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Review

A Systematic Survey on Fog and IoT Driven Healthcare: Open Challenges and Research Issues

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Abstract: Technological advancements have made it possible to monitor, diagnose, and treat patients remotely. The vital signs of patients can now be collected with the help of Internet of Things (IoT)-based wearable sensor devices and then uploaded on to a fog server for processing and access by physicians for recommending prescriptions and treating patients through the Internet of Medical Things (IoMT) devices. This research presents the outcome of a survey conducted on healthcare integrated with fog computing and IoT to help researchers understand the techniques, technologies and performance parameters. A comparison of existing research focusing on technologies, procedures, and findings has been presented to investigate several aspects of fog computing in healthcare IoT-based systems, such as increased temporal complexity, storage capacity, scalability, bandwidth, and latency. Additionally, strategies, tools, and sensors used in various diseases such as heart disease, chronic disease, chikungunya viral infection, blood pressure, body temperature, pulse rate, diabetes, and type 2 diabetes have been compared.

Keywords: Internet of Things; fog computing; healthcare; health monitoring; sensors

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1. Introduction

In the last two decades, electronic gadgets have revolutionised the world and have become an integral part of human life. Artificial intelligence and machine learning have made these electronic devices smart. Some of these smart devices are being used for health monitoring, diagnosis, and even treatment. For instance, now, a device can detect diabetes through an image of a patient's iris [1]. The medical devices can be connected to healthcare information technology systems using networking technologies to make medical data quickly available to healthcare practitioners. The interconnection of medical devices, popularly known as the IoMT, is an amalgamation of medical devices and applications that lessens hospital visits and allows practitioners to observe patients remotely [2,3]. The proliferation of IoMT can be judged by increases in the sale of IoT-enabled medical devices. It is estimated that the world's smart health market will expand at an average growth rate of 16.2% between 2020 and 2027 [4]. The reasons behind the proliferation of IoMT are high accuracy, low cost, and low delay in delivering healthcare services. The recent advancements in IoMT have made preliminary diagnostics possible at the patient's home. For instance, blood tests and diabetic and blood pressure monitoring at the patient's doorstep in real-time are viable. Due to this, healthcare is shifting from the hospital to a home-centric service [5,6]. Further, the developments in telecommunication services, body sensor networks, fog, and cloud computing have made monitoring and detection, medical consultations, and prescribing treatment possible at the doorstep [7,8]. The number of people globally requiring regular monitoring due to chronic diseases such as cancer, asthma, cardiovascular disease, arthritis, dementia, Alzheimer's, visual impairment, and chronic obstructive pulmonary disease has been estimated to be over 200 million [9,10]. China and India have around 110 million and 69 million diabetic patients, respectively. The total number of diabetic patients worldwide is expected to increase from 415 million to 642 million. These numbers are increasing daily and need to be processed through different technologies. IoT devices coupled to sensors in healthcare systems perform automated patient monitoring, activity tracking, detecting heart rate, calculating caloric expenditure/intake, and more. The data generated by these IoT devices are processed and analysed at either fog/edge devices or cloud data centres. Current cloud models do not appear to be the best answer for handling IoT challenges since high-transmission capacity imperatives, organised framework reliance, and flighty response time from the cloud render them inadmissible for basic applications. Another issue emerges when deciding what to offload: data, computation, or application, and more specifically where to offload: fog or cloud, and how much to unload. In terms of task-related variables such as task size, duration, arrival rate, and necessary resources, fog-cloud collaboration is stochastic. Dynamic task offloading becomes critical in order to better utilise fog and cloud resources [11]. The solution to these requirements is fog computing with the IoT [12]. IoT implementation creates enormous changes in the healthcare system, which helps reduce the volume of transmitted data and network bandwidth [1]. Fog computing is one of the characteristics of cloud computing that lies near the end-user. It has introduced services to enhance user efficiency, authenticity, and usability and provided space to store data, compute, and communicate with edge devices, improving privacy and security in real-time [13]. The fog healthcare architecture comprises three layers: (i) An IoT layer/Sensor layer, (ii) a fog layer, and (iii) a cloud layer, as shown in Figure 1. The body sensor network captures the physiological states of the patient, such as blood pressure, pulse rate, body temperature, pressure rate, electrocardiogram, and an electroencephalogram. The wearable sensors monitor the patient continuously and transfer the physiological data to the fog layer using wireless networks such as Bluetooth, Zigbee, IEEE 802.11, and WiMAX [14,15]. The fog layer analyses the physiological data to provide alerts on the patient's health condition to various concerned individuals, such as family members, caretakers, and authorised medical practitioners, to observe vital signs through diverse applications [16,17]. The patient's medical data are regularly pooled and sent to cloud servers for examination. In the medical field, the demand for fog computing with IoT bears distinctive characteristics for health monitoring systems.

1.1. Major Contributions

The prime focus of this paper is to survey the different technologies used by different researchers in the field of fog computing, IoT, and cloud computing in the healthcare system. The different challenges have also been discussed in various papers to assist researchers in determining future research directions and exploration. The significant contributions of this survey paper are given below:

1. A thorough examination of IoT devices utilized in the healthcare industry.
2. A detailed analysis of IoT-based devices and the cloud in a fog computing environment.
3. Highlights of recent IoT-based research in the field of healthcare.
4. A comparison of several healthcare technologies with varied ailments and sensors employed by researchers.
5. Comparing past studies of various parameters of healthcare techniques.
6. A visualized systematic review technique using a flow diagram.
7. The methodological quality of the systematic review technique is evaluated through standard checklists.
8. Highlights of various challenges and open research issues in IoT-based healthcare.

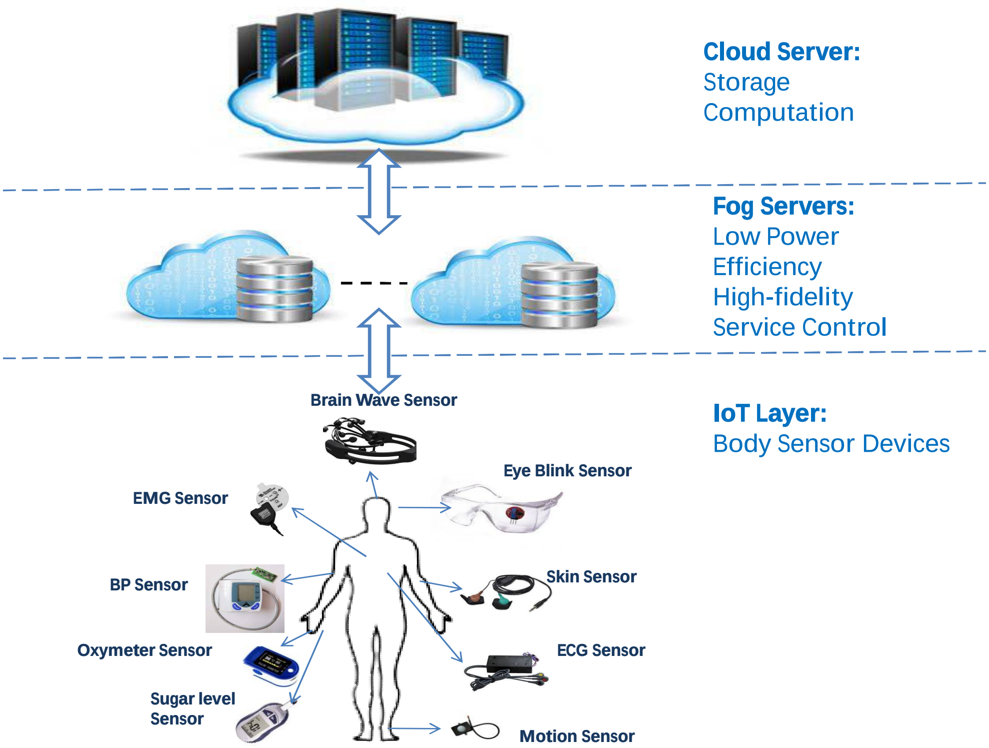

Figure 1. Architecture of fog computing in healthcare.

