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Cloud support for large scale e-healthcare systems

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Abstract Rapid development of wearable devices and mobile cloud computing technologies has led to new opportunities for large scale e-healthcare systems. In these systems, individuals' health information are remotely detected using wearable sensors and forwarded through wireless devices to a dedicated computing system for processing and evaluation where a set of specialists namely, hospitals, healthcare agencies and physicians will take care of such health information. Real-time or semi-real time health information are used for online monitoring of patients at home. This in fact enables the doctors and specialists to provide immediate medical treatments. Large scale e-healthcare systems aim at extending the monitoring coverage from individuals to include a crowd of people who live in communities, cities, or even up to a whole country. In this paper, we propose a large scale e-healthcare monitoring system that targets a crowd of individuals in a wide geographical area. The system is efficiently integrating many emerging technologies such as mobile computing, edge computing, wearable sensors, cloud computing, big data techniques, and decision support systems. It can offer remote monitoring of patients anytime and anywhere in a timely manner. The system also features some unique functions that are of great importance for patients' health as well as for societies, cities, and countries. These unique features are characterized by taking long-term, proactive, and intelligent decisions for expected risks that might arise by detecting abnormal health patterns shown after analyzing huge amounts of patients' data. Furthermore, it is using a set of supportive information to enhance the decision support system outcome. A rigorous set of evaluation experiments are conducted and presented to validate the efficiency of the proposed model. The obtained results show that the proposed model is scalable by handling a large number of monitored individuals with minimal overhead. Moreover, exploiting the cloud-based system reduces both the resources consumption and the delay overhead for each individual patient.

Keywords Cloud computing · Mobile edge computing · Health monitoring · Map reduce · Decision systems · Reactive · Proactive

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1 Introduction

Recently, healthcare costs are becoming higher for both individuals and healthcare agencies. In fact, healthcare agencies are facing many challenges due to the increasing costs for the health services they are supposed to provide.

For example, healthcare agencies are sometimes forced to spend a lot of money to meet the increasing product and service demands while complying with many regulations and healthcare legislations that need to be enforced and guaranteed [1]. At the same time, healthcare agencies face pressure from many tech-savvy consumers who increasingly demand higher levels of interaction such as instant online access to information, products, and services through their computers and mobile and handheld devices.

Many healthcare agencies and providers need to provide their services in a long-term interactive setting. Elderly people, particularly those who have medical problems and especially those with chronic conditions, are examples of such people who require long-term monitoring to detect abnormal trends and signs in their conditions as early as possible which will increase the chance of a quick and accurate diagnosis leading to better treatment decisions.

This opens the door for presenting new solutions which will help in saving lives and improving the quality of life for those who need long-term health monitoring. These solutions will in fact present long-term healthcare systems that respond to patients' daily and special needs in real time as well as solutions that have longevity in mind. Here, the role of IT tools and solutions can be of great importance. These IT solutions [1–3] should consider the special characteristics of the long-term healthcare monitoring process involving a large number of patients who might need treatment in a timely fashion. In fact, utilizing the new advancement of IT technologies opens the door for systems and applications that help in analyzing collected data in a specific area and make proactive decisions about some health trends for people in this area. These proactive decisions help in dealing with different health problems, health activities, and life styles. They can also help in avoiding many health problems and diseases from spreading in and beyond the area of interest.

Recently, especially with the explosion of the IT industry, many IT solutions have been presented and many systems have been built that try to take care of the aforementioned problems. These systems concentrate on different aspects of healthcare, namely, medical records, remote communication between the patients and healthcare agencies and clinics, remote treatments, real time treatment for emergency cases, etc. However, they ignore an important aspect of such problems which is the huge number of patients that the system usually deals with. In fact, the extensive use of the new IT technologies generates huge amounts of data of different nature gathered from many patients. Dealing with such a huge amount of heterogeneous data needs novel approaches beyond what is currently available in classical systems. Hence, the use of big data management systems and the use of cloud infrastructures is a must for any system to be successful and have potential benefit for both individual patients as well as healthcare agencies. Thus, the aforementioned facts make building an affordable system that takes care of the patients health records—whose number might be huge—in a long-term, nonintrusive, and a timely manner a challenge.

Many IT aspects have huge advancements and progress, such as mobile services, big data management, cloud computing, security, and privacy. Such advancements need to be utilized in finding new solutions that will take care of patients' healthcare in the best manner. In fact, some healthcare agencies already started moving to cloud computing to reduce operational costs. Also, such agencies look forward to managing, processing, and making decisions of data in an accumulated manner rather than considering the data as it exists now in silos. Moreover, dealing with such huge amount of data as big data might be considered as a powerful motivation that will overcome the overblown security and privacy issues from which many healthcare agencies suffer.

In this paper, we address different aspects of IT by integrating many of these IT disciplines including but not limited to (health information systems (HIS), wireless sensors network, mobile computing, big data collection and management, cloud computing, mobile edge computing, map reduce concepts, decision support systems, etc.) to build a long-term healthcare decision making system for huge number of patients in a timely and a proactive manner.

In this system, the patients are expected to wear smart wearable textiles that have sensors strategically distributed across their bodies. These sensors are distributed according to well-planned predetermined manner. This guarantees that these textiles have the smallest number of sensors whilst being distributed efficiently. These sensors will collect many measurements of various types of physiological signals such as (but not limited to): blood pressure, blood glucose concentration, heart rate, body temperature, and many other vital signs [18, 19]. These measurements (parameters or biosignals) will be collected via smart phones (or tablet pcs) through a mobile application (probably IOS, Android, or Windows phone). The mobile application will be capable of transmitting the collected data to a specialized dedicated cloud servers (henceforth called cloudlet) using wireless communication technologies such as Wi-Fi. Having these sensors installed within the textiles that the patients wear relieves the patients from the burden of worrying about their operation. The patient will only be required to carry a cell phone (or tablet pc) equipped with Bluetooth and GPS technologies. When the system detects serious abnormalities such as a heart attack, it will alert the cell phone, which in turn, will automatically call for help and provide the patient's location. The goal—from one side—is to provide early detection of dangerous diseases so that the patient will be given medical attention within the first few critical hours, thus greatly improving his/her chances of survival.

