A Survey on Healthcare Systems using Internet of Things

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Abstract: The Internet of Things allows things to become active users, facilitating interaction with things and the sharing of data between them. The most interesting issue in the science world, the public sector and industry in the IoT is unavoidable. It ensures a seamless relationship between doctors and patients that results in medical treatment with high quality results. This is accomplished by constant surveillance of patients through the use of sensors. The collected data is registered for potential uses and used for analytics. The analytical approach offers the opportunity for disease detection in healthcare results. This paper concerns the Internet of Things in healthcare and explores the different algorithms used in it. The system involved in analytics of healthcare and data sources involved in analytics are further clarified. Finally this paper demonstrates the Internet of Things and Big Data survey of healthcare systems with a reference table.

1 Introduction

The traditional internet makes communication with the number of small devices and individuals, through a comprehensive network of interrelated machine knowledge whereas IoT incorporates all sorts of connected things without the presence of human. The IoT acceptance and development in wireless communication Technologies allows the patient health issues to be streamed in real time to the caregivers [1]. In addition, mobile devices and various available sensors can measure the basic human physiological parameters such as Blood Pressure(BP), Heart Rate(HR) and Respiration Rate(RR) with a simple click. While it is still at an early stage of growth, corporations and businesses have increasingly accepted the power of IoT in their current processes, and have seen changes in both manufacturing and consumer experiences [2]. However the introduction of IoT Technologies into Healthcare has many challenges including data exchange between devices, data storage, security and privacy, data analysis, unified and ubiquitous access.

In order to connect, participate and cooperate on things, the Internet of Things (IoT) extends human individuality. Heterogeneous technologies of specialized protocols and algorithms have been steadily developed by IoT. The IoT plays a vital role in the global connectivity between millions of wired and wireless sensor systems, electronic devices such as TVs, refrigerators, etc., linked to the Internet [3]. In several sectors, such as agriculture [4, 5] , healthcare [6], entertainment [7], automotive [8], sports, home [9, 10], industrial appliances, business [11], etc., it then plays an enormous position. Fast precision, short expenditure, and dropping instance by better forecasting the futures are the explanations for the successful growth of the IoT. Using Wi-Max,Wi-Fi, IEEE 802.11, Bluetooth, Zigbee,etc., the IoT gadgets such as sensors

and actuators is installed in physical devices such as home appliances, cars and smart manufacturing machines to track and transmit data using wireless networks.

Sensors that monitor physiological state such as electroencephalogram(EEC) [12], electrocardiogram(ECG), pressure rate, body temperature, pulse rate, blood pressure are implantable in the body or wearable. For individuals who had elders, kids alone in the house, monitoring ailing people is more comfortable. The user-connected sensor also tracks the user 24/7 and sends warnings to the family physicians, and emergency providers about the changing health status of the user. Significant attention from the global science community is required to meet the growing demands of better technology to address real-time problems in the production of broader data without losing security and privacy.

Big Data analytics [13, 14, 15] has emerged as a good technique for the extensive data process and boosts the decision-making of 6 V: length, variety, pace, veracity, authenticity, and volatility. Volume, which refers to the amount of information being used and evaluated to achieve the desired outcome, is the key attribute. Scanner, cellphone, sensor, digitiser, film, email, Social Network and the internet are all part of a torrent of data from diverse outlets. An information that has been collected, analyzed and interpreted. Text, pictures, multimedia and the mixture of each sort can be the form of data. For Big Data the quality of data is referred by the veracity which is good enough. To collect, interpret and support the Big Data poses a problem[16]. Cloud computing [17, 18] arises as a fundamental help to store and process resource information obtained from every place across the internet to solve the problems of Big Data. To access cloud-based services they are grouped as public cloud, private cloud and hybrid cloud. Third-parties can access, exchange and process the tools of the public cloud. The services accessible by the enterprise

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are made possible by a private cloud. A hybrid cloud is often used to replace the internal data with public orchestration which incorporated both public and private clouds. Cloud applications or tools accessible to users on demand via the internet or Software as a Service(SaaS), Infrastructure as a Service(IaaS) and Platform as a Service(PaaS). The cost of cloud-based services or increased day-by-day as a volume of data to be processed, analysed, handled and stored in the cloud are overwhelmed. We are implementing fog computing [19, 20] the pre-processing of generated data to solve the issue, the fog computing is implemented at the edge of the cloud. Within millions of connected devices, Fog allows even data delivery, guarantees high scalability and safe data transaction. Big Data processing is a voluminous approach of data mining which involves both localization and cloud globalization of fog.

