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A Comprehensive Survey on Pandemic Patient Monitoring System: Enabling Technologies, Opportunities, and Research Challenges

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Abstract
Sporadic occurrences of transmissible diseases have severe and long-lasting effects on humankind throughout history. These outbreaks have molded the political, economic, and social aspects of human life. Pandemics have redefined some of the basic beliefs of modern healthcare, pushing researchers and scientists to develop innovative solutions to be better equipped for future emergencies. Numerous attempts have been made to fight Covid-19-like pandemics using technologies such as the Internet of Things, wireless body area network, blockchain, and machine learning. Since the disease is highly contagious, novel research in patients' health monitoring system is essential for the constant monitoring of pandemic patients with minimal or no human intervention. With the ongoing pandemic of SARS-CoV-2, popularly known as Covid-19, innovations for monitoring of patients' vitals and storing them securely have risen more than ever. Analyzing the stored patients' data can further assist healthcare workers in their decision-making process. In this paper, we surveyed the research works on remote monitoring of pandemic patients admitted in hospitals or quarantined at home. First, an overview of pandemic patient monitoring is given followed by a brief introduction of enabling technologies i.e. Internet of Things, blockchain, and machine learning to implement the system. The reviewed works have been classified into three categories; remote monitoring of pandemic patients using IoT, blockchain-based storage or sharing platforms for patients' data, and processing/analyzing the stored patients' data using machine learning for prognosis and diagnosis. We also identified several open research issues to set directions for future research.

Keywords Covid-19 · Remote patient monitoring · IoT · Blockchain · Patient data processing · Machine learning

1 Introduction

In the past century, there have been various health crises caused by pandemics and outbreaks that were unparalleled in human history. The majority of these pandemics were attributable to influenza viruses, including H1N1, H2N2, and H3N2 [1]. For instance, Spanish Flu and swine flu pandemics were caused by the H1N1 virus [2] and Asian flu

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and Hong Kong flu were caused by the H2N2 and H3N2 viruses. Various coronavirus outbreaks have also occurred in the last 20 years, such as the outbreak of SARS-CoV in 2002 and MERS-CoV in 2012 [3]. At present, the world is grappling with a severe global pandemic known as Covid-19, which is caused by a novel and highly contagious strain of the coronavirus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). This disease poses a significant threat to human health and well-being [4]. The disease has infected people globally in many countries. As the number of infections rose exponentially, health workers' primary concern was to end the spread of coronavirus. Some preventive measures were taken such as social distancing, wearing masks, and washing hands regularly. Many countries took substantial steps such as imposing curfews and lock-downs, calling for work from home, and social distancing to combat the spread of Covid-19 infection [5]. Till July 2022, an estimate of 6,369,510 deaths has been reported globally [6, 7]. The pandemic also caused huge global economic losses with the enormous disruptions in many areas such as agriculture, transport, supply chain, tourism, and industry, compelling governments and owners to shut down most operations globally [8]. An overview of Covid-19 symptoms, preventive measures, worldwide effect and mitigation efforts is shown in Table 1.

The infection levels may vary from asymptomatic and mild to severe or fatal. General categorization of Covid-19 cases is shown in Table 2. A Covid-19 patient's health deteriorates rapidly, leading to patients being admitted to the hospital's Intensive Care Unit (ICU) [9]. According to statistics from China, almost 15–20% of Covid-19 cases were hospitalized, including 15% of cases of severe illness and 5% of patients needing intensive care [10]. In Spain and Italy, 40–50% of Covid-19 cases were hospitalized, and 7–12% were admitted to ICUs [11].

Even though medical professionals worked day and night to save lives, the rapid growth in the cases of Covid-19 hard-pressed the existing healthcare systems to their limits. A traditional health care systems manage multi-party workflows such as diagnosis, patient care, testing, prescriptions and remote monitoring. It is worth mentioning that patients' data between different centers are not shared on a common platform. Hence, when patients are referred from one place to another, sometimes reexamination of patients is observed. This promotes tedious manual work and makes treatment costly and time-consuming [12]. During this, the treatment of critical patients may be delayed, which risks the life of the patients as well. Moreover, the healthcare data management system is not coordinated between healthcare facilitators. The absence of an unfailing data surveillance system that would disseminate relevant information to healthcare institutions was also noticed [13]. Main sources of Covid-19 information include government websites, hospitals, news portals, and clinical labs. However, getting the correct and reliable information was very difficult and a real challenge for the Covid treatment system. Another challenge was to process huge volumes of Covid-19 data using human-dependent medicine tools [14]. Furthermore, as the disease is highly infectious, the patients were quarantined to disrupt the spread of the disease. Isolation keeps the spread of the virus under control. Constant monitoring of patients' vital signs is essential in highly infectious diseases like Covid-19. It is required for both low or medium condition patients in home quarantine or severe patients in the hospital.

Technological advancements can aid in overcoming these challenges. Recently, the technologies such as the Wireless Body Area Network (WBAN), Internet of Things (IoT), Blockchain, and Machine Learning (ML) have been used widely in the medical domain [15]. These technologies facilitate in developing a smart healthcare system that can help in integration of diagnosis, treatment surgeries, clinical management,

Table 1 Overview of Covid-19symptoms, preventive measures, worldwide effect and mitigation efforts [9]

Symptoms	Preventive measure	Worldwide effect	Mitigation efforts
• Fever • Dry Cough • Fatigue • Difficulty in breathing	• Wearing mask • Washing hands for at least 20 s • Maintain a social distance of at least 2 m in public areas • Avoid touching the face	• Locked down cities • Restricted movements of millions • Suspended business operations • Slowed down the global economy and financial markets	• Contact tracing • National disinfection program • Drive through testing centers • Temporary hospitals

maintenance of supplies, remote monitoring of patients, smart and cost-effective supply chain in pandemic situations. In contrast to traditional medical systems, smart healthcare systems create a network where healthcare workers and patients can easily connect to exchange essential information whenever required. The smart healthcare system would assist us in being prepared for unprecedented pandemics and emergencies like Covid-19 [16].

Remote patient monitoring using IoT, Blockchain and ML is an essential part of smart healthcare systems. During the ongoing COVID-19 pandemic, the importance and need of remote monitoring has increased drastically. It enables healthcare professionals to record the vitals of a patient remotely in continuous manner. It also helps to improve the safety of the healthcare professionals as there would be minimal patient-doctor interaction. In remote monitoring process, a patient is admitted to a hospital or home quarantined and is assigned a set of sensors that measure the patient's vitals like heart rate and blood pressure, from time to time. The vast amount of data collected from the WBAN and the previous health records of the patients are stored securely in a database [17]. Healthcare data is considered highly sensitive and private and is primarily stored in centralized servers or cloud servers [18]. These storage methods suffer from single-point failure. Healthcare facilities can be discontinued and disrupted by attacks such as Denial of Services (DoS) and Ransomware attacks. Third-party organizations generally own cloud data centers; hence the issues related to privacy, tractability and accountability of patient data is inevitable [19]. Blockchain technology has huge potential to solve the security and privacy issues in a healthcare system. Blockchain stores the data securely using cryptographic functions in a decentralized way. The stored data on the blockchain is immutable; hence it cannot be changed by malicious users [20]. The stored patient data can be processed/analyzed using well-trained ML models for prognosis and diagnosis. Machine learning algorithm uses this monitored data as well as the previous health records of the patients for training the model. It can provide valuable insights into the patient's condition, hence assisting the healthcare workers for better decision making [18]. Machine Learning aids scientists, doctors, and researchers in aggregating, analyzing and processing the patients' data for several valuable purposes like vaccine development, supply chain management and predicting patients' health [15].

Hence, in Covid-19-like pandemic situations, emerging technologies may be utilized to build remote vital signs monitoring system. The sudden surge in the cases of Covid-19 globally has forced different people and communities to search for prompt solutions to weaken the effects of the Covid-19 outbreak. This paper aims to survey the recent literature on remote monitoring systems for pandemics like Covid-19.

Table 2 Classification of COVID-9 patients [12]

Infection level	Symptoms
Asymptomatic	Patients with positive nucleic acid tests and no clinical symptoms. The chest image is also normal
Mild	Patients with fever, cough, fatigue, myalgia, runny nose, sneezing, sore throat, or digestive symptoms like vomiting, nausea, diarrhea, and abdominal pain
Moderate	Patient with Pneumonia (cough, frequent fever) and no hypoxemia, chest CT scans have lesions
Severe	Patients with Pneumonia and hypoxemia (SpO_2 is less than 92%)
Critical	Patients with Acute Respiratory Distress Syndrome (ADRS) may have heart failure, acute kidney injury, and coagulation dysfunction

1.1 Research Methodology

We performed a scoping literature review related to remote monitoring of Covid-19 Patients. We searched 9 databases in May 2022: Google Scholar, IEEE Xplore, Springer, Taylor and Francis, Scopus, Science Direct, ACM Digital Library, Web of Science, and Wiley. These databases were explored using search terms related to the remote monitoring (e.g., 'Remote Monitoring' and 'Covid', 'Patient Health', 'IoT'), blockchain storage systems ('Covid' and 'Health', 'Blockchain Storage' or 'Blockchain Sharing') and processing/analyzing of medical data of Covid-19 like pandemics only (e.g., 'Processing Analyzing', 'Prediction', 'Covid Patient Sensed Health Data', 'Machine Learning'). We also examined the references of the included studies (i.e., checking references backward) to find more related works that could be reviewed for this survey. We also analyzed the works that referenced the included studies (i.e., checking references forward). We excluded studies that were related to other diseases. Our search was restricted to English works published after the advent of COVID-19 (i.e., December 2019). We have included only peer- reviewed and good quality articles, journals and conference proceedings.

1.2 Scope and Contributions

Recently, several research studies on combating pandemics using technology have been conducted. However, no comprehensive survey on remote monitoring of pandemic patients exists. Hence, unlike existing surveys on Covid-19 management, this work focuses on reviewing the research related to remote monitoring in pandemic-like situations.

In [21], the authors have reviewed various technologies, including IoT, drones, 5G, AI, and blockchain, for the Covid-19 pandemic. They have provided a detailed overview of Covid-19 and its impact in various sectors. Similarly, in [14], the authors have discussed the applications of artificial intelligence and blockchain in the Covid-19. In [22], the authors have demonstrated the prospects of vital signs monitoring for quarantined patients using image and signal-processing techniques and deep learning methods. Authors in [23] discussed some applications of blockchain and AI in the health care sector, such as early detection of outbreaks, supply chain management of drugs and other equipment and contract tracing. The authors systematically reviewed the applications, including contract tracing, vaccine monitoring, and pandemic control and surveillance. A systematic literature review has been conducted in [24] to analyze the role of blockchain technology in combating the coronavirus pandemic. The authors show that the blockchain can significantly aid in tackling the Covid-19 pandemic, focusing on the main features of the blockchain. Similarly, a complete review on the adoption of blockchain for handling the coronavirus pandemic has been discussed in [25]. The authors have also detailed a case study on blockchain-based digital vaccine passports. Another study in [26] discusses the advantages of blockchain for combating the Covid-19 pandemic. Authors in [27] review various data analysis methods for health monitoring sensors. They have classified the related research works based on the types of sensors used, i.e., contactless and contact sensors.

In [28], the authors have presented the architecture of blockchain-enabled IoMT and discussed the various solutions offered by blockchain-enabled IoMT to fight Covid-19. The solutions discussed were based on five perspectives; social distancing and quarantine, medical data provenance, smart hospital, tracing pandemic origin, remote healthcare, and telemedicine. Authors in [29] reviewed smart health monitoring systems based on IoT that can efficiently monitor multiple patients remotely in a cost-effective manner. The roles of AI, Robotics, IoT, and blockchain in combating the Covid-19 pandemic were investigated in [30]. It reviews the potential of these technologies to handle Covid-19. The authors in [31] explored the use of AI and its applications in managing the Covid-19 outbreak. Authors in [32] discuss enabling technologies and systems to handle the Covid-19 pandemic. The work mainly focuses on three areas. Firstly, wearable devices suitable for monitoring quarantine and Covid-19 suspects; secondly, sensing systems for detecting the infected and monitored patients; and lastly, telehealth technologies for diagnosing Covid-19 and remote monitoring.

After reviewing state-of-the-art and going through the literature, the requirement of a detailed survey on pandemic patient monitoring system is felt. A complete survey that covers all the aspects related to remote monitoring, storing/sharing platforms and analyzing the monitored data is missing. Thus, we have conducted a comprehensive literature survey to fill the research gap. The proposed study is a complete survey of the work done on pandemic patient monitoring system. To the best of our knowledge, this is the first survey paper that reviews all the works specifically related to remote monitoring system of patients during Covid or similar pandemic-like situations. This paper may play a vital role in assisting professionals and academicians in identifying how emerging technologies such as blockchain, machine learning, and IoT can be used to develop a remote monitoring system. Table 3 summarizes the relative comparison of our work with the existing survey works. Figure 1 shows the scope of our work by highlighting the broader categorization of work.

