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Edge computing in smart health care systems: Review, challenges, and research directions

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Abstract

Today, patients are demanding a newer and more sophisticated health care system, one that is more personalized and matches the speed of modern life. For the latency and energy efficiency requirements to be met for a real-time collection and analysis of health data, an edge computing environment is the answer, combined with 5G speeds and modern computing techniques. Previous health care surveys have focused on new fog architecture and sensor types, which leaves untouched the aspect of optimal computing techniques, such as encryption, authentication, and classification that are used on the devices deployed in an edge computing architecture. This paper aims first to survey the current and emerging edge computing architectures and techniques for health care applications, as well as to identify requirements and challenges of devices for various use cases. Edge computing application primarily focuses on the classification of health data involving vital sign monitoring and fall detection. Other low-latency applications perform specific symptom monitoring for diseases, such as gait abnormalities in Parkinson's disease patients. We also present our exhaustive review on edge computing data operations that include transmission, encryption, authentication, classification, reduction, and prediction. Even with these advantages, edge computing has some associated challenges, including requirements for sophisticated privacy and data reduction methods to allow comparable performance to their Cloud-based counterparts, but with lower computational complexity. Future research directions in edge computing for health care have been identified to offer a higher quality of life for users if addressed.

1 | INTRODUCTION

In terms of computing power and response time, modern and next-generation health care provide a multitude of services that have created a new set of requirements. In order to function at the peak of their ability, these newer devices require swift and energy-efficient computing, greater storage capacity, and location awareness that traditional cloud computing cannot cope with.[1,2] Perhaps the most promising technology, proposed first by Bonomi et al,[3] is fog computing, which is sometimes termed "edge computing" due to fog referring to the movement of computing to the edge of the network. The predecessor of edge computing, mobile cloud computing (MCC), is characterized by high data transmission costs, long response times, and limited coverage. Two similar computing methods, cloudlet and local cloud, offer inferior quality of service (QoS) for new devices. The high costs associated with data transmission come from the high network traffic, which affects the transmission times.[4] Although cloudlet-based solutions have lower latency than MCC, they still fail to secure the needed mobility for devices because of limited Wi-Fi coverage.[1] Many works have compared the performance of cloud-based and edge-based computing and found that only edge-based computing can fulfill modern requirements for latency,[5,6] mobility,[7-9] and energy efficiency.[10] In one instance,[5] the use of cloud-only computing in video analytics resulted in a doubled response time compared with client-only computing. The improved performance of edge computing compared with traditional cloud computing can be utilized especially by the health care sector for many applications. Edge-based solutions provide the framework for reduced latency for time-dependent solutions, such as vital sign monitoring[7,9] or fall detection for the elderly.[11,12] They can also give users added security compared to traditional computing, which allows for blood pressure, heart rate, blood sugar, and health history data to be transmitted to caregivers via a connected system.[7,8,13] As a result of improvement in tracking and mobility that comes with edge computing systems, health providers can care for people with chronic illnesses in their own homes using ambient sensors placed around their homes in conjunction with wearable vital sign sensors.[14,15] These sensors can collect location-dependent data, both indoor and outdoor, which allows health care workers to determine whether a patient is in danger. Health care can now become a personalized service, tailored specifically to each individual and their needs. To properly provide real-time quality service to patients, the edge devices and nodes need data operations to perform with low latency, energy efficiency, location awareness, and a high level of security. The identification of specific data operation techniques that allow for quality performance of an edge-based health care system is the main goal of this survey. In turn, this information can be used to provide the optimal classification, authentication, encryption, and data reduction methods for the deployment of an edge device. In the remaining sections of this paper, various topics will be discussed, including the following.

- Review of current surveys on health care
- A background of health care applications and their quality-of-experience requirements for future edge computing–based health care systems. These requirements include low cost, low latency, high level of security, location awareness, and energy efficiency.
- A discussion of cloud and cloudlet-based solutions and their outdated capabilities
- Edge-based solutions and their architecture, benefits, and enabled applications
- Taxonomy of edge computing–enabled health care classified by data operation and meeting the 5G performance targets
- Open research areas and issues

2 | PAST WORK AND CONTRIBUTIONS

Health care–related technology surveys have appeared in publications since the early 2000s. These legacy surveys, however, do not take into account recent growth in the Internet of Things (IoT), fog computing, 5G, and requirements associated with these areas. Table 1 represents an overview of the different attributes covered in past health care surveys, as well as new attributes added by this survey. These attributes cover different aspects of IoT-based health care, such as security, energy efficiency, and cost. More recent surveys that do consider these new topics in the health care domain tend to focus on the types of available monitoring that edge computing provides, such as EEG, heart rate monitoring, and fall detection. Architecture types, including the communications standards and platforms used by these applications, is another popular topic. However, discussion of specific computing techniques was left untouched in the existing surveys. This survey provides an exhaustive review of the most recent literature on optimal computing techniques for edge computing platforms and details on how each of the health care requirements are fulfilled.

Apart from the health care surveys shown in Table 1, there is a considerable number of surveys[26-36] solely focusing on mobile edge computing (MEC) applications. Although these surveys cover extensive topics in edge computing, they fall short on providing enough considerations for the requirements that are specific to health care. These surveys also fail to outline actual computing techniques that can aid in the creation of an edge computing system for health care. Computing techniques cannot be overlooked as it is a major part of deployment success for health care edge/fog applications.The unique contributions of this survey are as follows:

- This paper identifies a needed shift from centralized cloud architectures to distributed fog- and edge-based architectures that better meet the needs of a modern health care system with an excess of medical data as compared to legacy systems. For this purpose, we have created a taxonomy to clearly identify the literature related to 5G performance targets that can support these health care applications.
- This paper gives a short description of the evolution of health care services offered throughout the 21st century, their shortcomings, and how low-latency networks enable efficient remote medical monitoring in the next-generation 5G-enabled health care systems.

TABLE 1 Previous surveys in health care

Reference	Topics covered								Focus
	Security	Privacy	Usability	Energy efficiency	Low latency	Cost	Fog/Edge	5G	
Varshney[16]	✓	✓	✓			✓			**Infrastructure reliability**
Postolache et al[17]	✓	✓	✓						**Sensor and monitoring types**
Aun et al[18]				✓				✓	**Material and antenna types**
Elayan et al[19]	✓		✓					✓	**Wearable device types**
Thakar and Pandya[20]									**Monitoring types**
Kumar[21]							✓		**Architectures, sensor types**
AbdElnapi et al[22]									**Sensor types, uses**
Baker et al[23]	✓	✓							**Architectures, sensor types**
de Mattos and Gondim[24]	✓			✓	✓			✓	**M2 M communications**
Mahmoud et al[25]	✓	✓		✓			✓	✓	**IoT technologies, protocols**
This survey	✓	✓	✓	✓	✓	✓	✓	✓	**Optimal data operations**

- This paper goes beyond existing surveys in health care by offering a comprehensive review on research done in the state-of-the-art low-latency, energy-efficient, and secure computing for health care edge devices. This is categorized by type of data operation, including transmission, encryption, authentication, classification, data reduction, and prediction. Metrics for each category are discussed and techniques are compared for optimal performance. This comparison can serve as a benchmark for identification of the ideal edge computing techniques in a given deployment scenario.
- This paper presents comprehensive discussion on challenges in edge computing for health care and identifies the research directions therein. Notably, it discusses the three primary challenges faced by health care edge computing: (1) coping with large data sets produced by medical sensors, (2) the legal issues associated with a patient's personal medical data, and (3) the integration of artificial intelligence in a 5G environment.

3 | EVOLUTION OF HEALTH CARE COMPUTING

This section discusses preliminaries of health care computing and motives for progressing from centralized cloud computing to a more distributed architecture, which is the basis of edge and fog computing. Figure 1 shows this shift from legacy medical technology to an edge-enabled vision of health care. Also discussed are the specific qualifiers of edge health care in terms of cost, energy efficiency, and quality of experience.

