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Multi-dimensional Well-being Recognition System Using Daily Activity Data for Sustainable Living

by

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"Be the change that you wish to see in the world."

Mahatma Gandhi

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SHIBAURA INSTITUTE OF TECHNOLOGY

Abstract

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Several studies suggested that older adults see digital technology devices as a tool that could facilitate not only daily activities but also maintain social relationships whilst overcoming some of the physical and geographical barriers associated with aging. The study demonstrate how older generation also value technology devices and how they are ready to adopt them into their daily life. On one hand, this will influence their behavior, on the other hand, this is an opportunity in encouraging better well-being.

Challenges and opportunities of using these technologies to develop the monitoring platform for healthcare was discussed in another study. There are numbers of discussion in challenges in system architecture, data acquisition and sensing, data storage and processing, data analytics, and visualization. This provide a complete view of opportunities in using the emerging technology to build a monitoring platform where technology and technique like Internet of Things and machine learning are integrated into the system. Ethical issues like privacy and security were also the concern.

This study conducted development of a well-being monitoring platform where it recognizes the well-being level in multi-dimension manner. The development of the system was based on the idea that it should raise awareness in person's current well-being level and to encourage the person toward a better behavior. We developed a total of 6 systems to address the solution of raising ones well-being. The changes

made in the development process of the first system to the final system show the improvements and how this study slowly started from tackling the smaller problem to the bigger problem with more generic solution from the foundation we had built. In total, we had over 90 human subjects participated in all of our experiments. Moreover, we have implemented numbers of machine learning algorithms, such as K-Nearest Neighbors, Support Vector machine, and Decision Tree for building a classification model. Numerous sensor devices were implemented and tested throughout the development of the systems to find out the best set of devices for monitoring behavior and classify the well-being level. This study also used a trending approach of deep learning in order to extract useful information from video and sound, and use that information in classifying the well-being level. Moreover, an unsupervised learning method were also used as a part of developing the classification model for multi-dimensions well-being level classification. Finally, a visualization platform was developed to provide meaningful feedbacks to users.

In general, the emerging technologies provide a great opportunity in developing a platform in raising awareness, especially in encouraging well-being. However, the development of this platform should concern the effect of excessive use of technologies device itself as well. The thorough monitoring should be done effectively, but avoid being invasive, and in that respect, this study proposed a solution to that problems. This well-being platform will not only help raise awareness in users well-being level from its complete system, but will also serves as a foundation for developing health monitoring platform where multiple sources of data and multi-dimension health are the concerns.

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Chapter 1

Introduction

This chapter introduce the overall of the study, which include the overall discussion on the problems that led to this study and the current limitation of existing work at the time we conducted this study. The main objectives and contributions are described to clearly outline the scope of this study. Finally, the organization of this dissertation is presented.

1.1 Well-being problems and concerns in the digital world

In general, the access to technology, especially smartphone, has been increasing rapidly in recent years. The report by Pew Research Center [1] suggested that from 39 countries, including 17 advanced economies country and 22 emerging developing economies countries, a median of 75% have access to the use of Internet. Further in the report, a median of 59% represent the ownership of smartphone where South Korean is a leading country in the statistic as 94% of the people own a smartphone. The growth of this usage statistic is especially large in emerging developing economies countries, where the report suggested that countries like Lebanon, Jordan, and Philippines have 28%, 25%, and 22% change in smartphone ownership between 2015 and 2017 respectively. This suggested that the technology is embedded deeper and deeper into our daily life and that has come with changes in behavior and as well as healthcare concerns.

A study suggested that older adults see digital technology devices as a tool that could facilitate not only daily activities but also maintain social relationships whilst overcoming some of the physical and geographical barriers associated with aging [2]. The study demonstrate how older generation also value technology devices and how they are ready to adopt them into their daily life. On one hand, this will influence their behavior, on the other hand, this is an opportunity in encouraging better well-being. Another study show that the use of activity tracker can help encourage better health and well-being through predefined challenges [3]. The study suggested that the participants are significantly more active during the experiment period. However, health can be impacted by the technologies as well. A study on computer related health problems suggest that from the survey experiment, 77% of the study group would have musculoskeletal problem, while 76% would have visual problems, and 35% in stress problem [4].

Challenges and opportunities of using these technology to develop the monitoring platform for healthcare was discussed in another study [5]. The study discuss challenges in system architecture, data acquisition and sensing, data storage and processing, data analytics, and visualization. This provide a complete review of opportunities in using the emerging technology to build a monitoring platform where technology and technique like Internet of Things and machine learning are integrated into the system. Ethical issue like privacy and security were also pointed out in the study.

In general, the emerging technologies provide a great opportunity in developing a platform in raising awareness, especially in encouraging well-being. However, the development of this platform should concern the effect of excessive use of technologies device itself as well. The thorough monitoring should be done effectively, but avoid being invasive. This dissertation conducted the study to develop a well-being monitoring platform where it recognize the well-being level in multi-dimension manner. The well-being in this dissertation refer to subjective well-being, where it concerns the well-being level relates to emotional and psychological factors, namely, positive affects, negative affect, and stress, which this study refer to these components as 'multi-dimension'. More detail of subjective well-being is discussed in Chapter 2 section 2.1.2. The development of the system was based on the idea that it should raise awareness in person's current well-being level and to encourage the person toward a better behavior for better well-being.

1.2 Objectives

1. To develop machine learning model for recognizing and monitoring well-being level based on the collected data:

This dissertation aim to provide a smart system in assisting users with their awareness in well-being level. To that end, the dissertation aim to develop a machine learning model where it will automatically recognize the well-being level based on the collected data. This model's accuracy should be able correctly provide the recognition result that can be used by another component of the system to communicate with the users.

2. To implement new technology in medical application for promoting better well-being

As new technologies are emerging, to promote a better well-being, this dissertation aim to implement those technology to provide a service in medical application where it will be easier and faster when compare to a conventional method in medical or bioengineering domain.

3. To propose a complete system with visualization for raising awareness in users' well-being level:

This dissertation also has a goal in conveying an important message from the result of its development back to users. This will be done through the visualization where it will provide the recognition result as well as real-time monitoring data from the devices. This completed system is how the dissertation will raise awareness in users' level of well-being.

In general, this dissertation aim to contribute to the community by providing a complete monitoring system with well-being recognition where it will help raise awareness and promote better well-being level. This is the final results of combination of multiple studies, which this dissertation will discuss later in chapter 3, 4, 5, and 6. Finally, the dissertation aim to contribute to the society by making the well-being monitoring easier and more feasible in daily life without needing of more complicated method.

1.3 Structure of this dissertation

The rest of dissertation is organized as follow: chapter 2 discusses the literature review of related studies in both medical and technical aspects. Chapter 3 demonstrates the first part of this study where we developed a neck posture monitoring system to prevent physical syndrome from prolonged usage of smartphone. Chapter 4 discusses the development of stress recognition system using data from multiple type of sensors and used them for training the recognition model with machine learning algorithm. In chapter 5, it discuss the final outcome of this study, where we developed the well-being recognition model from multiple aspects along with the data collected from multiple sources. The visualization for the system is also discussed in chapter 5. Finally, chapter 6 concludes the study along with the discussion regarding future works opportunity of this study.

Chapter 2

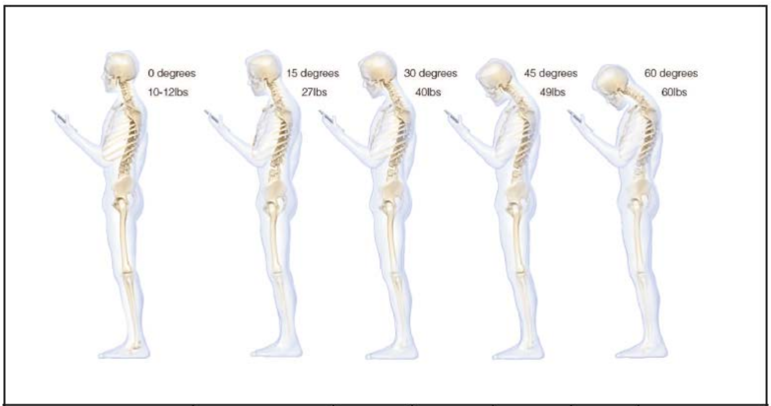
Related Studies

2.1 Importance of well-being

2.1.1 Smartphone related syndromes

The concern of well-being from technology usage has been increasing in recent years. As a result, researchers from medical field have conducted many studies to pointed out the issues and concerns. A study from Kennen K. Hansraj shows the possible effects from excessive use of smartphone [6]. The study performed an experiment to asses the stress in cervical spine caused by posture and head position. The posture can be referred as reading position, which the study also pointed out that it is a common posture for using smartphone. The results of this study shows that the weight seen by the cervical spine will increase dramatically as the users tilt their head forward. The normal weight seen by the cervical spine of an adult at $0°$ is around 10-12lbs (4.5-5.4kg.). However, the weight seen by the spine at $60°$ could be up to 60lbs (27.2kg). Figure 2.1 shows the weight seen by cervical spine at different angles.

