IoMT-Based Wearable Body Sensors Network Healthcare Monitoring System

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1 Introduction

The Internet of Things (IoT) is described as a set of recognizable items or nodes that can communicate through wired or wireless networks [1, 2]. IoT is the world's third wave of information after computer, Internet, and mobile communication technologies were introduced [3–5]. The IoT-based cloud has more than 26 billion connected devices and is estimated to produce global economic value revenues of $1.9 trillion by 2020 [6–8]. Moreover, 40% of IoT-related technology is health related, more than any other category, representing a market of $117 billion [9–11].

IoT tools in the healthcare sector such as sensors may have various applications like heart rate sensors, blood glucose monitoring, and endoscopic capsules [12–14]. The combination of sensors, actuators, and as well as other mobile technology equipment will transform the medical industry's functioning [15, 16]. Such systems, known as the Internet of Medical Things (IoMT), are a connected system of healthcare smart devices that receive information subsequently offered by web communications systems to healthcare IT systems [17–19]. Currently, 3.7 million medical equipment is already in use and linked to and monitored by different parts of the body to notify medical decisions [20, 21].

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The IoMTs are an important component of wearable healthcare systems like bio-systems, recovery robotics, and identification of events [22, 23]. The IoMTs is the core of mobile medical systems by combining implantable/wearable nodes to acquire bio-signals such as electromyogram (EMG) and electrocardiogram (ECG) [24–26]. IoMTs enable access to medical services to monitor patients at any time in any location. The IoMTs have begun to appear as the center of applications for tele-health supervision to improve the severe scarcity of resources available. The IoMT is an assortment of medical systems and platforms that connect through Internet-based computer systems to healthcare IT systems. Medical equipment connected with wireless communication that permits machine-to-machine connectivity, which is IoMT's principle.

These IoMT devices connect to cloud infrastructures such as Google Cloud Computing, Microsoft Azure Cloud, Amazon Web Services, or any other custom web services capturing storage and analytics information. Furthermore, IoMT services include remote medical observation of persons with chronic or long-term situations. These systems can monitor patient treatment instructions and track the position of patients who are placed on wearable healthcare tools in hospitals and clinics. The collected health information can be delivered to their care provider. Medical devices that can be integrated or deployed as IoMT technology are infusion pumps that attach to analytical dashboards and hospital beds with sensors that measure vital signs of patients. The IoMT receives its maximum capabilities through the use of objects, i.e., "Smart" objects, which use multiple sensors and actuators fully prepared to learn in their context, and through the use of embedded communication infrastructure to communicate with any possible alternatives.

Technological developments of low-cost, intelligent, small, and portable medical sensor nodes have been approved in wireless transmission and wireless sensor networks (WSN) to position themselves perfectly on the human psyche [27]. This helps to build a wireless body area (WBAN) network to supervise numerous important chronic physical illnesses for a long-term provide user and medical staff with real-time feedback, thus promising to revolutionize health monitoring [27]. WSN applications are considered as one of the major fields of research for improving quality of life in the computer science and healthcare applications industries [28].

Body sensor node system will help users by providing public healthcare services such as health tracking, memory improvement, home appliance control, access to health data, and emergency communication [29]. Constant monitoring with wearable devices will significantly raise the early diagnosis of a case of emergency conditions and diseases in patients at risk, as well as provide a wide range of health care for people with different levels of cognitive and emotional illnesses. These systems will benefit not just the elderly and chronically ill patients, but also the households where both parents are working to provide their babies and children with good quality care services. This chapter, therefore, proposes an architecture of an intelligent IoMT healthcare system for monitoring patients with diabetes mellitus using a WBSN.

The main contributions of this chapter are (1) the implanted of WBSN in the IoMT-based platform for healthcare monitoring system, (2) the use of WBSN in the IoMT-based platform to monitor a patient with diabetes mellitus, and (3) the use of hybrid sensors for the proposed system. The result of the chapter shows that a Systolic Blood Pressure (SBP) < 110 is normal and ≥160 is in stage II diabetes; Diastolic Blood Pressure (DBP) < 70 is normal and ≥100 is in stage II; Plasma Glucose Concentration (PGC) ≤ 71–100 is normal and ≥122 is in stage I; (INS) 2-h Serum Insulin ≤ 97–138 is normal and ≥191 is in stage II; and Body Mass Index (BMI) ≤30 is normal and ≥50 is in stage III. The length of days of diabetes is a relevant determinant risk factors of diabetes mellitus.