3.1 | Health care application types

There are several ways of categorizing health care applications. They can be grouped by device type, data type, or by specific use cases. Based on use cases, the main health care classes are the following:

- Real-time health monitoring
- Emergency management systems
- Health-aware mobile devices
- Health care information dissemination

Real-time health monitoring can utilize multiple platforms simultaneously. As an example, health monitoring of vital signs can be done on a smartphone device,[8] wearable sensors,[7] or both,[14] which can be seen from Figure 2. Emergency monitoring systems are similar to real-time health monitoring except that they generate an alarm when a patient's vitals drop below a certain threshold. With the advent of advanced mobile devices, patients are equipped with diagnostic faculties in the palm of their hand. Health care information is readily available on many websites, and now, through mobile devices, personalized applications further provide health information and advice for patients, especially regarding specific chronic illnesses.[37,38] Modern health care also comes in different forms for the user:

- Wearable sensors
- Smartphone-based sensors
- Ambient sensors

Wearable sensors can detect heart rate abnormalities, blood pressure, body temperature, or glucose levels faster than legacy technologies, such as finger prick glucose testers. Sensor data from an edge computing application is commonly sent longer distances to a server. Smartphones are capable of harnessing built-in sensors, such as the microphone or gyroscope, for medical purposes.[39,40] Unlike wearable and smartphone-based sensors, which are physically closer to the patient, ambient sensors are placed around a room or number of rooms to collect data on user position without the patient wearing them. They allow for a greater amount of ease, and this setup is frequently used in applications involving fall detection or, in dementia cases, for location tracking of the elderly. Ambient sensors can have standalone indoor or standalone outdoor location capabilities, or both in some specialized sensors.

3.2 | Cloud-based solutions

Cloud-only medical architectures comprise of a mobile device, cloud servers, and a network. These components may have large distances between components, which further aggravates the problem of high latency (shown in Figure 2). Recently, many medical monitoring solutions have included a comparison between traditional cloud architectures and a distributed, or fog, approach. When using cloud-only solutions, the data retrieval times are too high for a real-time emergency scenario, such as fall detection or stroke mitigation, both of which require swift response times from medical professionals.[8] Frequently sending information to the cloud for computation accounts for higher power consumption and

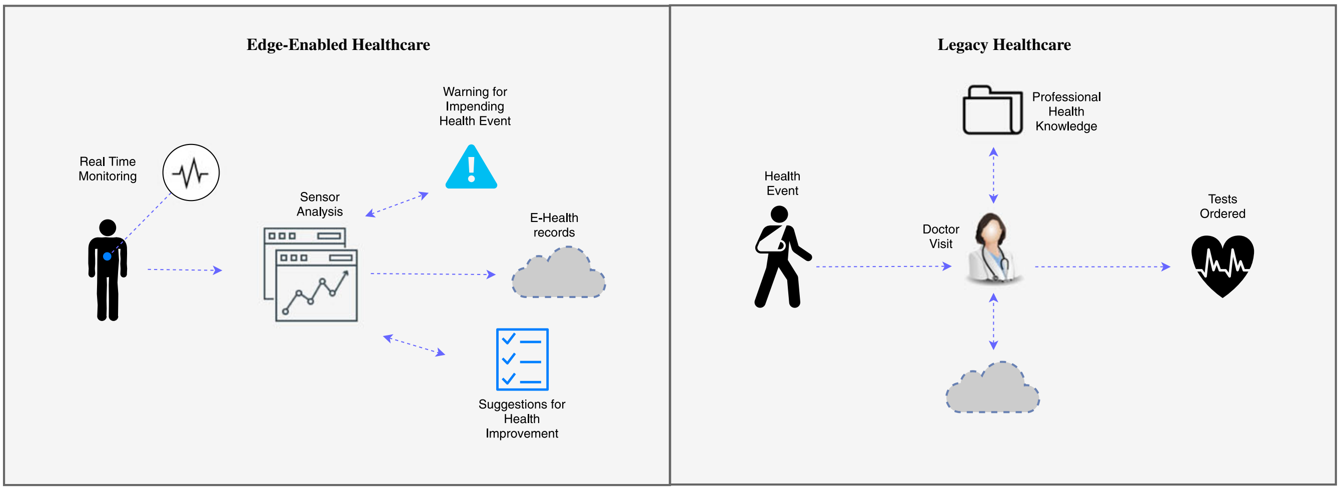

FIGURE 1 Comparison of edge-enabled and legacy health care

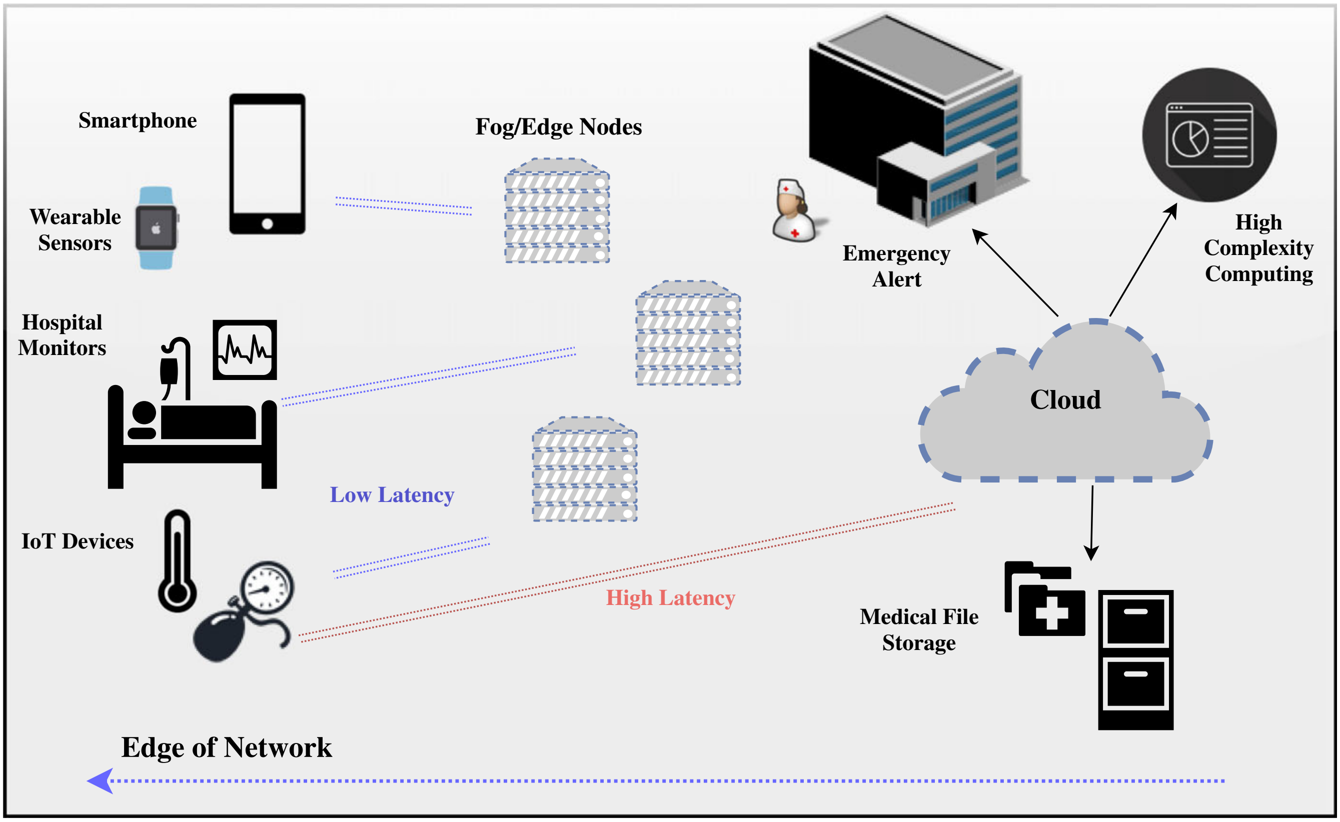

FIGURE 2 General fog/edge architecture for health care systems. IoT, Internet of Things

costs associated,[2] even more so today, when the amount of data generated by sensors is very large. A typical cloud service proved to have high latency and low sustained performance compared to distributed computing architecture with several computing nodes at different geographical locations.[6] Cloud-based solutions also do not offer the user a low-cost mobile environment, which is required for many of the patient monitoring scenarios.[12]

3.3 | Edge- and fog-based solutions

Edge- and fog-based solutions move the data processing closer to the network edge, which allows for faster response times and increased energy efficiency. Instead of constantly moving data to the cloud for computing operations, which

