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Review

Comprehensive Survey of IoT, Machine Learning, and Blockchain for Health Care Applications: A Topical Assessment for Pandemic Preparedness, Challenges, and Solutions

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Citation: Imran, M.; Zaman, U.; Imran; Imtiaz, J.; Fayaz, M.; Gwak, J. Comprehensive Survey of IoT, Machine Learning, and Blockchain for Health Care Applications: A Topical Assessment for Pandemic Preparedness, Challenges, and Solutions. *Electronics* **2021**, *10*, 2501. https://doi.org/10.3390/electronics10202501

Academic Editors: Ismaeel Al Ridhawi, Safa Otoum, Ali Karime and Nadra Guizani

Received: 4 September 2021
Accepted: 11 October 2021
Published: 14 October 2021

Abstract: Internet of Things (IoT) communication technologies have brought immense revolutions in various domains, especially in health monitoring systems. Machine learning techniques coupled with advanced artificial intelligence techniques detect patterns associated with diseases and health conditions. Presently, the scientific community is focused on enhancing IoT-enabled applications by integrating blockchain technology with machine learning models to benefit medical report management, drug traceability, tracking infectious diseases, etc. To date, contemporary state-of-the-art techniques have presented various efforts on the adaptability of blockchain and machine learning in IoT applications; however, there exist various essential aspects that must also be incorporated to achieve more robust performance. This study presents a comprehensive survey of emerging IoT technologies, machine learning, and blockchain for healthcare applications. The reviewed articles comprise a plethora of research articles published in the web of science. The analysis is focused on research articles related to keywords such as 'machine learning', blockchain, 'Internet of Things or IoT', and keywords conjoined with 'healthcare' and 'health application' in six famous publisher databases, namely IEEEXplore, Nature, ScienceDirect, MDPI, SpringerLink, and Google Scholar. We selected and reviewed 263 articles in total. The topical survey of the contemporary IoT-based models is presented in healthcare domains in three steps. Firstly, a detailed analysis of healthcare applications of IoT, blockchain, and machine learning demonstrates the importance of the discussed fields. Secondly, the adaptation mechanism of machine learning and blockchain in IoT for healthcare applications are discussed to delineate the scope of the mentioned techniques in IoT domains. Finally, the challenges and issues of healthcare applications based on machine learning, blockchain, and IoT are discussed. The presented future directions in this domain can significantly help the scholarly community determine research gaps to address.

Keywords: IoT; machine learning; healthcare; pandemic; blockchain; convergence; health monitoring

1. Introduction

Internet of Things (IoT) integrates large numbers of physical devices through the Internet to collect, share, and assess a vast amount of data [1]. Internet of Things (IoT) communication technologies have brought immense revolutions in various domains, especially, IoT has become elementary for the second phase of the digital revolution [2,3]. Cisco statistical analysis remarked in a study that 50 billion devices could be integrated into a single network using the Internet [4]. The integration of a large number of devices leads to scalability and data management problems. The contemporary management systems usually become old-fashioned due to the advancement and latest trends and technologies. Orchestration is one of the latest automated approaches to tackle management and scalability issues [5]. Orchestration is considered as the most cost-effective and innovative way to manage the significant number of integrated things using IoT technology [6–8]. Wireless sensor networks (WSNs), machine-to-machine (M2M), and cyber–physical systems (CPS) are the key elements in IoT [9,10]. These networks are processed and communicated using standard IP protocol with security concerns, which requires the safety of the whole network against security attacks. Otherwise, these cyber attacks can harm IoT services, data security, data privacy, and data integrity of the entire system [11,12].

Due to the incredible economic prospect in IoT, IT organizations and academic institutes participate in the research and advancement in IoT technologies to develop sustainable solutions. They have introduced many free and commercial plans over the last few decades; however, due to the lack of adaptability among IoT application development platforms, these technologies use many data formats, boosting the critical issue of heterogeneity; therefore, the requirement for better network management solutions to tackle the extensive amount of data generated by this integrated system arises gradually. The existing data storage and central processing model is unsuitable; hence, edge-computing solutions play an essential role in analyzing data to refine these utilities in IoT technology. Big data solutions in IoT are a new paradigm that introduces practical applications based on the enormous data generated from extensive IoT devices. Many studies have been proposed to handle various IoT issues and features such as IoT challenges, opportunities, and applications [13,14]. In IoT technologies, security and privacy are the leading research-oriented challenging problems. Other such challenges include IoT and cloud integration [15], IoT standardization [16], IoT scalable architecture, and IoT security [17–20]. Further, earlier literature on IoT did not consider all the issues in detail, such as dealing with Quality of Service (QoS), internet applications, and security challenges.

Figure 1 shows applications of machine learning, blockchain, and IoT for the healthcare domain. Artificial intelligence and IoT have been consolidated to form a new specification named Artificial Intelligence of Things (AIoT). The primary purpose of AIoT is to improve human–machine interactions, enhance data management, and carry out data analysis. Researchers communicate and collect data using IoT devices, and collected data are stored in a centralized database. Then, anomaly detection and automatic pattern recognition in the collected data can be performed with machine learning models. Machine learning technologies predict more accurately and faster than traditional business intelligence (BI) tools [21].

Machine learning algorithms are trained on historical network data to obtain better models that analyze data and provision network services efficiently [22]. In recent studies, machine learning offers clear instructions to implement machine learning algorithms to networking. Thus, machine learning enhances the security, efficiency, and performance of network applications [23]. The innovations and discovery of new data processing, data analysis, and predictive analysis enable the development of intelligent applications [24–26]. Many smart architectures are proposed and based on the Internet of Things, blockchain, machine learning, and their integrated mechanisms [26–28].

Blockchain is considered a public ledger and a type of database distinct from traditional databases such as relational databases [29,30]. Alternatively, blockchain saves data in blocks and then chains them together based on digital signatures in a distributed network. As new data are collected, it is passed through a new block. Blockchain key attributes include persistency, anonymity, auditability, and decentralization. Some examples of the usage of blockchain in the financial market are digital assets, remittance, and online payment systems [31]. Recently, blockchain has been applied to emerging technologies such as IoT-based public and security services. In addition, organizations use blockchain for high reliability and security to attract customers. Furthermore, blockchain can ignore the single point of failure issue since it is a distributed environment.

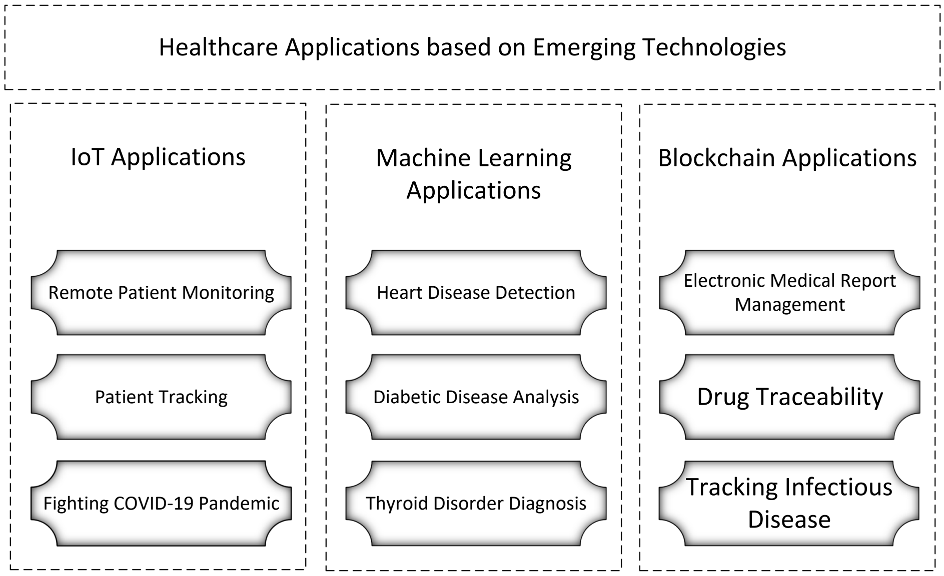

Figure 1. Healthcare applications based on IoT, machine learning, and blockchain.

Currently, there is accelerated development in healthcare because of the progression of advanced technologies such as IoT, blockchain, and machine learning. To date, contemporary state-of-the-art techniques have presented various efforts on the adaptability of blockchain and machine learning in IoT applications [32,33]. These technologies benefit healthcare systems by predicting diseases, drug tracing, patient tracking, and combating deadlier pandemics such as COVID-19. In addition, IoT and network applications security has been addressed using mechanisms based on blockchain technology [34]. Furthermore, machine learning models based on the huge amount of data collected from medical sensors and devices are used to predict and classify different healthcare diseases [35]. Machine learning techniques coupled with advanced artificial intelligence techniques detect patterns associated with diseases and health conditions. For instance, IoT-enabled applications integrate blockchain technologies with machine learning models to benefit medical report management, drug traceability, tracking infectious diseases, etc.

This study presents a comprehensive survey of emerging IoT technologies, machine learning, and blockchain for healthcare applications. These health care applications are derived from the recent web of science indexed literature. Lastly, we briefly discuss IoT, machine learning, and blockchain-based approaches that can be used to defeat the COVID-19 outbreak. A topical survey of the contemporary IoT-based models is presented in healthcare domains as follows:

- A detailed analysis of healthcare applications of IoT, blockchain, and machine learning demonstrates the importance of the discussed fields.
- The adaptation mechanism of machine learning and blockchain in IoT for healthcare applications are discussed to delineate the scope of the mentioned techniques in IoT domains.
- The challenges and issues of healthcare applications based on machine learning, blockchain, and IoT are discussed.
- COVID-19 applications based on blockchain, machine learning, and IoT are discussed as use cases for future pandemic preparedness.

The presented future directions in this domain can significantly help the scholarly community pick the accurate research gap to address; however, various essential aspects must also be incorporated to achieve more robust performance.

The rest of the paper is divided as follows: Section 2 explains the methodology of the review study. Section 3 describes the background of IoT, machine learning, and blockchain. Section 4 presents the emerging technologies based on IoT, machine learning, and blockchain for healthcare applications. In Section 5, we briefly discuss the COVID-19 outbreak and research contributions. Section 6 presents the convergence of machine learning, blockchain, and IoT for health care applications and future research directions. Section 7 presents the conclusion and future research directions.

2. Research Methodology and Results

In this section, the methodology of the topical survey of the contemporary IoT-based models is presented in healthcare domains based on blockchain, IoT, and machine learning. In addition, the research objectives, questions, and research selection conditions of this study are discussed. Finally, this survey article investigates current academic works proposed in machine learning and blockchain for secure IoT systems. First, background to machine learning, blockchain, and IoT will be presented. Second, healthcare applications based on these emerging technologies will be presented. Third, the COVID-19 case study based on these emerging technologies will be presented. Moreover, we will discuss the convergence and adaptability of these technologies with their challenges and solutions. Figure 2 shows the research methodology of papers collection and selection for the topical survey of healthcare applications based on machine learning, blockchain, and IoT.

The primary purpose of this review study is focused on the latest research papers and upcoming trends in blockchain, machine learning, and IoT applications to combat pandemic diseases. Table 1 shows the research keywords criteria for selection of research papers. These keywords are based on IoT, blockchain, machine learning, COVID-19, and adoption of blockchain in IoT. Furthermore, keywords such as artificial intelligence and machine learning in IoT were used to filter the search criteria of articles and review papers. Table 2 presents research questions for the literature selection and review.

Table 1. Criteria and the searched keywords.