Moreover, our goal, from the other side, is concerned with presenting intelligent solutions via the cloud and the mobile edge servers. Here, we are concerned with the collected data which will be of huge nature. This huge or big data will be handled and processed intelligently in the cloud and the mobile edge servers via a decision making system. This decision making system will be considered as part of the cloud as well as the mobile edge servers. This is because the intelligent decisions will be made in both servers as part of the reactive phase and the proactive phase as discussed later in the paper. Such big collected data will be refined, analyzed and then smart decisions will be made. These intelligent decisions will play a vital and an important role in improving the healthcare of patients either on daily basis or on long-term basis.

Handling and processing the patients data will be in a reactive manner as well as a proactive manner. The reactive treatment involves direct responses to any abnormality—if found—in the patient's collected data by any individual taking care of this patient life and health (such as family member, family doctor, hospitals, healthcare agencies, etc.). This treatment depends on the collected health data for this specific patient. On the other side, the proactive treatment involves several processes in which the collected data will be studied, refined, and analyzed. This will ensure that all the data (newly collected as well as previously saved data for the same patient) will be processed and analyzed looking for any abnormal sign or pattern. In case any abnormal pattern is detected and observed then, appropriate intelligent decisions will be made. Such decisions will not only be helpful in the direct treatment of patients, but it will also improve the quality of life and health of patients. Advices can be made, precautions can be advised, problems can be avoided, risks can be minimized and hence, patients' life style and health will be accordingly improved.

We can summarize some of the benefits and advantages that can be reaped from our system as follows.

1. Improve patients' quality of life.
2. Easing some of the difficulties faced by the patients. For example, some of the needed measurements and readings that are usually taken from the patients while they are waiting for their appointments at clinics can be taken in advance while the patients are in their personal homes before visiting the clinics. This will make the patients' life easier and shorten the length of period the patients' need to spend in clinics.
3. Easing some of the difficulties faced by clinics/agencies that are taking care of patients. For example, taking many measurements and readings of the patients' in advance leaves them with enough/extra time to analyze the collected measurements and hence, take the right decisions and the right treatments. This will also save time for clinics/agencies to take care of more patients in a given working day.
4. Support healthcare systems and agencies to make their patients' healthcare systems sustainable.
5. Early detection of risks associated with patients' life style and, hence, minimizing these risks.
6. Improvements in the diagnosis process, treatment, and future decisions concerning the patients' health.
7. Because of the nature of our system that deals with big data collected from patients' through a long period of time, this allows our system to refine, cluster, associate, and analyze the data. This kind of processing will help agencies in studying any trend of illness (health problems) or abnormalities in the data. Such processing will lead to many decisions that can be generalized to all people within small area, society, city, country, or even a continent.

It is important to mention here that most of the processing tasks in our system that involve clustering, refining, analyzing, and proactive long-term decisions will be implemented in the mobile edge computing MEC servers instead of the cloudlet servers. This in fact is due to several limitations of cloudlets [33] which can be summarized as follows.

1. Cloudlets cover only a very small area due to the fact that they can be only accessed via Wi-Fi which is not suitable to our system that is expected to cover wide and large areas.
2. Cloudlets have limited scalability in both the provided services as well as provisioning resources. This second limitation contradicts the core advantage of our system which is intended to be scalable in order to take care of the health of huge crowds of people.

Hence, we, in our system, adopt the mobile edge computing (MEC) paradigm to overcome the above-mentioned limitations of the cloudlets.

The rest of the paper is organized as follows. Section 2 discusses some of the related works. Section 3 introduces our proposed e-health monitoring system. In Section 4, we show our evaluation and experimental results. Finally, we conclude our work and drew some future highlights in Section 5.

2 Related work

New IT technologies are now being used heavily in the healthcare sector due to the extensive use of electronic devices such as computers, sensors networks, and smart phones as well as the use of social communication sites in several daily activities (which might be health-related), which leads to a better and smoother interactions among patients and healthcare agencies. This extensive use of new IT technologies leads to an explosion in the amounts of health data that are being generated in a daily and even an hourly basis. In 2012, the world has produced about 2.5 Exabytes of data daily (good portion of such data is health related) [4, 5]. Because of the nature of this huge amounts of data that include private health data, such data need to be handled momentarily, accurately, securely, and privately. Hence, novel and efficient data management systems are needed giving rise to the field of big data. The term "Big Data" is currently used to represent such huge and complex data sets that traditional data processing systems cannot handle efficiently [6–8]. Relevant to big data is cloud computing which is a parallel distributed system with scalable resources. It provides services via a collection of inter connected and virtualized computers [9, 10]. It offers a good environment for techniques that need scalable resources and distributed systems such as map reduce framework, which is one of the major big data management systems introduced by Google in 2004 [11]. It is mainly based on massive parallel computing infrastructure that exploits different computing capabilities and services available to tackle the big data major issues. The map reduce framework provides a set of features such as user defined functions, automatic parallelization and distribution, fault tolerance, and high availability by data replication. It hides the details of parallel processing and helps in fault tolerance by replicating data into multiple nodes.

Many researchers tired to build e-health systems that monitor patients' health in an automated manner. Most of the models presented systems that take care of patients in an individual manner. Authors of [12] built the iCare system to take care of an elder's health. In their system, a set of sensors installed in a textile collect the elder's data and send it via a mobile application to a health agency. The health agency collects the data, analyzes them, and takes appropriate decisions based on the provided data. Although the system is helpful, however, it is a system that takes care of elder people in an individual manner. In case of many elder people who have some medical problems and their data are sent to the system, the system will take care of the patients individually in a first-in-first-served fashion. Hence, there will be delay in taking care of many elders which might put their lives at risk.

In fact, most of the systems that exist in the literature have the same problem. Most of the existing health systems presented health services to patients in an individual manner [13–16]. They can not take care of many patients at the same time. And because of this nature of existing systems, they do not utilize the collected data in making intelligent decisions that have good impacts on the lives of the individuals, societies and countries.