The rest of this chapter is organized as follows: Sect. 2 discusses the IoMT. Section 3 presents an extensive discussion on wearable body sensors networks in health care. Section 4 highlights and discusses the sensor devices on the Internet of Medical Things. Section 5 presents the IoMT-based wearable body sensors network framework for the healthcare monitoring system. Section 6 presents a practical case of the diabetes IoMT-based WBSN monitoring system. Section 7 explains the results and Sect. 8 presents the discussion and future research directions. Finally, Sect. 9 concludes the chapter and discusses future works for the realization of efficient uses of IoMT-based WBSN in healthcare monitoring systems.

2 The Internet of Medical Things

In developing countries, the healthcare sector is shifting rapidly as life expectancy grew dramatically during the 1990s [30]. Infectious illnesses are also placing increasing pressure on healthcare systems in these countries [31]. The life expectancy in advanced nations during the twentieth century has been raised by about 30 years. As a result, the number of elderly people has risen rapidly [30]. Also, chronic disease proliferation has put pressure on healthcare systems in other countries due to a lack of funding [31]. Increasing infectious illnesses and aging populations present significant challenges, as health systems have to deal with a multitude of ailments and treatment options, but similarly a rising patient number. To avoid overloading health infrastructure and reducing the costs of healthcare, successful approaches have been shown in-house telemedicine services [32].

Telemedicine platforms are extremely diversified and typically designed to respond to a single therapeutic purpose, like mobile cardiac monitoring and stroke recovery [33]. This attribute of telehealth systems makes them cost effective and overloading health systems, but reflects a weakness as patient numbers and disease variety increase. The IoMT can handle the need for stronger genericity and reliability. Admittedly, the IoMT integrates both the efficiency and security of traditional medical equipment and the traditional capacity for dynamics, genericity, and scalability of IoT. It devises the potential to fix the aging problem and terminal illnesses by managing various sensors deployed for millions of patients and as well as being broad enough to deal with various illnesses requiring precise diverse checking and action specifications.

Additionally, IoMT offers a solution to challenges like the movement of patients. Therefore, it is possible to make an omnipresent evaluation of patients in their

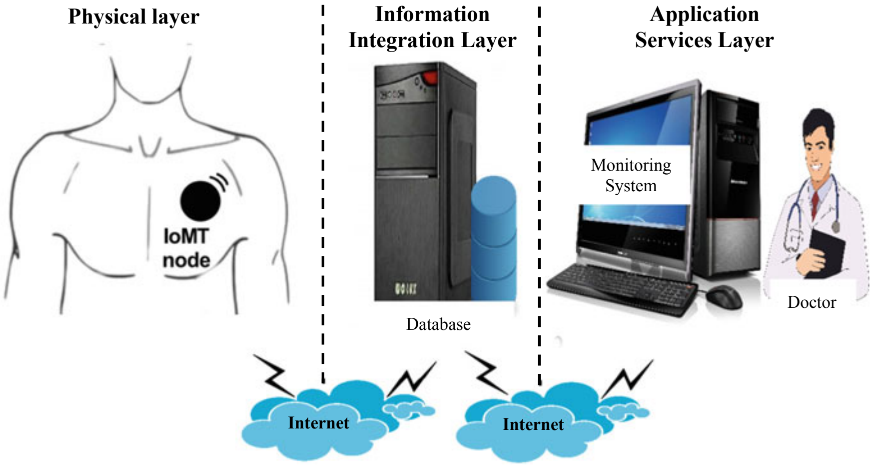

Fig. 1 Structure of IoMT

everyday routines, as opposed to telemedicine services which are strongly focused on home treatment. Given the challenging existence of these concerns, the way we achieve medical services is evolving with new technology innovations to requesting health services in advanced countries. The development of computers and other devices, along with the benefits in computing capabilities in these devices, promotes the implementation of the IoMT and propose clarifications to the requirements of both our elderly people and chronic illness patients. The IoMT is the connectivity not only of multiple medical types of equipment but likewise of devices and health professionals like hospitals, medical experts, or private enterprises.

The IoMT displays an essential role in improving the accuracy, consistency, and performance of electronic equipment in the healthcare sector. To improve the health of patients [34], the IoMT describes the interconnection of medical-grade devices allowed for communication and their incorporation into broader health networks. The introduction of the IoMT is primarily due to the increased usage and advancement of coupled and dispersed medical equipment which brings both enticing possible applications and problems that occurred [35]. Since personal medical devices also come as wearable devices, the chapter focuses on wearable medical devices being incorporated into the IoMT. Figure 1 presents the structure of IoMT.

