A Mobile Dietary and Emotional Diary System for Eating Disorder Care on the Smart Phone

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***Abstract*—The advancement of the Internet of Things (IoT) and wireless sensors have paved the way for the development of new services for next-generation healthcare systems. Eating disorders are real, complex medical, psychiatric illnesses that can have serious consequences for health, productivity and personal relationships. We designed and implemented a mobile dietary and emotional diary system on the smart phone in order to detect eating disorder based on patients eating history and facial status detection. Through an analysis of normal and abnormal dietary input and emotional states, this system is intended for providing eating disorder healthcare service as a service in the cloud. The initial experimental results are presented and further research topics are discussed.**

Keywords—IoT, Eating disorder care, mobile dietary system, emotional diary system, slow intelligence system.

I. INTRODUCTION

The advancement of the Internet of Things (IoT) and wireless sensors has paved the way for the development of new services for next-generation healthcare systems to enable superior communication between healthcare professionals. However, in order to add value to raw sensor data we need to understand it by context aware mechanisms.

Context awareness from an IoT perspective introduces IoT paradigm and context-aware fundamentals with in-depth analysis of context life cycle. It evaluates 50 projects over last decade (2001-2011) [4]. There is a survey about techniques, methods, models, functionalities, systems, applications, middleware solutions related to context awareness and IoT. Context life cycle has 3 techniques which are context modelling techniques, context reasoning decision models, and context reasoning techniques. Context modelling techniques are key-value, markup schemes, graphical, object based, logic based, and ontology based modelling. Context reasoning decision models are decision tree, naive Bayes, hidden Markov models, support vector machines, k-nearest neighbor, and artificial neural networks. Lastly, context reasoning techniques are supervised learning, unsupervised learning, rules, fuzzy logic, ontological reasoning and probabilistic reasoning. From this survey, we have learned that development aids and practices has toolkits in general are suitable for limited scale application, middleware provide more functionality towards [1]managing data, standardization makes it easier to learn and use, and intelligibility toolkit helps faster adaptation of the users. Mobility, validity, and sharing are that IoT solutions need to track user movements, facilitate context-aware functionalities over different forms of devices and has different platforms, devices have different resource limitations, and different versions should be built on different devices. On Demand Data Modelling is data models need to be extensible on demand, and the ability to add knowledge when necessary is critical for wider adaptation. It also stores different types of context to help in a variety of situations. Hybrid Reasoning is multiple modelling and reasoning techniques can mitigate individual weaknesses using each other's strengths. For the hardware layer support, there are context awareness allows sensors to act more intelligently and save energy and significant amounts of energy can be saved by following fairly simple optimization. Dynamic configuration and extensions are pluggable rules that allow insertions when necessary, it is a major requirement as in IoT middleware applications, where domains and required knowledge cannot be predicted during the development stage. Distributed processing is real time processing and significant in the IoT, and cross domain context is queried to answer complex requirements.

There is the IoT for health care survey [5] which is about IoT based health care technologies, reviews network architecture and platforms, applications, industrial trends, and analyzes distinct IoT security and privacy features. From this survey, we can learn about what kind of IoT healthcare services and applications are possible, what kind of IoT healthcare products and prototypes are out there, and what kind of security requirements we can consider. Healthcare trends are ease of cost-effective interactions through seamless and secure connectivity across individual patients, clinics, and healthcare organizations is an important trend, and up-to-date healthcare networks driven by wireless technologies are expected to support chronic diseases, early diagnosis, real-time monitoring, and medical emergencies.

Enabling health monitoring as a service in the cloud [6] is wiki-health analysis framework that enables an ecosystem to support scientists, developers, and professionals to publish their data analysis models as utilities in the cloud and allow users to access those services and utilize their collected sensor data without any expert knowledge. Their ECG-based health monitoring service application deployed and wiki-health platform. There is Adaptive Learning Approach (ALA) which

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reduces the training time while showing improved performance over existing methods.

