Received December 6, 2020, accepted December 22, 2020, date of publication December 30, 2020, date of current version January 7, 2021.

Digital Object Identifier 10.1109/ACCESS.2020.3047960

A Comprehensive Survey of the Internet of Things (IoT) and AI-Based Smart Healthcare

FATIMA ALSHEHRI AND GHULAM MUHAMMAD, (Senior Member, IEEE)
Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

Corresponding author: Ghulam Muhammad (ghulam@ksu.edu.sa)

The authors extend their appreciation to the Deputyship for Research and Innovation, ''Ministry of Education'' in Saudi Arabia for funding this research work through the Project no. (IFKSURP-158).

ABSTRACT Smart health care is an important aspect of connected living. Health care is one of the basic pillars of human need, and smart health care is projected to produce several billion dollars in revenue in the near future. There are several components of smart health care, including the Internet of Things (IoT), the Internet of Medical Things (IoMT), medical sensors, artificial intelligence (AI), edge computing, cloud computing, and next-generation wireless communication technology. Many papers in the literature deal with smart health care or health care in general. Here, we present a comprehensive survey of IoT- and IoMT-based edge-intelligent smart health care, mainly focusing on journal articles published between 2014 and 2020. We survey this literature by answering several research areas on IoT and IoMT, AI, edge and cloud computing, security, and medical signals fusion. We also address current research challenges and offer some future research directions.

INDEX TERMS Internet of Things (IoT), Internet of Medical Things (IoMT), edge computing, cloud computing, medical signals, smart health care, artificial intelligence.

I. INTRODUCTION

The rising number of chronic patients and the aging of the population render the avoidance of diseases an important requirement of healthcare. Prevention is not only defined by regular exercise, nutrition, and periodic preventive controls as a way to sustain a healthier environment but also as a method of keeping serious conditions from becoming worse. The future health sector must tackle an increasing number of chronic problems and the scarcity of treatments to satisfy patient demands [1]. COVID-19 has recently highlighted the importance of quick, comprehensive, and accurate eHealthcare and intelligent healthcare involving different types of medical and physiological data to diagnose the virus.

The use of emerging technology in protective policies and behavioral systems can help identify potential health conditions early and enable the scheduling of appropriate steps, such as concurrently monitoring treatments and preparing new assessments. The world's smart health market is forecast to reach USD 143.6 billion in 2019, which will expand by an average growth rate of 16.2% between 2020 and 2027 [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Diana Patricia Tobon.

Smart healthcare refers to platforms for health systems that leverage devices such as wearable appliances, the Internet of Things (IoT), and the mobile Internet to easily enter health documents and link people, resources, and organizations. Intelligent medical treatment includes diverse actors, including physicians, staff, hospitals, and research bodies. It comprises a dynamic framework with many facets, including disease prevention and identification, assessment and evaluation, management of healthcare, patient decision-making, and medical research. Elements of intelligent healthcare involve automated networks like the IoT, mobile Internet, cloud networking, Big Data, 5G, and artificial intelligence (AI), along with evolving biotechnology.

Sensors have been gradually embedded into diverse systems of our lives through computer technology, automation, and automated signal processing. Sensor-produced data can enable clinicians to more quickly and reliably recognize critical situations and help patients become more informed of their symptoms and future treatments. Intrusive and noninvasive tools—ranging from devices to read bodily temperature to dialysis control systems—provide personal and multimedia details and assistance to patients and the health care sector.

Medical signals come in the form of 1D and 2D signals such as electrocardiograms (ECGs), electroencephalograms (EEGs), electroglottographs (EGGs), electrooculograms (EOGs), electromyograms (EMGs), body temperature, blood pressure (BP), and heart rate. A health care monitoring system may use these medical signals to monitor a patient.

The IoT is slowly starting to connect both doctors and consumers through health care. Ultrasounds, BP readings, glucose receptors, EEGs, ECGs, and more continue to monitor patients' wellness. Conditions like follow-up visits to doctors are critical. Several health care facilities have started to utilize smart beds, which can detect a patient's movement and automatically adjust the bed to the correct angle and location. The Internet of Medical Things (IoMT) refers to the IoT used for medical purposes. When developing a fully integrated health environment, the IoMT can play an important role.

Sometimes, relying on only one type of medical signal may not fulfill the requirements for a complete diagnosis of a certain disease. In such cases, multimodal medical signals can be deployed for a better diagnosis. These signals can be fused at different levels, including the data level, the feature level, and the classification level [3]. When fusing signals, many challenges may be encountered. These challenges include synchronization when acquiring signals from different sensors, data buffering, feature normalization, and classification fusion [4].

In order to ensure patients' and stakeholders' satisfaction, intelligent health care has been revolutionized with the development of AI and machine learning (ML) algorithms in the context of deep learning (DL) and wireless local area network (wLAN) technologies [5]. The medical industry has been able to manage numerous medical signals from the same user—simultaneously improving disease detection and prediction precision—due to these technologies' high computational performance, high data volume, accommodation of several terminal units, and the introduction of 5G and beyond 5G wireless technology.

In this paper, we present a detailed survey of IoT- and IoMT-based smart health care systems. The survey is limited to academic papers written between 2014 and 2020, located via the IEEE Xplore, ScienceDirect, SpringerLink, MDPI, Hindawi, the ACM Digital Library, and Google Scholar. The survey's aim is to look at different related research areas such as the state-of-the-art IoT-based smart healthcare, data fusion of IoTs, AI in smart healthcare, cloud- and edge-based smart healthcare, and privacy and issues of IoT-based smart healthcare. At the end of this paper, we give few recommendations and make suggestions of future research directions.

The paper is organized as follows. Section II describes the methodology adopted to select the papers. Section III presents a comprehensive survey of the literature and answers several research questions. Section IV mentions some challenges and offers future research directions in this field. Finally, Section V concludes the paper.

II. METHODS

We used the systematic review process PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to identify studies and narrow down results for this review, as shown in Fig. 1. In the review process, there are three sequential steps, which are identification, scanning, and eligibility testing. In the identification step, papers are identified through Google Scholar search; after this step we identified 168 papers. In the scanning step, duplicate and non-conforming papers are removed; after this step 132 papers were selected. Then in the eligibility testing step, we removed the papers that were non-healthcare related. After this final step, we selected 110 papers to be included in the survey.

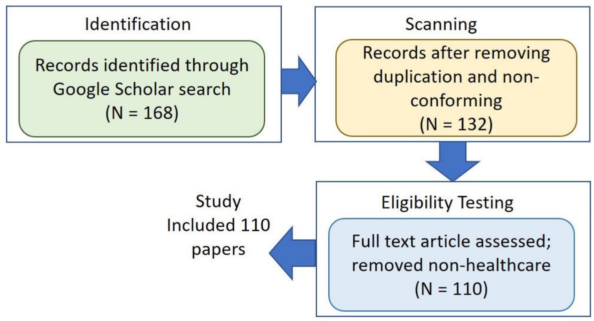

FIGURE 1. PRISMA study selection diagram. N represents the number of papers.

A. RESEARCH AREAS

The research areas we used to select the articles were as follows: "state of the art regarding IoMT and medical signals for smart health care"; "the techniques of multimodal medical data fusion"; "cloud- and edge-based smart health care"; and "security and privacy of the IoMT".

B. SEARCH STRATEGY

Our survey of articles used a combination of keywords and involved formulating a search strategy and selecting data sources. We used the following combination of keywords: a) "Internet of Medical Things"; b) "Fusion medical signals"; c) "Multimodal medical data"; d) "Cloud/edge based smart health care"; and e) "Security and privacy Internet of Medical Things." The number of papers elicited by each search strategy (item) after searching is shown in Fig. 2.

The search strategy was implemented based on the content of the main research areas. We restricted our selection to papers written between 2014 and 2020, as shown in Fig. 3. To locate appropriate papers, we scanned for related publications in major online research repositories, including IEEE Xplore, ScienceDirect, SpringerLink, MDPI, Hindawi, the ACM Digital Library, Google Scholar,. and other health and engineering journals.

C. SELECTION OF STUDIES

Our initial search identified 168 papers. The "Internet of Medical Things" keyword got the largest number of papers.

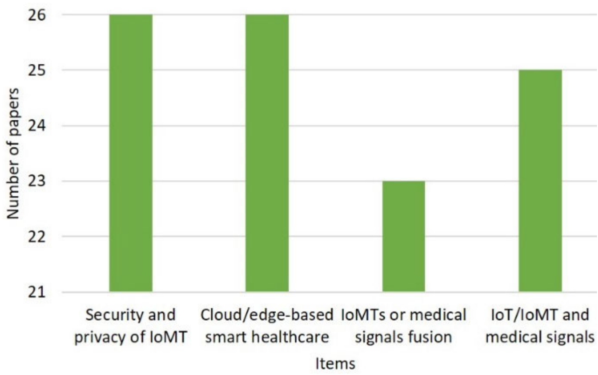

FIGURE 2. Number of papers by item.

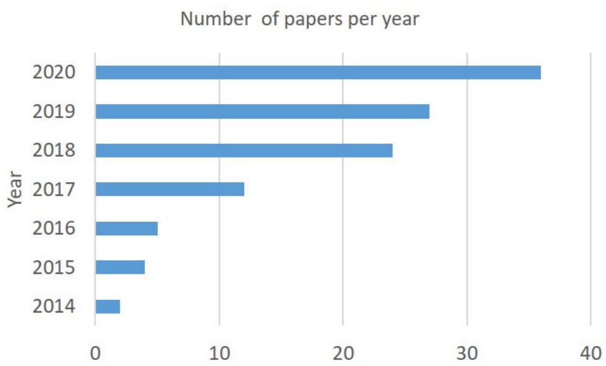

FIGURE 3. Number of papers by year.

After removing duplicate and irrelevant articles, the search was reduced to 110 articles.

D. DATA EXTRACTION

The following data categories were collected from articles:

a. Application or tasks
b. IoT/IoMT
c. Features
d. Classifier
e. Dataset
f. Accuracy

III. RESEARCH AREAS

The survey is divided into four areas: IoT or IoMT and medical signals; IoMT or medical signals fusion; edge- and cloud-based smart health care; and security and privacy in IoMT-based health care.

A. IoT OR IoMT AND MEDICAL SIGNALS

The research in [3] used a multi-sensor platform with two-channel pressure pulse wave (PPW) signals and one-channel ECG to estimate BP. From the collected signals, a total of 35 physiological and informative features were extracted. For dimension reduction and to obtain the most promising indicators for each subject, they presented a weakly supervised feature (WSF) selection method. Furthermore, a multi-instance regression algorithm was used to fuse features and enhance the blood pressure model.

Authors in [4] presented a technique for emotion recognition and classification across subjects. It integrated the significance test and sequential backward selection with a support vector machine (ST-SBSSVM) to enhance the precision of emotion recognition. The input modalities used included 32-channel EEG signals; four-channel EOG signals; four-channel EMG signals; and vital signals measuring respiration, plethysmography, galvanic skin response, and body temperature. Ten types of linear and non-linear EEG, EOG, and EMG features were extracted and fused with the vital signals to produce a high-dimensional feature vector. The features were fused and selected using significance tests and a backward selection search. The selected features were then fed into a support vector machine (SVM) classifier. The experiments were performed using two publicly available datasets, namely DEAP and SEED. The proposed method achieved 72% accuracy on the DEAP dataset and 89% accuracy on the SEED dataset.

One of the serious threats to the worker life is the disaster in mine area. Gu *et al.* [5] proposed a real-time monitoring system to ensure accuracy and reduce the risks to the mine worker. Authors discussed multi-sensor data fusion, situation awareness, and covering theories including the Internet of Things. A random forest (RF) SVM-based model was used to identify the level of the situation and to merge the data. The simulation analysis showed a root mean square error (RMSE) below 0.2 and a TSQ no greater than 1.691 after 200 iterations.

A data fusion enabled Ensemble approach was proposed in [6]. The collected data from body sensor network (BSNs) were fused to and inserted into an ensemble classifier for heart disease prediction. The ensembles were placed in a fog computing environment and the output from the individual predictors were fused. A prediction accuracy of 98% was shown in the result when the number of estimators was set to 40 at a tree depth of 15.