Key	Criteria
Search keyword	(“blockchain” or “Blockchain”) AND (IoT OR “Internet of Things”) AND (COVID-19 OR “coronavirus”) AND (“machine learning”) AND (applications of blockchain OR “IoT challenges” OR IoT solutions using blockchain) AND (AIOT OR “Artificial intelligence-enabled Internet of Things”)
Limiters	Article date between 2015 and 2021.
Expanders	Without the word “healthcare”.
Search keyword	Search keyword appear anywhere in the research paper.

Table 2. Research questions for the literature review.

S.No	Question	Description
1	What is blockchain, and different concepts in blockchain-related to healthcare?	Examine review role to blockchain and finding better techniques in healthcare based on blockchain.
2	What is machine learning, and different concepts of machine learning related to healthcare?	Examine review role to machine learning and finding better techniques in healthcare based on machine learning.
3	What is the Internet of Things (IoT), and different concepts in healthcare-related to IoT?	Examine review role to IoT and finding better techniques in healthcare based on IoT technology.
4	What is COVID-19 disease, and how to tackle COVID-19 challenges using the latest technologies?	To investigate different IoT, machine learning, and blockchain concepts associated with healthcare, issues, and solutions used to overcome these challenges.

Table 2. *Cont.*

S.No	Question	Description
5	Which machine learning algorithms have been used in healthcare applications?	To pick out the most used and suggested machine learning techniques applied with healthcare-based methods.
6	Which blockchain techniques have been used in healthcare applications?	To identify the most utilized and suggested blockchain applied with healthcare-based methods.
7	Which IoT technologies have been used in healthcare applications?	To recognize the most used and recommended IoT technologies applied with healthcare-based methods.
8	How IoT, machine learning, and blockchain technologies can tackle COVID-19 challenges?	To megitate pandemic diseases such as COVID-19 disease, these technologies are being utilized with medical systems.
9	How to overcome the challenges of the adoption of blockchain in IoT?	Some characteristics are being upgraded using the latest research studies to overcome issues while adopting blockchain in IoT.
10	How artificial intelligence-enabled IoT systems can improve interactions between machine-to-human and machine-to-machine?	Analysis and comparison of AIOT applications. Analyzing if AIOT based applications significantly enhance IoT solutions.

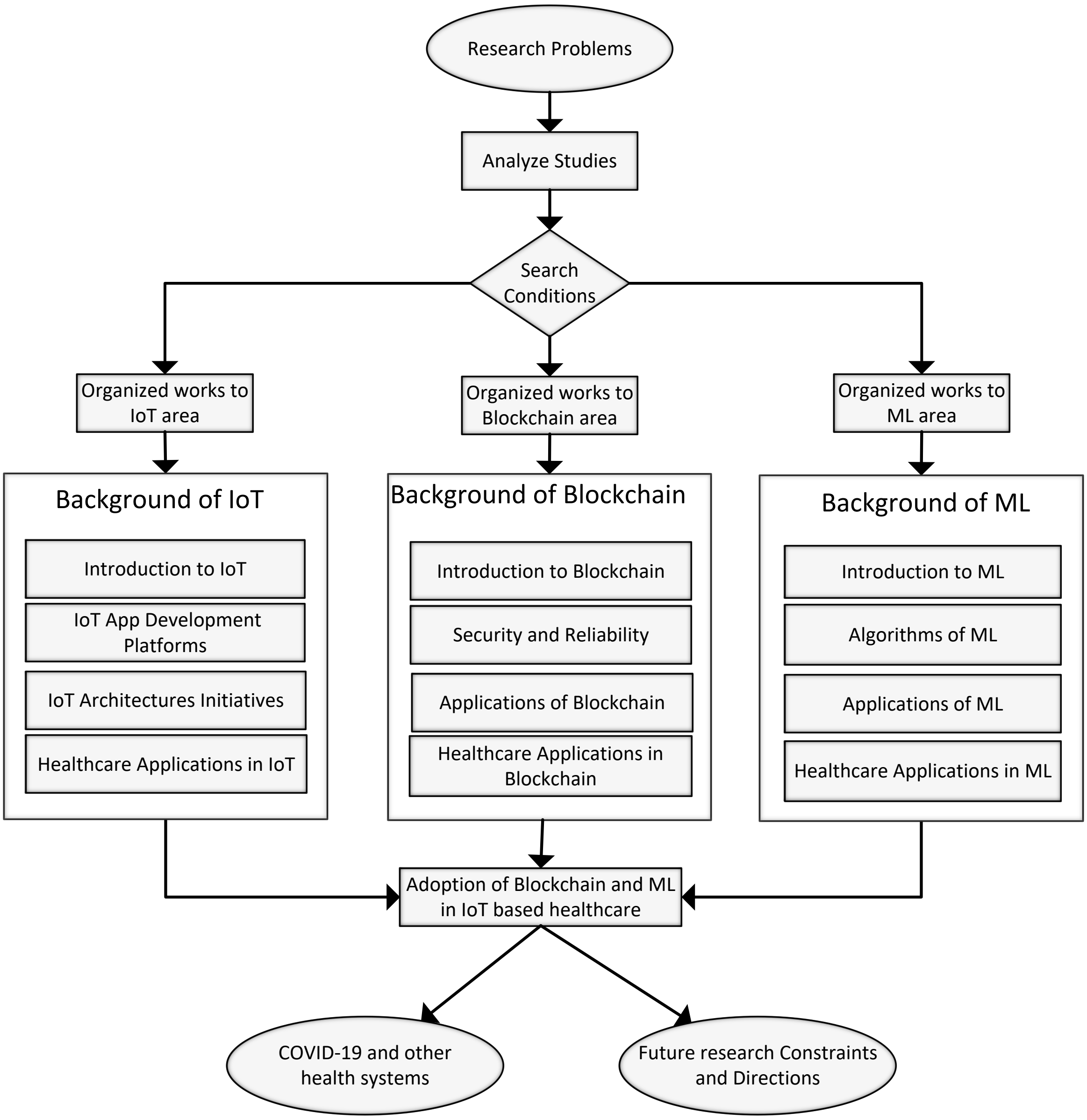

Figure 2. Methodology for Topical Survey of IoT, Blockchain and Mchine learning for Healthcare Applications.

A total of 263 research papers and articles were selected and cited in this topical review paper. The selection was made based on different panoramas such as search engines, sources, years of publications, to name a few. We consider the recent literature to be the basis for developing a research model that heads in the right direction. This topical review paper is based on a variety of articles based on the last six years. Figure 3 illustrates the number of publications per year that have been cited in this paper.

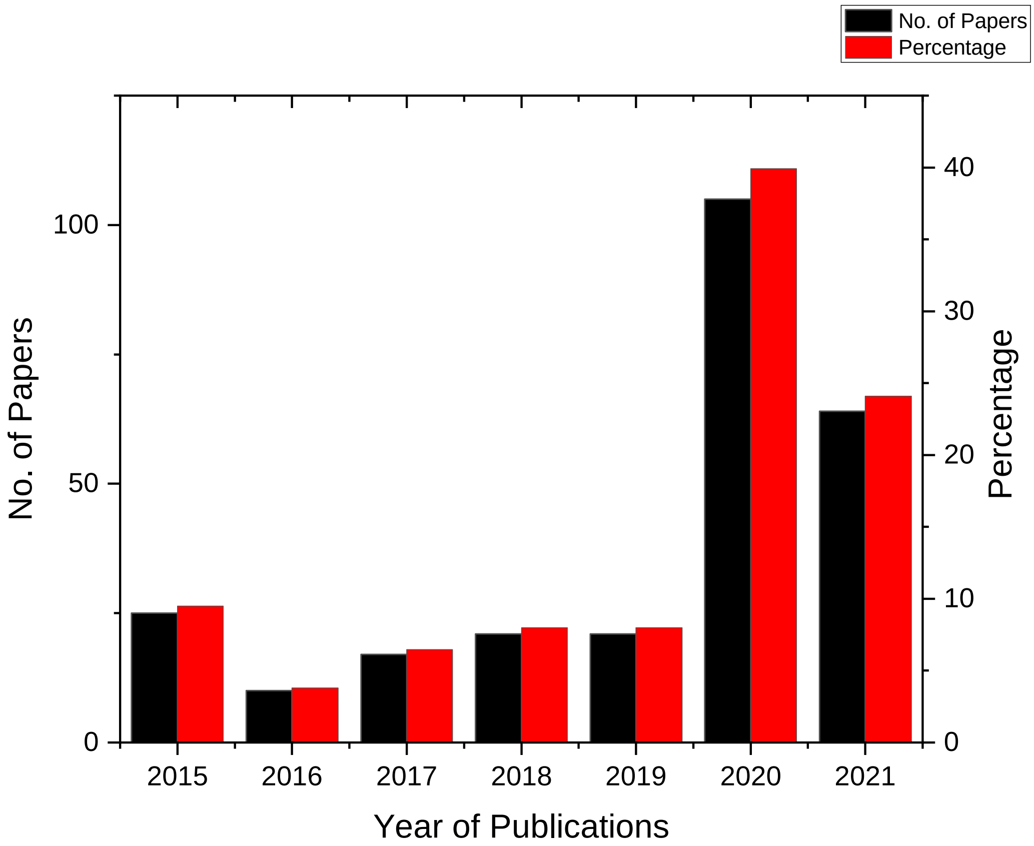

Figure 3. Publications in the last 6 years (2015–2021).

The illustration depicts that most of the research studies are based on the year 2020, with 105 articles counted. After 2020, 2021 is the most noticeable year, with 64 research articles. The second bar in the figure shows the percentage of the research articles that contributed to this review article. The percentage of research papers from the year 2020 is 40%, and the remaining 60% cited articles from the remaining five years. These publishers and the selected journals are indexed by the web of science, and are well-known among the researchers, for instance, IEEE, Springer, MDPI, Google Scholar, and Elsevier. IEEE is the leading portal where articles and review papers were searched. A total of 107 research papers were selected from the IEEE database, which is the highest among all other search portals. For instance, 40.68% of selected research papers are from the IEEE portal. In addition, some of the research papers were searched using Google Scholar, Science Direct, and other research search portals. For instance, 56 papers were selected from Google Scholar and 32 journal papers from Elsevier. Research articles in other categories include less-known search engines such as Bing. These search portals include various publisher databases as illustrated in Figure 4. The selection criteria for publishers was their familiarity with the scientific community.