With the introduction of IoT and cloud technologies into the healthcare industry, healthcare providers are able to deliver healthcare facilities that are quicker, more effective and cheaper, resulting in better customer engagement. As a result, better hospital facilities, better customer engagement, and fewer paperwork for health workers are brought in.

The paper's outline is as follows: Section 2 focuses on IoT healthcare analytics. For Healthcare Analytics, section 3 explains multiple data sources. In section 4, various machine learning algorithms and their performance are discussed. Section 5 includes a literature review on healthcare systems and the comparative table on the quality and deficiency of the healthcare systems discussed is presented in Section 6. Finally conclusion is given in Section 7.

2 IOT IN HEALTHCARE ANALYTICS

Data processing is carried out by keeping electronic health records, updating clinicians with decision-making abilities with medical information obtained from imaging devices, and allowing people to take care of their health. The analysis aims to avoid patients suffering from chronic diseases.

Data review is conducted by holding electronic health records, medical information obtained from imaging equipment upgrades decision-making experts and allows patients to take care of their health [21]. The research helps keep people with debilitating conditions from suffering. Using analytics can enhance precision, earlier medical detection, allow customization and reduce costs by avoiding laboratory procedures, and also reduce the rate of infection. A blend of the medical sector and the IT industry is IoT Healthcare. The size of the IOT healthcare industry is projected to hit $12.4 billion by 2018, according to a report published by IDC.

Analytics can make use of pattern recognition and machine learning algorithms on wearable sensors. To obtain classification, the machine learning algorithm is used and helps to make decisions about the disease [22]. The machine learning algorithm is defined as the adoption of computational methods from trained data to detect and characterize consistencies and patterns.

3 HEALTHCARE ANALYTICS DATA SOURCES

3.1 Electronic Health Record

The digitised version of medical records for individuals is the Electronic Health Record. It offers medical services to people through the exchange of data with medical organizations [23]. It also makes it easier to edit documents for registered medical users. The data is processed and collected effectively, contributing to better decision support and quality control. They make the diagnosis of diseases easier.

3.2 Biomedical Image analysis

By providing anatomical structures of human beings, Medical Picture plays a critical function in health care [22]. The study of these photographs helps doctors and researchers to track illnesses and prepare care. This produces quantitative data from the images.
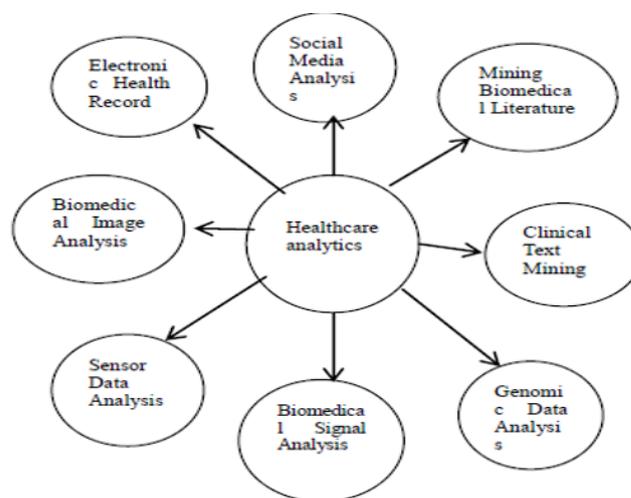

Fig.1. Healthcare analytics Data Sources

3.3 Sensor Data Analysis

Electroencephalogram sensors gather data from different areas of our body, such as electrocardiograms. This is used for real-time analytics that produce immense volumes of data leading to complexity overloading. These are regulated by the use of analytical instruments.

