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A Decade of Internet of Things: Analysis in the Light of Healthcare Applications

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ABSTRACT Impressive growth in the number of wearable health monitoring devices has affected global health industry as they provide rapid and intricate details related to physical examinations, such as discomfort, heart rate, and blood glucose level, which enable doctors to efficiently diagnose sensitive heart troubles. The Internet of Medical Things (IoMT) is a phenomenon wherein computer networks and medical equipment are connected through the Internet to provide real-time interaction between physicians and patients. In this article, we present a comprehensive view of the IoMT and its related Machine Learning (ML)-based developed frameworks designed, or being utilized, in the last decade, i.e., from 2010 to 2019. The presented techniques are designed for monitoring limbs, controlling rural healthcare, identifying e-health applications, monitoring health through mobile apps, classifying heart sounds, detecting stress in drivers, monitoring cardiac diseases, making the decision to predict heart attacks, recognizing human activities, and classifying breast cancer. The aim is to provide a clear picture of the existing IoMT environment so that the analysis may pave the way for the diagnosis of critical disorders such as cancer, heart attack, and blood pressure among others. In the end, we also provide some unresolved challenges that are confronted in the deployment of the secure IoMT-based healthcare systems.

INDEX TERMS Health apps identification, Internet of medical Things, IoMT security, patient monitoring, patient privacy.

I. INTRODUCTION

A set of medical tools and applications to link computer networks to the healthcare field is known as Internet of medical things (IoMT), which is a second name to healthcare IoT. Machine-to-machine interaction, which is the core idea of IoMT, is allowed by medical tools having Wi-Fi connections [1]. For the administration or deterrence of several chronic diseases, various tools are utilized to reduce the overall cost. These include tools that continuously supervise health values/signs, tools that manage treatments automatically, and tools that follow real time information when a patient self-manages a treatment. Due to the fact that IoMT has access to the Internet, several patients are using mobile apps to administer their health conditions [2]. IoMT examples include wearable devices that transfer patients' data to physicians, tracing patient treatment instructions/commands, remote patient monitoring of individuals with long-lasting conditions [1], [3].

IoMT gained a noticeable consideration in the last decade. The notion embroils the utilization of electronic tools (which are connected to a public or private cloud) for supervising information [4], [5]. In the recent past, medical specialists were observing the progress of IoT to realize if it can be utilized in the medical field. At present, this reality is exposed where the life has become comfortable for patients as well as medical practitioners. In the last decade, network-associated tools, which are monitored by the Internet, became popular among patients. Thus, the patient-doctor interaction (for some common diseases) has been largely reduced. Initial

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FIGURE 1. Internet of Medical Things at a glance.

IoMT applications also included smart beds, which can adjust themselves to confirm a suitable weight and aid is provided to patients with no interference of nurses [1]. However, with the advancement of technologies, IoMT has become more viable to establish a strong hold of how various tools and machinery can be mingled to work jointly [6]. Figure 1 exhibits a convincing clamp of how various medical-related tools/technologies are grouped together to form IoMT.

In this paper, we present the prominent healthcare-related work done in the last decade, which is divided into a year-wise explanation and described in the following sections. Though Internet of Things (IoT) can be utilized in various fields [7]–[14], our focus here is on the most prominent area, i.e., healthcare. In the best of our knowledge, this is the first effort to present a year-wise elaboration of IoMT-designed applications. The rest of this article is structured into 12 sections such that Section II to Section XI present different IoMT related proposed frameworks, Section XII offers challenges that IoMT may face during deployment, and Section XIII concludes the paper. The generally used acronyms are listed in Table 1 for the comfort of reading.

II. MONITORING OF LIMBS [2010] [15]

The restless legs syndrome (RLS) usually causes an unpleasant sensation in legs, due to which the patient moves its legs or arms to get some relief. Mostly the symptom appears at night or when a person is at rest position. A disturbed sleep at night causes the performance degradation at daytime. The RLS and periodic limb movement (PLM) are common causes of the sleep disorder [16]. The RLS is diagnosed by the medical history. Polysomnography (PSG) or movement recording is used to diagnose PLMs [17]. Nowadays, wearable devices are used at ankles or legs to calculate the movement irrespective of which muscles produce that motion [18]. The authors present the feasibility of the passive radio frequency identification (RFID) technology for the wireless monitoring of the RLS disease. The authors have checked the feasibility of the system on electrical and mechanical model. Their proposed

TABLE 1. List of acronyms and their description.

