Chapter 20
Intelligent Healthcare Solutions

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Abstract IoT technology has been present for more than a decade but has shown rapid growth in recent years, a process catalysed by advancements in sensors, smartphone technology and application software. The impact of IoT in healthcare sector has been so huge that it has paved way to a new frontier, Internet of Medical Things (IOMT). IOMT aims at achieving an intelligent and collaborative model capable of independent and isolated work with minimum security risks. Rapid advancements in sensing technologies, data processing techniques and end user applications helped establish IoT as an effective and adaptive technology in PHS.

Keywords IoT · Healthcare · Intelligent heath · e-health · M-health

20.1 Introduction

The literature of IoT in healthcare introduces one to the architecture and workflow of IoT platforms in healthcare, a gist of which is presented in this chapter. Open source technologies are often assigned meaning with reference to context, a habit leading to misinterpretations. This chapter aims at understanding this multi layered and multi flavoured approach at a level that would encompass the literature, not at the cost of shifting focus from the foundations of this technology.

The flow of data at each stage of intelligent healthcare systems is researched upon as data and various intelligent models associated with data form a vital part of this field. Various approaches exist for processing the large amounts of real time data generated by multiple devices and applications. Diving deep into the actual mathematical models involved might deviate the work towards understanding algorithms devised for intelligent learning of systems. Hence this chapter would abstract itself and apply more focus on understanding the "centric" approaches.

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The ultimate aim of healthcare services is to be able to cover a larger fraction of the population than the current extent with minimum usage of financial and human resources with no compromise on quality. "Pervasive Healthcare" has emerged to be one technology assisted solution to this problem. Personalised healthcare systems (PHS) present an inclusive picture for the potential and challenges of IoT technology in healthcare. This chapter understands these healthcare systems at a suitable depth taking it as a case study. The chapter concludes by taking a peek into the future of this decade long technology that involves introducing oneself to the modern half baked marvels like hearables, ingestible sensors and moodables.

Personalised healthcare systems (PHS) present a suitable application that brings out the potential and also the challenges of using IoT technology in healthcare. Pervasive healthcare in it's true essence means to be able to provide healthcare to anyone, anywhere and anytime thereby overcoming any geographical, demographic and technological barriers. Personalised healthcare systems make a fitting case of the above.

20.2 IT Platforms in Healthcare

Internet of Things (IoT) in the healthcare sector, better described as Internet of Medical Things (IOMT), has shown an impressive growth accompanied by ample implementation and deployment of systems, which was possible due to the advancements in sensing technologies such as those obtaining physiologic data such as pulse rate, respiratory rate, blood pressure and body temperature and those obtaining other kinds of data such as geolocation, physical orientation etc., and due to advancements in end user applications, gateway devices and network devices. IoT has helped reduce the pressure on the healthcare sector to meet the demands of an ever-growing population to provide good healthcare services at the minimum possible cost.

IoT approach to healthcare makes use of a network of interconnected devices, which is said to form the IoT network, to provide healthcare related services. They harness the power of wireless technologies such as WiFi or Bluetooth technology to obtain data from medical devices as well as more non-conventional devices such as wearables. Current implementation include systems for continuous and remote monitoring of patient's health, applying intelligent prediction models to patient's data and also enable clinicians to provide healthcare guidance to patients in cases of chronic diseases. A more indirect application would be the use of face recognition technologies (Jabarullah et al. 2012; Saxena et al. 2018) to help identify accident patients using a cloud enabled storage facility.

This chapter aims at understanding the structure of the IoT based healthcare systems, considering the problem in a hollistic manner. It also aims at understanding the various models and approaches involved with handling, storing and processing the enormity of data generated in such applications. The chapter looks at the various centric approaches that exist and also the intelligent models that are employed to develop a smart system. A branch of the healthcare industry i.e. Pervasive Healthcare is looked upon in this chapter as it is seen to be a typical example of such systems. Real world applications have also been considered to get a more clear understanding of the idea behind Pervasive Healthcare and also to provide the reader with an idea of such live implementations. The chapter concludes by looking at the various threats that exist to such systems. It also discusses some of the modern day marvels that are being extensively researched upon.

IoT enabled healthcare platforms are seen to confirm to the architectural trends seen in traditional IoT systems i.e. they tend to have a multi layered design to a system. The bottom layer is populated with physical systems that function as data hoarders that generate the mass of the data. The intermediate layer tries to strike a balance between the various heterogeneous devices that obtain data and the ones that perform network operations or may work on the network edge or close to an end user application. This layer also subjects the data to a rigorous data analytics routine to process and validate data. The top layer comprises of end user applications that are mainly concerned with information rendering and at times are also utilised for data processing due to computational advantages. The following paragraph aims at providing an overview of the workflow of an IoT enabled healthcare system to the reader before diving into the required specifics or detailing.

