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Review

A Systematic Review and IoMT Based Big Data Framework for COVID-19 Prevention and Detection

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Abstract: The Internet of Medical Things (IoMT) is transforming modern healthcare systems by merging technological, economical, and social opportunities and has recently gained traction in the healthcare domain. The severely contagious respiratory syndrome coronavirus called COVID-19 has emerged as a severe threat to public health. COVID-19 is a highly infectious virus that is spread by person-to-person contact. Therefore, minimizing physical interactions between patients and medical healthcare workers is necessary. The significance of technology and its associated potential were fully explored and proven during the outbreak of COVID-19 in all domains of human life. Healthcare systems employ all modes of technology to facilitate the increasing number of COVID-19 patients. The need for remote healthcare was reemphasized, and many remote healthcare solutions were adopted. Various IoMT-based systems were proposed and implemented to support traditional healthcare systems with reaching the maximum number of people remotely. The objective of this research is twofold. First, a systematic literature review (SLR) is conducted to critically evaluate 76 articles on IoMT systems for different medical applications, especially for COVID-19 and other health sectors. Secondly, we briefly review IoMT frameworks and the role of IoMT-based technologies in COVID-19 and propose a framework, named 'cov-AID', that remotely monitors and diagnoses the disease. The proposed framework encompasses the benefits of IoMT sensors and extensive data analysis and prediction. Moreover, cov-AID also helps to identify COVID-19 outbreak regions and alerts people not to visit those locations to prevent the spread of infection. The cov-AID is a promising framework for dynamic patient monitoring, patient tracking, quick disease diagnosis, remote treatment, and prevention from spreading the virus to others. We also discuss potential challenges faced in adopting and applying big data technologies to combat COVID-19.

Keywords: IoMT; Internet of Medical Things; big data framework; remote diagnosis; remote patient monitoring; COVID-19 outbreak detection

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1. Introduction

The Internet of Medical Things could establish a network of interconnected healthcare devices having sensors for diagnosing and monitoring patients' health status [1]. These sensors build smart devices, which help patients and healthcare workers to communicate smartly even from distinct locations. This massive connectivity permits devices and sensors to detect, analyze, and connect. Therefore, these devices alert patients, doctors, and other health workers by interacting with them automatically, to provide services smartly [2]. These smart applications are growing exponentially, and, as a result, there is an incredible rise in the number of interconnected IoMT devices that increase the data traffic over the network [3]. The diverse sensors, devices, and applications become the source of big data [4]. Big data frameworks incorporate conventional devices and components to acquire, store, and analyze various types of data by utilizing equal handling ability to accomplish complex changes and analysis [5]. However, structuring and developing a big data framework for a particular task is not an inconsequential or simple function [6]. Subsequently, the data acquired from several heterogeneous and self-ruling sources with evolving and complex collections is continuously developing [7]. Besides, the ascent of big data applications, where data acquisition has increased exponentially, has led to the ability to commonly utilize equipment and software platforms to store, analyze, and maintain within an acceptable measure of time [8]. In some countries, COVID-19 has been combated using IoMT technology in conjunction with other approaches. The use of IoMT enhances the protection of front-line personnel, boost efficacy by reducing the disease's toll on people's lives, and reduce fatality rates [8].

The extraction of values from big data sources must be analyzed for predictions to prevent and cure diseases [9]. The COVID-19 pandemic, which began in late 2019 [10], has been a focus of medical research [11]. COVID-19 is a virus that infects humans and causes respiratory illnesses [12]. Because of the profoundly contiguous nature of COVID-19, it is difficult to examine COVID-19 patients physically [13,14]. Several researchers have proposed solutions for this problem. Fangyu Li et al. [15] offered a framework plan for a COVID-19 patient monitoring platform that is end-to-end, non-invasive, and uses WiFi. Aman et al. [4] surveyed the IoMT technology, application, architecture, and security developments for COVID-19. Qiong Jia [16] provided a big data framework, comprising prevention mechanisms, prevention, response, and recovery. Nasajpour [7] presented a study to define the role of IoT in monitoring and diagnosing the COVID-19 symptoms. Swayamsiddha [17] proposed a framework—Cognitive IoT (CIoT)—for remote patient monitoring of COVID-19 patients. Abdel-Basset [18] used disruptive and emerging technologies for COVID-19 analysis, such as IoT, IoMT, AI, big data, autonomous robots, drone technology, virtual reality (VR), and blockchain.

The objective of this research is to present a comprehensive review of the state-of-the-art solutions to support traditional healthcare systems remotely. Specifically, this work provides a systematic literature review of the existing IoMT based systems. Moreover, we analyze the limitations of the existing systems and proposed a novel framework 'cov-AID' to overcome the shortcomings. All the aforementioned frameworks do not provide a layered architecture to elaborate the functional tasks explicitly in a detailed manner.

Therefore, this work proposes a layered big data framework 'cov-AID' that utilizes the IoMT remote assessment technology for the detection and prevention of COVID-19. The cov-AID framework consists of six layers. These layers are altogether built as a comprehensive framework that provides remote sensing, data integration, data analytics, and various applications specific to COVID-19. The proposed framework enables devices and software applications to be used for preventing the spread of COVID-19 through early diagnosis and patient monitoring.

1.1. Motivation

Patients with chronic diseases, such as heart diseases, hypertension, pulmonary conditions, or older adults, who needs long-term monitoring have to be admitted to hospital for a long period of time. This increases the expenses and mental stress for both patients and their caretakers. Moreover, COVID-19 has exposed a hidden paradigm for contagious diseases. Hospitals are not enough to cater all the patients at a time and could not manage the isolation for every patient. Therefore, there is a need to monitor and provide medical assistance remotely to reduce the load from the hospitals.

This research is motivated by the need of IoMT-based systems to facilitate the healthcare sector in reaching out to maximum people. The systematic literature review presented in this research serves as a suitable starting point for understanding the existing IoMT research and applications. Further, the proposed framework 'cov-AID' lays the foundation of layered approach towards developing IoMT-based solutions.

1.2. Contribution

The major contributions of this research are summarized below:

- Contribution 1. We studied the existing work for remote patient monitoring and medical assistance for patients and presented a detailed SLR of around 76 research articles.
- Contribution 2. We proposed an IoMT-based framework 'cov-AID' that lays the foundation of layered approach towards developing IoMT-based solutions.
- Contribution 3. We discussed the major challenges in adoption of IoMT-based framework.

The rest of the paper is organized as follows: Section 2 defines the research methodology of SLR, Section 3 elaborates the findings of the literature review according to the classified research articles while Section 4 presents the proposed framework cov-AID while Section 5 exposes the adoption challenges of the IoMT-based framework, Section 6 discusses the proposed framework and the future research directions and Section 7 concludes the research.

2. Research Methodology

This research aims to provide an overview of the current trends of IoMT-based techniques through a systematic literature review. Systematic reviews provide overviews of specific research topics and indicate areas where a considerable study has previously been conducted or where research results are lacking. In this study, a systematic literature review has been performed using the protocol, having the following steps:

- Identification of relevant literature sources.
- Data Extraction and Synthesis.
- Classification of the literature according to concepts.

2.1. Identification of Relevant Literature Sources

The initial step has been taken by locating the relevant literature sources. This review was conducted based on content analysis. IoMT is an emerging technology, therefore, there is limited research available. Moreover, the topic's timeline is too short, therefore, both peer-reviewed scientific publications and conference proceedings were considered for review. To target the finest research, premium research sources have been adopted that are Science Direct, Springer, Wiley, IEEE, and MDPI. To search the relevant articles, three search terms "IoMT", "Internet of Medical Things", "COVID-19", and four attributes of the search syntax were selected:

1. TITLE-ABS-KEY: The keywords chosen are looked for in the research paper's title, abstract, and keywords.
2. AND: Both keywords in the searched item must be present, according to this operator.
3. OR: One of the terms in the searched item must be present, according to the operator.
4. Year: To select the range of topic timelines for the publication period.

2.2. Data Extraction and Synthesis

To acquire highly accurate information, a well-developed search method is required. This step delves into the search strategy for the review, which includes the scope (publication era), search method (automated or manual), and search string. The publications included in this systematic literature review were published between December 2019 and December 2021. The duration was chosen, since COVID-19 research began in late 2019.

An automated literature search was employed for this systematic analysis. The term "automated search" refers to the process of searching electronic databases for search strings. Boolean operators were used to construct the search string. Through many pilot searches, the search phrases were tweaked iteratively to improve the precision and recall of the literature search. Additionally, the search strings were adapted to fit each database, as shown in Table 1.

Table 1. Search string for different publication databases.

Electronic Database	Search String
ScienceDirect	((“IOMT” OR “Internet of Medical Things”) AND “COVID-19”)
IEEE	(“IoMT”) AND (“COVID-19”) OR (“Internet of Medical Things”) AND (“COVID-19”)
Springer	‘“COVID-19” AND “IoMT” OR “Internet of Medical Things”’
MDPI	((“IOMT” OR “Internet of Medical Things”) AND “COVID-19”)
Wiley	“IoMT” AND “COVID-19” OR “Internet of Medical Things” AND “COVID-19”

The search string has been kept in a broad sense intentionally to reach out to all the studies of the concerned field and to not skip any study. From the finalized search strings, we have retrieved 203 research papers, as shown in Figure 1.

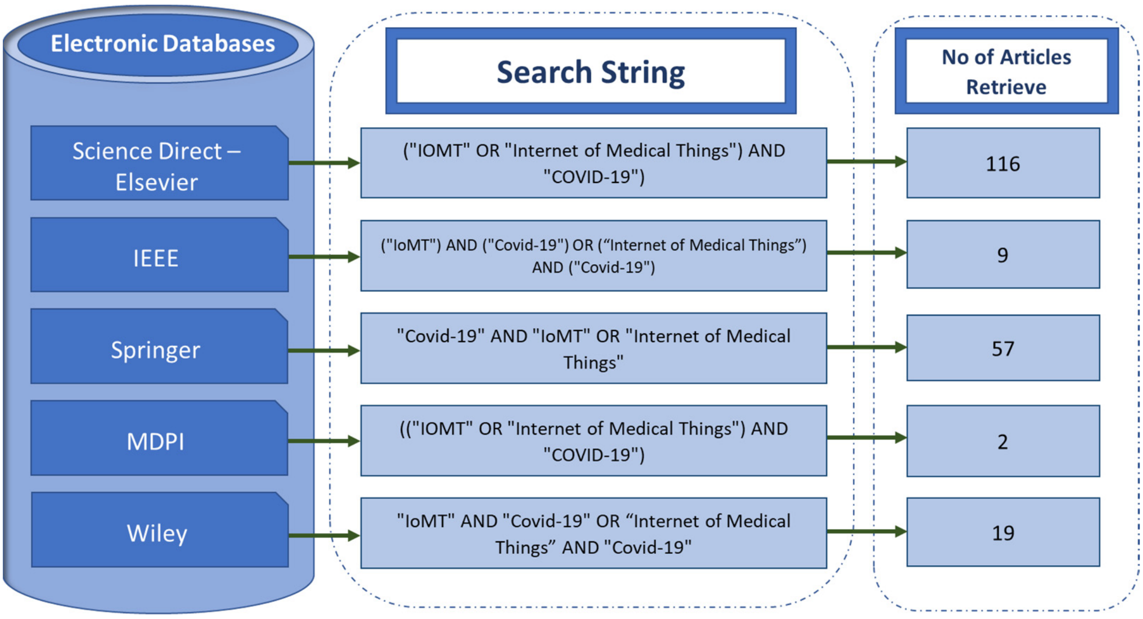


Figure 1. Research publications retrieval data summary.