Other studies address other issues and concerns as well. The study in 2008 by Zhen Yan, et al. shows a review on Computer Vision Syndrome (CVS) [7]. The syndrome has been an issue from excessive use of personal computer, where



Position	Neutral	15 °	30°	45 °	60 °	90°
Force To Cervical Spine	10-12lbs.	27lbs.	40lbs.	49lbs.	60lbs.	Not Measurable

FIGURE 2.1: The weight seen by cervical spine at different angles

users tend to blink their eyes less and cause users to have dry eyes. In severe cases, this could lead to severe headache and other side effects. The concern in this syndrome has been addressed and pointed out due to the use of smartphone as well. A statistical study also shows that out of 795 university students in Malaysia of aged between 18 and 25 years old, 89.9% of them had experience at least one symptom of CVS [8]. Several studies proposed a technological solution to counter the issue. Multiple studies proposed method for eye blink detection [9, 10], the approach of eye blink detection is then used to develop CVS prevention system [11]. The system focused on the eye-fatigue detection where the true positive detection rate was as high as 95%. The study proposed that this approach can be used to detect dangerous eye behavior and can help in timely prevention of CVS-related symptoms.

In general, both of the issues are the concern from excessive use of technology, especially from smartphone. The solution to this concerns and issues are further addressed in chapter 4 and chapter 5.

2.1.2 Stress, mood, and well-being

One of the study pointed out that daily stress has an impact on general health and mood [12]. Where the authors further explained that participants with unsupportive social relations ships and low self-esteem were more likely to experience increases in somatic problems. Thus, managing stress level was considered as an important solution to the issue. Another study pointed out the different stress level in two subjects group [13], where the first group had gone through an 25-30 minutes work-out and exercise for 10 weeks, while the second group had not. The results of this study found a significant lower stress level in the first group where it also suggested that good amount of exercise and physical activities help manage stress level. In term of mood, a study discussed the daily diaries for assessment of mood state and behaviors. The results of this study suggested that strategies such as positive reinforcement support could affect mood state [14], especially in depressed individuals. This aligned with this dissertation's interests, where it intended to raise awareness and provide support in changes of individuals' behavior.

In general, when the term well-being is being discussed, the definition of the term is related to the state of the mood and level of stress. A study by Ed Diener, et al. [15] pointed out that well-being or subjective well-being is a broad category of phenomena that includes people's emotional responses, domain satisfactions, and global judgments of life satisfaction. The components of well-being suggested by the study includes pleasant affect, unpleasant affect, life satisfaction, and domain satisfactions. Another study supported the argument by extending the definition that well-being was often subsumed as one of many domains comprising the concept of health [16]. Where the subjective well-being in the studied was also related to individual perceive of stress, emotional, and psychological factors and interpretation. In general, the well-being being discussed in this dissertation will be related to subjective well-being, where it concerns the psychological factors of emotion and stress, as pointed out in the published studies.

In a bigger perspective, a study suggested that in terms of well-being, a personal well-being if often found to be related to personality and personal traits [17]. Despite the results of the study, another study suggested that an interaction was one of the predictors that supported the hypothesis, which was that daily variations may be understood in terms of the degree to which three basic needs; autonomy, competence, and relatedness [18]. Moreover, the study also pointed out that general daily activities are importance factor to daily well-being. A general review pointed out important factors that help increase general happiness and well-being level [19], these factors supported the previous discussed study where it pointed out one of the factor as daily activities where exercise were also discussed. On the other hand, a study discuss the importance of well-being level and how it could easily affect the outcome of work and organization [20]. The study conducted a one year study and found the significant relationship between change in employee's well-being and employee's outcome. This supported this dissertation proposal in raising awareness and increase well-being level of the each individual.

On the other hand, the effects of well-being on a single individual were also studied in multiple published researches. A thorough study published in 2011 by Ed Diener and Micaela Y. Chan in Applied Psychology: Health and Well-being showed that the evidence for the influence of subjective well-being on health and all-cause of morality is clear and compelling [21]. An example mentioned in the study about the effect well-being was that the various form of negative effects, which may include mood and stress, are associated with deleterious changes in the cardiovascular system [22]. Another example low well-being level effect was a 4 years study by Paterniti et al. [23] where it concluded that patients with high trait anxiety had greater thickening of carotid arteries than those low in anxiety, and this was the case for both men and women. In conclusion, the same study by Diener and Chan [21] stated that even it is difficult to specifically point out how the low level of well-being could influence a certain type of disease, the evidence in all the studies that were reviewed in the paper were clear and it showed that the low level of well-being has influences on those diseases. The point to the well-being is that if the high level of well-being could add 4-10 years to life compare to those with low-level of well-being, then it is worthy of national attention. In other word, in order to maintain the higher level of well-being, it is essential to encourage sustainable living, which consist of life with higher positive components of subjective well-being and lower negative components of subjective well-being. This reason is also align with our novelty and contribution

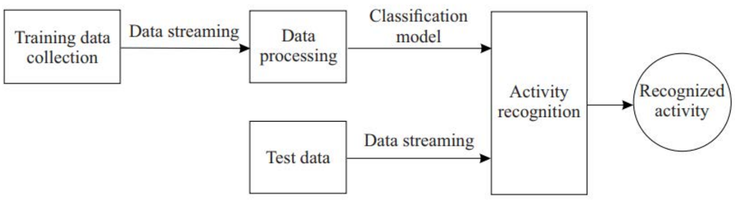


FIGURE 2.2: Smartphone activity recognition process

of this research where we aim to bring the new technology into application where it will be easier for people to be aware of their well-being level.

2.2 Data collection methods

2.2.1 Internet of Things devices

As the technology is advancing, the used of the emerging device as a data collecting tools has provided more possibility in developing a smart system. In this studies' context, it is important to consider the possibility of utilizing most suitable data collecting method in developing an efficient system. Thus, this section provide a review of a famous data collecting method related to the development of the system.

The emerging of smartphone was one of the good opportunity in collecting data from daily activity. A study by Xing Su, et al. has provide a overview of recognizing activities using sensors from smartphone [24]. The study demonstrated a good example in collecting data from multiple sensors, preprocessing the data, and training the data for activity recognition. Figure 2.2 shows an flow of the system from collecting data to recognizing the activity. This flow is a basic concept of collecting data from sensors that can also be applied with other kind of systems. Where the study by Wanmin Wu, et al. shows a similar conclusion that the smartphone sensors can provide the accurate activity recognition model [25].

Beside from smartphone, another technology that have been used widely in recent developments are wearable devices. Subhas Chandra Mukhopadhyay provided a thorough review on the device and the opportunity that the device can provided [26]. The study highlighted that technological advancement of wearable has reached the point that it possible to develop the system and actually implement it in the household. Although, the cost of the system may vary and may not be affordable. The study also pointed out that with sensors embedded in the device, it has provided opportunities for using those data to determine various states of a person, such as emotion. While another study by Bozidara Cvetkovic, et al. shows the possibility of using the combination of wristband activity tracker and smartphone for real-time activity monitoring [27]. The study shows a great example of combining data from multiple sources, especially from hand-held and wearable device, and extract variable knowledge out of it. The study achieved a high accuracy in the recognition model while pointing out that the results were essential for developing a system that can help people maintain their physical condition. Beside from wearable study, a clinical study by Julian F. Thayer, et al. demonstrate how heart rate variability can be used as a marker of stress and health [28]. Despite using data from small sensors, the study used high quality heart rate analysis tool. However, the important of this study lies at how the heart rate can be affected when the level of stress and health change. As an addition to these studies, Raggaele Gravina, et al. proposed a cloud based framework for human activity monitoring [29]. The study presented a suitable way of handling data and recognizing them. The framework support 24/7 service as well as both on-line and off-line human activity recognition, which proved to be a good example in implementing any system for real time recognition.

2.2.2 Video and deep learning

2.2.2.1 Image detection

Image detection methods and algorithms were proposed by many studies using different approaches. In general, the results of the detection has contributed to many research in developing smart system. This section review the image detection studies that are related to this dissertation.

Several studies have suggested the use of a Haar-like feature classifier because such classifiers have been proven to be accurate and fast[30]. Haar is a feature-based cascade classifier originally proposed by Paul Viola and Michael Jones[31]. An implementation of Haar-like feature classifiers has been demonstrated in a system to detect the drowsiness and distraction level of a driver using a smartphone camera[32], a system to detect fatigue [33], and a smartphone photo software program for face detection[34]. In addition to these studies, a Haar-like feature classifier was used in another system for advance face feature recognition [35]; however, this system did not process the image locally, instead, it used a cloud service. Therefore, there were additional computational resources available for the system. Conversely, another famous algorithm for image detection is Local Binary Pattern (LBP) [36]. The working mechanism of LBP is similar to Haar; however, LBP uses integers in its calculations while Haar uses floating point numbers. As a result, LBP consumes much less resources and provides better computational times. Nonetheless, there is a trade-off in the accuracy for LBP.

