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Review

Intelligence in the Internet of Medical Things era: A systematic review of current and future trends

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ABSTRACT

Internet of Medical Things (IoMT) envisions a network of medical devices and people, which use wireless communication to enable the exchange of healthcare data. Healthcare costs and prices for services have been increasing with the growing population and the use of advanced technology. The combination of IoMT and healthcare can improve the quality of life, provide better care services and can create more cost-effective systems. This paper introduces the status of IoMT for healthcare industry, including research and development plans and applications. The implementation of the IoMT in healthcare has exponentially increased across the world, but still, it has many technical and design challenges. This paper depicts such challenges and shows a generic IoMT framework that consists of three main components, data acquisition, communication gateways, and servers/cloud, to meet the aforementioned challenges. Finally, this paper discusses the opportunities and prospects of IoMT in practice while emphasizing the corresponding open research issues.

Contents

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1. Introduction

Internet of Things (IoT) is changing our lives in a way never imagined before. Unlike traditional paradigm, everything in IoT world is considered as smart objects, which are connected with each other. IoT is defined as dynamic, self-configuring network of physical and virtual things powered with interoperable communication protocols, media and standards [1–4]. These things have identities and attributes, are capable of connecting to information networks such as Internet, and can perform sensing, data processing, networking and communication. Therefore, IoT can be considered as a new version of information and communications technology (ICT).

Ranging from smart appliances to smart cities, IoT has also opened a new challenge in the healthcare domain, which is called the Internet of Medical Things (IoMT). IoMT offers significant benefits for wellbeing of people by increasing the quality of life and reducing medical expenses. As shown in Fig. 1, critical elements are wireless sensors, which can be used to remotely monitor the status of patients' health and communication technologies to send the information to caregivers.

The main step towards a smart healthcare ecosystem is to utilize the potential of existing technologies in delivering the best services to users and making their lives better. Artificial Intelligence is the other enabling technology that helps IoMT, which can assist medical professionals in almost every area of their proficiencies such as clinical decision-making. With Machine Learning and Deep Learning techniques, computers can learn normal and abnormal decisions using the data generated by the health professionals and the patient feedbacks.

IoMT devices supported by Artificial Intelligence can continuously monitor people's health. Smart robots, smart homes and virtual assistants can provide the necessary support to elderly and disabled people. By combining the information gathered with the IoMT sensors and the information obtained from the health system, epidemic diseases can be monitored and prevented. During disasters, intelligent systems can help authorities for providing the right assistance to people, and taking necessary measures in a timely manner.

In the context of IoMT, input components such as biosensors, communication modules and users work cooperatively to provide the best healthcare service in an efficient and secure way. With the assist of IoMT technologies, self-care and early diagnosis are considered to be the great influential services in strengthening healthcare ecosystem, especially those which utilize remote monitoring systems [5]. Remote monitoring system depends crucially on processing and analyzing the real-time information collected via bio-sensors. Data exchange between such devices require secure mechanisms and communication technologies. On the other hand, data leakage and information theft are serious problems, if these devices are not properly secured.

In this study, we discuss data acquisition, communication and processing aspects of IoMT. Such topics might be intriguing to researchers from academia, as well as, the healthcare industry. This survey is a source for those who are concerned with computer science and healthcare technologies. Additionally, it paves the way for further developments and implementations in future healthcare. The abbreviations used in this survey are defined in Table 1 for more readability.

1.1. Comparison to other surveys

In literature, there are similar surveys published on IoMT. In this subsection, we overviewed these surveys and highlighted how they differ with our survey. Such as, a short survey on IoMT in healthcare was discussed in [6]. Implementation of IoMT in medical applications was briefly analyzed with examples. However, it failed to cover other aspects of IoMT, such as sensing technologies, communication technologies, and data processing techniques. The study was mainly on security challenges for IoMT and countermeasures. Another survey was provided in [7], which comprehensively discussed recent developments in IoMT-based healthcare technologies and overviewed several applications, network platforms, and drifts in healthcare industry. Further, this paper presented a smart concerted security model in order to reduce security issues and discussed how IoMT-based healthcare technologies could contribute to sustainable development of economies and societies. Again, this paper failed to discuss bio-sensors, data processing techniques and IoT communication gateways used to transfer data. In [8], the missing issues of the previous studies were outlined and better explained with more illustrations. However, the communication aspects of bio-data between devices and servers were not outlined. In [9], the tasks of communication modules in IoMT were briefly discussed. Both short-distance and long-distance communication modules were overviewed and differences were highlighted. At the end of this survey, authors also discussed some future research areas in IoMT with open issues and challenges standing in the way of its continued development. Similarly, low power healthcare communication networks were discussed in [10] and [11]. Various WSNs with suitable communications protocols were also presented. However, the authors did not show example applications in both studies. In another survey, different data mining techniques were explored for classification and clustering data in medical domain [12]. Similarly, Jothi et al. reviewed several papers and identified different data-mining models involved in biomedical data processing [13]. Highlighting several applications and challenges, authors of [12] and [13] commented that there is no sole algorithm that results in accordant outputs for all types of input data. Therefore, a hybrid approach could be a good option for achieving better performance.

In this paper, we intend to provide a comprehensive survey and a state-of-the-art architecture for IoMT devices. Also, we would like to inform the readers about the current and new trends in healthcare. Table 2 lists the topics covered in the aforementioned surveys. Key design factors and elements of IoMT ecosystem were not address by most of them.

The rest of this paper is structured as follows. Section 2 classifies the existing IoMT systems into body-centric and object-centric applications and explores their main attributes. In Section 3, standard components of IoMT architecture are listed under three main categories: data acquisition, communication gateways, and servers. In data acquisition, utilized sensors are also classified as wearable and non-wearable technologies. Various communication networks are presented and discussed in the context of both local and broad area networks. Fundamental approaches and data processing algorithms that may be useful in bio-data processing and medical analysis, in addition to their advantages and disadvantages, are outlined. Section 4 overviews the main design factors of IoMT and the challenges. Section 5 pinpoints the gaps in promoting the development IoMT systems ranging from the sensory curbs to communication problems. Finally, Section 6 concludes the survey.

2. IoMT applications

Combined with the other enabling technologies, IoMT has opened new opportunities in the medical domain to save and improve the quality of people's lives. It created new applications areas and changed the way of doing things in the existing areas such as clinical decision making, data acquisition and patient record management.

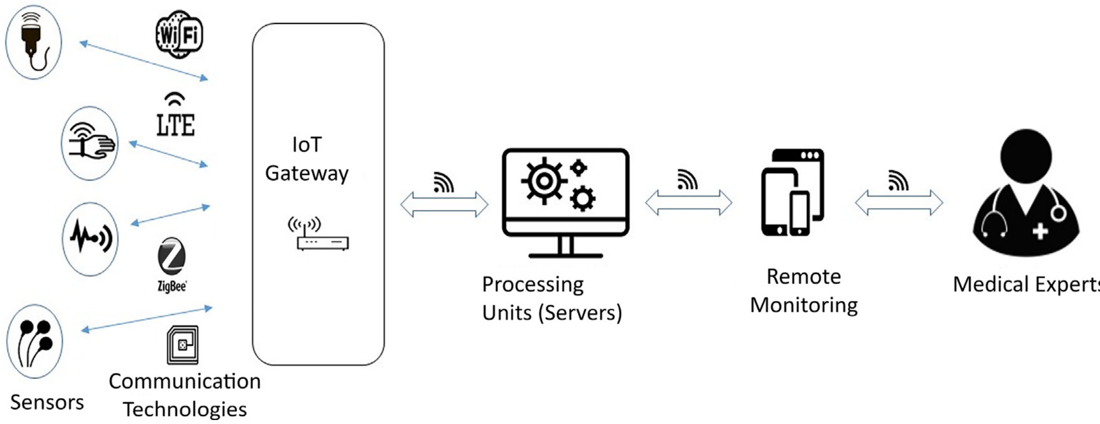

Fig. 1. General architecture of internet of medical things.

Table 1
List of used abbreviations.

Abbreviation	Description	Abbreviation	Description
ADC	Analog to digital converter	K-C	K-means clustering
ANN	Artificial neural network	LAN	Local area network
CAD	Computer aided diagnosis	LCD	Liquid-crystal display
CAN	Controller area network	LDA	Linear discriminant analysis
CNN	Convolutional neural network	LED	Light emitting diode
CPU	Central processing unit	LTE	Long term evolution
CT	Communication technology	MAN	Metropolitan area network
CTC	Circulating tumor cells	NB	Naïve-Bayesian
DM	Data mining	NFC	Near field communication
DT	Decision tree	OSA	Obstructive sleep apnea
ECG	Electrocardiography	PAN	Personal area network
EEG	Electroencephalogram	POC	Point of care
EHR	Electronic health record	PSG	Polysomnography
FDA	Food and drug administration agency	RFDD	Real-time facial disorder detection
FFT	Fast-Fourier transform	RFID	Radio-frequency identification
FL	Fuzzy logic	SI	Swarm intelligence
FPGA	Field programmable gate array	SNR	Signal-to-noise ratio
GPRS	General packet radio services	ST	Sensing technology
HAN	Home area network	STFT	Short-time Fourier transform
HR	Heart rate	UCS	Union of concerned scientists
HRZ	Heart rate zone	VQ	Vector quantization
ICT	Information and communications tech.	WAN	Wide area network
IoMT	Internet of medical things	WFC	Wireless field connector
IoT	Internet of things	WSN	Wireless sensor network
IR	Infrared	WT	Wavelet transform

Table 2
Summary of related surveys.