Acronym	Definition
AI	Artificial Intelligence
ANN	Artificial Neural Network
CAGA	Chain-like Agent Genetic Algorithm
CART	Classification And Regression Tree
CMF	Context Management Framework
CVD	Cardiovascular Diseases
DMS	Decision Making System
DPI	Deep Packet Inspection
DSS	Decision Support Systems
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
GSR	Galvanic Skin Response
HAR	Human Activity Recognition
HDP	Health Data-exchange Protocol
HIMSS	Healthcare Information and Management Systems Society
HIS	Hospital Information Systems
IdM	Identity Management System
IHR	Intermittent Heart Rate
IoMT	Internet of Medical Things
KBS	Knowledge Base Systems
LPC	Linear Predictive Coding
LQTS	Long QT Syndrome
MCS	Modified Cuckoo Search
ML	Machine Learning
MRI	Magnetic Resonance Imaging
PAN	Personal Area Network
PCG	Phonocardiography
PSG	Polysomnography
PLM	Periodic Limb Movement
PMSS	Physiological Multi Sensor Studies
QoS	Quality of Service
RF	Rotation Forest
RFID	Radio Frequency Identification
RLS	Restless Legs Syndrome
SNR	Signal-to-Noise Ratio
SVM	Support Vector Machine
TCP	Transmission Control Protocol
UDP	User Datagram Protocol
UHF	Ultra High Frequency
WASM	World Association of Sleep Medicine
6LoWPAN	IPv6 based Low-power Wireless Personal Area Networks

system uses passive tags to monitor the motion of a patient in the clinic or home environment and provide detailed data that help in the diagnosis of the sleeping disorder with some enhancement in the internal switches of the tag to capture the movement.

The authors also discuss the key parameters for monitoring sleeping disorders. These include body antenna design for which the ultra high frequency (UHF) RFID tags to be placed in accordance with [19] and [20] with proper distance, numbering, and position. The key parameters for the motion capturing in restless sleep disorder are chosen as per the world association of sleep medicine (WASM) [21]. Tag sensitivity and useful read regions are adapted from [22] using the RFID technology according to European recommendations [23].

This system provides a monitoring strategy for assisting the RLS disease. In a conventional environment, an antenna is used to assist the movement of the sensor and it is beneficial for monitoring people. The tag can capture the motion as well as the position of the movement. Moreover, this strategy is helpful for a patient during night by using tags that are placed on the patient's shoulder or chest. Since the sensors in this method should be attached directly to the patient's ankle or chest, this is somewhat unfavorable and exasperating [24].

III. MONITORING AND CONTROL OF RURAL HEALTHCARE [2011] [25]

In 2011, a study was proposed to monitor patients by utilizing the concept of IoT. The study was predicted to deal with the death rate as it is higher in several countries due to the unavailability of services in case of emergency in rural areas. The proposed approach utilizes the parameters of blood pressure, blood sugar, and hemoglobin among others.

IoT is an environment wherein different objects are connected to each other. The RFID system can detect the objects, where these objects are in turned connected and monitored through the Internet. There should be some mechanisms to control and keep track of the immensely growing objects so that they can be connected with every day's objects in home, office, transportation, industrial ecosystems, etc. in a cost efficient and valuable fashion [26]. The proposed concept has a personal area network (PAN) that consists of objects with hardware constraint devices, i.e., IoT nodes. Each node in the network has limited memory, energy, and processing power, and have physical links such as Bluetooth, WiFi, etc. [27]. Each node is capable of sending information to the sink node, which gathers all data and send it via gateways with higher data rates.

In the proposed model, consumer radio nodes are considered to be half duplex. It is assumed that the sink node can send and decode messages when its signal to noise ratio (SNR) is greater than and/or equal to the modulation-dependent threshold value [28]. The simulation results between the outage probability and SNR show that for the high value of SNR, the system consumes less energy, which is in line with the expectations. Simulation results also confirm that the proposed approach is able to achieve higher throughput. The proposed system provides the tradeoff among end-to-end delay, system throughput, and energy consumption, which make the system suitable for the IoT environment. However, the authorization and authentication of this method in cooperative IoT systems is yet to be revealed by extensive simulations or practical implementation.

IV. IDENTIFICATION OF E-HEALTH APPS [2012] [29]

The current Internet system is enough to facilitate users by providing healthcare services remotely. The emerging e-health system is contributing a lot in the delivery of healthcare services in the area where doctors may not be available or patients are not able to visit the physician in order to save time, energy, and resources. The e-health system is established by deploying different sensor equipped devices on edge nodes to monitor patients continuously. These e-health applications help in the identification of diseases, efficient diagnosis, and appropriate treatment. One of the challenges in the deployment of e-health system is the quality of services (QoS) in a life-critical situation where the delay of a single moment or loss of any data can lead to the loss of a precious life [30], [31].

The provision of quality services of e-health applications can be achieved by two approaches. The first approach is to design a special application layer mechanism that can prioritize diverse applications on different bases. But this approach seems to be very difficult to implement. The second approach is adopted by the authors, which is relatively easy. They use predefined mechanisms (which are already working in different networks) for the detection of e-health applications that ensure the network resources necessary to deliver healthcare services. But currently, e-health applications do not have priority, they are treated just like ordinary applications, which normally have no concern with delays and classifications of applications. To cope with these problems, the following three basic requirements are necessary to apply: i) Classification of traffic in some advanced way, ii) scheduling techniques, and iii) resources reservation

According to [32], a lot of efforts has been made on priority assignment and scheduling of tasks, but these approaches do not lead to an accurate classification and require QoS for e-health applications. There is no such mechanism that can distinguish between healthcare apps and ordinary applications. Moreover, the variety of e-health applications is introduced on daily basis with the advancement of Internet technology. Each application needs a different level of QoS regarding bandwidth, reliability, and delay. Some of the e-health applications require at most proficiency in reducing higher bandwidth utilization. The e-health traffic identification can be done by analyzing the characteristics and traffic patterns of different health-related applications. To resolve these problems, the authors focus on the development of advanced traffic classification methods and propose some requirements (listed below) to aid the accomplishment of that traffic identification as well as classification.

