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E-health-IoT Universe: A Review

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***Abstract*— The Internet of Things (IoT) devices are able to collect and share data directly with other devices through the cloud environment, providing a huge amount of information to be gathered, stored and analyzed for data-analytics processes. The scenarios in which the IoT devices may be useful are amazing varying, from automotive, to industrial automation or remote monitoring of domestic environment. Furthermore, has been proved that healthcare applications represent an important field of interest for IoT devices, due to the capability of improving the access to care, reducing the cost of healthcare and most importantly increasing the quality of life of the patients. In this paper, we analyze the state-of-art of IoT in medical environment, illustrating an extended range of IoT-driven healthcare applications that, however, still need innovative and high technology-based solutions to be considered ready to market. In particular, problems regarding characteristics of response-time and precision will be examined. Furthermore, wearable and energy saving properties will be investigated in this paper and also the IT architectures able to ensure security and privacy during the all data-transmission process. Finally, considerations about data mining applications, such as risks prediction, classification and clustering will be provided, that are considered fundamental issues to ensure the accuracy of the care processes.**

***Keywords*— IoT; E-health; sensor; personalized and precision medicine; security and privacy**

I. Introduction

The Internet of Things (IoT) application are today part of our life and used in almost every human and industry activity: from e-health [1] to Cultural Heritage [2],[3],[4],[5],[6] not forgetting legal domain [7][8][9], Public Administration domain[10][11][12],[13], and Humanitarian Assistance and Disaster Relief[14][15][16], but also home automation, autonomous and connected vehicles [17], and wearable technology. IoT promises to change our lives to make them easier, more efficient and "smart".

This paper aims to provide an analysis of the E-Health-IoT universe from different point of view in order to underline the growing importance of this kind of technologies in medical environment.

Starting from his introduction in e-health environment, IoT technologies are continuously growing in term of device installations (see Figure 1) this trend shows as IoT has become a fundamental technology in the medical environment.

We aims to analyze the existing IoT architecture for E-Health, the sensor devices employed into the E-Health-IOT universe with particular attention to new trends in wearable devices, the data collection, and management technologies implemented into the IoT architectures with particular attention to Personalized Medicine, Precision Medicine and security and privacy issues related to E-Health-IOT universe.

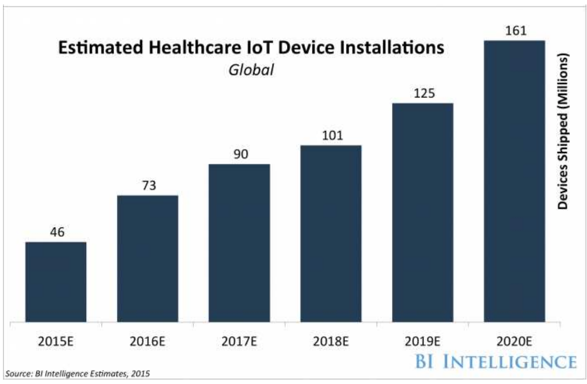

Fig. 1 IoT device installations trend

The paper is organized as follow: In Sect. I the background of IoT the medical environment is analyzed, in Sect. II issues and state of the art relative to wearable sensor nodes, data collection and management are discussed and finally in Sect. IV conclusions are provided.

II. Material and Method

As mentioned above, IoT in medical environment has become a widespread technology. To analyze this phenomenon, first of all we consider the different scenarios of IoT systems.

Recently, many applications have been realized in different scenarios from home healthcare to hospital healthcare not forgetting doctor's office and smart cities. In Table 1 we show a list of papers classified into four categories of IoT scenarios: Hospitals: IoT medical systems implemented into the medical structure, Home healthcare: IoT medical systems realized for the smart home, Doctor's Offices: smart system ideated to support doctors in their activities, and Smart Cities: e-health systems for smart cities.

Has showed in Table 1 many different implementations of IoT medical application has been provided, to realize them are been implemented different devices as radio frequency identification (RFID), wireless sensor network (WSN), smart mobile technologies and wearable devices.

TABLE I
DIFFERENT APPLICATION SCENARIOS FOR IOT MEDICAL SYSTEM

Scenario	Articles
Hospitals	[18][19] [20][21][22][23][24][25]
Home healthcare	[26][27][28]
Doctor's Offices	[29]
Smart Cities	[30][31][32][33] [34] [35]

In Table 2 has shown a list of research work that exploit different devices to realize the IoT in the medical environment.