The selection of research articles has been conducted using the following inclusion and exclusion criteria. Figure 2 shows the result summary of the articles retrieved and selected for the findings.

2.2.1. Inclusion Criteria

We included studies that:

- IC1: presents a review or survey of the IoMT framework or applications.
- IC2: discusses the role of IoT or IoMT in the healthcare sector including COVID-19.
- IC3: proposed an IoMT framework.
- IC4: proposed the IoT or IoMT framework for COVID-19.
- IC5: discuss IoT or IoMT frameworks using big data analytics.
- IC6: discuss the IoMT challenges and issues.
- IC7: are published in peer-reviewed conferences, journals, or early access articles.

2.2.2. Exclusion Criteria

We excluded those studies which:

- EC1: does not propose the IoMT framework for COVID-19.
- EC2: were not published in peer-reviewed conferences, journals or early access articles.
- EC3: are not written in the English Language.

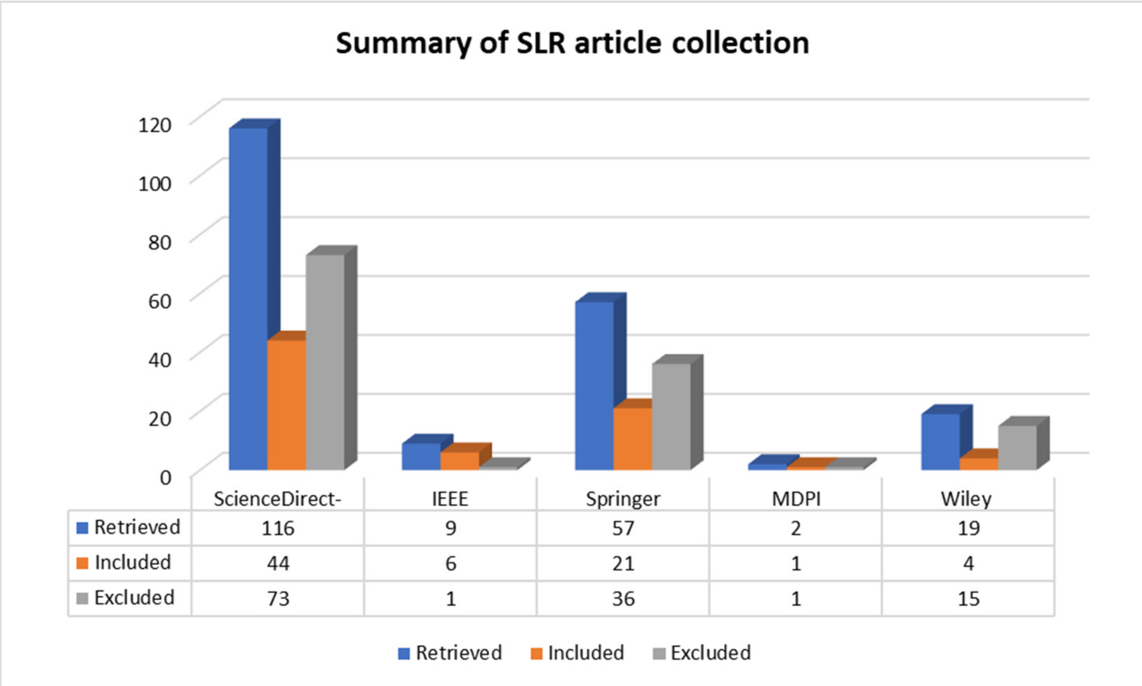


Figure 2. Articles found from the electronic research databases.

2.3. Classification of the Literature According to the Concept

The retrieved articles from the selection criteria were classified into two major categories, review and proposed framework, which is further classified into studies discussing COVID-19 or other health sectors. The classification criteria was applied by reading the title, abstract, results, and findings, which were later reduced in the number of included studies. These articles are classified into the following six categories:

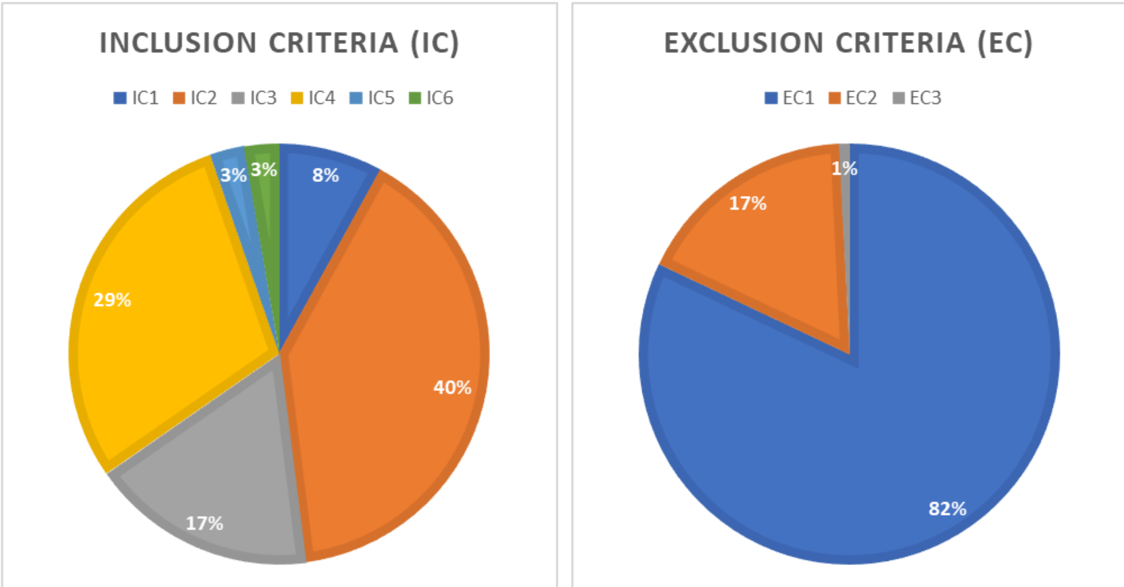
1. Review: IoMT framework or applications review.
2. Review: IoT or IoMT, including COVID-19.
3. Proposed IoMT framework.
4. Proposed IoT or IoMT framework for COVID-19.
5. Review: IoT or IoMT frameworks using big data analytics and their adaptation challenges.

3. Findings of Literature Review

According to Figure 1, Science Direct has the highest number of articles retrieved while IEEE is the second successor to collect the premium IoMT-based research as a field of study. MDPI has the least research found in the field of IoMT-based solutions in the tight publication timeline. The selected research articles, according to inclusion and exclusion criteria, are shown in Figure 3. Reviews in the field of IoMT-based solutions for COVID-19 got the highest category results in the Science Direct database, which is considered IC2. The adoption challenges got the lowest results, which is IC6. The selected research articles are explained briefly in the subsections according to the classified categories.

3.1. Review: IoMT Framework or Applications Review

Zarlish Ashfaq et al. [18] present a thorough overview of many studies undertaken to further the development and enhancement of IoMT. In the healthcare context, several digital system designs were reviewed on the basis of their methodology, constraints, and the issues that the e-health sector faces. Ruby Dwivedi et al. [19] examine the current level of research, establishing the efficacy of IoMT advantages to patients and the healthcare system and the role of existing IoT applications in enhancing the healthcare system. Furthermore, it briefly looks at technologies that supplement IoMT and the challenges of developing an intelligent healthcare system. Lydia Skolrood et al. [20] discusses smartphones, single-board computers (such as Raspberry Pi systems), and 3D-printed microscopy platforms as tiny, lab-on-a-chip systems and high-sensitivity imaging instruments. A thorough literature study by Rahmani et al. [21] demonstrated IoT applications' benefits, unresolved issues, risks, and limitations. Vu Khanh Quy et al. [22] compared several computing technologies and presented a common architectural framework for Internet of Health Things applications based on fog computing. Nasajpour et al. [7] explore cutting-edge architecture, industrial IoT-based solutions, applications, and platforms for fighting COVID-19 in three stages: early detection, quarantine, and recovery.



(**a**) (**b**)

Figure 3. Publication ratio using: (**a**). inclusion criteria (**b**). exclusion criteria.

3.2. Review: IoT or IoMT including COVID-19

Ruby Dwivedi et al. [19] review the role of existing IoT applications that are participating to improve the healthcare system and also investigate the current state of research representing the efficacy of IoMT aids to patients and the medical assisting system. Furthermore, it also provides a brief look at technologies that supplement IoMT and the challenges that come with implementing a smart healthcare system. An extensive survey about emerging virtual smart health monitoring and its challenges is provided by Elliot Mbunge et al. [23]. Sujith et al. [24] suggested a smart health monitoring framework that combines blockchain, deep learning, and machine learning technologies to create a cost-effective and real-time health monitoring system. Rahman et al. [25] proposed a smart health framework that assists in automatic community-wide symptom severity monitoring, as well as individualized monitoring, paving the way for early disease outbreak surveillance in a smart and connected community. In the context of the IoHT area, a complete analysis of the various IoT device authentication techniques and identity management systems, with an emphasis on current achievements, open difficulties, and future possibilities is provided by Moustafa Mamdouh et al. [26]. D.Campos- Ferreira et al. [27] examined the various problems that must be overcome in order to reach an ideal situation for both containing the current COVID-19 epidemic and preventing future pandemics. According to the author, IoMT can connect and remotely monitor patients, lowering the danger of exposure to healthcare professionals. Kashani et al. [28] looked into the remote monitoring requirements for telemedicine, especially in developing countries and concluded that the IoT has the potential to decrease the pressure on sanitary systems while also offering personalized health care to improve people's quality of life. However, Weiping Ding et al. [29] provide a comparative examination of the various types of data, emerging technology, and methodologies employed in the diagnosis and prediction of COVID-19. The authors suggested that IoMT technology has been efficiently used in the healthcare system to improve worldwide efforts in epidemic monitoring, infection tracking, illness detection, vaccine and medicine development, resource allocation, and outbreak prediction. XuranLi et al. [30] examine the advantages of this architecture and how blockchain-enabled IoMT might be of use. In the COVID-19 pandemic, the authors also discuss how blockchain-enabled IoMT can aid in infectious disease prevention, location sharing, contact tracing, and injectable drug supply chain management. To comprehend and explain the skepticism and resistance to IoMT among clinical users, Nastaran Hajiheydari et al. [31] established an integrative theoretical paradigm that incorporates system, information, and individual positive and negative variables. Jiuchuan Guo [32] devised a method that allows patients and their family to remotely record their medical data and daily circumstances, alleviating the strain of having to go to a central hospital. Bayin et al. [33] developed an IoMT-based cost-effective and time-efficient method for healthcare staff to assess and keep a record of infection in COVID-19 patients, with excellent usability. Intawong et al. [34] use a bottom-up method to explore COVID-19 issues and control mechanisms by examining the invention of three real-time application technologies, as well as their implementation. Hemant Jain et al. [35] presented a 5G network slice architecture for digital real-time healthcare systems that capture biometric data and send it via the 5G network slice, as well as an integrated analytics framework. The IoMT architecture, technologies, applications, and security advances that have been made to IoMT in countering COVID-19 were emphasized by Aman et al. [4]. Greco et al. [36] covered early health monitoring systems based on wearable sensors to the current trends in fog/edge computing for smart health, the general usage of IoT technologies in health care. By laying out a strategy for combating the COVID-19 epidemic, R.P. Singh et al. [37] aimed to study, discuss, and emphasize the overall applicability of the well-proven IoT philosophy. The introduction of IoT reduces healthcare expenses and improves the treatment outcome of infected patients, according to the findings. Lim & Rahmani [38] performed a systematic analysis of the current cutting-edge ontology of IoT resolutions that are utilized in the health sector, recognize the associated obstacles, and suggest a federated edge-cloud semantic IoT architecture to promote HC-PH collaborations for individual and population health and well-being.