- Real time operations: e-Health traffic is identified with real-time applications where deferrals ought to be kept to minimum and uphold continuous activities.
- Low number of essential packets: In early diagnosis.
- High accuracy: To perform right identifications.
- Ability to analyze single application with multiple services.
- Small processing overhead: A trivial solution is needed, yet higher overhead is tolerable only in the offline mode.
- Potential to classify unidentified applications.
- Facility to work with encrypted data: e-Health applications need a protected channel and deploy encryption when transmit personal information.

The above mentioned properties indisposed various classification techniques such as port based methods, which are fast enough but not highly accurate. On the other hand, machine learning approaches seem to be better for the traffic identification because these work close to real time and highly accurate as compared to DPI methods [33], [34]. In the experimental phase of this research, mobile phones are used to run e-health applications where authors choose e-health applications working on android phones with a packet capture software (Wireshark), which captures and transmits three types of data to the monitoring station, i.e., medical reports, sensors driven data, and video teleconferencing (see Figure 2). In video conferencing, SIP proxy server by Tivi enables the signaling functionality, sensor data transmitted using UDP (these files were selected from [35]), and file transfer which is implemented through TCP sockets (these files were selected from [36]). Traffic classification is started by analyzing traffic traces wherein these traces are divided into three sets, i.e., training set (20%), first test set (40%), and second test set (40%). In the second step, recorded traffic traces are examined to identify packet flux generated by the e-health application.

In the current e-health applications classification machine learning approach, limited features selection and multiple classification techniques are used together [37]. The obtained results show excellent performance as compared to

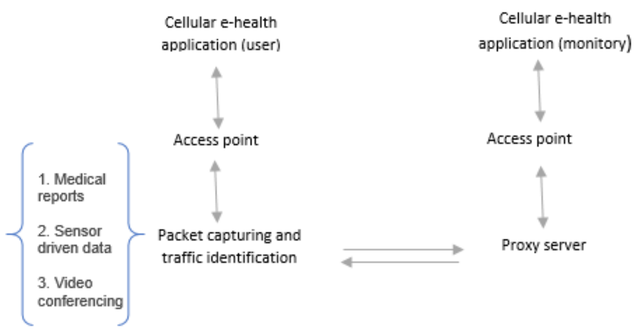

FIGURE 2. **Demonstration of the interim setup along with typical applications.**

previous approaches. Almost 100% accuracy is achieved for sensory data, images, and registration data. However, the accuracy in video conferencing remains relatively low.

V. IOT-BASED M-HEALTH AND SECURE REMOTE MONITORING [2013] [38]

m-Health (mobile health) is a common term for the usage of mobile phones and other wireless devices in medical care. A personalize mobile healthcare is getting popular with every coming day to monitor a patient's current health condition from its own environment. In fact, this evolution is dependent on the advancement in sensing, monitoring, and processing technologies. These monitoring and remedial solutions need intelligent physiological sensors, which should be energy efficient and supportive in wireless communications. In fact, IoT has the potential to provide solutions to identification, sensing, location, and connecting people with machines [39]–[41], and also helpful in the detection of drug level in blood [42] and the collection of data at any place and time [43].

The goal of this study is to integrate the modern day technology into monitoring, processing, and making it more accessible. The proposed work is mainly focused on providing an integrated system that gathers clinical equipment to sophisticated systems, i.e., joint decision support systems (DSS), personal health data assistance, and integrated electronic health data among various clinics. The authors have proposed "Monere" multi-protocol card acting as a gateway, which is a distant monitoring platform that can be implemented at patient's side. It provides a link between the patients' environment and peripherals for processing and management to look for anomalies.

Monere is supplemented by a connector, known as Movital, which resembles an IEEE specialist following the idea from the health data-exchange protocol (HDP). Movital extends existing sensors to a portable and Wi-Fi gadget. This manages assistance for gadget lifecycle organization and complex network exchanges. Medical sensors can share information with Monere with the help of a guided medium, 6LoWPAN, ZigBee, Bluetooth, and USB.

To achieve integration, the interoperability among devices must be achieved for which the focus was to put on integrating existing and supporting equipment compatible with standards, for example, ISO/IEEE 11073-20601 personal HDP [44] via Monere platform. Expansibility is known as an appropriate industrial evolution to link innovative equipment. This is required for the assurance of security, anonymous consultation, integrity, and patient privacy. Lastly, the availability and robustness is considered since a system's failure can be fatal for lives. The integration should be in their present solutions or the utilization maybe occasional. Motival and Monere could be aided by other systems in various fields.

For information systems, hospital information systems (HIS), context management framework (CMF), and knowledge base systems (KBS) [45] will be put in work. For security management, the identity management system (IdM) is used [46]. Connecting all kinds of devices and context information makes it robust and expandable.