Ref.	Applications				Design factors						DM	ST	CT
	Body-centric		Object-centric										
	Indoor	Outdoor	Indoor	Outdoor	Cost	Energy	Precision	Safety	Security	Usability			
[6]	✓	–	–	–	–	–	–	–	✓	–	–	–	–
[7]	✓	✓	–	–	✓	✓	–	–	✓	–	–	–	–
[8]	✓	–	–	–	–	–	–	–	–	–	✓	✓	–
[9]	✓	–	–	–	–	–	–	–	✓	–	–	–	✓
[10]	–	–	–	–	–	✓	–	–	–	–	–	✓	✓
[11]	–	–	–	–	–	–	–	–	–	–	–	–	✓
[12]	✓	–	✓	–	–	–	–	–	–	–	✓	–	–
[13]	–	–	–	–	–	–	–	–	–	–	✓	–	–
[Our study]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

With the advancements in the field of Artificial Intelligence (AI), telemedicine and sensor technology, IoMT can be used for clinical decisions. Human decisions supported with virtual assistants that can learn hidden features from massive healthcare data by using sophisticated algorithms such as Deep Learning are already used in some hospitals especially in the field of radiology [14,15]. With IoMT, additional self-correcting abilities can also be equipped to improve decision accuracy following feedbacks. Virtual assistants can keep doctors up-to-date by providing new information from different articles, journals, and clinical practices for proper patient care [16]. IoMT can be used for continuous monitoring of patient vitals, can create alerts in changing health conditions and sometimes take necessary precautions.

Another enabling technology for IoMT is block-chain. A block-chain is defined as data chunks linked to each other using time-stamps. Every new block contains the hash of the previous block and the data, thus forming a chain. This chain is continuously extended as new blocks are added to the end. The record of data is managed by the clusters of computers without the ownership of single entity or any third party (de-centralized). The blockchain technology revolutionized the financial sector and we have seen many new technologies such as crypto currencies. In the context of IoMT, blockchain technology has potential for addressing health data integration, integrity, ownership, and access control [17,18]. It has been proposed for storing hash of sensor data to prevent alterations and ensure patient ownership [19]. Supply chain can utilize block chain technology to trace and track drugs and medical items from the producer to the end user using IoMT devices and prevent any wrongdoing. Temperature and humidity sensors can be used to monitor environmental conditions during transportation and storage. Another important application area is the storage of patient records in a global ledger that can be accessed by other health data providers.

Some of the other applications areas are shown in Fig. 2. We classify the applications based on their environment and as being body-centric or not.

2.1. Body-centric applications

Body-centric applications refer to healthcare systems or devices that generate psychological data by directly interacting with human body. Acquired data is then processed and sent to caregivers for medical analysis. Medical wearables and non-wearables are common examples of body-centric applications. Medical wearables are the smart sensing devices that can be worn on a human body as implants or accessories. Whereas, non-wearables are the smart sensing devices that cannot be worn on human bodies. Based on the environment, body-centric applications are divided into two groups, indoor and outdoor.

2.1.1. Indoor body-centric applications

IoMT is ushering indoor healthcare with a promising potential of success due to its intelligent communication technologies. Some of the smart indoor monitoring solutions that are using new and innovative IoMT ideas are listed below.

Bio-Acoustic Sensors and Continuous Activity Monitoring — With the advances in mobile communication and IoT, various new bio-acoustic sensors have been developed to monitor body sounds, respiration, blood pressure and heartbeat. In a study by Mills et al. [20], a Bluetooth e-stethoscope for bio-acoustic sounds was introduced to process short and long-term body sounds. As a novel example, a bio-acoustic sensor is devised for gastrointestinal activity monitoring after surgery for people who lose their muscle strength in the digestive tract and have motility problems. Regular patient visits and auscultation using analog stethoscope are the traditional ways to observe bowel activities. Instead, a digital bio-acoustic sensor combined with IoMT protocols were used to detect the bowel activity and sent data for further processing [21]. Similarly, in another study, researchers developed an electronic stethoscope employing two microphones, one for environmental noise and one for body sounds [22]. This way they could be able to eliminate interfering environmental sounds from body sounds. Also, instead of Bluetooth protocol, they used ZigBee for wireless communication. Even though Bluetooth is the leading wireless technology for consumer electronics, they concluded that ZigBee based communication is more reliable and offers better communication performance.

Heart Rate Monitoring — Heart sound auscultation, heart rate variability and electrocardiography (ECG) are the common monitoring techniques for heart conditions. Various devices were designed that are suitable for body-centric applications. In [23], Tang et al. developed an e-stethoscope for heart monitoring. After signals are gathered, this device performs signal pre-processing and power amplification. An embedded processor was used to sample signals and display on LCD. This data was transmitted to a PC for further processing using Bluetooth technology.

Typically, previously mentioned devices are suitable for assisted health care. In another study, Aguilera-Astudillo et al. devised a new low-cost 3D printed stethoscope that can connect to a smartphone [24]. This device was suitable for the use of inexperienced users to perform preventive self-care. Also, users could run various tests on observed signals using a mobile application and send data to a doctor for diagnosis.

Sleep Monitoring — Sleep monitoring systems are typically used in hospitals because of the high equipment cost. With IoMT, medical experts can remotely monitor and, also observe the body posture and breathing patterns of patients. Polysomnography (PSG) is a standard method commonly used to monitor obstructive sleep apnea (OSA). Sometimes patients have to wait for a long time due to lack of availability of sleep labs in hospitals. Also, sleeping conditions and restricted mobility of patients in lab environments can alter their sleeping patterns and cause misdiagnoses. Therefore, performing PSG in patients' home could be more expedient. In order to address this issue, Lin et al. developed an IoMT-based portable low-power wireless polysomnography system which could operate up to 16–20 h [25]. They compared PSG systems with IoT-based wireless PSG system and performed experiments on patients. Findings indicated that IoMT-based wireless PSG systems were more reliable for PSG based sleep apnea observations.

IoMT-Enabled Medical Scanners — IoMT has created new opportunities for the areas where healthcare facilities are not properly equipped or not available. For example, in most of the developing countries, 75% of the radiologists are in urban areas. That is why, there is a need for portable radiography devices that can be used to generate images of internal organs and send data to medical experts. With the help of Artificial Intelligence, these systems can also detect anomalies, assist radiologists and save lives.

Sonography is a widely used imaging technology. Kim et al. developed a low-cost portable ultrasound system for point-of-care (POC) applications [26]. It works as an autonomous device employing a single Field Programmable Gate Array (FPGA). The system can transfer images directly to other systems via external memory without requiring any video processing unit. It provides real-time imaging at 30 frames per second. The system operates on a battery, which could last up to 1.5 h. Hence, it offers improved flexibility for POC applications.

For rural areas, where there is a lack of radiologists, tele-radiology using IoMT enabled ultrasound devices is beneficial. However, having a wireless connection all the time for these systems may not be possible. For such circumstances, Krishna et al. developed a portable ultrasound device with computer-aided diagnosis (CAD) [27]. This system was a modified version of the scanner developed in [26].

2.1.2. Outdoor body-centric applications

Advanced IoMT protocols and communication standards enable enhanced communication for outdoor healthcare services. Some of the smart monitoring solutions for outdoor healthcare that are using new and innovative IoMT ideas are listed below.

Outdoor Heart Rate — IoMT has not only enabled people to monitor heart rate in indoor environments but also in outdoor environments. When it comes to intense physical activities like fitness training or sports, heart rate monitoring is the essential tool for evaluation of the condition of cardiovascular system. Intensity of physical activity increases heart rate [28]. Therefore, it is vital to keep track of heart rate zone (HRZ) during intense activities. Different smartwatches and Bluetooth devices are available for heart rate monitoring for both outdoor and indoor environments.

Photo-plethysmography is a simple method for measuring blood volume variations in small vessels [29]. Heartbeat alters blood volume that is passing through the small skin vessels. Skin is illuminated with a light source and intensity of propagated light is measured using photodetector. Changes in blood volume cause variations in propagated light intensity. These variations are analyzed to derive heartbeat.

