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

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ABSTRACT
Smart health care is an important aspect of connected living. Health care is one of the basicpillars of human need, and smart health care is projected to produce several billion dollars in revenue inthe near future. There are several components of smart health care, including the Internet of Things (IoT),theInternetofMedicalThings(IoMT),medicalsensors,artificialintelligence(AI),edgecomputing, cloudcomputing, and next-generation wireless communication technology. Many papers in the literature deal withsmart 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 and2020. We survey this literature by answering several research areas on IoT and IoMT, AI, edge and cloudcomputing, security, and medical signals fusion. We also address current research challenges and offer somefutureresearchdirections.

INDEXTERMSInternetofThings(IoT),InternetofMedicalThings(IoMT),edgecomputing,cloudcomputing,medicalsignals,smarthealthcare,artificialintelligence.

I. INTRODUCTION

The rising number of chronic patients and the aging of thepopulation render the avoidance of diseases an importantrequirement of healthcare. Prevention is not only defined byregular exercise, nutrition, and periodic preventive controlsas a way to sustain a healthier environment but also as amethodofkeepingseriousconditionsfrombecomingworse.Thefuturehealthsectormusttackleanincreasingnumberof chronic problems and the scarcity of treatments to satisfypatientdemands[1].COVID-19hasrecentlyhighlightedtheimportance of quick, comprehensive, and accurate eHealth-care and intelligent healthcare involving different types ofmedicalandphysiologicaldatatodiagnosethevirus.

Theuseofemergingtechnologyinprotectivepoliciesandbehavioral systems can help identify potential health condi-tions early and enable the scheduling of appropriate steps,such as concurrently monitoring treatments and preparingnewassessments.Theworld'ssmarthealthmarketisforecasttoreachUSD143.6billionin2019,whichwillexpandbyanaveragegrowthrateof16.2%between2020and2027[2].

Smart healthcare refers to platforms for health systems thatleveragedevicessuchaswearableappliances,theInternetofThings (IoT), and the mobile Internet to easily enter healthdocuments and link people, resources, and organizations.Intelligentmedicaltreatmentincludesdiverseactors,includ-ing physicians, staff, hospitals, and research bodies. It com-prises a dynamic framework with many facets, includingdiseasepreventionandidentification,assessmentandevalua-tion, management of healthcare, patient decision-making, andmedical research. Elements of intelligent healthcare involveautomatednetworksliketheIoT,mobileInternet,cloudnet-working,BigData,5G,andartificialintelligence(AI),alongwithevolvingbiotechnology.

Sensors have been gradually embedded into diverse sys-tems of our lives through computer technology, automation,and automated signal processing. Sensor-produced data canenableclinicianstomorequicklyandreliablyrecognizecrit-ical situations and help patients become more informed oftheirsymptomsandfuturetreatments.Intrusiveandnoninva-sive tools—ranging from devices to read bodily temperatureto dialysis control systems—provide personal and multime-dia details and assistance to patients and the health caresector.

Medicalsignalscomeintheformof1Dand2Dsignalssuchaselectrocardiograms(ECGs),electroencephalograms(EEGs),electroglottographs(EGGs),elec-trooculograms(EOGs),electromyograms(EMGs),bodytemperature, blood pressure (BP), and heart rate. A healthcare monitoring system may use these medical signals tomonitorapatient.

The IoT is slowly starting to connect both doctors andconsumers through health care. Ultrasounds, BP readings,glucose receptors, EEGs, ECGs, and more continue to mon-itor patients' wellness. Conditions like follow-up visits todoctorsarecritical.Severalhealthcarefacilitieshavestartedtoutilizesmartbeds,whichcandetectapatient'smovement and automatically adjust the bed to the correct angle andlocation.TheInternetofMedicalThings(IoMT)referstotheIoTusedformedicalpurposes.Whendevelopingafullyinte-grated health environment, the IoMT can play an importantrole.

Sometimes, relying on only one type of medical signalmaynotfulfilltherequirementsforacompletediagnosisofacertain disease. In such cases, multimodal medical signals canbedeployedforabetterdiagnosis.Thesesignalscanbefusedat different levels, including the data level, the feature level,and the classification level [3]. When fusing signals, manychallenges may be encountered. These challenges includesynchronization when acquiring signals from different sen-sors,databuffering,featurenormalization,andclassificationfusion[4].

In order to ensure patients' and stakeholders' satisfaction,intelligenthealthcarehasbeenrevolutionizedwiththedevel-opment of AI and machine learning (ML) algorithms in thecontext of deep learning (DL) and wireless local area network(wLAN) technologies [5]. The medical industry has been ableto manage numerous medical signals from the same user—simultaneously improving disease detection and predictionprecision—due to these technologies' high computationalperformance, high data volume, accommodation of severalterminal units, and the introduction of 5G and beyond 5Gwirelesstechnology.

In this paper, we present a detailed survey of IoT- andIoMT-basedsmarthealthcaresystems.Thesurveyislimitedto academic papers written between 2014 and 2020, locatedvia the IEEE Xplore, ScienceDirect, SpringerLink, MDPI,Hindawi,theACMDigitalLibrary,andGoogleScholar.Thesurvey'saimistolookatdifferentrelatedresearchareassuchasthestate-of-the-artIoT-basedsmarthealthcare,datafusionofIoTs,AIinsmarthealthcare,cloud-andedge-basedsmarthealthcare,andprivacyandissuesofIoT-basedsmarthealth-care.Attheendofthispaper,wegivefewrecommendationsandmakesuggestionsoffutureresearchdirections.

Thepaperisorganizedasfollows.SectionIIdescribesthe methodology adopted to select the papers. Section IIIpresents a comprehensive survey of the literature and answersseveral research questions. Section IV mentions some chal-lenges and offers future research directions in this field.Finally,SectionVconcludesthepaper.

II. METHODS

We used the systematic review process PRISMA (PreferredReportingItemsforSystematicReviewsandMeta-Analyses)to identify studies and narrow down results for this review,as shown in Fig. 1. In the review process, there are threesequential steps, which are identification, scanning, and eli-gibility testing. In the identification step, papers are identifiedthrough Google Scholar search; after this step we identi-fied 168 papers. In the scanning step, duplicate and non-conforming papers are removed; after this step 132 paperswere selected. Then in the eligibility testing step, we removedthe papers that were non-healthcare related. After this finalstep,weselected110paperstobeincludedinthesurvey.

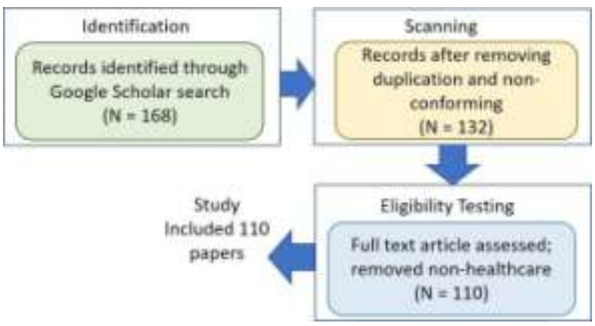

FIGURE 1.PRISMA study selection diagram. N represents the number ofpapers.

A. RESEARCHAREAS

The research areas we used to select the articles were as fol-lows: ''state of the art regarding IoMT and medical signals forsmart health care''; ''the techniques of multimodal medicaldata fusion''; ''cloud- and edge-based smart health care''; and''securityandprivacyoftheIoMT''.

B. SEARCHSTRATEGY

Our survey of articles used a combination of keywords andinvolved formulating a search strategy and selecting datasources.Weusedthefollowingcombinationofkeywords:a)‘‘InternetofMedicalThings’’;b)‘‘Fusionmedicalsignals’’;
c)‘‘Multimodalmedicaldata’’;d)‘‘Cloud/edgebasedsmarthealth care’’; and e) ‘‘Security and privacy Internet of Med-ical Things.’’ The number of papers elicited by each searchstrategy(item)aftersearchingisshowninFig.2.
Thesearchstrategywasimplementedbasedonthecontentof the main research areas. We restricted our selection topapers written between 2014 and 2020, as shown in Fig. 3.To locate appropriate papers, we scanned for related publica-tions in major online research repositories, including IEEEXplore, ScienceDirect, SpringerLink, MDPI, Hindawi, theACMDigitalLibrary,GoogleScholar,.andotherhealthandengineeringjournals.

C. SELECTIONOFSTUDIES

Our initial search identified 168 papers. The ‘‘Internet ofMedicalThings’’keywordgotthelargestnumberofpapers.