Steenkiste *et al.* [7] provided a reliable model for improving the performance and reliability of predicting sleep apnea based on sensor fusion method. In order to collect and integrate multi-sensor data, including oxygen saturation, heart rate, thoracic respiratory belt, and abdominal respiratory belt, the proposed approach used backward shortcut connections. To assess robustness and analyzed the performance of the proposed fusion method, both Convolutional neural network (CNN) as well as long short-term memory (LSTM) deep learning base-models were used.

A multi-sensor fusion (HBMF)-based hybrid BSN architecture has been developed by Lin *et al.* [8] to enable smart medical services. Medical services included data processing technologies, robot, and different sensors. To ensure that the robot make the right decision and to guarantee the quality of medical services, a multi-sensor fusion approach based on an interpretable neural network (MFIN) which used AI technologies has been proposed (see Fig. 5). Reliability

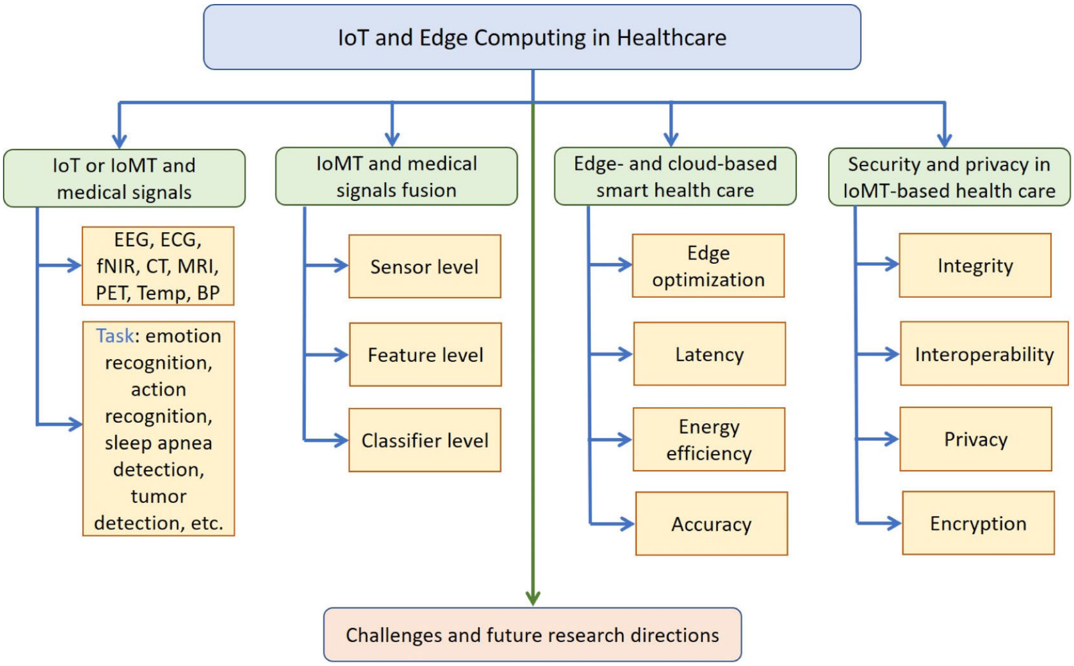

FIGURE 4. Taxonomy of the survey.

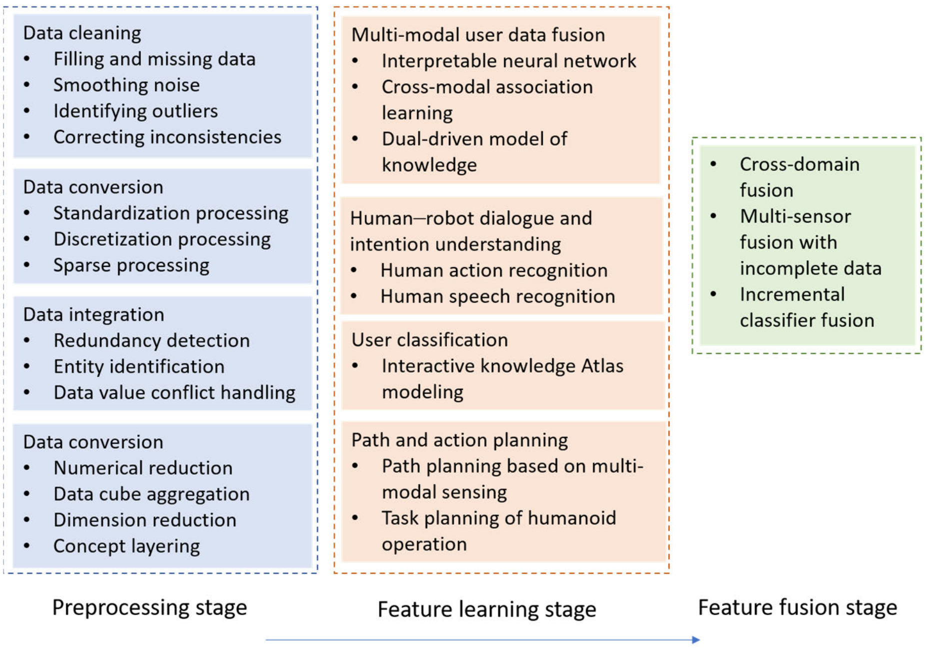

FIGURE 5. Overview of multi-sensor fusion framework.

and flexibility were improved compared with existing multi-sensor fusion approaches. In [9], seven channels from functional near-infrared spectroscopy (fNIRS) were fused with seven EEG electrodes to improve the detection of mental stress. Simultaneous measurements of fNIRS and EEG signals were carried out on 12 subjects. These measurements were conducted while subjects solved arithmetic problems under two different conditions (control and stress). The performance of the fusion of fNIRS and EEG signals was superior to the performance of each separately.

In [10], a fusion of EEG and ECG videos was proposed using three different transforms to improve video resolution: discrete cosine transform (DCT), discrete wavelet transform (DWT), and hybrid transforms. Both peak signal-to-noise

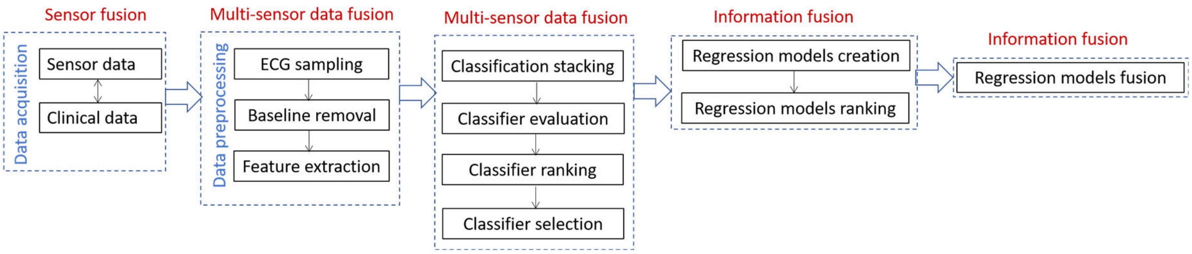

FIGURE 6. **Fusion model for to predict blood pressure from ECG data.**

ratio (PSNR) and mean squared error (MSE) parameters were used to measure the fusion effect. This empirical study found that hybrid transforms improved image reconstruction.

Authors in [11] suggested a method of medical image fusion using rolling guidance filtering (RGF). The study used an RGF to filter input images into either low-frequency or high-frequency components. First, the RGF separated the input images into low-frequency and high-frequency components, each of which had its own fusion role. A Laplacian Pyramid (LP)–based fusion rule and a sum-modified-laplacian (SML) based method were used to fuse the structural components and the detailed component respectively. The last step was image reconstruction. The proposed method achieved the best high-frequency information compared with other existing approaches.

A potential field segmentation (PFS) algorithm was presented by Cabria and Gondra [12]. PFS was used to segment brain tumors in magnetic resonance imaging (MRI) scans and the results produced by PFS were fused by ensemble approaches to achieve a fused segmentation. The proposed method was based on the physics notion of potential field and viewed the intensity of a pixel in an MRI scan as a "mass" which produces a potential field. The performance was validated on a publicly available MRI benchmark database called Brain Tumor Image Segmentation (BRATS) and showed that both PFS and FOR were similar methods. However, PFS was an exclusive segmentation algorithm and required fewer parameters.

An approach using particle filtering was suggested by Nathan and Jafari [13] to improve heart rate tracking with existing artifacts and the use of wearable sensors. They estimated heart rate apart from other signal features and to exploit the known steady, they designed observation mechanisms. This has contributed to the fusion of information from various sensors and signal modalities to increase the accuracy of monitoring. The performance of the proposed approach was examined on actual motion objects caused by ECG and PPG data with corresponding accelerometer observations, and results showed encouraging average error levels of less than 2 beats per minute.

A method based on multi-level information fusion was proposed by the authors in [14] to develop a predictive model to calculate BP from ECG sensor data. In this method, the data were fused in five levels (see Fig. 6). Data from multiple ECG sensors were fused and they used different techniques to extract the features from the input data in level one and two respectively. The fusion of output information from seven different classifiers was input into the meta-classifier in level 3. Knowledge from multi-target regression models for each BP type was integrated into level 4, and a single predictor for systolic BP (SBP), diastolic BP (DBP), and mean arterial pressure (MAP) was obtained in level 5.

In [15], the author presented a method based on physiological signals fusion to improve the accuracy of emotion recognition. Its performance was validated by comparing both fused and non-fused physiological signals on two publicly available datasets. A feedforward neural network classifier was trained using both fused and unfused signals. The result of the proposed method showed an improvement in performance on the DEAP and BP4D+ datasets compared with other current methods.

Chen *et al.* [16] modified an existing real-time system to produce a recognition system for human action. The device obtained data from various sensor types, such as depth cameras and wearable inertial sensors. Low-computation effective depth perception features and inertial signal features were inserted into two computationally powerful shared collaborative representation classifiers (CRCs). The proposed method was tested on a publicly available dataset called UTD-MHAD, and the results showed an improvement in overall classification rate ($> 97\%$) compared to using each sensor separately.

A data fusion cluster-tree construction algorithm based on event-driven (DFCTA) was presented in [17]. They designed a data fusion system for intelligent health monitoring in the medical IOT. By calculating the nodes' fusion waiting time, the minimum fusion delay path was provided, and the fusion delay problem within the network was analyzed. The empirical study showed an improvement in reliability and timely in the proposed method compared with traditional method.

In [18], two procedures built on intrinsic image decomposition (IID) was proposed to address the complexity of complexity in extracting structural and functional information from both MRIs and positron emission tomography (PET) images utilizing the same decomposition scheme. The presented IID was used to decompose both MRIs and PET images into two components in the spatial domain. two algorithms were used, algorithm 1 for extracting the structural information and eliminating the noise from MRI images, while algorithm 2 was used for averaging the color information from the PET image. Based on IID models, three fusion methods were employed. IID+PCA, IID+IIC, and IID+HIS were superior to other existing methods when the planned method was tested.

Guanqiu [19] proposed a framework for medical image fusion that combined two methods: dictionary learning and clustering based on entropy. A Gaussian filter was used to decompose source images into high-frequency and low-frequency components. High-frequency and low-frequency were fused by using dictionary learning and L2-norm based weighted average algorithms respectively. The comparative experiments showed that the proposed method enhanced performance compared with other existing methods.

Baloch *et al.* [20] presented a layered context-aware data combination tactic for IoT health care applications. It included three phases: situation building, filtering and context acquisition, and intelligent inference. Reliable, accurate, and timely data were gathered from various sources. The aim of the analysis was to resolve issues such as uncertainty, irregularity, restricted range, and sensor deficiency. The drawback of this analysis was that no particular method was used to evaluate the suggested solution.

In [21], a distributed hierarchical data fusion architecture at various levels was employed using complex event processing (CEP) technology to improve decision accuracy and timely. It divided the task of data fusion into three-level processing models (low, middle, and high levels of data fusion). A smart health care scenario was prepared with appropriate IoT network topologies to prove the effectiveness of the proposed architecture. This empirical research found that the proposed solution allowed for effective decision-making at various stages of data fusion and showed an overall increase in the efficiency and response time of primary health services.

Survey Papers on IoMT and Medical Signals: Herrera *et al.* [22] presented state-of-the-art regarding sensor fusion for hand rehabilitation applications. Authors classified the research on hand rehabilitation into three categories: exoskeletons, hand movements, and serious games for hand rehabilitation. Of the types of sensors used, sensors based on EMG signals were the most common.