The authors of [17] classified solutions that should take care of health issues into three categories. The first category takes patients biosignals and takes appropriate procedures for abnormal signals offline. The second category has much more utilizations of IT and the Internet as it collects the biosignals and vital signs from patients remotely. However, appropriate procedures for abnormal signals will also be done offline. The third category takes into consideration real time processing and medications for patients. Although the second and third categories usually take advantage of IT solutions and Internet services; however, all are based on individual solutions that take care of the patients health one by one. They also fail to provide any long-term solutions that will improve the health and life style of patients and societies. They also do not have any kind of intelligence that might help in future policies in order to improve the health of people and reduce the risk of any arising problems and diseases.

The authors of [20] presented healthcare and emergency system with sensors installed in textiles worn by patients to collect vital signs. These vital signs will be transmitted via Bluetooth devices to a mobile phone, which performs some local processing tasks and can periodically report users' health status to the healthcare center and issue alert alarms when detecting abnormal behavior. Although it gives some good results, it only develops static monitoring in which the status is set statically and doctors are called when mobile phone send alert messages. This system suffers from the same problem as others: the monitoring process is done in an individual fashion and several problems are faced in case many patients with abnormal behavior are detected.

Our model involves a decision support system that adopts algorithms in the cloud-assisted mobile health (mhealth) monitoring. This in fact improves the quality of healthcare services and reduces health costs. However, using the cloud to store patients' records needs robust methods to preserve health information privacy. Proving the security of health information in the cloud is crucial to achieve patients' trust on cloud services. Multi-tenancy could be a source of vulnerability. For instance, an insider may use shared resources (including patients' data) to breach the security of other insiders' tasks [21]. Moreover, the guarantee of protecting data that resides on the cloud from the threat of cloud providers' employees is a major requirement by customers. Encryption is one of the methods suggested to protect data. For instance, CryptDB, Homomorphic Encryption (HOM), and Encryption Deterministic (DET) are encryption methods that can execute the operations of queries on encrypted data [22]. Similarly, anonymous Boneh-Franklin identity-based encryption (IBE) [23] can be used to protect patients' privacy. The aforementioned methods prevent the cloud providers' employees from exposing patients' health records. Besides protecting data, authentication of users is another major concern when using the cloud. Thus, the development of a secure system that preserves the patients identity and privacy is crucial for cloud computing and e-health systems [24].

3 Proposed model

The aim of this paper is to build an unobtrusive system that takes care of the patients' healthcare in both a short-term and a long-term, non-intrusive and timely manner. This system will be very helpful in taking care of the monitoring process of a patient's daily (or even hourly) health and life style. The system will also take care of long-term and future decisions that concern patients' health and life style. Moreover, It will have very helpful future decisions for global/internal healthcare agencies regarding any medical issue, problem, disease, etc. that might have risk on the people health and life. Additionally, governments as well as healthcare agencies might use our system decisions to direct their funds towards the right direction so that they can save a lot of money by avoiding many chronic diseases, health issues/problems from spreading. Figure 1 shows the top level overview of the proposed system.

Our model works in two phases:

Reactive Phase

In this phase, all the collected data (patients data and vital signs) through different cloudlets will be handled per individual patient. In fact, the collected data will be immediately forwarded to a specific prearranged healthcare agency or hospital who will immediately start processing the data. The data will be studied and analyzed and if the data have any trend of abnormality, the agency will take care of this individual patient by taking the right decision that could possibly save his/her life. Furthermore, all the individual patient collected data (measurements and vital signs) will be stored to be analyzed through a dedicated decision support system (DSS). The DSS will also collect other related data about each individual patient (will be called supportive data as discussed later) concerning, but not limited to, life style, everyday activities, behavioral activities, social activities, etc. These data as well as all the stored measurements for a predefined period of time will be refined, analyzed, and processed. Based on that, many health trends relating to this particular individual patient can be studied. Hence, decisions that will improve the lifestyle and health of this particular individual can be taken.