IoT has a variety of application domains, including health care. However, enormous amount of raw sensor data need to be processed. As we describe above, there are many survey and researches about what kind of context modelling/reasoning, what health care application/services can be a target, what products/prototypes are out there, what security aspect we can consider, and ECG-based health monitoring service application trained by minimized data analysis.

We focus on treating eating disorder based on daily eating habit and knowledge base. However, it can be enhanced to other health disease care system such as asthma, cancer depression, anxiety, eating disorders, diabetes self-management, autism learning disorders, medication abuse, epilepsy or other seizure disorders, food allergies inflammatory bowel disease, obesity, organ transplant, sickle cell disease, and stuttering.

Eating disorders which are our primary focus are real, complex medical, and psychiatric illnesses that can have serious consequences for health, productivity, relationships. In the United States, 20 million women and 10 million men suffer from a clinically significant eating disorder at some time in their life. It includes anorexia nervosa, bulimia nervosa, binge eating disorder or EDNOS. Anyone can develop an eating disorder regardless of gender, age, race, ethnicity, culture, size, socioeconomic status or sexual orientation. Also, enabling eating disorders health care is a one of the behavioral health care we need to take care of. The treatment strategy is determined by the severity of illness and the specific eating disorder diagnosis, and cognitive-behavioral therapy and interpersonal therapy produce substantial and long-lasting changes and pharmacological treatment has often a useful role [8]. Therefore our mobile dietary and emotional diary system for eating disorder care will provide the long-lasting tracking system by writing the diary from the patient and checking the facial emotion to analyze the cognitive-behavioral.

On the other hands, to build E-health care system, it can be collaborated with healthcare professionals, regulators, pharmacies, insurance companies, vendors, hospitals, and patients [7]. Also, there are many challenges in E-health such as how the medical and healthcare information has been collected and stored, lack of technologies and potential cost to digitize the existing processes and tasks. Since one of the major challenge is to convert all of the medical and healthcare information to electronic format, we provide the healthcare system that the patients and professionals can easily write or update the information by using the smart phone.

In this paper, enabling health care service that could detect the eating disorders by 4 aspects. First, enable eating disorders health care as a service through the cloud and smartphone. Second, dynamic diet information from the cloud database. Third, real-time diet diary system on the smartphone to take care of behavioral health care. Lastly, emotion state recognizing can be confirm the patient facial status as needed. Section 2 describes the eating disorder diary system, and section 3 shows the emotion state recognizing. Then, abnormal state monitoring algorithm and equations are shown in section 4. Experiment and results explain in section 5 and we conclude our work with possible future work.

Fig. 1. Eating disorder diary system scenario

II. Eating Disorder Diary System

For the mobile dietary system, the eating disorder diary system has 3 major parts which are prevention, diagnosis, and treatment. Prevention aims to promote a healthy development before the occurrence of eating disorders. It also intends early identification of an eating disorder before it is too late to treat. Children as young as ages 5–7 are aware of the cultural messages regarding body image and dieting. Internet and modern technologies provide new opportunities for prevention. On-line programs have the potential to increase the use of prevention programs. The development and practice of prevention programs via on-line sources make it possible to reach a wide range of people at minimal cost. Such an approach can also make prevention programs to be sustainable. For the prevention, we design the professional suggestion part toward individual patents by building communication platforms for sharing information.

The diagnostic workup typically includes complete medical and psychosocial history and follows a rational and formulaic approach to the diagnosis. There are multiple medical conditions which may be misdiagnosed as a primary psychiatric disorder, complicating or delaying treatment. These may have a synergistic effect on conditions which mimic an eating disorder or on a properly diagnosed eating disorder. This typically involves counselling, a proper diet, a normal amount of exercise, and the reduction of efforts to eliminate food. Hospitalization is occasionally needed. Medications may be used to help with some of the associated symptoms. At five years about 70% of people with anorexia and 50% of people with bulimia recover. Recovery from binge eating disorder is less clear and estimated at 20% to 60%. These diagnosis and treatment can be solved by depression recognition, monitoring psychological status, machine learning to make better diagnosis, real-time diary system, positive feedback to encourage having healthier eating habits, and so on.