3.4 Biomedical Signal Analysis

Electroneurogram (ENG), electrogastrogram (EGG), phonocardiogram (PCG) etc. signs are used to assess

medical disorders and help to determine an appropriate pathway of treatment. The assessment of these signals offers a visual examination of the human body. Invasively or non-invasively, these signals may be obtained. Any of the methods used for the study of these signals [24] are Singular Value Decomposition (SVD), wavelet transformation and Principal Component Analysis (PCA).

3.5 Genomic Data Analysis

Most diseases are hereditary in nature, but the association has not been completely developed between the genetic markers and the diseases. A extremely non-trivial job with a lot of technological difficulties is the transformation of genetic findings into personal medical care [25]. Analytical methods such as Normalization and Quality Control, Differential Expression Identification, Clustering and Labeling, Pathway and Gene Set Enrichment Analysis, etc., solve these problems.

3.6 Clinical Text Mining

Patient knowledge is in the form of an unstructured format of data that forms the foundation of healthcare. Because of the difficulty involved in translating unstructured data text to a standard format, it becomes impossible to analyze automatically. Natural Language Processing is the key technique for extracting information, including clinical details, from unformatted text.

3.7 Mining Biomedical Literature

Text mining techniques are used in biomedical applications for the storage, availability and accessibility of data resources. They provide the leading researchers in information discovery with the extraction, study, and summary of textual data [26]. Biomedical science profits from this by connecting textual evidence to biomedical pathways.

3.8 Social Media Analysis

The creation of multiple social media tools offers valuable details on different facets of healthcare regarding people's views. These are used to collect population health and public health reporting data. They concentrate on identifying comprehensive health patterns such as infectious disease outbreaks, monitoring adverse drug interaction data, and strengthening health-related activities.

4 MACHINE LEARNING ALGORITHMS

Different algorithms are used in healthcare analytics to classify diseases from collected data. An efficient way to classify diseases is given by a machine learning algorithm. When considering data mining, disorders such as heart disease, liver diseases, kidney disease prediction

can be achieved successfully by using machine learning algorithms.

There are numerous machine learning algorithms that are successful in the identification of different diseases. Machine learning algorithms are self-learning algorithms through predictive processing, improve the precision of diagnosis. They are categorized as algorithms for supervised machine learning and unsupervised machine learning. Machine learning algorithms that are supervised make predictions based on the qualified sample collection. Whereas the unmonitored machine learning algorithm organizes data into clusters to define its structure and draw inferences without a named response from input data datasets [25].

4.1 Supervised Machine Learning Algorithms

Machine learning algorithms predict based on specified sample sets. It looks for data points within the value labels that are given. The supervised algorithm is composed of regression and classification. Classification, for example, predicts when the patient may experience a heart attack where an observation is consistently calculated as a regression.

4.2 Unsupervised Learning

There are no labels associated with data points. This machine learning algorithms organize the data into a series of clusters to clarify the architecture and to make composite data appear smooth and organized for analysis. It is used in bioinformatics, data mining for sequence and pattern extraction, medical imaging for image segmentation, computer vision for object recognition for sequence analysis and genetic clustering.

4.2.1 Decision Tree

The Decision Tree is used to arrange details in graphical form on the future results and end value of choices. For quick decision making, they are statistical models used. The description is carried out on the basis of an arrangement of characteristic values [27].

4.2.2 Classification of Naive Bayes

Naive Bayesian networks consist of directed acyclic graphs in which the non-observed node is represented by the parent and the nodes are represented by children. In comparison to parents, there is only one parent having multiple children and having independence between child nodes. The use of the robust Bayes classifier increases the precision of disease diagnosis by up to 78-84 percent for patients in intensive care.

4.2.3 Bayesian Theory of Networks

Bayesian networks often referred to as belief networks play a stronger function in the precision of the classification of diseases such as Hepatitis, Pima Indian,

Thyroid, etc. [28] These are graphic models that reflect unknown domain information.