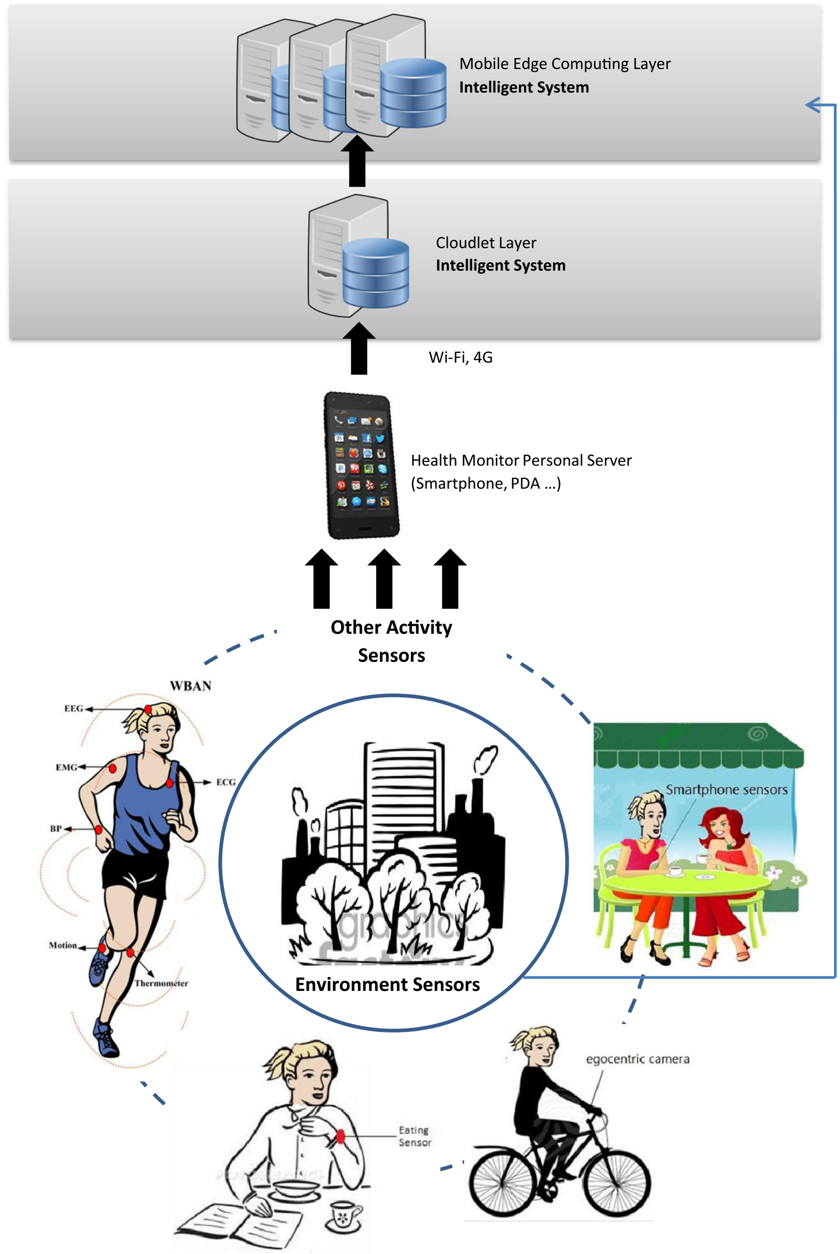
Proactive Phase

All the collected data (patients data and vital signs) from all cloudlets will be forwarded as packets (packets details and specifications are discussed in the next section) to the mobile edge computing (MEC) layer. The MEC layer will send all the packets to the map reduce (MR) component and the DSS component of our system for further processing. The MR part will process all the collected data from all patients from areas under consideration. Such collected and processed data constitute huge amounts of data that no typical system can handle. Hence, a MR component will process such huge amounts of data. The processed data will be then sent to the DSS component which will associate the newly collected and processed data with old collected data as well as a set of supportive data concerning the same area under consideration in order to make intelligent decisions concerning patients' health in that considered area, patients' health in surrounding areas, patients' life style in the considered area, and all surrounding areas. In fact, the DSS component will take samples of the collected data and study them according to predefined trends (representing problems, illnesses, etc.). If a noticeable trend is detected, then decisions will be made. Such decisions are expected to improve the life style of all patients. A particular example of this is the illnesses from which many elder people suffer. These trends might give highlights (steps, treatments, etc.) that need to be followed (considered, avoided) to solve this kind of issue.

Hence, this phase of our system takes care of the life style and health of a crowd of people (mainly the elder people) proactively over long period of times (considered as requested) where the data of the crowd will be associated, clustered, and analyzed. Decisions will be taken in case any noticeable trends are detected according to predefined trends that are susceptible to have impact on the life style, health of all the people in the considered area.

The system will process the collected patients' measurements and make decisions based on noticeable associations that might uncover significant trends that might affect the patient health. This will help in early risk detection and will also help in the minimization of risks associated with many life styles aspects, including but not limited to cognitive impairments, frailty, depression, and falls. This will also be extended to have greater values. In fact, such data will be used in making future decisions for specific health trends

Fig. 1 The proposed system model



(problems) that patients (or non-patients) might suffer from. Such decisions can be popularized for all people within a society, city, country, or even a continent (Africa which suffers from the spread of many diseases such as the Ebola virus outbreak). Such property makes the proposed system of unique nature which will consider a reactive management for patients health as well as a proactive management of their health and hence their life style.

3.1 Data collection

In our model and as we mentioned earlier, patients are supposed to wear textiles with a set of sensors (comprise a sensor network) distributed on them. The sensors should be reconfigurable, lightweight, and ultra-low power consumption. The distribution and the placing of such sensors will be according to an optimal algorithm. This optimality ensures that only the minimal number of sensors will be integrated and distributed on the textile. It will also ensure that no interference will occur among the sensors. Moreover, it will ensure that all the needed data will be collected from the patient's body. Having these sensors installed with these textiles that patients will wear, they need not worry about their operation. The patient will only be required to carry a cell phone (or tablet pc) equipped with Bluetooth and GPS technology to capture the collected data transmitted from the sensors. Many measurements (signals) will be extracted out of the collected data. Such measurements will be then used for diagnosis, treatment, and making intelligent decisions concerning patients' health.

A set of cloudlets should be distributed within predefined positions in each area under consideration. A set of cloudlets can be expanded to cover a small city. It can be further expanded to cover big cities, countries, or even a continent. The cloudlets positions are determined such that it covers the monitored area efficiently. Monitored individuals have the ability to move from one cloudlet to another or to be fixed in one cloudlet area. Monitored individuals will transmit the collected data to the cloudlet using low cost communication technology. This cloudlet should support such technology with multiple transceivers to avoid any delay and data lost.

3.2 Proposed model architecture

As shown in Fig. 1, our proposed model has the following components:

1. Cloudlets subsystem
2. Mobile edge computing MEC subsystem
3. Decision support system
4. Supportive data collection subsystem

In the following paragraphs, we give more details about each of the above-mentioned components that comprised our system.

3.2.1 Cloudlets subsystem

As mentioned earlier, patients are supposed to wear textiles with a set of sensors distributed on them according to a predefined optimal topology. Such sensors topology will ensure that all the needed data will be collected from the patient's body. The patient will only be required to carry a cell phone (or tablet pc) equipped with Bluetooth and GPS technology to capture the collected data transmitted from the sensors. The patients' data will be transmitted through mobile and handheld devices to the closest cloudlet which will receive it. A cloudlet can be defined to be as a complete cloud system in a small scale. It is composed of a number of servers (24 server or more), a medium storage capacity, and it is connected to the backbone network. Each cloudlet should be stateless where stateless can be defined to mean:

Stateless Cloudlet: *the cloudlet does not need to know previous records or data of the patient and it does not need to remember the patients' data once the cloudlet handles and transmits the patents' data to the mobile edge computing MEC*.