The current research work is initiated by the deployment of previous techniques used in hospitals, i.e., Clínica del Vallés. The platform is integrated in headboard of beds of 14 rooms to evaluate the performance of AIRE project, where three types of clinical devices are needed to connect, such as electrocardiogram (ECG), pulse oximeter, and capnographs. These all devices generate continuous data and some security operations, and preprocessing of raw data are essential to execute the whole system. These operations cause additional latency, thus, to cope with this problem, a new communication model is required to attain proficiency in power consumption, security, and preprocessing of raw data obtained from sensors.

The study reveals that HDP is dependent on ECG sampling frequency, thus, it deals with the high rate of sampling and requires excessive power supply. YOAPY is proposed to solve this problem and it works perfectly in every aspect, but its algorithm depends on field information. Hence, this is unsuitable to use it as a common algorithm in various domains.

VI. HEART SOUNDS CLASSIFICATION [2014] [47]

The cardiovascular diseases (CVD) usually refer to diseases that involve the heart or blocked blood vessels, which are the cause of myocardial infarction, angina, or stroke. Other heart diseases involve affected heart arteries, heartbeat, and heart muscle. CVDs are the major cause of death all over the world. In Poland, each year a large number myocardial infractions is reported. To avoid heartbeat problems, regular tests are advised. Many scientists are researching on the development of ways to analyze the initial medical condition remotely.

Phonocardiography (PCG) is a method to observe the CVD system by examining hearts' biomechanical activities. Although this is a simple method, it has a problem in the interpretation of the results. Efficient self-diagnosis methods are under consideration for the early detection of health states. Due to an unwanted noise and signal behaviors in PCG, the diagnosis task is divided into two steps, i.e., the first one would differentiate all signal types and the second one deals with the classification of signals. These techniques are constructed on ANN and SVM. The SVM based technique, to identify heart sounds, achieves 95% accurate results through wavelet transform to extract the PCG signals. Initially, a system is developed for in-home usages based on a case study. Then a diagnostic system is developed, which is connected to an adaptive network using principal component analysis. This system ensures 96% accuracies in normal states and 95% in abnormal heart states [48].

The main issue is the identification of appropriate algorithm for checking heartbeat to measure the disease. Concentration is paid to the checking of a variety of heart sounds and improvement in their measurement accuracy. The new system consists of linear predictive coding (LPC) for feature extraction and SVM with modified cuckoo search (MCS). The emphasis of the proposed work is to accurately recognize the synchronous identification of much pathological heart sounds. Moreover, the performance comparison with different functions among the SVM-MCS classifier, ANN classifier, and the three types of SVM classifiers is done.

For the suitable information of classifiers, PCG signals should be accurately processed. Spectral analysis (LPC algorithm) provides necessary information for classifiers with less complexity. It uses a large search space that makes the system unsuitable for diagnosis. The proposed system comprises two parts. The first is the solution to provide the LPC algorithm [49], which solves the non-stationary problem of PCG signals and increases the distinguishable states. The second one is that signals are identified by SVM-modified cuckoo search classifier (SVM-MCS).

To simulate heart sounds, the LPC algorithm is used [50]. The LPC algorithm uses fixed 30 ms rectangular window to differentiate between the original and simulated signals in addition to maximize the impulses in excitation function. The PCG signals are categorized as non-stationary as most biological signals, thus, they cannot be divided by using fixed size time windows. Therefore, the development of a specific algorithm is necessary that splits each heart quality through a variable size time window. The SVM technique is used to resolve the problem of binary classification by designing a hyper plane that separates two classes and provides a linear decision boundary. The nonlinear feature space is handled by the kernel function.

The problem of multiclass classification is handled by using three SVM techniques, i.e., one-against-one, one-against-others, and all together [51]. In the one-against-one technique, the results of classification are achieved by matching of data sets from different classes giving m(m-1)/2 classifiers. In one-against-others, the classification result is achieved by separating each class from other classes and builds m classifiers. The all-together technique solves the individual problem from all other classes, which are under consideration. The proposed technique chooses the one-against-other technique, which provides the best initial results and less computation as compared to one-against-one strategy. In the development of SVM classifier, one should select values of the support vector parameters which have an effect on the classification of the problem and the training efficiency of the classifier.

The MCS is an optimized method for tuning particular classifiers. It uses swarm intelligence established on the assistance of too many simple units, which distress the complete procedure. The swarm algorithm is an effective technique for the building of classifiers and it has proved better than other methods [52]–[54]. The Cuckoo search is also a new swarm algorithm motivated by the brood parasitism phenomenon grasped from some cuckoos species which lay their eggs in different species nests. The main supposition of this algorithm is based on describing the coordinates of a point in the search space where each cuckoo lays one or more eggs. Some nests are considered as suitable for next repetition by fixing them with some probability at the end of individual repetition. When the MCS is compared with previous algorithms, it has a difference of using golden mean method for the new nests creation by the inconstant flight of the cuckoo. In addition, it also offers multiple strategies to deliver better solutions [55]. When compared with the LPC classification, the modified PCG signals with an SVM introduced some changes.

