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A Systematic Analysis of Internet of Things in Healthcare Applications : A Review

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Abstract The Internet of Things (IoT) is a network of physical devices, software, and hardware that communicate with one another. As the population ages, healthcare resources become scarce, and medical expenses rise, IoT-based solutions must be adapted to meet these issues in healthcare. To enhance the monitoring efficiency of the IoT-based healthcare system, several studies have been conducted. In this paper, the architecture utilized in the IoT, particularly cloud-integrated systems and security in IoT devices is explored. Factors like accuracy and power consumption are major concerns in the Internet of Things, therefore research projects aimed at enhancing the performance of IoT-based healthcare systems are highlighted. In this work, data management strategies in an IoT-based healthcare system with cloud capabilities are thoroughly examined. The performance of the IoT-based healthcare system is examined, as well as its benefits and drawbacks. Moreover, a comparative analysis is also done on some existing technologies that are utilized in healthcare. It has been observed from past studies that IoT protocol such as 6LoWPAN is mostly utilized in the domain of health care. The majority of research studies are effective in detecting many symptoms and accurately predicting illnesses. The IoT-based healthcare system built specifically for the elderly is an effective way to keep track of their medical concerns. High power consumption, a scarcity of resources, and security concerns major drawbacks of current systems are included in the proposed study.

Keywords Internet of Things · Healthcare · Smart Home · Big data

1 Introduction

The Internet of Things (IoT) is now widely used in so many applications that its significance in our daily lives is growing. IoT technology is also being developed in the healthcare monitoring system to provide patients with effective emergency services [1]. It is also utilized as an E-health application for a variety of purposes, including early detection of medical problems, emergency notification, and computer-assisted rehabilitation. Smartphones have become an essential part of people's daily lives, and they are now linked to sensors that monitor the subject's health [2]. IoT has been described from several views in the research community. IoT is defined by the RFID group as interconnected items that are exclusively recognizable using standard communication protocols [3]. The Internet of Things (IoT) is a complex network of uniquely identified "things," each of which links to a server that effectively provides appropriate services [4]. According to this concept, each of these "things" has distinct qualities and participates actively in various situations. By exchanging relevant data from the physical and virtual worlds, they can communicate with each other and with the physical world. These objects are also capable of responding to events in their environment on their own. All of these processes can use human intervention or machine-to-machine communication to trigger some operations and provide services [5]. Due to the growth in the development of smart objects, IoT has enriched almost all aspects of our daily lives and is continuously doing so with a diverse range of novel, innovative, and intelligent applications [72, 73], such as crowdsensing [74, 75] sourcing [76], smart agriculture [77], smart cities [79], smart healthcare [78] shown in Fig. 1. These developments, along with creative applications, are extremely encouraging, indicating a bright future for IoT on the one hand, but many obstacles on the other. Security, big data analytics, interoperability, Quality of Service (QoS), and energy management are just a few of the

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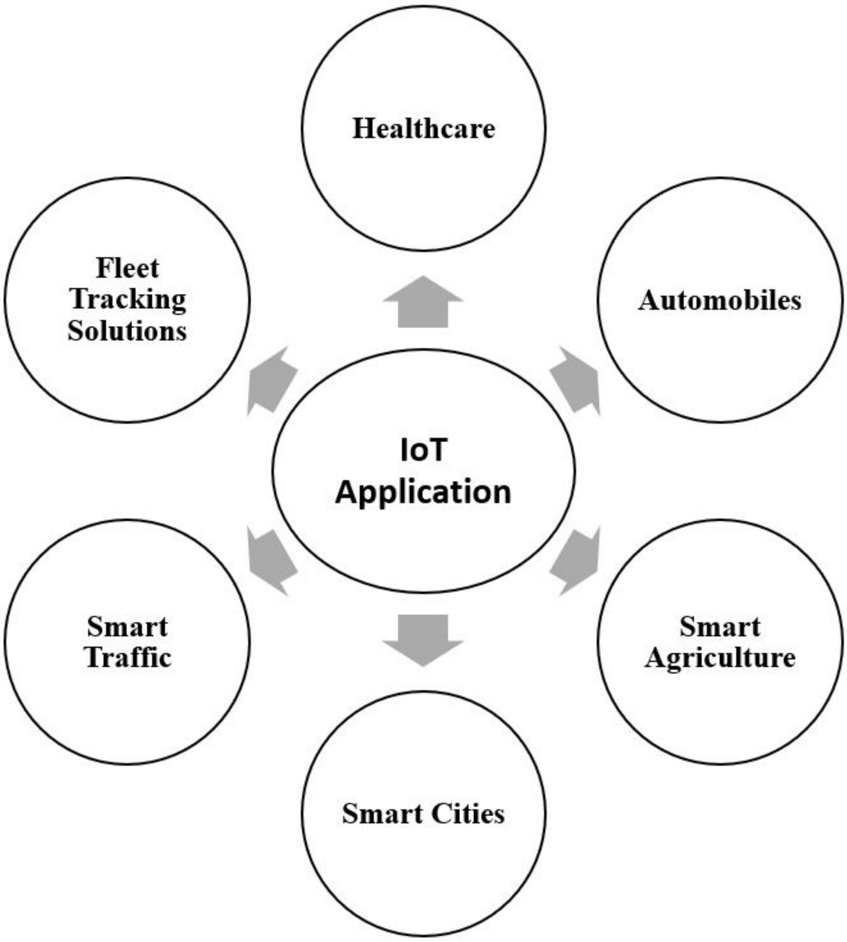