Wearable devices play a vital role in long-term health monitoring systems and are currently at the heart of IoMT [23]. In [23], a comprehensive study was presented with the goal of presenting the most important wearable health care monitoring devices, including biophysiological signs, motion trackers, EEG measurement devices, ECGs, BSCs, and so on. Based on expert, authors suggested that the most critical elements in health monitoring are motion trackers, vital signs, and gas detection

In [24], the authors argued that it was complicated to detect and resolve obstructive sleep apnea (OSA), although it is one of the most common diseases. The paper highlighted IoT systems that had supportive technologies and were utilized to diagnose OSA, including FC, smart devices, ML, the cloud, and Big Data. It further considered the improvement in the monitoring of sleep quality and other remote monitoring in AI-based health systems. In addition to the survey, a novel IoMT optimization paradigm was proposed to improve the quality of remote OSA diagnosis. The model showed an enhancement in the sensitivity, accuracy, energy consumption, and specificity of the system of remote OSA diagnosis.

A thorough and systematic analysis of current multi-sensor fusion technologies for BSNs was presented by Gravina *et al.* [25]. In the context of physical activity, they have presented an in-depth analysis and assessment of data fusion. Furthermore, they presented a systematic categorization by pinpointed specific properties and parameters that affected data fusion design choices at each level of the traditional classification (data-level, feature-level, and decision-level).

A comprehensive overview of different modalities fusing, such as MRI- PET imaging, computed tomography (CT)-MRI, X-ray, and ultrasound, was given by Sumithra and Malathi [26]. The research pinpointed different types of multimodal fusion and found that the exact boundary of the tumor in the brain could be identified by merging both CT frames and MRI slices.

Authors in [27] presented a thorough overview of the application of image fusion technology in tumor treatments and diagnosis, in particular liver tumors. It highlighted the key values of image fusion techniques by considering their limitations and prospects. It further presented an extensive review of the procedures and algorithms used in medical image fusion and concluded with a discussion of the research challenges and trends in medical image fusion. Table 1 presents a summary of the papers described above on the IoT or IoMT and medical signals.

B. IoMT AND MEDICAL SIGNALS FUSION

Swayamsiddha and Mohanty [28] discussed different applications of the cognitive IoMT (CIoMT) to tackle the COVID-19 pandemic. Their review showed that the CIoMT was a successful tool for fast detection, decreasing the workload of the health industry, dynamic monitoring, and time tracking.

Yang *et al.* [29] proposed a combination of point-of-care diagnostics and the IoMT to assist patients in receiving proper health care at home. The proposed platform might reduce national health costs and monitor disease spread.

Singh *et al.* [30] highlighted the overall applications of the IoT philosophy in tackling the COVID-19 health crisis. This study aimed to decrease costs and improve treatment outcomes by employing an interconnected network for efficient flow and exchange of data. Singh *et al.* [31] also presented an IoMT concept based on ML approaches to tackle the COVID-19 health crisis. It provided treatments and solutions to issues related to orthopedic patients.

Kaleem *et al.* [32] discussed ways to actively apply the IoT in the medical and smart health care sectors and provided a method named k-Healthcare in IoT. The proposed method

TABLE 1. **Summary of papers regarding IoT/IoMT and medical signals.**

Ref.	Task	IoMTs	Classifier	Database	Accuracy
[3]	Cuff-Less Blood Pressure Measurement	One ECG, two photoplethysmogram signals (pulse pressure wave sensors)	multi-instance regression algorithm	Private; total 85 participants including 17 hypertensive and 12 hypotensive	Estimation error: around 1.50
[4]	Emotion recognition	32-ch EEG signals, 4-ch EOG, 4-ch EMG, respiration, plethysmograph, galvanic skin response, body temperature.	SVM	Physiological signals (DEAP) dataset and the SJTU Emotion EEG Dataset (SEED)	72% (DEAP); 89% (SEED)
[5]	Health and risk assessment for miners	Multi sensors	RF-SVM (Regression Forecast -SVM) and ELM	Private	RMSE=0.017
[6]	Heart disease prediction	Multi sensors	Random Forest and Kernel Random Forest ensemble	NA	98%
[7]	Sleep Apnea Detection	Abdominal respiratory belt, thoracic respiratory belt, heart rate and oxygen saturation	CNN, LSTM	Sleep-Heart-Health-Study-1 database	AUPR = 0.67 (CNN); AUPR = 0.71 (LSTM)
[8]	Medical human–robot interaction scenario	BSNs	Cross-domain, Incremental classifier and multi-sensor fusion	NA	NA
[9]	Rate of mental stress	Functional Near infrared Spectroscopy (fNIRS) and Electroencephalograph (EEG)	SVM	12 healthy subjects with no history of psychiatric, neurological illness or psychotropic drug use	Mean detection rate 98%
[10]	Medical video fusion	ECG and EEG videos	DCT, DWT and Hybrid Transforms	Each video comprises 36 frames with 18 frames per second	NA
[11]	Medical image fusion	MRI and CT images	LP-based fusion rule, Sum-Modified-Laplacian SML and LP-based fusion rule	The test image pairs are from public website [42]	The Avg is: $Q^{AB/F}$ =0.669 MI=4.249 VIF=77.178
[12]	brain tumor detection	MRIs	Intersection and union	Brain Tumor Image Segmentation (BRATS) MRI benchmark database.	Avg=0.62 Std=0.211 Med=0.68
[13]	Heart rate estimates	Wearable sensors ECG, PPG	A particle filter	Database was taken from 2015 IEEE Signal Processing Cup (SP Cup) [43] The MIT-BIH Noise Stress Test Database was also used	Error < 2 beats/min
[14]	Blood pressure predictive	Multiple ECG sensors	Bagging, Boosting, SVM, K-means, RF, Naive Bayes, J48, META	Private database and the Physionet database.	MAE: 7.93, 6.41, and 5.72 for SBP, DBP, and MAP (the traditional approach). 16.60, 9.24, and 9.80 for SBP, DBP, and MAP (custom approach)

TABLE 1. Summary of papers regarding IoT/IoMT and medical signals.

[15]	Emotion Recognition	Physiological signals	Feedforward Neural Network	BP4D+ and DEAP	95.81% on DEAP 91.51% on BP4D+
[16]	A human action recognition	A depth camera and wearable inertial sensor	CRC	University of Texas at Dallas Multimodal Human Action Dataset (UTD-MHAD)	>97%
[17]	Medical data fusion	Multi sensors	Cluster tree data fusion	Private dataset having 120 nodes	NA
[18]	Intrinsic image decomposition	MRI and PET images	Image coefficients (IIC), PCA, IHS	30 pairs of abnormal brain from Harvard University and clinical cases 6 pairs of images with resolution changes.	Avg running time IID+PCA=0.5 IID+IIC=0.5 IID+IHS=0.7
[19]	Medical image fusion	CT, MRI, PET, and SPECT images	Gaussian filter, weighted average algorithm, dictionary-learning based algorithm	Data were collected from two public repositories [42],[44]	$Q^{AB/F}$ =0.6291 MI=2.1045 VIF=0.3426

used smartphone sensors to collect and transmit data to the cloud for processing and then to stakeholders.

In [33], an event-driven data fusion tree routing algorithm was presented. The paper discussed the theory of health information and the sports information gathering system, which is divided into terminal nodes and client management systems. The proposed algorithm designed communication mechanisms according to the characteristics of IoT communication and used visual methods for modeling. The outcomes showed an enhancement in accuracy and timeliness compared with other methods.

Chiuchisan *et al.* [34] provided the design for a health care network to track at-risk patients in smart intensive care units (ICUs) based on the IoT model. It used a series of sensors and the Xbox Kinect to track patient motions and any required adjustments in environmental parameters to notify physicians in real time.

Sharipudin and Ismail [35] proposed a health care monitoring system to manage and process data in the patient monitoring system. The proposed system was combined with health care sensors that measured health parameters. The extracted parameters were then sent to cloud storage for medical staff's reference.

Dimitrov [36] presented a discussion of IoMT applications and Big Data in the health care field which permitted innovative commercial models and allowed for variations in work progression, customer experiences, and output enhancements. Wearable sensors and mobile applications were used to fulfill numerous health needs and to collect Big Data from patients to advance health education.

Authors in [37] established early warning score systems based on the characteristics of vital signs. The proposed system supported the estimation of a health state by providing a helpful decision and cause for critical care interference. It investigated the most appropriate ML technique to predict the risk associated with input medical signals.

Sanyal *et al.* [38] proposed a federated filtering framework (FFF) based on the forecast of data at the central fog server using aggregated model from IoMT devices. This framework used models provided by local IoMT devices and then shared with the fog server. It presented a solution for many common issues, such as energy efficiency, privacy, and latency for resource-constrained IoMT devices.

Luna-delRisco *et al.* [39] addressed recognition, obstacles to implementation, and threats to the usage of wearable technology in the Latin American health care system. Major problems that the authors noted included the training and allocation of human capital in health care, the connectivity of public care, funding arrangements for health programs, and inequality in health. They considered smart wearable sensors in health care to be part of the solution.

Adali *et al.* [40] used a system where joint independent component analysis (ICA) and transposed independent vector analysis (IVA) were employed to fuse functional MRI, structural MRI, and EEG data. Results were obtained from healthy controls and schizophrenia patients using an audible oddball (AOD) function. The presented system was validated on a private dataset which included 36 subjects. The analysis was performed using the Infomax and entropy bound minimization (EBM) algorithms. The experiment revealed that the joint ICA model could be superior to the transposed IVA model. In the case of joint ICA, a robust ICA algorithm such as EBM was superior to the Infomax algorithm.

Authors in [41] presented a deep CNN model for seizure detection utilizing an excellent cross-patient seizure classifier. The visualization method demonstrates the spatial distribution of the characteristics learned by the CNN in various frequency bands when studying the seizure and non-seizure classes.

Bernel *et al.* [45] presented a DL method for the fusion of multimodal data to assist and monitor a user in performing multi-step tasks. Furthermore, they extracted deep features from individual data sources by a deep temporal fusion scheme. The Insulin Self-Injection (ISI) dataset consists of motion data captured with a wrist sensor and video data obtained from the wearable cameras of eight subjects. When the performance of the fusion method was evaluated, the proposed method was superior to other state-of-the-art fusion approaches.

Torres *et al.* [48] proposed a formulation that merged two features from three different modalities to categorize human sleep poses in an ICU atmosphere. Unlike other methods that extract one feature by merging data from various sensors, this method extracted features independently and then utilized them to estimate labels. Various properties and scenes were obtained from different modalities, cameras, and RGB (red, green, and blue) and depth sensors. Both shape and appearance features were extracted and used to train single modal classifiers and generate an estimation of the trust level of each modality.

Using the quantum-behaved particle swarm optimization (QPSO) algorithm, Xu *et al.* [46] presented an updated pulse-coupled neural network (PCNN) model to solve the problem of PCNN parameters and to improve the efficacy and correctness of medical image fusion. Different metrics, including mutual knowledge, standard deviation (SD), spatial frequency (SF), and structural similarity (SSIM), have been used to determine the efficiency of various methods. The result showed that the proposed algorithm has high estimation Accuracy. The proposed method was validated on five pairs of multimodal medical images from a publicly available dataset [42] and showed an improvement in performance over other current methods.

In [47], an approach based on weighted principal component analysis (PCA) for multimodal medical fusion in the contourlet domain was presented. One of the contourlet transform's limitations was capturing limited directional information. In this study, the contourlet transform was combined with PCA to overcome this limitation and improve the fusion of medical images. It used max and min fusion rules to merge the decomposed coefficients, and the results showed improvement.

Using a hybrid technique combining non-subsampled contourlet transform (NSCT) and stationary wavelet transform (SWT), Ramlal *et al.* [49] produced an enhanced multimodal medical image fusion scheme. NSCT was used to decompose the source image into various sub-bands, and SWT was used to decompose the NSCT approximation coefficients into sub-bands. The efficiency of the proposed procedure was assessed through four sets of experiments. The suggested system was compared to other existing fusion schemes and showed improvement in brightness, clarity, and edge information in the merged image.