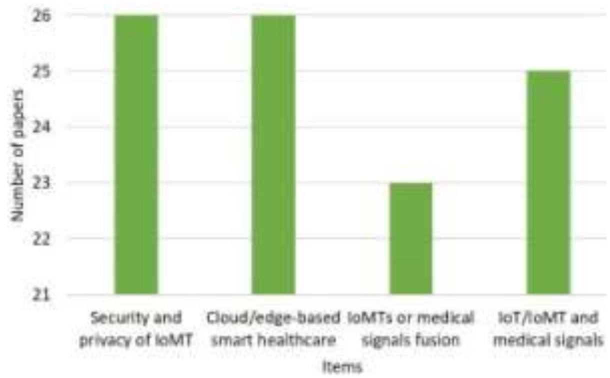

FIGURE2. Numberofpapersbyitem.

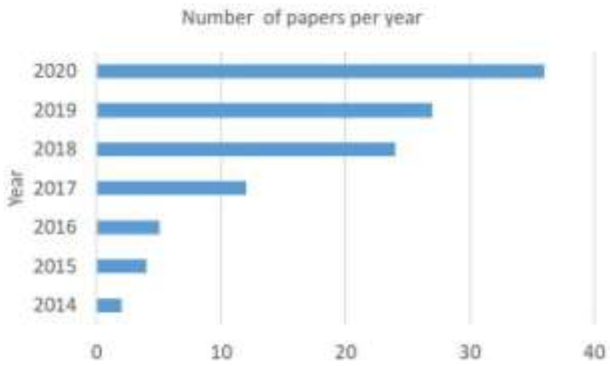

FIGURE3. Numberofpapersbyyear.

After removing duplicate and irrelevant articles, the searchwasreducedto110articles.

D. DATAEXTRACTION

Thefollowingdatacategorieswerecollectedfromarticles:

a. Applicationortasks
b. IoT/IoMT
c. Features
d. Classifier
e. Dataset
f. Accuracy

III. RESEARCH AREAS

The survey is divided into four areas: IoT or IoMT andmedical signals; IoMT or medical signals fusion; edgeandcloud-based smart health care; and security and privacy inIoMT-basedhealthcare.

A. IoTORIoMTANDMEDICALSIGNALS

The research in [3] used a multi-sensor platform with two-channelpressurepulsewave(PPW)signalsandone-channelECGtoestimateBP.Fromthecollectedsignals,atotalof 35 physiological and informative features were extracted.Fordimension reductionandto obtainthemost promis-ing indicators for each subject, they presented a weaklysupervisedfeature(WSF)selectionmethod.Furthermore,
a multi-instance regression algorithm was used to fuse fea-turesandenhancethebloodpressuremodel.

Authors in [4] presented a technique for emotion recog-nition and classification across subjects. It integrated thesignificance test and sequential backward selection with asupport vector machine (ST-SBSSVM) to enhance the pre-cision of emotion recognition. The input modalities usedincluded 32-channel EEG signals; four-channel EOG sig-nals;four-channelEMGsignals;andvitalsignalsmeasuringrespiration, plethysmography, galvanic skin response, andbody temperature. Ten types of linear and non-linear EEG,EOG, and EMG features were extracted and fused with thevital signals to produce a high-dimensional feature vector.Thefeatureswerefusedandselectedusingsignificancetestsand a backward selection search. The selected features werethenfedintoasupportvectormachine(SVM)classifier.Theexperiments were performed using two publicly availabledatasets, namely DEAP and SEED. The proposed methodachieved72%accuracyontheDEAPdatasetand89%accu-racyontheSEEDdataset.

One of the serious threats to the worker life is the disasterin mine area. Guet al. [5] proposed a real-time monitoringsystem to ensure accuracy and reduce the risks to the mineworker.Authorsdiscussedmulti-sensordatafusion,situationawareness, and covering theories including the Internet ofThings. A random forest (RF) SVM-based model was usedto identify the level of the situation and to merge the data.The simulation analysis showed a root mean square error(RMSE)below0.2andaTSQnogreaterthan1.691after200iterations.

A data fusion enabled Ensemble approach was proposedin [6]. The collected data from body sensor network (BSNs)were fused to and inserted into an ensemble classifier forheartdiseaseprediction.Theensembleswereplacedinafogcomputing environment and the output from the individualpredictors were fused. A prediction accuracy of 98% wasshown in the result when the number of estimators was setto40atatreedepthof15.

Steenkisteetal.[7]providedareliablemodelforimprov-ingtheperformanceandreliabilityofpredictingsleepapneabased on sensor fusion method. In order to collect and inte-grate multi-sensor data, including oxygen saturation, heartrate,thoracicrespiratorybelt,andabdominalrespiratorybelt,the proposed approach used backward shortcut connections.To assess robustness and analyzed the performance of theproposedfusionmethod,bothConvolutionalneuralnetwork(CNN) as well as long short-term memory (LSTM) deeplearningbase-modelswereused.

A multi-sensor fusion (HBMF)-based hybrid BSN archi-tecture has been developed by Lin et al. [8] to enable smartmedical services. Medical services included data process-ingtechnologies,robot,anddifferentsensors.Toensurethat the robot make the right decision and to guarantee thequality of medical services, a multi-sensor fusion approachbasedonaninterpretableneuralnetwork(MFIN)whichusedAItechnologieshasbeenproposed(seeFig.5).Reliability

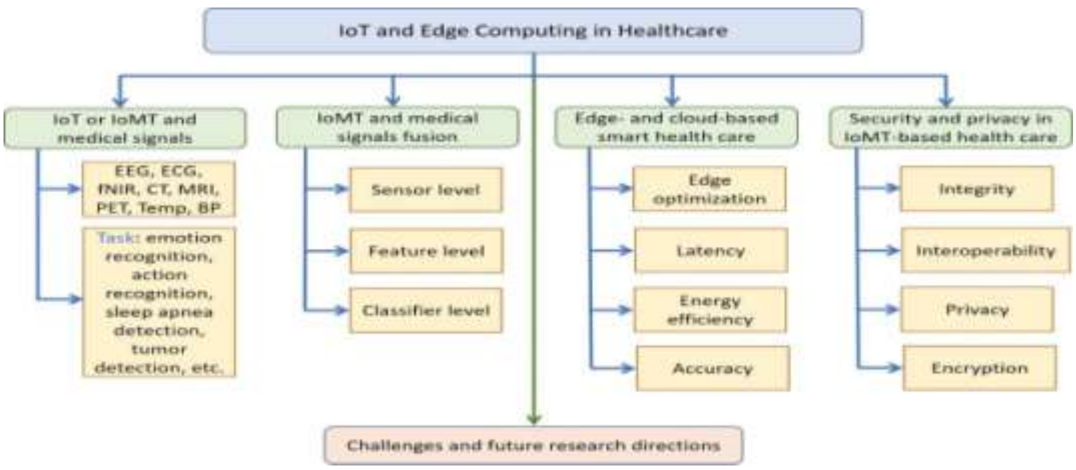

FIGURE4. Taxonomyofthesurvey.

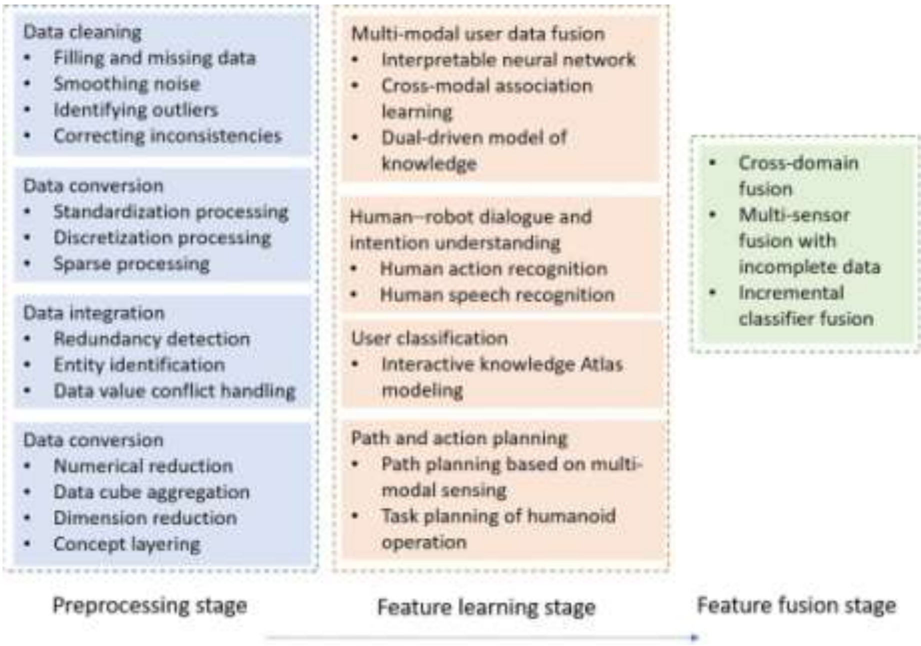

FIGURE5. Overviewofmulti-sensorfusionframework.

