IOT in Healthcare System with Body Sensor by machine learning

1st Hussein Barham
Computer Science
An Najah University
Qalqilya , Palestine
s11820602@stu.najah.edu

2nd Ahmad ibrahim
Computer Science
An Najah University
Jenin, Palestine
s11820885@stu.najah.edu

3rd Khalil omari
Computer Science
An Najah University
Jenin, Palestine
Khalil3omari@gmail.com

***Abstract*—n the recent period, communication technologies have brought about a remarkable revolution in the field of healthcare applications. One of these applications is iomts used to transmit medical information to patient-centered systems. Patient data is extremely important, so its secure transmission is of paramount importance in care applications, where machine learning (ML) is used for authentication and anomaly detection to secure medical systems in IOMTS. Personal health care is a new patient-centered approach to health care that expects to improve the traditional health care system by collecting patient data from electronic health records. On multiple sensors, which in turn sense blood glucose, body temperature, heart rate, electrical activity, etc. Based on this data, healthcare applications provide advice on lifestyle, special treatment, and care plans for the patient. These systems lower the cost of healthcare. on the patient. However, clinicians and caregivers remain in the care plan process to validate lifestyle advice because when it comes to ill learning, the validity of these advice remains questionable.**

I. Introduction

The Internet of Things facilitates integration between the physical world and computer communication networks, and application(s) applications such as infrastructure management and environmental monitoring make privacy and security technologies essential for future IoT systems. These systems consist of interconnected Internet of Things devices that perform predictive analysis, diagnosis, remote monitoring, preventive analysis, and in some cases, surgery. With the increasing use of medical devices for sensors that give data on a person's condition, we can analyze this data using machine learning algorithms[1] Remote and continuous monitoring of patient health is made possible. Medical Devices (IoTMD)[1], a network of sensors, actuators, and other mobile communication devices, is about to revolutionize the healthcare industry. The connected doctor-patient relationship creates a healthcare environment that facilitates the rapid exchange of information and enables easy access to it. Improvements in home care facilities and regular health updates for clinicians can reduce the risks of redundant or inappropriate care, improve patient care and safety, and reduce the overall cost of care. It is possible to analyze data in real time using IoT - MD which enhances the evidence-based medicine system [2].

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II. Planing

Research Questions: the study goal has been achieved by investigating four research questions, reported in Table 1:

article

A. Table Reserch Question

RQ ID	Reserch Question
RQ1	How is the Internet of Things (IOT) used in healthcare?
RQ2	How smart devices contribute to health care?
RQ3	How to use machine learning in healthcare?
RQ4	What are the algorithms on which machine learning depends?
RQ5	How the Internet of Things and ML changing the world of health care for the better?
RQ6	What are the Concerns of using the Internet of Things and ML in healthcare?

B. Search Strategy

Search Strategy: A manual search combined with an automatic search is used in the search strategy. It is a multi-stage process to choose all the primary studies that are relevant for our study . Listed below is a brief description of each stage of our search and selection process. Stage 1: The manual search was conducted on Google Scholar using IOT in Healthcare System with Body SensorNetworks. Then, we manually searched relevant journals and conference proceedings (available in the replication package). This stage culminates in 8 pilot studies, 22 primary studies, the definition of an initial search string, and the definition of inclusion and exclusion criteria. Stage 2:Automatic search. We performed automaticsearches one of the largest and complete scientific databases:IEEE Xplore Digital Library. We used the following search string:

IOT OR Healthcare System) And(Body Sensor OR remote health monitoring OR analytics) AND(patient risk stratification ORMachine learning)

Stage 3: In this stage, all the results from previous stages are combined into a single spreadsheet, and duplicates are removed. Stage 4: The primary objective of this step is to filter all the selected studies according to a set of well-defined inclusion and exclusion criteria. These criteria are described below. Stage 5: Avoidance of studies during information extraction. This stage was acted in corresponding with information extraction. When perusing a concentrate exhaustively (to extricate the information), and in view of incorporation and ex clusion models, concentrates on where absolutely chose or dismissed. Inclusion and Exclusion criteria: An investigation have been chose On it satisfies at Incorporation criteria, Also disposed of Assuming that it meets any of the exclusion criteria.

