Artificial Intelligence (AI), Big Data, and Healthcare

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Abstract

This paper provides a state of the art review of sensors in healthcare and a projection as to how Artificial Intelligence (AI) along with Big Data can improve and reduce the cost of healthcare. Reducing the cost of healthcare is dependent on leveraging 5 technologies, i.e. the Internet of Things (IoT), sensors, IPv6, AI, and Big Data. A IoT architecture is provided using the Cloud Standards Customer Council (CSCC) Cloud Components [15]. The described architecture will provide better and cheaper healthcare and allow researchers access to data that are not available today to further their understanding of the human body and its abnormalities.

Keywords: Artificial Intelligence, Internet of Tings, Big Data, Healthcare, Sensors

Section 1 Introduction

The US Administration of the Aging states that in 2013 the number of persons older than 65 was about 44.7 million or 14% of the US population and that in the year 2060 this number should approximately double [1]. Similar changes are occurring worldwide according to [2] "…by 2050 approximately 20% of the world population will be at least 60 years old". This increase in longevity can be attributed to our healthcare industry in general and the results garnered from the medical research community e.g. heart, cancer, and diabetes research. The numbers are staggering when considering dementia. According to [3] Alzheimer's patients will reach 16 million by 2050. Currently these patients are disabled for 9 to 20 years. However, it is projected that these numbers will increase to 40 to 50 years because of medical advances. The cost of medical treatment will also increase from $172 billion per year in the US to $1.08 trillion by 2050. Today's adults will spend more time caring for their parents than they have for their children.

Part of the increase in cost within the healthcare industry will be due to the raising of minimum wages, some to the increase cost of education, and some due to increases in the cost of medical services i.e. hospitals, nursing homes, prescription drugs and physicians [4]. To combat some of these projected cost increases the US government is changing the way doctors and hospitals bill their services. This new approach is called Capitation [5]. Capitation allows the government, which started with Medicare-Medicade, to pay one amount for each client. Doctors, nurse practitioners, hospitals, insurance companies, and other health providers formed groups called Accountable Care Organizations (ACO). These organizations, both government and private, take on the risk of collectively providing quality preventative healthcare since "…there is greater financial reward in prevention of illness than in treatment of the ill." The ACO approach will require all parties to accept a collaborative approach to "…focus on the whole patient or on populations of patients, encouraging and requiring teamwork among clinicians across specialties, as well as coordination among clinical care units and healthcare organizations of all types across the continuum of care (e.g., physician groups, hospitals, health systems, payers, and vendors)". This approach puts the direct risk in keeping healthcare costs down with the healthcare industry rather than the government.

Efforts are abundant in trying to maintain or reduce the cost of healthcare. The elderly are being cared for in their homes by family, friends, visiting nurses and aids. Independent living centers have been created to help those who can still help themselves and, for those who are in physical and mental need and require 24/7 care, there are nursing homes. For those that have medical emergencies there are health clinics, physician offices, ACOs and hospitals.

A goal of this paper is to provide a state of the art review of the sensors in healthcare and provide a projection as to how Artificial Intelligence (AI) along with Big Data can improve and reduce the cost of healthcare. Section 2 provides a description of some of the current sensors being used, studied and deployed for enhancing the care of patients. Section 3 provides our Internet of Things (IoT) architecture that will reduce the cost of healthcare, provide state of the art healthcare to millions of people, and provide researchers the data they need to diagnose and prevent abnormalities that is not available today. Section 4 presents our summary and conclusions.

Section 2 Sensors and AI.

In the USA there is a commercial on TV where an elderly woman is shown on the floor and she presses a button on a device attached to a necklace, and she is heard saying “Help I have fallen down and I can’t get up”. There are many devices on the market that provide help for those individuals who wish to stay in their homes and have family members, visiting nurses, next door neighbors, friends etc. periodically check on their health status. To accelerate and enhance this capability there are numerous wireless body area network (WBAN) sensors that can be used to automatically alert 911, family members, or neighbors.