Fig. 1 Different application of Internet of Things

issues [80]. Because of the interconnection between IoT items and the abundance of data streams created by them, big data is essential among them. A massive amount of data is created by a wide range of IoT devices and applications. To mine such data and improve decision-making, several big data analytics are used. Big data is categorized and characterized in an IoT context by many academics from diverse viewpoints, and numerous models have been suggested [81–83], the most common of which is the 5 V model. Based on different features related to big data, this approach divides information into five groups. The amount of the data (volume), real-time data collecting (velocity), heterogeneous data collection from a broad range of resources (variety), unexpected data (veracity), and ultimately the use of such data in many sectors, such as industry and academia, are some of these qualities (value). Due to its usefulness in a variety of fields, big data research has exploded in popularity recently. This trend is accelerated by the integration of IoT and big data, which opens up possibilities for improving services in a variety of complex systems, such as the healthcare system. A vast range of big data technologies has been utilized in the IoT literature for the analysis of huge amounts of data from a variety of resources in the smart healthcare sector. Machine learning (ML) is a dominating approach for performing sophisticated analysis, intelligent judgments, and creative problem solving on huge data among these technologies.

1.1 Reasearch Area and Problem Identification

Consumers of the Internet of Things can dramatically increase their decision-making abilities by using augmented intelligence [6,7]. Businesses have been able to enhance their work processes and increase productivity by collecting and reporting data collected from the environment thanks to the widespread use of IoT technologies. According to various prior studies, IoT will be the next large investment destination for many businesses [9–11]. Healthcare surroundings will be altered in the near future as a result of IoT prospects. In hospitals and, more crucially, at home, this technology will play a significant part in patient telemonitoring [11, 12]. Remote patient monitoring offers enormous potential for improving healthcare quality while also lowering costs by detecting and avoiding diseases and dangerous situations [13, 14]. Remote patient monitoring offers enormous potential for improving healthcare quality while also lowering costs by detecting and avoiding diseases and dangerous situations [15].

1.2 Contribution

In this context, several research articles have been examined in the field of IoT and Machine learning techniques in health care in terms of accuracy, computational power, architecture, and current problems in the development. The monitoring of cardiac patients, which is accomplished via sensor devices, is one of the significant and vital research projects. ECG data is utilized to keep track of patients, and the information is sent to professionals for analysis. There is no systematic review of the literature addressing IoT architecture in healthcare. The goal of this systematic research is to give a comprehensive survey of IoT architecture in the healthcare sector.

1.3 Need and Importance of the Proposed Study

Researching the area of Indoor environment especially for Irregularity determination will inform about the quality of the environment in which we are living. Moreover, we can analyze the cause and impact of the contaminants on the individual's health which can be the root cause of numerous diseases. We believe that monitoring the environment can save us from many diseases which can develop health abnormalities due to contamination. We trust that this information will lead us to new procedures to assist people and society as a whole. In the future study, we will develop a novel approach will that will a combination of IoT, machine learning, and healthcare for the prediction of the health status of an individual and regularly monitoring the status of an individual automatically.

1.4 Article Structure

The remaining portion of the proposed study is divided into the following section. Section 2 describes the related work on IoT and healthcare. In section 3 a comparative analysis based on different IoT techniques is utilized. Section 4, presented the different communication models used in IoT and At last, the conclusion of the proposed study is concluded in Section 5.

2 Background Work

In this section the background work on IoT healthcare is briefly discussed:

2.0.1 Application of IoT Healthcare:

IoT technology will be widely used in the healthcare industry in the future years [16]. The healthcare sector is continually looking for innovative orders to obtain services while reducing costs and improving quality [17]. Patients are better capable of following self-care principles as a result of the usage of these innovations, which leads to higher patient satisfaction and better self-management. IoT-based solutions can also be utilized for remote monitoring of physiological status in patients who require constant monitoring [18]. The convergence of diverse IoT designs has recently enabled the development of smart healthcare systems [19]. IoT-driven solutions may be advantageous in developing a coherent system with the interconnectivity of heterogeneous objects to gain a complete image of a patient's health status.

Few existing studies have looked into how IoT devices can aid elderly persons and how they can be monitored [21, 22]. The elderly monitoring services are a component of the socializing platform, and they can be successfully monitored with the help of IoT devices. RFID data and location identification data are stored in the designated region. Using such information, determine where the seniors belong in the designated region. These studies enable the elderly to remain in their homes, where they feel safe and secure, while also efficiently monitoring their health and alerting hospitals and family members if the gadget detects an urgent situation [22].

Parthasarathy and Vivekandan [70] developed a system for monitoring and diagnosing patients with arthritis at an early stage. The suggested framework is divided into three layers, the first of which collects data from sensors. The data is stored in the cloud at the second level. The third level is utilized to optimize the information obtained, which includes edema and uric acid (UA). This suggested approach will be implemented using Apache Redshift and OpenStack. Moreover, the sensor devices were created and plotted in the living room and other places where chronic illness patients conduct their daily lives as the setting by Kim and Chung [71]. This experiment does not handle real-time data, and this approach is quite expensive. The procedure of architecture may be studied and a sensor can be utilized instead of a camera to lower the total cost of the procedure illustrated in Fig. 2.