1.2. Research Motivation

There has been no wide and thorough assessment of IoT and fog-based healthcare systems in the literature. These systems help monitor the patient's physiological condition remotely through various sensors to allow for quick judgments and agile response thereafter. The service delays in these systems should range from milliseconds to microseconds. When the amount of data increases, so too does the reaction time for healthcare applications, which degrades the real-time operations of healthcare IoTs. Therefore, a systematic review is conducted to identify the various healthcare technologies, compare the tools and parameters considered, and different sensors used in health monitoring. It provides the challenges and a comparative overview of recent research works to facilitate knowledge sharing among researchers.

1.3. Paper Organization

The content of this article is structured as follows: Section 2 describes the background of fog computing with IoT and sensors used in healthcare. Section 3 presents a literature survey and related work conducted by different researchers. Section 4 is a review technique of this survey with the help of a flow graph and quality assessment diagram. Section 5 describes challenges and open research issues in healthcare. Section 6 discusses the result. Section 7 presents the conclusion.

2. Background

Technological advancements have fostered stiff competition in the already expensive industry of healthcare. Many hospitals have converted their systems to Electronic Health Records (EHRs), as required by the Health Information Technology for Economic and Clinical Health Act (HITECHA) and the American Recovery and Reinvestment Act (ARRA) of 2009. EHRs employ an old method called client-server architecture. However, IT tech has designed more efficient and patient-centric methods, and cloud computing has made it convenient and cost-effective. The word "cloud" refers to a big area, and computing refers to calculating, enumerating, measuring, figuring out, etc. So, cloud computing implies computing large amounts of data. A "cloud" is a data centre available on the internet for users that demand extra storage [18]. Cloud computing is a good choice for healthcare businesses because it is more economical than previous methods. The services that the cloud provides are beneficial for medical facilities, with some of these services including SaaS, IaaS, and PaaS. First, with Software as a Service (SaaS), the cloud can provide on-demand managed services to healthcare organisations, provide easy access for business applications, and fulfill Customer Relationship Management (CRM) [19].

Cloud technology is an Infrastructure as a Service (IaaS) that enables on-demand processing and the storage of large amounts of medical data [20,21]. Regarding Platform as a Service (PaaS), the cloud will provide a security-improved platform for web-based applications and software application deployment [22]. It also has the advantage of connecting cloud users and medical centres to exchange health data about patients over the internet. Transforming healthcare across the cloud requires more than just delivering medical information from several computers at any moment and on almost every mobile phone device [23–25].

Fog computing: fog computing lies between the cloud and the location of the user's devices [26]. Fog computing trends in all fields, such as smart homes, industries and hospitals. The use of fog computing to make smart hospitals. Many authors have designed proposals and architectures [27,28]. Many researchers have reviewed the studies and designed various architectures to show the basic concept of fog computing in healthcare [17,29]. The architecture showed fog data, which could reduce the data, make them flexible with more security, and then transfer them to the cloud [30–32]. Figure 1 depicts the sensor devices collecting the relevant information from patients in the form of signals, which are transferred to the embedded computers, called "fog computers". After filtering the signals and investigating the data, it is sent to the cloud [33]. The advantage of the architecture is that it uses less power, reduces the quantum of data, and improves the system's efficiency. This architecture has monitored Electrocardiogram (ECG) signals and speech disorders.

The words "internet" and "things" are very common, but their practical combination is impactful [34]. The objects' internet is used to collect and transfer data on the network. It does not need any interactions such as user-to-user and user-to-system [35]. IoT has used version 6 of the Internet Protocol (IPv6). There are sensors inbuilt into devices that are used to connect to the internet and transfer data. Many home appliances are IoT: smart refrigerators, smart TVs, smart ACs, and even edge-IoT-based smart healthcare [36]. Some of the medical care devices of the IoT include smart wearable watches which sense the pulse rate from the wrist, smart heart sensors, blood pressure sensors, and many more [37]. The architectures studied in this survey use IoT-based devices with inbuilt sensors and are connected in the network through the Internet, generally known as Intelligent Internet of Health Thing [38].

Sensors Used

Sensors play a significant role in medical innovation intending to make medical gadgets much more powerful and more secure while streamlining their activity. There are a variety of sensors in technical as well as medical fields [39,40]. Some of the successful applications of sensors in medical technology are:

1. Respiratory devices
2. Sleep diagnostic devices
3. Sleep apnea therapy devices
4. Spiro meters
5. Anesthetic meter
6. Dialysis machines
7. Infusion pumps
8. Oxygen concentrator
9. Vacuum suction pumps
10. Videoscopes

11. Blood sugar measuring device
12. Pulse oximeters
13. Computer tomographs
14. Gamma probes

From 2015 to 2021, body, glucose, skin, and other sensors were used in healthcare to detect diseases and alert doctors early. After using these sensors with fog computing and IoT technologies, some sensors have been used to transfer data from healthcare devices to cloud layers to process the patient's health data and early disease detection. Some popular fog-enabled IoT-based healthcare applications (such as CareNX, Yostra and more) are working successfully [41–43]. Figure 2 exhibits several notable technical advancements in the healthcare sector (between 2015 and June 2021). Figure 3 depicts the estimated number of IoT devices in the healthcare industry based on the Cisco Global mobile data traffic prediction. During a literature survey, the number of IoT devices used in the last five years was gathered from several sources [44,45]. In addition, the number of devices that will be used in the next five years has been predicted based on prior data and current trends in the healthcare sector [46].

Figure 2. Technological enhancement of IoT-based healthcare.

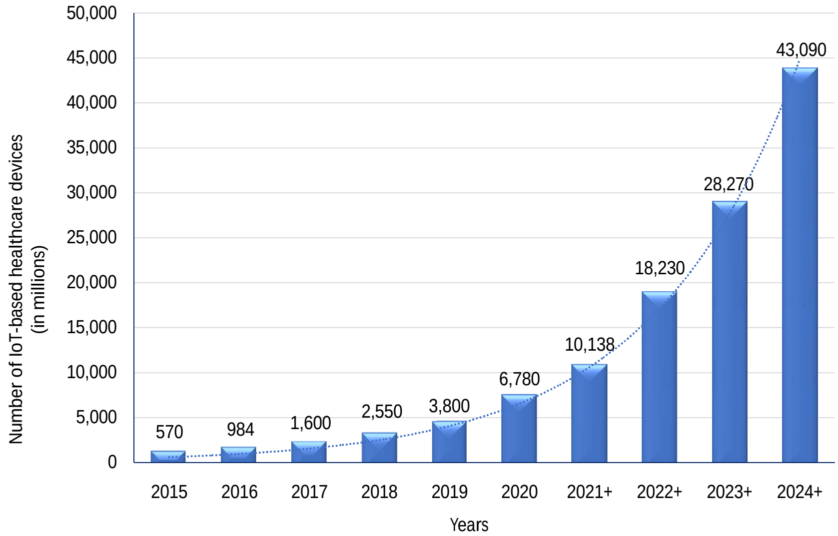

Figure 3. Expected number of IoT-based healthcare devices.

3. Literature Survey and Related Work

Several papers have explored the perspective of the fog computing architecture, claiming effective bandwidth consumption, ensuring Quality of Service (QoS), and delivering notifications in emergency scenarios. The majority of their job is dependent on elements such as fog layer bandwidth, latency, and data processing. They also utilized a variety of sensor nodes, communication protocols, as well as heterogeneity and interoperability. Moreover, they work on online analytics at the fog layer when the connection is poor. They improve the IoT-based health monitoring system in households and hospitals. In addition, they essentially examined ECG to determine heart rate. The extraction of pulse and heart rate is visible on a secure Graphical User Interface (GUI) as well as the warning system for contemporaneous notification in an emergency. Furthermore, they offer gateways that support wireless devices such as Bluetooth, Wi-Fi, and 6LoWPAN. The papers dicuss how the user interface should be user-friendly for universal accessibility. Different network protocols should be used to improve security, and employees should be trained in data security. Researchers have used the Arduino tool to put their ideas into action [1,47].