Volkov et al. [39] analyzed existing methodologies and technology in digital twins, the IoT, and telemedicine to examine present healthcare concerns. The key characteristics of contemporary platforms that support telehealth applications were reviewed. In addition, the notion of a smart healthcare platform was developed, focusing on activities linked to enabling the development of mobile health applications, such as arranging user data access, management, and sharing. The technical foundations of machine learning, big data analysis, cloud computing, and IoT in clinical medicine were investigated by Zhao-xia Lu et al. [40].

The uses of IoT and AI in clinical medicine are thoroughly summarized, the major hurdles are assessed, and future trends and advances were also discussed in numerous studies. Alharbi et al. [41] examine current attempts to address the COVID-19 problem using technology improvements, including IoMT. M. Hasnain et al. [42] offer an overview of recent research on frontline medical worker safety concerns and how technology is being used to combat the COVID-19 epidemic. Many different types of wearable health equipment to monitor oxygen saturation, temperature, heart rate, and respiration rate, as well as respiratory support systems, such as oxygen treatment and ventilators, are widely used to support coronavirus patients were discussed by Md. Milon et al. [43]. Vafea et al. [44] looked at the new technologies that are being employed in COVID-19 research, diagnosis, and treatment. During the COVID-19 outbreak, Monaghesh and Hajizadeh [45] conducted a comprehensive evaluation on the utility of telehealth services in disease prevention, diagnosis, treatment, and management.

Mbunge et al. [46] reviewed robotics, IoMT, smart applications, 5G technologies, blockchain, telemedicine, big data, artificial intelligence (AI), geospatial technology, and additive manufacturing as emerging technologies for combating COVID-19, focusing on features, challenges, and domiciliation country. Anand et al. [47] examined emerging technology for dealing with pandemic threats. Virtual reality, 5G, artificial intelligence, the Internet of Healthcare Things, wearable sensing, mobile APK, drone facilities, and blockchain are examples of upcoming technologies that can address these important concerns. Vikram Puri et al. [48] suggested a decentralized healthcare architecture powered by artificial intelligence (AI) that accesses and authenticates Internet of Things (IoT) devices while also instilling confidence and transparency in patient health records. The applications of IoT in healthcare are defined by Juneja et al. [49], as well as how these applications can be employed with various sensors. In an IoMT-enabled COVID-19 situation for patient home monitoring, Basudeb Bera et al. [50] combined fog computing and blockchain technologies to create a more secure solution. Alam and Rahmani [51] investigated using medical data and decision support systems, COVID-19 identification, and lung area segmentation detection, as well as IoMT application-centric settings and concluded that such a system may benefit all IoMT stakeholders.

3.3. IoMT Framework

Elliot Mbunge et al. [52] present the significant perceived challenges, trends, benefits, technologies, and in virtual health care, where there are ethical concerns about the emotive sensory Web. Ismael et al. [53] created a medical system based on the Internet of Things, which allows doctors and patients to communicate remotely. Doctors might prescribe medications and request fresh information about a patient's symptoms. Yadav et al. [54] combine biomarker-based immune sensors, smart sensing methodologies as AI, and IoMT with bioinformatics approaches to monitor non-invasive SARS-CoV-2 during early stage of development, with the primary objective being quick point-of-care (POC) diagnoses. Shikha Jain et al. [55] discussed newly developed POC diagnostics that have been integrated with IoMT, with the base on emerging and re-emerging infectious diseases, such as influenza A (H1N1), dengue fever, malaria, human papillomavirus (HPV), Ebola virus disease (EVD), Zika virus (ZIKV), and coronavirus (COVID-19). Ahmed et al. [56] show how to analyze and predict COVID-19 using a health monitoring framework. Fagroud et al. [57] focused on the impact of IoT devices on COVID-19 and its variations transmission. Bassam et al. [58] implemented IoT-based wearable monitoring equipment to track COVID-19-related vital indicators. Any violations of quarantine for potentially infectious individuals are quickly alerted to the concerned medical authorities by monitoring their real-time GPS data. Tanzila et al. [59] proposed an IoMT-based secure and energy-efficient framework for e-healthcare. The primary goals are to reduce communication overhead and energy consumption between biosensors while conveniently transmitting healthcare data and to protect patient medical data from unauthenticated and malicious nodes to improve network privacy and integrity. Mishra et al. [60] presented an architecture for an e-healthcare system that employed 5G technology.

Viswanadham [61] offered a platform business model to alter the traditional hospital paradigm. Fatema Al-Dhaen et al. [62] created a model to investigate the role of responsible AI in the adoption of IoMT in healthcare. Colorectal cancer (CRC) in the elderly is predicted using an IoT-based prediction model, which was proposed by Asghari et al. [63]. It creates a CRC prediction model by gathering crucial medical data via IoMT devices and sensors, allowing the medical team to track an aged person's biological markers over time with smart wearable embedded systems and medical IoT devices.

Uslu et al. [64] examine the optimization variables, problems, accessible technologies, and opportunities, as well as the system architecture, that result from the use of IoT technology in the smart hospital environment.

3.4. IoT or IoMT Framework for COVID-19

Sharma et al. [65] implemented a remote access IoT-based model with a bio wearable sensor system for early detection of COVID-19 utilizing an ontology method and biomedical signals, including ECG, PPG, temperature, and accelerometer. Renugadevi et al. [66] investigated the importance of big data in smart health applications, which are critical in ensuring human safety. Seda Savaşcı Şen [67] presented an Internet of Things-based surveillance system for coronavirus pandemics in particular. In this study, symptoms of the Coronavirus, such as respiration rate, body temperature, blood pressure, oxygen saturation, and heart rate, may be tracked, and the proposed IoT software may be used to indicate the social distance between people. In IoT adoption, the relevance of the risk–trust relationship was emphasized by Arffi et al. [68]. The finding suggests that performance expectations have no bearing on the intention to use the Internet of Things for eHealth. For smart monitoring, proactive prevention and control, and mitigation of COVID-19 and related outbreaks, Deepti Gupta et al. [69] envisioned a connected ecosystem powered by the IoT and data. Mohamed Abdel-Basset et al. [70] presented an IoMT-based approach for limiting the development of COVID-19 outbreaks while ensuring the safety of healthcare workers and maintaining patients' physical and psychological wellness. Adarsh Kumar et al. [71] explored drone-based systems, as well as COVID-19 pandemic settings, and architecture was provided for coping with pandemic events in real-time and simulation-based situations. This took place in isolated and heavily congested pandemic regions where either wireless or internet connection is a big worry or the odds of COVID-19 spreading are high. In a push-pull data fetching mechanism, its architecture leverages wearable sensors to capture observations in body area networks (BANs). Otoom et al. [72] proposed an Internet of Things-based framework for collecting real-time symptom data from users in order to detect suspected coronavirus cases early, monitor the treatment response of those who have already recovered from the virus, and better understand the virus's nature by collecting and analyzing relevant data. Swayamsiddha et al. [17] advocated for the employment of Cognitive IoMT disruptive technology in smart healthcare and in the fight against the COVID-19 pandemic, as well as outlining the primary benefits and application areas. Singh et al. [73] explored the possibility of using the IoMT strategy to combat the continuing COVID-19 epidemic while treating orthopedic patients. The many clouds and connected network-based services of IoMT include data sharing, report monitoring, patient tracking, information collection and analysis, hygiene medical care, and so on. To prevent and guard against COVID-19, P. Singh et al. [74] create a quality-of-service framework based on the Internet of Things with the help of fog. It forecasts COVID-19 infection based on the user's symptoms using real-time health data processing provides users, their guardian, and doctors/experts with an emergency alarm, medical reports, and important precautions. It uses patient IoT devices to collect sensitive data from hospitals/quarantine shelters in order to take the decisions or necessary actions. It also conveys a message of warning to government health organizations, ordering them to control the spread of chronic illness and take appropriate action as soon as possible. Ameni Kallel et al. [75] employing a framework that incorporates machine learning (ML), cloud, fog, and Internet of Things (IoT) technologies, offer a new smart COVID-19 illness monitoring and prognostic system. Khowaja et al. [76] underlined the necessity of integrating technologies to assist in dealing with COVID-19 and offered a hypothetical framework that connects smart sensors with the Internet of Medical Things to cover the gamut of best practices in an automated manner. Poongodi et al. [77] proposed a sophisticated health-based IoT solution that can improve COVID-19 administration and generate better results with less money. Anichur et al. [78], during COVID-19 of the smart industry, proposed the "EdgeSDN-I4COVID" architecture for intelligent and efficient management of IoT networks. Madhavan et al. [79] used an IoMT-based framework for a web-based service that uses chest X-ray images to diagnose and classify different types of pneumonia or COVID-19. In a cloud-based IoT environment, a remote health monitoring model is proposed by Akhbarifar et al. [80] that uses a lightweight block encryption mechanism to provide security for health and medical data. Abdur-Rahman and Hossain [81] developed an edge IoMT system that employs deep learning to detect a variety of COVID-19 symptoms and delivers reports and warnings for medical decision support. During the COVID-19 pandemic, Zhang [82] proposed a revolutionary IoMT platform that enabled remote health monitoring and decision-making concerning emotion, providing convenient and continuous emotion-aware healthcare services. Jikui Liu et al. [83] created a system for remote monitoring of cardiopulmonary health using the IoMT. It is a remote monitoring device that can help with the follow-up and treatment of COVID-19 patients who have been discharged. Rinku, a system for remotely validating COVID-19 symptoms, was proposed by Rodriguez et al. [84]. Rinku can handle data from several patients at the same time and provide useful information on the intensity of the symptoms reported, which could aid healthcare professionals in making management decisions to maximize their clinical resources. Yonghang Tai et al. [85] propose a novel paradigm for COVID-19 diagnostic integration and introduces a new line of inquiry into the integration of XR and deep learning for IoMT deployment.

3.5. Review: IoT or IoMT Frameworks Using Big Data Analytics and Their Adoption Challenges

Early warning and monitoring, screening and diagnosis, medical treatment, and scientific research are all factors to be considered and summarized the significance of information technology in the healthcare sector's fight against COVID-19 by MingZhang et al. [86]. By comparing the properties of psychophysiological signals with the specific features of the participants, Baran [87] assesses the potential of a low-cost mobile thermal imaging camera in detecting and assessing stress.

Nagarajan et al. [88] suggested a new IoT-based FoG-assisted cloud network architecture that collects real-time health care data from patients via several medical IoT sensor networks and analyses the data using a fog-based healthcare deep learning algorithm. To stop the virus from spreading, Elagan et al. [89] proposed a unique strategy based on artificial intelligence and the Internet of Things (IoT) for remotely detecting COVID-19 patients.