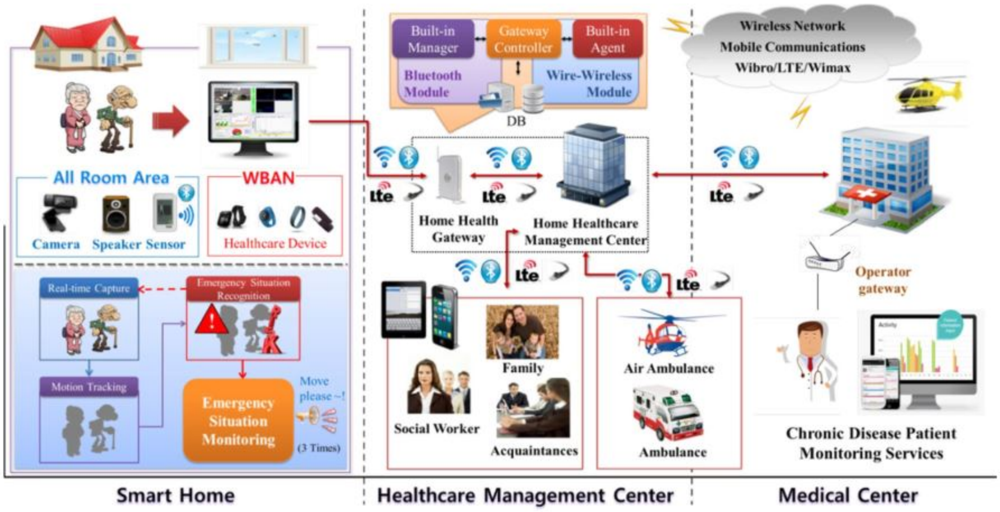

Fig. 2 Overview of the IoT architecture [71]

2.0.2 IoT Technologies and Cloud Integration:

Smart devices are playing an increasingly essential role in shaping the IoT vision. In reality, because of qualities like cheap cost, shrinking size, and lower energy consumption rates, IoT in healthcare will continue to progress steadily in the future years. This technical breakthrough has the potential to fundamentally change healthcare activities due to these qualities [23]. There are number of IoT technologies where utilized in multiples domain of IoT such as RFID and NFC [24–28], LR-WPAN [29–31], Bluetooth [32–34], ZigBee [35, 36], WiFi [37], and Wireless Sensors Network (WSN) [38–41].
Remote health monitoring through a smartphone application IoT data is stored in the cloud platform, which provides more flexibility, scalability, and processing capacity. Because the IoT data is collected from a separate sensor, it is essentially saved on a cloud storage repository server. In a few research medical procedures are connected into the cloud utilizing cloud technology, which improves healthcare. Students' physiologically based features are measured and saved in a distinct sort of format in cloud storage. Once the data from IoT medical equipment has been collected by the user subsystem, it is transmitted to the cloud subsystem for diagnosis. In case of any emergency about patient health a real-time alert has been sent to the doctor or caretaker for medical supervision and the process of sending an alert message is illustrated in Fig. **??**. Azimi et al. [42] developed a hierarchical computing architecture (HiCH) to monitor the patient that contains autonomous data management.
The network delay is a major problem in remote health care monitoring systems, and to provide a solution for network delay in healthcare processing by remote, a framework is known as UbeHealth has been proposed to analyze challenges in network delay and QoS (Quality of Service) parameters to improve healthcare performance in smart cities [43]. The fuzzy rule-based neural classifier has been presented as a method for detecting illness and decreasing its severity. This technique examines how data is processed from the cloud using a safe storage mechanism, which includes phrases like data retrieval, data aggregation, data partitioning, and data merging [44].

2.0.3 Big Data and Security in IoT Healthcare:

Big data storage technology has been increasingly important in recent years for storing large amounts of clinical data. The technology known as Big Data is used to manage cloud storage as it grows in size. According to recent research, the combination of Big data and the cloud has an impact on distant healthcare. EMR (Amazon Elastic MapReduce) is a new way to handle large data and get it into the cluster. To import data into an Hbase cluster, the Amazon EMR uses a separate function. Using the tool as an Apace pig to load sensor data from Amazon S3 to Hbase. Apace pig is used to analyze data in a distributed database, allowing healthcare applications to significantly increase their scalability [46]. A lightweight approach for semantic annotation of Big data in IoT heterogeneous data has been devised [46]. The innovative technique is presented for forecasting air quality in metropolitan areas and providing a healthier lifestyle for city dwellers. The suggested UHBigDataSys uses Spring Framework to evaluate the parameters of Air Quality Indicators (AQIs) for Metropolitan Healthcare [47].

Because of hackers or attackers accessing the sensor data, security has been a big issue in the IoT, therefore it's crucial to look into the most recent security measures. Xu et al., [48] developed an IDP, which is an IoT-oriented data placement mechanism that preserves privacy. The major goal of this suggested technique is to minimize data access time, enhance resource utilization, and reduce energy consumption while fulfilling data privacy restrictions. The Non-dominated Sorting Genetic Algorithm II algorithm is used to maintain privacy while also conserving energy