In summary, the main contribution of this work is as follows:

- The article provides an in-depth analysis of the architecture of a remote monitoring system for patients during a pandemic, with a particular focus on its layered structure.
- A description of IoT, blockchain, and machine learning with their relevance and applicability for remote monitoring systems is provided.
- A comprehensive survey of various works related to pandemic patient monitoring system is presented.
- Finally, open issues and challenges in the realization of a pandemic patient monitoring system are discussed along with future research possibilities.

1.3 Organization of the Paper

The structure of the rest of the paper is outlined as follows. Section 2 details a brief background on patient monitoring and enabling technologies, including IoT, WBAN, blockchain, and machine learning. Section 3 reviews all the research studies related to remote monitoring of pandemic patients. Section 4 presents a detailed assessment of the works based on various parameters. Section 5 discusses the issues and challenges. Lastly, in Sect. 6 we conclude our work. Table 4 list out all the abbreviations used in the work.

2 Background

This section discusses the overview of pandemic remote monitoring system. Detailed background knowledge of enabling technologies such as IoT, WBAN, blockchain, and machine learning is also given.

2.1 An Overview of Pandemic Patient Monitoring System

Continuous measurement of the Covid patients' vitals is essential as this gives first-hand information about abnormal conditions [22]. During hospitalization of severe cases or home quarantined patients, these systems provide a tool for healthcare givers to monitor the patient's health. Primarily, five vitals are monitored, including oxygen saturation, pulse rate, blood pressure, respiratory rate and temperature. The normal range of vital parameters for an adult is shown in Table 5 [34].

Table 3 A Comparison of our work with the existing survey works

References	Remote monitoring of patients	Storage/sharing of patients' health data	Analyzing/processing patients' data	Patient monitoring system
Chamola et al. [21]	Yes	Yes	Yes	No
Dai et al. [33]	Yes	Yes	No	No
Ding et al. [32]	Yes	No	No	Yes
Nguyen et al. [14]	No	Yes	Yes	No
Ng et al. [23]	No	Yes	No	No
Botene et al. [24]	No	Yes	No	No
Shah et al. [25]	No	Yes	No	No
Abd-Alrazaq et al. [26]	No	Yes	No	No
Sobhan et al. [27]	Yes	No	No	Yes
Rohmetra et al. [22]	No	No	Yes	Yes
Firouzi et al. [30]	Yes	Yes	Yes	No
Peng et al. [31]	No	No	Yes	No
Hossain et al. [29]	Yes	No	No	Yes
Our Survey Work	Yes	Yes	Yes	Yes

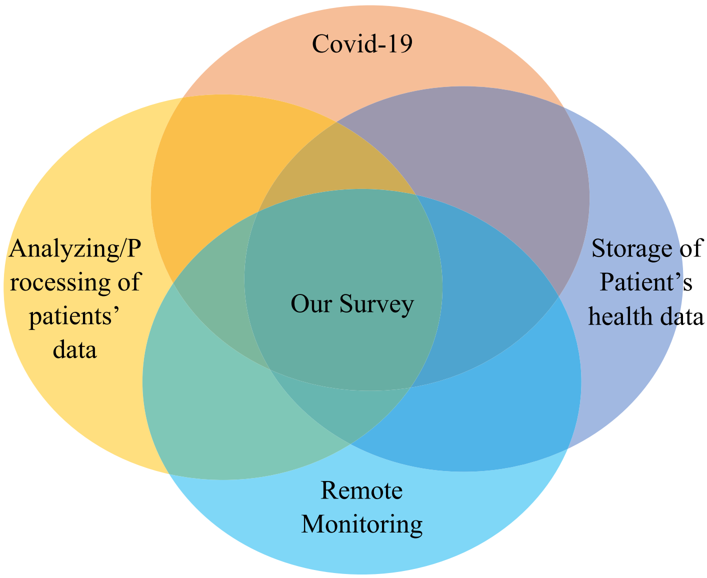

Fig. 1 Scope of the survey work

Vital signs are the first indicators of patients' deteriorating conditions in most diseases including Covid-19. The coronavirus has an incubation period of 1–14 days in the human body. Upon incubation, disruption of vitals is observed [34]. One of the first disruptions includes an increase in the body temperature, i.e., greater than 100.4 F. As coronavirus disease is related to lung inflammation, the attenuation of oxygen uptake capacity is also observed, leading to a decrease in the level of saturation, resulting in a reduced supply of oxygen to the body organs. To meet the requirements of oxygen in body cells, the rate at which the heart pumps blood increases; thus, an increase in heart rate is observed. Simultaneously, the body increases the number of breaths per minute to restore oxygen levels to normal, leading to an increased respiratory rate [35]. Thus, the vitals of the body are disrupted upon Covid-19 infection.

Real-time monitoring of pandemic patients through wearable sensor devices [36] is one of the most popular applications of IoMT in medical field. IoMT and Wireless Body Area network collects medical data from biosensors continuously. These IoT devices in healthcare generate a huge amount of sensitive data, whose unauthorized access can lead to dire consequences. Though IoT has shown massive potential in the healthcare sector, ensuring data security is an important aspect. Hence, a secured gateway-based architecture is needed for utilizing IoT in medical fields with a proper authentication system [37]. Many researchers have attempted to develop a secure IoT network between healthcare IoT equipment and cloud services. However, they suffer from challenges like data privacy, single-point failure, system vulnerability, and centralized supervision [38].

Since medical data is highly susceptible, it needs to be stored securely. Blockchain provides an novel way to store and disseminates data in a secured manner [39]. It offers a robust network to form a distributed and secure method for sharing and storing data owing to its properties of immutability, traceability and decentralization. Blockchain enhances the overall security by ensuring accountability and data integrity [40]. First, the blockchain security schemes, including asymmetric encryption/decryption schemes

Table 4 Abbreviations

Abbreviation	Description	Abbreviation	Description
6LoWPAN	IPv6 over low-power wireless personal area network	KGC	Key generation center
AI	Artificial intelligence	KNN	K-Nearest neighbor
ANN	Artificial neural network	LAN	Local area network
ARDS	Acute respiratory distress syndrome	LDA	Linear discriminant analysis
BHDSF	Blockchain-based hierarchical data sharing framework	LoRaWAN	Low-power wide-area network
BLE	Bluetooth low energy	LSTM	Long short-term memory
BoNN	Bag-of-neural network	LWL	Locally weighted learning
BSN	Biomedical sensor network	MEWS	Modified early warning score
CEMRs	Covid-19 electronic medical record	MFCC	Mel frequency cepstral coefficients
CNN	Convolution neural network	ML	Machine learning
Covid-19	Corona virus disease	MLaaS	ML as a service
CSP	Cloud service provider	MRI	Magnetic resonance imaging
CT	Computerized tomography	NB	Naive bayes
d-ABE	Distributed attribute based encryption	pBFT	Practical byzantine fault tolerant
DDoS	Distributed denial of service	PCA	Patient centric agent
DO	Data owner	PCI	Patient-centered Interoperable
DPoW	Delayed proof of work	PHR	Personal health records
DU	Data user	PoS	Proof-of-stake
ECG	Electrocardiograph	PoW	Proof of work
EEG	Electroencephalogram	PPG	Photoplethysmography
EHR	Electronic health record	QLDA	Quadratic linear discriminant analysis
eRF	Ensemble random forest	SHAP	Shapely adaptive explanations
GDPR	General data protection regulation	SARS-CoV-2	Severe acute respiratory syndrome coronavirus 2
HCU	Healthcare control unit	SSS	Shamir's secret sharing
HIPAA	Health insurance portability and accountability act	SVM	Support vector machine
H-IoT	Healthcare internet of things	TCP	Transmission control protocol

Table 4 (continued)

Abbreviation	Description	Abbreviation	Description
IBFT	Istanbul byzantine fault tolerant	tps	Transaction per second
ICU	Intensive care unit	UWB	Ultra wide band
IDBGSC	Identity-based broadcast group signcryption	WAN	Wide area network
IoMT	Internet of medical things	WBAN	Wireless body area network
IoT	Internet of things	WSNs	Wireless sensor Networks
IPFS	Interplanetary file system	XGB	Extreme gradient Boost

and the digital signature, gives the enhanced protection to the collected data [41]. Second, blockchain has other security mechanisms, including access control and authentication, to provide added security. Moreover, the decentralized nature of blockchain removes the problem of single-point failures and DDoS kind of attacks. Immutability achieved by cryptographic hash functions does not allow data to be changed by malicious users, hence increasing the reliability. The data stored on the blockchain is traceable throughout. Data traceability and non-repudiation properties are ensured by the decentralized consensus algorithms and asymmetric cryptographic mechanisms, i.e., digital signature. The medical data stored in the blockchain should be analyzed so as to understand the symptoms and further decision making regarding the prognosis and diagnosis.

Machine learning along with image processing techniques can be used to find patterns from the patients' data stored on the blockchain network. This analysis can further assist healthcare workers in their decision-making process. The usage of machine learning also aids in minimal interaction between healthcare professionals and patients as these systems give immediate medical outputs to problems based on historical data, hence accelerating the recovery process and reducing the costs of treatment. ML can also be employed in diagnosis, prognosis evaluation, drug discovery, and epidemic prediction for Covid-19. The learning capability of ML could assist in forecasting future cases and the impact of a potential outbreak. The system can also create alerts for healthcare facilitators, authorities, and families during an emergency. A generalized patient remote monitoring system is shown in Fig. 2. It integrates IoMT, blockchain and machine learning in a remote monitoring system. The architecture is conceptually divided into three layers including, IoT data or data collection layer, blockchain or data storage layer and machine learning or data processing layer. In the next section, scope and contributions of our work is discussed.

2.2 Enabling Technologies

The rapid advancements in science, technology, medicine, and the usage of smart medical devices in the medical domain have transformed the medical field entirely. This subsection gives a brief background of the technologies, i.e., the IoT, blockchain, and machine learning, that play a vital role in developing of a pandemic patient remote monitoring system.

2.2.1 Internet of Things

Internet of Medical Things (IoMT) systems are diverse and widely used in the medical domain. The Internet of Things is a network of things or physical devices communicating

Table 5 The normal range for vital parameters

Parameter	Normal range
Oxygen saturation	95–100%
Blood pressure	120/80 mm of Hg
Temperature	97–99 F
Respiratory rate	12–20 breaths per minute at rest
Pulse rate	60–100 beats per minute at rest

with each other [42]. IBM defines IoT as, "*The Internet of Things is the concept of connecting any device (so long as it has an on/off switch) to the internet and other connected devices. The IoT is a giant network of connected things and people – each of which collects and shares data about how they are used and about their environment*". IoT has bought an immense revolution in various domains, including healthcare, supply chain management and industries. The technology aims to integrate technologies like cloud computing, electronic devices, sensor networks, and mobile services. This technology connects sensors and actuators that are integrated into digital devices linked to the internet, utilizing unique Internet Protocol (IP) addresses to identify these devices through both Transmission Control Protocol (TCP) and non-TCP methods.

Many transmission protocols, like ZigBee, Z-Wave, Long-Range Wide Area Network (LoRaWAN), Wi-Fi and Bluetooth Low Energy (BLE) are used to transmit IoT data [43]. In IoT, no human intervention is required. It means devices automatically transfer and store the sensing information to cloud severs or local servers or blockchain. The collected data is generally processed by fog or cloud servers. Smart gateways can act as Fog or edge nodes. Some functions of smart gateways include collecting and filtering data, preprocessing, and reconstructing data to a proper format. A standard framework for IoT systems is required to overcome the devices' interoperability, heterogeneity, and diversity issues. Some typical applications of IoT include wireless inventory trackers, smart healthcare, biometric scanners, remote monitoring of patients and smart home security [44]. Remote monitoring of patients in hospitals or at home is an important use case of IoT.