In the LPC filter parameters, a huge number of feature space that does not produce the essential classifier information is a basic issue. Consequently, the MCS algorithm contains 24 binary variables necessary for the training set to produce the output. Support vector count is one of the functions that is used for the optimization of SVM classifications [51]. The balanced accuracy calculates the binary output of classifiers by using arithmetic means of sensitivity and specificity. The correctly classified samples of the class are tested and represented as true positive and true negative. On the other hand, the misclassified samples show the result as false positive and false negative.

This work is appropriate for the smooth communication, however, in the case of distortion, the proposed strategy may not work properly.

VII. STRESS DETECTION IN DRIVERS [2015] [56]

Driving is a task that requires full concentration and balance between alertness and calm attitude. While driving, drivers are exposed to fast-changing circumstances such as road condition, weather, speed limits, traffic signals, and road obstacle etc. Stress and strong emotions can affect this balance. Stress is caused by a change in the environment. Driving is also a stressful activity, but any neglect can cause fatal consequences. In stress, the driver gets irritated easily. This research shows that angry drivers are more likely to take the risk, i.e., over speeding, switch lanes, and overtaking. Mental stress has become a social issue that may cause functional disability as work routines [57].

The increase in stress can upsurge the likelihood of stroke, depression, heart attack, and cardiac arrest, which can easily lead to cardiovascular disorders. To deal with these issues, there is a need for continuous and personalized stress measuring technology. For this purpose, a lot of wearables and implanted devices are available. To detect stress in healthcare, a physiological multi-sensor studies (PMSS) came up with numerous success rate depending on respiration rate, heart rate, body temperature, blood pressure, electromyogram (EMG), electrocardiography (ECG), and electroencephalogram (EEG). There is a substantial variety of machines and learning methods to study stress detection. Various studies have been conducted focusing on drivers' internal state (physical and emotional wellbeing) such as fatigue, stress, and drowsiness, as these are the major causes behind many fatal road accidents. The study shows that most automobile divers' skin temperature and heart rate are more closely related to their stress level. One of the simplest ways to deal with stress is continuous monitoring.

In the growing IoT era, due to the availability of many moveable and wearable devices, the physiological sensor analytics are being used for monitoring health. Here, the focus is on the ECG monitoring that can now use many hand-wear and portable patches and sensors for developing an accurate and efficient stress identification. ECG is a test device that detects cardiac abnormality by measuring electrical activities generated by hearts [58]. The ventricles and atria work together and produce tiny impulses which contract/spread the heart muscle [59]. The ECG machine detects these impulses. This study analyses individual stress and multiple stress classes, i.e., low, medium, and high, in automobile drivers under dissimilar environmental conditions during driving. The authors have proved that their proposed framework has successfully detected stress with the accuracy of 88.24% using machine learning (ML) algorithms. The significant advantage of adopting ML is to achieve higher accuracy.

The ML-stress detection is further classified into four major categories, i.e., data, feature extraction, classification, and assessment, which are discussed below:

- **Data**: In this scheme, the ECG signals of automobile drivers have been taken from the MIT-BIH PhysioNet multi-parameter database [60]. The datasets of ECG are part of the experimentation of Picard & Headley [57]. The Picard and Headley experiment is based on 17 drivers, which uses raw data consisting time, respiration, EMG, ECG, intermittent heart rate (IHR), foot galvanic skin response (GSR), hand GSR, and marker. The major source of collecting all this data is the wearable sensors.
- **Feature Extraction**: After collecting datasets, the extraction feature is carried out using the NetBeans Java Platform. The extraction from ECG signals consist of 14 different features such as average RR interval and average QRS interval among others.
- **Classification**: Calculating the stress level from ECG signals is a task which has been classified in three classes, i.e., class 0, class 1, and class 2. Class 0 illustrates low-stress level and class 1 and 2 signify moderate stress and represent high-stress level, respectively. The proposed study utilizes Weka [61] to classify the data because it provides numerous algorithms for the classification of data. Out of these classifiers, 10 algorithms were selected to detect stress, namely multilayer perception, Naïve Bayes, SVM, logistic regression, IB 1 (1-nearest neighbour), ZeroR, J48 (decision tree), IBK (k-nearest-neighbours), random forest, and random tree [61].
- **Assessment**: The result of this research is used for stress level indicator based on time monitoring of drivers, i.e., low or moderate stress where drivers may be allowed to use navigational tools. On the other hand, if a high-stress level is detected, the driver may be advised to focus on driving or take rest in between.

In the coming years, it is expected that vehicles should be more responsive and intelligent. Physiological sensing is one method of accomplishing this task. This research may contribute towards the advancement in developing machines that can respond wisely to human while understanding human mental states. However, such real time ML algorithms are needed that respond quickly so that drivers may know their health status and take as much rest as required.