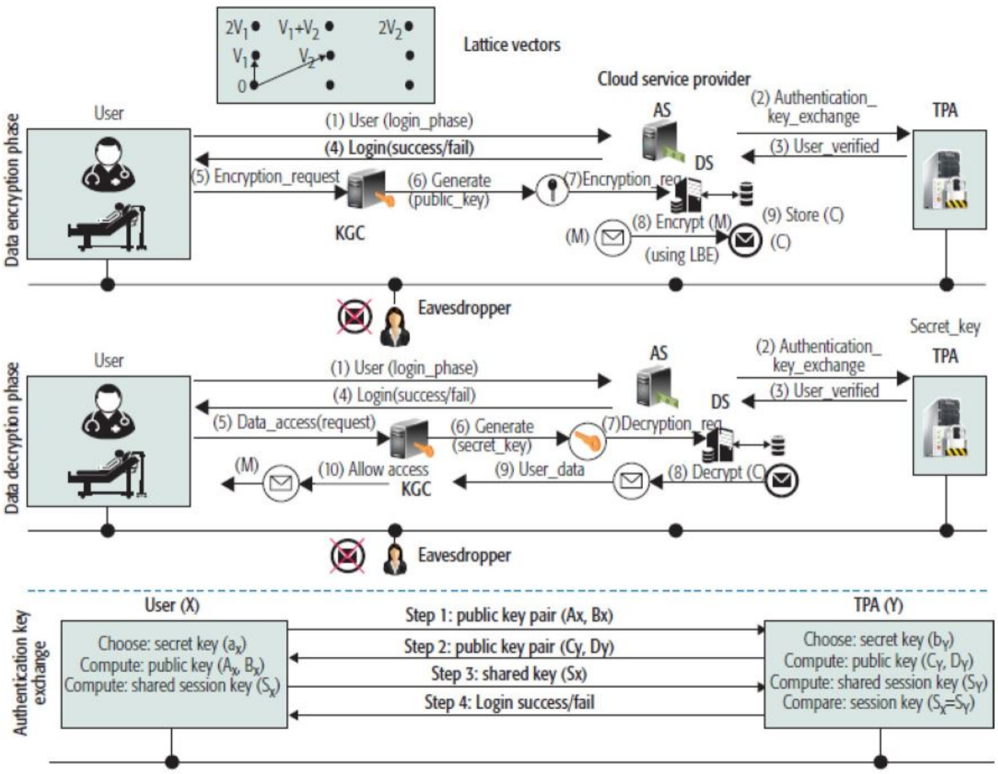

Fig. 3 LSCSH architecture in healthcare IoT [52]

(NSGA-II). The trustworthy computation is performed locally on the user's health profile's genuine health data, and the recommendation process is handled by the cloud healthcare recommender service [49]. Zhou et al., [50] uses a radio-frequency identification encryption method to secure medical data on the Internet of Things. Data flow in the network environment is essential for health information. The objective of this study is to create a data privacy framework that combines a biometric-based security system with a resource-constrained wearable health monitoring system [51]. Information from the Internet of Medical Things (IoT) is examined to improve security in medical applications. The Authentication Server (AS), the Key Generation Center (KGC), and the Database Server are the three servers that make up the Cloud Service Provider (CSP) (DS). The Lattice-based Safeguard Cryptosystem is used in smart healthcare to secure data. There are four steps in this process: setup, key creation, data encryption, and data decryption. The lattice polynomial vectors are utilized as input in the first phase, and the KGC (private and public key) is created and shared with the Database Server in the second phase (DS). The message is utilized as an input parameter in the last step, which mixes it with the random polynomial. If a user requests access to medical data, the KGC uses a secure channel to send the secret key pair to the DS. The input parameters and secret key pair are used by the DS to process the plaintext message. The LSCSH architecture is depicted in Fig.3, which also includes the key exchange procedure [52]. This approach has been compared to other suitable systems in terms of communication and computing costs.

Several areas, including computer science, healthcare, and medical informatics, have researched IoT technologies and architectures. As a result, published research articles are dispersed among several databases. To construct a thorough bibliography for a research paper on IoT architectures in healthcare, we have suggested a few prominent electronic resources. IEEE, Springer, Wiley, Science Direct, Emerald, Google Scholar, PubMed, and Scopus were the eight digital databases used. We conducted a search of IoT architecture-related literature published between 2000 and 2019. In addition, studies were found using the following search terms: architecture, internet of things, smart hospital, home healthcare, m-health, remote healthcare monitoring, and their impacts. We looked at the abstracts, introductions, and conclusions of the articles during the research selection process.

3 Big Data Analytics and Machine Learning for Internet of Things

The machine learning approaches used in Big data are discussed in this section. Pattern recognition and computational learning theory developed into machine learning [84], which is a subfield of computer vision. It is a form of AI that allows computers to learn without explicit programming by making complicated judgments [85]. Computer vision [86], computer graphics [87], natural language processing (NLP) [88], speech recognition [89], computer net-