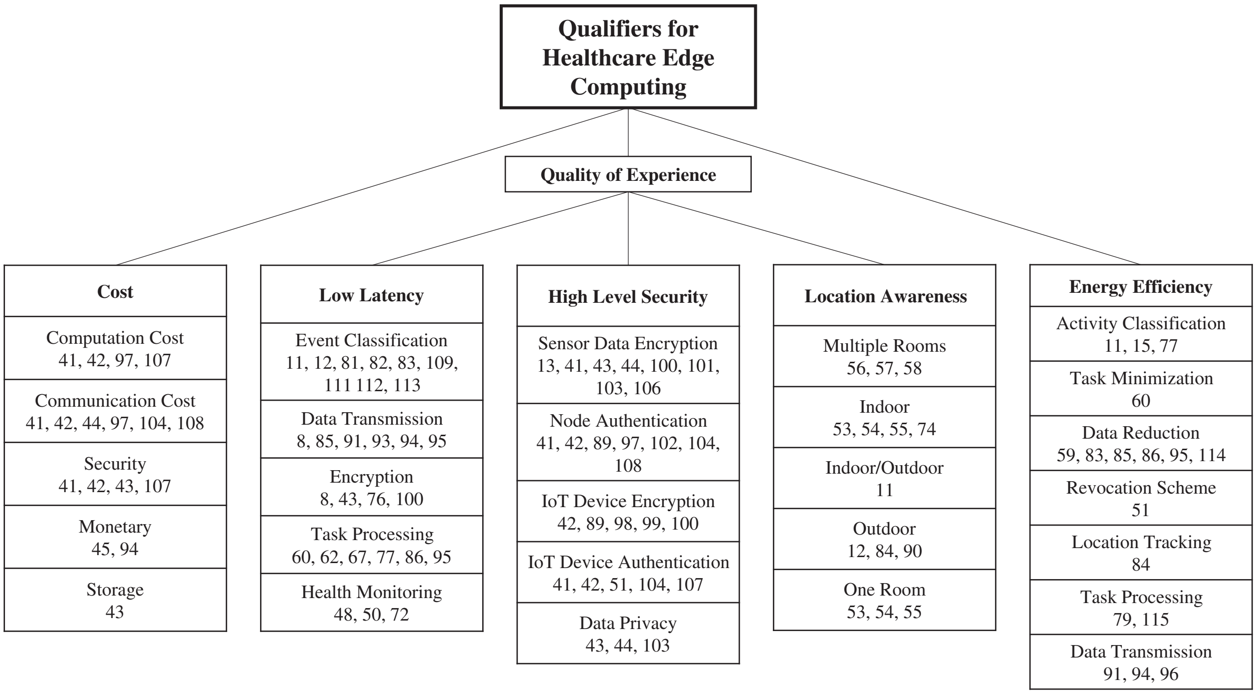

FIGURE 3 Quality-of-experience literature survey

accounts for the energy costs, data can be mined and processed on edge devices and servers closer to the user.[12] For cases involving health monitoring, low latency driven by edge and fog solutions allows for emergency medical help to arrive in a timely manner. Due to the large amount of data traditionally sent to cloud services, privacy and security remains a key issue, especially in cases where a patient's medical data could be hacked. By distributing information across a fog instead of concentrating important information in one part of the network, enhanced privacy can be achieved.[41] Ease in usability in the devices is also important because these sensors must be user friendly enough for untrained personnel to use correctly for accurate data transmission. The next section addresses the specifics of edge- and fog-based solutions that have achieved the requirements for the next generation of medical devices. Existing works that focus on each of the requirements are outlined in Figure 3. The specific requirements addressed are as follows:

- Cost
- Low latency
- High-level security/privacy
- Location awareness
- Energy efficiency
- Usability

3.3.1 | Cost

Of the multitude of challenges associated with implementation of MEC in health care applications, the operating cost for the provider as well as the user are critical. There are several variants of cost, for instance, high memory usage (function of encryption block size, key length), sensor power consumption, memory usage, and computational costs. As preservation of client data is of utmost importance in health care applications, comparison of different security models in terms of key generation time, memory requirements, bandwidth requirement, and encryption/decryption time have been examined in recent literature.[41-43] While maintaining security and privacy of individual patient data is important, it must be done within manageable computational constraints, both from the perspective of clients' decryption load as well as the provider's edge computing resources. Identity-based encryption techniques assisted by decryption outsourcing has been shown to enable small firms to shift the computational burden to the edge at a lower latency cost and throughput overhead.[44] Another factor to consider in the deployment of tele-health and tele-care services is the expenditures (CAPEX, OPEX) for a robot-care service provider. One study carried out[45] demonstrated the financial feasibility of a robot-based service care deployment architecture in a health care facility. The return on investment is shown to be negative for at least four years after the deployment based on present estimates. Such a deployment would make a stronger case if it can outperform human force and yield higher service duration for the same cost.[46]

3.3.2 | Low latency

For many health care–related use cases, real-time processing is a key requirement. Fog and edge solutions offer a lower latency compared to traditional cloud solutions,[47] and some specific elements of the system design allow for this. In existing fog deployments, an increased number of fog nodes contributes to a lower latency in data transfer.[9] Various edge mining techniques can also contribute to lowering the amount of time spent transferring data to cloud or fog/edge nodes for computation or storage. In current literature, the most popular case requiring low latency is elderly monitoring in homes. In some setups,[48-50] sensors collect patients' data on current body status and transmit to a personal digital assistant (PDA) or mobile phone, which does local processing and alerts family or emergency services if a fall is detected or a deviation from healthy heart rate or blood pressure is recorded.

3.3.3 | High level security/privacy

Due to the confidential nature of health and location information, it is important to guarantee users a high level of security.[31] Health information at the edge of the network, often on mobile devices, must be encrypted before transmission to other nodes. Due to the energy constraints, this must be done in an efficient but effective manner. A large number of possible computing nodes give rise to new ways of obtaining a patient's information, but at the same time, could allow for a higher level of privacy due to distribution of vital information. To mitigate the possibility of intrusion, authentication protocol and trust ratings are used in edge computing applications.[51] A more in-depth review of security mechanisms is included in a later section of this paper. Patient information intrusion has legal implications in many countries. For example, in the United States, HIPAA (Health Insurance Portability and Accountability Act of 1996) calls for the safeguard of health information and any breach of health data could result in a lawsuit.[52]

3.3.4 | Location awareness

Location awareness is also a critical requirement for health-related edge computing because it allows for the patient to be found in case of a health-related emergency. By using localization techniques specifically made for edge applications as opposed to more expensive GPS location systems, a greater level of accuracy can be achieved.[53] Using only a cloud server and a simple infrared sensor, a person's position within the home, indoor or outdoor, can be inferred using algorithms. There are different levels of coverage for location tracking applications. For instance, some[54,55] have systems that allow for a single room to be monitored, whereas others[56-58] give location awareness for multiple (three to four) rooms in a home.

3.3.5 | Energy efficiency

Edge computing continues to outperform cloud computing in terms of energy efficiency. Several works[9,47] show that a distributed architecture consumes less power than traditional cloud computing. However, with the distributed computing being performed on smaller devices, a primary concern is developing computing applications that will preserve limited battery life. Lower energy thresholds can be achieved by carefully creating or choosing encryption schemes and classification techniques for the health care applications.[7,11] Edge mining, which reduces the amount of packets transmitted to fog or cloud nodes, can also significantly decrease the amount of energy consumed.[59] Proper resource management can also be a contributor of high energy efficiency.[60,61] In this context, Dey et al[62] proposed a scheme for idle resource management that aims to utilize free computation slots on smartphones in edge clusters.

3.3.6 | Usability

Mobile devices, such as smartphones, have sufficient computing capabilities to run edge computing health care applications. However, these applications must also be easy enough for patients with no medical or technical training to use. For example, in one study,[11] a smartphone fall detection system design takes into account the changing position of a phone in a person's pocket. The algorithms that run on the phone are robust to orientation and location of phone on the body. Other elderly monitoring systems use ambient sensors placed around a room or multiple rooms so that very little human intervention is needed. Similarly, wearable sensors in health applications must be simplistic in their design and not too cumbersome for a patient to wear in everyday life. Overall, health edge computing devices must be simple to use, robust to changes in position, and allow for natural body movements.