andflexibilitywereimprovedcomparedwithexistingmulti-sensor fusion approaches. In [9], seven channels from func-tional near-infrared spectroscopy (fNIRS) were fused withseven EEG electrodes to improve the detection of mentalstress. Simultaneous measurements of fNIRS and EEG sig-nals were carried out on 12 subjects. These measurementswereconductedwhilesubjectssolvedarithmeticproblems

under two different conditions (control and stress). The per-formanceofthefusionoffNIRSandEEGsignalswassupe-riortotheperformanceofeachseparately.
In [10], a fusion of EEG and ECG videos was proposedusingthreedifferenttransformstoimprovevideoresolution:discrete cosine transform (DCT), discrete wavelet transform(DWT),andhybridtransforms.Bothpeaksignal-to-noise

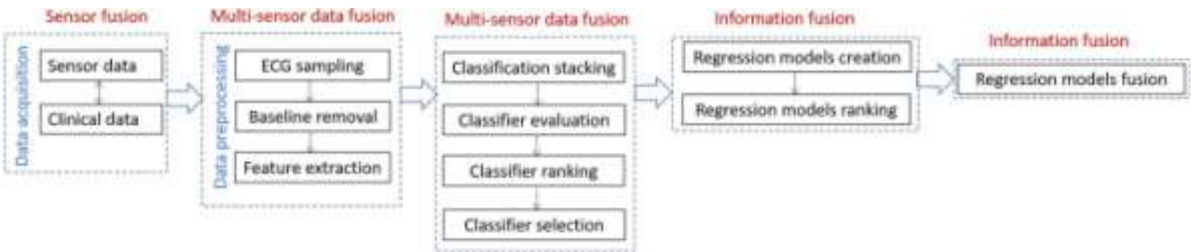

FIGURE6. FusionmodelfortopredictbloodpressurefromECGdata.

ratio (PSNR) and mean squared error (MSE) parameters wereusedtomeasurethefusioneffect.Thisempiricalstudyfoundthathybridtransformsimprovedimagereconstruction.

Authors in [11] suggested a method of medical imagefusion using rolling guidance filtering (RGF). The studyusedanRGFtofilterinputimagesintoeitherlow-frequency or high-frequency components. First, the RGFseparated the input images into low-frequency and high-frequency components, each of which had its own fusionrole. A Laplacian Pyramid (LP)–based fusion rule and a sum-modified-laplacian (SML) based method were used to fusethe structural components and the detailed component respec-tively.Thelaststepwasimagereconstruction.Theproposedmethod achieved the best high-frequency information com-paredwithotherexistingapproaches.

A potential field segmentation (PFS) algorithm was pre-sentedbyCabriaandGondra[12].PFSwasusedtosegmentbrain tumors in magnetic resonance imaging (MRI) scansand the results produced by PFS were fused by ensembleapproaches to achieve a fused segmentation. The proposedmethod was based on the physics notion of potential field andviewed the intensity of a pixel in an MRI scan as a ‘‘mass’’which produces a potential field. The performance was vali-dated on a publicly available MRI benchmark database calledBrainTumorImageSegmentation(BRATS)andshowedthatboth PFS and FOR were similar methods. However, PFSwasanexclusivesegmentationalgorithmandrequiredfewerparameters.

An approach using particle filtering was suggested byNathan and Jafari [13] to improve heart rate tracking withexisting artifacts and the use of wearable sensors. They esti-mated heart rate apart from other signal features and to exploitthe known steady, they designed observation mechanisms.This has contributed to the fusion of information from var-ious sensors and signal modalities to increase the accuracyof monitoring. The performance of the proposed approachwas examined on actual motion objects caused by ECG andPPG data with corresponding accelerometer observations,and results showed encouraging average error levels of lessthan2beatsperminute.

A method based on multi-level information fusion wasproposedbytheauthorsin[14]todevelopapredictivemodelto calculate BP from ECG sensor data. In this method, thedatawerefusedinfivelevels(seeFig.6).Datafrommultiple ECG sensors were fused and they used different techniquesto extract the features from the input data in level one and tworespectively. The fusion of output information from seven dif-ferentclassifierswasinputintothemeta-classifierinlevel3.Knowledgefrommulti-targetregressionmodelsforeachBPtype was integrated into level 4, and a single predictor forsystolic BP (SBP), diastolic BP (DBP), and mean arterialpressure(MAP)wasobtainedinlevel5.

In[15],theauthorpresentedamethodbasedonphysiolog-icalsignalsfusiontoimprovetheaccuracyofemotionrecog-nition. Its performance was validated by comparing bothfused and non-fused physiological signals on two publiclyavailable datasets. A feedforward neural network classifierwas trained using both fused and unfused signals. The resultof the proposed method showed an improvement in perfor-mance on the DEAP and BP4Ddatasets compared withothercurrentmethods.

Chen et al. [16] modified an existing real-time system toproduce a recognition system for human action. The deviceobtained data from various sensor types, such as depth cam-eras and wearable inertial sensors. Low-computation effec-tive depth perception features and inertial signal featureswereinsertedintotwocomputationallypowerfulsharedcol-laborative representation classifiers (CRCs). The proposedmethod was tested on a publicly available dataset calledUTD-MHAD, and the results showed an improvement inoverall classification rate (>97%) compared to using eachsensorseparately.

Adatafusioncluster-treeconstructionalgorithmbasedonevent-driven(DFCTA)waspresentedin[17].Theydesigneda data fusion system for intelligent health monitoring in themedical IOT. By calculating the nodes’ fusion waiting time,theminimumfusiondelaypathwasprovided,andthefusiondelayproblemwithinthenetworkwasanalyzed.Theempiri-calstudyshowedanimprovementinreliabilityandtimelyintheproposedmethodcomparedwithtraditionalmethod.

In [18], two procedures built on intrinsic image decom-position (IID) was proposed to address the complexity ofcomplexity in extracting structural and functional informa-tion from both MRIs and positron emission tomography(PET)imagesutilizingthesamedecompositionscheme.Thepresented IID was used to decompose both MRIs and PETimagesintotwocomponentsinthespatialdomain.twoalgo-rithmswereused,algorithm1forextractingthestructural

information and eliminating the noise from MRI images,while algorithm 2 was used for averaging the color informa-tionfromthePETimage.BasedonIIDmodels,threefusionmethodswereemployed.IIDPCA,IIDIIC,andIIDHISwere superior to other existing methods when the plannedmethodwastested.

Guanqiu [19] proposed a framework for medical imagefusion that combined two methods: dictionary learning andclusteringbasedonentropy.AGaussianfilterwasusedto decompose source images into high-frequency and low-frequency components. High-frequency and low-frequencywere fused by using dictionary learning and L2-norm basedweighted average algorithms respectively. The comparativeexperimentsshowedthattheproposedmethodenhancedper-formancecomparedwithotherexistingmethods.

Balochetal.[20]presentedalayeredcontext-awaredatacombinationtacticforIoThealthcareapplications.Itincludedthreephases:situationbuilding,filteringandcon-textacquisition,andintelligentinference.Reliable,accurate,andtimelydataweregatheredfromvarioussources.Theaim oftheanalysiswastoresolveissuessuchasuncertainty,irreg-ularity,restrictedrange,andsensordeficiency.Thedrawbackof this analysis was that no particular method was used toevaluatethesuggestedsolution.

In [21], a distributed hierarchical data fusion architecture atvariouslevelswasemployedusingcomplexeventprocessing(CEP) technology to improve decision accuracy and timely.It divided the task of data fusion into three-level processingmodels(low,middle,andhighlevelsofdatafusion).Asmarthealth care scenario was prepared with appropriate IoT net-work topologies to prove the effectiveness of the proposedarchitecture.Thisempiricalresearchfoundthattheproposedsolution allowed for effective decision-making at variousstages of data fusion and showed an overall increase in theefficiencyandresponsetimeofprimaryhealthservices.