Some of the researchers have created a health monitoring system based on IoT secondary networks and contains various sensors such as Wi-Fi and Bluetooth secondary networks. The intermediary processing layer is established by obtaining a number of smart gateways in order to demonstrate the notion of fog computing for healthcare systems in IoT. They employed a fog system to aid medical situations known as early-warning scores, and used it to monitor patients with serious illnesses by employing sensors to continuously monitor individual health problems such as ECG, Electromyogram (EMG), pulse oximeter, mica2 motes, and SpO_2 sensor. They also employed a 4G network for continuous patient monitoring [16]. Atlam et al. cite6 and Kaur et al. [48] have described the work process of a variety of objects in the fog-assisted smart-home atmosphere where the layer of fog can extract vital information related to a patient's health. The Temperature Humidity Index (THI) of the patient is calculated in the cloud layer to identify the emergency. Information can be delivered to the receiver from the cloud layer to handle emergencies. Furthermore, the last one is the real-time alert generation according to the severity of the patient's condition [23,49,50]. In [7], the authors introduced an innovative IoT-based approach for a smart healthcare system that gives a medical warning for the patient monitoring system. They employed machine learning algorithms to computerize the management of the system. This monitoring system is for cardiac patients where an ECG is used to monitor the heart rate. Here, they used the improvement of local data analytics to present warnings and latency when the internet connection is absent. They used Raspberry-pi Zero and Jetson-TK1 with different processing systems. The proposed work is to enhance the users and system and enable the method to receive local notifications in case of an emergency situation. They improve the reaction time and consistency of the system when the internet connection is lost. Bibani et al. [9] designed a demonstrative version of one of the cloud services, called PaaS. They used the Body Area Network (BAN) to collect vital information. It is connected to patients' smartphones and while they are doing their normal daily life work, it monitors them. If something happens to the user or patient, it immediately warns the emergency services, i.e., calling an ambulance and contacting the stored number of family members to warn them immediately. They used the shimmer platinum development kit known as BAN. It is a wearable and wireless sensor device that senses the health of a patient and other data and is user-friendly.

Some of the papers are reviewed based on the fog computing architecture. They investigated the state-of-the-art in fog computing, as well as its characteristics and benefits. They provide the benefits and challenges of the combination of IoT with fog computing. They reviewed many papers and discussed the comparisons to other surveys such as the IoT challenges, and will be resolved by combining fog and various applications. They report that the IoT has attracted the attention of both academic and commercial organizations. It connects almost everything to everything. They also discussed the traditional centralized cloud and its challenges, such as that they had many issues regarding latency and network failures, but soon recovered their drawbacks with the help of fog computing, which is an extension of the cloud but close to IoT devices, which is processed by fog nodes. This will reduce latency and improve time-sensitive applications [51]. In addition, they also focused on different IoT applications that will be improved by the fog. They find that many of the tasks that can benefit from fog computing can be automated. The flexibility in network structure is better in healthcare as it can alter data and also protect confidentiality and decrease the network load [26]. Moreover, it has a divided flat framework that improves the capacity of storage, computation, and networking resources with cloud computing. They have covered the difficulties of health industry 4.0 by collaborating with big data, cloud computing, EHR, and AI systems. Fog computing improves several of the significant points of cloud computing, which are: privacy, low latency against cloud network failure, and predictability [52]. They solve some of the challenges with their method, such as intelligent health sensors, service composition, cloud-edge service management, sensor-edge service management, distributed health care applications, and security and privacy solutions. They find they achieve a better result in comparison with other architectural styles [53]. In paper [54], the authors outlined the architecture, application, and analytics of a medical system. According to market analysts, the market for medical equipment, software, systems, and services will be worth $300 billion by 2022. Government initiatives are also encouraging this obligation for e-healthcare. This includes the Body Area Sensor Network (BASN), the cloud, an internet-connected smart gateway, and massive data. The data, which are produced from sensors attached to the patient, are accessible to both the doctor and family members anywhere and anytime. The advanced machine learning techniques and algorithms automatically learn from sensor measurements and patients' previous data to facilitate their health information for future purposes and can raise the alarm if required. Their records will be stored by dissimilar sensors, which are body-worn or implanted sensors, and record the different parameters of vital signs in addition to environmental information such as date, time, and temperature. Akrivopoulos et al. [55] have proposed to develop the workings of a current medicinal services framework safely by applying homomorphic encryption and, furthermore, by creating and surveying a calculation of their plan. They also plan to study the homomorphism security instrument to assemble secure human services applications for groups of individuals yet to come.

Healthcare applications over the fog computing have been discussed and deployed [56]. They enlarge the cloud computing model through moving processed data close to the production site; speed up the system's awareness to actions next to its complete awareness; and by removing the data round-trip to the cloud. Now, there is no need to off-load a large amount of data to the network; the most important thing is to improve the security and quality. This method improves the services with low acceptance of mistakes for industrial and health-care applications. This paper improves the issues of fog architecture with end-to-end computing stages. Another focus is on the application of health-care by integrating the sensors into a fog computing platform. They evaluate the ECG device with different operating parameters such as sampling rate and the number of different channels.

Sood et al. [37] basically detect and monitor the Chikungunya Virus (CHV) and are planning a method to find and manage the wearable IoT sensor-based healthcare system. The detection and observation of this contagious disease are greatly needed to control it in real-time. They have studied many published works based on some specifications such as maximum contributions, the domain of application, cloud computing, IoT, fog computing, real-time perspective, prediction model, outburst role index, awareness generation, safety mechanism, and evaluation of contagious diseases. Some of the challenges in this system are to improve the quality of the system, such as latency issues, location alertness, and broadcasting of data. They have proposed a framework for diagnosing CHV which is a mix of 3 layers: the IoT layer, the fog layer, and the cloud layer. The IoT sensor layer's job is to gather information from various well-being sensors, position sensors, sedate sensors, and some more. At that point, the information is sent to the fog layer for continuous preparation and diagnosis of contaminated clients from CHV. Subsequent to recognizing

CHV, second layer fog promptly reacts to the caution on the patient's cell phone to take a prudent step on schedule. Simultaneously, this will store in the cloud aggregated clinical data of every client and compute oxygen reserve index for each of them to speak to their chances of spreading and contracting the disease. The main calculation was done by [57] which rethinks the class of client and produces an alarm; the subsequent calculation is to create and refresh the Time and Action (TNA) graph messages. They have built up a framework for expectation and forestalling chikungunya infection utilizing wearable sensor innovation, decision trees, and TNA. The J48 choice tree is utilized here to arrange the clients into various classifications. The main focuses are keeping a health record in relation to time, getting the framework ready on time, and creating a TNA chart to speak to the episode of the chikungunya infection.

The wearable telehealth was designed by some of the researchers. In [17], they have designed and implemented a prototype system that is wearable telehealth and is based on the Intel@ Edison embedded processor. The fog data architecture is useful in this type of speech disorder because it can validate the Echo-wear device. They find some aspects that can be done in the future, such as some speech features including jittery and sensory pleasantness that are the useful quality of speech. Similarly, ref. [58] have proposed a model which is a modest and remote-check IoT-based framework with fog computing and power-effective wearable sensor gadgets. The utilization of intensity is diminished by the gathering of equipment and programming-based methods. Using advanced mobile phone or PC frameworks, specialists can remotely screen a patient's well-being and speak to it in content and graphical structure. The structure of this strategy has a remote health checking framework dependent on IoT and a customized high-force 2.4 GHz radio frequency convention. They executed this framework by partitioning it into two sections; one is node usage and the other is gateway and back-end framework usage. The use of hubs such as ADS1292 is a reasonable, less loud, and simple front-end gadget for getting multi-channel ECG with high information rates of 1000 examples/s. Elmisery et al. [59] have proposed the topological development of IoHT gadgets when assembling the client's information for cloud administration. They have introduced the new methodology of the two-arrangement disguise process, which gives total security control to persistent over the essential estimations. Fast Moving Consumer Product (FMCP) guarantees the authorization of security inclinations by permitting the approach operator to naturally watch the separated inclinations for explicit solicitation, which could not abuse their protection. In addition, FMCP permits control by using Ciphertext-Policy Attribute-Based Encryption (CAABE). The fog nodes aggregate the critical estimations obtained from the concealed IoHT gadgets, type and specifically encode them in a gathering profile, and after that send them to the cloud medicinal services recommended administration.