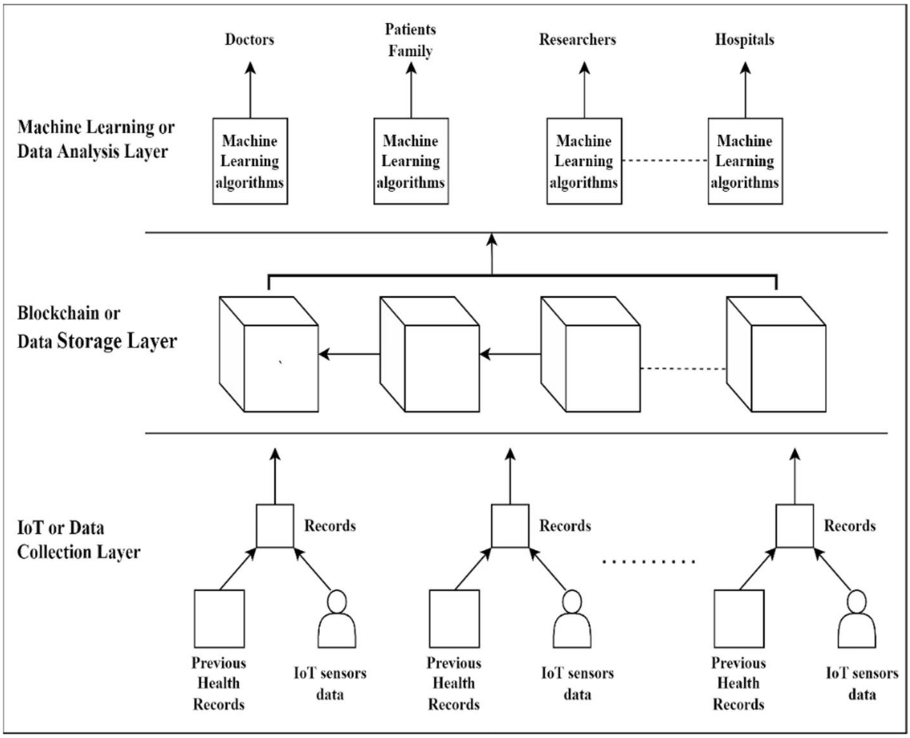

Fig. 2 A generalized architecture of a pandemic patient remote monitoring system

The currently used remote monitoring systems are complicated and bulky as wires are used to establish a connection between the sensors and a wearable wireless transmitter [45]. This system suffers from disadvantages such as patient movement restriction and comfort. Therefore, a monitoring system composed of sensor nodes with wireless capability is required to overcome these issues, as shown in Fig. 3. A special-purpose wireless sensor network, Wireless Body-Area Network (WBAN), which consists of various wireless devices and networks can be used for this purpose [46]. One of the crucial applications of WBAN is in the medical domain for real-time monitoring of several patients. In WBAN, two sensor signals may collide or can interfere with other external wireless devices. WBAN is more easily managed than a traditional wired network [46].

The sensors used in WBAN should be low powered and small in size. The architecture adopted in WBAN comprises wireless sensor nodes that transmit a patient's vital parameters such as heart rate, ECG, and blood pressure via a wireless network. Sensor nodes must meet essential requirements of miniaturization and low-power operation [46].

2.2.2 Blockchain

S. Nakamoto first highlighted blockchain in 2009 by introducing the world's first cryptocurrency, bitcoin [47]. Blockchain consists of consensus protocol, immutable ledger, mining, hash cryptography, and distributed peer-to-peer networking [48]. It uses transactions to store each data record e.g., land registry or medical data. Blocks are composed of multiple transactions, and multiple blocks are linked together to form a blockchain. Each block's header field contains the previous block's hash, thus creating a chronologically ordered chain. Blockchain stores these data records permanently. A generalized blockchain structure is shown in Fig. 4.

Blockchain provides a platform for a safe and trustworthy transaction eliminating the need of a third party. The most notable feature of blockchain is decentralization, which solves the problem of single-point failure [49, 50]. The database is not kept in one place, but a copy of the blockchain is present at each node in the blockchain, which provides security and robustness to the network. Consensus mechanism is used to get consistency between all the copies of the blockchain present at different nodes. Consensus algorithms are a set of rules to ensure agreement among all the nodes on the status of the blockchain ledger. Some examples of consensus algorithms include Proof-of-stake (PoS), Proof of Work (PoW) and Practical Byzantine Fault Tolerant (pBFT).

Blockchain can be of three types, Public (permission-less), private (permissioned), and consortium. In a public blockchain, everyone can join the blockchain network, have access to the data and participate in the consensus process. Bitcoin and Ethereum are public blockchains [51, 52]. In contrast, in private blockchains, a central entity manages the whole blockchain system. A node can join or participate in the consensus algorithm only if it has permission from the blockchain owner. Hyperledger is a private blockchain [53]. A consortium blockchain is a combination of both private and public blockchains. The ledger access can be private or public, but more than one entity controls the consensus process. The term "smart contract" was defined by Nick Szabo as "*a computerized transaction protocol that executes the terms of a contract*" [54]. They are stored on the blockchain at a unique address. They are executed by sending a transaction to it.

In the past few years, blockchain has grabbed colossal attention globally, in many areas, including finance, banking, insurance, energy, and healthcare [55, 56]. Blockchain technology is in huge demand due to its distributed, decentralized, and secure network features.

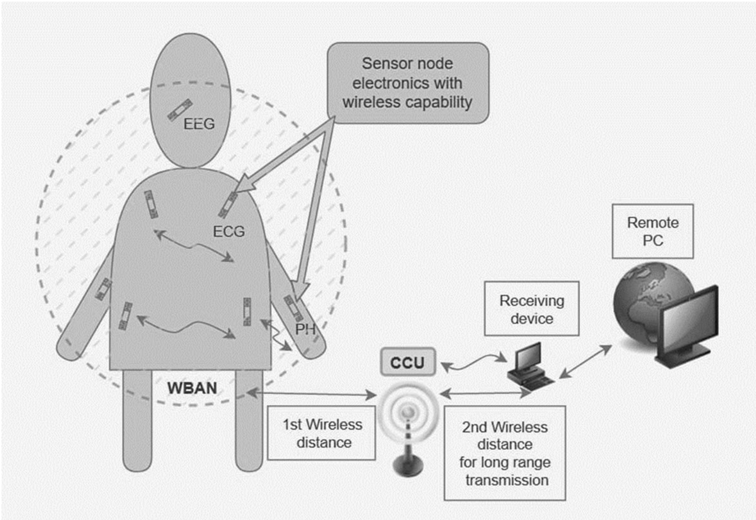

Fig. 3 The general architecture of A WBAN [46]

Blockchain has various applications in the healthcare sector [57-60]. Table 6 compares the two storage mechanisms, i.e., traditional storage platforms and blockchain platforms.

2.2.3 Machine Learning

Machine learning provides the ability to learn in computers without being explicitly programmed [61]. It is a technique where data is used to train the model to get future predictions with minimal human intervention. The machine learning model uses data to learn some pattern based on the specific task. According to the data, machine learning algorithms automatically create rules [62]. Machine learning can be categorized into supervised, unsupervised, semi-supervised, and reinforcement learning [63]. In supervised learning, data is labeled, i.e., for a set of features, some label is defined, while in unsupervised learning, the label is not defined. Semi-supervised learning lies between supervised and unsupervised learning, in which, for training, some data is labeled while most of the data is unlabeled. Reinforcement Learning is a machine learning technique in which an agent learns the rules by performing actions in an environment and analyzing the results of the actions [64]. The

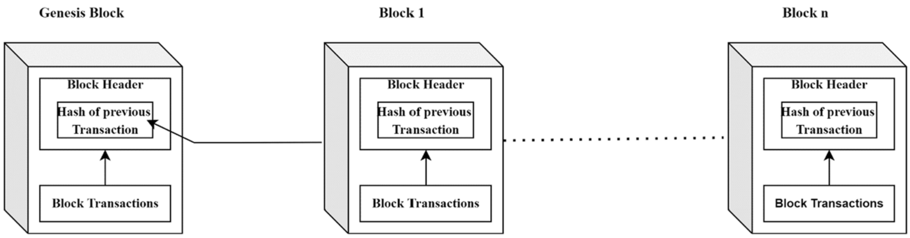

Fig. 4 General architecture of blockchain

agent gets rewarded for each action closer to the specific goal, and the agent receives a penalty for each action that takes it away from the specific goal [65].

Supervised learning is used for prediction and classification, whereas unsupervised learning is used for clustering. Prediction gives insights about the future, for example, the performance of the stock market in the future, weather forecasting and heart disease prediction. Classification gives class labels, i.e., handwritten digits, identifying spam emails, and sentiment analysis. Clustering is an example of unsupervised learning. In clustering, similar data points or sets of similar objects are grouped. For instance, movie recommendation on Netflix uses an unsupervised learning approach.

Nowadays, vast amounts of data are generated by various applications. Machine learning algorithms have become very beneficial in giving valuable insights and producing meaningful information from raw data. Machine learning has enormous applications in multiple domains, such as the manufacturing, healthcare, finance and transportation. Specifically, ML applications in healthcare include patient remote monitoring, education, electronic medical records management, biomedical applications, drugs and medical supply chain management, and medical data analysis [66].

3 Related Works

In this section, we have categorized the works according to the layers shown in Fig. 2 in Sect. 2.1. All the works discussed are related to remote monitoring of pandemic patients. In the generalized architecture of the system, there are three layers; remote monitoring of pandemic patients, storing or sharing patient's data and processing stored patients' data. The first layer helps to gather and aggregate patients' data from various IoT devices. So, several works related to gathering patient data through IoT devices are discussed. Next, blockchain is considered for storage to maintain patients' privacy and securely store data. Hence multiple works related to blockchain storage have been explored next. Lastly, we have discussed the articles that analyze the stored data using machine learning techniques.

3.1 Remote Monitoring of Pandemic Patients

The Internet of Medical Things in the healthcare domain facilitates remote diagnosis and real-time decision-making [67-69]. Numerous research studies have been proposed in this direction. This subsection discusses the research studies related to remote monitoring of pandemic patients using IoT devices.

A framework for an intelligent edge-centric healthcare system is proposed in [70] that collects various Covid-19-related parameters using Wireless Sensor Networks (WSNs) as shown in Fig. 5. WSNs are infrastructure-less and self-configured wireless networks that are used to monitor conditions related to environment and physical conditions such as sound, pressure, temperature, and motion. The system stores the data in a central location through the network where it can be analyzed and observed. The network comprises hundreds of thousands of sensor nodes that communicate using radio signals. The framework utilizes advanced wearable sensors and a machine learning model to predict communicable diseases remotely. The wearable sensors store the sensed data in the distributed edge device. Finally, the monitored data is stored on the centralized cloud server's storage using a gateway/edge device connected through Wi-Fi.

Table 6 Comparison of traditional centralized storage platform and blockchain based platform

Parameters	Centralized storage platforms (traditional)		Blockchain platforms	
Fault tolerance	Highly prone to Single Point Failure	×	Distributed Ledger makes the network highly fault tolerant	✓
Data handling	Four main operations: write, update, read, and delete are available	×	Only two operations: read and write operations are available	✓
Cost	Easy to maintain and implement as old technology is used	✓	Requires maintenance cost and uncertainty in operations	×
Transparency	Database transparency is not maintained	×	Transparency is ensured. Data are stored in a distributed network	✓
Authority	Administrator	×	Decentralized. No single authority	✓
Quality assurance	Data needs to be authenticated by the Administrators	×	Data is immutable	✓
Data integrity	Malicious users can alter the data	×	Data is auditable and immutable	✓
Data privacy	Prone to malicious attacks	×	Cryptographic algorithms are used to ensure the privacy of data	✓
Performance	Fast and offers great scalability	✓	Slow and less scalable	×

✓- Advantage; ×- Disadvantage

In another work [71], a novel architecture for an IoT-operated alarm-equipped biosensor system is proposed. It detects Covid infection using 1D biomedical signals such as Photoplethysmography (PPG), Electrocardiogram (ECG), Accelerometer, and Temperature. The data is stored in the cloud using Wi-Fi, Ethernet, or cellular connection. A cloud manager manages the data flow from and to the servers. Cloud manager also handles efficient communication, data storage, and other data related queries. The data collected is analyzed to detect if a person is infected or not. An IoT-based healthcare platform is proposed in [72], which aims to assist in remotely monitoring patients in an emergency. The platform integrates doctors, patients, and ambulance services to enhance care and take quick urgent, and preventive actions. The proposed solution was implemented in the ICU in Natal, Rio Grande do Norte, Brazil.

Similarly, authors in [73] proposed a cost-effective wireless smart monitoring system to treat patients in medical centers. The system is efficient in terms of consumption, size, simplicity, and power cost. The proposed method comprises wearable sensor nodes to monitor vital signs, such as body temperature, blood oxygen level, respiratory rate, electrocardiogram, and heart rate of Covid-19 patients. The system also contains the software capable of detecting abnormal signs of deteriorating health for early treatment. Clients can use GUIs to manage profiles, monitor health-related parameters in real-time, process and analyze the collected parameters. Clients can also identify the abnormal conditions based on some predefined algorithms. These algorithms can run on the client device also. A low-cost and lightweight cloud-based mobile health monitoring system to measure heart rate, oxygen saturation and electrocardiogram of Covid patients was proposed in [74]. The collected data is forwarded to doctors' mobile devices for monitoring. The vital signs are measured using AD8232 (ECG) and MAX30100 (SpO_2) to be analyzed by doctors.

