AI based Smart Healthcare Monitoring in India in response to COVID 19: A Concept Based Approach for Patients with Non-Communicable Diseases

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Abstract
In this 'New Normal' post-COVID-19 modern world, people's health is becoming increasingly important to track. An advanced technology that uses sensory instruments to track and record critical parameters and communicates with others is the need of the time. It's difficult to keep track of all of the medical parameters and post-operative data of people with non-communicable diseases like diabetes and heart disease on a continuous basis. The system discussed here to be designed for patients who are confined to their homes, particularly when going out and being exposed to the outer world is prohibited. This paper proposed a groundbreaking health management system based on the Internet of Things (IoT) for accessing patient medical parameters in both local and remote areas. When a person's wellbeing becomes urgent, this initiative seeks to send an emergency alert to family members or loved ones. A cloud server records data from the patient's temperature sensor and pulse sensor; the data is analyzed using support vector machine algorithms to identify irregular conditions, and an emergency message is sent to the rest of the family via a mobile application, as well as a warning message to the nearest hospital.

Keywords: Healthcare, Internet of Things, Smart hospitals, Big data, Cloud computing, Blockchain, Electronic health records, Smart-health, IOT-Healthcare, Healthcare sensors, Remote health monitoring, Healthcare Blockchain

Introduction

The invention of Smart Healthcare Systems, as well as major advances in medicine and public healthcare, have increased the Quality of Life (QoL) in developing countries. As a result, there is an increasing need for low-cost remote health monitoring that is simple to use for the elderly and patients with non-communicable diseases. Recent technology allows for the recording of parameters through sensory devices and communication with others. It's difficult to keep track of all of the medical parameters and post-operative data of people with chronic diseases like diabetes and heart disease on a continuous basis. The system was created for in-home patients, particularly when going out for routine check-ups with healthcare professionals is difficult due to limitations during pandemic such as COVID 19 or when the individual is alone. This paper proposed an AI-based groundbreaking health tracking system that uses the Internet of Things to access the patient's medical parameters in both local and remote locations. When a person's wellbeing becomes urgent, this initiative seeks to send an emergency alert to family members or loved ones. A cloud server records data from the patient's temperature sensor and pulse sensor; the data is analyzed using support vector machine algorithms to identify irregular conditions, and an emergency message is sent to the rest of the family via a mobile application, as well as a warning message to the nearest hospital.

The entire remote health-care monitoring system consists of sensors, actuators, advanced communication technology, AI & ML algorithm-based prediction system, and allows the patient to remain in the comfort of his or her own home. These devices can constantly monitor a person's physiological signs in real time, assess any health problems, and anticipate any potential anomalies in order to provide feedback to doctors.

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A microcontroller is used in a Health-Care Monitoring System (HMS) to track and process health data and send an SMS to a doctor's phone or any family member who can take emergency steps (Fig. 1).

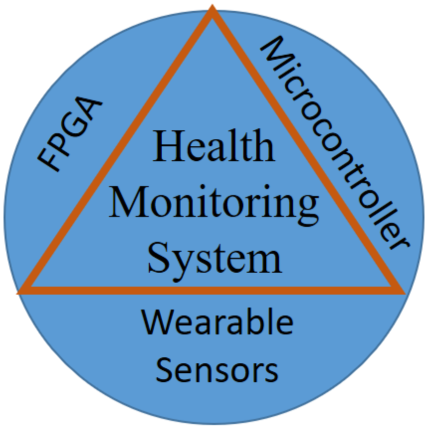

Fig. 1. Block diagram of Health-care Monitoring System (HMS).

The key benefit of the above mentioned device is that it can constantly track any health issues in real time. HMSs are widely used in hospital environments, home care, and to monitor the vitals of athletes (heart rate, blood pressure, and body temperature). All of this crucial information is handled by numerous sensors built into the systems. Microcontrollers and wearable sensors, as well as Field-programmable Gate Arrays, are commonly used in the health monitoring systems shown above (FPGA). An attached transmitter receives physical heartbeat signals, processes the information, and sends it via Wi-Fi/3G/4G/5G. The receiver then passes this critical data to the machine in the next step. A microcontroller in the transmitter senses the patient's pulse, converts it to a voltage signal, and shows it. The same concept is used in HMS, where wearable sensors detect body temperature, blood pressure, and pulse rate without the use of wires. Protocols like Bluetooth are used for wireless data communication over short distances. The HMS makes use of analogue-to-digital converter technology. The FPGA is digitally linked to the entire device. As shown in Fig. 2, the electronic health management architecture is divided into three main layers.