3 The Wearable Body Sensors Network in Health Care

WSN has transformed the power to change our lifestyle with abundant technologies in areas of health care, entertainment, transportation, retail, business, and emergency services control in addition to many other areas. The integration of wireless sensors and sensor networks with simulation and intelligent systems research has developed an interdisciplinary definition of ambient intelligence to address the obstacles we face in our everyday lives [36].

The WSNs with smart sensor nodes have become a substantial technology enabling a wide spectrum of uses. New technologies in the incorporation and mass production of single-chip sensing devices, computer chips, and radio interfaces have allowed WSN to be appropriate for several applications [28, 37, 38]. They could be used, for instance, for emergency preparedness, factory equipment, surveillance systems, seismic surveillance, environmental control, agricultural practices, and health monitoring. Among the most hopeful usage of WSN is monitoring healthcare [39, 40].

A sensor network is a network of several nodes furnished through a sensor module, a memory chip, a microprocessor, a wireless connectivity interface, and a multi-hop power source [41, 42]. With routing responsibilities, the nodes in the same proximity can interact with one another [42]. Opposing to the popular sensor nodes that are meticulously crafted and installed in the defined locations, WSNs could install an ad hoc, making them resilient, fault-tolerant, and increasing coverage area [43, 44]. They can be used widely to control and track patient conditions in both towns and cities using an internal network. Therefore, these methods can minimize pressure and tension on healthcare professionals, eliminating medical faults, reducing workload and medical staff productivity, reducing long-term healthcare costs, and enhancing patient satisfaction [27, 45, 46].

These inaccuracies happen as a result of a lack of comprehensive and accurate information at the time and place required, leading to an erroneous treatment and issues with particular medication [46, 47]. The risk of death can be lowered if appropriate measures are provided to patients at the proper moment [27, 48]. To ensure the safety of patients and to save lives, hospital personnel must have the right to information about patients at the right and within a short period. Therefore, it is necessary to provide a safe and low transmission latency for patients with life-threatening diseases like diabetes mellitus, heart diseases, and blood pressure. To build a cluster WBAN, sensor networks can be well-positioned on the human body and, therefore, used to retrieve symptoms from patients [49, 50].

For effective and convenient transmitting of data between WBAN and personal server, a battery cell sensor network is required, and their energy consumption during transmission should be relatively low. The examples of IoT devices using for communication technology are smartphones, which use the Internet, General Packet Radio Service (GPRS), 2G–5G technology. These technologies enable us to keep patients, physicians, and caregivers informed while also setting a pattern and identifying health variations. This is called biomedical sensor wireless networks (BWBSN) when applied to biomedical technology [51, 52]. The WBSN enables low-power, remotely operated, smart pervasive sensor nodes to be embedded to monitor body systems and physical vicinity. Every node will sense, monitor, and then forward information to the Super Sensor. The benefits of wearable sensors are shown in Fig. 2.

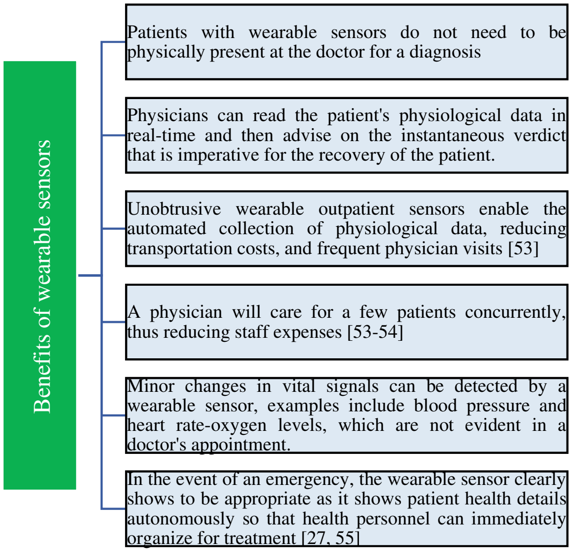

Fig. 2 The benefits of wearable sensors

4 Sensor Devices on Internet F Medical Things

Billions of smart devices and applications, such as WSNs, are not expected to be segregated but linked to and incorporated with communications networks in future IoT [56]. To manage these sensor devices well, systems also need to be designed to operate properly by allowing system management organizations to track and control systems remotely without the need for substantial resources.

The IoMT is known as a network that comprises of collecting medical devices and sensors that are intimately connected via digital technologies. Furthermore, IoMT uses embedded sensors, cameras, thermometers, air quality sensors, ECG/EEG/EMG sensors, pressure gauge, gyroscope sensors, sensors for saturation of blood oxygen, temperature, and humidity sensors, heart rate, and respiratory sensors to monitor and supervise the health of the patient continuously. The IoMT senses the health status of the patients and then transfers the clinical data to doctors and caregivers using remote cloud data centers [18].

