Chapter 9
Remote Human's Health and Activities Monitoring Using Wearable Sensor-Based System—A Review

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9.1 Introduction

Enhancements in the development of wearable sensors have improved monitoring healthcare conditions of humans. In recent research studies, with the arising of technology, new and tremendous increase in the usage of modern devices such as smart watches, smartphones, and wearable sensor-based embedded devices can be connected with wired or wireless means of communication, and hence, the attention of the next-generation human health is concerned with a detailed analysis through Internet of Medical Things (IoMT). The various sensors are connected to the parts of a human to receive the biopotential, which is an indication of clinical disorders. The clinical data collected by those sensors are periodically stored as electronic medical records and electronic health records collected from healthcare workers like physicians, nurses, and paramedical workers. The data that are collected are vital for many pharmaceutical companies, researchers, and academicians for clinical data Analysis. The Big Data Analysis is mandatory to deal with an enormous amount of biological datasets collected from associated wearable sensors. Smart Health care has introduced an increased demand for biomedical datasets, which periodically generates signals by sensors planted on the embedded devices. The novel technical challenges are also created alongside with innovation and emerging business prospects [1, 2].

The signals generated by the embedded wearable sensors are in huge volume, and the rate of receiving the signals is dealt with the velocity of signal reaching the storage space. Numerous sensors collect the data from multiple nodes in human body to provide a stream of data in large volume continuously to characterize the clinical data of patients in Smart healthcare technology [3, 4]. The embedded wearable sen-

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sors are interconnected with either gateways to the smartphones, and the resultant data could be very huge, and hence, those big data are analyzed by the data analysts. The necessary information could be retrieved by the machine learning using a neural network. The data with useful information are extracted by collecting the real-time data from the wearable sensors in the available and manageable time with few innovations. The boundless number of healthcare data can be analyzed by storing those data in the cloud services like Microsoft Azure, Google cloud, etc.

This chapter is structured as follows: Section 9.1 describes the introduction about the wearable sensor and remote monitoring of patients. Section 9.2 deals with the challenges faced by the wearable sensors through integration for online monitoring. Section 9.3 describes Internet of Things (IoT) and Internet of Medical Things (IoMT) for collecting patient data through internet. Section 9.4 describes role of wearable sensors in modern healthcare systems. This chapter is further classified in terms of three major disease monitoring for diabetes, heart, and Alzheimer. Section 9.5 deals with blood glucose monitoring and diabetes management through online. Section 9.6 deals with cardiac monitoring and its associated issues. Section 9.7 discusses about the online monitoring of Alzheimer patients under Active Assisted Living. Section 9.8 deals with Samrt Healthcare system through big data analytics. Section 9.9 gives the conclusion on the integration of sensors and data handling in the online healthcare monitoring.

9.2 Challenges and Issues in Integration of Data From Wearable Sensors for Online Healthcare Monitoring

Data gathered from multiple sensors vary in quality and integrity. Data format also varies due to the absence of common approach for gathering data from different types of physiological variables. Data gathering and analysis methods vary depending upon the wearable sensor manufacturers.

Data analysis could be done on board directly from the incoming data streams, or data stream is taken and analyzed using a secondary data acquisition system. Methods for analyzing data vary upon the factors like quality, integrity, type of dataset, etc. Structured approaches are required for validating the data from wearable sensors and analyzing data and feedback from the data analysis. Common approaches are required for data acquisition, transmission, and integration and processing.

9.2.1 Challenges in Building a System Integrated with Multisensor-Based Wearables

Big Data play an important role in the massive growth of wearable technology in which speed and reliability are important parameters. Big Data speaks about the enormous variety of data collected and their velocity and volume. The constant data stream calls for huge data processing and storage capabilities. The real Challenge arises with computation limitations and multitasking requirements.

A robust strategic system is required for integrating multisensor inputs. The steps involved in integrating the data from wearable are as follows:

1. Identification of the type of disease present in the patient
2. Identify the types of sensors based on the patient's health record. Type of sensor must be precise enough to get the physiological parameters pertained to the nature of the disease.
3. Identification of the methods for analyzing the data (Different approaches are to be analyzed depending upon the quality of output of the system).
4. Integration of different datasets from different sensors.
5. Analyzing datasets of different sensors and indication of the output parameters.
6. Measures taken to treat the nature of disease.
7. Methods to store and reproduce datasets as and then depending upon the requirement.

Acceptance of wearable sensor technology is based on the ease of usage of software and hardware devices, ease of usage, area occupied by the system, total eight of the devices, and power consumption of the battery. Superior performance, accurateness in measurements, and higher suitability for a variety of applications in health care are important. Major constraints are the absence of universal platform and interoperability. Safety, confidentiality, and ethics are other needs of concern. Common safer methods of storage and authentication techniques are present and realized successfully in many systems. Privacy and ethical principles are handled in an ad hoc way, and advantage could be obtained by applying universal frameworks that are available with different vendor.

Body Sensor Networks (BSNs) have emerged as a revolutionary technology in many application domains in health care, fitness, smart cities, and compelling Internet of Things applications. In particular, BSNs have demonstrated great potential in health care. These systems hold the promise to improve patient care/safety and result in significant cost savings. Recent years have seen considerable research demonstrating the potential of BSNs in a variety of physical activity monitoring applications [5–8].

9.3 Internet of Things

The Internet of Things can be illustrated as networking of a variety of embedded gadgets such as sensors and transducers interacting with each other to communicate themselves like machine to machine communication for provision of grouping and exchanging of data among them [1, 9–11]. The Internet of Things and its associated technology not only enable the automation of industries but also play an inevitable role in the medical stream, which aims at allowing for the collection of big clinical data. IoTs are extensively used for intelligent structural health monitoring [12–14].

9.3.1 Internet of Medical Things

Nowadays, Internet of Things plays a major role in healthcare sector. It provides various services as Internet of Medical Things (IoMT). It serves the public by providing user interface Health mobile app, smart watch, Blood Glucose monitor, smart wheel chair, Respiratory belt, etc. Figure 9.1 shows the pictorial illustration of Real-time IoMT services in healthcare industry.