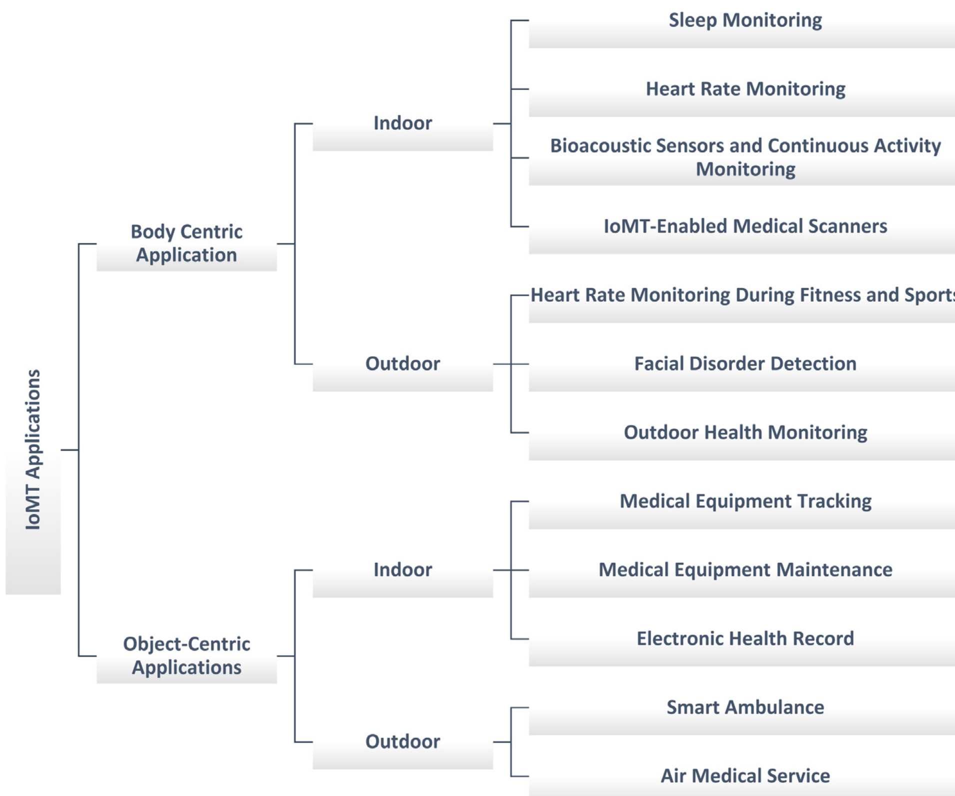

Fig. 2. Examples of IoMT applications classified as object and body centric for indoor and outdoor environments.

PulseOn and MioLINK are the two-leading wrist-worn HR monitors using photo-plethysmography. Delgado-Gonzalo et al. [30] compared these HR monitoring devices to evaluate their accuracy and reliability for outdoor activities (resting, running, walking, and cycling). Based on their findings, PulseOn monitors were 94.5% reliable with an accuracy of 96.6%, whereas Mio LINK were 86.6% reliable with 94.3% accuracy [30].

Facial Disorder Detection — It is also possible to develop mobile monitoring devices to detect and diagnose facial skin disorders. Installing such devices to the entrance of hospitals, schools or public places may help early diagnosis of such disorders or prevent unnecessary hospital visits.

In computer vision, face detection technique offers great potential in monitoring and surveillance applications [31]. In 2016, a real-time facial disorders detection (RFDD) technique was proposed by Al-Turjman [32]. In this study, he developed a technique which detects and segments the infected area of the face. The proposed technique was also effective and useful for cold, flu and facial temperature detection. In crowded places like hospitals, railway stations, or airports the RFDD could be used to identify people with contagious diseases and prevent them from spreading among people [33,34].

Outdoor Health Monitoring — These intelligent systems allow to monitor patients at their homes or outdoor. Mobile phone compatible sensors can monitor patients with chronic diseases, high blood pressure, and fever. If there is any abnormality, monitoring devices warn concerning medical professional through mobile application.

Abdullah et al. [5] developed a real-time wireless health monitoring system. The proposed system can detect patient's health conditions such as heartbeat rate, blood pressure, temperature, muscles and glucose level. It also can store the data for future references. In life threading situations, the system can alert medical experts for early diagnosis. This system works very fast, offers high efficiency and accuracy.

For elderly patients, a real-time mobile-based health monitoring system has been presented in [35] for indoor or outdoor environments. A wearable bio-sensor is employed to collect patient's physical data. This data is then transmitted to the intelligent server via GPRS for further analysis. Remote users can access the collected data via online web application. The proposed system can monitor the vitals and location of a patient.

2.2. Object-centric applications

Unlike body-centric applications, object-centric applications are not directly related to human body. However, object-centric applications refer to healthcare solutions and services that can be efficiently used to improve healthcare delivery. A key example of object-centric applications is hospital management system. Based on the environment, object-centric applications are further divided into two areas, indoor and outdoor.

2.2.1. Indoor object-centric applications

Some of the solutions for indoor healthcare that are using new and innovative IoMT ideas are listed below.

Medical Equipment Tracking — In an emergency situation, quick localization of critical assets is required. RFID technology is considered to be one of the most reliable and efficient technology used for indoor localization. It enables devices to identify objects and record metadata through radio waves. RFID consists of RFID tags and readers. Tags are the transponders (microchip with antenna) which act as identifier attached to an objects. And the readers (transmitters/receivers), which are also known as interrogators, communicate with the tag using radio waves. Some of the healthcare applications of RFID technology are equipment tracking systems. Tsai et al. developed an RFID equipment tracking system that assists medical staff to quickly locate and track healthcare equipment [36]. The proposed system improved service quality, work performance, and inventory control.

Medical Equipment Maintenance — IoMT devices provide solutions for the maintenance of healthcare equipment. Wang et al. developed an IoMT application that can detect faults in medical devices [37]. The proposed application can discover the causal relationship between physical devices. After detecting faults in specific devices, the proposed application can predict faults in other related devices using the causal relationship. Therefore, early warnings can be generated to prevent future failures. Similarly, Jamal Maktoubian and Keyvan Ansari presented an IoMT architecture for preventive maintenance and inspection of medical devices [38]. In this study, they proposed a framework which could detect the fault and monitor the status of medical devices using big data and IoMT technologies. Typically, technicians monitor a small number of devices at a time. However, the proposed framework can monitor a greater number of devices at the same time.

Electronic Health Record — Ink and paper system is the traditional way of managing medical records. The adoption of electronic medical records (EHR) is a game changer in smart hospitals. Unlike traditional medical records, EHR system offers a single place to keep all the information. The information can be easily accessed and shared to the concerning people. By improving healthcare efficiency and safety, EHR systems can save millions of lives. Different types of EHR have been implemented in medical centers. The first EHR system, known as a clinical information system, was developed in the 1960s by Lockheed, which was later handed to other medical companies [39]. Nowadays, more advanced EHR systems have been developed by academia and institutes. Moreover, IoMT is playing an evolutionary role in the advancements of EHR systems.

2.2.2. Outdoor object-centric applications

IoMT can offer efficiency for outdoor emergency services. Improved emergency services could result in better safety and potential of reducing number of incidents. Some of the advanced emergency and survivability service ideas based on IoMT are listed below.

Smart Ambulance — Rapid response to a medical emergency is critical to prevent losses. Under such circumstances, reaching hospitals faster is a serious issue. Therefore, fast and smart ambulance vehicles are a dire necessity in emergencies.

Sivaraj et al. [40] proposed an IoMT idea that consists of two parts. First, the IoMT devices observe the vitals of a patient inside the ambulance and send information to the hospital for pre-arrangement. Second, in order to prevent delays, the system automatically alters the traffic lights and clears the ambulance's path. Another study aims to find the fastest route for the ambulance [41]. WSNs were used in the proposed study to monitor road conditions. The information originating from these sensing nodes were used to estimate the fastest route for the ambulance.

Air Medical Service — Due to an increase in population, road traffic is increasing dramatically worldwide [42], which causes delays in transporting patients to hospitals. Air medical or air transportation service is an alternative solution. Use of helicopters is common in air medical in developed countries. In underdeveloped countries, this service is excluded due to its high cost. However, it has manifested significant improvements in morbidity and mortality for developed countries. The first air ambulance made publicly available in an under developing country was on January 12, 2010 in Haiti after a massive earthquake incident [43]. In the first year of its operation, 76 patients were transported. Nowadays, additional air ambulances are deployed and especially used for the transportation of cardiac patients [44].

3. IoMT components

IoMT ecosystem consists of three main components, data acquisition, communication gateway, and server/cloud. Fig. 3 shows the connection between IoMT components and their specific operations.

Data acquisition is the first component of IoMT which depends significantly on sensors and users. The data from patients is collected via sensors and undergoes pre-processing stages before being sent to the server/cloud. Various data processing techniques are implemented in order to extract and classify useful information. This information is then used by medical experts for further analysis. The data between components and the user is exchanged via communication gateways. In this section, all the three components of IoMT and their features are explained.

3.1. Data acquisition

In IoMT, data acquisition is a process of acquisition of biological data for useful applications. Data is usually collected by bio-sensors which exists in the form of analog signals. Most of the time, biological signals are low amplitude and contaminated with noise. Therefore, these signals are preprocessed and digitized.

Fig. 4 shows the general architecture of data acquisition and its preprocessing steps. Pre-processing includes amplification and filtration operations. During data acquisition, it is imperative to ensure that the information is well-persevered and not lost, otherwise, it could lead to wrong decisions during diagnosis.

3.1.1. Biosensors

Biosensors are the electronic devices used in the acquisition of biomedical signals. Biosensors can transform traditional healthcare system significantly by connecting people to the health system. These smart devices can generate an incredible amount of data and transmit to caregivers. Also, biosensors can automatically process the data and speed up diagnosis by allowing people to monitor their health. In IoMT, biosensors are classified into wearable and non-wearable technologies.

