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Edge Intelligence and Internet of Things in Healthcare: A Survey

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ABSTRACT With the advent of new technologies and the fast pace of human life, patients today require a sophisticated and advanced smart healthcare framework that is tailored to suit their individual health requirements. Along with 5G and state-of-the-art smart Internet of Things (IoT) sensors, edge computing provides intelligent, real-time healthcare solutions that satisfy energy consumption and latency criteria. Earlier surveys on smart healthcare systems were centered on cloud and fog computing architectures, security, and authentication, and the types of sensors and devices used in edge computing frameworks. They did not focus on the healthcare IoT applications deployed within edge computing architectures. The first purpose of this study is to analyze the existing and evolving edge computing architectures and techniques for smart healthcare and recognize the demands and challenges of different application scenarios. We examine edge intelligence that targets health data classification with the tracking and identification of vital signs using state-of-the-art deep learning techniques. This study also presents a comprehensive analysis of the use of cutting-edge artificial intelligence-based classification and prediction techniques employed for edge intelligence. Even with its many advantages, edge intelligence poses challenges related to computational complexity and security. To offer a higher quality of life to patients, potential research recommendations for improving edge computing services for healthcare are identified in this study. This study also offers a brief overview of the general usage of IoT solutions in edge platforms for medical treatment and healthcare.

INDEX TERMS Internet of Things, smart healthcare, artificial intelligence, edge computing, fog computing.

I. INTRODUCTION

Healthcare currently uses IT to provide smart systems that speed up health diagnosis and provide accurate and effective treatment. Intelligent health surveillance frameworks and automated medical diagnosis systems provide services in various environments and scenarios, which include hospitals, workplaces, and homes, and transportation support to dramatically cut the cost of doctor visits as well as to increase the overall quality of patient care [1]. Smart healthcare IoT sensors and applications for general healthcare have dramatically altered the approach to healthcare, as the number of healthcare IoT devices used globally is estimated to be more than 162 billion as of 2020 [1].

Wearable and embedded smart IoT sensors can collect real-time data, including data relating to user habits, mobility, and device usage. These data are collected and processed using machine learning (ML) or deep learning (DL) techniques to reveal hidden patterns in the data and to track users to diagnose and warn about critical conditions. Cloud-based frameworks, which often employ big data analysis techniques, can achieve reliable and accurate results for general IoT applications that require a rapid response [2]–[4]. However, for critical medical IoT-based applications that require higher accuracy, real-time responses, and robust behavior, cloud-based architectures can have a significantly adverse impact in cases of network failure or bandwidth delay, and this may result in medical emergencies or even the loss of life [5].

Recently there has been growing interest in sophisticated cloud architectures that employ edge intelligence and fog computing. The key objective of this amalgam is to exploit the maximum benefits from edge and fog computing capabilities for data collection, interpretation, processing, and

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analysis [6]. Such architectures provide promising solutions for increasing reliability and responsiveness in the case of distributed applications involving healthcare, because intelligent device and sensor mapping as well as resource management are key issues for smart healthcare IoT systems [5]. Hence, this study aims to highlight the advantages of edge computing for intelligent solutions for the distributed processing and analysis of smart IoT healthcare sensors.

Edge intelligence can be used on smart devices that have sensors attached to them, and on devices that are available at gateways near the smart sensors: wearable smart devices with sensors, like smart phones or smart watches, and gateway devices like microcontrollers can serve as edge nodes. Fog computing can be implemented on local area networks and can integrate powerful, larger devices like personal computers or servers that are installed at a greater distance from the smart sensor devices. Both edge and fog computing architectures are widely used together to take advantage of sensors within the users' proximity to deliver healthcare services with greater availability, lower latency, and location awareness [7]. Recently, many researchers have proposed methods based on hierarchical computing to leverage techniques like DL and ML for the distribution and allotment of inference-based tasks among edge and fog nodes, which could tremendously improve the computing power and computational capabilities of edge devices [8], [10]–[16].

In the smart healthcare domain, mobile cloud architectures that incur high cost for data transmission and cover a limited area are gradually being transformed to mobile edge computing architectures that employ edge ML, have the characteristics of lower latency and higher coverage, and are more reliable than cloud-based models [17]. In this article, we provide a review of the edge-based IoT healthcare frameworks that focus on health surveillance. This study discusses the trends in the advancement of edge IoT-based smart healthcare frameworks, including systems that employ edge computing for functional processes to the more recently proposed edge architectures that also exploit fog computing and ML techniques.

Edge computing can be used with multiple edge devices and local servers for the collaborative and efficient processing of healthcare sensor data. By employing AI techniques, edge intelligence is moving toward smart healthcare frameworks that have human-like intelligence and even cognitive intelligence. Edge intelligent architectures can be totally or partially trained at the edge level, while further processing can be distributed among edge and fog nodes, or cloud processing can be done for computationally intensive applications. The surge in smart sensors and IoT devices has now made the Internet of Everything (IoE) [18] achievable. Edge intelligence also works with platforms for Industry 4.0, and Healthcare 4.0, thus making IoT architectures smarter and more resilient [19]. Edge intelligence is being used in smart cities for ambient-assisted living (AAL) [20]. It is also being employed to build cognitive intelligence systems for ECG and EEG data monitoring and classification [21].

TABLE 1. List of abbreviations.

Abbreviation	Full Form
AAL	Ambient Assisted Living
5G	Fifth Generation
AI	Artificial Intelligence
AR	Augmented Reality
BAN	Body Area Network
BCI	Brain Computing Interface
BSN	Body Sensor Network
CNN	Convolution Neural Network
CVD	Cardiovascular Diseases
DBN	Deep Belief Network
DL	Deep Learning
ECG	Electrocardiogram
EEG	Electroencephalogram
H-IoT	Healthcare Internet of Things
kNN	k-Nearest Neighbor
KPI	Key Performance Indicators
MEC	Mobile Edge Computing
ML	Machine Learning
NFV	Network Function Visualization
OS	Operating System
PoP	Point to Point
QoL	Quality of Life
QoS	Quality of Service
RF	Random Forests
SDN	Software Defined Network
SVM	Support Vector Machines
TI	Tactile Internet
VR	Virtual Reality
WBAN	Wireless Body Area Network
WSN	Wireless Sensor Network

Hence, we are witnessing a convergence of various types of AI, ML, and DL-based technologies for the automation of complex decision-making tasks, which results in multi-purpose intelligent inference architectures. In fact, edge intelligence cannot be restricted to ML or DL-based techniques only [22], but it is now being researched for every domain of smart healthcare involving IR 4.0, Healthcare 4.0, 5G, and tactile internet.