An improved algorithm based on a fuzzy transform (FTR) for multimodal medical image fusion was presented by Manchandaa and Sharmab in [50]. They considered the error images obtained using FTR pair to improve the performance of multimodal medical image fusion algorithm. To validate the proposed algorithm, different datasets were used, and the result was compared with other multimodal medical image fusion algorithms. The proposed algorithm showed a significant improved in edge strength, standard deviation, and feature mutual information.

Survey Papers on IoMT and Medical Signals: Joyia *et al.* [51] presented the contributions of IoT in the medical field and their major challenges in the IoMT. Numerous applications and research in IoMT were discussed in terms of how they solved issues faced by the global health care industry.

Irfan and Ahmad [52] reviewed current architectural models and produced a new one for the IoMT. They pinpointed the motivations that would lead medical practitioners to decide to adopt the IoMT and further demonstrated privacy and security problems in the IoMT.

Authors in [53] presented a comprehensive review of the current architecture for IoMT devices and discussed different aspects of the IoMT, including communication modules and major sensing technologies. The paper further discussed the challenges and opportunities related to using the IoMT in the health care industry. Communication gateways, data acquisition, and cloud servers were the main components of the IoMT framework.

In [54], the author presented a comprehensive overview of multimodal fusion of brain imaging data. This survey addressed the merits of multimodal data fusion in depth and summarized different methods of multivariate voxel-wise data fusion. A number of multimodal medical data fusion studies, particularly related to psychosis, have been reviewed. The author summarized this analysis by highlighting the importance of multimodal convergence in minimizing misdirection and perhaps discovering links between the brain and mental illness.

Table 2 presents a summary of the papers described above regarding IoMT and medical signals fusion.

C. EDGE-INTELLIGENT AND CLOUD-BASED SMART HEALTH CARE

An edge- or cloud-based privacy-preserved automatic emotion recognition system utilizing a CNN was proposed in [55]. In [56], the authors suggested an appropriate training system for a deep neural network named ETS-DNN in an edge-computing environment. In order to change DNN parameters, ETS-DNN was combined with a hybrid algorithm for hybrid

TABLE 2. Summary of papers regarding IoMT or medical signals fusion.

Ref.	Task	Modality	Fusion / classifier	Database	Accuracy
[40]	Auditory oddball task for control and schizophrenia patients	fMRI, sMRI, EEG	Joint ICA and transposed IVA	Private; 22 healthy and 14 patients	Mutual information = 0.59
[45]	Human action and activity recognition for health monitoring	Google glass wearable camera (video) and Invensense motion wrist sensor (motion)	CNN-LSTM	Insulin Self-Injection (ISI) Dataset; 4 male and 4 female participants	90% (clip)
[46]	Similarity measures of different CT scan images	CT-MR, CT–MR T2, MR T1–MR T2, MR T1–FDG and MR T2–SPET images.	PCNN, QPSO-PCNN	Group 1 from (http://imagefusion.org), Groups 2-5 from [42]	Group 1: STD= 65.1832 SF= 22.8200 MI_AF= 3.2100 Entropy for Group 2-5: G2= 4.5362 G3= 5.4726 G4= 5.4726 G5= 3.7875
[47]	Fusion of obligatory anatomical minutiae images to progress medical diagnosis	CT and MRI	Min–Max fusion rule	3 datasets downloaded from Brain Atlas [42]	E= 6.3364 SSIM= 0.9957 $Q^{AB/F}$ =0.6511
[48]	Sleep Pose Recognition	A Carmine camera, RGB and depth sensors	Linear Discriminant Analysis (LDA) and SVM	26,400 images from five actors Available at http://vision.ece.ucsb/research.	100% accuracy in bright and clear scenes; 70% in poorly illuminated scenes; 90% in occluded scenes
[49]	Fusion of brain images obtained from CT scan and MRI.	CT, MRI	Entropy of square, weighted sum-modified Laplacian	-38 CT and MRI images of 14 patients. -Harvard Medical School website (http://www.med.harvard.edu/AANLIB/home.html)	MI= 4.3780 $Q^{AB/F}$= 0.7780 SD= 58.0671
[50]	Generate a fused medical image from error images	MRI/CT, MRI T1/MRI T2, CT/PET, MRI/SPECT	Fuzzy transform	8 datasets the same size 512 51 × 2 with 256 grayscale levels.	Fusion factor=5.946 SSIM=0.8871 Table 7 Feature similarity index measure (FSIM)=0.8581

modified water wave optimization (HMWWO) In order to minimize data traffic and latency, data preprocessing and classification was carried out at the edge of computation. The results showed that ETS-DNN was superior to the compared approaches.

Han *et al.*, in [57] provided effective communication by developing a clustering model for medical applications (CMMA)) for cluster head selection. The proposed CCMA aimed to enhance lifetime of communication, improve reliability, and offering energy efficiency in medical application.

When choosing a cluster head, some criteria should be taken into consideration such as remaining energy, distance from the base station, capacity, delay, and queue of the IoMT devices. An improvement in terms of energy-efficient communication was shown in the proposed method compared with other existing methods.

Authors in [58] presented a cognitive IoT (CIoT) cloud-based smart health care framework with an EEG seizure detection method using DL. Authors in [59] proposed a voice pathology monitoring system integrating IoT and cloud technology.

In [60], Olokodana *et al.* used the ordinary kriging method to present a real-time seizure detection model in an edge computing paradigm. Fractal dimension features were extracted from EEG signals, and an ordinary kriging model was then used for classification. Computational time complexity is one of the limitations of kriging. In the proposed model, a previously trained ordinary kriging model was moved to an edge device for real-time seizure detection. The empirical study achieved a training accuracy of 99.4% and a mean seizure detection latency of 0.85 seconds.

In [61], an energy-efficient smart-health system based on fuzzy classification was proposed for seizure detection. The raw EEG data was processed at the edge before being transmitted to the mobile–health cloud (MHC). The proposed system minimized energy consumption by reducing the amount of transmitted data and provided high classification accuracy. The result showed an extension in battery life of 60% and a classification accuracy above 98%.

A new network paradigm, CIoT, has been proposed based on the application of cognitive computing technologies [62]. In [63], Chen *et al.* combined the advantages of edge computing and cognitive computing to create an edge-cognitive-computing–based (ECC-based) smart health care system which allocated maximum edge computing resources to higher-risk patients. The empirical experiments showed that the proposed system was capable of improving energy efficiency and user quality of experience (QoE).

Authors in [64] presented an edge-IoMT computing architecture which minimized latency and improved bandwidth efficiency. It consisted of two components: edge computing unit modules which compressed and filtered real-time video data, and cloud infrastructure modules which securely transmitted medical information to the physician.

Akmandor *et al.* [65] discussed different edge-side computing options which were designed to address challenges in smart health care systems. They demonstrated an edge-side reference model comprised of three levels: sensor node, communication, and base station. The compatibility between sensors and edge-side requirements enabled smart edge-side decision-making.

DL was utilized on a mobile health care platform to investigate a speech pathology detection method in [66] and an EEG-based remote pathology detection system in [67].

In [68], an automated voice disorder recognition system was used to monitor people of all age groups and professional backgrounds. By identifying the source signal from the speech using linear prediction analysis, the proposed system could determine the voice disorder.

In [67]–[69], the authors developed a voice disorder detection and monitoring system. In [69], they collected voice samples sent to the edge, which offers low latency and reduces delays in data traffic flow. After processing data using edge computing, data were transferred to the cloud for more processing and assessment. The medical information was then sent to a specialist, who prescribed suitable treatments for patients. The authors tested voice disorder classification and detection and compared the results with two related systems. The study found that the proposed technique improved performance in terms of detection and classification with 98.5% accuracy.

Oueida *et al.* [70] provided a resource preservation net (RPN) framework which integrated a custom cloud, edge computing, and Petri net. The framework improved reliability and efficiency and reduced both resources and time consumption. The proposed system was suitable for emergency departments and other types of queuing systems.

In [71], Kharel *et al.* used Long Range (LoRa) wireless communication and FC to produce an architecture for smart remote health monitoring. LoRa radio provides long-range communication and energy consumption for IoT devices and is used in the proposed system to link the edge user's device with health centers. FC preserves network bandwidth and reduces latency by minimizing data exchange with the cloud. Tests showed that LoRa and FC had promising performance in remote health care monitoring.

In [72], the author utilized several wearable sensors and a DL method (namely a recurrent neural network [RNN]) to introduce a human activity prediction system. Data, features, and activity prediction were processed on fast edge devices like personal computers. To predict human activities from a public dataset, the RNN was trained based on the features, achieving 99.69% mean prediction performance.

Authors in [73] produced a task scheduling approach called HealthEdge that assigned priority to each task based on its emergency level in order to decide whether to process the given task remotely (i.e., in the cloud) or locally. They also provided a priority-based task queuing method which allowed emergency tasks to be processed earlier. The results showed that increasing the local edge workstation reduced processing time.

In [74], Vasconcelos *et al.* proposed a new method called adaptive brain tissue density analysis (adaptive ABTD) to improve the detection and classification of strokes. Edge computing devices provided low computation and cost and reduced time consumption in detection and diagnosis. The integration of the adaptive ABTD with edge devices and the IoT introduced speedy and efficient stroke diagnosis.

Authors in [75] presented a model for cloud-IoT–based health service applications in an integrated Industry 4.0 environment by enhancing the selection of virtual machines (VMs). They implemented their cloud-IoT model using three optimizers: particle swarm (PSO), genetic algorithm (GA), and parallel particle swarm (PPSO). The proposed architecture consists of stakeholders who use IoT devices to send tasks through cloud computing in order to receive services such as telemedicine and disease diagnosis. The cloud broker works in the middle to send and receive tasks over the cloud.

Authors in [76] proposed a tree-based deep model for efficient load distribution to edge devices. The input image was divided into volume groups and a tree structure passed through each volume. The tree structure had several branches and levels, each of which was defined by a convolutional layer.

In [77], Chung and Yoo increased the effectiveness of analyzing Big Data by proposing an edge-based health model using peer-to-peer DNNs. An edge-based health model and a server model were established separately to tackle the issue of response time delay. The results showed that combining DNN techniques and parallel processing models minimized response time delay.

Limaye and Adegbija [78] provided a comprehensive review of medical applications and algorithms in IoMT architectures and their integration with edge computing. IoMT workloads were compared using MiBench, an existing open source embedded system benchmark suite. The comparison showed that the IoMT applications differed from MiBench, indicating the need for a new benchmark sufficient for the IoMT microarchitecture. A cloud-based healthcare framework was proposed in [111]. In the framework, several aspects of data transmission and latency were discussed. An edge-enabled DNN-based method was proposed in [110].

Table 3 presents a summary of the papers described above on edge- and cloud-based smart health care.

D. SECURITY AND PRIVACY IN IoMT-BASED HEALTH CARE

The security and privacy of medical data are very important in smart health care frameworks. A patient's data should be handled privately. If privacy is breached, the patient may be harassed in public, which can lead patients to become traumatized and depressed. If medical sports data are leaked, rival sports team members might use these data to solicit illegal advantages. Therefore, medical data should be dealt with privately and securely transmitted over communication channels [123]. This important issue has been addressed in a great deal of prior research.

Alsubaei *et al.* [79] presented a taxonomy of security and privacy in the IoMT. They categorized IoT layers (perception, network, middleware, application, business); intruder types (individual, organized group, state-sponsored group); impact (life risk, brand value loss, data disclosure); and attack method (social engineering, implementation layer, software or hardware bugs, malware). The perception layer includes wearable devices such as fitness trackers, BP sensors, and respiratory sensors; implantable devices such as capsule cameras; ambient devices such as door sensors and daylight sensors; and stationary devices such as CT scanners and X-rays. While there are many ways to fuse data from these devices, the authors did not discuss them in the paper.

In [80], the authors identified the potential security threats that can affect IoMT-based health care systems and recommended a series of security measures to tackle these threats. Some of the security issues mentioned in this paper include overlooking the aspects of built-in security, stakeholders' unfamiliarity with security solutions and focus on marketing and financial gain, and a lack of consensus between stakeholders for overlapping solutions. Based on these threats, the authors proposed some ontology-inspired, stakeholder-centric, and scenario-based recommendations in line with available guidelines.

Ivanov *et al.* [81] introduced OpenICE-lite, a middleware for medical device interoperability designed to provide security for IoMT devices. Several applications were investigated for this middleware, including a critical pulmonary shunt predictor and a remote pulmonary monitoring system.

