IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 14 February 2023, accepted 24 February 2023, date of publication 1 March 2023, date of current version 8 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3250849

RESEARCH ARTICLE

An Integrated Scalable Framework for Cloud and IoT Based Green Healthcare System

MD. MOTAHARUL ISLAM, (Member, IEEE), AND ZAHEED AHMED BHUIYAN
Department of Computer Science and Engineering, United International University, Badda, Dhaka 1212, Bangladesh

Corresponding author: Md. Motaharul Islam (motaharul@cse.uiu.ac.bd)

This work was supported by the Institute of Advanced Research (IAR), United International University (UIU), through the Research Grant Scheme, under Grant UIU/IAR/01/2021/SE/27.

ABSTRACT Recent developments in IoT-enabled cloud computing and interactive applications have made researchers rethink how healthcare services are currently provided. The IoT-cloud-based systems facilitate remote monitoring and support for patients. However, in the existing area, much emphasis has not been given to making the healthcare systems green. So, in this paper, we present an integrated framework for green healthcare and use cutting-edge technology to make an interactive user interface. We have also ensured the system's scalability and performance ratio. This system interface has been designed and developed for patients and doctors, where patients can send their healthcare data using wearable sensors, and doctors can receive those data in real-time. For data identification and analysis, we have adopted Hierarchical Clustering Algorithms. Finally, we have come up with a solution for how to make the interactive healthcare experience better for everyone.

INDEX TERMS Internet of Things, smart healthcare framework, cloud computing, interactive digital healthcare, green healthcare.

I. INTRODUCTION

In recent years, a good number of research and development has been carried out in the field of IoT-Cloud platforms for providing healthcare services in smart cities. Every day, almost 1.3 million individuals relocate to urban areas. By 2040, cities will be home to almost 65% of the world's population. Smart and connected cities are rapidly becoming a platform for innovation. IoT, AI, wearables, sensors, Big Data, and BI all aid in meeting the evolving demands of the healthcare environment [1]. IoT helps medical personnel be more observant and responsive in their correspondence with patients. From the standpoint of smart healthcare, the first thing we can notice is a massive increase in the number of gadgets and intelligent gadgets that can connect to an Internet of Things (IoT) platform [2].

The focus of the research will be on an IoT-based scalable framework for smart healthcare systems that are integrated with cloud-based mobile applications. The utilization of cloud-based services to enhance the cost-efficiency and continuity of care has become increasingly popular among healthcare organizations and providers, particularly in the context of patient-centered medical services and system compatibility. The use of cloud services provides a secure and efficient method for storing and managing health data [3].

In recent years, for a variety of reasons, a large amount of research and technology development has been committed to the IoT platform aimed towards smart city ideas, which are mostly smart healthcare development-oriented [4]. The networked things collect data at regular intervals and use it to do what needs to be done. This creates a smart network that can be used to analyze, organize, and plan for the future. Data received from IoT devices may aid doctors in establishing the appropriate medical method for individual healthcare seekers and attaining the best result [5], [6].

The possibilities for IoT platforms in the healthcare industry appear to be limitless, but by far, the most intriguing areas include Interactive Healthcare, Online Patient Health Mental Monitoring, Digital Medical Data History, Unsuitable for Non-Technical Individuals, and Security & Privacy.

The associate editor coordinating the review of this manuscript and approving it for publication was Tyson Brooks.

There are still some significant and debatable concerns and risks associated with such effective and helpful-oriented areas of IoT-based smart healthcare, such as Inappropriate Activity, Unsuitable for Non-Technical Individuals, and Security & Privacy.

Inappropriate Activity: Since this system allows users to post their issues, there is a concern that users might take advantage of the system's benefits. Even though patients' posts are monitored, there is still a chance of encountering an uncomfortable situation [7].

These concerns have the potential to jeopardize the whole IoT healthcare system. So, it's important to talk about these problems and come up with ways to help users focus on the benefits of IoT healthcare facilities instead of worrying about their risks.

This paper will help anyone understand how important IoT is in mobile cloud-based healthcare applications. The paper will be about an independent mobile application system that healthcare professionals and their patients can use to update regular health conditions for monitoring and even get a prescription from a doctor based on a regular illness. In our country, IoT and cloud-based mobile applications, interactive medical blogging, and patient monitoring have been scarce, making it difficult for physicians and patients to transact medical-related concerns, debate health situations, and gather information [8], [9], [10]. Traditional testing at specialist health facilities was the normal way for tracking blood pressure and sugar level, and heart rate for many years. Professionals in the healthcare industry, including doctors, lab technicians, and others, can access a patient's complete medical history instantly, regardless of their location. With the availability of patient data, data analytics will be able to provide insights and/or projections about a patient's health status [11]. A smart healthcare system may lower on-time treatment costs using real-time data connectivity for IoT smart healthcare services. With a huge growth in the number of Internet-connected devices nowadays, IoT enables medical professionals to be more attentive and responsive to patients. Through our proposed system, Doctors will get daily readings and prescribe medicine and exercise treatments to help patients enhance their quality of life and battle ailments [12], [13].

Further, medical professionals can advertise their services and connect with potential patients through blog posts [14]. The use of this technology will make it easier for a patient to receive follow-up therapy from a doctor because the health reports will be stored. In addition, our proposed system can set up a connection with the hospital to guarantee the presence of doctors and the prompt delivery of relevant clinical data about these patients to the hospital, where they can be admitted to undergo medical testing without having to wait for extended periods of time [15]. They can also monitor themselves on a daily basis, contrary to the popular belief that traditional testing at professional medical centers was the normal way for monitoring patient health for many years [16], [17]. Technology has allowed for the development of a variety of sensors that can detect vital signs, such as a blood pressure monitor, body temperature sensor, electrocardiogram (ECG), and a sensor that measures oxygen saturation (SpO2), making it easier for patients to take their medications and keep track of their progress on a regular basis. Daily readings are transmitted to doctors, who will propose medicine and exercise methods to help them enhance their quality of life and overcome such ailments [18].

This work seeks to reduce the potential for human error in clinical documentation through the use of an Internet of Things-based smart platform, with the ultimate goal of providing better care to patients. Managing patients over long distances and over extended periods of time may be made easier if their medical records are available electronically.

Recent years have seen a surge of interest in "green computing," which has become one of the most active research areas. Systems for computing and communications rely heavily on the system and software architectures that play a significant role in Green Computing [19].

There has been a rise in the prevalence of smart devices due to the widespread adoption of IoT technology in recent years. By 2023, the Internet of Things (IoT)-connected devices are expected to have surpassed 40 billion. That means there will be a larger need for power. That's not all; it'll also spur further carbon emissions. The idea of green computing has been introduced and disseminated to address the above difficult and critical environmental challenges. Murugesan and Gangadharan [20] definitions of "green computing" or "green IT" refers to systems that are both environmentally conscious and efficient. Information technology (IT) eco-efficiency refers to the research and practice of designing, manufacturing, utilizing, and disposing of IT hardware with as little environmental impact as possible [21].

Sensors and actuators are the two primary components of smart objects. Sensors can be found in everyday objects, from surveillance cameras to healthcare devices and environmental monitors. Electronic components such as microcontrollers, central processing units, graphical processing units, transceivers, batteries, memory, and protocols are built into these sensors and actuators [22].

Regarding the hardware side of green healthcare systems, having a sleeping state in the sensors means less energy is consumed when the sensors are not actively collecting data. Most up-to-date microcontrollers provide both a shallow sleep model and a deep sleep model for when they're not actively being used [23]. All of the experimental smart devices can be put into a sleep state. While there is some energy loss due to the actual devices that make up the Internet of Things, this is far outweighed by the energy required for transmission. Selective Connectedness [24], Data Compression [25], and several Low-power needed Communication Protocols for IoT are just a few methods for achieving green network communication and hence the goal of green and energy-efficient IoT. In particular, we have emphasized the Bluetooth Low Energy (BLE) protocol for this work.

The major contributions of this paper are summarized below:

- An integrated and scalable framework for IoT and cloud-based platforms have been proposed for individualized healthcare service and to monitor patients' well-being.
- We have implemented an IoT and cloud-based mobile application for patient monitoring and interaction to collaborate with all the doctors, patients, and healthcare centers all in one platform.
- Several techniques have been used during the implementation phase of the proposed system. The goal of using numerous health monitoring sensors is to verify each sensor is functioning with our cloud-based mobile application.
- We have analyzed the 'Green' attribute of the proposed system in terms of evaluating the energy efficiency supported by experimental data. We have also proposed some further enhancements to make the system greener by using energy-efficient communication protocols (Bluetooth Low Energy version 5 or higher)
- We have addressed the data availability issue faced by the research community and have depicted a few scenarios which show the main obstacle for healthcare research, especially in developing countries.

The article has been organized as follows. Section II introduces the literature reviews. Section III describes the architecture of our proposed system. Section IV shows the implementation. Section V includes simulation, optimization techniques, results, and comparative performance analysis, which especially discusses the green attribute of our proposed system. Section VI describes the system's scalability. Section VII mentions the strengths and limitations of the proposed system. Finally, Section VIII mentions some future research prospects, which is followed by the conclusion in Section IX.

II. LITERATURE REVIEWS

The research conducted by Gatouillat et al. [26] examined the topic of IoMT-based systems and IoMT devices from multiple angles. They provided an in-depth evaluation of recent works that leverage formal methods established by the cyber-physical systems (CPS) community to improve the Internet of Medical Things (IoMT). They showed how the CPS strategy improves not just system resilience, security, and dependability but also verification and validation. CPS is a well-known design approach for creating, building, testing, and deploying such systems.

Yang et al. [16] presented a new perspective on the homecare robotic systems that depended upon cyber-physical systems (CPS-HRS) that emphasized closed loops. Evidence-based deployment of CPS-HRS enabling technologies has been looked at, which shows how well each CPS-HRS method works. This research shows that the CPS-HRS presented here have the potential as useful tools for home care services; nevertheless, they need to be expanded upon and enhanced.

In order to forecast when an elderly person may fall, Pinheiro et al. [27] recommended using a mobile network robot equipped with mapping and positioning capabilities in an indoor context. It uses sensor fusion, simultaneous localization and mapping (SLAM), and wall-following to see and map its surroundings. Breadth-First Search, DFS, and Wall-Following were the algorithms investigated and compared.