Author proposed a model dependent on fog and IoT for recognizing and observing Type-2 diabetes persist progressively. The technique for this kind of illness utilizes the Multiple-Criteria Decision-Making (MCDM) methodology. This method is used for sorting out and explaining choices and controlling issues. Here, the two regions presented the new calculation with type-2 neutrosophic numbers. This can be determined to have VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique and developing notice. They recommend the WBAN for remote transmission highlights, which is capable of arranging customary framework disadvantages. The principal component of this model is the WBAN, or clinical sensor hub. It is a mixture of different sensor gadgets and little remote modules for gathering information that helps the specialist to distinguish type-2 diabetes in the early stages [60].

Fog engineering made by various gadgets specifically intended for the organization of preventing social insurance applications, utilizing extensive quality control. They used Field Programmable Gate Array (FPGA)-based devices for fog hubs, and their methodology includes a Xilinx Pynq-Z1 development board built with IoT in XC7Z020 FPGA. The utilization of FPGA based frameworks as fog hubs brings numerous advantages, including reconfiguration of the equipment custom-made for the particular application, high execution in information control and sign preparation, and low force, tantamount to other board PCs such as Raspberry PI or Beagle Board. The model has two cases: the first shows how engineering can be used to generate energy and bring issues to light about the quality of air in the workplace; the result is solid and ready to reduce CO_2 levels in the earth without the use of mechanical components. The subsequent framework is to screen for cardiovascular issues, and crisis requires a poor one [12]. Furthermore, ref. [61] proposed a technique combining the expansion of fog computing and IoT-based social insurance. They represent a new trend in imaginative e-health arrangements, with improved dormancy, vitality utilization, portability, and quality of service. They proposed a strategy of high-intensity alert for the situation of the utilization module. They contrasted their work and edge-ward technique with the default distribution strategy, which shows their proficient work, which has improved by 8.27%. The entire vitality was smaller by 2.72% and 1.61% compared with cloud-just methodologies and default models individually. It additionally limits the postponement in a full circle, undermining the default model and cloud-just techniques by 0.53% and 17.73%, respectively. Additionally, the cloud technique improved by 94.65%, which is practically equivalent to the default methodology. Saxena et al. [62] have investigated the fundamental Named Data Networking (NDN) design to build up the NDN-IoT stage for the smart healthcare system. The home server utilizes the NDN correspondence for gathering, handling, and distributing the crucial indications of the patient normally, which is controlled utilizing the Hidden Markov Model (HMM). Cloud servers and different servers can buy in the information through NDN-based distribution utilizing push-based multicast. By using the HMM and grouping, respectively, S and CS recognize the possibility of a crisis early on. Another NDN-based setting, mindful versatile sending (cumulative distribution function), is used for sending healthcare crisis traffic in the most extreme system conditions. They have additionally broadened the Workflow Instinctive Formal Approach (WIFA) model to check the precision of the NhealthIoT work process during a crisis. They are the first to develop this intuitive and insightful ongoing social insurance framework without any preparation using the NDN-IoT.

Researchers have also designed a new model for medical services. In [63], had structured a new design based on fog computing for the application of medical services. Their engineering has four layers. The first layer is the check machine, which is constantly observed by specialists for patients. This layer is associated with layer 3 fog nodes since fog nodes quickly react to the issue in the patient and guide the prudent step immediately. The subsequent layer is the bunch of physiological sensor hubs, which are associated with one another just as they are through the web. They shaped the IoT bunch and sent their information to layer 2 and ceaselessly sent the checked information to the third layer—the fog nodes. The third layer is the nearby access point or temporary storage. This can hold the information for a couple of moments, as it were. This is the significant layer that takes the physiological information constant from the layer 2 sensor hubs. The upside of having the fourth layer is that it helps in moving beyond the data of the patient and helps in the assessment of their or her clinical issues. Similarly, ref. [64] have designed the architecture of fog computing with integrated IoT for healthcare services. They have mainly used the fog server as a virtualized platform because it is closer to the equipment in order to maintain the time complexity as it is lower than the cloud and can evaluate and process the data. It is an edge network and can provide improved features such as location awareness, low latency, etc. Fog computing has more benefits, such as scalability, low bandwidth, etc. The model consists of IoT devices like medical sensors and wearable sensors that monitor the patient's vitals. IoT devices can communicate both directly and indirectly with other technologies such as Wi-Fi and internet data. Tuli et al. [65] have proposed a new system called Health-Fog for gathering deep learning in edge processing gadgets and introducing it for the genuine use of programmed coronary illness examination. It effectively deals with the information of heart patients. They used fog bus to convey and test the proposed model's performance in terms of force utilization, network data transmission, dormancy, jitter, exactness, and execution time. Their strategy for Health-Fog is configurable to different activity modes that give the best quality of service, forecast, and precision in haze calculation situations and for various client prerequisites.

Jia et al. [66] have proposed the technique for fog-driven IoT healthcare services and portrayed and planned the layers of cloud and fog. They try to minimize the latency. They are fundamentally centered on conventions planned explicitly for a fog-driven IoT individual healthcare check system. The convention which they have utilized is for matching bi linear. This convention is for the protection and security of patients. They present the defense model and show the proper security verification, just like a safety examination against basic attacks. They executed the convention and the IoT and fog layer were validated by the server cloud and imparted a typical key to three substances. This technique is officially in the Block Resource Persons (BRP) security model. They exhibited its security in the discretionary prophet model. The exhibition assessment was likewise introduced, which showed its capability to be sent to a certifying world healthcare organization. In paper [67] have proposed a technique for patient healthcare. In this case, he used Raspberry-pi to collect a patient's vitals. The strategy they have utilized is the docker compartment. The Raspberry-pi is used as an entry point for distributing the information collected by the various sensors. The sensors are connected to the clinical gear, and from this, the report is put away on the cloud, and from that point, the information is prepared by the specialists. The docker holder is the client on the server-side and the nearby database is utilized further for handling the information and giving it to the medical clinic for diagnosis. It gathers indispensable data. With the assistance of bluetooth, the information screens are sent to the Raspberry pi and afterward sent to different clients. This gadget detects the information at standard intervals. It has an amazing processor that gathers and handles them simultaneously.

The problem of task offloading in the fog-cloud model was researched by the authors [11,68]. They have used a logistic regression approach to offer a machine learning-based intelligent task offloading model in the fog-cloud collaboration network. First, an offloading-related optimization problem is handled by taking into account the threshold values of the relevant cloud data center parameters. Numerous sorts of applications, including time-sensitive and computation-intensive apps, must accomplish their intended duties in accordance with their computing resource requirements, which must be provisioned proportionally. Second, the suggested approach employs an automated task offloading management system that predicts incoming tasks generated by heterogeneous IoT and mobile devices placed in scattered remote locations.

3.1. Comparison of Various Healthcare Techniques

This section compares various healthcare techniques used in the last ten years. This comparison has been conducted on five significant parameters—diseases name, tools and techniques, sensors, and description. Overall comparisons have been summarized in Table 1 to facilitate future research.

3.2. Comparative Analysis of Various Parameters of Healthcare Techniques

This section compares the different parameters of healthcare techniques. The comparison has been done on accuracy, sensitivity, specificity, area under curve, precision, F1-score, area under curve hall, minimum error rate, and receiver operating characteristic curve. Table 2 shows the brief description on these factors with their techniques.

Table 1. Comparative analysis of various healthcare techniques.