Lu and Cheng [82] proposed a secure data-sharing scheme for IoMT devices. First, the system guarantees the protection of and permitted access to mutual information. Second, the system conducts effective integrity tests until the customer opens mutual data to prevent an erroneous application or calculation performance. Ultimately, the system provides a lightweight procedure for both consumer and customer. The scheme removes the burden of generating encryption and decryption keys solely on end devices.

Mohan [83] presented some cyber threats to IoMT devices and provided some solutions to these threats. As IoMT devices are limited by their battery life, they have only limited encryption capability and are thus at risk in terms of integrity, confidentiality, and privacy. Sensitive patient data can be leaked, and denial of service attacks can be made by draining the battery. As solutions, IoMT devices must be installed during deployment and software details transferred to the cloud-based system provider. IoMT devices encrypt all patient data using lightweight cryptographic methods and store patient data on the cloud-based system. Only approved entities who send their verifiable attribute-based certificate to the cloud provider may access this data.

Nkomo and Brown [84] proposed a cybersecurity framework for IoMT devices in smart health care systems that had five attributes: identify, protect, detect, respond, and recover. First, asset management and risk assessment should be identified. Second, access control, data security, and protective technology should be developed. Third, anomalies and events should be detected. Fourth, response planning should be designed through analysis and mitigation. Fifth, a recovery path should be planned.

Rathnayake *et al.* [85] realized a security mechanism for a smart healthcare system using the IoMT. First, data from different IoMT devices were encrypted using asymmetric cipher and advanced encryption standard (AES) keys. The keys were protected using a ciphertext attribute-based encryption (ABE) protocol. The encrypted data were transmitted through an insecure network. At the receiver end, AES keys were

TABLE 3. Summary of papers regarding edge- and cloud-based smart health care.

Ref.	Task	IoMTs	classifier	Database	Accuracy
[34]	Seizure detection	EEG's	Kriging method	The University of Bonn dataset consisting of 5 healthy subjects and 5 epilepsy patients; The Children's Hospital Boston (CHB) dataset having 22 patients	A training accuracy of 99.4%
[61]	Seizure detection	A wearable EEG device	Swift In-network Classification (SIC)	EEG dataset [87]	98%
[69]	Voice disorder	Smart sensors	CNN	The Saarbrucken Voice Disorder (SVD) database[88]	98.5%
[72]	Human activities	ECG, magnetometer, accelerometer and gyroscope sensors	RNN	MHEALTH public dataset [89]	99.69%
[74]	Stroke detection	CT	k-Nearest Neighbors (KNN), SVM, Bayes, Multilayer Perceptron (MLP), and Optimum Path Forest (OPF)	CT images dataset [90] 174 healthy + 142 hemorrhagic stroke patients + 157 ischemic stroke patients	98.13% and 97.83%, respectively

decrypted using the ABE protocol. Data were then decrypted using the ASE keys. This mechanism maintained the privacy and the security of patients' data.

Seliem and Elgazzar [86] proposed a blockchain for IoMT (BIoMT) to preserve security and privacy in a smart health care framework. The BIoMT had four layers. The first layer was a device layer, which contained IoMT and user interface devices. The second layer was a facility layer, which had a bolster to look after IoMT devices. The facility layer provided the basic blockchain modules for attribute number selection, security generation, and identity issuance. The third layer was a cloud layer that provided the computational power and storage, and the fourth layer was a cluster layer which contained medical facilities and the service provider.

Wang *et al.* [91] designed a fog-based access control (AC) method for the IoMT. The authors developed a method that installed an extra layer of control on fog servers to improve protection for local mobile devices. A register in the AC server was important for compliance with devices. Data access requests were submitted to the AC server, where the status of the application could be reviewed. The registry needed to ensure that the incoming function had been recorded in the past. The comparison should be performed as the work form was recorded to ensure that the privacy setting was changed. The architecture was situated in the fog layer, where functional-oriented servers could provide the required AC service to each device.

Dilawar *et al.* [92] introduced cryptography as a solution for the safe exchange of patient safety records using blockchain technologies to protect medical data. A unified blockchain-based technique would solve many of the difficulties related to a centralized cloud solution. Authors in [93] introduced an access management model that safeguarded patients' medical data from internal information security attacks. It enabled only legally permitted people to connect despite physical limitations. The suggested model incorporated authorization consistent with permits and responsibilities, rather than positions for medical personnel only. It eliminated the contradictions of current AC models.

Omotosho *et al.* [94] identified and incorporated some of the main characteristics of a patient's health report that should be published and made accessible at all times as well as qualities that should be disclosed only during emergency conditions or pre-hospital treatment. Creating medical features from patient health information that may be retrieved in critical cases is a proactive step that allows technicians to obtain access to required details in pre-hospital services while protecting patients' dignity and confidentiality.

Farahat *et al.* [95] introduced a data encryption scheme that involved first encoding data, then encrypting those data with a rotated key until they were sent across the network. Doctors can recover the protected data using their login keys and credentials. The scheme was implemented using low-cost equipment and reliable applications to ensure safety in the delivery of medical information.

Guan *et al.* [96] proposed a differential private data clustering scheme to allow privacy-preserving IoMT using the MapReduce system. For large-scale data sets, MapReduce is a parallel programming system that abstracts parallel computing procedures into two functions: Map and Reduce. In this scheme, the authors refined the distribution of privacy budgets and the collection of initial centroids to boost the performance of the k-means clustering algorithm. In addition, an enhanced method for collection of the initial centroids was suggested to maximize the precision and reliability of the clustering algorithm.

Hamidi [97] proposed a modern paradigm for the application of biometric technologies to the advancement of smart health care using the IoMT, which, in addition to being simple to use, requires broad-scope data access. While card IDs and passwords control entry, these systems can be quickly broken and are known to often be inefficient. A biometric trait has four main features: universality, distinctiveness, permanence, and collectability. The author anticipated four levels of security strategies: IoMT device, communication, analytical, and management.

Alsubaei *et al.* [80] outlined a web-based IoMT security assessment framework focused on an ontological scenario-driven methodology to propose security steps in the IoMT and to evaluate safety and deterrents in IoMT solutions. The framework encouraged the development of a strategy that fits stakeholders' protection goals and facilitates decision-making.

Elhoseny *et al.* [98] proposed a hybrid optimization of asymmetric encryption for IoMT security. An ideal private and transparent key-based authentication was used in IoT therapeutic images. Various approaches were considered to achieve optimal hybrid optimization, from which the researchers differentiated and analyzed the critical open-ended difficulties in enhancing IoT in healthcare.

Shakeel *et al.* [99] introduced learning-based Deep Q-Networks to reduce ransomware attacks when handling health records using IoMT devices. The approach analyzed the medical knowledge in various layers per the Q-learning principle, which allowed transitional attacks to be eliminated with less difficulty. Efficiency was measured in terms of energy, lifetime, throughput, accuracy, and malware error detection rate. Yi and Nie [100] proposed a multivariate quadratic equation–based cryptographic security system for IoMT devices. A physical analysis model of the cryptographic system was designed by analyzing fault tolerance and differential power on a cloud platform.

Survey Papers on Security and Privacy in IoMT-Based Health Care: A survey on security and privacy in the IoMT was presented in [101]. The authors identified four requirements for security and privacy: data integrity, data usability, data auditing, and patient information privacy. Existing solutions to these requirements were discussed and included data encryption, access control, trusted third-party auditing, data search, and data anonymization. For example, some encryption methods for access control include attribute-based encryption and symmetric and asymmetric key encryption. The paper ended by noting some future challenges, such as how to deal with insecure networks, develop lightweight protocols for devices, and share patients' private data.

Hatzivasilis *et al.* [102] reviewed security and privacy in the IoMT. In an IoMT-based health care system, there are three main application settings: hospitals, homes, and body sensors. Three security aspects—confidentiality, integrity, and availability—should be enforced in device, connectivity, and cloud security. The survey analyzed different types of security components. Various types of protection mechanisms, identification and anonymity techniques, and data destruction for device reuse were also discussed.

Sun *et al.* [103] provided an outline of the latest problems, requirements, and possible risks to the protection and confidentiality of IoMT-based health care systems. To design an IoMT networks, one must address postural body movements, rises in temperature, energy efficiency, transmission range, quality of service, and heterogeneous environments. The security and confidentiality requirements have different attribute levels. At the data level, care must be taken regarding confidentiality, integrity, and availability. At the sensor level, the design must address tamper-proof hardware, localization, self-healing, over-the-air programming, and forward and backward compatibility. At the personal server level, device authentication and user authentication should be considered, while at the medical server level, important requirements include access control, key management, trust management, and resistance to denial of service attacks.

Li *et al.* [104] provided a survey of secured IoMT with friendly-jamming schemes. The authors reviewed the IoMT's existing protection systems and defined key security issues in the IoMT. They recommended friendly-jamming schemes to protect patients' sensitive diagnostic data obtained from medical sensors. They concluded that, when properly planned, friendly-jamming approaches could substantially reduce the probability of effectiveness of eavesdropping activity while having no substantial impact on legal transmission.

Ghoneim *et al.* [105] introduced a new medical image forgery detection method to verify that health care images had not been changed or altered. The method generates an image noise map, realizes a multi-resolution regression filter to the noise map, and feeds the output to SVM-based and

ELM-based classifiers. Another copy-move image forgery detection method was proposed in [112]; the method could be used in medical image forgery detection.

Lin *et al.* [106] reviewed the security and privacy issues, challenges, and future directions in the IoMT field. There are four major categories of medical sensors: disposable health sensors, connected health sensors, IoT-supported sensors, and IoT market cap sensors. The authors provided a systematic review of these sensors in terms of their security and privacy, followed by the challenges they present. Some of these challenges included the integration of multiple sensors with proper protocols, data bursts, and social acceptance. In a related survey, Masud *et al.* [117] outlined some limitations and issues related to the security of IoMT devices and provided some recommendations. They listed risks such as the disclosure of personal information, data falsification, lack of training, and reasonable accuracy.

IV. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The major challenges of IoT and AI-based smart healthcare include sensors' interoperability, device communication, security and privacy, device management, information management barrier, and efficient use of AI. In some health care environments, the bulk of IoMT devices can be used to identify and diagnose an illness, and the data collected from heterogeneous sensors contains a variety of issues, such as hardware glitches, drained batteries, or connectivity problems [106]. There are certain basic problems that are normal and unregulated. In particular, there are sometimes unexplained errors in the usage of popular medical sensors, such as mobile phones and smartwatches. There are also regular complexities, such as battery power, distinctions between particular physical characteristics, and variations in the environment.

The above problems indicate that several difficulties exist in smart health care, though multimodal signals and several IoMT devices are being used. A simplified and easier fusion solution should be discussed to facilitate the general adoption of such smart health care [115], [119], [121], [123]. Below, we discuss some of these problems and potential solutions.

The healthcare system can get inconsistent data from the multiple sensors because of the unawareness from the researchers. Incomplete data may get thieved or faked by other people. Radio frequencies of IoTs might have an effect on reading areas, and readers might give false readings. Tag collisions and tag detuning should be corrected, along with metal/liquid effects and tag misalignment. The system can get redundant data which need to be refined.

Wearable sensors are equipped with batteries, Bluetooth, and other materials and were designed to be attached to human skin. For human safety, it is important to consider toxicity, flammable materials, and other factors when designing wearable sensors. Wearable sensors that constrain body movement, such as a belt worn at the waist or ankle, are uncomfortable, especially for the elderly and children. One challenge is to develop sensors that continuously monitor human vital signs using suitable materials and without reducing user comfort.

There is an increase of the number of connected sensors, devices, and IoTs in any smart system. A massive healthcare network will work only if it has sensing capabilities plus the capacity to produce important information. In the healthcare system, many millions of sensors and IoTs are linked that provide massive amounts of data to be studied. In the IoT, the entities should have compatible data model and knowledge representation model.

There is a need to recognize interoperability of IoTs or partnership between nations when it comes to the development of digital health infrastructure. This disadvantage, along with lack of IT infrastructure, is attributed to both a lack of IT skills and the need for international collaboration in the sharing of confidential medical data, which will promote remote telemedicine and the provision of high-quality medical care. Shibboleth is a distributed identification key, which allows individuals to be authenticated inside and through organizational systems. The conventional Shibboleth mechanism requires a user to confirm to an ID provider and then directs a demand for a site to be hosted by a service provider. With this distributed approach, Shibboleth allows digital health organizations to have a single sign-on capability, as in the case of digital health.