Data Item	Data Field	Reserch Question
F1	Study Title	Doc
F2	Publication Year	Doc
F3	Venue	Doc
F4	Context study	Doc
F5	IOT HEALTHCARE INDUSTRY TRENDS	RQ1
F6	IOT HEALTHCARE INDUSTRY TRENDS	RQ2
F7	MACHINE LEARNING IN HEALTH C	RQ3
F8	Model Building	RQ4
F5	BENEFITS	RQ5
F6	Fears of using the Internet of Things	RQ6

Index Terms—**Internet of Things, Helthcare, Sensor**

III. MOTIVATION

One of the most challenging goals in today's society is improving the efficiency of healthcare infrastructures. Delivering quality care to patients while reducing healthcare costs is a key issue. In the near future, Internet of Things (IoT) technologies will be used to develop smart healthcare systems for supporting and improving healthcare. The average person carries on average one or two mobile devices nowadays. Therefore, by taking advantage of the increasing presence of mobile devices, the cost of equipment can be reduced significantly, especially in the healthcare field.

IV. IOT HEALTHCARE INDUSTRY TRENDS

Healthcare IoT has experienced a burst of activity and creativity, exciting entrepreneurs and venture capital firms alike. There are new start-ups as well as large firms that seem eager to be a part of what may be a huge market as well as providing enabling products and technologies. Here is a comprehensive list of these products and technologies for a better understanding of the IoT market. We have developed a prototype wearable sensor for real-time tracking. This information is then passed on to a third party, such as adult children or other caregivers [3].

A Chinese firm has developed miPlatform, an integrated all-in-one medical imaging and information management platform capable of cloud-based image storage and computation, web-based 3D image post-processing and visualization, and integrated telemedicine capabilities [4]. Withings has developed a number of healthcare products [5], among them internet-enabled scales, a blood pressure device/app, and a baby monitor.

China's medical industry has relied on Neusoft's comprehensive IT solutions for personal health network services [6], and hospitals, public health facilities, and health management have benefited from their services. LiftMaster's IoT potential can be easily seen for home applications for elderly individuals, as Neusoft focuses on IoT-based healthcare services.

With Fitbit's Vivosmart smartwatch, the wearer is able to decide whether to take action or continue on their active path. Jawbone's UP3 includes many state-of-the-art sensors to provide a complete picture of the wearer's health status, including activity tracking, sleep tracking, smart coaching, and heart health monitoring [7]. Angel is a wearable that monitors the wearer's heart rate, temperature, and activity [8].

The wristband transmits this information to the user's smartphone. Researchers in Korea have developed a wearable blood pressure sensor that can be used nonstop for a long period of time without affecting the daily routine of the user [9] The iHealth Lab has developed a set of IoT healthcare devices including a wireless blood pressure monitor, BP dock, a wireless body analysis scale, iHealth Lite, iHealth Edge, a wireless pulse oximeter, iHealth Align, and a wireless smart glucose-monitoring device [10]..

Basis has created a health tracker that can help users improve their fitness, sleep, and stress levels [11]. A heart rate monitor and body intelligence quotient (IQ) are included in the device. Phyode has developed a health wristband that measures the user's heart rate variability, measures the agility of the autonomic nervous system, and displays their mental state .

Rejiva from Rejuven measures ECG, heart rate variability, respiratory rate, sleep position, sleepiness, breathing index, and energy level. It also assesses the state of the autonomic nervous system.
By using such smart devices, we can obtain important information from which to predict the health status by analyzing this data using machine learning algorithms.

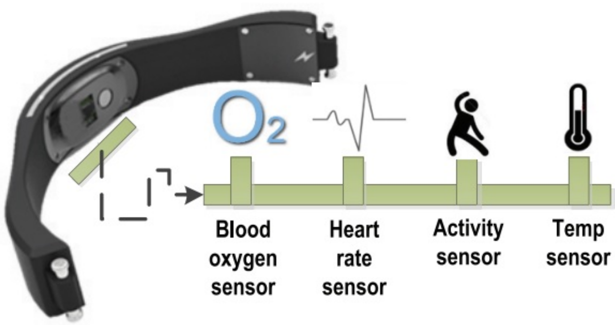

Fig. 1. smart watch.