Figure 1 shows the taxonomy as a pictorial view of the sections and subsections discussed in this study. The rest of this study is organized in the following manner. Section II provides a brief comparison of related surveys. The basic architecture of edge IoT healthcare systems is described in Section III. Section IV provides a review of state-of-the-art IoT healthcare systems based on different areas of application. The application of ML, edge intelligence, blockchain, and big data for IoT healthcare frameworks is explored in Sections V to VII. Section VIII discusses trends in the field of intelligent edge applications for IoT healthcare, and the conclusion is given in Section IX.

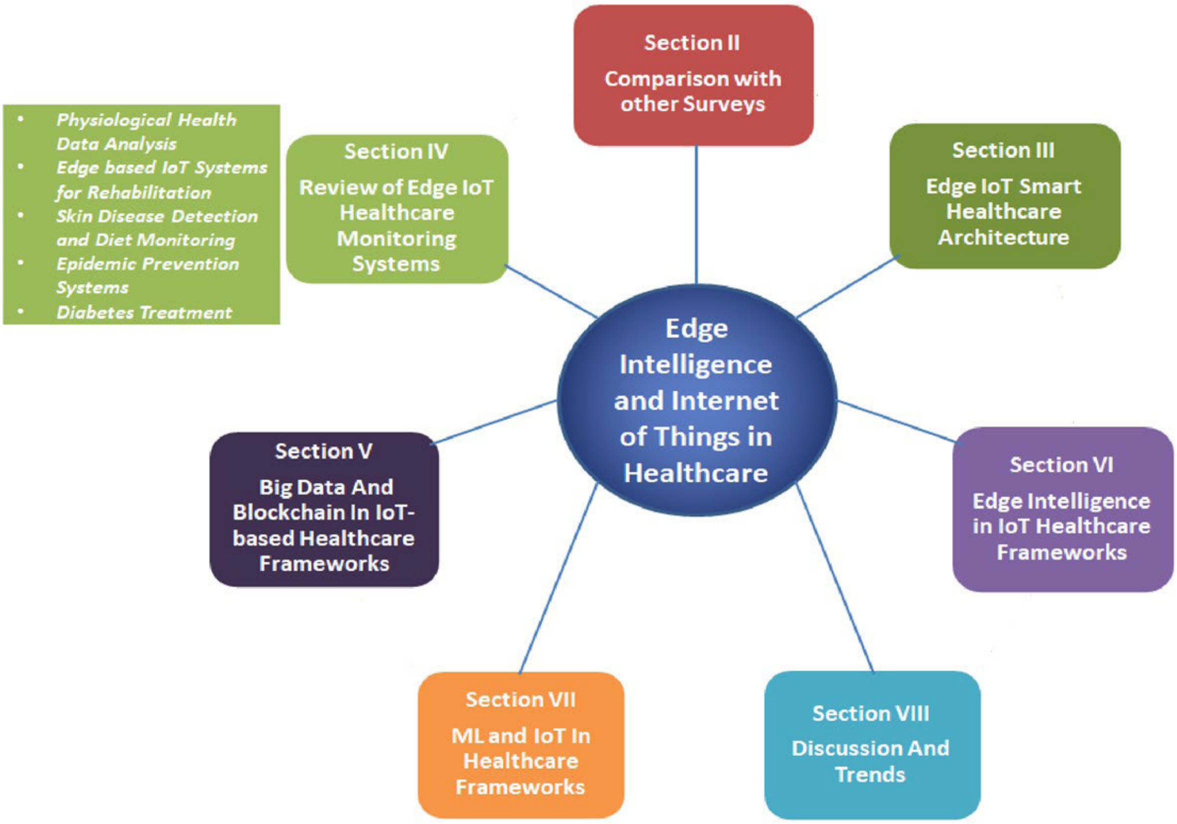

FIGURE 1. Taxonomy.

II. COMPARISON WITH OTHER SURVEYS

From a review of the literature and surveys of the state-of-the-art architectures, the essential aspects and applications of IoT healthcare systems were identified. Employing ML and DL techniques is an integral part of smart healthcare IoT systems. ML/DL models can be applied in the device, data processing, or communication layers [3], [23]. In this study we discuss in detail the application of ML and DL models at the various layers and nodes of IoT healthcare architectures, which has not been addressed by other surveys. Study [24] presents a good evaluation and discussion of fog-based architectures, but the authors do not discuss the architectures from an application point of view. We also discuss the application of blockchain in IoT healthcare systems, something else that is not covered by many studies. A survey in [25] provides a detailed discussion of many ICT-based architectures, but it is quite dated and does not include more recent advancements. Another detailed survey in [26] available focuses on the application aspects of IoT healthcare but not on emerging technologies. This study focuses on evolving and revolutionary techniques for IoT healthcare systems. Table 2 presents a comparison between the content of previous study on IoT healthcare systems [17], [27]–[36], [100] and that of the present study.

III. EDGE IoT SMART HEALTHCARE ARCHITECTURE

Edge-based IoT healthcare frameworks generally involve remote monitoring systems that exploit different types of smart sensors for the implementation of healthcare systems that are diagnostic, sensitive, and preventive [1], [37]–[39]. In most recent studies, fog computing nodes work as local servers: they gather, analyze, and process health IoT sensor data and give rapid-response services [40]. For many years, healthcare researchers have been exploring solutions for the remote monitoring of patients and for the transmission of health reports to provide clinicians with patient data in real time. Previous researchers like Liu *et al.* [41] primarily suggested simple computers and microcontroller-based monitoring systems for patients, such as using ECG and heartbeat sensors to warn about high heart rate or for the prediction and filtering of vital situations. These physiological data are then collected from smart ECG sensors for further analysis and processing [42], [43].