Automatic health care programs depend on self-sensing, self-adjustment, and self-tuning [108], [113]. As background such as sensor noise and recording environment, varies, fusion of sensors and IoTs can deal with the modifications, since they can have a direct impact on system properties such as precision. Information transfer methods for transfer learning should be used to permit the system to adjust to particular circumstances by collecting and transferring acquaintance from one situation to another.

Unauthorized access to IoT devices may contribute to extreme health and private information threats to patients. Linked computers, including the compilation, aggregation, retrieval and transmission of patient knowledge to the cloud. Cloning, spoofing, RF jamming and cloud polling is prone to system type. In the cloud survey, traffic is diverted such that commands can be injected directly to a computer by an individual in the center.

Attacks with denials of service (DoS) can impact health organizations and the security of patients. Although replication (use of several devices on the network) is a standard protection of DoS, it might not often be feasible to replicate resources in a healthcare setting since some of the devices are essential systems implant. Owing to the amount and sophistication of new device and hardware bugs, the quick identification of possible security hazards remains a problem. This problem is escalating as the Internet links more and more users. Standard security is also widespread today and unsecure user interface access raises the threat surface more.

Many wireless networking devices have also recently been used in the health care industry, including Wi-Fi, BLE and ZigBee, for linking various medical equipment and sensor forms to each other. Defense from eavesdropping, sybil assault, plunger hole attacks and sleep loss attacks must be applied with these wireless sensor and sensor technologies. In order to preserve protection and privacy, core data sets of personal details, family histories and electronic medical documents can also be guarding against hackers and malicious devices.

The misuse of access privileges by allowed insiders is a big concern. This kind of information sharing occurs when health facilities disclose sensitive medical information to unauthorized people, either due to irresponsibility, for individual or criminal purposes, or in return for illegal benefits. Celebrities' health reports and the lawmakers' information also leaks to the public from a centralized healthcare system. This could cause a breach of the regulation by the insiders and the documents that they would not have access to. For example, medical personnel who are not taking care of real patient and former staff who are not yet restricted from data query. A disgruntled party will cause problems to each other by accessing the protected details of each other. Intruders are trying to pretend to be healers in order to infiltrate. Cybercrime as a virus of today's Internet sector is a big issue and a menace to health. There are high costs for unsafe medical practice such as negative impact on their reputation, penalties, legal liability, and many more.

Traditional AI-based healthcare systems may not gain acceptability to the doctors. Therefore, explainable AI-based system can be deployed, where the doctors can visualize the detection or classification of diseases. The optimization of edge resources can be efficiently done edge-intelligent algorithms [105], [107], [109], [114].

The practical usefulness IoMT activated healthcare systems is rarely addressed in literature. The main concern is that the most relevant data is owned by companies and is not accessible to the public. The efficient deployment and utilization of data fusion in practice will allow for more reliable measurement and evaluation of day-to-day physical activity utilizing low-cost monitors that can lead to easier and better preventive care for chronic diseases. We assume that hosting medical data in a public archive with appropriate protection precautions and exploring current data fusion strategies using such public data will be a crucial potential direction for future research.

The advancement of next-generation wireless networks poses a great prospect in smart healthcare [118], [120], [122]. With the help of 5G and beyond 5G networks, now the healthcare system can be reached anywhere in the world faster than before. In addition, federated DL and edge-based computing become easier and powerful [2], [104], [116].

V. CONCLUSION

Smart healthcare is a well-researched area. In the smart health care domain, there is a breadth of literature covering IoT, IoMT, medical signals, AI, edge and cloud computing at various rates and utilizing varied tactics. However, to the best of our knowledge, there was a lack of a thorough and systematic analysis of state-of-the-art IoT, IoMT, AI, medical signals use and fusion, edge and cloud computing, privacy and security in the smart health care domain. The purpose of this survey was thus to offer a formal classification and specific comparative context for IoT, IoMT, AI, edge and cloud computing, privacy and security in smart health care. The survey included the use of IoT, IoMT, and medical signals, the fusion of sensors, and the use of edge and cloud computing in smart healthcare. It further provided a survey of security and privacy issues involving IoMT devices. Finally, some research challenges and future research directions were discussed.

REFERENCES

[1] M. S. Hossain, G. Muhammad, and N. Guizani, "Explainable AI and mass surveillance system-based healthcare framework to combat COVID-I9 like pandemics," *IEEE Netw.*, vol. 34, no. 4, pp. 126–132, Jul. 2020.

[2] G. Muhammad, M. F. Alhamid, and X. Long, "Computing and processing on the edge: Smart pathology detection for connected healthcare," *IEEE Netw.*, vol. 33, no. 6, pp. 44–49, Nov. 2019.

[3] F. Miao, Z.-D. Liu, J.-K. Liu, B. Wen, Q.-Y. He, and Y. Li, "Multi-sensor fusion approach for cuff-less blood pressure measurement," *IEEE J. Biomed. Health Informat.*, vol. 24, no. 1, pp. 79–91, Jan. 2020.

[4] F. Yang, X. Zhao, W. Jiang, P. Gao, and G. Liu, "Multi-method fusion of cross-subject emotion recognition based on high-dimensional EEG features," *Frontiers Comput. Neurosci.*, vol. 13, p. 53, Aug. 2019. Accessed: Jul. 1, 2020. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6714862/

[5] Q. Gu, S. Jiang, M. Lian, and C. Lu, "Health and safety situation awareness model and emergency management based on multi-sensor signal fusion," *IEEE Access*, vol. 7, pp. 958–968, 2019.

[6] M. Muzammal, R. Talat, A. H. Sodhro, and S. Pirbhulal, "A multi-sensor data fusion enabled ensemble approach for medical data from body sensor networks," *Inf. Fusion*, vol. 53, pp. 155–164, Jan. 2020.

[7] T. Van Steenkiste, D. Deschrijver, and T. Dhaene, "Sensor fusion using backward shortcut connections for sleep apnea detection in multi-modal data," 2019, *arXiv:1912.06879*. [Online]. Available: http://arxiv.org/abs/1912.06879

[8] K. Lin, Y. Li, J. Sun, D. Zhou, and Q. Zhang, "Multi-sensor fusion for body sensor network in medical human–robot interaction scenario," *Inf. Fusion*, vol. 57, pp. 15–26, May 2020.

[9] F. Al-Shargie, "Fusion of fNIRS and EEG signals: Mental stress study," *engrXiv*, vol. 2019, pp. 1–5, Apr. 2019, doi: 10.31224/osf.io/kaqew.

[10] A. A. Mergin and M. S. G. Premi, "Pixel level fusion of medical signals using DCT, DWT and hybrid(DWT-DCT) transform based on maximum selection rule—A comparison," in *Proc. Int. Conf. Comput. Methodologies Commun. (ICCMC)*, Erode, India, Jul. 2017, pp. 898–903.

[11] J. Chen, L. Zhang, L. Lu, Q. Li, M. Hu, and X. Yang, "A novel medical image fusion method based on rolling guidance filtering," *Internet of Things*, Feb. 2020, Art. no. 100172.

[12] I. Cabria and I. Gondra, "MRI segmentation fusion for brain tumor detection," *Inf. Fusion*, vol. 36, pp. 1–9, Jul. 2017.

[13] V. Nathan and R. Jafari, "Particle filtering and sensor fusion for robust heart rate monitoring using wearable sensors," *IEEE J. Biomed. Health Informat.*, vol. 22, no. 6, pp. 1834–1846, Nov. 2018.

[14] M. Simjanoska, S. Kochev, J. Tanevski, A. M. Bogdanova, G. Papa, and T. Eftimov, "Multi-level information fusion for learning a blood pressure predictive model using sensor data," *Inf. Fusion*, vol. 58, pp. 24–39, Jun. 2020.

[15] D. Fabiano and S. Canavan, "Emotion recognition using fused physiological signals," in *Proc. 8th Int. Conf. Affect. Comput. Intell. Interact. (ACII)*, Cambridge, U.K., Sep. 2019, pp. 42–48.

[16] C. Chen, R. Jafari, and N. Kehtarnavaz, "A real-time human action recognition system using depth and inertial sensor fusion," *IEEE Sensors J.*, vol. 16, no. 3, pp. 773–781, Feb. 2016.

[17] W. Zhang, J. Yang, H. Su, M. Kumar, and Y. Mao, "Medical data fusion algorithm based on Internet of Things," *Pers. Ubiquitous Comput.*, vol. 22, nos. 5–6, pp. 895–902, Oct. 2018.

[18] J. Du, W. Li, and H. Tan, "Intrinsic image decomposition-based grey and pseudo-color medical image fusion," *IEEE Access*, vol. 7, pp. 56443–56456, 2019.

[19] G. Qi, J. Wang, Q. Zhang, F. Zeng, and Z. Zhu, "An integrated dictionary-learning entropy-based medical image fusion framework," *Future Internet*, vol. 9, no. 4, p. 61, Oct. 2017.

[20] Z. Baloch, F. K. Shaikh, and M. A. Unar, "A context-aware data fusion approach for health-IoT," *Int. J. Inf. Technol.*, vol. 10, no. 3, pp. 241–245, Sep. 2018.

[21] R. Dautov, S. Distefano, and R. Buyya, "Hierarchical data fusion for smart healthcare," *J. Big Data*, vol. 6, no. 1, p. 19, Feb. 2019.

[22] I. Herrera-Luna, E. J. Rechy-Ramirez, H. V. Rios-Figueroa, and A. Marin-Hernandez, "Sensor fusion used in applications for hand rehabilitation: A systematic review," *IEEE Sensors J.*, vol. 19, no. 10, pp. 3581–3592, May 2019.

[23] M. Haghi, K. Thurow, and R. Stoll, "Wearable devices in medical Internet of Things: Scientific research and commercially available devices," *Healthcare Informat. Res.*, vol. 23, no. 1, p. 4, 2017.

[24] M. Abdel-Basset, W. Ding, and L. Abdel-Fatah, "The fusion of Internet of intelligent things (IoIT) in remote diagnosis of obstructive sleep apnea: A survey and a new model," *Inf. Fusion*, vol. 61, pp. 84–100, Sep. 2020.

[25] R. Gravina, P. Alinia, H. Ghasemzadeh, and G. Fortino, "Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges," *Inf. Fusion*, vol. 35, pp. 68–80, May 2017.

[26] M. Sumithra and S. Malathi, "A brief survey on multi modalities fusion," in *Emerging Trends in Computing and Expert Technology* (Lecture Notes on Data Engineering and Communications Technologies), vol. 35. Cham, Switzerland: Springer, 2020, pp. 1031–1041.

[27] C. Li and A. Zhu, "Application of image fusion in diagnosis and treatment of liver cancer," *Appl. Sci.*, vol. 10, no. 3, p. 1171, Feb. 2020.

[28] S. Swayamsiddha and C. Mohanty, "Application of cognitive Internet of medical things for COVID-19 pandemic," *Diabetes Metabolic Syndrome, Clin. Res. Rev.*, vol. 14, no. 5, pp. 911–915, Sep. 2020.

[29] T. Yang, M. Gentile, C.-F. Shen, and C.-M. Cheng, "Combining point-of-care diagnostics and Internet of medical things (IoMT) to combat the COVID-19 pandemic," *Diagnostics*, vol. 10, no. 4, p. 224, Apr. 2020.

[30] R. P. Singh, M. Javaid, A. Haleem, and R. Suman, "Internet of Things (IoT) applications to fight against COVID-19 pandemic," *Diabetes Metabolic Syndrome, Clin. Res. Rev.*, vol. 14, no. 4, pp. 521–524, Jul. 2020.

[31] R. Pratap Singh, M. Javaid, A. Haleem, R. Vaishya, and S. Ali, "Internet of medical things (IoMT) for orthopaedic in COVID-19 pandemic: Roles, challenges, and applications," *J. Clin. Orthopaedics Trauma*, vol. 11, no. 4, pp. 713–717, Jul. 2020.

[32] K. Ullah, M. A. Shah, and S. Zhang, "Effective ways to use Internet of Things in the field of medical and smart health care," in *Proc. Int. Conf. Intell. Syst. Eng. (ICISE)*, Islamabad, Pakistan, Jan. 2016, pp. 372–379.