VIII. CARDIAC HEALTH MONITORING [2016] [62]

Old-style healthcare is incapable to lodge every person's needs due to the continuous growth in population. Regardless of having brilliant cutting-edge technologies and infrastructures, medical facilities are not amicable or affordable to everyone. To overcome such issues, smart healthcare is used to aid patients/users by guiding them about their physical and medical position/status. Smart healthcare allows users to deal some emergency situations independently [63]. It emphasizes on refining the experience and quality of users. Smart healthcare is helping users to utilize existing resources to their supreme potential. It helps to monitor patients remotely and reduces the burden of cost for patients' treatment. Another significant advantage of the smart healthcare is to extend the services of medical practitioners by removing geographical barriers. With a growing tendency towards smart cities and healthy living for their citizens, the smart healthcare system is playing a very important role by using low-priced monitoring devices, i.e., ECG machines, patches, blood pressure, glucose monitoring system, etc. [64].

In the current time, medical and healthcare devices have become portable as well as efficient. For instance, AliveCor presented a budget-friendly smartphone ECG attachment for sampling and calculating ECG signals of individuals and sharing the recordings with concerned physicians. Portable medical devices produce more accurate data much faster than older systems and offer scientists and engineers to design DSS and health-monitoring to improve healthcare level or standards. A device can check millions of medical records and reports to detect previously unknown drug involvements/interactions [65]. For instance, the DSS, which is based on ML, reduces the burden of review by sifting errors, noise, and inappropriate information such that the data to be studied has only related clinical markers. The ML algorithms acquire and work within the data patterns to predict patients' health.

To provide decision support and quick response to a clinician, the proposed scheme uses devices, linked to a cloud-based DSS, to obtain data over the Internet [66]. All components of the proposed system and advanced devices to acquire medical data are commercially available [67]. ML algorithms are handy and already well understood [68]. However, physicians are still the most significant part of any medical DSS. Hence, the aim of this research is to deliver the most relevant and precise information to clinicians or other physicians to upsurge their diagnostic accuracy and efficiency.

An operative ML-based healthcare system takes the advantage of computational power of a computer and the ability of physicians' reasoning. The machine analyzes every disease nuances and heartbeat of patients and then presents the results to physicians for endorsement. The proposed system foresees three types of decision support, i.e., visualization, alert, and classification, which are discussed below:

- **Visualization**: To minimize the data burden of physicians and enable timely and accurate decision making, the visualization sets a continuous monitoring data in a brief and spontaneous format [69].
- **Alerts**: The alarms that are activated when a value marks a recognized threshold, while the threshold is a clinical standard to measure the severity of a disease.
- **Classification**: It is the procedure to envisage the group which a patient belongs to. The primary goal of classification is to predict the short-term outcomes. For instance, the machine may predict a patient at high risk for myocardial infarction in the next 12 hours.

The visualization and recommendations of the machine are simply additional decision-making tools. However, the clinician or physician is the head of the entire process including analyzing records, ordering tests, and adjusting prescriptions.

The authors used ML pattern-recognition capabilities to categorize the risk in LQTS patients. This study focuses on congenital LQTS rather than the drug-induced form. The data is collected through ECG recordings/signals. The collected raw ECG data is transformed into clinically useful measurements by removing immense redundancies and ectopic heartbeats with noticeable errors and noise. Individual clinically related markers from the raw data are extracted to reduce the data to be fed into the ML algorithm and to improve the execution time and accuracy. The ML algorithm is trained by the supervised learning mechanism to use input variables fetched from raw ECG data for the detection of risks in patients having LQTS symptoms. Different classifiers/algorithms, such as SVM, k-nearest neighbors, random forest, AdaBoost, and a database comprising 24-hour ECG recordings of 480 LQTS patients having demographic material such as gender, age, and explicit LQTS genotype, were accessed [70]. Only 434 patients recordings with the LQTS genotypes and the most completed demographic information is selected for this study. For the accuracy of classifiers, only 70 percent of the samples were selected to train the algorithm while 30 percent of samples were set aside due to the inherited randomness of some algorithms. Each classifier was given 48 sample values as input by using 30 percent of the 434 samples. The accuracy of each classifier is based on the obtained results. The SVM performed well with few training samples and the accuracy was high, while the random forest having faster runtime was superior for large data, i.e., thousands of samples.

Since ML and AI systems are trained, not programmed, to accomplish complex tasks at the level of humans, they entail massive volumes of data. Moreover, the labeling of data is a tedious job, while in supervised learning, labeling is a mandatory phase of data processing.

IX. DMS FOR HEART ATTACK [2017] [71]

Advancement in IoT promotes the medical field at a great deal. A doctor can have closely observed his/her patient by using smart devices [72]. In the proposed decision making system (DMS), to remove unwanted data samples from the collected information, two techniques are used, i.e., box-plot and control chart. Regarding the dataset, these techniques play an important role with the help of pointing outliers. Alongside, the Pearson model is applied to determine the association between the properties that how closely a feature is associated with different properties [73], [74]. Finally, the linear regression model displays the association between the dependent variable (y) and independent variable (x) [75]. In the proposed framework, the datasets of about 300 patients are examined with the selection of 12 features that represent the conditions of their heart. On the basis of calculated results, the study decided that which property is useful and which one can be neglected in analysis.

