A Development of Classification Model for Smartphone Addiction Recognition System Based on Smartphone Usage Data

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Abstract. The rapid growth of smartphone in recent years has resulted in many syndromes. Most of these syndromes are caused by excessive use of smartphone. In addition, people who tends to use smartphone excessively are also likely to have smartphone addiction. In this paper, we presented the system architecture for e-Health system. Not only we used the architecture for our smartphone addiction recognition system, but we also pointed out important benefits of the system architecture, which also can be adopted by other system. Later on, we presented a development of the classification model for recognizing likelihood of having smartphone addiction. We trained the classification model based on data retrieved from subjects' smartphone. The result showed that the best model can correctly classify the instance up to 78%.

Keywords: Smartphone addiction · Activity recognition · Data mining · e-Health system · Smartphone application

1 Introduction

Smartphone device has been increasing rapidly. A report [11] suggested that from a total population in South Korea, 88% of them own a smartphone and most developed countries remain above 50%. This information has proven that smartphone has become a part of people's modern lifestyle. Thus, consequences of excessive use of smartphone should be concerned.

In 2014, a medical research [7] presented the weight feel by cervical spine in each angle range of reading position, where reading position is also refer to the position when using smartphone. The work has shown that the more the head tilts forward, the more the weight feel by cervical spine will increase. This results in severe next pain, blurred vision, and headache.

Other well-known symptoms are, Computer Vision Syndrome (CVS) [2], pain in the wrist [14], and smartphone thumb (cellphone thumb) [8]. For example, CVS occurs from a low blink rate. The symptoms of CVS are dry eyes and headache. However, all this syndromes, including Text Neck, are results of excessive smartphone usage. Thus, people with smartphone addiction are likely to have one or more of these syndromes.

I. Czarnowski et al. (eds.), *Intelligent Decision Technologies 2017*,
Smart Innovation, Systems and Technologies 73, DOI 10.1007/978-3-319-59424-8_1

In this paper, we present a development of classification model for smartphone addiction recognition system. The development includes the design of the system architecture and training of the classification model. For the experiment, we demonstrate the training processes of the classification model and how it is possible to use data from users' smartphone to predict whether they are likely to have smartphone addiction or not.

2 Related Works

In the past decades, there are many works that proposed solutions to overcome issues in healthcare system by using technologies. In this section, we outlined some of the important works that related to our proposal.

In 2014, Yang et al. [15] developed an intelligent medicine box. The purposes of the system were to monitor the patient behavior and to provide them with various of services, such as, reminder for taking medicines and a remote communication with a physician. The system showed a good example on using multiple Internet of Things (IoT) devices in one system. However, it did not contain or outline the uses of data mining in the work.

In term of smartphone addiction, several works have proposed statistical models what link the smartphone addiction to mental problems. In 2014, a work [1] shows a statistical model that presented the evidence that the use of smartphone for certain purposes and certain kind of smartphone addiction symptoms have significant impact on social capital building. Another work in 2015 [4] showed another perspective, and pointed out that social stress also has a positive influences on addictive smartphone behavior. However, in 2016, a research paper [12] presented a test on relation ship between smartphone addiction, stress level, and academic performance. The work showed a positive relationship between the smartphone addiction and stress level, but a negative relation ship between smartphone addiction and academic performance.

In term of a recognition system, Sano and Picard [13] presented a work to recognize stress by using wearable sensors and mobile phones. The work showed a possibility in recognizing mental issues by evaluating the model with perceived stress scale (PSS) [3]. The results showed that the system is capable of recognizing high or low perceived stress level with the highest accuracy of 75%.

For smartphone addiction, in 2014, Lee et al. presented a Smartphone Addiction Management System and Verification (SAMS) [10] to show the statistical analysis on the relationship between the application used on smartphone and possible smartphone addiction. The result of the SAMS showed a strong correlation between smartphone addiction and daily use count. Thus, we also considered this as one of the main attributes in our experiment.

3 Methodology

In this section, we discuss the techniques used in development of the classification model for smartphone addiction recognition system, which includes system architecture, and the smartphone application.