3.4 | Edge computing trade-offs in health care systems

Edge computing contributes in improving the health care standards by providing faster and more comprehensive treatment ubiquitously. Through large-scale deployment of health sensors, patient visits to hospitals and clinics can be reduced, especially through deploying devices that can provide computing capabilities for diagnosis of disease and patient monitoring. These edge sensor devices can be easily maintained by patients and lead to new data insights on health care through their continuous monitoring of vital signs. Computing on the edge can also lower data transmission costs by migrating necessary data from the servers to the edge. Having data in close vicinity also reduces latency issues in the Cloud platforms. Although edge computing offers many benefits, there are multiple trade-offs and challenges when using a decentralized approach. Using diverse types of platforms and servers introduces and induces a multitude of challenges that include connectivity, scaling, resource and data management, and reliability of nodes. The integration of these heterogeneous sensors and nodes would require additional resource and data management techniques on edge nodes, whereas cloud-based computing only requires one centralized management and processing facility.[31] For seamless connectivity, the interface of multiple coding languages is necessary and is one research area that requires substantial research and development. As the needs of a health care system become greater, the scale and complexity of work flows will become more difficult to manage.[63] Potential sources of bottlenecks and constraints in this dynamic system must be detected and managed in real time. Additionally, these IoT devices have lower computation and storage resources, which complicates allocation. A recent work[64] introduces the concept of EdgeMesh, which distributes the decision making for resource and computation management among edge devices within the network. EdgeMesh also has built-in capacity for resource discovery, which is necessary because IoT devices have limited knowledge of other nearby working platforms. However, additional work on optimization of the management schemes is essential. Security of personal data is another challenge that IoT for health care must address before large-scale distribution.[65] Reliability of new communication protocols for IoT usage is not extremely high, which causes failures in the network.[33] Because these failures are not reported to a centralized body, detection of flaws in an IoT network are difficult to diagnose. Furthermore, there is a dire need to conduct substantial research in the health care service management sector. The reason is that some medical requests require urgent attention before others. This requires a predefined protocol for priority services within the distributed edge network.

4 | EDGE COMPUTING SOLUTIONS FOR HEALTH CARE

This section outlines existing solutions for health care edge computing. Figure 4 outlines the basic structure of the section and includes all of the relevant citations from the main body of the section. The first topic discussed is proposed architectures, where within the architectures are the individual components, including edge device, fog or edge nodes, and the Cloud, as shown in Figure 5. This figure also shows the locations where the different computations within an edge- or fog-based network take place. These types of operations performed on edge and fog nodes or devices is the topic of Section 4.2. We discuss in depth the retrieval, encryption, classification, and compression techniques and analyze their performance in terms of energy efficiency, latency, and accuracy.

4.1 | Architectures

General architecture of an edge computing solution typically consists of a user device, sensor, or IoT device, a smartphone with computing capabilities, and an edge, fog, or cloud computing node. The computing is often distributed between the user device and the fog node. The relationship between edge and cloud is an important aspect of the architecture. The edge focuses on fast intervention, whereas the cloud's benefits are realized in terms of long-term data. This relationship brings about challenges in load balancing and routing on edge and cloud servers.[66] Table 2 shows the general architecture and the usual types of devices used. A recently proposed architecture[61] includes considerations for an IoT layer in addition to a fog and cloud layer, which is a common setup in literature for a fog or edge health care system. In this IoT layer, all medical sensors are operated over an IoT network with each device having a unique identifier. The data are then transferred to a fog layer via Bluetooth, ZigBee, or Wi-Fi for computations and aggregation. The destination of this medical data is a data center layer or Cloud for more intensive processing tasks. This common setup allows for computing to be done with lower latency as compared to a purely centralized approach. The individual components of a common fog computing environment are outlined in the following subsections.

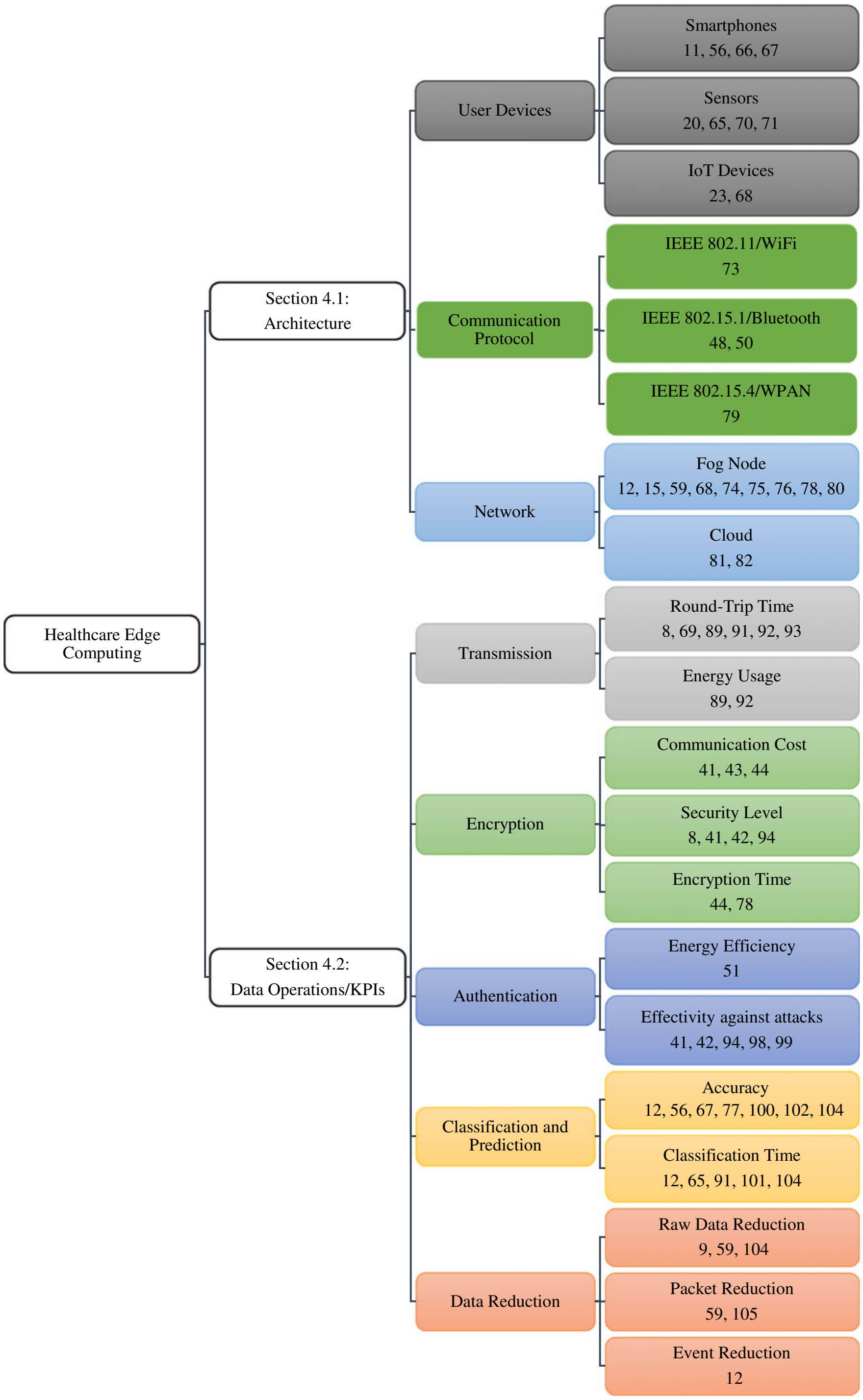

FIGURE 4 Key paper sections. IoT, Internet of Things; KPI, key performance indicator

4.1.1 | User devices

At the very edge of the network is the user device. Often the user devices can manage some computing before more power-intensive tasks are performed in a separate edge or fog node. These devices can be categorized in three major groups-smart devices, legacy medical instruments, and IoT-based sensor kits. Earlier versions of edge computing utilized low cost devices, such as Nokia mobile phones or PDAs.[78] As companies began releasing smart devices in bulk, smartphones such as the Samsung Galaxy S3[11] became more affordable for health care applications. Mobile phones can utilize built-in sensors or microphones to generate health data such as heart rate or to measure detailed heart sounds. Although the smartphone-based sensors offer ease of usage to patients, it is limited in the variety of sensors that can be embedded in its hardware. On the other hand, dedicated medical sensors have the capability to generate and handle larger sensor data, which leads to more accurate diagnoses. Common uses of sensors include heart and respiration rate, blood pressure, and