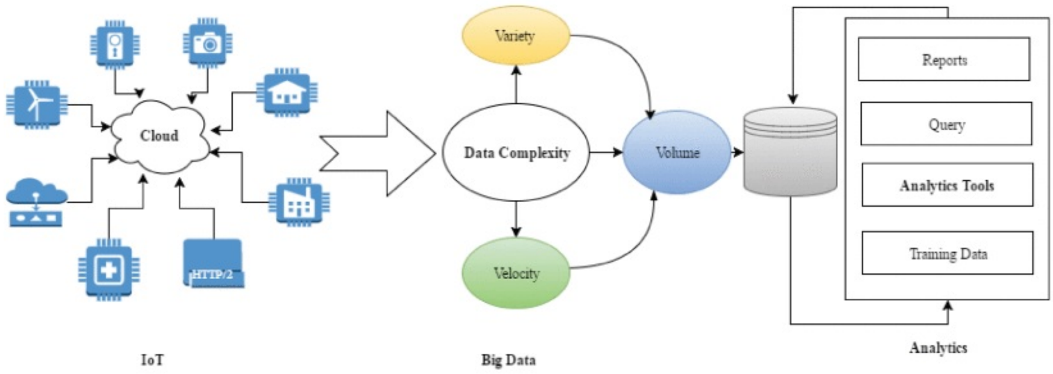

Fig. 4 Iot and Bigdata relationship

works [90], and intelligent control [91] have all been effectively utilized in the past. Due to its remarkable growth with a broad variety of creative applications, it has played an increasingly important role in IoT and big data analytics in recent years. Due to its remarkable growth with a broad variety of creative applications, it has played an increasingly important role in IoT and big data analytics in recent years. As a result of these diverse and complicated data sources, such as IoT devices, highly linked data is created. As a result, data management in these systems becomes exceedingly complex, posing plenty of problems for researchers [92–94]. By creating innovative big data analysis methodologies, it is critical to managing data from these vast numbers of sources with enhanced velocity and scalability. Existing approaches are unsuccessful because they have lesser precision and use more energy, and they don't cater to such a wide range of applications. To adapt to diverse applications, these approaches must be improved. In IoT eHealth, machine learning methods play a critical role [95]. It enables us to acquire in-depth analyses from a broader pool of available data. It extracts important information and characteristics from IoT data, making the decision-making process easier. It also aids us in the creation of effective and intelligent IoT applications. For IoT big data analytics, and IoT analysis model comprises of different components such as data sources, edge/fog computing, and machine learning algorithms. Wearable devices, such as sensors, and body area networks, are examples of potential data sources in this approach. They collect data on human health, such as temperature and ECG, as well as environmental data, such as humidity and camera images. For further analysis, several machine learning algorithms are used to the data acquired by these sources. ML approaches have been effectively utilized for large data analysis in different IoT applications such as smart traffic [96,97], smart agricultural [98], smart human activity control [99], smart weather prediction [100, 101], healthcare [102, 103], and smart cities [19], as evidenced by the literature. In a wide range of IoT sectors, big data has been investigated. However, a thorough literature analysis that only studies big data analytics in IoT healthcare is lacking. Even though several of the aforementioned surveys devoted only a portion to this topic, a lack of research has looked at the importance of machine learning techniques for big data analysis in IoT healthcare. Fig. 4 shows the relationship of IoT, big data, analytic tools.

4 Comparative Analysis

The Internet of Things (IoT) may be used in the healthcare system to continually monitor the patient's status. Wearable IoT devices are quite useful in monitoring a patient's status. The Internet of Things (IoT) in healthcare is evolving, and current research on IoT-based health monitoring is summarised in Table 1. IoT-based healthcare systems are very useful in monitoring patients' cardiac conditions, and machine learning can improve their efficiency for medical emergency alerts. The majority of the research is more efficient, however, power consumption must be decreased.

Short-range communication technologies such as Wi-Fi (75%), Bluetooth (58.3%), RFID (37.5%), and ZigBee (37.5%) were the most important technology in IoT designs in healthcare presented in Table 2. Furthermore, 6LoWPAN was the most commonly utilized protocol in most of the research. This protocol allows sensor networks to access the internet, and it was created to assure sensor network and internet compatibility.

4.1 IoT, Machine Learning, Big Data Analysis in Healthcare System

The Internet of Things (IoT) seeks to improve the quality of human life by automating some of the most fundamental operations that humans would otherwise have to conduct manually. In this scenario, human monitoring and decision-making are delegated to robots. Sensors are attached to the health monitoring device used by patients in IoT-based supported living applications, for example. The data collected by these sensors is sent over the network

Table 1 Comparative Analysis of Several Methods

Author	Approaches	Performance Analysis	Limitations
Abawajy et al., [53]	The infrastructure for a pervasive patient health monitoring (PPHM) system is proposed in this study. This entails observing the patient's health remotely. PHM connects IoT to the cloud and keeps the patient's ECG data online. The data is grouped, and minimum optimization is done in a sequential manner	When the number of clusters is two, the average response time for 50 requests is 45 milliseconds and the F-measure is around 98	Instead of manual monitoring, machine learning may be used to analyze ECG data. This allows for the process to be unattended while also lowering costs
Muhammad et al., [54]	The goal of this study is to use IoT to identify vocal pathology. On a Mel-spectrum representation of the speech signal, the local binary pattern (LBP) is used to represent the voice signal. The focus of this study is on a health IoT-based monitoring platform.	Precisionvlaue of LBP + ELM = 98.1% and LBP + GMM = 95.7%	The use of smart devices and microphones can further enhance scalability. This technique does not need managing big amounts of data
Hossain et al., [55]	The framework sends ECG and other medical data to healthcare providers. Mobile gadgets and sensors are used to monitor the situation	Existing SNR = 58.38; projected SNR = 64.35 While extracting 37 features, the classification accuracy was 91.1 percent. Time to execute: 3.3 milliseconds while utilizing three instance servers	Machine learning may be used to monitor a signal, which helps to reduce mistakes and improve accuracy. To extract more characteristics from the data, the execution duration must be increased
Yang et al., [56]	This is a framework for maintaining privacy based on IoT healthcare data. The IoT group key is used to encrypt IoT communications, which are then shared with the patient.	When there are 60 attributes, encryption takes 0.025 seconds and the access policy update query takes 0.0011 seconds	Flexibility and scalability must be improved
Lomotey et al., [57]	This study focuses on tracing data back to the router using Petri Nets to solve the complexity and heterogeneity of data in IoT	96% accuracy, 95% sensitivity, and 97% precision	To process in a real-time system efficiently, this technique requires the development of an unsupervised model
Gia et al., [58]	For patients with cardiovascular disorders, ECG data is monitored. Despite the fact that their connection is quite strong. To address this problem, the suggested technique includes ECG, glucose, and body temperature monitoring, as well as fall detection	The smart gateway's latency, is 43 milliseconds. 717.82 mW power usage with AES-256	The wearable gadgets' batteries must be replaced on a regular basis. The size of the data must be decreased