Bhuiyan et al. [28] developed an interactive system for providing effective and efficient treatment. An extensive medical profile is provided through a unique healthcare system that maintains vast volumes of patient data. They created a system to collect and analyze unstructured data. In addition to medical data, it may also deal with a patient's emotional and genetic data. They collected medical data probabilistically. This data warehouse stores data and connects to an HPC or cloud server. Finally, medical diagnosis is performed by a remote server. They looked at the differences and similarities between ANNs, Naive Bayes, C5.0, SVM, and Random Forest.

Richards and Caldwell [12] proposed eADVICE, an interactive website. Chronic health problems that are not life-threatening but affect the quality of life of a patient or their family put a strain on specialists (doctors, etc.) and make the treatment take longer. A virtual expert for patients could help solve this issue. On the interactive website, we can save individualized healing recommendations and personal information about the patient.

Besher et al. [29] addressed security problems from the start, preventing third-party data spying. In the past few years, the Internet of Things (IoT) has become a common and useful way to keep information safe. Things like mobile phones, electrical gadgets, wearable devices, and so on are connected via the Internet. As medical data is sensitive and confidential, and security is crucial in the IoT network, they suggested encrypted security for IoT sensor devices. It prevents data from being decrypted before reaching the cloud. Before sending patient health data packets, this system uses a method of cryptography that is based on sensor devices. They talked about the benefits of IoT for healthcare data transfer to help with remote medical treatment, as well as the risks of sending data without security, especially between IoT sensor devices and network routers.

In this research, Santos et al. [30] proposed using density-distance-centrality (DDC) to identify potential outlier prescriptions. Using data on 563,000 medications, they compared the suggested solution to other cutting-edge ways to find outliers. Compared to what was done before, this method is more accurate at finding overdoses and underdoses in prescriptions. Moreover, their algorithm's majority of false positives could be attributable to pharmacological mistakes. Telehealth services give remote care to the elderly and medically challenged. In order to work right, telehealth networks must meet many structural requirements, such as security. The inclusion of patient papers in electronic health records has greatly enhanced patient care. In reality, having access to this data will help doctors avoid making mistakes that could be fatal since they don't know of any research on how to automatically find prescriptions with a dose or frequency that isn't typical.

Márquez et al. [31] developed a systematic mapping study (SMS) to identify, coordinate, and classify security concerns in Telehealth systems. They selected and listed over 1,000 primary studies. They are (i) detecting assaults, (ii) avoiding or mitigating attacks, and (iii) responding to attacks. According to the SMS results, software architecture, requirements, and templates are crucial to establishing stable Telehealth systems.

Zhu et al. [4] used a home-based cardiac rehabilitation (CR) exercise program to look at the relationship between the patient and the healthcare provider in the context of heart management. The concept incorporates a wearable device, a portable application, and a stationary medical facility. The standard CR activities that can be done at home were added, and their usefulness was discussed. In addition, they validated that the proposed approach will be a useful CR fitness tool for the electronic transmission of CR exercise prescriptions and activity records between a patient and a healthcare professional.

IoT common standards are being actively studied and adopted, and Bhuiyan et al. [2] laid out in detail all of the main application, service delivery, and infrastructure protocols. The security of the Internet of Things (IoT) healthcare system was also investigated. Security for the Internet of Things (IoT) systems was a topic of conversation. To address the existing security flaws in the Internet of Things, a Blockchain-based solution was also described. They then went on to discuss how IoT helps the healthcare industry by talking about the applications and services it makes possible. The investigation we conducted also found this to be a possible advantage of the Internet of Things.

The Internet of Things (IoT) encompasses a vast network of diverse devices that afford innovative applications and services. However, device heterogeneity and lack of standardization present significant hurdles in the IoT domain. Ali et al. [32], in their research article, endeavor to furnish a thorough examination of the enabling technologies and standards that constitute the IoT technology stack, including the implementation of a layered architecture, the part played by middleware platforms in IoT application development and integration, and the interfacing between Fog/Edge Networks and the IoT technology stack. The authors address the open challenges in each aspect and proffer comprehensive steps toward optimizing the IoT stack. The primary objective of this study is to provide an in-depth analysis of the IoT technology, middleware, and networks that are imperative to the development of future-proof applications.

The rapid growth of the Internet and the popularity of the Internet of Things (IoT) have necessitated a comprehensive understanding of IoT technology and its many uses. IoT technology can improve daily living and healthcare, but its complexity and lack of standardization may prevent its wider use. Islam et al. [33] have explored IoT technologies and healthcare applications thoroughly in their research. This research summarizes the most prevalent designs, protocols, and hardware and software platforms for IoT devices. The authors reviewed IoT-based healthcare applications and summarized current knowledge. They identified gaps and suggested future research. This study also intends to help researchers and practitioners comprehend IoT technology and develop creative and practical healthcare solutions. The study summarizes current information and suggests further research to develop IoT technology and its healthcare applications.

Patient care and quality of life can both be enhanced by implementing Internet of Things (IoT)-based healthcare monitoring systems, which are quickly gaining in popularity. However, there are problems with confidentiality, privacy, and QoS that need fixing. Abdulmalek et al. [34] have reviewed the current state of healthcare monitoring systems that utilize the Internet of Things. To compare the efficiency, efficacy, data protection, privacy, security, and monitoring of various systems, a literature analysis was conducted. The authors not only outlined the constraints and outstanding concerns related to healthcare security, privacy, and quality of service, but they also gave a classification of healthcare monitoring sensors. Finally, future perspectives for technology developments and recommendations for IoT healthcare applications were presented.

The increasing number of IoT devices causes a dramatic increase in the carbon footprint of IoT networks, which is already a major problem due to the devices' lengthy expected runtimes between battery changes. Benhamaid et al. [35] have compiled an extensive and up-to-date survey of methods for managing energy consumption in IoT networks. In this paper, we discuss the issues surrounding energy consumption in IoT networks and provide a thorough review of current energy management solutions for the IoT ecosystem. Here we provide both the lesser-known and more well-known energy management strategies for the Internet of Things, with an eye on the most up-to-date proposed solutions for each. The authors also provided recommendations on how to make use of the methodologies presented in the survey to meet the QoS needs of IoT applications, as well as new trends and research views that can be used for energy conservation in IoT networks.

The proposed system encompasses the key techniques necessary for the application, including algorithms designed for efficient performance, monitoring systems integrated with IoT technology, and a secure cloud server to store data. The utilization of a cloud service in healthcare has become increasingly popular due to its ability to securely store and manage health data while also reducing costs and facilitating inter-system compatibility. In this regard, the system aims to provide remote patient monitoring through the use of smart body sensors and precise health tests. In the event of a detected issue, IoT devices can trigger notifications to healthcare providers. The proposed system also incorporates clustering techniques for the effective utilization of classified data. The literature review is summarized in Table 1, and a comparison between the proposed system and other related works can be found in Table 2.

A. GAP ANALYSIS OF ANALOGOUS WORKS

Following a study of the literature, the most important characteristics and uses of cloud and Internet of Things (IoT) healthcare systems were identified and discussed. The Internet of Things (IoT), cloud computing, and interactive applications are all important components of smart healthcare in smart cities. IoT sensors may be used to monitor health data remotely, and cloud-based application systems can be utilized to store data safely and securely so that it can be used effectively. This study focused on the development of new and innovative strategies for Internet of Things (IoT) healthcare systems. The main gap between this research and other IoT-based Smart healthcare is a sustainable framework. Through the literature reviews, we acknowledged that there is some research conducted by Conceptual Frameworks, and we found those frameworks have some implementation inequity. But we got some ideas from those conceptual frames.

In Figure 1, we have shown the methodology for our proposed system.

III. ARCHITECTURE FOR OUR PROPOSED SYSTEM

For our system, we have proposed a three-layered architecture, where the first layer is an IoT-based data collection layer, and the second layer is a sophisticated cloud system that enables massive data analysis from individual patients and hospitals for potential disease forecast and pattern discovery. Finally, mobile application technology will improve real-time data exchange and treatment efficiency by analyzing data using interactive patient monitoring ways. To illustrate our three layers all in one detailed view and their ways of interconnection between the three layers, Figure 3 presents how our proposed architecture for IoT and a cloud-based mobile platform makes the interaction between patients and doctors more efficient and effective [28].

From the sensing layer, the system collects biomedical data by using healthcare sensors presented in Figure 2. It includes different types of sensors such as temperature, blood pressure, SpO2, ECG, etc. These sensors are wearable and can be used to monitor different vital signs of the patients. The sensing devices send data to the NodeMCU ESP8266 microcontroller. The ESP8266 is a low-cost system-on-a-chip (SoC). NodeMCU is an open-source software and hardware development platform based on the ESP8266. Medical-based IoT solutions are crucial to offering advanced results when it comes to collecting healthcare data [36].

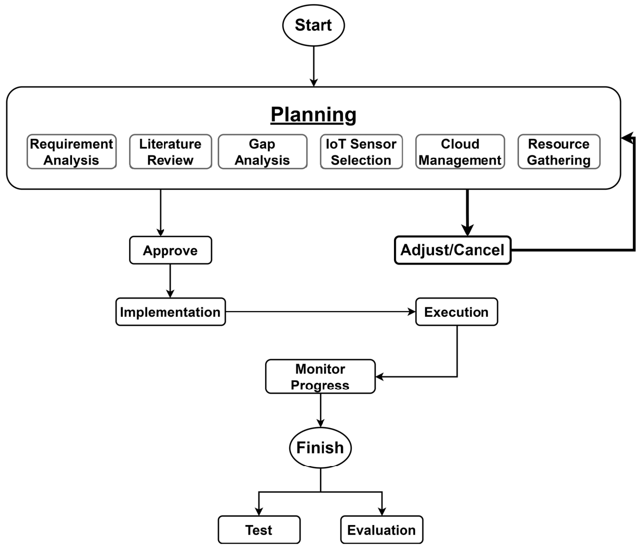

FIGURE 1. Methodology of proposed system.

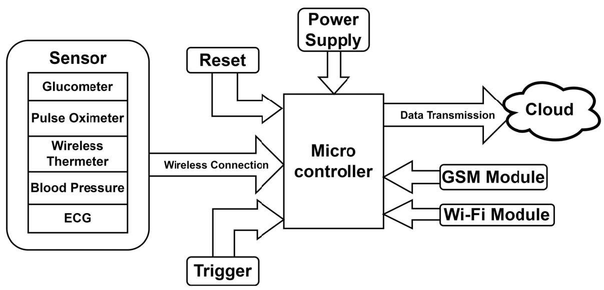

FIGURE 2. Sensors setup and components connection block diagram.