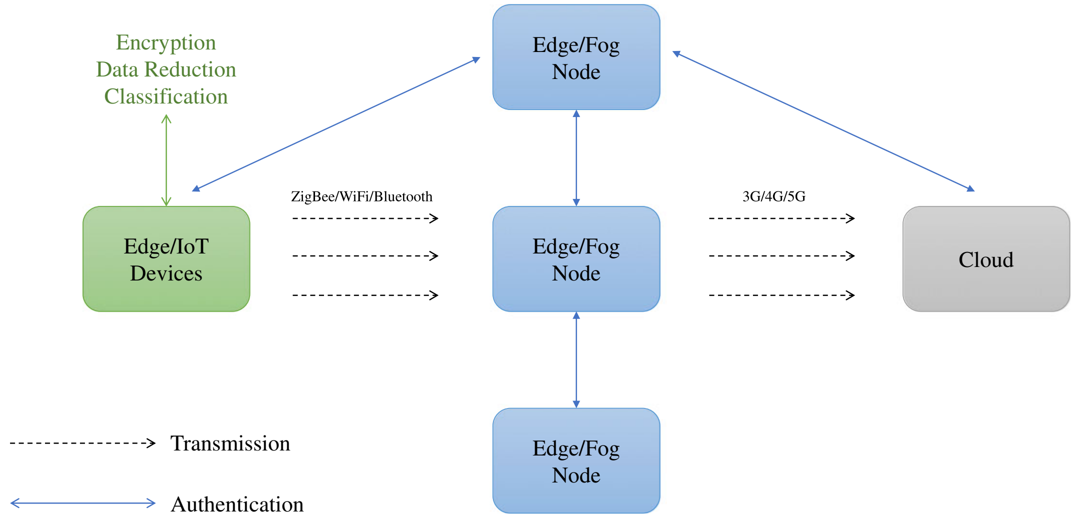

FIGURE 5 Locations of data operations in relation to architecture. IoT, Internet of Things

glucose levels for health monitoring. Additional sensing capabilities include determining motion states, such as activity type, number of steps, or sleep cycle.[20] The newest trend for health edge computing is the use of IoT devices. These devices diverge from the traditional sensor category due to their mutual interconnectivity, which is absent in legacy health care sensors. Multiple devices, sometimes placed across the body, are connected to a network and can also communicate with each other using different machine-to-machine (M2M) protocols.[23] However, an aspect that has been explored in recent times is the optimal placement of these sensing devices. Table 2 summarizes common sensor types and placement on the body for wearable devices in literature. Novel user devices, such as the wireless capsule endoscope (WCE),[79] or specialized prototype device,[80] could also potentially be used as an edge user device. Another aspect of creating an easy-to-use health care system is to provide users with an acceptable level of visualization on their device. For example, the authors of one application[37] talked to front-line health professionals and discovered that resources for pregnant women were often lost, and in the cases involving multicultural women, interpreters were often limited, so their application was created with plenty of information for these soon-to-be mothers. Some applications[4,38] take usability to a higher level by providing customizable applications for patients. Ensuring that information provided to patients over an application is clearly understandable to nonprofessionals is another issue. The authors of another publication[81] use graphs and other visuals to aid patients in understanding health data and provide a clear menu for navigation of an application.

4.1.2 | Communication protocols

Communication between a device and fog node is done with short-range communication protocols, such as IEEE 802.15.1 or 802.15.4. Often a sensor node will be connected to additional computing devices or cloud services using a wireless 802.11 protocol[82] that involves using a sensor node, mobile computing devices, and a cloud service. Many applications[48,50] utilize IEEE 802.15.1 or Bluetooth as a protocol for communication between a medical device and a smartphone, where computation is done. Once a small amount of computing is finished on the smart device, data are transferred to a doctor or an additional server via a mobile communication service such as 4G or 5G.

4.1.3 | Network

Once information is gathered at the very edge of the network where the sensors exist, it travels toward the near end and far end of the network to be stored or, in some cases, additionally processed. Using a fog node can give a health care system greater computing power that smaller handheld devices might not be able to achieve. In an edge computing architecture, data operations, such as classification or compression, are completed at the edge of the network. These edge nodes are often small servers that allow for the fast processing of data that mobile devices cannot achieve. Edge or fog nodes can be a multitude of devices, deployed at different distances between the Cloud and edge user device, depending on the operating range. In previous literature, commercially available products such as Raspberry Pi,[12] Arduino,[15,83,84] and field-programmable gate array (FPGA)[85] platforms served as edge gateways. These are popular solutions because of low cost and simple programming. Other research studies use a graphics processing unit in cases where pictures are the data input to be computed.[67] Other popular nodes are Telos Mote[59,77] and Intel Edison,[86] especially for cases involving

TABLE 2 Sensor architecture and design of wearable health Interent-of-Things devices

Sensor placement	Operating platform	Measurement	Reference(s)
Helmet	ZigBee	Galvanic skin response, brain wave	Liu et al[1]
Around neck	Smartphone	Images	Castro et al[67]
Chest	Google Nexus 4 smartphone	Heart sounds	Thiyagaraja et al[8] and Chandrasekaran et al[40]
Arm	Arduino Lilypad	Motion	Dasios et al[58]
Wrist	Fitbit ChargeHR	Motion, heart rate, sleep	Hu et al[56] and Yacchirema et al[68]
	MPU-9255 Inertial Motion Unit	Activity events	Bhargava and Ivanov[12]
	Android smartwatch	ECG, speech	Dubey et al[69]
	Light emitter, accelerometer	Heartbeat, motion, temperature	Wu et al[50]
Trouser pocket	Samsung Galaxy S3 smartphone	Fall events	Cao et al[11]
	Samsung Galaxy Note2 smartphone	Location	Ozen et al[70]
Multiple body parts	Libelium sensor kit	Temperature, ECG	Bhunia et al[15]
		Blood pressure, pulse	Lv et al,[48] Azimi et al,[71]
	Traditional ECG leads and sensors	ECG, blood oxygen	Gia et al,[72] and
		Temperature, pulse	Wang et al[73]
	Arduino	ECG	Jusak et al[74]
Ankles	Inertial measurement unit (IMU)	Gait	Mazilu et al[75]
Walking stick	Cellular module	Location	Tang et al[76]
Shoe	Pressure sensor	Freezing of Gait (FoG)	Jamthe et al[55] and Ghosh et al[77]

Abbreviation: ECG, electrocardiography.

ambient sensing. Telos is a collection of sensing devices developed by the University of California Berkeley for wireless sensor network research that utilizes WPAN/IEEE 802.15.4.[87] Intel Edison,[88] although now discontinued, it is similar to the Telos mote, except that it is compatible with IEEE 802.11 and IEEE 802.15.1. Most of the papers surveyed have some connection to the Cloud; however, the focus of these papers is to demonstrate that the majority of computing should be done at the network edge to decrease the strain on the Cloud and to reduce latency. After computation is done at the edge of the network, additional computation or storage might be necessary, which is why information is sent further away from the user to the Cloud. The Cloud has a higher computing capacity than fog or edge nodes because it utilizes multiple servers for parallel computing and further analysis. Additionally, the Cloud has data centers that allows for more data storage that is sometimes needed for patient records.[89] Some research[90] also explores the relationship between fog and cloud, which outlines a fog-cloud architecture for the balancing of node workloads for large event streams.

4.2 | Data operations

Current research in edge computing for health care focuses on measuring certain key performance indicators (KPIs) that are important for the progression of health services, such as response time, energy efficiency, and bandwidth cost. Papers tend to focus on optimizing the KPIs related to a particular section of the edge computing architecture, for instance, either the edge device or fog node in a given system. The aim of this section is to provide a detailed overview of best data operation techniques for a health care edge computing scenario. The six basic operations discussed are retrieval, encryption, classification, authentication, data reduction, and prediction. Because security is a major focus for health care because of sensitive personal data, the trade-off between low latency and high security within protocols is discussed.

4.2.1 | Transmission and retrieval

Data retrieval accounts for some latency in health care applications. Table 3 outlines related works on energy-efficient and low-latency data transmission and retrieval. For example,[8] transferring data to a cloud service increases the latency of the system by 2.71 seconds. Using a smartphone for distributed computing decreases the latency in transmission to 0.13 seconds versus 2.84 seconds using cloud-only architecture. Some techniques focus on using data selection to choose which information gets sent to the server or Cloud for further computing. Another research[91] uses a Nash bargaining approach for selecting anomalous data to be transferred to the Cloud for further storage. This approach outperforms the traditional Cloud in terms of latency and power consumption. A similar approach, called HiCH,[71] shows that the HiCH architecture has a lower data dissemination delay as compared to a baseline IoT system. Electrocardiography, or ECG, is a common medical procedure in which the electrical activity of the heart is analyzed over a period of time.[96] Abnormalities in this measurement can point to health conditions that normally go unnoticed, which makes it a popular test for edge computing devices. In some cases,[92] ECG data are transferred to an Amazon cloud server for computing and the round-trip time is compared for sending the same information to an edge gateway. As expected, the edge gateway transmission has a much lower round-trip time as compared with the Cloud.

