]. Also, the aged group cannot be physically present at the health center each time they face a health issue. The reason may be either the increased cost or the unavailability of a good health center with all advanced technologies. This has inspired various research communities to go for other alternatives that can reduce the expenditure while delivering quality healthcare services to the patients. With the wide use of advanced technologies and Internet services, and sensors, it is now possible to avail a range of healthcare services at home. This allows the geriatric people to lead an independent life while receiving standard clinical service at home.

In the last decade, several state-of-the-art technologies such as machine learning, deep learning, the Internet of things (IoT), data analytics, and artificial intelligence have opened up a new arena of research in the field of healthcare services. In particular, IoT has shown substantial growth in recent years and is expected to continue even in the future [4]. IoT is defined as a network of physical objects with embedded technology that can sense and interact with the surrounding environment and provide autonomous communication [5]. It is a platform for seamless and better integration between computer-based systems and the physical world. This has enabled humans to connect with anyone, anywhere and anytime [6]. IoT has taken maximum use of real-time monitoring technology to provide efficient healthcare services [3]. The description of the basic architecture of an IoT-based healthcare system is provided in supplementary section S1. The application of IoT technologies in healthcare systems reduced the repeated manual examination of various physiological parameters such as body temperature, blood pressure, blood oxy gen levels, and heart rate. Further, these systems provide an automatic and precise collection of health information that could potentially speed up the process of treatment, lower the cost of hospitalization, and enhance the user experience [7]. This helps to build digital health records that can be accessed from a distance/remote location. Though numerous IoT-based systems such as smart homes, smartwatches, and many more have been developed in recent years, smart wearables are widely used as they provide the advantage of continuous monitoring of the physiological parameters without discomforting the patients [8]. These devices also provide a platform that can connect patients with healthcare providers through the Internet. Furthermore, such devices allow the collection of a huge amount of data and help to develop more precise clinical guidelines [9]. These data sources can also be used to develop automated IoT devices for real-time monitoring [10]. The IoT technology is efficiently used to provide rehabilitation, diagnosis, and healthcare monitoring [11]. However, to track the evolution and recent trends of the ongoing research in the field of IoT and elderly care, we performed a bibliometric analysis (using the software VOSviewer) on the collected articles from the "Web of Science" database with a keyword search {"Internet of Things" AND ("Elderly" OR "healthcare") AND "Elderly care"}. The result showed 184 articles. Using these articles, we have analyzed the evolution of important keywords used in the aforementioned field over time (Figure 1) as well as their correlation. The density plot shows that "healthcare services," "elderly patients," "elderly care," and "wearable devices" are some of the important keywords in the previously published literature. A cluster of keywords, namely, "medical things," "elderly healthcare," "elderly patients," and "health conditions," were found to represent the association between the Internet of medical things and elderly healthcare. Unfortunately, the cluster shows a weaker density that represents an insignificant growth over time. This may be due to the existence of limited research in the field of geriatric care. Further, only a few articles have discussed the issues and challenges in employing the IoT-based technology in providing the elderly healthcare services. Hence, there is a need for a detailed review in the aforementioned field of study.

Consequently, this paper aims to provide comprehensive information emphasizing the recent or possible application of IoT technology in geriatric care services. The outcome of this research could be beneficial for researchers, especially the IT professionals who want to use the technology in various healthcare applications. The current paper discusses the need for health monitoring in the geriatric population, current sectors that are getting influenced by the IoT technology, the applications in various healthcare services, present issues, and future challenges. The knowledge shared in this research will help the researchers/scientists to develop technologies that can deliver healthcare services to the needy, promote service delivery to the elderly, and increase their quality of life.

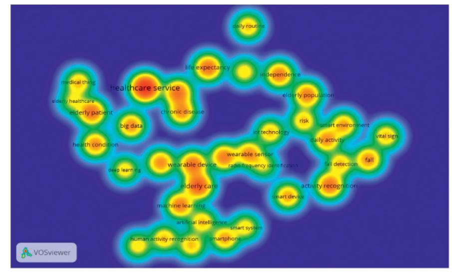

Figure 1: Density plot showing the evolution of trending keywords on the application of IoT in geriatric care. The plot was generated using VOSviewer software.

2. Need for Health Monitoring in the Geriatric Population

Aging is a normal biological process that leads to the occurrence of age-related diseases. Such diseases are caused due to either endogenous or exogenous factors. This results in functional and morphological changes in all organs and systems [12]. The physiological changes may result in the precipitation of chronic diseases like osteoporosis and depression. Quite often, such diseases are hidden and remain atypical for a longer duration. In the case of the geriatric population, the diseases progress at a faster rate and may get complicated easily. The treatment of geriatric-related diseases results in polypharmacy. Unlike in the middle-aged and young adults, the diagnosis and treatment modality in the geriatric population generally requires a different approach. However, many a time, after receiving suitable treatment and diagnosis, the geriatric patients become weak both mentally and physically. Hence, rehabilitation of the geriatric population has been regarded as essential for a healthy society. The rehabilitation process helps the healthcare givers to maintain optimum health and quality of life for geriatric patients. Though the list of health issues in older age is large, some of the most common issues are discussed in the current section.

2.1. Auditory and Visual Impairment. Visual and hearing impairments restrict the patient's ability to express clearly and interact with the immediate environment. Hearing loss can result in depression, irritability, frustration, isolation, loneliness, cognitive impairment, and compromised physical mobility [13]. The solution to auditory impairment empowers one's daily routine work and psychological behavior. This shows a positive effect in various areas like a family relationship, enjoyment of leisure activities, telephone communication (emergencies and social touch), and communicating the health issues and daily needs to others. This empowers them to live safely and independently. Along with auditory, there is also a gradual deterioration of visual sensory function with aging. As compared to hearing impairment, visual impairment exerts a deep impact on the health status of the geriatric population. Vision loss is associated with high-risk consequences like increased social isolation, reduced self-image, depression, and physical disability [14]. The physical disability includes a lack of ability to perform daily activities, mobility, and reduced participation in other activities. The elderly population with both visual and auditory impairment undergo two times more difficulties than the single-impairment population. They face difficulties in managing medication regimens, ambulation, and performing their daily activities [15].

2.2. Falls. Every year, 30% of the geriatric population aged 65 years and older suffer from falls. About 14–50% of people who encounter falls are unable to rise after it [16]. In most cases, they are found lying on the ground and are later discovered by others. Moreover, the women population experience a greater proportion of falls. This observation can be due to the fact that women constitute a majority of the total population due to the higher mortality rate of the elderly men population [17]. Geriatric patients with gait dysfunction have a high risk of falls. The risks may include traumatic brain injury, fractures, and joint dislocation. Patients associated with falls undergo pain, loss of stamina, and declined function. Around 40% of people sustaining falls had reported continued pain and hence have been prescribed bed rest for a few months after the fall. Suffering a fall can damage self-confidence and self-trust and jeopardize the independence of a geriatric patient as it is associated with long-term treatment and care [18].

2.3. Osteoporosis. Osteoporosis is extremely prevalent in old age. It affects nearly one-half of the population that is aged above 75 years and one-third of the postmenopausal women population [19]. It may result in bone fracture even with minimal trauma. Around the globe, millions of elderly people suffer from osteoporosis that commonly leads to vertebral, hip, or wrist fractures [20]. Around 25% of women who are aged 50 years and older have one or more vertebral compression fractures that can be related to osteoporosis. Unlike falls, patients with osteoporosis undergo long-term hospitalization and have to receive medication for a long time. This can result in compromised physical mobility, irritability, frustration, and damage to the self-esteem of the patients.

2.4. Malnutrition. Malnutrition occurs when there is a deficiency of vitamins, minerals, protein, and other essential substances that the human body needs for its proper functioning [21]. Additionally, various psychological factors such as loneliness, depressive symptoms, bereavement, and cognitive decline also contribute to malnutrition in elderly persons [22]. A poor nutritional status may also be found in old-aged people who rely on others for meals. Poor nutrition directly affects the patient's medical condition and functional status. This can decrease one's immunity and results in poor recovery from diseases.

2.5. Depression. Depression is one kind of mental health disorder, which has been diagnosed among most of the geriatric population. The disease shows symptoms of fatigue, sleep disturbances, and weight loss. It has quite often been associated with coexisting medical conditions. Various medical conditions like Alzheimer's disease, Parkinson's disease, malnutrition, cancer, stork, HIV infection, hypothyroidism, hyperparathyroidism, hepatitis, arthritis, skin problems, and speech disorders may lead to depression [23]. In the geriatric population, depression can decrease walking speed, standing balance, ability to rise from a chair, and functions that are associated with daily activities [24]. Moreover, it contributes to the individual's disability, functional failure, and losing hope to live a quality life. Patients with depression usually need prolonged treatment and diagnosis. Proper diagnosis and care of depression can significantly decrease further disability, restore functions, and help to maintain a healthy life in the geriatric population.

2.6. Delirium and Dementia. Cognitive impairment, such as delirium and dementia, is quite common in the elderly population. Generally, delirium is caused due to severe or chronic illness, changes in metabolic balance, medication, and infection [25]. It is a disorder of attention that affects mental, sensory, behavioral, and emotional functioning. This disease is usually acute and temporary. Around 40% of delirium patients face hallucinations that get worse at nighttime. The symptoms of delirium in the geriatric population may last for hours to weeks [26]. However, dementia is not a part of aging. It is a cognitive impairment that resulted in the loss of memory, thinking ability, and other mental abilities. Patients with dementia have short-term memory problems. They tend to forget the events quickly and hence have been found to repeatedly ask the same question. This disease in the geriatric population disrupts their daily activities and leads to social impairment.

3. Influence of IoT on Geriatric Health Monitoring

Healthcare technologies that employ IoT, artificial intelligence, cloud computing, and mobile computing are crucial in the development of an efficient medical system that can facilitate a better life for the aging population. These technologies are used to design portable devices such as wearable devices and sensors, smartphones, and rehabilitative devices. Such devices promote public healthcare services at remote locations. The efficient use of these techniques helps to educate customers/patients, reduces the medical load of the health centers and doctors, and improves real-time monitoring. These devices have significantly influenced geriatric healthcare monitoring. The healthcare monitoring domains can be categorized based on the services they provide to the patients. Some of the most widely influenced areas are discussed in the subsequent section.

3.1. Wearable Devices and Sensors. Wearable devices and sensors are the measuring tools that are used for real-time monitoring. These devices collect physiological information from the human body and can also monitor physiological activities. In elderly people, the application of wearable sensors has diverse uses such as fall detection [27], sleep pattern monitoring [28], cardiac health monitoring [29], and sedentary behavior [30]. The wearable devices are capable enough to alert the patients and healthcare providers when an adverse situation arises. Real-time monitoring can be achieved through a continuous recording, storing, and upgradation of the healthcare data at the cloud server. Due to the advantage of easy handling and affordability, these devices have become popular in the recent years. Seneviratne et al. have discussed various commercially available wrist-worn devices in the market such as Samsung Gear S2, Empatica, Apple iWatch, Fitbit Flex, Pebble Time and other accessories such as smart jewelry, skin patches, and e-textiles. The authors further reported the challenges associated with these commercial wearables which include security threats and confidentiality of information [31]. In another study, the consumer wearable sensors such as headbands, camera clips, smartwatches, and various embedded sensors in clothing have been explored (Figure 2). These devices give direct access to the patients to analyze their healthcare data and contribute to their better health [32]. Kekade et al. had performed a survey to evaluate the usefulness of commercially available devices. The findings of this study proposed that more than 60% of elderly people showed interest in the future use of wearable devices. This inferred the positive and significant growth of this technology in the future.

3.2. Ambient Assisted Living. Ambient assisted living- (AAL-) based medical devices/systems use the information and communication technologies to transform the lives of elderly people and other patients by providing them an independent life [33, 34]. These devices integrate into the home and life of patients in an intelligent and prevalent way. This further increases the quality of life and significantly reduces healthcare expenses. The AAL-based devices mainly focus on monitoring the patient's daily activities, detect health abnormalities, and deal with emergency conditions. Various AAL-based systems have been reported in the literature which help in achieving the aforementioned goal in elderly people. Dohr et al. had introduced the "Keep In Touch (KIT)" technology in AAL, which combined smart objects and technologies such as near-field communication (NFC) and radiofrequency identification (RFID) to efficiently process healthcare information obtained from the patient's body [35]. The KIT technology also provides a communication channel for the sharing of information among geriatric patients, healthcare providers, and doctors. In [36], the AAL system captured user information through various sensors

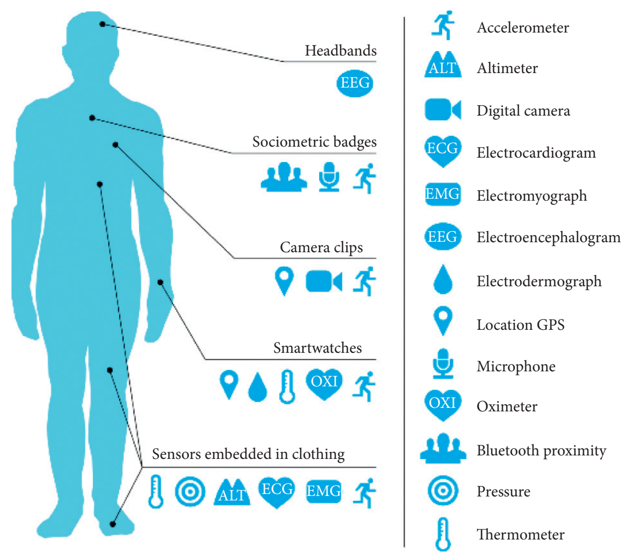

Figure 2: Example of different consumer wearable sensors and devices (reproduced from [32]).

and detected the activity of daily living (ADL). Herein, the authors have tried to correlate the probability of calculating various illnesses with the environmental scenario (season, air quality, the intensity of sunray, etc.). Loza-Matovelle et al. had developed an AAL system by integrating the robotic technology with another network sensor to provide assistant service for elderly people [37]. Smart homes [38], wearable sensors [39], and mobile technologies [40] have also been integrated with the AAL technologies to provide remote monitoring with a functional support system.

3.3. Telemedicine. A telemedicine system provides medical care through establishing audiovisual communication between doctors and patients. The term "medical care" involves diagnosis, treatment, consultation, and prescription of medicines [41]. Provision of secure and safe medical care involves the use of mobiles and communication technologies, home sensors, wearable sensors, and so forth. In [42], a telemedicine system has been reported, which can monitor and record physiological signals such as heart rate, blood flow, and myoelectric signals. The recorded data could be accessed through a mobile phone or tablet and further processed and analyzed. Stradolini et al. have developed a cloud-based telemedicine system for anesthesia monitoring. The system allows the anesthesiologist to closely monitor the sedated patients through an android app [43]. In [44], a smart healthcare service model has been designed and proposed. The system provides an authorized telemedicine infrastructure for geriatric patients where the healthcare professional can continuously monitor the activity of the caregiver and patients and also can interact with the patients.

3.4. Mobile Healthcare Services. The mobile healthcare system helps in preserving a patient's vital information in the form of electronic medical reports and allows healthcare professionals to access this information when needed. Most of the mobile healthcare systems use the cloud server to store the information and use a mobile app as an interface to connect patients, caregivers, and doctors. This process enhances the accessibility of medical information and the efficiency of the system. It has been reported that older adults mostly prefer a mobile phone over other electronic devices such as computers. The portability of these devices and the ease of accessibility may be the reason behind their huge popularity. In many IoT-based systems, the smartphone is used as a gateway for data communication among hospitals, pharmacies, medical authorities, and patients (Figure 3). Saraubon et al. have proposed a smart geriatric care system using IoT and mobile technology to detect falls, monitor heart rate, and provide real-time video monitoring [46]. In another study [47], a data mining-based approach was employed in the mobile healthcare system for activity recognition. Some of the other explored areas where efficient use of mobile technology has been employed for geriatric care include chronic diseases, cardiac diseases, diabetes, and mood [48–50]. The use of mobile devices also allows elderly people to share their health-related information with their families.

3.5. Robotic Technology. Robotic technology has transformed elderly healthcare by taking into consideration the potential use of human-automation interaction. This technology assists the geriatric population in their daily activity, alerts the patients about their health issues, ensures the safety of the patient, and provides social support. Bogue has mentioned three different types of robots that could be employed in geriatric care. These include household robots, companion robots, and assistive robots [51]. The integration of robots in IoT-based healthcare systems helps elderly disabled persons to perform physical tasks. The components of an IoT-based system with robotic technology are represented in Figure 4. It is possible to create a sense of the physical presence of the caregivers and doctors from a distance that can virtually interact with the patients through a robotic body [52, 53]. The literature also reported the efficient use of telepresence robotic technology in monitoring ECG, video conferencing, and reminding patients to take medicine [52]. In [54], IoT, wireless communication, and automation technologies were integrated into a wheelchair for real-time monitoring. The system could visualize the surrounding environment with the help of an array of cameras. This helped the system to achieve safer navigation tasks. In a recent study, researchers have combined robotics with other sensing technologies in an IoT-based AAL environment to provide a higher human-robot interaction. Such systems can understand the patient's needs and can act accordingly in a more adaptive manner [37].

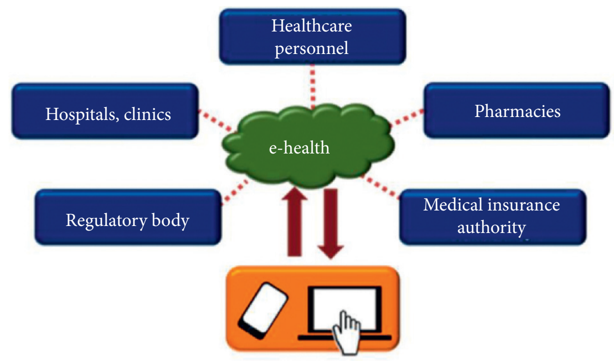

Figure 3: A mobile IoT environment (reproduced from [45]).

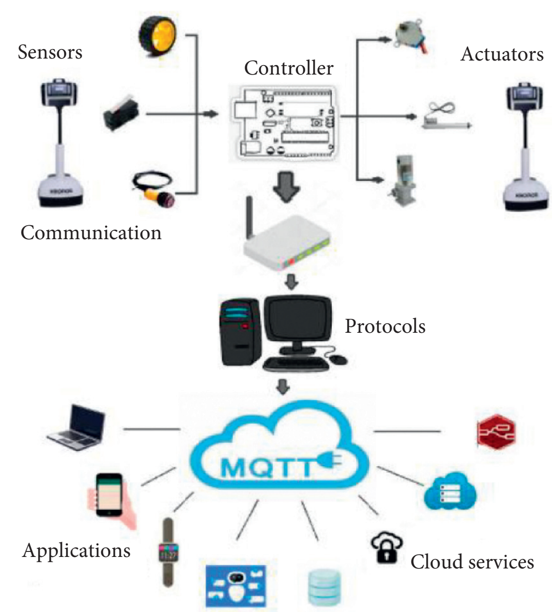

Figure 4: Components of an IoT-based healthcare system integrated with robotic technology (reproduced from [37]).

4. IoT Applications in Geriatric Care

IoT has transformed the healthcare industry with advanced sensing technologies, communication protocols, and data analytics techniques. This has influenced the life of geriatric people by improving their quality of life and providing a wide range of healthcare applications. In the subsequent sections, some of the most prominent applications of the IoT in the healthcare industry with special attention to geriatric care are discussed.

4.1. Monitoring Clinical Health Parameters. The clinical health parameters (e.g., blood pressure, pulse rate, temperature, oxygen saturation, blood glucose, balance, gait, and lipid profile) act as vital signs for various diseases and health abnormalities. In the case of the elderly, early attempts must be made to regularly obtain the health status. This would help in the timely diagnosis of a disease and avoid sudden complicacy. Hence, continuous observations of these parameters are needed. Several studies [55–58] in the past have addressed the role of IoT technology for monitoring different health parameters.

Blood pressure fluctuation is one of the most common diagnostic parameters for measuring several health issues. The use of a conventional device requires a helping hand for the measurement of blood pressure. These issues could be eliminated through the integration of IoT technology that brings about more independence to the patients. Anh Dinh et al. designed a device that makes use of the electrocardiogram (ECG) and the photoplethysmogram signal from the fingers to obtain blood pressure from the fingertip [59]. In [60], a device for obtaining both systolic blood pressure and diastolic blood pressure separately has been proposed. The results showed a higher confidence interval than that of the results obtained from the oscillometric method. Body temperature is a vital sign in many health issues. The inaccuracy in measuring this parameter may lead to failure in identifying patient complications and adversely influence the diagnosis process [61]. The IoT-based devices enable real-time monitoring of temperature from a distance. In [62], a single-chip computer (Raspberry Pi) board was used to collect and process data from the various sensors. Further, the recorded information was displayed using a monitor.

Aging people are highly prone to diabetes. Continuous monitoring of the glucose levels helps the physicians to provide medication at right time. One of the possible solutions to avoid a repeated visit to the hospital is the IoT-enabled remote monitoring technology. In [63], a noninvasive method named "Gloco" has been proposed. This method used an infrared LED in the fingertip and calculated the blood glucose level based on received light intensity. The glucose level reading was then sent to a mobile phone where the recorded data could be accessed through a mobile application. In another research [64], a smart device was developed, which used a single-chip computer (Raspberry Pi), a power bank, a visible laser beam, and a Pi camera, all integrated into a hand glove. The glove provides the body glucose level information. The generated data then processed by an artificial neural network and the results could be viewed on any smartphone.

In recent studies, researchers have focused on measuring multiple health parameters at the same time. Kumar et al. have proposed a system that monitors pulse rate, respiratory rate, and body temperature using noninvasive sensors. The system used a microcontroller to process the sensor data and display the same using the "ThingSpeak android application" [65]. In another study [66], a remote health monitoring system has been proposed, which used a single-chip computer (e.g., Raspberry Pi) and IoT for measuring the body temperature and pulse rate concurrently. Along with these two measures, the device is also capable of recording other health parameters including blood pressure, heart rate, and respiration.

Most of the conventional devices, which measure the important health parameters, are mostly used in the intensive care unit (ICU) and operation theaters. However, they still have not achieved a high acceptance by common people. This is due to its higher cost. In the future, IoT devices must be designed at a lower cost with the use of cheaper sensors and materials. Currently, conventional devices are transforming into electronic devices that are user-friendly and need less human intervention. For example, the use of infrared (IR) technology in measuring body temperature is more popular [67]. The infrared thermometer measures the body temperature from the forehead using the IR sensor without any physical contact with the patient. The method not only reduces the risk of cross-contamination but also prevents the spread of contagious diseases including COVID-19. This type of technological intervention allows reducing the use of mercury, which is used in conventional thermometers [68]. The main challenge associated with the measurement of the blood glucose level is that it is unstable and depends on the food intake status of a person. As per the National Institute for Health and Care Excellence (NICE), one of the possible indicators for the measurement of blood glucose level can be HbA1c (glycated hemoglobin). It has also been experimentally found that an average increase of 2 mmol/L in the blood glucose results in the rise of the HbA1c level by 11 mmol/L [9]. Sensing and measuring HbA1c is still a potential challenge and is being explored as a measurement tool by many researchers.

4.2. Activity Recognition. The real-time monitoring of human activity is a useful and efficient tool in elderly care as it is associated with maintaining daily activities, health monitoring, and enhancing the safety and security of elderly people. Though fall detection of the user is the prime focus, the recognition of different activities can also be employed to analyze the user behavior. As per the data given by the World Health Organization, more than 28% of the aged population gets affected by falls each year [69]. It is also expected that a lack of preventive measures may double this value by 2030. A fall event may not only cause physical injuries but also have psychological consequences including anxiety, depression, and fear of falling. The IoT devices that are capable of tracking human activity can contribute to reducing this kind of adverse event. This can be achieved by employing advanced algorithms and various body-worn sensors in an IoT environment [70]. Numerous studies [71–73] in the past have investigated the potential of IoT in delivering different solutions to activity recognition and fall detection. The authors in [74] reviewed various state-of-the-art wearable technologies in geriatric care for activity recognition, position monitoring, and vital sign monitoring (Figure 5). They investigated the use of various sensors and their integration in monitoring positions and activities. The authors have also discussed the future aspects of developing a "smart clothing" system. In [75], a framework for IoT-enabled Personalized Intelligent Assistant has been proposed for helping geriatric patients in performing their daily activities. The system also analyzes the daily activities and reports if any abnormality in behavior was observed. Arifoglu and Bouchachia have developed a wearable device that used a 3D-axis accelerometer embedded with a 6LoWPAN for falls detection in elderly people [76]. The sensor data was processed using a tree-based big data model that functioned in an IoT gateway. If falls were detected, an emergency alert was activated to notify the caregivers. Further, it generates an emergency alert to the family members or caregivers when a fall was detected. The IoT-based systems have employed various machine learning algorithms for detecting and classifying multiple activities. Arifoglu and Bouchachia have proposed a similar method for geriatric patients with dementia. Three

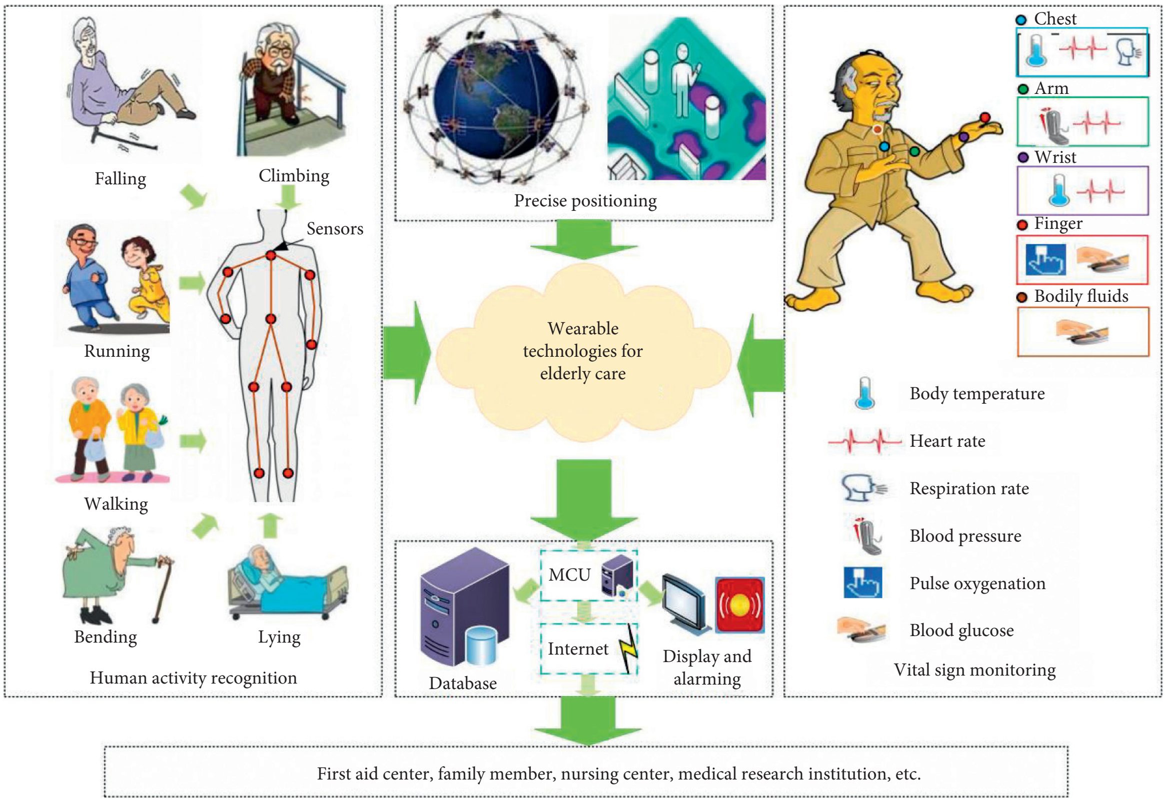

Figure 5: Schematic functions of elderly care including real-time monitoring of indoor positioning, physical activities tracking, and vital signs (reproduced from [73]).

variants of Recurrent Neural Network have been used for the detection of abnormal behavior and activity [76]. In [77], the authors have employed various wearable sensors and machine learning models for monitoring activities of geriatric patients with Parkinson's disease. Herein, gyroscopes and triaxial accelerometers have been used for sensing these activities. Additionally, machine learning algorithms were used for recognizing these activities. In [77], a fall detection cum emergency response system has been presented. The system employed deep sensors to get binary images of the elderly persons who were tracked by Microsoft Kinect SDK. The features of the binary image were extracted using the histogram of oriented gradient (HOG) method. The status of the fall was evaluated using the support vector machine (SVM) algorithm.