4. cov-AID—Proposed Framework

The cov-AID framework was designed after the thorough review and analysis of literature during the course of study. The cov-AID framework is unique in many aspects. First, it is a layered architecture comprising of six exclusive layers. Second, the architecture is highly scalable as each of its layers can be scaled independently. Third, this framework can serve as a middleware for other healthcare applications. Finally, the cov-AID framework is not only limited to COVID-19 but it can be successfully employed for real-time monitoring in any large scale applications

COVID-19 is a highly contagious disease that spreads through respiratory droplets and even through fecal–oral transfer. That is, human coronaviruses are spread mostly through direct contacts, such as saliva, coughing, or sneezing, from one infected individual to another. Therefore, its prevention, detection, and monitoring is difficult and need to be accessed remotely. After collecting and organizing the systematic literature review, we have proposed a layered framework, named cov-AID.

The cov-AID framework aims to apply IoMT and other big data tools and technologies in the prevention, detection, and spreading of COVID-19. The framework encompasses all steps from the big data generation to analysis and applications needed to assist healthcare in preventing and treating COVID-19. The framework comprises six layers: (1) Big data generation layer; (2) Big data acquisition layer; (3) Big data storage server layer; (4) Big data query and processing layer; (5) Big data analytical layer; and (6) Big data application layer, as shown in Figure 4. Each of the framework layers are discussed using the bottom-up approach as follows.

Figure 4 represents the different technologies, platforms, and approaches to process the healthcare big data for analyzing different COVID-19 diseases with the proposed work. All the technologies are open source, and their applications programming interface (API) are available on the public data centers.

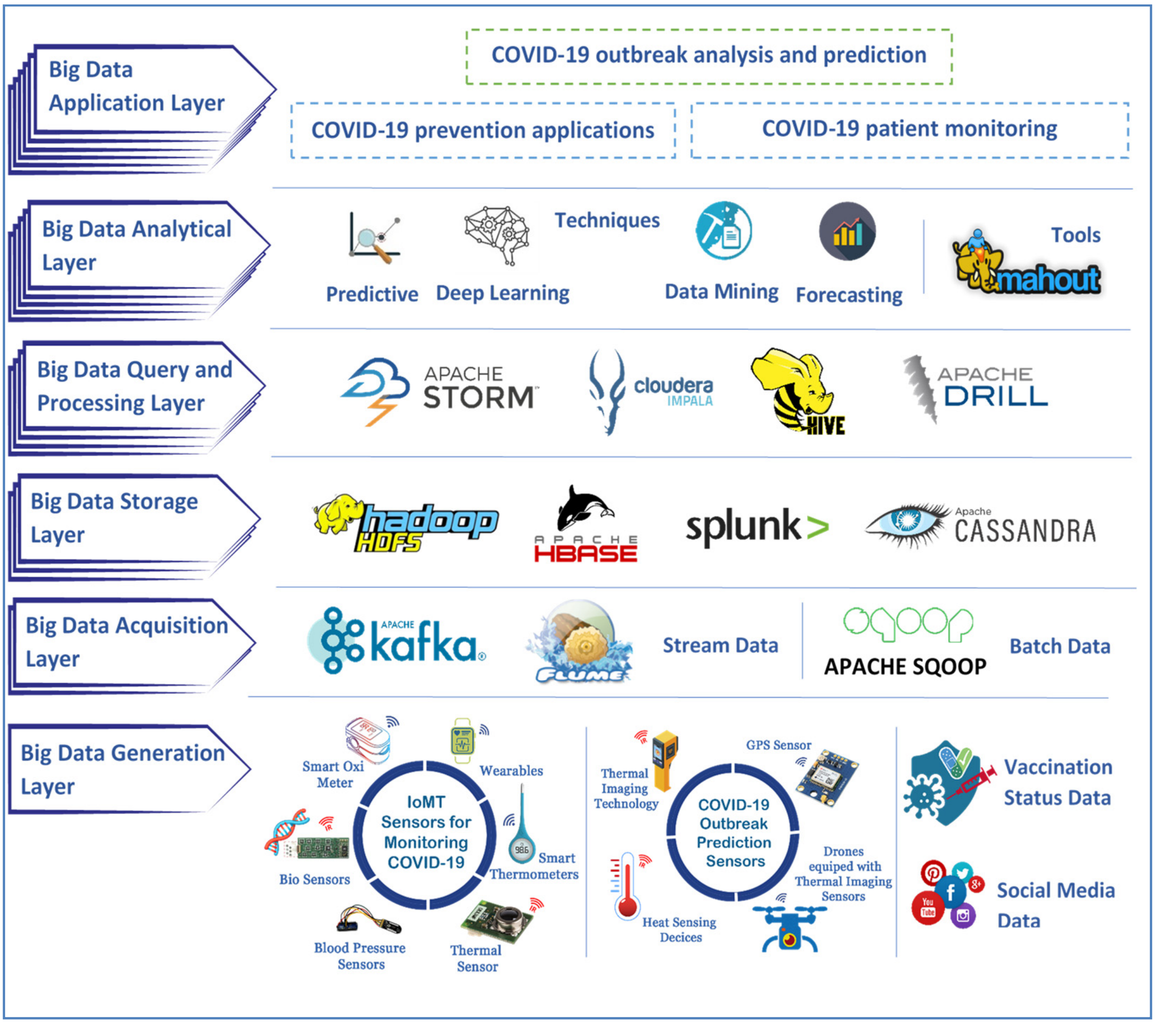


Figure 4. cov-AID—an IoMT based framework, for preventing, monitoring, and predicting outbreak regions of COVID-19.

Algorithm 1 defines of the method for cov-AID framework for IoMT-based solution that has six steps to run the applications with the different schemes. The main goal is to show the flowchart of the system with the different schemes and methods for the different applications.

Algorithm 1. Methodology for cov-AID

Step-1 Big Data Generation Layer;
Step-2 Big Data Acquisition Layer;
Step-3 Big Data Storage Layer;
Step-4 Big Data Query and Processing Layer;
Step-5 Big Data Analytics;
Step-6 Big Data Application.

4.1. Big Data Generation Layer

Every few seconds, millions of smart devices generate data streams using IoMT sensors [90]. The data for cov-AID has been collected from big data sources; IoT and IoMT sensors, centralized vaccination status records, and social media platforms. Various medical applications, such as drug discovery, disease detection, toxins of defense interest, prosthetic devices, etc., enforce IoMT biosensors [55]. Temperature sensors are used to measure the environmental temperature and body heat [91]. Thermal heat sensors are used that measure the environment heat density for the calculation of the crowd in a particular area [92]. Infrared sensors support remote access to thermal imaging cameras [93], and non-contact infrared thermometers [94]. Sensors for electrocardiogram (ECG) [95], photoplethysmography (PPG) [96], and ballistocardiogram (BCG) [97] are used with determining blood pressure using pulse transit time or pulse wave analysis [98]. Electroencephalogram (EEG) sensor [98], pulse oximeter [99], electromyography (EMG) sensor [100], etc., help in the collecting real-time medical health parameters. The data of locations where COVID-19 symptoms are detected is generated by GPS sensors [40] with thermal imaging technology [101]. IoMT sensors are also used in cov-AID for tracking the origin of the outbreak and help people to identify COVID-19 positive patients, ask them to maintain saved distance, and complete the quarantine period.

The data from other sources, such as records of vaccination status is also collected by this layer of the cov-AID framework. Social media feed from different areas is monitored, which leads to identifying the current COVID-19 situation in the locations. Furthermore, it helps in recognizing the false indications, evaluating mental health, detecting or anticipating COVID-19 instances, examining government reactions to the epidemic, and assessing the quality of health information depicted in awareness videos. Additionally, the vaccination status of the public gives an estimate of the safety precaution taken for the virus. The information indicates the number of unvaccinated people at risk from the novel COVID-19 virus [102].

4.2. Big Data Acquisition and Storage Layers

The data acquisition stage does not perform by collecting data but also includes transmission, and pre-processing of data. The data, which is gathered from the prior data generation stage is compiled proactively by distributed or centralized servers. This compiled data block is now transmitted to master node(s) in the Hadoop cluster. Once the compilation of data is completed, it is transported towards the data storage layer, which subsequently starts analyzing it. The account of this extensive source of data may have various formats and structures accordingly, therefore, data pre-processing is a necessity. To provide a unified view of combined data acquired from the different sources, data integration can be used. The inaccurate and incomplete data are amended or removed in the pre-processing stage of data to improve its worth and validity.

The further processing of data is handled by Hadoop's HDFS [103]. HDFS cluster comprises the collection of DataNodes and a single NameNode. DataNode stores the acquired actual data, while NameNode manages the metadata of the file system. One or more blocks are generated by the splitting of big data and then a set of DataNode stores these blocks.

4.3. Big Data Query and Processing Layer

Hadoop Yarn [104] provides core computations for big data examination. The YARN and HDFS execute on a similar arrangement of nodes, allowing tasks to be analyzed on the nodes in which data related to COVID-19 identification is present.

Impala and Hive are utilized for cov-AID to peruse the COVID-19 data from the HDFS to select, process, or create data of interest. After creating a Hadoop cluster, data querying layer executes on top of it, which permits getting immediate outcomes. It ought to be noticed that different data querying components, for example, Apache Pig [105], which makes MapReduce activities, can be utilized.

4.4. Big Data Analytical Layer

There are two main objectives for the data analytics stage, to learn and to respond. Remote health advice can be offered to the patient by sharing the health status with the doctors and paramedical staff. The sustainability of the system is maintained by the active participation of patients and their caretakers by data visualization of the COVID-19 patient and outbreak status. The data in the response stage, is analyzed by doctors and health practitioners. They diagnose the disease and prescribe medicines and monitor the health status of the patients. Data security needs to be maintained when sharing such data. Various tools are used to analyze data, such as SAMOA [106] and Mahout [107] for mining big data and Tableau for big data visualization [108].

The acquired COVID-19 data are shared to improve the efficiency of patients' diagnosis and monitor them remotely, providing a protected environment for doctors and medical health workers from the virus. The diagnosis is performed on the trained dataset for the similar symptoms' patterns found in the patients of COVID-19. To help the government take possible actions that avoid the spread of the virus, the locations of the COVID-19 outbreak are identified. The infected areas can then be sealed so no one can travel in and out of those areas. The analytics utilize the data for proposing new big data applications by applying the techniques of data visualizing, correlations, and mining.

4.5. Big Data Application Layer

The huge amount of data generates from the patients' monitoring IoMT applications from their homes or hospitals are supported by the scalability of big data. Biometric readings from patients, such as blood pressure and heart rate, may be sent to big data servers for analysis without exposing healthcare staff to the virus. Big data solutions based on the Internet of Things are a critical tool for medical professionals dealing with infectious diseases. COVID-19 symptoms detection via IoMT sensors and detection of COVID-19 outbreak origin are the two directions in which the cov-AID applications' analysis moves.

4.5.1. COVID-19 Outbreak Analysis and Prediction Applications

COVID-19 is a virus that spreads from one individual to another, subsequently, its avoidance is a preferred solution over its cure [109]. WHO [110] announces precautions to forestall the disease that incorporates the directions to individuals to keep away from swarmed places and close contact with COVID-19 symptoms patients, clean and disinfect hands and things that interact with different people, wear a careful mask openly places to keep from transmitting the virus, starting with one individual then onto the next while breathing, sneezing, and cough. These precautions can be checked and kept up with by a few anticipation applications, for example, home isolate revelation and insights, emergency supplies and gear, rapid screening, and reconnaissance, and close contact COVID-19 positive patients as shown in Figure 5.