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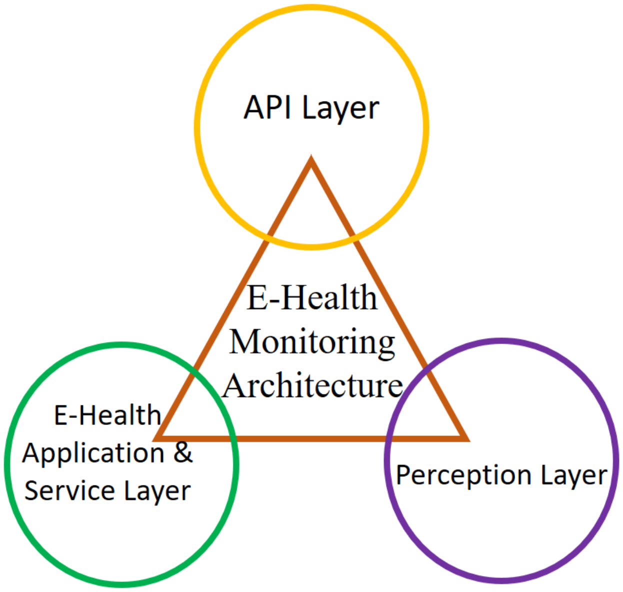

Fig. 2. E-health Monitoring Architecture.

Cardiovascular diseases, cancer, chronic respiratory diseases, and diabetes are the leading causes of death around the world. Every year, more than 36 million people (63 percent of total global deaths) die as a result of the aforementioned causes, including 14 million people who die very young, before the age of 70. More than 90% of NCD-related deaths occur in low and middle-income countries, and could have been avoided to a greater degree. Around 5.9 million people died in India as a result of NCDs, with 23% of those being premature deaths that could have been avoided (WHO, 2020).

Diabetes affects approximately 463 million adults (20-79 years) worldwide, with this figure expected to grow to 700 million by 2045. Diabetes affects 79 percent of the population in low and middle-income countries. Diabetes has resulted in the deaths of 4.2 million people. Diabetes affects approximately 69.2 million people in India, with the number projected to increase to 123.5 million by 2040 (IDF Atlas, 2019). Diabetes chronicity is linked to long-term damage and dysfunction of multiple organ systems, including the eyes, nerves, kidneys, and heart (Diabetes care, 2016).

Diabetes microvascular complications are long-term issues with small blood vessels. Retinopathy, nephropathy, and neuropathy are the most common. The coronary arteries, peripheral arteries, and cerebro-vasculature are all affected by macro-vascular complications of diabetes. Atherosclerotic plaque in the vasculature that supplies blood to the heart, cerebrum, limbs, and various organs is connected to early macro-vascular disease. Atherosclerotic plaque in these blood vessels can increase the risk of myocardial infarction (MI), stroke, claudication, and gangrene in late stages of macro-vascular disease. Cardiovascular disease (CVD) is the leading cause of morbidity and mortality in diabetic patients (Zimmerman, 2016). This paper stresses the importance of introducing early detection, screening, and awareness measures to alleviate the stress of coping with complications (Chawla et al., 2016). Data mining techniques and tools were used in this study to resolve the problem of urgency in potential hospitalization needs for patients based on a collection of patient data patterns. The support vector machine model (SVM) has demonstrated expertise in identifying people with common diseases such as diabetes and pre-diabetes in the general population (Yu et al., 2010). Artificial intelligence (AI) is readily assisting in clinical decision-making in the area of medicine. Most of the entirely attributable AI algorithms in this area are derived from related fields of statistics and probability theory; examples include neural networks, deep learning, classification and association rules, support vector machines, and text mining pipelines; others include Decision trees, nave Bayes, logistic regression, and random forests. The systems described above should be integrated into analytics pipelines that extract information from data in the form of understandable models and actionable decision-support recommendations. Data mining is a term used to describe the process of designing such pipelines (Guidici et al., 2009; Fayyad et al., 1996). Various data mining techniques are used to generate new predictive models based on existing risk prediction calculators and data from a single clinical site for accurate disease control and patient care (Cichosz et al., 2015).