Integration of IoT for activity/fall detection brings about many advantages and has been widely used in terms of remote access. However, some major challenges need to be addressed in the future. The use of wearable sensors in these systems questions their real-time use. This can be explained by the fact that it is not possible to wear a sensing device all the time. Moreover, the use of these wearable sensors also has its inherent flaws. This includes the loss of wearable devices, maintenance burden, discomfort in wearing, and lower battery life [77]. Hence, device-free systems must be developed in the future with minimal use of wearable sensors. The use of multiple sensors and different communication modules used for the detection of multiple activities increases the computational complexity and processing time. Another major challenge for such types of devices is identifying the human poses and detecting a change in a pose while detecting a fall event. In a recent study, this issue has been eliminated with the applications of convolutional neural network algorithms [78]. The authors have used a series of poses to differentiate between a fall event and a nonfall event. In [79], the authors proposed a method that used three-axis accelerometer and gyroscope to detect fall in elderly person by differentiating static position from dynamic position. The device also provided information about the four kinds of positions, falling backward, falling front, jumping, and sitting fastly, by considering the velocity and acceleration of patients. Although these systems are incorporated with many advanced features, they lack in achieving higher functionality and customer demands.

4.3. Chronic Diseases Monitoring. Chronic diseases are one of the leading causes of death in elderly people [79]. As per a medical survey [80], about 80% of geriatric people aged above 65 suffer from at least one chronic disease. The most common chronic illnesses associated with elderly people include diabetes, cardiovascular diseases, cancer, depression, Alzheimer's disease, osteoporosis, lung disease, kidney disease, Parkinson's disease, and dementia. It is difficult for elderly people to take care of themselves in presence of the aforementioned clinical conditions. This leads to poor quality of life. Further, the diagnosis and monitoring of chronic diseases need continuous effort. In this regard, various IoT-driven devices have shown potential in dealing with these diseases. Several studies [81–85] in the past have proposed IoT-based solutions to improve the living standard of geriatric patients with the aforementioned diseases. Winkler et al. asserted that remote monitoring in geriatric care can reduce the mortality rate along with hospitalization rate and delivered quality chronic disease treatment [86]. In [84], the authors proposed a system to monitor vital signs that help to detect various chronic diseases of geriatric patients using a range of wearable sensors. Data mining approaches were adopted for training the system. In [87], a fuzzy ontology-based healthcare system (Figure 6) was employed to ensure continuous monitoring of diabetic patients. The system ensured the monitoring of diet status and health conditions. The device was able to provide recommendations for leading a healthy life. Demirl et al. have reported the application of IoT, which helped geriatric patients to deal with dementia [4]. Elderly people with dementia mostly show decreased mental and physical efficiency due to memory loss. The authors designed a system to collect, transmit, and record the data from various sensors that were placed in the patient's home (in the kitchen, bedroom, toilet, and bathroom). All routine behaviors of the patients were recorded, which were used to train the machine learning model. The system also alerted the patients when there was a deviation from the routine activity. Cardiovascular diseases (CVD) can be a potential reason for the high mortality rate among the geriatric population. CVD may further lead to other health issues such as angina, myocardial infarction, atrial fibrillation (AF), and heart attack. Hence, aging people with CVD need care and continuous monitoring. Electrocardiograph (ECG) signals reflect the functionality of the cardiac muscle and act as an indicator of various cardiac abnormalities. Hence, in most IoT-based healthcare systems, ECG has been a recording parameter of choice for researchers. In [88], the authors proposed a smartwatch (from Apple) with Kardia Band (KB) technology that can detect AF effectively using a single-lead ECG signal. The proposed device could effectively differentiate sinus rhythm from AF by comparing the cardiac expert interpreted ECG with KB recorded ECG. Such a device was paired with a mobile application for automated detection of AF. In another research [89], the authors proposed a portable IoT-driven ECG monitoring device (3 electrodes) by integrating a single-chip computer and various sensors. Herein, the acquired data was stored in the cloud, which was made accessible to authorized personnel only. A reminder e-mail was automatically sent to the patient and doctors in case of abnormal ECG. The proposed device was also capable of measuring other health parameters like temperature, BP, and blood sugar level. In a similar study [90], a multisensory device was designed, which collected heart rate, temperature, and body activity data from the patients. These data were used for the predictions of heart attack or cardiac arrest. The integrated system employed signal processing and machine learning algorithms for the prediction. In the clinical environment, the ECG was acquired using a 12-lead ECG system, where the signal was recorded using 10 electrodes. The electrodes were connected to specific locations on the body surface [91]. However, when it comes to continuous ECG monitoring, using a 12-lead system is not comfortable. Hence, the single-lead ECG signals were acquired using a smart device such as a smartwatch and smart fabric. These signals can be used to diagnose various heart-related abnormalities. Kardia Mobile 6L [92] is the first IoT-based personal 6-lead ECG recording system that has been approved by the Food and Drug Administration (FDA). This is a compact medical-grade personal ECG device, which has been integrated with a mobile application called "Kardia" to monitor cardiac activities. In the future, enzyme-based heart abnormality devices may be developed. Troponin is a cardiac enzyme that is released on the damage of heart muscles and can act as a measure for the early diagnosis of the acute coronary syndrome [93]. Unfortunately, there is no on-site testing device available for measuring troponin levels. The development of such a device could speed up the diagnosis process for clinicians and helps in saving a life. This could be explored in the future.

Chronic kidney disease (CKD) is a condition that impairs the excretory functions of the kidney. CKD causes a reduction in urine output and fluid imbalance of the body. Diabetes, hypertension, and other health issues are the leading cause of CKD. These associated health conditions are making the diagnosis of CKD a complex process. The application of IoT, along with other healthcare technologies, is helping the physician for easy and efficient diagnosis and monitoring. In [94], the authors proposed an IoT-based system for diagnosing CKD by measuring salt intake, water intake, activity level, and sleeping pattern. This health information was stored in the cloud and later can be accessed by the physicians who analyze these data for diagnosis. Hosseinzadeh et al. [95], in their study, have developed a predictive model using the IoT-multimedia database for CKD detection. Using the health information from the database, the performance measures of the predictive models were computed. Herein, the selection of information was based on the clinical observations made by the physicians. Despite the efficient use of technology, most hospitals still rely on the manual monitoring of the urine output of the patients using the urine bag, which may be susceptible to human error. Numerous researches have already been dedicated to designing an IoT-based system [9, 94] for measuring urine output. However, these developed systems are still lacking acceptance by health professionals. Some of the potential reasons behind this may be the lack of commercialization of these devices, validation before their application, and insufficient awareness of their use.

4.4. Monitoring Mental Health and Cognitive Diseases. The mental illness severely impacts the routine life and social-economic status of elderly people. Mental health declines with progressing age. This may be the potential reason behind the increased mental illness in the elderly population. The most commonly observed mental health issues in the elderly include Alzheimer's disease, Parkinson's disease, dementia, depression, and schizophrenia.

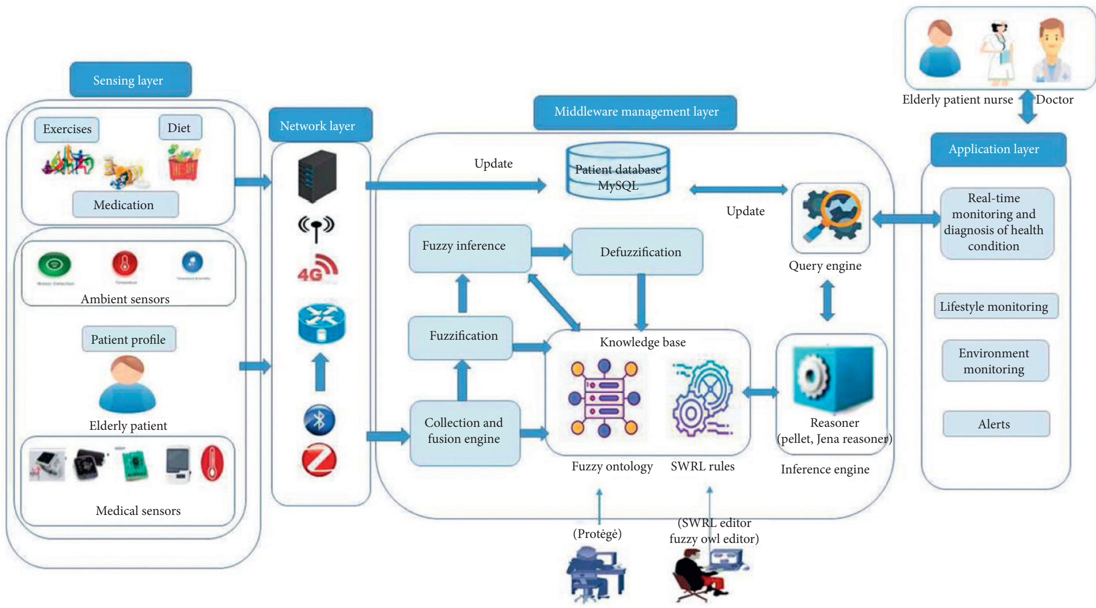

Figure 6: Basic architecture of fuzzy ontology-based healthcare system (reproduced from [87]).

Numerous studies [58, 96–98] have employed IoT-based technology in the detection of these conditions and provided better care. de la Torre Díez et al. have reviewed the contribution of IoT in dealing with mental illness. The authors have summarized how different IoT-based solutions had revolutionized the process of monitoring and diagnosis of these diseases [99]. In [100], the authors reported a system that can be used for tracking and monitoring mentally ill patients. In another study [101], the behavioral changes (e.g., sleeping pattern, repetitive action, and excess active level) in geriatric population have been assessed using various IoT-based sensors, which were employed to diagnose Alzheimer's conditions. In a similar study [102], an IoT-based system has been proposed to analyze the efficacy of the medication by monitoring the symptoms of Parkinson's disease. The device consisted of an electronic dosing machine, a smartphone, a bed, and wrist sensors. The proposed device was able to monitor motor function, physical exercise, medication compliance, and meal intake time. The authors concluded that the proposed system can assist mentally ill geriatric patients to have an insight into the correlation between medication and symptoms of the disease. Parkinson's disease causes a deterioration of functions and leads to slower movement and restricted activity. The conventional methods follow a "pull test" for the early diagnosis of Parkinson's disease. The test detects postural instability using the Unified Parkinson's Disease Rating Scale (UPDRS) [103]. The primary challenge in such an IoT-based system for diagnosing mental illness is the efficient handling of a large volume of data that is acquired from various sources. A large dataset, generated from these devices, needs extra effort for processing and analysis to provide smart healthcare services. It has also been reported that various psychiatric biomarkers such as proteins and other macromolecules have potential in detecting mental disorders [104, 105]. However, more research is needed to reach the stage where it can be used clinically. In the future, biosensors that can efficiently detect these biomarkers may be employed in IoT-based systems for the efficient detection of various mental disorders. The elimination of the aforementioned issues can provide a long-lasting solution to deal with mental health issues, especially in the case of the elderly.

4.5. Telerehabilitation. Rehabilitation plays an important role to counteract physical disability and impairment caused due to either aging or postillness (e.g., heart attack, falls, total hip, knee, and joints replacement) surgery. Numerous researches [41, 106] have employed sensor-integrated systems, wearable sensors, and virtual reality for providing rehabilitative services to geriatric patients. In [107], the authors have facilitated in-home rehabilitation of the geriatric patient through monitoring of the activity (still, up/down, walking, idle, running, and cycling) and movement (arm press, arm twist, arm circles, curls, and shoulder rolls) recognitions. These movements are monitored using a smartphone embedded with accelerometer sensors. Further, the prediction of these activities could be made using different machine learning algorithms. Nave and Postolache (2018) have designed an IoT-based smart walker rehabilitation system for geriatric patients. Such a system can monitor the walking matrics during a rehabilitation session. Various sensors such as ultrasound sensors, load cell sensors, and inertial management sensors have been included in this system. Herein, the recorded data was transmitted to the cloud using a smartphone [108]. A number of research articles have also been reported on monitoring postoperative rehabilitative therapy [107, 109, 110]. These studies have also proposed the concept of developing a smart home that is integrated with numerous embedded sensors (e.g., room occupancy, silhouette sensors, etc.) for the in-home monitoring of geriatric patients.

The most common cause for adopting telerehabilitation is to avoid a repeated visit to the physiotherapy center and its associated cost. In this regard, the acceptability of a rehabilitative device mostly depends on its costs. However, the current rehabilitative devices are having a high cost as compared to the cost of accessing physiotherapy. Hence, there is a need to develop low-cost rehabilitative devices in the future [111]. Although several IoT-based rehabilitation systems have been reported in the past for elderly people, rehabilitation for persons with disabilities has been ignored. This should be explored in the future. Easy accessibility of these devices is another major challenge for their acceptance. A user-friendly interface and improved accessibility in system design will help patients to complete the treatment process without much assistance from other individuals. Further, it will encourage the participants to stay with the rehabilitation program and encourage them to actively participate in the exercise. Most of the conventional rehabilitation systems restrict their outcome to the training results. However, the outcome measurement should also include the quality of practice in terms of speed, accuracy, kinematics, and daily home activities outside the training session [112]. The inclusion of such type of outcome measurement unit will enable the IoT-based rehabilitation system to qualitatively assess the patient's improvement and manage their exercise routine [113].

4.6. Monitoring Nutrition and Medication. Nutrition plays an important role in the overall well-being of a person. The deficiency of a healthy diet may lead to malnutrition. The possibility of malnutrition is comparatively high in the elderly population. Lack of timely diagnosis may later cause various health issues such as cardiovascular diseases, diabetes, and osteoporosis. Hence, it is necessary to track food habits and daily nutrition, especially for elderly people who are at higher risk of malnutrition. Lin et al. [114] have proposed a system for daily diet control of elderly persons using a single-chip computer (Raspberry Pi), two LEDs, and RFID cards. The system contains a list of foods that may cause various diseases (CVDs, degenerative diseases, and osteoporosis). Further, it recommends food to the patients based on their health reports. In a similar study [115], a device that can recommend daily nutritional diets and exercise for elderly people has been proposed. Apart from nutrition, various other factors influence the health of the elderly. Through proper nutrition, one can improve the health status, but it is not sufficient for people who are already dealing with one or more chronic diseases. Maintaining a routine medication regime is essential for them in addition to the diet. With the passing age, elderly people experience a decline in cognitive as well as mental ability. Hence, maintaining timely and proper medication is becoming challenging. A smart pillbox or pill dispenser can be a potential solution to the aforementioned issue, which can remind the patient of their medication. The IoT-integrated smart pillboxes have gained much popularity in the recent years. These devices enable the caregivers and doctors to remotely monitor and control the medication routine of the patients. An IoT-based smart pill dispenser has been proposed in [116] for monitoring the medication regime of geriatric patients. Herein, a mobile application has been used to alert the patients and caregivers in case of an incorrect medication schedule. In [113], the authors have proposed a reminder-cum-memory aid system that can assist geriatric patients with dementia. The proposed system could generate an e-mail, audiovisual display, and text message to remind the patients of their medication schedule.

Managing polypharmacy is a potential challenge during medication. The management of multiple drugs, maintaining their dose information, and medication time require efficient algorithms. Again, different medicines do not follow the same storage condition. Maintaining different storage environments for the pills in a single pill chamber is difficult. This issue can be solved by creating different subchambers in the pill tray, where the storage condition for each subtray can be maintained as per requirement. It may be possible that some users may accidentally consume the wrong medicine either due to their forgetfulness or due to any system error that may suggest the intake of an incorrect medicine. For these issues, the IoT-based smart medication system may include a feature that will provide the details of the pills to be consumed to the user. Most of the IoT-based medication systems focus only on giving the correct medicine at the right time to the patients. However, these systems have ignored the requirement of the "pill-restocking alerts" system. Inclusion of the pill-restocking information will remind the family members as well as the caregivers to refill the medicine before time so that the medication regime of the patients will not be hampered. This may be incorporated in the future. Also, in the future, the medication system must include multiple reminder signals such as voice, text, vibration, and sights (as in [113]) which can help elderly people with impairment. Such devices will increase their acceptability.

4.7. Emergency Healthcare Service. Emergency healthcare services deal with various sudden and unpredicted health crises such as accidents, falls, and heart attacks. Aging causes functional impairment and forgetfulness that make these elderly people prone to a sudden health crisis. Emergency care services are an integral part of every care service and can be employed while monitoring either health parameters, human physical, and behavioral activities or falls and so forth. In the past, the emergency service was only accessible in the hospital under the direct supervision of the health professional. However, with the rapid growth in technology and Internet services, it is now possible to avail of these services at home. Numerous studies [114, 117, 118] have been reported in the past for remote monitoring of daily activities through IoT-based systems. An IoT-based living assistance system has been proposed in [119], which can monitor and register patient's vital information. The system also poses a triggering system in the case of an emergency. In [24], an IoT-aware health monitoring system has been implemented, which sends alerts to health professionals when elderly people require either hospitalization or emergency medical attention. An emergency system has been integrated with the telemedicine system in [120]. Herein, the system shows the user location as well as emergency information to the caregivers and also provides instructions to help the patient. Korzun et al. [121] proposed digital assistance services for emergencies. In case of an adverse medical situation, when the patients feel the need for emergency care, a signal can be sent to their relatives with a single button press. However, the emergency message is automatically generated and sent to the caregiver in case of a fall event [122].

The current IoT-based emergency healthcare monitoring system for elderly care only focuses on handling a single medical condition of elderly people. Since a medical emergency may arise from a wide array of health conditions, monitoring a single health parameter would be insufficient to achieve an efficient healthcare service. In [109], the authors reported that there is a need for an integrated emergency system that will employ more sensors (like blood pressure meter and heart rate meter) and new services to diversify the healthcare features and benefits. Immediate and fast communication is crucial while dealing with an emergency. Elderly people need to contact either a family member or the caregivers to get swift support. Most of the IoT-based emergency systems use the Internet for the communication purpose, where a network disconnectivity may fail the whole system. Hence, in the future, these systems must include an alternate mode of communication which will be activated at the time of network disconnectivity.

5. Current Issues, Challenges, and Future Scope

The development of an efficient healthcare device/system for the geriatric population must be based on three important aspects, a fast response time during first-aid service, an effective communication system, and a user-friendly interface, for its efficient use. Lacking a user-friendly interface may lower the efficiency of the system. The current healthcare devices are incapable of providing fast access and a valid communication system. Hence, it is inevitable to develop futuristic devices that overcome these issues and provide more reliable solutions. An ample amount of research in the literature is focused on IoT-based healthcare applications for geriatric patients. IoT technologies have significantly transformed healthcare services and have provided novel solutions to various healthcare problems. Despite its wider applications, many challenges still exist in this research domain. Most of the currently available solutions for elderly care have ignored the functional limitations associated with age and cognitive performance. The types and modes of disabilities in old age are person-specific and demand the development of adaptive systems. The recently developed IoT-based systems are relatively user-friendly as compared to the devices developed in the past. However, these systems have ignored the fact that, as compared to younger people, elderly people are slow learners. Moreover, elderly people face difficulty in operating advanced gadgets and take a longer time to adapt to a new system. One potential solution for this aforementioned issue is to consider the comprehensive knowledge on behavioral analysis as a feedback mechanism while designing the IoT-based healthcare system.

A large number of vendors who provide a range of products, protocols, and devices are present in the healthcare industry. However, there is no compulsion on these vendors to follow specific rules and regulations. Due to the variations in the communication protocols, standards, and design, various interoperability issues may arise. Hence, standardization of these aforementioned areas is crucial. The employment of standardization to these medical devices may provide fundamental protection and support robust security solutions for software development. Two examples of such standardization agencies are Systematized Nomenclature of Medicine (SNOMED) and Logical Observation Identifiers Names and Codes (LOINC). Although the advancement in the IoT healthcare applications makes the process of standardization more complex, no dedicated study was found in the literature which had addressed these issues and demands future attention. IoT-based healthcare network connects a large number of medical devices and sensors generating a higher volume of medical data. These data are distributed across various data sources/repositories. Hence, to avoid complexity in the data flow among various sources, a suitable method for data integration is required. Since healthcare data contains private and sensitive information of the patients, the privacy and security of data can be a major issue that needs to be handled with caution and using suitable protocols. Currently, there are no standard protocols and regulations available which will control the way the health information is collected in an IoT-embedded system [123]. Hence, the use of an efficient security and privacy safety protocol is the primary requisite during data transmission. Personalized healthcare services include the involvement of multiple doctors and caregivers from different geographical areas. This requires smooth communication among these service providers. For this purpose, the future healthcare system would require a data model that can not only identify and integrate various data sources but also provide an efficient data-handling mechanism. The IoT-based solutions capture personal data about the location, health parameters, and daily habits during monitoring. These data were then stored in a cloud server that can be accessed and shared by third-party solution providers. The cloud layer acts as a repository of the details, medical history, and other physiological parameters of the patients. Unfortunately, the extraction of healthcare data from the cloud reveals the personal information of the patients. This may hamper the privacy of elderly people who usually stay alone at home and may put them at a higher risk category. Hence, there should be a provision for selective sharing of the data. Further, the system may take the consent of the patients before using their health information. Data encryption can be a potential solution to the privacy issue that can reduce information security risks and should be explored in the future.

Despite various technological and design advancements in IoT-based systems, evaluating usability and acceptability is still a major challenge. The measurement of willingness to use and keep, simplicity, patient satisfaction level, reliability, and wearable time are some of the measures to assess usability and acceptability. To make an IoT-based healthcare system more popular, modifications in manufacturing are required to address some critical issues such as power consumption, restricting the user movement within a confined area, and cost [124]. The cost of a device is directly related to its acceptability. Hence, more research must be dedicated in the future to develop low-cost healthcare devices. This can be achieved using low-cost materials and cheaper sensors in future development. A cost analysis can be performed to have an overall idea of the cost of the commercially available devices developed so far. This will help geriatric patients to opt for accurate and cost-effective solutions to their health problems.

6. Conclusion

The substantial growth in the aging population in the recent years has caused various health and socioeconomic challenges in the day-to-day life of geriatric people. Numerous technological advancements in the healthcare sector have addressed these challenges. They have also contributed to the development of various solutions associated with the underlying problems and help them to live a normal life. The current study discussed the need for IoT-based systems in addressing the health issues associated with geriatric persons. Further, the paper also discussed the role of IoT in influencing various healthcare domains (AAL, telemedicine, robotic technology, wearable sensors, etc.) in the elderly population. Up-to-date information regarding the current status of the IoT-based healthcare systems that deal with various healthcare issues such as chronic diseases, mental illness, cognitive diseases, and medication adherence is discussed in the paper. Finally, various issues and potential limitations of the existing healthcare systems/devices are also mentioned. The review paper will help future researchers to have a piece of comprehensive knowledge in the aforementioned field, which they can analyze to understand the gaps in the current research and subsequently use this information to develop advanced and intelligent healthcare systems.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding publication of this article.

Supplementary Materials

The supplementary file S1 contains information regarding the basic architecture of an IoT-based system used for the health monitoring of the geriatric population. The section describes the three basic layers of the IoT system architecture. (*Supplementary Materials*)

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Review Article

Internet of Things and Robotics in Transforming Current-Day Healthcare Services

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Technology has become an integral part of everyday lives. Recent years have witnessed advancement in technology with a wide range of applications in healthcare. However, the use of the Internet of Things (IoT) and robotics are yet to see substantial growth in terms of its acceptability in healthcare applications. The current study has discussed the role of the aforesaid technology in transforming healthcare services. The study also presented various functionalities of the ideal IoT-aided robotic systems and their importance in healthcare applications. Furthermore, the study focused on the application of the IoT and robotics in providing healthcare services such as rehabilitation, assistive surgery, elderly care, and prosthetics. Recent developments, current status, limitations, and challenges in the aforesaid area have been presented in detail. The study also discusses the role and applications of the aforementioned technology in managing the current pandemic of COVID-19. A comprehensive knowledge has been provided on the prospect of the functionality, application, challenges, and future scope of the IoT-aided robotic system in healthcare services. This will help the future researcher to make an inclusive idea on the use of the said technology in improving the healthcare services in the future.

1. Introduction

The advancements in modern technology have facilitated researchers and scientists in transforming healthcare services. The leading-edge technologies have been extensively applied in designing and implementing various medical devices that are used for diagnosis, treatment, monitoring, and testing. This has been possible not only due to the development of the clinical-grade sensors but also due to the sensor networks that are implemented in hospitals. The combination of the sensors and sensor network has significantly helped to optimize healthcare delivery from a remote location. Due to the aforesaid advancements, healthcare services have become more adaptable, accessible, and affordable. Some of the most widely used advanced technologies that are proficient in the revolution of healthcare applications include big data analytics, machine learning, artificial intelligence, cloud computing, computer vision, and the Internet of Things (IoT) [1–5]. Data analytics have shown potential in identifying patterns and hidden features from the health data and helps in improving the quality of healthcare through an efficient decision-making capability [6]. Moreover, artificial intelligence (AI) techniques including machine learning (artificial neural networks, deep learning, etc.) have also augmented the work of healthcare professionals by processing a huge amount of healthcare data that are available in the form of electronic health records. Some of the healthcare applications of AI include diagnosis of respiratory conditions using chest X-rays, early detection of cancers, heart diseases, and predicting human health conditions [7]. Similarly, in the case of surgeries and therapeutic applications, the various advanced imaging techniques, including computer visions and computer tomography, have been efficiently employed [5]. The use of cloud services in healthcare provides a platform to store, process, and share healthcare records and reports, patient's personal information, etc. This delivers more flexibility to the healthcare services by using intercloud infrastructures to share health information, generate bills, etc. [8]. Although numerous advanced technologies have recently emerged in the healthcare industry, the one that shows potential in employing multiple technologies into a single environment is the Internet of Things (IoT).

In recent years, IoT has shown great efficiency in meeting the healthcare needs of people. Internet of Things (IoT) represents a network that connects multiple physical things (devices) through Internet connectivity. This allows unambiguous data and information sharing among the connected users. The integration of IoT technology can transform a device into a smarter, effective, and efficient device. Furthermore, IoT technology shows competence to connect the device with the real world. This has led to a substantial increase in the application of IoT technology in various sectors including healthcare. Experts believe that the IoT market in healthcare will hit more than 117 billion in 2021 [9]. The main contributors to this growing market are the sedentary lifestyle, the increased population, and the gradual spike in healthcare issues. Moreover, these aforesaid factors have also burdened the healthcare industry with the increase in the number of patients and new diseases with every passing day. Hence, it is more challenging to find a futuristic solution that provides more efficient and cost-effective healthcare services. In this regard, IoT is uncovering various other technologies, including robotics for better diagnosis, treatment, monitoring, and patient management. The integration of IoT and robotics provides an ecosystem where humans, robots, and IoT-system work cooperatively. The system is mostly inspired by the cloud-robotic system [10]. Cloud-robotic relies on "cloud computing" to access a large amount of data and process that information to perform specific operations. Herein, all operations, including sensing, computing, and memory, are integrated into a single network robot. The inclusion of robotic technology is meant to achieve some extent of human-like automation with a reduction in human intervention. This integrated system employs machine learning algorithms to program and train machines that will be able to perform in the medical environment. The system receives the patient's health information from the robotic system, shares these data through a network among the health professionals, and acts either based on the received feedback or using an intelligent computation. In recent days, IoT and robotics have been extensively applied in solving various healthcare problems from assisting the doctors remotely during surgery to providing rehabilitation to the differently abled [11–13]. Moreover, it is reducing the burden of medical personnel by relieving them from a routine task and making the medical procedure safer and cheaper than before. The use of robots allows for achieving higher accuracy and reducing human error. Although there is a remarkable evolution in the application of these two widely used technologies, the literature lacks comprehensive knowledge on the application of the integrated system where IoT and robotics will work cooperatively.