TABLE II
DIFFERENT DEVICES FOR IOT MEDICAL SYSTEM

Device	Articles
RFID	[36][24][18]
WSN	[37][18][19][38][37][23][25]
Smart Mobile technologies	[33][35][27][18]
Wearable devices	[39][37][40][41][42][43][44][45]

Each of these devices is able to collect data about patients, doctors, nurses, caregivers etc., furthermore these devices can be able to: send alarms in case of emergency, tutoring patients during therapy (medications, rehabilitation therapies, etc.), and manage information about medical services (doctors' rounds, nurse's rounds, patient medical visits calendar etc.) (Table 3Table).

TABLE III
DIFFERENT APPLICATIONS FOR IOT MEDICAL SYSTEM

Application	Articles
Real-time patients monitoring	[43][23][35][39][45]
Patients information management	[21] [44][46]
Risk alarms	[23][47][35][27]
Rehabilitation therapies	[30][26]
Medications	[25][48][49]

Thanks to the cost reduction, the user-friendliness of monitoring and wearable devices and the technological achievements in the area of IoT, the diffusion of environmental sensors, physiological parameters monitoring devices, and home automation devices, are becoming the "hardware" of a dedicated IoT eHealth layered architecture as illustrated in figure 2. In this architecture, it is assumed that the system would create ad hoc web services exposed through a dedicated cloud infrastructure. The user's data could be then collected and stored, being available for healthcare service provisioning applications by possibly multiple third parties.

Figure 2 shows a typical 3-Layer architecture, where a set of heterogeneous devices belonging to the device layer are connected to the eHealth cloud and security services provided by the network layer.

The data provided by the devices are collected, stored and analysed by BI technologies and data analytics methodologies in order to obtain reactions (e.g.: alarms) to be re-transmitted towards the users.

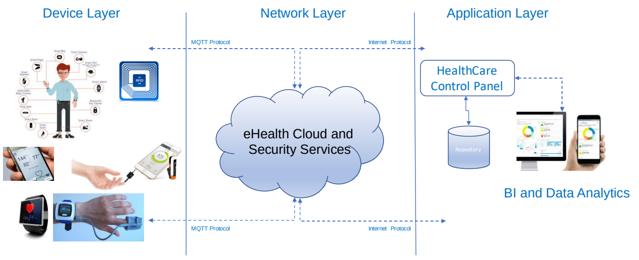

Fig. 2: IoT eHealth Layered Architecture

III. Results and Discussion

In this Section will be provided issues and state of the art relative to wearable sensor nodes, data collection and management in the E-health IoT field

The actual sensor, it is the element that transforms the health parameters in an electric signal. In the following a review about the trends on the most common sensors used in wearable healthcare systems

A. *Wearable sensors for Healthcare IoT*

In this section will be analyzed Health IOT wearable sensors, such sensors play an important role in Health IOT. They acquire medical data from people and transmit such data using different wireless technologies to other devices like smartphones, gateway or directly to the Internet.

Human health can be monitored observing different parameters, and for each parameter different sensors could be required. Most common solutions proposed in the literature are focused on[50]: Diabetes, Heart rate monitoring, Oxygen Saturation Pulmonary diseases etc.

Medical sensors involved in IoT should be small enough in order to be easily wearable and must be characterized by a reduced power consumption. In facts, wearable devices are not directly connected to the power grid and consequently, power consumption should be limited in order to avoid frequent battery change. For this reason, there are many works in literature focused this issue. [51],[52].

In this paragraph, electronic devices involved in Health wireless sensor nodes are analyzed. Analysis is focused on sensors, analog to digital converters, and processing elements.

B. Diabetes sensors

Today's medical records present that type 1 diabetes mellitus is a major health problem worldwide [53]. For this reason, literature presents several solutions for diabetes monitoring. The most common way to monitoring diabetes consists of monitoring glucose level in the blood. Glucose sensors can be implanted under local anesthesia in abdominal tissue [54]. In order to avoid the implanting, innovative non-invasive techniques have been introduced. Among these, the ones based on the breath acetone monitoring and sudomotor dysfunction are the most interesting.

Breath acetone concentration is reported to be elevated in type 1 diabetes mellitus, and it can be used to diagnose the onset of diabetes [55].