4.2.2 | Encryption

Some encryption techniques used on edge devices are more energy efficient than others. If a device has a lower energy encryption scheme, a higher percentage of available energy is able to be utilized for computing. Table 4 summarizes the different encryption schemes proposed for edge computing–based health care devices. One very popular encryption technique on smart edge devices is elliptic-curve cryptography (ECC). As an example,[101] a key is generated using ECC on the edge device and key agreement is performed using the Diffie-Hellman (DH) scheme. In another work,[8] the authors show a way of efficiently measuring heart rate and blood pressure using smartphones and extend their work to include a secure encryption mechanism. They choose ECC primarily because it requires a much lower key size, which is optimal for a smartphone with relatively limited storage and computing resources. Another work[41] also uses the ECC form in combination with bilinear pairing IBE to lower the bit cost for a 256-bit security level compared with an RSA form in a fog architecture. Another source of encryption is hardware based, such as the lightweight KATAN ciphers on field FPGAs.[102] Tang et al presented a framework called the privacy-preserving fog-assisted information sharing scheme (PFHD).[43] This scheme has privacy preservation on both the fog and cloud layers. Their encryption scheme (PFHD) is compared with traditional ciphertext policy attribute-based encryption (CP-ABE) in terms of cost. The storage cost and encryption time of PFHD is lower because of ciphertext storage on the fog device. A proposed personal access policy method by Tang et al is compared with CP-ABE and is found to have a lower energy consumption for the same number of attributes.[103] A comparison[77] shows that, for the same level of security, RSA and Diffie-Hellman have a higher key size as opposed to ECC

TABLE 3 Related works on data transmission and retrieval

Reference	Technique	Contribution	Results
Thiyagaraja et al[8]	Smartphone computing	Comparison of distributed versus cloud computing	Blood pressure analysis done fully on smartphone has lower latency than cloud platform; data retrieval from Cloud incurs time overhead
Azimi et al[71]	Hierarchal fog-assisted computing (HiCH)	Low-latency transmission	HiCH architecture has lower latency than the baseline IoT system
Roy et al[91]	Critically-aware data transmission (CARE)	Low-latency and energy-efficient transmission	Compared with Cloud, CARE has reduction of data dissemination delay and power consumption
Hosseini et al[92]	EEG data transmission	Low-latency transmission	Lower round trip time for edge gateway compared with Amazon Cloud
Mahmud et al[93]	Distributed fog computing	Low-latency transmission	Using fog node for computing reduces data size and transmission time compared with sending all raw data
Wang et al[94]	Fault-tolerant transmission	Low-latency transmission	Fault-tolerant data transmission increases reliability of medical fog system
Pace et al[95]	Distributed computing	Low-latency transmission	Reduced round trip and processing time for edge-assisted computing

or symmetric encryption. Therefore, the authors use an ECC-based method over IEEE 802.15.4 standard for an indoor monitoring application. Fully homomorphic encryption (FHE) is used by many works for its ability to analyze data in an encrypted form.[97,104] In their large-scale medical smart cities architecture proposal, Sun et al[97] reduce the number of ciphertexts sent back to a receiver, which is an energy-efficient revision to an existing scheme using FHE. Achieving an efficient form of privacy is another security concern for health care systems. One such method is presented by Saha et al.[105] Their identity manager framework protects data with low time complexity by using a one-point cryptographic exchange between nodes. Recent research[98] into concealment of patient records has shown that enhanced value substitution (EVS) can achieve a high level of privacy. One of the papers[41] surveyed provided a privacy protocol called Decoy Medical Big Data (DMBD). In this method, decoy files are retrieved for every file, versus previous techniques that only have decoy files when an attacker is present. A privacy management framework ensures anonymity of patient files by storing health profiles at the user side of a fog node. Each Internet-of-Health-Things (IoHT) device is protected with a pseudonym to reduce linkage to real health data for each patient. Furthermore, a clustering technique ensures privacy by a two-stage concealment process that disfigures data structures in patient health data. A recently developed framework[99] provides additional defense against quantum attacks, which have emerged from recent advances in quantum computing.

4.2.3 | Authentication

Authentication is another requirement for a secure health care computing system that is closely related to encryption, so it has also been a focus for fog and edge computing technologies in health care. Table 5 provides a review on proposed literature in secure and energy-efficient authentication protocols for edge-based health care systems. Authenticated key agreement (AKA) proves to be a guarantor of privacy for health care applications, based on a study by Jia et al.[101] AKA achieves perfect forward privacy and is immune to many different types of attacks, including offline dictionary, stolen verifier, and replay. Another work[108] introduces a novel way of generating a message authentication code by calculating values of interest from a patient's ECG signal and comparing the value to previously stored values. This saves the device from having to generate a key and, instead, simply sends the patient data that are verified or rejected by the server based on the data characteristics. Because fog computing has been a recent trend, a multitude of papers on fog node authentication has been published.[41,42,51] One such paper[51] provides certificate revocation scheme for increased energy efficiency. It outperforms two other schemes, namely, certificate revocation list (CRL), and online certificate status protocol (OCSP), in terms of packet size reduction and communication overhead. Other fog node authentication schemes[106] deviate from the quantitative cost analysis and instead provide attack immunity explanations. The node authentication in this work is immune to attacks such as replay, user impersonation, and session key discloser attacks. Al Hamid et al use a mutual authentication protocol so that each party (node) must authenticate the other to ensure security before any messages

TABLE 4 Related works on encryption

Reference	Technique	Contribution	Results
Al Hamid et al[41]	Bilinear pairing IBE	Energy-efficient encryption	For 256-bit security level, ECC performs with lower bit cost than Rivest-Shamir-Adleman (RSA)
Giri et al[42]	Elliptic curve cryptography (ECC)	Low-latency encryption	ECC has low time complexity but has higher communication cost
Tang et al[43]	Privacy-preserving fog-assisted information sharing scheme (PFHD)	Low-latency encryption	Encryption time for PFHD is lower than ciphertext policy attribute-based encryption (CP-ABE)
Lin et al[44]	Boneh-Franklin identity-based encryption (IBE)	Energy-efficient encryption	For 50 attributes, 11 MB of overhead and 1000 s of time cost
Ghosh et al[77]	Modified elliptic curve cryptography (MECC)	Energy-efficient encryption	Marginal amount of overhead
Sun et al[97]	Fully homomorphic encryption scheme (FHE)	Energy-efficient and low-latency encryption	Their scheme has lower implementation time than a comparable scheme with the same security parameter
Elmisery et al[98]	Enhanced value substitution (EVS)	High level of concealment of patient records	Trade-off between privacy level and accuracy for higher orders of EVS
Aujla et al[99]	Lattice-based cryptosystem	High-level security	Effective against quantum attacks
Elmisery et al[100]	Ciphertext policy attribute-based encryption (CP-ABE)	CP-ABE performance Evaluation	Trade-off between the number of fog nodes and key generation times

TABLE 5 Related works on authentication

Reference	Technique	Contribution	Results
Al Hamid et al[41]	Decoy Medical Big Data (DMBD) mutual authentication protocol	Energy-efficient node authentication	Their scheme has lowest computational cost compared with other schemes
Giri et al[42]	SecHealth authentication phase	Secure authentication	SecHealth is able to protect against extraction of key and replay attacks
Alrawais et al[51]	Certificate revocation scheme	Energy-efficient fog node authentication	Their scheme has lower packet sizes than two other schemes: certificate revocation list (CRL) and online certificate status protocol (OCSP)
Jia et al[101]	Authenticated key agreement (AKA) scheme	Secure fog node authentication	Perfect forward privacy is guaranteed with the AKA scheme and is immune to offline dictionary attack, stolen-verifier attack, man in the middle attack, and replay attack
Amin et al[106]	Distributed cloud environment authentication scheme	Energy-efficient node authentication	Their scheme is immune to replay attack, impersonation attack, and session key discloser attack
Zhou et al[107]	Attribute-based designated verifier scheme	Energy-efficient authentication scheme	Low communication cost and storage overhead for their method

are sent via a mutual authentication key generated randomly.[41] A very similar authentication is used by the proposed SecHealth architecture[42] where a key is determined as equal and accepted by both parties or not equal, and is rejected.