On this note, the current review aims to provide extensive information regarding the application of robotics and IoT technology in healthcare. Furthermore, we have discussed some of the most widely used applications of the IoT-aided robotic system in healthcare that includes assistive surgery, telepresence, rehabilitation, prosthetics, sanitization, and prescription dispensation. This review may form a reference for future researchers in deciding their prospects in the aforesaid field by highlighting the existing issues and future challenges.

2. Definition, Architecture, and Basic Functionalities of IoT-Aided Robotic System

The IoT-aided robotic system can be defined as a wireless network that provides advanced robotic services by interconnecting multiple robots with the smart environment (Figure 1). It also makes use of advanced information and communication technologies such as cloud computing and big data analytics that enables the robotic system to share information and make use of the enormous amount of data stored in the cloud. Earlier studies in the field of robotics were mostly focused on increasing robot autonomy, perception, and data processing, which are important criteria for the independent functioning of a robot. However, in the IoT-aided robotic system, the functionalities of a robotic system are integrated with various sensors to achieve a common healthcare goal. Besides monitoring, diagnosing, and performing simple tasks, the integrated systems are designed to perform complex operations. Furthermore, at the same time, the sensor information from the smart environment can be efficiently shared and used by the robotic system. In simple words, the IoT-aided robotic system can be defined as an extension of the IoT that possesses the advantage of robotic technology.

The architecture of an IoT-aided robotic system consists of three layers: the physical layer, network control layer, and the application layer. Since the architecture of the integrated system is not the primary focus of this study, only a brief introduction to the architecture is provided herein. However, a detailed description of the architecture is given in [15]. The sensors are used for collecting the vital health information of the patient's body and information depicting the surrounding environment. This layer also includes switches, actuators, and other drives that can be used to perform simple actions. Robots are intelligent devices that can connect either with other robots to create a multi-robot network or with sensors/actuators. The network layer is responsible for all the interconnections within the network sensors and the robots. It includes routers, controllers, and communication and network protocols. For information storage, the system may use local as well as remote storage using cloud computing technology. With help of the physical and network layer, the application layer performs specific tasks using the information collected from the physical layer. The application layer architecture solely

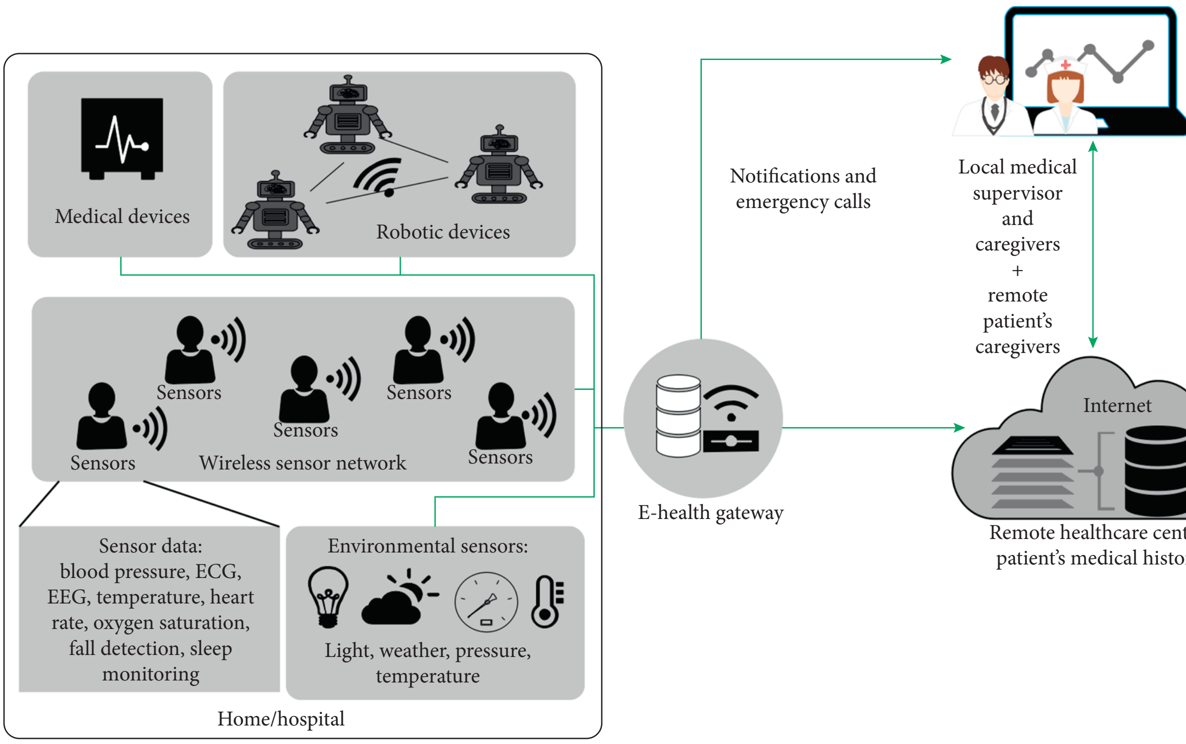

Figure 1: A basic IoT-aided robotic healthcare system (modified from [14]).

depends on the objective of the integrated system. However, depending on the healthcare applications and the nature of tasks, an IoT-aided robotic system must be able to show a set of functionalities to meet the demands. In this section, several such abilities (Figure 2) of an IoT-aided robotic system have been discussed in detail.

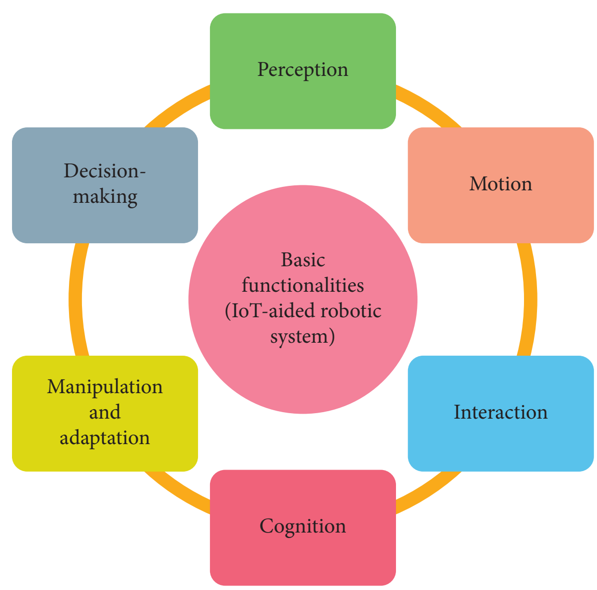

Figure 2: Basic functionalities of an IoT-aided robotic system.

2.1. Perception Ability. Perception is defined as the ability of a system to perceive, understand, and sense the surrounding environment [16]. The perception ability of a robot makes the system efficient to perform complex tasks and allows it to function in diverse situations [17]. Furthermore, it enables a robotic system to access data from multiple sensors and record real-time information such as speech, image, and video. In the healthcare environment, the perception ability can be utilized to observe human behavior related to anomalous activities and unhealthy habits [18]. Presently, it has been used in various healthcare applications such as clinical measurements (blood pressure, temperature, and activity recognition), disease diagnosis, monitoring patient's recovery, and disinfecting/cleaning of hospital premises [19, 20]. Instead of placing a sensor onboard, the use of a mobile robot allows collecting of information from the flexible and dynamic positions. Furthermore, the sensing and data analytics technology that is used in IoT provides a wider perspective to robots as compared to local sensing. This lets the medical system implement time-resolved sensing strategies. One of the most challenging tasks during perception in an IoT-aided robotic environment is the ability to sense information that is distributed in space and time [21]. Hence, while designing an IoT-aided robotic system, it is of primary focus to use some techniques that allow the system to perceive the distributed information [22]. Moreover, the information regarding the location of a robot is also crucial as it helps in collecting environmental information. Despite, remarkable growth in this field, self-localization is continued to be a challenging task in more crowded areas and places where global positioning system (GPS) does not work properly. In that case, the integration of IoT provides reliable location information to domestic robots. This is achieved using various IoT-based communication technologies such as Radio-frequency identification (RFID), Wi-Fi, Zigbee, and Bluetooth [23].

2.2. Motion Ability. The motion ability can be an added value for a robotic system as it increases the working range of the system. Usually, in robotic systems, increasing of the working range is achieved with help of advanced mechanical design and using an efficient navigation system. The mechanical design helps in creating the movement while the navigation system helps in deciding the path for the motion. A perfect navigation system enhances the comfort of the patients during assistance. The use of IoT technology may help in assisting the robotic system to achieve some extent of human-like automation in various healthcare services. In addition, it collects information from different locations and acts collectively to perform specific operations such as lifting and moving patients and assisting patients to do their daily activities [24]. In some healthcare applications, a continuous movement of the robot is necessary as in the case of touring the caregiver's activity area or fall prevention. Herein, the robot has to find an optimal path to reach the destination efficiently by avoiding the obstacles in crowded areas. Hence, achieving efficient navigation is the prime focus in many researches. This is due to the inability of the traditional robot to handle a dynamic environment where there is a stochastic movement of people. Furthermore, due to the unpredictable movement of people, the avoidance of collision for a robotic system is difficult, particularly while working in a narrow space. Recently, numerous studies in the literature have addressed the issue of collision avoidance of robotic systems [25–27]. Safeea et al. in their study have proposed an online collision-avoidance system in a surgical environment. Herein, IoT is used to achieve this without any physical contact [28]. Mišeikis et al. have developed a healthcare robot called "Lio," which is used for autonomously assisting staff and patients in a hospital. The robot uses a combination of visual, audio, ultrasound, laser, and a mechanical sensor for safe navigation that enables the robotic system to avoid collision [29]. In [30], a smart-walker called "Guido" has been proposed for visually impaired persons. The system uses a map-based navigation system that creates a map of its surrounding environment and also tracks its position. The system creates a path based on the generated map and uses a collision avoidance algorithm to reach a destination without any obstacle. When the healthcare environment is associated with multiple robots as in the case of surgery, it is important to have an alternate mode of communication among them. This is to avoid miscommunication among the robots after the loss of Internet connectivity.

2.3. Interaction Ability. The ability of an IoT-aided robotic system to interact with the users, operators, and various other systems that are present in the environment makes the system user-friendly and efficient. Moreover, it can act as a companion to the disabled and elderly people who need special attention [31]. Although the machine-to-machine interaction is well adopted in a robotic system, the integration of IoT technology can facilitate efficient human-robot interaction. The disadvantage of using the onboard sensors of the robotic system for detection is that it limits the range of operation. However, external sensors, cameras, and wearable sensors provide a broader perspective that enhances the interaction ability of a system. The physical expressions, voice, and gestures have been used not only for estimating the human emotional states but also to enable the robot to respond to these emotions. Various body-worn sensors have been used to predict human emotions. Chen et al. [32] have used human-robot interaction through hand gestures as a control mechanism for households and wheelchairs. Herein, the hand gesture was sensed and captured using a wrist-worn camera. In [33], the authors have used heart rate and skin conductance parameters for estimating the motivation and attention in due course of human-robot interaction. Agrigoroaie and Tapus have proposed a framework for behavior control that makes customized interaction between the robot and the patient with mild cognitive impairment. The models created will help the robot to interact with the patient both verbally and nonverbally [34]. In a recent study [35], the authors have reported the development of a socially assistive robot that enables people to maintain not only their health condition but also support them during social interaction. The designed robot can help the patients to improve their perception ability, social behavior, and provide structure for interaction. Furthermore, it can also change the feeling of a person [35]. Sharif and Alsibai have developed a "Nao Robot" that can analyze the medical data and interact with patients. After interaction with the robot, the patients will able to understand the vital signs of their body and make inferences regarding their health status [36]. Furthermore, it can predict the risk of heart diseases in the future and recommend the necessary changes in the lifestyle to avoid medical risks.

2.4. Cognitive Ability. The cognitive ability enables a robot to understand its relationship with the environment or a specific object. There are different aspects of cognition including perception, intelligence, encoding/decoding of information, reasoning, problem-solving, and thinking [37]. In an IoT-aided robotic environment, the robot makes use of the cloud and obtains knowledge from multiple sources, e.g., the human body and its surrounding environment. This helps the robot to create a virtual environment for simulating robot control policies. In IoT, cognitive techniques have been introduced recently in the management of distributed architecture. However, the inclusion of robots has not yet been sufficiently explored and demands more attention. In [38], the authors tried to design a cognitive architecture for the humanoid robot. The proposed architecture is the integration of a hierarchical module and a behavioral module. These modules were designed to keep the important aspects of cognition (e.g., perception, learning, planning, and motor control) in mind. This is to achieve a higher level of cognitive ability in the device. Literature suggests that cognition is interlinked with emotion and both are necessary to achieve a healthy social interaction [39].

This concept can be employed in the next-generation robotic systems for achieving a higher level of cognitive function.

2.5. Manipulation, Adaptation, and Decision-Making Ability. The basic application of a robot in an IoT environment is its ability to modify the sensor data [10]. In the healthcare environment, the robots can either be used for monitoring patient's health or detecting health abnormalities. In both cases, first, the robot has to acquire the health information using various sensors. This information follows various processing steps before providing meaningful information. The processing of the extracted data includes denoising, preprocessing, and thresholding. The implication of IoT technology in this process is to enable the integrated system to calculate those features that are not easily observable by the robots. Furthermore, a system needs to decide the best course of action to be taken during treatment. This can be achieved with help of a predictive algorithm designed using artificial intelligence, machine learning, or predictive analytics. However, the accuracy of predictions solely depends on the quality of the model and the efficiency in detecting the initial state. The integration of IoT provides a better perception and improves the decision-making ability of the integrated system. Again, it diversifies the ability of a robotic system in decision-making by integrating more sensors into the system. This will increase the information available to the predictive model and boost up the rate of accurate prediction. Another important functionality of the integrated system is its ability to work in a dynamic environment, which is called adaptability. This ability makes the system ready to deal with unforeseen events, faults, change in environmental conditions, tasks, or human behavior. Adaptability can be achieved with the help of other aforementioned abilities such as perception, cognitive, and decision-making. In [34], a robotic system was designed that can adapt and react based on the input user profile. Here, the profile information contains the level of disability, emotional states, personality, and preferences, etc. These robots can learn through their prior experience and adjust their behavior based on the individual response.

3. Application of IoT-Aided Robotic Technology in Healthcare

There are several fields in healthcare where the IoT and robotic technology have been efficiently employed in the past. Some of the most notable healthcare applications (Figure 3) of these technologies have been discussed. Furthermore, issues, challenges, and future implications are identified and reviewed in this section.

3.1. Rehabilitation. The employment of correct and scientific rehabilitative procedures plays an important role in the recovery of the motor ability of a patient [40]. The most common reason behind the motor disability may be a brain injury, chronic pain, stroke, tremor, etc. Among different rehabilitation categories, limb rehabilitation is the most common, which can be further classified into upper and lower limb rehabilitation. Rehabilitation training is difficult for many patients as it requires the help of a trained healthcare professional. An increase in cost, unavailability of medical staff, and geographical barriers make it difficult for these patients to access rehabilitative services. A more suitable solution for this problem is remote treatment using various home-based medical devices [41]. Over a decade, much-advanced technologies such as robotics, machine learning, and artificial intelligence have satisfied the need of many clinicians and patients in providing rehabilitation. A detailed description of the most commonly available technologies for limb rehabilitation is provided in [42, 43]. However, the application of IoT brings the patients, rehabilitative systems, and the physiotherapist into a common environment where they can work cooperatively. Numerous researches in the past have employed the IoT-aided robotic technology for rehabilitation [44–47]. Wai et al. have developed a low-cost portable home rehabilitation device that can improve various upper limb (hand, forearm, and wrist) movements. Li and Zhong have proposed an IoT-based upper limb rehabilitation system that was based on remote control [40]. Here, the pressure sensors are used as the source of control information. In [48], an IoT-aided robotic system for stroke rehabilitation has been reported that enables the doctors to remotely monitor the type, strength, and duration of the training at home. Furthermore, it will provide optimal prescription by analyzing the intensity of the rehabilitative training as feedback. Thakur et al. have used an accelerometer and a magnetometer sensor-based smart band that can recognize the hand motions such as flexion, extension, and adduction. The information collected from these sensors acts as a control signal for the robot that reflects the movement of the smart band [49]. In [50], an IoT-aided robotic system has been proposed that uses a natural user interface for rehabilitation. The system enables the therapists to record specific motions that will act as a control signal for the robot to create a similar motion in the patient's lower limb.

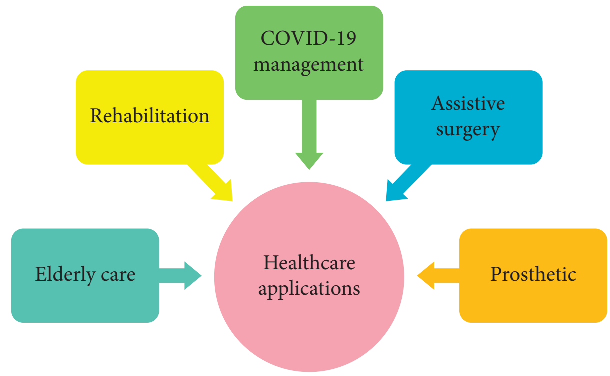

Figure 3: Some notable healthcare applications of IoT-aided robotic technology.

Despite the evolution of the aforesaid technologies, it is still a major challenge for the researcher to assemble the maximum skill of a physiotherapist. Although the IoT-aided robotic system is one of the most advanced tools, it is not a replacement for the physiotherapist. Presently, these systems are only capable of performing simple repetitive therapies. However, the importance of employing these technologies lies in the ability of a robot to provide longer and more intensive repetitive movements with the same consistency. The integration of IoT-technology enables physiotherapists to not only observe and manage multiple patients but also suggest the best suitable therapy for them. Moreover, it is important to give the patients a feeling of independence during their rehabilitation. This brings positivity and enhances their self-esteem. Hence, in future rehabilitation systems, the addition of various human movements is needed to design a multi-modal rehabilitation system. The ROBIN [51], a rehabilitative robot, was developed on a similar concept where the rehabilitation system not only provides stability to the trunk during a change in body position but also encourages the patients for simple arm and hand movements (reach and grasp). Current research in the said field is mostly exploring the use of augmented reality, videogames, and plays for rehabilitation. This is to increase the engagement and participation of the patients in the therapeutic process. It has also been reported that the use of video games during rehabilitative activities also improves motor function and hastens recovery. The cost of using a rehabilitation robot is still high as compared to drug-based or human-based therapies. This is limiting the wide-scale evaluation of these services and hence questioning their acceptance in the clinical practice. Also, a patient with restricted movement cannot pay regular visits to a hospital/rehabilitation center. Hence, in the future, efforts must be made for developing systems with low cost that will be suitable for an unsupervised environment. More attention is to be given to the adaptability of the rehabilitative systems so that they will work dynamically according to user needs. This may allow changing the therapeutic routine of the patients after evaluating the improvement in the patients' conditions.

3.2. Assistive Surgery. The invasive nature of the surgical procedure makes it a risky process. This provides a strong motivation for the use of numerous advanced state-of-the-art technologies to transform the conventional surgical process into minimally invasive and less complex. On that note, robotic technology is delivering a flexible work environment for surgeons and making the surgical process more precise and accurate. The use of the assistive robot requires continuous training for the surgeon and expertise in controlling the robotic system [52, 53]. Usually, the minimally invasive surgery is performed through a small incision point (diameter less than an inch) on the abdomen, which is also called the remote center of motion. Due to the use of a small incision point, controlling the robotic system involves multiple tasks such as control of surgical tip, handling the constraints generated at the incision point [54], and collision avoidance in the workspace [55]. The integration of the IoT technology enables the existing system to communicate and connect with external devices (such as wearable sensors, smart devices, and mobile phones), doctors, and nurses. An IoT-based surgical robot provides an environment where the surgeons can connect for teleoperation through the Internet. The advantage of using an IoT-aided robotic system is its increased operational workspace as compared to open surgery [56]. Numerous studies have been reported in the literature that have employed an IoT-aided robotic system in many applications including microsurgery, robotic assistive-minimally invasive surgery, and remote surgery [52, 57–59]. Ishak and Kit [60] have developed a robotic arm that can assist a doctor during surgery and take care of the patients. The robotic arm could be controlled through gesture and posture information. In [61], an IoT-based collaborative control scheme has been developed for robot-assistive minimally invasive surgery. The proposed scheme can handle multiple tasks on a priority basis and also ensure the control of motion constraints and collision during the surgery. Recently, the IoT-aided robotic system is also employing haptic technology [62] to enable the surgeon to operate the patients from an isolated part through the robotic interface [63]. Although the aforesaid field possesses the advantage of two widely used technologies, namely, IoT and Robotics, the major concerns of such systems include reliability, robustness, and security [64]. Furthermore, to make the system efficient and improve safety during surgery, it is essential to develop accurate models of both the human body and the robot characteristics. Proper validation of the systems developed for assistive surgery is also required before its commercialization. Despite the substantial growth, the employment of an IoT-aided robotic technology is still associated with few unique limitations that are making this field more challenging. Some of these limitations include establishing secure and adequate access, 2-D vision, restricted instrument flexibility, decreased depth perception, and reduced tactile feedback [65, 66]. Furthermore, the use of the Internet for the interconnectivity among various robots and the doctors may suffer from network disconnectivity, slow Internet speed, and service quality [57]. This may severely affect the accuracy and the success of a surgical procedure. The future of robotic surgery lies in developing more miniaturized devices, incorporating smarter instruments with the robotic system using IoT technology. These futuristic systems will be capable of sensing and informing the surgeon about various bodily parameters such as blood flow, tissue oxygenation, and tumor margin.

3.3. Prosthetics. According to the reports by the World Health Organization (WHO), more than 15% of the world's population is suffering from some form of disability [67]. If statistics are to be believed, 30 million people across the globe need an assistive device, out of which 10 million are amputees. Unfortunately, only 27–56% of the total upper-limb amputees and 49–95% of the total lower-limb amputees uses prosthetics [68]. Prosthetics are artificial body parts (limb, tooth, heart halve, and eye) that help a differently abled person to live independently with comfort. It not only compensates for the physical function but also the appearance of the lost part. The loss of a body part may be due to a tumor, accident, disease, trauma, or congenital defects. There is two common classification category for the prosthetic devices, i.e., either based on the way the prosthetic device receives power or the lost body part. Based on the received power source, it can be either body-powered or electrically powered. Various other sources of power, such as gas and hydraulics, have been proposed in recent years [69–71], but they lack in their practical applications. Similarly, based on the lost body part, the prosthetic can be classified into the limb, dental, somatic, and craniofacial prosthesis, among which the limb prosthetic is the most common and is further classified into the upper- and lower-limb prosthesis. The development of these prosthetic devices is time-consuming, complex, and involves a series of repetitive processes. This is due to the large variability in the size of the lost parts and also the response of the patient to these devices. In addition, the patient needs a thorough medical examination and training for the comfortable use of prosthetic devices. However, in recent years, prosthetic devices are becoming more realistic and comfortable for the patient with the application of more advanced technologies. Here, the contribution of robotic and IoT technologies in the development of various prosthetic devices has been discussed.

Lee et al. have developed a multi-fingered robotic hand that can mimic the hand movement more accurately [72]. The proposed robotic hand consists of four fingers on each hand and 12 joints that consist of linked knuckles and linear actuators. Under the project "Hand of Hope," low-cost robotic hand prostheses with an efficient grasp control mechanism were developed that can perform object catch function [73]. In another study, a crude robotic hand has been proposed that resembles the human hand [74]. The hand was covered with a layer of artificial skin, which was made using soft silicon to give a feel and appearance of a real hand. It was capable of lifting small weights, up to 1.5 kg. The mechanism of the attachment used to create the movement of the body comes with its own disadvantage. Moving the prosthesis usually requires a large force. Furthermore, the number of control signals generated by the prosthesis is limited that restricts the movement with a lesser degree of freedom. A substitute to the body-powered control is the use of a myoelectric control mechanism where the electrical activity of the muscle contraction is used as a control mechanism. The myoelectric control works based on the basic principle of a "two-site two-state" [75]. Here, a pair of electrodes is placed on two different muscles where the contraction of one muscle causes opening while the other causes closing of the hand. Inspired by the working principle of the muscle-tendon system, Pfeifer et al. have developed a prosthetic hand (also called the Zurich-Tokyo hand) that gives a total of 13 degrees of freedom [76]. A high degree of freedom was achieved by tracking the joint movement using a set of sensors (tactile and nontactile). The sensors also measure the finger-space position. The advantage of a Zurich-Tokyo hand is: it can learn by itself while performing a movement or grasping an object. This was achieved by the morphology of the hand, the elastic tendons, and the deformable fingertips. However, the issue of the myoelectric control method is that finding two groups of muscles that give the opposite control is not always possible. The stochastic nature of the myoelectric signal results in error and inaccuracy of the system [77]. Also, the learning method involves the interpretation of the myoelectric signal by the user, which demands continuous training and mental efforts. Hence, other training modes and control mechanisms have been adopted for limb prosthetics [78, 79]. In a recent paper, an exoskeleton robot for the lower limb was developed that showed an efficient mass adjustment mechanism to maintain stability during movement. This helps the patients in correcting their posture [80].

Connecting the robotic prosthetic devices to the Internet and making them a part of IoT will enhance the device's productivity. The IoT technology enables the system to produce a rich information base for data processing. This helps in eliminating the issue of a lower degree of freedom as in the case of conventional limb prosthetics. Fukuda et al. have employed IoT technology to design a multifunctional prosthetic hand using a set of sensors placed on the objects, users, and the surrounding environment [81]. The collected information from these sensors is stored in the data management server. The control signal, generated after evaluating the collected information, is sent back to the prosthetic device. Moreover, the inclusion of smart sensors in the IoT-aided robotic environment provides an efficient feedback mechanism for the prosthetic system. In [82], the authors developed a mind-controlled robotic arm that is decorated with a smart sensor network. The smart sensors include a temperature sensor, pressure sensor, accelerometer, gyroscope, potentiometer, and proximity sensor. The electroencephalogram (EEG) signals were used for controlling the robotics arm whereas the set of smart sensors allowed the prosthetic device to interact with the surrounding environment. Li et al. have integrated IoT, artificial sensory perception, and haptic feedback to develop a robotic arm that can restore the grasping function in a patient [83]. Also, the system provides information at the point of contact that includes the surface properties and force of interaction. The integrated system improves the manipulation performance as well as the perception ability of the user.

In defiance of the improvement in the field of prostheses, there are still many issues that need to be addressed. One of the most basic challenges in designing a prosthesis is to achieve patient satisfaction. It has been reported that the desire for a prosthesis changes with time and with the individual. Also, there exists a complex relationship between a patient's desire for like-life replacement and the level of loss. For example, a patient with minimal loss wishes his prosthetic to be more natural, whereas a patient with a high level of loss prefers function more than appearance. This demands the customization of the prosthetic devices with human needs, loss, and cognitive ability [84, 85]. The control of a prosthetic device still needs high mental effort, which makes it inefficient for the patients having a mild cognitive disability. Though numerous studies have employed pattern recognition technology for controlling the prosthesis, the efficacy of this method is still unclear due to the lack of clinical evidence. Unfortunately, the cost of such devices is one of the major constraints in its popularization. The commercially available prosthetic devices range from \$15000 to 100000 or even higher if additional customization is required [86]. Several research groups have worked for the development of low-cost prosthetic devices but they lack in their real-life application and catering to the customer need. This needs to be emphasized in the future.