3.1 System Architecture

In recent years, there has been many development of e-health system to overcome technical limitations. Most of these developments started using IoT devices and data mining technique to provide a better system.

As in 2013, European Telecommunications Standards Institute (ETSI) has proposed a architecture that can be used by developers in building a service application [6]. As a result, a group of researchers has proposed a Next Generation e-Health Framework [5]. The framework adopted the concept from ETSI framework and extended the it further to match e-Health application requirements. From those proposed works, we have taken the idea and improved the design to better match the requirements of our system.

Figure 1 shows the design of the proposed system architecture. We took the idea of dividing data mining tasks into layers from a prior work [16] and separated the system into four main parts.

Body area network consists of sensor devices, which sense and transmit all raw sensor data to a body gateway. The Body gateway device must be capable of preprocessing raw data and send them over the Internet to the cloud services. By doing preprocessing at the body gateway, it also increases the abstraction level of the data. Thus, easier for personnel operating the cloud service to handle the data.

Mechanisms are the definition of how each part operates. In security mechanism, the architecture needs to specify how it handles the security issues of the system. For example, how the system will encrypt the data, which security protocol will it use to communicate between body area network and cloud services, and how will the system handle the privacy of users. On the other hand, sensor network mechanism specifies the protocol used between sensor devices and body gateway. This is different from the communication between the body gateway and cloud services, which is done over Internet, as there are more options to choose from. The chosen network protocol should consider the requirements of the system as well as sensor devices' capabilities.

Cloud services consists of several possible services. The cloud service should provide resource and services for data processing tasks, as most of e-health applications and systems have implemented with intelligence system, such as activity recognition. Thus, it is not suitable to perform those task in the body area network. Moreover, this will separate the tasks of data scientists and medical experts from handling the technical issues in body area network. Other services that the cloud service could provide are e-Health services, which are various services that need interaction between patient and medical personnel, and management service, which ease up the task of managing the whole system for administrators.

On the other hand, data processing does not concern the hardware nor the component of the system. However, data processing outlined four main tasks of data mining in e-health system and where it should be done. Raw data sensing (also known as data collection) and context management should be done at body area network level. While knowledge extraction (e.g., classification or clustering) and visualization and interaction should be done on the cloud services.

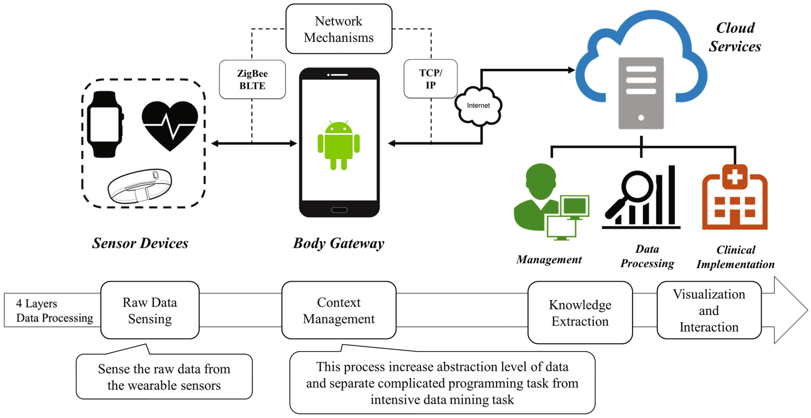

Fig. 1. Overview of the proposed system architecture for healthcare system

3.2 Smartphone Addiction Scale

Smartphone Addiction Scale (SAS) [9] is a self-diagnostic scale, which consists of 33 questions and each question is weighted equally on a 6-point scale. The SAS provides a score range between 0 to 188 where higher score indicates more serious smartphone addiction. As in this work, we used SAS as an evaluation tool. We recorded the SAS scores of all subjects and used the mean value of a total score as a separation point.

3.3 Application Overview

For the development of smartphone addiction recognition system, we developed an application to collect the data from the subjects. Figure 2 shows the 3 main application interfaces. The application consists of three main parts as follows.

The registration part is an interface for user to input important information, including, name, e-mail, date of birth, and gender. All information are kept in the cloud database, and it was not used publicly.