4.2.4 | Classification and prediction

Classification of raw data collected by health sensors is normally completed using simple or advanced algorithms, depending on the computing power of the device, and is a very common research theme in health care–related computing. Table 6 summarizes techniques used to classify or predict different health care information types and their results. Activity-based recognition is the most popular research related to classification in health care edge computing because robust techniques are needed for devices that have lower storage and computing capabilities. Low energy fall detection algorithms, for example, can be deployed on a smartphone device. In Bhargava and Ivanov's work,[12] fall detection algorithms are run both on a smartphone initially and, then, on a back-end module connected to a cloud server. Different works in literature have

TABLE 6 Related works on classification/prediction

Reference	Technique	Information type	Contribution	Results
Bhunia et al[15]	Fuzzy logic classifier	Heart rate, respiration rate, skin conductance	Low-power consumption technique	Reduction in energy consumption for the fuzzy system compared with the nonfuzzy system
Hu et al[56]	One-class support vector machine (SVM) with Gaussian kernel	Visiting events, heart rate, sleep patterns	Greater classification accuracy	75% detection rate for labeled data set when Fitbit is added to the system
Aicha et al[57]	Markov-modulated multidimensional nonhomogeneous Poisson process (M3P2)	Visiting events	Comparison of classification methods	Outperforms the standard Markov modified Poisson process (MMPP)
Rodriguez et al[78]	Weka AnswerTree	ECG	Increased number of inputs than similar classifiers	Correctly classifies 96% of 17 rhythm types
Borthakur et al[86]	K-means clustering	Speech samples	Comparison of low-latency device classification	Raspberry Pi has a lower runtime compared with Intel Edison
Yacchirema et al[68]	Artificial neural network (ANN)	Gas pollution	Comparison of classification accuracy	ANN has the lowest root mean square error (RMSE) compared with linear regression and decision tree
Hosseini et al[92]	Convolutional neural network (CNN)	EEG	Low-latency classification and data transmission	Using edge gateway in place of cloud computing yields lower round trip time
Bhatia and Sood[109]	Bayesian belief network (BBN)	Vital signs, environmental data	Comparison of classification methods	BBN reached the highest accuracy compared with the support vector machine (SVM) and K-nearest neighbors (KNN)
Verma and Sood[110]	Bayesian belief network (BBN)	Vital signs, environmental data	Comparison of low-latency classification methods	BBN has the lowest classification time compared with linear regression, nearest neighbor, and KNN methods
Sood and Mahajan[111]	Weka J48 decision tree	Vital signs, environmental data	Comparison of low-latency classification methods	J48 has the lowest classification time compared with fuzzy C-means (FCM) and random tree (RT)

TABLE 7 Related works on data reduction

Reference	Technique	Information type	Contribution	Results
Bhargave and Ivanov[12]	Iterative edge mining + ClassAct	Activity state	Low-latency and accurate event reduction	Less than 0.5 second latency for ClassAct + Bare Necessities (BN) algorithm
Gaura et al[59]	Iterative edge mining-L-SIP	Temperature	Raw data and packet reduction	L-SIP performs with 95.5% packet reduction
Dubey et al[69]	Dynamic time warping (DTW)	ECG	Low-latency data reduction	DTW reduces ECG data sent to cloud by 98%
Basu et al[114]	Inexact computing + morphological filtering	ECG	Energy-efficient data reduction	Using inexact computing and filtering reduces data processing compared with zero-error computing

tried to improve the existing classification/prediction accuracy for edge-based health care device algorithms. One-class support vector machine (SVM) with Gaussian Kernel's accuracy is assessed to be up to 75% in classifying visiting events in an elderly person's home when room sensors in combination with a wearable Fitbit device is used as a data source.[56] Other works have compared several standard machine learning (ML) techniques to determine the most energy-efficient or low-latency classification method. For example, Bhatia and Sood[109] compare three types of ML techniques, namely, Bayesian belief network (BBN), SVM, and K-nearest neighbors (KNN) on a data set of breath rate and humidity level. The Bayesian belief network attained the highest accuracy compared to SVM and KNN. However, this work does not provide any quantitative analysis of the energy efficiency of these approaches, which is an oversight of much of the research surveyed. Artificial neural networks (ANNs) have exploded recently in classification because they have shown to accumulate a lower classification error than other techniques, such as linear regression and decision trees.[68] Others[92] have used a neural network, specifically convolutional neural network (CNN), to classify EEG rhythms with low latency at an edge gateway. Increasing the number of attributes can also make for a more useful program. In an early work,[78] a Weka AnswerTree correctly classified 96% of 17 different heart rhythm types, which is the highest number of heart rhythm types at the time of publication.

A small portion of recent work in edge computing for health care is prediction algorithms for different data sets such as images of daily activity. The goal of Castro et al,[67] for example, is the prediction of daily activities based on the input of annotated egocentric images taken using a smartphone worn around the neck. The authors use a CNN combined with a random decision forest (RDF) to predict activities in 19 classes. For individual classes, some ML techniques scored slightly higher than the chosen CNN technique. For reading and socializing classes, KNN had a higher accuracy in prediction than the CNN combined with RDF. A similar activity prediction method[112] uses a Bayesian network to predict the next daily activity of participants. The input in this study is sensor information from five to six rooms of the home over 4 to 6 months. The Bayesian network correctly classifies about 60% of 11 activity classes. This result is compared to SVM, naïve Bayes (NB), and multilayer perceptron (MLP) classification ability, and the Bayesian network outperforms all of these in terms of accuracy. A recent work by Sood et al uses ML techniques with patient information to predict and model the stages of hypertension in adults.[113] Using an ANN, the authors were able to obtain a lower classification time than KNN and MLP.

Another issue is predicting future network traffic to optimize data rates and routing decisions for a health care system. Muhammed et al designed and tested a deep learning network traffic analysis and prediction (DLNTAP) component that can aid this optimization.[47] Deep learning network traffic analysis and prediction relies on recurrent neural networks distributed across a cloudlet layer.

4.2.5 | Edge mining and data reduction

To cater to the exponential data storage and processing requirements at the Cloud, *edge mining* is leveraged on the edge computing devices to decrease the amount of data transmitted to a Cloud service. The existing works that include this approach to data reduction are discussed in Table 7. Based on the definition, edge mining is "processing sensory data near or at the point at which it is sensed, in order to convert it from a raw signal to contextually relevant information."[59]

Edge mining focuses on saving packets rather than individual bits of information. The General Spanish Inquisition Protocol (G-SIP) senses, filters, detects, and conditionally transmits events through the network. One setup[69] uses a GNU zip application on a fog computer to compress and decompress data to be sent. Reducing and compressing data sent across the network can account for a major part of energy-efficient systems. Bhargava and Ivanov[12] used a combined ClassAct and Bare Necessities edge mining algorithm to classify anomalous wandering activity in adults with Alzheimer's disease. They were able to classify walking and standing events with more than 97.9% accuracy and low latency. According to the authors, this approach is favored over Linear SIP (L-SIP) because the raw signal does not need to be completely constructed. Althebyan et al[9] outlined a detailed architecture for data reduction when using MEC servers as a computing resource. In this proposed system, patient sensors collect data such as temperature, blood glucose, and activity, and transmits it to cloudlets in the vicinity. The cloudlet sends only the abnormal values associated with a patient to the MEC servers and immediately wipes its memory to conserve patient privacy. The MEC system and attached decision support system therefore only has to process and give feedback for the abnormal values instead of analyzing a bulk of normal values. A reduction technique that lowers the computing complexity, called inexact computing, is used in conjunction with morphological filtering to reduce data processing for ECG data compared with zero-error computing.[114] Data reduction is also needed for the diagnosis of medical images, which often contain too high a resolution to be sent for real-time analysis. A solution proposed for this problem is compressed cellular neural networks,[115] which are superior to CNN in cases involving image processing tasks on an edge device. The authors investigate edge segmented images on an FPGA, which can be used as an edge device.

5 | FUTURE RESEARCH CHALLENGES

To allow the future 5G network paradigm to support the edge computing–based health care systems and truly realize benefits to the community, several research challenges that serve as a hindrance must be overcome.

5.1 | Large-scale health care

Most of the edge computing solutions for health care are tested in small-scale environments. One paper by Althebyan et al[9] proposes architectures that may work well in large-scale health care scenarios. The proposed system has an average delay of about half a second and about 0.003 kWH of power consumption for 150 000 users using 50 cloudlets. This accounts for a large number of users and considers a decision-making model that could help public health workers notice trends in disease spread. Similar prototype systems[86,116] simulate a medical service that can handle a large number of fog nodes. The system modeled by Borthakur et al[86] contains up to 25 fog nodes and 1000 users in each of the 10 community service nodes, whereas Kafhali and Salah's system can handle up to 25 fog nodes. However, even though both of these studies use a large number of users, they still do not compare to the actual needs of a large medical community. A health care system will need to accommodate a huge number of patients being treated in a hospital. The number of staffed beds in registered hospitals in the United States was 894 574 in 2006. The hospital admission for same year stood at 35 158 934. These numbers do not include smaller specialized hospitals such as gynecology, ENT, and rehabilitation hospitals.[117] Edge-enabled health care systems will help reduce the glaring disparity between the existing infrastructure and hospital requirements for simultaneous record storage and patient monitoring.