Once each cloudlet receives pateints' data, the system starts looking for any abnormality within each patient's data. Abnormality here refers to any deviation from predefined ranges for patient's biosignals and vital signs. For example, sensors usually send vital signs for each patient to the closest cloudlet. Example of these vital signs includes, but not limited to, temperature, blood pressure, heart rate, sugar rate, etc. These vital signs have normal upper and lower values for normal people. Such values of normal people are saved in each cloudlet to be compared with received patents' values. Any deviation from these normal values for each vital sign will be labeled to be abnormal.

Once the abnormal values for all patients with abnormal behaviors are collected and saved within packets, they will be transmitted to the mobile edge computing MEC layer subsystem which will further take care of these collected packets of data. It is important to mention here that each abnormal vital sign value will be saved in a separate packet. This means that if a patient has three abnormal vital signs one for the temperature, one for the blood pressure, and one for the sugar rate, then these abnormal values will be saved in three separate packets one for each abnormal vital sign detected, but, all for the same patient sent from the same cloudlet.

Since all cloudlet are stateless, then the patients' data that have abnormalities will not be saved within the cloudlet that took care of it. Hence, all cloudlet packets will be wiped out after the transmission of the packets.

The packet that will be transmitted to the mobile edge computing MEC layer has the following fields:

1. Patient ID: This refers to a sequence number that is assigned to each patient within each cloudlet. This number is in fact associated with the patient real private information (name, address, phone number, etc.) in the agency that is taking care of him/her. This indicates that the real private information of the patient is not saved or binded with the packet in the cloudlet.

2. Separator: A set of four zero's bits to separate the patient ID from the remaining fields.

3. Cloudlet ID: Refers to the cloudlet ID within the set of all cloudlets where each cloudlet has a specific ID.

4. Vital sign ID associated with its abnormal value: This includes the abnormal values for any of the vital signs that will be measured.

This cloudlet processing will be referred to be the map phase in the map reduce architecture as it will be discussed later in the coming sections.

3.2.2 Mobile edge computing MEC layer

Unlike the cloudlets, mobile edge computing MEC layer is stateful cloudlets where stateful can be defined to mean:

Stateful Cloudlet: *The cloudlet keeps track of the values of each patient by saving all the received values of each field in a storage designated for this purpose*.

Mobile edge computing MEC layer starts refining all the received packets by identifying all the received packets that pertain to the same patient. If more than one packet that contain more than one abnormal vital sign value, these abnormal vital sign values will be combined and saved for that patient in its appropriate record if the patient has a previously created record. If the patient does not have a previous record, then a new record for this patient will be created and saved. The values that will be saved are in fact all the values of each field in the packet sent by the cloudlet which include the patient id, the cloudlet id, all the abnormal values of each vital sign detected. The mobile edge computing MEC layer will then behave in two ways:

1. Reactively: Reactively in a sense that after combining all the newly received abnormal data of a patient, an immediate evaluation of the data will be performed and further appropriate procedures should be taken by either calling the patient and try to help him or by calling a hospital or the health agency taking care of this patient so that the patient life should be saved.

2. Proactively: Proactively in a sense that the newly received abnormal data of a patient will be combined and validated against the already existing data of that patient. Here, several tests, statistics, validations, and trends of diseases or problems that are expected for this patient will be performed. If any trend of disease or any other health problem is suspected for this patient, then further appropriate procedures should be taken by calling the hospital or the health agency taking care of this patient to warn them against the suspicious behavior of disease that is shown after evaluating the patients abnormal data

After refining all the packets and saving all the abnormal data in each patient record, the packets will be transmitted to a decision support system at the same layer that will refine, cluster, and analyze the data for long-term decisions about many issues, problems, and many chronic diseases. The packet that will be transmitted to the decision support system has the following fields:

1. Patient ID: This refers to a sequence number that is assigned to each patient within each cloudlet. This number is in fact associated with the patient real private information (name, address, phone number, etc.) in the agency that is taking care of him/her. This indicates that the real private information of the patient is not saved or binded with the packet in the cloudlet.

2. Separator: A set of four zero's bits to separate the patient ID for the remaining fields.

3. Cloudlet ID: Refers to the cloudlet ID within the set of all cloudlets where each cloudlet has a specific ID.

4. Vital sign ID associated with its abnormal value. This includes the abnormal values for any of the vital signs that will be measured.

5. Mobile Edge Computing MEC ID: Refers to the MEC server ID within the mobile edge computing layer where each server has a specific ID.

3.2.3 Decision support system component

This system, which is indicated by Intelligent System at MEC layer in Fig. 1, will process the collected patients' measurements and then will make decisions based on noticeable associations' that might uncover significant trends that might affect the patient health. This will help in early risk detection and will also help in the minimization of risks associated with many life styles aspects, including but not limited to cognitive impairments, frailty, depression, and falls. This will also be extended to have of greater value. In fact, such data will be used in making future decisions for specific health trends (problems) that patients (or non-patients) might suffer from. Such decisions can be popularized for all people within a society, city, country, or even a continent (Africa which suffers from the spread of many diseases).

Several infected areas can be detected. In fact, the decision support system will study all the provided packets and try to associate all neighboring cloudlets that transmit abnormal data from patients and group them within a cluster. This in fact needs further studies to capture if this cluster (infected area) suffers from a chronic disease or has a trend among all patients of a specific problem that needs to be handled.

For our model (specifically the decision support system) to draw accurate results, the decision support system component takes into consideration different life style aspects, behaviors, and daily life habits of both normal as well as patient people which will be called the supportive information. These supportive normal information will be combined with the collected abnormal information for all patients within a cluster so that any trend of diseases, problems, and/or health issues (if exists) should be detected. This will be very helpful for healthy societies where diseases and health issues can be detected and remedied in advance before happening.

3.2.4 Supportive data component

Most research in healthcare monitoring focuses on using biological sensors for health information collection. The biological information is used to predict diseases or to issue alerts in case of possible health problems. In this research, we will use activity sensors and environment sensors along with biological sensors to better predict health problems and analyze the causes of such problems. Furthermore, the information can be used to build patterns for paths leading to specific diseases, or life styles and conditions for healthy life. In addition, this information can be used to guide people to the best healthy places to live in or bad places to avoid living in. We call the information collected from activity sensors and environment sensors supportive information.