There are three types of sensors, i.e. ambient, physiological and biokinetic. These sensors can be partitioned into active or passive. An active sensor is sometimes called an actuator where based upon its sensed value it may take some action such as dispensing insulin for a diabetic. Ambient sensors record what is in the environment that the wearer is immersed within e.g. outside/inside temperature, humidity, chemical, biological, radiation and nuclear (CBRN) sensors, a wearer’s location using Global Positioning System (GPS), audio, video, images, etc. Biokinetic sensors measure acceleration and angular rate of rotation in which one can determine human movement e.g. whether the wearer is walking or is at rest. Physiological sensors or biological sensors measure human parameters as shown in Table 1 [6]. Some of these sensors can be embedded in a wearer’s clothing such as their vests, bra, etc.

Many applications use sensors embedded on smartphones that will record a person’s heartbeat, GPS location, number of steps taken, etc. However, the accuracy of these applications have gotten mixed reviews lately as to how they compare to individual sensors. See [7] for the American Heart Association’s take on mobile health technologies, mHealth.

There are newer sensors that have AI embedded within them. For example, there is the Wriskwatch [8], with a piezoelectric disk strapped to the wrist. It detects the arterial swelling at the radial pulse and can identify episodes of ventricular fibrillation, or v-fib, the most serious cardiac rhythm disturbance. Wriskwatch uses Bluetooth to send a signal when loss of pulse occurs. The device has AI software that integrates the information regarding pulse rate with a motion sensor to reduce the number of false alarms. A future instantiation will have the device emit an audible signal which will allow the patient to shut off the unit before summoning the paramedics due to a false alarm.

Table 1 Example of WBAN Medical Devices

Application	Data rate	Bandwidth (Hz)	Accuracy (bits)
ECG (12 leads)	288 kbps	100 1000	12
ECG (6 leads)	71 kbps	100 500	12
EMG	320 kbps	0 10,000	16
EEG (12 leads)	43.2 kbps	0 150	12
Blood saturation	16 bps	0 1	8
Glucose monitoring	1600 bps	0 50	16
Temperature	120 bps	0 1	8
Motion sensor	35 kbps	0 500	12
Cochlear implant	100 kbps		
Artificial retina	50 700 kbps		
Audio	1 Mbps		
Voice	50 100 kbps		

There are many types of sensors in the medical field that measure and record oxygen levels, blood pressure, heart monitors, etc. Research is occurring in the micro and nano chemical sensors that will provide continuous monitoring and medical diagnosis in near real time. One example of this type of research is being performed at University of Illinois at Urbana-Champaign [9]. Their research involves deploying a sheath around the heart. They have noted that current methods that sense one portion of the heart and activate defibrillators sometimes measure activity from other portions of the heart and thereby providing unnecessary electric shocks to the heart. With hundreds of electrodes in contact with the total heart via their new membranes they will be able to provide more accurate readings of heart rhythms and better-targeted electric shocks. They are also investigating: pH sensors (that can be used to predict sudden cardiac arrest,), how to power their membrane, how to store sensor data and how to upload the information to other devices.

Sensors for the medical community are being tested both within and out of living organisms. According to [10] the future will look like the following: “Present wearable health devices include heart rate monitors, ECG monitors, glucose monitors, pulse oximeters and blood pressure monitors. In the near future, they are expected to be complemented with micro and nano chemical sensors that will provide continuous medical diagnostics. These miniaturized smart sensors will be able to detect additional chemical signatures, e.g. in breath and sweat, which can be translated into medical monitoring (e.g. diabetes patients, other metabolic diseases, skin diseases and drug pharmacokinetics).”

These future devices will power themselves using the human body. They will transmit their findings via protocols such as Bluetooth Low Energy (BLE) and Low Rate WPAN or IEEE802.15.6. In addition the FCC has approved a specific spectrum for wireless Medical Body Area Networks (MBAN) with 40 megahertz of spectrum in the 2360-2400 MHz with the 2360-2390 MHz range for indoor use and the 2390-2400 MHz range for outdoor use. These protocols and spectrum will allow access to these devices via nearby computers and the Internet allowing distant personnel to monitor patients in their own homes.