The Internet of Medical Things (IoMT) permits a device-to-device intercommunication and relies on providing solutions for real-time applications that have an ability to modify health care and enhance delivery and reliability in the upcoming

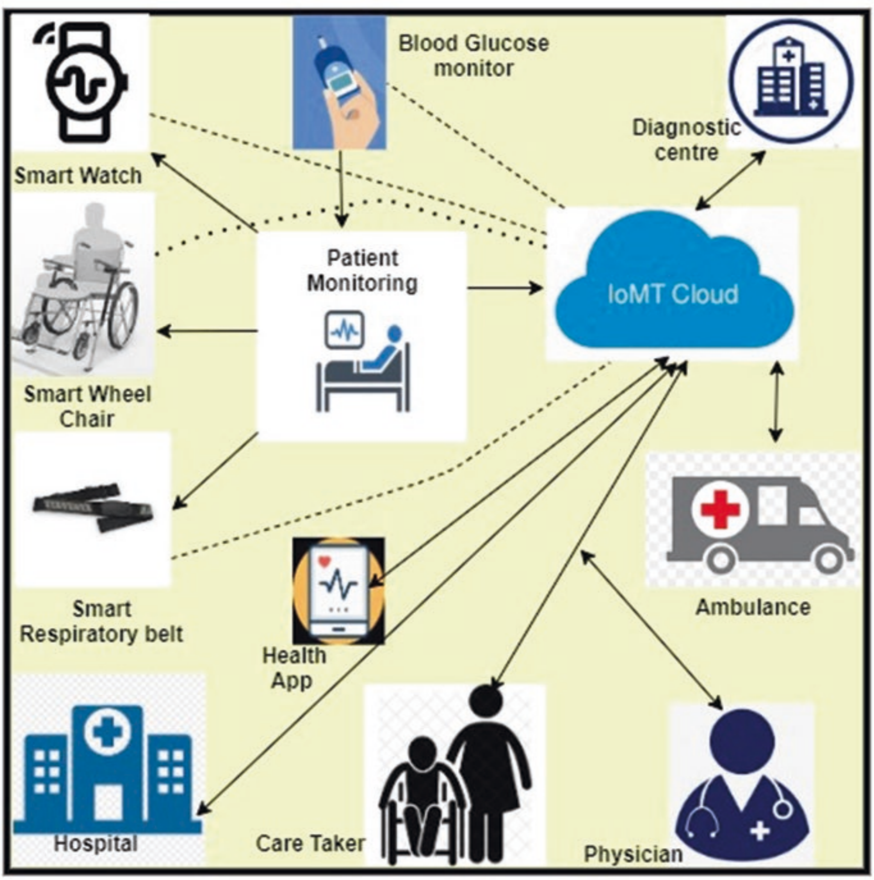


Fig. 9.1 Illustration of Real-Time IoMT services

era. IoMT supports the interaction of the sensors and large wireless networks through technologies like Body Area Networks (BAN), Wireless sensor network (WSN), Near-Field Communication (NFC), and Long-Range wide area networks (LoRa). Additionally, increase in the patient engagement in decision-making will enhance the healthcare service compliances.

9.4 Roles of Wearable Sensors in Healthcare

An enormous development in the field of construction and use of wearable (e.g., wellness trackers, wearable sensors for biometric applications etc.) change the way by which the data are collected and analyzed [15, 16]. Figure 9.2 shows the wearable sensors used by humans to monitor the physiological parameters continuously.

Internets of Medical things associated with wearable-embedded sensor technologies have improved the life style of each and every human. It can provide intelligent and reliable healthcare systems that are necessarily responsible for not only tracking but also managing the health of human under all circumstances. The improved fea-

Fig. 9.2 Wearable Sensors for Humans

tures such as near-field communication and wireless technologies enable the transmission and analysis of biological data by healthcare professionals based on identification of earlier symptoms of many chronic diseases[15–17]. Improving the overall efficiency and cost-effective smart health care is one of the rights of every citizen in the developed as well as developing countries.

The wearable sensors support everyone to do their routine life. If the sensed information deviates from the threshold level of normal range, then it indicates the person to go for clinic. These sensors are popular because these are embedded into anyone of the wearable things such as smart wrist band, smart belt, smart shirt, smart shoe, smart glass, etc [18, 19]. In some cases, these sensors are linked with special devices as smart glucose monitor, smart wheel chair, smart ECG sensor, smart position sensor, etc.

9.4.1 Motivation for Smart Healthcare System

Internet of things provides better solution for remote smart health monitoring because of the numerous benefits associated with it. In a few implementations, IoT healthcare systems extend the best solution for chronic diseases including diabetes, cardiac diseases, and Active Assisted Living (AAL) for physically challenged and elderly persons. While these technical advancements meant for a huge range of applications, they are robustly linked through the usage of available resources.

9.5 Blood Glucose Monitoring

Continuous real-time Glucose Monitoring of diabetes patient helps them to correct insulin injection level and avoid accidental overdose. Smart wearable device displays the glucose level and alerts the doctor and patient on their mobile phone using Internet of Things (IoT) platforms. These wearables keep track of insulin dosage and glucose level in cloud platform and give visualization to the doctors for proper prescription [20]. The smart glucose monitoring device could be embedded in the wristbands, watches, and even in shoes of the patients. The doctors can give virtual care to patients easily.

9.5.1 Diabetes Management

Diabetes mellitus, commonly stated as diabetes, is one of the worldwide epidemics. Diabetes is a long-standing metabolic disorder that occurs due to variation in blood glucose level due to the absence of secretion of insulin. There is a tremendous increase in the number of diabetes patients due to aging, huge population growth in countries like India, and increase in obesity because of physical inactivity. It is caused by either insufficient insulin production in the human body or inability of human body to utilize insulin produced in human body. Type 1 diabetes is caused in human because of destruction of β-cells, which usually leads to deficiency in absolute insulin (T1D). Type 2 diabetes is caused because of lower secretion of insulin, which can possibly cause defect in the background of insulin resistance (T2D).

Gestational diabetes mellitus (GDM) is also common in highly populated countries, which can be diagnosed during the pregnancy [21]. It is impossible to provide suitable healthcare need for diabetes patients for the entire population in developing countries, which seems quite cumbersome. Also, entire population could not afford the low-cost diabetes medication especially the insulin. Due to various reasons such as family environment, poor diet control, and malnutrition, diabetes is common in many countries. Because of the limited resources, the population has to focus on high-calorie protein-rich foods that cause diabetes often.

The modern healthcare technology with right communication ability can be utilized to monitor the diabetes patients. Because of the advances in the available healthcare technologies and wearable sensors, continuous monitoring of a patient's condition in real time is possible and one can manage the diabetes continuously and efficiently [22].