In yet another work, Authors in [75] proposed an architecture that transfers the patient's monitored data to cloud storage. The cloud server runs the software to provide useful information about the patient's conditions. The system sends SMS to the healthcare workers based on the Modified Early Warning Score (MEWS). The proposed application uses a

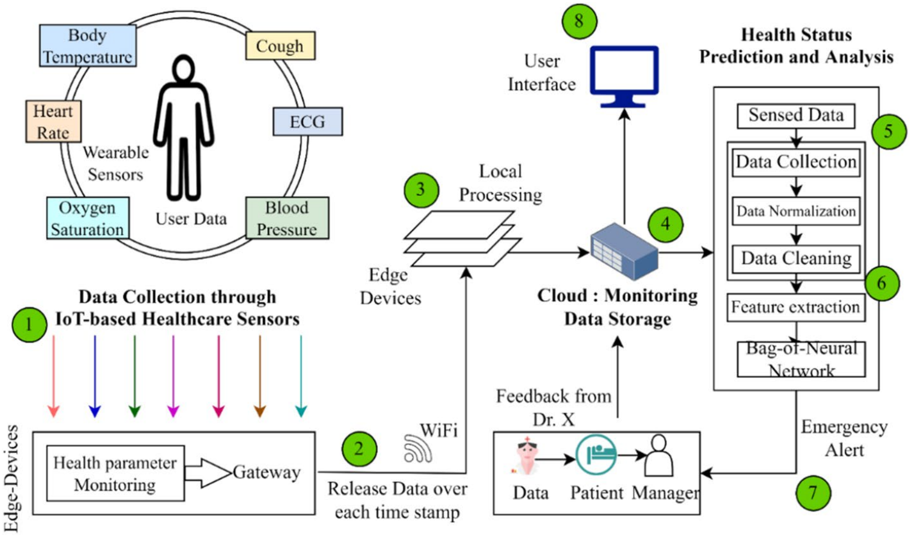

Fig. 5 Edge-centric communicable disease prediction model [70]

turnkey sensor monitoring kit that comprises the following components; a multi-parameter wearable sensor, a tablet as an edge device with Wi-Fi and cellular connection, and the monitoring software. The lightweight wearable sensor measures vitals like electrocardiogram, respiratory rate, blood oxygen, heart rate, Body temperature, non-invasive blood pressure, and pulse rate. The setup involves the calculation of the MEWS score to determine a patient's level of illness. The MEWS score is calculated by assigning scores to each of the six vital measured using Table 7. The sum of scores of the vitals gives the MEWS score. If the score exceeds 3 then the doctors are notified for necessary actions.

In [76], an ultra-wideband radar sensor and smart wrist bracelet are used to keep track of a Covid patient's symptoms. The radar sensor can detect daily motions like walking or emergency like a fall along with other physiological signals through chest movements as shown in Fig. 6. The smart bracelet is used to monitor blood oxygen saturation and heart rate. The proposed system uses a hybrid approach using Edge and Cloud infrastructures for data processing and transmission. Edge computing reduces data transmission delay. As the system utilizes the cloud for data storage, it leads to a lack of data privacy as third parties usually own cloud servers, and they may also suffer from the challenge of single-point failure.

Many researchers have used blockchain to store data to overcome these drawbacks. For example in [77], authors have proposed a patient-centric system for remote monitoring based on blockchain. In the proposed architecture, the body sensor network utilizes wearable devices and motion trackers, such as EEG and ECG to send data to Patient-Centric Agent (PCA). Data categorization is performed by the PCA using Sensor Data Provider software. Similarly, a framework that monitors the oxygen saturation in the blood is proposed in [78] as shown in Fig. 7. Oxygen saturation is considered a critical factor for Covid severity assessment. In the perception layer, mobile phones and oximeters are employed. Oxygen saturation read by the oximeter is passed to the smart devices wirelessly. It also utilizes the IoT-fog framework and consortium blockchain to transmit and analyze the collected data.

Further, the authors in [79], proposed a smart healthcare framework for a smart city. It enables stakeholders to utilize smart sensor devices to monitor the health of pandemic patients. The stored electronic health information can be viewed anytime using IoT and cloud computing technologies. Smart IoT sensors are used to transmit CT scan images. The LAN comprises low-range networking equipment. Largescale network WAN connects intelligent devices and transfers data from smart devices to the cloud. Network protocols like Cellular LAN, 4G, or 5G are used in WAN to transfer data to the cloud in real-time. In a similar work, authors in [80] have proposed a framework for implementing cloud-enabled IoT. They have also implemented an E-Health Remote Patient Monitoring system to demonstrate the practicality and real-time implementation of the healthcare system.

Similarly, researchers in [81] proposed a WBAN architecture for pandemic patient remote monitoring. The architecture consists of IoT technology and a GPS-based geographic routing algorithm. The proposed system can monitor vitals such as oxygen saturation, body temperature, blood pressure, respiration rate, and heart rate. It has one extra functionality compared to other similar work i.e., it also displays the social distance with humans' 'mask-wearing status'. Total eight body sensors are used in the proposed system. Authors in [82] have developed a real-time IoT-based patient vital signs monitoring system using smart wearable sensors. An Android mobile application has also been developed to assist the stockholders. An Arduino microprocessor has been used to process the data collected from the sensors. The proposed system collects vital parameters, including oxygen

Table 7 MEWS score [75]

MEWS score	3	2	1	0	1	2	3
Blood pressure	<45%	30%	15% down	Normal for patient	15% up	30%	>45%
Oxygen saturation	<85	>85	>90	>95	–	–	–
Respiratory rate	<8	–	8–11	12–20	21–25	26–30	>30
Temperature	–	<35	–	35.0–38.4	–	>38.5	–
Heart Rate	<30	<40	41–50	51–100	101–110	111–130	>130

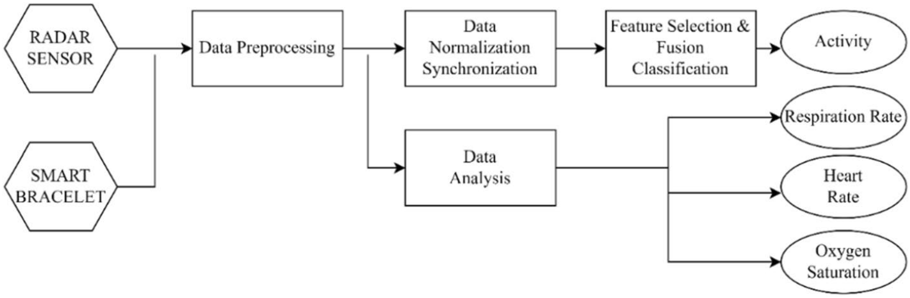

Fig. 6 Overview of workflow proposed in [76]

saturation levels, blood pressure, electrocardiogram, body temperature, heart rate, and glucose levels. The Arduino microprocessor transfers the processed data through Bluetooth to an Android mobile application. MySQL database is used to store the data. In [83], a system to monitor health is developed using IoT technology to monitor heart rate, blood pressure, the temperature of a person, and oxygen level. This IoT-based health monitoring system aids healthcare workers in gathering real-time data in an efficient manner. The developed system can be deployed on the patient's bed to collect data, and the collected data can be shared with doctors using smart devices via the internet.

3.1.1 Summary and Discussion

In this section, we have discussed the research works in which various heterogeneous IoT devices have been employed in the remote monitoring of Covid-19 patients. These devices have limited memory and computation power compared to other traditional networks, which have powerful servers. The conventional networks can be secured and protected by various complex security layers and protocols. These protocols cannot be applied to real-time IoT networks due to its constrained environments. IoT networks use less secure communication protocols, such as LoRa, 802.11a/b/n/g/p, ZigBee, and 802.15.4. Hence these protocols are more prone to security attacks.

IoT remote monitoring applications collect the patient data using contact or contactless technologies. Contact sensor technologies can be defined as sensors that is either a wearable or is in touch with the person. The contactless technologies employ radars, cameras, audio recorders to capture signals and movements of the patients. Most of the surveyed

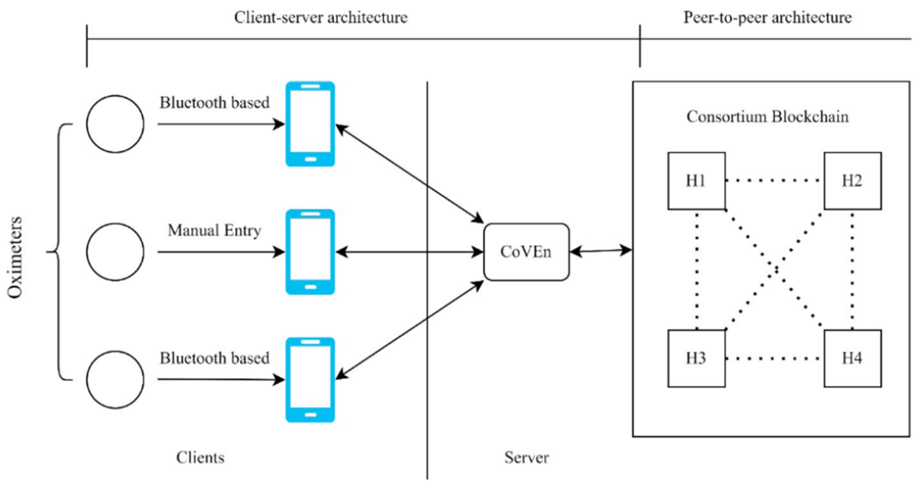

Fig. 7 Architecture of proposed work in [78]

papers are based on contact sensors technologies. Oxygen saturation, body temperature, heart rate and blood pressure of Covid-19 patients are widely measured vitals as seen from the papers. We have observed that majority of IoT remote monitoring applications utilize a local server or cloud server to store the data collected. Security and privacy of data is an important issue in the healthcare domain. A tabular comparison of all the above-discussed works on remote monitoring of Covid-19 patients using IoT is presented in Table 8.

3.2 Storing or Sharing Patients Data

Blockchain technology helps in overcoming the problems of traditional storage systems [84]. The intrinsic properties of blockchain, i.e., immutability, decentralization, and security, make it appropriate for various applications. Data, the new resource nowadays, must be stored securely, especially healthcare data. Interoperability is also required between organizations [28, 85-87]. To safeguard the privacy of data while sharing, various international and national laws have been enacted, including compliance with the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) [88-90]. Hence storing electronic medical records has become an important use case for blockchain. Several research studies have been carried out in this domain which are discussed in this subsection.

Authors in [91] proposed an architecture to provide a secure and decentralized way to store Personal Health Records using the Ethereum blockchain. They have used an Interplanetary File System (IPFS) to store the files. Only the hashes of the records are stored on the blockchain; hence the system is more scalable. Before storing PHR data on IPFS, they used a steganography algorithm to hide sensitive data. The returned hash from the IPFS is divided into parts using Shamir's Secret Sharing (SSS) algorithm, hence enhancing the security. In another work, a novel smart, distributed, and secure framework for sharing information among the IoT systems is proposed in [92]. Authors have combined the advantages of blockchain, IoT, and AI and proposed a privacy-preserving and secure data processing and data sharing platform. The platform includes three steps; IoT devices for monitoring and collecting the data, smart edge devices to analyze the collected data using AI and ML, and sharing of the AI results using blockchain platform. A new customized honest-based Delayed Proof of Work (DPoW) consensus mechanism is also proposed in the paper. It distributes the PoW work among the IoT devices, each performing hashing calculations in a small amount. The proposed consensus mechanism is appropriate for implementation in public blockchain-IoT applications. Thus, the authors have categorized the IoT devices into three categories i.e., Leader Nodes (LN), Hybrid Nodes (HN), and Participant Nodes (PN) based on the battery power and CPU usage.

Medical images such as X-ray reports, CT scans and ECG are quite useful in deciding the treatment of patients in the medical field. Hence sharing and availability of medical images to healthcare professionals and patients is of utmost importance. A secure framework to share medical images is proposed in [93]. Blockchain technology is used in the proposed framework which gives secure access of the medical images to the patients. The authors have used a blockchain to store a list containing image studies and patients' details to which it belongs, the list of entities that the patient authorizes to access each study, and the end point of each study from which it may be retrieved. In [77], a novel remote patient monitoring approach has been proposed that uses a private blockchain to safeguard patients' privacy and improve the system's efficiency. The paper presents a three-tier architecture; tier one manages Patient Centric Agent (PCA), the second-tier handles Healthcare Control Unit (HCU), and the last tier operates cloud storage and Hyperledger fabric network. Combining two consensus algorithms, i.e., Proof of Validity and Proof of Integrity adds more data integrity and privacy to the system.