Studies are being performed to track patients in their own homes using passive Radio Frequency Identification (RFID) tags [11 and 12]. Algorithms have been developed that either distribute the sensors around a room and signal strength measurements are made throughout the room in a grid fashion. Based upon the signal strengths measured at all the RFID sensors for each grid point, one develops a pattern of signal strengths recorded at each RFID sensor and stores the pattern in a database. Another approach [12] uses less RFID sensors and employs a path loss prediction model along with measurements to determine a tag’s location. The RFID tags may be inexpensive but the time and labor to map out a home may be expensive and the algorithm’s accuracy will deteriorate over time if people rearrange furniture and/or add or remove furniture.

If we integrate multiple sensors together can we reduce the number of nurses and aides that are required to monitor elderly patients who wish to live alone? Pouke, et al [13] performed a study in Finland over a two month period with monitoring the healthcare of elderly patients with varying memory diseases. They were equipped with wearable sensors to measure the patients various activities and environmental sensors to determine their location in their facility. These sensors were connected as shown in Figure 1. The patients were asked to perform normal activities such as washing dishes, cleaning their living quarters, etc. During this period data were gathered and annotated in a database indicating what the patient was performing. The researchers divided their performance into 18 classes and created avatars to mimic these classes to be viewed at the central server. These classes include for example walking, getting up, and washing their hands. The extension of this study will lead to less people monitoring the care of multiple people living in multiple locations hence bringing down the cost of caring for the elderly living alone. There are some issues that will need to be addressed such as security, battery power of sensors, cost to install and maintain, privacy, speed in which to provide aid to the patient, and the minimization of false alarms. Monitoring numerous patients while reducing cost will require the use of AI to alert the medical staff whether a patient has fallen, stopped breathing, has slept way beyond their normal time, has been in the bathroom too long, etc. We need to extend the quality of our sensors, the signal processing, and the use of AI to ultimately perform the level of care that technology can bring to the elderly.

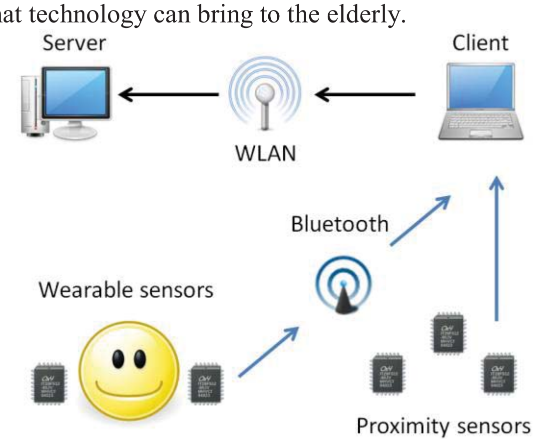

Figure 1 Abstract View of Sensor Network

Section 3 Internet of Things (IoT) and AI.

A recent paper [14] brings to light where we believe the future is headed by leveraging 5 technologies for enhancing healthcare. These are: the IoT, sensors, IPv6, AI, and Big Data. In [14] the authors develop a system design based upon the interfacing of several patient’s Electrocardiogram (ECG) via a Raspberry PI (small single board computer) connected via a Global System for Mobile Communications (GSM) module which can send and receive text messages and/or voice calls. See Figure 2 for a description of their system. The system records the ECG for multiple patients, has software to analyze the ECG where it can compute heart rate, continuously monitor each patient, alert local staff via a buzzer if the continuous analysis indicates an issue with a patient, and send messages to remote personnel regarding a patient’s status via the GSM module.