Patient information such as body temperature, blood pressure, ECG pulse, heart rate, blood oxygen saturation levels (SpO2) can be obtained by a wearable sensor attached to the patient body. One of the critical layers in IoMT architecture is the connectivity of sensors and the network. This component is an essential part of the IoT ecological system which offers access to other layers in the network. IoMT environment sensors serve as frontend. These devices may be closely relevant to IoT networks whenever the transformation and processing of the signal have been identified. Nevertheless, not all sensors are the same, and nowadays, there are several types available in the market. For instance, two to three days of continual physicochemical measures based on sensor devices were monitored by scholars and used to collect related parameters to update specific healthcare records [28, 57]. Sensors allowed the collection of personalized health data and behaviors of patients and these data can be transferred to the cloud for further analysis.

Healthcare services focused on smartphones have a clear propensity to have a cost-effective long-term healthcare management alternative [58]. These systems can enable healthcare physicians to monitor their patients' health status remotely without invading into their daily routines [59]. Smartphones also have numerous embedded sensors including an image sensor, an accelerometer, an ambient light sensor, a GPS sensor, a gyroscope, a microphone, and a fingerprint [60]. These sensors help to evaluate numerous patients' health parameters including heart rate, variability in heart rate, respiratory rate, body glucose, and blood pressure only to consider a few. This makes the communication device a continuous and long-term monitoring tool for health care. Figure 3 presents some of the sensors used in IoMT for information gathering. These sensors allow health personnel including a doctor to monitor the progress and health parameters of the patient in real time.

There is a growing amount of wearable technology (smartphones, tablets, and watches) that must be taken into account when developing an IoMT-based human monitoring application. Smart-watches can form a wireless network called the WBAN, with the primary aim of obtaining human body physiological data. At this moment, when formulating connectivity between WSN and wearable devices, a

Fig. 3 Sensor devices for collection data on IoMT

significant problem appears when varying standards for various system components need to work in this same environment.

IoMT offers the chance for healthcare scientific advancements to continue to flourish and also enables the solution to stay abreast of time [60, 61]. Moreover, IoMT provides a huge amount of data, often called big data, which cannot be analyzed through conventional data processing algorithms and applications. By constructively researching and capturing vast quantities of medical data, IoMT can increase decision making and early diagnosis of diseases.

5 IoMT-Based Wearable Body Sensors Network Framework for Healthcare Monitoring System

IoMT-based WBSN Healthcare Monitoring System Architecture is a complex task, and a variety of systems were examined. Data collection and combination from multiple IoMT devices is one of the major challenges facing IoMT's realization in designing smart customized healthcare systems. In most cases, data is not always available in real time, so there is a challenge in evaluating or integrating a wide range of data since IoT devices obtain dynamic and complex data on medical assessment, tracking, treatment plan, and prediction in health care. The aggregation of data from specific sensor data sources is a major problem that needs to be addressed critically.

Therefore, it would be encouraging to investigate which of the IoT sensors enhances the efficiency of the intelligent systems with a collection of biomarkers of multiple diseases. So it would be crucial to investigate whether any other background data existed which could improve the efficiency of the model. Besides, further studies are required to determine the quality of the attributes selected from each biomarker. Other relevant matters in IoMT implementation for monitoring of patients, evaluation, treatment plan, and prediction is the need to design a system that can accurately switch between cloud and local classification methods with minimal processing time to ensure real-time and up-to-date provision for the patient.

This chapter proposes the framework for the IoMT-based wearable body sensors network healthcare monitoring system (IoMTWS), which applies a range of wearable sensors interconnected to track a patient's health condition. The use of body temperature and pulse, for instance, helps to collect physiological signals. The sensor data collected from these wearable sensors will be transferred directly to the cloud server due to the small computing power of the sensor nodes and the storage, as well as to avoid the use of a smartphone as a processing device.