Recent advances in IoT technology have opened a door for intelligent solutions that take advantage of software platforms and system architectures. These solutions, such as for monitoring chronic illness, epidemic surveillance and control, elderly and pediatric care, and management of health and fitness [44]–[50], are intended to resolve healthcare issues at various levels.

TABLE 2. Comparison of state-of-the-art for IoT-based healthcare.

Reference	Use Case: Architecture	Machine Learning/ Deep Learning	Edge/ Fog Computing	Big Data	Blockchain
Hartmann *et al.* [17]			✓		
Alam *et al.* [27]	✓				
Mutlag *et al.* [28]	✓		✓		
Qadri *et al.* [30]	✓		✓	✓	
Greco *et al.* [31]	✓	✓	✓		
Yu *et al.* [32]		✓			
Hossain & Ghulam [33]	✓	✓		✓	
Habibzadeh *et al.* [34]	✓		✓	✓	
Aceto *et al.* [35]	✓	✓	✓	✓	
Dhanvijay *et al.* [36]	✓				
Baali *et al.* [100]	✓	✓			
This Work	✓	✓	✓	✓	✓

In this work, we focus primarily on the challenges for health surveillance systems. These issues can be divided into two parts, static and dynamic patient monitoring. Static patient monitoring can be done in a home, office, or hospital, and dynamic patient monitoring would track the patient in an outside environment.

A general edge/fog computing-based approach uses an architecture with multiple levels [51], which is illustrated in Fig 2. The three basic levels are:

- Level for edge nodes, where data are collected from IoT body sensors. Low-level processing takes place in hand-held or portable devices like smart watches, smartphones, tablets, or embedded devices or local gateway devices.
- Level for fog nodes, where data are collected from IoT field sensors or edge devices. Storage and local processing are performed here using servers or PCs.
- Level for cloud processing, where all the data are gathered and stored. High-level processing takes place here, including the application of sophisticated algorithms and data analysis.

It is not necessary that all three levels of edge architecture are contained simultaneously in the same architecture. In non-dynamic solutions, fog nodes can be used to collect data directly from sensors, and they may be assisted by cloud service providers. Similarly, edge devices explicitly interact with cloud providers in certain complex dyn1mic situations where a fog level cannot be enforced.

IV. REVIEW OF EDGE BASED IOT HEALTHCARE MONITORING SYSTEMS

Several research studies have proposed IoT-based smart health monitoring frameworks during the last few years. In this study, we review a variety of such research studies to demonstrate the advances in IoT-based healthcare systems that employ edge intelligence, as shown in Table 3. This study discusses the trends in the advancement of edge

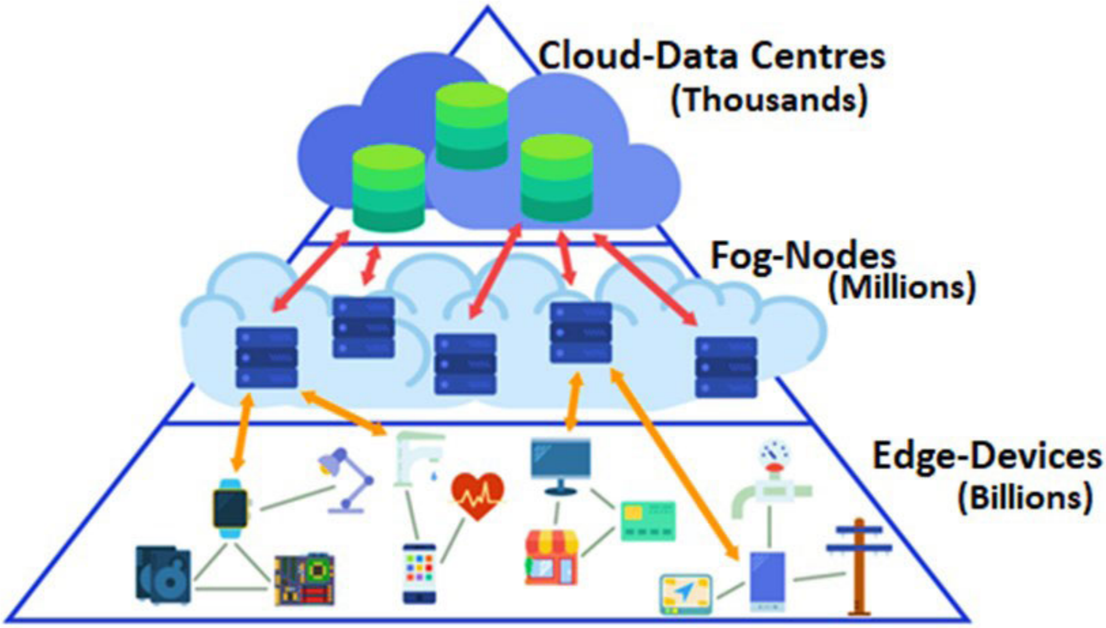

FIGURE 2. Simple three-tier architecture for IoT-based healthcare systems.

IoT smart healthcare frameworks, including systems that employed edge computing for functional processes, to the recently proposed edge architectures that also exploit fog computing and ML techniques.

The research studies reviewed here include various fields of IoT smart healthcare applications for the monitoring of physiological health data including skin, voice, posture, and movement. The studies are grouped according to the application area.

Figure 3 shows the application of edge intelligence in combination with ML for IoT smart sensor based scenario. The data that is collected from the IoT smart sensors are collected and preprocessed by edge devices. These devices also apply AI techniques for preprocessing and initial data analysis, but for intensive processing and classification tasks it is sent to the ML backend core where advanced deep learning algorithms are employed for in-depth analysis and decision making.

A. PHYSIOLOGICAL HEALTH DATA ANALYSIS

Recently, many research studies have proposed IoT-based healthcare systems that focus on physiological health data for accessing and diagnose critical health situations.