2.3 Measurement of well-being level

In order to fully utilize the benefit of emerging technology, a lot of studies were conducted to develop recognition system to encourage, prevent, and raise awareness in health-related concerns. This section discuss the systems that are related to this dissertation in each perspective.

2.3.1 Healthcare system architecture

For general healthcare monitoring system, one of the topic that has been widely discussed lies on the interest of its architecture for using wireless sensors and wearable sensors. Two studies discuss this topics and challenges about these devices [37, 38]. Where one of the study demonstrated the examples of technology with the design considerations of unobstructiveness, scalability, energy efficiency, and security. The study further provide a comprehensive analysis of the benefits and drawbacks of these systems. Challenges that were pointed out in the study for developing healthcare system are the combination of multiple source of data and the method used to analyze them must be carefully taken into consideration. The second study were focusing on the use of body sensor network to provide pervasive healthcare monitoring. This study demonstrated a great example of using body sensor network along with network communication technology to provide a healthcare monitoring platform. Both of these studies show and overall of components that should be taken into consideration when designing a healthcare monitoring system. Furthermore, challenges in wearable technology were further discussed in another study [39]. The main challenges that this study focused on were related to the handling of collected data. It mentioned the possibility of having big data approach in healthcare as well as making data meaningful. These are two topics that should be considered as well, especially in this era where large amount of data can be collected and handled in numerous ways. In term of security, a study by Huang, et al. [40] provided an approach to develop secure sensors-based healthcare monitoring system, where it implemented multiple security protocols to the study. This approach of considering security protocols, especially for data communication, should always be implemented in developing healthcare system. Finally, a study by Manogaran, et al. [41] proposed a new architecture for healthcare monitoring with IoT and big data. The architecture showed a thorough consideration of each components in a healthcare system as well as how each components should perform tasks on handling the data

2.3.2 System requirement

For the system requirement of the system developed in this dissertation, we have reviewed couple of key points in the published studies and adopted them. First, the privacy and security concerns, the recent published study suggested several key consideration in developing application in digital healthcare [42]. The concept of privacy-by-design was mentioned in this study where it suggested that the concern of privacy should be initiated since the design of the system. This include integrating privacy in the development cycle, practice data minimization techniques (without sacrificing applications' functionality and user experience), use privacy-protective default settings, employ state-of-the-art security practices, and maintain user awareness over control over data collection and use. By following these guidelines and strictly following the laws in handling the data, it ensure that the privacy of the user will be maintain within the application. Further sharing of the information between the system and third parties system must also follow this practice.

In term of the persuasive system requirements, Oinas-Kukkonen et al. demonstrated the key points that need to be consider in designing the system [43]. The system requirement for the primary task support should include the following:

- **Reduction:** The system should reduce effort that users expend with regard to performing their target behavior.
- **Tunneling:** The system should guide users in the attitude change process by providing means for action that brings them closer to the target behavior.
- **Tailoring:** The system should provide tailored information for it user groups/
- **Personalization:** The system should offer personalized content and services for its users.
- **Self-monitoring:** The system should provide means for users to track their performance status.
- **Simulation:** The system should provide means for observing the link between the cause and effect with regard to users' behavior.
- **Rehearsal:** The system should provide means for rehearsing target behavior.

Other important key points suggested in the study were dialogue support where it suggested that a principle of praise, rewards, reminders, suggestion, similarity, liking, and social role can contribute in a system to persuade user to change their behavior in a persuasive system. All of this requirement key points were considered during the development of this dissertation and the full system requirement is later discussed in chapter 6.

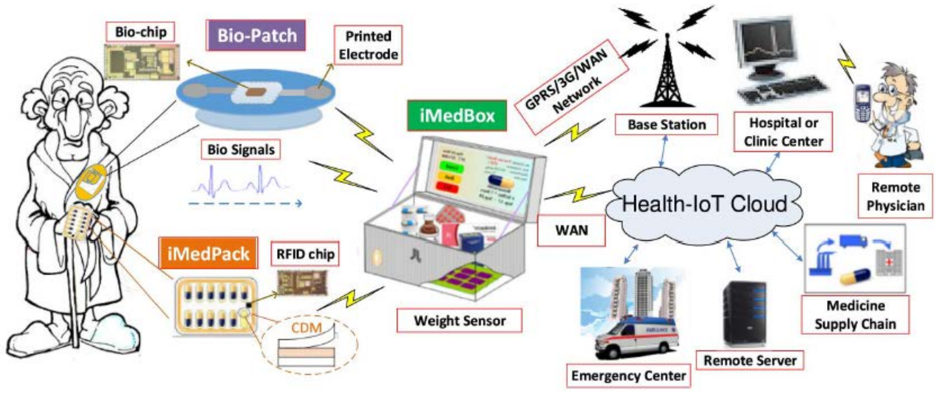


FIGURE 2.3: Overall of health-IoT system

2.3.3 Overall health-related recognition system

One of the first approach in promote better health among tech-device users were recognition system for overall health or physical condition. The study by Geng Yang, et al. demonstrate how IoT technology can be implemented in a complete system for healthcare monitoring [44]. The system implemented an intelligent packaging as well as intelligent medicine box. Figure 2.3 shows an overview of the system from the study.

Another system by Mu Lin, et al. proposed a solution in using smartphone along with the developed application to collect data and recognize the well-being in multi-dimensional manner [45]. This study collected several data from smartphone and rate the user's well-being in three categories; physical activity, sleep, and social interaction. The score of each category were based on medical study, guidelines from institution, or collaboration with medical researchers. The study provided a good example in raising awareness and providing feedback to users for promoting better well-being. Another study by Gary M. Weiss also proposed an activity recognition for improving health and well-being [46]. This system also used smartphone as a main data collection device. The study focused mainly on building a recognition model from smartphone to detect physical activities like walking, jogging, and walking up/down stairs.

2.3.4 Text neck syndrome recognition studies

In term of preventing specific syndrome like text neck, Noura Farra, et al. proposed a system using mobile sensing and imaging system to monitor spine health [47]. In stead of monitor the cervical spine, which is related directly to text neck, the study develop a wearable vest that detect the movement and position of overall spine. The system was capable of calculating the spine position correctly. However, with the wearable vest, it make this system lack of mobility. Another study called SEPTIMU developed earphones to monitor the movement of a user [48]. The earphones were embedded accelerometer sensor and gyroscope. As a result, the system was capable of detecting the movement of the users head, thus, raise awareness in preventing office syndrome, which is result from lack of movement. However, the study did not proposed a solution to calculating an accurate angle of the current neck posture. While another study proposed a smartphone based system to monitor and prevent text neck syndrome [49]. The system operates on smartphone and uses its sensors for neck angle calculation. However, the system limitation was that it would work accurately only if the user's face pan is parallel with the smartphone screen pane.

2.3.5 Smartphone addiction recognition

In preventing smartphone addiction, which is also the caused of text neck and CVS, the study by Mengwei Bian and Louis Leung pointed out further that the smartphone addiction significantly impacted social capital building as there are strong links between smartphone addiction and smartphone usage, loneliness, and shyness [50]. Another study by Alexander J.A.M. van Deursen, et al. suggested that smartphone addiction is likely to be the effect from social stress as well as failure of self-regulations [51]. This pointed out the importance of raising awareness this concern. Meanwhile, Maya Samaha and Nazir S. Hawi proposed in one of their study that smartphone addiction was positively related to perceived stress [52] . The study was conducted on a total of 300 university students. These studies show an important of raising awareness to smartphone addiction, which are related to multiple syndrome, both physical and mental.