The design process of the IoMT-based Network Healthcare Monitoring System for wearable body sensors is depicted in Fig. 4. The IoMTWS comprises three major elements, the IoMTWS body area network (I-BAN), the IoMTWS server (I-Cloud), and the IoMTWS users. The I-BAN constitutes any sensing instruments, including sensors such as body temperature, cardiovascular disease sensor, pulse sensors, and blood pressure sensor. With the advent of cloud-based services, the IoMTWS BAN

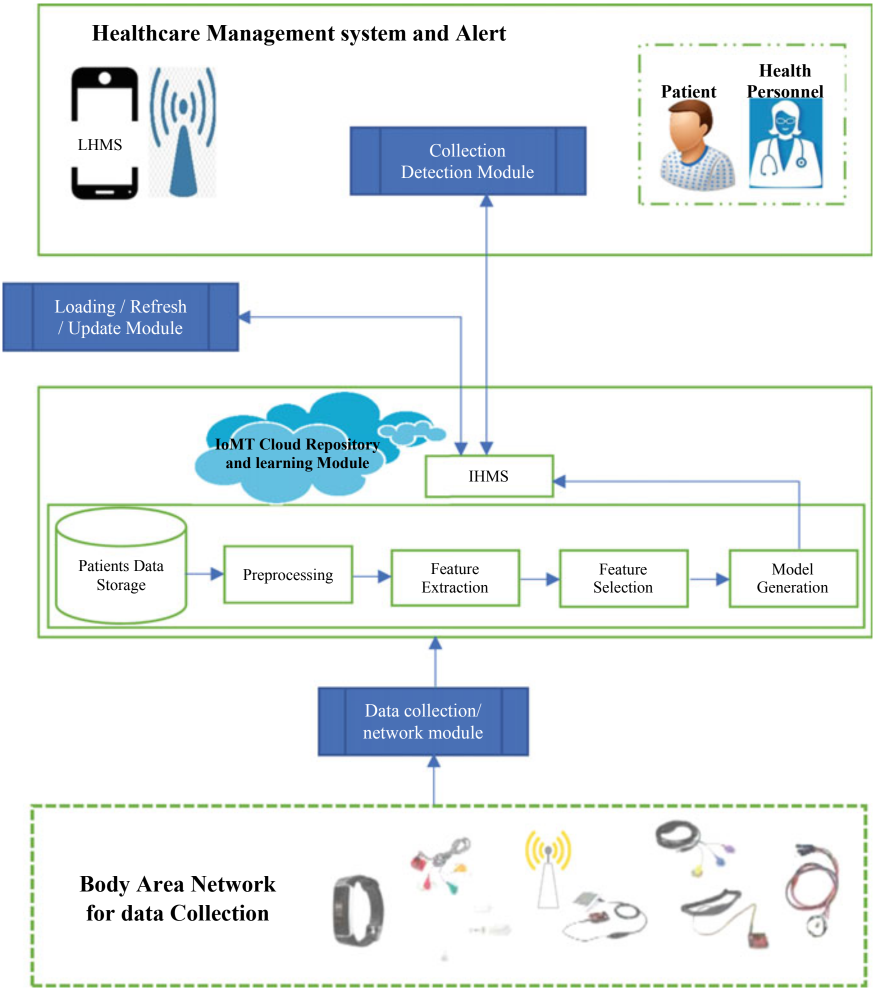

Fig. 4 Proposed IoMT-based WBSN framework for healthcare monitoring system

information could be easily and securely stored and processed on the Internet. With IoMTWS cloud, several implementations like disease identification, data collection, and storage, verification, and data visual analytics can be implemented.

There is a growing number of wearable technology that must be considered in designing an IoMT scenario-based human monitoring program. Wearable devices can form a wireless connection called WBAN, the primary aim of which is to collect physiological parameters from the body of the patient. At this level, a significant element between WSN and wearable devices are different requirements for different system components.

This chapter proposes a method that aims to address the aforementioned research issues for the management system in health care. The proposed framework consists of five modules: data collection/network module, cloud-based data repository and learning module, model update module, a connection detection module, and a module for review, tracking, prediction/diagnosis, and alert management. The first module operates as WBAN, which consists of sensors, communication, and networking as the module for data capture. The data from this module is transmitted for modeling into the cloud data repository.

On the cloud layer, an adequately equipped and validated IoMT-based Personalized Healthcare Model (IPHM) could be used to test, track, predict, or evaluate any patient whenever a connection has been established. This system also includes an upgrade module, which updates the Local Personalized Healthcare Model (LPHM) on the mobile phone automatically. In case of Internet access interruption to the IPHM, the LPHM interface acts as the local intelligent device. The system includes a link detection module to accomplish this switching, which automatically identifies whether the user's smartphone is connected to the network or not. This connection ensures a simple, robust, and accurate cloud-based architecture for patient examination, tracking, forecasting, and treatment plan.