3.4. Elderly Care. The population of elderly persons is growing rapidly. People above the age of 60 are expected to increase in number from 605 million (in 2000) to two billion (in 2050) [87]. Hence, there will be an increased need for a caregiver in the future. Although care centers and nursing homes provide services with other nutritional and social supports, they lack the feeling of independence. Elderly people usually prefer to live in their homes than living with residential care. This provides them a sense of individuality and comfort [88]. But, maintaining a healthy life at an older age without any support becomes difficult as aging is associated with various physical, sensory, and cognitive issues. Recently, the innovation in advanced technologies such as robotic technology, sensor technology, IoT, human-robot interaction, and navigation technology have provided potential solutions to the aforesaid issues by creating a physical environment for active aging [89]. The robotic system, which provides such an environment, is called a service robot. These service robots act as a companion for older people. Some of the most notable service robots reported in the past are Care-o-Bot, Aibo, CAESAR, JoHOBBIT, and PT2 [90, 91]. The service robot, with help of IoT technologies (sensors, RFID, GPS, infrared, and wearable sensors) connects the elderly with health professionals as well as family members. This helps them maintain a quality of life by providing reminders, fall detection, and interfacing with other home appliances.

In the last decade, several articles have reported the application of service robots in elderly care [92, 93]. Tanabe et al. have proposed a robot-operated elderly assistive system that combines the hand robot with an environmental control system [94]. In this case, the information assist system acts as a connecting link between the home automation and the remote location. Furthermore, with the integration of IoT, the system provides comfort and security. In [95], the authors proposed architecture for socio-technical development in elderly care. This is achieved by connecting both healthcare sensors and social robots into a common platform (Figure 4). The robotic system gives the physical health status of the elderly person by analyzing the various vital signs such as heart rate, temperature, and brain activities. The system also records the patient-reported outcome measure (PROMs) during their interaction with the robot. Combining the information from PROMs and the sensors, a health assessment report is generated at the end that will be available for the patient, caregivers, and doctors. One of the most common social challenges for the elderly population is mild cognitive impairment. A higher percentage of elderly people get affected with MCI. This leads to lower physical and cognitive performance in older people. Kostavelis et al. in their project "Robotic assistant for MCI patient at home (RAMCIP)" has designed a service robot that can efficiently support elderly people with MCI [96]. The designed system is capable of performing higher-level cognitive function through advanced human and environment perception mechanism that helps the robot to decide when to assist a patient. Fighting depression is another challenge for people who are living alone. Randall et al. have tested the feasibility of the socially assistive robot (SARs) as in-home therapeutic support for elderly persons who are dealing with depression [97]. The authors compared the human mental state of the elderly before and after the in-home installation of the robotic system. The results suggest that the assistive robot can be employed as a potential solution for in-home depression of the older population. The use of robotics in depression management for the elderly is also reported in [98–101]. Marques et al. have developed "AirBot" for the elderly to monitor indoor air quality using IoT technology [102]. Using the social network platform, the system alerts the caregiver when detecting poor air quality in the home environment. The system aims to improve the living environment for elderly people.

A major issue in the application of service robots in elderly care is their acceptance by professional caregivers. Although the recently developed assistive care systems are integrated with many advanced functions and features, they lack in their affordability. It is also essential to evaluate these systems based on their caregiving benefits. Moreover, the challenges they face during their practical implementations should also be considered for their acceptance by the elderly population. The second most important factor for the elderly population is their adaptation to advanced technology. Elderly people are slow learners and are not updated with the technology in comparison to the younger generation. This fact should not be avoided while designing the assistive system for the elderly. Most of these assistive systems work in a cooperative environment where the information is collected from various sensors and robots. This requires efficient data storage and management system.

3.5. Managing Disease Outbreak (COVID-19). COVID-19, a novel respiratory syndrome disease, is now the most critical challenge to the world after the influenza pandemic outbreak of 1918 [103]. Many countries have been successful in reducing the spread of the infection, mortality, and morbidity associated with the disease. The cooperation of administration, healthcare system, and people played an important role in checking the spread of the disease. However, there are still some countries that are struggling to control the spread. This is due to the unpredictable nature of the virus in the human body. The new strain of the virus is the reason for its rapid outbreak. The virus is characterized by its highly contagious nature and the long incubation period (1–14 days). However, the recovery period may vary from 6 to 41 days depending on the person's age, health, and underlying conditions. The most common symptoms for the diagnosis of the disease include fever, cough, and fatigue, which are similar to flu symptoms. Also, it is possible that during this period, a person is infected but not showing any symptoms. In such cases, the infected person may act as silent carriers unknowingly; thus, making the disease highly contagious as

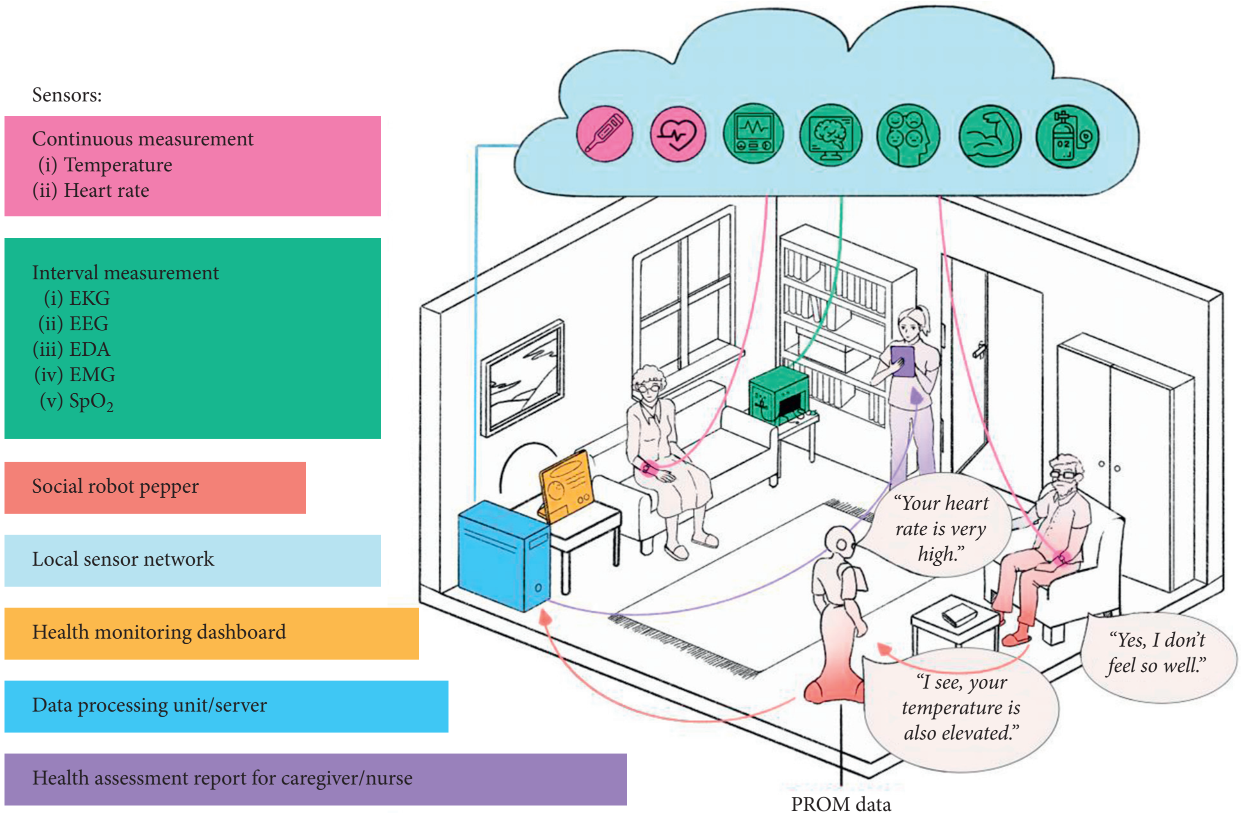

Figure 4: An ecosystem for elderly care that integrates healthcare sensors, robots, sensor networks, data processing unit, and a health assessment unit (reproduced from [95]).

compared to similar diseases in the coronavirus family. To alleviate the spread of the disease, various efforts with the use of advanced technologies have been suggested.

During the outbreak of a pandemic, the health workers are at a higher health risk. This is due to their direct contact with patients. The exposure of patients to health workers can be minimized if robots can be employed for some sort of nursing duty. Even though robotic technology has shown a wide range of healthcare applications (nursing, ambulance management, telemedicine, cleaning/disinfecting the hospital, reception, etc.), it failed to provide an effective solution in the fight against the pandemic. However, researchers have suggested various upgrades in healthcare robots that may help to deal with the COVID-19 pandemic (Figure 5). Nowadays, autonomous robots have been employed in the hospital premises to disinfect hospital wards, handle contaminated waste, and deliver medicine, food, or medical supplies to patients [104]. A wheeled telepresence robot can be employed in healthcare centers and hospitals for a virtual face-to-face patient assessment. The robots are capable of performing diagnostic tests after collecting the swab samples from the patients. This will facilitate the screening of patients while protecting the frontline health worker from direct contact. Indirectly, the robot reduces the time of exposure for health workers, avoids the use of personal protective equipment, and negates the chances of contamination during its removal. These robots can also be employed in crowded places such as airports, railway stations, and ports, where large-scale screening is necessary. Integrated with IoT technology, these robots can be used in various COVID-19-related applications. This includes checking whether a patient is following a quarantine rule or not, collecting temperature information from a remote location, and transmitting these data to healthcare centers to diagnose and alert patients about getting the COVID-19 infection. During quarantine, socially assistive robots may provide companionship to the patients and enable them to withstand social contact. For the elderly, and the physically impaired, the rehabilitation services can be continued with the help of robots without any physical contact with the therapist. In addition, mobile robots are installed in various public areas to check the maintenance of social distancing and the wearing of masks. Aerial robotics is used to supervise the quarantine areas and border control operations. In diagnosis, the teleoperated robotic system can play an efficient role in detecting the disease without the physical presence of the doctor. These systems can be used to check the pulmonary condition. In a recent study [105], a telerobotic system has been proposed for the cardiopulmonary assessment of the COVID-19 patients. Karmore et al. have developed a cost-effective medical diagnosis humanoid (MDH) that can provide a complete diagnostic test to check the COVID-19 infection [106]. In [107], the authors implemented an IoT-based drone technology to detect the coronavirus infection using the thermal images obtained from a thermal camera. Alsamhi and Lee have proposed a futuristic concept of collaborating multiple robots using blockchain technology

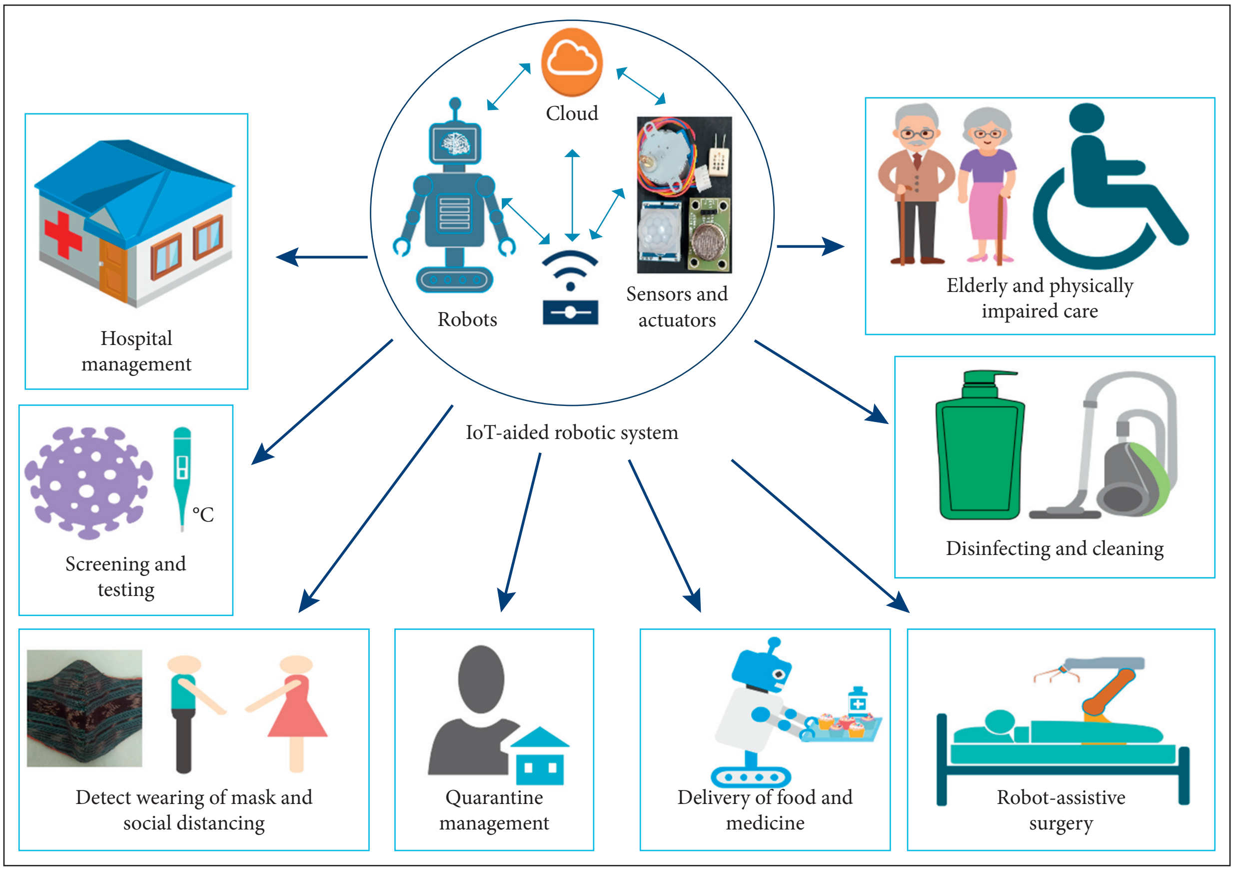

Figure 5: Application of IoT-aided robotic system in managing COVID-19.

and IoT to fight against COVID-19. This concept can be employed in the future for patient monitoring, outdoor, and hospital end-to-end delivery systems [108]. The technology is believed to manage multi-robot collaboration, improve interaction, and share health information more efficiently. In another study [109], the authors have developed a phone application infused with intelligent IoT features such as complex data analysis and intelligent data visualization for contact tracing of the infected persons. The intelligent data analysis techniques enable the system to improve public health and can be applied in the future health crisis.

In the future, IoT-aided robots may employ artificial intelligence and machine learning algorithms to detect the COVID-19 infection. A probable option can be the use of computer tomographic (CT) images for this purpose. The CT imaging technique has been used in many biomedical applications and is expected to be efficient in the diagnosis of COVID-19 infection. Some of the common biomedical applications of CT imaging include cancer detection [110], tumor identification [111], analysis of the interstitial lung images [112], pancreas segmentation [113], dental restoration, and tooth cavity detection [114, 115]. Recently, CT imaging is considered an effective method for the detection and monitoring of the symptoms of COVID-19 patients. These imaging methods have shown great potential in detecting the virus, especially in the case of asymptotic patients with negative nucleic acid testing [116]. Even though reliable criteria for the diagnosis of COVID-19 with CT-imaging technique have been developed (for example, the so-called effect of frosted glass), in practice, the volume of lung damage determined by CT does not always correspond to both the degree of lung damage and the severity of the development of pulmonary pneumonia. This also makes the development of IT methods for CT imaging highly relevant [107]. Herein, deep learnings can be applied for the analysis, interpretation, and tracking of a large number of CT data. While managing the COVID-19 infection, it is also crucial to look into the discharge criteria of a patient from the quarantine ward. The three most usual criteria include being nonfeverish for more than three days, resolved respiratory syndromes, improvement in the radiological signs for pulmonary illness, and a negative COVID-19 nucleic acid test. AI-based automated tools can be integrated with the IoT-aided robotic system to track the discharge criteria for patients with infection. In addition, it can be employed to differentiate healthy people from the infected ones.

4. Future Directions and Conclusions

The purpose of the current article was to give a comprehensive idea regarding the applicability of IoT and robotics technology in the current healthcare services. Furthermore, it provides a detailed description of the functionalities of an ideal IoT-aided robotic system for healthcare applications.

Based on the above review, it is possible to say that although numerous studies have been dedicated to the healthcare applications of the aforementioned technologies, the field lacks controlled and clinical trials that will validate their practical applications. Whether it is the design of an assistive robot for surgery, a rehabilitative robot, a prosthetic device, or a smart-home for the elderly, the studies are mostly restricted to a future proposal or research projects. Hence, future studies must be highly focused on practical applications of these technologies and their acceptance in society. Furthermore, universal evaluation criteria must be employed for the developed devices. The evaluation should be followed by the implementation of various control strategies. This will help in maintaining the interconnectivity and interoperability of such devices, developed across the globe. A most common issue while employing these technologies in healthcare is measuring the success of the healthcare devices/systems and technology. This should be based on their ease of handling, cost, and satisfaction of patients and healthcare professionals. The real use of these technologies can only be assessed either by directly comparing them with the conventional methods or the way they are minimizing the efforts of the healthcare professionals. Various comparative studies on the same must be performed in the future. Also, the problems faced by the patients and healthcare professionals while operating these devices must be accessed and used as feedback for future development.

One of the drawbacks of the present robotic systems for healthcare applications is the limited scope for customization. The need for the customization of the healthcare service systems is of utmost importance for the healthcare professionals and patients, as the need varies from one patient to another. Hence, the current healthcare system demands more flexibility in the robot-based service devices that can easily adjust as per a patient's health status. The functioning of the robotic systems is highly influenced by the learning and training methodology used for their operation. Also, a prior study suggests that degradation of the skills has been observed in the case of newly trained robotic surgeons after a prolonged period of inactivity [117]. Hence, a new training methodology must be developed in the future, which not only enhances the device functionality but also its usability. For most of the studies, the cost is a major concern that restricts its wider application. A lower-cost system can significantly increase the popularity and acceptability of the system. Hence, more attention must be given to designing cheaper sensors and computer systems in the future. Furthermore, while installing a cooperative network as in the case of smart-homes, smart-hospitals, smart rehabilitative systems that integrate the IoT, various sensors, and robots, practical issues in their smooth functioning must be evaluated. This will enhance the acceptability and popularity of these systems in the future. Unfortunately, these systems have to deal with a large volume of information that is acquired from various sensors that are present in the network. The use of a high volume of data requires more advanced data management, analysis, and security techniques for the efficient use of the information. It has been reported that patients are adopting the newer technology but they are concerned about the privacy of their data. Hence, the patients must be aware and informed about the data sharing policies of the developed IoT-based robotic devices. Despite the claim of superiority of the IoT and robotic systems as compared to the traditional healthcare methods, these healthcare systems mostly depend on the skill and training of the patients and healthcare professionals for their efficient use. The aforementioned points will form a reference for future development in the said field. Also, the knowledge shared in the study will help the readers and future researchers to gain a comprehensive idea of the applications of the IoT-aided robotic technology in transforming healthcare services for people.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare no conflicts of interest in publishing this article.

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Research Article

EERP-DPM: Energy Efficient Routing Protocol Using Dual Prediction Model for Healthcare Using IoT

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Healthcare is one of the most promising domains for the application of Internet of Things- (IoT-) based technologies, where patients can use wearable or implanted medical sensors to measure medical parameters anywhere and anytime. The information collected by IoT devices can then be sent to the health care professionals, and physicians allow having a real-time access to patients' data. However, besides limited batteries lifetime and computational power, there is spatio-temporal correlation, where unnecessary transmission of these redundant data has a significant impact on reducing energy consumption and reducing battery lifetime. Thus, this paper aims to propose a routing protocol to enhance energy-efficiency, which in turn prolongs the sensor lifetime. The proposed work is based on Energy Efficient Routing Protocol using Dual Prediction Model (EERP-DPM) for Healthcare using IoT, where Dual-Prediction Mechanism is used to reduce data transmission between sensor nodes and medical server if predictions match the readings or if the data are considered critical if it goes beyond the upper/lower limits of defined thresholds. The proposed system was developed and tested using MATLAB software and a hardware platform called "MySignals HW V2." Both simulation and experimental results confirm that the proposed EERP-DPM protocol has been observed to be extremely successful compared to other existing routing protocols not only in terms of energy consumption and network lifetime but also in terms of guaranteeing reliability, throughput, and end-to-end delay.

1. Introduction

The IoT is a new paradigm that is rapidly gaining ground in the modern wireless telecommunications applications. The basic idea behind this concept is the ubiquitous presence of a variety of things or objects around us such as Radio Frequency Identification (RFID), sensors, actuators, and cell phones. This happens through unique addressing schemes that enable nodes to interact with each other and cooperate with their neighbores to achieve common goals [1]. There are numerous IoT applications in many fields, such as smart buildings, industrial automation, medical aids, mobile health, smart education, assistance to the elderly, and intelligent energy management [2–8]. Moreover, research and development of employing intelligent sensors in medical field are vast, including home hospitalization, integration of microsensors in body, and emergency management [3].

In wireless sensors, the absence of restrictive electrical installations and the reduction of wire clutter connecting the sensors to the processing unit afford more liberty of movement for the patient [6]. Moreover, using IoT in the medical field offers many advantages and brings new comfort to patients such as patient mobility, remote monitoring of the elderly, and people with reduced mobility, efficient monitoring, monitor certain vital signs, enhanced quality of care, and long-term care [4, 5]. The healthcare using the IoT does not only improve the quality of life of patients, but also facilitate their real-time remote monitoring and the quick intervention in case of emergency (if the measurements reported by the sensors are abnormal) [7].

Medical sensors are characterized by small size, less storage, less processing capabilities, and energy constraint resources. These sensors are battery-powered, where frequent replacement of its battery is a sophisticated, costly and complicated medical procedure as some sensors get implanted inside the body, so surgical replacement is necessary [8–10]. In sequence, real-time monitoring of patients with sensors sending reliable medical information in regular bases requires extremely low power disruption [11]. Figure 1 shows typical structure of the healthcare surveillance system using IoT, where sensors are deployed in the human body to monitor parameters like temperature, heart rate, blood pressure, etc. These values can be read from the sensors and then get transmitted to the server, where physicians can access this data and evaluate it.

Motivated by the mentioned observations, and the upcoming related studies, this paper develops a novel Routing Protocol called "Energy Efficient Routing Protocol using Dual Prediction Model for Healthcare using IoT (EERP-DPM)" for Healthcare using the IoT that is designed to reduce the requirements of existing routing protocols, where the DPM is used to reduce transmissions between the sensor nodes and the medical server. This technique allows sensor nodes to avoid transmitting its sensed data to medical server if the predictions match the sensing data. Meanwhile, the medical server always presumes that its prediction reflects the real observation, unless it receives the data from the sensor node. The data is transmitted if it is different from the data predicted, where normal health data is forwarded to the Aggregator through deployed relay nodes. The data is considered critical if it is beyond the upper/lower limits of previously defined thresholds, where emergency data can be sent directly to the Aggregator. The proposed system was developed and tested using MATLAB software simulation, as well as being tested experimentally using MySignals HW V2 hardware platform. Both simulation and experimental results are compared to the E-HARP [12] and PCRP [13] protocols. The remainder of this paper is organized as follows: the related works are investigated in Section 2. Proposed network model design solution and goals are presented in Section 3, followed by the performance evaluation and discussion in Section 4. Finally, Section 5 concludes this paper.

2. Related Work

This section covers a survey of different approaches of routing protocols for IoT-based healthcare applications. Then, we used this review to highlight the research gaps and report our own research motivations by comparing it against existing works in the literature as presented in Table 1.

By knowing that sensors could consume about 70% energy on wireless communication with other nodes and/or with the server, solutions should be considered to work on this aspect [20]. Hence, routing protocols play vital role in providing effective communication between the sensors, to prolong the overall lifetime of networks via minimizing energy consumption that required forwarding data from sensor nodes to a medical-related server efficiently [21]. The traditional routing protocol is not a suitable solution for this type of network due to resource limitations [22], where, in the last decade, many works have been proposed by different researchers who focused on developing adaptive and robust routing protocols [10–27]. The various works use the congestion control techniques and maximizing battery efficiency to extend the network lifetime. However, several key issues stay as open challenges, where most researches did not widely focus on heterogeneity of healthcare data and deal with it [23].

The authors in [12] presented a routing scheme known as "Energy-Efficient Harvested-Aware Clustering and Cooperative Routing Protocol for Wireless Body Area Networks (E-HARP)." This scheme is a multiattribute-based harvested energy routing protocol, which takes different network-related parameters into consideration and selects an optimal forwarder node towards the sink node using two-phased technique. In the first phase, optimum CH is selected among the cluster members based on calculated Cost Factor (CF). The parameters used for calculation of CF are residual energy of SN, required transmission power, communication link signal-to-noise ratio (SNR), and total network energy loss. In the second phase, data are routed with cooperative effort of the SN, which saves the node energy by prohibiting the transmission of redundant data packets.

A Priority-based Congestion-avoidance Routing Protocol (PCRP) is proposed in [13], which is a technique that used IoT-based heterogeneous medical sensors for energy efficiency in healthcare wireless body area networks. Data criticality and QoS requirements are the prime importance of the proposed work. For normal data packet, the fitness function will be calculated based on three parameters, namely, signal-to-noise ratio (SNR), residual energy (RE), and node congestion level (NCL). SNR parameter is used for a better selection of path between sender and receiver. For highly important data, they have supposed a priority bit.

Researchers in [14] introduced a new routing protocol named "Green Communication for Wireless Body Area Networks: Energy Aware Link Efficient Routing Approach (ELR-W)." This protocol considers four parameters, residual energy, link efficiency, node to coordinator distance, and hop count, to construct a path cost model, which is used to select the next-hop node for transfer data. This cost function is subject to change with respect to parameters like hop count, link efficiency, and residual energy. The comparative performance evaluation has been carried out focusing on energy-oriented metrics under WBANs medical environments.

Ullah et al. in [15] proposed a complete novel scheme, which is proposed for WBANs, named as "Robust and Energy Harvested-aware Routing Protocol with Clustering Approach in Body Area Networks (EH-RCB)." The proposal is based on a system, in which tiny sensors nodes are placed on the human body to sense important health-related parameters and forward them to two sink nodes. It is designed to stabilize the operation of WBANs by choosing the best

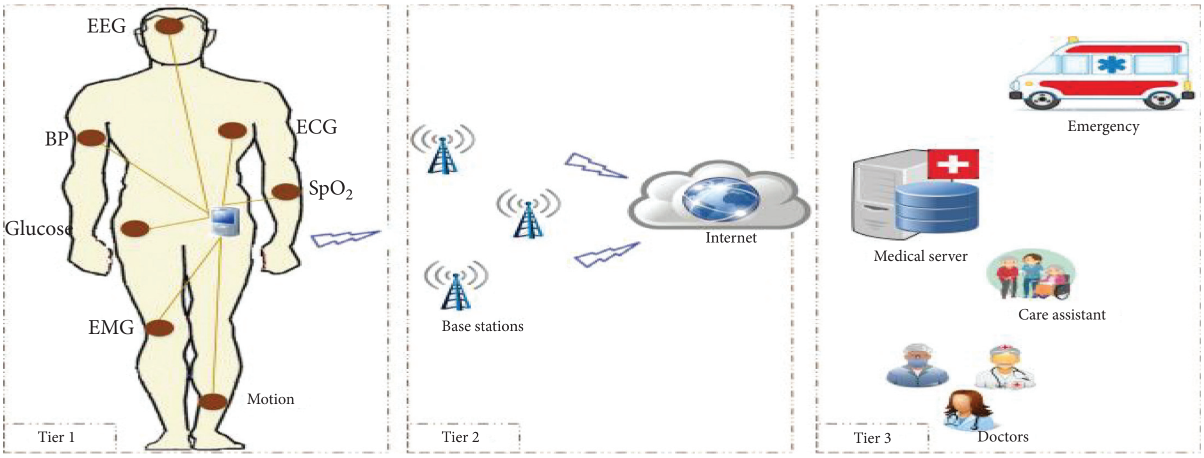

Figure 1: IoT-based healthcare monitoring architecture [3].