2.3.6 Stress recognition

In another perspective, stress could be a result from variety of reasons and not just smartphone addiction. One of the most conventional way in recognizing stress was through surveys and daily diaries. Perceived Stress Scale (PSS) [53] was developed to serve this purpose. The survey consists of 10 questions where the results represent the level of participant's stress. This was one of the conventional way to assess stress level, though, it is lack in the ease of use and self monitoring. A study by Hong Lu, et al. called StressSense was proposed to detect stress using smartphone in an unconstrained environment [54]. The system used smartphone to capture voice from subject in different scenarios and used those data to train the recognition model. Another important proposal of this study was that it pointed out the possibility of building universal model for every users and personalized model one specific user with model adaptation. This approach reflect the importance of building a personalized digital healthcare service. Beside from using audio based detection, a study by Mario Salai, et al. proposed a system that detect stress level using low cost heart rate sensor [55]. The system was based on a commercial chest belt heart rate sensor that capable of detecting heart rate variability (HRV). The results of the study proved that even a low cost heart rate monitoring device can correctly classified stress level, thus, make it more feasible for real world usage. Another study that was based on a physiological data was based on electrodermal activities (EDA), heart rate activities(ECG RR / ECG R Wave) and respiration activities (Respiratory Rate) [56]. Despite not achieving an extremely high accuracy in recognition model, the study still present important of using physiological data as a feature in training stress recognition model. Other studies develop the stress recognition system using smartphone and wearable devices, where wearable devices are refer to smart watch or activity tracker. [57–59]. All of the studies achieved a good results and presented a good approach in combining multiple devices for stress recognition. In other words, the models built in these studies gave a wider perspective as more features from daily life were used in the training. Another approach from these studies that this dissertation adopted was the use of surveys as a ground truth data

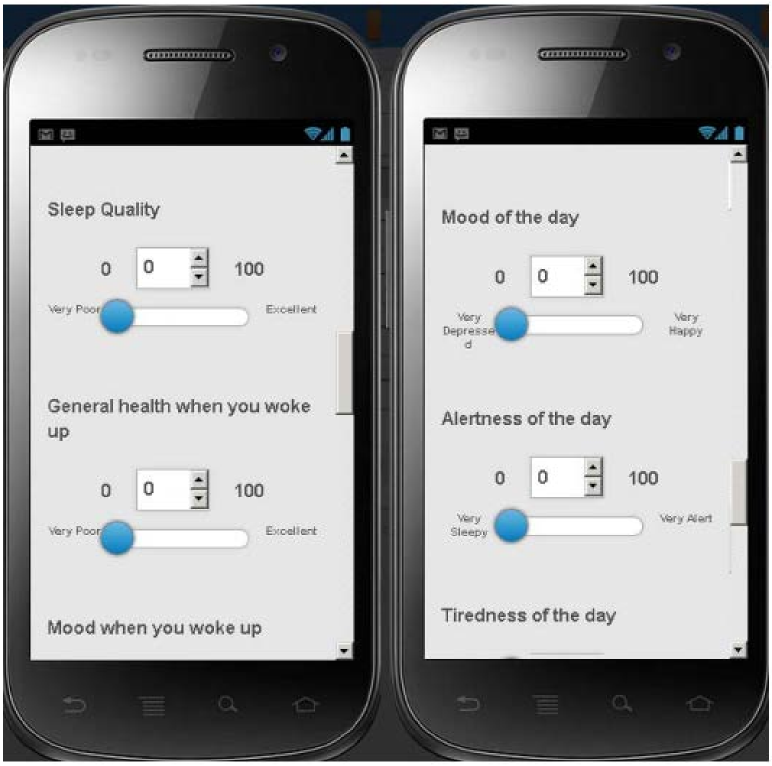


FIGURE 2.4: Example of mobile survey from related study

for labeling data instance before training. Figure 2.4 shows an example of mobile survey that was used in one of the study.

As an extension to smartphone based system, Andrey Bogomolov, et al. proposed a system that used activity data from smartphone, weather data, and personal traits to recognized the stress level in a 2-class classification problems (stress and not stress) [60]. Despite that this study also used a survey approach in retrieving the ground truth data, the study demonstrated the possibility of integrating data from multiple sources, which may not necessary from the sensors. Other studies proposed a stress recognition based on office environment [61, 62]. One of the study made a thorough review on the current status of study in early stress recognition for office environment and pointed out main physiological features that were used in building the model [62]. Other features that were reviewed include keystroke and mouse dynamics, posture, facial expressions, speech analysis, mobile phone usage, computer exposure, and text linguistics. On the other hand, the other study demonstrate a system that recognize stress level using computer software and wearable sensor [61]. The study aligned with the review that pointed out the behavioral feature from computer usage can be used to recognize stress level.

In general, these studies provided opportunity in develop stress recognition model where multiple approaches were proposed. However, each approach has its flaws, and there are room for improvements for the system to be more accurate, less intrusive, as well as more feasible for real world implementation.

2.3.7 Mood recognition and Well-being recognition

On another perspective, mood also effect daily well-being of a person. Thus, several studies were conducted to develop a technological solution recognize mood level as well as raise an awareness to the users. One of the generic proposal to this recognition problem was to use mobile phone sensing for daily mood assessment [63]. The study used data from smartphone sensors, which were acceleration, light, ambient sound, location, and call log as a feature to train the model. However, the trained model only achieved 50% accuracy in prediction. Gaetano Valenza, et al. develop a system to recognize mood using heart rate variability specifically for people with bipolar disorder [64]. The study developed a wearable vest, which embedded with sensors, and conducted a long term analysis on the collected data. Despite the bipolar disorder shows an extreme different in mood, this study demonstrated a good approach in recognizing the mood level. Beside from heart rate data, body movement and posture were also used in recognizing mood as well [65]. The study by Michelle Thrasher, et al. demonstrated the deep statistical analysis that show relationship between mood and body movement. However, the study did not present a technological solution to detecting posture or body movement, but it used observation technique to monitor the movement instead.

A study that developed an interesting technological solution to the problem was by Saket S Kulkarni, et al. [66]. The study presented a solution using neural network for facial expression recognition. The facial recognition in this study was

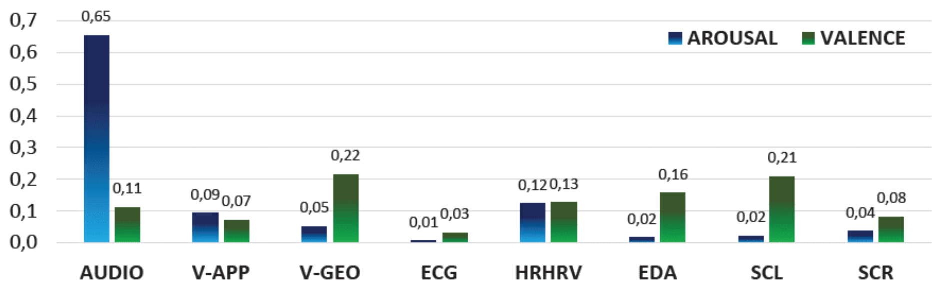


FIGURE 2.5: Percentage of contribution of each modality in the prediction of emotion

refer to as mood. The experiment was conducted on a total of 282 images from 60 subjects, where the highest accuracy the system achieved in identifying the correct mood was 90.43%. This presented the possibility of using deep learning technique to recognize features that could be related to mood. Finally, a study by Michel Valstar, et al. discussed the current status and challenge in developing depression, mood, and emotion recognition [67]. The study discussed an interesting in choosing modality or features for developing the recognition system. Figure 2.5 shows the percentage of contribution of each modality in the prediction of emotion. From the information, audio played an important part in recognizing emotional arousal. Another interesting modality is that the heart rate and heart rate variability contributed to both emotional arousal and valence recognition at almost the same rate. All in all, these studies presented the possibility of recognizing mood and emotion using different approaches, which has its own strong point. A combination of this system to a previously discussed systems like stress recognition will provide a more complete multi-dimension well-being recognition system.

For well-being, to assess the level of each person's well-being is more difficult. Currently, the approaches taken to asses the well-being by medical or bioengineering are often an observation method. Sonnentag proposed a diary study on well-being where 100 dutch teachers participated in the experiment [68]. Each participant completed a diary on activities and situational well-being for 5 days. Questionnaire were also used to assess work situation variables. Sonnentag used the diary along with the questionnaire results to analyze the well-being of each individual. Emmons proposed a study where it assessed the well-being using an observation method [69]. The study tracked 40 subjects and study each subject well-being and how each component affected the well-being level. The opportunities lie in the study by Diener where he demonstrated an assessing the subject's well-being [70]. The study suggested that if the any study should be conducted to recognize the well-being level, it should consider at least the major components of well-being, which include positive affect, and negative affect. Another study suggested the importance of recognizing stress could provide for sustainable living, which will eventually lead to higher level of well-being [60]. In general, this study take the results of the discussed study to develop them into an application to provide an easier solution in recognizing well-being level. The detail of the proposed method is later discussed in chapter 6.