Clustering algorithms are a crucial component of an IoT-Cloud-based healthcare system as they facilitate the analysis and organization of data generated by a large number of connected devices. The ability to categorize and group similar data points enables healthcare providers to identify patterns and correlations in the data that would otherwise be difficult to uncover. By utilizing clustering algorithms, the system can perform data-driven predictive modeling, supporting informed decision-making processes related to patient care. Furthermore, clustering algorithms can also be used to optimize resource allocation by grouping patients based on their health conditions and needs. Additionally, clustering algorithms can reduce the amount of data that needs to be stored and transmitted, improving system efficiency and reducing costs. The results of clustering algorithms can also be visualized to provide a clear and intuitive understanding of the data, making it easier for healthcare providers to understand and interpret the information. So, clustering algorithms are an essential aspect of an IoT-Cloud-based healthcare system as they support data analysis, decision-making, and resource allocation, ultimately leading to improved healthcare delivery.

Figure 4 shows the cloud layer, which can be used in a healthcare setting to access data stored in a continuous-time domain and analyze it using hierarchical clustering

TABLE 1. Summary of literature review.

Author and Year	Study Description	Limitations	Method Adopted
Bhuiyan et al. (2021) [2]	Evaluates the latest IoT-based healthcare technologies, assess their advancements and categorize current IoT-based healthcare networks to reflect all prospective networks.	Structural risks and the need for personnel vigilance.	Internet protocols, cloud storage, and domain-specific applications are used to move data between wearable and intelligent wireless technologies.
Gatouillat, et al. (2020) [26]	A detailed analysis of recent contributions aimed at strengthening the IoMT by utilizing formal approaches developed by the CPS.	Makes no reference to the process of addressing data storage methods.	CPS approach technique increases system verification and validation as well as durability, security, and dependability.
Yang et al. (2020) [16]	Update the understanding of the CPS-HRS by revealing its inner workings and the unique benefits that closed loops provide.	Reduce scalability and flexibility, high-level processing, a lack of data confidentiality, technical problems, and privacy.	Research, solutions, and groundbreaking initiatives in areas such as AI, sensing fundamentals and machine learning, cloud computing, and connectivity, motion capture & mapping.
Pinheiro et al. (2020) [27]	Design, construct and test an IoT mobile network robot with mapping and location capabilities in an interior environment.	The approach for the central and environmental models of patient care is lacking.	Incorporate effective communication between the android app and IoT and alert users in urgent situations.
Bhuiyan et al. (2019) [28]	Maintain a large volume of patient information and provide an in-depth analysis of their health. A data warehouse is added to an HPC and a cloud server so that the two can exchange data.	Data quality, cyber security risk, compliance cost.	A probabilistic data collection technique using a medical data warehouse.
Besher et al. (2020) [29]	The suggested technique encrypts patient health data packets before transmission to the sensor device.	Costly; Lack of data modification private keys.	End-to-end secure data transmission via cloud storage by the simple data encryption algorithm.
Richards et al. (2018) [12]	Patients consultation using virtual expert through an interactive system called eADVICE contains the patient's medical history and therapy suggestions.	eADVICE's website is missing many elements, including medical blogging and physician review through a rating system.	Smart face-to-face conversation agent, which users may employ in suggested systems' chatbots.
Zhu et al. (2019) [4]	The dynamics between patients and healthcare providers during cardiac rehabilitation (CR) programs that are delivered remotely.	Needs for the CR system to detect or deal with unexpected emergencies.	Wearable devices transmit data to cloud-based software while the patient is at home.
Márquez et al. (2020) [31]	A telehealth system allows the physically challenged to receive remote care.	Requires a lot of storage; Vulnerable to malicious security attacks.	Needed to create smart healthcare systems, which is their fundamental purpose in addition to patient monitoring.
Santos et al. (2018) [30]	The centrality index number is used to classify prescriptions into two groups; this will be used to decide whether an excessive dose of medication is given.	Before the dosage is given, it must be confirmed that the disease is correct.	Getting multiple doctors' opinions before issuing a final prescription, reducing the margin of error.
Ali et. al. (2022) [32]	A complete understanding of the supporting technologies and standards that make up the IoT technology stack, including a layered architecture approach and middleware platforms' role in IoT.	Only provides an idea of the current state of IoT technology but doesn't provide original research findings.	A thorough review and analysis of the current research and open challenges.
Islam et. al. (2022) [33]	This study highlights the most common IoT device designs, protocols, hardware, and software platforms.	Lacks attention to privacy, security, and ethics in favor of a focus on the features, structures, protocols, and innovative uses of IoT in healthcare.	A systematic review of IoT technologies in the healthcare domain.
Abdulmalek et. al. (2022) [34]	This research takes a look at how IoT-based healthcare monitoring systems are performing at the moment.	Doesn't discuss the scalability and sustainability of IoT-based healthcare systems	Explores recent studies of IoT-based healthcare-monitoring systems through a systematic review
Benhamaid et. al. (2022) [35]	A comprehensive and up-to-date survey on recent energy management techniques in IoT networks is conducted	Doesn't discuss the practical implementation and deployment of the solutions and techniques.	A comprehensive survey on recent energy management techniques in IoT networks.

algorithms (HCA) [37], [38]. The proposed framework can be deployed using large-scale public cloud infrastructure or on-premise private cloud-like infrastructure, making it scalable on demand.

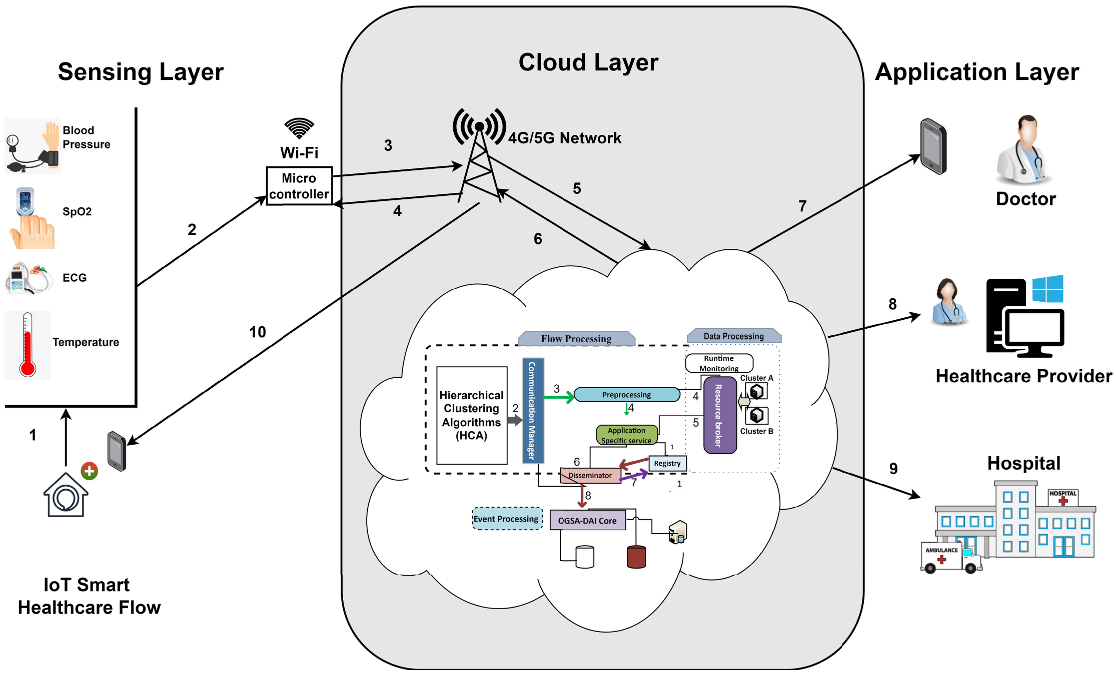

FIGURE 3. A Framework for cloud and IoT-based interactive healthcare.

TABLE 2. Comparison between contemporary research.

Reference	Hierchical Clustering	Cloud Computing	Interactive System	Smart City	Framework Scalability
Elhoseny et al.	✗	✓	✗	✗	✗
Bhuiyan et al. [28]	✗	✓	✓	✗	✗
Yang et al. [16]	✗	✓	✓	✗	✗
Pinheiro et al. [27]	✗	✗	✗	✗	✗
Gatouillat et al. [26]	✗	✓	✓	✗	✗
Bhuiyan et al. bhuiyan2021internet	✗	✓	✗	✗	✗
Besher et al. [29]	✗	✓	✗	✗	✗
Muhammed et al. [10]	✗	✓	✓	✗	✗
Rahman et al.	✗	✓	✓	✗	✗
Proposed Work	✓	✓	✓	✓	✓

HCA works by clustering collected data into a tree-like structure. Algorithm 1 illustrates its pseudo code. The original set of data from IoT sensors is used as the input space; Data Acquisition Network (DAN) collects the uncategorized and unorganized health data, which results in a large number of unique features that must be considered as a hierarchical clustering algorithm being used, which does not require the number of clusters to be specified beforehand. Clustering data hierarchically permits the discovery of groupings of data while acquiring information about the relationships between those groups of data. As a result, these algorithms provide more information than flat clustering methods. Although additional hierarchical clustering algorithms (HCAs) exist, we shall be primarily concerned with the AGNES (agglomerative nesting) algorithm, which sequentially clusters data based on the closest distance measure of all pairwise distances between points [39]. Again, the distance between data points is computed, after which the distances are considered, and sub-clusters are generated. These are then sorted and assigned unique classified identifiers depending on individuals [40].

The clustering scenario has a set of objects that coincide with the set of users and the set of feasible places. Selecting an object as a representative object (or a median) of a cluster is analogous to deciding where to put a service center. At last, it is possible to ignore user needs by substituting an object's distance for the representative object of the cluster to which it belongs for the distance traveled by a user. These notations and definitions will be used to formally describe the clustering model:

- We will refer to the collection of n items as X from here on out: $X = \{1, 2, 3, \ldots, n\}$
- Each object is characterized by the values of variables, an object is denoted by an index $i(i = 1, 2, \ldots, m)$ and a variable by an index $j(j = 1, 2, \ldots, n)$
- The measurement minimum value of variable j for object i is called $min_d[(i), (j)]$
- The distance between two objects i and k is called $d[(k), (r, s)]$.