4.2.4 Learning Based on Neural Network

Neural networks and multilayered neural networks are categorized into single layered neural networks. The full volume of information in the output unit is maintained by the single layered neural network. Hepatobiliary diseases can be identified using neural networks. Improvements in precision and speed are given by the single layer neural network.

4.2.5 Support Vector Machine

By constructing an N-dimensional hyper plane that is divided into two groups, SVM classifies details. A set of features that characterize a case called vector. Vectors close to the hyper plane are called vectors of support. The highest distance separation to the closest training data in any class is obtained by successful separation. The smaller the margin, the greater the generalization error. For the detection of heart diseases, SVM algorithms are more fitting. The comparison of different algorithms is seen in the table.

For the classification of the health data set and for the successful identification of diseases, machine learning algorithms are needed. Many classification algorithms exist. Taking into account the different parameters such as efficiency, speed, classification, tolerance rate, etc the performance of algorithms is analyzed. The comparison between different algorithms is seen in Table 1 below by considering these parameters. The description of health data sets by the Supervised Machine Learning Algorithm appears more detailed.

Table 1. Comparison of Learning Algorithms

Parameter	Decision Trees	Rule Based	Naïve Bayes	Neural Network	SVM
Efficiency	Medium	Medium	Low	High	Very High
Speed	High	Medium	Very High	Low	Medium
Classification	High	Medium	High	Very High	Very High
Event Attributes	High	Medium	Medium	Low	Very High
Tolerance	Medium	Medium	Low	Medium	High
Prevention	Medium	Medium	High	Low	Medium

In both linear and non-linear data sets, supervised machine learning algorithms perform well. In order to diagnose coronary disorders, renal failure, thyroid disease, diabetics, etc., SVM is more fitting. It needs more running time for the SVM, but the accuracy rate is good in disease detection. SVM decreases the error in classification and increases the output rate.

In general, in continuous and multidimensional functions, SVM and neural networks perform well. Prediction accuracy in SVM is improved when large datasets are used. On small data sets, the Naive Bayes classifier is less precise. The decision tree algorithm does not work well with data involving diagonal partitioning and it requires a complicated data representation due to replication problem. This needs extended running time. SVM performs well on knowledge comprising numerous features of input and output. It's really forgiving of meaningless characteristics. SVM performs best among the classifiers in general, offering better precision. The next SVM arrives, the better output of the neural networks. In performance terms, the table shows the distinction of different algorithms.

5 Literature Survey

A wireless device which was developed by Kovuru Chandu Chowdary [29] is used for calculating oxygen saturation, pulse rate, temperature and blood pressure. The fingerprint sensor is attached to the microcontroller to grant access only to the physician concerned. For visualisation to a web server, acquired data is received from a Raspberry Pi which functions as a sensor node of the provided device. Every 20 seconds, the calculated real time physiological parameters are modified. Zigbee module and GSM interfaces are also available in Raspberry Pi. Once the health data reaches threshold values, an emergency SMS will be sent to the mobile doctor.

E.T.Tan and Z.Abdul Halim [30] implement the AI system to forecast the possible risks such as kidney disease and diabetes as a result. The machine monitors three key fundamental signs, such as internal heat speed, pulse rate, and pulse, high-precision preparation and adjustment of sensor signs to meaningful yield, and showing, for example, the observation results on mobile apps. The technology structure of the medical care sector is broken into a front-end (introduction layer) and a back-end (information access layer). Throughout the front-end sheet, the device coordinates microcontroller-powered sensors to quantify the vital signals of a client and uses Arduino Nano and Intel Edison as discernible yields to travel across the known indicators. An interactive UI (GUI) or software framework is included in the front-end layer that allows the two patients and specialists to access and view the gathered information and data. In the back-end layer, the yield from the information acquisition system is placed on the cloud data set and the prior information expertise is evaluated. Synchronized sensors are connected to the Intel Edison point, and yield readings are sent to IBM Bluemix for the cloud information database and view. The accuracy of the generated model between a healthy human and patients with diabetes and kidney disease is 90.54 percent and 87.88 percent respectively.