Infirmity/condition	Sensors used; operations; IoT roles/connections
Diabetes	A non-invasive opto-physiological sensor; the sensor's output is connected to the TelosB mote that converts an analog signal to a digital one; IPV6 and 6LoWPAN protocol architectures enabling wireless sensor devices for all IP-based wireless nodes.
Wound analysis for advanced diabetes patients	A smartphone camera; image decompression and segmentation; the app runs on the software platform in the smartphone's system-on-chip (SoC) to drive the IoT.
Heart rate monitoring	Capacitive electrodes fabricated on a printed circuit board; digitized right on top of the electrode and transmitted in a digital chain connected to a wireless transmitter; BLE and Wi-Fi connect smart devices through an appropriate gateway.
BP monitoring	A wearable BP sensor; oscillometric and automatic inflation and measurement; WBAN connects smart devices through an appropriate gateway.
Body temperature monitoring	A wearable body temperature sensor; skin-based temperature measurement; WBAN connects smart devices through an appropriate gateway.
Rehabilitation system	A wide range of wearable and smart home sensors; cooperation, coordination, event detection, tracking, reporting, and feedback to the system itself; Interactive heterogeneous wireless networks enable sensor devices to have various access points.
Medication management	Delamination materials and a suit of wireless biomedical sensors (touch, humidity, and CO_2); the diagnosis and prognosis of vitals recorded by wearable sensors; the global positioning system (GPS), database access, web access, RFIDs, wireless links, and multimedia transmission.
Wheelchair management	WBAN sensors (e.g., accelerometers, and ECG, and pressure); nodes process signals, realize abnormality, communicate with sink nodes wirelessly, and perceive surroundings; smart devices and data center layers with heterogeneous connectivity.
Oxygen saturation monitoring	A pulse oximeter wrist by Nonin; intelligent pulse-by-pulse filtering; ubiquitous integrated clinical environments.
Eye disorder, skin infection	Smartphone cameras; visual inspection and/or pattern matching with a standard library of images; the cloud-aided app runs on the software platform in the smartphone's SoC to drive the IoT.
Asthma, chronic obstructive pulmonary disease, cystic fibrosis	A built-in microphone audio system in the smartphone; calculates the air flow rate and produces flow-time, volume-time, and flow-volume graphs; the app runs on the software platform in the smartphone's SoC to drive the IoT.
Cough detection	A built-in microphone audio system in the smartphone; an analysis of recorded spectrograms and the classification of rainforest machine learning; the app runs on the software platform in the smartphone's SoC to drive the IoT.
Allergic rhinitis and nose-related symptoms	A built-in microphone audio system in the smartphone; speech recognition and vector machine classification; the app runs on the software platform in the smartphone's SoC to drive the IoT.
Melanoma detection	A smartphone camera; the matching of suspicious image patterns with a library of images of cancerous skin; the app runs on the software platform in the smartphone's SoC to drive the IoT.
Remote surgery	Surgical robot systems and augmented reality sensors; robot arms, a master controller, and a feedback sensory system giving feedback to the user to ensure telepresence; real-time data connectivity and information management systems.

Fig. 2. IoT applications in health care.

V. MACHINE LEARNING IN HEALTH CARE

Healthcare sectors have large size databases. These databases may contain structured, semi-structured, or unstructured data. Big data analytics is the process that analyzes large data sets and reveals hidden information and hidden patterns to discover knowledge from the provided data.
Using this data, we can predict a patient's condition using machine learning algorithms based on five units. To apply these units, we used data from National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the dataset is to diagnostically predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. Several constraints were placed on the selection of these instances from a larger database. In particular, all patients here are females at least 21 years old .
This model contains five different modules. These units include

A. Dataset Collection

This module includes data collection and understanding the data to study the patterns and trends which helps in prediction and evaluating the results. Dataset description is given below This Diabetes dataset contains 768 records and 9 attributes.fig(3)

Attributes	Type	
Pregnancies	int64	X1
Glucose	int64	X2
Blood Pressure	int64	X3
Skin Thickness	int64	X4
Insulin	int64	X5
BMI	int64	X6
DiabetesPedigreeFunction	float64	X7
Age	int64	X8
Outcome	int64	Y

Fig. 3. Dataset Information.

B. Model Building

This is most important phase which includes model building for prediction of diabetes. In this we have implemented various machine learning algorithms for diabetes prediction. These algorithms include Support Vector Classifier, Random Forest Classifier, Decision Tree Classifier, Logistic Regression, K-Nearest Neighbor, Gaussian Naïve Bayes, neural network.