The mathematical model can then be written as:

$$f(p) = Min \sum_{i=1}^{m} \sum_{k=1}^{m} d_{ik} x_{ik} \tag{1}$$

Algorithm 1 Hierarchical Clustering Algorithm

Input: Dataset D, Distance metric d
Output: Cluster hierarchy represented as a dendrogram
distance_matrix[i][j] = $d(D[i], D[j])$ **for** $i \neq j$, distance_matrix[i][i] = infinity
for i in $range(len(D))$:
  cluster_list[i] = $D[i]$
  min_distance = infinity
  for i in $range(len(cluster\_list))$:
    for j in $range(i+1, len(cluster\_list))$:
      avg_distance = average distance between all data points in cluster_list[i] and cluster_list[j]
      if avg_distance < min_distance:
        min_distance = avg_distance
        closest_cluster1 = i
        closest_cluster2 = j
    new_cluster = union of cluster_list[closest_cluster1] and cluster_list[closest_cluster2]
  cluster_list.remove(cluster_list[closest_cluster2])
  cluster_list.remove(cluster_list[closest_cluster1])
  cluster_list.append(new_cluster)

subject to:

$$\sum_{i=1}^{m} x_{ik} = 1 \tag{2}$$

$$x_{ik} \leq y_i \tag{3}$$

$$\sum_{i=1}^{m} y_i = \rho \tag{4}$$

$$y_i, x_{ik} \in \{0, 1\} \tag{5}$$

$$\sum_{i=1}^{m} d_{ik} x_{ik} \tag{6}$$

$$\sum_{k=1}^{m} \sum_{i=1}^{m} d_{ik} x_{ik} \tag{7}$$

The hierarchical clustering algorithm is more efficient than the Hadoop MapReduce algorithm which is another data processing algorithm useful to process huge amounts of data in parallel, reliably, and efficiently in cluster environments [41]. Input tasks are broken down into more manageable chunks, allowing for parallel processing. The MapReduce methodology relies on physically moving the system that does the processing to the location of the data being manipulated [42]. In order to create a structured distributed database from raw unstructured and semi-structured data, the MapReduce algorithm relies on two core classes: the mapper class and the reducer class. The data record is stored as input in the mapper class, and each key is given a value from the data record. The records are then shuffled, sorted, and sent to the reducer class using the Map function. The reducer class takes the instruction from the algorithm and combines the same keyed data to produce the HDFS-stored structured database. Let's say we want to use the MapReduce framework, and

Algorithm 2 Pseudo Code for Map 1 Function

Procedure: Mapper. (Key, value = Ti)
  If $Ti \leq Bo$ **Then**
    For each item a_i in T_i **do**
      $(< key = a_i, value = 1 >)$
    end for
  end if
end
Output: $F_1 - list$\{set of Frequent one Itemset list in descending order from sensor data\}

Algorithm 3 Pseudocode for Reduce1 Function

Procedure: Reducer (key = a_i, value = $S(a_i)$)
  count = 0
  For each 1 in S_{a_i} **do**
    count += 1
  end for
  If $(count \geq M(S)$ **Then**)
    call function Sort(F_1)
Output $(< key = a_i, value = count >)$

HPC supplies a cluster of servers represented by a set $S = \{S_1, S_2 \ldots\ldots S_\theta\}$. In the MapReduce framework, the server group is responsible for carrying out the parallel processing in the application layer. There is a lot of data that has to be analyzed. Each server gets a copy of the input data set and divides it up into numerous parts for parallel processing. Assume k is the number of divisions or chunks used to divide the input data collection. Because of this, the size of each partition will be C,

$$C = |\frac{\beta}{K}| \tag{8}$$

For this reason, C data quantities are split up across all the partition blocks on all the servers, analyzed, and then given to the group of Mapper classes M where $M = \{M_1, M_2 \ldots\ldots\ldots M_m\}$ also m is the total number of map functions. All the key-value pairs in the input records are then tokenized by map() before being sent on to the reducer class. Let r denote the reducing function's position in a set of reducers of class R where $R = \{R_1, R_2 \ldots\ldots R_r\}$ and $R \leq M$. In order to transfer the mapped data to the data warehouse along with all of the associated information and log files, reducer() receives the data, shuffles and sorts it, and then returns a structured database.

Information, such as medical records, pictures, health records, etc., is transferred to the Flow Processing phase via the Communication Manager for an initial examination before moving on to the Data Processing phase. Flow Processing's "Pre-Processing" section transforms raw data into an Application Oriented Service (AOS). The data are then dispersed via Open Grid Service Architecture Data Access and Integration (OGSA-DAI) Core [43], [44] to many storage distributions, after which the Disseminator portion trades them with AOS. This data is then transferred to the Data Processing

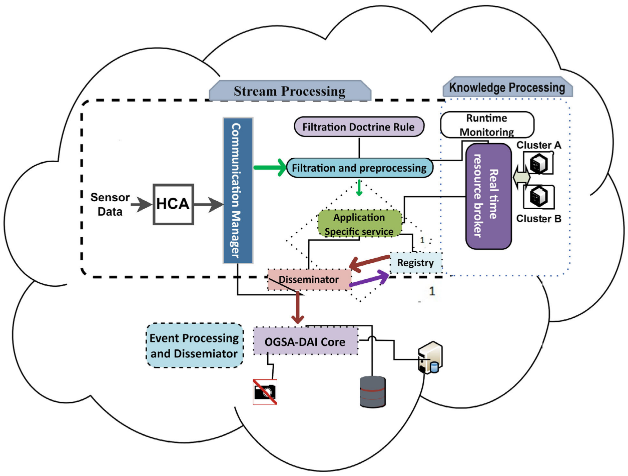

FIGURE 4. Cloud management.

phase, where it is compiled and sent to the Resource Broker, where it is split into two clusters: cluster A (for patients whose health is improving) and cluster B (for patients whose health is deteriorating). These clusters are useful for creating a structured group of log files and metadata that can be used for fast searching and analysis.

In Figure 3, we see the application layer, which is a web-based service. The cloud's rapid processing speeds make it possible to use it for everything from making a diagnosis to making predictions about the spread of disease in the future and activating additional services based on those forecasts. In order to use the system, users must first register an account on a cloud server and supply the relevant information. This is the foundation of the Application layer. This is critical for connecting users to their relatives, which is necessary for the system to obtain genetic data from all users. This interactive app can also be used to compare different e-prescriptions using smart attestation to find similar instructions from various doctors, as well as upload several details about the patient's health condition and receive feedback from doctors by bridging the vocabulary gap between doctors and patients. As a result, the patient doesn't have to waste time and money traveling to the clinic or emergency room to get the results of any necessary tests; instead, the hospital receives the information immediately.

IV. IMPLEMENTATION

To collect healthcare data that can be instrumental in offering complex outcomes, we apply our three-layer design with a primary focus on the initial data-collection IoT layer. We conduct our tests with a concentration on traditional, widespread forms of sense. Our proposed IoT framework centers on both patient-specific and hospital-wide data sets. As a result, we dig deeper into the diagnostic process by focusing on the primary layer, which is the patient's interface with a smart device [28]. Numerous Internet of Things (IoT) gadgets, motion sensors, and wearable devices, such as smartphones and smartwatches, are currently in development to monitor a patient's vital signs, body temperature, respiration rate, electrocardiogram (ECG), back pain, and other symptoms. A user's biological state can be calculated by such a gadget and sent to any server. Information about the patient's health will be retrieved from the hospital's network. Electronic prescriptions are used to obtain a medical note. Moreover, the electronic health record (EHR) offers a great deal more information regarding a specific patient. The hospital and medical practice also provide valuable information. These medical center records are obtained from the hospital's computer system. The patients and medical facilities that care for them are the key sources of information for us. A patient creates data when they interact with a healthcare provider, either by making regular hospital visits or by using a wearable gadget. Medical records, medical billing data, and the findings of scientific studies and diagnostic tests all contribute to a hospital's data pool. Our suggested approach uses patient-generated data analysis to improve medical outcomes and facilitate productive doctor-patient dialogue. Patients and hospitals provide the bulk of our data, with patients generating their own data via a wearable gadget. The minimum output from a single patient is:

$$\sigma_t = \sum_{u=1}^{u}(V_u + V_{\rho u}) + r + s \tag{9}$$

amount of data in an IoT device.

Let's assume a patient's IoT-connected wearable device generates r data points. Since a person's biological factors evolve with time, we use the most up-to-date information available from the connected device. A patient's IoT usage frequency is denoted by u over the period t. Some medical tests, health data, and patient information are received via IoT devices V, and some data can be generated by the patient via the doctor's e-prescription generated when the patient contacts the doctor virtually. When we consider the intersection between medical professionals and Internet of Things gadgets, we get:

$$Vk_{ij} = Vk_{1j} \cup Vk_{2j} \cup Vk_{3j} \ldots\ldots \tag{10}$$

and:

$$V_{\rho i} = V_{\rho 1} \cup V_{\rho 2} \cup V_{\rho 3} \ldots\ldots\ldots \tag{11}$$

Since a patient's vital signs rarely deviate from their usual rate of fluctuation, we will assume that every sequence of health data changes is constant s.

Access to data is made possible in the second layer by a cloud-based healthcare environment hosted by Amazon Web Services (AWS). This is advantageous because AWS is adaptable, letting users choose their preferred operating system, programming language, web application platform, database, and other services. Additionally, AWS is inexpensive, scalable, reliable, secure, and capable of high performance in a continuous time domain and deep analysis by means of high-performance computing (HPC). In healthcare, the HPC gathers and organizes raw data for processing, allowing researchers to sift through it for the most relevant insights. Hospitals are the primary data generators in conventional healthcare systems. We take into account both hospitals and individual patients as important contributors to the proposed interactive healthcare setting. Think of a patient-centered, online healthcare system where patients are in set:

$$P = \{P_1, P_2, \ldots\ldots.\} \tag{12}$$

where $m = |P|$ denotes the total number of patients. Some people see a doctor but only require an appointment; their condition does not necessitate a hospital stay. Many biosensor gadgets are constantly monitoring those patients. Many people who see a doctor have to stay overnight because of their condition. In set P, we include all patients. When it comes to biological big data, hospitals are where it all starts. A set of hospitals with size k is considered:

$$H = \{H_1, H_2 \ldots ..\} \tag{13}$$

where $k = |H|$.