Glucose level monitoring of the diabetic patients using a real-time system in the blood was proposed in Ref. [23]. The proposed system enables the diabetic patients to check manually and obtain the blood glucose level at the regular time intervals. The existing system checks the unusual levels of blood glucose and also blood glucose count that is missed. It not only analyses abnormality in the blood glucose level but also make decision on its own to indicate, and the notification will be sent to the patient themselves as well as family members and the emergency healthcare persons such as nurses, doctors, etc. Even though this system is feasible, it can be additionally improved by the automation of measurements of blood glucose level.

Wearable Sensor technology enables a professional way of monitoring the diabetic patients, and hence, personal health of the individuals can be improved. Ganjar et al. proposed a personalized healthcare monitoring system that constitutes low energy-based bluetooth sensor devices to analyze data in real-time domain by using machine learning-techniques to assist diabetic patients to handle their health conditions [24].

9.6 Cardiac Monitoring

Heart rate is a primary factor in the identification of health of patients for long time. Since people all over the world are paying extensive awareness on their health and fitness, monitoring of heart rate for long term is an essential part of early diagnosis of plenty of illness. Persons like athletes, Sports persons, and elderly people who suffer from diabetes and high pressure require continuous monitoring of heart rate. In view of these needs, it is essential and vital procedure to devise and manufacture system that is appropriate for monitoring of heart rate on long-term basis, which should also be free from noises. The embedded and wearable sensors are used for this purpose.

The wearing device should be compatible and cost-effective for daily use to measure heart rate regularly. Numerous conventional methods have been proposed previously to calculate heart rate, which are usually based on electrocardiogram (ECG or EKG) [25], Photoplethysmography (PPG) (PPG), [26] and piezoelectric effect-based devices [27–29]. Many other techniques for measurement of heart rate have been proposed, demonstrated, and verified by some researchers [30–32]. By analyzing the methods already proposed for examining heart rate monitoring, ECG is the most commonly used technique. It is often the standard diagnosis method for heart rate measurement in healthcare centers, but a specific kit is required for use in household applications. Heart rate monitors based on wearable technology using ECG technique are available in the market, but chest strap transmitters are generally required, which are not suitable for daily usage.

Recently, a few research projects are aiming to combine the well-known benefits of Wireless Body Sensor Network (WBSN) technologies to monitor the HRV continuously and noninvasively. Currently, few research prototypes based on BSNs exist that allow for heart rate variability analysis. Many BSN applications need handling of multiple sensor signals at the same time, which is sometime referred to as sensor data fusion and context awareness [33–35].

9.6.1 Principles of the ECG

The ElectroCardioGram (ECG) is nothing but the recording of the electrical activity performed by the heart. An electrical recording can be produced by using one myocardial muscle cell. Each myocardial cell will record an action potential, that is, the electrical movement that happens when the cell is invigorated. The electrical activity of the heart is recorded in the form of the vector whole, i.e., the mixture of every single electrical sign for the activity possibilities of the myocardium, and generates a consolidated trace.

During resting state, the potential difference developed across the myocardial membrane is around -90 mV. This is because a higher concentration of intracellular potassium may be kept up by the sodium/potassium pump. Depolarization of a cardiovascular cell happens when there is an abrupt change in the permeability of the layer to sodium. Sodium floods into the cell, and the negative resting voltage is lost. Calcium continues the sodium, the slower calcium diverts bringing about authoritative between the intracellular proteins actin and myosin, which brings about withdrawal of the muscle fiber.

The depolarization of a myocardial cell causes the depolarization of neighboring cells, and in the typical heart, the depolarization of the whole myocardium follows in a coordinated design. During repolarization, potassium moves out of the phones and the resting negative layer potential is reestablished.

These existing methods deploy a distant observing diagnostic system to identify abnormal heart conditions in real time, which facilitates in staying away from heart diseases in early stages, and treatment of the patients makes progressing from cardiac diseases.

An existing model identifies the heart attacks with a help of sensor, signal processing unit, and a conventional antenna in Ref. [36]. ECG picks up the heart rate, which is the processed by a microcontroller. The actuating signal from microcontroller is transmitted to smartphone by using Bluetooth. The signal is then plotted in the smartphone or recorder. The authors identified that building up software for predicting heart attack will improve the system. Even more the improvements could be made by measuring the signals such as respiratory rate, so as to predict the heart attack in earlier stages [37].

Figure 9.3 shows the block diagram of IoT-based ECG signal processing module. It consists of three units. They are

1. Sensing Unit
2. Processing Unit
3. Master Data Management

Usually, sensing unit consists of physiological sensors to capture the bioelectric potential of human. For ECG recording, there are several electrodes used to capture the raw ECG signal. The obtained raw ECG signal is then processed and analyzed in Processing unit. In this, Signal conditioning and communication module are used

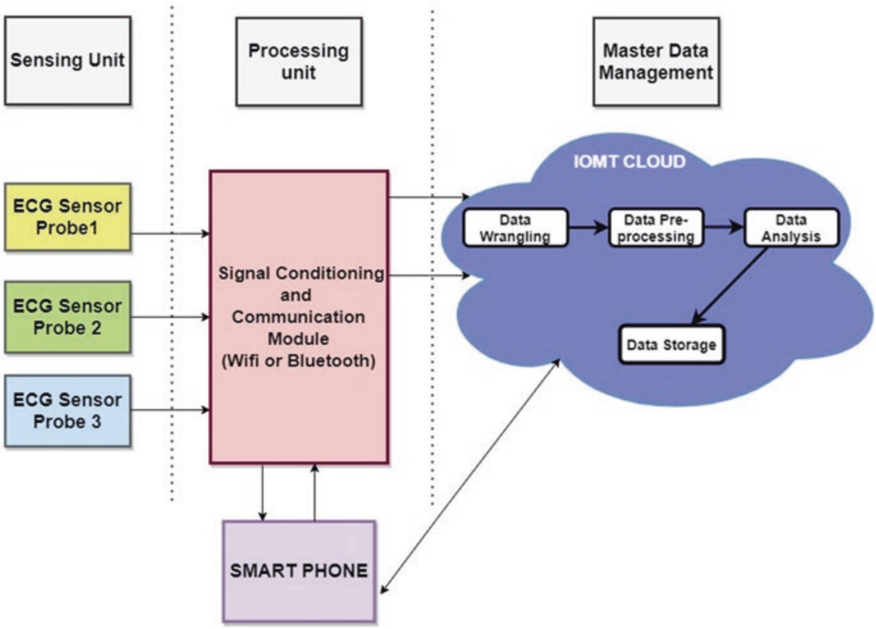


Fig. 9.3 IoT-based ECG Signal processing module

for ECG signal processing and communicating with external interface. The processed ECG signal is stored in IoMT cloud for future reference.