The purpose of the survey part is to collect the SAS score from subjects. After the application calculates the total SAS score, it sends them to cloud service to store them in database.

In monitoring part, the application handles all monitoring through Android service. The service allows the application to collect necessary data from the smartphone periodically without interfering users. The service runs for a total of 7 days and will stop itself after it finishes monitoring. The data collected are number of phone unlock, average phone usage time per phone unlock, maximum phone usage time per phone unlock, minimum phone usage time per phone unlock, total phone usage time, and total walking step count.

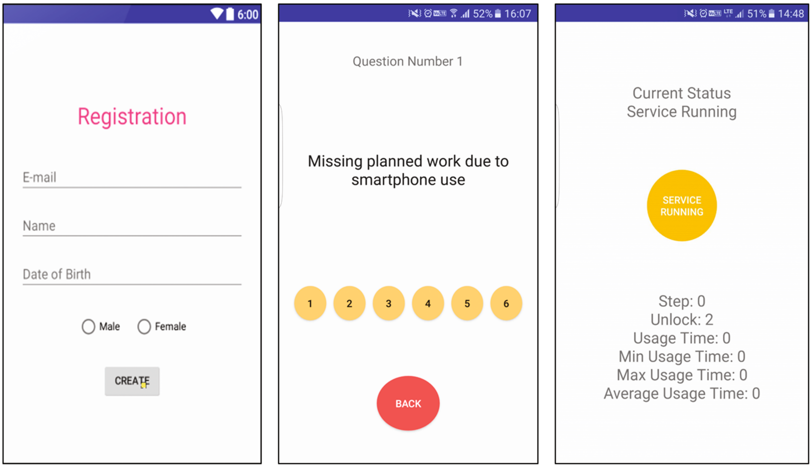

Fig. 2. Three main page of the developed application

4 Experiment

We conducted an experiment to prove that it is possible to predict the likelihood of having smartphone addiction by using data from smartphone sensor and logs. There were a total of 8 subjects participated in the experiment.

4.1 Experimental Design

We separated the experiment into three main stages. Figure 3 shows the overview of the experiment design. The first stage is to explain the detail and purpose of this work to the subject as well as allowing them to decide whether they want to participate in the experiment or not. If the subject chooses to participate in the experiment the application will be installed on the subject's smartphone. Then, the subject register their account to the system. In stage 2, all subject complete the SAS pre-survey, this survey score will be used later for evaluation. The detail of SAS is discussed later in this section. All pre-survey scores are stored in the cloud database. After the subject completes the survey, they can start the monitoring. The monitoring operates as a background service. Thus, it is possible for the subject to close the application and use their smartphone normally. In stage 3, after all subjects have completed the monitoring, which was lasted for 7 days, we retrieved all data and analyzed them. The attribute combinations and evaluation of each classification model is discussed later in this section.

4.2 Data Collection and Data Preprocessing

We developed the application on an Android 5.0 (API level 21) platforms. The application is responsible for three main features as mentioned earlier in Sect. 3.2.

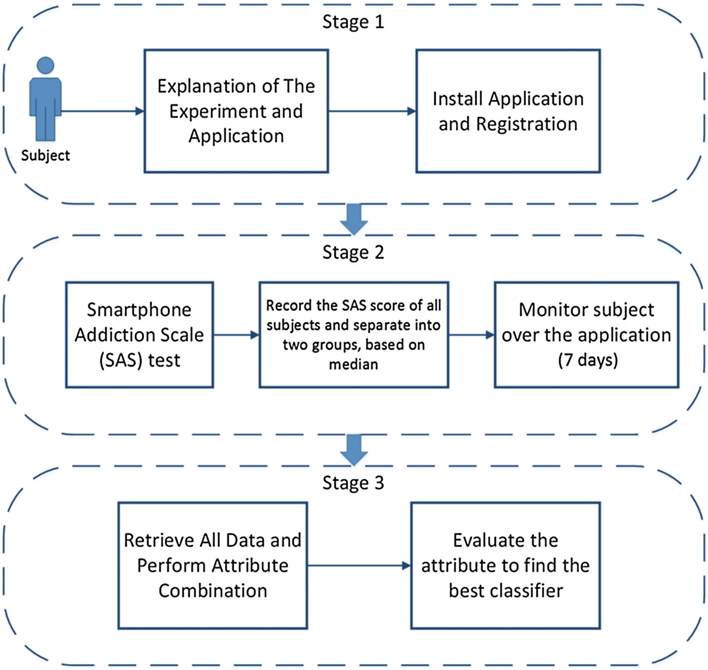

Fig. 3. Overview of the experiment design

The application collects the data periodically and preprocesses them before sending them to the cloud service. The application started the monitoring process and stopped itself after it reaches 7 days mark.