As Anonymity and privacy are crucial factors in storing medical data from IoMT devices, an anonymous system based on blockchain for IoMT, GarliMediChain, is proposed in [94] that ensures privacy and anonymity in information sharing as shown in Fig. 8. GarliMediChain integrates blockchain and garlic routing to provide anonymity, trust, privacy, and security. Also, data is encrypted multiple times before transmitting to several nodes. A blockchain-based hierarchical data sharing framework (BHDSF) was also proposed in [95]to provide an efficient retrieve a land access control mechanism over encrypted Personal Health Records (PHRs). To increase trustworthiness while disseminating PHRs, the method employs effective authentication from IoT devices, and decentralized verification and integrity auditing for PHR retrieval with blockchain technique to ensure integrity and correctness in trustless cloud. The proposed framework is efficient in key distribution as it distributed the keys through users' hierarchy. The framework utilizes outsourced computing and online/offline techniques to offload most of computations eliminating information leakage to improve efficiency of resource-limited user devices. The feasibility of the proposed network is shown by extensive experimentation using real-world datasets of Enron and NSF [96].

In another application, a decentralized telehealth solution for remote monitoring was proposed in [97]. The proposed system provides remote services to patients at home by doctors and medical professionals. Doctors use teleconferencing to attend to the patients and their needs. Medical drugs are monitored whenever required, and medical tests are carried out. Video calls are recorded and uploaded on the cloud or IPFS. Blockchain is used to manage, trace and track the system. Authors in [98] introduce a blockchain-based method to integrate the trained machine learning model weights locally from various medical institutions, thus solving the privacy issue of the organizations. Federated learning protects the privacy of data collected from multiple locations. As healthcare data is sensitive and is huge in size, storing it on a blockchain can be expensive. Hence the CT scans of patients are stored in the servers of hospitals. Blockchain is primarily used to retrieve the trained

Table 8 Comparison of IoT-based remote monitoring systems

References	Objective	Sensors used	Database platform	Communication protocols used	Pros	Cons
Li et al. [76]	Assessment of continuous remote monitoring symptoms	Respiration, Oxygen saturation, heart rate	Cloud server	Ultrawide band radar (UWB)	Edge computing is used hence reducing transmission delay	Privacy issue
Wadud et al. [77]	Patient remote monitoring model	EEG, ECG	Private blockchain	Biomedical Sensor Network (BSN) technologies	Ensure Security of the data	Data analysis is not done
Balasubramanianet al. [75]	A real-time application for IoMT-based remote monitoring using edge and cloud computing	A wearable device, ECG, respiration rate, Non-Invasive blood pressure, oxygen saturation, temperature and heart rate	Cloud Server	Bluetooth, Wi-Fi, and cellular	Gateway and local storage are used as edge nodes for minimizing the latency	Privacy issue
Nasser et al. [79]	Classification of Covid-19 patients	Smart sensors for the transfer of medical images	Cloud Server	Cellular LAN, 4G, or 5G	End to End classification model	Implementation details are not provided
Sharma et al. [71]	Remote monitoring using alarm-enabled wearable sensors	1D biomedical signals including PPG, ECG, accelerometer, and temperature	Cloud Server	Wi-Fi, ethernet, or cellular connection	The model achieved 96.33% accuracy and is also power efficient	Implementation details are not provided
Filho et al. [72]	Remote monitoring of critical patients	Respiratory rate, heart rate, blood pressure, oxygen saturation, ECG, levels of carbon dioxide (CO_2), room temperature and body temperature	Cloud Server	6LoWPAN protocol	Real-time deployment in an ICU of a Brazilian hospital is also discussed	Comparison with other works is not provided
Nandy et al. [70]	Remote monitoring and prediction of disease using edge devices	Body temperature, heart rate, cough, blood pressure, ECG and oxygen saturation	Cloud server	Wi-Fi	Distributed edge devices are used for preprocessing the data	Privacy issue

Table 8 (continued)

References	Objective	Sensors used	Database platform	Communication protocols used	Pros	Cons
Atta [73]	To develop a wireless microcontroller-based monitoring system	SpO_2 temperature heart rate Respiratory rate	Management server	LoRa wireless protocol	Cost-effective system	Privacy issue
Prasanth et. al. [74]	To design and develop a healthcare remote monitoring system	ECG, Heart rate and oxygen saturation	Cloud Server	Wi-Fi	A review is also provided	Comparison with other works is not provided
Gupta et al. [80]	To implement a Remote Patient Monitoring (RPM) use case	Smart blood pressure, oximeter, and thermometer	Cloud server	Not mentioned	Main door sensors and bedroom door sensors are used	No discussion on data communication protocols
Saha et al. [78]	To monitor oxygen level and predict the severity of patients	Oximeter	Blockchain	Not mentioned	Privacy is preserved	Only one parameter is considered
Sen et al. [81]	To monitor the patients and also monitors social distancing with '*mask-wearing status*'	Oxygen saturation, blood pressure, heart rate, and body temperature	Not mentioned	Not mentioned	Provides 'mask-wearing status' of persons	Security and privacy issues of patients' personal data have not been covered
Ahmed et al. [82]	To develop a real-time patient vital signs monitoring system	Heart rate, ECG, glucose levels, oxygen saturation levels, body temperature, and blood pressure	Not mentioned	Wi-Fi	A detailed implementation description is provided	Security and privacy issues of patients' personal data have not been covered
Bhardwaj et al. [83]	To develop a smart health monitoring system	Blood pressure, Heart rate, temperature, and oxygen level	Local Server	High-speed internet	A detailed implementation description is provided	Data security is not considered

model through data retrieving transactions. Data sharing transactions are used in the permissioned blockchain system for sharing the patients' data among the stakeholders.

Yet another application, an IoT solution based on blockchain for anti-Infodemics and identity preservation is proposed in [99].A huge amount of information, including unreliable or misleading information on media or the physical environment during pandemic-like situations, is called Infodemics. Infodemics can cause confusion and irrational behaviors among the masses, leading to devastating losses. It also causes mistrust in health authorities and weakens the public health response. Blockchain helps in fighting Infodemics as it is immutable. The data is encrypted using a distributed attribute-based encryption (d-ABE) scheme. Fog nodes reduce the load on the miner nodes in the blockchain network. Each block in the blockchain represents a patient. The corresponding block is deleted as the patient recovers, and the information is stored in a forked CovChain.

Countries worldwide are making a joint effort to combat Covid-19. Still, hospitals worldwide manage Covid-19 electronic medical records (CEMRs) independently. Due to privacy concerns, CEMRs cannot be shared publicly. A solution to this problem is provided in [100] to offer a decentralized blockchain-based platform for medical data that is privacy-preserving and efficient. Medical research institutions and hospitals are nodes on the alliance chain; thus, data sharing and consensus between the nodes are attained. Fabric certificate authority registers doctors, Covid patients, and researchers. CEMRs can be uploaded on the alliance chain by the doctors and can also be retrieved from the alliance chain by researchers. Finally, the research results are published on the blockchain for the benefit of doctors worldwide. A consortium blockchain-based system "HonestChain," was proposed in [101] that ensures auto-assurance and auto-auditability. It is equipped to ensure distributed trust by calculating requester Reputation and Provider Reputation. A reputation value, computed using the contributions of the other consortium peers, is assigned to the Peers. In the blockchain network, peers are rated using metrics such as dataset risk, compliance score, and user feedback. They have also included Chatbot assistance to help data requesters to submit data requests.

Authors in [102] proposed MedBlock which provides easy accessibility and secure maintenance of EHRs to various authorities, including doctors, researchers, and the government, ensuring patients' privacy is not violated. The architecture of MedBlock is shown in Fig. 9. Blockchain is used to store EHRs of the suspectedCovid-19 patients, ensuring privacy and security. EHRs are available for researchers, doctors, and government authorities. Authors have also used IPFS and 6G network for reducing the storage cost and reliable, low latency communication respectively.

The proposed work in [103] uses blockchain technology and fog computing to build a secure patient monitoring system. Authors have also used the IoMT in their system. A Private blockchain called P2P CSN is created and verified using fog nodes. In [104] a lightweight and hybrid Federated Learning framework is introduced, which is based on blockchain smart contracts. This framework manages reputations and uploaded models or datasets of edge nodes, edge training, the authentication of participating federated nodes, and trust management. Additionally, it handles the inferencing process, model training, and full encryption of datasets. The framework utilizes Multiplicative encryption to aggregate updated model parameters by the blockchain, while the federated edge node executes additive encryption. It also includes support for lightweight differential privacy, ensuring complete anonymization and privacy of IoT data.

Researchers in [105] proposed an three-layer architecture used for a pandemic. The layers were the user layer, blockchain layer and storage layer. The encrypted patients' data and their hashes are stored in off-chain storage file system. The information like meta data, ownership and permission management services are stored in blockchain layer. Three types of smart contract i.e., registry, data and permission are proposed for implementing the tasks of blockchain layer. The authors have used the Istanbul Byzantine Fault (IBFT) Tolerant consensus algorithm in the proposed system. User layer consists of a decentralized application to access the data stored in blockchain layer.

The work in [106] suggests using an attribute-based encryption cipher text policy to store Covid-19 medical records. A blockchain is used for uniform identity authentication, storing all revocation lists and public keys. A system server generates system parameters and publishes private keys for Covid-19 caregivers and users. Cloud service providers (CSPs) are responsible for storing Covid-19 Electronic Medical Records (CEMRs) and generating intermediate parameters for decryption. To calculate the decryption key, users can utilize private keys and decryption parameters. The system proposed in [107], called MedHypChain, ensures authenticity, immutability, confidentiality, and access control. MedHypChain utilizes identity-based broadcast group signcryption (IDBGSC), which encrypts using the recipient's identity and the user's private key to enhance security. Signcryption is a public-key primitive that simultaneously performs digital signature and encryption functions in cryptography. The purpose of MedHypChain is to create a patient-centered interoperable (PCI) data-sharing platform between two entities: the medical server and the patient. The system maintains two distributed ledgers: the patient-prescription blockchain supported by the medical server and the patient-proposal blockchain created by the patient. A security attack model has also been proposed, ensuring confidentiality, security, traceability, anonymity, and access control. Figure 10 shows the architecture of MedHypChain.

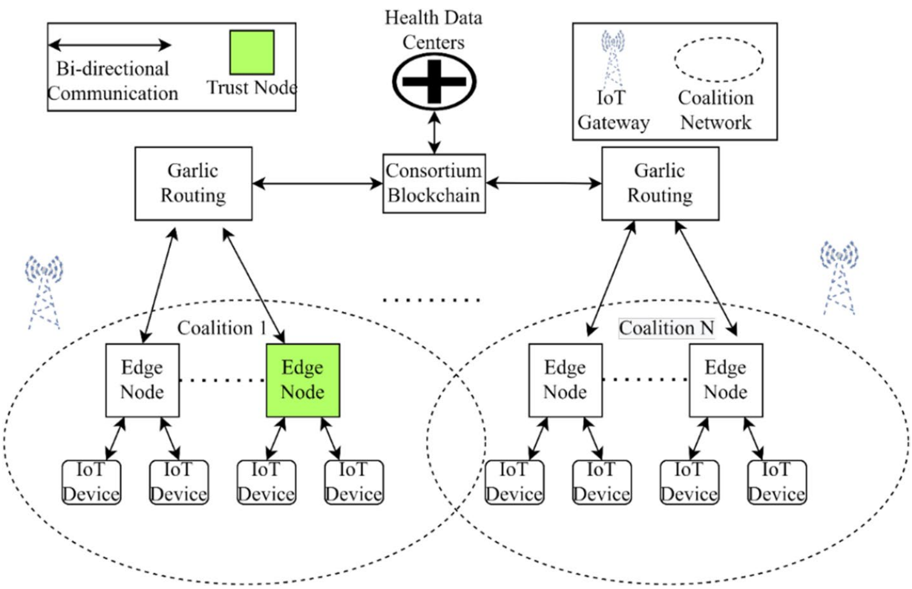

Fig. 8 Anonymous IoT-based E-Health monitoring system [94]

3.2.1 Summary and Discussion

The current electronic healthcare record-keeping systems store the records on a cloud server or local server via a wireless communication channel, which is associated with the risks of numerous security threats such as information leakage, replay attacks, information modification, hacking of systems, malicious access, and man-in-the-middle. In this section, we have discussed and compared the various works related to storing Covid-19 patients' data on the blockchain platforms. According to our survey, we have inferred that almost equal articles have used Ethereum and Hyperledger platforms.

Multimedia data, i.e., images or videos, non-transactional, or data that needs to be changed or deleted, should not be stored on the blockchain. Data storage on the blockchain can be costly and inefficient; hence it is advisable to keep data on off-chain storage such as IPFS. It has been observed from the survey that majority of blockchain storage systems utilize off-chain data storage for storing extensive data. To further improve the security and privacy of the systems, access control policy and encryption of data are highly desirable features of the intended system. Access control policies give complete control to the authorities or the patients to allow who can access the data. Encryption acts extra layer of security to the healthcare data. Most of the works have included both of these features in their system. One of the critical issues that the researchers have given significantly little or no attention is the performance and scalability aspects of blockchain system. A few studies have considered the performance and scalability issues in the healthcare system context based on Blockchains. A comparative study of blockchain-based data storage and data sharing platforms for Covid data has been shown in Table 9.