9.6.2 ECG Monitoring in Theater

Heart-Related Diseases/Wearable Watch Strap monitors continuously the health status of a patient's heart and displays the captured data through a mobile app. Electrocardiogram (ECG) is the key sensor for Heart rate monitoring and to identify serious medical conditions such as stroke and heart attacks. It gives the patient accurate information about the heart health.

ECG wearables have optical monitoring device inside them. There are watch-based and chest-based ECG wearables that measure 20 million data points in a day. If the captured data detect any possibility of heart arrhythmia, this device prompts the user to start the recording of electrical activity of heart, that is, ECG signals. This allows the patient to study their own ECG anytime and anywhere they want without having to go to any specialist, any lab, or emergency room. Also, it saves both time and money for the patients and their healthcare provider.

The regular CRO-based ECG is considered as one of the most broadly utilized anesthetic screens. In addition to monitoring arrhythmias, it can also be utilized to diagnose the myocardial ischemia, electrolyte imbalanced characteristics, and to evaluate pacemaker work. A 12-lead recording is one of the standard lead systems to record Electrocardiogram. It will give significantly more data about the electrical activity of the heart than is accessible on a theater ECG screen. This should be conceivable and received preoperatively for any patient with suspected heart sickness.

Electrocardiography (ECG) is a pictorial portrayal of electrical conduction and myocardial excitation in the heart. As action potential travel through the heart, they produce a positive current (depolarization) that is quickly trailed by a flood of negative current (repolarization). Finally, it results in the fact that the ECG recognizes and records Placement of the leads, which may provide positive or negative deflections in various regions of the heart.

The recording of the electrical action of the heart was stated as ECG. It doesn't provide any information about the pumping activity of the heart. Also, it cannot be utilized to assess cardiovascular output or pulse. Heart work under sedation is normally evaluated utilizing continuous estimations of circulatory strain, end tidal CO2 concentrations, pulse rate, saturated oxygen level, and peripheral perfusion. Cardiac performance is once in a while estimated straightforwardly in theater utilizing catheters or Doppler procedures, in spite of the fact that this is exceptional.

The ECG monitor ought to consistently be associated with the patient with prior acceptance of sedation and/or establishment of a provincial square. It will permit the anesthetist or specialist to recognize some modification or adjustment in the presence of the cardiogram complexes during anesthesia.

9.6.3 Connecting an ECG Monitor

Even an ECG signal might be acquired from placed electrodes connected in changes with positions. Expectedly, these electrodes are placed in a standard position each and every time so that the variations from the norm are simpler to recognize. Most of the recordings have 3 electrode leads, and they are associated as follows:

- Electrode lead in Red color is placed in Right Arm, that is, second intercostal space on the privilege of the sternum.
- Electrode lead in Yellow color is placed in Left Arm that is located in second intercostal space on the left of the sternum.
- Electrode lead in Black or Green color is placed in Left Leg that is located more frequently in the area of the summit beat.

These may permit the Lead I, II, and III setups to be chosen to monitor the ECG waveform. Among all 3-lead setup, Lead II was considered as the most widely preferred in the medical field.

The connectivity link from the electrodes is ordinarily end in a solitary link. It is connected to the port on the ECG screen.

A better electrical connectivity among the patient and the electrodes is achieved to limit the electrical resistivity of the skin. Hence, gel cushions or suction cups with electrode gel were preferred to link the electrodes with the patient's skin. Suppose if the skin is sweat-soaked, the electrodes cannot be placed well, and it may lead to an insecure follow. At this point, suppose the electrodes are in short supply, they might be reused frequently by soaking with saline or gel before being taped to the patient's chest.

Once again, a void 1000 milliliters of IV mixture bag might be sliced open to permit it to a bit level (as a level bit of plastic) on the patient's chest. In this activity, 3 little openings are formed with 3 of the corner's terminals. It might be placed on one side of the plastic, permitting the electrode gel to reach the skin. Thus, the gadget can be washed toward the finish of the activity. It may be placed on the following patient, permitting electrodes to be utilized over and over.

9.6.4 Lead Positions

The ECG might be utilized in two distinct categories. This 12-lead standard ECG system might be analyzed, which examines the heart electrical action from various electrodes situated on the limbs and over the chest. A major scope of variations from the norm might be distinguished including arrhythmias, myocardial ischemia, and left ventricular hypertrophy.

The Electrocardiogram might be checked by utilizing just 3 (or sometimes 5) electrodes during anesthesia, which give a progressively confined examination of the cardiovascular electrical movement and can't give a similar measure of data that might be uncovered by using the standard bipolar 12 lead system. "LEAD" in ECG corresponds to the following of the voltage difference between two of the electrodes and is truly what is conveyed by the ECG machine.

9.6.5 Graphical Recording

ECG wave is recorded on a paper in a period size of 0.04 seconds/mm. Also, in the paper, the center point and a voltage affectability of about 0.1 mv/mm are compared to the vertical hub. In like manner, on normal ECG recording paper, 1 minimal square corresponds to 0.04 seconds. The one large square relates 0.2 seconds duration in ECG. In the normal ECG waveform, the P wave relates to atrial depolarization and the ventricular depolarization is represented by QRS complex and the ventricular repolarization by T wave.

- The P–R length is taken from the earliest starting point of the P wave to the start of the QRS complex. It is the time taken for depolarization to go from the SA hub by methods.
- The QRS relates to the time taken for depolarization to experience the His-Purkinje structure and ventricular muscles. It is deferred with infection of the His-Purkinje system.
- The Q–T range is taken from the earliest starting point of the QRS complex to the uttermost furthest reaches of the T wave. This addresses the time taken to depolarize and repolarize the ventricles.
- The S–T partition is the period between the completion of the QRS complex and the start of the T wave. The ST area is changed by pathology, for instance, myocardial ischemia or pericarditis.

9.7 Monitoring Patients Under Active Assisted Living (AAL)

The population in all countries has increasing tremendously due to the availability of advanced medical facilities. There is also an increase in the number of elderly people in each country who require additional care, [18, 19] which is also increasing. Even in the well-developed countries, the materialization of an ageing people is rapid and the measures are to be taken to closely monitor the public health. The price of health care and service is rapidly increasing to meet the quality of services, which is not in proper concern in modern societal developments [38].