Figure 1 shows the eating disorder diary system scenario. Whenever the patent writes the diary to update the eating history, the system will dynamically update and check knowledge base which is located in the cloud database.

Meanwhile, real-time analysis and suggestion mechanism from the knowledge base in the cloud come to the eating

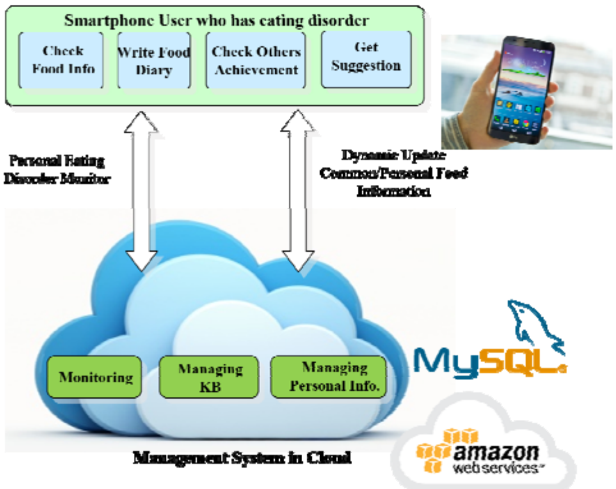

Fig. 2. Eating disorder architecture on Android platform and MySQL database on the cloud environment

disorder diary system on the smart phone. On the other hand, all the patients' information will be uploaded to the professional people to get the individual feedback.

Figure 2 explains the eating disorder diary architecture. On the smart phone side, there are 4 components which are checking food information, writing food diary, checking others achievement, and getting professional suggestion for the mobile dietary app which is implemented on Android platform. These components are used to monitor the personal eating disorder as well as dynamically update the common and personal food information to the management system in the cloud. In the cloud server side, there are 3 components which are monitoring, managing knowledge base, and managing personal information. All these information is implemented on the top of MySQL and Amason Web Service cloud servers.

III. Emotion State Recognizing

The user's emotional information can be collected through the emotional diary system. The emotional diary system is a smart phone app implemented on iOS platform, which utilizes the smartphone camera to detect user's facial expression. Human facial expression can be sensed and analyzed through "Affdex SDK", which is distributed as CocoaPod. "Affdex SDK" provides open source API support for Swift projects in the task of detecting different emotional expressions such as joy, disgust, surprise, etc. [1]. Through the camera, the emotional diary system is able to localize the key facial landmarks and capture the user's facial expressions.

The emotional diary system is able to recognize 7 different emotional expressions of the user. Each emotion is represented by a numerical value expressed in the progress bar. After the user confirms the most representative emotion, a detailed facial expression report will be generated and are available for user to

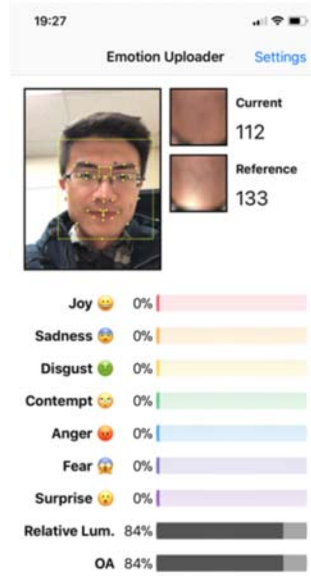

Fig. 3. A sample user-interface of emotion diary app on iOS platform.

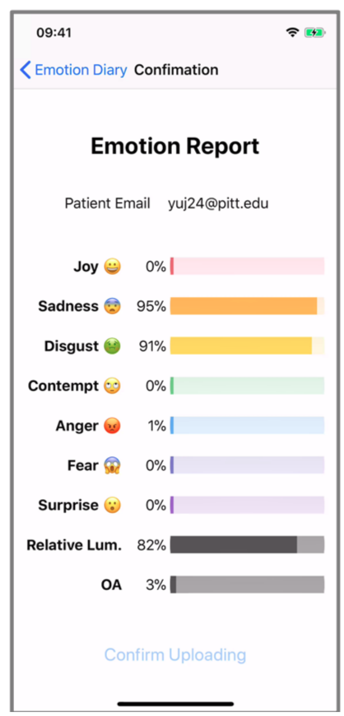

Fig. 4. A sample report generated by emotion diary app

read (shown in figure 3 and 4).