[33] Y. Zhang, Y. Zhang, X. Zhao, Z. Zhang, and H. Chen, "Design and data analysis of sports information acquisition system based on Internet of medical things," *IEEE Access*, vol. 8, pp. 84792–84805, 2020.

[34] I. Chiuchisan, H.-N. Costin, and O. Geman, "Adopting the Internet of Things technologies in health care systems," in *Proc. Int. Conf. Expo. Electr. Power Eng. (EPE)*, Iasi, Romania, Oct. 2014, pp. 532–535.

[35] A. Sharipudin and W. Ismail, "Internet of medical things (IoMT) for patient healthcare monitoring system," in *Proc. IEEE 14th Malaysia Int. Conf. Commun. (MICC)*, Selangor, Malaysia, Dec. 2019, pp. 69–74.

[36] D. V. Dimitrov, "Medical Internet of Things and big data in healthcare," *Healthcare Inform. Res.*, vol. 22, no. 3, pp. 156–163, 2016.

[37] A. Pazienza, R. Anglani, G. Mallardi, C. Fasciano, P. Noviello, C. Tatulli, and F. Vitulano, "Adaptive critical care intervention in the Internet of medical things," in *Proc. IEEE Conf. Evolving Adapt. Intell. Syst. (EAIS)*, Bari, Italy, May 2020, pp. 1–8.

[38] S. Sanyal, D. Wu, and B. Nour, "A federated filtering framework for Internet of medical things," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Shanghai, China, May 2019, pp. 1–6.

[39] M. Luna-delRisco, M. G. Palacio, C. A. A. Orozco, S. V. Moncada, L. G. Palacio, J. J. Q. Montealegre, and I. Diaz-Forero, "Adoption of Internet of medical things (IoMT) as an opportunity for improving public health in Latin America," in *Proc. 13th Iberian Conf. Inf. Syst. Technol. (CISTI)*, Caceres, Spain, Jun. 2018, pp. 1–5.

[40] T. Adali, Y. Levin-Schwartz, and V. D. Calhoun, "Multimodal data fusion using source separation: Application to medical imaging," *Proc. IEEE*, vol. 103, no. 9, pp. 1494–1506, Sep. 2015.

[41] M. S. Hossain, S. U. Amin, M. Alsulaiman, and G. Muhammad, "Applying deep learning for epilepsy seizure detection and brain mapping visualization," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 15, no. 1s, pp. 10:1-10:17, Feb. 2019.

[42] *The Whole Brain Atlas*. Accessed: Jul. 17, 2020. [Online]. Available: http://www.med.harvard.edu/aanlib/home.html

[43] Z. Zhang, Z. Pi, and B. Liu, "TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 2, pp. 522–531, Feb. 2015.

[44] *Image Fusion Organization,Image Fusion Source Images*. Accessed: Oct. 20, 2019. [Online]. Available: http://www.imagefusion.org

[45] E. A. Bernal, X. Yang, Q. Li, J. Kumar, S. Madhvanath, P. Ramesh, and R. Bala, "Deep temporal multimodal fusion for medical procedure monitoring using wearable sensors," *IEEE Trans. Multimedia*, vol. 20, no. 1, pp. 107–118, Jan. 2018.

[46] X. Xu, D. Shan, G. Wang, and X. Jiang, "Multimodal medical image fusion using PCNN optimized by the QPSO algorithm," *Appl. Soft Comput.*, vol. 46, pp. 588–595, Sep. 2016.

[47] A. Moin, V. Bhateja, and A. Srivastava, "Weighted-PCA based multimodal medical image fusion in contourlet domain," in *Proc. Int. Congr. Inf. Commun. Technol.*, Singapore, 2016, pp. 597–605.

[48] C. Torres, S. D. Hammond, J. C. Fried, and B. S. Manjunath, "Sleep pose recognition in an ICU using multimodal data and environmental feedback," in *Computer Vision Systems*. Cham, Switzerland: Springer, 2015, pp. 56–66.

[49] S. D. Ramlal, J. Sachdeva, C. K. Ahuja, and N. Khandelwal, "An improved multimodal medical image fusion scheme based on hybrid combination of nonsubsampled contourlet transform and stationary wavelet transform," *Int. J. Imag. Syst. Technol.*, vol. 29, no. 2, pp. 146–160, Jun. 2019.

[50] M. Manchanda and R. Sharma, "An improved multimodal medical image fusion algorithm based on fuzzy transform," *J. Vis. Commun. Image Represent.*, vol. 51, pp. 76–94, Feb. 2018.

[51] G. J. Joyia, R. M. Liaqat, A. Farooq, and S. Rehman, "Internet of medical things (IOMT): Applications, benefits and future challenges in healthcare domain," *J. Commun.*, vol. 12, no. 4, pp. 240–247, 2017.

[52] M. Irfan and N. Ahmad, "Internet of medical things: Architectural model, motivational factors and impediments," in *Proc. 15th Learn. Technol. Conf. (L&T)*, Feb. 2018, pp. 6–13.

[53] F. Al-Turjman, M. H. Nawaz, and U. D. Ulusar, "Intelligence in the Internet of medical things era: A systematic review of current and future trends," *Comput. Commun.*, vol. 150, pp. 644–660, Jan. 2020.

[54] V. D. Calhoun and J. Sui, "Multimodal fusion of brain imaging data: A key to finding the missing link(s) in complex mental illness," *Biol. Psychiatry, Cognit. Neurosci. Neuroimaging*, vol. 1, no. 3, pp. 230–244, May 2016.

[55] M. S. Hossain and G. Muhammad, "Emotion recognition using secure edge and cloud computing," *Inf. Sci.*, vol. 504, pp. 589–601, Dec. 2019.

[56] I. V. Pustokhina, D. A. Pustokhin, D. Gupta, A. Khanna, K. Shankar, and G. N. Nguyen, "An effective training scheme for deep neural network in edge computing enabled Internet of medical things (IoMT) systems," *IEEE Access*, vol. 8, pp. 107112–107123, 2020.

[57] T. Han, L. Zhang, S. Pirbhulal, W. Wu, and V. H. C. de Albuquerque, "A novel cluster head selection technique for edge-computing based IoMT systems," *Comput. Netw.*, vol. 158, pp. 114–122, Jul. 2019.

[58] M. Alhussein, G. Muhammad, M. S. Hossain, and S. U. Amin, "Cognitive IoT-cloud integration for smart healthcare: Case study for epileptic seizure detection and monitoring," *Mobile Netw. Appl.*, vol. 23, no. 6, pp. 1624–1635, Dec. 2018.

[59] G. Muhammad, S. M. M. Rahman, A. Alelaiwi, and A. Alamri, "Smart health solution integrating IoT and cloud: A case study of voice pathology monitoring," *IEEE Commun. Mag.*, vol. 55, no. 1, pp. 69–73, Jan. 2017.

[60] I. L. Olokodana, S. P. Mohanty, E. Kougianos, and O. O. Olokodana, "Real-time automatic seizure detection using ordinary kriging method in an edge-IoMT computing paradigm," *Social Netw. Comput. Sci.*, vol. 1, no. 5, p. 258, Aug. 2020.

[61] A. Awad Abdellatif, A. Emam, C.-F. Chiasserini, A. Mohamed, A. Jaoua, and R. Ward, "Edge-based compression and classification for smart healthcare systems: Concept, implementation and evaluation," *Expert Syst. Appl.*, vol. 117, pp. 1–14, Mar. 2019.

[62] Y. Zhang, X. Ma, J. Zhang, M. S. Hossain, G. Muhammad, and S. U. Amin, "Edge intelligence in the cognitive Internet of Things: Improving sensitivity and interactivity," *IEEE Netw.*, vol. 33, no. 3, pp. 58–64, May 2019.

[63] M. Chen, W. Li, Y. Hao, Y. Qian, and I. Humar, "Edge cognitive computing based smart healthcare system," *Future Gener. Comput. Syst.*, vol. 86, pp. 403–411, Sep. 2018.

[64] C. Dilibal, "Development of edge-IoMT computing architecture for smart healthcare monitoring platform," in *Proc. 4th Int. Symp. Multidisciplinary Stud. Innov. Technol. (ISMSIT)*, Istanbul, Turkey, Oct. 2020, pp. 1–4.

[65] A. O. Akmandor and N. K. Jha, "Smart health care: An edge-side computing perspective," *IEEE Consum. Electron. Mag.*, vol. 7, no. 1, pp. 29–37, Jan. 2018.

[66] M. Alhussein and G. Muhammad, "Voice pathology detection using deep learning on mobile healthcare framework," *IEEE Access*, vol. 6, pp. 41034–41041, 2018.

[67] G. Muhammad, M. S. Hossain, and N. Kumar, "EEG-based pathology detection for home health monitoring," *IEEE J. Sel. Areas Commun.*, early access, Aug. 31, 2020, doi: 10.1109/JSAC.2020.3020654.

[68] Z. Ali, G. Muhammad, and M. F. Alhamid, "An automatic health monitoring system for patients suffering from voice complications in smart cities," *IEEE Access*, vol. 5, pp. 3900–3908, 2017.

[69] G. Muhammad, M. F. Alhamid, M. Alsulaiman, and B. Gupta, "Edge computing with cloud for voice disorder assessment and treatment," *IEEE Commun. Mag.*, vol. 56, no. 4, pp. 60–65, Apr. 2018.

[70] S. Oueida, Y. Kotb, M. Aloqaily, Y. Jararweh, and T. Baker, "An edge computing based smart healthcare framework for resource management," *Sensors*, vol. 18, no. 12, p. 4307, Dec. 2018.

[71] J. Kharel, H. T. Reda, and S. Y. Shin, "Fog computing-based smart health monitoring system deploying LoRa wireless communication," *IETE Tech. Rev.*, vol. 36, no. 1, pp. 69–82, Jan. 2019.

[72] M. Z. Uddin, "A wearable sensor-based activity prediction system to facilitate edge computing in smart healthcare system," *J. Parallel Distrib. Comput.*, vol. 123, pp. 46–53, Jan. 2019.

[73] H. Wang, J. Gong, Y. Zhuang, H. Shen, and J. Lach, "Healthedge: Task scheduling for edge computing with health emergency and human behavior consideration in smart homes," in *Proc. Int. Conf. Netw., Archit., Storage (NAS)*, Shenzhen, China, Aug. 2017, pp. 1213–1222.

[74] A. Al-nasheri, G. Muhammad, M. Alsulaiman, and Z. Ali, "Investigation of voice pathology detection and classification on different frequency regions using correlation functions," *J. Voice*, vol. 31, no. 1, pp. 3–15, Jan. 2017.

[75] M. Elhoseny, A. Abdelaziz, A. S. Salama, A. M. Riad, K. Muhammad, and A. K. Sangaiah, "A hybrid model of Internet of Things and cloud computing to manage big data in health services applications," *Future Gener. Comput. Syst.*, vol. 86, pp. 1383–1394, Sep. 2018.

[76] G. Muhammad, M. S. Hossain, and A. Yassine, "Tree-based deep networks for edge devices," *IEEE Trans. Ind. Informat.*, vol. 16, no. 3, pp. 2022–2028, Mar. 2020.

[77] K. Chung and H. Yoo, "Edge computing health model using P2P-based deep neural networks," *Peer-to-Peer Netw. Appl.*, vol. 13, no. 2, pp. 694–703, Mar. 2020.

[78] A. Limaye and T. Adegbija, "A workload characterization for the Internet of medical things (IoMT)," in *Proc. IEEE Comput. Soc. Annu. Symp. VLSI (ISVLSI)*, Bochum, Germany, Jul. 2017, pp. 302–307.

[79] F. Alsubaei, A. Abuhussein, and S. Shiva, "Security and privacy in the Internet of medical things: Taxonomy and risk assessment," in *Proc. IEEE 42nd Conf. Local Comput. Netw. Workshops (LCN Workshops)*, Singapore, Oct. 2017, pp. 112–120.

[80] F. Alsubaei, A. Abuhussein, and S. Shiva, "Ontology-based security recommendation for the Internet of medical things," *IEEE Access*, vol. 7, pp. 48948–48960, 2019.