The only solution is to ensure the remote and real-time health monitoring to overcoming the existing challenges. Periodic smart health monitoring of the elderly and needy people can be achieved by using wearable devices and smartphones.

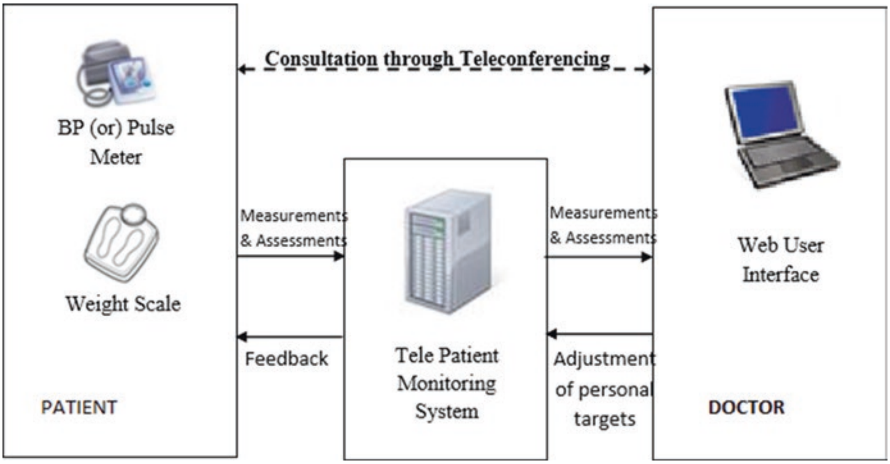


Fig. 9.4 Basic setup for Teleconsultation

Figure 9.4 shows the basic setup used for teleconsultation. This is possible through videoconferencing. From last decade, this type of consultation becomes more popular among the healthcare sector.

The Project SPHERE [39] aims at monitoring the elderly and physically challenged persons, which includes wearable sensors and vision (i.e., camera) sensors for monitoring the regular daily activities and also for monitoring their health. The ultimate aim of this model is to help the elderly and chronically ill patients to lead their life with full comfort at their homes, and the mean time of their health is also regularly monitored without any discomfort. The patients under the critical illness will be on utmost care by nurses, caregivers, and doctors if there exist abnormalities. Academicians and researchers are working for improving the project using machine learning since the machine learning is advantageous for providing better results and taking decisions regarding the health care of patients.

Figure 9.5 shows the pictorial description of one healthcare setup used to observe the daily health care of the elderly aged people. They used wireless sensor network (WSN) to collect the health information in this technique. Each sensor node is placed along with Elderly people home. These nodes collect the health information and store in the cloud database. The stored information is retrieved from the cloud and continuously monitors the health status in the monitoring unit.

9.7.1 *Alzheimer's Disease*

Alzheimer's disease and dementias can be noticed during earlier periods by observing the changes in the behavior of the person who is suffering from that disease. Alzheimer Patients experience difficulties like loss in memory for short intervals of

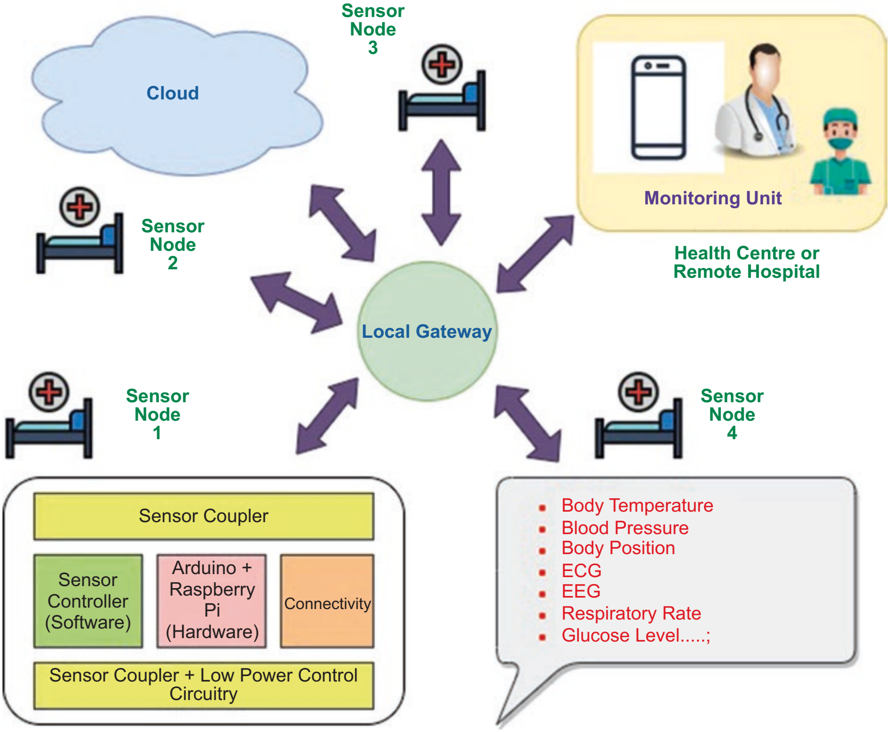


Fig. 9.5 WSN-based Healthcare setup for Elderly people

time, learning of subjects, counting numbers, and confusion in the process of decision-making. Alzheimer's disease affects the patient's abilities mentally. Individual symptoms of this disease might vary from person to person, depending on the person's personality, routine life style, and overall health condition of the patients. Alzheimer's disease is divided into three stages, namely,

1. Early Stage
2. Mild Stage
3. Advanced Stage.

All patients do not know-how a progression has occurred from one stage to another. The transition from one stage to another stage will happen several years. During the early stages, activities like speech, memory, socializing skills, judgment, thinking logically, and mobility are affected. All senses and skills get worsened where a substitute can be used to eliminate problems. During the mild stages, activities like speech, memory, socializing skills, judgment, thinking logically, and mobility are affected. Symptoms of mild stage include loss of the ability of the people to take care of themselves. Lose in the ability in decision-making and the orientation starts deteriorating.

Activities affected in the advanced stages are capability to do difficult tasks (expressing them self) is reduced, and the patient is in need of caretakers and members from family. Difficulty in movement is noticed and becomes often bed-bound patient. Symptoms of advanced stage are requiring assistance for fulfilling routine actions as well as the ability to speak, walk, sit, and stand. Patients will lose the communication abilities with other people.