Each hospital in a set is believed to be linked to n departments:

$$D\rho = \{D_{\rho 1}, D_{\rho 2} \ldots\ldots.\} \tag{14}$$

For example, $n = |Drho|$ indicates that the unknown variable is the rho value. Take, for example, a hospital department staffed by 'l' doctors. We think of the set Dk_ij to be such that:

$$j = \{1, 2, 3 \ldots\ldots.\} \tag{15}$$

and $l = |j|$. If for all $i \in D$ rho and for all $k \in H$, then the relationship depicts the kth hospital within the ith department. As an illustration, "D5 14" would indicate the fourteenth physician working in the first department of the fifth hospital. All of the huge data will be analyzed on a shared HPC server, and the corresponding patient and doctor pair will be:

$$Pk_{ij} = Pk_{1j} \cup Pk_{2j} \cup Pk_{3j} \ldots\ldots \tag{16}$$

and:

$$Dk_{ij} = Dk_{1j} \cup Dk_{2j} \cup Dk_{3j} \ldots\ldots \tag{17}$$

respectively.

The proposed model is based on the assumption that measurements are made in a continuous time domain. For the primary prediction analysis, the HPC will perform a linear regression with the Y-axis representing the data and the X-axis representing time. The data is then evaluated and uploaded to a cloud server. With HPC, the medical records are uploaded to the cloud at regular intervals of time, say every t seconds, where t represents the rate of change in the healthcare records. Assuming that you are a data center:

$$D_C = \{D_{C1}, D_{C2} \ldots ..\} \tag{18}$$

where $\mu = |DC|$ relate to data warehouses,

$$WH = \{WH_1, WH_2 \ldots\ldots\} \tag{19}$$

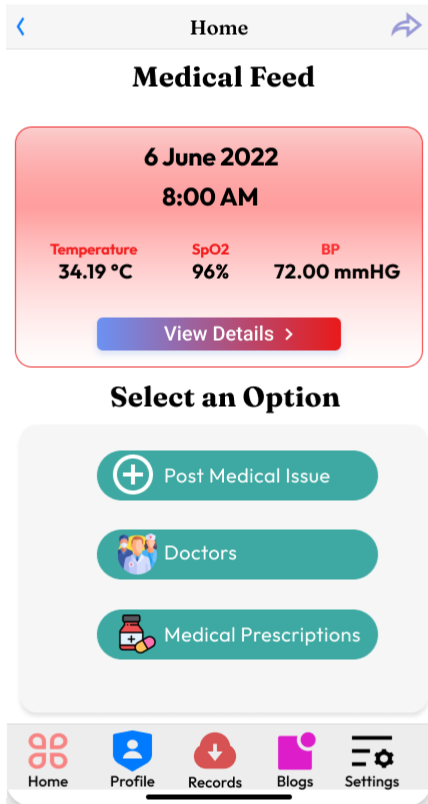

FIGURE 5. Flutter interface.

where $q = |WH|$. The future prediction analysis will be done on the cloud server.

Finally, we implement the application layer using a Flutter-specific solution tailored to the framework's structure and inner workings. The front-end and back-end of the mobile application will be written using the Flutter framework. As for storing data, an AWS Cloud Platform database will be used. In Figure 5, we have the interface of the patient homepage of the app. It is designed conveniently so that the patient can easily view their latest medical readings, and by swiping, they can navigate to past readings. The medical sensor readings will be fetched live from the AWS Cloud database at blazing-fast speed. The advantages of designing our app with flutter include the following:

- Same UI in all platforms.
- Works on both Android and iOS.
- Custom UI Designs

Advantages of integrating AWS Cloud Platform to our app include:

- Medical Data Security
- Fast

V. PERFORMANCE EVALUATION

A. USER EXPERIENCE

Table 3 shows the user experience according to different features.

TABLE 3. User experience table.

Features	User Experience	Comments
Simple Navigation	Excellent	Easy navigation options available from page to page of app.
Health tracking	Excellent	Patients and doctors medical data is updated instantly.
Smooth Registration	Excellent	Easy and quick registration procedure from the app available.
Content Minimization	Good	The patient and doctor are not flooded with information by the app.
Security	Good	AWS cloud platform provides secure data protection.
IoT Integration	Good	IoT hardware is cleverly integrated with the Cloud.
Patient Friendly	Good	App provides special and aiding features for patients.
Doctor Friendly	Good	Interface and fields and forms are specially designed for doctors.

B. TEMPERATURE

There are many types of temperature sensors and out of these some are regularly utilized such as NTC thermistors, Resistance Temperature Detectors (RTDs), thermocouples, and thermopiles. These are dependable, simple to install, efficient, and responsive to human movement. RTD sensors depend on the relationship between the metals and temperature to be able to operate because the device's resistance is inversely proportional to temperature. DHT11 sensor is used for measuring humidity and temperature. This sensor is widely used because of its basic design, affordable pricing, digital technology, and being a capacitive sensor. This sensor can be used with cloud-based Internet of Things platforms and it does not require analog pins. Figure 6 compares the temperature readings from the DHT11 (IoT) sensor and the conventional sensor. We have taken 12 readings on different occasions and plotted the graph against the temperature readings in degrees Celsius. During our experiment, we have been able to obtain a 95.5% accuracy rate. Assuming the traditional mercury-based temperature sensor gives out accurate temperature readings, we have compared the data gathered from DHT11 with the traditional sensor data to measure the accuracy rate (%). The purpose of this experiment is to determine the performance level of the DHT11 (IoT-enabled) sensor against the traditional sensors.

C. SPO2

The MAX30100 pulse oximeter is a commonly used biomedical sensor that measures both pulse rate and the body's blood oxygen saturation level. With the necessary hardware and software, this sensor is IoT-capable. In Figure 7, the SpO2 readings from the MAX30100 sensor and the conventional SpO2 device are compared. We have taken 12 readings on different occasions and plotted the graph against the oxygen saturation readings in percentage (%). During our experimentation, we have been able to attain 94.8% accuracy. Assuming the traditional SpO2 sensor gives out accurate oxygen saturation readings, we have compared the data gathered from MAX30100 with the traditional sensor data to measure the accuracy rate (%).

The purpose of this experiment is to determine the performance level of the MAX30100 (IoT-enabled) sensor against the traditional SpO2 sensors.

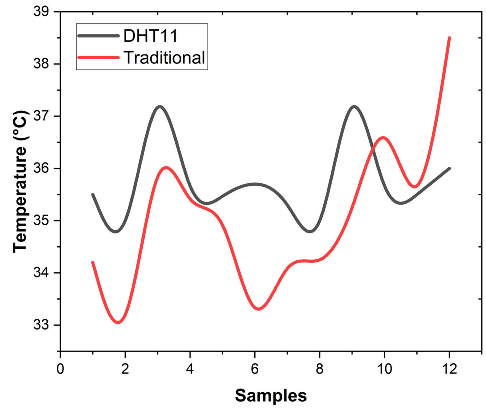

FIGURE 6. Performance comparison between IoT-enabled temperature sensor & traditional temperature sensor.

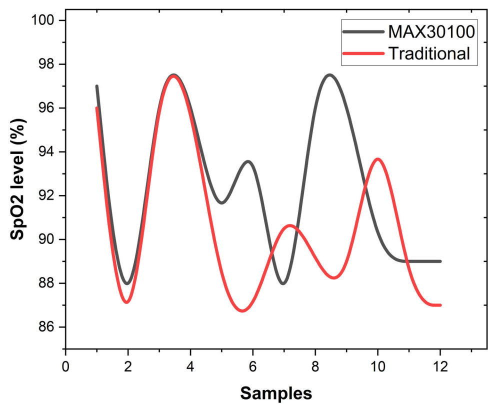

FIGURE 7. Performance comparison between IoT-enabled SpO2 sensor & traditional SpO2 sensor.

D. BLOOD PRESSURE

Figure 8 compares the blood pressure readings from a regular blood pressure sensor and an IoT-enabled blood pressure sensor. We have taken 12 readings on different occasions and plotted the graph against the blood pressure readings in mmHG. During our experimentation, we have been able to attain 92% accuracy. Assuming the traditional blood pressure sensor (Sphygmomanometer) gives out accurate blood pressure readings, we have compared the data gathered from the smart blood pressure monitor with the traditional sensor data to measure the accuracy rate (%).

The purpose of this experiment is to determine the performance level of the blood pressure sensor (IoT-enabled) against the traditional blood pressure sensors.

We have studied two categories of medical sensor data:

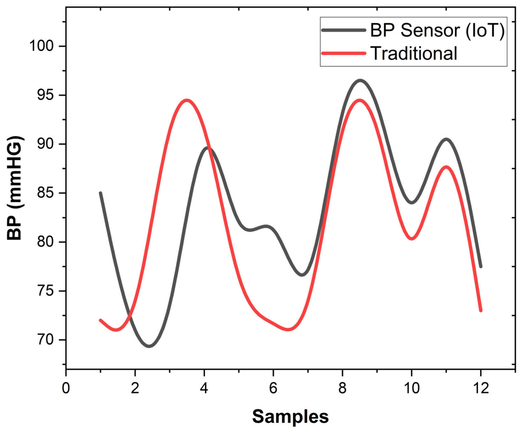

FIGURE 8. Performance comparison between IoT-enabled BP sensor & traditional BP sensor.

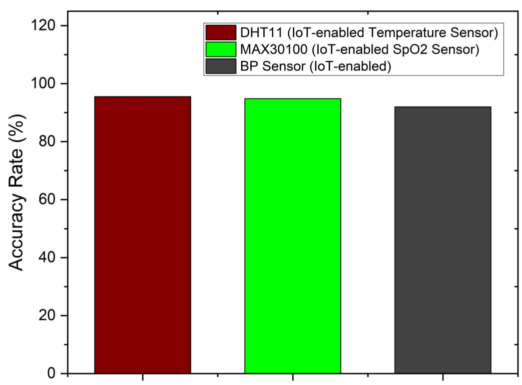

FIGURE 9. Efficiency rate comparison of the IoT-enabled sensors with respect to corresponding traditional sensors.

- Our System Sensors
- Traditional Health Devices

The data also included three types of primary sensors which are:

- Temperature Sensor
- SpO2
- Blood Pressure

All three types of IoT-enabled sensors' data accuracy rate (%) with respect to readings from the traditional sensors have been shown in Figure 9 side by side.