In [101], a wireless body sensor network is employed for movement and heart data monitoring for individuals inside living places. The edge layer enables members of patient's family or healthcare experts to receive health alerts on their smartphones. Sudden changes in sensor values are calculated, which help to detect falls or critical health conditions early. Likewise, another IoT smart healthcare system [102] was proposed for the home monitoring of critical heart conditions of patients using ECG sensor data. The proposed method performed system interaction through the use of a TV interface.

In [35], the researchers explored the cloud-based Bluemix technology for collecting and storing physiological information. They employed IBM Watson IoT platforms to make it possible for health experts to remotely access and analyze analytical findings using health data. In another study [54], researchers proposed an embedded system for fever diagnosis that monitors patient temperature in real time. An ECG telemetry system [55] based on the IoT is proposed, where health assessment can be carried out on a smartphone in real time. Various physical activities have been evaluated on the proposed system, illustrating its usefulness.

Field sensors can be used for collecting static monitoring physiological data, and can be employed in multimodal activity detection. In one study [104] for this researchers used a smartphone, smartwatch sensors, and a camera to gather audio, video, and motion information. In fact, the cloud architecture was used for fog computing, where activity recognition, data preprocessing, and localization were done using a local gateway, and cloud processing was employed for remotely accessible data storage.

Similar studies [68], [11] have proposed activity recognition using fog-based frameworks. In [11], twelve human activities were detected by employing wearable body sensors. These studies used an LSTM based RNN model that was implemented on the fog nodes of local servers, whereas [68] proposed other types of movement monitoring sensors and used SVM and random forests for activity classification. Edge-based ML models (Edge ML) have been explored in

TABLE 3. Overview of IoT-based healthcare.

Research Study	Aim	Smart Sensors	Devices (Fog/edge)	Method Adopted
Abdellatif *et al.* [8]	EEG classification and analysis	EEG headset and smart sensors	Not mentioned	Employed stacked autoencoders on edge nodes for feature extraction
Uddin *et al.* [11]	Activity recognition using wearable smart sensors	Many types of wearable sensors including ECG, accelerometer, and gyroscope	GPU-based fog server	Activity detection done using RNN model
Greco *et al.* [24]	Real time health data anomaly detection	Gyroscopes and accelerometers	Raspberry Pi	Proposed distributed edge framework for stream computing and HTM algorithm employed for anomaly recognition
Kaur *et al.* [25]	Pulse rate and body temperature monitoring	Heart rate and temperature sensors	Raspberry Pi	Bluemix technology used for remote data collection in the cloud
Orha *et al.* [42]	Physiological data recording using Arduino microcontroller	Special sensor	PC and Arduino microcontroller	No edge used, sensor data processed on PC
Yakut *et al.* [43]	ECG data recording, IoT Healthcare framework using Raspberry Pi.	Electronic health smart sensors	Raspberry Pi	Data processed on MATLAB environment using PC
Satija *et al.* [55]	ECG real-time monitoring	ECG smart sensors	Arduino microcontroller	ECG collection during activities and abnormality detection using DFT
Mathur *et al.* [56]	Gait detection for lower limb rehabilitation using hand orthosis	Hand movement and temperature sensors	Arduino, Raspberry Pi and smartphone	Machine learning employed for temperature detection using MATLAB
Muhammad *et al.* [57], [58]	Detection of voice pathology	Voice, temperature, ECG, and humidity sensors	Smartphone	IoT devices used for data collection; ELM technique employed on the cloud for feature extraction and classification; LBP and Mel-spectrum features used for voice.
Dubey *et al.* [59]	Parkinson's disease detection using speech and ECG signals	Microphone and smartphone	Intel Edison	DTW technique used for pattern identification in ECG signal. Pitch estimation used for speech signals
Sood *et al.* [62]	Chikungunya virus detection and alert system	Environmental and wearable smart sensors	No edge support	Data analysis and real-time processing done on fog nodes; main processing and storage done in the cloud
Sareen *et al.* [63]	Zika virus detection and prevention system	Insect sensors	Smartphone	Fog-based servers used for data processing, computations and analysis done on cloud
Hegde *et al.* [64]	Detection and prevention system for COVID-19, symptom	Infrared camera	Raspberry Pi	Forehead detection for temperature monitoring, and lip detection for symptoms

TABLE 3. ***(Continued.)*** **Overview of IoT-based healthcare.**

Research Study	Aim	Smart Sensors	Devices (Fog/edge)	Method Adopted
	screening, temperature monitoring			
Liu *et al.* [65]	Different types of food classification for diet analysis	Smartphone	Smartphone	Segmentation and preprocessing of image done using smartphone and classification done using CNN model implemented in the cloud
Dai *et al.* [66]	Skin cancer recognition	Smartphone	Smartphone	Pre-trained CNN implemented on smartphone for skin lesion classification without the use of cloud services
Queralta *et al.* [67]	Fall detection for monitoring heart disease and diabetes	EEG, ECG, blood pressure	Raspberry Pi	RNN implemented on edge gateway for detecting falls
Ram *et al.* [68]	Activity recognition using multimodal signal	ECG, gyroscopes, accelerometers and other movement sensors	PC	SVM and random forest used for activity precognition
Abdel-Basset *et al.* [69]	Type-2 diabetes detection and monitoring	Heart rate, blood pressure, activity, blood glucose sensors	PC	Hybrid deep learning model for Type-2 diabetes prediction
Devarajan *et al.* [70]	Real time remote monitoring, diabetes patients	ECG, blood glucose and movement sensors	Smartphone	Decision tree for diabetes risk prediction
Priyadarshini *et al.* [71]	Stress prediction and classification for monitoring heart rate and diabetes	Various wearable body sensors and embedded devices	PC	Deep learning employed for stress detection for predicting early symptoms of Type-2 diabetes
Magaña *et al.* [101]	Fall detection and alert system, heart disease detection and classification	Heart rate sensors	Microcontroller	Proposed data encryption; smartphone-based application and alert notifications
Villarrubia *et al.* [102]	Patient monitoring inside the homes	ECG sensor and accelerometer	Arduino microcontroller and Raspberry Pi	Home tracking of patients with accelerometer on Wi-Fi
Monteiro *et al.* [103]	Parkinson's disease treatment using telemetry and speech signals	Microphone on smartwatch	Intel Edison	Cloud processing done by extracting acoustic speech features
Pham *et al.* [104]	Motion data and voice signal monitoring done at home	Infrared, OptiTrack camera, ECG, breath sensors	Arduino	Wearable sensors signal sent to a local gateway for activity recognition and pre-processing

recent studies, and involved the analysis of physiological health data using wearable sensors. The research in [24] discussed the issue of anomaly detection by proposing an architecture based on edge stream computing. They used a distributed HTM algorithm [72], which was implemented on edge nodes for classification. Another study [67] suggested a model for fall detection using an LSTM-based RNN implemented on edge nodes.