2.4 Visualization of real-time monitoring

In terms of visualization techniques, several studs in user's experience (UX) development fields have proposed multiple approaches to visualize the data back to users for raising awareness for certain proposes. One study developed a 3D-visualization to show activity pattern in different contexts [71], while another developed a activity density map visualization for eldercare monitoring [72]. Other studies related to visualization may include a study by Maurice Mulvenna, et al. demonstrated an visualization of data for ambient assisted living services [73], a visualization technique for sustainable living [74], and a visualization technique for personal context [75]

To further discussed a visualization in the context of machine learning, a study by Maria Riveiro, et al. [76] discuss the development of machine learning model for anomaly detection with surveillance system and how to properly visualize the date through and application. The study discussed that the surveillance system is a good example where larger amount of multidimensional data from multiple sensors are collected and processed for visualization. The machine leaning technique helps improve the performance of processing all the data. Meanwhile, the visualization part can support the involvement of the users in the system, as specially, in the

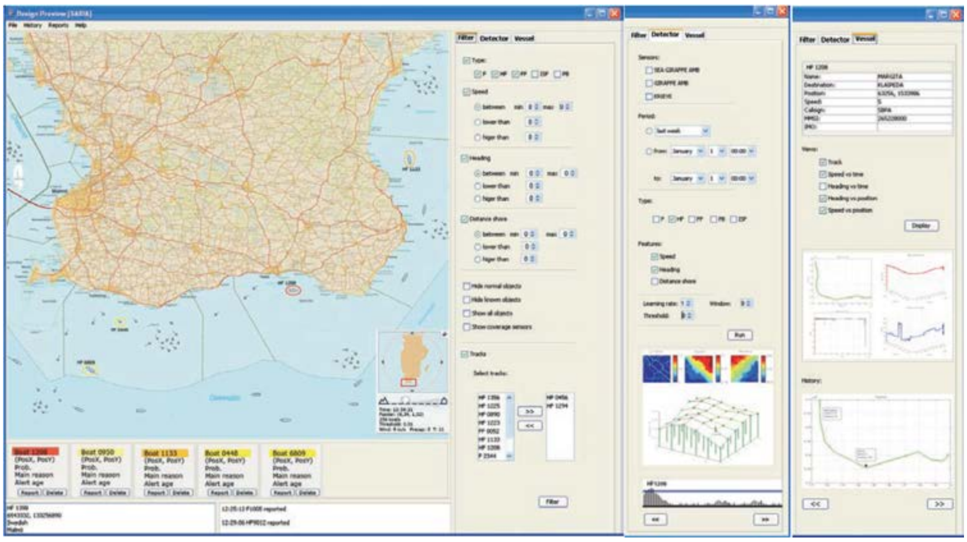


FIGURE 2.6: Interactive graphical user interface developed to raise awareness in anomaly detection

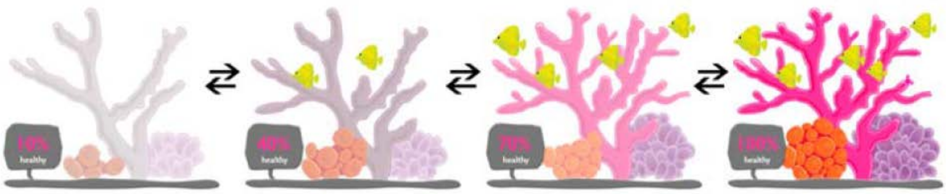


FIGURE 2.7: Coral reef image for representing health condition based on saturation

interactive visualization system. Figure 2.6 shows an example of graphical user interface (GUI) developed in the study.

Another study by Tanyoung Kim, et al. [77] suggested in order to develop a effective visualization application, an ambient display technique should be considered for a more effective results in encouraging behavior change. The study used a coral reef image to represent the excessive use of computer instead of visualizing them in a normal statistic manner. The study further addressed that a good visualization should be visually pleasing but not too abstract to the users and that the feedback itself should provide a way of reward to encourage the users more to a behavior change. Figure 2.6 shows an example of the coral reef image visualization in the study.

The study by Margaret-Anne D. Storey et al. [78] proposed a framework that support discussing visualization technique of human activities. The study proposed interesting research agendas that need to be taken into consideration when developing visualization interface. While another study by Moushumi Sharmin, et al. provide a thorough review of visualizing time-series data [79]. The study focused specially on visualization for stress management. The study developed a visualization tool that support an understanding of overall stress level by offering a personalized stress profile. Furthermore, the visualization also support a pattern-identification across and over time. In general, it also addressed challenges to development of visualization for stress monitoring, where the notable challenges include:

- Privacy concern: The intrusive monitoring system could effect the collection of data and eventually resulted in an ineffective visualization system.
- Stressor identification: An appropriate way of identifying stressor for each user could result in an effective design of intervention in the visualization where it should effectively alert the user and intervene in high stress situation.
- Personalize stress visualization: The generic or universal visualization would not work effectively as each person has different stressor. The system should be able to identify the stressor of each person and personalized the visualization for them based on the collected data.

In conclusion, the discussed studies in this section demonstrate an effective way as well as challenges in developing a visualization system to raise certain kind of awareness based on behavior and collected data. All of this studies align with this dissertation in the visualization part, especially, the stress management visualization. All in all, we considered all the techniques used in these studies to develop a personalizable visualization system where it encourages users for a better behavior that will lead to having better well-being.

Chapter 3

Overview of System Development

In this chapter, the general idea of the development flow for well-being recognition system is discussed. The development flow consists of multiple studies of subsystems, each subsystem study focus on specific problem. All subsystems are later integrated into the well-being recognition system. The chapter focuses on explaining the concept of each system and how it relates to the overall well-being recognition. Furthermore, it describe the techniques that were adopted from each system to be used in the final system development.

3.1 System overview

Figure 3.1 shows an overview of the well-being recognition system. In the figure, the subsystems that were developed in this study were separated into two main categories; physical condition and mental condition. In the physical section, the subsystems were developed as a preventive measure for physical condition, while the subsystem in the mental subsection was developed to prevent the mental-related condition. Each subsystem proposed a solution to a problem toward the well-being issues where its results or outcomes are adopted and used in the next or another subsystem. The final system is an integration of all results and outcomes to propose a solution to a stable well-being recognition system.

3.1.1 Neck posture monitoring system

The neck posture monitoring system was developed to demonstrate the used of image detection along with sensor data to calculate neck angle while using the smartphone. The goal of the system was to provide feedback and raise awareness to users in order to reduce the chance of having neck pain from bad smartphone usage posture. This system focused on the physical effects from excessive use of technological device, specifically related to smartphone and neck pain, which eventually can affect life satisfaction on daily basis. The results of this system were used as a guideline in smartphone addiction recognition system in order to proposed a system with larger perspective of physical condition prevention. The detail of this system is further discussed in chapter 4.

3.1.2 Smartphone addiction recognition system

The smartphone addiction recognition system was a extended system to the neck posture monitoring system. Instead of focusing on only posture itself, it addressed further physical syndrome that may be the result of excessive use of smartphone. Thus, the system focused to raise awareness in overall usage of smartphone and help users improve the usage behavior. This system also focused more on collecting data from smartphone and used them in machine learning. The experiment were also a survey based experiment. This study demonstrate a monitoring system that focus on a larger perspective instead of on a single specific condition. Moreover, the use of survey approach demonstrated the possibility of evaluating a person's condition and use them in the machine learning. This outcome is adopted in another subsystem to study in recognition system for stress. Chapter 5 discusses this system in detail.