3.1.1.1. Wearable sensors. Wearable technology is a category of the smart sensing devices that can be worn on a human body as implants or accessories. These devices offer high potential to generate data and communicate with other devices without human intervention. Some of the most trending wearable technologies are as follows.

Hearing Aids — are small electronic devices that are worn behind ears. A typical hearing aid device consists of a microphone, speaker, and amplifier. Today, millions of people are suffering from hearing loss. Hearing aid devices help people hear clearly both in quiet and noisy places. Microphone collects sound waves from environment and converts them into electrical signals. Electrical signals are enhanced by an electronic amplifier which then sends them back to ear through speakers.

Hearing aids are the oldest form of wearable technologies, but now they are more advanced and smarter. Smart hearing aids are rechargeable devices that can be connected to user's mobiles, TVs, computers, tablets and more. Users have the options to adjust volume and program these devices according to their need using mobile applications [45].

Fitness Trackers — Similar to wristwatches, fitness trackers or fitness bands are wrist-worn devices that can detect the physical activities of a person together with other data such as HR, temperature and distance covered. Most fitness trackers can connect to mobile phones via Bluetooth. Users of wearable technologies are seen to be more physically active [46]. Some researches indicate that fitness trackers motivate people to set health goals and be consistent by monitoring and keeping record of daily activities [47].

Chronic Pain Wearables — Chronic pain is a central nervous system disease which differs from acute pain. When you get hurt your brain gets an alarm instantly that your body is damaged, and you feel pain. However, chronic pain is an ongoing pain which remains for several weeks or months even if there is no apparent reason. Key examples are headache and back pain. In US, it is reported that more than 100 million people are suffering from chronic pain [48].

Many innovative companies developed wearable technologies to relieve chronic pain without hospital visits and medication. It is a new field in IoMT, some products are already approved for use while

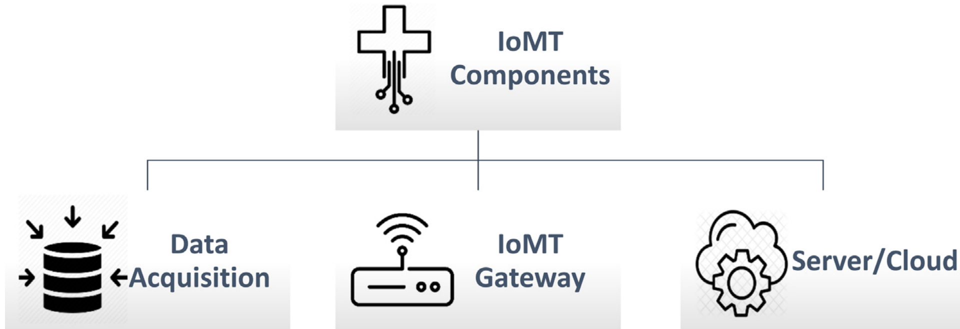

Fig. 3. Three main components of IoMT ecosystem.

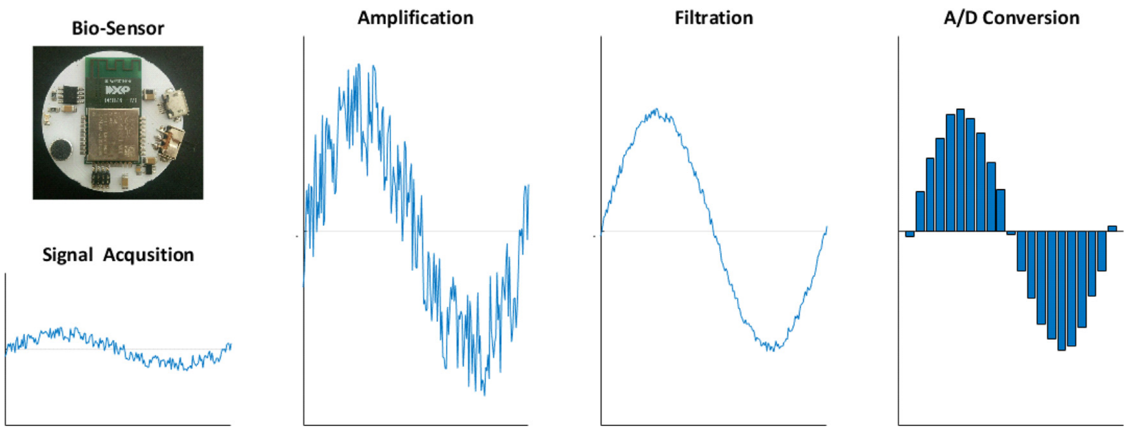

Fig. 4. Basic operation of data acquisition.

sleeping [49]. In order to block chronic pain, a tiny sleek band device is worn on upper calf. Device works by sending neural pulses to the brain.

Personal Skincare Wearables — These device has built-in hi-tech sensors that collect skin information and send data to mobile app using Bluetooth technology [50]. A mobile app analyzes the data and chooses the best LED color and skin patch based on your skin type. Patches are then applied onto the skin with LED shinning.

Cancer Cell Detecting Wearables — Typically, cancer is detected by taking a sample from the patient's body. This sample is then used to examine more closely in order to look for cancer or tumor cells. Typically biopsy is invasive. Taking a blood sample is another typical method in order to identify circulating tumor cells (CTCs) in the blood. Similarly, blood draws may have negative health impacts on patients with cancer.

IoMT has enabled researchers to develop non-invasive techniques for CTCs detection. Such as a wearable CTC detector developed by researchers from University of Michigan [51]. The proposed system could potentially be used in clinical decisions by analyzing large number of CTCs. The technology was validated in a canine model. The results showed that the device can detect 3.5 times more cancer cells per milliliter of blood than traditional blood drawing method.

3.1.1.2. Non-wearable sensors. Non-wearable technology is a category of smart sensing devices that cannot be worn on a human body. These devices can also generate massive amounts of data and communicate with other devices without human intervention. Some of the most trending non-wearable technologies in bio-sensors are as follow:

Smart Pillbox — Many people sometimes mixed up their medications due to a busy schedule. Untimed medication has very adverse effects on health. Especially for chronic diseases, patients have to consume medicine over a period. Therefore, it is imperative to take right dose at appropriate times. Most of the time, elders are the ones who forget to take medications or sometimes overdose, which may have adverse effects.

A systematic way to solve such issue is necessity. In 2018, Minaam et al. proposed a prototype smart pillbox [52]. It is a small programmable device that can organize different pills by itself. It consists of nine separate sub boxes. Users or caretakers can easily determine the amount of dose and timings to consume for every day.

Smart Beds — Smart beds have broad use in hospitals. This technology allows doctors or caregivers to monitor patients remotely. Smart beds contain biosensors for respiration, temperature, and heartbeat. Long term data can be reviewed for sleeping analysis, heart rate, and breathing rate trends of patients using smart bed technology [53]. In emergency situations, these devices can generate an alarm or send an alert to the caregivers for immediate action.

Human Activity Detection — Obesity, cardiovascular disorders, stroke and musculoskeletal diseases have become the biggest issues of health. For such issues, health monitoring and human activity detection systems provide the best opportunity of health recovery guidance and early alarm of healthcare emergency [54]. IoT technology allows us to operate these healthcare systems remotely by employing different wireless sensors and collecting data.

A typical example is detecting human activities in the home using different WSNs. However, these multiple interconnected sensors require high maintenance and deployment costs and they also consume high power. A low-power radar enabled sensor network is developed by Bodanese et al. in order to detect human activities [55]. Fifteen activities performed in kitchen were analyzed. The study showed that the proposed system offers 92.81% overall activity detection accuracy. Moreover, in real-time detection mode, it recognizes human activities more than 89% of the time.

3.1.2. Pre-processing

Biological signals are usually weak and noisy, which makes processing difficult. Therefore, bio-signals are first amplifies using appropriate amplifiers. A typical amplifier consists of an electronic circuit, which produces a high amplitude output signal when a weak signal is given into its input. It amplifies the signal without altering other parameters such as its frequency or morphology. A typical circuit of the amplifier consists of resistors, conductors and transistors. An amplifier with one transistor is known as a single-stage amplifier, and the one with multiple transistors is known as multi-stage amplifier. In practical application, multi-stage amplifiers are used widely. The amount of amplification of an amplifier can be measured by its gain. The gain is defined as the ratio of the output value to the input value of amplifier as depicted in Eq. (1).

$$Gain(voltage) = \left(\frac{output\ voltage}{input\ voltage}\right) \tag{1}$$

After amplification process, signals are filtered out to remove unwanted parts of the signal. Several filters are used to carry out filtration process. Filters are further divided into four categories; high-pass filter, low-pass filter, band-block and band-pass filter. A high-pass filter is used to attenuate low-frequency components of the signal while low-pass filter attenuates high-frequency components of the signal. However, band-pass filter can be used to eliminate both high and low frequency components of the signal [56]. Adaptive filters is also known to be effective for signal denoising [57–59].