Background

Because of the widespread availability of low-cost, secure wearable sensors, healthcare informatics is undergoing a revolution. Smart hospitals have taken advantage of the innovation of Internet of Things (IoT)-based sensors to build Remote Patients Monitoring (RPM) models that track patients at home. The RPM model is a real-world example of Ambient Assisted Living (AAL). The long-term tracking of patients using AAL framework systems produces vast volumes of data on a regular basis. As a consequence, to store, process, and analyze big health data, AALs can use cloud-based architectures. In the healthcare sector, the use of big data analytics for handling and analyzing large amounts of big medical data has begun to change the paradigm. Advanced software systems, such as Hadoop, have progressively promoted medical assistive applications because they allow for data collection in its native form, which can be stored in data warehouses as electronic medical records. Spark and its machine learning libraries, on the other hand, can analyze large amounts of medical data ten times faster than MapReduce. State-of-the-art cloud technologies are capable of processing large amounts of data, which bodes well for the development of smart healthcare networks capable of providing life-saving advanced medical services. Patients with Non-Communicable Diseases (NCDs) and the elderly who live alone will benefit from smart Remote Patient Monitoring (RPM) models that use cloud-based technologies. The use of a cloud-based monitoring model to track the RPM of patients with chronic diseases (blood pressure problems) for 24 hours with a reading every 15 minutes is useful in predicting the patients' health status.

The RPM technology allows patients' vital signs to be tracked outside of a typical clinical environment, such as at home, in a clinic, or in a hospital. Incorporating RPM into NCD and chronic-disease treatment increases a person's quality of life by helping patients to preserve their independence, avoid complications, and reduce personal costs (Bayliss et al., 2003). RPM helps to accomplish these goals by using IoT and cutting-edge technologies to provide treatment. When patients are handling their complex self-care processes, such as home hemodialysis, this type of patient monitoring is most desired (Cafazzo et al., 2009). RPM's core features, such as remote tracking and data pattern analysis of critical physiological parameters, allow for early identification of deterioration, minimizing emergency admissions, morbidity, and hospital stay length (Centre for Technology and Aging, 2010; O'Donoghue et al., 2012; Coye et al., 2009; Vavilis et al., 2012).

RPM's numerous implementations have resulted in a plethora of RPM technology architecture variations. Most RPM technologies, on the other hand, are designed around a four-part architecture (Smith et al., 2010).

• Sensors connected to a device that can calculate physiological parameters and that too enabled with wireless communications.

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• Local data management with patient's site having interfaces between sensors and centralized data servers and/or healthcare providers.

• Data sent from sensors, local data storage, diagnostic applications, and/or healthcare providers is stored in a centralized repository.

• Software applications that diagnose and generates treatment suggestions and intervention alerts based on data analysis.

Depending on the disease and parameters controlled, various combinations of sensors, storage, and applications will be deployed (O'Donoghue et al., 2012; Smith et al., 2010).

Sensors on peripheral instruments such as blood pressure cuffs, glucometers and pulse oximeter gather medical data such as blood pressure and other subjective patient data. Wireless telecommunication systems are used to send the obtained data to healthcare providers. The data is then analyzed by a healthcare practitioner or a clinical decision support algorithm for possible issues, and the patient, caregivers, and health professionals are automatically notified if a problem is discovered (Centre for Technology and Aging, 2010). As a result, prompt action guarantees successful treatment and patient management. Education, test and drug reminder reminders, and a means of contact between the patient and the provider are also included in the newer applications (Centre for Technology and Aging, 2010). RPM applications are used exclusively in the following disease conditions or ailments, but RPM is not limited to such conditions.

Diabetes

Multiple parameters, such as blood pressure, weight, and blood glucose, must be continuously monitored and controlled in order to manage diabetes. Real-time monitoring of critical parameters such as blood glucose and blood pressure readings, for example, provides urgent warnings to patients' families and healthcare providers, allowing for timely intervention. There is proof that regular diabetes management with RPM is just as successful as a three-month clinic visit (Chase et al., 2003).