C. Diabetes sensors Heart rate monitoring sensors

The electrocardiographic signal (ECG) is one of the most commonly bio-signals used for the analysis and monitoring of health conditions. Today, thanks to the development of advanced wearable devices, it is possible to track patient conditions outside hospital setting for several days [56]. Ecg sensors are usually electrodes that attached to the skin surface, convert ion current in the body to electron current in the biopotential circuit. In ECG signal, the QRS complex is the most important waveform and represents the electrical activity of the heart during the ventricular contraction. The position of its peak (R-peak) is the most evident feature and the distance between more consecutive R-peaks (RRperiod) is a relevant parameter in the analysis of heart pathologies [57]. For this reason, wearable ECG sensor offers the capability to extract the QRS complex [58],[59].

D. Oxygen Saturation sensors

Blood oxygen saturation (SpO2) measurement is a clinical procedure involved in the diagnosis of several health diseases[60].

SpO2 is measured using arterial blood gas (ABG) test where a sample of blood is drawn from an artery of a person.

Although the ABG test provides an accurate representation of blood oxygen saturation, it is an expensive, invasive, and time-consuming procedure that cannot be used for continuous monitoring [61]

Near-infrared spectroscopy (NIRS) is becoming a widely used research instrument to measure tissue oxygen (O2) status non-invasively. For this purpose, are usually used continuous-wave spectrometers. Such devices, provide semi-quantitative changes in oxygenated and deoxygenated haemoglobin in small blood vessels.

In the last few years several wearable devices are proposed, in [60] a device has been designed to study the feasibility of extracting photoplethysmogram (PPG) signals at the neck in reflectance pulse oximetry mode.

The proposed device is very interesting for two main reasons. It offers the possibility to acquire signals from the neck, a position used for the monitoring other parameters of the body such as the breathing and heart rates. The second interesting aspect is the reduced power consumptions that allow batteries to operate for over 36 hours continuously when powered using a coin cell.

E. Pulmonary diseases sensors

Several Pulmonary diseases are correlated with the presence of a cough, Coughing is a prominent indicator of several problems such as Chronic Obstructive Pulmonary Disease COPD. For this reason, literature offers several solutions for the coughing detection and classification. These solutions are usually based on the using of audio microphones[61],[62].

Other interesting sensors for pulmonary disease monitoring are [63] and [64]. In the first authors present a pulmonary edema monitoring sensor with integrated Body-Area Network. In the second, it is shown a system that permits a better understanding of the impact of increased ozone levels and other pollutants on chronic asthma conditions

F. Analog To Digital Conversion

Analog to digital conversion represents a crucial aspect of the wireless sensor node. Data acquired by the sensor must be digitalized before the wireless transmission. The digitalization is necessary for two main reasons:

1) Wireless IoT standards are able to manage only digital data

2) Data could require digital signal processing before the transmission.

The ADCs involved in Healthcare IoT usually don't require high sample rates. This is because signals coming from the human body are usually slow. The main capability required for these devices is the low power consumption to preserve battery life.

Literature offers several solutions, in [65] A 0.4-to-1 V Voltage Scalable ADC with Two-Step Hybrid Integrator in 65 nm CMOS is presented. Such devices present a scalable power consumption and bandwidth with maintaining an SNDR higher than 60dB. In [66] a very low power ADC has been presented. This device is characterized by a very low power consumption (1µW) and consequently a very low conversion rate

G. Processing Element

Health IoT sensor nodes must be able to process data acquired by sensors and provide these data to the wireless transceivers. These two operations are performed by a processing element that usually is a Microcontroller. The choice of Microcontrollers as processing element has three main reasons:

- Health parameters are usually low-speed signals and consequently, the processing speed of microcontrollers is sufficient.
- Microcontrollers are provided with several standard interfaces that allow an efficient communication with IoT wireless transceivers available on the market.
- Microcontrollers are characterized by ease of use and flexibility.

Considering all these motivations, Microcontrollers vendors introduce on the market several solutions for the IoT integrating low power Microcontrollers and wireless transceiver [67][68].

As previously discussed the power consumption represents one of the most important aspects of Health wearable systems [69], [70]. For this reason, it could be interesting investigate solutions to further reduce the power consumption microcontrollers. An interesting solution could be the introduction of hardware accelerators [71], [72], [73],[74].

The speedup introduced by the hardware accelerator allows the reducing of the processing time and consequently the energy required for the processing

H. Data Collection and Management

The adoption of the IoT in medicine is able to allow collecting a large quantity of medical data related to monitored patients [75].

This data can be stored and analysed to provide useful information about the patient's diseases.