The literature of IoT systems in healthcare reveals that data is primarily obtained from sensing devices or applications running on smartphone devices, for example inertial sensors, physiological sensors, Global Positioning System (GPS), Electrocardiogram (ECG) and Electroencephalogram (EEG). The primary challenge at this stage is standardisation and interoperability of heterogeneous data generated from all these devices. These static and mobile devices are connected via a network, designing which takes into consideration the cost, pros and cons involved in mapping this inconsistent heterogeneous network onto a consistent and more meaningful hybrid computing grid. The raw data, that is now part of the IoT network, is digested to obtain meaning so that it may be fed to suitable end user applications.

As mentioned in Sect. 20.2 of this work, various intelligent models are put to use to obtain the same. Big data, learning methods such as supervised learning, unsupervised learning, knowledge based learning are tenacious research areas to name a few that are aiming at new frontiers and better solutions. For instance, Convolutional Neural Network (CNN) based model (Raza and Alam 2016) of Gene Regulatory Network (GRN) resulted in a powerful model which could be used for disease diagnosis, disease response and also to identify effective drug targets. The uniqueness of the Big Data problem (Khan et al. 2015), due to the 4Vs associated with it, was identified. This causes handling of such data a difficult task by using conventional methods. The author harnesses the power of cloud computing technologies to solve the Big Data problem. Cloud and Big Data are two important technologies utilised in any IoT based system. The unique problem presented by Big Data was analysed and cloud computing technology was used as the solution (Khan et al. 2017; Shakil and Alam 2017).

The data storage and processing that takes place at this stage of an IoT system makes use of all such technologies and implementations. This processed data is then fed to the applications that are responsible for user interfacing, implementing an alert system, enforcing authorisation at an application level and quality rendering of data. With the wide and diverse use of applications involved, the area is gaining more research attention leading to development of handy tools such as an application programming interface that would generalise the technology thereby enabling cross platform usage. This presented workflow summarises the operation of an IoT enabled personalised healthcare system. The observant reader would have noticed that this indicates a migration of healthcare centered around hospitals and healthcare centres, the traditional approach, to a personal level and thereby fulfilling the motives of pervasive healthcare to provide healthcare to anyone, anywhere and at any time.

The four tier architecture of a typical IoT based healthcare system (Qi et al. 2017) is shown in Fig. 20.1 which is quite complete and informative in its nature. Each layer is discussed in suitable depths below and the data processing layer is discussed as a separate section pertaining to its vastness in content.

20.2.1 Device Layer

As mentioned in the starting parts of this section, this layer is populated with sensor devices that are responsible for collecting the majority of data. These sensors form a set of key components to an IoT enabled healthcare system as they offer remote

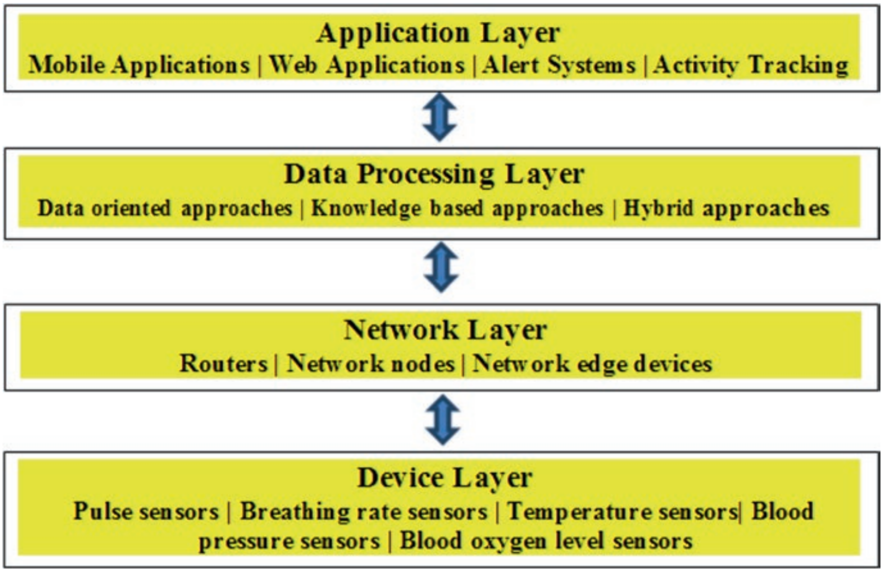

Fig. 20.1 IoT based healthcare system

gathering and transmission of data, a non compromisable asset to the IoT system. Though the data may be inconsistent pertaining to the variants of a natural environment (methods to handle which, have been discussed further in the chapter), these devices cannot be replaced or disposed off. This sub-section aims at looking at some of these sensing technologies (Baker et al. 2017), their functioning and use, that are widely used in healthcare environments.

Pulse Sensors: Pulse rate of an individual can be read off by making use of wearable devices such wrist watches or chest straps, both of which are used as commercial fitness products. The literature of such sensors reveals that these devices are being intensely researched and can be classified as pressure sensors, Photoplethysmographic (PPG) sensors, ultrasonic and radio frequency sensors. PPG sensors make use of an Light Emitting Diode(LED) light which is made incident on the blood stream and the amount of unabsorbed light is measured to detect the pulse rate.