Supportive information can be used to understand better the society of patients. Using appropriate sensors, the supportive information unit collects information about patient habits and environment conditions that may directly or indirectly affect health. The unit gathers information about

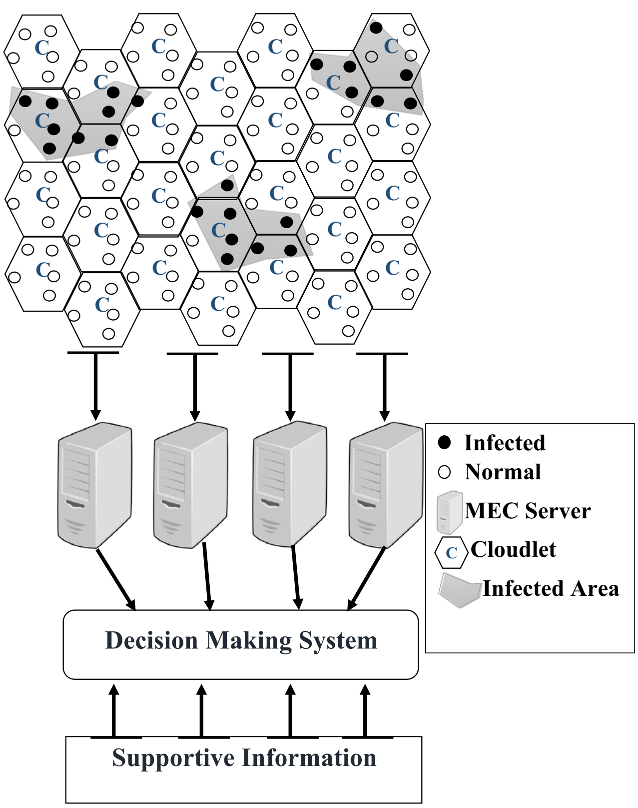


Fig. 2 Architecture of the EHealth monitoring system

eating habits, the daily activities of patients such as running, walking, hiking, reading, etc. and the average amount of exercising time daily. Moreover, the supportive information unit gathers information about the environment such as pollution and surrounding water pools. A personal server such as smartphones receives the information and sends it to the closest cloudlet using Wi-Fi, 4G, or other available networks. Figure 2 gives an image of how the supportive data component is integrated into our system and how it incorporates the collected data with other collected vital signs data.

Some research has been conducted on daily activities recognition, and several models have been set for this purpose. Some researchers used wearable sensors [22][23], and some of them discussed the best positions to place sensors[24]. Other researchers used smart phone sensors in predicting daily activities; a survey about this interesting topic was conducted by Su et al. [25]. In addition, daily activities recognition can be performed using egocentric images as proposed by Castro et al. [26]. Predicting the next activity of a patient may be crucial in some cases to prevent unhealthy activities. Nazerfard et al. [27] proposed an approach for predicting daily activity based on Bayesian Networks.

Basically, getting more information about a patient (his/her biological information, his/her daily activities, and his/her surrounding environment) leads to a more clear view about the patient health. In addition, getting enough information on the right time leads to precise proactive steps that can be taken to protect the patient health. Therefore, our model is designed to gather information using all available and possible means such as wearable sensors, egocentric images, smartphone sensors, and environmental sensors. Figure 1 shows the proposed model, which demonstrates that data from different sources are gathered and using different means. As shown in the model, data is sent to personal servers such as smartphones, which in turn forward the data to a local cloudlet.

The decision maker unit links patient' diseases with the supportive information, by using data mining methods, in an attempt to determine its possible causes or reasons that may increase its severity. The unit classifies patients into disease types. Next, it classifies patients that hold a specific type of disease according to their food habits, environment conditions in which they live and exercises types and periods. The produces clusters can boost the decision maker unit in many aspects. Firstly, the unit may offer advices to patients to leave some habits that were found to cause some types of illness such as not eating some kind of food from restaurants or leave an area. Furthermore, it may issue an advice to people to live in some healthy areas that were discovered in the clustering process. Secondly, the decision maker may issue a guide for tourists who plan to visit some area or country about the clean places (of diseases) that they may stay in or to avoid restaurants in some area. Finally, this type of clustering may provide an easy method for governmental agencies in countries to determine the cause of the spread of some diseases and how to control and cure it quickly.

3.3 Map reduce architecture

Our model as shown in Fig. 2 relies heavily on the map and reduce process in both data collection and data processing reactively and proactively. In fact, the following components can be distinguished:

- Patients: Supposed to wear textiles with a set of sensors distributed on them. These sensors will transmit all vital signs signals to be collected by cloudlets (mappers).
- Map Phase: A set of M mappers that correspond to the set of cloudlets. Each cloudlet will be designated as a mapper with a specific id in the map phase. Each cloudlet (mapper) covers a specific area within which a set of N patients are fixed. Mappers collect vital signs and health biosignals from patients and check for abnormalities considering different vital signs including, but not limited to, temperature, blood pressure, heart rate, sugar rate, etc. For each patient, the associated mapper will save abnormal values for each vital sign in a packet that includes the patient id, the cloudlet (mapper) id, and the vital sign with its abnormal value and transmits this packet to the mobile edge computing MEC (reducer). The mapper (cloudlet) will then be wiped out after transmitting the data to the associated reducer.
- Reduce Phase: A set of N reducers that correspond to the set of mobile edge computing MEC servers. Each server will be designated as a reducer with a specific id in the reduce phase. Reducers start refining all the received packets by identifying all the received packets that pertain to the same patient. If, for the same patient, more than one packet containing more than one abnormal vital sign value is received, then these abnormal vital sign values will be combined and saved for that patient in its appropriate record. Mappers will then transmit each patient records with all abnormal vital signs to the decision support system.
- Decision Support System: It will process the received data and then will make decisions based on noticeable associations' that might uncover and reveal significant trends that might affect the patients' health in a specific area (could be as small as a small town or it can be as big as a continent). In making long-term intelligent decisions, supportive information will be considered and taken into consideration.