Moreover, in literature, there are many attempts to create systems able to provides collaborative management tools [76][77] and appealing graphical interfaces[78][79] for data that can be adopted in the IoT environment.

Following we investigate the data collection and correlation methodologies adopted in the E-Health-IoT Universe.

I. Big Data for Healthcare IoT

There are a number of application areas medicine for which computer-aided decision support systems have become designed and implemented. After decades of technological laggard, the field of medicine has begun to acclimatize to today's digital data age. New technologies make it possible to capture vast amounts of information about each individual patient over a large timescale. Today, a variety of devices monitor every sort of patient behaviour – from glucose monitors to fetal monitors to electrocardiograms to blood pressure. Many of these measurements require a follow-up visit with a physician. But smarter monitoring devices communicating with other patient devices could greatly refine this process, possibly lessening the needs for direct physician intervention and maybe replacing it with a phone call from a nurse.

The conceptual framework for Big Data analytics in healthcare differs from that of a traditional health informatics for how processing is executed while the algorithms and models are similar. The innovation in Healthcare Big Data systems is to analyze very large data sets as healthcare providers start to tap into their large data repositories to gain insight for making better-informed health-related decisions. Big data analytics tools are extremely complex and require the application of a variety of skills (Figure 3) [80].

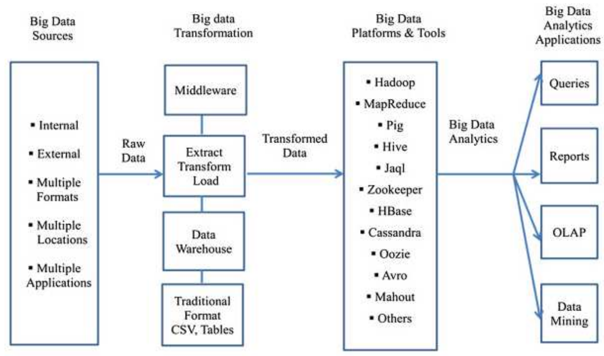

Fig. 3: An applied conceptual architecture of big data analytics

The complexity of them begin with the data itself (e.g., electronic health records, clinical decision support systems, government and laboratories sources, etc.) often in multiple formats (flat files, .csv, ASCII, etc.) with sources and data types different (web and social media data, human-generated unstructured and semi-structured data such as email, and paper documents, and Biometric data such as finger prints, genetics, handwriting, retinal scans, etc.).

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J. Information Ingestion

The *Information Ingestion* focuses on intelligently transform and store IoT data and to prepare and retrieve it for analysis. APIs bridge the divide between the data and the cloud, making it easy to pull in the data that's needed. The volume of medical data is growing exponentially. For instance, ImageCLEF medical image dataset contained around 66,000 images between 2005 and 2007 while just in the year of 2013 around 300,000 images were stored everyday [81].

Data is ingested from diverse data sources and platforms, then the essential values are extracted using rich analytics.

Typically, each health system has its own custom relational database schemas and data models which inhibit interoperability of healthcare data for multi-institutional data sharing or research studies.

Research community has interest in consuming data captured from live monitors for developing continuous monitoring technologies [80]. There are also products being developed in the industry that facilitate device manufacturer agnostic data acquisition from patient monitors across healthcare systems. For example, *HereIsMyData* [1], is a database where patients can store their health data and determine who can access them and MongoDB[2] is becoming much more common with the healthcare research communities. MongoDB is a free cross-platform document-oriented database which eschews traditional table-based relational database.

Based on the Hadoop platform, a system has been designed for exchanging, storing, and sharing electronic medical records (EMR) among different healthcare systems [82]. This system can also help users retrieve medical images from a database. Medical data has been investigated from an acquisition point of view where patients' vital data is collected through a network of sensors [83]. This system delivers data to a cloud for storage, distribution, and processing. A prototype system has been implemented in [84] to handle standard store/query/retrieve requests on a database of Digital Imaging and Communications in Medicine (DICOM) images.

Integration of disparate sources of data, developing consistency within the data, standardization of data from similar sources, and improving the confidence in the data especially towards utilizing automated analytics are among challenges facing data aggregation in healthcare systems [85].

There are considerable efforts in compiling waveforms and other associated electronic medical information into one cohesive database that are made publicly available for researchers worldwide [86].

By illustrating the data with a graph model, a framework for analyzing large-scale data has been presented [87].