Congestive heart failure

RPM improves QoL, patient-provider relationships, shortens hospital stays, lowers mortality rates, and lowers healthcare costs, according to home monitoring for heart failure patients (Martinez et al., 2006).

Telemedicine in correctional facilities

The prison and correctional facility in Florida was a pioneer of RPM adoption, experimenting with telemedicine for the first time in the late 1980s (Illove, 2016). Oscar W. Boultinghouse and Michael J. Davis are two of the doctors involved in this initiative, and from 1990 to 2007, Glenn G. Hammack led the University of Texas Medical Department in developing a groundbreaking telehealth programme in Texas state prisons (Freudenheim, 2010).

Veterans Health Administration

The United States Veterans Health Administration (VHA) is the country's largest integrated healthcare system, was one of the first to introduce, incorporate, and evaluate RPM technologies. RPM use should be expanded to include post-traumatic stress disorder, common chronic disorders, cancer treatment also including palliative care. As a result, VHA has recorded improvements in a number of metrics, including fewer visits to emergency rooms, hospitalizations and nursing home admissions (Kim et al., 2016). The

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implementation of RPM has led to a reduction in operating costs, according to results from the VHA Care Coordination/Home Telehealth program (Darkins et al., 2008).

Trial of a Whole System Demonstrator in the United Kingdom

The Whole System Demonstrator (WSD) (WSD: A Telecare and Telehealth Summary) was launched by the UK Department of Health in May 2008. The world's first randomized controlled study of telehealth and telecare, involving 6191 patients and 238 GP practices across three regions, was conducted in Newham, Kent, and Cornwall. London City University, Oxford University, Manchester University, Nuffield Trust, London Imperial College, and the London School of Economics all looked into the studies listed above.

• Death rates have fallen by 45 percent.

• A 20% drop in the number of hospital admissions

• A 15% reduction in A&E visits

• A 14% decrease in elective admissions

• A 14% decrease in bed days

• Prices of tariffs are decreased by 8%.

In the United Kingdom, Paul Burstow, Minister of Government Care Services, announced that telehealth and telecare will be expanded to include three million people within the next five years (2012-2017). (3 Million Lives Announcement).

It is important to identify the signs and manage the illness as soon as possible. Data mining techniques are used in a variety of applications. It is an exercise in determining a large amount of pre-existing database in order to produce new content. In the health-care sector, data mining is important for predicting illness based on symptoms and classifying disease as diabetes or heart disease.

The development of a new digital tool for evaluating and disseminating effective health care information is the primary reason for data mining in the health-care system. Various attributes are fed into the system here. According to those attributes, the code compares the given symptoms to the actual dataset and predicts the associated disease based on user feedback.

The development of predictive models for the onset of chronic microvascular complications in T2DM patients could aid in the evaluation of the relationship between individual factors and the risk of developing a specific complication, as well as the stratification of the patient population at the medical center and the implementation of resources to support this risk.

Purpose

Instead of going to an assisted-living facility or nursing home frequently during Pandemic, this paper presents an expansion of opportunities by remote supervision for people affected by chronic diseases to stay in their homes. Wireless user preferences for monitoring purposes (Mainetti et al., 2011), through the development of Wireless Sensor Networks (WSNs), which make up a significant portion of IoT (Khalil et al., 2014). Thanks to their benefits and diversity, WSNs are widely used in healthcare applications. In an inquiry (Rotariu et al., 2012), C. Rotariu and V. Manta's propose WSN for heart rate and oxygen saturation monitoring of patients. W. Y. Chung, S. C. Lee, and S. C. Lee, S. C. Electrocardiography (ECG) and blood

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pressure sensors were embedded into a mobile phone by H. Toh (Chung et al., 2008). An instance of a suitable solution to the IoT healthcare model is the wireless body area network. S. -L. Tan, J. García-Guzmán, F. Villa-Lopez transmits data about blood pressure, heart rate, body temperature and oxygen saturation to the base station using Wi-Fi technology (Tan et al., 2012). J.Wannenburg as well as R. To track the health parameters of the patient, Malekianc uses Bluetooth technology and a smartphone to (Wannenburg et al., 2015).