Table 2 Comparative analysis based some existing technologies

Authors	Wi-Fi	Mobile communication	Bluetooth	RFID	ZigBee	GPRS	IoT protocol
Rohokale et al. [59]	⋆	⋆	⋆	✓	⋆	⋆	⋆
Yang et al. [60]	✓	✓	✓	⋆	✓	⋆	COAP
Woznowski et al. [61]	✓	⋆	✓	⋆	✓	⋆	✓
Mainetti et al. [62]	✓	✓	⋆	⋆	⋆	⋆	⋆
Santos et al. [63]	✓	✓	⋆	⋆	⋆	⋆	COAP
Spanò et al. [64]	✓	✓	✓	⋆	⋆	⋆	
Rahmani et al. [65]	✓	✓	⋆	⋆	⋆	⋆	6LoWPAN
Jara et al. [66]	⋆	⋆	⋆	NFC	⋆	⋆	6LoWPAN
Istepanian et al. [67]	✓	✓	⋆	⋆	⋆	⋆	6LoWPAN
Lee et al. [67]	✓	⋆	⋆	⋆	✓	⋆	6LoWPAN

and made available to anybody interested. This not only aids in prompt patient care, but it also enhances the sensitivity and reliability of the underlying application [105, 106]. Furthermore, the patient's existing medications are monitored, and the risk of a new drug is assessed for potential adverse reactions [107, 108]. As a consequence, not only is time saved but monetary value is preserved as well. Only a few machine learning approaches for large data analytics in IoT eHealth are discussed in this section. In addition, Table 3 summarises the important ideas, including their similarities and contrasts, strengths, and shortcomings.

4.1.1 Recommendation and Prediction System-based on Machine Learning

In [114]The authors presented a recommendation method based on an individual's demands that designed the most viable IoT wearable devices. The suggested system begins by gathering all accessible data on a patient's health, such as prior history, demographic information, and data retrieval from the patient's sensors. To forecast the incidence of illnesses, several ML-based classification approaches such as decision trees, logistic regression, and LibSVM are employed. Finally, for each individual, a mathematical model is utilized to propose a tailored IoT solution. In [115]

Table 3 The parallels and contrasts between key technological ideas

‘ Authors	Application	Findings
Mohammadi et al., [109]	Big data and characteristics of Big data	Discuss IoT from the big data approach. The 6 Vs dimensions, i.e. Volume, Velocity, Variety, Veracity, Variability, and Value, are often discussed as properties of big data. Analyze and describe significant research efforts in the IoT sector that use deep learning. Finally, it highlighted some of the issues that need to be addressed as well as some perspective paths for future study in this field.
Cui et al., [110]	In a wide range of applications, machine learning, and big data analytics are utilized	The book focuses on the use of machine learning for IoT, as well as important methods such as traffic analysis, IoT device recognition, encryption, edge computing architecture, network management, and common IoT applications. In addition, explore the most current developments in machine learning methods, as well as their many applications, difficulties, and outstanding concerns.
Mahdavinejad et al., [111]	In the field of smart cities, machine learning approaches for large data analysis are being used.	Aarhus smart city traffic data was used to demonstrate the use of a modified Support Vector Machine (SVM). Create a taxonomy of machine learning algorithms as well. It goes on to describe how these approaches may be used in big data analytics in the context of smart cities. Finally, the article discusses research difficulties and potential research objectives.
Ge et al., [112]	In a variety of IoT application fields, big data analytics is being used	Discuss, evaluate, and divide the most recent big data analytic research across diverse IoT application fields. It instructs readers on how to select the best appropriate approach for big data analytics in various fields from a wide variety of options. In addition, a comprehensive examination of different big data technologies in these areas is given.
Pourghebleh and Navimipour [113]	Provide a thorough examination of the most recent data aggregation strategies for IoT.	Sort data aggregation approaches into tree, cluster, and centralized categories depending on their underlying topologies. It also looks at the difficulties that these approaches confront. For an appropriate evaluation of these approaches, a discussion of different performance measures such as energy efficiency and latency is also included. A comparison of various approaches is presented, along with their strengths and limitations, as well as ideas for future expansion.

the authors presented a disease prediction system based on real-time electrocardiogram (ECG) data. To begin, the suggested technique uses several ML classifiers such as KNN and bagging tree to evaluate and classify ECG waveforms recorded in real-time from ECG monitoring equipment. Any symptoms of sickness or irregularities in the ECG are then anticipated and sent to the cloud in real-time via a purpose-built IoT network owned by the National Health Services (NHS) of the United Kingdom. According to simulation findings, the suggested scheme's accuracy can reach 99.4 percent. However, additional measures such as time complexity and energy efficiency must be used to assess accuracy and performance. In [116] The authors suggested an IoT architecture with five distinct but interconnected levels. The sensing layer is the initial layer, and it consists of numerous sensing devices that are used to collect data. Sensors, actuators, and a wide range of wearable gadgets are just a few examples of these devices. The transmitting layer, which is comparable to the physical layer in the Open Source Interconnection (OSI) architecture, is the second layer. Its primary job is to design various data transfer communication technologies. For transferring data to the cloud, this layer addresses communication methods such as Wi-Fi, Bluetooth, ZigBee, and Long Term Evolution (LTE). The processing layer is the third layer, and it is responsible for data processing based on pre-defined criteria. Notifications and alerts are created in response to the data processing. Smartphones, microcontrollers, and microprocessors are examples of processing devices. The data is kept in the fourth tier, the storage layer, at the desired place such as clouds and hosted servers. Finally, the fifth layer, also known as the mining layer, turns data into judgments by employing a variety of data mining or machine learning techniques to arrive at a conclusion. Various comments and recommendations are given based on the decision. Some recommendation systems are prested in Table 4.