Table 1: A Critical Review of Routing Protocols for Healthcare using the IoT.

Protocols	Focus area(s) of the paper	Limitations
E-HARP [12]	(i) Multiattribute-based technique for dynamic cluster head (CH) selection (ii) Cooperative routing (iii) Optimum CH is selected based on calculated cost factor (CF)	(i) Packet delay is high (ii) Network lifetime is far short (iii) Temperature of nodes in the network is very high
PCRP [13]	(i) Emergency data will get higher priority and less delay over normal data (ii) The node with greater fitness value will be selected as a next-hop node (iii) SNR parameter is used for better selection of path between sender and receiver	(i) Packets drop ratio is high (ii) Network lifetime is less (iii) End-to-End delay is high
ELR-W [14]	(i) A link efficiency-oriented network model is presented considering beaconing information and network initialization process (ii) Path cost calculation model is derived focusing on energy aware link efficiency	(i) Network lifetime is less (ii) High End-to-End delay
EH-RCB [15]	(i) Clustering approach to enhance nodes connectivity with each other to balance out load on single sink node (ii) CF is calculated using node total energy, distance from other nodes, link SNR and required transmission power	(i) Network lifetime is far short (ii) Packet delay is high
EB-MADM [16]	(i) Dynamic cluster head selection (ii) An optimum node as cluster head which has higher residual energy level (iii) Selects a new cluster head for each transmission round (iv) Cooperative effort of cluster nodes	(i) Path loss is high (ii) Network lifetime is less
PriNergy [17]	(i) Selecting appropriate parent member node in the RPL protocol (ii) Increasing network efficiency in terms of optimal speed of packet transmission in the IoT environment	(i) Network lifetime is less (ii) Packet drop is high
EHCRP [18]	(i) Link efficiency network model is presented which calculates the capability of the forwarder node in terms of its ability to send received/sensed data (ii) Selects the forwarder node by calculating its PCE function	(i) Path loss is high (ii) Network lifetime is less (iii) Packet drop is high
OPOT [19]	(i) Routing path is established by determining the temperature of sensor nodes to avoid hotspot region (ii) Distance between sources to destination is measured and connection is established through shortest path to minimize delay and energy consumption	(i) Path loss is high (ii) Network lifetime is less (iii) End-to-End delay is high
Proposed EERP-DPM	(i) DPM is used to reduce transmissions between sensor nodes and the medical server (ii) Data is transmitted if it is different from the data stored in previous data sensing (iii) The medical server always presumes that its prediction reflects the real observation if it receives corrections from sensor nodes (iv) Health data with high priority should be directly transmitted to the aggregator	(i) Add vital computational overhead

forwarder node, which is based on optimal calculated Cost Function (CF). The CF considers the link SNR, required transmission power, the distance between nodes, and total available energy (e.g., harvested energy and residual energy). To note, energy harvesting technique is adopted to provide additional energy to the sensor nodes in order to help out in prolonging the network lifetime.

The authors in [16] presented the "Energy Budget-based Multiple Attributes Decision Making Algorithm (EB-MADM)," which was designed to be low power and cluster-based routing mechanism. The algorithm selects an optimum node as cluster head, which has higher residual energy level and performs data routing at the cost of least network residual energy loss. EB-MADM selects a new cluster head for each transmission round and distributes cluster head load evenly among cluster nodes. Simulation results show better performance in terms of network stability, propagation delay, throughput, and network lifetime as compared to its counterparts.

Priority-based and energy-efficient routing for IoT systems (PriNergy) is considered in [17]. The proposed method is based on routing protocol for low power and lossy network (RPL) model, which determines routing through contents. Each network slot uses timing patterns when sending data to the destination, while considering network traffic, audio, and image data. In the proposed RPL model, if an error occurs in a parent member node, its members can remain alive until the convergence and configuration of the parentless parenthesis and their packets expire due to the time lapse.

Khan et al. [18] proposed the Energy Harvested and Cooperative Enabled Efficient Routing Protocol (EHCRP) for IoT-WBAN. The proposed protocol considers multiple parameters of WBANs for efficient routing such as residual energy of SNs, number of hops towards the sink, node congestion levels, Signal-to-Noise Ratio (SNR), and available network bandwidth. A path cost estimation function is calculated to select forwarder node using these parameters. Due to the efficient use of path-cost estimation process, the proposed mechanism achieves efficient and effective multihop routing of data and improves the reliability and efficiency of data transmission over the network.

Researchers in [19] proposed a protocol named Optimum Path Optimum Temperature Routing Protocol (OPOT). The proposed protocol maintains the temperature of node and communicates the sensed information to remote server with minimum delay and energy, thereby increasing the lifetime of sensor networks. It also considers the critical data signals to be sent when the temperature of node exceeds the admissible threshold limit. The obtained simulation results are compared with conventional routing protocols and analyzed that the proposed protocol has decreased delay, minimum energy, reduced power, uniform temperature distribution, and maximum lifetime of sensor node.

Motivated by the mentioned observations through the related studies, major portions that collected data from medical sensors are usually redundant, which means unnecessary transmission and, thus, high energy consumption. In this context, the reduction of transmission of such redundant data can be achieved using the proposed DPM. The idea of the proposed solution EERP-DPM runs a prediction model at both the sensing nodes and the base station to allow sensor nodes to avoid transmitting its sensed data to the base station, as long as the predictions match the readings. Meanwhile, the base station always presumes that its prediction reflects the real observation, unless it receives the corrections from the sensor node (since the sensor can compare the prediction with the real sensed measurement). The most essential benefit from the DPM is the ability to shrink traffic volume exchanged in the networks quite significantly. Besides, transmitting less data certainly saves sensor energy and, therefore, prolongs the lifetime of the entire network [12, 25–27].

To sum up, the proposed EERP-DPM system was developed and tested using MATLAB software simulation, besides hardware implementation using MySignals HW V2 platform, which is a noticeable and comprehensive contribution from the existing work in the literature. Moreover, the proposed solution runs a prediction model at both the sensing nodes and the base station to allow sensor nodes to avoid transmitting their sensed data to the base station, as long as the predictions match the readings. The medical server always presumes that its prediction reflects the real observation unless it receives the data from the sensor node. The data is transmitted if it is different from the data predicted, where normal health data are forwarded to the Aggregator through deployed relay nodes. The data is considered critical if it is beyond the upper/lower limits of previously defined thresholds, where emergency data can be sent directly to the Aggregator.

3. Proposed Design System and Architecture Model

This section contains system network architecture, followed by the proposed EERP-DPM solution.

3.1. System Network Architecture. The architecture considered in the proposed work is shown in Figure 2, where it can be utilized in a hospital and even locate remote patients. The architecture model of our proposed scheme comprises four architectural components: Medical Sensors Nodes, Relay Nodes, an Aggregator, and Medical Server.

(i) Medical Sensor Nodes: patients are equipped through wearable devices that form Wireless Medical Sensors (MSs). These heterogeneous sensors are either strategically implanted or placed on the body as wearable devices on human body to monitor body functions. Each sensor node is integrated with biosensors, which are body temperature, electromyography, electrocardiography, blood pressure, pulse-oximeter, and electroencephalography.

(ii) Relay Nodes: patients are equipped through devices, named relay nodes, which can be easily replaced or recharged. The relay nodes reduce the transmitting

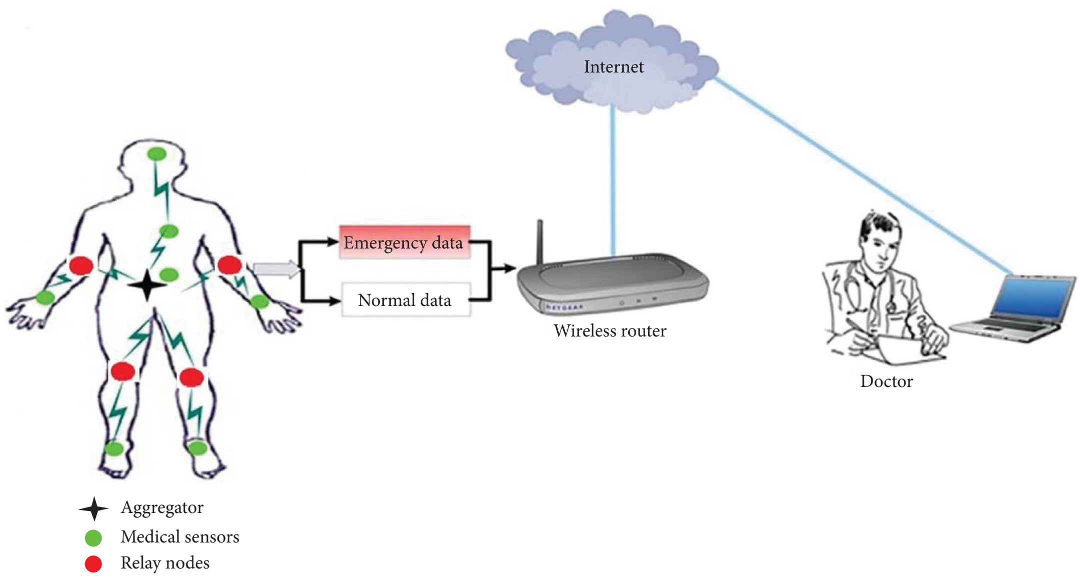

Figure 2: The proposed architecture of DPM-EERP solution.

distance between sensor nodes and Aggregator, where these nodes have two major advantages: (1) protecting the human tissues from heating effect and radiation and (2) decreasing energy consumption of sensor nodes during forwarding of sensing data. In this proposed solution, we placed three relay nodes, as discussed in Table 2.

(iii) Aggregator: it is a special sensor node with a superior certain ability to calculate and communicate. Aggregation nodes, as the name suggests, will aggregate sensed data using aggregation functions. The patient's mobile device is used as the Aggregator. The Aggregator works as a router between the Medical Sensors nodes and the medical server. The placement of the Aggregator is at the centroid of placed sensor nodes. It uses different technologies such as cellular mobile networks (2G–5G) or WLANs for communication with medical server placed at distant location.

(iv) Medical Server: it includes healthcare providers (e.g., doctors, physicians, nurses, and researchers). It possesses almost infinite storage capability and the computation of the resources. The server has the computation abilities to execute the calculations over the stored data including disease learning and prediction. On receiving the patient's health data, the doctor can get real-time situational awareness.

3.2. Proposed EERP-DPM Solution. In this subsection, we present the proposed solution of EERP-DPM protocol using the IoT, which mainly consists of the following four phases: (1) Network Setup Phase; (2) comparing predicted values against sensed data; (3) adding the priority level; and (4) path-loss selection. A detailed flowchart of the four phases of EERP-DPM routing protocol is shown in Figure 3.

3.2.1. Network Setup Phase. Each patient should put an admitted-on medical sensor based on the recommendation of a doctor. According to the patient's health data needs, the medical personnel place the medical sensors on the patient's body. First, each patient must be registered into the Medical Server prior attaching sensors to anybody. The Aggregator initiates instructions to the network by sending control packet messages to all other sensor nodes and relays nodes about its location on the human body. The Aggregator sends a Config message to all nodes, which contains the position of Aggregator in the body; then, the position of the Aggregator gets stored. All medical sensors and relay nodes back a message, which contains sensor IDs, its position, and available residual energies in each round. In this way, all medical sensors update the Aggregator position, relays information, available residual energy, and available routes to the Aggregator. The contents of Config message are shown in Figure 4.

3.2.2. Comparing Predicted Values against Sensed Data Phase. Healthcare Monitoring applications based IoT requires near real time and continuous mode data transmission to data acquisition center for a long period of time. However, in medical sensors, due to limited power resources sensing, storage and retrieval of data become critical issues, and it is difficult to perform such extensive tasks over a long period of time. Moreover, one of the most significant features of the observations collected from sensors nodes is the presence of Spatio-temporal correlation in the data, which is usually redundant. Therefore, the unnecessary transmission of these redundant data has a significant impact on reducing energy consumption.

The reduction of transmission redundant data can be achieved using the Dual Prediction Mechanism (DPM). The idea of the DPM has run the same prediction model at both the sensing nodes and the Medical server. This technique

Table 2: Detail description of used sensors in EERP-DPM.

Node #	Sensor name	Function	Node location X-axis (m)	Node location Y-axis (m)	Position on human body	Deployment
1	EEG sensor	Measures electrical activity of muscles	0.32	1.77	Head front side	On body
2	ECG sensor	Measures electrical activity of heart	0.35	1.37	Chest (left-side)	On body
3			0.22	1.35	Chest (right-side)	On body
4	Glucose sensor	Finds blood glucose level	0.36	1.01	Stomach (left-side)	In body
5			0.35	0.01	Stomach (right-side)	In body
6	Motion sensor	Monitor the physical movement of human body	0.08	1.45	Right-side shoulder	On body
7	EMG sensor	Electrical signal is measured which is produced by human muscles	0.06	0.98	Right hand wrist	On body
8	Blood pressure sensor	Measures human body blood pressure	0.37	1.27	Left hand triceps	On body
9	Pulse oximeter sensor	Measure the amount of oxygen dissolved in blood	0.4	1.01	Left hand wrist	On body
10	Lactic acid sensor	Measure the level of lactate concentrations in blood	0.22	0.91	Right-side thigh	In body
11	Accelerometer/ Gyroscope sensor	Monitor and recognize the posture movement of human body	0.45	0.45	Right-side knee	In body
12	Respiration sensor	Device used to measure the breathing rate in a patient	0.15	0.5	Left-side thigh	On body
13	Pressure sensor	Measuring the pressure through the piezoelectric effect of human tissue	0.15	0.45	Left-side lower leg	On body
14			0.25	0.17	Right-side lower leg	On body
15	Relays node 1	Multihop communication	0.3	1.03	Right-side hip	On body
16	Relays node 2		0.09	1.05	Left-side hip	On body
17	Relays node 3		0.23	1.43	Left-side thigh	On body

allows the sensor nodes to avoid transmitting its sensed data to the Medical server if the predictions match the collected data. In the meantime, the Medical server always presumes that its prediction reflects the real observation, unless it receives detected data from the sensor nodes. The data is transmitted if it is different from the data predicted, or data is considered critical. In this case, the critical data is transmitted to Medical server directly if it is beyond the upper/lower limits of the defined thresholds. It should be noted that the transmitting and receiving ends use the same prediction model, and they perform the same model updates for the sake of synchronization. The most essential benefit from the DPM is the ability to shrink traffic volume exchanged in the networks quite significantly. Besides, transmitting less data certainly saves sensor energy and, therefore, prolongs the lifetime of the entire network. Figures 5 and 6 illustrate the DPM work at the sensor nodes and medical server.

Sensor nodes are turned active only in their assigned time slot; else they are in sleep mode. When the sensor node gets active, it starts sensing data. Let us assume that a data memory of size N is used to hold the last N observations. At the nth time slot, the data memory is represented as $Vn = [Vn-1,\ Vn-2,\ ...,\ Vn-N]$. After that, when the Newly Detected Value (NDV) is made at time slot n, the information in Vn is used to predict the detected value. The prediction algorithm takes Vn as input and generates a prediction Pn at time slot n.

If the predicted value Pn was not close enough to the observed value NDV (that is, $|Pn - \mathrm{NDVn}| > e_{\max}$, where $e_{\max}$ is the maximum acceptable prediction error), then the data memory will be updated as $Vn+1 = [\mathrm{NDV},\ Vn-1, \ldots,\ Vn-N+1]$. In this case, the prediction value and the detected value do not respect the error budget, and the sensor nodes transmit NDV to the medical server. The value NDV is used to update the prediction model variables.

However, if the predicted value Pn was close enough to the observed value NDV (that is, $|Pn - \mathrm{ND}Vn| \leq e_{\max}$), then $Vn+1 = [Pn,\ Vn-1, \ldots,\ Vn-N+1]$. Therefore, no transmission occurs because this observation can be predicted accurately. Also, the value Pn is used to update the prediction model. Meanwhile, when the medical server does not receive anything, it assumes that its prediction is within the error threshold.

3.2.3. Adding the Priority Level Phase. As previously mentioned, if the predicted value P_n was not close enough to the observed value NDV (that is, $|Pn - \mathrm{ND}Vn| > e_{\max}$), in this case, the prediction value and the detected value do not respect the error budget, and then, the sensor nodes transmit the NDV to the Medical server. For example, if the blood pressure readings suddenly exceed 180/120 mmHg, it may be signs of organ damage, and it requires immediate transmission of emergency data since the human body is

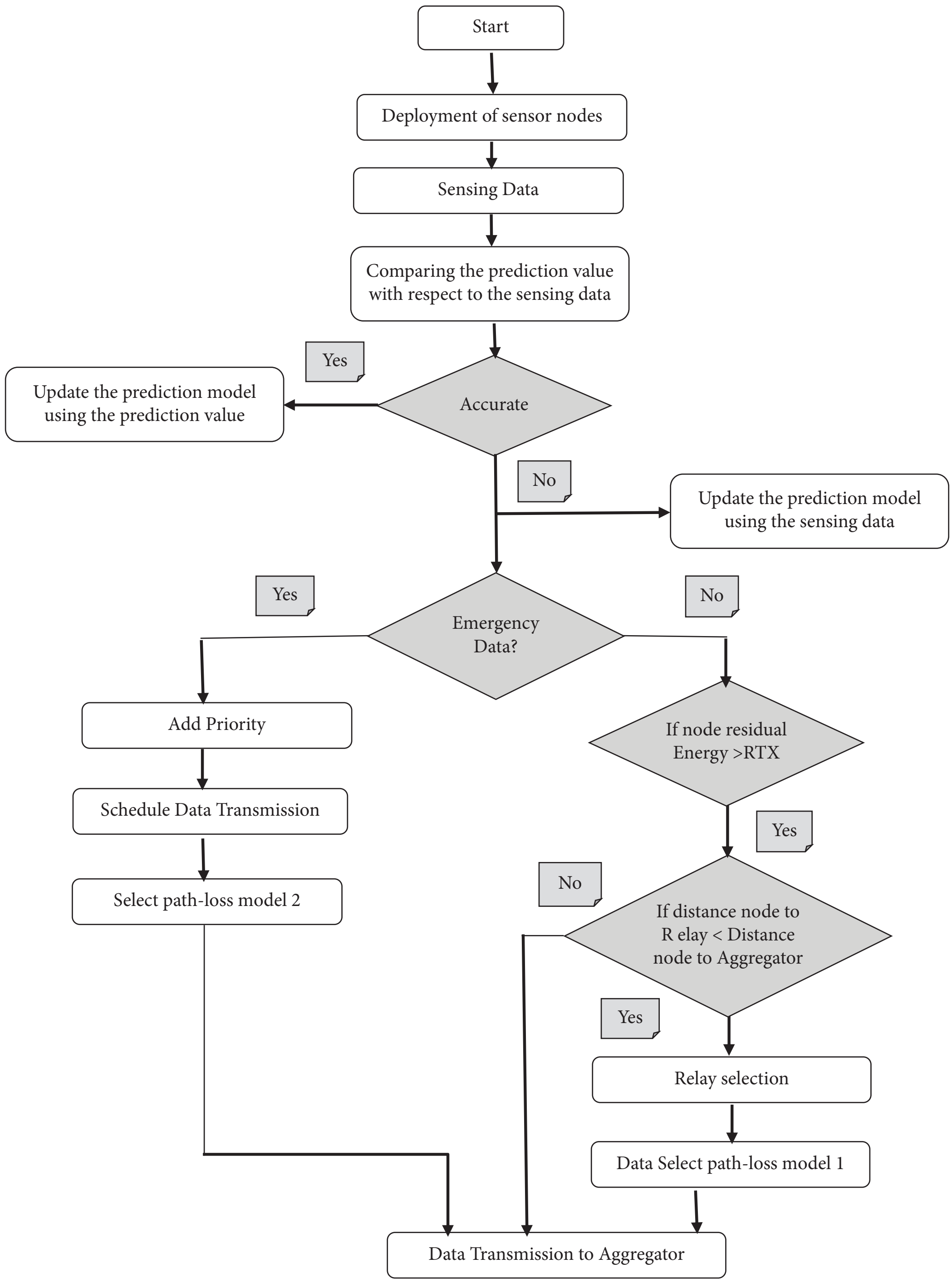

Figure 3: Flowchart of the DPM-EERP solution.

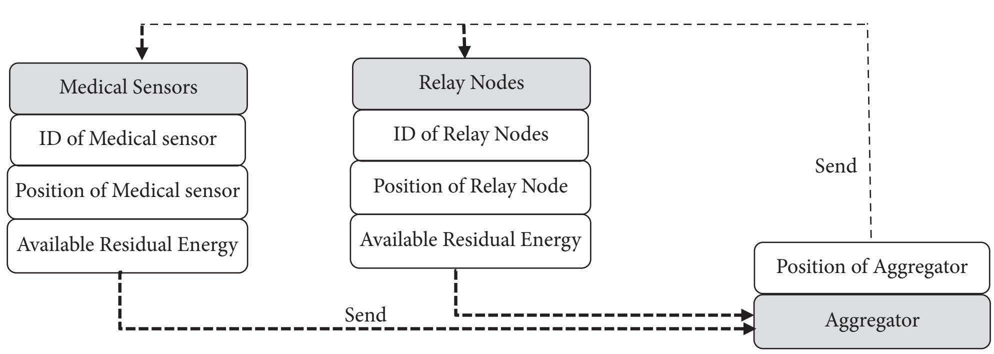

Figure 4: Format of Config message.

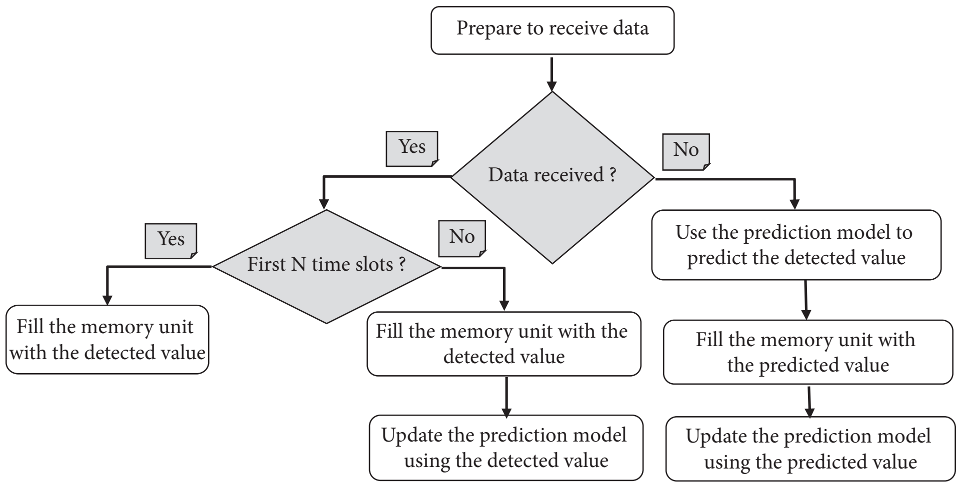

Figure 5: Flowchart of the Dual-Prediction Mechanism at the Medical server.

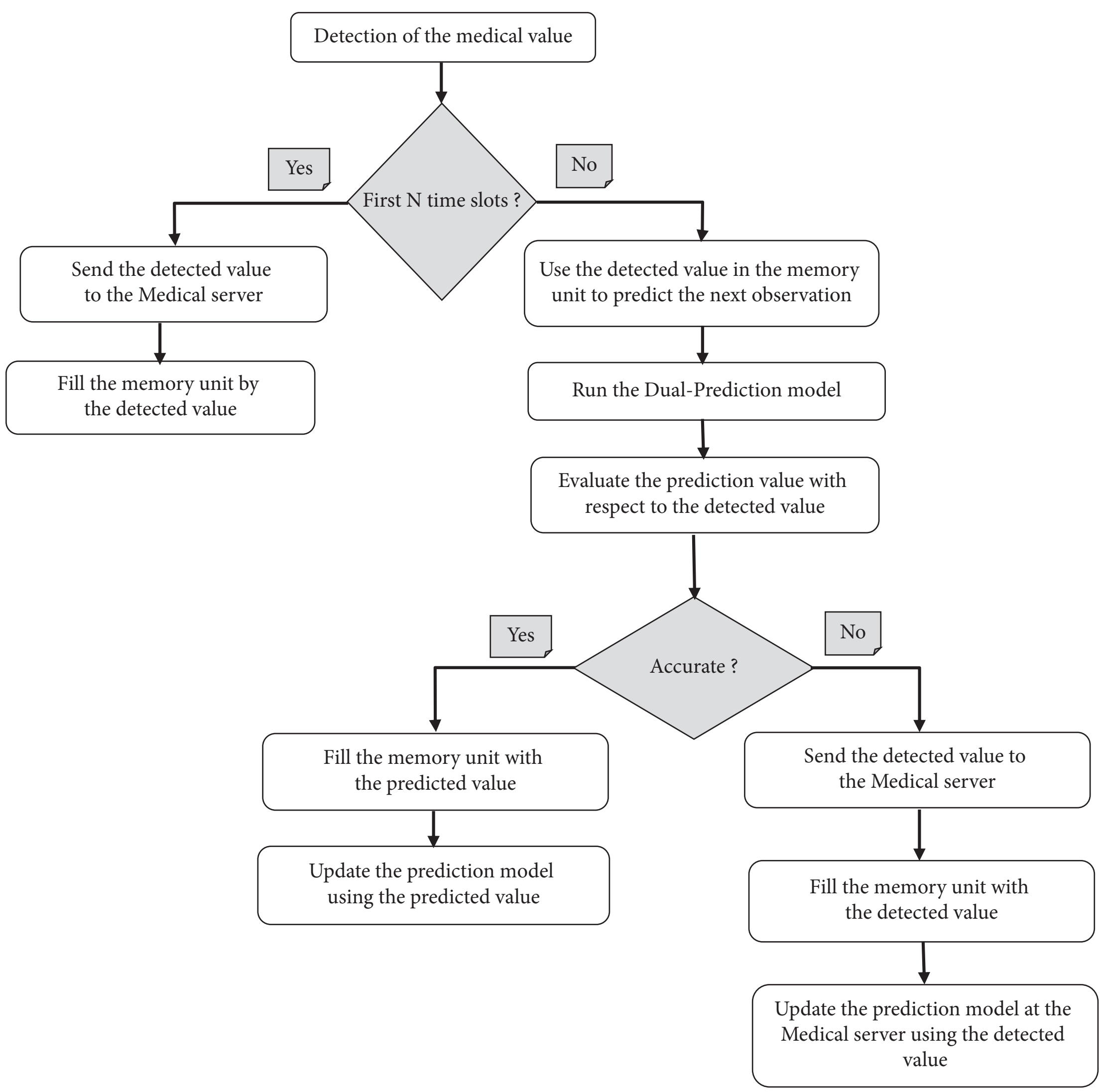

Figure 6: Flowchart of the dual-prediction mechanism at the medical sensor nodes.

suffering from severe emergency. Hence, an alert message should be sent to a doctor immediately. So, the emergency situations represent the highest priority data and should be delivered successfully to the Medical Server as soon as possible, while when the data are not critical, they are treated as a low priority packet. The direct communication is used for critical data, while multihop communication is used for normal health data delivery. After the reception of data forwarded from all the sensor nodes in a transmission round, the Aggregator aggregates the whole data into single message. This packet contains the sensor nodes IDs and their forwarded data. The pseudocode of the Added the priority level phase can be seen in Algorithm 1.