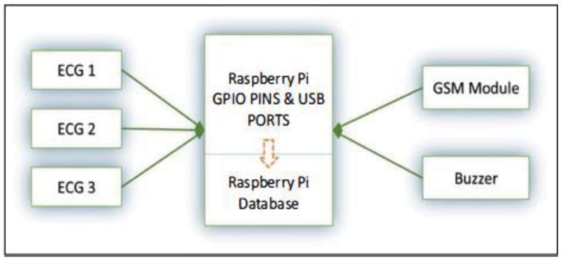

Figure 2 A Healthcare System

It is important to monitor heart patients in real time. According to [10] a monitored heart patient would have approximately 48% chance of surviving a cardiac arrest compared to a 6% chance for an unmonitored patent. What if the ECGs of these patients were analyzed in real time, beyond computing the patient's heart rate? The technology exists to retrieve these continuous readings from many sensors on a patient's body, provide alert mechanisms for extreme heart rate levels, temperature, blood sugar levels, etc. performed locally via a personal computer, similar to what was described above. However, with the advent of Internet Protocol version 6 (IPv6) we will be able to not only monitor every sensor connected to the Internet in almost real time but we will be able to activate some sensors, thereby providing healthcare via AI algorithms at various locations. (IPv6 has128 bits to identify a unique IP address or 3.4 x10^{38} or 340 Undecillion available addresses.) In addition if we could capture sensor data from many people on a continuous basis we could not only look for triggers when sensor data are out of range but we could build sophisticated signal processing and AI tools to diagnose abnormalities, actuate sensors when and where needed (e.g. deliver medications) and mine data over time. This will allow one to gain more insight into solving known abnormalities but also discover new relations between measured data and patient ailments. Scientists will be able to perform cause and effect studies, analysis, monitoring, diagnosis, and prediction based upon Big Data analytics, where Big Data relates to volume, velocity, variety, data quality and provenance of data.

With the advent of the Internet, the exponential growth in deployed sensors and the need to process data in real time has caused IoT technologies to flourish. Amazon, Google, IBM and many others are building and deploying cloud-based platforms for IoT developments. There even exists a Cloud Standards Customer Council (CSCC) that is concerned about IoT and cloud computing in general. It is an end user advocacy group dedicated to accelerating cloud's successful adoption. The healthcare industry needs to leverage these technologies to bring down the cost of healthcare. We foresee the need to implement the IoT along with stream processing, AI, data mining, and distributed fault tolerant secure data storage.

In order to describe an architecture for the healthcare industry we will overlay our thoughts onto an IoT architecture. Figure 3 depicts a high level architecture acquired from CSCC [15]. This reference provides a description of all the key elements contained within a IoT architecture i.e. the User Layer, Proximity Network, Public Network, Provider Cloud and the Enterprise Network. In our design of the IoT the thing that we wish to physically monitor is the human/patient. It is the “thing” in Internet of Things. The sensors and actuators are the devices that sense or act upon the human. The instantiation of our architecture pertains to patients living for example, in their homes, day care buildings, nursing homes, and/or hospitals. We can easily extend our architecture for patients out in the environment e.g. in automobiles, ambulances, walking in the park, trains, planes, etc. (That will be covered in another paper.)

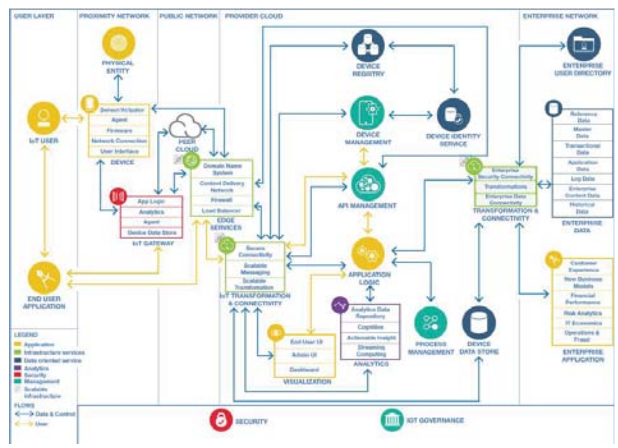

Figure 3 Detailed Components Diagram of a Cloud – based IoT Solution Architecture

In this architecture there are 3 cloud layers, the edge, the platform and the enterprise components layer.