S#	Author(s)	Diseases	Tools and Technique	Sensors Used	Description
1	Gia et al. [69]	Cardiac disease	WBAN, Arduino with Wi-Fi shield, TI CC2538, Zigduino, Z1	HC-05 Bluetooth module as wireless sensor network nodes	A health monitoring system by exploiting the concept of fog computing at smart gateways providing advanced techniques and services such as embedded data mining, distributed storage, and notification service at the edge of network.
2	Dubey et al. [47]	Speech disorder and Heart Disease	Pan-Tompkins algorithm, The DTW algorithm was implemented in C program and UCR Suit	Smartwatch, ECG sensor	have implemented a system that is wearable telehealth based on the Intel@ Edison embedded processor which work for the speech disorder
3	Rahmani et al. [17]	Cardiac Disease	LZW algorithm,6LoWPAN	Arduino Due, Bluetooth, Wi-Fi, ZigBee or 6LoWPAN.	A monitoring system for health that uses secondary networks based on IoT and includes many sensors such as Wi-Fi and Bluetooth
4	Manogaran et al. [16]	BP, Sugar, Heart rate and body temperature.	S3, cmd method, Apache Pig-Pig algorithm, Amazon S3 bucket, EMR, Apache Hbase	Wearable sensor devices	Used some sensors to monitor individual health conditions in a constant manner, such as ECG, EMG, pulse oximeter, mica2 motes, and SpO_2 sensor.
5	Verma et al. [51]	Cardiac disease, diabetes, other problems	Bayesian belief network, THI, Weka tool	Smart wearable sensors, gastro sensors, heart sensors	They expertly monitor by using IoT devices, smart sensors, and other internet-connected devices to capture various patient records
6	Mahmud et al. [52]	Health issues	VM, MCI, iFogSim	Intelliegent health sensors	Their method, such as intelligent health sensors, service composition, cloud-edge service management, sensor-edge service management, distributed health care applications, and security and privacy solutions.
7	Negash et al. [50]	Cardiac disease	LZW algorithm, Python-tornado	6LoWPAN, Bluetooth	They gather the data from sensor nodes with bio-signals such as ECG and EMG. The sensor node is made up of medical sensors, a microcontroller, and a wireless communication IC.
8	Akrivopoulos et al. [56]	Heart rate	Integrated 4Gbit (8x512Mb) NAND Furthermore, ADC converter, Spark-IoT	Smart devices, wearable devices	They enlarge the cloud computing model through moving processed data near to the production site; speed up the system's awareness to actions next to its complete awareness; and by removing the data round-trip to the cloud.
9	Sood et al. [37]	Chikungunya	Fuzzy C-Means SNA graph, Matlab	Body sensor, water sensors, GPS sensors, climate detector sensor	Using fog architecture, the information is sent to the fog layer for continuous preparation and diagnosis of contaminated clients from CHV

Table 1. *Cont.*

S#	Author(s)	Diseases	Tools and Technique	Sensors Used	Description
10	Sood et al. [57]	Chikungunya	J48 decision tree, TNA, Weka 3.6, Gephi 0.9.1 tool	GPS Sensor, RFID, Bio Sensors and Body Sensors, climate sensor, mosquito sensor, water quality detector sensor, temperature sensor	Their calculation rethinks the class of client and produces an alarm; the subsequent calculation is to create and refresh the Time and Action (TNA) graph
11	Gia et al. [58]	Respiration and heart rate	AES-256, Orange Pi	BME280 sensors	The little wearable gadget will be ready to assemble and communicate a huge high-gain signal remotely
12	Basset et al. [60]	Type 2-diabetes	Decision tree, WBAN and mobile application, Neutrosophic with VIKOR method, TOPSIS method	Glucose detection sensor, the skin-like sensor	A model dependent on fog and IoT for recognizing and observing Type-2 diabetes persist progressively
13	Cerina et al. [12]	Respiratory problems	FPGA, Xilinx Pynq-Z ARM Cortex A9 CPU and a Zynq XC7Z020 FPGA.	Cozir CO_2 sensor	A fog engineering made by various gadgets specifically intended for the organization of preventing social insurance applications, utilizing extensive quality control
14	Mahmoud et al. [61]	Chronic disease	DVFS, two-tier CoT, iFogSim	Wearable sensors devices	They represent a new trend in imaginative e-health arrangements, with improved dormancy, vitality utilization, portability, and quality of service.
15	Saxena et al. [62]	Chronic diseases , other vitals	Expectation-Maximization (EM) algorithm, NDNoT, HMM, S, Raspberry Pi, Arduinos	Health sensors,	Investigated the fundamental Named Data Networking (NDN) design to build up the NDN-IoT stage for the smart healthcare system.
16	Elmisery et al. [59]	Blood pressure, heart rate, electrocardiogram, blood glucose, and respiratory rate	Local concealment algorithms, Paillier encryption scheme, EVS, C++, octave libraries, Number Theory Library (NTL)	Implantable medical sensors	Proposed the topological development of IoHT gadgets when assembling the client's information for cloud administration.
17	Azimi et al. [7]	Cardiac Disease	Machine learning algorithm, Raspberry pi, Biopsy toolbox in Python	Real sensor network	An innovative IoT-based approach for a smart healthcare system that gives a medical warning for the patient monitoring system.
18	Kaur et al. [48]	Pulse rate, heart rate and temperature	Node-Red, MQTT protocol, Raspberry pi, Arduino	Wearable sensors devices	Proposed a system for monitoring the different parameters of the patient such as pulse rate and temperature with the help of a sensor connected to the Raspberry Pi and IoT.

Table 1. *Cont.*

S#	Author(s)	Diseases	Tools and Technique	Sensors Used	Description
19	Tuli et al. [65]	Heart disease	Deep learning in Edge computing, Python, scikit library	Medical sensors, activity sensors and environment sensors	Proposed a new system called Health-Fog for gathering deep learning in edge processing gadgets and introducing it for the genuine use of programmed coronary illness examination.
20	Rajan et al. [19]	Oral cancer	Deep convolutional neural network, myRIO-1900	Intelligent medical sensors	Proposed a novel method which utilizes a modified vesselness measurement and a Deep Convolutional Neural Network (DCNN) to identify the oral cancer region structure in IoT based smart healthcare system.
21	Kumar et al. [70]	Mosquito-borne diseases	Fuzzy KNN classifier, MATLAB	Wearable and IoT sensors, Mosquito sensors	Utilized similarity coefficient to differentiate the various mosquito-borne diseases based on patient's symptoms, and the fuzzy k-nearest neighbor approach is employed to categorize the user into infected or uninfected class
22	Muhammad et al. [4]	Chronic and psychological diseases	Deep Learning, Edge computing	TUH EEG Abnormal Corpus v2.0.0, EEG	Proposed a new smart pathology detection system using these technologies. Sensors will capture EEG signals of a person and send the signals to a nearby edge computing server.
23	Kishor et al. [71]	Healthcare heart disease	Random forest machine learning algorithm, Python 3.7	Wearable and IoT sensors	They improve the latency minimization in e-healthcare through fog computing.
24	Hassan et al. [72]	Pain Conditions	FCFS, iFogSim	Bio-sensors	Proposed for deploying a remote pain monitoring system by adopting the fog paradigm to reduce latency and network consumption.
25	Sood et al. [73]	Dengue Virus	Naive bayesian network, Java-based simulator Cup Carbon U-one 3.8.2, Weka 3.6	IoT, Environmental sensor and mosquito sensor	Proposed an intelligent healthcare system which identifies, monitors, and alerts Dengue Virus (DeV) infected individuals in real-time and control the DeV infection outbreak using Fog computing
26	Shynu et al. [74]	Diabetic-Cardio disease	Blockchain, Java (version 1.8)	Medical sensors	Proposed an efficient Blockchain-based secure healthcare services for disease prediction such as Diabetes and cardio diseases
27	Kumar et al. [75]	Alzheimer's disease	K -means clustering and graph-cut methods, MATLAB	MRI	An effective segmentation and classification techniques are proposed for Alzheimer's disease, mild cognitive impairment and normal control subjects
28	Ahmad et al. [76]	Diabetes	Machine learning algorithm, scikit-learn library	Glucose detection sensor	Investigated the prediction of diabetic patients and compare the role of HbA1c and FPG as input features.