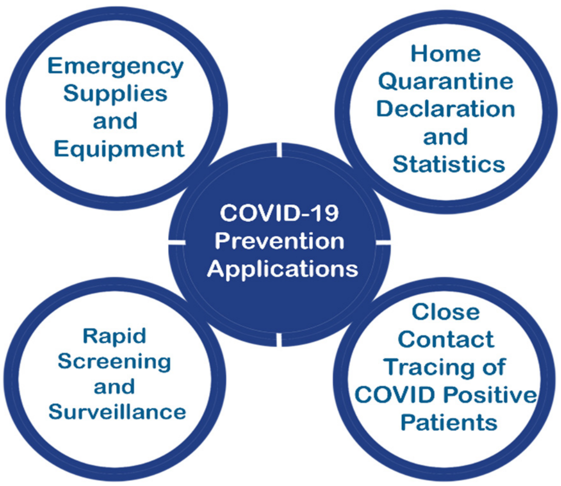


Figure 5. Proposed framework for prevention of spreading COVID-19.

These applications guarantee that COVID-19 precautions must be taken by the residents, and in any case an alarm will be produced to the concerned specialists. The travelers and suspected patients are isolated regardless of whether or not they have any clear clinical symptoms of COVID-19; in this way, the quick identification of such cases can be achieved. The application of cov-AID empowers these people with venture-out history to associate themselves with medical benefits for rapid diagnosis with minimal issues through organization applications. The territorial joining of electronic wellbeing records of suspected COVID-19 people as they move from one country to the next is also a benefit. Moreover, the spread of the virus can be constrained by the ideal medication of the medical services and public specialists just as with singular readiness. The application of cov-AID empowers people to recognize there are COVID-19 positive patients nearby and to maintain distance and precautions.

4.5.2. COVID-19 Patient Monitoring Applications

COVID-19 virus is exceptionally infectious; the para-medical staff are in a highly vulnerable state to this infection during examining COVID-19 patients. Therefore, cov-AID supports applications for remote monitoring and meetings between medical care professionals and COVID-19 patients, utilizing shrewd telemedicine and video conferencing platform. These applications incorporate remote patient monitoring; real-time disease surveillance system; real-time query and report of disease; patient counseling against COVID-19 fear, stress, and anxiety; and rapid remote diagnosis as shown in Figure 6. Moreover, these applications allow patients to self-isolate and self-screen at home, with results being sent to medical specialists remotely. The computed tomography (CT) scans or X-rays can also be performed remotely from the control room through the real-time videos and pictures that can be additionally handled by AI-enabled visual sensors [111–113]. Other health services, such as mental stress relief apps, can be easily integrated into IoMT systems to assist COVID-19 victims and affected persons with counselling and therapy.

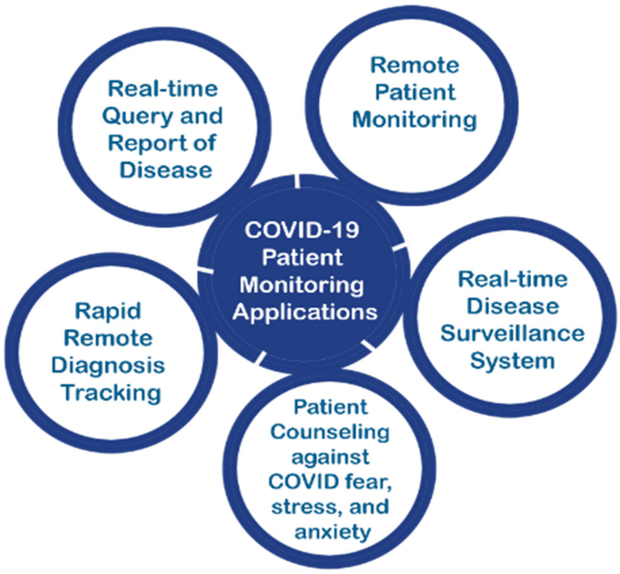


Figure 6. Proposed framework for COVID-19 patients' remote monitoring.

4.5.3. COVID-19 Outbreak Analysis and Prediction Applications

To identify the outbreak of COVID-19, real-time daily update data can be analyzed. This data includes cases of COVID-19 positive patients, the number of cured cases, and the number of deaths due to COVID-19 in various locations. The severity of the increased number of cases can be predicted by analyzing big data collected from the IoMT sensors using AI and machine learning. Based on this data analysis, better decision-making solutions can be proposed to help medical authorities and policymakers to control the situation of COVID-19 in a particular region. Each one who is connected to the cov-AID network will have access to the big data applications, which are connected to the centralized government programs and hospitals healthcare programs, such as precautionary, diagnosis, and treatment programs. The demonstration of the proposed framework using the aforementioned applications is shown in Figure 7. For screening and surveillance purposes several national and international arrival stations, such as railway stations, bus stands, airports, hostels, hotels, etc., have been installed with thermal imaging-based facial recognition [114–116].

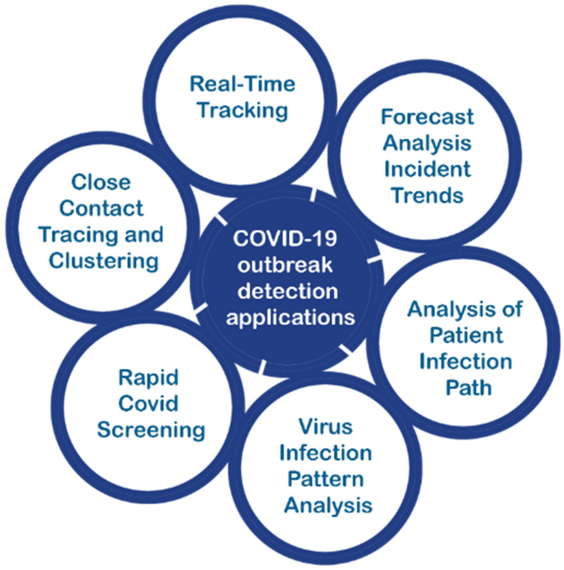


Figure 7. Proposed framework for COVID-19 outbreak detection.

5. Adoption Challenges for IoMT-Based Frameworks

The cov-AID framework can help to lower the impact of a global pandemic to a great extent, however, there are a few challenges that need to be addressed. The security and privacy of the individuals' data is a major concern. The resilience to malicious attacks, and vulnerable communication protocols are also another problem in a massive interconnected heterogeneous big data network. Healthcare IT is also facing the three topmost challenges: mobile and remote workforce, security of medically connected gadgets, and cloud security. This causes an increase in the use of remote IoMT devices that are connected with cloud platforms, cloud-based applications, and services to operate healthcare functions. This has led to an increase in security risks, such as malware attacks, breaches, and phishing. The performance guarantees of IoMT-wearable sensors are still an open challenge. These sensors work in a real-time environment; hence, low latency is a key requirement to avoid unnecessary delays and inaccurate results. The mental health due to the stress and fear of COVID-19 patients during a pandemic can be monitored, and personalized therapy solutions can be provided by integrating emotion-aware abilities into IoMT and mental state assessment. This may lead to ethical and privacy issues.

Cybersecurity and data security issues, and lack of basic cybersecurity awareness among medical staff are some other challenges that have been raised by the adoption of IoMT systems. In many countries, the regulations and lack of licensing for IoMT systems reside, preserving and fortifying the safety of patients, which gets difficult to adjust connectivity when it is mattered the most. Different health organizations execute diversity in monitoring systems and IoMT diagnosis and the inter-operability of system devices by different manufacturers. IoMT-based systems still have standardization issues. It is also needed to reduce human errors to improve the adoption scale of patients' remote monitoring and diagnosis systems.

6. Discussion and Future Work

The cov-AID framework assists to control the further spread of the virus by automatic screening and surveillance of the suspected and positive cases. To simplify the tedious work of controlling the spread of the pandemic government and health care authorities can access the database servers having records of COVID-19 screening results with location history. This can also be helpful to alert other personnel against contracting such suspected or confirmed cases. The cov-AID framework enables the system to categorize area-wise distribution by clustering the location data of the COVID-19 confirmed cases. The infected areas can be marked as containment zones, depending upon the number of confirmed cases. This can be done by interconnecting medical healthcare systems with the big data systems having data with the location of the suspected or confirmed cases. Through this framework, the government can alert the hospitals about these areas to perform a health screening and provide medical aid rapidly. The cov-AID framework also assists government authorities to take rapid actions to prevent the further outbreak. Applications, such as real-time tracking, forecast analysis of incident trends, analysis of patient infection path, virus infection pattern analysis, rapid COVID-19 screening, and close contact tracing and clustering, are provided in the cov-AID framework.

This framework has the potential to facilitate COVID-19 frontline workers along with the government in preventing further outbreak. We intend to deploy this framework by creating a testbed on a large scale for better evaluation. Realizing the need for security and privacy, especially in the healthcare context, we would be willing to undertake the extension of this framework by incorporating a security and privacy layer in the future. Keeping in view the importance of scheduling and task management in remote healthcare [117–127], we intend to incorporate this feature in the framework. Moreover, this framework is by no means limited to COVID-19, it has the potential to be utilized for all remote healthcare solutions that can be shown in further studies.

7. Conclusions

This research presents a comprehensive survey of the IoMT-based system designed for different healthcare applications, particularly in the context of COVID-19. Several types of research have been studied for the IoMT applications and frameworks. In addition, this research presents an IoMT-based big data framework, cov-AID, which facilitates in preventing the COVID-19. The proposed framework not only assists in providing remote healthcare facilities to COVID-19 patients by monitoring and treating them but also helps in detecting the outbreak regions of COVID-19. The cov-AID framework is promising for remote diagnosis, dynamic monitoring, rapid treatment at-home comfort, and prevention from spreading the virus. Likewise, the rapid strategies can be carried out cost-effectively to handle the emergency conditions of patients. The cov-AID framework also maintains systematic storage for big data analysis and prediction of the disease and remote online consultation.