3.4 Security and privacy issues

Proving the security of health information in the cloud as well as proving the privacy of patients' is crucial to achieve patients' trust on cloud services. Moreover, the guarantee of protecting data that resides on the cloud from the threat of cloud providers' employees is a major requirement by customers. Our proposed system guarantees both the security of the patients' data measurements and the privacy of patients throughout the whole system.

As stated in the previous sections, all the collected data will be transmitted from smart phones and tablets via wireless communication technologies to the closest cloudlet. To provide security and confidentiality of the patients' data, all the data will be protected by using encryption. For instance, CryptDB, Homomorphic Encryption (HOM), and Encryption Deterministic (DET) are encryption methods that can execute the operations of relational databases queries on encrypted data [28]. Similarly, anonymous Boneh-Franklin identity-based encryption (IBE) [29][30] can be used to protect patients privacy.

The patients' private data will be initially processed in the cloudlets which constitute the map phase. In the cloudlet system, each patient will be assigned a unique id (which will be assigned by arranging with the local health agency or hospital taking care of this patient) where all data comes from him/her will be associated with this id. However, after associating the data with the id in a packet, the data will be transmitted to the mobile edge computing MEC subsystem. The data will be immediately wiped out from the cloudlet storage because of the stateless property of each cloudlet. This in fact is an advantage that supports the privacy issues of the system because no private data of any customer will be saved.

In the mobile edge computing MEC which constitutes the reduce phase, more processing will be performed in the patients' data. However, the packet received from the cloudlet includes only an id of the patient without binding any private information (such as name, address, phone number, etc.) of the patient with this id. Hence, the data

Table 1 Physical host specification

ISA	X86
Operating system	Linux
Virtual machine monitor (VMM)	Xen
Storage capacity	1 Terabyte
Number of CPU	2 with 4 cores per CPU
MIPS for each core	2660
Memory capacity	8 GB
Virtual machine scheduler	Space shared
Network bandwidth	10 Mbps

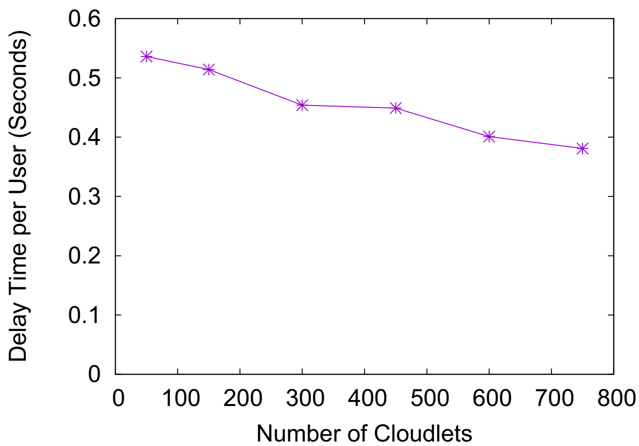


Fig. 3 Total incurred delay per user with increasing the number of cloudlets

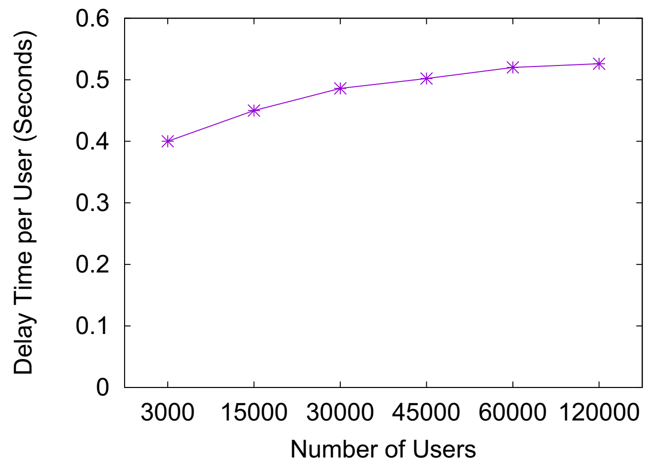


Fig. 5 Total Delay Behavior with Increasing Number of Users

is considered as anonymous, and therefore, no privacy violation can be considered for data (not binding any private data of the patients with the id). The same fact can be applied to the decision support subsystem which considers huge amounts of data (measurements) without binding any private data to such measurements.

Hence, our proposed system guarantees violations of the confidentiality and privacy of the patients' data and identities are minimized and in fact avoided.

4 Experimental results

To evaluate our proposed system accuracy, we conducted a rigorous set of evaluation experiments using simulation. For this simulation, we used the CloudExp simulator which is an extended version of the CloudSim simulator [31, 32] that supports map reduce infrastructure. For our map reduce system, we used some of the CloudSim characteristics to prove goodness and improvements achieved by our proposed model. In this simulation, the physical host specification is fully described in Table 1.

Our evaluation metrics emphasis will be on two major issues. First, the proposed system scalability to handle large number of users and second, the system efficiency in reducing system resource consumption and delay per user. Figure 3 shows the total delay per user with increasing number of deployed cloudlets. The decreasing trend related to the fact of having larger number of deployed cloudlets will increase the opportunity of each user to send the collected health data to a closer cloudlet system. This will reduce the incurred delay for sending the data by other costly technologies. Similar justification for Fig 4, increasing the number of cloudlets, will reduce the need to use a non-power efficient communication technology. This will reduce the power consumption per user. Figures 5 and 6 aim to demonstrate the

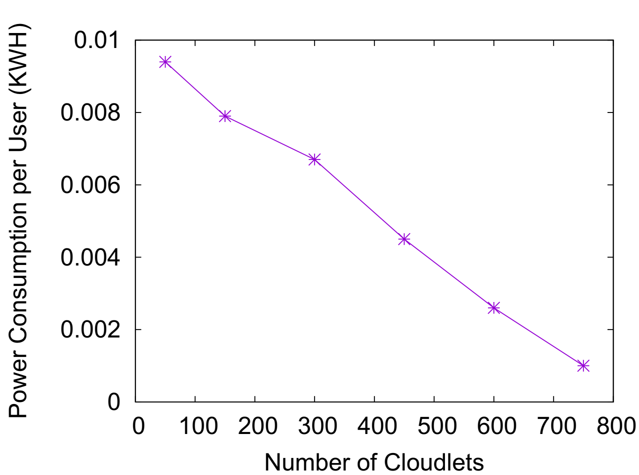


Fig. 4 Total incurred power consumption per user with increasing the number of cloudlets