Pressure sensors try and mimic the actual procedure of manual measurement of pulse i.e. by applying pressure on the wrist and the response to the pressure applied is taken for generating a pulse waveform. Both the sensors can be made part of a wearable device and as is the pitfall pertaining to any wearable device, both are sensitive to user movement and hence may produce somewhat inaccurate readings. Sensitization of the sensors results in increased presence of noise in the readings. Hence, these devices are being actively researched upon to produce more motion resistant and noiseless sensors.

Breathing Rate Sensors: A survey of breathing rate sensor technologies (Baker et al. 2017) reveals that several devices have been developed to measure the breathing rate of remote patients that make use of a wide array of parameters to arrive at a correct reading. Nasal sensors make use of thermally sensitive sensors that mainly detect the temperature changes caused when a person exhales. Breathing rate may also be obtained from the ECG readings of a patient.

Microphone based sensors are also used to measure respiration but as is evident are highly susceptible to external noise. Similarly optic fibre based vibration detection sensors are also used and these carry a disadvantage of generating incorrect readings when the user is in motion. In another example, capacitor plates were used, and the relative movements of which were used to measure the respiration rate.

While in another example, a ferroelectric polymer transducer was used which generated charge on application of tensile force, changes in which was used to measure the respiration rate. As the esteemed reader would agree, the major performance issue that arises in all of the above mentioned sensors is the accuracy of the reading when the device is used in a noiseful environment along with the user being in motion. Future scope of research would also be in developing such adaptable sensors.

Body Temperature Sensors: Recent studies show that body temperature sensors are mainly centered around thermistor based sensors (Baker et al. 2017), the scope of research in such sensors lies in making them as wearable as possible, as proximity to the human body results in a more accurate measurement of the body temperature.

Motion Sensors Devices that are used to monitor motion (Haghi et al. 2017) are also widely used in healthcare systems. Application of such sensors include remote patient monitoring in case of patients requiring exercise schedules which could be a part of their treatment. They are also used to monitor the amount of activity exercised by obese patients in order that guidelines by the clinician may be given accordingly.

Blood Pressure Sensors: Studies suggest that measurement of blood pressure using wearable sensors that would provide continuous data and also obtain the same in a non-invasive manner are somewhat of a challenge to researchers and technologists. On inspecting the work that has been performed, it would be somewhat suitable to say that the aforementioned difficulty may exist due to the absence of any direct way of measuring blood pressure. Pulse Transit Time (PTT), conventionally defined as the time it takes for a pulse measured at the heart to travel to another point in the body for example the earlobe, radial artery etc., is measured and processed to obtain the blood pressure readings of the individual.

This could be made possible by making use of an ECG chest-strap and a PPG sensor perhaps connected to the earlobe. But as pointed out by (Baker et al. 2017), this kind of a setup becomes obstructive as the connection between the devices will tend to be a wired one. Hence, modern and slightly different applications of the same have been to measure the PTT between the palm and the fingertip or between the ear and the wrist. But as is the case with all sensing technologies the readings have been seen to be reasonably accurate in the case of manually controlled environment. Developing sensors that are adaptable, accurate and are also less obstructive becomes the aim of further rigorous research in this sector.

Blood Oxygen Sensors: Blood oxygen level measurement sensors or pulse oximetry sensors are mainly based on the above mentioned PPG technology, using a pair of LEDs to measure the amount of light absorbed by the haemoglobin in the blood to determine the amount of oxygen content in the blood. Studies indicate that major work is being carried out on making the sensors more portable as conventional ones are seen to reduce the flexibility of the individual using them. The author of (Baker et al. 2017) provides an extensive survey of the various research implementations that exist for the same.

For example the author mentions about the development of a low power consumption sensor that continuously tracks the signal to noise ratio and also the peaks and troughs generated in the PPG reading, to try and moderate the intensity of the LED light accordingly. Another example proposes an in-ear based reflective oximetric sensor that stands out as it is seen to successfully obtain the readings in cases where the measuring the same from finger tips would be difficult such as when the patient suffers from conditions such as shock that lead to blood centralisation. The most mobile implementation was the design of a wrist wearable reflective oximetric sensor that would be least obstructive in nature.

20.2.2 Network Layer

Network layer performs the task of providing a means of communication to the various "things" in an IoT enabled healthcare system. The various devices, mainly sensing devices, need to be integrated to work together and as pointed out by various studies, IoT systems are seen to generate a requirement for protocols that facilitate machine-to-machine communication, instead of the conventional human-to-human communication in a network. The various tasks that may be performed as part of networking or connecting this wide array of devices would be to establish Quality of Service (QoS) management and standardisation that is specific to the end user applications or devices in the subsequent layers of the system. As mentioned in (Da Xu et al. 2014), these devices should be able to deploy, manage and schedule the behaviour of the "things" in the network, which may be the same device or some neighbouring device as coherence is expected of such a system.