(1)The Edge Layer: is composed of the Proximity and the Public Networks. This is where data are gathered from devices/sensors and transmitted to devices/actuators. Data flows through the IoT gateway and/or from/to the devices through the edge services to the cloud provider by way of the IoT Transformation and Connectivity. In our architecture this is where heart monitors, diabetic sensors, temperature sensors, X-Ray machines, MRI machines, etc. would interface e.g. via RF or Ethernet enabled devices to the local area network where processors will analyze results and pass it onto the cloud or process the data to determine if the sensors are out of range and an alarm needs to be sounded for the local nurse to be summoned or call 911, etc. The local processing machine could be a local PC or a Raspberry Pi computer as described above. Here resides the first line of defense software and AI algorithms to assess the status of the patient's health. It may integrate more than one sensor or actuator to determine for example if a patient has fallen, requires more insulin, etc. In addition the computing device will have a user interface so that the healthcare provider can review past data, change settings, print reports, send messages and/or data, and manage the sensors and actuators monitoring the patient. The data collected from these sensors and nodes are passed on to the next cloud layer. This Edge Layer of processing is sometimes called edge or fog computing. This approach is relevant for a large nursing home or hospital.

For smaller institutions or for elderly patients living alone the architecture shown in Figure 4 from [2] may be more appropriate where alarms and diagnosis are performed in the platform layer as opposed to the Edge Layer. In either case the system should be built with fault tolerance and redundancy in mind, employing backup generators, multiple Internet connections and eliminating any single points of failure, regardless of whether the alarms and diagnosis are performed at the edge or in the cloud. The driving factor is best stated by [2] "Intervention response time is paramount, since it is well known that time is of the essence in treating falls or heart attacks. This is true not just to avoid fatalities, but to minimize the secondary damage that might be difficult to treat. It is also important to learn the nature of the incident as soon as possible: whether the person is conscious, their exact location, etc."

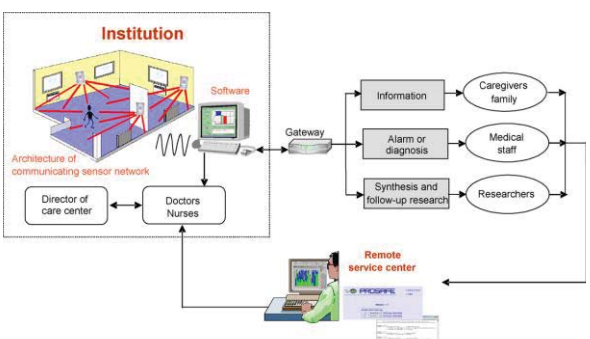

Figure 4. A IoT Architecture Design [2]

(2) The Platform Layer: is the provider cloud. This is where the data is received from the edge layer, processes and analyzes the data and provides application programmers interface (API) Management and Visualization for the total process. It also provides the connection between the public network and the enterprise network. In our design we foresee that the processing performed at the edge will also be performed in the platform layer for redundancy in case one fails since this is the crucial point or first line of care, alarm and diagnosis. This layer will provide real time analysis and diagnosis where the data from all the relevant sensors will be sent to numerous processors that will analyze the data using stream processing.

Conventional processing acquires data from sensors, medical devices, human input, or outside sources, stores these data in a database management system (DBMS) and then searches and processes these data to acquire information. However, given the severity of identifying and treating patients in real time we must process the data before storing it in a DBMS especially when considering that our architecture is monitoring multiple sensors on multiple patients in multiple homes, hospitals and/or nursing homes, or multiple ACOs. Stream processing is a byproduct of Big Data and the need to answer pressing questions in shorter time periods. Probably some of the first stream processing systems were developed for digital signal processing e.g. radar systems, where the data are continuously arriving and each return must be filtered, targets detected, tracks formed, targets classified, and identified. Imagine the healthcare domain where hundreds of patients have multiple sensors/actuators monitoring their every move 24/7. The data are encrypted and streamed to numerous processors or operators in the cloud where they are buffered slightly and operated upon and moved on to the next operator. The stream processing algorithms are operating on data from numerous and various sensors such as ECG sensors, location sensors, temperature, blood pressure, diabetes, etc. Our design is to stream all of these data and operate upon them such that we can detect if they require more insulin and how much, or whether they have fallen, or are having a heart issue and if so to take the proper action.