A recent study [8] proposed an EEG classification approach based on multi-access edge architecture. In order to satisfy the necessary requirements, like robust feature detection and classification, data reduction, and fast processing, the authors implemented key modules on edge nodes. In order to evaluate the performance, they also compared the results with methods like k-nearest neighbors, naive Bayes, and random forests.

Another research study proposed a new architecture based on hierarchical computing [5] to categorize anomalies in ECG signals. In order to dispense these computations in the cloud, fog, and edge layers, the authors used a version of MAPE-K architecture by IBM.

The architecture consists of four key processing modules. A monitoring module is used to link the sensors and the edge, in which all the preprocessing, data collection, and storage is carried out. Then, an analyzer module is created that performs the main computing and processing tasks like the training of the model, and is implemented in the cloud. The third one is the planning module, which is implemented at the edge level and is controlled by the analyzer module. This module runs the trained model and is responsible for making decisions. The model was tested on two approaches, SVM [5] and DL [5].

B. EDGE BASED IOT SYSTEMS FOR REHABILITATION

There are many recent studies for post-operative cases in which researchers proposed edge-based rehabilitation systems [1] for monitoring health complications or infections after treatment. One such study [56] proposes a system for monitoring the health of an orthotic for an amputated limb by tracking patient's gait and temperature. They employed edge nodes in the form of smartphones to collect and transfer health data to fog nodes, where ML-based techniques were implemented for feature extraction classification. Another similar study [74] proposed IoT -based arm kinematics using accelerometers.

Several research studies have proposed speech synthesis and voice pathology IoT-based smart systems. Voice-related ailments and diseases were studied in [57] and [58] using smartphones and wearable sensors that recorded data and send it to a cloud-based module where an extreme learning machine was employed for feature extraction classification tasks. Dubey *et al.* [59] employed fog computing to provide Parkinson's patients with teletherapy. They collected audio data using smartwatch sensors, which was then transferred to fog nodes for acoustic feature identification and then to the cloud for further classification.

C. SKIN DISEASE DETECTION AND DIET MONITORING

Recently, advanced deep models have been built for mobile platforms, smartphones and other industrial applications [75], [105]. Many new research studies have offered phenomenal solutions for mobile IoT-based smart healthcare. One study [66] proposed a skin cancer diagnosis system based on a pretrained, lightweight CNN model implemented for a standalone mobile platform that classified skin cancers.

Another researcher [65] proposed food classification and recognition for dietary evaluation. They performed preprocessing on a mobile device and implemented a CNN model using cloud processing.

D. EPIDEMIC PREVENTION SYSTEMS

In the field of diagnostics and treatment, IoT smart healthcare systems have provided many feasible solutions for infectious disease management. Such systems have made real-time processing, location detection, motion information, and several types of data fusion a possibility. With the help of biosensors, and location and environmental sensors, epidemic disease detection and diagnostic systems have become state-of-the-art. The importance of such systems is all the more evident in cases where viral infectious diseases must be detected in the early stages so that timely treatment can be provided to patients. One study [62] proposed a system for Chikungunya diagnosis using fog computing for the analysis of disease-related symptoms, including environmental condition data. The system also alerted users to disease-prone areas using Google Map information. Another study [63] provided a solution to diagnose and prevent the Zika virus from spreading using a mobile cloud computing architecture. Fog nodes were used to carry out preprocessing, and the cloud layer was used for processing, storage, and results analysis.

The present COVID-19 conditions have dramatically changed the global scene, hence smart healthcare systems are the need of the hour. Many IoT-based smart architectures have been proposed for accurate screening, maintaining a 1-meter social distance, and the diagnosis of symptoms like fever, cough, and body pain. For example, in study [64], an auto triage method was proposed based on real-time DL techniques implemented in the edge layer. DL has been used to detect the forehead area and to measure temperature using an infrared camera. In other studies [76]–[79], a multimodal DL-based system was proposed that employed smartphone sensors to determine user location and to warn about risk-prone areas.

E. DIABETES TREATMENT

Many research studies have focused on prevalent diseases like diabetes and high blood sugar, and have proposed IoT-based smart healthcare systems for diagnosis and treatment. Additionally, many wearable body sensors have been produced for managing diabetes, like real-time blood glucose sensors and insulin pens. In such systems, devices like smartphones can act as edge devices, providing analysis and diagnosis services without using the cloud [36]. In one study [69], researchers proposed a system to predict the early symptoms of Type-2 diabetes. In another study [70], decision trees were used for the classification of diabetes risk level, and the smartphone