SurveyPapersonIoMTand Medical Signals:Herrera et al. [22] presented state-of-the-art regarding sensorfusion for hand rehabilitation applications. Authors classifiedthe research on hand rehabilitation into three categories:exoskeletons, hand movements, and serious games for handrehabilitation.Ofthetypesofsensorsused,sensorsbasedonEMGsignalswerethemostcommon.

Wearable devices play a vital role in long-term health mon-itoring systems and are currently at the heart of IoMT [23].In [23], a comprehensive study was presented with the goal ofpresentingthemostimportantwearablehealthcaremonitor-ing devices, including biophysiological signs, motion track-ers, EEG measurement devices, ECGs, BSCs, and so on.Based on expert, authors suggested that the most criticalelements in health monitoring are motion trackers, vital signs,andgasdetection

In [24], the authors argued that it was complicated to detectandresolveobstructivesleepapnea(OSA),althoughitisoneof the most common diseases. The paper highlighted IoTsystemsthathadsupportivetechnologiesandwereutilizedtodiagnoseOSA,includingFC,smartdevices,ML,thecloud, andBigData.ItfurtherconsideredtheimprovementinthemonitoringofsleepqualityandotherremotemonitoringinAI-basedhealthsystems.Inadditiontothesurvey,anovelIoMToptimizationparadigmwasproposedtoimprovethequalityofremoteOSAdiagnosis.Themodelshowedanenhancementinthesensitivity,accuracy,energyconsump-tion,andspecificityofthesystemofremoteOSAdiagnosis.Athoroughandsystematicanalysisofcurrentmulti-sensorfusiontechnologiesforBSNswaspresentedbyGravinaetal.[25].Inthecontextofphysicalactivity,theyhavepresentedanin-depthanalysisandassessmentofdatafusion.Furthermore,theypresentedasystematiccatego-rizationbypinpointedspecificpropertiesandparametersthataffecteddatafusiondesignchoicesateachlevelofthetraditionalclassification(data-level,feature-level,and decision-level).

A comprehensive overview of different modalities fus-ing,suchasMRI-PETimaging,computedtomography(CT)-MRI, X-ray, and ultrasound, was given by Sumithraand Malathi [26]. The research pinpointed different types ofmultimodal fusion and found that the exact boundary of thetumor in the brain could be identified by merging both CTframesandMRIslices.

Authors in [27] presented a thorough overview of theapplication of image fusion technology in tumor treatmentsand diagnosis, in particular liver tumors. It highlighted the keyvalues of image fusion techniques by considering their limi-tations and prospects. It further presented an extensive reviewof the procedures and algorithms used in medical imagefusion and concluded with a discussion of the research chal-lengesandtrendsinmedicalimagefusion.Table1presentsasummary of the papers described above on the IoT or IoMTandmedicalsignals.

B. IoMTANDMEDICALSIGNALSFUSION

Swayamsiddha and Mohanty [28] discussed different appli-cationsofthecognitiveIoMT(CIoMT)totackletheCOVID-19 pandemic. Their review showed that the CIoMTwasasuccessfultoolforfastdetection,decreasingthework-load of the health industry, dynamic monitoring, and timetracking.

Yang et al. [29] proposed a combination of point-of-carediagnostics and the IoMT to assist patients in receiving properhealth care at home. The proposed platform might reducenationalhealthcostsandmonitordiseasespread.

Singhetal.[30]highlightedtheoverallapplicationsoftheIoTphilosophyintacklingtheCOVID-

19healthcrisis.Thisstudy aimed to decrease costs and improve treatment out-comesbyemployinganinterconnectednetworkforefficientflowandexchangeofdata.Singhetal.[31]alsopresentedanIoMT concept based on ML approaches to tackle the COVID-19healthcrisis.Itprovidedtreatmentsandsolutionstoissuesrelatedtoorthopedicpatients.
Kaleemetal.[32]discussedwaystoactivelyapplytheIoTin the medical and smart health care sectors and provided amethodnamedk-HealthcareinIoT.Theproposedmethod

TABLE1. SummaryofpapersregardingIoT/IoMTandmedicalsignals.

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 oxygen saturation BSNs	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	CNN, LSTM	Sleep-Heart-Health-Study-1 database	AUPR = 0.67 (CNN); AUPR = 0.71 (LSTM)
[8]	Medical human–robot interaction scenario		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 and	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, 5.72 for SBP, DBP, and MAP (the traditional approach). 16.60, 9.24, and 9.80 for SBP, DBP, and MAP (custom approach)

TABLE1. SummaryofpapersregardingIoT/IoMTandmedicalsignals.

[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 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 public repositories [42], [44]	$Q^{AB/F}$=0.6291 MI=2.1045 VIF=0.3426

used smartphone sensors to collect and transmit data to thecloudforprocessingandthentostakeholders.

In[33],anevent-drivendatafusiontreeroutingalgorithmwas presented. The paper discussed the theory of health information andthesportsinformationgatheringsystem,whichisdividedintoterminalnodesandclientmanagementsystems. The proposed algorithm designed communication mechanismsaccordingtothecharacteristicsofIoTcommunicationand used visual methods for modeling. The outcomes showedan enhancement in accuracy and timeliness compared withothermethods.

Chiuchisanetal.[34]providedthedesignforahealthcarenetworktotrackat-riskpatientsinsmartintensivecareunits(ICUs) based on the IoT model. It used a series of sensorsand the Xbox Kinect to track patient motions and any requiredadjustments in environmental parameters to notify physiciansinrealtime.

Sharipudin and Ismail [35] proposed a health care monitor-ing system to manage and process data in the patient monitor-ing system. The proposed system was combined with healthcare sensors that measured health parameters. The extractedparameterswerethensenttocloudstorageformedicalstaff'sreference.

Dimitrov[36]presentedadiscussionofIoMTappli-cationsandBigDatainthehealthcarefieldwhichpermitted innovative commercial models and allowed forvariations in work progression, customer experiences, andoutput enhancements. Wearable sensors and mobile applicationswereusedtofulfillnumeroushealthneedsandtocollectBigDatafrompatientstoadvancehealtheducation.

Authors in [37] established early warning score systemsbased on the characteristics of vital signs. The proposedsystemsupportedtheestimationofahealthstatebyprovidingahelpfuldecisionandcauseforcriticalcareinterference.It investigated the most appropriate ML technique to predicttheriskassociatedwithinputmedicalsignals.

Sanyaletal.[38]proposedafederatedfilteringframework(FFF) based on the forecast of data at the central fog serverusingaggregatedmodelfromIoMTdevices.ThisframeworkusedmodelsprovidedbylocalIoMTdevicesandthen sharedwiththefogserver.Itpresentedasolutionformanycommonissues, such as energy efficiency, privacy, and latency forresource-constrainedIoMTdevices.

Luna-delRiscoet al. [39] addressed recognition, obsta-cles to implementation, and threats to the usage of wearabletechnology in the Latin American health care system. Majorproblems that the authors noted included the training andallocationofhumancapitalinhealthcare,theconnectivityofpublic care, funding arrangements for health programs, andinequalityinhealth.Theyconsideredsmartwearablesensorsinhealthcaretobepartofthesolution.

Adaliet al. [40] used a system where joint independentcomponent analysis (ICA) and transposed independent vec-tor analysis (IVA) were employed to fuse functional MRI,structural MRI, and EEG data. Results were obtained fromhealthy controls and schizophrenia patients using an audibleoddball(AOD)function.Thepresentedsystemwasvalidatedonaprivatedatasetwhichincluded36subjects.Theanalysiswas performed using the Infomax and entropy bound min-imization (EBM) algorithms. The experiment revealed thatthejointICAmodelcouldbesuperiortothetransposedIVAmodel.InthecaseofjointICA,arobustICAalgorithmsuch asEBMwassuperiortotheInfomaxalgorithm.

Authors in [41] presented a deep CNN model for seizuredetection utilizing an excellent cross-patient seizure classi-fier. The visualization method demonstrates the spatial distri-bution of the characteristics learned by the CNN in variousfrequency bands when studying the seizure and non-seizureclasses.