As brought out by (Riazul Islam et al. 2015), IoT enabled healthcare systems are seen to utilise the IPv6 based 6LoWPAN (IPv6 based low power wireless personal area network) to form the basis of the network model. The various devices and applications operating in the network can be accommodated to separate layers of operation. The devices i.e. the sensors use the IPv6LoWPAN to transmit data over the 802.15.4 protocol, which forms the base layer of operation. The overlooking network layer makes use of the standard IPv6 and RPL (Routing Protocol for Low Power and Lossy Networks) protocols for communication.

The transport layer abstraction finally relays data by subjecting it to conventional TCP (Transmission Control Protocol) and UDP (User Datagram Protocol) protocols. The end user applications have a relatively larger array of options presented to them, which are also seen to be convenient in terms of support to the applications, which contain HTTP, CoAP (Constrained Application Protocol) and SSL (Secure Socket Layer) as their prime constituents. Figure 20.2 shows 6LoWPAN protocol stack (Riazul Islam et al. 2015) which encompass the above mentioned layers. The CoAP protocol (Ali Khattak et al. 2014) would require special attention, in the interest of application developers, as it aims at handling all the work involved with data querying and response based on HTTP methods alone to be able to develop powerful REST (Representational State Transfer) based applications.

It can be said as a powerful protocol as it provides with features such as asynchronous communication, HTTP to CoAP and CoAP to HTTP translations. It also ensures reliable message exchange. As brought out by (Ali Khattak et al. 2014), CoAP is seen to provide with the ability to design and develop a very flexible and resource intensive (in terms of the end user application which takes up most of the interfacing and rendering tasks) system. The network layer is also subjected to rigorous research in the aim to develop more efficient networks in terms of latency, cost, real time and guaranteed delivery of data.

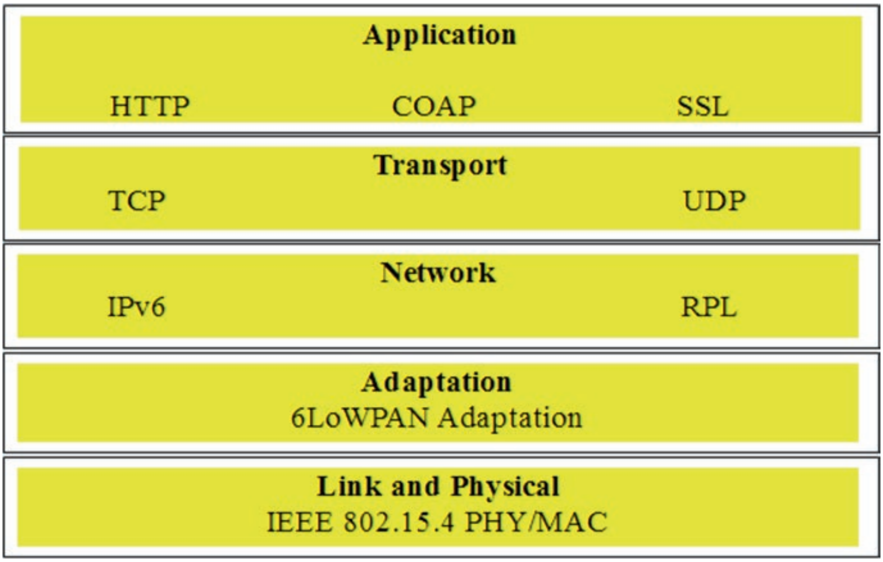

Fig. 20.2 6LoWPAN protocol stack

20.2.3 Application Layer

The final layer of a typical IoT enabled healthcare system, this layer is populated with the end user application that perform all the heawylifting related to rendering, interfacing and even data processing at times. This layer is mainly composed of powerful computing devices such as smartphones, tablets, PDAs and other such computing devices. Pertaining to the way the rest of the system has been implemented, this layer would be desgined to react in a dynamic sort of way. The logic associated with this layer would be mainly concerned with concepts that try and harness the power of data visualisation techniques.

Design implementations to tackle with security issues such as unauthorised access to sensitive data would be handled here. As suggested by the literature on IoT based healthcare implementations, these final applications could occur in various forms such as a website rendering data obtained either from the cloud or from a server that accumulates and processes data obtained from further below in the system, or in the form of a mobile application that may make use of some the computing powers of the mobile computing device to reduce the heawylifting of data processing performed by lower layers of the system or it could in the form alert based system that would simply work on a wearable such as smart watches. This layer is more under the eye of application developers to come up with better approaches to handling intelligent models, rendering data and providing even more secure ways of handling data.