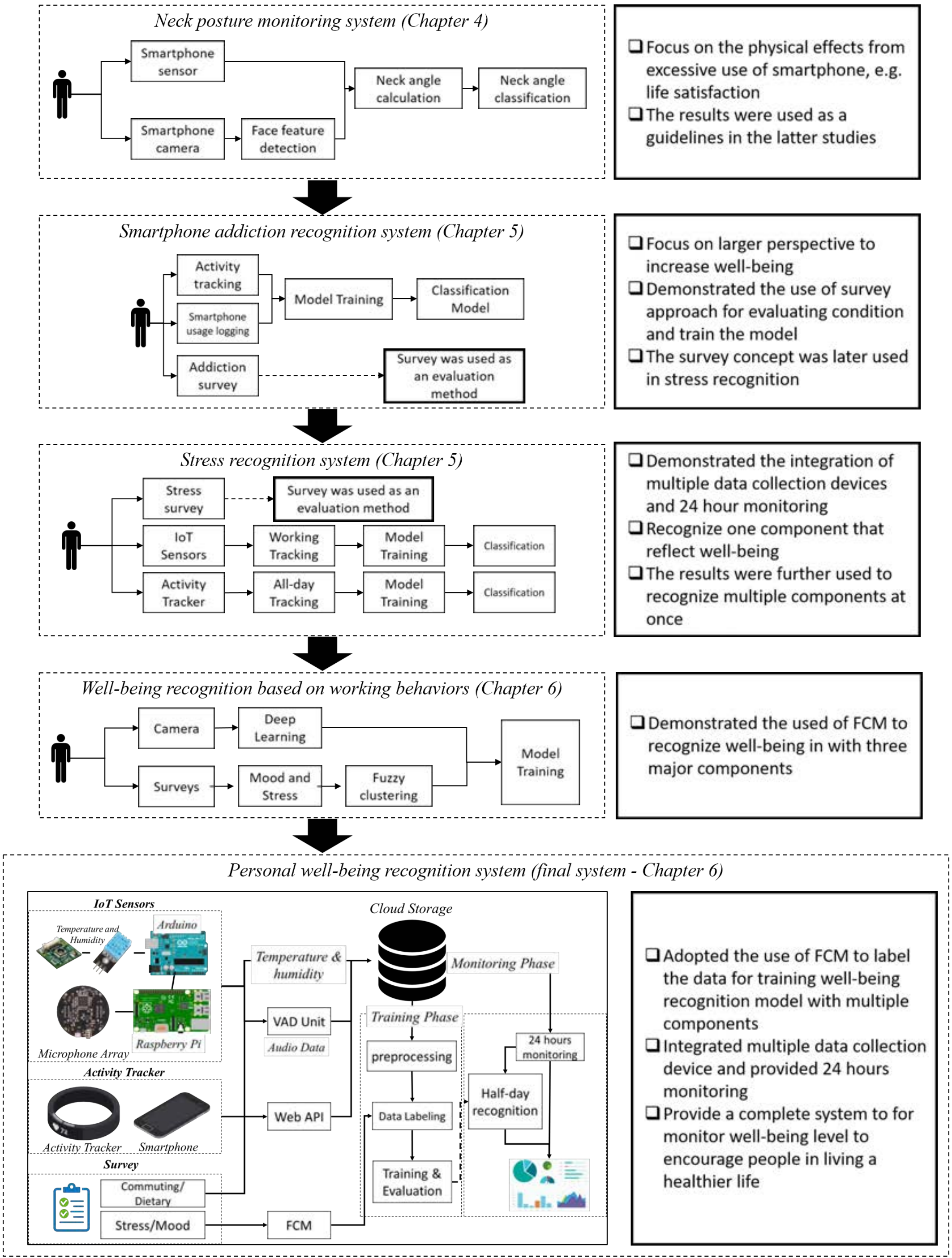


Figure 3.1: Overview and relationship of the systems in this study

3.1.3 Stress recognition system

The stress recognition system were conducted with the concept of providing the preventive measure for mental-related effects from daily behavior. Stress can be considered to reflect life satisfaction [80], which is one of the component for recognizing well-being [70]. This study conducted two approaches in developing the system. The first approach was to use the IoT sensors to collect the data and the second approach was to use activity tracker as a data collection device. The study focus on extracting the behavior throughout the day, where IoT sensors were capable only collecting the data while the subject was at the workstation and activity tracker were capable for collecting data for 24 hours per day. The study proved that it is possible to recognize stress by using combination of devices and machine learning. Moreover, as stress is one of the component in recognizing well-being, this subsystem demonstrate the possibility in doing so. Chapter 5 discusses the system further in detail.

3.1.4 Well-being recognition system based on working behaviors

In well-being recognition system, this study extended the condition of well-being's components to not only stress, but also the overall mood of the subject, namely positive affect and negative affect. As mentioned earlier in chapter 2, these are the three components that should be considered in well-being recognition. This study implemented clustering technique to consider survey results of stress, positive affect, and negative affect. The results of the clustering were used as the data labeling method for the study. The results from this subsystem demonstrated the possibility of using all three components in recognizing well-being, which this study refer to them as multidimensional well-being recognition. The results of this approach were further used in the final system where the development proposed a final system and solution to well-being recognition. The detail of this approach is further explained in chapter 6.

3.1.5 Personal well-being recognition system

The daily personal well-being recognition system was developed based on the foundation laid by the all studies in the development flow. This system adopted more generic approach by considering more input attributes from more data sources as well as less intrusive way of collecting data, which was the results from studies conducted in developing stress recognition (chapter 4,5). The FCM was adopted from the previous system as well to train the multidimensional well-being recognition. Furthermore,this study provide a dashboard visualization where users can monitor their current statistic of physical activity throughout the day and how is there progress when compare to others. This help raise awareness and encourage them to engage in more physical activities as well as improving their behaviors. By providing 24 hours monitoring, and data collection, this study proposed a solution to well-being recognition where it considered all three major components of subjective well-being as discussed in chapter 2. The results of this final system is a complete well-being recognition and monitoring system where it consist of all major components, which are data collection devices, cloud processing and analysis, and client application. This system demonstrated the use of technologies in medical application field to raise awareness in improving well-being level in order to live a healthier life.

3.2 Adopted methods and approaches

Throughout each development period of each system, the study adopted several kinds of techniques to provide a recognition system. Each study demonstrated the effective way to used the technique. Table 3.1 shows the data used in each system where the final system combined multiple type of data for model building. Table 3.2 shows the techniques and approaches used in developing each subsystem.

Table 3.1: Collect data in each system

Systems Name	**Smartphone**			**Activity Tracker**			**Sensors**						**Others**		
	Camera	**Accelerometer**	**Usage Log**	**Activity Data**	**Sleep Data**	**Heart Rate Data**	**Temperature**	**Infrared**	**Ambient Light**	**Pressure Sensor**	**Microphone Array**	**Camera**	**Weather**	**Commuting**	**Dietary**
Neck Posture Monitoring System	✓	✓	-	-	-	-	-	-	-	-	-	-	-	-	-
Smartphone Addiction Recognition System	-	✓	✓	-	-	-	-	-	-	-	-	-	-	-	-
Stress Recognition System Using IoT Sensors	-	-	-	-	-	-	✓	-	✓	✓	-	-	-	-	-
Stress Recognition System Using Activity Tracker	-	-	-	✓	✓	✓	-	-	-	-	-	-	-	-	-
Well-being Recognition System Based on Working Behaviors	-	-	-	-	-	-	-	-	-	-	-	✓	✓	-	-
Personal Well-being Recognition System	-	-	-	✓	✓	-	✓	✓	✓	-	✓	-	✓	✓	✓

Table 3.2: Techniques and approaches used in developing each subsystem

Systems Name	**Machine Learning**					**Deep Learning**		**Surveys**						
	KNN	**Decision Tree**	**SVM**	**Naive Bayes**	**Rule Based**	**Video Recognition**	**Voice Recognition**	**PSS**	**SAS**	**GSE**	**Generic Stress Surveys**	**VAS Mood Scale**	**VAS Stress Scale**	**PANAS**
Neck Posture Monitoring System	-	-	-	-	✓	-	-	-	-	-	-	-	-	-
Smartphone Addiction Recognition System	✓	✓	✓	✓	-	-	-	✓	-	-	-	-	-	-
Stress Recognition System Using IoT Sensors	✓	✓	✓	✓	-	-	-	✓	-	-	-	-	-	-
Stress Recognition System Using Activity Tracker	✓	✓	✓	✓	-	-	✓	-	✓	✓	-	-	-	-
Well-being Recognition System Based on Working Behaviors	✓	✓	✓	✓	✓	-	-	-	-	-	-	-	✓	✓
Personal Well-being Recognition System	-	-	-	✓	✓	✓	✓	-	✓	-	-	✓	✓	-

3.2.1 IoT Sensors

The concept of using IoT sensors is adopted in almost every subsystems in this study. This is because the IoT sensors provide a better way of monitoring certain features in a more pervasive manner. The stress recognition from IoT sensors proved this concept clearly. Therefore, in the final system we integrated various IoT sensors with the widely used activity tracker for data collection device.

3.2.2 Deep learning

The technique of face feature detection in neck posture monitoring system was the first technique used in the study that is similar to deep learning method, as it was related to image detection. In later study of well-being recognition, this study adopted the approach of image detection. However, this study adapted the approach by changing the algorithm into a deep learning algorithm, which provide a better accuracy. The approach of deep learning was also further used in order to perform voice activity detection for well-being recognition system.

3.2.3 Survey-based experiment

The study first adopted the survey based experiment in smartphone addition recognition system. The approach was proved to be an effective way in many related studies. All the latter studies adopted this approach by using the related surveys based on each system's purpose. The surveys were taken from a reliable published studies. The detail of each survey is further discussed in chapter 4, 5, and 6.

3.2.4 Machine leaning for model training

In the neck posture recognition system, the study did not used machine learning for training the recognition model, instead, the classification of neck angle values were a rule-based classification. However,all the study afterwards had adopted the machine learning approach for training the recognition model. This approach provided the study with the possibility to recognize certain condition with multiple features. For example, in the stress recognition system with IoT sensors, the recognition model was trained with the total of 10 features, and the activity system for stress recognition used 17 features. The machine learning used in each system was different from the deep learning ad the deep learning was considered to be a tool for extracting knowledge from collected data (i.e. image detection, voice activity detection), but the machine learning approach will further used the data extracted from the deep learning method, then combine with other features to produce a recognition model for each condition.

Chapter 4

Neck Posture Monitoring System for Promoting Better Smartphone Usage Behavior

4.1 Overview

Figure 4.1 shows an overview of the system. The system has been designed according to Machine-to-Machine (M2M) architecture [81]. The main components of the architecture are M2M devices, an M2M gateway, and an M2M cloud service.

In our case, the smartphone works as the M2M device and M2M gateway. The sensors and camera embedded in the smartphone are responsible for collecting data from the user, while the network communication capability of the smartphone allows it to communicate with various services on the cloud via the Internet.