Table 1. *Cont.*

S#	Author(s)	Diseases	Tools and Technique	Sensors Used	Description
29	Syed et al. [77]	Type 2-diabetes	Machine learning algorithm, SPSS	Glucose detection sensor	Implemented a questionnaire-based cross-sectional study using conventional diabetes risk factors for studying the prevalence and the association between the outcomes and exposure
30	Roy et al. [78]	Health criticality of any patient	Cooperative game-theoretic Nash bargaining approach, MATLAB	Body sensors	Proposed a scheme, Criticality Aware data transmission (CARE), in CPS-based healthcare systems, for increasing the processing rate of the sensed physiological parameters' values of a patient
31	Misra et al. [79]	Critical patients	Dynamic radio protocol selection and linear regression, MATLAB R2015a	Body sensors	Proposed "DROPS", a scheme which Dynamically selects Radio Protocols in an energy-constrained wearable IoT healthcare system
32	Aladwani [80]	Patient Monitoring	Max-Min scheduling algorithm, Cloud simulator	Body sensors	Improved the static task scheduling algorithm by using task classification and VM categorization
33	Guo et al. [81]	COVID-19	Public key homomorphic encryption technologies such as ElGamal, Microsoft Azure	Medical sensors	Presented two attack games to demonstrate that our approach is secure (i.e., chosen-plaintext attack resilience under the computational Diffie–Hellman assumption), and evaluate the complexity of its computations
34	Azeem et al. [82]	Patient Monitoring	Secure Message Aggregation and Decryption algorithm, NS 2.35	Medical sensors	An Efficient and Secure Data Transmission and Aggregation (ESDTA) scheme to enhance aggregation efficiency and data security

Table 2. Comparative analysis of various parameters of healthcare techniques.

Author(s)	Techniques	A	B	C	D	E	F	G	H	I
Sood et al. (2021) [73]	Naive Bayesian Network (NBN)	√	√	√	×	√	√	×	×	√
Ahmad et al. (2021) [76]	Random Forest, Recursive Feature Elimination	√	×	×	×	√	×	×	×	×
Jayroop et al. (2021) [83]	SVM, Logistic Regression, Neural Network and Deep-NN	√	√	√	×	×	×	×	×	×
Shynu et al. (2021) [74]	Block chain	√	√	×	×	×	×	×	×	×
Ahmad et al. (2021) [76]	Machine Learning Classifiers	√	√	×	√	√	×	×	×	×
Chatrati et at. (2020) [84]	SVM, Logistic Regression, KNN, Decision Tree	√	√	√	√	×	×	×	×	×
Kishor et al. (2020) [71]	Random forest machine learning algorithm	√	√	√	×	×	×	×	×	×
Rajan et al. (2020) [19]	Deep convolution neural network	√	√	√	×	×	×	×	×	×
Hasan et al. (2020) [85]	Random Forest, KNN, Decision tree, Naïve Bias	√	√	√	√	√	√	√	×	×

Table 2. *Cont.*

Author(s)	Techniques	A	B	C	D	E	F	G	H	I
Kaur et al. (2018) [86]	Cloud IoT based framework	√	√	√	×	√	√	×	×	×
Verma et al. (2018) [51]	Bayesian belief network	×	×	√	×	√	√	×	×	√
Kumar et al. (2019) [70]	Fuzzy K-means	√	√	√	×	√	×	×	×	×
Reddy et al. (2020) [87]	Randon Forest, AdaBoost, Logistic Regression, KNN, Grid Search	√	√	√	×	×	×	×	×	×
Manogaran et al. (2017) [16]	S3, cmd method, Apache pig-Pig algorithm	√	√	√	×	×	√	×	×	√
Sood et al. (2017) [37]	Fuzzy C-Means, SNA graph	√	√	√	×	√	√	×	×	√
Sood et al. (2017) [57]	J48 decision tree, TNA	×	√	√	×	√	√	×	×	√
Cerina et al. (2017) [12]	FPGA	√	√	√	×	√	√	×	×	×

A: Accuracy, B: Sensitivity, C: Specificity, D: Area Under Curve, E: Precision, F: F1 Score, G: Area Under Curve Hall, H: Minimum Error Rate, I: Receiver Operating characteristic Curve.

4. Review Technique

The survey technique mentioned here is based on the guidelines by Kitchenham et al. [88]. The papers from reputed journals, conferences, book chapters, and magazines are segregated according to the research review and the phases of segregation. Figure 4 depicts the different phases of collecting relevant papers for the survey based on some segregation.

The systematic review technique described in past literature used the Assessment of Multiple Systematic Reviews (AMSTAR) checklist to assess the methodological quality of the review Vu-Ngoc et al. (2018) [89]. As per the assessment result, the AMSTAR total score correlated with systematic review flow diagram scores in 40 titles (as shown in Figure 4). Five phases, including identification, screening, eligibility, inclusion and qualitative synthesis, were opted to complete this review paper. Articles were sorted into six years, from 2016 to 2021+. Each phase has its criteria for selecting and rejecting the titles as described below:

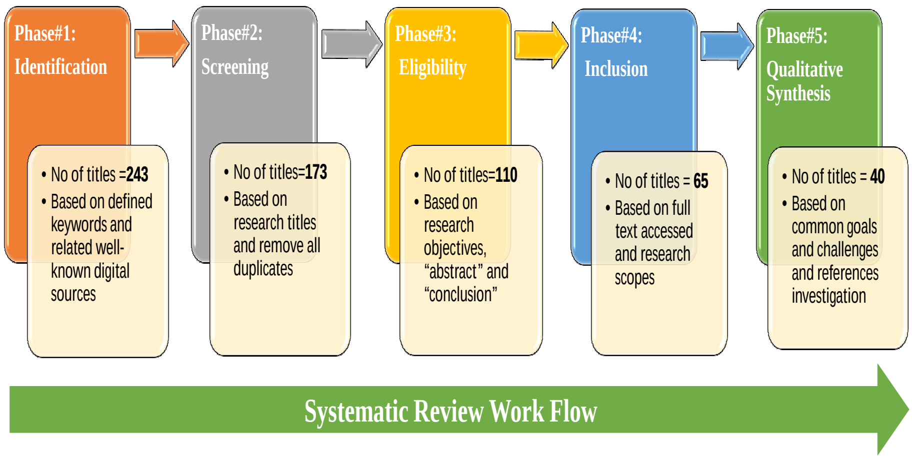

Figure 4. Quality assessment review flow diagram.

Initially, 243 research titles were shortlisted from different sources, including journal databases, book chapters and web reports. More than 80% of titles were accessed from reputed digital libraries. The rest of the titles were directly taken from physical books, web reports and recorded content. All duplicate articles were removed from the title list. Despite this, an overall screening process was conducted based on research titles and fields, including fog computing, healthcare, technologies, and IoT. In this phase, 173 research titles were shortlisted for further investigation. 65% of articles were eliminated based on duplicity, 23% on their paper titles. The remaining 12% of articles were segregated according to their aims and scopes. Assessing the eligibility is a crucial process in which overall shortlisting was done based on each article's "Abstract" and "Conclusion". One hundred ten papers were selected as eligible for this survey paper. Sixty-five papers were listed according to the full text and were critically surveyed, which indicates the different technologies used in the healthcare system for different diseases. Finally, 40 papers could qualify for the qualitative synthesis analysis based on the common challenges and references of the papers. Figure 5 shows the total number of paper has been used from the different sources like IEEE, springer, MDPI and so on.