3.2.4. Path-Loss Selection Phase. As previously stated, the emergency situations are the highest priority data and should be effectively delivered to the Medical Server as soon as possible. If the data are not critical, they are treated as a low priority packet. The direct communication is used for critical data, while multihop communication is used for normal health data delivery to reduce energy consumption. Furthermore, the critical sensed data is also sent quickly without any delay by utilizing the communication channel bandwidth in an efficient way. In this scheme, we have introduced two types of existing path loss models: path loss in (dB) for networking models, which represents the difference between transmitted power and received power.

In this paper, we have introduced two types of existing path loss models. The relation between the transmit and receive power is given by Friis free space equations [28, 29], which is a formula in free space that can be used for computing the Path-Loss (PL) based on the distance d between two communicating nodes [14]. The transmitting distance between sensor nodes and relay is denoted as $D1$, and transmitting distance between sensor nodes and the Aggregator is denoted as $D2$.

(i) If $D1 \leq D2$, the sensor nodes will follow the path loss mode 1, and it is given in [14]

$$\mathrm{PL}(d, f)[dB] = a \times \log_{10}^{D1} + b \times \log_{10}^{f} + N_{(D,f)}. \quad (1)$$

To obtain the coefficients a, b, and $N_{(D,f)}$ of the approximation plane of equation (1), LMS algorithm was used. The obtained values for a, b, and $N_{(D,f)}$ are −27.6, −46.5, and 157, respectively.

(ii) If $D1 \geq 1\ D2$, the sensor nodes will follow the path loss model 2, and it is given by

$$\begin{aligned}\mathrm{PL}\left(d_{i,j}\right)[dB] &= PL_0 + 10n\log_{10}^{D2} + X_\sigma,\\ \mathrm{PL}_0 &= 10n\log_{10}^{(4\pi f)^2/c}.\end{aligned} \quad (2)$$

4. Performance Analyses and Discussion

This section assesses the performance of the proposed EERP-DPM scheme from two main perspectives: first, simulation using MATLAB software; second, experimentally using the MySignals HW V2 hardware platform, which is a noticeable and comprehensive contribution from the existing work in the literature. The performance analysis of the proposed EERP-DPM scheme takes place in five indicators, namely, Network Lifetime, Residual Energy, Throughput, Path-Loss, and End-to-End Delay. This section is concluded with Table 3 that compares the proposed protocol from simulation and experimental perspectives against existing routing protocols for healthcare using the IoT.

4.1. Hardware Components. The vital sensing signs unit of this system is the MySignals HW V2 platform, which is a development platform for medical devices and healthcare applications. Figure 7 represents the MySignals HW V2 platform. It monitors patients' health by deploying different medical sensors on patients' body to get sensitive data of patients for subsequent analysis by physicians. The MySignals HW V2 platform is the most complete one in the market, as it supports more than 17 biomedical sensors to measure biometric parameters such as ECG signals, blood pressure, blood oxygen, pulse, respiratory rate, and body temperature. The MySignals HW V2 platform relies on the ATmega328 microcontroller to manage various sensors and allows smart devices to communicate with it. The information gathered can be wirelessly sent using any of the 6 connectivity options available: Wi-Fi, 3G, GPRS, Bluetooth, 802.15.4, and ZigBee depending on the application. A summary of the medical sensors and the location is discussed in Table 2.

Therefore, to minimize transmitting coverage of biosensor nodes, we placed three relay nodes. The positions of these relay nodes are discussed in Table 2. In this work, we chose a low power and short-distance wireless communication module CC2540 BLE 4.0 Module made by Texas Instruments as the Relay, as Figure 8 shows. CC2540 is a highly integrated RF transceiver module for industrial use complying with Bluetooth specification V4.0 BLE. Its work spectrum locates in 2.4 GHz, which is free and is widely used in science and medical fields. This chip can ensure short-distance communication effectiveness and reliability with little components. It supports data rates as high as 250 kbps and multipoint to multipoint communication. It is characterized of small size, low cost, and low power battery [30, 31].

In contrast to the medical sensor, the Aggregator should be a device that has access to major power and resources. We have chosen a tablet that could act the Aggregator role to be a focal point between the MySignals HW V2 platform and the medical server. Therefore, the medical server is used to fill in the purpose of receiving, storing, and distributing the medical data from patients. In the proposed solution, the medical server is a PC, which has relatively powerful processing, memory, transmission capacity, and long battery life, where there is no power constraint. Further, it can be displayed in an easy-to-read format for fast assessment and action. The medical information of the patient that is stored in the medical server will be accessible by specific people who have the authorization to access such as patient himself, doctor, and patient's family member.

Agg: Aggregator for current Sensing/Transmission round
D (i; j): Distance between node i and node j
D (i; Agg): Distance between node i and Aggregator
D (i; RN): Distance between node i and Relay Node
N: Total number of sensor nodes
Condition 1: $|P_n - \mathrm{ND}V_n| > e_{\max}$
Condition 2: $|P_n - \mathrm{ND}V_n| \leq e_{\max}$
Condition 3: Data is not critical. Condition 4: Data is critical
for each node i of N do
if (Condition 2 is true) then
This observation can be predicted accurately, and detected value is discarded as it is redundant.
else
if (Condition 1 is true) then
if (Condition 4 is true) then
Node-i Transmit data directly to Aggregator
else
if (Condition 3 is true) then
if $D(i;\ \mathrm{Agg}) < D(i;\ RN)$ then
Node-i Transmit data to Aggregator
else
if $D(i;\ RN) < D(i;\ \mathrm{Agg})$ then
Node-i Transmit data directly to Relay Node
end if
end if
end if
end if
end if
end if
end for
Data Aggregation at Aggregator:
Aggregator receives the data from sensor nodes, aggregates it and forward it to Medical Server.

Algorithm 1: Adding the priority-level phase.

Table 3: Simulation parameters.

Parameters	Value
Number of nodes	14
$E_{\text{trans-elect}}$	16.7 nJ/bit
$E_{\text{rec-elect}}$	36.1 nJ/bit
ϵ_{amp}	1.97 nJ/bit/mn
DC current (Tx)	10.5 mA
DC current (Rx)	18 mA
Supply voltage (min)	1.9 V
Packet size	4000 bits
Initial energy of sensor	0.5 J
Initial energy of relay nodes	1.0 J

4.2. Simulation Parameters. The simulation is performed using MATLAB software to evaluate the performance and to validate the effectiveness of proposed EERP-DPM scheme. Each simulation is executed over 15,000 rounds. The simulation parameters have been indicated in Table 3. Simulation results are highlighted in Table 4.

4.3. Evaluation of Performance Indicators. In this subsection, we analyze the efficiency of the proposed EERP-DPM scheme in terms of five performance indicators, namely, Network Lifetime, Residual Energy, Throughput, Path-Loss, and End-to-End Delay [1, 32–35]. The rest of this subsection discusses the evaluations of these five indicators from the perspective of our proposed EERP-DPM system against two existing systems, PCRP and E-HARP, due to implantation of Dual-Prediction Mechanism and deployment of relay nodes.

4.3.1. Network Lifetime. In this work, the network lifetime is defined as the total time that the nodes are alive. Figure 9 shows simulation predictions of the proposed EERP-DPM scheme in comparison to the existing systems PCRP and E-HARP in terms of network lifetime. The average network lifetime of the EERP-DPM proposed scheme has achieved better values with average of 21,43% and 35,71%, respectively, in comparison to PCRP and E-HARP routing protocols. Clearly, the proposed EERP-DPM scheme ensures the energy-efficiency compared to the existing routing protocols. In this work, the Dual-Prediction Mechanism is used to reduce transmissions between the sensor nodes and the medical server, which has a direct impact on the network lifetime. Furthermore, the deployment of relay nodes plays a significant role to balance the energy in EERP-DPM. The better performance of the proposed EERP-DPM scheme in terms of network lifespan is due to implantation of Dual-Prediction Mechanism and deployment of relay nodes.

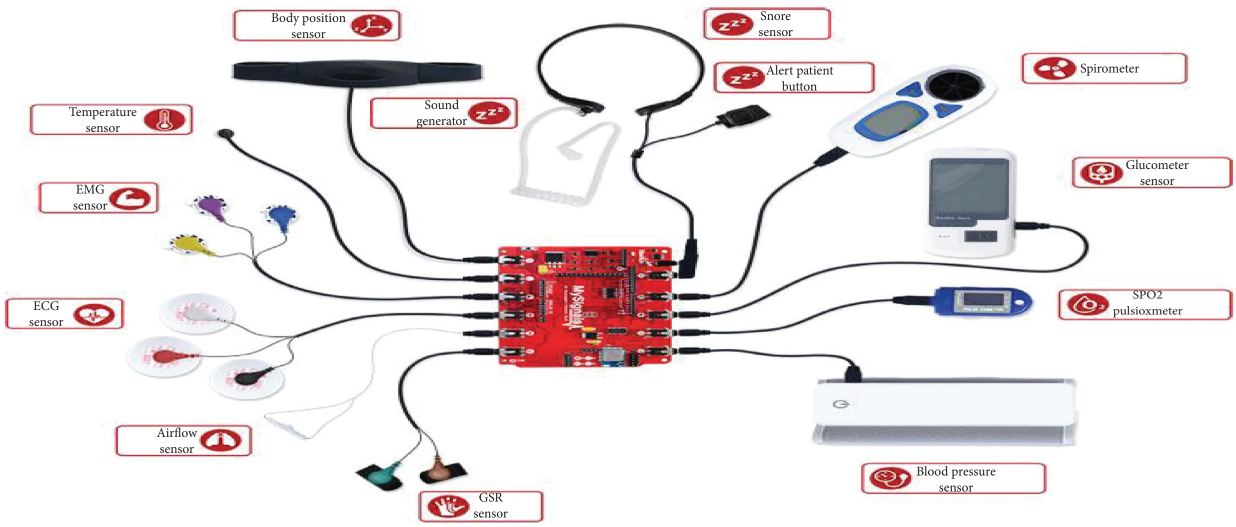

FIGURE 7: MySignals HW V2 platform [19].

FIGURE 8: The CC2540 platform.

TABLE 4: Qualitative comparison between EERP-DPM and other existing routing protocols.

Protocols	Performance of EERP-DPM against benchmark protocols						
	Simulator	Emergency support	Network lifetime	Residual energy	Throughput	Path-loss	End-to-end delay
E-HARP [12]	MATLAB	No	35,71% ↑	45.5% ↑	57.62% ↑	55.1% ↓	37.14% ↓
PCRP [13]	MATLAB	Yes	21,43% ↑	51.52% ↑	27.11% ↑	55.3% ↓	47.61% ↓
ELR-W [14]	NS-2	No	28.57% ↑	18% ↑	47.16% ↑	19.7% ↓	59.25% ↓
EH-RCB [15]	NS-2	No	21,43% ↑	46.54% ↑	49.15% ↑	39.44%↓	43.01% ↓
EB-MADM [16]	MATLAB	No	35,71% ↑	67,16% ↑	46.05% ↑	45.22%↓	37,71% ↓
PriNergy [17]	NS-2	Yes	21,43% ↑	24.86% ↑	25.42% ↑	11% ↓	56.25% ↓
EHCRP [18]	NS-2	No	25,71% ↑	12.83% ↑	61.01% ↓	6.3% ↓	13.39% ↓
OPOT [19]	MATLAB	No	28.57% ↑	27.86% ↑	18.98% ↑	21.3% ↓	29.23% ↓
EERP-DPM (Simulated)	MATLAB	Yes	10.37% ↑	7.68% ↑	12.31% ↑	8.78% ↓	14.36% ↓
EERP-DPM (Experimnted)	Mysignals HW V2 platform	Yes	8.77% ↑	6.36% ↑	10.98% ↑	7.3% ↓	12.43% ↓

4.3.2. Residual Energy. The node energy is always an important indicator for designing and evaluating the performance of energy-efficient routing algorithms. Figure 10 shows predicted results from the simulation of the proposed EERP-DPM scheme in comparison to existing systems PCRP and E-HARP in terms of residual energy. As shown, we can conclude that our EERP-DPM scheme raises the residual energy beyond 51.52% and 45.5% in comparison to PCRP and E-HARP protocols, respectively. Thus, the EERP-DPM scheme conserves the energy more than PCRP and E-HARP protocols, thanks to the Dual-Prediction Mechanism. This technique allows the sensor nodes to avoid transmitting its sensed data to the medical server, as long as the predictions match the collected data, which in turn leads to a decrease in the load of the nodes and conserves the energy of sensor nodes, in addition to the deployment of relay nodes, which gives the sensor nodes more chance for direct communication via short distance. Since the relay

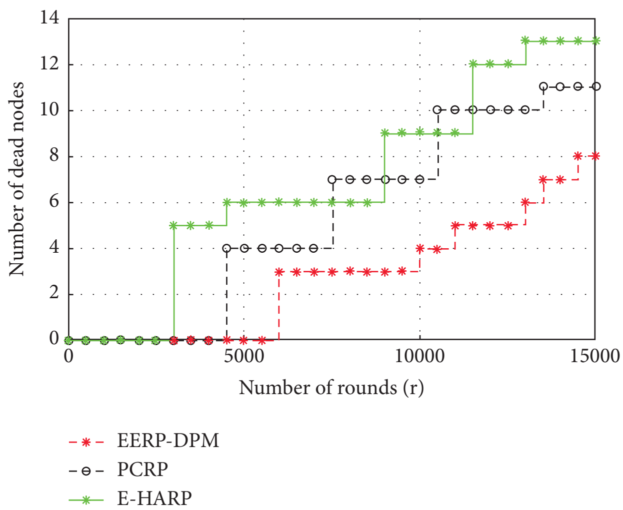

Figure 9: Simulated results of Network Lifetime of our EERP-DPM compared to PCRP and E-HARP protocols.

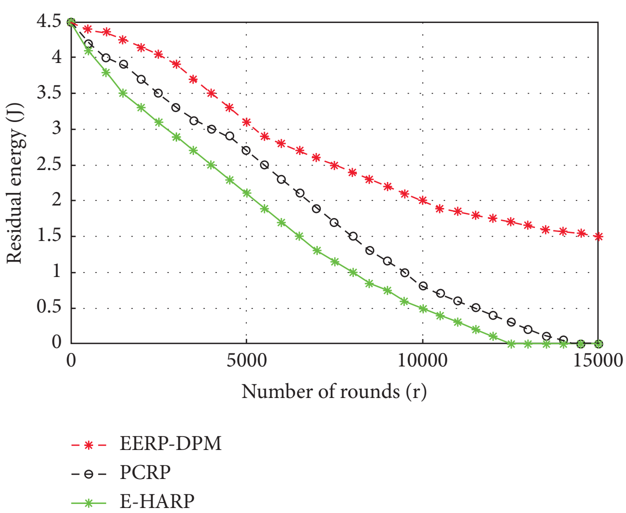

Figure 10: Simulated results of Residual Energy of our EERP-DPM compared to PCRP and E-HARP protocols.

nodes minimize the transmitting range of sensor nodes, the energy consumption of sensor nodes is reduced.

4.3.3. Throughput. This performance indictor aims to measure the number of packets that can be transmitted successfully to the end medical server, where higher throughput reflects improved quality of the network. The patient monitoring system requires routing protocols that should have maximum throughput and minimum packet loss. The number of the packets received at the medical server depends on the average network life, while the average network life corresponds to the number of sensor nodes alive. The more the number of sensor nodes alive, the greater the probability of packets received at the medical server. Figure 11 shows simulation predictions of the proposed EERP-DPM scheme in comparison to the existing systems PCRP and E-HARP in terms of throughput. The EERP-DPM protocol achieved

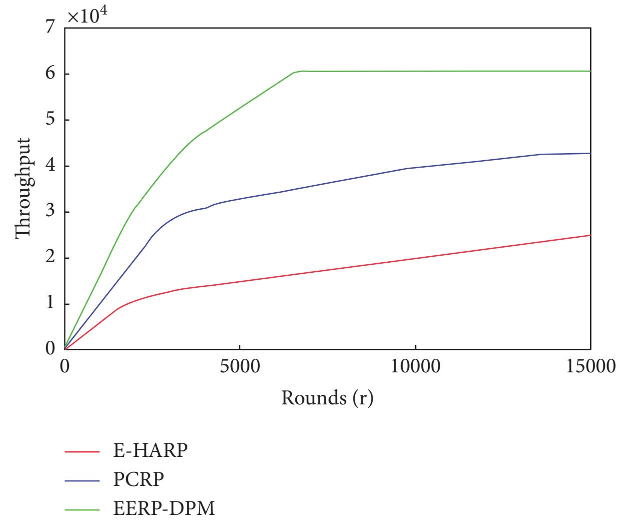

Figure 11: Simulated results of Throughput of our EERP-DPM compared to PCRP and E-HARP protocols.

higher throughput with average range beyond 57.62% and 27.11% in comparison to E-HARP and PCRP protocols, respectively. We can notice that the Dual-Prediction Mechanism prolongs the node's lifetime, which improves the chances of data transfer in the EERP-DPM scheme.

4.3.4. Path-Loss. Path-Loss (PL) is a vital parameter for monitoring wireless system performance and network planning, which decays over distance. Basically, it is loss of power density as signals get diverted from source the destination. This term is mostly used in the wireless network for transmission of data over the network. Figure 12 shows predicted results from the simulation of the proposed EERP-DPM scheme in comparison to existing systems PCRP and E-HARP in terms of path loss. The proposed EERP-DPM protocol shows reduced path loss with average 290 dB, which in turn reflects significant improvement in comparison to the existing data routing PCRP and E-HARP protocols.

4.3.5. End-to-End Delay. End-to-End Delay is referred to as the time taken by data packet to travel from the source node to the destination node. The IoT in healthcare applications is applied for transmitting sensitive information (vital signs) from sensor nodes to the medical server. The sensed data are not always normal, where it may be critical in nature; thus, it needs to be transferred to the destination system rapidly. Figure 13 shows simulation predictions of the proposed EERP-DPM scheme in comparison to the existing systems PCRP and E-HARP in terms of End-to-End Delay. The proposed EERP-DPM is improved by 37.14% and 40% in comparison to E-HARP and PCRP protocols, respectively. The results confirm that the EERP-DPM achieves overall minimum end-to-end delay as compared to other compared protocols, due to the presence of relay nodes on the human body, which minimizes the distance between the medical sensors and the Aggregator node.

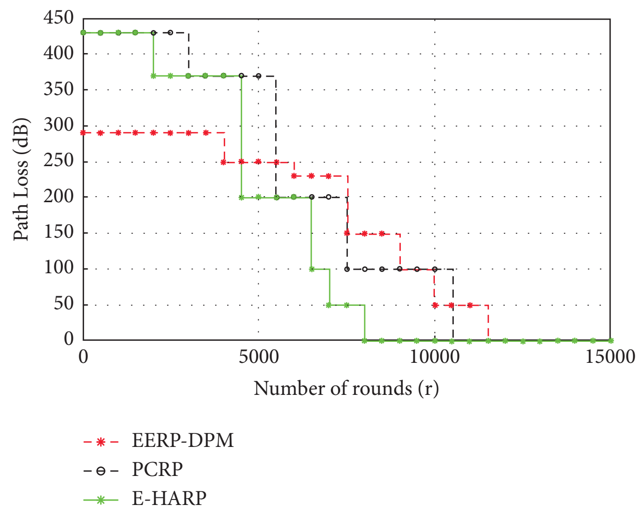

FIGURE 12: Simulated results of Path Loss of our EERP-DPM compared to PCRP and E-HARP protocols.

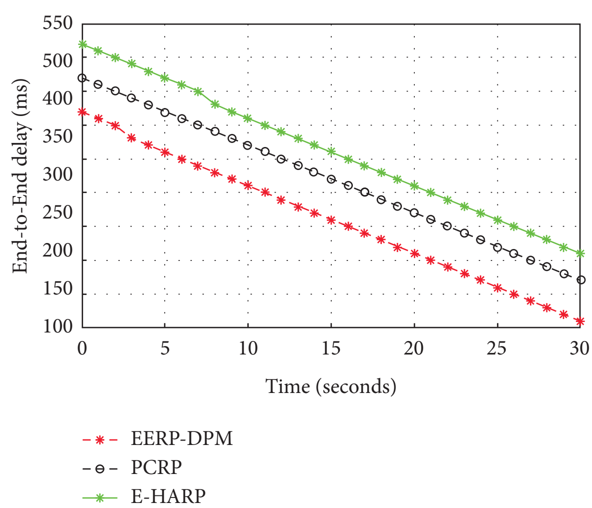

FIGURE 13: Simulated results of End-to-End Delay of our EERP-DPM compared to PCRP and E-HARP protocols.

4.4. Comparison between the EERP-DPM Scheme against Existing Routing Protocols. A comparison between the proposed EERP-DPM algorithm and existing routing protocols is presented in Table 4 with percentage of the increase (↑) or decrease (↓). This comparison is based on the Simulation methods, Emergency support, Network lifetime, Residual Energy, Throughput, Path-Loss, and End-to-End delay. As it can be seen, it is evident that the proposed EERP-DPM scheme of both the simulated step and experimented step satisfies most of the performance, unlike other related data routing protocols in IoT-Based Healthcare applications. In this work, the Dual-Prediction Mechanism is used to reduce transmissions between the sensor nodes and the medical server, which has a direct impact on the Evaluation of Performance Indicators. Furthermore, the deployment of relay nodes plays a significant role to balance the Performance in EERP-DPM.

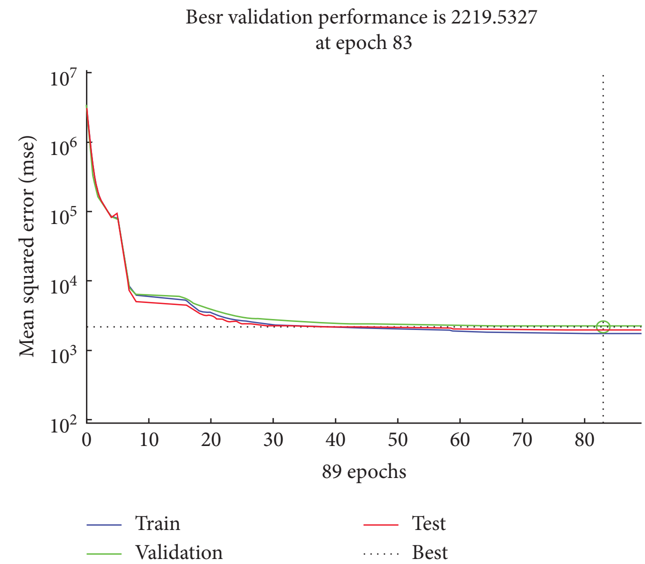

FIGURE 14: MSE performance of the proposed EERP-DPM simulated against experimented in MATLAB.

Using NN fitting tool in MATLAB, the mean squared error (MSE) is measured between the proposed EERP-DPM simulated (y_i) against experimented (d_i) results, as per

$$\mathrm{MSE} = \frac{1}{2}\sum_{j=1}^{N}\left(y_i - d_i\right)^2. \tag{3}$$

Figure 14 shows the MSE regression plot of training, test, and validation steps, where the process determines the best number of iterations, during which validation produces a minimal value. After initial training, the process continues for 82 more iterations, during which error rates do not drop lower. During the 83 iterations, however, training stops as the error rate increases. MSE result seems reasonable since the final MSE is small; besides, there is no significant overfitting that has occurred by iteration 83, before which the best validation performance occurs.

5. Conclusions

The recent developments in IoT promise for providing solutions for healthcare. The medical sensors are typically equipped with batteries, which may have limited resources such as storage capacity, battery life, computational power, and channel bandwidth. Therefore, the energy-efficiency can be achieved through the development of an effective routing mechanism to prolong the network lifetime. In this paper, we propose EERP-DPM for healthcare using the IoT in order to reduce transmissions between the sensor nodes and the medical server. This technique allows the sensor nodes to avoid transmitting its sensed data to the Medical Server, as long as the predictions match the readings. The proposed system was developed and tested using a MATLAB software, and MySignals HW V2 hardware platform. We analyze the efficiency of the proposed EERP-DPM scheme in terms of five performance indicators, namely, Network Lifetime, Residual Energy, Throughput, Path-Loss, and End-to-End Delay. Both simulation and experimental results of our proposed EERP-DPM system have been evaluated from these five indicators perspective against two existing routing systems. The numerical results show that the proposed EERP-DPM protocol improves the energy utilization of the sensor nodes and prolongs the network lifetime while guaranteeing the delivery ratio besides wireless connectivity and reliability. In future, we will devise a routing protocol that considers the mobility of sensor nodes due to body movement.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

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Review Article

IoT-Based Applications in Healthcare Devices

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The last decade has witnessed extensive research in the field of healthcare services and their technological upgradation. To be more specific, the Internet of Things (IoT) has shown potential application in connecting various medical devices, sensors, and healthcare professionals to provide quality medical services in a remote location. This has improved patient safety, reduced healthcare costs, enhanced the accessibility of healthcare services, and increased operational efficiency in the healthcare industry. The current study gives an up-to-date summary of the potential healthcare applications of IoT- (HIoT-) based technologies. Herein, the advancement of the application of the HIoT has been reported from the perspective of enabling technologies, healthcare services, and applications in solving various healthcare issues. Moreover, potential challenges and issues in the HIoT system are also discussed. In sum, the current study provides a comprehensive source of information regarding the different fields of application of HIoT intending to help future researchers, who have the interest to work and make advancements in the field to gain insight into the topic.

1. Introduction

In recent years, the healthcare industry has shown rapid growth and has been a major contributor to revenue and employment [1]. A few years ago, the diagnosis of diseases and abnormality in the human body was only being possible after having a physical analysis in the hospital. Most of the patients had to stay in the hospital throughout their treatment period. This resulted in an increased healthcare cost and also strained the healthcare facility at rural and remote locations. The technological advancement that has been achieved through these years has now allowed the diagnosis of various diseases and health monitoring using miniaturized devices like smartwatches. Moreover, technology has transformed a hospital-centric healthcare system into a patient-centric system [2, 3]. For example, several clinical analyses (such as measuring blood pressure, blood glucose level, pO_2, level, and so on) can be performed at home without the help of a healthcare professional. Further, the clinical data can be communicated to healthcare centers from remote areas with the help of advanced telecommunication services. The use of such communication services in conjunction with the rapidly growing technologies (e.g., machine learning, big data analysis, Internet of things (IoT), wireless sensing, mobile computing, and cloud computing) has improved the accessibility of the healthcare facilities.

IoT has not only enhanced the independence but also diversified the ability of the human to interact with the external environment. IoT, with help of futuristic protocol and algorithms, became a major contributor to global communication. It connects a large number of devices, wireless sensors, home appliances, and electronic devices to the Internet [4]. The application of IoT can be found in the field of agriculture [5], automobiles [6, 7], home [8], and healthcare [1, 9]. The growing popularity of the IoT is due to its advantage of showing higher accuracy, lower cost, and its ability to predict future events in a better way. Further, increased knowledge of software and applications, with the upgradation of mobile and computer technologies, easy availability of wireless technology, and the increased digital economy have added to the rapid IoT revolution [10]. The IoT devices (sensors, actuators, and so on) have been integrated with other physical devices to monitor and exchange information using different communication protocols such as Bluetooth, Zigbee, IEEE 802.11 (Wi-Fi), and so on. In healthcare applications, the sensors, either embedded or wearable on the human body, are used to collect physiological information such as temperature, pressure rate, electrocardiograph (ECG), electroencephalograph (EEG), and so on [11] from the patient's body. Additionally, environmental information such as temperature, humidity, date, and time can also be recorded. These data help in making meaningful and precise inferences on the health conditions of the patients. Data storage and accessibility also play an important role in the IoT system as a large amount of data are acquired/recorded from a variety of sources (sensors, mobile phones, e-mail, software, and applications). The data from the aforesaid sensing devices are made available to doctors, caregivers, and authorized parties. The sharing of these data with the healthcare providers through cloud/server allows quick diagnosis of the patients and medical intervention if necessary. The cooperation between the users, patients, and communication module is maintained for effective and secure transmission. Most of the IoT systems use a user interface that acts as a dashboard for medical caregivers and performs user control, data visualization, and apprehension. An ample amount of research has been discovered in the literature that has reported the progress of the IoT system in healthcare monitoring, control, security, and privacy [12]. These accomplishments illustrate the effectiveness and propitious future of IoT in the healthcare sector. However, the main concern while designing an IoT device is maintaining the quality of service matrices that include privacy of information sharing, security, cost, reliability, and availability.