The wearable devices can be used to send patient location of Alzheimer's Patients data over an Internet of Thing cloud network to a caretaker. The device can produce alerts to the caretaker if the patient goes outside of a selected "safe" zone. The device provides a safety measure for the patients and a relief for the caretakers, thus enabling the patients to stay in their home without moving to hospitals. Innovations are to be included in assistance, and monitoring for Alzheimer's Patients helps them to attain the independent and comfortable life.

Increase in population and unhealthy and stressful lifestyle in turn increases Alzheimer's disease in Indian population. Numerous technological solutions are provided for people suffering with dementia and Alzheimer's disease. Technology-assisted living improves the day-to-day life of these people. The patients with Alzheimer disease in rural areas do not have access to assistive technology like the patients living in urban areas. Training the caretakers and staff members involving with the patient plays a vital role in the success of this technology-assisted living. Security concerns over the use of wireless technology, legal, privacy, and ethical issues are also need to be considered before choosing the method of implementation.

9.8 Hexagon Chart of Smart Healthcare System Through Big Data Analysis

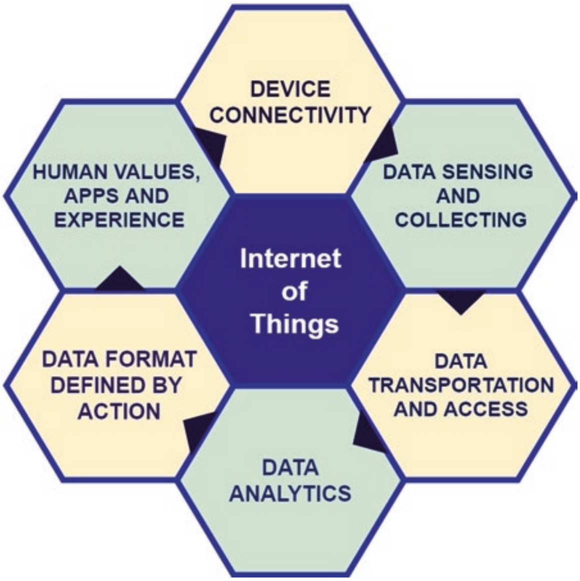
Device Connectivity is a major issue since the patients may or may not aware of the signals collected from the wearable sensors. If more than 10 to 15 sensors are needed for elderly people who are affected by Alzheimer's disease, then connectivity will be achieved by some routers with the help of some near-field communication devices such as RFID, Wireless Area Networks, and Body Area Network.

Figure 9.6 shows the hexagon diagram of smart healthcare system through big data analytics. It consists of six phases. These phases are listed as follows:

1. Connectivity of devices
2. Sensing and Collecting of data
3. Transport and access of data
4. Data Analytics
5. Actions defining data values
6. Human values, applications, and experiences.

Data that are sensed by different sensors may be of different varieties. For example, the blood sugar level is a real valued data ranging from 70 mg/dL to

Fig. 9.6 Hexagon Chart of Smart Healthcare System through Big Data Analysis



maximum 500 mg/dL. The data that are collected from ECG may be pulse rate that is a real valued number or graphical form such as ECG, which is 2-dimensional images. If the data are taken from Alzheimer's patient, it is necessary to obtain the clear color image of the patient, also the real-time values for position monitoring, etc. The collection and integration of these data can be done by various sensors that are also wearable. These wearable sensors must be chosen such that they are compatible with the patient under monitoring to ensure the proper transmission of data from sensors to the servers.

Data transportation can be done by any of the suitable and affordable Near-Field Communication networks like Wire Networks or Body Area Networks. There should be a sufficient number of Access points needed for each and every sensor to ensure proper connectivity.

In order to analyze the data that are stored in remote server could be very large since these data were stored periodically to monitor the patients under observation. Because of increase in the modern healthcare technologies, the prevention of many chronic diseases was possible and the mortality rate could be considerably reduced. Since the data collected are streaming with high velocity, variety, and huge volume, they are analyzed using deep learning. Before applying any deep learning algorithm, the data wrangling and data cleansing have to be done and the best optimization has to be done to choose the neural network to learn data from the available sensors.

Neural network analyses data by preprocessing and involve in training the available data types for a sufficient number of times. The processed data have to be sent to the end user for further processing of clinical data. Hence, the patient with abnormal values should be immediately handled by the healthcare persons like doctors, nurses, or caretakers. In order to enable quick accessibility of the patient, these data have to be sent to the healthcare person's mobile through well-organized mobile application. Hence, the data that are collected from the patients may be immediately transmitted to the family persons also in the case of emergency or healthcare persons through mobile applications in a presentable form.

9.8.1 Data Analytics

Data Analytics play a vital role in analyzing the data associated with healthy and unhealthy patients who suffer from different diseases. Analyzing the data of both healthy and unhealthy might be helpful to predict the risk factors and complications of various drugs for future reference. Data mining in healthcare data follows some rules and regulations. By following rules, disease management is possible by which one can get best treatment and health insurance.

The sensor output is compared with available model using regression algorithm or decision tree algorithm in healthcare analysis. Association rules are designed to evaluate the health of the patient. Positive and negative association rule generation and creating associative rule-based classifier are needed for the prediction analysis in health care.

The medical data should be accompanied by personal information, and medical test results, etc., are essential to predict the probability of occurrence of a certain disease. It might be used for physicians and also for the patients' caretaker regarding the probable risk of certain disease.

9.8.2 Data Mining in Healthcare

Data mining is one of the most inevitable popular techniques that is necessary to observe the health care of the patients. Since there is a huge increase in essential healthcare data, Data mining would be preferable one. There will be huge benefits available not only for healthcare industries, but the right healthcare facilities can be afforded for many needy patients.

The huge amounts of complex data that include patient database, hospital resources, diagnosing capability, electronic record of the patients, and medical devices were to be analyzed continuously. The wearable sensor provides various datasets that are to be integrated to create a medical database. That database makes a lucid depiction of the whole data that may be useful for the medical information system.

Enormous amount of data extracted and transmitted from the wearable sensors is a major resource for data processing. The analysis and extraction of knowledge enable support for decision-making. Data mining algorithms are used to extract information or patterns from raw data.

9.8.3 Data Classification

Classification deals with predicting a label and regression to predict a quantity. Once multiple data are received in the medical data base management system, it is necessary to extract the useful data from the available set of data. The classification enables the prediction of data to create discrete class label output from the received medical datasets. The regression enables the prediction of a continuous data as output.