3.3 Processing Stored Patients' Data

Machine Learning has several applications in combating the effects of Covid-19 like pandemics such as detection of Covid-19, prediction of severity level of patients, prognosis of disease and prediction of oxygen requirement. Once the patients' data is collected using IoT sensors, this data needs to be analyzed for useful purposes. A framework for edge-centric intelligent healthcare, which analyzes measured parameters using smart wearable sensors, has been proposed by the authors in [70]. They employed an advanced machine learning technique called Bag-of-Neural Network (BoNN) for this purpose. The dataset was prepared using various preprocessing techniques and then deployed on the edge network for analyzing the symptoms to predict the severity of the disease. The proposed algorithm ensures minimum training time and higher accuracy of 99.8% on the benchmark Brazil dataset.

Testing is one of the critical steps to fight against coronavirus by identifying the infected persons. The primary difficulty in identifying the Covid-19 patients was the shortage and dependability of testing kits. Hence, healthcare workers faced difficulties in identifying and diagnosing positive cases. This results in an urgent need to develop an autonomous system for diagnosing suspected patients. A user-friendly, time and cost-effective solution is needed to identify Covid-19 patients quickly. Several research works have been proposed in this direction.

A model for automatic diagnosis based on a smart contract node is presented in [109]. The model takes in online-monitored health parameters as input. Coughing is considered a significant factor in identifying whether a patient is infected with Covid-19 or

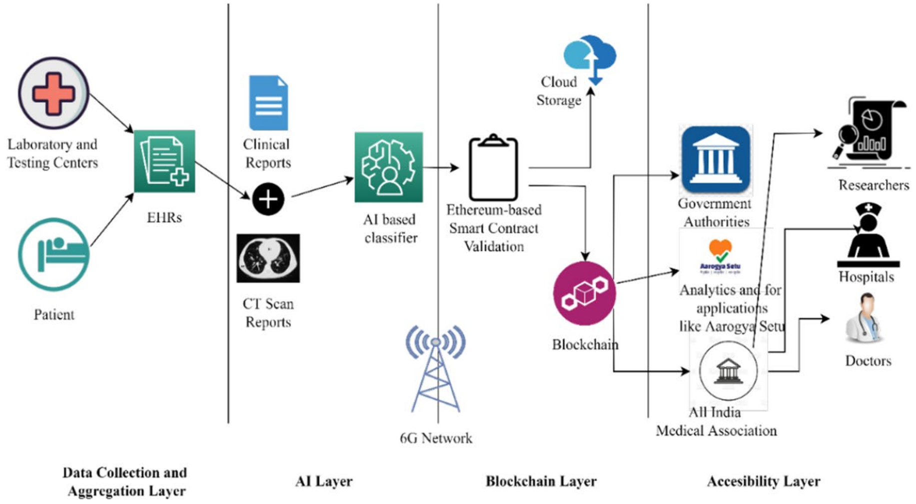

Fig. 9 Architecture of MedBlock [102]

not. To extract features from the coughing audio of suspected patients, Mel Frequency Cepstral Coefficients (MFCCs) are utilized in the algorithm. The detection model is built on the Convolution Neural Network-Long Short-Term Memory (CNN-LSTM) architecture, consisting of convolution and pooling layers for extracting spatial features and LSTM layers for temporal feature extraction. The proposed algorithms ensure user privacy and achieve 90% detection accuracy using coughing signals.

The study described in [110] proposes a model that can detect Covid-19 within a few minutes by using various patient parameters such as temperature, pulse rate, age, and contact with high-risk individuals. The proposed framework utilizes nine classifiers, including Support Vector Machine, Naive Bayes, Random Forest, Quadratic Linear Discriminant Analysis, Decision Tree, Linear Discriminant Analysis, Gradient Boost, K-Nearest Neighbor, and Extreme Gradient Boost. The XGB algorithm exhibits the highest tenfold cross-validation accuracy and the best performance when considering the recall rate vs. decision threshold boundary. The study employs SHapely Adaptive exPlanations analysis to identify the most influential features, which include “cough,” “fever,” “loss of smell,” and “high risk exposure occupation.” To optimize the hyperparameters of the classifier and balance the classes in the dataset, the study utilizes a Bayesian optimizer.

In [98], the issue of preserving patient data privacy on a data-sharing platform during the pandemic is addressed. To solve this problem, the authors proposed a blockchain-based framework that employs federated learning to collect data from multiple hospitals for training a deep learning model. The use of blockchain provides data authentication, while federated learning ensures the privacy of the organizations. To deal with the heterogeneity of the data from different Computed Tomography (CT) scanners at various hospitals, a normalization technique is initially applied. Capsule Network-based segmentation and classification are then utilized to identify Covid-19-positive patients. Lastly, a federated learning-based model is proposed that guarantees privacy and security. The dataset used in this study comprises CT scan slices for 89 subjects. The architecture is depicted in Fig. 11.

In [102], the authors propose a method for identifying Covid-positive patients using CT-scans and clinical reports, employing an Artificial Neural Network (ANN). The patient data is stored on the blockchain, but only for positive patients. The ANN algorithm takes the CT-scan and clinical reports as input to categorize the patients as positive or negative. The clinical reports are given 30% weightage, while the CT-scan report prediction results are given 70% weightage. In [112], the authors propose an online data monitoring framework that predicts the risk level of Covid patients. The framework aggregates data using edge computing, where local gateways and edge nodes are used for aggregating the monitored data. The authors utilize Random Forest on synthetic data for prediction, which achieves 97% accuracy.

Authors in [111] predicts the patients' prognosis using the radiomics features of CT scans. In radiomics, features are extracted from the medical images using data-characterization algorithms. More specifically, duration of a patient's stay in hospital is predicted using the radiomics features of initial CT scans. They have classified the patient into two categories, i.e., short-term stay and long-term stay. This is done so as to give more attention to infected patients with long-term stay. Two machine learning algorithms, Logistic Regression and Random Forest are employed for prediction of patients' stay in the hospital. Authors in [113] have proposed an federated learning based model for processing medical records. The model uses data from 20 institutes worldwide to predict oxygen demands of Covid-19 infected patients. Some of the criteria for prediction were chest X-rays, vital signs and lab reports.

Among the Covid-19 infected people, acute respiratory distress syndrome (ARDS) is more prone to a life-threatening severe respiratory system failure. Monitoring Vital signs (e.g., heart rate) has been proven very effective for the early detection of different respiratory diseases. Authors in [114] have conducted the study on ARDS patients by monitoring their vital parameters. They observed the daily log of Heart Rate (HR) and Blood Pressure (BP) of 150 ARDS patients for long-term use. For extracting the features and statistical analysis, deep learning is utilized. Federated learning is used to maintain data anonymity where data was collected from multiple sources.

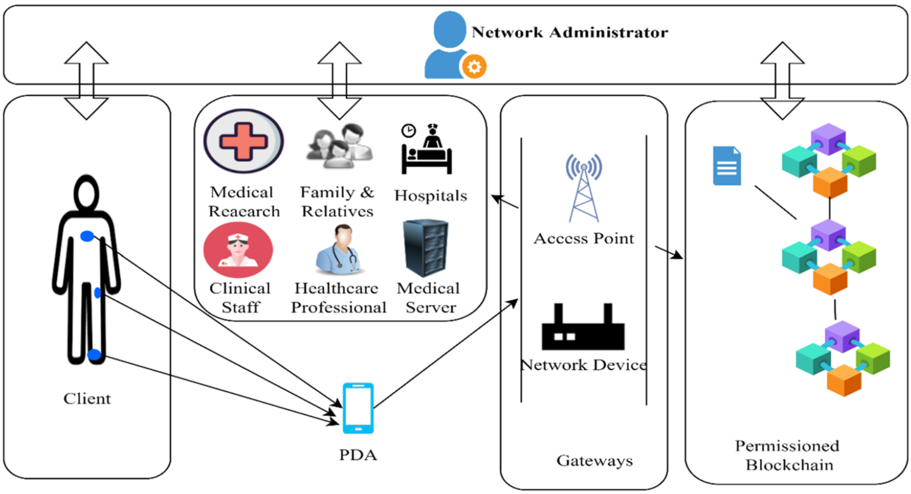

Fig. 10 Architecture of MedHypChain [107]

Table 9 Comparison of blockchain-based data storage and data sharing platforms

References	Objective	Blockchain Platform	Off chain-data storage	Encryption and decryption algorithm	Access control policy	Pros	Cons
Ghani et al. [91]	Platform to share patient healthcare data	Ethereum	IPFS	Stenography Algorithm and Shamir's Secret Sharing	Yes	Highly secure as records are controlled by patients	Comparison with other works is not provided
Patel [93]	Framework for sharing images using a blockchain	Not mentioned	Not mentioned	No	Yes	Medical Image Sharing is considered	Implementation details are not provided
Wadud et al. [77]	To develop privacy-preserving remote patient monitoring model	Hyperledger Fabric	Cloud Sever	No	Yes	Patient-Centric	No discussion on encryption algorithms
Alrubei et al. [92]	Patient data processing and sharing system	Customized blockchain Platform	Not Used	No	No	New consensus algorithm suitable for blockchain- IoT network	No off-chain data storage
Samuel et al. [94]	Information sharing system to provide privacy and anonymity	Own blockchain using python	Not used	Layered identity-based encryption algorithms	No	A new consensus algorithm called Proof of epidemiology of interest	No off-chain data storage
Zhang et al. [95]	Hierarchical data sharing framework	Ethereum	Cloud	Linear Secret Sharing Scheme	No	Anonymity and privacy are considered	Scalability issue
Hasan et al. [97]	A platform for telehealth services	Ethereum	Cloud or IPFS	No	Yes	Generalized solutions for any pandemic	Scalability issue
Kumar et al. [98]	A privacy-preserving storage platform for classification	Private blockchain	Personal database	Yes	No	The approach uses federated blockchain hence protecting privacy	No discussion on access control mechanisms

Table 9 (continued)

References	Objective	Blockchain Platform	Off chain-data storage	Encryption and decryption algorithm	Access control policy	Pros	Cons
Deb et al. [108]	To store the monitored data	Own private blockchain using python	Cloud and fog nodes	Distributed attribute-based encryption scheme	Yes	Reduced latency and efficient storage schemes	No comparison with other works
Yu et al. [100]	A platform for medical research support	Hyperledger Fabric	No	No	Yes	Well defined access control mechanisms	No off-chain storage
Purohit et al. [101]	A system for real-time health information sharing	Hyperledger Fabric	IPFS	No	Yes	Trust values of data requesters are calculated	No discussion on encryption algorithms
Mistry et al. [102]	To securely store the patient's HER	Ethereum	IPFS	No	Yes	Low storage cost	Scalability issue
Kumar et al. [107]	Privacy-preserving medical data sharing system	Hyperledger Fabric	No	Identity-based group broadcast signcryption	Yes	Unforgeability, confidentiality, and authenticity	No off-chain storage
Bera et al. [103]	To develop a home monitoring framework using fog-based private blockchain	Private blockchain	Cloud server	Yes	Yes	Fog computing is used to reduce the work on cloud nodes	Comparison with other works is not provided
Rahman et al. [104]	A framework for IoMT to store medical records	Ethereum, Hyperledger	IPFS	Yes	Yes	Supports full privacy and anonymization of the data	Scalability issue
Shauib et al. [105]	To implement a healthcare data sharing system	Hyperledger Besu	IPFS	Threshold signature scheme	Yes	Well defined access mechanisms	Data description is not given
Tan et al. [106]	A scheme for storing of medical records	Ethereum private chain	Cloud Server	Attribute based encryption policy	Yes	Mathematical analysis	Scalability issue

Most of the previous research works have focused on assisting healthcare workers in predicting the severity level of Covid-19. However, there is a lack of research on developing efficient models for predicting the recovery time of Covid-19 patient. A deep learning model '*iCovid'* based on multimodal clinical data to predict the recovery time of Covid-19 infected patients was proposed in [115]. The prognostic model development of '*iCovid*', as shown in Fig. 12, is a regression model which generates the recovery probability distribution for a patient at admission within 48 h. The research demonstrates that parameters like treatment schemes, symptoms, comorbidities, age and biomarkers have high impact in recovery-time predictions. The authors have utilized a large-scale dataset containing data collected from 2530 Covid-19 patients. All the patients were admitted in Huoshenshan Hospital in Wuhan, China. The following parameters were collected from each of the patients; treatment schemes used, clinical features, CT scans, outcome (recovered, censored or decreased), severity-level and time (in days) after which outcome is observed after admission in hospital. iCOVID utilizes treatment schemes, clinical features and lung CT images as inputs. VGG-16 network30 is used to extract convolutional features from the lung CT scans, which are inputs to fully connected layers along with clinical features schemes for prediction of recovery-time of patients.