3.1.3. A/D conversion

A/D converters are used to convert analog signals to digital signals. Fig. 5 compares the analog and digital version of a recorded signal. Digital signal comprises of a sequence of numeric values. Modern computers can easily store and process these values. A/D conversion consists of two main processes that are sampling and quantization. Sampling process is used to convert continuous time to discrete-time. It involves measuring value of a signal at certain time intervals. Each measurement is then known as a sample. If x(t) is an analog signal, it is sampled every T seconds, and x(kT) is the amplitude value where k (k = 0,1,2,3,…n) is the sample number of the data sequence, and T is the sampling interval. The sampling frequency fs is the reciprocal of sampling period (1/T). To prevent distortions, it is crucial to set sampling frequency higher than the maximum frequency of original signal. According to Nyquist's theorem, sample rate should be equal to, or greater than twice the maximum frequency of the original signal. Nyquist frequency, $f_{nyquist}$, is given as

$$f_{nyquist} = 2 \cdot f_{max} \tag{2}$$

where f_{max} represents the maximum frequency of signal. Practically sampling is done with sampling frequency 5–10 times greater than the f_{max} of the original signal.

The quantization is the second function of A/D converter which converts the continuous range of numeric values into finite discrete values. Every sample is quantized and stored in binary bits. A/D converter can be of any number of bits but typically 16 bit or 8 bit resolutions are used. 16 bit A/D converter can represent 65,536 amplitude levels while 8 bit A/D converter is capable of representing only 256 amplitude levels.

3.2. IoMT gateway

Internet of things (IoT) gateways are the physical devices or software programs that connect the sensors, intelligent devices, cloud and data systems to one another. The data transferred to the cloud/data system or vice versa goes through the gateway. Hence it can be said that IoMT gateways provide communication bridge between the smart things in the field.

3.2.1. Roles of IoMT gateway

Data Normalization — Data is collected by many sensors. These datasets usually exist in different data formats. Gateways take various datasets and convert them into standard data format.

Data Preprocessing — Before transferring data to the cloud, a preprocessing of data is carried out by the gateway. This step minimizes and filters the data that needs to be forwarded to the cloud. Preprocessing of data decreases the transmission, processing and storage requirement.

Network Connectivity — Sensors have the minimal capability of networking connectivity. They cannot be connected directly to more extensive networks like Wide Area Network (WAN). Therefore, IoMT gateway provides a connection to external networks using Wi-Fi, mobile data, or some other type of connectivity.

3.2.2. Architecture of IoMT gateway

Fig. 6 represents the most common architecture of IoMT gateway systems. Generally, it consists of the central processing unit (CPU) and wireless field connectors (WFC). Sensors usually do not come with the gateway itself. However, the gateway acquires information from wireless sensors using field connectors such as Bluetooth, NFC, ZigBee, or some other connection types. The data is collected in the form of small packets and sent to the CPU for pre-processing, which is the core component of the system.

Gateway contains embedded software, which is considered as the heart of the system. Gateway software is responsible for data collection, preprocessing, and data management. After the data is collected from sensors, during pre-processing, gateway decides whether the data should be stored or discarded. It is also responsible for handling external problems to stabilize the operation. These obstructions may result in interruption of gateway processing. One of the typical examples of external problems is power outage. In this case, the software must ensure that system can turn on automatically when power is back and continue processing from the point where it was interrupted.

After the data is pre-processed and filtered out, IoMT gateway sends the data to the cloud/data center for further processing and analysis. Short-distance WFCs can hardly communicate in more extensive networks. Therefore, in order to send data, the gateway uses long-distance WFCs such as Wi-Fi, cellular data, Satellite, LTE, etc.

3.2.3. Wireless field connectors

Wireless field connectors (WFCs) are the communication protocols that are widely used in IoMT applications. These devices and protocols connect different devices by exchanging data through different networks. In simple words, WFCs act as communication-bridge between smart devices. In Table 3, we summarize the main parameters for both short and long-range WBCs in addition to their IoMT applications. According to their applicability in different areas, we categorized WFCs into two groups, close area networks and broad area networks.

3.2.3.1. Close area networks. Close area networks belong to those networks in which devices are connected to one another within close distance. Typical examples of these networks are PAN, HAN, and LAN networks.

Personal Area Networks (PAN) — PAN is a type of communication network in which devices relate to one another within the workspace of an individual person (typically within 10–15 m). These interconnected devices can be personal computers, mobiles, printers, scanners, and other personal use devices.

Home Area Networks (HAN) — HAN is a type of network which offers communication between smart devices and appliances within the vicinity of user's home. These devices can be smart TVs, home security system, telephones, washing machines, and other smart home devices.

Local Area Networks (LAN) — LAN is a type of communication network for connecting computers or devices within a building or group of

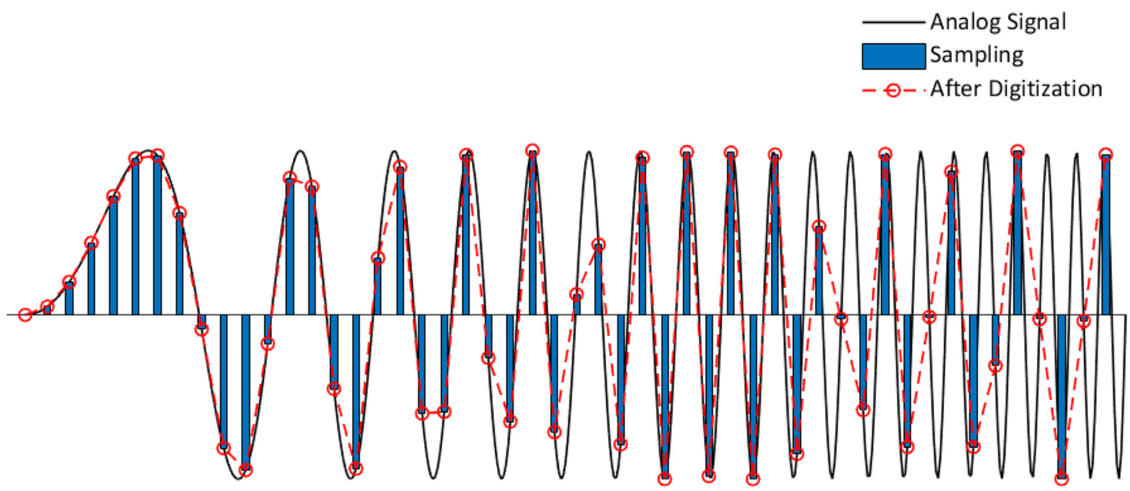

Fig. 5. Analog to digital signal conversion. Due to the sampling ratio or sampling frequency of the converter some part of the analog signal is not digitized correctly.

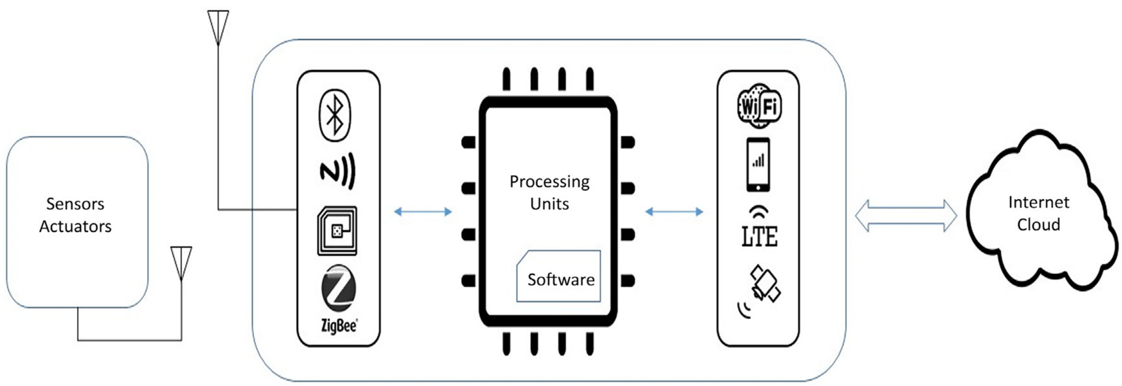

Fig. 6. General architecture of IoMT gateway.

buildings. These buildings must be located in a specific area covering few square kilometers. For example, university campus buildings, small residential areas, and hospitals are the best suitable locations for LAN networking.

Inter-connected devices in these network areas communicate with each other using short-distance WFCs. Short-distance WFCs offer less power consumptions and exchange data in small packets between devices. Some of the most trending communication technologies and WFCs are listed below.

Bluetooth — Bluetooth technology was developed by Ericsson in 1994 which is now widely known as best wireless transmission technology. It is a standard technology in many electronic devices such as laptops, smartphones, speakers and printers. IoMT is another area of broad Bluetooth adoption. Bluetooth evolution in healthcare systems is still underway such as low-cost Bluetooth enabled digital stethoscope designed by Frank and Meng to detect cardiac murmurs [60]. Similarly, Tang et al. developed an e-stethoscope for measuring heartbeats using embedded processors and transferred data using Bluetooth for further analysis [23]. There are also several wearable tracking devices like the popular FitBit [61]. These wearables can be easily synchronized to smartphones using Bluetooth.

ZigBee — ZigBee is one of the trusted standard protocol used for wireless communications. It consumes more power than Bluetooth, which allows devices to interconnect and pass commands back and forth. Both ZigBee and Bluetooth operate in the same frequency range (2.4 GHz). Communication range of ZigBee technology is a couple of times more than Bluetooth.