There are many research areas that need to be addressed to make this happen from optimization of stream processing [15], to pattern recognition in real time, to natural language processing, to diagnosing different heart issues, to AI algorithms for merging the signals from numerous sensors, to identifying that a patient has injured themselves in the kitchen while boiling water. Figure 5 shows the basic features of an ECG and images of T Wave abnormalities. By embedding AI, signal processing, and stream processing we should be able to determine T Wave abnormalities on the fly. Work is going on using AI, signal processing and knowledge bases where software can diagnose many heart ailments when a physician is not available. The future is to automate this capability so we can outperform the physician by using stream processing on numerous heterogeneous sensors along with searching the history of the patient, contained in the enterprise network, all done in near real time. It should be noted that engineers have been embedding AI in signal processing for radar and communications systems for years under the names of cognitive radar and radio. As examples see [17 & 19]

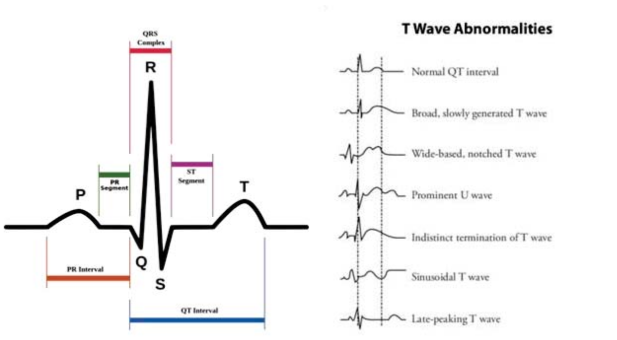

Figure 5. ECG Diagrams

3. The Enterprise Layer: consists of Enterprise Data, Enterprise User Directory, and Enterprise Applications. It is represented as the Enterprise Network. This layer communicates and exchanges data, such as the real time streaming data, from and to the Platform Layer via the Transformation and Connectivity component. In our architecture the enterprise layer contains the storage of all the data contained from all the sensors within our IoT along with structured and un-structured data related to the medical community such as audio and video files and connections to other structured files such as Electronic Medical Record (EMR) systems that reside on multiple computers in the cloud. These data are sometimes called the system's data warehouse (DWH). The data from the stream processing need to be stored for data mining and modeling. Selected data will be stored in a patient's EMR system e.g. OpenEMR, Centricity, CareCloud. The data from the stream processing are normally stored in Hadoop, an open source programming framework for the processing of large data sets in a distributed computing environment. Hadoop, or a variant, will be needed as a computational secure system for data mining and analytic processing. See [18] for an overview of different architectures for the processing and storing of Big Data arising from stream processing. We also need to be assured that the data are encrypted within the distributed system, as per Health Insurance Portability and Accountability Act (HIPAA), and may require the integration of Tahoe-LAFS, which is an encrypted fault tolerant secure method of storing files on distributed processors.

4.0 Summary/Conclusions

We have provided a motivation of our work via a description of our aging population and the rise in cost of our healthcare system within the USA. We have provided an overview of body area sensors and actuators being used and studied today. To help bring costs down and to enhance the quality of care we have described an IoT driven architecture including edge computing at the sensor level, stream processing, distributed computer processing, EMR systems, AI, and a encrypted fault tolerant secure method of storing files. The described architecture will provide better and cheaper healthcare and allow researchers access to data that are not available today to further their understanding of the human body and its abnormalities. The architecture presented here must be studied further and developed as a test bed for medical and engineering researchers.

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