6 Practical Case of Diabetes IoMT-Based WBSN Monitoring System

Diabetes mellitus (DM) has been one of modern society's chronic and debilitating diseases and describes not just a medical condition but also a socioeconomic issue, thus the immediate need to help stop pandemic expansion in society. Diabetes mellitus (DM) is increasingly becoming a major epidemic, compiling the severity of DM, negatively impacting both genetic and environmental factors and a complicated disease [62, 63]. The World Health Organization (WHO) estimated that by 2030 some 350 million individuals globally will suffer from diabetes [64, 65]. The four cases of diseases are pre-diabetes, Gestational, type 1, and type 2 diabetes mellitus. Insulin-dependent diabetes is type 1 [66, 63] unless developed by the insulin hormone. Non-insulin-dependency diabetes is type 2, where the brain cannot use insulin from the body [66]. Diabetes is called gestational diabetes during pregnancy [67]. Pre-diabetes occurs when blood glucose levels are elevated but not as high as diabetes for diagnosis [68, 63].

Diabetes mellitus is responsible for multiple diseases such as kidney failure, nerve damage, artery damage, blood vessel damage, blindness, and heart disease [69]. Furthermore, IoMT based has been described as among the key components in the management of diabetes disease, risk assessment, patient tracking, and prediction in the medical field. Type 1 diabetes accounts for 5–10% of all diagnosed diabetes cases. The category is formerly referred to as insulin-dependent diabetes mellitus (IDDM). Compared to type 2 diabetes, risk factors are not well distinguished. The most likely cause of type 1 diabetes is hereditary and hormonal factors. Type 2 diabetes is responsible for about 90% of patient diabetes, making it the most common diabetes among all diabetes types, and is an earlier adult-onset diabetes called non-insulin-dependent diabetes mellitus (NIDDM). Old age, family history, history of gestational diabetes, impaired tolerance of glucose, obesity, physical inactivity, and ethnicity/race are the type 2 diabetes risk factor.

Gestational diabetes in all pregnant patients is responsible for 2–5%. It occurs during pregnancies and normally vanishes after patient delivery. Pregnant women have enough insulin; this effect is called insulin resistance, partly due to the variation of other hormones produced in the placenta. Kidney disease development can be diabetes aids, increases the case of heart disease, damage to the blood vessels, blindness, and nerve damage. The precise prevalence of diabetes and the analysis of its data can help with the issue of diabetes classification. In gestational diabetes, the body is not using insulin properly, which is insulin resistance associated with absolute insulin deficiency. Table 1 shows the ratings of the data for the proposed system for monitoring and diagnoses of diabetes mellitus. Table 1 shown the rating indicators for DM by physicians [63].

Therefore, both IoMT-based and WBSN is seriously needed to develop effective and useful surveillance and prediction method for DM to assist in early detection and diagnosis of DM to promote prompt blood glucose regulation which will lead to improved health outcomes for those who may develop DM and DM patients. This section presents the experimental findings of the preliminary investigation of

Table 1 Rating of indicators for DM by physicians

Input field	Range				Fuzzy set
	1st physician	2nd physician	3rd physician	4th physician	
1. Glucose	≤71–110	≤90	≤120	≤121	Low(L)
	94–120	95–130	97–138	96–145	Medium (M)
	≥121	≥122	≥124	≥125	High (H)
2. INS	≤15–80	≤15–78	≤20–86	≤17–87	Low (L)
	15–100	20–150	17–90	15–100	Medium (M)
	≥89–194	≥95–193	≥192	≥194	High (H)
3. BMI	≤24	≤27	≤33	≤30	Low (L)
	24	35	39	40	Medium (M)
	≥33	≥35	≥37	≥40	High (H)
4. DPF	≤0	≤0.2	≤0.3	≤0.4	Low (L)
	0.2	0.3	0.4	0.6	Medium (M)
	≥0.4	≥0.6	≥0.7	≥0.4	High (H)
5. Age	≤30	≤29	≤38	≤35	Young (Y)
	33	40	42	43	Mid
	≥45–55	≥47–54	≥50	≥58	Old (O)

the proposed WBSN Platform for Healthcare Monitoring Program based on IoMT. For this chapter, an inter-digital sensor-based sensor network was used to create a monitoring system for diabetic neuropathy patients. To monitor the tremor in a different part of the body, embedded sensors in clothing have been identified as a unique method thus helps in the day-to-day analysis of the activities of patients and monitor patients' progress and thereby result in early detection diabetic neuropathy variations.

Health wearable systems are relevant to patient tracking in the routine operation of preventive medicine and safety promotion. Both systems that use the network layer and intelligent networks can be integrated to enhance individual medical devices. The metabolic symptoms sets describe the condition that exceeds standard values. The most metabolic symptoms are three of the five factors, obesity, cholesterol, glucose, blood pressure, and triglycerides, thus can result in multiple health issues, like cardiovascular disease and stroke. For type 2 diabetes, the most risk factors are age, obesity, alcohol consumption, hereditary disease, and gender-sensitive, or illness known to the patient [70].