An IR sensor has been developed for a smart heart rate control system by Puneet Bansal [31]. The heart rate signal values are built in the range of 1Hz to 3Hz by Arduino Uno processes and philtres. To send the values between Messsage Queuing Telemetry Transport (MQTT) protocol to node-red cloud, the Raspberry Pi is used as an IoT gateway. An SMS and email update is transmitted via the cloud to a physician or another registered individual reminding the person of the heart rate. The real-time heart rate level can be observed in Things Peak.

In order to make early provision for quickly approaching heart failure, AKM Jahangir et al [32] adopted a new tactile method by using a keen IoT that obtained input from the Body Area Sensor. The goal behind the current work was to create a genius coordinated IoT that implemented a lower power correspondence unit such that pulses could unnoticeably accumulate alongside internal heat levels using a mobile phone without blocking their usual everyday life. The sign preparation along with ML techniques was presented for sensor knowledge analysis for detecting and forecasting sudden coronary failure with greater accuracy.

A device has been developed by Vikas Vipapalapalli [33] for calculating the temperature, blood pressure and heart rate by using the Arduino Fio transmitter-receiver and XBee module. The instruments capture and exchange information seamlessly with each other and also archive the information, allowing data to be captured and analyzed. The graphical interface used by LabVIEW for the acquisition, retrieval and dissemination of physiological health data. As a URL is created by labVIEW, which can be accessed from anywhere, the provided device supports real-time monitoring.

Pack Yang et al [34] developed a compact gadget with a bio-detecting facial cover to track the tormenting power of a patient using electromyogram facial surface (sEMG). The wearable gadget serves as a remote sensor centre and is combined into an Internet of Things system for distant surveillance of pain. In order to allow the full recurrence range, up to eight sEMG channels could be examined inside the sensor centre at 1000 Hz and progressively transmitted via the entryway to the cloud worker. Expanding this both poor vitality use and wearing solace are considered by the portable gadget technique for long-term tracking. For continuous gushing of high-volume sEMG information, advanced sign preparation, deciphering, and representation to detail endless pain information remotely to guardians, a portable web application is developed. The cloud stage inside the device supervises interactive contact with the worker and the web application as an interface between the sensor centre and the applications. In summary, this study proposes an adaptable IoT framework for continuous biopotential control and a wearable response for programmed torment evaluation by external appearances.

The Healthcare System for the diagnosis and control of chikungunya virus was developed by Sood and Mahajan [35]. Wearable IoT monitors, such as fitness sensors, location sensors, opioid sensors, meteorological and environmental sensors, the data were collec**ted by sensors. For real-time processing and diagnosis of potentially compromised CHV users, the acquired data is transmitted to the fog and produces warnings to the cell phones of the patient. Every user's results and compiled medical records are processed in the cloud to measure each user's ORI to reflect their chance of transmitting and receiving the infection.

A. Alani [36] has developed a smart healthcare system based on IoT, which uses the Intel Galileo board to monitor blood pressure, pulse rate and temperature. It has an ethernet shield, a 32-bit CPU and Arduino Uno compatibility with its pins. The Arduino IDE is programmed on the Intel Galileo computer. Over the Xampp-based storage server, the board processes and uploads the sensor data. A doctor visualizes the data from a database server using a login ID and password.

Ashwini Gutta [37] has developed an IoT-based health management system for elderly people and chronic patient. A PC, an IoT server and Raspberry Pi are available for a device. The temperature, ECG and the pulse rate sensor data are moved to the Raspberry Pi and then loaded into the database server. The Message Queuing Telemetry Transport (MQTT) protocol is used for correspondence. The state of the patient is deemed serious once the number of email/ SMS notification reaches 3, then the doctor is informed by an email or SMS. A doctor can view clinical records remotely to assess the patient's current health status.

This literature review depicts detecting various chronic diseases by using different sensors, techniques like Machine Learning, Deep learning, Artificial Intelligence on different datasets. Each work has its own strength and weakness. Future work can be focused on the development of framework that detects Heart, Kidney and diabetics diseases using Raspberry Pi by applying Deep Learning algorithm. The framework would provide 2-way chat box so that victims can have direct communication with physician.