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References

1. Qureshi, F.; Krishnan, S. Wearable Hardware Design for the Internet of Medical Things (IoMT). *Sensors* **2018**, *18*, 3812. [CrossRef] [PubMed]
2. Nayyar, A.; Puri, V.; Nguyen, N.G. BioSenHealth 1.0: A Novel Internet of Medical Things (IoMT)-Based Patient Health Monitoring System. *Lect. Notes Netw. Syst.* **2019**, *55*, 155–164.
3. Syed, L.; Jabeen, S.; Manimala, S.; Alsaeedi, A. Smart healthcare framework for ambient assisted living using IoMT and big data analytics techniques. *Futur. Gener. Comput. Syst.* **2019**, *101*, 136–151. [CrossRef]

4. Mohd Aman, A.H.; Hassan, W.H.; Sameen, S.; Attarbashi, Z.S.; Alizadeh, M.; Latiff, L.A. IoMT amid COVID-19 Pandemic: Application, Architecture, Technology, and Security. *J. Netw. Comput. Appl.* **2021**, *174*, 102886. [CrossRef] [PubMed]
5. Munshi, A.A.; Mohamed, Y.A.-R.I. Big data framework for analytics in smart grids. *Electr. Power Syst. Res.* **2017**, *151*, 369–380. [CrossRef]
6. Mohamed, A.; Najafabadi, M.K.; Wah, Y.B.; Zaman, E.A.K.; Maskat, R. The state of the art and taxonomy of big data analytics: View from new big data framework. *Artif. Intell. Rev.* **2019**, *53*, 989–1037. [CrossRef]
7. Nasajpour, M.; Pouriyeh, S.; Parizi, R.M.; Dorodchi, M.; Valero, M.; Arabnia, H.R. Internet of Things for Current COVID-19 and Future Pandemics: An Exploratory Study. *J. Health Inform. Res.* **2020**, *4*, 325–364. [CrossRef]
8. Sivarajah, U.; Kamal, M.M.; Irani, Z.; Weerakkody, V. Critical analysis of Big Data challenges and analytical methods. *J. Bus. Res.* **2017**, *70*, 263–286. [CrossRef]
9. Venkatesh, R.; Balasubramanian, C.; Kaliappan, M. Development of Big Data Predictive Analytics Model for Disease Prediction using Machine learning Technique. *J. Med. Syst.* **2019**, *43*, 272. [CrossRef]
10. Lin, Q.; Zhao, S.; Gao, D.; Lou, Y.; Yang, S.; Musa, S.S.; Wang, M.H.; Cai, Y.; Wang, W.; Yang, L.; et al. A conceptual model for the coronavirus disease 2019 (COVID-19) outbreak in Wuhan, China with individual reaction and governmental action. *Int. J. Infect. Dis.* **2020**, *93*, 211–216. [CrossRef]
11. Varsavsky, T.; Graham, M.S.; Canas, L.S.; Ganesh, S.; Pujol, J.C.; Sudre, C.H.; Murray, B.; Modat, M.; Cardoso, M.J.; Astley, C.M.; et al. Detecting COVID-19 infection hotspots in England using large-scale self-reported data from a mobile application: A prospective, observational study. *Lancet Public Health* **2021**, *6*, e21–e29. [CrossRef]
12. Subbarao, K.; Mahanty, S. Respiratory Virus Infections: Understanding COVID-19. *Immunity* **2020**, *52*, 905–909. [CrossRef] [PubMed]
13. Cimolai, N. Environmental and decontamination issues for human coronaviruses and their potential surrogates. *J. Med. Virol.* **2020**, *92*, 2498–2510. [CrossRef] [PubMed]
14. Sicari, S.; Rizzardi, A.; Coen-Porisini, A. Home quarantine patient monitoring in the era of COVID-19 disease. *Smart Health* **2022**, *23*, 100222. [CrossRef]
15. Li, F.; Valero, M.; Shahriar, H.; Khan, R.A.; Ahamed, S.I. Wi-COVID: A COVID-19 symptom detection and patient monitoring framework using WiFi. *Smart Health* **2021**, *19*, 100147. [CrossRef]
16. Jia, Q.; Guo, Y.; Wang, G.; Barnes, S.J. Big Data Analytics in the Fight against Major Public Health Incidents (Including COVID-19): A Conceptual Framework. *Int. J. Environ. Res. Public Health* **2020**, *17*, 6161. [CrossRef]
17. Swayamsiddha, S.; Mohanty, C. Application of cognitive Internet of Medical Things for COVID-19 pandemic. *Diabetes Metab. Syndr. Clin. Res. Rev.* **2020**, *14*, 911–915. [CrossRef]
18. Ashfaq, Z.; Rafay, A.; Mumtaz, R.; Zaidi, S.M.H.; Saleem, H.; Mumtaz, S.; Haque, A. A review of enabling technologies for Internet of Medical Things (IoMT) Ecosystem. *Ain Shams Eng. J.* **2022**, *13*, 101660. [CrossRef]
19. Dwivedi, R.; Mehrotra, D.; Chandra, S. Potential of Internet of Medical Things (IoMT) applications in building a smart healthcare system: A systematic review. *J. Oral Biol. Craniofacial Res.* **2021**, *12*, 302–318. [CrossRef]
20. Skolrood, L.; Wang, Y.; Zhang, S.; Wei, Q. Single-molecule and particle detection on true portable microscopy platforms. *Sens. Actuators Rep.* **2022**, *4*, 100063. [CrossRef]
21. Rahmani, A.M.; Bayramov, S.; Kalejahi, B.K. Internet of Things Applications: Opportunities and Threats. *Wirel. Pers. Commun.* **2022**, *122*, 451–476. [CrossRef] [PubMed]
22. Quy, V.K.; Hau, N.V.; Anh, D.V.; Ngoc, L.A. Smart Healthcare IoT Applications Based on Fog Computing: Architecture, Applications and Challenges. *Complex Intell. Syst.* **2021**, *2021*, 1–11. [CrossRef] [PubMed]
23. Mbunge, E.; Muchemwa, B.; Jiyane, S.; Batani, J. Sensors and healthcare 5.0: Transformative shift in virtual care through emerging digital health technologies. *Glob. Health J.* **2021**, *5*, 169–177. [CrossRef]
24. Sujith, A.; Sajja, G.S.; Mahalakshmi, V.; Nuhmani, S.; Prasanalakshmi, B. Systematic review of smart health monitoring using deep learning and Artificial intelligence. *Neurosci. Inform.* **2022**, *2*, 100028. [CrossRef]
25. Rahman, J.; Morshed, B.I.; Harmon, B.; Rahman, M. A pilot study towards a smart-health framework to collect and analyze biomarkers with low-cost and flexible wearables. *Smart Health* **2022**, *23*, 100249. [CrossRef]
26. Mamdouh, M.; Awad, A.I.; Khalaf, A.A.M.; Hamed, H.F.A. Authentication and Identity Management of IoHT Devices: Achievements, Challenges, and Future Directions. *Comput. Secur.* **2021**, *111*, 102491. [CrossRef]
27. Campos-Ferreira, D.; Visani, V.; Córdula, C.; Nascimento, G.A.; Montenegro, L.M.L.; Schindler, H.C.; Cavalcanti, I.M.F. COVID-19 Challenges: From SARS-CoV-2 Infection to Effective Point-of-Care Diagnosis by Electrochemical Biosensing Platforms. *Biochem. Eng. J.* **2021**, *176*, 108200.
28. Kashani, M.H.; Madanipour, M.; Nikravan, M.; Asghari, P.; Mahdipour, E. A systematic review of IoT in healthcare: Applications, techniques, and trends. *J. Netw. Comput. Appl.* **2021**, *192*, 103164. [CrossRef]
29. Ding, W.; Nayak, J.; Swapnarekha, H.; Abraham, A.; Naik, B.; Pelusi, D. Fusion of Intelligent Learning for COVID-19: A State-of-the-Art Review and Analysis on Real Medical Data. *Neurocomputing* **2021**, *457*, 40–66. [CrossRef]
30. Li, X.; Tao, B.; Dai, H.N.; Imran, M.; Wan, D.; Li, D. Is Blockchain for Internet of Medical Things a Panacea for COVID-19 Pandemic? *Pervasive Mobobile Comput.* **2021**, *75*, 101434. [CrossRef]
31. Hajiheydari, N.; Delgosha, M.S.; Olya, H. Scepticism and resistance to IoMT in healthcare: Application of behavioural reasoning theory with configurational perspective. *Technol. Forecast. Soc. Change* **2021**, *169*, 120807. [CrossRef]

32. Guo, J.; Chen, S.; Tian, S.; Liu, K.; Ni, J.; Zhao, M.; Kang, Y.; Ma, X.; Guo, J. 5G-enabled ultra-sensitive fluorescence sensor for proactive prognosis of COVID-19. *Biosens. Bioelectron.* **2021**, *181*, 113160. [CrossRef] [PubMed]
33. Bayin, Q.; Huang, L.; Ren, C.; Fu, Y.; Ma, X.; Guo, J. Anti-SARS-CoV-2 IgG and IgM Detection with a GMR Based LFIA System. *Talanta* **2021**, *227*, 122207. [CrossRef] [PubMed]
34. Intawong, K.; Olson, D.; Chariyalertsak, S. Application technology to fight the COVID-19 pandemic: Lessons learned in Thailand. *Biochem. Biophys. Res. Commun.* **2021**, *538*, 231–237. [CrossRef]
35. Jain, H.; Chamola, V.; Jain, Y.; Naren. 5G network slice for digital real-time healthcare system powered by network data analytics. *Internet Things Cyber-Phys. Syst.* **2021**, *1*, 14–21. [CrossRef]
36. Greco, L.; Percannella, G.; Ritrovato, P.; Tortorella, F.; Vento, M. Trends in IoT based solutions for health care: Moving AI to the edge. *Pattern Recognit. Lett.* **2020**, *135*, 346–353. [CrossRef]
37. Singh, R.P.; Javaid, M.; Haleem, A.; Suman, R. Internet of things (IoT) applications to fight against COVID-19 pandemic. *Diabetes Metab. Syndr. Clin. Res. Rev.* **2020**, *14*, 521–524. [CrossRef]
38. Lim, S.; Rahmani, R. Toward Semantic IoT Load Inference Attention Management for Facilitating Healthcare and Public Health Collaboration: A Survey. *Procedia Comput. Sci.* **2020**, *177*, 371–378. [CrossRef]
39. Volkov, I.; Radchenko, G.; Tchernykh, A. Digital Twins, Internet of Things and Mobile Medicine: A Review of Current Platforms to Support Smart Healthcare. *Program. Comput. Softw.* **2021**, *47*, 578–590. [CrossRef]
40. Zhou, Y.; Zhao, D. Application of convolutional neural network-based biosensor and electroencephalogram signal in sleep staging. *J. Ambient Intell. Humaniz. Comput.* **2021**, *12*, 1–11. [CrossRef]
41. Alharbi, A.; Rahman, A. Review of Recent Technologies for Tackling COVID-19. *SN Comput. Sci.* **2021**, *2*, 460. [CrossRef] [PubMed]
42. Hasnain, M.; Pasha, M.F.; Ghani, I.; Jeong, S.R. Emerging technologies and their roles during the COVID-19 pandemic and safety challenges of frontline medical staff: A rapid review. *Res. Biomed. Eng.* **2021**, *38*, 279–291. [CrossRef]
43. Islam, M.; Mahmud, S.; Muhammad, L.J.; Islam, R.; Nooruddin, S.; Ayon, S.I. Wearable Technology to Assist the Patients Infected with Novel Coronavirus (COVID-19). *SN Comput. Sci.* **2020**, *1*, 320. [CrossRef] [PubMed]
44. Vafea, M.T.; Atalla, E.; Georgakas, J.; Shehadeh, F.; Mylona, E.K.; Kalligeros, M.; Mylonakis, E. Emerging Technologies for Use in the Study, Diagnosis, and Treatment of Patients with COVID-19. *Cell. Mol. Bioeng.* **2020**, *13*, 249–257. [CrossRef]
45. Monaghesh, E.; Hajizadeh, A. The role of telehealth during COVID-19 outbreak: A systematic review based on current evidence. *BMC Public Health* **2020**, *20*, 1193. [CrossRef]
46. Mbunge, E.; Akinnuwesi, B.; Fashoto, S.G.; Metfula, A.S.; Mashwama, P. A critical review of emerging technologies for tackling COVID-19 pandemic. *Hum. Behav. Emerg. Technol.* **2020**, *3*, 25–39. [CrossRef]
47. Anand, R.; Sindhwani, N.; Saini, A.; Shubham. Emerging Technologies for COVID-19. In *Enabling Healthcare 4.0 Pandemics*; Wiley: New York, NY, USA, 2021; pp. 163–188.
48. Puri, V.; Kataria, A.; Sharma, V. Artificial intelligence-powered decentralized framework for Internet of Things in Healthcare 4.0. *Trans. Emerg. Telecommun. Technol.* **2021**, *32*, e4245. [CrossRef]
49. Juneja, S.; Juneja, A.; Dhankhar, A.; Jain, V. IoT-Enabled Effective Healthcare Monitoring System Using Semantic Web. In *Semantic Web for Effective Healthcare*; Wiley: New York, NY, USA, 2021; pp. 175–189.
50. Bera, B.; Mitra, A.; Das, A.K.; Puthal, D.; Park, Y. Private Blockchain-Based AI-Envisioned Home Monitoring Framework in IoMT-Enabled COVID-19 Environment. *IEEE Consum. Electron. Mag.* **2021**, 1. [CrossRef]
51. Alam, M.; Rahmani, R. Federated Semi-Supervised Multi-Task Learning to Detect COVID-19 and Lungs Segmentation Marking Using Chest Radiography Images and Raspberry Pi Devices: An Internet of Medical Things Application. *Sensors* **2021**, *21*, 5025. [CrossRef]
52. Mbunge, E.; Jiyane, S.; Muchemwa, B. Towards emotive sensory Web in virtual health care: Trends, technologies, challenges and ethical issues. *Sens. Int.* **2022**, *3*, 100134. [CrossRef]
53. Ismael, M.H.; Maolood, A.T. Developing Modern System in Healthcare to Detect Covid 19 Based on Internet of Things. *Mater. Today Proc.* **2021**, *in press*. [CrossRef]
54. Yadav, A.K.; Verma, D.; Kumar, A.; Kumar, P.; Solanki, P.R. The perspectives of biomarker-based electrochemical immunosensors, artificial intelligence and the Internet of Medical Things toward COVID-19 diagnosis and management. *Mater. Today Chem.* **2021**, *20*, 100443. [CrossRef] [PubMed]
55. Jain, S.; Nehra, M.; Kumar, R.; Dilbaghi, N.; Hu, T.Y.; Kumar, S.; Kaushik, A.; Li, C.Z. Internet of Medical Things (IoMT)-Integrated Biosensors for Point-of-Care Testing of Infectious Diseases. *Biosens. Bioelectron.* **2021**, *179*, 113074. [CrossRef] [PubMed]
56. Ahmed, I.; Ahmad, M.; Jeon, G.; Piccialli, F. A Framework for Pandemic Prediction Using Big Data Analytics. *Big Data Res.* **2021**, *25*, 100190. [CrossRef]
57. Fagroud, F.Z.; Toumi, H.; Ben Lahmar, E.H.; Talhaoui, M.A.; Achtaich, K.; El Filali, S. Impact of IoT devices in E-Health: A Review on IoT in the context of COVID-19 and its variants. *Procedia Comput. Sci.* **2021**, *191*, 343–348. [CrossRef]
58. Al Bassam, N.; Hussain, S.A.; Al Qaraghuli, A.; Khan, J.; Sumesh, E.P.; Lavanya, V. IoT based wearable device to monitor the signs of quarantined remote patients of COVID-19. *Inform. Med. Unlocked* **2021**, *24*, 100588. [CrossRef]
59. Saba, T.; Haseeb, K.; Ahmed, I.; Rehman, A. Secure and energy-efficient framework using Internet of Medical Things for e-healthcare. *J. Infect. Public Health* **2020**, *13*, 1567–1575. [CrossRef]