For each type of sensor, we have first calculated the accuracy rate (%) for each reading and after all the readings had been taken, we have calculated the overall accuracy rate (%) by taking the average. Finally, we have plotted the bar chart based on the accuracy calculated for each sensor.

E. ENERGY EFFICIENCY

In this paper, we have proposed a green healthcare system. So, we have done some experimentation according to our hypothesis, and the data we have received also supports our initial thoughts. Table 4 lists some equipment.

TABLE 4. Equipment list.

Equipment	Brand	Model
SpO2 + Heart Rate	Beurer	PO60 Bluetooth
Smart Weight Machine	Etekcity	ESF24
Smart Blood Glucose Monitor	i-SENS	CareSens N Plus Bluetooth
Smart Thermometer	Withings	Thermo
Smart BP Monitor	Withings	BPM Connect
Smart BP Monitor	Greater Goods	Smart Pro-Series Blood Pressure Monitor
Smart ECG	Beurer	ME 90 mobile ECG device

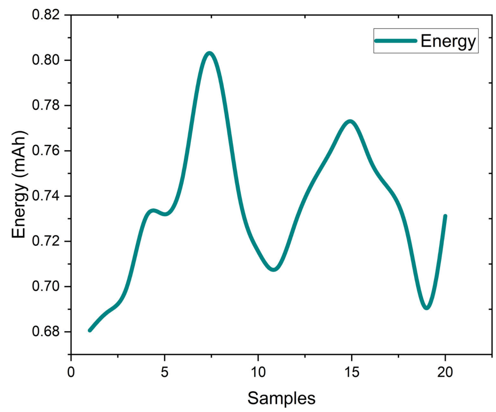

FIGURE 10. Energy consumption per reading for several samples.

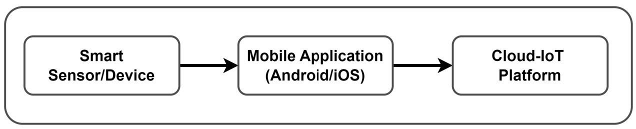

FIGURE 11. Data flow scenario for smart devices.

Here, we've looked at how "green" the proposed system is from two different points of view. One is directly related to evaluating energy efficiency and comparing traditional medical sensors to IoT-based medical sensors.

The energy consumption for a smart SpO2 device is shown in Figure 10. According to many sample readings that we have gathered, the average energy consumption is roughly 0.73 mAh. We employed a commercial smart SpO2 device for our experiments, and Table 4 lists the product information. The actual device simultaneously displays the heart rate (in bpm) and the SpO2 readings. Through Bluetooth, this data can be instantly synchronized with a mobile application. It means we can use our app to record these health readings and send them directly to the cloud-based IoT platform via comparable APIs.

But when we use a traditional SpO2 sensor or device, this kind of information would be tied to a specific place. Healthcare data must first be manually entered into the on-site system before it may be shared off-site.

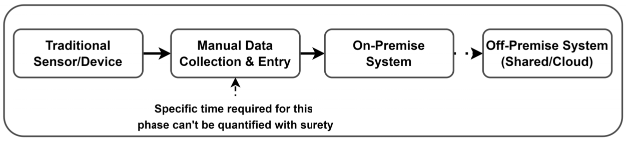

FIGURE 12. Data flow scenario for traditional devices.

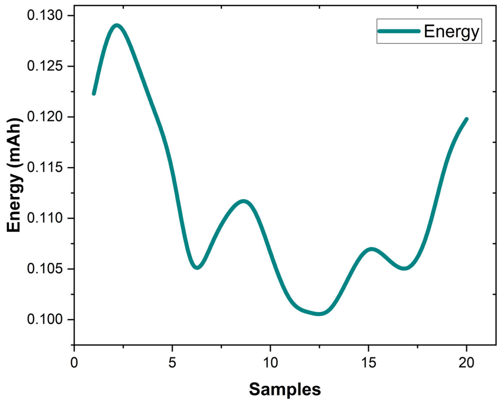

FIGURE 13. Energy consumption per reading for several samples.

When it involves sharing data, and when it is collected via traditional healthcare devices, the block diagram in Figure 12 demonstrates that there would be many different devices and systems involved.

Figure 13 shows how much energy the readings from the smart blood glucose monitor use. Various readings we have taken show that the average amount of energy used is about 0.1125 mAh. Additionally, this device utilizes Bluetooth to automatically synchronize the data. The concept of Figure 11 also applies to this smart blood glucose monitor device.

The energy consumption for readings from the smart thermometer is represented in Figure 14. Several sample measurements show that the average amount of energy used is about 8.57 mAh. For automatic data synchronization, this device includes options for Bluetooth and WiFi. This smart thermometer device falls under the discussion of Figure 11 as well.

F. DATA AVAILABILITY

The second way we'll look at how green the proposed system is is from a more indirect point of view. We have discussed some scenarios in the following regarding data availability, and after describing all three scenarios, it will be evident how they support the green computing attribute.

Scenario 1: In our first scenario, everything is hospital-centered. We will have to collect the traditional sensor data from the hospital, either by going directly there or by having any authorized hospital official send over those sensor data. So, for the doctors, patients, or any other concerned individuals, getting these data will be a tedious process, and the hospitals in this scenario will also have to maintain these data in an on-premises system.

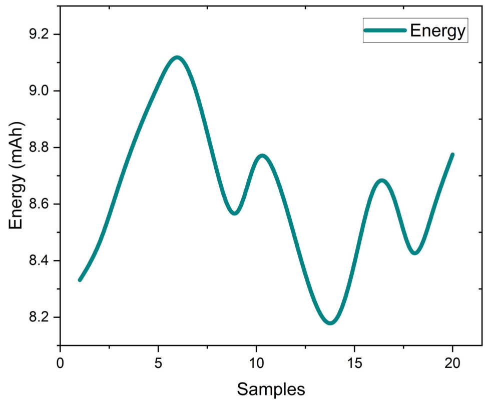

FIGURE 14. Energy consumption per reading for several samples.

Scenario 2: In our second scenario, there can be a consortium of hospitals that shares a common network, database, and related systems. Here, hospital-to-hospital data sharing is possible, and compared to the previous scenario, it is more direct and less complex. Also, if doctors/patients are given access to the shared database of the hospital consortium/group, getting services from these networked hospitals will be easier.

Scenario 3 (IoT-Cloud Based): If there is a central database that is a public (AWS/Azure/GCP) cloud-based system, access can be granted to doctors/patients/concerned individuals. In that case, they can access the database from anywhere in the world and at any time. In this particular scenario, international-level medical consultancy will be possible with the assistance of patients' live data.

Here, in the IoT-cloud-based system (Scenario 3), there is no consideration for the power consumption of any computational or storage-based infrastructure because all that infrastructure is being provided by the cloud provider. Let's have a look at Figure 15 and Figure 16. From these two figures, we can understand the simple fact that in any traditional scenario, there are way more devices in the system, and more devices will require more power. Hence, the IoT-Cloud-based system can be considered a green system.

When we use the system, there are also some other benefits, which we talked about in scenario 3. The following advantages may be attained with the system stated in scenario 3, which can be implemented on a global or national scale.

1) *Data Availability to Researchers:* The lack of real medical data is one of the biggest problems in the field of health care research. With the help of the proposed IoT-Cloud-based system, researchers will not only have sufficient data for their research but also, in some special cases, they will be able to access live patient data.
2) *Better Treatment Planning:* Due to the ubiquitous nature of accessibility in an IoT-Cloud-based system, local doctors will be able to share the live patient data and the data analytics with their international

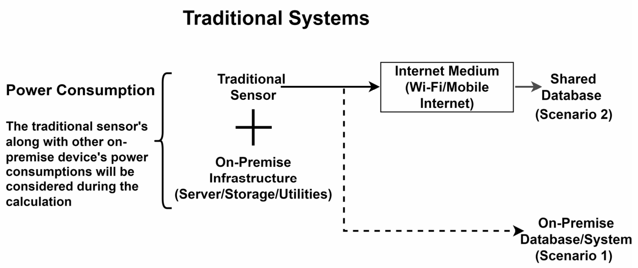

FIGURE 15. **Power consumption situation according to Scenario 1 & 2.**

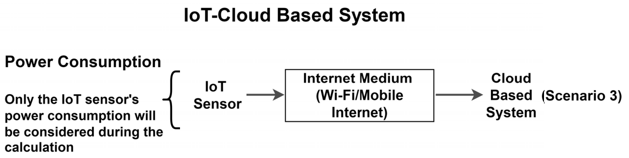

FIGURE 16. **Power consumption situation according to Scenario 3.**

counterparts or subject matter specialists. By working together, doctors will be able to come up with a much better treatment plan for their patients.

From the above discussions and figures supported by test data, we can observe the benefits of using IoT-based sensors — SPO2, weight, glucose meter, thermometer, blood pressure, etc.

G. USING BLUETOOTH LOW ENERGY (BLE)

Bluetooth Low Energy (BLE) is available in version 4 and above. Compared to Wi-Fi, BLE is about 30% more energy efficient. In BLE versions 5 and up, the rate at which data can be sent from one device to another is 2 Mbps, up from 1 Mbps in earlier versions. Thus, IoT sensors & devices will spend less time in active mode and more time in idle mode. This data rate enhancement will result in less energy consumption. Also, the newest versions of BLE choose frequency channels dynamically, which makes it less likely that two sensors or devices on the same frequency channel will interfere with each other. It further improves energy efficiency.

Figure 17 shows a simplified data flow diagram with data traversing from the IoT sensor or device to the cloud.

VI. SYSTEM'S SCALABILITY

The design of our system prioritizes scalability, with an existing foundation in cloud technology to support this goal. As the proposed architecture have to be a scalable system, it should comprise various technical components, including a load balancer, containers or microservices, host servers, a database and storage layer, monitoring and analytics tools, disaster recovery and backup solutions, and auto-scaling mechanisms. Figure 18 shows the necessary components for the system to be regarded as scalable.