For this project, we are mainly interested in the most three representative different emotions: joy, disgust, sadness to detect the abnormal amount of calories intake and track the care procedure for eating disorder.

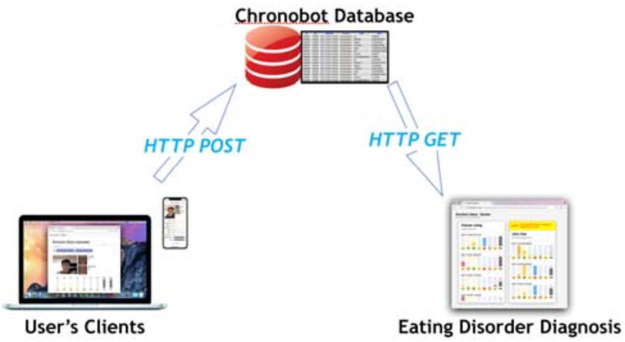

Fig. 5. Emotional diary system architecture

```
Input: D_i
for Centroid Φ_j in all Centroids do
    calculate the distance d(D_i, Φ_j)
    if (d(D_i, Φ_j) == min) then
        c(D_i) = Φ_j
    end
    add D_i into the data instances
    update the Φ_j
end
if Ψ(c(D_i)) == e_1 then
    return completely normal event
end
if Ψ(c(D_i)) == e_2 then
    return normal event
end
if Ψ(c(D_i)) == e_3 then
    return slightly abnormal event
end
if Ψ(c(D_i)) == e_4 then
    return abnormal event
end
Output:{Φ_1, Φ_2, Φ_3, Φ_4}
```

Algorithm 1: algorithm shows the procedure of detecting the event types

Figure 5 demonstrates the architecture of the emotional diary system. The system can be divided into three components interacting with each other. A mobile component (smartphones, personal computer) collect user's emotions at different time stamps and uploads the emotions into Chronobot MySQL Database of a Mobile Slow Intelligence System [2]. Then, eating disorder diagnosis component sends the request to the database to continuously monitor the emotions for each user. The emotion state can be one of the criteria for evaluating the caring procedure of eating disorder.

IV. Abnormal State Monitoring

The goal of eating disorder care is to identify the abnormal events in the data. The system uses the data-driven model to identify the 3 different events in the data: {abnormal-event, almost-abnormal event, almost normal event, normal event}, also denoted as {e1, e2, e3, e4} The basic idea of abnormal event identification is to "customize" for each user, that is the definition of the abnormal event can be automatically adjusted with respect to users.

In the system, the problem of identifying the abnormal events can be seem as the problem of clustering with three centroids (Φ1, Φ2, Φ3, Φ4). Each centroid is equivalent to different type of event.

Definition 1: For the new data instance D_i, the Euclidean distance between the data instance D_i and the three centroids (Φ1, Φ2, Φ3) is denoted as $d(D_i, \Phi1)$, $d(D_i, \Phi2)$, $d(D_i, \Phi3)$; $C(D_i)$ is cluster of the data instance D_i: If $C(D_i) = \Phi1$, then $\Psi(D_i) = e1$. If $C(D_i) = \Phi2$, then $\Psi(D_i) = e2$. If $C(D_i) = \Phi3$, then $\Psi(D_i) = e_3$. If $C(D_i) = \Phi_4$, then $\Psi(D_i) = e_4$.