The application collected all the attributes mentioned earlier in the Sect. 3.3. Then, the application performs preprocessing by calculating the following values periodically:

1. Average Smartphone Usage per Unlock
2. Maximum Smartphone Usage per Unlock
3. Minimum Smartphone Usage per Unlock
4. Total Smartphone Usage Time
5. Amount of Walking Steps
6. Time Period (6.00–12.00, 12.00–18.00, 18.00–24.00PM, 24.00–6.00)
7. Phone Unlock Count

We set the application to update one instance of data to the cloud server every 30 min. Please note that, we set the period to 30 min in order to make sure that this data set can be used with any application or classification training, which require the period to be 30 min or longer, as well.

4.3 Modeling

The data retrieved from the cloud server is used in the training. We combine 2 instances into 1 instance. Therefore, an instance used in the modeling process is an instance with monitoring period of 60 min. All data were randomly sorted to avoid any biased in the training. The training set and test set were separated from all data with 70:30 ratio.

For performing supervised learning tasks, we labeled each instance as either ‘High’ or ‘Low’ for classification. However, as each subject has instance which was updated to the cloud during their inactive time. Thus, we labeled the instance where ‘Total Smartphone Usage Time’ equal to 0 as ‘Inactive’. The lowest SAS for the experiment was 86 while the highest was 124 and the average score of all subjects was 110. Data instance from subject with score equal to or lower than 110 were labeled as ‘Low’ while the data instance from subject with score higher than 110 were labeled as ‘High’.

In order to train the best performing classification model, we took all 7 attributes and calculated all possible combinations with at least two attributes. As a result we have a total of 120 attribute combinations. We used each combination as a training attributes with 4 classification algorithms, which are Naive Bayes, K-Nearest Neighbor (K-NN) (K = 5), Decision Tree (J48), and Support Vector Machine (SVM). We performed the training process using the same training set with 10-fold cross validation technique. Then, we tested the trained model on the same set, which we prepared earlier.

4.4 Experiment Result

The 20 most accurate results of all attribute combinations are discussed in this section. Table 1 shows the accuracy of each attribute combination. Please note that the number in attribute column represents the attribute according to the attribute list mentioned in Sect. 4.3.

The result shows that the combination of attributes 1, 3, 4, 5, 6, 7 and 2, 3, 4, 5, 6, 7 have the most accurate results when trained with Decision Tree (J48) algorithm, which the accuracy were equal at 78.74%. The two combinations also equal the accuracy at 68.11% with Naive Bayes algorithm. The accuracy with K-NN (K = 5) were 70.08% and 70.07% respectively and 61.42% and 61.45% respectively with SVM algorithm.

The least accurate attribute combination of this top 20 list was the combination of attributes 1, 2, 3, 4, 6. The accuracy was 65.76%, 70.47%, 73.62% and 58.27% with Naive Bayes, K-NN (K = 5), Decision Tree (J48), and SVM respectively.

From the algorithm perspective, Decision Tree (J48) has out performed all other algorithms in every attribute combinations. The most accurate combination with Decision Tree (J48) was 78.74% while the least accurate was 73.62%. For Naive Bayes, the most accurate was 68.50% and the least accurate was 65.76%. The most accurate for K-NN (K = 5) was 73.62% and the least accurate was 68.50%. For SVM, the performance was fairly poor as the most accurate combination was only 61.81% and the least accurate combination was 55.59%. The average accuracy of Naive Bayes, K-NN (K = 5), Decision Tree (J48), and SVM are 67.62%, 70.91%, 75.15%, and 58.80% respectively.