Berneletal.[45]presentedaDLmethodforthefusionofmultimodal data to assist and monitor a user in performingmulti-step tasks. Furthermore, they extracted deep featuresfromindividualdatasourcesbyadeeptemporalfusionscheme. The Insulin Self-Injection (ISI) dataset consists ofmotion data captured with a wrist sensor and video dataobtainedfromthewearablecamerasofeightsubjects.Whenthe performance of the fusion method was evaluated, theproposedmethodwassuperiortootherstate-of-the-artfusionapproaches.

Torres et al. [48] proposed a formulation that merged twofeatures from three different modalities to categorize humansleepposesinanICUatmosphere.Unlikeothermethodsthatextract one feature by merging data from various sensors, thismethod extracted features independently and then utilizedthem to estimate labels. Various properties and scenes wereobtained from different modalities, cameras, and RGB (red,green, and blue) and depth sensors. Both shape and appear-ance features were extracted and used to train single modalclassifiers and generate an estimation of the trust level of eachmodality.

Using the quantum-behaved particle swarm optimization(QPSO)algorithm,Xuetal.[46]presentedanupdatedpulse-coupled neural network (PCNN) model to solve theproblem of PCNN parameters and to improve the efficacyand correctness of medical image fusion. Different metrics,including mutual knowledge, standard deviation (SD), spatialfrequency (SF), and structural similarity (SSIM), have beenused to determine the efficiency of various methods. Theresult showed that the proposed algorithm has high estima-tion Accuracy. The proposed method was validated on fivepairsofmultimodalmedicalimagesfromapubliclyavailabledataset [42] and showed an improvement in performance overothercurrentmethods.

In [47], an approach based on weighted principal compo-nent analysis (PCA) for multimodal medical fusion in thecontourlet domain was presented. One of the contourlet trans-form'slimitationswascapturinglimiteddirectionalinforma-tion. In this study, the contourlet transform was combinedwithPCAtoovercomethislimitationandimprovethefusionof medical images. It used max and min fusion rules tomerge the decomposed coefficients, and the results showedimprovement.

Usingahybridtechniquecombiningnon-subsampledcon-tourlet transform (NSCT) and stationary wavelet transform(SWT),Ramlaletal.[49]producedanenhancedmultimodalmedicalimagefusionscheme.NSCTwasusedtodecomposethesourceimageintovarioussub-bands,andSWTwasused todecomposetheNSCTapproximationcoefficientsintosub-bands. The efficiency of the proposed procedure was assessedthroughfoursetsofexperiments.Thesuggestedsystemwas compared to other existing fusion schemes and showedimprovement in brightness, clarity, and edge information inthemergedimage.

Animprovedalgorithmbasedonafuzzytransform(FTR)formultimodalmedicalimagefusionwaspresentedbyMan-chandaa and Sharmab in [50]. They considered the errorimagesobtainedusingFTRpairtoimprovetheperformanceof multimodal medical image fusion algorithm. To validatetheproposedalgorithm,differentdatasetswereused,andtheresult was compared with other multimodal medical imagefusion algorithms. The proposed algorithm showed a sig-nificant improved in edge strength, standard deviation, andfeaturemutualinformation.

SurveyPapers on IoMTand Medical Signals:Joyiaet al. [51] presented the contributions of IoT in themedical field and their major challenges in the IoMT. Numer-ous applications and research in IoMT were discussed interms of how they solved issues faced by the global healthcareindustry.

IrfanandAhmad[52]reviewedcurrentarchitecturalmod-els and produced a new one for the IoMT. They pinpointed themotivations that would lead medical practitioners to decide toadopt the IoMT and further demonstrated privacy and securityproblemsintheIoMT.

Authors in [53] presented a comprehensive review of thecurrentarchitectureforIoMTdevicesanddiscusseddifferentaspects of the IoMT, including communication modules andmajor sensing technologies. The paper further discussed thechallengesandopportunitiesrelatedtousingtheIoMTinthehealth care industry. Communication gateways, data acqui-sition, and cloud servers were the main components of theIoMTframework.

In [54], the author presented a comprehensive overviewof multimodal fusion of brain imaging data. This surveyaddressedthemeritsofmultimodaldatafusionindepthand summarized different methods of multivariate voxel-wisedata fusion. A number of multimodal medical data fusionstudies, particularly related to psychosis, have been reviewed.The author summarized this analysis by highlighting theimportanceofmultimodalconvergenceinminimizingmisdi-rection and perhaps discovering links between the brain andmentalillness.

Table2presentsasummaryofthepapersdescribedaboveregardingIoMTandmedicalsignalsfusion.

C. EDGE-INTELLIGENTANDCLOUD-BASEDSMARTHEALTHCARE

An edge- or cloud-based privacy-preserved automatic emo-tion recognition system utilizing a CNN was proposed in [55].In[56],theauthorssuggestedanappropriatetrainingsystemfor a deep neural network named ETS-DNN in an edge-computing environment. In order to change DNN parameters,ETS-DNNwascombinedwithahybridalgorithmforhybrid

TABLE2. SummaryofpapersregardingIoMTormedicalsignalsfusion.

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 (http://imagefusion.org), Groups 2-5 from [42]	Group 1: from 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 sites. Available at http://vision.ece.ucsb.edu/data.	100% accuracy in bright and clear scenes; 70% in poorly illuminated scenes; 90% in occluded scenes
[49]	Fusion of brain images obtained from CTscan 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 tominimize data traffic and latency, data preprocessing andclassificationwascarriedoutattheedgeofcomputation.TheresultsshowedthatETS-DNNwassuperiortothecomparedapproaches.

Hanetal.,in[57]providedeffectivecommunicationby developing a clustering model for medical applications(CMMA)) for cluster head selection. The proposed CCMAaimed to enhance lifetime of communication, improve relia-bility,andofferingenergyefficiencyinmedicalapplication.

Whenchoosingaclusterhead,somecriteriashouldbetakeninto consideration such as remaining energy, distance fromthe base station, capacity, delay, and queue of the IoMTdevices. An improvement in terms of energy-efficient com-munication was shown in the proposed method comparedwithotherexistingmethods.

Authors in [58] presented a cognitive IoT (CIoT) cloud-based smart health care framework with an EEG seizuredetection method using DL. Authors in [59] proposed avoicepathologymonitoringsystemintegratingIoTandcloudtechnology.

In[60],Olokodanaetal.usedtheordinarykrigingmethodto present a real-time seizure detection model in an edge com-puting paradigm. Fractal dimension features were extractedfrom EEG signals, and an ordinary kriging model was thenused for classification. Computational time complexity is oneof the limitations of kriging. In the proposed model, a previ-ously trained ordinary kriging model was moved to an edgedevice for real-time seizure detection. The empirical studyachieved a training accuracy of 99.4% and a mean seizuredetectionlatencyof0.85seconds.

In [61], an energy-efficient smart-health system based onfuzzy classification was proposed for seizure detection. Theraw EEG data was processed at the edge before being trans-mittedtothemobile–healthcloud(MHC).Theproposedsys-tem minimized energy consumption by reducing the amountoftransmitteddataandprovidedhighclassificationaccuracy.The result showed an extension in battery life of 60% and aclassificationaccuracyabove98%.

Anewnetworkparadigm,CIoT,hasbeenproposedbasedontheapplicationofcognitivecomputingtechnologies[62].In [63], Chen et al. combined the advantages of edge com-puting and cognitive computing to create an edge-cognitive-computing–based(ECC-based)smarthealthcaresystemwhichallocatedmaximumedgecomputingresourcestohigher-risk patients. The empirical experiments showed thatthe proposed system was capable of improving energy effi-ciencyanduserqualityofexperience(QoE).

Authorsin[64]presentedanedge-IoMTcomputingarchi-tecture which minimized latency and improved bandwidthefficiency. It consisted of two components: edge computingunit modules which compressed and filtered real-time videodata,andcloudinfrastructuremoduleswhichsecurelytrans-mittedmedicalinformationtothephysician.

Akmandoret al. [65] discussed different edge-side com-putingoptionswhichweredesignedtoaddresschallengesin smart health care systems. They demonstrated an edge-sidereferencemodelcomprisedofthreelevels:sensornode,communication,andbasestation.Thecompatibilitybetween sensors and edge-side requirements enabled smart edge-sidedecision-making.

DLwasutilizedonamobilehealthcareplatformtoinves-tigate a speech pathology detection method in [66] and anEEG-basedremotepathologydetectionsystemin[67].

In [68], an automated voice disorder recognition systemwasusedtomonitorpeopleofallagegroupsandprofessional backgrounds.Byidentifyingthesourcesignalfromthespeech using linear prediction analysis, the proposed systemcoulddeterminethevoicedisorder.