Algorithm 1 shows the process of the system detects the abnormal event with the data instance Di as the input and the types of the event as the output. The study of the clustering is data-driven. However, during the initial phase of the system, identifying the centroid may be a problem, due to the lack of data instances. We assume the initial three centroids are (μ-2σ, μ, μ+2σ), where μ = 2,200 calories, σ = 200 calories, following with the Gaussian distribution, based on the average amount of calories in taking on daily basis recommended by Dietary Guidelines Advisory Committee (DGAC) [3]. Clustering the new data instance D_i with d dimensions and updating the new centroids of the cluster are implemented through k-means algorithm illustrated in Equation 1 and 2, which enables the definition of the abnormal event gradually adjusted to each user.

$$argmin_{j\in\{\Phi_1,\Phi_2,\Phi_3,\Phi_4\}} dis(\mathbf{D}_i^{|d|}, j)(1)$$

Equation 1: identifying the cluster for the new data instance Di

$$\Phi_j = \frac{1}{|D_j|} * \sum_{D_{i,j}}^{|D_j|} \mathbf{D}_{i,j}^{|d|}(2)$$

Equation 2: updating the centroid based on the new data instance Di

The attributes in the data instances consist of continuous values (e.g. calories amount) and categorical values (e.g. emotions). The distance calculation between the Di to the centroids cannot be purely the calculation of Euclidean distance, which does not work well for categorical values. We separate the attributes of the data instance into two group ε and η, where ε is the set of attributes with continuous values and η is the set of attributes with categorical values. The difference between two ε: ε1 and ε2 and be simply calculated with distance function (e.g. Euclidean distance, city block, etc.). For η, the difference of the two η: η1 and η2 can be computed through a kernel function that calculates the dissimilarity scores between η1 and η2.

$$dist(D_i,\Phi_j) = \alpha_\epsilon * \lambda(D_i,\Phi_j) + \beta_\eta * \kappa(D_i,\Phi_j)(3)$$

Equation 3: the distance measurement between the data instance D_i and the centroid Φj

The λ is the normal distance calculation function and κ is the kernel function that used to measure the dissimilarities. The α and β are the weights assigned to each distance measurement.

Using this approach, it can take all attributes into account for the distance measurement, while avoiding the inference caused by categorical values. Besides, the value of α and β can dynamically change and be learned through continuous data stream collected from user in order to better detect the abnormalities.

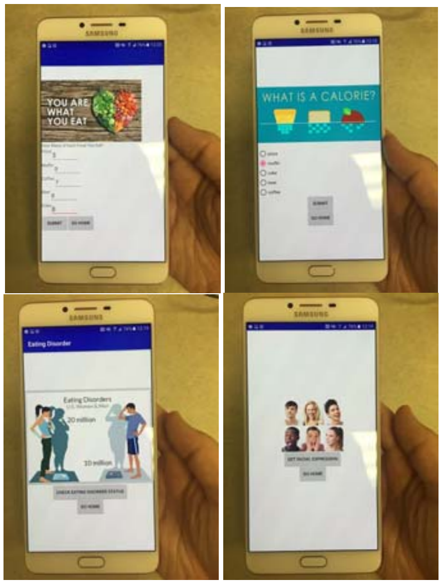

Fig. 6. Dietary System: updating dietary history (left-top), checking food information(right-top), checking eating disorder status(left-bottom), getting emotion status identification (right-bottom)

V. EXPERIMENTAL RESULTS

The application was implemented on iOS and Android platforms to collect users' emotional states and dietary information. All the records were stored in Chronobot MySQL database. We focus on identifying the abnormal events with incoming data stream collected from the applications. Table 1 shows the sample data stored and extracted from Chronobot that we used for analyzing the abnormal events. From the table, we can extract the total amount of calories in taking on daily basis associating with its corresponding emotional state. The total amount of calories and emotional state are the two criteria to evaluate the abnormality of the events.

Through the mobile dietary system on the top of Android platform, we can upload our dietary history several time per day, check food information such as calories, check eating disorder status among normal / almost normal / almost abnormal / abnormal, and get emotion status identification which is extracted from iOS platform as shown in figure 6.