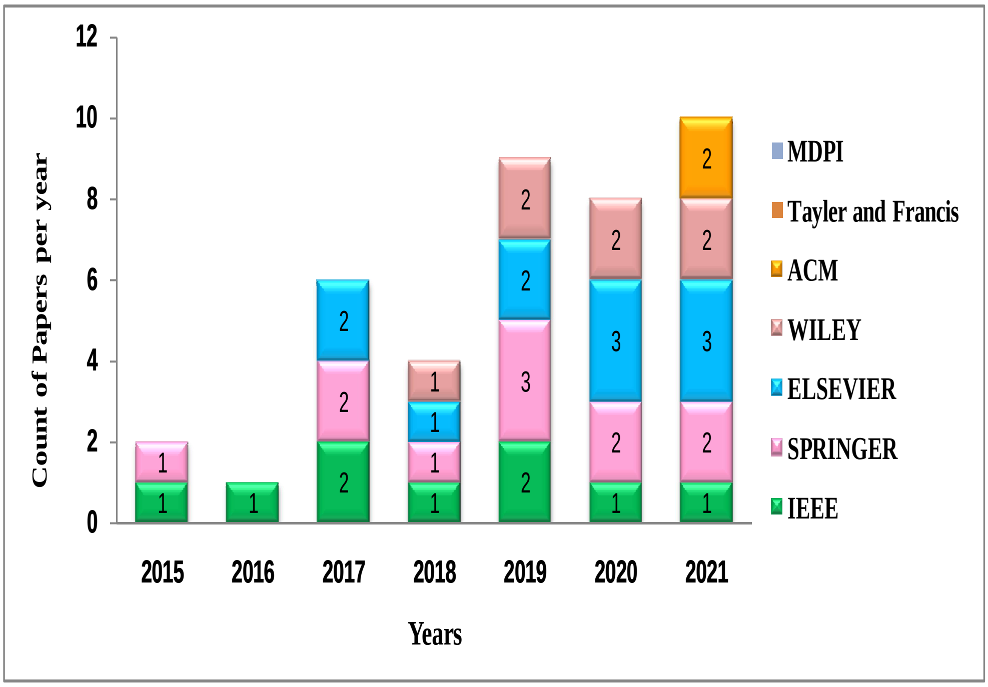

Figure 5. Number of papers per year grouped by publishers.

4.1. Quality Assessment of Flow-Diagram

The overall quality assessment criteria of proposed flow-diagram was taken from Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist [90]. A 16 grades scale was considered (as mentioned in Table 3) to assess the quality of the review technique. The proposed flow diagram comprised five phases: identification, screening, eligibility, inclusion and qualitative synthesis. Each phase has its selection criteria–identification (criteria no. 1–5), screening (criteria no. 6–8), eligibility (criteria no. 9–10), inclusion (criteria no. 11–12) and synthesis (criteria no. 13–16).

Table 3. Quality assessment criteria and title proportion.

Criteria No.	Criteria Description	Proportion of the Titles
1.	Identify the total number of titles	90.20%
2.	Define various sources including databases/search-engine	55.30%
3.	Identification of each databases	35.50%
4.	Identification of other sources such as search-engine, web-reports	20.10%
5.	Offline manual search	03.55%
6.	Number of duplicate titles removed	30.50%
7.	Tools and techniques used in filtering the duplicate titles	03.30%
8.	Assessed the publication year, language and status	94.50%
9.	Accessed the abstract and conclusions of the titles	91.30 %
10.	Number of titles eliminated	85.60%
11.	Accessed te full-text title for inclusion	74.90%
12.	Number of titles removed after full-text accessed	52.80%
13.	Conduct synthesis process	59.80%
14.	Conduct qualitative synthesis based on common challenges	37.40%
15.	Conduct quantitative synthesis based on common challenges	–
16.	References investigation	68.10%

4.2. Search Criteria

The keywords used for this survey were IoT, fog computing, cloud computing, healthcare, and the internet of medical things, which are included in almost every paper. The other search keywords used for searching the relevant papers and enriching this survey are healthcare, algorithm in healthcare, and IoT and fog driven healthcare.

5. Challenges and Open Research Issues in Healthcare

Fog computing is critical in sharing and moving data from one place to another. The user data stored in a fog server provides higher quality and more exciting services. It also shares the data efficiently and provides a quick response to healthcare users. However, in the healthcare sector, there are flaws in IoT-based storage systems. This section addresses some major challenges related to IoT-based storage in the fog computing environment.

5.1. Loss of Data

IoT-based devices face numerous challenges, including data discontinuity, unknown regions, and large amounts of data transmission in fog computing environments [1]. Generally, it creates some errors while transmitting data over a network. Bit errors and packet dropping are the major issues that happen. In the healthcare sector, most of the data is generated by IoT devices, which is very important for patient diagnosis. Making a proper diagnosis due to any data loss is not possible and could also create a problem for emergency treatment. Therefore, it is necessary to use fewer transmissions over the network while maintaining the quality of service. However, this can be solved by creating an additional layer in the fog computing environment to control data loss [56].

5.2. Time Limits and Prospective

In the current scenario, there is no provision to give a quick response to patients. Due to a lack of time, the doctors cannot check each patient's data daily, which is an integral part of the diagnosis. It is also challenging to find an efficient way to store such large volumes of data in IoT-based devices [47]. Big data sets need much processing and storage time. So, an efficient algorithm is necessary to process such big data frequently and provide a quick response to healthcare users. Adherence monitoring: a patient's failure to receive a proper diagnosis may result in hospitalization and an increased financial burden on the family. Ageing Population: More facilities are required for ageing people. Urbanization: Big cities demand better healthcare infrastructure to serve their residents because disease spreads fast and more frequently in dense areas. Another issue is the health of doctors, physicians, and other medical officers; because there is a shortage of doctors, they must also take care of their health while serving the patients; thus, expanding e-health services is necessary. Rising Medical Costs: The most significant factor in the healthcare industry is the rising prices of medical facilities and medicines.

5.3. Storing and Analyzing the Enormous Quantum of Unstructured Data

Most data generated from medical sensor devices are complicated to store and analyze [17]. In the healthcare sector, mainly unstructured data has been generated as images (MRI scans, X-rays, ultrasounds, etc.). The velocity and variety of this data are very high. This data may be in different sizes and formats. It is tough to store and analyse this data for medical personnel. We need efficient frameworks and algorithms instead of traditional approaches to overcome these issues [16,91].

5.4. High Energy Consumption Issue

Generally, healthcare related IoT devices do not have enough power backup and sufficient space. Energy is consumed by various devices such as sensors, cameras, etc. As per Amazon's survey report, the sensors extracting the information from the environment consume approximately 60% of energy, and about 20% of energy is consumed to maintain the device, such as cooling, backup, etc. Many researchers are working to optimise the energy consumption rate. Nowadays, all healthcare IoT devices need to be energy-efficient to develop an energy-efficient fog-oriented model for IoT-based devices that will monitor without interruption due to power [92–94].

5.5. Discrete Transmission of Data

The major problem is the sensor, which has a periodic transmission of data such as the humidity and temperature that varies accordingly. When real-time data is required, the main problem is managing the streaming data in various applications of E-Health. So, significant bandwidth is consumed during data transmission [16]. For example, the bandwidth requirement for ECG signal transmission is 4 kbps per channel. Another challenge is multi-processing which needs high-powered processors to handle the workloads, such as multi-core processors, for better treatment in smart hospitals.

5.6. Security of the Data

It is a challenging issue to secure the patient's data in a fog computing environment during transferring and managing processes. Fog contains the data of the cloud and the IoT environment and is therefore susceptible to cyber-attacks. Therefore, it must be protected with a robust security system that can protect the healthcare data such as patient's credentials, reports, medical practitioner details, etc. Maintaining trust is another challenge in IoT-Cloud services because the security mechanisms of both platforms are different. An efficient algorithm is needed for securing healthcare data in a fog computing environment to overcome these challenges [15,51,95].

5.7. Lack of Communication between Fog and Cloud Layer

The primary purpose of the cloud is to store and manage all the applications and healthcare-related data. However, in fog, only some local applications are synced with the cloud. The problem is delivering and updating the patient's data from fog to cloud and vice versa. It depends on a suitable communication between cloud and fog that would provide high performance and low intermission. Another challenge is the communication between the different fog servers that manage a group of resources in different regions. If the collaboration between the fog servers is increased, the whole system's performance improves [51].

5.8. Interoperability, Dependability, and Cost

The healthcare industries are now information-centric, monitor the patient remotely, increase the quality, accessibility, efficiency, and continuity, and make a difference in overall cost. The primary requirements for healthcare applications to make them smarter are bandwidth, latency, dependability, interoperability, and security. These challenges need improvement in E-healthcare [23,26].

5.9. Synchronization and Standardization

Currently, there is no standard format for suitable communication between IoT and the cloud in a fog computing environment. There is also no standard for developing IoT-based applications, especially in the healthcare sector. There must be harmony between different cloud merchants, posing a challenge to providing the services in real-time and interoperate [50].