The authors suggested an IoT framework [117] for predicting whether or not the individual under observation is stressed by monitoring his or her heartbeats. The suggested framework uses a specifically built WiFi-enabled the board to identify pulse waveforms and sends the data to a pre-defined server. Following that, the data collected at various time intervals are combined, and stress prediction is assessed using various machine learning algorithms such as SVM and logistic regression. The suggested framework's accuracy can reach up to 68 percent, according to simulation findings. However, with the use of suitable categorization models, it may be enhanced much further. The authors [119] presented a voice recognition-based smart telehealth monitoring system. Its design objective is to use the K-mean algorithm to identify and forecast the onset of Parkinson's disease. The suggested system is device agnostic and may be used with a wide range of wearable devices. Because the wearable devices have limited

Table 4 Comparative analysis based on differnt parameters

Authors	Findings	Characteristics	Advantages	Disadvantages
Asthana et al., [114]	Recommend the most practical wearable depending on an individual's needs.	Patient's health	Efficiency	Difficult to analyse numirical data
Yao et al., [115]	To conduct a real-time electrocardiogram, a disease prediction system is used.	Real time analysis of Cardiac abnormalities	Better accuracy	real-time monitoring
Moosavi et al., [116]	Five distinct yet interconnected layers make up the IoT architecture.	Sending layer, Processing layer, Sensing layer, Mining layer, Storage layer	Better Accuracy	Complex architecture
Subramaniyaswamy et al., [118]	Recommender system Pro-Trip	Allows users to plan activities before a journey or during a vacation that is already underway.	Accuracy	Climate and food dataset is used to evaluate the Pro-trip.

Table 5 Comparative analysis of precition-based machines learning using differnt parameters

Authors	Findings	Characteristics	Advantanges	Limitations
Khan et al., [117]	Heart rate monitoring with low-cost	By utilizing SVM cordiovascular stress is predicted	Better Accuracy	Privacy
Borthakur et al., [119]	Using speech recognition smart health monitoring is developed	Parkinson	Energy efficient and light weight	Security
Kumar et al., [122]	Based on ROC 3-tier model for heart disease is developed	Cardiovascular	Scalable	Accuracy
Azimi et al., [123]	Based on IBM MAPE-K is developed for disease prediction	Arrhythmia	Bandwidth, Memory	Accuracy

resources, the suggested system uses an edge computing paradigm. Edge computing's goal is to create distributed services while minimizing dependency on centralized infrastructure. A cloud-based IoT system for monitoring different illnesses was presented in [120]. It predicts the severity of various illnesses among students, ranging from mild to severe. It applies the computational science idea to data gathered from pupils via sensors and kept in a repository in order to forecast illness severity. Different categorization methods are also employed to forecast the incidence of such illnesses. The suggested technique is assessed using several performance measures such as specificity, sensitivity, and F-measure. The suggested technique beats existing approaches in terms of accuracy, according to simulation findings. In a Fog-assisted system design, the authors suggested a smart e-Health Gateway at the network's edge [121]. Locally, the gateway may do real-time data processing, mining, and storing. Furthermore, the suggested design has the potential to help us address some of the new and challenging challenges that ubiquitous healthcare systems confront, such as mobility, energy efficiency, scalability, and dependability. High-level elements of our health monitoring system, such as the Early Warning Score (EWS), were shown in a practical demonstration of the proposed prototype. In [122], the authors developed a three-layer architecture for storing huge amounts of sensory data in order to anticipate cardiac disease sooner. The initial layer of the proposed architecture is in charge of data gathering. The second layer deals with the cloud storage of huge amounts of sensory data. Finally, a prediction model for cardiac disorders is built in the third layer. This layer does "Receiver Operating Characteristic Curve (ROC) analysis, which detects possible symptoms before the onset of cardiac disease. For the IoT healthcare industry, the authors suggested a Hierarchical Computing Architecture (HiCH) in [123]. They designed and built an arrhythmia detection system that was comparable to IBM's MAPE-K model REF. The suggested fog computing system includes three distinct yet interconnected levels. The sensor devises layer, edge computing devices layer, and cloud computing layer are the three layers. The first layer, i.e., the sensor devices layer, is in charge of sensing and monitoring the phenomena of interest. Next, the edge computing devices layer is in charge of local decision-making and system administration. Finally, in the cloud layer, intensive training processes are carried out. Table 5 summarizes the prediction-based machine learning approach and its limitations.

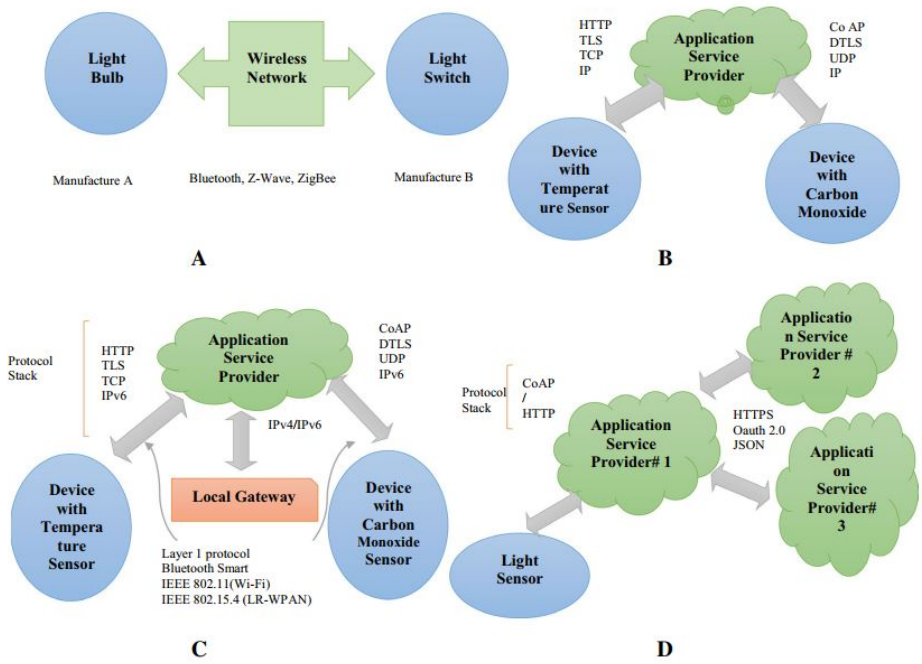

Fig. 5 Internet of Thing Communications Models (a) Device-to-Device Communications Model, (b) Device-to-Cloud Communications model, (c) Device-to-Gateway Model, d Back-End Data-Sharing Model [69]

5 Communicational IoT Models

The Internet of Things is a concept that involves connecting various items to the internet. These items can be used in a variety of ways. It's also crucial to figure out how these gadgets connect with one another. The internet architecture board (IAB) developed a set of rules based on which IoT may implement four communication models, including Device-to-Gateway, Device-to-Device, Device-to-Cloud, and Back-End Data-Sharing, as shown in Fig. 5 [69].