The success of wearable technology and IoTs has now brought great opportunities to the healthcare domain, along with challenges. Through cloud storage and big data analytics, the whole system is activated, data collected from individual devices contributes to big health data and useful insights can be extracted from that. This data can be used by hospitals, health centers and medical institutions to connect with other Electronic Health Record (EHR) data, such as clinical notes, to promote health surveillance, disease detection and treatment management.

With this paper, I propose a mobile device for personal health data sharing, such as a user-controlled, block chain-based framework for the exchange and collaboration of personal health data. The entire system can be based on Hyper-ledger Fabric (Cachin, 2016), which is nothing but a permitted block chain that often needs the authentication of the network nodes, and realizes a privacy preserving personal healthcare system with a wider coverage of the healthcare environment from end to end encrypted computer to the cloud, as well as the focus on health data consumer ownership. As follows, the remainder of the paper is structured. The overall system design, including the architecture, system organizations, main establishment and system procedures, comprises the methodology. Then there are substantial allegations relevant to work completed. The scheme discussion is defined, concludes the paper and talks about the future work.

Methodology

I. SYSTEM DESIGN

A. System Overview

The proposed model adapted from 'user-centered sharing of personal health data' is Figure 3. (Liang et al., 2017). Six entities are included, namely users, wearable devices, providers of healthcare, hospital bed/room, database cloud and network block chain.

Proposed Model

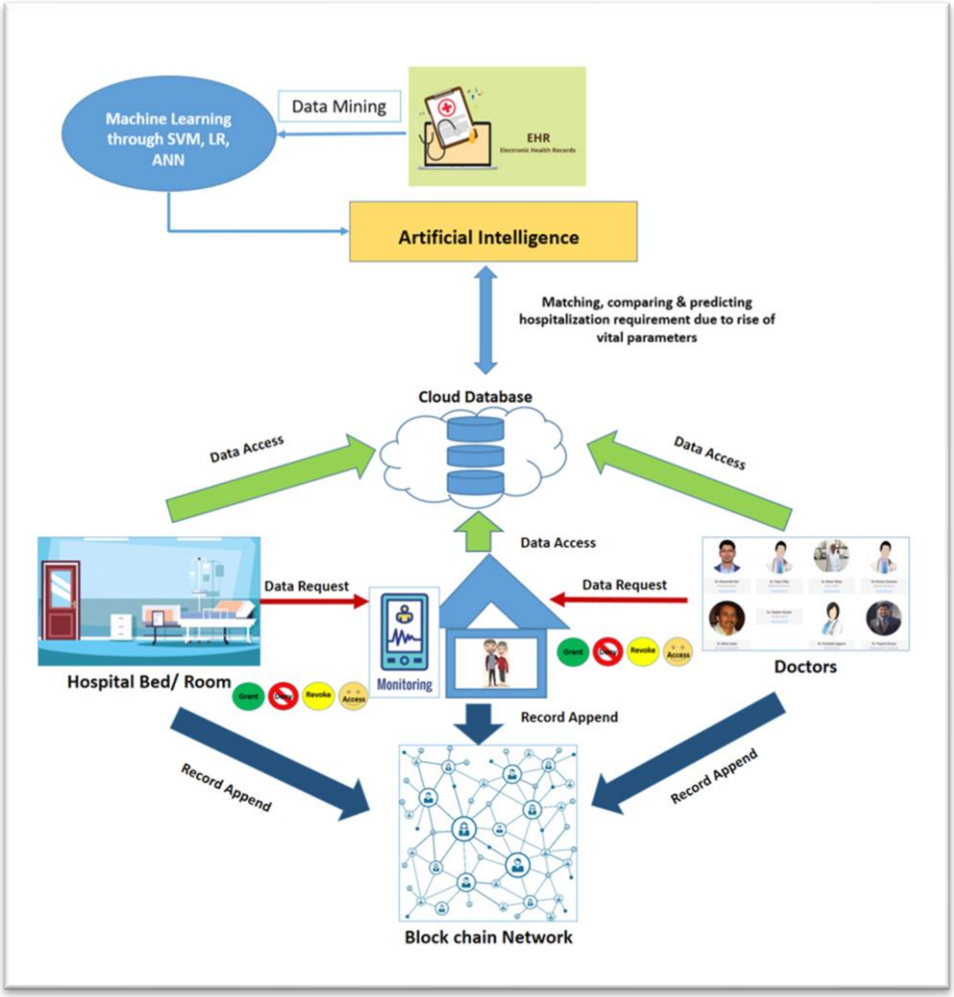

Figure 3. 'Exchange of Patient-centric personal health data' (Liang et al., 2017)