6. Discussions

This survey paper focuses on healthcare using the IoT, fog and cloud computing which widely use state-of-the-art technologies. The observations related to the various research articles from 2015 onward on various diseases and their impacts have been extracted and presented for discussion. The objective is to raise awareness about how technologies play a crucial role in healthcare. As shown in Figure 6, healthcare research was not much in 2015 and 2016. In 2017, it increased; from 2018 to 2021, harnessing technology increased in healthcare. Relevant information on the reviewed healthcare-related technologies presented would give the new researchers an idea and motivation to innovate further. This paper also reviewed different diseases, as shown in Table 4. The survey was done by calculating the diseases diagnosed using technology in the healthcare field. The pie chart Figure 7 shows that IoT technologies diagnose 29% of cardiovascular diseases and 14% of nephrology diseases. Diseases regarding endocrinology, genetics, and gastroenterology are regularly diagnosed 3%, 4%, and 6%, respectively, and need high-end technologies and IoT devices to improve healthcare. This pie chart provides researchers with an idea to improve their work in this field.

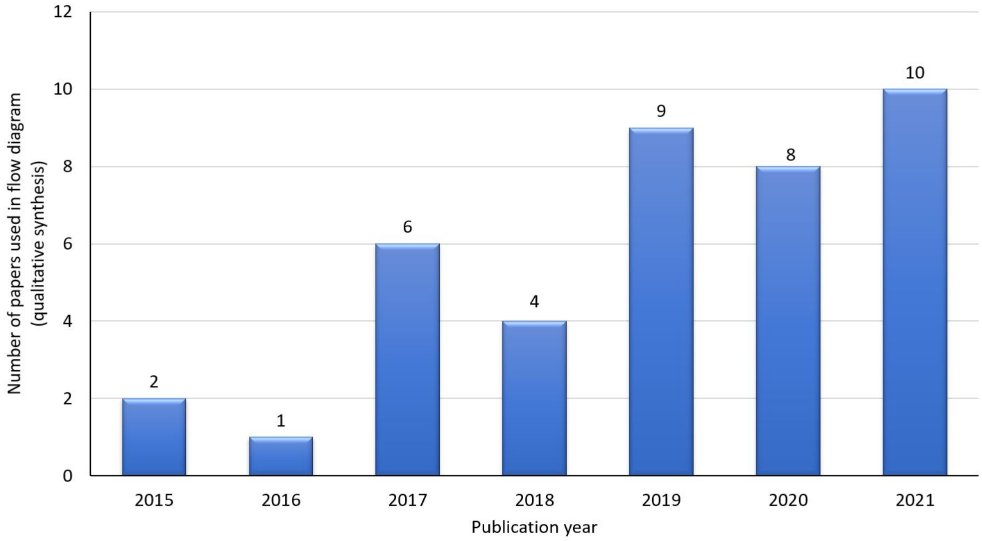

Figure 6. Number of papers used in flow diagram in order to complete qualitative synthesis.

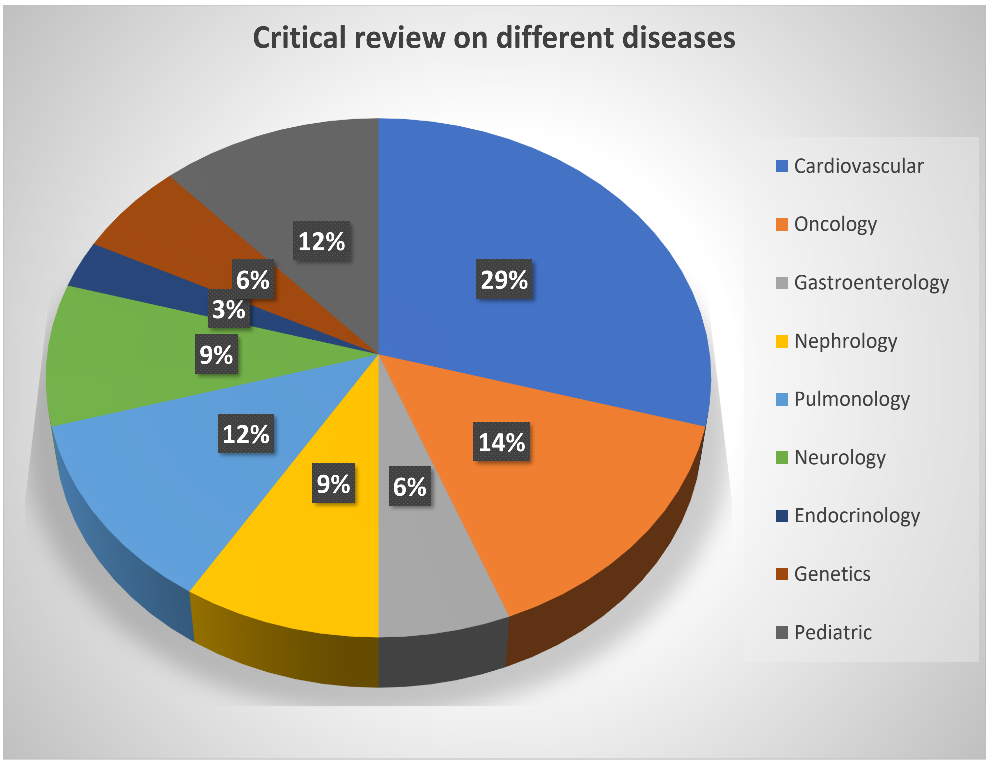

Figure 7. Critical review on different diseases.

Table 4. Critical review on various diseases research.

S.No	Diseases	Review%	References
1	Cardiovascular	29%	[1,3,5,7,10,12,50,58,59,65,71,74]
2	Oncology	14%	[9,10,19,51,78,79]
3	Gastroenterology	6%	[16,59]
4	Nephrology	9%	[9,10,12]
5	Pulmonology	12%	[60,74,76,77]
6	Neurology	9%	[51,52]
7	Endocrinology	3%	[16,72]
8	Genetics	6%	[37,57,61,62]
9	Pediatric	12%	[4,61,62]

7. Conclusions and Future Directions

Due to the fast propagation of smart phones and devices, the IoT has transformed healthcare from a traditional system to a more personalized one. Technical advancements have made healthcare quickly accessible everywhere to deal with healthcare issues remotely. Smart phone-based healthcare applications can furnish quick and precise forecasts with the ability to address difficulties such as avoidable expenses, stockpiling, and requests from experts to achieve the objective straightforward. Wearable IoT-based gadgets such as smart watches, smart phones, shrewd shirts, keen armbands, keen clasps, headbands, and keen dresses recognize the client's pulse, internal heat level, circulatory strain, and different exercises. IoT and fog computing has changed the lives of many, particularly elderly patients, by enabling regular tracking of health problems. Many papers concluded that the technologies have powered up the medical field, enabling faster results than manually organized data. This makes treatment faster and our lives more convenient. We have compared all the technologies of different authors with the results and patients tested by it. The surveys have been conducted in different phases. In our design phase, where the segregation process was performed, we selected some relevant information. The sensors have an essential role in the medical field; our chart shows application of different sensors annually in healthcare. Much research should be conducted in the future for more improved data. The improvement of the healthcare area is going through a high-level stage with countless innovations such as IoT sensors, gadgets, fog and cloud computing. It is implied for patient-driven predictions, diagnoses, treatments, and medicines. These days, all detecting information clients will convey well-being information to their cell phones to screen their well-being conduct and vital signs. As a result, health monitoring equipment that moves information faster while placing less strain on the currently available foundation is critical. Future work aims to further develop existing healthcare infrastructure by implementing homomorphic encryption, as in creating and estimating a system before computing time in an actual healthcare situation. Additionally, further plans are to study and operate the imminent age and the potential consequences of a homogeneous safety net for building safe healthcare applications for scientists.

Author Contributions: V.K. and A.K. (Ashok Kumar): Introduction, Organization, Literature survey, Sensors used, comparison techniques, analysis and Challenges; A.K. (Ajay Kumar): Background with Review Techniques and discussion; Y.-C.H.: Partial Background with review and editing. All authors have read and agreed to the published version of the manuscript.

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