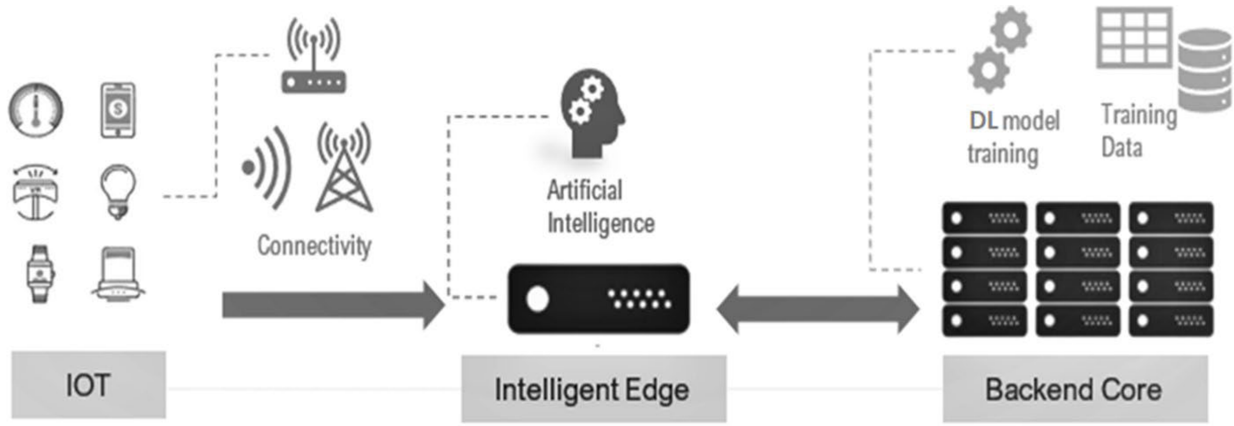

FIGURE 3. An Intelligent edge architecture with smart devices.

was used as an edge device. Another DL-based system was proposed in [71] to predict stress, hypertension, and diabetes using wearable body sensors, and it was implemented using the fog layer.

V. BIG DATA AND BLOCKCHAIN IN IOT-BASED HEALTHCARE FRAMEWORKS

An enormous amount of data is being generated at every moment, especially in an IoT network. Hence, the processing such a large amount of data needs intensive processing capabilities. Many big data analytics techniques have been suggested in the literature for real-time IoT frameworks [80], [81], however; the need for QoS has not been properly addressed. Machine and DL techniques combine with IoT architecture to boost big data processing ability, and advanced DL models in particular are extremely powerful for managing such data [82]. DL has been applied by researchers for various types of medical big data, including data from wearable body sensors and HER data [83].

Figure 4 shows some of the applications of big data in IoT healthcare. Big data analytics applications in IoT healthcare systems have revolutionized statistical analysis and real-time tracking of health data. Wearables sensor data is continuously tracked like sleep, exercise, walk, heart rate data, etc. New types of IoT smart sensors can also track blood pressure, glucose, pulse, etc. Big health data analytics helped patients out of healthcare facilities and provided diagnosis and improved healthcare facilities at home. Big data has also helped IoT healthcare systems to reduce overall treatment costs by reducing staff and travel. It has also enabled healthcare professionals to find high-risk patients and administer special care. It has also lowered errors due to human factors bringing in more confidence in artificial intelligence. Advanced AI tools like IBM's Watson can predict diseases in seconds by searching through huge amounts of medical data. Hence, big data and AI and IoT can help the smart healthcare industry progress rapidly.

In order to solve the issues related to big data, IoT health systems can implement blockchain to maintain data privacy and safeguard patient's interests. Blockchain has helped in the deployment of critical services in IoT healthcare architecture, but challenges like scalability, storage, and combined operation are a major concern [84]–[87]. The main healthcare application of blockchain is providing access and storage control for private medical information [85]. However, the advantages of blockchain have not been realized to the full for IoT healthcare (HealthIoT) systems [9].

As shown in figure 5, the blockchain for IoT healthcare can be designed in a way that blocks are created to store unique identifiers for each patient. Hence, all the health transactions consist of this secure identifier, and each health record is encrypted along with the timestamp for the health transaction. The blockchain consists of complete medical history, including wearable sensors and smartphone health data. This huge amount of data is stored in data lakes where all types of health data can be abundantly stored. Data lakes can be accessed by edge based intelligent algorithms like deep learning, and it supports all types of data queries. The data stored in the data lake is also encrypted and authenticated. Whenever data is saved in the data lake, a pointer is created using the patient's unique identifier and added to the blockchain. The patients receive this information every time any related data is added. The edge devices like smartphones and body sensors help the patient add his authenticated health information to the data lakes in a secure fashion using blockchain.

VI. EDGE INTELLIGENCE IN IOT HEALTHCARE FRAMEWORKS

While edge computing strives to combine various types of edge devices and servers that can collaborate for the efficient processing of locally generated data, edge intelligence strives to embed AI and cognitive intelligence related to human behavior into edge architectures.

FIGURE 4. Big Data applications in IoT healthcare.

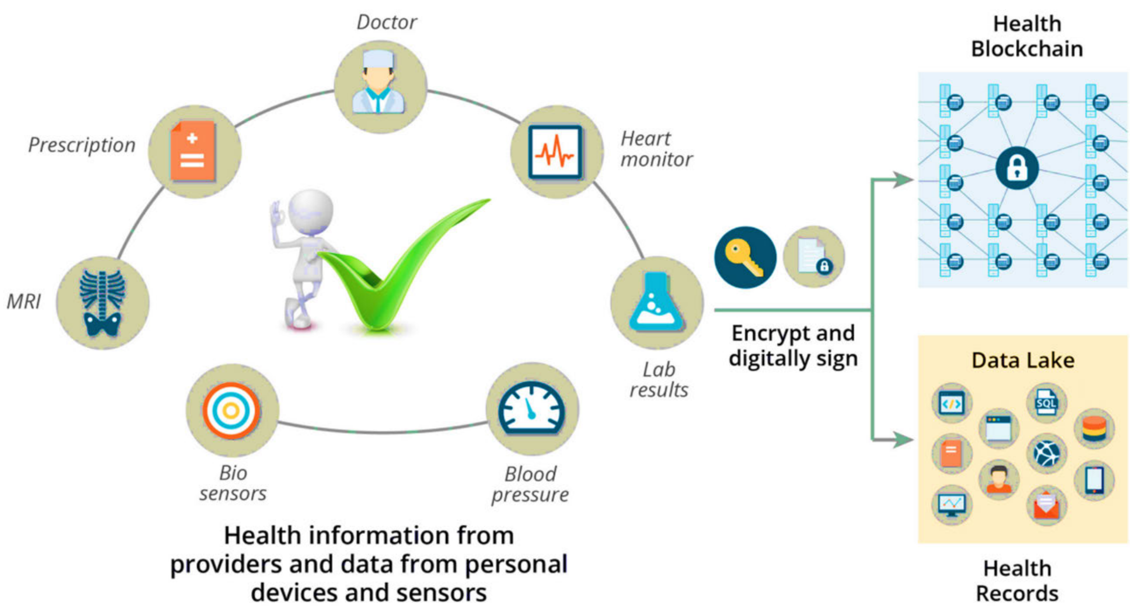

FIGURE 5. Blockchain use case in IoT healthcare scenario.