The classifier training process for face feature detection was done earlier, prior before real-time system operation. After the monitoring process starts, the system initiates three processes at the same time: face feature detection, phone tilt angle detection, and usage time logging. The face feature detection process uses the previously trained classifier. After it detects the facial features, which are the face,

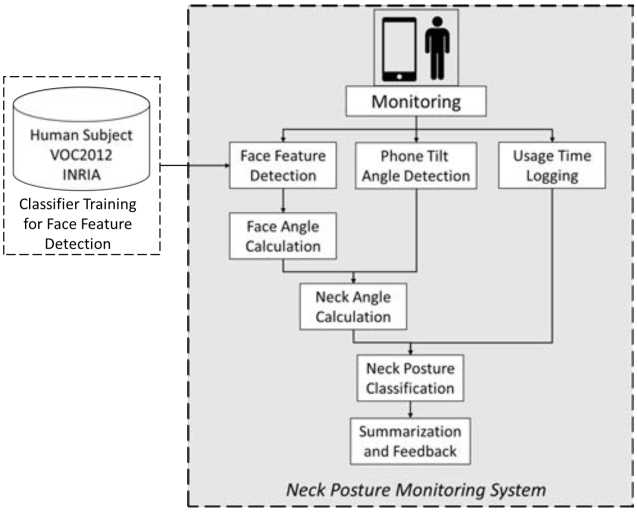


FIGURE 4.1: Overview of the proposed neck posture monitoring system

eyes, and mouth, it calculates the face angle based on the detection. The neck angle calculation uses the face angle and the phone tilt angle as input attributes for the process. Then, the system classifies the neck posture using the calculated neck angle and usage time. The system sends the result of the classification back to the users as feedback on their smartphone usage behavior. This information is also stored for weekly and monthly summarization to give users a better idea of their overall behavior.

4.2 Methodology

4.2.1 Face feature detection

Face feature detection allows the system to detect the face, eyes, and mouth. This detection process is crucial to our algorithm because it enables the face angle calculation. The process makes use of the OpenCV library, which provides the system with multiple detection algorithms. The two best-known algorithms for detecting facial features are the Haar-like feature algorithm and the LBP algorithm.

Both Haar-like feature and LBP use features in detecting sum of pixels for object of interest. Figure 4.2 shows the five features that were used in the training process for sum of difference calculation within each feature. The sum of difference was calculated by determining the difference between the pixel density in the black area and the pixel density in the white area. In practice, the window is defined to move along an image. In each window, each feature at all possible sizes is applied for sum of difference calculation. For example, a window size of $24x24$ pixels could result in more than 160,000 features in total (43,200, 43,200, 27,600, 27,600, and 20,736 features for each type of features in Figure 4.2 (a,b,c,d, and e), respectively). As this process can result in high computational time, AdaBoost and cascade approach were applied to reduce the overall computational time. The main difference between Haar and LBP is that Haar uses floating point number in calculation while LBP uses integer. In our case, during the training process, the sum of differences within the object area (either face, eyes, or mouth) was calculated for all positive images. Then during the detection process, the classifier performed the calculation on each feature within one window size for detection. Thus, if the result of the calculations was to match with what the classifier learned from the training process, then it would classify the object within that window as positive object. All in all, neither Haar nor LBP was specifically looking for the corner of the objects, which in our case were face, eyes, and mouth, but they focused on calculating the overall pixel density within the defined window using the five features. Note that the window size also changed during this process to handle different object sizes in each image. As a result, the detected object size might vary between each detection. In order to tackle this problem, we proposed the use of averaged calculation, which will be discussed further in section 4.2.6. Figure 4.3 shows an example how each feature can be used to calculate sum of difference of pixel density when assuming that the red rectangle box is the window. Please note that in one window, each feature will change to all possible sizes for calculation.

The training of the classifier for both the Haar-like feature algorithm and the LBP algorithm was conducted on a total sample of 3,742 images. We obtained this training set from human subjects, the INRIA database [82], and VOC2012 [83]. The training set consisted of 900 positive images and 2,842 negative images, where the

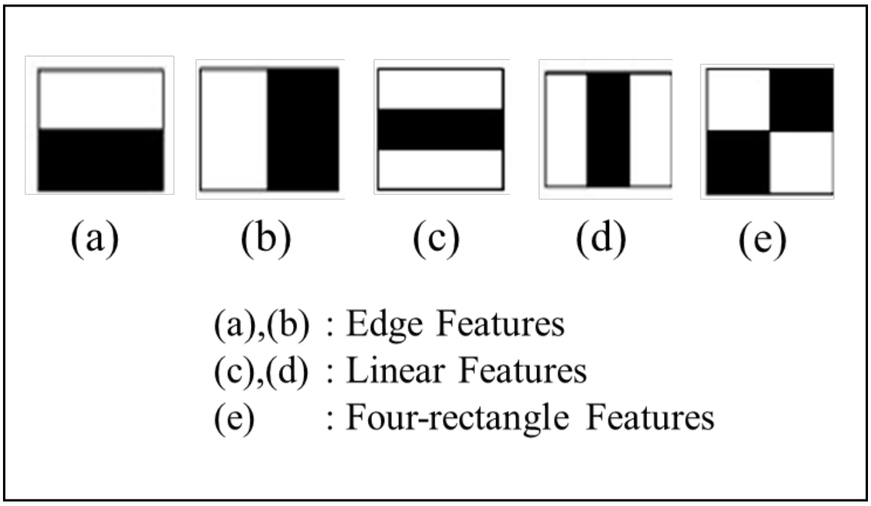


FIGURE 4.2: Five Haar-like features used in image detection

positive images were images with the objects of interest, which in our case were the face, eyes, and mouth, and the negative images were images without the objects of interest. The result of the training gave us a model for face, eyes, and mouth detection that was essential for face angle calculation.

In order to avoid false detection of face features during the process, we first reduce our Region of Interest (ROI) for face features detection. The system attempts to detect only the face from the image. If the system is unable to detect the face, it assumes that the user's not currently using or looking at the smartphone. If the system successfully detects the face, it will narrow down the ROI for other face features detection by cropping only the face area of the image. Thus, it's easier for the mouth and eyes classification model to avoid any false positive detection. In our previous study [84], we performed an experiment to compare the performance of the two algorithms: Haar and LBP with 500 images, where the objects of interest (human face with eyes and mouth) were present in all 500 images. Table 4.1 shows the results which include the detection accuracy and its false negative detection value. From a total of 500 images used in that experiment, the false positive within the ROI area (face area) is less then 3% in all cases. Please note that there is no result for 'False Positive within ROI' for face detection as face detection was used to define the ROI of each image. In terms of detecting the correct positions of outer canthi and

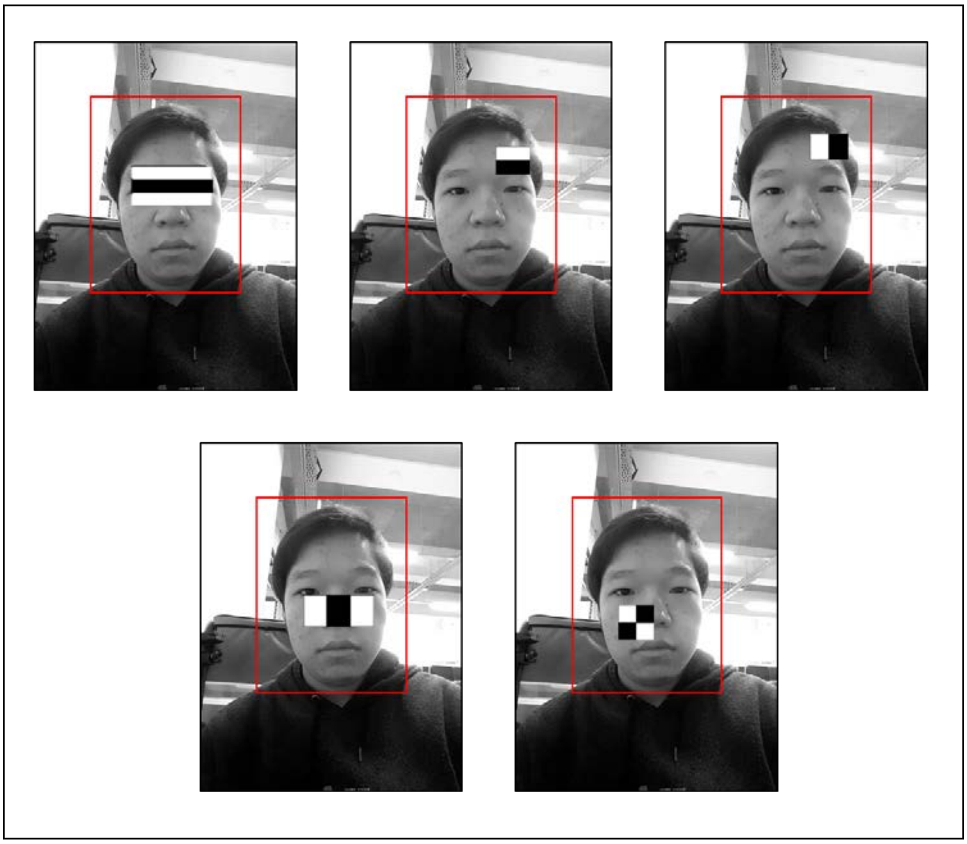


FIGURE 4.3: Example of using five Haar-like types of features within a window

left and right corners of the mouth, the system used the averaging approach, which we discuss further in section 4.2.6. The results also showed that a combination of the two algorithms works best in terms of accuracy and calculation speed. In addition, it was suggested that the system should implement the Haar-like feature classifier algorithm for face and eyes detection because it provided significantly higher accuracy than LBP. Conversely, the system should implement the LBP algorithm for mouth detection because it provided similar accuracy to the Haar algorithm but performed better in terms of calculation speed.