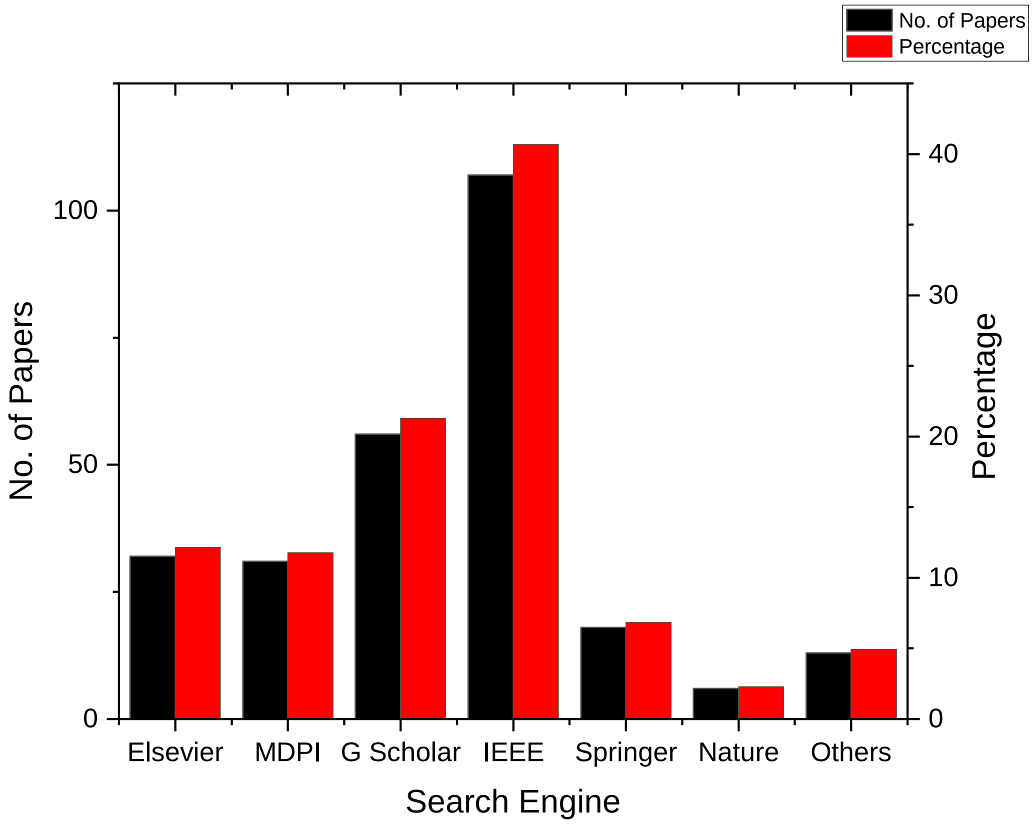

Figure 4. Research publishing websites used for research paper collection.

We analyzed the research papers based on the subject of the research articles. The collected articles are based on five major subject areas: machine learning, IoT, blockchain, healthcare, and COVID-19. The main focus of this study is the convergence mechanisms for tackling pandemic diseases such as COVID-19 using these emerging technologies. Most of the collected papers are based on IoT, with a total number of 102 articles. There are 63 collected articles associated with blockchain, 58 articles are proposed solutions based on the machine learning area, 35 research papers are based on the COVID-19 pandemic, and the five remaining papers are considered to be miscellaneous subject areas. Figure 5 presents the percentage analysis of the contribution based on subject areas.

Our study cites almost 72% of papers from the various web of science indexed journals and magazines, 19% from proceedings, 3% from books, and 6% from other sources such as websites. Figure 6 illustrates the comparative analysis research articles types.

The following keywords belong to the paper's central theme: IoT, COVID-19, blockchain, machine learning, adoption of blockchain in IoT, and artificial-intelligence-enabled IoT. Without the limitation on the scope of this topical review, the collected research papers from the literature review will be tremendous. Moreover, filtering and reducing the selected research papers is an extra benefit differentiating our research work from past studies and survey papers. Figure 7 shows the top journal papers cited in this work. Most of the journal articles have been collected from IEEE Access.

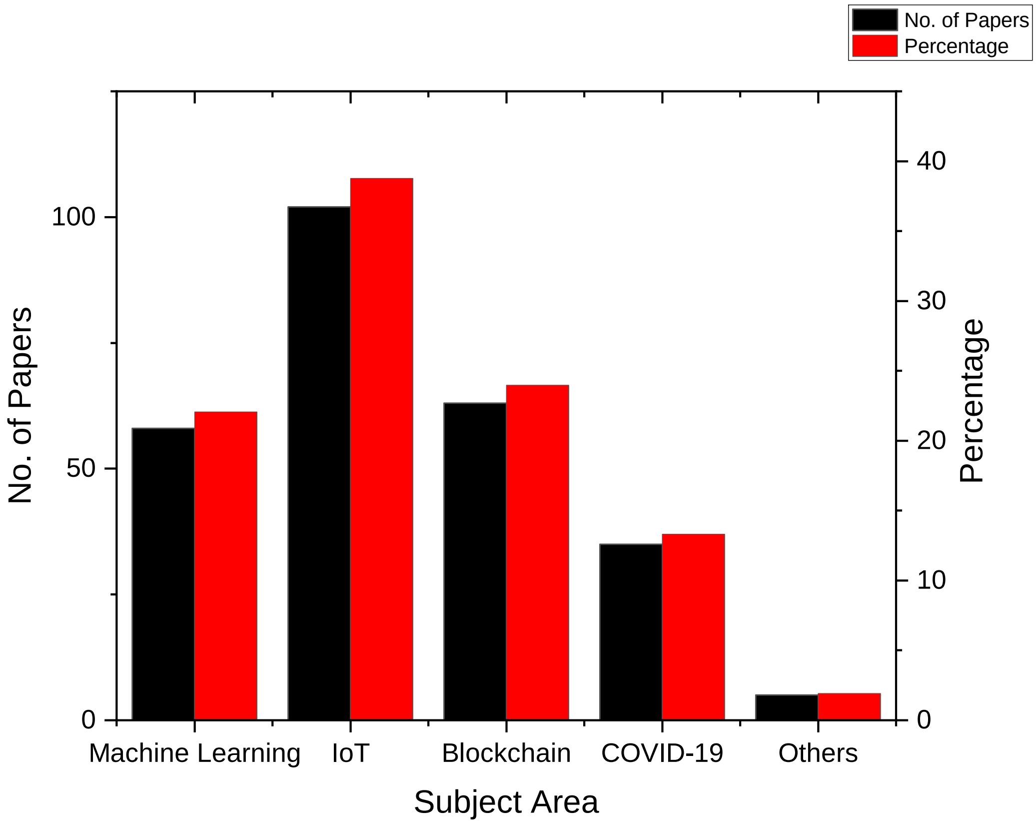

Figure 5. Research papers based on the subject area.

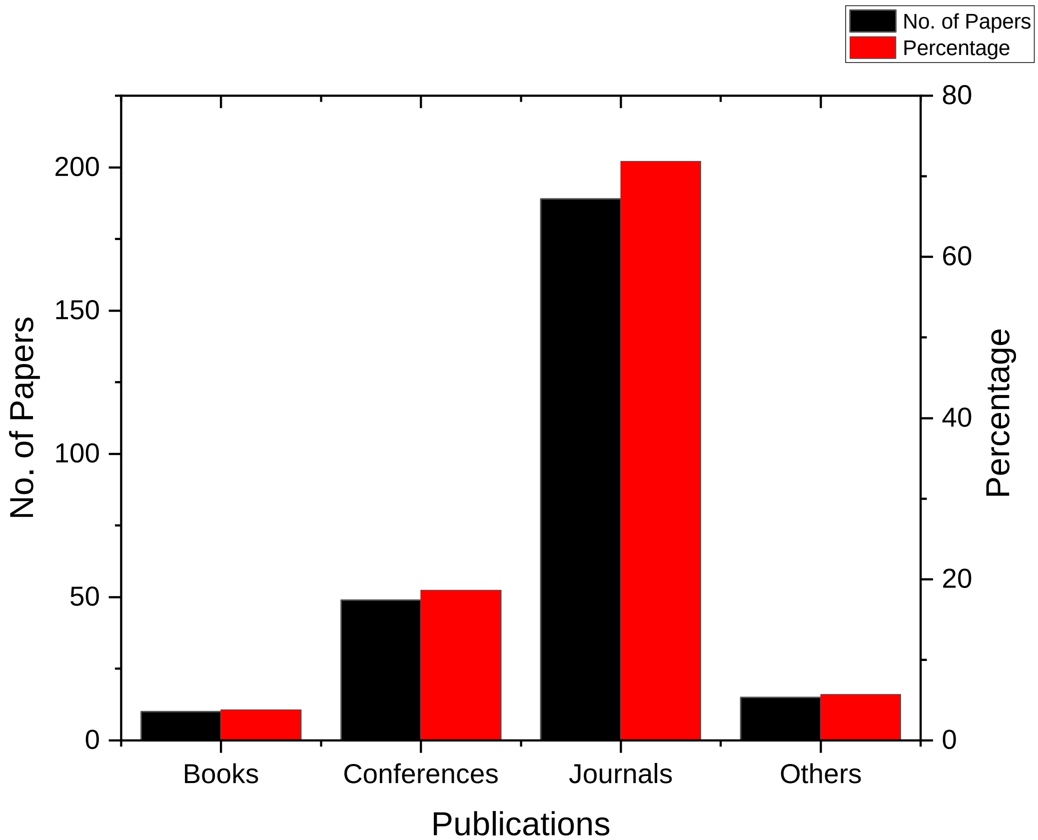

Figure 6. Research papers based on research articles types.

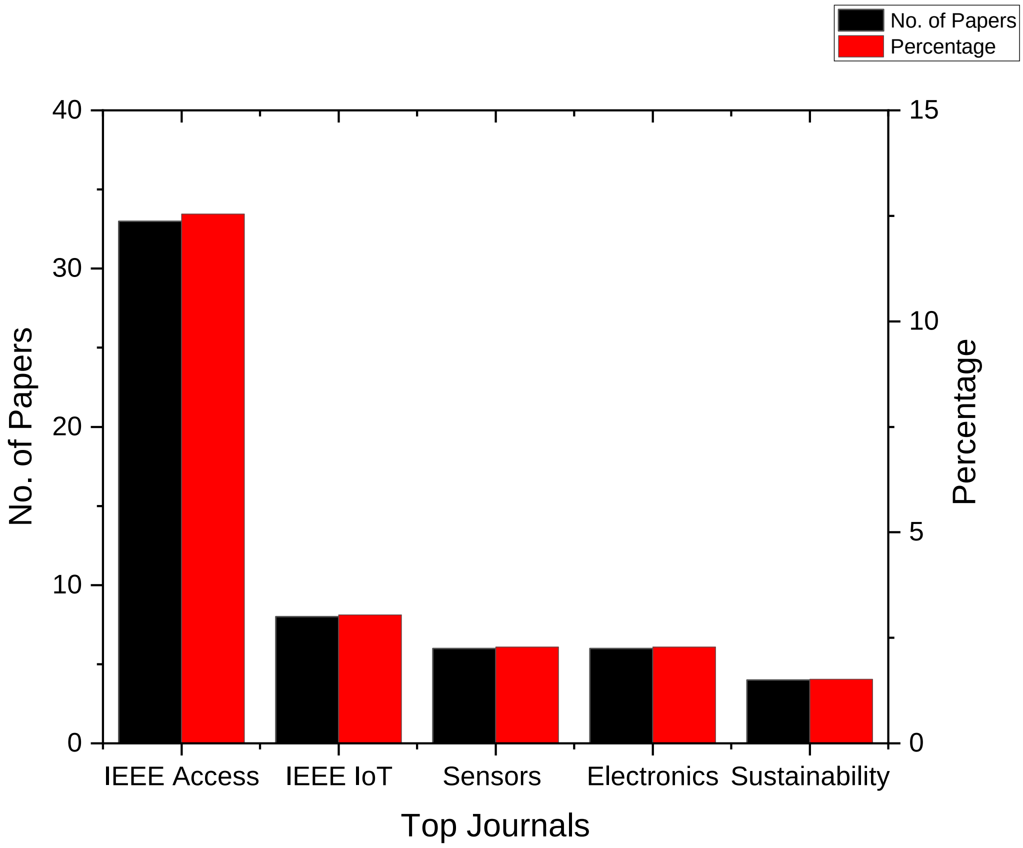

Figure 7. Research papers based on top-quality journals.

The most relevant research articles from the last couple of years were collected based on their top priority to perform effective analysis. Scholarly works older than two years were studied and utilized for background knowledge of the sections stated in this research. Research and survey papers with poor publisher and publication venue parameters were excluded; for instance, exclusion criteria include journal citation reports and other impact factors. This topical review paper preferred research papers that mainly focused on blockchain, machine learning, and IoT technologies to address the COVID-19 pandemic and other health-related challenges.