Based on big data on the cloud, the information given by an intelligent sensor is much more precise and detailed. The proposed system combined two sensors and fused various sensors to enhanced monitoring and prediction of the physical phenomenon, hence increasing the measurement accuracy when compared with using a single sensor. The convergence is described as "incorporating information from other sources to develop unified data relevant and comprehensive about an individual" [71]. A wired or radio can be used to communicate with an intelligent sensor and adjust their parameters to verify the accuracy of the measurements.

The system composed of a pressure sensor network and a microsystem that involves an acquisition block, a storage block, and a block for data transfer. The two subprocesses are attached via a 9-wire bus to one another. The micro-device is part of a belt that can be connected to the waist. From the pressure sensor network, the power is provided from a 9 V battery connected to the device for data collection and to pass data from the internal memory to the computer. The experiments were conducted using the R data analytics tool. The system has a random-access memory of 8 GB and 2.90 GHz Intel Core i5 with both CPU and GPU support. The operating system is Windows 10 Pro 32-bit.

7 Results

Figure 5 and Table 2 display the calculated findings within the context of blood pressure, blood glucose, body mass index (BMI), and waist circumference measured values. Consequently, apart from high blood pressure and diabetes, obesity was listed as another high-risk factor of high blood pressure, diabetes, and hypertension as it symptoms can leads to any of these diseases [70].

Blood vessel circulation can be disrupted due to high blood glucose, thus leading to pain, and lack of awareness in the blood vessels. Mild bruises in diabetic patients

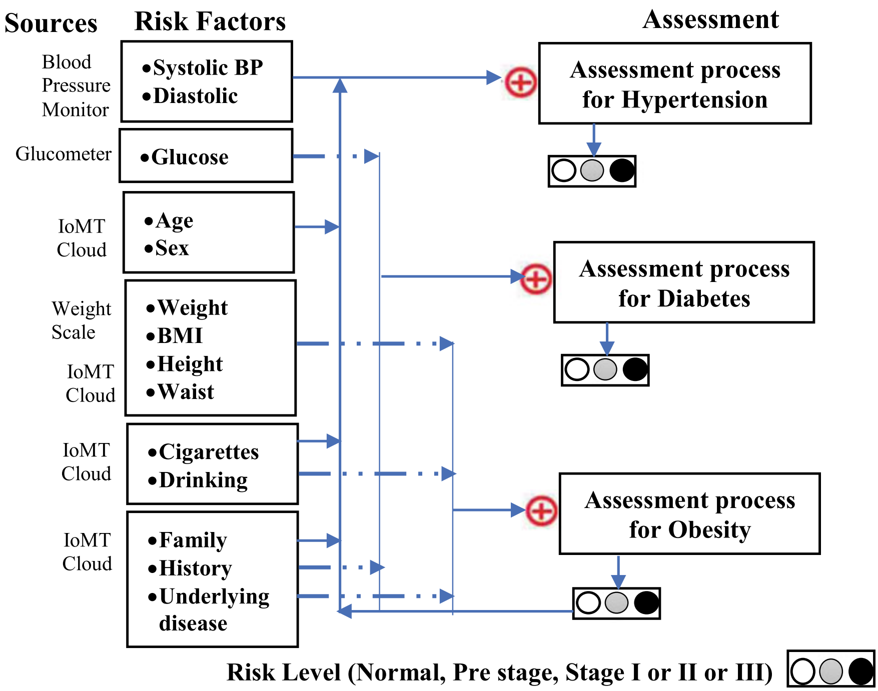

Fig. 5 Risk factors for diabetes, obesity and hypertension

Table 2 Classification of blood pressure, diabetes, and obesity

Risk factors		Normal	Pre-stage	Stage I	Stage II	Stage III
Blood pressure	SBP	<110	110–138	139–160	≥160	
	DBP	<70	70–89	90–99	≥100	
Glucose	PGC	≤71–100	100–121	≥122		
	INS	≤97–138	138–190	≥191		
BMI		≤30	30–39.9	40–44.9	45.0–49.9	≥50
Waist circumference		≤40, ≤30	>40, >30			

on foot could, therefore, become more serious issues when they are not properly treated in time [72, 73]. About 15% of diabetes cases resulted in diabetic foot and the side effect can endanger patient life [74]. The presence of diabetes in a body reduces the blood flow to the lower limbs, hence triggers an infection present in the patient body and easily escape control, thus has severe consequences that could lead to an ulcer, if untreated result to the amputation of the affected limb.