A boxplot technique is used to discover and disregard those outliers which perform the least part in the estimation. This technique represents weighable information in terms of base, first, middle, third, and greatest quartile by obtaining the medians of the data. First, the system takes out the age as the root attribute, which has a significant value of outliers, then the control chart is applied on the collection and the obtained outlier is matched by the control chart. The boxplot technique is applied to the collected information of 16 samples that plots the analysis chart. Here, the age is selected as the root attribute, which has 11 outliers, and removes the corresponding rows from the attributes that are 11 in number. After that, the relationship is applied on each other among different attributes by using the Pearson method. The Pearson correlation is used to measure the quality of an attribute between the given scales, i.e., +1 or -1. The study utilizes this model to create a table among different properties by the process of multiplication on attribute values. Then the aggregation of every attribute is found independently and at last, the substitution of every attribute is calculated on the basis of range (i.e., week<0.8>strong relation).

The linear regression model is a modeling technique that is used to model the association between a dependent and explanatory variable. It is used for predictive analysis.

Generally, the regression model is used to define the relationship between one dependent and one or more independent variables. In the proposed scheme, optimized cost values are used for evaluation. One attribute is evaluated using the estimated cost of other attribute. In order to predict the medical condition of a person, this analysis is very beneficial to provide health services to any person. Moreover, the analysis is also helpful in developing a mobile app for providing health services to remote areas. Since the proposed method is based on linear regression, which cannot indicate the relationship, the independent variable can affect the dependent one and therefore the whole system maybe affected.

X. M-HEALTHCARE SYSTEM FOR HAR [2018] [76]

Due to the predominant growth of the Internet, the emergence of advanced information and communication technologies lead to the utilization of IoT [77], which in turn increases the usage of various modern technologies, especially in the field of healthcare systems [78]. In advanced healthcare systems, mobile healthcare (m-healthcare) plays a vital role in order to provide, monitor, and assist the personal healthcare of elder people. The m-healthcare system is a framework that provides the facility to physicians for examining human activities by utilizing different mobile technologies.

To promote the modern healthcare applications, the authors have proposed an intelligent, robust, and precise m-healthcare system that provides human activity recognition (HAR) [79], [80] on a large-scale area and the system is based on the IoT technology. The proposed m-healthcare system addresses healthcare challenges and utilizes various data mining techniques to enhance the accuracy and effectiveness while providing different m-healthcare services to humans. A dataset is used by the system, which is evaluated against various data mining techniques, such as SVM, K-NN, ANN, random forest, classification and regression tree (CART), C4.5 (J48) decision tree, and rotation forest (RF). The dataset used by the m-healthcare system consists of body movement and vital signs of 10 distinct volunteers, while doing 12 physical activities such as standing still, sitting and relaxing, lying down, walking, climbing stairs, waist bends forward, frontal elevation of arms, knees bending, cycling, jogging, running, and jump front and back [81].

This dataset of physical activities is used in the human activity recognition process where physicians can use it to assist their patients in remote areas. In order to retrieve different values for the healthcare system, various sensors may be used in the human body to record vital signs and body motions. The proposed system utilizes wearable sensors to record body motions. These sensors are attached at the human's left ankle, right wrist, and chest in order to monitor the movement of the body. In the m-healthcare system, 10 volunteers are monitored and assisted for providing them with different healthcare services. From subject 1 to subject 10, each volunteer's dataset is evaluated against all data mining techniques. Each data mining technique gives different results while evaluating the dataset of each volunteer.

In the experimental procedure, the accuracy level of every data mining technique is tested against each subject. Moreover, the evaluation results show that the SVM and RF performed better than other data mining techniques with the average accuracy of 99.89%. Hence, in the advanced era of modern technologies, the SVM and RF are better choices for physicians to enhance the performance level of human activity recognition process in mobile healthcare applications. However, in addition to high algorithmic complexity, the SVM technique has various key factors that are required to be set appropriately to realize accurate categorizations of a particular problem [82]

XI. BREAST CANCER CLASSIFICATION FRAMEWORK [2019] [83]

Due to a rapid increase in the IoMT technologies, cloud-based e-Health care systems are growing at a prompt momentum. In a remote area where e-Health care units have restricted resources (e.g., the unavailability of medical equipment or physicians) to normalize the state of a patient having breast cancer. In such conditions, the district health unit sends the breast cells cytology images of the patient via ML-based equipment to the fog/cloud-based server. With the arrival of information, the proposed system professionally perceives and categorizes the malignancy of breast cells and sends the results back to the local health unit for essential medicinal protection.

The proposed system classifies the image in steps, i.e., first the image is obtained, next is it preprocessed, then segmented, and finally, extracted. The designed framework was examined on 400 cytology images, which were obtained from a local hospital in Peshawar. These images were combined via a microscope with dimensions of 640x400 lens size. Using confusion matrix, the test of each classifier is examined wherein the malignant cell and non-malignant cell cases are categorized as true positive and false positive, respectively. In addition, non-malignant cells are further categorized into false-negative, which are erroneously organized as negative, and true-negative, which are correctly organized as negative cells. The confusion matrix exhibits different factors, i.e., false-positive rate, precision, sensitivity, and accuracy among others. In this approach, contemporary technique, i.e., chain-like agent genetic algorithm (CAGA) is utilized to choose ideal structures from various features for the minimization of computational cost and clarification of accuracy.