[81] R. Ivanov, H. Nguyen, J. Weimer, O. Sokolsky, and I. Lee, "OpenICE-lite: Towards a connectivity platform for the Internet of medical things," in *Proc. IEEE 21st Int. Symp. Real-Time Distrib. Comput. (ISORC)*, May 2018, pp. 103–106.

[82] X. Lu and X. Cheng, "A secure and lightweight data sharing scheme for Internet of medical things," *IEEE Access*, vol. 8, pp. 5022–5030, 2020.

[83] A. Mohan, "Cyber security for personal medical devices Internet of Things," in *Proc. IEEE Int. Conf. Distrib. Comput. Sensor Syst.*, Marina Del Rey, CA, USA, May 2014, pp. 372–374.

[84] D. Nkomo and R. Brown, "Hybrid cybersecurity framework for the Internet of medical things (IOMT)," in *Proc. IEEE 12th Int. Conf. Global Secur., Saf. Sustainability (ICGS)*, London, U.K., Jan. 2019, p. 212.

[85] R. M. P. H. K. Rathnayake, M. S. Karunarathne, N. S. Nafi, and M. A. Gregory, "Cloud enabled solution for privacy concerns in Internet of medical things," in *Proc. 28th Int. Telecommun. Netw. Appl. Conf. (ITNAC)*, Sydney, NSW, Australia, Nov. 2018, pp. 1–4.

[86] M. Seliem and K. Elgazzar, "BIoMT: Blockchain for the Internet of medical things," in *Proc. IEEE Int. Black Sea Conf. Commun. Netw. (BlackSeaCom)*, Sochi, Russia, Jun. 2019, pp. 1–4.

[87] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 64, no. 6, Nov. 2001, Art. no. 061907.

[88] W. J. Barry and M. Putzer. *Saarbruecken Voice Database*. Accessed: May 23, 2019. [Online]. Available: http://stimmdatenbank.coli.uni-saarland.de

[89] O. Banos, R. Garcia, J. A. Holgado-Terriza, M. Damas, H. Pomares, I. Rojas, A. Saez, and C. Villalonga, "mHealthDroid: A novel framework for agile development of mobile health applications," in *Ambient Assisted Living and Daily Activities* (Lecture Notes in Computer Science), vol. 8868. Cham, Switzerland: Springer, 2014, pp. 91–98.

[90] P. P. Rebouças Filho, R. M. Sarmento, G. B. Holanda, and D. de Alencar Lima, "New approach to detect and classify stroke in skull CT images via analysis of brain tissue densities," *Comput. Methods Programs Biomed.*, vol. 148, pp. 27–43, Sep. 2017.

[91] X. Wang, L. Wang, Y. Li, and K. Gai, "Privacy-aware efficient fine-grained data access control in Internet of medical things based fog computing," *IEEE Access*, vol. 6, pp. 47657–47665, 2018.

[92] N. Dilawar, M. Rizwan, F. Ahmad, and S. Akram, "Blockchain: Securing Internet of medical things (IoMT)," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 1, pp. 82–89, 2019.

[93] M. S. Hossain, "Cloud-supported cyber–physical localization framework for patients monitoring," *IEEE Syst. J.*, vol. 11, no. 1, pp. 118–127, Mar. 2017.

[94] A. Omotosho, O. Adegbola, B. Adelakin, A. Adelakun, and J. Emuoyibofarhe, "Exploiting multimodal biometrics in E-privacy scheme for electronic health records," *J. Biol., Agricult. Healthcare*, vol. 4, no. 18, pp. 22–33, Feb. 2015.

[95] I. S. Farahat, A. S. Tolba, M. Elhoseny, and W. Eladrosy, "A secure real-time Internet of medical smart things (IOMST)," *Comput. Electr. Eng.*, vol. 72, pp. 455–467, Nov. 2018.

[96] Z. Guan, Z. Lv, X. Du, L. Wu, and M. Guizani, "Achieving data utility-privacy tradeoff in Internet of medical things: A machine learning approach," *Future Gener. Comput. Syst.*, vol. 98, pp. 60–68, Sep. 2019.

[97] H. Hamidi, "An approach to develop the smart health using Internet of Things and authentication based on biometric technology," *Future Gener. Comput. Syst.*, vol. 91, pp. 434–449, Feb. 2019.

[98] M. Elhoseny, K. Shankar, S. K. Lakshmanaprabu, A. Maseleno, and N. Arunkumar, "Hybrid optimization with cryptography encryption for medical image security in Internet of Things," *Neural Comput. Appl.*, vol. 32, no. 15, pp. 10979–10993, Aug. 2020.

[99] P. Mohamed Shakeel, S. Baskar, V. R. Sarma Dhulipala, S. Mishra, and M. M. Jaber, "Maintaining security and privacy in health care system using learning based deep-Q-networks," *J. Med. Syst.*, vol. 42, no. 10, p. 186, Aug. 2018.

[100] H. Yi and Z. Nie, "On the security of MQ cryptographic systems for constructing secure Internet of medical things," *Pers. Ubiquitous Comput.*, vol. 22, nos. 5–6, pp. 1075–1081, Oct. 2018.

[101] W. Sun, Z. Cai, Y. Li, F. Liu, S. Fang, and G. Wang, "Security and privacy in the medical Internet of Things: A review," *Secur. Commun. Netw.*, vol. 2018, pp. 1–9, 2018, 5978636.

[102] G. Hatzivasilis, O. Soultatos, S. Ioannidis, C. Verikoukis, G. Demetriou, and C. Tsatsoulis, "Review of security and privacy for the Internet of medical things (IoMT)," in *Proc. 15th Int. Conf. Distrib. Comput. Sensor Syst. (DCOSS)*, Santorini Island, Greece, May 2019, pp. 457–464.

[103] Y. Sun, F. P.-W. Lo, and B. Lo, "Security and privacy for the Internet of medical things enabled healthcare systems: A survey," *IEEE Access*, vol. 7, pp. 183339–183355, 2019.

[104] X. Li, H.-N. Dai, Q. Wang, M. Imran, D. Li, and M. A. Imran, "Securing Internet of medical things with friendly-jamming schemes," *Comput. Commun.*, vol. 160, pp. 431–442, Jul. 2020.

[105] A. Ghoneim, G. Muhammad, S. U. Amin, and B. Gupta, "Medical image forgery detection for smart healthcare," *IEEE Commun. Mag.*, vol. 56, no. 4, pp. 33–37, Apr. 2018.
[106] K. Lin, J. Song, J. Luo, W. Ji, M. Shamim Hossain, and A. Ghoneim, "Green video transmission in the mobile cloud networks," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 27, no. 1, pp. 159–169, Jan. 2017.
[107] M. S. Hossain and G. Muhammad, "Emotion-aware connected healthcare big data towards 5G," *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2399–2406, Aug. 2018.
[108] M. Chen, J. Yang, L. Hu, M. S. Hossain, and G. Muhammad, "Urban healthcare big data system based on crowdsourced and cloud-based air quality indicators," *IEEE Commun. Mag.*, vol. 56, no. 11, pp. 14–20, Nov. 2018.
[109] X. Yang, T. Zhang, C. Xu, S. Yan, M. S. Hossain, and A. Ghoneim, "Deep relative attributes," *IEEE Trans. Multimedia*, vol. 18, no. 9, pp. 1832–1842, Sep. 2016.
[110] M. S. Hossain, M. Al-Hammadi, and G. Muhammad, "Automatic fruit classification using deep learning for industrial applications," *IEEE Trans. Ind. Informat.*, vol. 15, no. 2, pp. 1027–1034, Feb. 2019.
[111] M. S. Hossain and G. Muhammad, "Cloud-based collaborative media service framework for HealthCare," *Int. J. Distrib. Sensor Netw.*, vol. 10, no. 3, Mar. 2014, Art. no. 858712.
[112] N. Muhammad, M. Hussain, G. Muhammad, and G. Bebis, "Copy-move forgery detection using dyadic wavelet transform," in *Proc. 8th Int. Conf. Comput. Graph., Imag. Visualizat.*, Singapore, Aug. 2011, pp. 103–108.
[113] G. Muhammad, T. A. Mesallam, K. H. Malki, M. Farahat, M. Alsulaiman, and M. Bukhari, "Formant analysis in dysphonic patients and automatic arabic digit speech recognition," *Biomed. Eng. OnLine*, vol. 10, no. 1, p. 41, 2011.
[114] M. A. Rahman, M. S. Hossain, M. S. Islam, N. A. Alrajeh, and G. Muhammad, "Secure and provenance enhanced Internet of health things framework: A blockchain managed federated learning approach," *IEEE Access*, vol. 8, pp. 205071–205087, Nov. 2020.
[115] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, and M. S. Hossain, "Deep learning for EEG motor imagery classification based on multi-layer CNNs feature fusion," *Future Gener. Comput. Syst.*, vol. 101, pp. 542–554, Dec. 2019.
[116] M. S. Hossain, M. A. Rahman, and G. Muhammad, "Cyber–physical cloud-oriented multi-sensory smart home framework for elderly people: An energy efficiency perspective," *J. Parallel Distrib. Comput.*, vol. 103, pp. 11–21, May 2017.
[117] M. Masud, M. S. Hossain, and A. Alamri, "Data interoperability and multimedia content management in e-Health systems," *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no. 6, pp. 1015–1023, Nov. 2012.
[118] M. F. Alhamid, M. Rawashdeh, H. Al Osman, M. S. Hossain, and A. El Saddik, "Towards context-sensitive collaborative media recommender system," *Multimedia Tools Appl.*, vol. 74, no. 24, pp. 11399–11428, Dec. 2015.
[119] M. S. Hossain, G. Muhammad, and A. Alamri, "Smart healthcare monitoring: A voice pathology detection paradigm for smart cities," *Multimedia Syst.*, vol. 25, no. 5, pp. 565–575, Oct. 2019.
[120] A. Vizitiu, C. I. Niţă, A. Puiu, C. Suciu, and L. M. Itu, "Applying deep neural networks over homomorphic encrypted medical data," *Comput. Math. Methods Med.*, vol. 2020, pp. 1–26, Apr. 2020.
[121] M. S. Hossain and G. Muhammad, "Audio-visual emotion recognition using multi-directional regression and ridgelet transform," *J. Multimodal User Interfaces*, vol. 10, no. 4, pp. 325–333, Dec. 2016.
[122] Y. Abdulsalam and M. S. Hossain, "COVID-19 networking demand: An auction-based mechanism for automated selection of edge computing services," *IEEE Trans. Netw. Sci. Eng.*, early access, Sep. 24, 2020, doi: 10.1109/TNSE.2020.3026637.
[123] E. M. Abou-Nassar, A. M. Iliyasu, P. M. El-Kafrawy, O.-Y. Song, A. K. Bashir, and A. A. A. El-Latif, "DITrust chain: Towards blockchain-based trust models for sustainable healthcare IoT systems," *IEEE Access*, vol. 8, pp. 111223–111238, 2020.

FATIMA ALSHEHRI received the B.Sc. degree in computer science and the M.Sc. degree in computer engineering from King Saud University, in 2006 and 2013, respectively, where she is currently pursuing the Ph.D. degree with the Department of Computer Engineering. From 2007 to 2019, she was a Computer Trainer with Technical and Vocational Training Corporation. Her current research interests include medical signal processing and smart healthcare.

GHULAM MUHAMMAD (Senior Member, IEEE) received the B.S. degree in computer science and engineering from the Bangladesh University of Engineering and Technology, in 1997, and the M.S. and Ph.D. degrees in electrical and computer engineering from the Toyohashi University and Technology, Japan, in 2003 and 2006, respectively. He is currently a Professor with the Department of Computer Engineering, College of Computer and Information Sciences (CCIS), King Saud University, Riyadh, Saudi Arabia. He is also affiliated with the Center of Smart Robotics Research, CCIS, King Saud University. He supervised more than 15 Ph.D. and Master Theses. He is involved in many research projects as a Principal Investigator and a Co-Principal Investigator. He has authored and coauthored more than 200 publications, including IEEE/ACM/Springer/Elsevier journals, and flagship conference papers. He has two U.S. patents. His research interests include image and speech processing, smart healthcare, and machine learning. He was a recipient of the Japan Society for Promotion and Science (JSPS) Fellowship from the Ministry of Education, Culture, Sports, Science and Technology, Japan, and the Best Faculty Award from the Department of Computer Engineering, KSU, from 2014 to 2015.