The load balancer is positioned at the network edge and performs the crucial role of distributing incoming network

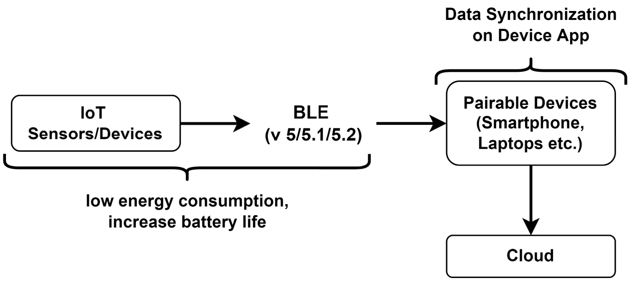

FIGURE 17. **Simplified data flow diagram from IoT sensor/device to cloud.**

traffic to the various containers or microservices (here X_{C_1}). Before reaching the microservice architecture, raw data needs to be sorted and processed, which is explained in Figure 3. The modular and scalable design of the containers or microservices allows for individual system components to be isolated and managed independently, improving overall system performance and scalability. As it is a healthcare system, many small services can be used by doctors, patients, healthcare institutions, etc. So, whenever there is a need for a new service, it can be deployed easily as it doesn't interfere with other services. The host servers act as the foundation for the containers or microservices, providing additional processing power and memory resources as needed.

The database and storage layer of the system is responsible for maintaining the persistence of the system's data and information. Monitoring and Analytics tools are deployed to gather and analyze performance and utilization metrics, providing actionable insights into areas of the system that can be optimized for scalability.

In order to ensure the continuity of the system in the event of a disaster or system failure, Disaster Recovery and Backup solutions are implemented. Auto-scaling solutions are used to dynamically allocate additional resources in response to real-time demand and system performance metrics.

The proper implementation of these components can be a complex and resource-intensive process. It requires investment in cloud infrastructure, hardware, and management tools, as well as proper configuration and maintenance to ensure the desired level of scalability.

VII. STRENGTHS AND LIMITATIONS

A. STRENGTHS

Here, we have drawn comprehensive diagrams for the proposed healthcare system and discussed its system components. A thorough performance evaluation is supported by hands-on experiments with both traditional and IoT-enabled sensors for comparative analysis. Our proposed system has been proven to be greener through some corroborating evidence gathered from our experiments. We have also proposed some approaches for further improving the system. Although we haven't overcome our limitations in this work, we have presented a possible solution that can be implemented in future experiments. Finally, we have

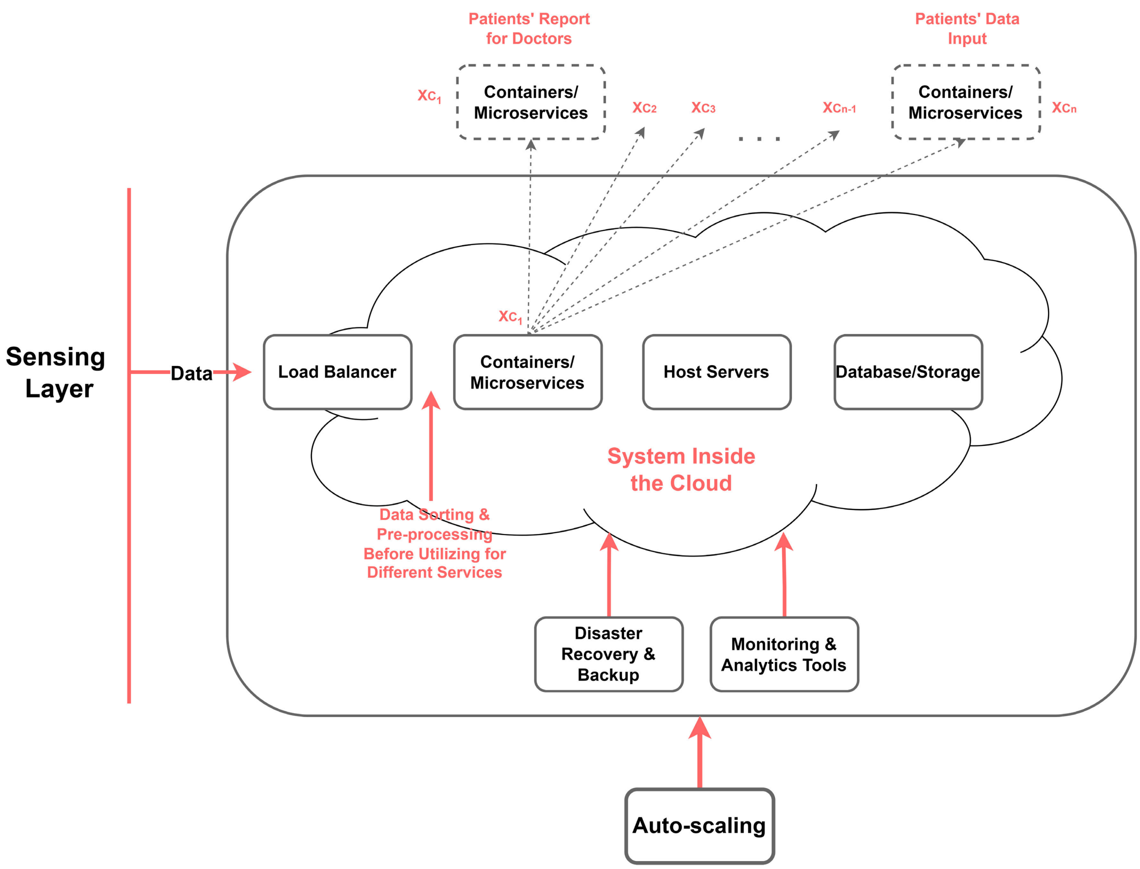

FIGURE 18. A simplified diagram for system's scalability.

described future research possibilities based on our proposed system.

B. LIMITATIONS

In this work, we have used smart devices shown in Table 4, with in-built sensors during our experiments. It would have been better if we could have used individual sensors with a single purpose. For example, a weight sensor only gives the weight data, but instead, we had to use a smart weight machine for the experiment. Due to a sourcing issue, we had to use those smart devices. According to the proposed system, if we could have used the single-purpose sensors, our experimentation would have been more precise. We would have a more vivid demonstration of the wireless technologies and communication protocols between the sensor area and the core system. Apart from that, our energy efficiency calculation would have been much easier, and the accuracy level of the gathered data would have been higher.

VIII. FUTURE WORKS

In future research, we aim to enhance the proposed system into an AI-assisted healthcare support system capable of making decisions based on sensor data. This could potentially reduce doctor-patient interactions and enable doctors to attend to more critical situations. The system will also benefit from research on signal analysis and image processing. Efforts will also be made to make the system more energy-efficient, with ongoing research into the impact of BLE and consideration of more advanced communication protocols. The proposed system currently uses smart devices/sensors for data collection, and in the healthcare sector, *in vivo* sensors may also be incorporated.

In future research, the scalability of our system will be of paramount importance. We have identified the necessary components for scalability, including using public cloud infrastructure with OGSA-DAI for authentication and authorization and a data filtering mechanism to prevent cyber-attacks. However, a private cloud solution is also required due to the sensitive nature of healthcare data. A hybrid architecture combining private and public clouds will provide a secure and flexible solution for sensitive healthcare data while leveraging the scalability and cost-effectiveness of the public cloud. Further research will aim to design an optimized hybrid architecture that balances security and scalability.

IX. CONCLUSION

The main goal of this article is to develop an IoT-based smart healthcare system. The proposed system takes advantage of a cloud platform and mobile application to ensure seamless healthcare access, which is interactive to patients, doctors, and healthcare givers. To make this system more functional, state-of-the-art wireless technologies are also incorporated. We have also discussed the system's scalability and the components needed to support it. Apart from developing the system, we also focused on lowering the margin of error, which we deemed essential to provide better healthcare. An important part of this system is its green attribute. We have analyzed it by taking into account the energy consumption for the devices used in the proposed system. We have also used different approaches to reduce energy consumption, such as – feeding the smart sensor data directly to the cloud-based healthcare system, using Bluetooth Low Energy version 5.0 or higher in the smartphone, tablet, etc., while synchronizing the health data from the sensors to the mobile application. Adopting these multitudes of measures may assist in making any similar system greener. Finally, the proposed healthcare system has outperformed the existing ones in terms of system architecture, energy efficiency, data availability, and better treatment planning.

REFERENCES

[1] Y. Mao and L. Zhang, "Optimization of the medical service consultation system based on the artificial intelligence of the Internet of Things," *IEEE Access*, vol. 9, pp. 98261–98274, 2021.

[2] M. N. Bhuiyan, M. M. Rahman, M. M. Billah, and D. Saha, "Internet of Things (IoT): A review of its enabling technologies in healthcare applications, standards protocols, security, and market opportunities," *IEEE Internet Things J.*, vol. 8, no. 13, pp. 10474–10498, Jul. 2021.

[3] X. Xue, Y. Zeng, Y. Zhang, S. Lee, and Z. Yan, "A study on an application system for the sustainable development of smart healthcare in China," *IEEE Access*, vol. 9, pp. 111960–111974, 2021.

[4] H. Zhu, C. K. Wu, C. H. Koo, Y. T. Tsang, Y. Liu, H. R. Chi, and K.-F. Tsang, "Smart healthcare in the Era of Internet-of-Things," in *IEEE Consum. Electron. Mag.*, vol. 8, no. 5, pp. 26–30, 1, Sep. 2019.

[5] B. Chen, S. Qiao, J. Zhao, D. Liu, X. Shi, M. Lyu, H. Chen, H. Lu, and Y. Zhai, "A security awareness and protection system for 5G smart healthcare based on zero-trust architecture," *IEEE Internet Things J.*, vol. 8, no. 13, pp. 10248–10263, Jul. 2020.

[6] W. Yuanbing, L. Wanrong, and L. Bin, "An improved authentication protocol for smart healthcare system using wireless medical sensor network," *IEEE Access*, vol. 9, pp. 105101–105117, 2021.

[7] J. Al-Jaroodi, N. Mohamed, and E. Abukhousa, "Health 4.0: On the way to realizing the healthcare of the future," *IEEE Access*, vol. 8, pp. 211189–211210, 2020.

[8] O. O. Ajayi, A. B. Bagula, and K. Ma, "Fourth industrial revolution for development: The relevance of cloud federation in healthcare support," *IEEE Access*, vol. 7, pp. 185322–185337, 2019.

[9] H. K. Bharadwaj, A. Agarwal, V. Chamola, N. R. Lakkaniga, V. Hassija, M. Guizani, and B. Sikdar, "A review on the role of machine learning in enabling IoT based healthcare applications," *IEEE Access*, vol. 9, pp. 38859–38890, 2021.