K. Informative Analytics

Informative Analytics gains insight from huge volumes of IoT data to make better decisions and optimize operations. Apply real-time analytics to monitor current conditions and respond accordingly characterizes the second challenge. The purpose is to leverage cognitive analytics with both structured and unstructured data to understand situations, reason through options, and learn as conditions change. For example, predictive artificial intelligence (AI) algorithms indicate people who may be at highest risk based on an analysis of available data collected from existing patient records.

Big Data Analytics in Healthcare: evolution of healthcare practices and research. Some of these major challenges with a focus on three upcoming and promising areas of medical research: image, signal, and genomics based analytics. Many areas in health care such as diagnosis, prognosis, and screening can be improved by utilizing computational intelligence [88]. Popular areas of research where the concepts of big data analytics are currently being applied are: Image Processing, Signal Processing, and Genomics [89].

Medical images are an important source of data frequently used for diagnosis, therapy assessment and planning [90]. Medical image data can range anywhere from a few megabytes for a single study to hundreds of megabytes per study. The integration of computer analysis with appropriate care could improve the accuracy of diagnosis and outcome prediction of disease [91]. In addition to the growing volume of images, they differ in modality, resolution, dimension, and quality which introduce new challenges such as data integration and mining specially if multiple datasets are involved. When utilizing data at a local/institutional level, an important aspect of a research project is on how the developed system is evaluated and validated. Having annotated data or a structured method to annotate new data is a real challenge. In order to benefit the multimodal images and their integration with other medical data, new analytical methods that deal with some aspects of big data are required.

In facing medical image analysis an application of data integration/mining is in finding dependencies/patterns among multimodal data and/or the data captured at different time points, in order to increase the accuracy of diagnosis, prediction, and overall performance of the system [18], [92]–[95]. Toro and Muller have compared some organ segmentation methods when data is considered as big data. They have proposed a method that incorporates both local contrast of the image and atlas probabilistic information[96]. Tsymbal et al. have designed a clinical decision support system that exploits discriminative distance learning with significantly lower computational complexity compared to classical alternatives and hence this system is more scalable to retrieval [97]. A computer-aided decision support system was developed by Chen et al. [94] that could assist physicians to provide accurate treatment planning for patients suffering from traumatic brain injury (TBI). In [98], molecular imaging technology is designed to aid in early detection of cancer by integrating molecular and physiological information with anatomical information. Using this imaging technique for patients with advanced ovarian cancer, the accuracy of the predictor of response to a special treatment has been increased compared to other clinical or histopathologic criteria. A hybrid digital-optical correlator (HDOC) can be employed to compare images in the absence of coordinate matching or geo-registration. In this multichannel method, the computation is performed in the storage medium which is a volume holographic memory which could help HDOC [99].

Similar to medical images, medical signals also pose volume and velocity obstacles especially during continuous, high-resolution acquisition and storage from a multitude of monitors connected to each patient, *"alarm fatigue"* for both care givers and patients [100], [101]. Research in signal processing for developing big data based clinical decision support systems (CDSSs) is getting more prevalent [102].

The cost to sequence the human genome is rapidly decreasing with the development of high-throughput sequencing technology [103], [104]. With implications for current public health policies and delivery of care analyzing genome-scale data for developing actionable recommendations in a timely manner is a significant challenge to the field of computational biology[105], [106].

L. Machine learning in IoT

In literature has been provided many approaches to manage data with the aims to extract knowledge from data. In this section, we provide a review of machine learning approaches in E-Health-Iot Universe.

[1] http://www.hereismydata.com/

[2] https://gigaom.com/2013/08/27/10gen-embraces-what-it-created-becomes-mongodb-inc/

Initiatives such as meaningful use are accelerating the adoption of Electronic Health Records (EHR), and the volume and detail of patient information is growing rapidly. Being able to combine and analyse a variety of structured and unstructured data across multiple data sources aids in the accuracy of diagnosing patient conditions, matching treatments with outcomes, and predicting patients at risk for disease or readmission. Predictive modelling of data derived from EHRs is being used for early diagnosis with the intention of reducing mortality rates from problems such as congestive heart failure and sepsis or to prevent complicances as VTE in oncological patients [107][108].

A machine learning example from Georgia Tech demonstrated that machine learning algorithms could look at many more factors in patients' charts than doctors, and by adding additional features, there was a substantial increase in the ability of the model to distinguish people who have CHF from people who don't.