9.8.4 Predictive Modeling

The predictive modeling enables to develop a new model from historical data to make a new set of predictions when the data are new within a received set of the time and resources available.

9.8.4.1 Sample Data

Data that are received from sensor are a real valued function. From the available Datasets, we need to classify the data that are required to identify the disease from the whole set of data. For diabetes patients, the blood sugar level will be in the range of 60–100 mg/dl. This range is taken as the label. Since the predictable data are known, they are considered as labeled data that can be implemented using supervised learning technique. The goal is to take some data with a known relationship so as to create a model of the required relationships. The learning is done by the supervised learning algorithm as shown in Figure 9.7. The model is able to learn the relationships.

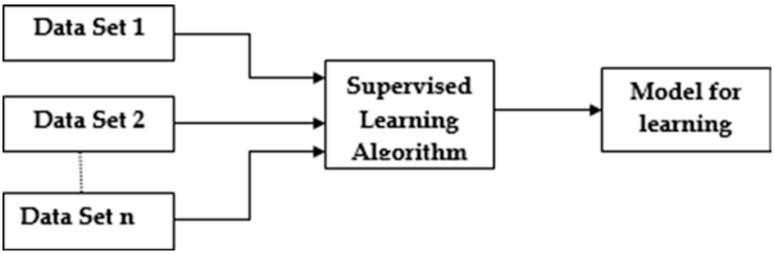


Fig. 9.7 Model for supervised learning algorithm

9.8.4.2 Making Predictions

The model will read the raw data observed by the wearable sensors and perform comparisons with model to make a prediction about real data that are necessary for the end user. If the sample data are good, a robust model learns from the data and it will provide the accurate result.

9.8.4.3 Predictive Modeling in Wearable Sensors

There are two protocols used in predictive modeling. The Classification and regression are the two-modeling algorithm that is used for analyzing the healthcare data. The function is developed from the available input to develop a discrete output dataset. Labels are given for the output data. The activation function thus predicts the signal from the wearable sensors.

A classification of data from wearable sensors requires that data to be classified into required set of classes. A data classification could be done for real-valued or discrete variables. If the given sensors involve two classes of data, then they are referred to as binary classification. During classification, continuous values from different sensors are predicted by obtaining the probability of each set of classes. Ones belonging to good data are termed as 'confident' data, and other belonging to error are 'bad' data. A predicted value can be converted into strongest class when it has highest probability. If a probability values of confident data, which are labeled as 'good data,' have the probability of 0.1, the other data are grouped as 'false data,' which have the probability value of 0.9.

The estimated predicted value will assure the best classification accuracy. The classification accuracy is properly classified with all set of predictions made. If a classification predictive model made 10 predictions, out of them 4 were correct and 6 were incorrect predictions.

$$\text{Prediction Accuracy} = \frac{\text{Correct predictions}}{\text{Total number of predictions}} \times 100$$

$$\text{Prediction Accuracy} = \frac{4}{6} \times 100$$

$$\text{Prediction Accuracy} = 66.66\%$$

A classification algorithm learns with a classification predictive model to get wearable sensor data with good accuracy.

9.8.4.4 Regression Predictive Modeling

Regression predictive modeling algorithms like k-Nearest Neighbors, Decision Tree algorithms, Support Vector Machines, and MultiLayer Perceptron are used to generate the best data output from available input variables. A continuous data output variable mentioned here is the data that are received from sensors from patients. When it is a real value, such as an integer or floating-point value, then Root mean Square would be calculated while training a set of predicted data. A regression predictive model would predict a best quantity from the available set of data, and it could generate root mean squared error. For example, if a regression predictive model could produce 2 predictions, one of that would be 1.3, where the expected value is 1.0 and another prediction is 3.8, and the expected value is 3.0, then the Root Mean Square Error is calculated as mentioned below.

$$\text{Root Mean Square Error} = \sqrt{\text{Average}\left(\text{Error}\right)^2}$$

$$\text{Root Mean Square Error} = \sqrt{\frac{\left(1.0-1.3\right)^2+\left(1.0-1.3\right)^2}{2}}.$$

$$\text{Root Mean Square Error} = \sqrt{\frac{0.09+0.64}{2}}.$$

$$\text{Root Mean Square Error} = \sqrt{0.73}.$$

$$\text{Root Mean Square Error} = 0.854.$$

The Root Mean Square Error has the same unit as the predicted data. Among Classification and Regression algorithm, Regression algorithm could provide a better result.

9.8.5 Data Format for Wearable Sensors

9.8.5.1 MQTT (Message Queuing Telemetry Transport)

The Publish/subscribe messaging scheme was enabled by MQTT protocol. It is a specific lightweight protocol used for connecting things at remote places. It handles minimal code as well as communication network bandwidth. MQTT-SN stands for Message Queuing Telemetry Transport for Sensor Networks. The important feature of this protocol is open type. Also it provides lightweight publish/subscribe protocol. It is designed specifically for machine-to-machine communications and mobile applications, and because of this, it is used in wearable sensors.

MQTT clients are very small, and hence, it requires minimal resources. It can be used even on small and low cost microcontrollers. Since the headers of the MQTT message are quite small, it will reduce the bandwidth. This protocol allows messaging between IOT device and cloud and vice versa. It leads to better broadcasting to deliver the information to needful places through IOT. This protocol is used for connecting millions of devices. The important factor in IOT is reliability of message delivery. MQTT accomplishes reliability by means of defined quality of service levels. Many IOT devices are connected to unreliable cellular network, but the MQTT supports for persistent and reliable way of connecting things to cloud. MQTT protocol encrypts the message using TLS and accomplishes authentication to the service provider.

9.8.5.2 Communication Protocol for IOT-Enabled Wearable Sensors

The Websocket API is one of the advanced powerful technologies. It enhances a two-way interactive communication among the server as well as application end user browser. This API sends frames of messages and receives responses from the connected devices without any acknowledgement from the server as shown in (Fig. 9.8).

9.8.5.3 *Internet Protocol*-IPv6

The term IPv6 stands for Internet Protocol version 6 (IPv6). IPv6 is a latest Internet Layer protocol. It is implemented for providing packet-switched networking devices. IPv6 assigns and operates with end-to-end data connection in the available IP networks. It ensures identification and location of connected devices on networking platform. It handles the routing and traffic across the Internet connection. A unique IP address is utilized for each device connected through the Internet.