Nowadays, the healthcare industry is rapidly adopting IoTs technologies. In order to improve accuracy, promote efficiency, reduce costs and enhance healthcare, wireless communication technologies have become a dire need in IoMT. As a new technology, ZigBee can also be used effectively to connect wireless medical devices. Such as a ZigBee based bowel activity monitoring device developed by Ulusar et al. [21]. This device was developed to detect gastrointestinal motility after abdominal surgery. Similarly, D. D. Kadam Patil and R. K. Shastri designed a wireless e-stethoscope to monitor heart sounds, which is also based on ZigBee protocol [62]. Another bandage-size non-ECG heart rate monitor was designed by Dinh et al. [63]. This system simply detects heart sounds using microphone. After data collection, it processes, samples and send the data wirelessly using ZigBee protocol.

RFID — RFID is an automated technology which assists devices or computers to identify object and record metadata through radio waves. It consists of tags and readers. Tags are the transponders (microchip with antenna) which act as identifier attached to an object. And the readers (transmitters/receivers), which are also known as interrogators, communicates with the tag using radio waves. This technology was discovered many years ago. Its evolution started only in the last decade since the cost has been the primary curb in IoMT design factors.

In the healthcare industry, RFID technology is an emerging trend. It can save a lot of money and time in hospitals by tracking supplies. Due to the lack of proper inventory record keeping hospitals keep buying things they already have [73]. Some of the applications of RFID technology in medical area are tracking systems. Tsai et al. developed a RFID medical equipment tracking system that assists the management staff to quickly locate and track healthcare equipment [36]. This proposed system improves work service quality, inventory control and performance. Similarly, a wearable RFID tag antenna was developed

Table 3
Wireless field connectors and their applicability in IoMT.

References	Standards	Range (m)	Data rate	Frequency	Applications	Criticality level	Purpose
[21]	ZigBee	10 m–20 m	250 kb/s	868/915 MHz; 2.4 GHz	Bowel activity monitoring device	High	Gastrointestinal motility detection after abdominal surgery
[23]	Bluetooth	10 m–100 m	1 Mb/s	2.4–2.5 GHz	Digital stethoscope	High	Heart sounds detection and monitoring
[36]	RFID	Up to 3 m	Varies with frequencies	LF/HF/UHF/ Microwave	Medical equipment tracking system	High	Quickly locating and tracking medical equipment under critical time constraints
[50]	2G/3G	1 km–8 km	Varies on network type	Varies on network type	Wireless wearable	Low	Real-time personal skin caring
[60]	Bluetooth	10 m–100 m	1 Mb/s	2.4–2.5 GHz	Digital stethoscope	High	Heart sound detection and monitoring
[61]	Bluetooth	10 m–100 m	1 Mb/s	2.4–2.5 GHz	Wearable FitBit tracker	Low	Fitness health tracking during physical activities
[62]	ZigBee	10 m–20 m	250 kb/s	868/915 MHz; 2.4 GHz	Digital stethoscope	High	Heart sound monitoring
[63]	ZigBee	10 m–20 m	250 kb/s	868/915 MHz; 2.4 GHz	Bandage-size non-ECG heartrate monitor	Low	Heart sound monitoring
[64]	RFID	Up to 3 m	Varies with frequencies	LF/HF/UHF/ Microwave	Wearable RFID tag antenna	Medium	Tracking
[65]	NFC	<0.2 m	Up to 424 kb/s	13.56 MHz	Alzheimer's day center	Low	Adopting identification technologies to support Alzheimer patients
[66]	NFC	<0.2 m	Up to 424 kb/s	13.56 MHz	Implanted medical data acquisition devices	Low	Data transmission and communication wirelessly to reduce power consumption and cost
[67]	NFC	<0.2 m	Up to 424 kb/s	13.56 MHz	Home monitoring applications	Low	Home monitoring for elder and unskilled people
[68]	Wi-Fi	45 m–90 m	Up to 54 mbps	900 MHz to 60 GHz	Wireless health monitor	Low	Monitor health status remotely
[69]	Wi-Fi	45 m–90 m	Up to 54 mbps	900 MHz to 60 GHz	Indoor localization	Low	Track patients at indoor environments
[70]	3G	1 km–8 km	Varies on network type	Varies on network type	Wireless health monitor	Medium	Monitor health status remotely
[71]	Satellite	160 km–3600 km	Varies on model	Varies on model	Disaster situations	High	Provide high speed data transfer in disaster situations
[72]	Satellite and 3G	160 km–3600 km	Varies on model	Varies on model	Real-time wireless health monitor	High	Track and approach patients upon emergencies

by S. López-Soriano J. Parrón [64]. The proposed RFID tag can be embedded in a patient's wristband for tracking purposes.

NFC — NFC enables two devices to connect within a very short distance. It works by exchanging data via radio waves. The NFC technology is similar to RFID, which uses electromagnetic induction to transmit the data. NFC devices are classified into passive and active devices. Passive devices include tags that send data to other NFC device without requiring power source. However active NFC devices are capable of both sending and receiving data and also can communicate to passive NFC devices. A typical example of active NFC device is smartphone.

This technology is relatively new in healthcare, even though the findings appear to be encouraging. Bravo et al. presented a proposal to adopt NFC and RFID technologies to support people with Alzheimer [65]. Another example is NFC communications for implanted medical data acquisition devices [66]. NFC technologies have the potential to improve feasibility and usability of home monitoring devices, especially for elder and unskilled people [67].

3.2.3.2. Broad area networks. Broad area networks belong to those networks in which devices/computers are connected to one another through large distance. Typical examples of these networks are CAN, MAN, and WAN networks.

Controller Area Networks (CAN) — CAN is a very high-speed communication network especially developed for automotive industry. CAN connects microcontrollers and devices to communicate with each other without host computer.

Metropolitan Area Networks (MAN) — MAN is similar to LAN networks but covers a region of the size of a metropolitan area. MANs are more extensive than LANs but smaller than wide-area networks (WAN). Such as computers interconnected in an entire city or a state.

Wide Area Networks (WAN) — WAN is a type of communication network which covers a wide geographical area. Such as connecting networks between different cities or states. WAN can also be used between countries.

Inter-connected devices in these network areas communicate with each other using long-distance WFCs. Typically, compared to short distance WFCs, long-distance WFCs consume more energy. Some of the most trending communication technologies and WFCs used in broad area networks are listed below.

Wi-Fi — Wi-Fi is the most popular networking protocol that allows devices to communicate wirelessly. It operates within a fixed location and consumes high energy. Wi-Fi transmits data in the form of radio waves through the air. It provides high-speed access to the internet. Typical examples of Wi-Fi connectivity are indoor networks.

Wi-Fi is playing an important role in IoMT applications. It has been estimated that almost 80% of medical facilities are using Wi-Fi [74]. Yu et al. developed a wireless physiological monitoring system [68]. The proposed system integrated two wireless technologies, Wi-Fi and Bluetooth, to remotely monitor the patient. Another example is indoor localization for patient tracking based on Wi-Fi technology [69]. The experiment presented in this study showed very decent accuracy with minimum setting effort.

Mobile Data — Smartphones with mobile internet can connect to a variety of devices, process data in real-time and communicate with available medical services. These widespread technologies are now offering new ways to improve medical things.

Mobile technology has transformed many aspects of healthcare delivery in IoMT. This evolution has led to rapid growth in the development of mobile medical applications. Mobile applications can help people to manage their own health independently. Lou et al. designed a wireless health monitoring system [70]. The proposed system detects physiological data from sensing nodes and transmits the data to the mobile device for processing. In severe conditions, it automatically generates an alarm and sends the data to a remote server via 3G network [70].

Satellite — In a fast-emerging world of IoMT, satellite communication is playing a leading role in healthcare services. It is reported that approximately 2000 artificial satellites are orbiting around the earth [75]. Signals from land stations are transmitted to the satellite. The satellite receives and amplifies the signals and sends back to the earth. Satellites allow communication in rural areas, in oceans and widely separated geographical points [76].

In remote areas where telecommunication is poor or not available, satellite communication can be very beneficial by offering instant access to broadband services. Satellite communication provides excellent quality and high speed data transfer, which is a dire necessity in disaster situations [71]. Aziz et al. presented a real-time health monitoring system using mobile and satellite communication technologies [72]. The proposed system has wireless sensors to collect data from patients. Under alarming health condition, this system communicates with the caregivers via text messages. The system tracks the patient's location to provide first aid if needed.

3.3. Server/cloud

Servers are the core part of the IoMT systems, which detects abnormal activities and performs analysis. After signals are acquired from sensors and pre-processed, the gateway sends the digital data to the servers or cloud for data mining. In IoMT, data mining is the process of classifying critical information about bio-signals. In the following sections, we outline some signal processing and data mining techniques.

3.4. Data and signal processing techniques

Fig. 7 shows the general architecture of data processing. Data processing includes signal identification and enhancement, feature extraction and classification, and finally analysis of results. During data-processing, due to the use of improper techniques, information can be lost or altered, which may lead to wrong decisions. The rest of this section is organized as follows. In Section 3.4.1, signals are also classified into time and frequency domain, in addition to their feature extraction capabilities. In Section 3.4.2, we outline the data mining models and methods that may be used in data processing and analysis, in addition to their advantages and disadvantages.

Table 4
The different disciplines in healthcare data mining [13].