Predictive modelling and machine learning on large sample sizes, with more patient data, can uncover nuances and patterns that couldn't be previously uncovered. Optum Labs has collected EHRs of over 30 million patients to create a database for predictive analytics tools that will help doctors make big data-informed decisions to improve patients' treatment.

Machine learning approaches in medicine aim to exploit significant patterns in data, in order to produce risk predictors. These predictors could be integrated into IoT architecture to realize the risk alarm systems or exploited to evaluate data collected from IoT architectures.

There are a lot of research works that adopt machine learning techniques to realize the precision medicine and the personalized medicine, following we provide some significant examples.

In [109] authors analyse machine learning techniques in the diabetes research with respect to a) Prediction and Diagnosis, b) Diabetic Complications, c) Genetic Background and Environment, and e) Health Care and Management.

In [110] authors realize a computerized decision support systems (DSSs) on transfusion practice.

In [111] authors apply the neural networks to the classification of breast cancer.

In [112] authors discuss the state-of-art of clinical data warehouse and show the possible solutions for this issue.

M. Security and Privacy Issues

From the introduction of the IoT architecture in the medical environment we need to facing major challenges: security, data protection and privacy [113]. Many initiatives to the regulation of the data collection have been provided both in the Europe and in the other countries. Article 29 of Directive 95/46/EC set up a Working Party (WP), an independent European advisory body on data protection and privacy. The WP has identified six significant privacy and data protection issues related to the Internet of Things:

1. *Lack of control and information asymmetry*
2. *Low-quality consent*
3. *Extrapolation of inferences from data and repurposing of original processing*
4. *Intrusive identification of behaviour patterns and user profiling*
5. *Limitations on the possibility of remaining anonymous whilst using services*
6. *Security risks"*[114].

In order to addresses these issues two new principles has been introduced: "Privacy by Design" and "Privacy by default" [115].

"Privacy by Design" principle affirm that privacy must be incorporated in the design and architecture of IoT systems.

"Privacy by default" principle states that every IT system should ensure that only the personal information necessary for each specific purpose of the processing are treated, by default, and that the amount of data collected and the duration of their preservation does not go beyond the minimum necessary for the purposes sought.

In particular, personal data should not be accessible to an indefinite number of people and those involved must be able to control the distribution of their personal data.

In conclusion, we can affirm that the analysis of the data flow in a IoT architecture should be designed in accordance with the above-mentioned principles of "Privacy by Design" and "Privacy by default".

N. Personalized Medicine and Precision Medicine

The "personalized medicine" [116] research field deal with the definition of a tailored therapy for a patient or a class of patients. To realize this, recently research methods provide solutions for the collection and correlation of big data related to patients able to determine a precise therapy.

Many of these solutions are provided by the introduction of IoT devices in medicine in order to collect a large amount of data related to the patients.

The considered data can be exploited to precisely tailoring therapies to subcategories of disease and to divided patients into different classes of similar individuals. Often this purpose is achieved by the exploitation of the genomics techniques.

Another important research field has been introduced thanks to the adoption of IoT in medical environment the "precision medicine". The "precision medicine" [117] paradigm has become very popular over recent years, powered by scientific as well as political perspectives.

In January 20, 2015, the president of United States Barack Obama announced:

"Tonight, I'm launching a new Precision Medicine Initiative to bring us closer to curing diseases like cancer and diabetes — and to give all of us access to the personalized information we need to keep ourselves and our families healthier."

We intend the precision medicine as the union of technologies and methodologies able to harvesting and managing a large set of data related to a patient.

Differently from the "personalized medicine", the set of data in "precision medicine" is related to a single patient and the determinate therapy is only for this particular patient.

All of these approaches are related to the necessity to harvest a lot of heterogeneous data and to manage them.

IV. CONCLUSIONS

In this paper, we analyze the state-of-art of IoT in medical environment. Despite the large number of applications of IoT in medicine many issues are still open and they need innovative solutions to be solved. One of the main problems is the prototyping of sensors able to recognize medical information in rapidly and precise way. These sensors should be small enough in order to be easily wearable and should be characterized by a reduced power consumption. Sensors will be the cornerstone of the IoT architecture, these architectures must be able to ensure security and privacy during the data transmission. The clinical data collected from the sensors in the IoT architectures need to be harvested and stored in secure data-warehouse. Finally, data mining applications, such as risks prediction, classification and clustering should provide more accurate results also considering the increase of the amount of data due to the improvement of IoT devices.

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