In[67]–[69],theauthorsdevelopedavoicedisorderdetec-tion and monitoring system. In [69], they collected voice sam-ples sent to the edge, which offers low latency and reducesdelays in data traffic flow. After processing data using edgecomputing, data were transferred to the cloud for more pro-cessing and assessment. The medical information was thensent to a specialist, who prescribed suitable treatments forpatients. The authors tested voice disorder classification anddetectionandcomparedtheresultswithtworelatedsystems.The study found that the proposed technique improved per-formanceintermsofdetectionandclassificationwith98.5%accuracy.

Oueidaet al. [70] provided a resource preservation net(RPN) framework which integrated a custom cloud, edgecomputing, and Petri net. The framework improved reliabilityand efficiency and reduced both resources and time con-sumption. The proposed system was suitable for emergencydepartmentsandothertypesofqueuingsystems.

In [71], Kharelet al. used Long Range (LoRa) wirelesscommunication and FC to produce an architecture for smartremote health monitoring. LoRa radio provides long-rangecommunicationandenergyconsumptionforIoTdevicesandis used in the proposed system to link the edge user's devicewith health centers. FC preserves network bandwidth andreduceslatencybyminimizingdataexchangewiththecloud.Tests showed that LoRa and FC had promising performanceinremotehealthcaremonitoring.

In [72], the author utilized several wearable sensors and aDL method (namely a recurrent neural network [RNN]) tointroduceahumanactivitypredictionsystem.Data,features,and activity prediction were processed on fast edge deviceslike personal computers. To predict human activities from apublic dataset, the RNN was trained based on the features,achieving99.69%meanpredictionperformance.

Authors in [73] produced a task scheduling approach calledHealthEdge that assigned priority to each task based on itsemergency level in order to decide whether to process thegiven task remotely (i.e., in the cloud) or locally. They alsoprovided a priority-based task queuing method which allowedemergency tasks to be processed earlier. The results showedthatincreasingthelocaledgeworkstationreducedprocessingtime.

In [74], Vasconceloset al. proposed a new method calledadaptive brain tissue density analysis (adaptive ABTD) toimprove the detection and classification of strokes. Edgecomputing devices provided low computation and cost andreduced time consumption in detection and diagnosis. Theintegration of the adaptive ABTD with edge devices and theIoTintroducedspeedyandefficientstrokediagnosis.

Authors in [75] presented a model for cloud-IoT–basedhealthserviceapplicationsinanintegratedIndustry4.0environment by enhancing the selection of virtual machines(VMs).Theyimplementedtheircloud-IoTmodelusingthree

optimizers:particleswarm(PSO),geneticalgorithm(GA),andparallelparticleswarm(PPSO).Theproposedarchitec-tureconsistsofstakeholderswhouseIoTdevicestosendtasksthroughcloudcomputinginordertoreceiveservicessuchast elemedicineanddiseasediagnosis.Thecloudbrokerworksinthemiddletosendandreceivetasksoverthecloud.Authorsi n[76]proposedatree-baseddeepmodelforefficientloaddistributiontoedgedevices.Theinputimagewasdividedintovolumegroupsandatrees tructurepassedthrougheachvolume.Thetreestructurehadseveralbranchesandlevels,eachofwhichwasdefinedbyacon volutional layer.

In [77], Chung and Yoo increased the effectiveness ofanalyzing Big Data by proposing an edge-based health modelusingpeer-to-peerDNNs.Anedge-basedhealthmodelandaserver model were established separately to tackle the issueof response time delay. The results showed that combiningDNN techniques and parallel processing models minimizedresponsetimedelay.

LimayeandAdegbija[78]providedacomprehensivereviewofmedicalapplicationsandalgorithmsinIoMTarchi-tecturesandtheirintegrationwithedgecomputing.IoMTworkloadswerecomparedusingMiBench,anexistingopensou rceembeddedsystembenchmarksuite.ThecomparisonshowedthattheIoMTapplicationsdifferedfromMiBench,indic atingtheneedforanewbenchmarksufficientfortheIoMTmicroarchitecture.Acloud-basedhealthcareframe-workwasproposedin[111].Intheframework,severalaspectsofdatatransmissionandlatencywerediscussed.Anedge-enabledDNN-basedmethodwasproposedin[110].

Table3presentsasummaryofthepapersdescribedaboveonedge-andcloud-basedsmarthealthcare.

D. SECURITY AND PRIVACY IN IoMT-BASED HEALTH CAREThe security and privacy of medical data are very importantin smart health care frameworks. A patient's data should behandledprivately.Ifprivacyisbreached,thepatientmaybe harassed in public, which can lead patients to becometraumatizedanddepressed.Ifmedicalsportsdataareleaked, rival sports team members might use these data to solicitillegal advantages. Therefore, medical data should be dealtwith privately and securely transmitted over communicationchannels[123].Thisimportantissuehasbeenaddressedinagreatdealofpriorresearch.

Alsubaeiet al. [79] presented a taxonomy of security andprivacy in the IoMT. They categorized IoT layers (percep-tion, network, middleware, application, business); intrudertypes (individual, organized group, state-sponsored group);impact (life risk, brand value loss, data disclosure); and attackmethod (social engineering, implementation layer, softwareor hardware bugs, malware). The perception layer includeswearable devices such as fitness trackers, BP sensors, andrespiratory sensors; implantable devices such as capsule cam-eras;ambientdevicessuchasdoorsensorsanddaylightsen-sors;andstationarydevicessuchasCTscannersandX-rays.

While there are many ways to fuse data from these devices,theauthorsdidnotdiscusstheminthepaper.

In[80],theauthorsidentifiedthepotentialsecuritythreatsthat can affect IoMT-based health care systems and recom-mended a series of security measures to tackle these threats.Some of the security issues mentioned in this paper includeoverlooking the aspects of built-in security, stakeholders'unfamiliaritywithsecuritysolutionsandfocusonmarketingand financial gain, and a lack of consensus between stake-holdersforoverlappingsolutions.Basedonthesethreats,the authors proposed some ontology-inspired, stakeholder-centric, and scenario-based recommendations in line withavailableguidelines.

Ivanovet al. [81] introduced OpenICE-lite, a middlewareformedicaldeviceinteroperabilitydesignedtoprovidesecu-rityforIoMTdevices.Severalapplicationswereinvestigatedfor this middleware, including a critical pulmonary shuntpredictorandaremotepulmonarymonitoringsystem.

LuandCheng[82]proposedasecuredata-sharingschemeforIoMTdevices.First,thesystemguaranteestheprotectionof and permitted access to mutual information. Second, thesystem conducts effective integrity tests until the customeropens mutual data to prevent an erroneous application orcalculation performance. Ultimately, the system provides alightweight procedure for both consumer and customer. Thescheme removes the burden of generating encryption anddecryptionkeyssolelyonenddevices.

Mohan[83]presentedsomecyberthreatstoIoMTdevicesandprovidedsomesolutionstothesethreats.AsIoMTdevices are limited by their battery life, they have only lim-ited encryption capability and are thus at risk in terms ofintegrity, confidentiality, and privacy. Sensitive patient datacanbeleaked,anddenialofserviceattackscanbemadeby draining the battery. As solutions, IoMT devices must beinstalled during deployment and software details transferredto the cloud-based system provider. IoMT devices encryptallpatientdatausinglightweightcryptographicmethodsandstore patient data on the cloud-based system. Only approvedentitieswhosendtheirverifiableattribute-basedcertificatetothecloudprovidermayaccessthisdata.

Nkomo and Brown [84] proposed a cybersecurity frame-workforIoMTdevicesinsmarthealthcaresystemsthathad five attributes: identify, protect, detect, respond, andrecover.First,assetmanagementandriskassessmentshouldbe identified. Second, access control, data security, and pro-tective technology should be developed. Third, anomalies andevents should be detected. Fourth, response planning shouldbe designed through analysis and mitigation. Fifth, a recoverypathshouldbeplanned.

Rathnayakeetal.[85]realizedasecuritymechanismforasmarthealthcaresystemusingtheIoMT.First,datafromdif-ferentIoMT devices were encrypted using asymmetric cipherand advanced encryption standard (AES) keys. The keyswere protected using a ciphertext attribute-based encryption(ABE) protocol. The encrypted data were transmitted throughaninsecurenetwork.Atthereceiverend,AESkeyswere

TABLE3. Summaryofpapersregardingedge-andcloud-basedsmarthealthcare.