20.3 Handling Data

As the reader would respond in affirmation that processed data (sometimes referred to as information in a few contexts) is more valuable than raw data. The enormous amount of data generated (also referred to as Big Data) thus needs to be processed and hence data processing is an important stage in the lifecycle of an IoT based intelligent system. As discussed in Sect. 20.1 of this chapter, the structure of an IoT based healthcare system can be seen as comprising multiple layers, each of which is capable of processing data with varied capacity and efficiency. Computation offloading (Samie et al. 2016) i.e. decentralising the computation process to the various layers of an IoT system is followed and the major design decision that accompanies it is, determining where the offloading should be done. Evaluation against various factors such as the availability of resources, network latency, capacity of data that can be handled with minimum deviation or error etc. needs to be done for a layer before arriving at a proposition. As described in (Samie et al. 2016), various 'centric approaches' exist for computation of data in an IoT system, which primarily outlines the various places in an IoT enabled system where data processing could be carried out.

20.3.1 Device Centric

Data computation can be performed at the base layer of an IoT system, the layer consisting of devices with embedded microcontrollers. As our esteemed reader would have realised that the major restriction with this approach is the minimum resource availability in terms of storage and computing power. The decision to perform computation at this stage could be pre-determined and in some cases could be determined at run time (Kim 2015).

20.3.2 Gateway Centric

Gateway devices bridge the communication gap between IoT devices, sensors and cloud. Due to the high extent of heterogeneity present in the devices, there may exist devices which may not support certain communication protocols and thus may require a translation medium. The various "things" in an IoT system communicate amongst themselves through a private network and with the external environment such as the cloud through a public network. Enforcing security and standardised protocols thus becomes a necessity, which can be achieved by making use of gateway devices. ARM Cortex-A, Cortex-M MCU and smartphones (Zachariah et al. 2015) are examples of gateway devices. They provide a computational processing advantage over the device centric approach. As pointed out by (Samie et al. 2016), network latency, guaranteeing content delivery and entropy of the wireless technologies pose as major challenges to processing data at the gateway devices. An implementation of this scheme is presented in (Samie et al. 2015), which makes use of a smartphone as a gateway device that processes the medical data.

20.3.3 Fog Centric

Fogs provide more computing power in comparison to microcontroller embedded devices or gateway devices and are seen to have less delay in comparison to the cloud servers. Fog computing techniques have also shown to consume less power as compared to a cloud network. The fog computing paradigm performs the tasks of data storage, computation and control closer to the end user applications. As pointed out in (Chiang and Zhang 2016), fog computing technique is seen to have an upper hand in data processing when compared to the previous approaches.

Through migration of data processing tasks to the network edge, fog computing techniques help achieve a cyber-physical system with minimum latency, a problem that was majorly observed in the gateway centric approach. IoT enabled healthcare systems face a major hurdle in tackling latency as the aim is in developing and implementing a system that works with real time data and provides applications with miniature response times.

Fog computing takes the burden off from resource constrained devices by performing all the resource intensive tasks in scenarios where migration of these tasks to the cloud is not preferred due to various reasons which may be related to cost minimisation or technical constraints. Fogs also overcome network bandwidth constraints by achieving a balance between the end user application requirements and the availability of networking resources.

20.3.4 Cloud Centric

Cloud computing techniques may be used for storing, processing and visualising the huge volume of data i.e. Big Data, generated in an IoT enabled intelligent healthcare system. Cloud offers a rich set of features such as impressive computational power, immense storage capacity, extensive implementation of security features, etc. and has always been an active field of research. Major challenges to this approach are seen to be centered around cost minimisation, latency and scalability as the cloud approach tends to be a resource intensive approach when best results are desired.

As mentioned in (Zhang et al. 2015), the amount of data in the IoT space is expected to exceed the trillion objects in Amazon S3, and a centralised cloud architecture for such huge volumes is quite unimaginable. Residing on the network edge, cloud computing may just add to the latency which is highly undesirable in a healthcare oriented application. Literature shows that the cloudlet architecture presents itself as a viable solution to the latency problem as it is seen to implement a direct communication between the data accumulator and the cloudlet, thereby avoiding all delays. IoT applications generate most of the data on the network edge thereby crowding network's upstream link bandwidth, which is one of the scalability challenges.

The author of (Zhang et al. 2015) also points out that durability of data, both acquired through sensors and data that is stored in the cloud, is also a major concern and needs to be ensured as part of an efficient model. Apart from processing, management of data is also vital as large amounts of data is not only processed but also stored in the cloud. The author of (Shakil and Alam 2014) presents a novel clustering approach towards data management in the cloud. The author presents the various places where data management tasks could be performed and proposes an efficient technique for the same.

20.3.5 Intelligent Approaches Towards Data Processing

IoT enabled healthcare systems harness the power of intelligent data processing models and approaches to perform data analytics (to try and obtain meaning from data), to indicate trends in data, to clean the heterogeneous data obtained and also to design and implement applications capable of performing predictions from patient legacy data for early diagnosis and treatment of disease. As brought out by (Qi et al. 2017), the decision of choosing the correct data processing approach from the wide array of available approaches cannot be done in an absolute manner as the size, type and format of data and the application that is going to digest the data, must be considered and the trade-off among time, space and cost must be evaluated before arriving at a proposition. This chapter aims at outlining the approaches (Qi et al. 2017), so that the reader gets a clear picture of the options that exist.