[10] T. Muhammed, R. Mehmood, A. Albeshri, and I. Katib, "UbeHealth: A personalized ubiquitous cloud and edge-enabled networked healthcare system for smart cities," *IEEE Access*, vol. 6, pp. 32258–32285, 2018.

[11] Y. Li, C. Liu, N. Du, W. Fan, Q. Li, J. Gao, C. Zhang, and H. Wu, "Extracting medical knowledge from crowdsourced question answering website," *IEEE Trans. Big Data*, vol. 6, no. 2, pp. 309–321, Jun. 2016.

[12] D. Richards and P. Caldwell, "Improving health outcomes sooner rather than later via an interactive website and virtual specialist," *IEEE J. Biomed. Health Informat.*, vol. 22, no. 5, pp. 1699–1706, Sep. 2018.

[13] H. K. Y. Almathami, K. T. Win, and E. Vlahu-Gjorgievska, "Barriers and facilitators that influence telemedicine-based, real-time, online consultation at patients' homes: Systematic literature review," *J. Med. Internet Res.*, vol. 22, no. 2, Feb. 2020, Art. no. e16407.

[14] M. S. Hossain, I. Hyder, I. A. Alvi, A. B. A. Bokor, T. Ahmed, M. Billah, and M. M. Islam, "DocBook: Online interactive health-care system," in *Proc. 3rd Int. Conf. Sustain. Technol. Ind. 4.0 (STI)*, Dec. 2021, pp. 1–6.

[15] G. Gindodia and D. Shrikhande, "Life care: GPS based medical emergency solution," in *Proc. 2nd Int. Conf. Inventive Res. Comput. Appl. (ICIRCA)*, Jul. 2020, pp. 124–129.

[16] G. Yang, Z. Pang, M. Jamal Deen, M. Dong, Y.-T. Zhang, N. Lovell, and A. M. Rahmani, "Homecare robotic systems for healthcare 4.0: Visions and enabling technologies," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 9, pp. 2535–2549, Sep. 2020.

[17] S. Lee, S. Gandla, M. Naqi, U. Jung, H. Youn, D. Pyun, Y. Rhee, S. Kang, H.-J. Kwon, H. Kim, M. G. Lee, and S. Kim, "All-day mobile healthcare monitoring system based on heterogeneous stretchable sensors for medical emergency," *IEEE Trans. Ind. Electron.*, vol. 67, no. 10, pp. 8808–8816, Oct. 2020.

[18] A. Alabdulatif, I. Khalil, X. Yi, and M. Guizani, "Secure edge of things for smart healthcare surveillance framework," *IEEE Access*, vol. 7, pp. 31010–31021, 2019.

[19] N. I. Sarkar and S. Gul, "Green computing and Internet of Things for smart cities: Technologies, challenges, and implementation," in *Green Computing in Smart Cities: Simulation and Techniques*. Cham, Switzerland: Springer, 2021, pp. 35–50.

[20] S. Murugesan and G. Gangadharan, *Harnessing Green IT: Principles and Practices*. Hoboken, NJ, USA: Wiley, 2012.

[21] A. Abugabah and A. Abubaker, "Green computing: Awareness and practices," in *Proc. 4th Int. Conf. Comput. Technol. Appl. (ICCTA)*, May 2018, pp. 6–10.

[22] Y. Cho, M. Kim, and S. Woo, "Energy efficient IoT based on wireless sensor networks," in *Proc. 20th Int. Conf. Adv. Commun. Technol. (ICACT)*, Feb. 2018, pp. 294–299.

[23] H. Jayakumar, A. Raha, Y. Kim, S. Sutar, W. S. Lee, and V. Raghunathan, "Energy-efficient system design for IoT devices," in *Proc. 21st Asia South Pacific Design Autom. Conf. (ASP-DAC)*, Jan. 2016, pp. 298–301.

[24] A. P. Bianzino, C. Chaudet, D. Rossi, and J.-L. Rougier, "A survey of green networking research," *IEEE Commun. Surveys Tuts.*, vol. 14, no. 1, pp. 3–20, 1st Quart., 2012.

[25] B. R. Stojkoska and Z. Nikolovski, "Data compression for energy efficient IoT solutions," in *Proc. 25th Telecommun. Forum (TELFOR)*, Nov. 2017, pp. 1–4.

[26] A. Gatouillat, Y. Badr, B. Massot, and E. Sejdić, "Internet of medical things: A review of recent contributions dealing with cyber-physical systems in medicine," *IEEE Internet Things J.*, vol. 5, no. 5, pp. 3810–3822, Oct. 2018.

[27] P. R. Pinheiro, P. G. C. D. Pinheiro, R. H. Filho, J. P. A. Barrozo, J. J. P. C. Rodrigues, L. I. C. C. Pinheiro, and M. L. D. Pereira, "Integration of the mobile robot and Internet of Things to monitor older people," *IEEE Access*, vol. 8, pp. 138922–138933, 2020.

[28] M. A. R. Bhuiyan, M. R. Ullah, and A. K. Das, "IHealthcare: Predictive model analysis concerning big data applications for interactive healthcare systems," *Appl. Sci.*, vol. 9, no. 16, p. 3365, Aug. 2019.

[29] K. M. Besher, Z. Subah, and M. Z. Ali, "IoT sensor initiated healthcare data security," *IEEE Sensors J.*, vol. 21, no. 10, pp. 11977–11982, May 2021.

[30] H. Dias Pereira dos Santos, A. H. D. P. S. Ulbrich, V. Woloszyn, and R. Vieira, "An initial investigation of the charlson comorbidity index regression based on clinical notes," in *Proc. IEEE 31st Int. Symp. Comput.-Based Med. Syst. (CBMS)*, Jun. 2018, pp. 6–11.

[31] G. Marquez, H. Astudillo, and C. Taramasco, "Security in telehealth systems from a software engineering viewpoint: A systematic mapping study," *IEEE Access*, vol. 8, pp. 10933–10950, 2020.

[32] O. Ali, M. K. Ishak, M. K. L. Bhatti, I. Khan, and K.-I. Kim, "A comprehensive review of Internet of Things: Technology stack, middlewares, and fog/edge computing interface," *Sensors*, vol. 22, no. 3, p. 995, Jan. 2022.

[33] M. Milon Islam, S. Nooruddin, F. Karray, and G. Muhammad, "Internet of Things device capabilities, architectures, protocols, and smart applications in healthcare domain: A review," 2022, *arXiv:2204.05921*.

[34] S. Abdulmalek, A. Nasir, W. A. Jabbar, M. A. M. Almuhaya, A. K. Bairagi, M. A.-M. Khan, and S.-H. Kee, "IoT-based healthcare-monitoring system towards improving quality of life: A review," *Healthcare*, vol. 10, no. 10, p. 1993, Oct. 2022.

[35] S. Benhamaid, A. Bouabdallah, and H. Lakhlef, "Recent advances in energy management for green-IoT: An up-to-date and comprehensive survey," *J. Netw. Comput. Appl.*, vol. 198, Feb. 2022, Art. no. 103257.
[36] B. Berger, M. S. Waterman, and Y. W. Yu, "Levenshtein distance, sequence comparison and biological database search," *IEEE Trans. Inf. Theory*, vol. 67, no. 6, pp. 3287–3294, Jun. 2021.
[37] C. K. Reddy and B. Vinzamuri, "A survey of partitional and hierarchical clustering algorithms," in *Data Clustering*. London, U.K.: Chapman & Hall, 2018, pp. 87–110.
[38] V. Cohen-Addad, V. Kanade, F. Mallmann-Trenn, and C. Mathieu, "Hierarchical clustering: Objective functions and algorithms," *J. ACM*, vol. 66, no. 4, pp. 1–42, 2019.
[39] M. Roux, "A comparative study of divisive and agglomerative hierarchical clustering algorithms," *J. Classification*, vol. 35, no. 2, pp. 345–366, Jul. 2018.
[40] A. Bakke, "Writing for patients on the participatory web: Heuristics for purpose-driven personas," *IEEE Trans. Prof. Commun.*, vol. 62, no. 4, pp. 318–333, Dec. 2019.
[41] A. Ghosal, A. Nandy, A. K. Das, S. Goswami, and M. Panday, "A short review on different clustering techniques and their applications," in *Emerging Technology in Modelling and Graphics*, J. K. Mandal and D. Bhattacharya, Eds. Singapore: Springer, 2020, pp. 69–83.
[42] K. Kalia and N. Gupta, "Analysis of Hadoop MapReduce scheduling in heterogeneous environment," *Ain Shams Eng. J.*, vol. 12, no. 1, pp. 1101–1110, Mar. 2021.
[43] M. M. Hassan, B. Song, and E.-N. Huh, "A dynamic and fast event matching algorithm for a content-based publish/subscribe information dissemination system in sensor-grid," *J. Supercomput.*, vol. 54, no. 3, pp. 330–365, Dec. 2010.
[44] M. J. Jackson, M. Antonioletti, B. Dobrzelecki, and N. C. Hong, "Distributed data management with OGSA-DAI," in *Grid and Cloud Database Management*, S. Fiore and G. Aloisio, Eds. Berlin, Germany: Springer, 2011.

MD. MOTAHARUL ISLAM (Member, IEEE) received the Ph.D. degree in computer engineering from Kyung Hee University, South Korea, in 2013. He has been working as a Professor with the Department of Computer Science and Engineering, United International University (UIU), Dhaka, Bangladesh, since 2020. Before joining UIU, he worked at many other universities at home and abroad, such as the Islamic University of Madinah, Saudi Arabia, the Islamic University of Technology, Brac University, and the University Grants Commission of Bangladesh. He has published around 100 articles over the last ten years. His research interests include the smart Internet of Things, IP-based wireless sensor networks (IP-WSN), WSN virtualization, cloud computing, and green computing.

ZAHEED AHMED BHUIYAN received the master's degree in computer science and engineering (CSE) from United International University (UIU), Bangladesh. He is currently working as a Research Assistant, under the supervision of Prof. Md. Motaharul Islam. His major concentration is cybersecurity. His research interests include the Internet of Things (IoT), cloud computing, cloud security, networking, software-defined networking, healthcare technologies, green computing, artificial intelligence, satellite internet communication, and grid-level energy storage systems. He has a huge interest in the fourth industrial revolution (4IR) because of its fusion of advances in AI, robotics, the IoT, and quantum computing.