We conducted a user-study experiment for a period of 15 days with 5 different patients. During the experiment, we kept track of users' daily food consumption and calculated the total amount of calories in taking based on the food types and amount, while recording user's emotional expression. Then to better projection the abnormalities of the events, we normalized the event abnormality values into the interval [0, 1] and classify the event based on its event abnormality values. The higher value indicates the higher degree of abnormality of the event.

User ID	Date	Emotion State	Total Calories	Food Types
11111	2018-03-21	Joy	2,013	Apple salad, milk, turkey sandwich, wheat bagel
11111	2018-03-25	Sadness	1,130	Apple, milk, salad
2222	2018-03-29	Disgust	2,514	Fried chicken, brownie, potato fries, burger
2222	2018-03-30	Disgust	2,201	Egg, ham, sea food, soup, fried rice

Table 1: A sample data stored in the Chronobot database

User ID	Date	Emotion State	Total Calories	Abnor-mality Value	Classifica-tion
11111	2018-04-21	Joy	2,013	0.0	Normal (blue)
22222	2018-04-25	Sadness	1,130	1.0	Abnormal (red)
33333	2018-04-29	Disgust	2,514	0.7	Almost abnormal (orange)
44444	2018-04-30	Disgust	2,201	0.3	Almost Normal (green)
55555	2018-04-21	Sadness	2197	0.3	Almost Normal (green)

Table 2: A simple table visualization of abnormal event identification

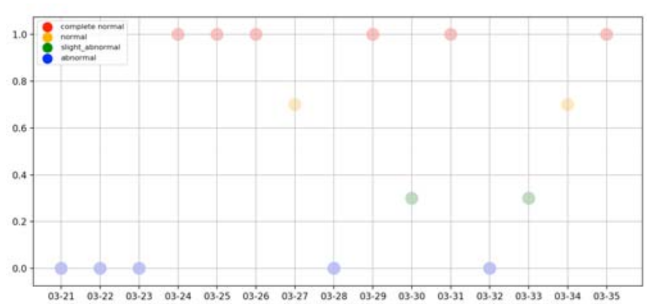

Fig. 7. A sample graph visualization of abnormal event identification

The types of the event also map to different color. Figure 7 and table 2 are the two different the visualizations of the types of events identified by our system. Event set {abnormal-event, almost-abnormal event, almost normal event, normal event} map to the color set (red, orange, green, blue) to allow users, physicians be aware of the abnormalities inside the data, or evaluate the caring process of eating disorder. In Table 2, it demonstrates a sample for 5 different users who accepted the test. Figure 7 is a sample visualization of a patient over the testing period.

VI. Conclusion and Future Work

Eating disorders are real, complex medical, psychiatric illnesses that can have serious consequences for health, productivity and personal relationships. We designed and implemented a mobile dietary and emotional diary system on the smart phone in order to detect eating disorder based on patients eating history and facial status detection. Through an analysis of normal and abnormal dietary input and emotional state, this system is intended for providing eating disorder healthcare service as a service in the cloud. In the future, we can check how social media feature will impact the human behavior for their healthcare and do some benchmark depends on cloud resource location compared with smartphone location. We can also build software engineering modeling with cloud architecture for the slow intelligence system and professional medical users' interface to collect recommendation. The reason why we build the dietary system and emotional diary system on the Android and iOS separately is to show the diversity, however, we can build into the one platform as well. Also, sensor fusion feature is possible by combining food information with location information, detecting user lie, reducing user's behavior by detecting order voice, location, camera or so. Our cloud environment can be more cost effective cloud resource usage by bidding resource, and it will be more effective when the medical information is getting massive in the real world since it can be scalable on demand. In the future, we also plan to increase the number of criteria that were used to determine the abnormalities of the event. For example, we could consider the patient's daily exercise and the types of the food. Even though a patient's daily total calories are high, he/her has a very active daily exercises, the system will still consider it is normal. Although a patient's daily calories are low, the food he/she ate are most junk food, and then the system still consider it is an abnormal event. We also plan to use different decision making methods such as building a neural network and decision tree.

Acknowledgement

The Emotion Diary was first conceived and implemented by Yuhuan Jiang.

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