Data Oriented Approaches: Supervised and unsupervised learning algorithms drive the data oriented approach for data processing. In layman terms, supervised learning algorithms are made use of to generate prediction models which can be reliably arrived at by training the model with legacy data by providing the actual outcomes for a few (at times large) input measurements. This is popularly referred to as the training data set which forms the basis of prediction. As is common to any learning algorithm, cost minimisation i.e. variation between actual outcome and predicted outcome (tested by providing a smaller dataset, commonly referred to as the testing set) is the ultimate motive as it proves to be a direct indicator of the reliability of the prediction model.

Activity recognition, clinical decision making and symptom rehabilitation (Qi et al. 2017) are few implementations of supervised learning approaches made in IoT enabled healthcare systems. Artificial Neural Networks (ANN), Bayes Network (BN), Support Vector Machines (SVM) etc. are supervised learning approaches to name a few. The literature of IoT enabled healthcare systems shows that these approaches have been used both individually and also in combinations, giving rise to a more hybrid sort of approach, with one another to derive suitable implementations. Unsupervised learning algorithms are mainly centered around clustering of the huge amount of raw data fed to these systems.

K-mean clustering algorithm and Gaussian mixture model are typical examples of the same. Clustering approaches find application deeper into the hierarchy by being utilised in laboratories for extensive research and diagnosis purposes thereby extending the reach of IoT systems. Clustering trends reported in genetic data of patients to indicate affinity trends in the genetic heredity and history of diseases in families of the patients, characterising the different types of physical activities using data generated from numerous wearables and sensors are examples of implementation of this approach.

Knowledge Based Approaches: Knowledge based approaches try and map the knowledge owned by individuals such as healthcare professionals or clinicians, to computer algorithms to achieve a system based on organisational knowledge model construction and inference rules. They can be simply understood as three module system.

The first module contains the interface that allows users to query the system, the second module interacts with the back-end knowledge base to arrive at decisions and the third module i.e. the knowledge base is loaded with expert knowledge as rules that are rigorously utilised to arrive at computerised decisions. These systems are applied as decision making systems and also utilised as tailor made software to act as a continuous aid to chronic disease patients and elderly patients living alone by providing services such as monitoring, day-to-day advice, clinical appointment reminder based on the condition of the patient etc.

The literature of implementations of this approach (Qi et al. 2017) shows various successful deployments that have incorporated this model. For example, an IoT enabled system has been proposed that supports home based care for breast cancer patients by providing structured advice to patients that are derived by the smart system. The author of (Kaur and Alam 2013) proposes an intelligent system that can be used to handle data related to atrial fibrillation, a disorder leading to irregular heat beat. The system makes use of a knowledge based approach that has been hybridised to emphasise the role of knowledge engineering in the development of such systems.

Other examples include a context based reasoning system for continuous monitoring of chronic patients, a smart system that generates disease assessment and recommendations of asthma patients to be made use by clinicians, etc. Knowledge based approaches can be subjected to further classification based on the idea behind the reasoning model that is used. Syntax based approaches contain two layers, the bottom layer being composed of Hidden Markov Model (HMM) and Bayes Network (BN) and the top layer being composed of Context Free Grammar (CFG), and it follows a language grammar based ruling to arrive at the structure of the reasoning model.

Logic based approaches define entities and a set of rules are inferred to achieve rationality. Ontology based approaches are seen to be the most bendable approach as it offers a more extensive control over specifying the tweaks of the organisational structure. It defines concepts, properties and relationships among the units of the organisational structure.

Hybrid Approach: Hybrid approaches are brought into the picture as both data oriented and knowledge based approaches are seen to have their own set of shortcomings. While it is difficult to deal with the heterogeneity present in the training samples prepared using data collected from a wide array of heterogeneous devices, the knowledge based approaches are seen to be less robust when dealing an uncontrolled environment such as that of a hospital or clinic.

Research suggests that adapting and interoping both of the above approaches to arrive at the hybrid approach proves to be beneficial and helps harness the power of both while ensuring that each approach complements the pitfalls of the other. The author of (Qi et al. 2017) mentions a few examples of the application of this approach such as the COASR, a suitable case which combines the two approaches to help elderly people at home with self-management.

20.3.6 Data Validation

Lifelogging data presents itself as one of the most important raw material to be fed into an intelligent system as it captures a satisfying extent of physiologic and geographic data of an individual. Obtaining individual specific information such as heart rate, body temperature, physical activity, geolocation etc. are examples of the same. But as is the major challenge to any IoT based system, the heterogeneity of the devices used and varied lifestyle patterns of individuals, the data so obtained is inconsitent and non standardised.