B. System Entities

User: System users obtain information from wearable devices that track the health information of users, such as walking distance, sleeping conditions, and heartbeat. The above data will then be submitted via a mobile application to a cloud service hosted on a trusted platform. The individual is the owner of personal health data and is responsible for granting, refusing and removing access to the data from any other entity, such as providers and institutions of health care.

When every client seeks medical attention, the patient will share the health details with the desired physicians. Access to the data is revoked after the operation is completed in order to deny doctors access to the data consecutively. Likewise, this relates to user-healthcare provider relationships. In addition, the user has a provision to report regular activities according to a recommended medical procedure, such as medication enforcement, to share changes and better improvements with the treatment provider.

Wearable Device. A very significant component of the entire system that translates original health information into human readable format and then synchronizes the data also by the user to their online account. Each account is associated with a set of wearable devices and possible medical devices.
It will be uploaded to the blockchain network for record keeping and protection of integrity when a piece of health information is created. Provider of Treatment. A certain user is appointed by healthcare providers such as physicians to conduct medical tests, provide any advice or provide medical treatment. Meanwhile, under the user's permission, the medical treatment data can be uploaded to the blockchain network for data sharing with other healthcare providers. And the current healthcare provider can request access from the user to past health records and medical services. On the blockchain, each data request and the corresponding data access is registered.
Bed/ Space Hospital. Users can request in any patient a hospital room/bed or ICU, doctors or ICU in-charge may request user data access, including user health data from wearable devices and medical care history, to provide better service duty. As such information is permanently registered on the blockchain network and transparency and trustworthiness is guaranteed, users can not hide or alter medical care history details.
Network Blockchain. For three reasons, the blockchain network is used. For health information obtained from both wearable devices and healthcare providers, each hashed data entry for integrity protection is uploaded to the blockchain network. For access to personal health data from healthcare providers and hospitals, each request for data access should be processed to obtain a decentralized permission management protocol authorization from the data owner. The policies for access control should be stored on the blockchain in a distributed manner that ensures stability. In addition, for further auditing or review, each of the permission requests and access activities should be registered on the blockchain.
Database Cloud. User health related data, data requests from healthcare providers and insurance agencies, data access history and data access management policies are stored in the cloud database. Access to data is accountable and traceable. Once data leakage is detected, the malicious entity can be identified.

C. Requirements

The features required by stakeholders and potential users consist of a device capable of monitoring the vital signs of the patient. If a current activity is common, suspicious or unsafe for the monitored individual, the system should identify it and alert the people responsible for treatment in the event of irregular occurrences. A subsidiary component should include additional details regarding such vital signs in the case of activity that is regarded as suspicious or hazardous. In addition, the criteria that the system should be easy to install, run and maintain and also guarantee the privacy of the subject are also the system's general constraints.
In addition, real-time safe non-invasive measurements are critical basic constraints of the monitoring of vital signs. As a basic restriction, the high validity of the behavior definition is also considered. In Table 1, both general and comprehensive functionalities, along with the relevant specifications, are summarized. The table consists of innovations and algorithms that are feasible.

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Functionalities		**Particular Constraints**	**Possible Technologies & Algorithms**
General	Itemized		
Vital Signs Monitoring	Heart Rate, Pulse Rate	Non-invasive method	acoustic, infrared, Photoplethysmography (PPG) or Heart Fitness apps in Smartphone (Heart Rate Plus, Cardiograph), Smart Watch Heart Rate Monitoring, Fitbit
Behavior Classification	Normal, Suspicious, Danger	High Validity	Decision trees, genetics algorithms, neural networks, support vector machines, k-nearest neighborhood
Control	Easy to handle	Fast	Inter-Integrated Circuit, Serial Peripheral Interface
Communication	Possible long range upto 40 m	Secure	Bluetooth,Wi-Fi, RFID, 3G/4G/5G
CCTV Surveilance	Video		Labour-based surveillance system
Contact or Non-contact Photoplethysmography	Camera Specifications		CMOS sensor, LED Flash, Pixel size of Smartphone Camera

Table 1. Possible Technologies and algorithms for each functionalities

Figure 2 shows the flow chart of the classification of actions as natural, suspicious or hazardous. Health data and vital data collected from the attached sensors are combined with information on the time of day, section and area of the apartment, thus describing the current operation.