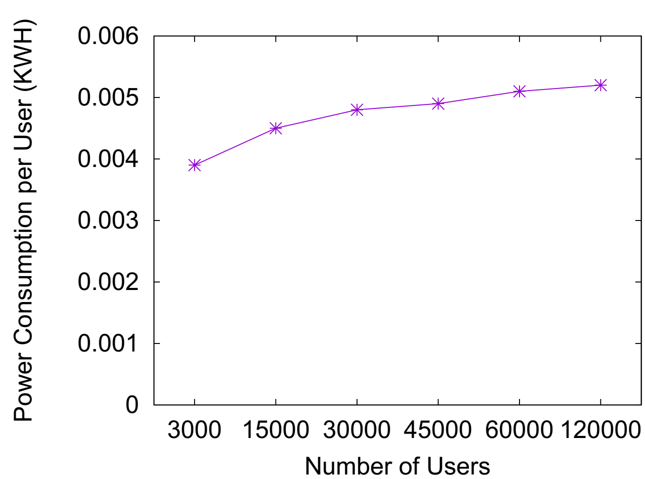


Fig. 6 Power Consumption Behavior with Increasing Number of Users

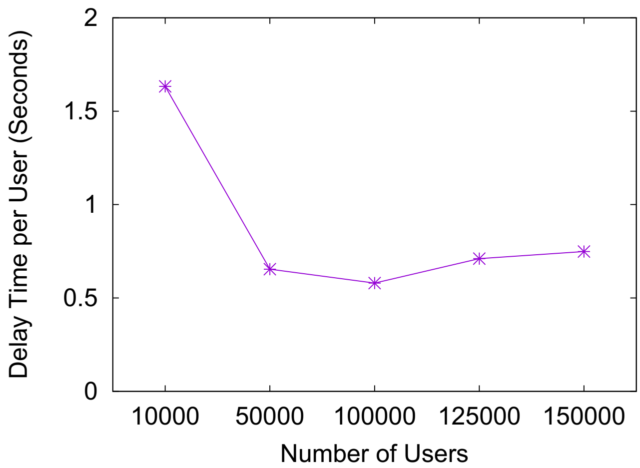


Fig. 7 Total Delay Behavior with Increasing Number of Users for 50 Cloudlets

scalability of the proposed system with increasing the number of users. Both figures show that a reasonable increase in the power and delay compared to 40-folds increase in the number of users. This behavior is justified by having the cloudlet closer to the users and the reasonable computing capacity of the cloudlet system. The number of cloudlets is set to be 300 in both experiments.

The last set of experiments shown in Figs. 7 and 8 is used to show the turning point in which the system is not any more capable of handling more users while maintaining a low delay and power consumption levels. In both experiments, we fixed the number of cloudlets to be 50 while increasing the number of users. Both system power and delay levels will decrease until the number of users reach to about 100,000 after which it will start increasing. These results help in the planing for the deployment of the cloudlets to insure sufficient number of cloudlets to efficiently handle the load in a specific area.

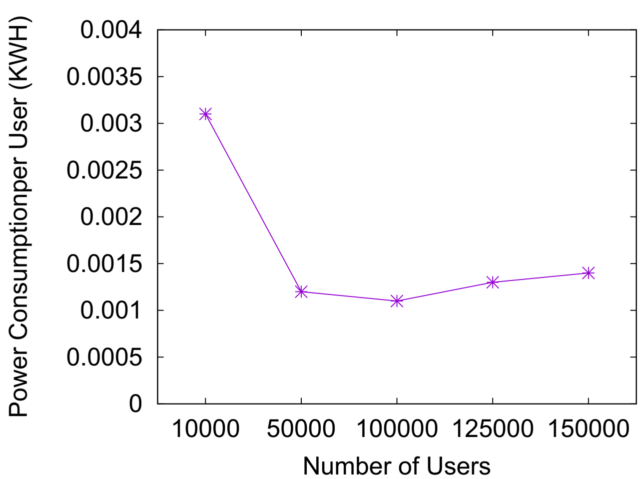


Fig. 8 Power Consumption Behavior with Increasing Number of Users for 50 Cloudlets

5 Conclusions

In this paper, we presented a cloud based monitoring system for a crowd of patients. The aim of this e-health system is not only to be as a living assistant of a huge number of patients by taking care of their arising abnormal health issues and behaviors but also provides a long-term solution that takes care of patients' health by associating all the patients' collected vital signs and make decisions about their health relating issues, problems, diseases and health habits that might affect the patients' life in advance and before happening. Hence, the presented system will improve the health of patients and reduce the risk of having medical problems, issues, and diseases by trying to avoid circumstances, habits, behaviors of patients that might lead to health problems and diseases. The proposed system is developed to handle huge number of patients simultaneously by collecting their vital signs and biosignal data by transmitting the data to a dedicated cloud. In such cloud a set of cloudlets and mobile edge computing MEC servers will handle the patients big data in a Map Reduce based processing environment which ensures scalability and efficiency. A decision support system is presented as part of our proposed system which collects the data, refine them, analyze them and will then make decisions based on noticeable associations' that might uncover significant trends that might affect the patients' health in a specific area that could be as small as a small town or it can be as big as a continent. Decisions will be then made (based on arising risk of a spread of a disease or a noticeable normal people habit that might lead to a medical problem) and sent to health agency to take appropriate decisions and precautions. To evaluate our system, we built a simulating for our proposed system using the cloudExp simulation tool. The conducted experiments showed that the proposed system is able to reduce the power consumption and the delay per user. Also, it showed that the system is scalable enough to handle large number of user (e.g., patients) with a minimum incurred overhead.

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