The Device-to-device model indicates a group of interconnected parties who communicate with one another. IP networks are mostly used in these conversations. Various protocols, including ZigBee, Z-Wave, and Bluetooth, might be used to provide a reliable connection in this architecture. In this paradigm, devices can exchange messages to obtain the desired functionality by following a specified protocol [69]. In Device-to-cloud communications model IoT-based devices are linked to the application service provider through the quickest path in this architecture to exchange data. Via this method, objects may create a link between devices and cloud services using TCP/IP or Wi-Fi networks [69]. An application program functions as a communication channel between IoT devices and the cloud in the device to gateway model. In most situations, smartphone applications serve as a gateway for data transmission between items and cloud services. This method is a good way to deal with interoperability difficulties that arise when integrating new smart devices with legacy systems [69]. The back-end data-sharing approach is founded on the concept that authorized users can access the sensed data from IoT devices. Users may collect, export, and interpret information from a centralized network using the back-end-data sharing model, then securely transfer it to another user for further action. An integrated cloud application is recommended by the back-end data-sharing paradigm to promote smart device interoperability in cloud settings [69].

6 Challenges and Future Direction

Interoperability studies in healthcare are still vanishingly rare. Diverse vendors provide various goods, equipment, and procedures in the healthcare area. Typically, they are not obligated to follow any rules. Interoperability difficulties arise as a result of the constant change of protocols and standards. As a result, standardization must take into account a wide variety of subjects such as devices, networking, applications, data, and semantic level. For standardization, consider the applications, data, and semantic levels. There was also a wide range of software and hardware with different communication protocols installed, however, there is no indication of technological compatibility. On the other hand, Semantic interoperability research on IoT in healthcare is still in its early stages. The systematized nomenclature of medicine (SNOMED) and read codes and logical observation identifiers names and codes are two of the most significant standards for health data (LOINC). These interoperability standards were not employed in any of the research on IoT architecture in healthcare that was evaluated.
Furthermore, interoperability is interconnected with technological and semantic interoperability, and all three are

required to obtain considerable benefits from healthcare services. Despite this, the rapid growth of IoT applications makes standardization a difficult task. There was no evidence in the studies examined that addressed these issues in depth. As a result, an in-depth research is required in this area. IoT has been implemented in a variety of applications that assist the healthcare system, including patient monitoring and a smart home system for diabetes patients. The following are some of the major issues that arise in the healthcare system:

– IoT allows for greater flexibility, for example, if a patient requires continuous care, he or she can remain at home rather than in a hospital and be monitored on a frequent basis utilizing IoT technology. By the use of some wearable equipment, such as sensors make the patient body unpleasant.
– The data sent from the sensor to the control device and then to the monitoring center will be affected by noise, lowering the data quality. A better design aids in the transmission of data without compromising its integrity. The use of a noise-reduction method can also aid to improve the data signal.
– The majority of contemporary ECG monitoring methods use a guided signal analysis. This raises the cost, and it may result in a detection mistake. Machine learning may be used to analyze the signal, resulting in increased efficiency and lower costs.
– As the number of sensors and devices increased, the amount of energy required to process them grows, resulting in increased power leakage and energy consumption. Energy consumption may be reduced using an optimization technique.
– In IoT, monitoring a large number of users necessitates more storage and infrastructure, which may be avoided by keeping data in the cloud. The IoT combined with the cloud, on the other hand, adds to the complexity.
– Another significant issue with the IoT is privacy, which is exacerbated by the fact that devices are increasingly prone to assault. Because these devices have limited resources, it is difficult to use encryption methods on them.

7 Conclusion

IoT can effectively monitor patients from remote and provide emergency assistance, which is especially useful for cardiac patients. The primary goal of this study is to examine the different research efforts associated with the Internet of Things-based healthcare system. The majority of previous studies are effective at monitoring patients and transmitting data to the monitoring center. The study comprises an ECG monitoring system that may readily anticipate illness signs using a machine learning approach. Some studies use optimization algorithms to reduce power consumption, and it is important to build a system that uses little power in order to attain high efficiency. Due to the lack of storage capacity required to execute various encryption techniques, privacy is a key problem in the IoT. When combined with IoT, cloud storage aids in the management of huge amounts of data from the system, but the complexity increases. In terms of scalability and dependability, the present IoT system provides efficient patient monitoring. Using a camera, speaker, and sensors, this technology assists in the monitoring of elderly patients. Increased security, adaptability, and power usage can all help to improve IoT. The outcomes of this study will aid government authorities and health policymakers in making strategic decisions about where to invest and deploy IoT technology. The primary potential applications of IoT in the healthcare industry, according to this report, are home healthcare services. Furthermore, the adoption of IoT technology is one of the em techniques for improving public health, self-management of chronic illnesses, and reducing patient readmission to the hospital. In the long run, IoT in health can boost productivity, improve quality of life, and help to alleviate poverty and eliminate health disparities. To overcome all the above mention challenges we are proposing a model for the prediction of health status of an individual by applying machine learning approaches and IoT technologies.

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