60. Mishra, L.; Vikash; Varma, S. Seamless Health Monitoring Using 5G NR for Internet of Medical Things. *Wirel. Pers. Commun.* **2021**, *120*, 2259–2289. [CrossRef]
61. Viswanadham, N. Ecosystem model for healthcare platform. *Sadhana* **2021**, *46*, 188. [CrossRef]
62. Al-Dhaen, F.; Hou, J.; Rana, N.P.; Weerakkody, V. Advancing the Understanding of the Role of Responsible AI in the Continued Use of IoMT in Healthcare. *Inf. Syst. Front.* **2021**, *23*, 1–20. [CrossRef]
63. Asghari, P. A diagnostic prediction model for colorectal cancer in elderlies via internet of medical things. *Int. J. Inf. Technol.* **2021**, *13*, 1423–1429. [CrossRef] [PubMed]
64. Uslu, B.Ç.; Okay, E.; Dursun, E. Analysis of Factors Affecting IoT-Based Smart Hospital Design. *J. Cloud Comput.* **2020**, *9*, 67. [CrossRef] [PubMed]
65. Sharma, N.; Mangla, M.; Mohanty, S.N.; Gupta, D.; Tiwari, P.; Shorfuzzaman, M.; Rawashdeh, M. A smart ontology-based IoT framework for remote patient monitoring. *Biomed. Signal Process. Control* **2021**, *68*, 102717. [CrossRef]
66. Renugadevi, N.; Saravanan, S.; Sudha, C.N. Revolution of Smart Healthcare Materials in Big Data Analytics. *Mater. Today Proc.* 2021, *in press*. [CrossRef]
67. Savaşcı Şen, S.; Cicioğlu, M.; Çalhan, A. IoT-Based GPS Assisted Surveillance System with Inter-WBAN Geographic Routing for Pandemic Situations. *J. Biomed. Inform.* **2021**, *116*, 103731. [CrossRef] [PubMed]
68. Ben Arfi, W.; Ben Nasr, I.; Kondrateva, G.; Hikkerova, L. The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technol. Forecast. Soc. Change* **2021**, *167*, 120688. [CrossRef]
69. Gupta, D.; Bhatt, S.; Gupta, M.; Tosun, A.S. Future Smart Connected Communities to Fight COVID-19 Outbreak. *Internet Things* **2021**, *13*, 100342. [CrossRef]
70. Abdel-Basset, M.; Chang, V.; Nabeeh, N.A. An intelligent framework using disruptive technologies for COVID-19 analysis. *Technol. Forecast. Soc. Change* **2021**, *163*, 120431. [CrossRef]
71. Kumar, A.; Sharma, K.; Singh, H.; Naugriya, S.G.; Gill, S.S.; Buyya, R. A drone-based networked system and methods for combating coronavirus disease (COVID-19) pandemic. *Futur. Gener. Comput. Syst.* **2021**, *115*, 1–19. [CrossRef]
72. Otoom, M.; Otoum, N.; Alzubaidi, M.A.; Etoom, Y.; Banihani, R. An IoT-Based Framework for Early Identification and Monitoring of COVID-19 Cases. *Biomed. Signal Process. Control* **2020**, *62*, 102149. [CrossRef]
73. Singh, R.P.; Javaid, M.; Haleem, A.; Vaishya, R.; Ali, S. Internet of Medical Things (IoMT) for orthopaedic in COVID-19 pandemic: Roles, challenges, and applications. *J. Clin. Orthop. Trauma* **2020**, *11*, 713–717. [CrossRef] [PubMed]
74. Singh, P.; Kaur, R. An integrated fog and Artificial Intelligence smart health framework to predict and prevent COVID-19. *Glob. Transit.* **2020**, *2*, 283–292. [CrossRef] [PubMed]
75. Kallel, A.; Rekik, M.; Khemakhem, M. Hybrid-based framework for COVID-19 prediction via federated machine learning models. *J. Supercomput.* **2021**, *78*, 7078–7105. [CrossRef]
76. Khowaja, S.A.; Khuwaja, P.; Dev, K.; D'Aniello, G. VIRFIM: An AI and Internet of Medical Things-driven framework for healthcare using smart sensors. *Neural Comput. Appl.* **2021**, *34*, 1–18. [CrossRef] [PubMed]
77. Poongodi, M.; Nguyen, T.N.; Hamdi, M.; Cengiz, K. A Measurement Approach Using Smart-IoT Based Architecture for Detecting the COVID-19. *Neural Process. Lett.* **2021**, 1–15. [CrossRef]
78. Rahman, A.; Chakraborty, C.; Anwar, A.; Karim, M.R.; Islam, M.J.; Kundu, D.; Rahman, Z.; Band, S.S. SDN–IoT Empowered Intelligent Framework for Industry 4.0 Applications during COVID-19 Pandemic. *Clust. Comput.* **2021**, *3*, 2351–2368. [CrossRef]
79. Madhavan, M.V.; Khamparia, A.; Gupta, D.; Pande, S.; Tiwari, P.; Hossain, M.S. Res-CovNet: An Internet of Medical Health Things Driven COVID-19 Framework Using Transfer Learning. *Neural Comput. Appl.* **2021**, 1–14. [CrossRef]
80. Akhbarifar, S.; Javadi, H.H.S.; Rahmani, A.M.; Hosseinzadeh, M. A secure remote health monitoring model for early disease diagnosis in cloud-based IoT environment. *Pers. Ubiquitous Comput.* **2020**, *24*, 1–17. [CrossRef]
81. Rahman, M.A.; Shamim Hossain, M. An Internet-of-Medical-Things-Enabled Edge Computing Framework for Tackling COVID-19. *IEEE Internet Things J.* **2021**, *8*, 15847–15854. [CrossRef]
82. Zhang, T.; Liu, M.; Yuan, T.; Al-Nabhan, N. Emotion-Aware and Intelligent Internet of Medical Things Toward Emotion Recognition During COVID-19 Pandemic. *IEEE Internet Things J.* **2021**, *8*, 16002–16013. [CrossRef]
83. Liu, J.; Miao, F.; Yin, L.; Pang, Z.; Li, Y. A Noncontact Ballistocardiography-Based IoMT System for Cardiopulmonary Health Monitoring of Discharged COVID-19 Patients. *IEEE Internet Things J.* **2021**, *8*, 15807–15817. [CrossRef] [PubMed]
84. Rodriguez, F.; Gutierrez, S.; Reyes, B.A.; Rosas, V.; Rubio, M.V.S.; Rodriguez, A.M.; Jimenez, R.M.; Olvera, F.J.H.; Hernandez, O.S. IoMT: Rinku's Clinical Kit Applied to Collect Information Related to COVID-19 Through Medical Sensors. *IEEE Lat. Am. Trans.* **2021**, *19*, 1002–1009. [CrossRef]
85. Tai, Y.; Gao, B.; Li, Q.; Yu, Z.; Zhu, C.; Chang, V. Trustworthy and Intelligent COVID-19 Diagnostic IoMT Through XR and Deep-Learning-Based Clinic Data Access. *IEEE Internet Things J.* **2021**, *8*, 15965–15976. [CrossRef]
86. Zhang, M.; Dai, D.; Hou, S.; Liu, W.; Gao, F.; Xu, D.; Hu, Y. Thinking on the informatization development of China's healthcare system in the post-COVID-19 era. *Intell. Med.* **2021**, *1*, 24–28. [CrossRef] [PubMed]
87. Baran, K. Stress detection and monitoring based on low-cost mobile thermography. *Procedia Comput. Sci.* **2021**, *192*, 1102–1110. [CrossRef]
88. Nagarajan, S.M.; Deverajan, G.G.; Chatterjee, P.; Alnumay, W.; Ghosh, U. Effective task scheduling algorithm with deep learning for Internet of Health Things (IoHT) in sustainable smart cities. *Sustain. Cities Soc.* **2021**, *71*, 102945. [CrossRef]