As a knowledgeable reader would understand that enforcing protocols or standards would not prove to be a good solution as an IoT based intelligent healthcare system is expected to work in an adaptive manner. Thus, validation of data so obtained from devices becomes an area of active research. LPAV-IoT model, is proposed by (Po et al. 2016) which validates the lifelogging data against a set of rules and provides a descriptive analysis of the reliability of data, noise introducing factors and errors causing uncertainty in the data.

It is seen as an adaptive model as it provides a dynamic standardised empirical analysis workflow that is capable of usage specific updation, IoT enabled Personalised Healthcare System being one. Legacy data is fed into the LPAV-IoT model to instantiate the validation rules. The model works as a dynamic recurrence, as is expected from any automated system, and the initial set of legacy data grows over time. The validation rules can be updated by replacing the initial set of legacy data with a new one. The model works on a four layer system of investigation, methodology, knowledge and action.

The uncertainty in data is categorised, based on the cause and frequency of occurrence, as irregular and regular. The investigation layer generates the uncertainty measurement matrix and a set of investigation approaches is proposed by the methodology layer. The knowledge layer establishes a set of validation rules and principles to effectively remove irregular uncertainty and try and minimise/manage regular uncertainties. The action layer provides with the set of actions, derived from the results of the previous layers that could be carried out. The proposed method in the LPAV-IoT model makes use of various descriptive statistical formulations for arriving at calculative conclusions to be able to propose the said model to eliminate irregular uncertainty and estimate the data reliability.

Rigorous research is being carried out in developing more models that can incorporate more impact factors, take into account more human specific diversities and error causing sources, so that one could increase the reliability and consistency of the huge volume of data generated.

20.4 Personalised Healthcare Systems

IoT enabled Personalised Healthcare Systems (PHS) present a befitting example for pervasive healthcare and aims at fulfilling its motive of being able to provide healthcare to anyone, anywhere and anytime (Varshney 2005) thereby overcoming any geographical, demographic and technological barriers. It makes use of the platform architecture and intelligent data processing models, discussed in above sections of this chapter, to perform various healthcare related activities such as realtime health monitoring, on demand availability of patient records, emergency assessment, remote surgeries, digital prescriptions and digital bill payment alternatives interoping.

ZigBee Based Monitoring: One such implementation is the system to monitor physiological parameters of patients admitted to a hospital which does not make use of the conventional WLAN or Bluetooth technologies, opting instead for ZigBee based implementation and deployment (Kodali et al. 2015). Making use of wireless technologies eliminates the need of a healthcare professional for periodic recording, a digital approach of Electronic Health Records (EHR).

The onset of IEEE 802.15.4 standard for physical and MAC layers of wireless communication paved way for a more rigorous implementation of the ZigBee protocol (Baronti et al. 2007), which proves to be a better alternative to conventional protocols that pose power consumption and scalability as challenges during implementation of a fully functional unit. As stated in (Kodali et al. 2015), this system makes use of LM35 temperature sensor to obtain physiological data (temperature data in this specific implementation), transmitted to the logic unit of the IoT enabled system.

This unit makes use of a gateway to collect data through a Universal Asynchronous Receiver and Transmitter (UART), at preconfigured periodic intervals, and relays the same after processing it to a web server. Once it reaches web servers, application developers may obtain the data easily and novel methods can be devised to render data, not in an obsolete format, to be able to cover the diversity of the end user. Suitable authentication and sensitive data protection measures may also be enforced accordingly.

Sepsis Detection: Another such implementation is a prediction model for Severe Sepsis (SS) of patients admitted to ICU, incorporated with an electronic alert generation mechanism (Kamaleswaran et al. 2018). Sepsis is a serious clinical condition occurring in patients admitted to the ICU, which according to (Sepsis https://en.wikipedia.org/wiki/Sepsis) arises when the body's response to infection (inflammation) causes injury to its own tissues and organs. Severe sepsis is a heightened version of sepsis leading to multiple organ failure. It is one of the major conditions having high mortality rate for patients admitted to the ICU.

The implementation proposed in (Kamaleswaran et al. 2018) uses intelligent learning approaches such as Logistic Regression (LR), Random Forests (RF) and Convolutional Neural Network (CNN) to establish a prediction model for SS using the physiomarker data of patients and completes the versatile system by making use of an alert mechanism. In this specific implementation the study was performed on children admitted to the ICU, presenting a paediatric case, but the same model could be extended to a more general application as well. Five statistical values and seven Probabilistic Symbolic Pattern Recognition (PSPR) features were obtained for each of the five physiologic data to be used, which produced a total of 60 physiomarkers to be fed to the intelligent system. This information was obtained from the Electronic Health Records (EHR) of the patient.