Next, the above map is compared using machine learning techniques against typical behavior patterns, and the event is labeled. Various machine learning algorithms such as decision trees, Support Vector Machines (SVM), k-Nearest Neighbor (KNN) and Behavior Vector (BV) have many advantages that the behavior classification approach can capitalize on. Developing the same six-component BV behavior classification consists of five components based on data collected, such as Time of Day (ToD), Apartment Segment (SoA), Zone of Operation (ZoA), Mode of Activity (FoA), Period of Activity (DoA), and Class of Behavior (CoB) will be the sixth component, these all are based on the previous observations of person being monitored. The ToD component measurement is performed by the timer of the microcontroller and its configurable timeframes, which can also be modified with personal habits and even seasonal changes. From the predefined layout of the apartment and estimates of the PDR, the SoA and ZoA components are determined.

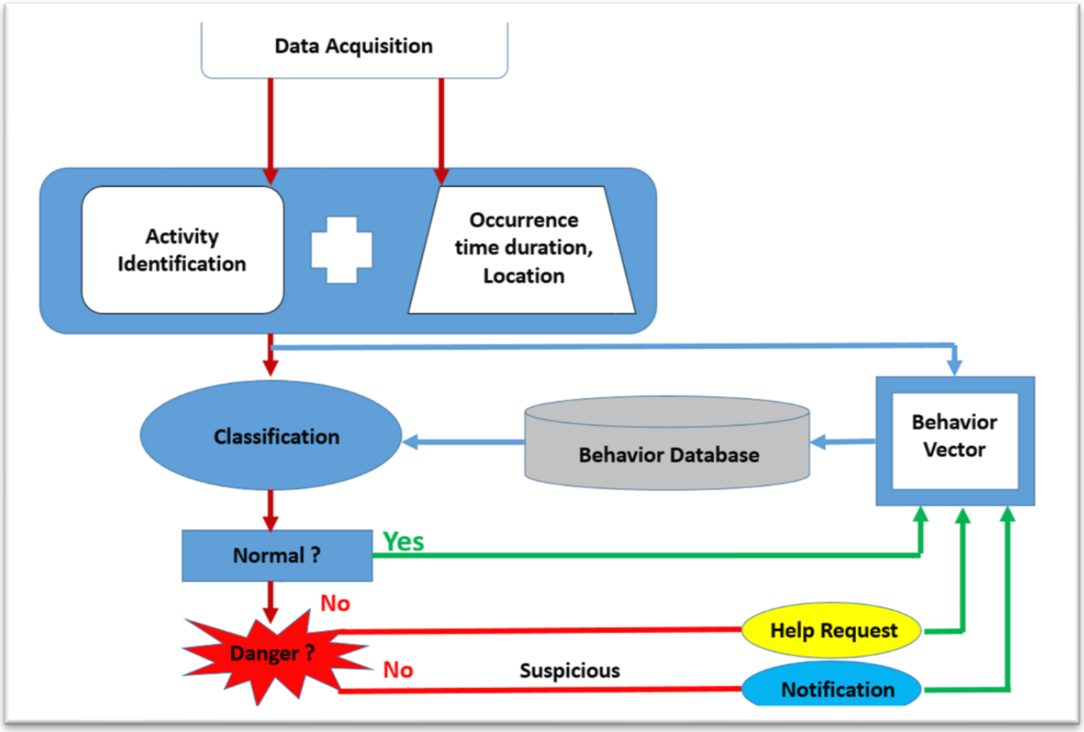

Figure 4 adapted from ‘Behavior classification scheme’ (Dziak et al., 2017)

The main objective of the method of behavior classification is to make use of the benefits of different machine learning algorithms, such as decision trees, Support Vector Machines (SVM), K-Nearest Neighbor (KNN) and Behavior Vector (BV).