Using intelligent AI-based edge in IoT architectures does not necessarily mean that the AI techniques are totally trained and analyzed at the edge layer; they may also involve a collaboration of cloud, fog, and edge computing. The innovation and advancement in IoT devices have made it possible to achieve the Internet of Everything (IoE) [18]. Huge cloud data centers are distributed worldwide, hence edge intelligence is all the more necessary for processing so much information.

AI techniques can be implemented with edge computing using many new platforms and scenarios, such as Industry 4.0, tactile internet, Healthcare 2.0, advanced DL, and territorial control, which could be embedded in IoT healthcare platforms to connect them with humans, which makes information more relevant and intelligible [88].

Similarly, for smart city healthcare applications like AAL [20], edge intelligence is proposed to offer healthcare systems based on intelligent agents. These agents can manage the environment according to the situation, provide contextual support to users, adapt to user's preferences, and monitor and control the environment automatically.

Intelligent edge platforms are also used in proposals for smart telemedicine systems [88], and for providing treatment, disease prevention and detection, and medical support to patients using advanced wearable sensors for real-time patient monitoring. Fog-based data analytics [89] was also proposed in a recent study for a smart healthcare framework. One study even proposed a cloud-to-fog architecture [90] for healthcare where intelligent edge nodes were placed in smart hospitals and homes, which made remote interaction easy.

Another study used edge intelligence to build a real-time health data gathering and analysis system [91], for which it proposed a three-layer patient-driven healthcare architecture for real-time data collection, processing, and transmission. This system provides insight into the application of fog nodes and servers in a Healthcare 4.0 environment. An ECG-based intelligent edge cognitive framework [92] was also proposed for real-time health monitoring. Cognitive intelligence makes the proposed edge computing system smarter, and allows for optimized resource allocation.

Hence edge intelligence is now an element of state-of-the-art IOT healthcare architectures that aim to work with more intelligence, reliability, privacy, and efficiency.

VII. MACHINE LEARNING AND IOT IN HEALTHCARE FRAMEWORKS

ML has been applied for multiple applications and domains by a number of researchers all over the world. The use of ML in the healthcare IoT domain has seen huge interests from researchers recently. ML helps in remote and real-time monitoring, and treatment of diseases in the H-IoT framework. ML has also been used in Assistive Systems to rehabilitate patients after accidents. ML has been very popular in diagnosis and prediction of cardiac arrest in heart patients, using IoT based smart sensors [68]. In heart patients the ECG signal is monitored continuously and after noise filtering it is sent to ML algorithms for feature extraction [68].

In the field of Ambient Assisted Living (AAL), there are many applications of machine learning for IoT based healthcare scenarios. ML has been used for fall detection of patients employing edge and cloud computing architecture [67]. In AAL domain ML has also been used by researchers for patient's sleep pattern monitoring. For analyzing sleep patterns, a multi-modal data is employed consisting of EEG, ECG, or EOG.

With the development and advancements in the field of prosthetics, now ML is being used for aiding and rehabilitation after accidents or trauma. Deep learning has revolutionized the way Brain-Computer Interfacing (BCI) systems are being developed to improve quality of human life and for providing smart cognitive healthcare as shown in Figure 6. Deep learning is being used to interpret brain patterns by analyzing EEG signals and convert the thought processes to speech [55]. It is also being used for emotion recognition and classification thereby making machines aware of human emotions [73]. It has enabled humans to control robots using their brains without doing any action. Hence ML based IoT healthcare systems are being used to help patients with severe disabilities to lead a normal life [56].

VIII. DISCUSSION AND TRENDS

In this study, we reviewed many important IoT-based smart healthcare systems using edge, fog, and cloud computing. The studies we discussed employed various types of artificial intelligence, and ML and DL techniques for disease diagnosis, anomaly identification, symptoms detection, disease classification, and prediction. In most of the studies, the main analysis and processing tasks were implemented in the cloud layer, as the edge devices had limited power, capability, and resources. However, many recent studies have started to combine edge, fog, and cloud layers to improve resource management and reduce latency. Recent studies have implemented ML and DL models for applications like fall prevention and detection, multimodal activity recognition, disease diagnosis, and treatment on local edge nodes, which are close to the data gathering devices. This helped to reduce data transfer time and consumption of resources, and increased the capability of real-time execution.

For non-dynamic monitoring scenarios, fog-based frameworks provided the best solution, where local servers added GPUs to cater to the demands of intense ML processing tasks. However, for dynamic tasks where resource optimization and saving power comes into the picture, limited-power edge devices were used.

Stream computing has been applied at the edge level to render the inference process among various edge nodes parallel, and ML techniques implemented with lightweight architectures have been adopted to optimize processing and resource management for embedded sensor devices [93]. Hence, advanced mobile DL architectures have been modified for limited resource utilization and low power edge nodes without compromising performance [94]. However, there are certain issues that these systems suffer from at the edge level:

- *Training data overfitting:* because processing is performed at local edge nodes, devices that use wireless body sensors usually collect data from the same set of users, which results in data redundancy. When DL models are retrained or updated using such data, they are usually poorly fitted or overfitted.
- *Limited computational power:* as the DL-based models need to be retrained and updated frequently,