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 [80] 174 healthy + 142 hemorrhagic stroke patients + 157 ischemic stroke patients	98.13% and 97.83%, respectively

decryptedusingtheABEprotocol.DatawerethendecryptedusingtheASEkeys.Thismechanismmaintainedtheprivacy andthesecurityofpatients'data.

SeliemandElgazzar[86]proposedablockchainforIoMT(BIoMT) to preserve security and privacy in a smart healthcare framework. The BIoMT had four layers. The first layerwasadevicelayer,whichcontainedIoMTanduserinterfacedevices. The second layer was a facility layer, which had abolster to look after IoMT devices. The facility layer providedthebasicblockchainmodulesforattributenumberselection,security generation, and identity issuance. The third layerwas a cloud layer that provided the computational powerand storage, and the fourth layer was a cluster layer whichcontainedmedicalfacilitiesandtheserviceprovider.

Wangetal.[91]designedafog-basedaccesscontrol(AC)methodfortheIoMT.Theauthorsdevelopedamethodthat installed an extra layer of control on fog servers toimprove protection for local mobile devices. A register inthe AC server was important for compliance with devices.DataaccessrequestsweresubmittedtotheACserver,wherethestatusoftheapplicationcouldbereviewed.There gistryneededtoensurethattheincomingfunctionhadbeenrecordedinthepast.Thecomparisonshouldbeperformedasthe workformwasrecordedtoensurethattheprivacysettingwas changed. The architecture was situated in the fog layer,wherefunctional-orientedserverscouldprovidetherequiredACservicetoeachdevice.

Dilawaretal.[92]introducedcryptographyasasolu-tion for the safe exchange of patient safety records usingblockchain technologies to protect medical data. A unifiedblockchain-based technique would solve many of the diffi-cultiesrelatedtoacentralizedcloudsolution.Authorsin[93]introduced an access management model that safeguardedpatients' medical data from internal information securityattacks. It enabled only legally permitted people to connectdespite physical limitations. The suggested model incorpo-rated authorization consistent with permits and responsi-bilities,ratherthanpositionsformedicalpersonnelonly.IteliminatedthecontradictionsofcurrentACmodels.

Omotoshoetal.[94]identifiedandincorporatedsomeof the main characteristics of a patient's health report thatshouldbepublishedandmade accessibleatalltimesaswell as qualities that should be disclosed only during emergencyconditions or pre-hospital treatment. Creating medical fea-tures from patient health information that may be retrievedin critical cases is a proactive step that allows technicians toobtain access to required details in pre-hospital services whileprotectingpatients'dignityandconfidentiality.

Farahatet al. [95] introduced a data encryption schemethat involved first encoding data, then encrypting those datawith a rotated key until they were sent across the network.Doctorscanrecovertheprotecteddatausingtheirloginkeysand credentials. The scheme was implemented using low-costequipment and reliable applications to ensure safety in thedeliveryofmedicalinformation.

Guan et al. [96] proposed a differential private data clus-tering scheme to allow privacy-preserving IoMT using theMapReducesystem.Forlarge-scaledatasets,MapReduceisa parallel programming system that abstracts parallel comput-ing procedures into two functions: Map and Reduce. In thisscheme, the authors refined the distribution of privacy bud-gets and the collection of initial centroids to boost the per-formance of the k-means clustering algorithm. In addition,an enhanced method for collection of the initial centroidswas suggested to maximize the precision and reliability oftheclusteringalgorithm.

Hamidi [97] proposed a modern paradigm for the appli-cationofbiometrictechnologiestotheadvancementofsmarthealth care using the IoMT, which, in addition to being simpletouse,requiresbroad-scopedataaccess.WhilecardIDsandpasswordscontrolentry,thesesystemscanbequicklybrokenand are known to often be inefficient. A biometric trait hasfourmainfeatures:universality,distinctiveness,permanence,andcollectability.Theauthoranticipatedfourlevelsofs ecu-ritystrategies:IoMTdevice,communication,analytical,andmanagement.

Alsubaeiet al. [80] outlined a web-based IoMT securityassessment framework focused on an ontological scenario-driven methodology to propose security steps in the IoMTandtoevaluatesafetyanddeterrentsinIoMTsolutions.Theframeworkencouragedthedevelopmentofastrat-egy that fits stakeholders' protection goals and facilitatesdecision-making.

Elhosenyet al. [98] proposed a hybrid optimization ofasymmetricencryptionforIoMTsecurity.Anidealpri-vate and transparent key-based authentication was used inIoT therapeutic images. Various approaches were consid-eredtoachieveoptimalhybridoptimization,fromwhichthe researchers differentiated and analyzed the critical open-endeddifficultiesinenhancingIoTinhealthcare.

Shakeeletal.[99]introducedlearning-basedDeepQ-Networks to reduce ransomware attacks when handlinghealth records using IoMT devices. The approach analyzedthe medical knowledge in various layers per the Q-learningprinciple,whichallowedtransitionalattackstobeeliminatedwith less difficulty. Efficiency was measured in terms ofenergy, lifetime, throughput, accuracy, and malware errordetectionrate.YiandNie[100]proposedamultivariate quadratic equation–based cryptographic security system forIoMT devices. A physical analysis model of the crypto-graphic system was designed by analyzing fault tolerance anddifferentialpoweronacloudplatform.

Survey Papers on Security and Privacy in IoMT-BasedHealth Care: A survey on security and privacy in the IoMTwas presented in [101]. The authors identified four require-ments for security and privacy: data integrity, data usabil-ity, data auditing, and patient information privacy. Existingsolutions to these requirements were discussed and includeddata encryption, access control, trusted third-party auditing,data search, and data anonymization. For example, someencryption methods for access control include attribute-basedencryption and symmetric and asymmetric key encryption.Thepaperendedbynotingsomefuturechallenges,suchas how to deal with insecure networks, develop lightweightprotocolsfordevices,andsharepatients'privatedata.

Hatzivasiliset al. [102] reviewed security and privacy inthe IoMT. In an IoMT-based health care system, there arethree main application settings: hospitals, homes, and bodysensors. Three security aspects—confidentiality, integrity,and availability—should be enforced in device, connectiv-ity, and cloud security. The survey analyzed different typesof security components. Various types of protection mech-anisms, identification and anonymity techniques, and datadestructionfordevicereusewerealsodiscussed.

Sun et al. [103] provided an outline of the latest prob-lems, requirements, and possible risks to the protection andconfidentiality of IoMT-based health care systems. To designan IoMT networks, one must address postural body move-ments, rises in temperature, energy efficiency, transmissionrange, quality of service, and heterogeneous environments.The security and confidentiality requirements have differentattributelevels.Atthedatalevel,caremustbetakenregardingconfidentiality,integrity,andavailability.Atthesensorlevel,the design must address tamper-proof hardware, localiza-tion, self-healing, over-the-air programming, and forward andbackward compatibility. At the personal server level, deviceauthentication and user authentication should be considered,while at the medical server level, important requirementsinclude access control, key management, trust management,andresistancetodenialofserviceattacks.

Li et al. [104] provided a survey of secured IoMT withfriendly-jamming schemes. The authors reviewed the IoMT'sexistingprotectionsystemsanddefinedkeysecurityissuesintheIoMT.Theyrecommendedfriendly-jammingschemestoprotect patients' sensitive diagnostic data obtained from med-ical sensors. They concluded that, when properly planned,friendly-jamming approaches could substantially reduce theprobability of effectiveness of eavesdropping activity whilehavingnosubstantialimpactonlegaltransmission.

Ghoneimet al. [105] introduced a new medical imageforgery detection method to verify that health care imageshad not been changed or altered. The method generates animagenoisemap,realizesamulti-resolutionregressionfiltertothenoisemap,andfeedstheoutputtoSVM-basedand ELM-based classifiers. Another copy-move image forgerydetection method was proposed in [112]; the method couldbeusedinmedicalimageforgerydetection.

Lin et al. [106] reviewed the security and privacy issues,challenges,andfuturedirectionsintheIoMTfield.Therearefour major categories of medical sensors: disposable healthsensors, connected health sensors, IoT-supported sensors, andIoT market cap sensors. The authors provided a systematicreview of these sensors in terms of their security and pri-vacy,followedbythechallengestheypresent.Someofthesechallenges included the integration of multiple sensors withproper protocols, data bursts, and social acceptance. In arelated survey, Masudet al. [117] outlined some limitationsand issues related to the security of IoMT devices and pro-vided some recommendations. They listed risks such as thedisclosureofpersonalinformation,datafalsification,lackoftraining,andreasonableaccuracy.