3. Background

IoT is acknowledged as one of the top emerging fields in the newest technologies, and its application is practical in various industries [36]. The IoT system provides communication between human-to-device, device-to-device, and human-to-human. IoT systems redefine the world where everything is connected and allows sharing data between humans with the help of electronic devices in a smart way [37]. Machine learning is a subtype of artificial intelligence and has become a vital technology in recent scientific studies. The progress and improvements in various areas, such as healthcare, banking, manufacturing, physics, chemistry, and bioinformatics, require innovative, intelligent techniques [38,39]. Nowadays, cryptocurrency is a very famous term in academic circles and businesses. It is a digital currency that can be used to buy goods and services. Bitcoin transactions could occur without any third party and are developed based on blockchain technology with a specially designed storing structure [40]. This section presents background studies of IoT, machine learning, and blockchain based on the recent web of science indexed literature.

3.1. Internet of Things

IoT integrates hundreds of thousands of physical devices through communication technologies and has brought immense revolutions in various research domains. IoT technologies focus on information service, understanding cognitive actions, and control of the real world by the equal number of connections between main and edge network [41]. IoT integrates cloud computing, sensor networks, electronic devices, mobile services based on advanced framework and information processing technologies. Many of us believe that IoT connects personal computers, tablets, smartphones, telephones, and servers; however, IoT connects sensors and actuators fixed in digital devices; usually, all devices are connected to the same internet protocol (IP). Smart home security, wireless inventory trackers, biometric scanners, and smart tennis rackets are some examples of IoT systems. These systems generate massive data that can be processed through statistical and machine learning analysis.

IoT applications are combined with blockchain technology in various areas such as insurance, education, healthcare, voting, stock exchange, to name a few. Blockchain is mainly used in smart cities where many IoT devices are placed in different locations. Adopting blockchain in IoT technology improves scalability, efficiency, robustness, time effectiveness, and computational cost-effectiveness. IoT generates data that can be stored in a blockchain managed by cloud-based servers. The authenticated users can access their private data from the cloud databases in a secure way [42,43]. IoT technologies identify integrated devices by unique internet protocol (IP) addresses using collections of transmission control protocol (TCP) and non-TCP. The approach of virtualizing electronic devices such as actuators and sensors into virtual objects is known as device virtualization [44–47]. IoT integrates virtual objects and electronic devices using transmission protocols such as WiFi, ZigBee, long-range wide area network (LoRaWAN), Bluetooth low energy (BLE), and Z-Wave, to name a few. The IoT devices have an adequate setup, and remotely available interfaces [48]. Latest research and development based on IoT introduces new terminologies, and IoT concepts such as artificial-intelligence-enabled IoT (AIoT), Internet of Anything (IoA), Internet of Everything (IoE), Industrial IoT (IIoT), Social IoT (SIoT), Web of Things (WoT), and machine-to-machine (M2M).

BLE is an enhanced version of Bluetooth, a widely used wireless method for a successful connection within 10 meters. Bluetooth 5.2 is the latest version that adds an advanced IP support profile. Research demonstrates that BLE is an entirely established and improved mechanism for IoT devices [49]. WiFi is a widely used internet protocol that communicates between IoT and physical devices. The communication range between most electronic devices is around 50 m, which is five times greater than BLE communication [50]. ZigBee is also short-range wireless, which transfers protocol with a data transmission rate of 250 kbps. For a productive transmission of data between IoT devices, ZigBee is the most acceptable solution due to its security, high-level scalability, low-power consumption, and durability [51]. Z-Wave is a low-power transmission protocol that uses wireless frequency, fashioned for computerization systems such as sensors and lamp regulators. Z-wave can communicate protocol within 30–100 m; Z-wave is better than other protocols such as WiFi, Bluetooth, and ZigBee [52]. The LoRaWAN protocol is used for electrically powered long-range IoT devices for devices connectivity at long ranges using power. It recognizes the noise level of signals assumed from a threshold range. LoRaWAN is used by those applications where a huge number of devices are integrated for securely sharing of data using memory, and require minimal power consumption such as smart cities, smart hospitals, and smart homes [53–55].

The concept of IoE is presented by Cisco as the integration of global network data, humans, things, and devices [56–58]. The sharing of data between machine-to-machine as well as a human is known as M2M [59]. M2M automates sharing of information among machines without any human intervention [60]. Analyzing data, discovering resources, and managing devices are the main activities performed by these systems. A cloud and fog-based computing platform was deployed to the gateway layer for the management of services [61]. The edge node has a limited number of resources in edge computing (EC). Thus, relocation of computing resources to the cloud is necessary for performing huge and complex tasks [62,63]. Data trimming is considered a major issue in the Cloud of Things

(CoT). Scientific community introduced efficient IoT architecture-based smart gateway to tackle the data trimming issue [64–66] . Data collection, pre-processing, data filtering, and data reconstruction into a more valued format are some of the operations performed by these smart gateways [67–69].

IT organizations are investing significantly in the development of fundamental IoT technologies due to strong economic potential. As a result, these organizations have introduced different IoT paid and open source applications in the last few years; however, a standard framework is required to introduce feasible IoT systems and overcome interoperability, heterogeneity, and diversity problems [70]. IoT applications have been implemented in many fields; the industrial area is considered the essential [71]. The fourth industrial revolution with IoT is named Industry 4.0, which integrates industrial observations using smart technologies. In industrial IoT applications, security and privacy are considered critical issues [72–74]. To handle and analyze these issues, Cisco, IBM, GE, and AT and T initiated a platform for the industrial IoT [75–77].

3.2. Machine Learning

Machine learning is a branch of artificial intelligence that provides data analysis that automates analytical model development. Machine learning can learn from data, identify patterns and make decisions with minimal human intervention. Advanced fields of machine learning, such as automated machine learning, further minimize human intervention by automating the model-building processes from preprocessing to model evaluation [78]. The traditional software systems are developed in program code that rules the system behaviors; however, in machine learning, these rules are deduced from training data with machine learning algorithms. Machine learning algorithms automatically create rules according to the kind of data [79]. Subfields of machine learning based on the kinds of algorithms are supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Prediction and classification are examples of supervised learning, and clustering is an example of unsupervised learning.

Prediction is about expecting what will happen in the future, such as weather forecasting, future market performance, predicting heart disease using risk factors. On the other hand, classification recognizes class labels, i.e., handwritten digits, sentiment analysis, and identifying spam emails; therefore, prediction and classification are performed on labeled data. Unsupervised learning is based on unlabeled data. Clustering is an example of unsupervised learning; clustering is a task that divides similar data points or similar sets of objects into groups, usually of larger datasets [80]. For instance, Netflix uses an unsupervised learning algorithm for movie recommendation [81]. Machine learning is used as a supplementary technology in emerging technologies such as IoT and blockchain. For example, machine learning with blockchain in healthcare applications has been used for medical data analysis, remote patient monitoring, electronic health data management, biomedical study, pharmaceutical supply chain management, and education. Blockchain technology has produced flexibility in the last few years, leading to its integration in a vast range of systems, including healthcare and biomedical applications [82]. The integration of blockchain and machine learning in IoT can play a vital role in Industry 4.0 and the internet of health things [83,84].

3.3. Background of Blockchain

Blockchain is considered a public ledger and a type of database different from traditional databases such as relational databases in which data are stored. Instead, blockchain saves data in blocks and then chains them together with digital signatures in a distributed network. As new data comes, they pass into a new block. The distributed consensus and asymmetric cryptography algorithms have been implemented to achieve overall system reliability, ledger consistency, and user security. In addition, blockchain technology has some key attributes such as persistency, anonymity, auditability, and decentralization. These attributes can significantly reduce the cost and enhance efficiency. Some examples of financial services that use blockchain are digital assets, remittance, and online payment systems [31].

Additionally, blockchain can be applied in many other areas, such as IoT, public services, and security services. Transactions cannot be edited once put into the ledger since the blockchain is unchangeable. Organizations use blockchain for high reliability and security to attract customers [85–87]. Furthermore, blockchain can ignore the single point of failure issue since it is a distributed environment. To date, contemporary state-of-the-art techniques have presented various efforts on the adaptability of blockchain and machine learning in IoT applications [88]. IoT and network applications security has been addressed using mechanisms based on blockchain technology. Furthermore, machine learning models based on the huge amount of data collected from sensing devices are used to predict and classify different problems. Machine learning techniques coupled with advanced artificial intelligence techniques detect patterns in data. For instance, IoT-enabled applications integrate blockchain technologies with machine learning models to benefit medical report management, drug traceability, tracking infectious diseases, etc.

4. Healthcare Applications

The emergence of IoT, machine learning, and blockchain technologies have greatly enhanced healthcare systems' functionality and services. This section aims to review the application of IoT, machine learning, and blockchain in smart healthcare based on the web of science indexed journals. We also find out the key issues and future research areas in applying machine learning and blockchain technologies in healthcare systems based on IoT [89].

4.1. IoT-Based Healthcare Applications

IoT is revolutionizing healthcare systems and is a powerful platform for healthcare applications [90–92]. For instance, IoT combines thermal cameras and embedded sensors in electronic devices that collect data from essential points. IoT devices collect real-time health statuses and other patient information and then share these data with healthcare personnel. Patient health monitoring systems have the capability of monitoring patients by using the latest technologies [93–100]. In addition, it allows the sharing of patient records with the healthcare teams for data analysis. A healthcare system was proposed based on e-Health sensors for hospital management to examine patient health status and send the analysis to healthcare personnel [101]. The researchers used electrocardiogram (ECG) sensors to analyze heart functions, regulate the patient's condition, body temperature measuring, and acceleration sensing [102,103].

Moreover, the scientists used environmental sensors to measure the patient's room environment. For instance, Moghadas et al. [104,105] introduced a health application for arrhythmia patients based on an ECG device to analyze the heartbeat and applied the k-nearest neighbor (KNN) algorithm to predict the types of arrhythmia disease. A mobile application named Alzimio is used to confirm secure area hotspots and activity detection for patients affected by autism, Alzheimer's, and dementia diseases. It also allows medical teams to select specific actions, and unsafe zones receive warning signals when any crucial actions are detected. GPS is also utilized in many IoT devices to track patients and alert healthcare teams when the patient walks outside a specific zone [106]. An IoT-based application was developed to measure a soldier's health status by using body temperature, pulse rate sensors, and an oxygen analyzer. The system can track the soldier's live location based on GPS [107,108]. Summary of various IoT-based healthcare applications is shown in Table 3.

Table 3. Summary of IoT-based healthcare applications.