Discipline	Count
Machine learning	40
Artificial intelligence	5
Statistics	3
Probability	2

3.4.1. Signals representation in time and frequency domain

Bio-signals are usually represented in time and frequency domains. Signals collected from sensors are recorded over time, known as time-domain signals. Time-domain signal provides amplitude information of a signal at a certain point in time. Using the time and amplitude information, it is possible to extract other features such as signal-to-noise ratio (SNR) and perform event detection.

Other form of representing time-domain signals is frequency-domain. The frequency-domain contains the information about the power at each frequency. To calculate the amplitude of each frequency, typically, a Fourier transform is performed. Several features can be extracted from frequency-domain signal including centroid frequency, sub-band energy, and spectral bandwidth.

3.4.2. Data mining

Data mining in IoMT is playing significant roles in early diagnosis and continuous monitoring of patients. It is a process of extracting useful information and discovering patterns in huge bio-data. Algorithms are executed on acquired and available information to build a model that could be useful in diagnosis of certain disorders. Jothi et al. reviewed several papers and identified different disciplines involved in healthcare data mining (Table 4) [13].

Data mining is typically classified into two broad models, supervised and unsupervised. In supervised model, a classification algorithm is trained using labeled data and used to classify unlabeled data. Labeled data means that each input variable is labeled with an appropriate output. Whereas, in unsupervised model, there is no labeled data. Therefore, an unsupervised classification algorithm tries to cluster the data into different groups and discovers relationships between themselves. In this section, we discussed some of popular data mining algorithms that include SI (Swarm Intelligence), LDA (Linear Discriminant Analysis), K-C (K-means Clustering), DT (Decision Tree), NB (Naive Bayes), VQ (Vector Quantization), ANN (Artificial Neural Networks), and FL (Fuzzy Logic).

SI — is a classification method used to design diagnosis models. Harish et al. used SI method to diagnose arrhythmia cordis disease [77]. Optimal solutions in large search spaces can be found efficiently by particle swarm optimization. The optimization problem resolved in the proposed study involves features mostly found in classification. Less number of features results in faster classification process. The study proved that overall classification results can be improved by using particle swarm optimization since suitable parameters are being selected.

LDA — is a standard classifying technique that generates a discriminant function to separate two or more samples efficiently. Each class possesses multiple features. Some features exist in higher dimension space and some in lower dimension space. LDA is used to project high dimensional features into lower dimension space. That is why it is also known as dimensionality reduction technique. Dimensions are usually reduced in order to maximize the separation between two or more classes. In medical domain, LDA method is widely used in face recognition systems [78]. Another example is predicting thyroid disease using LDA data mining technique [79].

DT — is a supervised decision-making algorithm mostly used in classification and regression problems. It represents a graphical model (in the form of a tree) of all possible solutions to a decision based on

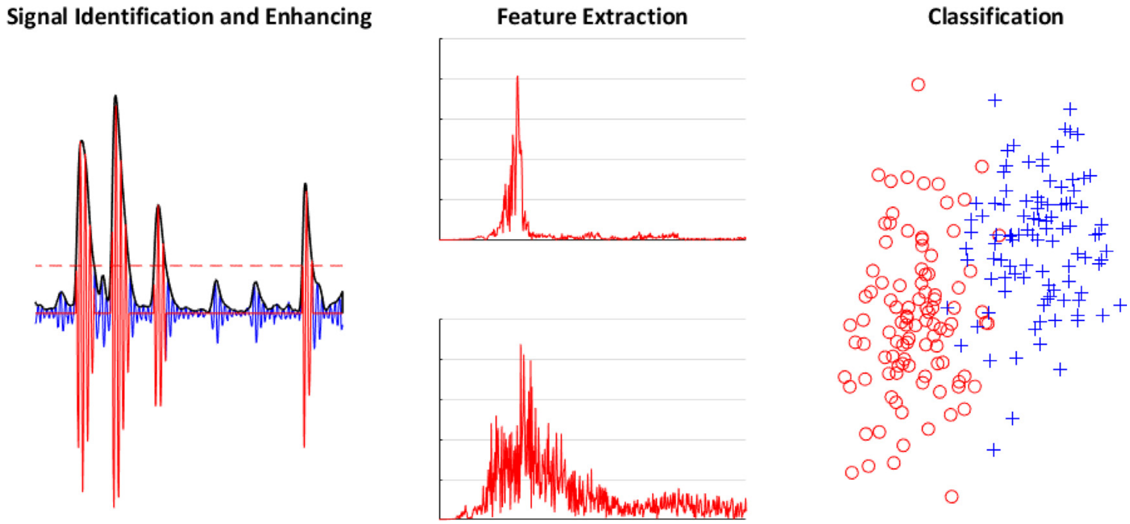

Fig. 7. Basic signal and image processing steps that can be performed in cloud/servers.

the features of input variables. A DT starts with a root node (sample data), splitting into sub-nodes (decision nodes). Decision nodes further split into terminal nodes/leaf nodes (solutions). DT based algorithm is considered one of the most effective and reliable techniques used in different areas of medical decision making. It provides high classification accuracy by simply representing gathered data in a structural model. Recent examples of DT-based analysis in healthcare includes assessment of predictors used in medical procedures [80], the development of screening and diagnostic tools [81], and the influenza treatment strategies [82].

NB — is the probabilistic machine learning algorithm widely used in classification problems. It is based on Bayes theorem where features that go into the model are assumed independent (naive) of each other. Bayes theorem describes the probability of activity detected, P(Y), which is based on the prior information of training dataset, P(X), where Y is the output, X is the input, and P is the probability function. Pattekari et al. developed a healthcare prototype system which predicts heart diseases using NB classification technique [83]. Another example is the liver disease prediction by using NB and SVM models [84].

VQ — is a non-supervised technique used to identify a finite set of categories. Rui Veloso et al. used VQ clustering to predict readmissions in intensive medicine [85]. VQ involved k-means, x-means, and k-medoids algorithms. To evaluate each of the algorithms, the Davies–Bouldin index was used. The best results were obtained by k-means. However, x-means obtained fair finding, whereas, k-medoids findings were the worst of all. The study by these researchers was found very helpful in characterizing different patients having a higher probability of readmission.

K-Means — is the most popular and straightforward unsupervised learning technique for cluster analysis. It involves clustering of input data points into k number of groups where k is predefined. K points are the randomly selected cluster centers. Data points assigned to the closed cluster center is based on Euclidean distance function. In short, k-means algorithm finds k number of centroids, which is the center point of the cluster and assigns all the data points to the closest cluster. K-means is a very powerful tool for discovering structures in datasets, with several valuable applications in IoMT domain. Such as classification of ECG signals to analyze cardiovascular diseases [86]. Another example is tumor detection in brain using color-based k-means clustering segmentation [87].

ANN — is the learning network of multiple neurons with many interconnections. Neurons are grouped into multiple layers. A typical ANN consists of three layers. The first layer is known as input layer. Second is known as hidden layer where most of the processing steps occur. The third layer is known as output layer where system generates output results with given input variables. ANN is first trained by the input examples given by the user. After training several times, ANN learns to generate particular outputs for specific inputs. A backward propagation is a common algorithm used to train ANN for supervised learnings. Backward propagation is a method to minimize errors in ANN. ANN is mostly used in pattern recognition and classification problems. It is widely used to classify ECG and EEG signals in order to analyze cardiac diseases [88–90]. Other examples include medical images such as brain tumor segmentation in MRI images [91].

FL — is used to find an approximate rather than a definite, precise pattern. Modern computers are usually based on Boolean logic where there are 1s and 0s (true or false). However, unlike Boolean logic, FL is based on "degrees of truth" which seems closer to human reasoning logic. In medicine, the decisions made by physicians are mostly based on linguistic concepts. Due to the complex nature of biological systems, conversion from fuzzy nature to computerized systems can cause loss of precision. Therefore, FL seems to be a suitable technology which can be applied in each area of medicine. Most of the applications of FL are found in the field of anesthesia. Some of the FL applications in medicine include arterial pressure control [92], post-operative blood pressure controlling [93], muscle relaxation [94], and mechanical ventilation during anesthesia [95].

Table 5 summaries the list of data-mining techniques that are commonly used in IoMT healthcare. Besides, it pinpoints numerous characteristics and parameters that are used to select a data-mining model for specific IoMT application.

4. Challenges and design factors

IoMT portrays a system of Internet-connected medical devices that can create and transfer data between one another, health application, and hospitals. According to the Deloitte report [96], the market of IoMT is expected to be worth $158.1 billion by 2022. However, there are still some challenges and factors that hinder its continued growth. Some of the main challenges and design issues in healthcare are discussed below:

Cost — In the 21st century, medicine is more dependent on technology. One of the main challenges in healthcare technology is its spiraling cost. For the advanced technological devices, hospitals are spending billions of dollars each year. Use of new technologies, procedures and medicines leads to an increase of healthcare costs, which makes medical care unaffordable for many people [97]. This situation must

Table 5
Comparison of different data-mining techniques in IoMT.