C. Evaluation

This is the final step of prediction model. Here, we evaluate the prediction results using various evaluation metrics like classification accuracy, confusion matrix and f1-score.
Classification Accuracy : It is the ratio of number of correct predictions to the total number of input samples. It is given as:
Accuracy = (Number Correct Prediction/Total Number of Prediction Made) Confusion Matrix- It gives us gives us a matrix as output and describes the complete performance of the model.
TP: True Positive FP: False Positive. FN: False Negative. TN: True Negative.
Accuracy for the matrix can be calculated by taking average of the values lying across the main diagonal. It is given as- Accuracy = (TP+FN)/N N: Total number of samples.

F1 score-It is used to measure a test's accuracy. F1 Score is the Harmonic Mean between precision and recall. The range for F1 Score is [0, 1]. It tells you how precise your classifier is as well as how robust it is. Mathematically, it is given as- F1 = 2 * (1/ (1/precision) + (1/recall)) F1 Score tries to find the balance between precision and recall.
Precision: It is the number of correct positive results divided by the number of positive results predicted by the classifier. It is expressed as: Precision = TP/ (TP+FP)
Recall: It is the number of correct positive results divided by the number of all relevant samples. In mathematical form it is given as- Recall = TP/ (TP+FN)

D. Results

After applying various Machine Learning Algorithms on dataset, we got accuracies as mentioned below.

Algorithms	Accuracy
Logistic Regression	73.37%
Random Forest	75.97%
KNN	72.72%
SVC	73.37%
Gaussian Naïve Bayes	70.77%
Decision Tree	70.12%
Neural network with 150 epoch	78.9%
Neural network with 1000 epoch	99.87 %

Fig. 4. Accuracy Table.

Confusion Matrix for Logistic Regression is given below:

	Diabetic	Non-Diabetic
Diabetic	87	13
Non-Diabetic	28	26

Fig. 5. Confusion Matrix for Logistic Regression.

Confusion Matrix for SVM is given below:

	Diabetic	Non-Diabetic
Diabetic	88	12
Non-Diabetic	29	25

Fig. 6. Confusion Matrix for SVM.

Confusion Matrix for random forest is given below:

	Diabetic	Non-Diabetic
Diabetic	84	16
Non-Diabetic	21	33

Fig. 7. Confusion Matrix for random forest.

The different performance measures that are being compared are Accuracy, F1-Score, Precision and Recall. The Confusion matrix for the algorithm with highest accuracy is mentioned in Table 3. Visualization of these accuracies helps us to understand variations among them clearly.

E. Clustering

Try to fix or develop the data in order to improve the accuracy :

Attempting to improve the data in order to improve the Accuracy by replacing all zero values to the values of the mean for every features.

Algorithms	Accuracy with normal Dataset	Accuracy with develop Dataset
Logistic Regression	73.37%	80.51%
Random Forest	75.97%	79.22%
SVC	73.37%	80.51%

Fig. 8. before and after improving the data.

Classification report before improving the data Fig(9)(10)(11):

	precision	recall	f1-score	support
0.0	0.80	0.84	0.82	100
1.0	0.67	0.61	0.64	54
accuracy			0.76	154
macro avg	0.74	0.73	0.73	154
weighted avg	0.76	0.76	0.76	154

Fig. 9. Random Forest.

	precision	recall	f1-score	support
0.0	0.76	0.87	0.81	100
1.0	0.67	0.48	0.56	54
accuracy			0.73	154
macro avg	0.71	0.68	0.68	154
weighted avg	0.73	0.73	0.72	154

Fig. 10. Logistic Regression.

	precision	recall	f1-score	support
0.0	0.75	0.88	0.81	100
1.0	0.68	0.46	0.55	54
accuracy			0.73	154
macro avg	0.71	0.67	0.68	154
weighted avg	0.73	0.73	0.72	154

Fig. 11. SVC.

Classification report after improving the data Fig(12)(13)(14):

	precision	recall	f1-score	support
0	0.84	0.86	0.85	107
1	0.67	0.64	0.65	47
accuracy			0.79	154
macro avg	0.76	0.75	0.75	154
weighted avg	0.79	0.79	0.79	154

Fig. 12. Random Forest.

	precision	recall	f1-score	support
0	0.85	0.88	0.86	107
1	0.70	0.64	0.67	47
accuracy			0.81	154
macro avg	0.77	0.76	0.76	154
weighted avg	0.80	0.81	0.80	154

Fig. 13. Logistic Regression.

	precision	recall	f1-score	support
0	0.83	0.91	0.87	107
1	0.73	0.57	0.64	47
accuracy			0.81	154
macro avg	0.78	0.74	0.75	154
weighted avg	0.80	0.81	0.80	154

Fig. 14. SVC.