Intending to maximize the employability of IoT in healthcare systems, many countries have adopted new technology and policies. This transformed the current research in the healthcare sector into a more beneficial field to explore. The motivation of this paper is to summarize the advancement of state-of-the-art studies in IoT-based healthcare systems and to provide a systematic review of its enabling technologies, services, and applications.

2. Architecture of Healthcare IoT (HIoT)

The framework of the IoT that is applied for healthcare applications aids to integrate the advantages of IoT technology and cloud computing with the field of medicine. It also lays out the protocols for the transmission of the patient's data from numerous sensors and medical devices to a given healthcare network. The topology of an HIoT is the arrangement of different components of an IoT healthcare system/network that are coherently connected in a healthcare environment. A basic HIoT system contains mainly three components (Figure 1) such as publisher, broker, and subscriber [14]. The publisher represents a network of connected sensors and other medical devices that may work individually or simultaneously to record the patient's vital information. This information may include blood pressure, heart rate, temperature, oxygen saturation, ECG, EEG, EMG, and so on [13]. The publisher can send this information continuously through a network to a broker. The broker is responsible for the processing and storage of the acquired data in the cloud. Finally, the subscriber indulges in the continuous monitoring of the patient's information that can be accessed and visualized through a smartphone, computer, tablet, etc. Herein, the publisher can process these data and give feedback after the observation of any physiological anomaly or degradation in the patient's health condition. The HIoT assimilates discrete components into a hybrid grid where a specific purpose is dedicated to each component on the IoT network and cloud in the healthcare network. Since the topology for an HIoT depends on the healthcare demand and application, it is hard to suggest a universal structure for HIoT. Numerous structural changes have been adopted in the past for an HIoT system [15–17]. It is crucial to list out all associated activities related to the desired health application while designing a new IoT-based healthcare system for real-time patient monitoring. The success of the IoT system depends on how it is satisfying the requirements of healthcare providers. Since each disease needs a complex procedure of healthcare activities, the topology must follow the medical rules and steps in the diagnosis procedure.

3. HIoT Technologies

The technologies that are used to develop an HIoT system is crucial. This is because the use of specific technology can enhance the ability of an IoT system [18]. Hence, to integrate different healthcare applications with an IoT system, various state-of-the-art technologies have been adopted. These technologies can broadly be categorized into three groups, namely, identification technology, communication technology, and location technology (Figure 2).

3.1. Identification Technology. A practical consideration in designing an HIoT system is the accessibility of the patient's data from the authorized node (sensor), which may be present at remote locations. This can be carried out with effective identification of the nodes and sensors that are present in the healthcare network. Identification follows the process of assigning a unique identifier (UID) to each authorized entity so that it can be easily identified and unambiguous data exchange can be achieved. In general, every resource associated with the healthcare system (hospital, doctor, nurses, caregivers, medical devices, and so on) is accompanied by a digital UID [19]. This ensures the identification of the resources as well as the connection among the resources in a digital domain. In the literature, numerous standards for identification have been reported [20]. The Open Software Foundation (OSF) has developed two different identifiers, namely, a universally unique identifier (UUID) and a globally developed unique identifier (GUID). UUID, a part of Distributed Computing Environment (DCE), can be operated without the requirement of centralized coordination [21]. In a healthcare network, the sensors and actuators are identified and addressed separately which helps in the proper functioning of the system. However, there may be a

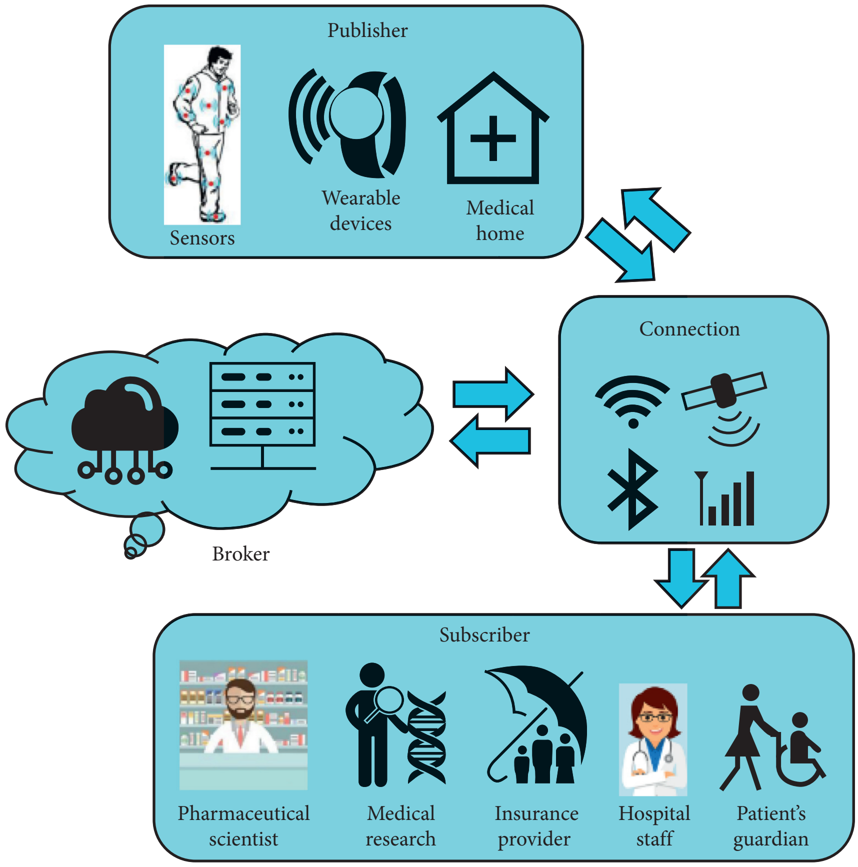

Figure 1: Architecture of an HIoT framework (reproduced from [13] under Creative Commons License).

chance that the unique identification of a component may change throughout the life cycle of the IoT system due to the continuous upgradation of the IoT-based technologies. Hence, the device must have a provision to update this information to maintain the integrity of the healthcare device/system. This can be reasoned to the fact that the change in the configuration not only affects the process of tracking the network component(s) but also may result in a flawed diagnosis. Additionally, the application of IoT in healthcare demands new technologies that have the capability to (1) locate things based on a global identification number, (2) safely manage the identity of the components using different encryption and authentication techniques, and (3) build a global directory search for efficient discovery of IoT services under the UUID scheme.

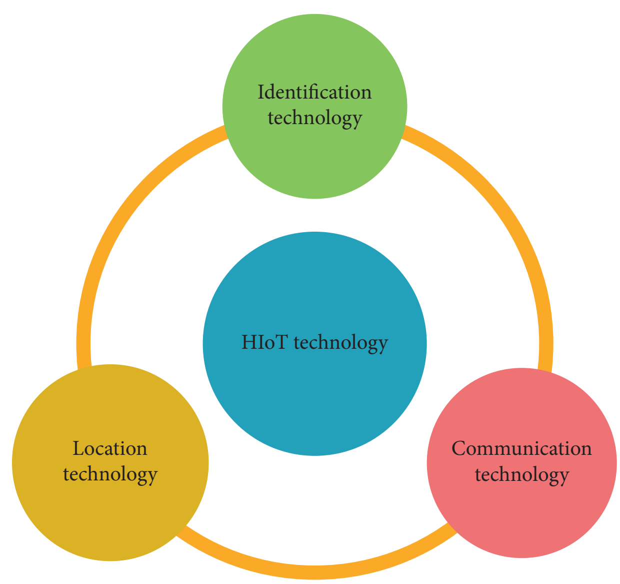

Figure 2: Classification of IoT technology.

3.2. Communication Technology. Communication technologies ensure the connection among different entities in an HIoT network. These technologies can be broadly divided into short-range and medium-range communication technology. The short-range communication technologies are the protocols that are used to establish a connection among the objects within a limited range or a body area network (BAN), whereas the medium-range communication technologies usually support communication for a large distance, e.g., communication between a base station and the central node of a BAN. The distance of communication may vary from a few centimeters to several meters in the case of short-range communication. In most of the HIoT applications, short-range communication technology is preferred. Some of the most widely used communication techniques include RFID, Wi-Fi, Zigbee, Bluetooth, etc.

Radio-Frequency Identification (RFID). RFID is used for short-range communication (10 cm–200 m). It consists of a tag and a reader. The tag is developed using a microchip and antenna. It is used to uniquely identify an object/device (healthcare equipment) in the IoT environment. The reader transmits or receives information from the object by communicating with a tag using radio waves. In the case of IoT, the data used in the tag are in the form of an electronic product code (EPC). RFID enables healthcare providers to quickly locate and track healthcare equipment. The main advantage of RFID is that it does not need an external power source. However, it is a highly insecure protocol and may show compatibility issues while connecting with a smartphone.

Bluetooth. Bluetooth is also a short-distance wireless communication technology that uses UHF (ultra-high frequency) radio waves. This technology allows wireless connection between two or more medical devices. The frequency range of Bluetooth is 2.4 GHz. The Bluetooth protocol presents a communication range of up to 100 m. Bluetooth gives data protection in the form of authentication and encryption. The advantage of Bluetooth lies in its low cost and energy efficiency. It also ensures a lower interference among the connected devices during data transmission. However, when the healthcare application demands long-range communication, this technology fails to meet the requirement.

Zigbee. Zigbee is one of the standard protocols that interconnects medical devices and transmits information back and forth. The frequency range of Zigbee is similar to Bluetooth (2.4 GHz). However, it possess a higher communication range than that of Bluetooth devices. This technology adopts a mesh network topology. It consists of end nodes, routers, and a processing center. The processing center is responsible for data analysis and aggregation. The mesh network ensures uninterrupted connection among other devices even when there is a fault in one or two devices. The advantages of Zigbee lies in its low power consumption, high transmission rate, and high network capacity.

Near-Field Communication (NFC). The basic concept of NFC is the electromagnetic induction between the two-loop antennas that are placed near to each other. This technology is similar to RFID that also uses electromagnetic induction for data transmission. The NFC devices can be operated in two modes: active and passive. In the case of passive mode, only one device generates the radiofrequency while the other device acts as a receiver. In the case of active mode, both devices can produce the radiofrequency simultaneously and can transmit data without pairing [22]. The main advantages of NFC are its easy operability and an efficient wireless communication network. However, it is applicable for a very short range of communication.

Wi-Fi. Wireless Fidelity (Wi-Fi) is a wireless local area network (WLAN) that follows the IEEE 802.11 standard. It provides a higher transmission range (within 70 ft.) as compared to Bluetooth. Wi-Fi builds a network very quickly and easily. Hence, it is mostly used in hospitals. The wide application of Wi-Fi lies in its easy compatibility with smartphones and its provision to support robust security and control. However, it shows a relatively higher power usage and the network performs inconsistently.

Satellite. Satellite communication is found to be more effective and beneficial in remote and widely separated geographical areas (such as rural areas, mountains, peaks, oceans, and so on) where other modes of communication cannot reach easily. The satellite receives signals from the land, amplifies those signals, and then resends them to Earth. More than 2000 satellites are orbiting around the Earth. The advantage of satellite communication technology includes high-speed data transfer, instant broadband access, stability, and compatibility of the technology. However, the power consumption associated with satellite communication is very high as compared to other communication techniques.

3.3. Location Technology. The real-time location system (RTLS) or location technologies are used to identify and track the position of an object within the healthcare network. It also tracks the treatment process based on the distribution of available resources. One of the most widely used technologies is the Global Positioning System, which is commonly known as GPS. It makes use of satellites for tracking purposes. An object can be detected through GPS as long as there exists a clear line of sight between the object and four different satellites. In HIoT, it can be employed to detect the position of the ambulance, healthcare provider, caregivers, patients, etc. However, the application of GPS is only limited to outdoor applications as the surrounding infrastructures can act as an obstruction to the communication between the object and the satellite. In such cases, a local positioning (LPS) network can be effectively used. LPS can track an object by sensing the radio signal that is emitted from the traveling object to an array of predeployed receivers [23]. Various short-distance communication technologies such as RFID, Wi-Fi, Zigbee, and so on can also be used to employ LPS. However, ultra-wideband (UWB) radio is preferred due to its advantage of higher temporal resolution. This enables the receiver to accurately measure the arrival time. Young [24] and Zetik [25] have employed UWB-based localization system that uses the time difference of arrival (TDOA) for tracking. In the literature, other measuring parameters have also been reported in designing a UWB-based localization system such as relative and differential time of arrrival [26], round trip time of flight [20], and so on. GPS, along with the different high bandwidth communication technologies, may be explored in the future to develop smart healthcare networks.

4. Services and Application of HIoT

The recent advancement in the IoT technology has enabled the medical devices to make real-time analysis that was not possible for doctors a few years ago. It has also supported the healthcare centers to reach more people at a time and deliver excellent healthcare service at a minimal cost. The application of big data and cloud computing has also made communication between the patient and doctors more reliable and easier. This resulted in an enhanced patient's engagement in the treatment process with a reduced financial burden on the patient. The considerable impact of IoT, which has been witnessed in recent years, is contributing to the evolution of HIoT applications that includes disease diagnosis, personal care for pediatric and elderly patients, health and fitness management, and supervision of chronic diseases. For a better grasp of these applications, it has been divided into two basic categories, namely, services and applications. The former includes the concepts that are being used while developing an HIoT device and the latter includes the healthcare applications in either diagnosis of a specific health condition or measurements of health parameters. The following sections have included an detailed description of the services and applications of HIoT.

4.1. Services. Services and concepts have transformed the healthcare industry by providing solutions to various healthcare problems. More services are added day-by-day with a rise in healthcare demands and upgradation of technology. These are now becoming an integral part of designing an HIoT system. Each service in an HIoT environment provides a set of healthcare solutions. The definition of these concepts/services is not unique. The uniqueness of the HIoT systems lies in their applications. Hence, it is hard to outline a generalized definition of each concept. However, to give an insight into the topic, some of the most widely used IoT healthcare services (Figure 3) have been described in the subsequent section.

4.1.1. Ambient Assisted Living. Ambient assisted living (AAL) is a specialized branch of artificial intelligence that integrates with IoT and is used for assisting aging people. The main purpose of AAL is to help elderly people to live independently at home with convenience and safety. AAL provides a technique for real-time monitoring of these patients and making sure that they will receive human service-like assistance in case of a medical emergency. This is possible with the engagement of advanced AI technologies, big data analysis, machine learning, and their application in healthcare industries. In general, three basic domains of AAL, namely, activity recognition, environment recognition, and vital monitoring, have been explored by the researchers. However, activity recognition got the utmost interest as it deals with detecting potential threats or emergency health conditions that may affect the well-being of elderly patients. The basic architecture of a smart healthcare framework for AAL is represented in Figure 4. Numerous studies have reported the application of IoT in AAL [28–31]. Shahamabadi [32] proposed a framework that dispenses healthcare solutions to elderly people. The author designed a modular architecture for automation, security, and communication for the AAL. During implementation, IPv6-based low-power wireless personal area networks (6LoWPAN) [33], RFID, and NFC were used as the communication protocol. The device employs a closed-loop communication service to connect the patient with the healthcare providers. The aforesaid architecture was later used as a basis for the development of the more advanced protocol, which can be used to design advanced IoT-based AAL systems (smart objects, devices, and kits). In a recent study, Sandeepa developed an emergency detector for elderly people that assists in monitoring chronic conditions and other potential health-related emergencies. Moreover, the system alerted the caregivers in case of an emergency [34]. IoT-based healthcare systems are now able to track indoor air quality with help of assistive robots. These systems check the quality of air in the environment where the patient resides [35, 36] and trigger alerts to the caregivers when there is a reduction in the air quality below a standard value. In [37], cloud computing has been integrated with IoT to propose a secure, open, and flexible platform for AAL where an IoT-based gateway was employed. The gateway helped in addressing various issues that are associated with security, data storage, and interoperability in the IoT system.

4.1.2. Mobile IoT. Mobile IoT or m-IoT depicts the association of mobile computing, sensors, communication technologies, and cloud computing to track patient's health information and other physiological conditions (Figure 5). In other words, it provides a communication interface between the personal area networks and mobile networks (such as 4G and 5G) to provide an efficient Internet-based healthcare service [33]. The use of mobile has made the HIoT services more accessible to the healthcare practitioner who can access the patient's data, diagnose, and swiftly provide treatment. Several pieces of research have been reported on the application of mobile computing in healthcare [38–40]. Istepanian et al. [41] have developed an m-IoT based system that could monitor the glucose level in diabetic patients which helped in hypoglycemia management. In another study, a mobile gateway-based HIoT system called "AMBRO" was designed where several sensors were used for fall detection and heart rate control. Further, it could locate the patients using an integrated GPS module. In [42], an IoT-based real-time monitoring system has been reported that detects an abnormality in the heart activity and alerts the patient when the heart rate goes beyond 60–100 beats per minute. The security and privacy of the user and user data is an important issue in an m-IoT system. In [43], various methods have been proposed that can be used to address these aforesaid issues including physical and technical safeguards, network security, audit reports, and technical policies.

4.1.3. Wearable Devices. Wearable devices help healthcare professionals and patients to deal with various health issues at a reduced cost. These devices are noninvasive and can be developed by integrating various sensors with wearable accessories used by humans such as watch, wristband [44], necklace, shirt, shoes, handbag, caps, and so on [45]. The sensor attached is used to collect the

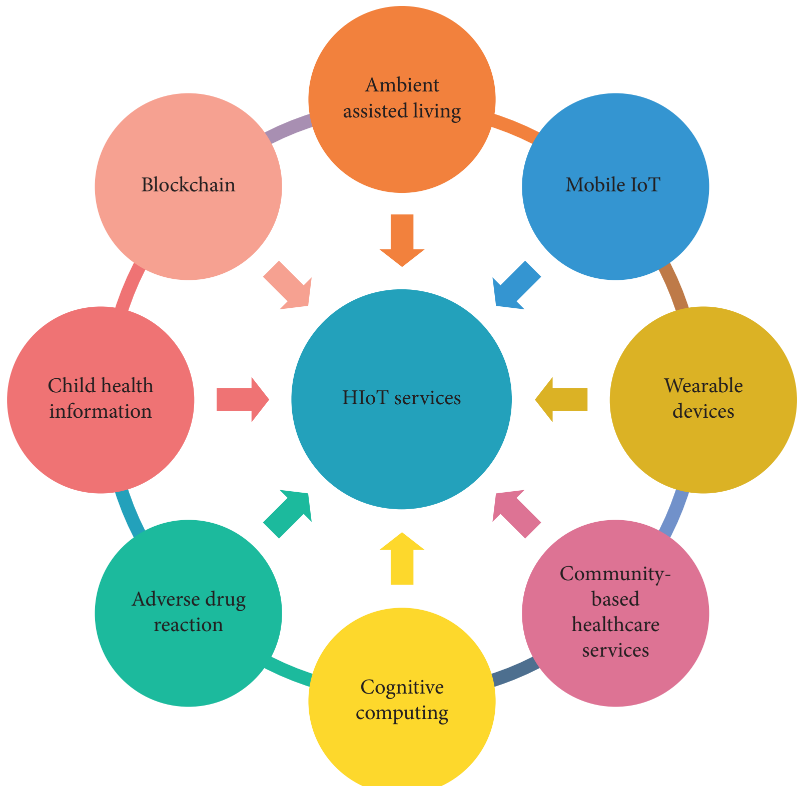

Figure 3: Widely used HIoT services.

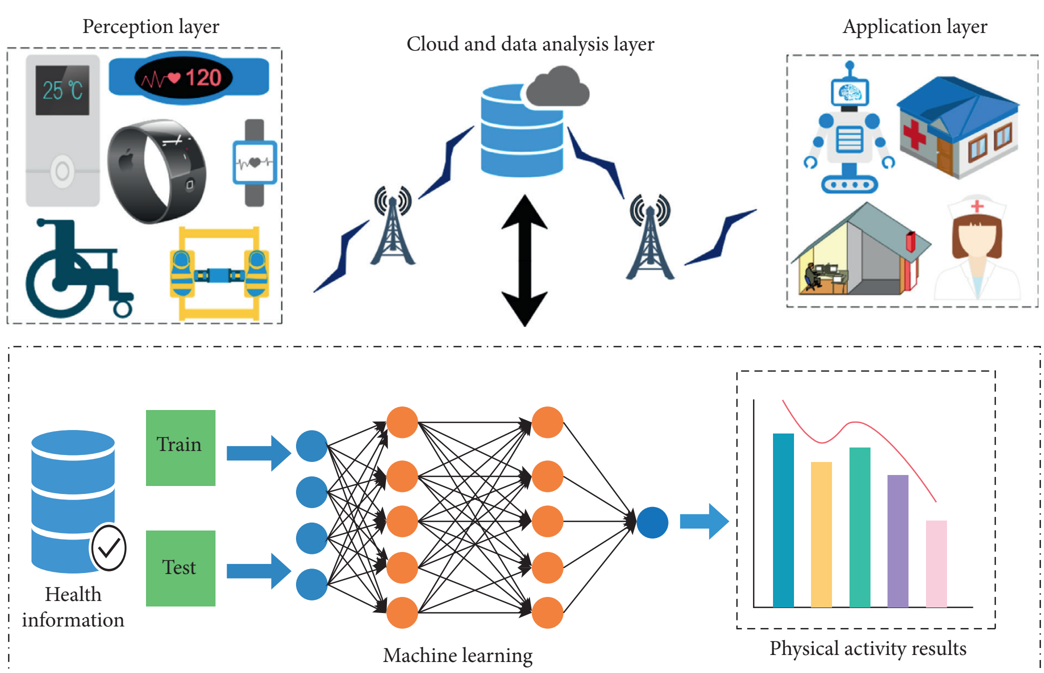

Figure 4: A smart healthcare framework for AAL (reproduced from [27], license no. 496010299387).

environmental and patient's health information. This information is then uploaded to the server/databases. Some wearable devices are also connected with mobile phones through health applications. Various studies have been reported in the literature showing the use of these wearable devices (Figure 6) and mobile computing in real-time monitoring [46–49]. Castillejo et al. have proposed an activity recognition method by integrating wearable devices in a wireless sensor network for remote monitoring of patients through an e-health mobile

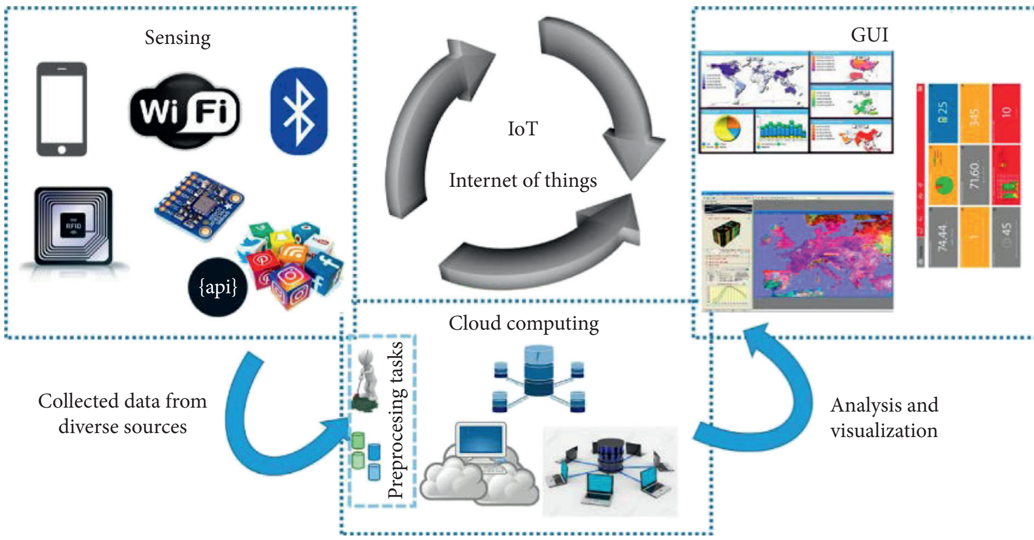

FIGURE 5: A generalized m-IoT environment (reproduced from [38] under Creative Common License).

FIGURE 6: Wearable sensors (reproduced from [27], license no. 496010299387).

application [50]. In a similar study, Jie Wan et al. have developed an IoT-enabled health monitoring device where several sensors (including heartbeat, body temperature, and blood pressure sensors) have been embedded to provide remote health monitoring. Biosignals such as electrocardiograph (ECG) and electromyography (EMG) signals were also analyzed with the help of IoT-enabled wearable systems to extract patient's vital information [51]. The interconnectivity of these wearable devices with a mobile application enhances the computational power of the device. The application can be further used for easy processing and visualization of the collected information.

4.1.4. Community-Based Healthcare Services. Community-based healthcare monitoring is a concept of creating a healthcare network that covers a local community such as a private clinic, a small residential area, a hotel, and so on to monitor the health conditions of the people residing in that area. In a community-based network, various networks are concatenated and can work cooperatively to give a collaborative service. In [52], an IoT-based cooperative medical network was set up to provide healthcare monitoring in remote areas. To establish a secure connection between the networks, different authentication and authorization mechanisms were employed. In another study [51], a community medical network was proposed that was considered as a "virtual hospital." This helped to provide medical facilities to the needy from a remote location. A resident health network has been proposed in [52]. Herein, a four-layer structural framework was designed for sharing health information that includes medical records of the patients. This information can be accessed by the health centers to provide proper medical advice to the patients who are residing in the locality.

4.1.5. Cognitive Computing. Cognitive computing refers to the process of analyzing a problem the way the human brain does. With recent advancements in sensor technology and artificial intelligence, IoT devices are now integrated with sensors that can mimic the human brain in solving problems. Cognitive computing in an IoT system helps in analyzing hidden patterns that are present in a large volume of data [53]. Further, it enhances the ability of a sensor to process healthcare data and automatically adapt to the surrounding. In a cognitive IoT network, all sensors collaborate with other smart gadgets and provide efficient health services. The use of cognitive computing in an IoT system helps the healthcare providers to make an effective observation of the patient's data and provide proper treatment. In [54], an EEG-based smart healthcare monitoring system has been proposed that uses cognitive computing to decide the pathological condition of the patient. The EEG data, along with other sensor data such as speech, gesture, body movement, and facial expressions, were used to assess a patient's condition. Further, it facilitates emergency help in case of pathogenic conditions. Kumar et al. have proposed a cognitive data transmission method that can effectively detect, record, and analyze patient's health data. During an emergency, the data of the patient, under critical condition, are transmitted with the utmost priority [55].

4.1.6. Adverse Drug Reaction. An adverse drug reaction (ADR) can be characterized as a side effect of taking a medication. The reaction may occur either after a single dose or a long-term administration. This can also be possible due to the adverse reaction when two different medicines are ingested at the same time. ADR does not depend on the type of medicine or the disease and it varies from person to person. In an IoT-based ADR system, a unique identifier/barcode is used to identify each medicine at the patient's terminal [56]. The information about the drug's compatibility with the patient's body can be checked using a pharmaceutical intelligent information system. The information system stores the allergy profile of each patient using e-health records. After analyzing the allergy profile and other vital health information, a decision is made whether the medication is suitable for a patient or not. In a similar study [57], an IoT-based prescription adverse drug event (prescADE) system has been proposed, which can improve patient safety by reducing the ADE.