To develop an accurate machine learning based model, a huge amount of good quality training data is required. Medical data is present at various locations globally. Transferring of patients' data across medical centers is a serious challenge as it causes privacy and security issues. A solution to mitigate this issue is to fine-tune the machine learning models locally with the annotations and local data. Usually, the quality and availability of local annotations differ due to the usage of heterogeneous types of equipment and the availability of medical resources at various locations worldwide. In [116], a solution is proposed using federated machine learning and semi-supervised learning. The authors developed an innovative federated semi-supervised learning technique that fully utilizes all the data, including annotations and without annotations. Federated learning deals with the privacy concern of various organizations while sharing sensitive data. Furthermore, semi-supervised learning reduces the pressure of annotating the data in a distributed environment.

H1N1 and Covid-19 infections have similar symptoms and are the most spread pandemic diseases globally. The researchers in [117] have utilized machine learning algorithms to classify H1N1 and Covid-19 patients. The system uses data from 1467 patients, including 70% of the patients infected with H1N1 and 30% of the patients infected with Covid-19 having 42 attributes e.g. temperature, diarrhea, coughing, Sore throat. Authors have demonstrated that machine learning algorithms gave promising results in classifying Covid-19 and H1N1 patients.

Authors in [118] propose a framework that integrates cloud computing, IoT, machine learning, and fog computing to develop a novel intelligent system for Covid-19 disease prognosis and monitoring. IoT devices gather streaming data from medical devices such as lung ultrasound machines and non-medical devices such as smartwatch devices. The authors have proposed a framework that utilizes federated ML as a service (federated MLaaS), a distributed batch MLaaS maintained on the cloud, and a distributed stream MLaaS implemented on a hybrid fog-cloud. The usage of Fog provides reduced latency and enhanced security to the framework.

Various researchers have proposed many machine learning models to diagnose and predict Covid. The existing models are not capable of deciding for the Covid-19 patient immediately and are also not capable of processing multiple sensor data for diagnosis. Thus, a framework for smart health monitoring and prediction called '*iCovidCare'* is proposed in [119] to solve these challenges. The architecture of *'iCovidCare'* is shown in Fig. 13. It uses the rule-based approach for quick decision making. Local edge devices are also used for minimizing the delay. For prediction, Ensemble Random Forest (eRF) algorithm is proposed. The trained model is also deployed on edge devices for minimizing the delay and latency. For evaluation synthetic data is used in which most dominant features are extracted using the proposed data fusion and feature selection methods.

The Covid-19 pandemic has heightened the sensitivity of public health information. The absence of controlled and reliable media information coupled with the evolving nature of Covid-19 has led to a proliferation of unverified news sources, which has overburdened call centers. To tackle this problem, a privacy-preserving model based on blockchain and federated learning is proposed by the authors in [120]. The proposed model aims to enhance the authenticity and reliability of Covid-19-related news dissemination. The framework is composed of four components, namely individuals, consortium blockchain, Center for Disease Control, and Federated Learning.

3.3.1 Summary and Discussion

Machine learning has enormous potential to help combat coronavirus-like pandemics. Machine learning applications include suspected Covid-19 patients' detection, classification of disease severity, prediction of the amount of oxygen requirement of patients and prognosis of the duration of hospital stay of the infected patients. Most studies focused on developing models for detecting Covid-19 and classifying the severity of Covid-19 patients. However, studies on other applications are still lacking. Lack of training data is a challenge for developing a machine learning model for smart healthcare system.

Further, the authors have not focused on the privacy of data. If data is spread across various hospitals and healthcare centers, it may cause privacy and security issues. Hence federated learning is suggested in the case of Covid-19 data, which ensures the privacy of data and shares only the trained model, not the actual data, with the central server. Also, the performance of a machine learning algorithm depends on the amount and quality of data provided during training. Most of the works consider the storage of patients' data on a centralized database. Therefore, there a need to focus on utilizing blockchain to store the monitored data. Table 10 lists a comparative study of all the works discussed in this section related to analyzing/processing of Covid-19 patients' monitored patients' data.

4 Discussion by Comparison

This section compares all the works referred in this survey related to remote monitoring of pandemic patients using technologies like the IoT, blockchain, and machine learning. The comparison and analysis are based on various factors, including applications and platforms. This statistical comparison is based on the research works considered in this survey and is shown in Figs. 14, 15 and 16.

Figure 14 shows the percentage of various blockchain platforms used for storing the patient data. Here, notable is that equal number of research studies have utilized Ethereum and Hyperledger to store and share the monitored data. Some research studies have also used their own customized blockchain. As IoT devices collect a massive amount of data during remote monitoring, continuous data is generated as long as the patient is monitored. Efforts must be made to develop blockchain solutions that can handle the over flooding of generated data. The processing and transactional speed of the blockchain system should be is in accordance with the rate at which the data is generated.

The generated data can also be stored and shared using other technologies such as cloud storage [70, 71] or hybrid storage consisting of both cloud and edge servers [70, 76, 126-128]. However, the storage of patient data in these systems must be done securely to protect patients' privacy and prevent unauthorized access.

Cloud storage is a convenient option for storing large amounts of patient data as proposed in several research works such as [70, 70-72, 75, 76, 79, 80]. For example the work proposed in [70] stores the data in a central location through the WSN and distributed edge devices. Here, the transition of the data will be from WSN nodes to edge devices and then from the distributed edge devices to remote cloud servers. This means that data is encrypted when it is being transmitted over the internet and also when it is stored in the cloud. In [71], a cloud manager manages the data flow from and to the servers. Cloud manager also handles efficient communication, data storage, and other data related queries. A low-cost and lightweight cloud-based mobile health monitoring system to measure heart rate, oxygen saturation and electrocardiogram of Covid patients was proposed in [74]. In yet another work, authors in [75] proposed an architecture that transfers the patient's monitored data to cloud storage. The cloud server runs the software to provide useful information about the patient's conditions. Hybrid storage combines cloud and edge storage to provide scalability and cost-effectiveness while maintaining control over sensitive patient data. By storing sensitive data on local edge servers and less sensitive data in the cloud, hybrid storage offers tailored solutions for organizations and patients [70, 76].

However, cloud based approaches have their own limitations. Cloud storage with encryption can still be vulnerable to cyber-attacks and unauthorized access. On-premise storage using edge servers may be costly and may not be scalable. Hybrid storage requires careful planning and coordination to ensure data is appropriately partitioned and stored. Blockchain technology can address these limitations by providing a decentralized and tamper-proof platform for storing patient data. It enables secure and transparent data sharing between multiple parties while maintaining patient privacy and consent. It also provides

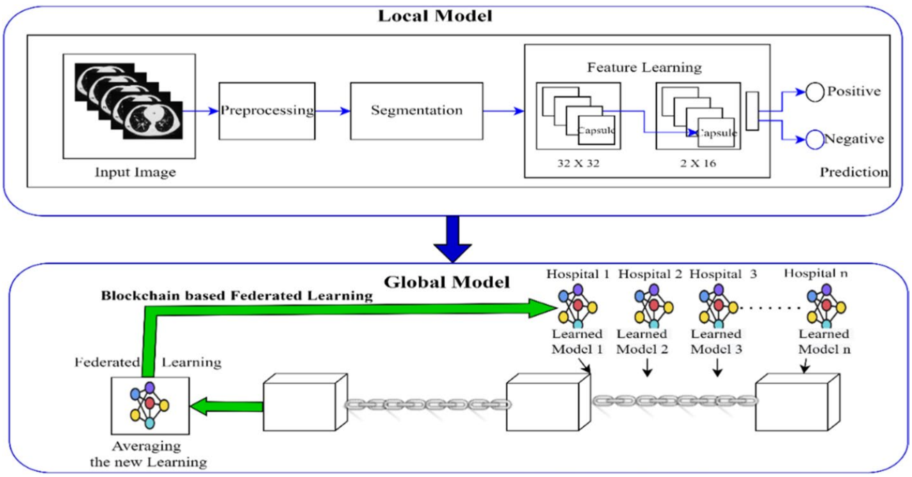

Fig. 11 Blockchain based federated learning [111]

an immutable record of all transactions, ensuring data integrity and auditability. These features make Blockchain a promising technology for securely storing pandemic patient data and other healthcare-related data.

- ***Decentralization and immutability***: The data is stored in a distributed network of nodes, making it extremely difficult for any unauthorized party to tamper with the data. For example authors in [91] stores the Personal Health Records using the Ethereum blockchain and IPFS which stores and synchronizes the data on multiple distributed nodes.
- ***Transparency and accountability***: Every transaction on the blockchain is recorded and can be accessed by authorized parties, ensuring that the data is trustworthy and accurate. Additionally, the patient can maintain control over their data and grant permission to access it. For example, the work proposed in [93] proposed a blockchain-based secure framework to access and share the medical images in a transparent manner among the patients. A consortium blockchain-based system "HonestChain," was also proposed in [101] that ensures auto-assurance and auto-auditability.
- ***Interoperability***: Blockchain allows different organizations to share data easily and securely. This is particularly important during a pandemic, where different organizations and healthcare providers may need to access a patient's data to provide necessary care. For example works such as [100] and [102] proposed decentralized blockchain-based platforms for sharing covid electronic medical records among medical research institutions, hospitals, patients, government organizations ensuring patients' privacy is not violated.
- ***Privacy***: Blockchain can enhance privacy by allowing the patient to store their data anonymously, ensuring that their sensitive information is protected while still being accessible to healthcare providers. For example, in [77], a novel remote patient monitoring approach has been proposed that uses a private blockchain to safeguard patients' privacy. In a similar work in [94], authors utilizes the blockchain for ensuring privacy of patients.

Figure 15 shows the problem domain in which machine learning has been applied on the remotely monitored data of Covid-19 pandemic. The considered applications are as follows: detection of Covid-19, prediction of recovery time, prediction of patient's hospital

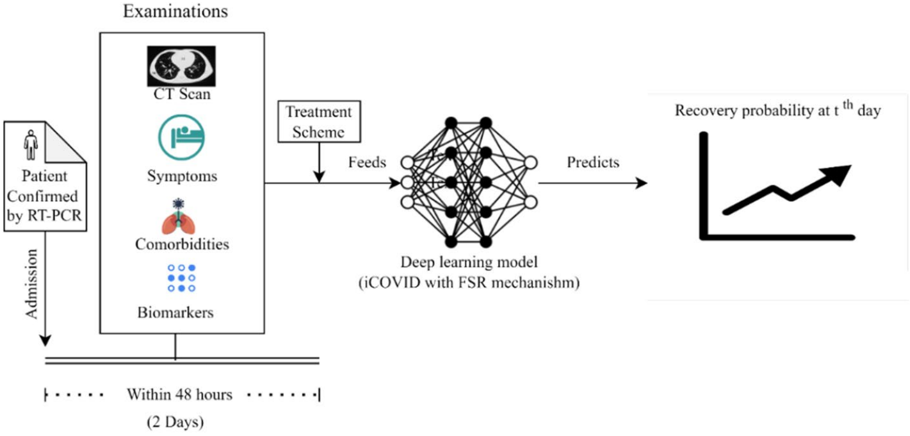

Fig. 12 Prognostic model development [115]

stay, prediction of the oxygen requirement of the patient and classification of disease severity. Here notable is that half of the work is on detecting Covid-19 using medical images like CT scans, x-rays, or clinical data collected from IoT devices. Low coverage attention has been given to other applications, which need to be explored further.

We infer from the survey that research works mainly used central cloud servers or local servers to store the data collected from the IoT devices, as shown in Fig. 16. Training the machine learning algorithms has also utilized the centralized approach, leading to privacy concerns. Hence researchers should focus on building decentralized systems. Blockchain and federated learning promote the decentralization of the whole workflow. These techniques should be utilized to effectively store and share the Covid patients' data. Federated learning is more suitable as Covid-19 data is generally not present at one central location. Further, these two technologies together have the capability to protect the privacy of the data, which is of top concern in the case of healthcare data.

5 Issues and Future Directions

Healthcare workers are vulnerable to getting infected by the disease during the treatment of the infected persons. Hence the demand for smart remote monitoring systems has increased tremendously after the Covid-19 pandemic. Even though technologies like IoT, blockchain, and machine learning are quite useful and have huge potential in realizing a patient monitoring system, there are several issues and challenges that should be addressed. This section discusses these issues and challenges in detail along with future research directions.