Reference	Methods	Classification	Clustering	Advantage	Disadvantage
[77]	SI	✓		1. Mesh networking and redundant data storage 2. Very fault-tolerant and hard to bring down. 3. Highly scalable and self-organizing 4. Short computational time 5. Global optimality.	1. Mesh networking is much harder to make it work. 2. High computational costs. 3. Cannot work out the problems of scattering. 4. Less efficient for local search and simple problems. 5. No guarantee for global optimality.
[78,79]	LDA	✓		6. Linear decision boundary. 7. Easy to implement. 8. Fast classification	6. Gaussian assumptions. 7. Training time. 8. Complex matrix operations.
[80–82]	DT	✓		1. Domain knowledge is not required in the construction of decision tree. 2. Minimizes ambiguity of complex decisions and assigns precise values to outcomes of actions. 3. Can process high dimensional data. 4. Easy to understand and interpret.	1. Restricted to single output attribute. 2. Generates categorical output. 3. Consistency is not guaranteed, performance of classifier may vary depending upon the type of dataset. 4. Complex decision tree is generated for numeric dataset.
[83,84]	NB	✓		1. Computation is easy. 2. Speed and accuracy for huge datasets are better.	1. Results may not be accurate in some cases when there exists dependency among variables.
[85]	VQ		✓	1. Discrete representation of speech sounds. 2. Less computation is required for estimating similarity of spectral analysis vectors. 3. Less storage is required for spectral analysis information. 4. Very efficient.	1. The storage required for the codebook is necessary: larger the codebook lesser the quantization error but more the storage required for the codebook. 2. As the size of the codebook increases, the size of the quantization error decreases so there is an inherent spectral distortion in representing the actual analysis vector.
[86,87]	K-Means		✓	1. Simple clustering approach. 2. Efficient. 3. Less complex method.	1. Number of clusters is required in advance. 2. Hard to process categorical attributes. 3. Cannot process non-convex shape clusters.
[88–91]	ANN	✓	✓	1. Easily identify complex relationships between dependent and independent variables. 2. Able to handle noisy data.	1. Local minima. 2. Over-fitting. 3. The processing of ANN network is challenging to interpret and require high processing time if there are large neural networks.
[92–95],	FL	✓	✓	1. Simple and flexible. 2. Can handle imprecise and incomplete data. 3. Can model nonlinear functions. 4. Easy to implement.	1. More fuzzy grades are required for more accuracy which results an exponential increase of rules. 2. Processing takes time.

be taken into account urgently, and new deployment strategies must be developed for minimum equipment and operation costs. In this regard, IoMT is playing a vital role in improving the current situation. Different IoMT-based monitoring devices have already been available in markets. These devices can send data through online applications directly to the caregivers instantly. It can save millions of lives by detecting severe health conditions in their early stages. Hence smart IoMT devices can save money and time as well.

Precision and Accuracy — Precision and accuracy of the data observed by sensors are critical design factor of medical things [98]. Inaccurate data may be misleading and could be harmful to the patients. It is imperative to ensure that after several uses, precision and accuracy of the device remains same. Otherwise, system should generate alerts or warnings to issue a maintenance or replacement. IoMT is playing very effective role to deliver healthcare more precisely such as integrating and analyzing diverse types of medical records and using them in clinical decision-support systems. This way, caregivers could get a complete picture of each patient's health, resulting faster and can perform more precise treatments. Such services are already being practiced in diagnosing sepsis [99], where speed and precision factors were critical for saving patient's lives.

Security and Privacy — In healthcare, a secure IoMT system is very crucial. As more and more things connect to each other, it is imperative to ensure security and privacy of patients' data. Security flaws let the hackers steal demographic information of patients and leads to crimes such as identity theft, access to controlled substances and fraudulent insurance claims. Also, secure preservation of illnesses, vitals and data collected via connected devices or sensors has become a significant concern of IoMT technology. Additionally, security flaws in the hospital system could result in significant damage to the infrastructure, which can also be fatal in some cases [100]. One of the essential components to secure an IoMT infrastructure is device authentication. Due to insufficient processing power and energy some devices do not support advanced authentication protocols [101]. Therefore, to overcome security issues, it is essential to develop faster and low power processors with new authentication schemes.

Electrical Safety — Almost everything in an IoMT ecosystem runs on electricity. If electrical devices are used or maintained improperly, they could be potentially hazardous and may cause severe pain, burn injuries, and even fatalities. Organizations and hospitals must take serious measures ensuring environment or devices free of electrical hazards. Also, before designing such devices, general safety measure standards such as IEC60601-1 must be followed to ensure full safety.

Energy Efficiency — Most of the wireless devices are operated 7/24 and consume significant amount of energy. Production of green energy efficient devices is a new challenge. IoMT has enabled researchers to develop new techniques in order to reduce energy consumptions of different wireless devices [102–104]. Several algorithms or routing protocols have been developed to reduce the overall energy consumption. However, still, there is a need to optimize the amount of data generated and reduce energy used for processing and transmitting. Also, due to the miniaturization of electronic components, there is a potential for energy harvesting modules which can convert different energy sources into electrical energy such as heat, sunlight, and vibration [105]. Energy-efficient devices can significantly reduce the amount of energy used in hospitals and generate worthwhile savings. These devices also have positive environmental impact by reducing electromagnetic radiations.

Usability — The main goal of the IoMT is to make life easier and, therefore usability is the final yet essential designing factor for enhancing patient safety and quality of care [106]. Typically, usability is tested using consumer feedbacks and design flaws are identified. Because the IoMT represents a complicated collaboration of devices, the standards for app development and user experience need to be adapted in order to make elements in the network work in harmony. The technology is approaching the age of smart devices that can predict and socialize, and the need for well-defined user experience standards is rising.

5. Open research issues

This paper surveyed the existing IoMT technologies, introduced various types of sensors and communication protocols. Such technologies have already and will revolutionize healthcare industry in the following years. However, there are still some notable challenges that IoMT technologies are facing today.

Energy Consumption — One of the main challenges associated with IoMT is power consumption. Most of the sensors/actuators employed in IoMT applications operate on battery. Such systems have a disadvantage of consuming large amounts of energy. Researchers have developed several algorithms and routing protocols in order to reduce the overall consumption of energy. However, due to increasing amount of data generated improvements and new technologies are still required. One solution might be energy harvesting modules which can convert different energy sources into electrical energy [107].

Data Storage and Privacy — It is estimated that healthcare industry will be generating more data than any other industry in the near future [108]. So there is a need for advanced data storage solutions. Also, confidentiality, integrity and availability of data are other research issues that need to be addressed to handle large amounts of data, keep it in a consistent state and verify its quality which otherwise can distort decision making process [108]. The hospitals should train their employees about the usage and functioning of IoMT devices. They must be aware of the risks and challenges in handling such devices. The patients should also be aware of possible health risks of not properly keeping critical information about IoMT devices (such as passwords).

Artificial Intelligence, Decision Support Systems — The development of an interdisciplinary technology with comprehensive monitoring and processing is critical for the advancement of future healthcare. Nowadays, a lot of research efforts are being spent on Artificial Intelligence, Machine Learning and decision support systems [109]. These technologies offer great potential of solving some of the mentioned challenges. In order to overcome the aforementioned obstacles, all the aspects of the IoMT are required to work in a coherent manner. These solutions will not only improve the quality of service but also secure the integrity and efficiency of all the elements that represent the ecosystem.

Network and Communication Technologies — Communication and physical security of deployed networks are continuous research areas. There is always a demand for faster, greener communication technologies. New protocols, standards and mechanisms to communicate with the existing technologies are also required.

Security — Security of smart critical systems are highly required. Access mechanisms, authentication and communication security are some of the challenges. The Blockchain based distributed solutions solve some problems, such as the need for the trust in a central authority for secure communication.

6. Concluding remarks

The engagement and consciousness of people regarding their health are increasing rapidly. Due to which the demand for home or remote monitoring is also proliferating. Researchers are putting a lot of efforts and time exploring technical solutions and integrating existing technologies to improve healthcare. This paper overviews interdisciplinary aspects of IoMT that include classification of the smart healthcare applications, major sensing technologies and communication modules. The main objective of this study is to offer a perception of new research endeavors for the development and advancement IoMT ecosystem. Both software and hardware aspects of IoMT elements were discussed and explained thoroughly. Software aspects such as signal enhancement, and machine learning were also introduced in addition to their key features. Several tables were created comparing the parameters and key factors about the main elements of IoMT ecosystem. Following are the conclusions drawn after reviewing the aforementioned technologies and challenges. The data is acquired by utilizing sensory technologies, wearable and non-wearable sensors. Wearable sensors are ideal solutions for patient monitoring. This way, patients can perform their daily activities without intervention. Sensor technologies also decrease the workload of caregivers and help lowering healthcare costs. Therefore, in the context of healthcare, sensory technologies should be regarded as part of interdisciplinary research because they really provide additional information in healthcare information systems.

Moreover, sharing information between sensors and healthcare systems require appropriate communication technology. This paper surveyed both long and short-range communication networks for IoMT in various use case scenarios. In terms of data accuracy, mobility, and patient safety, WANs are regarded as the most reliable, robust, and trusted network infrastructures in healthcare industry. However, they have a disadvantage of high-power consumption.

The DM is found very cost-effective and efficient tool for making clinical decisions and enhancing healthcare services. However, there is no sole DM model which performs consistently for all the types of datasets. Therefore, a hybrid approach could be a good option for achieving better results such as combining different classification models with rule based decision support system.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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