Title	Description	Advantages	Disadvantages
Super-resolution of Retinal Images [109]	Using multi-kernel SVR for IoT healthcare applications.	Processing retinal images, generate good quality retinal images which help image analysis.	The IoT-based eye-care system required minimal human intervention.
SilverLink [110]	Smart home health monitoring for senior care	A home-based mobile health system for reporting user activity and health status and for approaching with family members. Uses object and human sensors for specifying a patient's health status.	Average range of the object and human sensors was determined to be approximately 7.3 m, so signal transmission stability required improvements.
MOD-SET [111]	Mobile diagnosis system with emergency telecare in Thailand	Combination of emergency telehealth and smartphone-based system in order to find the nearest health center in case of emergency.	The system tested with a limited number of patients presenting conditions.
Smart space-based Approach [112]	Assistance service system for emergencies in personalized mobile healthcare	An assistance service healthcare system in emergencies for remote and mobile patients.	The system has needed overwhelming human intervention.
Vital Signs Monitoring [113]	Salah activities recognition model based on smartphone.	Correct or reject distorted signals of vital signs based on the data fusion approach.	High energy consumption and static platform for handling emergent conditions.
InterIoT [114]	Active and assisted living healthcare services support.	Living mobile healthcare services in the aspect of faster detection and correction of critical situations.	The performance evaluation of the integrated platform is not yet presented.
Smartphone-centric Platform [115]	A remote health monitoring platform for detecting heart failure.	Communicate through traditional client-server systems, the hub of data shared by sensors and smart processors, and autonomous sensors of the patients' activity using a high-accuracy motion detection algorithm.	The current system is not capable of precisely computing the patients' pedestrian speed, and the integration between smartphones and other sensor nodes is applied to other physical devices.
H2U Healthcare System [116]	Intuitive IoT-based H2U healthcare system for elderly patients	A healthcare application to increase the healthcare quality services, and can provide early treatment and recognize deteriorating conditions relatively early to prevent the need for hospitalization.	Privacy and security are vital treats while the central patient database is shared on the Internet.
Smart Healthcare System for Isolated Areas [117]	IoT-based smart healthcare monitoring system for rural areas.	To overcome the health issues facing in rural/isolated areas.	Demands 24 $\times$ 7 connectivity where rural areas facing Internet issues such as slow, expensive, and spotty.
ECG Web Services [118]	Patient health monitoring in the Internet of Things.	To diagnose body temperature, heartbeat, and blood pressure using IoT-based sensors.	ECG reveals the heartbeat rate only during the few seconds it takes to store the tracing.
Patient Monitoring System [119]	An IoT-based patient monitoring system using Raspberry Pi	An effective monitoring patient's body temperature, heartbeat, respiration rate, and body movement using Raspberry Pi board at a reduced cost.	Shares all the health data of the particular patient to the web database. Anybody can easily access the web and can see the health information of patients.
ECG Monitoring System [120]	An IoT-cloud-based wearable ECG monitoring system for smart healthcare	High bandwidth rates for healthcare data transmission, and web-based GUI for versatile services.	No scheduling mechanism for handling emergent conditions of remote patients.
Tracking COVID-19 [121]	Anonymity preserving IoT-based COVID-19 and other infectious disease contact tracing model.	Send and receive alerts when people are close to a confirmed case.	The cost of scaling this solution is expensive, and the prototype smart contract did not apply security and other fine-grained solutions.
NFS [122]	NFC Based Public Healthcare Monitoring System	To provide secure and reliable solutions to a patient with long-term disorders.	The system is not accessible to everyone due to geographical barriers.

4.2. Machine Learning Based Healthcare Applications

Machine learning models have been used to detect patterns associated with diseases and health conditions. Usually, machine learning models are trained using historical datasets of healthcare records and other patient data. Recent advancements in machine learning technologies helped healthcare systems in developing countries to innovate sustainable solutions for chronic disease such has cancer diagnosis and treatment [123–125]. Machine learning algorithms are very effective in classifying complex patterns in data. Hence, machine learning algorithms are particularly used in medical applications, especially those medical application that depend on advanced proteomics and genomics analyses. Machine learning algorithms are fundamentally used in several disease detection and diagnosing problems. Machine learning models based on different algorithms are used in healthcare applications such as support vector machine (SVM), naïve Bayes (NB) classification, k-nearest neighbors (KNN), fuzzy logic, and classification and regression trees (CART) for different types of diseases [126,127].

Summary of research articles and reviews relevant to machine-learning-based healthcare applications are shown in Table 4.

Table 4. Summary of machine-learning-based healthcare applications.

Title	Accuracy	Relative Demerits
Heart diseases detection using naive Bayes algorithm [128]	86.41%	The system is developed based on data mining models for classifying the data patterns and detecting the heart diseases and considered as the best algorithm for many healthcare problems. The naive Bayes algorithm performs positively with categorical data but poorly with numerical data in the training set.
Diabetes diseases classification using SVM and CNN [129]	95.83%, 95.24%	Used transfer learning from CNN as the input features for classification using the SVM that reduces the executed time required by the classification process using CNN with fine-tuning. Only 2 out of 8 CNN architectures give 90+ accuracy due to the small dataset.
Thyroid disease diagnosis using SVM [130]	97.49%	Classify thyroid data using optimal feature selection and kernel-based classifier process. Takes high computation time.
Breast cancer diagnosis using four algorithms [131]	SVM = 99.10%	Assess the preciseness in classifying data concerning efficiency and effectiveness of each algorithm.
Breast cancer prediction using SVM and DT [132]	91%	An accurate prediction model for diagnosing breast cancer using data mining techniques.
Diabetes Type-2 diagnosis using six algorithms [133]	RF = 94.10%	Forecasts the risk pertaining to diabetes mellitus type 2.
Classification of breast cancer data using J48 [134]	95.00%	The researchers discovered a method using the J48 decision tree algorithm to automatically recognize if a tumor is malignant or benign. The classification is performed through the analysis of cell features extracted by the X-cyt program.
Breast cancer classification using decision tree [135]	J48 = 99%	Analyzed best model for breast cancer data using decision tree classification algorithms performance.
COVID-19 detection using SVM, random forest, and K-NN [136]	98.14, 96.29, 88.89%	Detecting COVID-19 patients by using machine learning algorithms and chest X-ray images to prevent the spread of this pandemic as soon as possible.
Swallowing detection using DT, SVM, and NN [137]	93.2, 86.2, 93.7%	Achieved high accuracy binary swallowing recognition from audio recordings using machine learning algorithms.
Kidney disease diagnosis using SVM [138]	93%	Diagnosis of kidney disease using machine learning algorithms based on laboratory tests, clinical history, and physical tests that are cheap, safe, and noninvasive.
Kidney disease diagnosis using CNN-SVM [139]	98.04%	The proposed sensing module can be used with the skills of deep learning for recognizing CKD dataset more efficiently than existing techniques.
Kidney disease diagnosis using six algorithms [140]	RF = 99.75%, LR + RF = 99.83%	Suitable regarding samples and imputation diagnosis. The generalization performance might be limited due to relatively small available data samples in model development. The model cannot identify the severity of CKD because there are only two groups of data samples in the dataset, such as CKD and NOTCKd.
Alzheimer's disease diagnosis using five algorithms [141]	NN = 98.36%	Identifies of Alzheimer's in its initial stage by applying machine learning algorithms. It will reduce the chances of creating further complications of Alzheimer disease patients.

Machine learning algorithms have been used to diagnose heart disease based on publicly available datasets from UCI machine learning repository. SVM and multi-layer perceptron have been used for heart disease prediction [142]. Multi-layer perceptron algorithm offers 90.57% accuracy, and SVM provides 92.45% accuracy for two-class problem. Likewise, the multi-layer perceptron algorithm achieves 68.86% accuracy, and SVM provides 59.01% accuracy for five class problems. Many machine learning algorithms are used to increase the accuracy of diabetes disease analysis based on datasets from UCI machine learning repository. Researchers proposed a machine learning technique for diagnosing diabetes by applying the NB algorithm and decision trees. The NB algorithm offers 79.56% accuracy, and the decision tree algorithms' accuracy is 76.95%. Machine learning algorithms such as SVM and decision trees were also applied to predict thyroid diseases by using dataset from UCI machine learning repository [143]. For instance, Begum et al. [144] proposed an advanced system based on data mining algorithms for diagnosing thyroid disorder.

4.3. Blockchain Based Applications in Healthcare

Blockchain has extensive healthcare applications and ledger technology aids the secure transmission of patient medical data, maintains the medicine supply chain [145]. A summary of different research papers and reviews related to blockchain-based healthcare applications is shown in Table 5.

Table 5. Summary of blockchain-based healthcare applications.

Topic	Description	Advantages	Disadvantages
Blockchain for COVID-19 [82,146]	Blockchain and AI Technology for COVID-19	Self-testing blockchain and artificial-intelligence-based system for COVID-19 outbreak.	Relevant stakeholders' involvement will be crucial to ensure the proposed system's efficient implementation and viable development.
Tracing agri-food using BC [147]	Walmart's pork and mango pilots with IBM	Deployed blockchain solutions throughout the global food ecosystem to increase safety and reduce waste.	Recreation of the supply chain is not present in IBM's blockchain solution.
Smart Provenance [148]	A distributed blockchain-based data provenance system	Provides reliable data source collection, verification, and management.	Not completely secure.
Electronic healthcare using blockchain [149]	Blockchain-based electronic healthcare record system for healthcare 4.0 applications.	Utilizing ACP algorithms to improve data sharing between healthcare providers.	Lower TPS on large block size and Higher TPS on small block size reduced performance of the system.
BAKMP-IoMT [43]	Design of blockchain-enabled authenticated key management protocol for internet of medical things deployment	Provides secure management among health devices and local servers and cloud servers.	Entire health data stores in cloud servers (Data backup).
MBPA [150]	A MediBchain-based privacy-preserving mutual authentication	A privacy-preserving joint verification system for mobile medical cloud architecture.	MediBchain-based authentication threats.
MedChain [151]	Blockchain-based system for medical records access and permissions management	Time-based smart contracts are used to handle transactions and access to health data.	High cost.
BIoMT [152]	Blockchain for IoMT	A light Blockchain-based model focusing to secure the Internet of Medical Things (IoMT).	Interoperability.
Blockchain distributed ledger [153]	Blockchain distributed ledger technologies for biomedical and health care applications.	Introducing blockchain platforms to the health care and biomedical domains.	Consumes too much energy, no fault-tolerance.

Table 5. *Cont.*

Topic	Description	Advantages	Disadvantages
Blockchain for Healthcare [154]	Blockchain technology for healthcare: facilitating the transition to patient-driven interoperability.	Expedites data liquidity, aggregation, immutability, access rules, and identity.	Privacy and security considerations, scalability.
EMR data sharing using blockchain [155]	Secure and trustable EMR sharing using blockchain	Blockchain-based medical data management and sharing for cancer patient care.	The structure of patient data and their metadata are insufficient.
Tamper-resistant mobile health [156]	Tamper-resistant mobile health using blockchain technology	Introduces blockchain-based system, which allows trusted and auditable computing.	Poorly maintained and outdated codes provide vulnerability, and the theoretical limitation of the consensus model has flaws.
Secure sharing of health images [157]	Secure and decentralized sharing of medical imaging data via blockchain consensus	Removes third-party access to safeguard medical data.	Patient-specific issues, the ability to share data does not alone ensure its usability.
Governing drug supply chain [158]	Governance on the drug supply chain via gcoin blockchain.	Creating transparent transactions of drug data using Gcoin blockchain to prevent counterfeit drugs, to protect public health.	Not a cost-benefit, less consultant to key stakeholders.
Healthcare blockchain for secure RPM [159]	Healthcare blockchain system using smart contracts	Support real-time patient monitoring and health status.	Key management issue, not be used for emergency response, as the delay might increase response time.
OmniPHR [160]	A distributed architecture model to integrate personal health records.	Combining PHRs for patients and medical teams using a distributed model.	Possibility of occurring duplicate data entry, not fully secured, patient's data that are not in the model's scope will not be part of the sharing.

This system is based on a public blockchain that guarantees confidentiality and validity. The single point failure system is handled in the proposed system. A pioneer research work in EMR management applications is presented, which addresses the issue of scalability and data encryption [161]. Nevertheless, the proposed system still faces some shortcomings. Liang et al. [162] presented a mobile application to collect patient data and to share between medical teams, insurance companies, and patients. A private blockchain was used as a solution for privacy and access control. The efficiency and scalability problems of data processing were also addressed in the proposed system [162].