VI. BENEFITS

In the old days, patients could only communicate with doctors through hospital visits and telephone calls. Doctors had little interaction with patients, and continuous monitoring was impossible. Now that IoT is available, remote and real-time monitoring of patients is possible, which makes being healthy, safe, and allowing physicians to diagnose and treat patients in a timely manner possible. Figure 1 shows the benefits and challenges.
Faster disease diagnosis: Real-time monitoring of patients' conditions helps diagnose diseases earlier and even before symptoms appear. Proactive treatment: Enables proactive health management and even before symptoms appear. Cost-effective: Avoiding unnecessary clinic visits, and doctors' appointments and hospital stays avoided with the usage of wearable and assistive handheld electronic medical devices.
Error reduction: IoT devices reduce human errors and help in eliminating inaccurate decision making. Improved treatment: Helps doctors to make accurate decisions on patient's health reports and provide appropriate treatment. Fig. 15. Benefits and Challenges of IoT in Healthcare

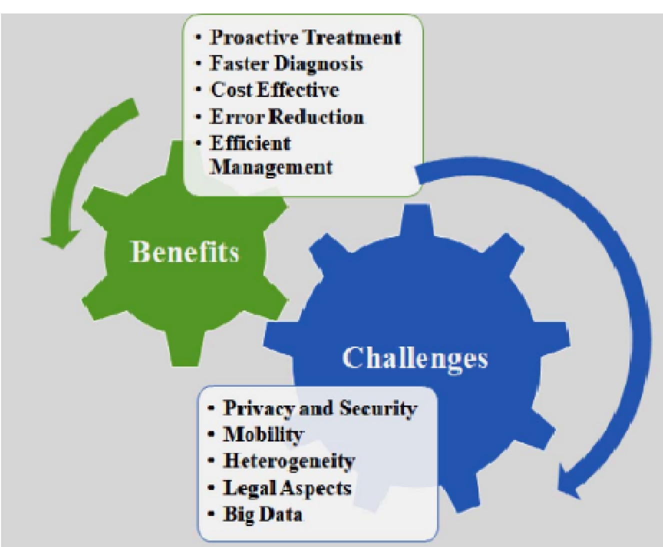

Fig. 15. Benefits and Challenges of IoT in Healthcare.

VII. RESEARCH CHALLENGES

There a number of challenges in handling the healthcareinformation and patient records. Some of the commonchallenges faced are listed below.Privacy and Security: In an IoT environment devices arevulnerable to attacks if they are left unattended. Due to thewireless nature of the devices, eavesdropping can happen. Soproper authentication and cryptographic techniques should beenabled to have access to devices and their data. In many cases,health reports contain sensitive data with personal informationthat have to be secured and maintained correctly. Therefore,the healthcare system requires stringent privacy regulations.clean
Mobility: Despite the use of medical gadgets and IoT devices in monitoring and diagnosis, huge complexities exist with mobility. Because of mobility, data creation and collection becomes complicated. Establishing connectivity between mobile devices to get real-time in certain situations is difficult.
Heterogeneity: This is one of the biggest challenges in IoT based health environments. The wide heterogeneity of sensors, wearable devices, clinical equipment, and varied operating systems with different platforms for new and improved application makes the health network complex to manage and maintain.
Legal Aspects: Legal and social aspects of storage and using the data should be maintained properly and service collection. The integration of sensor data from different sensor devices has to be handled with confidentiality and integrity. Data providers should confirm that they follow various international laws.
Big data: Specific attention must be paid for storage, processing and transportation of huge and vast data produced from the health network. Supporting a scalable network requires proper data management services. Appropriate data analytics tools are required to process th data to access the health data and improve patient and physician experience.

VIII. FEARS OF USING THE INTERNET OF THINGS

"Despite wearable IoT sensors can collect various patient physical data in real-time, there are often contains a large number of noises. In addition, the sensor is generally small size device, which can only handle lightweight computation and may cause data lost during the transmission process [1]. These two issues increase the difficulty of the subsequent machine learning process. "

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