Table 1. Results of classifier evaluation on the test set

Attributes	Algorithm accuracy (%)			
	Naive Bayes	K-NN (K = 5)	Decision Tree (J48)	SVM
1, 3, 4, 5, 6, 7	68.11	70.08	78.74	61.42
2, 3, 4, 5, 6, 7	68.11	70.07	78.74	61.45
1, 2, 3, 5, 6, 7	68.11	69.69	78.34	61.42
2, 3, 5, 6, 7	68.11	69.29	78.30	60.23
3, 4, 5, 6, 7	68.11	68.50	78.29	61.02
1, 2, 3, 4, 5, 6, 7	68.11	70.47	76.77	61.41
1, 3, 5, 6, 7	66.93	68.50	76.38	61.42
1, 2, 4, 5, 7	68.11	72.44	75.98	59.94
1, 4, 5, 6, 7	67.72	69.69	75.98	59.06
1, 2, 3, 6, 7	67.72	70.87	75.59	61.42
1, 2, 4, 6, 7	68.50	69.29	75.59	59.84
1, 2, 5, 6, 7	67.71	70.87	75.59	61.4
1, 2, 3, 4, 5, 7	67.71	73.62	75.20	61.02
1, 2, 3, 4, 6, 7	68.5	71.26	75.20	61.81
1, 3, 4, 5, 7	68.11	73.62	75.20	61.02
1, 3, 4, 6, 7	67.72	70.87	75.20	55.60
2, 3, 4, 6, 7	68.5	72.05	75.2	55.59
2, 3, 4, 5, 7	68.5	73.23	75.19	61.02
1, 2, 4, 5, 6, 7	68.11	71.26	74.41	59.45
1, 2, 3, 4, 6	65.76	70.47	73.62	58.27

Table 2 showed the confusion matrix of the best performing attribute combination. From the result, the model correctly classified 37% of all instances in 'High' class or 70% of all 'High' instances. For instance in 'Low' class, the model correctly classified 16.54% of all instance or 76.36% of all 'Low' instances. The model correctly classified all instances in 'Inactive' class.

4.5 Discussion

The experiment has shown a satisfying results, and the best performing model has the accuracy of 78.74%. However, the results have also pointed out the room for improvements. In this experiment, we considered a total of 7 attributes. More attributes from other sensors could improve the accuracy of the model. Moreover,

Table 2. Confusion matrix of the best attribute combination

	High	Low	Inactive
High	37.00%	16.14%	0%
Low	5.12%	16.54%	0%
Inactive	0%	0%	25.20%

as another possible way to improve the result is to implement the application with artificial intelligence algorithm. By doing so, it is possible for the application to learn and study the smartphone usage behavior of each individual user and compare them with others. Nonetheless, the mentioned possibilities is out of the scope of this paper.

The limitation concerned in this experiment was that the size of the subject was small, and further experiment with larger subject group will provide a classification model that can handle more diverse usage characteristic. Nonetheless, the result of this experiment showed a positive side of using data from smartphone to recognize likelihood of having smartphone addiction.

5 Conclusion

In this paper, we showed the importance of recognizing smartphone addiction and how it could prevent users from suffering other syndromes related to smartphone usage. We presented the system architecture which is possible to implement in developing other e-health system. The architecture consists of four main parts which are clearly separate from each other. The abstraction level of the architecture made it easier for personnel from different fields to coordinate with each other.

Moreover, we presented a development of a classification model based on the data collected from the subjects smartphone. The result of the development was accurate up to 78.74% in recognizing whether their smartphone are Inactive or they have High or Low smartphone addiction likelihood. The results showed good opportunities for improvement and implementation in the smartphone.

Finally, despite the results are preliminary with the limited number of participants in the experiment. We have shown that the data from the smartphone can be used to recognize likelihood of smartphone addiction. In the future, by increasing the subject size and integrating multiple device into the system could provide us with a more accurate classification model. We will also attempt to work on a more robust and dynamic system in which the interaction between the system and users should be personalized to prevent smartphone addiction.

Acknowledgments. This work was supported by JSPS KAKENHI Grant number 15K00929.

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