Many research papers have been proposed to monitor and trace health and medical products data. For instance systems were proposed to combine drug supply chains with blockchain throughout transportation. For example, Bocek et al. [163] implemented an Ethereum blockchain-based system for storing data of drug supply chain and provide publicly available data with immutability considerations. Thermal sensitive devices are introduced in this system to share temperature data throughout the transportation of medical commodities. A rule is defined in a smart contract for exact temperature requirements, and to confirm the submission of temperature data for every new consignment. Huang et al. [164] suggested a drug ledger system based on blockchain configured for medical product traceability and regulation.

Figure 8 presents conceptual reference layer architecture for leveraging the abovementioned technologies for healthcare applications development based on IoT, machine learning, and blockchain.

The reference layered architecture consists of several layers. The device layer consists of medical sensing and actuating devices. The virtualization layer virtualizes all devices connected to the IoT platform into virtual objects. Data owners' layers present the data generated by patients and electronic health record systems from the IoT platform. The data provider layer provides data to local blockchain and data storage systems and other data providers. Local blockchains and a central federated blockchain network allow the interconnecting of healthcare institutions and IoT orchestrating platforms. The reference layered architecture is designed to support healthcare stakeholders such as the data broker, computing, machine learning, and service provider. The data provider layer aims to share data faster, securely, and without losing essential, trusted properties such as accountability, traceability, and data privacy.

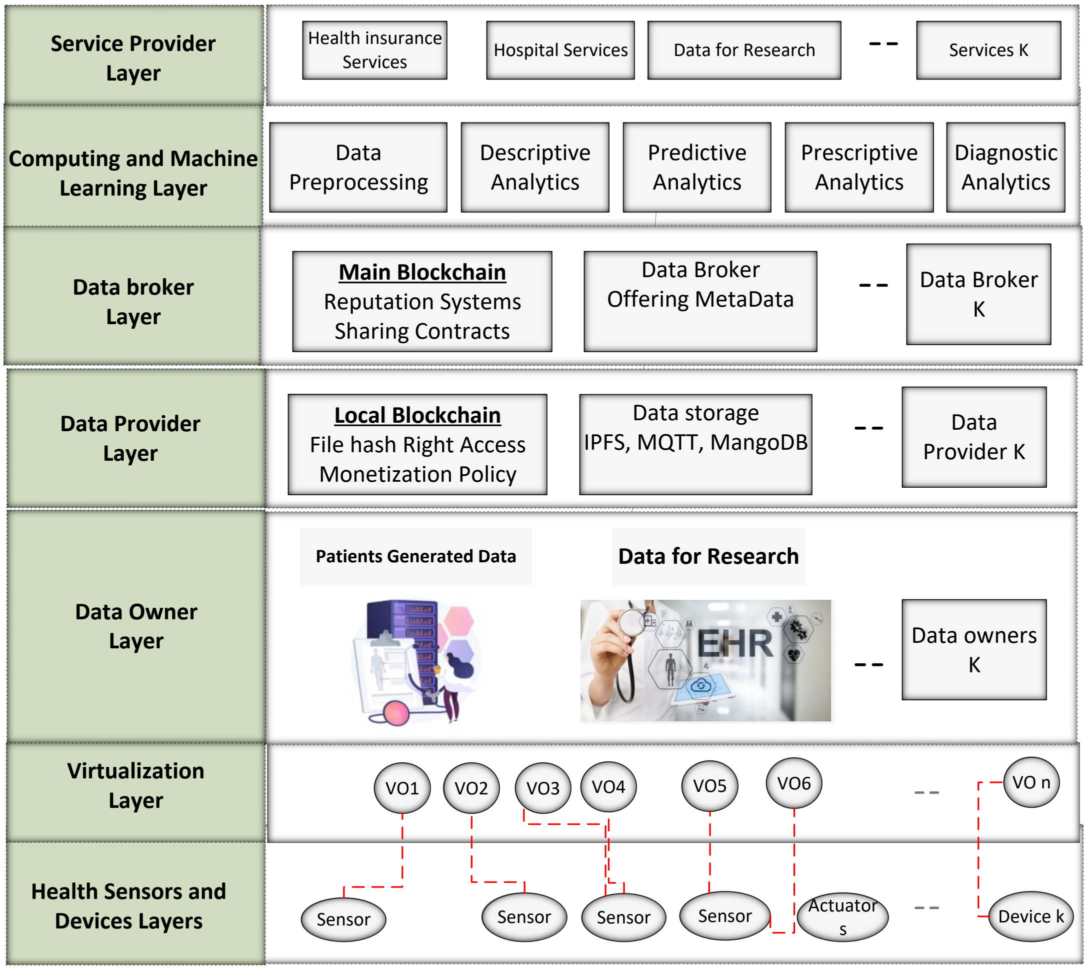

Figure 8. Conceptual layered architecture of IoT, blockchain, and machine learning for healthcare applications.

5. Leveraging Technologies for COVID-19 and Future Pandemics

Machine learning algorithms could be widely used to detect and notify deteriorating conditions in IoT and blockchain-based clinical and public health applications. These intelligent service management mechanisms can provide decision-making to manage the impacts of chronic diseases and pandemics effectively. This section aims to identify the case study of the COVID19 pandemic involving machine learning, IoT, and blockchain for pandemic readiness and response from the literature. World health organization (WHO) and centers for disease control and prevention (CDC) stated that digital technologies could play an essential role in enhancing health policy regarding COVID-19 disease [165]. Blockchain, machine learning, and IoT are the leading technologies to establish solutions for the different diseases [166,167]. The integration of artificial intelligence and IoT brings a new range of possibilities, even though AIoT is a new idea. The UAVs equipped with IoT sensors can collect raw data to make smart decisions without any human involvement. The scientific community considers thermal cameras as the best tools for data collection.

Nowadays, more systematic methods are needed to detect COVID-19 patients. In addition, healthcare organizations in developing countries face problems during testing COVID-19 patients due to a lack of testing kits. Another problem is privacy concerns in data sharing across different healthcare organizations. Solution based on CT images was proposed for detecting COVID-19 patients [168]. Firstly, they proposed a data normalization method that acts towards data heterogeneity as the data are collected from many healthcare organizations with various CT devices. A capsule network-based classification and segmentation mechanism is used for diagnosing COVID-19 patients. The proposed mechanism can train a general model using blockchain with a federated leaning to maintain the organization's privacy. In addition, the developed solution utilizes recent data for enhancing CT images diagnosis and detection accuracy. Remarkable applications of emerging technologies used to defeat COVID-19 are discussed in the upcoming subsection [169–171].

5.1. COVID-19

In December 2019, a pandemic epidemiologically associated with the Seafood Wholesale Market was reported in Wuhan, China. On the 12 March 2020, the World Health Organization declared a coronavirus disease (COVID-19) pandemic due to its rapid escalation. Since then, the world has experienced a significant increase in deaths and economic turmoil. Moreover, the pandemic has now reached more than 200 countries around the globe. Because of giant positive single-stranded RNA viruses, coronaviruses affect humans as well as animals. "Tyrell" and "Bynoe" discovered coronaviruses in 1966 by refining viruses from regular cold patients. There are four subgroups of coronavirus, namely, ALPHA, BETA, GAMMA, and DELTA. Mammals, specifically bats, cause ALPHA and BETA viruses, whereas birds and pigs cause GAMMA and DELTA. The BETA virus can lead to significant infection or possibly death, whereas the ALPHA virus causes symptom-less diseases. SARS-COV-2 is from the B lineage of the BETA version of coronavirus and is nearly associated with the SARS-COV virus [172]. In Wuhan, SARS-COV-2 seemingly resulted from a transmission from animals to humans. The early medical reports of the SARS-CoV-2 related to COVID-19 was pneumonia. Furthermore, current clinical signs also indicate gastrointestinal and symptom-less infections, mostly among young kids. The number of affected peoples who remain asymptomatic during the period of the disease is still to be measured. The manifestations of the pandemic in symptomatic patients typically start within a week, including fever, nasal congestion, cough, fatigue, and other symptoms of breath contamination. Pneumonia commonly arises between the second and third week of an asymptomatic virus. Unusual symptoms of virus-related pneumonia include showing changes through chest X-rays, reduced oxygen saturation, blood gas divergence, and other approaches [173]. Different diseases caused by coronavirus are mentioned in Table 6.

Table 6. Human diseases caused by the coronavirus.

S.No	Disease	Virus
1	Common Cold	HCoV-229E [174–176]
2	Common Cold	HCoV-HKU1 [177–179]
3	Common Cold	HCoV-NL63 [180–182]
4	Common Cold	HCoV-OC43 [183–185]
5	MERS	MERS-CoV [186,187]
6	SARS	SARS-CoV-1 [187–190]
7	COVID-19	SARS-CoV-2 [172,187,191–194]

The spreading ratio of both SARS and MERS is less than COVID-19 [195]. Anyhow, the number of cases in COVID-19 has outnumbered the number of cases in both MERS and SARS.

5.2. IoT-Based Technologies to Mitigate COVID-19 Challenges

IoT is leading research and analysis platforms in various academic and industrial areas, especially in health. The accelerated development in IoT technologies can remodel current healthcare systems by integrating social, economic, and technological views. For example, the COVID-19 pandemic has affected the world's economy since December 2019. The combination of artificial intelligence, blockchain, and IoT technology can help combat the COVID-19 pandemic. An application healthcare application based on IoT and artificial intelligence for diagnosing COVID-19 patients and detecting it at early stages was introduced [196]. The system's goal is to minimize direct interaction with COVID-19 patients with the help of several smart sensors such as blood sensors, pulse sensors, and thermal monitoring. The researchers introduced a COVID-19 detection and tracking application that collects real-time data from wearable sensors and mobile apps and then applied machine learning algorithms to analyze, classify, and predict the collected datasets. Moreover, an IoT-based framework utilizing smartwatches, infrared thermometers, optical and IP cameras is proposed to minimize the COVID-19 outbreak [197]. The sensors are operating automatically without any human involvement. The application operates in the following phases. In the first step, the application measures the patient's temperature using thermal sensors. Then, the pulse sensor measures the heartbeat if the patient has a specific temperature. Next, the blood sensor measures platelets and blood cell levels. Finally, if the patient has tested positive, they must be isolated for further tests and quarantine protocols.

5.2.1. Tracking COVID-19 Using Smart Thermometers

In 2012, a health company in the USA named Kinsa presented a smart thermometer to diagnose high fever patients. Smart thermometers were initially proposed to diagnose the common cold. Nonetheless, it is used to track COVID-19 patients effectively. Kinsa Health has arranged approximately a million smart thermometers for families in different states of the US during the COVID-19 pandemic. These smart thermometers are connected with a mobile application to monitor health status. Kinsa health company then combines the collected data to illustrate daily-based graphs of the US states that observe a high-temperature rise. Thus, allowing health organizations in the US to detect possible flashpoints. These charts have been proven to be more accurate in detecting the spread of fever throughout the US in recent times. In addition, Kinsa's smart thermometer is more reliable than CDC's official app concerning the performance of prediction [198].

5.2.2. Battery-Operated Buttons

Many health sectors in Canada have deployed IoT buttons known as Wanda Quick Touch to reduce the number of hospital-acquired infections (HAIs). Given below are the features that IoT buttons were designed for:

- Fast in any service,
- Regardless of their size,
- To send quick alerts to the management team,
- Notifying any health problem that can generate a risk to citizens' protection.