5.1 Scalability of Blockchain Based Platforms

The rapid growth of blockchain technology has acquired huge attention around the globe. Current blockchain systems suffer from the problem of poor scalability [129], which acts as a huge hurdle in the wide-scale adoption of blockchain in healthcare systems. In a blockchain system, transaction throughput is used to measure the scalability of blockchain

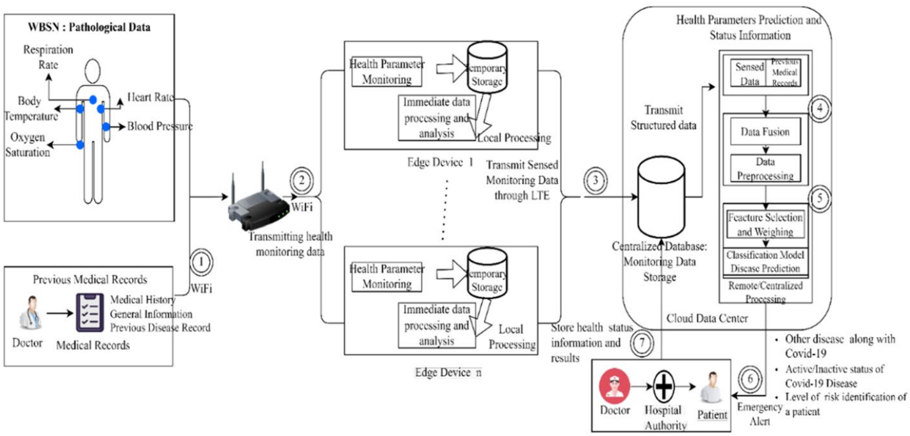

Fig. 13 Architecture of iCovidCare [119]

systems which is the number of transactions per second (tps). Blockchain has very low tps as compared to other matured commercial payment systems and conventional centralized databases. For instance, Bitcoin has a maximum throughput of only 7 tps while PayPal and Visa have a throughput of 170 tps and 200 tps respectively [33]. There should be a significant improvement in throughput and the scalability of blockchains to maintain the massive number of transactions. The different ways to improve the scalability are as follows:

- *Developing more scalable consensus algorithms*: One of the challenges in blockchain technology is developing more scalable consensus algorithms. Public blockchains tend to have lower throughput than private blockchains when it comes to confirming transactions. Consortium blockchains perform better than public blockchains, but worse than private ones. To overcome this challenge, researchers must explore newer distributed ledgers such as Tangle. Tangle is a chainless ledger implemented using Directed Acyclic Graph (DAG) that is ideal for storing IoT data. Tangle offers high network scalability, transactional throughput, and low transactional cost, as highlighted in [48].
- *Sharding*: The processing of transactions in blockchain is sequential which results in significant computation overhead as the network grows in size. To address this, sharding is a technique that divides a blockchain network into smaller partitions or shards. The ledger is also divided into multiple parts, each assigned to a different shard. This allows for faster validation of transactions, as each shard can process its assigned transactions in parallel. By dividing the blockchain into smaller partitions, sharding increases the number of transactions that can be processed by the network simultaneously.

5.2 Dataset Availability

The sudden and vast outbreak of the Covid-19 pandemic overwhelmed the current record-keeping application facility of the healthcare systems. Proper records were not maintained as the frontline workers were more focused on saving lives. Also, the records have been saved in various formats at different locations. Accumulating, aggregating, annotating and formatting enormous healthcare data is a huge challenge [130]. The available data is also not adequate for large-scale machine learning algorithms. Countries are highly reluctant to share their medical data. This phenomenon puts a challenge in evaluating the measures for combating the pandemic. Future research possibilities regarding this issue are as follows:

- Automated data augmentation and aggregation model can be deployed on edge locations to pre-process the patient monitored data.
- Efforts should be made to collect data from various locations and build datasets keeping in mind the ethical and privacy issues
- Interoperability standards need to be designed for data collected from multiple sources.

5.3 Data Security and Privacy

The security and privacy of the patient's data are of top concern and ensuring it is a big challenge. As vast volumes of data are aggregated, data security becomes a big concern as there is a risk of data breaching and manipulation. Hence a secure authentication system must be developed to secure sensitive data [106]. Data privacy can also be highly affected by transparent and distributed data storage. Privacy laws must always be adhered during

Table 10 Comparison of data analyzing/processing systems using machine learning

References	Objective	Dataset	ML Algorithm	Pros	Cons
Nandy et al. [70]	System for prediction of the severity of Covid-19 disease	Brazil Covid-19 dataset	Bag-of-Neural Network	Advanced ML model with high accuracy and minimum training time is utilized	Centralized storage
Abouyoussefet al. [109]	Online diagnosis of suspected patients using simple signals collected	Virufy Covid-19 [121] and COUGHVID [122]	Deep Neural Network, Deep LSTM, Deep CNN-LSTM Model	machine learning detection algorithms are implemented using smart contracts in python	Only one parameter is considered for diagnosis
Kumar et al. [98]	Identifying Covid positive patients using CT scans while preserving privacy	34,006 CT scans	Federated Learning	Privacy-preserving framework	–
Awal et. al. [110]	Detect Covid-19 within a few minutes	–	Quadratic-DA, LDA, RF, NB, KNN,EGB, DT, SVM	Inpatient facility data is used	Security and Privacy issue
Wang et al. [115]	Prediction of recovery-time of Covid-19 patients	Data of 3008 patients of three hospitals in Wuhan, China	Deep learning	Multimodal data is used	Privacy issue
Yue et al. [111]	Predict hospital stay of patients of Covid-19	–	Logistic Regression and Random Forest	High accuracy	A small sample size was used to test the model
Yang et al. [116]	Privacy-preserving reliable diagnosis of Covid-19	CT evaluation from three international centers	Federated semi-supervised learning	Privacy-preserving and can work on data without annotations	Dataset is not publicly available
Dayan et al. [113]	To predict the oxygen requirement of a patient	MGB COVID Cohort	Federated learning	Privacy-preserving	Small training data size
Mehrabadi et al. [114]	System to detectCovid-19disease	UC-CORDS data set	CNN and LSTM	Good accuracy with only two parameters	Privacy issue
Elbasi et al. [117]	To classify patients of Covid-19 and H1N1	Not mentioned	RF, BN, LWL, ANN and Naive Bayes classifier	Acquired high accuracy of 99.13%	Privacy issue
Ameni Kallel et al. [118]	A smart Covid-19 monitoring and prognosis system	[123]	Federated learning	Handles both the batch data and streaming data	A centralized database is used for storage

Table 10 (continued)

References	Objective	Dataset	ML Algorithm	Pros	Cons
Adhikari & Munusamy [119]	Detection of Covid-19 patients	Synthetic Dataset	Ensemble Random Forest	consideration of previous health record and sensor data	A centralized database is used for storage
O. Samuel et al. [120]	A secure epidemiological model for Covid-19	[124]	Federated learning	Privacy-preserving	–
Mistry et al. [102]	To predict disease severity	[125]	RF, KNN, DT, LR, SVM, ANN	Privacy-preserving	6G communication channel is used (only 5G has been implemented in many places)
Adhikari et al. [112]	Prediction of the risk level of Covid-19 patients	Synthetic dataset	Random Forest	Aggregation of redundant data hence space efficient	Privacy issue

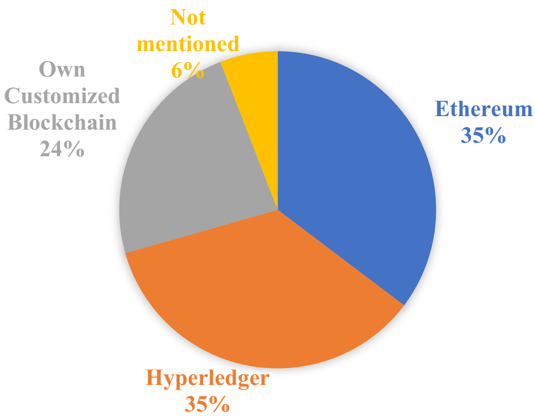

Fig. 14 Percentage of various blockchain platforms used in storage layer

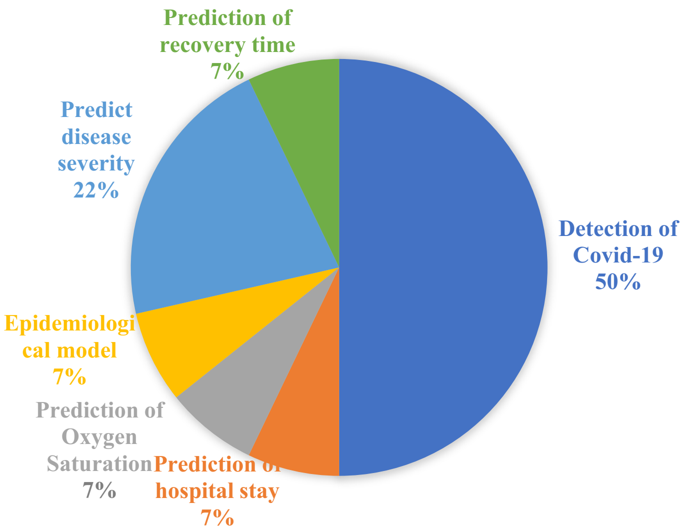

Fig. 15 Distribution of applications of machine learning for mitigating Covid-19 in the data analysis layer

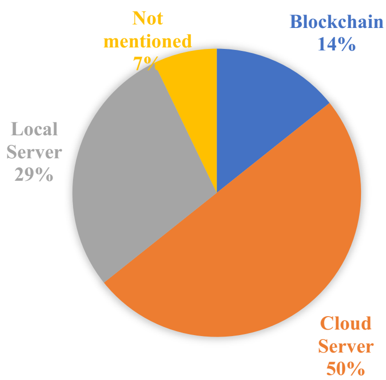

Fig. 16 Distribution of database platforms to store IoT data in the data collection layer

data processing, storage, and visualization. Although blockchain has tremendous potential, it is still a relatively new technology. It can preserve certain amount of privacy as users operate their accounts using private and public key, their real identity is hidden but blockchain cannot provide transactional privacy as values of all transactions are publicly visible on the network. Future research possibilities regarding this issue are as follows:

- *Developing well-defined access control mechanisms*: Access control protocols need to be designed so that patients can give access of their health data to various stakeholders such as relatives and doctors.
- *Designing encryption mechanisms*: Cryptographic encryption algorithm can be utilized to provide further privacy to the data stored on the blockchain.
- *Mixing*: Although transactions in blockchain occur without exposing the identity of the users, it can still be guessed by malicious nodes in the network by analyzing the transactions stored publicly on the network. Mixing provides anonymity by executing transactions from multiple account addresses to multiple output addresses.

5.4 Storage and Processing of Large Healthcare Data

In a remote monitoring system, IoT devices produce a huge amount of heterogeneous health data [131]. Hence, a robust and efficient framework is needed for storing and processing the voluminous data produced at high speed. Preprocessing such as removal of redundant data, filtering, and data pruning also becomes challenging as data size keeps increasing. IoMT data also pose challenges in data analysis as data is heterogeneous. This data analysis is done by machine learning which requires extensive feature extraction. Future research possibilities regarding this issue are as follows:

- *Optimizing the blockchain storage*: As the transactions keeps on increasing it becomes harder for a blockchain node to manage the full copy of the ledger. Hence, the solutions should be storage efficient as persistent data storage is involved. Utilizing the off-chain storage systems like IPFS and HDFS can be one of the promising way to tackle the above issue.
- *Usage of Machine Learning Models*: Different ML models can be used for different types of data such as deep CNNs for X-rays and MRI, and RNN for time-series and EEG data.

5.5 Lack of Training and Required Skills

The doctors and healthcare workers may be hesitant to adopt these new technologies over the traditional paperwork system in a remote monitoring system. Many technical difficulties would be inevitable and thus hamper the development of such systems due to lack of knowledge and required skills. Future research possibilities regarding this issue are as follows:

- Efficient and User-friendly technologies can be developed with well-defined access control mechanisms and mobile/web interfaces.
- Proper demonstrations and user manuals can be prepared to implement the technologies.

6 Conclusion

The coronavirus pandemic has exerted extreme pressure on the existing healthcare systems. Scientists and researchers are striving continuously to provide solutions for humanity to be better equipped for such emergencies in the future. Smart remote healthcare monitoring is essential for combating pandemics like Covid-19. This survey discusses the role of IoT, blockchain and machine learning in the remote monitoring of pandemic patients. It also details a comprehensive survey on how these technologies are utilized for conceptualizing and designing such systems. The relevant works in the domain are categorized into three sub-domains; remote monitoring of pandemic patients using IoT, storing or sharing patients' data securely using blockchain, and processing stored patients' data using machine learning. A comparative study of all the related research works in the respective sub-domains has also been done. The comparative study considers various parameters, viz. objective, merits and demerits of the work, dataset used and applied scheme. Finally, various challenges and future research directions have been given. As there is an urgent requirement for a smart remote monitoring system, this survey work will be helpful in assisting researchers to develop such a system.

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Declarations

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