4.1.7. Blockchain. The sharing of data among different medical devices and healthcare providers plays a crucial role in an HIoT network. However, one of the major issues in secure data sharing is data fragmentation. Data fragmentation may lead to a gap in information across healthcare providers, who are associated with a single patient. Insufficient information may hamper the treatment process. Blockchain technology is used to solve the problem of data fragmentation and helps the healthcare centers to establish a connection among the data repositories that are present in the network [58]. This further ensures secure and protective sharing of sensitive medical information and increases transparency between the doctors and patients. Blockchain technology also promotes collaboration among healthcare providers and organizations to do qualitative research (Figure 7). The secure transmission in blockchain technology can be due to three factors. First, it contains an immutable "ledger" that can be accessed and controlled by people. It ensures that once a record is stored in the ledger, it cannot be modified. Further, each transaction in the ledger must follow certain predefined rules. Second, blockchain is a distributed technology and operates simultaneously from multiple devices, computers, etc. Third, blockchain follows the agreement rules and data exchange policies with a smart contract mechanism. The smart contract manages identity and sets out permissions to access different electronic medical reports (EMRs) that are stored in the blockchain. It means doctors are only allowed to go through those EMRs to which they have been permitted. Numerous blockchain projects have been established in the healthcare industry in recent years for the management of EMR, medicine prescription, and clinical pathways [60–62]. Yue et al. have developed an app called healthcare data gateway (HDG) that uses blockchain technology and provides authority to patients to share their information. Herein, the patient can control and share their information without violating the privacy policy [63].

4.1.8. Child Health Information. Child health information (CHI) is a concept that deals with creating awareness for a child's well-being. The main purpose of CHI is to educate and empower children and their parents on the child's overall health including their nutritional values, emotional and mental state, and behavior. The application of IoT has helped researchers to achieve this goal with the development of a platform that can monitor and regulate a child's health. Nigar and Chowdhury have developed an IoT-based framework where a child's mental and physical state can be monitored [64]. Further, necessary measures can be taken with the help of doctors and parents in case of an emergency. In a similar study [65], an IoT-based medical network was developed that connects a medical device with a mobile app. The system collects five different body parameters: height, temperature, SpO_2, weight, and heart rate. This information is made available to the doctors and health professionals by the app. In [66], the use of an m-health service has been proposed to monitor the food habit of children by the teachers and parents. The app was used to attain good nutritional values in the children.

4.2. Applications. The HIoT services/concepts are used for the development of different IoT-based applications. Researchers working in the said fields have proposed different

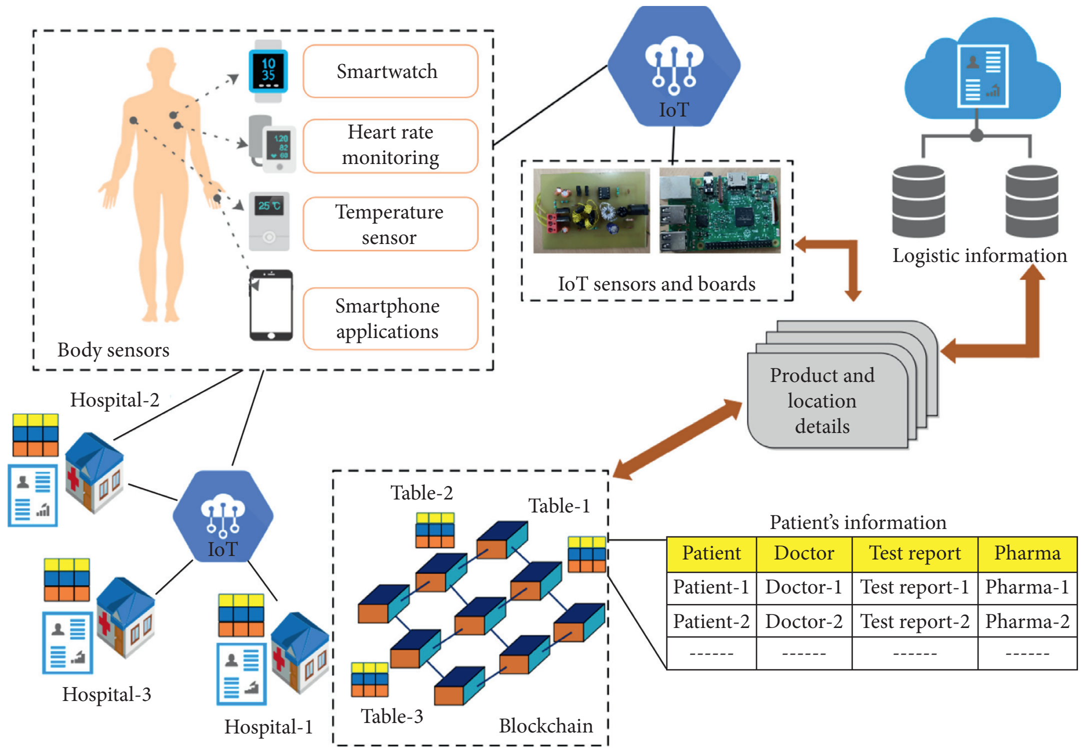

Figure 7: A blockchain-based health monitoring system (modified from [59] under Creative Commons License).

concepts to the service of mankind. In simple words, concepts are more developer-centric, whereas applications are user-centric. The rapid development in the IoT-technology has led to the development of more affordable and user-friendly wearable sensors, portable gadgets, and medical devices. These systems can be used to collect patient's information, diagnose diseases, monitor the health of the patients, and generate alerts in case of a medical emergency (Figure 8). In the following section, some of the most recent commercially available devices have been discussed. Further, various HIoT-based applications have been addressed including both single condition and multiple conditions (Figure 9).

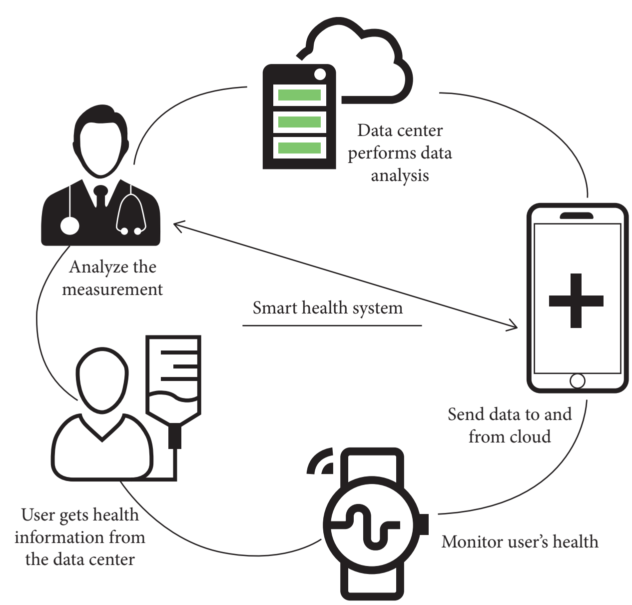

Figure 8: Application of HIoT (reproduced from [40]).

4.2.1. ECG Monitoring. Electrocardiogram (ECG) represents the electrical activity of the heart due to the depolarization and repolarization of atria and ventricles. An ECG provides information about the basic rhythms of the heart muscles and acts as an indicator for various cardiac abnormalities. These abnormalities include arrhythmia, prolonged QT interval, myocardial ischemia, etc. The use of IoT technology has found potential application in the early detection of heart abnormalities through ECG monitoring. Numerous studies in the past have employed IoT in ECG monitoring [67–72]. The study reported in [72] has proposed an IoT-based ECG monitoring system that is composed of a wireless data acquisition system and a receiving processor. It employed a search automation method that was used to detect cardiac abnormality in real time. In [73], a small wearable low-power ECG monitoring system was proposed that was integrated with a t-shirt. It used a biopotential chip to collect good quality ECG data. The recorded data were then transmitted to the end-users through Bluetooth. The recorded ECG data could be visualized using a mobile app. The proposed system could be operated with a minimal power of 5.2 mW. Real-time monitoring in an IoT system can be possible after integrating it with big data analytics to manage higher data storage. Bansals and Gandhi have proposed an ECG monitoring system that can handle long-term and continuous

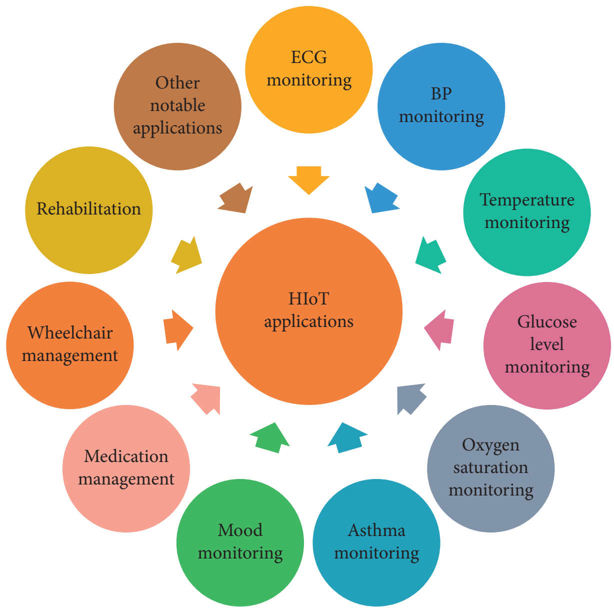

Figure 9: Category of HIoT application.

monitoring by integrating the concept of nanoelectronics, big data, and IoT [74]. It is worthy to note that in [75], the authors have tried to resolve the issue of power consumption associated with a wearable ECG monitoring system. They have proposed a unique method called compressive sensing that can optimize power consumption and provide optimal performance in ECG monitoring. IoT-based fall detection and ECG monitoring system has also been reported in [76] that uses a cloud-based server and a mobile application. This system was designed to provide real-time monitoring to elderly patients by continuously checking their ECG and accelerometer data.

4.2.2. Glucose Level Monitoring. Diabetes is the condition in which the blood glucose level in the body remains high for a prolonged period. It is one of the most common diseases in humans. Three major types of diabetes are generally found, namely, type-I diabetes, type-2 diabetes, and gestational diabetes. The disease and its types can be identified following three tests, namely, random plasma glucose test, fasting plasma glucose test, and oral glucose tolerance test. However, the most widely used diagnostic method for the detection of diabetes is “fingerpicking” followed by the measurement of blood glucose level. The recent development in IoT technologies has been used in designing various wearable gadgets for blood glucose monitoring that is noninvasive, comfortable, convenient, and safe [77–80]. In [81], m-IoT-based noninvasive glucometer has been proposed for real-time monitoring of blood glucose levels. Herein, the wearable sensors and the healthcare providers were linked through IPv6 connectivity. Alarcón-Paredes et al. have designed a glove for the measurement of blood glucose level that is integrated with a Raspberry Pi camera and a visible laser beam. A set of pictures taken from the fingertip was used for detecting the diabetic condition of the patients [82]. In another study [83], an algorithm based on a double moving average was employed in the IoT architecture for the measurement of the glucose level. It is worth specifying that optical sensors such as infrared LED and near-infrared photodiode have also been used for glucose level measurement. Herein, the light signal reflected from the human body is used to compute the glucose level in the human body [84].

4.2.3. Temperature Monitoring. Human body temperature is an indicator of the maintenance of homeostasis and is an important part of many diagnostic processes. Additionally, a change in body temperature can be a warning sign in some illnesses such as trauma, sepsis, and so on. Keeping track of the change in temperature over time helps the doctors to make inferences about the patient’s health condition in many diseases. The conventional way of measuring temperature is using a temperature thermometer that is either attached to the mouth, ear, or rectum. But, the low comfortability of the patient and the high chances of contracting an infection is always an issue with these methods. However, the recent development in IoT-based technologies has proposed various solutions to this problem. In [85], a 3D-printed wearable device was proposed that could be worn on the ear, which tracks the core body temperature from the tympanic membrane using an infrared sensor. The device was integrated with a wireless sensor module and data processing unit. Herein, the measured temperature is not affected by the environment and other physical activities. Gunawan has developed an IoT-based temperature monitoring system using Arduino and Raspberry Pi. The temperature data were stored in the database and were displayed on a web page, which could be accessed through a desktop or a mobile phone [86]. In another study [87], wearable and lightweight sensors were used for real-time measurement of the body temperature in infants. It can also alert the parents whenever there is a rise in temperature above a critical value.

4.2.4. Blood Pressure Monitoring. One of the compulsory procedures in any diagnostic process is the measurement of blood pressure (BP). The most accustomed method of measurement of blood pressure requires at least one person to do the recording. However, the integration of IoT and other sensing technology has transformed the way BP was previously monitored. For example, in [88], a wearable cuffless gadget has been proposed that can measure both systolic and diastolic pressure. The recorded information can be stored in the cloud. Further, the efficiency of this device was tested on 60 persons and the accuracy was validated. Guntha has implemented cloud computing and fog computing in the IoT-based BP measurement system [89]. This prepared the system for long-term real-time monitoring. The device could also store the recorded data for future references. In a similar study [90], a deep learning-based CNN model with time-domain characteristics was used for the evaluation of systolic and diastolic blood pressure. The measurement of BP using the ECG signal and photoplethysmogram (PPG), recorded from the fingertip, has been proposed in [91]. Herein, the BP was computed using the attached microcontroller module and then the recorded data were sent to the cloud storage.

4.2.5. Oxygen Saturation Monitoring. Pulse oximetry is the noninvasive measurement of oxygen saturation and can be used as a vital parameter in healthcare analysis. The noninvasive method eliminates the issues related to the conventional approach and provides real-time monitoring. The advancement in the pulse oximetry that comes from the integration of IoT-based technology has shown potential application in the healthcare industry. In [92], a noninvasive tissue oximeter was proposed that could measure the blood oxygen saturation level, along with heart rate, and pulse parameters. Further, the recorded information could be transmitted to the server using various communication technologies such as Zigbee or Wi-Fi. Based on the recorded data, a medical intervention decision was made. In another study [93], an alarm system that can alert the patients when the oxygen saturation reaches a critical level was reported. The system was integrated with a pulse oximeter and WLAN router that were connected using the Blynk server. Moreover, Von Chong et al. have proposed a multispectral sensor that reduces the adverse effect of a single LED [94]. A low-power and cost-effective remote patient monitoring system has been proposed in [95]. The device can be effectively used for real-time monitoring.

4.2.6. Asthma Monitoring. Asthma is a chronic illness that can affect the airways and may cause difficulty in breathing. In asthma, the airways shrink due to the swelling of the air passage. This follows many health issues such as wheezing, coughing, chest pain, and shortness of breath. There is no suitable time for an asthma attack to come, and an inhaler or nebulizer is the only lifesaver at that moment. Hence, there is a potential need for real-time monitoring of this condition. Numerous IoT-based systems for asthma monitoring have been proposed in recent years [96–98]. In [99], a smart HIoT solution for asthma patients was proposed that was used to record respiratory rate using a smart sensor. The health information was stored in a cloud server that gives access to caregivers for diagnostic and monitoring purposes. Raji proposed a respiratory monitoring and alarm system where an LM35 temperature sensor was used to measure the respiratory rate [100]. This was achieved by monitoring the temperature of the inhaled and exhaled air. The respiration data were sent to the health center and were displayed on a web server. The proposed system also triggered an alarm and automatically sent a message to the patient once a threshold value was reached. In another study [101], the proposed system not only monitored and warned the patients about the asthma condition but also suggested the patients about the right amount of the medication to be administered. Further, the system was capable to analyze the environmental conditions and direct the patient to move from a place that is not suitable for his health. Machine learning, cloud computing, and big data analysis techniques have also been integrated with IoT-based devices to effectively track asthma [102, 103]. A list of features that can be added while thinking about future development in the IoT-based asthma monitoring system has been proposed in [104]. Some of the most potential features include peak flows, pollen, humidity, air temperature, and asthma symptoms.

4.2.7. Mood Monitoring. Mood tracking provides vital information regarding a person's emotional state and is used to maintain a healthy mental state. It also assists healthcare professionals while dealing with various mental diseases such as depression, stress, bipolar disorder, and so on. Self-monitoring of the emotional state enhances a person's understanding of their mental condition**.** In [105], a mood mining approach was reported that uses a CNN network to evaluate and categorize a person's mood in 6 categories: happy, excited, sad, calm, distressed, and angry. In a similar study [106], the real-time mood measurement was achieved using an interactive system called "Meezaj." The app also showed the importance of happiness in decision making and assists the policymaker in identifying those important factors that play a crucial role in defining a person's happiness. With the integration of an advanced machine learning algorithm, now stress can be detected beforehand with the help of heartbeat rate. Further, the system can communicate with the patient about their stress condition [107]. It is interesting to note that the analysis of the stress condition can also be useful in designing an IoT-based system that can prevent an accident. Jasleen et al. have proposed a wearable device that can estimate four negative emotions/moods (anger, stress, terror, and sadness) of a person/driver. By analyzing the variation in these emotions, the intelligent system decides whether the driver is in a subconscious state or not. The system stops the dc motor of the vehicle once a driver achieved the subconscious state.

4.2.8. Medication Management. Medication adherence is a common issue in the healthcare industry. Nonadherence to the medication schedule may increase the adverse health complications in patients. Medication nonadherence is mostly found in elderly people as they develop clinical conditions like cognitive decline, dementia, and so on as the age progresses. Hence, it is difficult for them to strictly follow the prescriptions of doctors. Numerous research in the past has focused on tracking the patient's compliance with medication through the application of IoT [108–111]. In [112], a smart medical box was developed that can remind people of their medication. The box has three trays where each tray contains the medicine for three different times (morning, afternoon, and evening). The system also measures some of the vital health parameters (blood glucose level, blood oxygen level, temperature, ECG, and so on). All the recorded data are then sent to the cloud server. A mobile app was used to establish communication between the two end-users. The recorded information can be accessed by doctors and patients using the mobile app. In another study [113], the information about the storage condition of the medicine such as temperature and humidity was also recorded. This helped the patients to maintain the required storage environment. One of the more specific examples of medication management is "Saathi" [114]. This pill monitoring system was specifically designed for the woman going through in vitro fertilization (IVF) treatment. Since the IVF process demands a strict medication schedule, the proposed device gives women the facility to remind their daily medication and injections, track real-time medicine consumption, and communicate with the healthcare providers. Moreover, an adaptive IoT-based smart medication system was reported in [115] that uses fuzzy logic to analyze the data collected from the temperature sensor. The system is efficient to treat fever by continuous monitoring of body temperature and then automatically adjust the time and dose of medicine during treatment.

4.2.9. Wheelchair Management. A wheelchair is an inseparable part of the life of patients with restricted mobility. It provides them physical as well as psychological support. However, the application of a wheelchair is limited when the disability is due to brain damage. Hence, new research is focusing on integrating the navigation and tracking system with these wheelchairs. IoT-based systems are now showing potential results in achieving this goal [116–119]. In [120], an IoT-based steering system, integrated with a real-time obstacle avoidance system, has been proposed. The steering system can detect obstacles by employing image processing techniques on the recorded real-time videos. The use of mobile computing has enabled wheelchair management to be more interactive and easy for patients. A smart wheelchair as represented in [121] was developed by the integration of various sensors, mobile technologies, and cloud computing. The system includes a mobile app that can help the patients to interact with the wheelchair and the caregivers. The app also enables caregivers to monitor the wheelchair from a distance. In another study [122], an IoT-based wheelchair monitoring system has been proposed that used hand gestures for controlling the wheelchair. The designed model is especially applicable for patients having quadriplegia. The hand gesture information was recorded using the RF sensor that was present in the hand gloves and was used to control the wheelchair. Further, the sensor data were transmitted to the server and could be stored in the cloud. The doctors/caregivers can access the data from the cloud and can use this information for diagnosis. It is worth specifying that in [123], a more advanced and automated smart wheelchair was reported that not only monitored the wheelchair movement but also provided an umbrella, foot mat, head mat, and obstacle detection features. Herein, the designed system provided more efficient interaction with the living environment.

4.2.10. Rehabilitation System. Physical medicine along with rehabilitation is effective in restoring the functional ability of a patient with a disability. Rehabilitation involves identifying the problem and helping the patients to regain their normal life. The application of IoT in rehabilitation is diverse and can be seen in the treatment of cancer, sports injury, stroke, and other physical disabilities [124–127]. A smart walker rehabilitation system has been proposed in [128] that used a multimodal sensor to monitor the walking pattern of the patient and evaluate the movement metrics. When a patient used the smart walker, it measured different movement matrices such as orientation angle, elevation, force, and so on. A mobile app was used by the doctors to access these data and to provide diagnostic reports. Moreover, a stroke rehabilitation system was developed by integrating a smart wearable armband, robotic hand, and machine learning algorithm [129]. The armband was designed using a low-power IoT-based textile electrode that can measure, preprocess, and transmit the biopotential signal. Further, the 3D-printed robotic arm analyzed the muscle activity and assisted the patient to correct their motion pattern during the after-stroke recovery period. In another study, a sports rehabilitation system was reported that monitored temperature, motion posture, electromyography (EMG), electrocardiography (ECG), and so on and provided feedback to the athletes. The recorded information could be used by healthcare professionals to predict the patients' recovery and formulate rehabilitation programs.

4.2.11. Other Notable Applications. The application of HIoT is disparate and not limited to the aforesaid functions. With the rapid growth of technology, the number of HIoT applications is increasing significantly. Some of the research areas where the integration of IoT devices was not explicitly demonstrated previously are now using this technology efficiently. This may include cancer treatment, remote surgery, abnormal cellular growth, hemoglobin detection, etc. In [130], a new IoT-based framework for cancer treatment was proposed that integrated various stages of cancer treatment including chemotherapy and radiotherapy. A mobile app was used for online consultation from the doctors. The lab-test results of patients were stored in the cloud server and could be accessed by the healthcare provider to decide the time and dosage of medication. Another potential application is the detection of lung cancer using various state-of-the-art machine learning algorithms with an IoT-based system [131–133]. Moreover, a recent piece of research also suggested the detection of skin lesions using an IoT-based system [134]. Cecil et al. have employed IoT in designing the next-generation surgical training framework [135]. The device used virtual reality to develop a training environment and also provided a platform to interact with other surgeons from different locations. In [136], a human-robot collaborative system has been proposed that can effectively perform minimally invasive surgery. Using a portable device, the hemoglobin level in the blood can be monitored [137]. The device employed photoplethysmography (PPG) sensors, a light-emitting diode (LED), and photodiodes for the measurement of hemoglobin. The efficiency of the device was further validated by comparing the results with the established colorimetric test.

5. Challenges, Limitations, and Future Scope

In the last few years, the healthcare industry has witnessed remarkable technological development and its application in solving healthcare-related issues. This has significantly improved the healthcare services, which have now been brought at the fingertip. With the application of smart sensors, cloud computing, and communication technologies, IoT has successfully revolutionized the healthcare industry. Like other technologies, IoT also has certain challenges and issues that provide potential scope for future research. Some of the issues have been discussed in the subsequent section.

5.1. Servicing and Maintenance Cost. Of late, there are rapid technological advancements that would require continuous upgradation of the HIoT-based devices from time to time. Every IoT-based system involves a large number of connected medical devices and sensors. This involves high maintenance, servicing, and upgradation costs that may impact the financials of not only the company but also the end-users. Hence, the inclusion of sensors that can be operated with a lower maintenance cost is required.

5.2. Power Consumption. Most of the HIoT devices run on battery. Once a sensor is put on, the replacement of the battery is not easy. Hence, a high-power battery was used to power such a system. However, currently, researchers worldwide are trying to design healthcare devices that can generate power for themselves. One such potential solution may be the integration of the IoT system with renewable energy systems. These systems can help in alleviating the global energy crisis to a certain extent.

5.3. Standardization. In the healthcare industry, a large number of vendors are manufacturing a varying range of products. Most of these products claim to follow standard rules and protocols in the design process. However, there is a lack of validity. Hence, the construction of a dedicated group is required that can standardize these HIoT devices based on the communication protocols, data aggregation, and gateway interfaces. The validation and standardization of electronic medical records (EMRs) recorded by the HIoT devices are also to be considered extensively. This can be achieved when various organizations and standardization bodies such as Information Technology and Innovation Foundation (IETF), the European Telecommunications Standards Institute (ETSI), the Internet Protocol for Smart Objects (IPSO), and so on can collaborate with the researchers to form working groups for the standardization of the devices.

5.4. Data Privacy and Security. The integration of cloud computing has transformed the idea of real-time monitoring. But, this also has made healthcare networks more vulnerable to cyberattacks. This may lead to mishandling of patients' valuable information and may affect the process of treatment. To prevent an HIoT system from this malicious attack, several preventive measures must be taken while designing a system. The medical and sensing devices included in an HIoT network must evaluate and employ identity authentication, secure booting, fault tolerance, authorization management, whitelisting, password encryption, and secure pairing protocols to avoid an attack. Similarly, the network protocols such as Wi-Fi, Bluetooth, Zigbee, and so on must be integrated with secured routing mechanisms and message integrity verification techniques. Since IoT is a connected network where each user is linked to the server, any glitch in the security services of IoT may compromise the privacy of the patient. This could be fixed with the creation of a more secure environment through the integration of advanced and protected algorithms and cryptographies.

5.5. Scalability. Scalability represents the ability of a healthcare device that can adapt to the changes in the environment. A system with higher scalability works smoothly without any delay and makes efficient use of the available resources. Hence, it is crucial to design a device with higher scalability. This further makes a system more efficient for present and future uses. An HIoT system is the interconnection of different medical devices, sensors, and actuators, which are used to share information through the Internet. The lack of uniformity among the connected devices of an HIoT system decreases the scalability of the system and hence must be managed efficiently.

5.6. Identification. Healthcare professionals deal with multiple patients and caregivers at the same time. Similarly, when a patient deals with multiple health issues, he interacts with multiple doctors. Thus, it is crucial to exchange the identity of the patient, caregiver, and doctors among each other during a single treatment process to avoid confusion and maintain the smooth functioning of the healthcare system.

5.7. Self-Configuration. The IoT devices must give more power to the users by including the feature like manual configuration. This will enable the users to change the system parameters according to the application demand and also with the change in the environmental conditions.

5.8. Continuous Monitoring. Many healthcare situations demand long-term monitoring of the patient during treatment as in the case of chronic diseases, heart diseases, etc. In such situations, the IoT device must be able to perform real-time monitoring efficiently.

5.9. Exploration of New Diseases. With the rapid growth in mobile technology, new healthcare apps are added with passing days. Though a large number of mobile apps are available for healthcare applications, the types of diseases for which these apps were designed are still limited. Hence, there is a need to include more diseases that were either neglected or got inadequate consideration in the past. This will add up to the diversity of the HIoT applications.

5.10. Environmental Impact. The development of an HIoT system requires the integration of various biomedical sensors with semiconductor-rich devices. The manufacturing and fabrication mostly require the use of earth metal and other toxic chemicals. This may create an adverse effect on the environment. Hence, a proper regulatory body must be created to control and regulate the manufacturing of the sensors. Further, more research must be devoted to making sensors using biodegradable materials.

6. Conclusion

The current review investigated different aspects of the HIoT system. Comprehensive knowledge about the architecture of an HIoT system, their component, and the communication among these components has been discussed herein. Additionally, this paper provides information about the current healthcare services where the IoT-based technologies have been explored. By employing these concepts, the IoT-technology has helped healthcare professionals to monitor and diagnose several health issues, measure many health parameters, and provide diagnostic facilities at remote locations. This has transformed the healthcare industry from a hospital-centric to a more patient-centric system. We have also discussed various applications of the HIoT system and their recent trends. Further, the challenges and issues associated with the design, manufacturing, and use of the HIoT system have been provided. These challenges will form a base for future advancement and research focus in the upcoming years. Moreover, a comprehensive up-to-date knowledge on the HIoT devices has been provided for the readers who are not only willing to initiate their research but also make advancements in the said field.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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