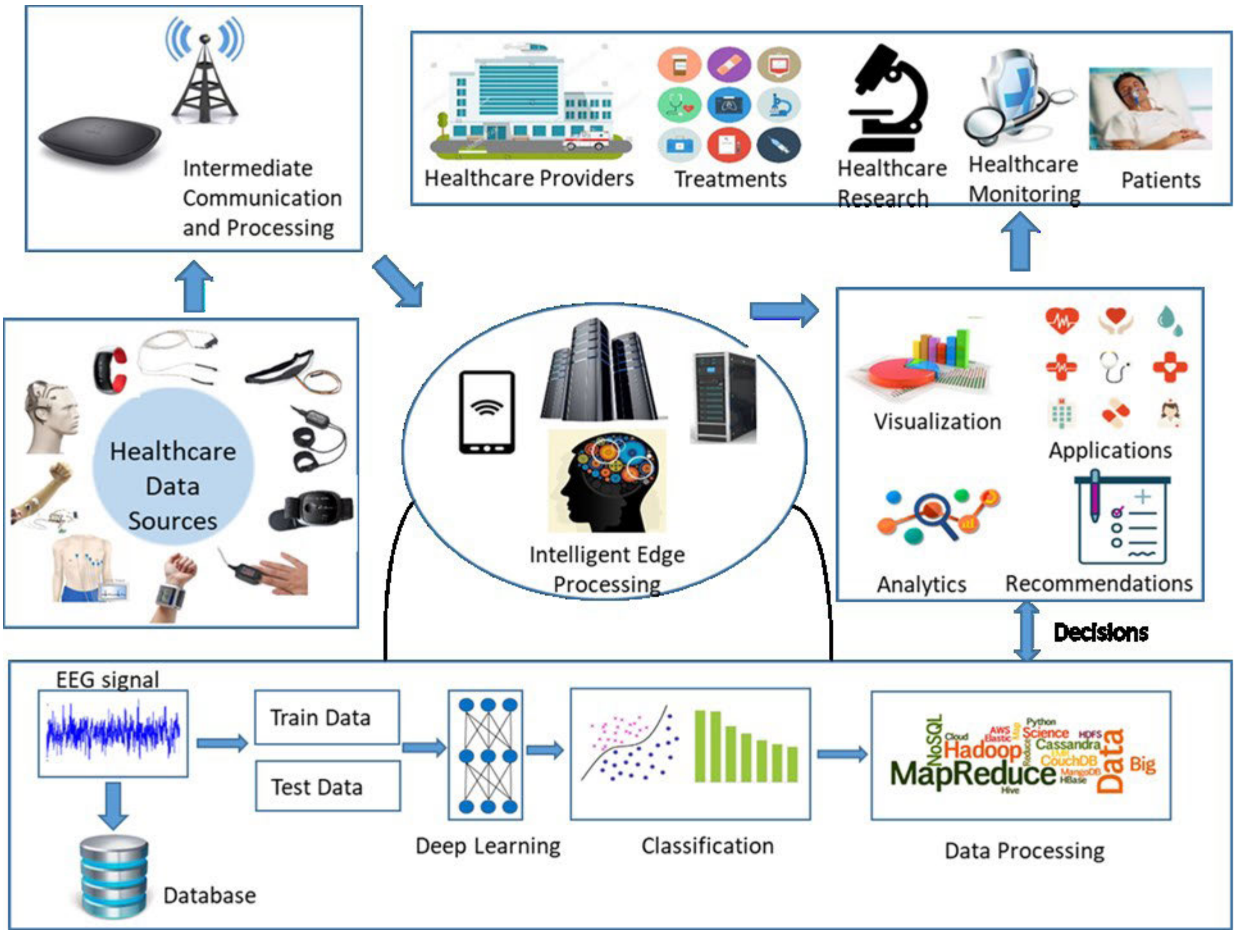

FIGURE 6. Cognitive edge intelligence for EEG classification.

the computation overhead can be high in terms of cost, even if lightweight models are implanted. Hence, such intensive processing is often offloaded to the cloud.

To solve such issues, many researchers have proposed new IoT architectures and concepts [95]. Based on the distributed DL concepts proposed in some studies [96], many researchers have employed such distributed networks to build point-to-point architectures. In [97], the authors propose a distributed deep network implemented on local edge nodes. They used a simple neural network at each edge node and exchanged weights with other nodes to train the nodes in a distributed fashion.

In another study that may offer a viable solution to such problems, the researchers proposed distributed training for DL models and ML algorithms that collaborate at the edge layer to process classification tasks in a decentralized manner [98]. In addition to the issues discussed here, such architectures also promise to alleviate data distribution issues over time, as these issues may adversely affect IoT-based healthcare systems. As in the case of covariate shift, distributed edge-based DL models can easily cope with this issue using segmentation at the edge nodes [99]. Through the findings of this review, we expect edge-based smart IoT healthcare systems to alleviate these issues by implementing the solutions proposed in the literature. We also need further investigation to amicably solve such issues, so that edge intelligence can be used with all its advantages and computational capabilities.

IX. CONCLUSION

IoT-based smart healthcare frameworks are advancing from simple models used for data collection, preprocessing, transmission, and analysis to sophisticated and intelligent systems that can do intensive processing and remote data analytics, and make smart decisions. These advanced models require DL methods to be wisely implemented and to increase computational ability without increasing resource overhead. Sometimes, such models can only be implemented in the cloud layer due to the enormous amount of data being produced by real-time smart sensors. However, such approaches present many drawbacks, as we discussed in this study, such as issues with data availability, data quality, and real-time processing in an environment where prevention and the timely detection of symptoms are the main requirements.

Data security and storage is also a major concern in healthcare systems, as personal and confidential information is used in such systems. However, local storage and information processing management has still not been addressed in edge-based solutions, especially those that involve a dynamic health environment. Some researchers have also proposed models for distributed DL that employed edge and fog nodes, which enabled them to reduce training and processing time. Local decision-making responsibility was relegated to the edge nodes, while model training was allocated to the cloud layer. The increased importance of the edge nodes was mainly because the GPU devices were embedded at the edge level. These GPU-powered nodes were also employed at the fog level to increase the computational power and data processing capabilities of the model. In smart healthcare systems where training DL-based models at the fog and edge level is still not feasible, the distribution of workload and partitioned deep network approaches are a viable solution.

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