Systemic Inflammatory Response Syndrome (SIRS), which was previously considered a sufficient enough marker for mortality prediction, was used as a criteria to determine the chances of SS and once the physiologic data met the pre determined conditions a flag was raised and an alert sent to the healthcare officials and teams on their smartphone with alert characteristics for immediate response and course of action. In addition a SS label was also recorded with a timestamp and added to the patient's EHR as part of a more standardised observation recording system for future use.

Etiobe: Apart from patient care, implementations have been devised to support and promote a healthy lifestyle, a variant system that is moderately active and distances from a manually controlled environment, as in the above applications. Etiobe (Baños et al. 2011), is an e-health platform comprising of three independent factions, coordinating in real time, to help prevent and treat obesity in children. It presents itself as an application that is well connected, in the sense that it establishes a routine between the healthcare official, the child and also the parents or guardians.

Clinical Support System (CSS), a tool used by the clinician to store and maintain patient records and also to provide digital prescriptions and routines to be followed by the kids. An alert system is also built into this tool to raise alarms towards trends that indicate severe cases obesity in the patient. Home Support System (HSS), a tool rich in user interface elements that is designed and implemented to resemble a smart electronic personal trainer. Data obtained from this is immediately sent to CSS for clinician monitoring and analysis. Mobile Support System (MSS) is comprised of a personal digital assistant and a sensor recognition platform called Therapy Intelligent Personal Sensor (TIPS).

TIPS is used to obtain the context based information (geoposition, posture, physical activity) and physiological information (heart rate, skin conductance, breathe frequency) that is relayed to the application enabling remote monitoring for the clinician. MSS tool is primarily used to track the dietary trends and physical activity of the individual. Each tool of the platform is equipped with an appropriate authentication system to prevent unauthorised access to sensitive data and is observed to follow the security patterns and conventions of a network enabled smart application that entertains a diverse set of users.

The Etiobe e-health platform, wraps around this three tools, and is seen as an implementation that is smarter, secure and robust than relative conventional applications as discussed above, in the sense that it presents a working model in the natural environment of the users, rather than a manually controlled environment of a clinic, and also is seen to align relatively more towards de-centralisation, features that are expected from an IoT enabled PHS.

20.5 Conclusion

Since its advent decades before, IoT enabled healthcare systems have been seen to undergo rapid and powerful changes. As mentioned at the beginning of this chapter, this process was catalysed by the growth in sensing technologies, storage facilities, processing capabilities and also in versatility and flexibility of end user applications. This chapter aimed at providing a comprehensive understanding of the architecture, devices, network implementations, data processing models and various deployments of IoT enabled healthcare systems to the esteemed reader. As the literature of such systems reveal, information security and ensuring privacy of users prevails to be a major concern in this domain. IoT enabled systems present an even more tougher case as the heterogeneity of devices involved is large and also the amount of data generated is massive.

Vulnerabilities may exist in the network where MiTM (Man in The Middle) attacks could be carried out to obtain the data that is being transmitted. Securing data in the cloud is seen to have emerged as a separate field of research pertaining to its vastness. Attacks may be carried out extensively at the application side. If the end user applications of the IoT based healthcare system are web based systems then they may be prone to various web based attacks such as injection, cross-site scripting, cross-site request forgery etc. Much of the data is stored and processed at the cloud, therefore having a secure cloud service becomes vital. Securing the cloud is an area being actively researched upon.

For instance (Bashir et al. 2013) presents an extensive coverage of the various threat models in cloud based services and also thereby presents novel solutions to a few. Another work done by (Alam and Sethi 2013) analyses the risk factors that a government organisation may face in migrating to the cloud and how to mitigate them. Such works can find application where government based healthcare systems are to be implemented which may involve processes like identification of users based on some global identification repository. This tends to increase the risks as even more sensitive data gets involved. In another example, a particular but dangerous attack, Distributed Denial of Service (DDOS) (Alam et al. 2014) was introduced.

The author analyses the various reasons that make a cloud based system vulnerable to this attack and also proposes an intelligent system based on neural networks that would help mitigate the same. Hence developing, implementing and deploying a fully functional and highly secure IoT based healthcare system remains to be a big challenge and also an area that is being highly researched upon.

IoT based healthcare systems are continuously evolving to become more robust. This has given rise to a new range of healthcare devices that could be looked upon as modern day marvels. Ingestible sensors, which are nothing but pill sized electronic devices composed of biocompatible materials that provide with power, micro processing and control capabilities to the device, is one such example. Gut gas sensors and bacteria on a chip are a few actual implementations of the same. Moodables are another example of these modern day marvels. Head mounted, these mood altering devices send low intensity current to the brain to alter and in some cases replace the mood of the patient that is admitted to the hospital.

Hearables are devices that have been changing the scenario for patients with hearing problems. These small and portable devices are growing rapidly both in usage and also in features, to help patients with hearing problems. These marvels could be justly called as half baked as they lack complete implementation. But these devices have paved way to a new phase in the life of IoT enabled systems and it would be safe to say that these devices could change the landscape of such systems.

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