Diabetes length is a relevant determinant of diabetes risk factors. Diabetes patients of over 15 years of age feel to a much greater degree than their standard of living has been compromised over the last month by the need to follow the physician's recommended care, dietary limitations on disease control, lack of blood glucose regulation, blood sugar monitoring and the effect on their vision issues. Nonetheless, patients with a relatively short and medium diabetes period (below 5 years or between 5 and 10 years after diagnosis) appear to be substantially more comfortable with the time needed to control diabetes.

8 Discussion and Future Research Directions

The basic concepts of IoMT-based and wearable body sensors network applications in the field of healthcare monitoring systems have been elaborately discussed in this chapter. The use of IoT devices in health systems, which are linked to the IoMT, is a relatively new and rapidly growing trend in health-related areas. From the broad range of research disciplines related to the implementation of IoMT technologies and wearable body sensors network applications in many medical case studies, it has been identified that IoMT and wearable body sensors network have offered a large number of new frontiers for generating, developing, analyzing, and managing large amounts of data frequency, particularly online and other, In this regard, IoMT and wearable body sensors network technology, as a common method to managing a large volume of health care data, has provided convenience from the perspective of personalized e-Healthcare.

In this chapter, an IoMT-based and wearable body sensors network architecture for Healthcare Monitoring System was proposed to answer some of the research questions highlighted in the chapter. The structure for the Healthcare Management Program of Mellitus Diabetes has been introduced for both the IoMT-based architecture and WBSN. Using the system, appropriate patient-related data are collected from sensors and analyzed, including the frequently changing health parameters.

The results show that the proposed IoMT-based and WBSN platform helps track and spread chronic diseases such as diabetes mellitus. For future research purposes, it should be noted that progress has been recorded in the study on the healthcare monitoring system in customized e-healthcare, but it is necessary to address a series of research questions and operational problems. In previous studies, various challenges concerning information safety and confidentiality, mobility control, and applications are identified during design processes. Thus, there is a need to concentrate on such challenges, particularly as they relate to IoMT and prediction, diagnosis, exams, and monitoring of disease. In this context, an intelligent security model should be thoroughly studied to minimize the risks identified.

Although different IoMT applications are widely available online, they are due to many deficiencies including lack of confidentiality and protection, reliability, efficiency, and appropriateness. Addressing the issue of load balancing and spreading knowledge through the cloud servers is of significant concern for future study. More effective security algorithms such as DNA encryption, fully homomorphic encryption, and decryption on the cloud need to be implemented just to mention a few.

Data privacy and security are challenging objectives in IoMT-based healthcare system monitoring [75]. Majorly because cloud's recorded healthcare data may be subject to different types of security risks, like connecting attacks and illegal users. Machine learning techniques should be further incorporated in a similar perspective to solve the issue referring to diverse and ever-evolving sensory inputs. Furthermore, it is often difficult to compare or connect data varieties from numerous sensor devices since sensors produce complex and heterogeneous data on clinical tests, tracking, and health care. It will thus be important to decide which one of the IoMT sensor data performs better for a collection of biomarkers, in order to obtain a better diagnostic result.

9 Conclusion

The proposed system is non-invasive, flexible, cost effective, and the framework empowers users to enhance monitoring of health-related signs and symptoms, vulnerabilities, and reduces hospital costs and expenses by recording, gathering, and sharing all-encompass health information on IoMT cloud platform effectively, continuously, and productively. The results show that the length of diabetes in a patient is very relevant and good determinant risk factors, also all the risk factors of obesity are related to diabetes risk factors; therefore, obesity is an important illness of diabetes mellitus. Furthermore, the results reveal that glucose, INS, BMI, and DGC are high-risk factors of diabetes. The framework can be used for monitoring other diseases using sensors that are related to that illness and well equipped with features that can help doctors to examine their patients anytime and anywhere. The proposed system was used to monitor only diabetes; future work can be extended to other related illness like heart alzheimer disease and dementia, cardiovascular disease, arthritis, asthma, cancer, crohn disease, and cystic fibrosis. Data privacy and security for IoMT-based monitoring of healthcare systems should be looked into for future work. Machine learning methods should be combined to solve the issue related to changing sensory inputs. Developing countries, especially African hospital, should be thinking of how to deploy IoMT in hospitals to reduce cost since it is feasible and economical. The collaboration of government, medical personnel, and researchers is very relevant to improve the implementation and deployment of IoMT in our hospital.

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