6 Comparison Table

Table 2 displays the comparative table for the procedures checked, sensors, equipment, network and data set used, along with the intensity and lack of the relevant work.

Table 2 – Comparison table on techniques, devices, senosrs, network and data set used in survey

Year	Techniques	Sensors used	Device	Network	Data set	Strength	Weakness	Ref.
2018	No algorithm	PR, Temp, BP, Finger Print	Raspberry Pi 3 Model B	Zigbee, Internet	Public data set	This scheme decreases time for action Patient in a low-cost hospital situation.	No optimization algorithm has been used by the machine and it needs to be evaluated on real time results.	[29]
2018	Machine Learning	Temp, BP, PRSensors	Arduino Nano and Intel Edison	Wi Fi	UCI ML Repository	The study provides a method for the normal prediction of possible risks, such as diabetes and kidney infection, for example.	The framework review initiated is a critical review that involves further clinical research and continuous knowledge in order to better authorise the ML concept prior to the coordination of the framework.	[30]
2018	Machine Learning	Finger Tip Sensor	Arduino Uno, Raspberry pi	Internet	Tested on 25 people	The real-time cardiac rate Values on Thingspeak are observed	The device must enhance the utilisation of power, scalability and cost effectiveness.	[31]
2019	Multisensory utilizing a systemwith smart IoT	PR, Temp Sensor	Arduino Uno™, Smart Phone, Wrist band	Bluetooth	Public Data sets	In comparison to ML calculations, the combination of sign handling viably understood the sudden cardiovascular malfunction with higher accuracy.	Since the system is not savvy, the estimate did not improve information security.	[32]
2016	Deep learning	BT, PR, BP Sensors	Arduino Fio	Internet	Self Data	Various critical patient parameters are tracked and distributed to doctors with limited time and low cost.	The ECG sensor can be added to the current device and several entities can also be checked.	[33]
2017	Big Data Processing and Deep Learning	sEMG sensor facial mask	Not mentioned	Wi Fi	Public Data Set	Low use of vitality and compatibility extends the potential for long-haul assessment to track facial cover and sensor centre.	On wide data sets, the device needs to be checked.	[34]
2017	Fuzzy- C means Algorithm	Health, Location, Environmental, Meteorological Sensors	Not mentioned	Internet	Symptom based data is generated	High bandwidth of the Performance, quick warning The generation	Consumption of electricity is High with the use of multiple cameras	[35]
2018	No Algorithm	BP, HR, Temp Sensors	Arduino Uno	Internet	Self Data	In order to save lives in emergency situations, this system is deployed at low cost.	No optimization algorithm has been used by the machine and it needs to be evaluated on real time results.	[36]
2018	Big Data Processing	Temp, HB, ECG, BP Sensors	Raspberry pi	Internet	Self Data	Concentrate on the health of older people and improved management of chronic diseases	For improved results, the optimization algorithm must be applied to	[37]

HR – Heart Rate, BP – Blood Pressure, PR – Pulse Rate, Temp – Temperature Rate, HB – Heart Beat, BO – Blood Oxygen, BR – Breathing, ECG - Electrocardiogram

7 Conclusion

Internet of Things analytics helps companies to capture and interpret sensor data in the environment, which in certain cases offers improved decision-making, lowers maintenance costs, etc., leading to technological growth. Analytics increases performance in the area of IoT healthcare by accurately detecting illnesses and supplying patients with improved medication. We illustrate the relevance of the Internet of Things in the healthcare sector in this article. Continuous wearable tracker tracking of patients helps them to self-care about their own wellbeing. Machine learning algorithms used in analytics help to efficiently classify diseases. Different machine learning algorithms for data classification are also supported. More importantly, we provided an elevated level of representation of different IoT-enabled medical care applications. Nevertheless, we recognize that the targets discovered for IoT in medical care are not efficiently feasible, and there are still various problems to be met and thus this area of research is getting more and more traction. We are also optimistic that from this synergistic approach will come the whole theory of the IoT and its full application of medical care and human prosperity.

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