Though the achieved accuracy of the proposed approach is 98%, it can be more precise if a deep learning technique is applied to validate the precision in pinpointing breast cancer [84].

Table 2 presents the summary of contributions and limitations of the surveyed approaches.

XII. CHALLENGES TO IOMT

IoMT technology applications introduce a huge set of challenges, which are discussed in this section.

TABLE 2. Contributions and limitations of the presented approaches.

Scheme	Contribution	Limitation
Monitoring of Limbs [15]	Helpful for patients during night by using tags that are placed on their shoulders or chest.	Somewhat unfavorable and exasperating as the sensors in this method are attached directly to the ankles of patients.
Monitoring and control of rural healthcare [25]	Provides the trade-off among end-to-end delay, system throughput, and energy consumption, which make the system suitable for the IoT environment.	The authorization and authentication of this method in cooperative IoT systems is not clear.
Identification of E-health Apps [29]	Provides almost 100% accurate results for sensory data, images, and registration data.	The accuracy in video conferencing remains relatively low.
IoT-based m-health and remote monitoring [38]	Solves the problems of high rate of sampling and reduces the excessive requirement of power supply.	This is unsuitable to use it as a common algorithm in various domains.
Heart sounds classification [47]	Appropriate for smooth communications.	It may not work properly in the case of distortion.
Stress detection in drivers [56]	Contributes towards the advancement in developing machines that can respond wisely to human while understanding human mental states.	Requires such real time ML algorithms that may respond quickly so that drivers may know their health status and therefore take rest.
Cardiac health monitoring [62]	Delivers the most relevant and precise information to clinicians/physicians to upsurge their diagnostic accuracy and efficiency.	Though the labeling is a mandatory phase of data processing in supervised learning, it is a tedious and time consuming job.
DMS for heart attack [71]	The analysis is helpful in developing a mobile app for providing health services to remote areas.	The system is based on linear regression wherein the relationship is not indicated, therefore, the independent variable can affect the dependent one and hence the entire system may compromise.
M-healthcare system for HAR [76]	Enhances the performance level of human activity recognition process in mobile healthcare applications.	Increases algorithmic complexity and requires several key factors to realize accurate categorizations of a particular problem.
Breast cancer classification framework [83]	Minimizes computational cost and increases accuracy in the detection of breast cancer.	Though the system achieves 98% accuracy, a deep learning algorithm needs to be applied to validate the precision in pinpointing breast cancer.

A. PERSONAL DATA SECURITY
Though various healthcare-related tools use tested communication techniques for information transfer to the cloud, they may still be susceptible to hackers. Apart from misusing personal information, IoMT tools can be utilized for destruction. For instance, the 2012 episode of a TV series, Homeland, established a hacked pacemaker provoking a heart attack [1]. Therefore, the security of IoMT tools is indispensable.

B. REINFORCING PATIENT PRIVACY
As per the 2019 HIMSS survey [85], 82% of medical bodies faced major privacy/security confrontations in 2018. The main reason of these incidents is the utilization of legacy technologies by the hospitals. For instance, MRI machines are used for 11 years, whereas some hospitals use them for more than 22 years [86]. In addition, since one third of IoMT tools are outdated and not maintained by their manufacturer, they may not be restructured/modernized to defend against susceptibilities [87].

C. SUSTAINING CONNECTIVITY
Full connectivity is inevitable in IoMT where doctors, nurses, and patients should be connected all the time. The Internet connectivity fluctuates or disrupts due to several reasons, for example, limited network bandwidth, inexperienced network/web administrators, or any other physical impediments that disturb Wi-Fi signals. The above mentioned probabilities are intolerable in IoMT-deployed sanatoria [88]. Thus, the question arises that how can the bandwidth be sufficiently utilized to provide uninterruptible connectivity in the IoMT environment. The answer is to foster a secure network structure where Internet professionals be allowed to distribute the bandwidth according to the needs of functioning IoMT equipment [86].

D. MODERATING PERSONNEL ERROR
Yet sanatoria are more complex and technology-dependent than ever before, IoMT funds and human resources are not emerging at equal pace. According to a survey [89], less than 30% sanatoria claim that their IoMT personnel is fully functional. Thus, the IoMT community needs to take system and procedures into consideration when advancing the technology. The majority is thinking about improving the network automation [86], which has largely upgraded the infusion pump technology. That is, the infusion pump is attached to the patient medical history which is saved on the cloud. Therefore, it is presumed that network automation can considerably reduce personnel error in addition to improving patients' perception and practices in the future hospitals.

XIII. CONCLUSION

Internet of Medical Things (IoMT) is inevitably a leading environment for the future healthcare. In this paper, we attempted to provide a deep analysis of the IoMT research exertions. First, we described the general notion of IoMT framework. Then, we presented a comprehensive view of IoMT-related applications, which are developed and/or deployed in the last decade. The deployment of proposed approaches encounter several challenges ranging from equipment cost and security to patients' information confidentiality. This argument is supported by the presented challenges at the end of this article, which are utmost important to be taken into consideration when deploying a future healthcare unit.

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