5.2 | Big data management

A large-scale health care system combined with real-time data acquisition guarantees that a large amount of data needs to be analyzed and secured. This issue is partially addressed in edge mining techniques, which significantly reduces the amount of data sent to cloud services; however, further reduction is needed for long-term and continuous data collection from medical sensors. Often, this data does not necessarily need to be reduced, but analyzed in bulk quantities, sometimes as large as exobytes.[118] This means that new analysis techniques that rely on data features must be developed.

5.3 | Patient information privacy

While edge-enabled health care devices enable better quality of life for patients and open revenue avenues for health care providers and 5G network operators, there are considerable concerns related to patient information privacy that will exaggerate with large-scale deployment. Currently, existing HIPAA laws are not sufficiently established to be applicable on edge-enabled health care monitoring systems. As several stakeholders such as research organizations and insurance companies view patient information as a valuable asset, any data breach will be accompanied by legal implications for both the health provider as well as the network operator.[52] To complicate matters, these laws and restrictions on patient data storage vary on country and region.[119] For example, Italy and Germany have no such restrictions. Current patient information privacy protocols focus on safeguarding personal details, such as name, address, and social security number.

In their work on ensuring health care privacy, Cavoukian et al reveal that "any information, if linked to an identifiable individual, can become personal in nature, be it biographical, biological, genealogical, historical, transactional, locational, relational, computational, vocational, or reputational."[120] Additionally, as patients acquire and own their own medical data through IoT devices, methods of patient permission-based authorization are needed. One such method is described in a blockchain-based MEC framework and is immune to unauthorized access and single point of failure.[121] In light of the stated facts, sophisticated privacy and anonymization structures are prerequisites for large-scale health care systems. Computational complex cryptographic techniques jeopardize computation efficiency, but anonymization may also have risk of breach or theft.[122] The distribution of the workload between sensor nodes and edge computing platforms without any compromise on privacy and security also remains an investigable challenge.

5.4 | Integrated AI-5G for MEC-enabled health care

Current network deployments do not have the capabilities or capacity to handle large-scale distributed sensor-based medical monitoring and reporting. Converging telecommunications and IT services from the centralized cloud platform to the edge is essential but dependent on success of multiple enabling technologies. One of the key enablers is virtualization techniques including virtual machines (VMs) and containers. While VMs provide its users a fully functional machine, regardless of the underlying hardware architecture, container environments such as Docker facilitate edge computing devices by offering light weight virtualization solutions at user devices.[123] Similarly, network function virtualization (NFV) decouples network functions and services from proprietary hardware, allowing colocation of multiple service instances over the same VM and consequentially saving in the operator's capital and operational expenditures. In an MEC-based health care environment, NFV provides the operator the ability to transfer system processes from one edge platform to another when required, for instance, when there is congestion due to flash crowd events.[124] Another crucial enabling technology is software-defined networks (SDNs). The main principal behind SDN is the decoupling of control and data plane, and introduction of a logical centralized control through which multiple virtual network instances can be initiated and offered via edge to the users. Coordination of dynamic provisioning of distributed services at the network edge is a challenge with existing network architectures. Software-defined networks are expected to play a key role in providing network connectivity and service management across heterogenous MEC platforms.[125] In addition to this, network slicing allows partitioning of one network into multiple instances, each optimized for a particular application/use case.[126,127] For instance, we may have different 5G network slices for mobile broadband, automotive communication, and massive IoT.[30] Because enhanced mobile broadband in 5G requires high capacity, several other related technologies deployed in the RAN would enable shorter transmission time interval (TTI), pipelined packet processing, efficient radio resource control (RRC), and support of larger bandwidth. Some of these supporting technologies include user-centric architectures,[128,129] massive MIMO (mMIMO),[130] and transmission in millimeter wave (mmWave) spectrum.[131-133]

While 5G deployment is a key enabler to large-scale MEC-based health care infrastructure deployment, integration of artificial intelligence (AI) is essential to provide the most appropriate and timely services to the users. Artificial intelligence will leverage many factors, such as user mobility patterns, device usage patterns, patients' vital monitoring records, and existing medical conditions to provide timely diagnosis of health problems. Recent breakthroughs in ML, and in particular deep learning, have enabled advancements in several areas from face recognition,[134] to medical diagnosis,[135] and natural language processing.[136] However, they involve complex processing of huge data sets in centralized and remote data centers and require massive amount of storage and computing power. As the entire premise behind shifting processing at the edge hinges on ultrareliable and low-latency communication (URLLC), it is imperative that distributed, low-latency, and reliable edge ML models are trained on local data. Edge ML provides dual benefits of low cost and reduced latency, which is important for mission-critical IoT sensor devices on patients. An AI-integrated 5G infrastructure for a distributed health care system may include any combination of the three major ML categories, ie, supervised learning, unsupervised learning, and reinforcement learning. More details about these techniques in relevance with edge platforms can be found in a recent survey.[137] When it comes to neural networks, there are some architectures that are more suited for MEC deployment. These include (i) auto encoders (AEs) and (ii) generative adversarial networks (GANs). An AE is a stack of two feed-forward neural networks. The first phase called encoding involves compressing the original data into a short code representation, whereas in the second phase the compressed representation is decompressed in the same dimension space as the original input.[138] Auto encoders learn distinct features of the data set, which are vital for anomaly detection, or from the perspective of health care MEC, for diagnosis of rare occurring diseases. To overcome the issue of nonavailability of huge data sets for localized learning in edge ML, GANs generate new data samples given by the estimated distribution of the input data samples. This is done from two NNs, a generator that produces fake data samples, and a discriminator that tries to identify the fake data samples created by the generator from the data set. The training reaches a Nash equilibrium when the discriminator is unable to distinguish between real and fake data points within the data set. The AI implementation at the edge can be implemented using a helper-device (h-d) split, where each device individually builds a learning model from the local data and then transfers the local model to a helper that aggregates all the models uploaded from multiple devices.[139,140] In case a local model is exceeding a device's memory constraints, the model can be split and distributed between multiple devices. The intermediate model, in this case, will be transferred between devices during forward and backward training operations.[141]

Similar to its application in self-organizing network–enabled 5G wireless networks,[142,143] the use of artificial intelligence in health care systems is common in literature, as outlined in the previous section on classification and prediction. Artificial intelligence can take in several inputs such as patient variables (age, gender, medical conditions) and use these to give more insights on abnormal values for classification, as doctors do when diagnosing a patient. This ensures a context-aware health system, which is important for personalized results.[16] Artificial intelligence techniques in literature have shown to be more useful than simple threshold-based methods. One of these described a task involving the diagnosis of lung cancer in which IBM Watson achieved a higher precision in diagnosis than the average hospital.[14] Similarly, other works for smart health care using edge computing has demonstrated higher accuracy for a voice disorder assessment[144] and high prediction of pain emotion detection[145] to allow the caregivers to proactively attend to patients' needs. Despite all the research and IoT device advancements, there is still much work to be done in improving the energy efficiency aspect of highly complex AI methods. In particular, the trade-off between performance and data computational efficiency must be proactively managed. Researchers should focus on developing low-latency decentralized training models on the edge devices that can use diverse input data from health sensors (voice, gait, etc) and yield accurate individualized inferences. Additionally, many social concerns about the use of artificial intelligence, especially involving health care decisions, must be addressed.

6 | CONCLUSION

Edge computing is an interesting domain of the future cellular networks that aims to support multitude of IoT devices through low-latency processing. From the multitude of use cases, our focus in this survey paper was its application in health care systems. Through this work, we attempted to fill the gap in current health care surveys, which tend to focus on architecture and application types as opposed to maximum QoS for data operations. Moreover, we have presented the associated architecture, data operations, and the consumer perspective as detailed in the reviewed studies. We have also surveyed the studies from the perspective of qualifiers of edge computing that include cost, latency, security, location awareness, and energy efficiency. Based on our extensive literature review, we recommend further research to address the challenges related to large data volume, information security, compatibility with ultrareliable low-latency communication, and AI complexity-accuracy trade-offs. It is difficult to directly compare much of the research because experiments are done on a variety of platforms and with different data sets. However, even with these limitations, detailed comparative analysis of each data operation presented in this paper can help researchers/health professionals choose the best authentication, data reduction, encryption, classification, or prediction method for a particular edge computing deployment use case in a health care setting.

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