9.8.5.4 802.1x/EAP-TLS-Based Access Control

An authenticated network access is provided by 802.1X. It is an IEEE standard for network to ensure security for wired Ethernet networks and wireless 802.11 net-

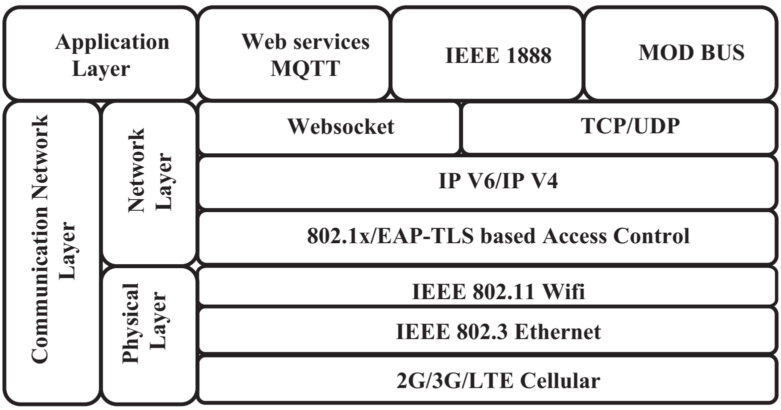


Fig. 9.8 Communication Protocol for IOT*7.52 Websocket API*

works. It enhances security by identifying the user with the help of dynamic key management.

9.8.5.5 IEEE 802.11 WiFi

WiFi otherwise called wireless local area network uses the IEEE 802.11 standard whose operating frequency ranges from 2.4 GHz UHF and 5 GHz. WiFi enables secured Internet access to the connected devices of range about 66 feet from access point. It is an affordable way of secure connection between IOT devices and Cloud where the huge device data are stored periodically. The connection could also be controlled with proper control unit. Wi-Fi is always Access point centered where its client-server connection could be implemented via router with many access points. WiFi is useful for connecting many Internet of Things sensors or devices, but such connections typically should be connected to an external cloud-server. Its usage is limited for battery-powered devices due to its relatively high power consumption. WiFi requires high speeds of internet connectivity as network access could be made with the help of an n number of access nodes.

9.8.5.6 IEEE 802.3 Ethernet

IEEE 802.3 Ethernet cable supports networking among wired systems and devices. It is used for supporting network with higher bit rates. It is used for connecting many nodes for short and long distances too. If an advanced networking system is needed, it can also be replaced by Token ring, ARCNET, etc. The devices connected with Ethernet divide a particular data stream into many frames. Every data frame contains source address and destination addresses in all the frames. It also has dedicated error-checking capability. The damaged frames could be identified and eliminated among the device in the network.

9.8.6 IOT Cloud Platform

Amazon Web Services (AWS) is a managed cloud service that not only provides connectivity but also helps to exchange the secured data among the connected IoT devices. AWS can support millions of devices connected in IoT. It communicates among the things with messages between AWS end points and other devices with high-end security. The wearable sensors are connected to AWS Cloud Platform. It tracks and communicates with all those wearable sensors for even a second even though there is no live internet connectivity. AWS gathers the data in regular time interval, and it analyzes the data and acts according to predefined data that are set in the control algorithm. It does not require additional infrastructure to manage the Big Data received by the sensors in real time.

The huge amount of data that are expected to be generated by BSNs requires a powerful and scalable storage and processing that is able to support both online and offline analyses of data streams. Such requirements can be met by an integrated platform based on Cloud computing [23] with the following characteristics: (a) the ability to utilize heterogeneous sensors; (b) scalability of data storage; (c) scalability of processing power for different kinds of analysis; (d) global access to the processing and storage infrastructure; (e) easy sharing of results; and (f) pay-as-you-go pricing for using BSN services [40, 41].

9.8.7 Analysis of Big Data

Data are aggregated in sequential time and analyzed by a fully managed service. It is very easy to analyze the massive volume of big data received by the wearable sensors connected in IoT. The usage of AWS cloud platform is available at low cost and least complexity to build a medical Internet of Things in a real time. It takes accurate and precise decisions in the absence of human with the help of advanced machine learning techniques. The wearable sensors provide the data of huge volume and different variety. Hence, traditional data analytics is replaced by special built-in intelligence to process the structured and variable data. The data received might have noises, corrupted data, and assumption of readings. They should be cleaned periodically to ensure the third-party access. AWS used in built data analytics filters and transforms, which could enrich IoT data. In a regular time instance, the series of sensor data are stored in a cloud of Amazon and it could be retrieved when it is necessary.

It is possible to set up the service to receive the required data with respect to the need and availability. It is possible to schedule queries of the stored data by utilizing the built-in SQL query engine. The complex data analytics might be done using a specialized machine learning algorithm by implementing the same with prebuilt models for common IoT use cases. It is possible to customize the data analytics with respect to the users need by tools such as MATLAB or Octave.

9.9 Conclusions

Wearable technology has motivated human being toward monitoring health and wellness. This review work focuses on the data analytics part in the wearable sensor and includes review on diabetes management, heart rate monitoring, and Alzheimer patient monitoring. This work summarizes techniques and devices materialized over the past few years and highlights on current methods using wearable sensor systems and systems in the area of clinical applications. The significance of researchers for tracking applications of wearable sensor-based systems has created a change in the field of wearable technology from the progress of sensors to the design of systems. Data analysis methods play an important role in the integration of wearable sensors for a variety of diseases. Integration of inputs from the different sensors helps the researchers to develop a model for remote monitoring of patients in home and hospitals. Researchers have developed methods to integrate multiple sensors in the remote monitoring systems so that monitoring could be carried in home itself. In future, robotics will be integrated into patient care monitoring systems to achieve the goal of establishing a telepresence in the home environment. Remote monitoring of patients in undergoing treatments will soon face challenges regarding the establishment of a variety of models to cover up the costs incurred for the whole process. The implementation problems will be important to promise that wearable sensors and systems communicate on their promise of improving the superiority of care provided to patients who are suffering from chronic diseases and ailments via monitoring of wellness remotely from home and hospitals.

Battery lifetime constraints play a vital role in determining the success of wearable sensors. Challenges encountered in interfacing machine with other machines as well as human need to be rectified. Security is key factor in present IOMT deices as huge data are handled in cloud. Connectivity issues while networking needs to be taken care. Data handling has to be enhanced by utilizing advanced machine learning algorithms. Sampling rate and speed of conversion should be taken care during the transmission of data through online.

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