An excellent functionality of IoT buttons is their independence on exterior structure, for example, their capability to stick to some specified aspect [199].

5.2.3. Drone Technologies

Drones may be used to track those peoples who came in contact with the virus-infected person [200]. Drones can support tracking infected people who are leaving quarantine early as well as enforce individuals to wear masks. Recently, drones were used in Europe and the USA to confirm that social distancing and lockdown laws were strictly followed or not [201]. Camera-fitted drones were deployed to issue guidelines and cautions to persons for violating rules of COVID-19-related lockdowns and procedures [201,202]. Moreover, drones were deployed in remote inspecting of infected residents and extremely contaminated regions. Drones have been used to provide the necessary equipment to medical teams as well as collect and share tracks for verification during nearby services.

5.2.4. Telehealth in a Pandemic

The usage of the Internet of Medical Things (IoMT) mechanism to provide remote patient monitoring (RPM) is called telehealth, also known as telemedicine. It allows healthcare providers to predict, identify, and medicate patients without requiring any physical contact [203,204]. Several telehealth technologies and IoMT platforms are facing challenges due to rapid overload on servers. An e-commerce technology for healthcare problems named JD Health has reported a significant increment in requests for the online meeting due to the rapid spread of COVID-19 [205]. Table 7 shows telehealth mechanisms are being implemented in many countries to control the influence of COVID-19. Two key benefits of implementing telemedicine approaches are minimizing the load on the overworked medical personnel. It reduces the risk of the transformation of disease from patient to hospital staff.

Table 7. Telemedicine platforms implemented to control the impact of COVID-19.

Country	Organization	References
United States of America	George Washington University Hospital (GWUH)	[206]
United States of America	Rush University Medical Center	[207]
India	The state governments of Andhra Pradesh and Assam	[208,209]
Israel	Sheba Medical Center	[210,211]

5.3. Machine Learning Technologies to Mitigate COVID-19 Challenges

Machine learning stands to be the most suitable technology to defeat COVID-19 disease efficiently [212]. Machine learning has been verified to be an innovative technological development. The scientific community presents remarkable research on machine learning that can support healthcare organizations to efficiently contend the COVID-19 disease [213–217].

5.3.1. Face Recognition System

Thermal imaging with face detection is used in the first step of the proposed work [21]. The suspected patient is required to be tested to confirm the indefinite disease. According to researchers, the face recognition system identifies a person and is labeled with a name in four steps. Localization of a person's face in an image is the first step in the pipeline using a method called histogram of oriented gradients (HOG) to encode an image and to generate a smaller size of the original image [218]. The proposed mechanism locates the area of an image that resembles a generic HOG encoding of a person's face with the help of a reduced version of the image. Secondly, the person's face may not always be straight, and it could be rotated in different positions. There can be some issues, such as brightness, which is solved using a model proposed in literature called named Dlib invigorated with ResNet [219]. The third step refers to object detection using YOLO to increase accuracy because it is challenging to select unique features from a person's face that can be used to differentiate them from other persons. Lastly, machine learning algorithms have been used to find the person's name from the encoded data.

5.3.2. Temperature Identification System

This section discusses a body temperature measuring system using an onboard-thermal-camera-equipped UAV. The average human body temperature is 37 °C, more than 38 °C is considered a high temperature; however, throughout the day, the average temperature differs from person to person. If a person's body temperature is unusual, they will be referred for doctor consultation. The temperature identification system consists of two parts: users and the UAVs. In the first part, the system obtains personal information and 6–9 photographs as input from the users. Then, the system converts these images to 128×1 vectors rather than sending the full image to protect the user's privacy. UAV responsibilities include extraction of all faces with their coordinates and verifying and comparing human faces coordinates captured from normal and thermal cameras. If the body temperature is higher than 37 °C, then it takes that person's face and converts it to a 128-dimensional vector and sends it to the central server. The system compares the selected face with the existing database using machine learning algorithms, finds matches, and sends a notification to the suspected person to consult a doctor soon [21].

5.3.3. Voice-Based Detection

Voice detection technology is one of the most convenient systems as it may be introduced to recognize potential COVID-19 patients. A voice detection system is used to measure and to choose who is required to be tested throughout these challenging times since there is a lack of testing kits. Mobile application has been introduced based on machine learning algorithms by university students from the DY Patil Institute, Mumbai, India, to detect COVID-19 patients [220]. In the first stage, one has to speak into their mobile; the values of these parameters are then compared with a normal person's voice to confirm if the candidate is infected with COVID-19 or not [221]. It is difficult to measure the performance accuracy of machine learning models to aid the screening of COVID-19 patients rather than detecting them all at once. Research work is required to use machine learning algorithms to appropriately diagnose all possible symptoms of COVID-19.

5.3.4. Face Mask Detection

Detecting the face of a person wearing a mask is a very challenging task. The heat discharged from the human body is affected by wearing masks, and many heat sensors are based on the forehead, which is usually visible. An algorithm for differentiating faces with and without masks was presented. The detection of the face with the mask is made using the YOLOv3 model, detecting persons. The model is advanced enough to recognize face-mask mode. The system collects accurate stats such as the number and percentage of persons wearing masks [21].

5.4. Blockchain Technologies to Mitigate COVID-19 Challenges

Nowadays, our globe is challenged with the rapid increase in novel coronavirus disease and has created massive suffering. As of 28th June 2021, it had infected more than 180 million people, and almost 4 million individuals died [222]. After its early discovery in Wuhan, China, the novel virus has been spread to 220 countries and territories. The European parliamentary research service recognized blockchain as the various important technology to mitigate COVID-19 challenges [223]. Potential blockchain solutions for the COVID-19 pandemic include medical supply chain management, contact-tracing purposes, and sharing of patient data across heterogeneous systems [224].

Several worldwide techs and research organizations developed applications and platforms based on blockchain to tackle the COVID-19 pandemic, such as securing and sharing COVID-19 data. For example, WHO launched a project named MiPasa based on hyperledger fabric for supporting the collection of COVID-19 associated data. MiPasa provides sharing of data with researchers, public health officials, scientists, and health professionals. It also helps to introduce feasible methods to support pandemic management and manage epidemics [225]. Moreover, Azbeg et al. [226] presented a precise solution for COVID-19 to develop digital passports and track transmission. Blockchain technology has been used to verify the records of COVID-19 testing and tracking transmission. Further, it offers a health application that facilitates the interaction of patients with professionals to recognize symptoms of COVID-19. Doctors can also use the application to keep track of the health status of the patients.

5.4.1. Sharing Patient Data

Nowadays, healthcare sectors digitally store COVID-19 patient data, including doctor prescriptions, diagnostic reports, and personal information. For example, COVID-19 patient data are stored in a centralized database; however, maintaining the privacy of patient information is one of the main issues in such centralized databases, such as unauthorized access to patients' sensitive data [227]; therefore, consortium blockchain and interplanetary file system (IPFS) proposed distributed storage framework for sharing COVID-19 patient's data [228]. Furthermore, the proposed framework makes things easier for authorized users such as healthcare operators. A blockchain-based solution for handling and storing vaccination data and proof of immunity for persons was proposed [229]. The method offers a secure and well-organized way to maintain vaccination records. The solution is based on Ethereum and relies on the idea of smart contracts in blockchain [230].

5.4.2. Social Distancing

Social distancing, i.e., avoiding gatherings and keeping social distances, is the understood guideline for prevention from the COVID-19 pandemic. Blockchain-enabled IoMT presents adequate isolation and quarantine solution to monitor social distancing during the growth of the global pandemic [231]. Individuals with wristwatch sensors will be automatically notified when leaving certain defined regions. Moreover, the combination of IoT-based technologies with blockchain maintain and assures data traceability. Tech giants such as Google and Apple provide APIs for software programmers to trace social distancing using their wearable products [232].

5.4.3. Smart Hospital

Many hospitals cannot treat other diseases since most of the clinicians are summoned to handle COVID-19 patients. In addition, there is significant pressure on health systems due to the rapid increase in coronavirus patients. Blockchain-enabled IoMT can assuredly handle pandemic situations [231]. Initially, RFID tags and IoMT devices are used to support tracking and controlling the status of health resources such as ambulances, availability of beds in the hospital, and flaws or failures in healthcare devices such as respirators. Furthermore, blockchain-enabled IoMT is used in hospital buildings to facilitate real-time monitoring of temperature and air quality. Blockchain-enabled IoMT also manages actives devices other than passive components such as tags and sensors. For example, robots are active devices responsible for disinfecting health centers, sanitizing hospital wards and public areas. In the literature, blockchain envisioned software embedded multi-swarming UAVs was proposed to minimize human intervention and to handle the COVID-19 situation. These multi-swarming UAVs have key advantages of reliability, high bandwidth, and very-low latency [233].

5.4.4. Tracing Epidemic Origin

Tracing the origin of the COVID-19 pandemic is a challenging and important task for future pandemic preparedness and response. The broad adoption of heat sensors and thermal cameras in many public areas such as educational institutes, hospitals, cafes, airports, and malls can notify deteriorating situations quickly. Different transportation hubs, thermal cameras have been used in public places such as airports and railway stations [234]. The thermal cameras have been implemented to detect people with infection of COVID-19 and other symptomatic diseases. The heat sensors and thermal cameras have been connected with blockchain-enabled IoMT for securing data privacy and ensuring data traceability. Moreover, with the rapid increase in DNA, RNA, and other coronavirus tests, these systems can accelerate the detection of infected people. The connectivity of blockchain-enabled IoMT systems can provide extensive data for many healthcare organizations for AI and machine learning based analysis and tracing the epidemic's origin [231].

6. Convergence Challenges and Solutions

Although machine learning, IoT, and blockchain are very different technologies and different from each other. In literature, many studies present solutions based on their combinations as a remarkable paradigm shift. Blockchain, machine learning provides solutions to the gaps and vulnerabilities of IoT systems [235]. The security concerns are efficiently solved using intelligent IoT where every IoT device is interconnected using the public trustless environment. Moreover, the distributed peer-to-peer nature of blockchain has been used to address the deficiencies of the IoT client–server paradigm. The distributed architecture of blockchain happens to be an essential technology to solve the traditional single-point failure in IoT. A single point of failure in an IoT system may break the whole system, which is detrimental to achieving high reliability and availability in any system [236]; therefore, the peer-to-peer architecture in blockchain technology is a feasible solution to handle the bottleneck and the point of failure in an IoT system [237,238]. Additionally, peer-to-peer networks process and store the IoT data securely and efficiently [239]. Machine learning applications in blockchain include smart home gateway [240,241], transactional data systems in edge computing applications [242,243], tracing supply chains [244], and wireless body area network applications [242,245]. Although the convergence of IoT, machine learning, and blockchain can tackle significant weaknesses of IoT solutions, the adoption is still in its infancy, suffering from various challenges; solutions are needed to address these significant challenges. In addition, there is no consent and consensus mechanism for reference paradigm or model specification on the adaptation of blockchain in IoT. This section presents the fundamentals challenges, advancements, and possible solutions to leveraging the convergence of blockchain, machine learning, and IoT.