IV. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

ThemajorchallengesofIoTandAI-basedsmarthealth-careincludesensors'interoperability,devicecommunica-tion,securityandprivacy,devicemanagement,informationmanagementbarrier,andefficientuseofAI.Insomehealthca reenvironments,thebulkofIoMTdevicescanbeusedtoidentifyanddiagnoseanillness,andthedatacollectedfromhetero geneoussensorscontainsavarietyofissues,suchashardwareglitches,drainedbatteries,orconnectivityproblems[106]. Therearecertainbasicproblemsthatarenormalandunregulated.Inparticular,therearesometimesunexplainederrorsint heusageofpopularmedicalsensors,suchasmobilephonesandsmartwatches.Therearealsoreg-ularcomplexities,suchasbatterypower,distinctionsbetweenparticularphysicalcharacteristics,andvariationsintheenvi ronment.

The above problems indicate that several difficulties existin smart health care, though multimodal signals and severalIoMTdevicesarebeingused.Asimplifiedandeasierfusionsolutionshouldbediscussedtofacilitatethegeneralad optionof such smart health care [115], [119], [121], [123]. Below,wediscusssomeoftheseproblemsandpotentialsolutions.

Thehealthcaresystemcangetinconsistentdatafromthe multiple sensors because of the unawareness from theresearchers. Incomplete data may get thieved or faked byotherpeople.RadiofrequenciesofIoTsmighthaveaneffecton reading areas, and readers might give false readings. Tagcollisions and tag detuning should be corrected, along withmetal/liquid effects and tag misalignment. The system can getredundantdatawhichneedtoberefined.

Wearable sensors are equipped with batteries, Bluetooth,and other materials and were designed to be attached tohuman skin. For human safety, it is important to considertoxicity,flammablematerials,andotherfactorswhendesign-ing wearable sensors. Wearable sensors that constrain bodymovement, such as a belt worn at the waist or ankle, areuncomfortable, especially for the elderly and children. Onechallengeistodevelopsensorsthatcontinuouslymonitor humanvitalsignsusingsuitablematerialsandwithoutreduc-ingusercomfort.

There is an increase of the number of connected sensors,devices,andIoTsinanysmartsystem.Amassivehealthcarenetwork will work only if it has sensing capabilities plus thecapacity to produce important information. In the healthcaresystem, many millions of sensors and IoTs are linked thatprovidemassiveamountsofdatatobestudied.IntheIoT,theentities should have compatible data model and knowledgerepresentationmodel.

There is a need to recognize interoperability of IoTs orpartnership between nations when it comes to the develop-ment of digital health infrastructure. This disadvantage, alongwithlackofITinfrastructure,isattributedtobothalackofITskillsandtheneedforinternationalcollaborationinthesh ar-ing of confidential medical data, which will promote remotetelemedicine and the provision of high-quality medical care.Shibboleth is a distributed identification key, which allowsindividuals to be authenticated inside and through organi-zational systems. The conventional Shibboleth mechanismrequiresausertoconfirmtoanIDproviderandthendirectsademand for a site to be hosted by a service provider. Withthis distributed approach, Shibboleth allows digital healthorganizationstohaveasinglesign-oncapability,asinthecaseofdigitalhealth.

Automatic health care programs depend on self-sensing,self-adjustment,andself-tuning[108],[113].Asbackgroundsuchassensornoiseandrecordingenvironment,varies,fusion of sensors and IoTs can deal with the modifications,sincetheycanhaveadirectimpactonsystempropertiessuchasprecision.Informationtransfermethodsfor transferlearn-ingshouldbeusedtopermitthesystemtoadjusttoparticularcircumstances by collecting and transferring acquaintancefromonesituationtoanother.

Unauthorized access to IoT devices may contribute toextreme health and private information threats to patients.Linked computers, including the compilation, aggregation,retrievalandtransmissionofpatientknowledgetothecloud.Cloning, spoofing, RF jamming and cloud polling is proneto system type. In the cloud survey, traffic is diverted suchthat commands can be injected directly to a computer by anindividualinthecenter.

Attackswithdenialsofservice(DoS)canimpacthealthorganizationsandthesecurityofpatients.Althoughrepli-cation(useofseveraldevicesonthenetwork)isastandardprotectionofDoS,itmightnotoftenbefeasibletoreplicateresour cesinahealthcaresettingsincesomeofthedevicesareessentialsystemsimplant.Owingtotheamountandsophisticationo fnewdeviceandhardwarebugs,thequickidentificationofpossiblesecurityhazardsremainsaproblem.Thisproblemisescal atingastheInternetlinksmoreandmoreusers.Standardsecurityisalsowidespreadtodayandunsecureuserinterfaceacces sraisesthethreatsurfacemore.Many wireless networking devices have also recently beenusedinthehealthcareindustry,includingWi-Fi,BLEandZigBee,forlinkingvariousmedicalequipmentandsensor formstoeachother.Defensefromeavesdropping,sybilassault, plunger hole attacks and sleep loss attacks must beapplied with these wireless sensor and sensor technologies.In order to preserve protection and privacy, core data sets ofpersonaldetails,familyhistoriesandelectronicmedicaldoc-uments can also be guarding against hackers and maliciousdevices.

The misuse of access privileges by allowed insiders is a bigconcern. This kind of information sharing occurs when healthfacilities disclose sensitive medical information to unautho-rized people, either due to irresponsibility, for individual orcriminal purposes, or in return for illegal benefits. Celebrities'health reports and the lawmakers' information also leaks tothe public from a centralized healthcare system. This couldcause a breach of the regulation by the insiders and thedocuments that they would not have access to. For example,medicalpersonnelwhoarenottakingcareofrealpatientandformer staff who are not yet restricted from data query. A dis-gruntledpartywillcauseproblemstoeachotherbyaccessingthe protected details of each other. Intruders are trying topretend to be healers in order to infiltrate. Cybercrime as avirusoftoday'sInternetsectorisabigissueandamenaceto health. There are high costs for unsafe medical practicesuch as negative impact on their reputation, penalties, legalliability,andmanymore.

TraditionalAI-basedhealthcaresystemsmaynotgainacceptabilitytothedoctors.Therefore,explainableAI-basedsystemcanbedeployed,wherethedoctorscanvisualizethe detection or classification of diseases. The optimizationof edge resources can be efficiently done edge-intelligentalgorithms[105],[107],[109],[114].

The practical usefulness IoMT activated healthcare sys-tems is rarely addressed in literature. The main concern isthatthemostrelevantdataisownedbycompaniesandisnotaccessibletothepublic.Theefficientdeploymentandutiliza-tion of data fusion in practice will allow for more reliablemeasurement and evaluation of day-to-day physical activityutilizing low-cost monitors that can lead to easier and betterpreventivecareforchronicdiseases.Weassumethathostingmedical data in a public archive with appropriate protectionprecautionsandexploringcurrentdatafusionstrategiesusingsuch public data will be a crucial potential direction for futureresearch.

The advancement of next-generation wireless networksposes a great prospect in smart healthcare [118], [120], [122].Withthehelpof5Gandbeyond5Gnetworks,nowthehealth-caresystemcanbereachedanywhereintheworldfasterthanbefore.Inaddition,federatedDLandedge-basedcomputingbecomeeasierandpowerful[2],[104],[116].

V. CONCLUSION

Smart healthcare is a well-researched area. In the smart healthcare domain, there is a breadth of literature covering IoT,IoMT,medicalsignals,AI,edgeandcloudcomputingatvar-iousratesandutilizingvariedtactics.However,tothebestofourknowledge,therewasalackofathoroughandsystematic analysis of state-of-the-art IoT, IoMT, AI, medical signals useand fusion, edge and cloud computing, privacy and security inthesmarthealthcaredomain.Thepurposeofthissurveywasthustoofferaformalclassificationandspecificcomparative context for IoT, IoMT, AI, edge and cloud computing, privacyand security in smart health care. The survey included theuseofIoT,IoMT,andmedicalsignals,thefusionofsensors,andtheuseofedgeandcloudcomputinginsmarthealthcare. It further provided a survey of security and privacy issuesinvolving IoMT devices. Finally, some research challengesandfutureresearchdirectionswerediscussed.

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