89. Elagan, S.K.; Abdelwahab, S.F.; Zanaty, E.A.; Alkinani, M.H.; Alotaibi, H.; Zanaty, M.E.A. Remote diagnostic and detection of coronavirus disease (COVID-19) system based on intelligent healthcare and internet of things. *Results Phys.* **2021**, *22*, 103910. [CrossRef]
90. Ray, P.P.; Dash, D.; Kumar, N. Sensors for internet of medical things: State-of-the-art, security and privacy issues, challenges and future directions. *Comput. Commun.* **2020**, *160*, 111–131. [CrossRef]
91. Jauregi, I.; Solar, H.; Beriain, A.; Zalbide, I.; Jimenez, A.; Galarraga, I.; Berenguer, R. UHF RFID Temperature Sensor Assisted with Body-Heat Dissipation Energy Harvesting. *IEEE Sens. J.* **2017**, *17*, 1471–1478. [CrossRef]
92. Masao, C.; Hirozumi, Y.; Teruo, H.; Yoshiyuki, S. Human Thermal Comfort Estimation in Indoor Space by Crowd Sensing. In Proceedings of the 2016 IEEE International Conference on Smart Grid Communications (SmartGridComm), Sydney, NSW, Australia, 6–9 November 2016; pp. 45–50.
93. Shorfuzzaman, M.; Hossain, M.S.; Alhamid, M.F. Towards the sustainable development of smart cities through mass video surveillance: A response to the COVID-19 pandemic. *Sustain. Cities Soc.* **2021**, *64*, 102582. [CrossRef]
94. Khan, S.; Saultry, B.; Adams, S.; Kouzani, A.Z.; Decker, K.; Digby, R.; Bucknall, T. Comparative accuracy testing of non-contact infrared thermometers and temporal artery thermometers in an adult hospital setting. *Am. J. Infect. Control* **2021**, *49*, 597–602. [CrossRef] [PubMed]
95. Tang, S.; Tang, J. Electrocardiogram Classification Using Long Short-Term Memory Networks. In *Advances in Computer Vision and Computational Biology*; Springer: Cham, Switzerland, 2021; pp. 855–862. [CrossRef]
96. Alian, A.A.; Shelley, K.H. Photoplethysmography. *Best Pract. Res. Clin. Anaesthesiol.* **2014**, *28*, 395–406. [CrossRef] [PubMed]
97. Sadek, I.; Biswas, J. Nonintrusive heart rate measurement using ballistocardiogram signals: A comparative study. *Signal Image Video Process.* **2018**, *13*, 475–482. [CrossRef]
98. Lokharan, M.; Kumar, K.C.L.; Kumar, V.H.; Kayalvizhi, N.; Aryalekshmi, R. Measurement of Pulse Transit Time (PTT) Using Photoplethysmography. In Proceedings of the 16th International Conference on Biomedical Engineering, Singapore, 7–10 December 2017; pp. 130–134. [CrossRef]
99. Zamanifar, A. Remote Patient Monitoring: Health Status Detection and Prediction in IoT-Based Health Care. In *IoT in Healthcare and Ambient Assisted Living*; Springer: Singapore, 2021; pp. 89–102.
100. Bonnevie, T.; Gravier, F.-E.; Elkins, M.; Dupuis, J.; Prieur, G.; Combret, Y.; Viacroze, C.; Debeaumont, D.; Robleda-Quesada, A.; Quieffin, J.; et al. People undertaking pulmonary rehabilitation are willing and able to provide accurate data via a remote pulse oximetry system: A multicentre observational study. *J. Physiother.* **2019**, *65*, 28–36. [CrossRef]
101. Chakkor, S.; Baghouri, M.; El Oualkadi, A.; El Hangouche, J.A.; Laamech, J.; Belfkih, R. Intelligent Monitoring System to Aid in the Proactive and Early Detection of People Infected by COVID-19. In *Artificial Intelligence for COVID-19*; Springer: Cham, Switzerland, 2021. [CrossRef]
102. Grech, V.; Borg, M. Influenza vaccination in the COVID-19 era. *Early Hum. Dev.* **2020**, *148*, 105116. [CrossRef] [PubMed]
103. Balusamy, B.; Abirami, R.N.; Kadry, S.; Gandomi, A.H. Driving Big Data with Hadoop Tools and Technologies. *Big Data* **2021**, *1*, 111–160. [CrossRef]
104. Indrakumari, R.; Poongodi, T.; Suresh, P.; Balamurugan, B. The growing role of integrated and insightful big and real-time data analytics platforms. *Adv. Comput.* **2019**, *117*, 165–186. [CrossRef]
105. Manogaran, G.; Varatharajan, R.; Lopez, D.; Kumar, P.M.; Sundarasekar, R.; Thota, C. A new architecture of Internet of Things and big data ecosystem for secured smart healthcare monitoring and alerting system. *Futur. Gener. Comput. Syst.* **2018**, *82*, 375–387. [CrossRef]
106. Hoelscher, J.; Mortimer, A. Using Tableau to visualize data and drive decision-making. *J. Account. Educ.* **2018**, *44*, 49–59. [CrossRef]
107. Prajapati, M.; Patel, S. A Review on Big Data with Data Mining. *Lect. Notes Data Eng. Commun. Technol.* **2021**, *52*, 155–160. [CrossRef]
108. Goswami, P.K.; Sharma, A. Realtime analysis and visualization of data for instant decisions: A futuristic requirement of the digital world. *Mater. Today Proc.* **2021**, *in press*. [CrossRef]
109. Lunn, P.D.; Timmons, S.; Belton, C.A.; Barjaková, M.; Julienne, H.; Lavin, C. Motivating social distancing during the COVID-19 pandemic: An online experiment. *Soc. Sci. Med.* **2020**, *265*, 113478. [CrossRef] [PubMed]
110. World Health Organization. WHO | World Health Organization. Available online: https://www.who.int/ (accessed on 15 August 2021).
111. Alhasan, M.; Hasaneen, M. Digital imaging, technologies and artificial intelligence applications during COVID-19 pandemic. *Comput. Med. Imaging Graph.* **2021**, *91*, 101933. [CrossRef] [PubMed]
112. Banerjee, A.; Chakraborty, C.; Kumar, A.; Biswas, D. Emerging trends in IoT and big data analytics for biomedical and health care technologies. In *Handbook of Data Science Approaches for Biomedical Engineering*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 121–152. [CrossRef]
113. Muhammad, G.; Alshehri, F.; Karray, F.; El Saddik, A.; Alsulaiman, M.; Falk, T.H. A comprehensive survey on multimodal medical signals fusion for smart healthcare systems. *Inf. Fusion* **2021**, *76*, 355–375. [CrossRef]
114. Pandey, S.; Barik, R.K.; Gupta, S.; Arthi, R. Pandemic Drone with Thermal Imaging and Crowd Monitoring System (DRISHYA). In *Technical Advancements of Machine Learning in Healthcare*; Springer: Singapore, 2021; pp. 307–325. [CrossRef]

115. Sepúlveda, A.; Periñán-Pascual, C.; Muñoz, A.; Martínez-España, R.; Hernández-Orallo, E.; Cecilia, J.M. COVIDSensing: Social Sensing Strategy for the Management of the COVID-19 Crisis. *Electronics* **2021**, *10*, 3157. [CrossRef]
116. Levashenko, V.; Rabcan, J.; Zaitseva, E. Reliability Evaluation of the Factors That Influenced COVID-19 Patients' Condition. *Appl. Sci.* **2021**, *11*, 2589. [CrossRef]
117. Mastoi, Q.-U.; Memon, M.S.; Lakhan, A.; Mohammed, M.A.; Qabulio, M.; Al-Turjman, F.; Abdulkareem, K.H. Machine learning-data mining integrated approach for premature ventricular contraction prediction. *Neural Comput. Appl.* **2021**, *33*, 11703–11719. [CrossRef]
118. Lakhan, A.; Mohammed, M.; Rashid, A.; Kadry, S.; Panityakul, T.; Abdulkareem, K.; Thinnukool, O. Smart-Contract Aware Ethereum and Client-Fog-Cloud Healthcare System. *Sensors* **2021**, *21*, 4093. [CrossRef]
119. Lakhan, A.; Mastoi, Q.-U.; Elhoseny, M.; Memon, M.S.; Mohammed, M.A. Deep neural network-based application partitioning and scheduling for hospitals and medical enterprises using IoT assisted mobile fog cloud. *Enterp. Inf. Syst.* **2022**, *16*, 1883122. [CrossRef]
120. Mutlag, A.A.; Ghani, M.K.A.; Mohammed, M.A.; Lakhan, A.; Mohd, O.; Abdulkareem, K.H.; Garcia-Zapirain, B. Multi-Agent Systems in Fog–Cloud Computing for Critical Healthcare Task Management Model (CHTM) Used for ECG Monitoring. *Sensors* **2021**, *21*, 6923. [CrossRef]
121. Mohammed, M.A.; Kozlov, S.; Rodrigues, J.J. Mobile-fog-cloud assisted deep reinforcement learning and blockchain-enable IoMT system for healthcare workflows. *Trans. Emerg. Telecommun. Technol.* **2021**, e4363. [CrossRef]
122. Lakhan, A.; Mastoi, Q.-U.; Dootio, M.A.; Alqahtani, F.; Alzahrani, I.R.; Baothman, F.; Shah, S.Y.; Shah, S.A.; Anjum, N.; Abbasi, Q.H.; et al. Hybrid Workload Enabled and Secure Healthcare Monitoring Sensing Framework in Distributed Fog-Cloud Network. *Electronics* **2021**, *10*, 1974. [CrossRef]
123. Lakhan, A.; Dootio, M.A.; Sodhro, A.H.; Pirbhulal, S.; Groenli, T.M.; Khokhar, M.S.; Wang, L. Cost-efficient service selection and execution and blockchain-enabled serverless network for internet of medical things. *Math. Biosci. Eng.* **2021**, *18*, 7344–7362. [CrossRef]
124. Lakhan, A.; Mohammed, M.A.; Kadry, S.; AlQahtani, S.A.; Maashi, M.S.; Abdulkareem, K.H. Federated Learning-Aware Multi-Objective Modeling and blockchain-enable system for IIoT applications. *Comput. Electr. Eng.* **2022**, *100*, 107839. [CrossRef]
125. Lakhan, A.; Sajnani, D.K.; Tahir, M.; Aamir, M.; Lodhi, R. Delay Sensitive Application Partitioning and Task Scheduling in Mobile Edge Cloud Prototyping. In Proceedings of the International Conference on 5G for Ubiquitous Connectivity, Nanjing, China, 4–5 December 2018; pp. 59–80. [CrossRef]
126. Lakhan, A.; Mohammed, M.A.; Elhoseny, M.; Alshehri, M.D.; Abdulkareem, K.H. Blockchain multi-objective optimization approach-enabled secure and cost-efficient scheduling for the Internet of Medical Things (IoMT) in fog-cloud system. *Soft Comput.* **2022**, *26*, 6429–6442. [CrossRef]
127. Lakhan, A.; Khoso, F.H.; Arain, A.A.; Kanwar, K. Serverless based functions aware framework for healthcare application. *Int. J. Emerg. Trends Eng. Res.* **2021**, *9*. [CrossRef]