Components of the Behavior vector					
ToD	**SoA**	**ZoA**	**FoA**	**DoA(Min)**	**CoB**
Morning	Bathroom	Of Lying	Lying	10/15/30/120	Normal
Afternoon	Bedroom	Of Sitting	Standing	15/23/45/180	Suspicious
Evening	Antechamber	Of Standing	Sitting	>15/>23/>45/>180	Danger
Night	Kitchen	Of Walking	Walking		
	Living Room		Tumble		

Major Arguments along with Supporting Literatures

A research published in the New England Journal of Medicine based on a randomized controlled trial involving patients with congestive heart failure found that tele-monitoring was not as effective as routine treatment while offering a benefit (Langreth, 2010). The tele-monitoring patients were instructed to call a specific number on a regular basis and answer a set of questions about their symptoms using a keyboard (Chaudhry et al., 2010). Actually, Chaudhry et al. (2010)'s method is somewhat different from the technique of remote patient monitoring (RPM) described in the preceding overview, which involves the collection and transmission of real-time physiological data through point-of-care devices. Tele-monitoring is analogous to Remote Patient Monitoring (RPM) in the sense of Forbes' (Langreth, 2010; Krumholz, 2010) research, and Chaudhry et al. (2010) also correlates RPM with negative results, and this needs to be explained at the outset. It's more difficult to distinguish between various types of patient monitoring involving modern and cutting-edge technologies without RPM terminology calibration and definition.

Discussion

Remote Patient Monitoring (RPM) is largely based on the willingness of someone to control their wellbeing. Also fresh or cutting-edge technology-based RPM implementation will go for a toss if the patient is not able to be an active participant in their treatment. In the Indian sense, cost is also an obstacle to its widespread use. Its integration into clinical practice has also been a challenging in the absence of adequate reimbursement criteria for RPM services (Smith et al., 2010). RPM incorporation is also correlated with the shift in responsibility that leads to problems with liability (Smith et al., 2010).

These recommendations are not explicit for clinicians to act any time they are going to receive a warning, regardless of the need of urgency or not. To manage the constant patient data flow, there should be dedicated professionals in healthcare. New & cutting-edge technology can become an obstacle to certain essentially non-technological healthcare providers, although it is implemented with the goal of increasing the productivity of the same. There are some common challenges that are usually faced by health informatics and cutting-edge innovations that relate to RPM.

RPM offers plenty of device options in its implementation, always depending on the illnesses or comorbidities monitored. The only major requirement is data transaction and interoperability between many components. In addition, the deployment of RPM and the successful operation of the same, largely depending on an extensive and seamless wireless communication system, may not presently be feasible to make this available in rural parts of India. As RPM involves the transmission through telecommunications networks of sensitive information of patients, there might be a concern of the information security and data privacy (Smith et al., 2010).

As discussed in this paper, Blockchain Technology can solve that. In (Kim et al., 2016) for healthcare data sharing, a mobile application is implemented but is limited to patients and doctors. (Petersen et al., 2016) suggests an interoperability proof in order to avoid the cost of computation, but did not mention access control. (Zhang et al., 2016) addresses the social network domain adoption of blockchain, but does not fully explore the benefits of blockchain. Patientory (McFarlane, 2017) is designed to use Ethereum for the healthcare storage network, but the cryptography methods are highly dependent on data privacy. The blockchain adoption in the Internet of Things environment (Liang, 2017) is addressed. MedRec (Azaria et al., 2016) is a record management system focusing on EMRs using smart contract, but raises privacy concerns.

Conclusion

I proposed a design in this paper to implement a handheld mobile healthcare system for the collection, sharing and collaboration of personal health data between individuals and healthcare providers, as well as healthcare institutions. It is also possible to extend the system to accommodate the use of health data for research purposes. The system is implemented in a distributed and trustless manner through the adoption of blockchain technology for secure exchange of patient health data. The functions of the algorithms mentioned are such that they ensure that data records are handled and that both their integrity and privacy are preserved at the same time. The unique concept of the Hyperledger Fabric-supported channel to deal with the isolated communication required by specific scenarios are also mentioned here. For future study, there is a need to explore a combination of both personal health data and medical data together and to cover a broader scenario.

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