6.1. Adaptation Challenges

The performance of machine learning models relies on the availability and quality of data, information sharing and privacy regulations, and conditions reliant on system infrastructure and interoperability. Usually, even the most essential health framework is required to share data between medical institutes. For example, according to a survey in 2018, 41% of medical institutions in the United States were unable to digitally share observed data to health care firms [246]. Furthermore, the lack of publicly available diverse and comprehensive datasets is a significant need for future research. In situations where training data technically removes parts of the population data, the relevance of the model to larger populations could be discredited. The inconsistent and incomplete labeling of ethnic, demographic, and other racial information may also affect data quality [247–249]. Machine learning algorithms may unexpectedly increase inconsistency by exaggerating the trial of pandemics and improperly notifying resource allocation based upon insufficient or incomplete data instances. Machine learning models also deal with issues at the deployment level. Healthcare technologies and providers must be careful when using algorithms in different settings. Models trained in a particular socio-economic or cultural context system may not offer similar outcomes for populations with different data features. These models must be experienced with analytical estimation when deployed between different conditions and settings that require time, cost, and human resources. The importance of machine learning applications can also limit the approval, adoption, development of these models in a real-world situation. Usually, there is a compromise between the interpretability and complexity of the models being examined essentially in health care organizations, given adequate and ethical implications of determination. A few surveys studies were identified by comparing machine learning with traditional techniques. For example, more simplistic algorithms showed similar or improved estimation while providing the alternative advantage of interpretability; however, highly complicated algorithms are significantly important for several problems, e.g., for tasks such as image classification.

Blockchain technology initially used in cryptocurrencies has been used with IoT for securing systems and IoT applications. Blockchain is a combination of traditional and distributed databases in which data are publicly available for users in the form of an encrypted and unchangeable ledger [250]. Unfortunately, the current IoT framework produces massive data that may prevent the network from service quality disruption. Furthermore, the quality-of-service (QoS) is associated with non-functional attributes such as reliability, security, and cost [251]. Some significant challenges of adopting blockchain in IoT are illustrated in the given Figure 9. Privacy is among the significant challenges in blockchain technology since each block is associated with and can access data of another block, so anyone who wants to look on the blockchain can see whole transactions. Traditional IoT data management is at risk as the collected data are cautious and access unauthorized users such as malicious insiders and external hackers—this is why it is challenging to utilize corrupt data. IoT devices must be connected to a high-quality networking resource and computing storage to share IoT data with different stack holders; however, an IoT network has a smaller number of abilities to connect with blockchain to facilitate innovative business opportunities to advance new applications and services in many areas. Blockchain technology needs more power and memory capacity, while IoT devices are developed with less resources, such as less capacity of storage and data-processing [252]. The need for resources for mining blocks on the peer-to-peer blockchain exceeds the abilities of resource-limited IoT devices.

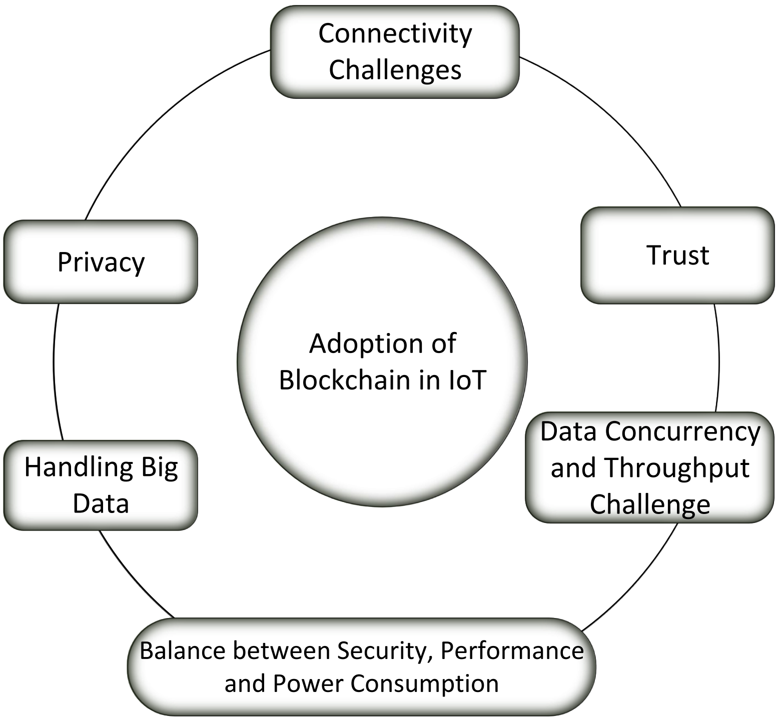

Figure 9. Challenges of adoption of blockchain in IoT.

Furthermore, IoT devices simultaneously generate an immense amount of data, which creates high concurrency. Since the blockchain throughput is restricted due to its security and concurrency processes, quick contemporization of new blocks between nodes requires a high bandwidth speed, hence increasing the blockchain throughput. Despite this, each block contains a replica of the whole distributed ledger. Thus, the distributed storage structure resolves bottleneck issues, enhances efficiency, and eliminates the need for the third party's trust protocols [253]; however, the data management of an IoT system puts overload on the user's private device storage [254]. So, the data storage requirement is a considerable challenge while handling the big data of IoT networks.

6.2. Solution of Adaptation Challenges

Many blockchain features are convenient for diverse IoT applications, such as anonymity, decentralization, immutability, and automation; however, these features integrate several new regulative issues [255]. The immutability feature permanently retains data in distributed ledger technology on the peer-to-peer network and cannot be erased or changed. The data cannot be filtered to maintain privacy before putting them on the blockchain due to a lack of governance. It is not easy to differentiate between groups to perform transactions for unauthorized services because of the anonymity of distributed ledger technology. Actions ensuing from self-executing contracts between two parties, such as smart contracts on distributed ledger technology, can violate the law. The automation feature of the blockchain introduces many advantages to IoT systems. Table 8 shows prospective solutions to the convergence challenges.

Table 8. Convergence challenges and solutions.

Challenges	Possible Solutions
Privacy	Ring signatures blockchain is an encrypted technology commonly used to handle privacy issues [256]. Additionally, blockchain-based smart parking with fairness, reliability, and privacy protection (BSFP) [257] system has been proposed to overcome privacy concerns. The blockchain-based method exerts group signatures, vector-based encryption, and bloom filters to protect user's privacy.
Trust	This paper [254] presents a blockchain-based decentralized trust management scheme called BlockBDM to handle the trust and security issues of IoT big data management. Data processing can be stored in cryptography-signed and tree-based transactions and blocks with top-quality public and distributed ledger security.
Connectivity challenges	For resolving the connectivity issues of an IoT with blockchain, multi-access edge computing (MEC) [258] can host side-chain. The side-chain allows IoT devices to connect with the main chain. IoT devices are connected with low bandwidth on the edge network. Side-chain is a type of blockchain technology that presents a distributed peer-to-peer architecture to maintain data while sharing critical information between various systems.
Balance between security, performance, and power consumption	These studies [259,260] proposed a patient-centric agent network to balance between security, performance, and power consumption which operates on the cloud and edge server and can manage blockchain actions concerning the IoT devices. Another patient-centric agent platform in [260] runs a concurrent tool and handles various blockchains for IoT data.
Data concurrency and throughput challenge	To tackle data concurrency and throughput challenge, researchers presented a method called sharding [261] in which the peer-to-peer network of blockchain is divided into various groups. The authentication and processing of transactions are generated in the sharding. Members of that sharding handle the transactions. Sharding can reduce bandwidth by preventing the propagation of transactions over the whole system.
Handling big data	Many researchers presented off-chain techniques to overcome big data issues in an IoT system by integrating blockchain storage with standard cloud storage. The alternative method is used to handling big data challenges is splitting IoT-generated data over different storage's including many on-chain of blockchain-based on the characteristics, local computers, and cloud service providers [262].

Current IoT practices are becoming obsolete with the novel approaches and technologies based on blockchain. These requirements need to be updated according to the latest requirements of distributed ledger technology (DTL). Alternatively, directed acyclic graph (DAG)-based architecture facilitates more advantages than traditional blockchain. Andrew et al. [263] presents a DAG-based distributed ledger based on the Markov chain model to tackle the parasite chain attack. Parasite chain attack aims to obstruct the immutability and irreversibility of the ledger.

6.3. Future Pandemics Preparedness

The following section contains a summary of the lessons learned for future pandemic preparedness: Several studies were deeply analyzed from the healthcare domain based on IoT, machine learning, and blockchain applications. For future pandemic preparedness, diseases, and global outbreak such as SARS can provide research preparation for techniques that might have allowed advanced governance of the coronavirus outbreak. The coronavirus pandemic's underlying phase investigated machine learning, IoT, and blockchain. Approximately, all this work was at the development and research level, and real-world applications were less common. Developing publicly available immense databases based on clinical information at the domestic or global level would be significantly helpful for researchers. AI-based tools should be developed to enable designing multiple synopses to make better decisions about various options that must be considered, such as the distribution of expensive rare devices and types of equipment such as ventilators, elderly patient monitoring, school, and university education, to name a few.

6.4. Limitations of the Study

This comprehensive survey article has many limitations. Most of the research analyzed in this study are applications of IoT and blockchain, machine learning and IoT, and blockchain and machine learning, while unified studies are lacking. Despite the limitations of the existing convergence solutions for IoT, machine learning, and blockchain, several studies have been revealed for future research. This study's main objective was to summarize the critical use cases of IoT, blockchain, and machine learning instead of comprehensively evaluating particular datasets or machine learning algorithms. Our future study will be based on the unified architecture of IoT, machine learning, and blockchain to evaluate convergence inclination and value in experimental conditions. The survey consists of reviews, articles, conference papers to quickly review publications about the coronavirus disease and other future pandemics. The research article survey contained legitimate commercial and business research to discover uses of particular IoT, machine learning, and blockchain applications by governments or organizations to handle coronavirus. Despite the lack of publicly available research resources, this study can be considered a feasible starting point for researchers and commercial firms to understand the background and promising future directions for future pandemics preparation.

7. Conclusions

Advancements in IoT communication infrastructure and physical devices have brought immense revolutions in remote health monitoring systems. Machine learning techniques coupled with advanced artificial intelligence techniques detect patterns associated with diseases and health conditions. In this decade, IoT-enabled health monitoring applications have been developed using the integration of blockchain technology with machine learning models to benefit medical report management, drug traceability, and track infectious diseases. To date, contemporary state-of-the-art techniques for the adaptability of blockchain and machine learning in IoT applications are presented. This study presents a comprehensive survey of emerging IoT technologies, machine learning, and blockchain for healthcare applications. The reviewed articles comprise a plethora of research articles published in the web of science in the domain of machine learning, blockchain, and IoT. Firstly, a detailed analysis of healthcare applications of IoT, blockchain, and machine learning demonstrates the importance of the discussed fields. Secondly, the adaptation mechanism of machine learning and blockchain in IoT for healthcare applications are discussed to delineate the scope of the mentioned techniques in IoT domains. Thirdly, leveraging machine learning, blockchain for IoT is discussed from the perspective of pandemic preparation and mitigation. Finally, we discuss challenges in the adaptation of these emerging technologies for IoT-based health care applications. Moreover, a comprehensive summary of several challenges in adapting blockchain in IoT technologies is discussed. The presented future directions in this domain can significantly help the scholarly community to determine research gaps to address.

Author Contributions: I. conceived the idea for this paper, designed the methodology, and assisted in write-up of the paper. M.I. and U.Z. Write the original article and assisted in the experimental design and paper write-up. J.I., J.G. and M.F. assisted in review and editing. J.G. supervised and proofread this study of Topical Assessment for Pandemic Preparedness, Challenges, and Solutions. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Acknowledgments: This work was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (Grant No. NRF-2020R1I1A3074141), the Brain Research Program through the NRF funded by the Ministry of Science, ICT and Future Planning (Grant No. NRF-2019M3C7A1020406), and "Regional Innovation Strategy (RIS)" through the NRF funded by the Ministry of Education.

Conflicts of Interest: The authors declare no conflict of interest.

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