Table 4.1: Comparison of Haar and LBP classification model performance

Classifier	Algorithm	Detection Time (seconds)	True Positive	False Negative	False Positive	False Positive within ROI
Face	Haar	578.02	487	13	79	-
Face	LBP	155.99	429	71	77	-
Mouth	Haar	284.11	490	10	25	3
Mouth	LBP	143.20	486	14	75	13
Eye	Haar	211.78	457	43	57	5
Eye	LBP	145.67	343	157	45	10

4.2.2 Face angle

To calculate the user's neck angle, the system first obtains a face angle value. The face angle is the angle between the cervical spine and the imaginary line of the smartphone screen. This is done using trigonometry. Figure 4.4 shows two example scenarios for calculating the face angle. In Figure 4.4(a), the camera plane, which refers to the imaginary line of the smartphone screen, is exactly parallel to the face plane, where the distance from the eyes to the camera is equal to d_2. Conversely, Figure 4.4(b) shows a situation where the face is pitching slightly forward toward the camera while the camera remains in the same position and the user's eye gaze is perpendicular to the camera plane. Lines A and B are parallel, and line C is parallel to the line drawn from the eyes to the mouth. In this case, the distance d_2 between the eyes and the camera is shorter than that in the previous scenario and the distance between the camera and the mouth is longer. The angle β in the Figure 4.4(b) represents the face angle used in the calculation for the neck angle. In this scenario, line A is the smartphone screen and the angle β can be calculated using trigonometry.

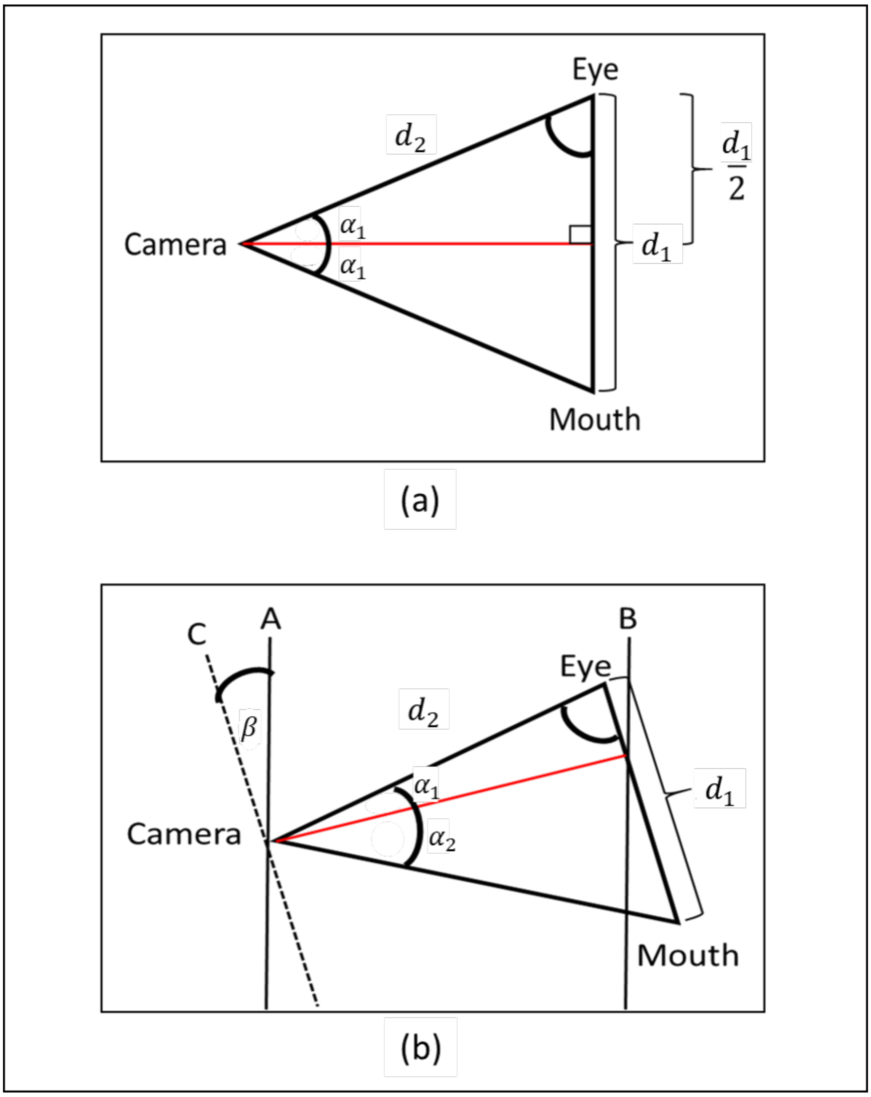


FIGURE 4.4: Example scenarios for calculating the face angle

In our calculation, the distances between the eyes and mouth to the smartphone cannot both be determined. Therefore, we need to use the face ratio approach. If the user's face is pitching forward toward the screen, the distance between the eyes and the smartphone screen decreases, while the distance between the mouth and the screen increases. Figure 4.5 shows the differences in the widths of two objects from the top view when the distance between the object and the camera changes. As an example in Figure 4.5(a), the object could be a user's face from the top view. Let

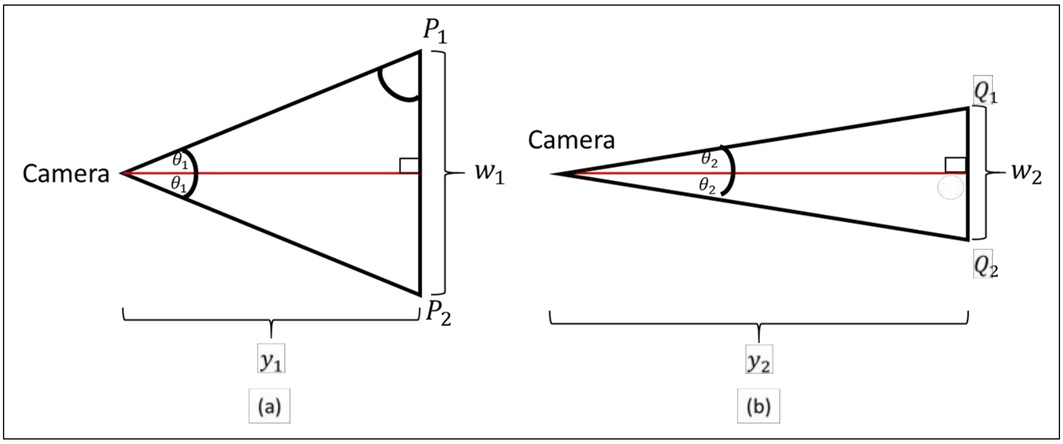


FIGURE 4.5: Changes in object width at different distance between the object and the camera

w_1 be the distance (width) from P_1 to P_2, w_2 be the distance (width) from Q_1 to Q_2, and y_1 and y_2 be the distances from the camera to the corresponding objects; the visual angle, which is the angle $\theta_1 + \theta_1$ in Figure 4.5(a), is larger than the angle $\theta_2 + \theta_2$ in Figure 4.5(b), and the value w_1 is considered to be larger than w_2[85]. As a result, we can calculate the face angle using the face ratio. Figure 4.6 shows an example of face ratio differences when looking from different camera angles. Figure 4.6(a) shows the width of the eyes as 290 dot pixels at a face angle equal to 0°. Meanwhile, Figure 4.6(b) shows that the width of the eyes is reduced to 220 dot pixels when the face angle is at $-15°$.

Equation 1 shows the calculation of the face angle where DFR represents the Default Face Ratio. The DFR is the default face ratio of each user when the face plane is parallel to the camera plane. This value is obtained when the user trains the application. This process occurs when the user first uses the application. The system asks the user to train the application by taking five pictures with the user's line of sight perpendicular to the screen. The system calculates the face ratio of each image by dividing the width of the upper part of the face (the distance between eyes) by the width of the lower part of the face (the width of the mouth). Then, it calculates the average of the five images and stores this value in the database for later use. The Current Face Ratio (CFR) is the face ratio obtained from the current picture taken from the smartphone's front camera. The value 0.05 is the percentage

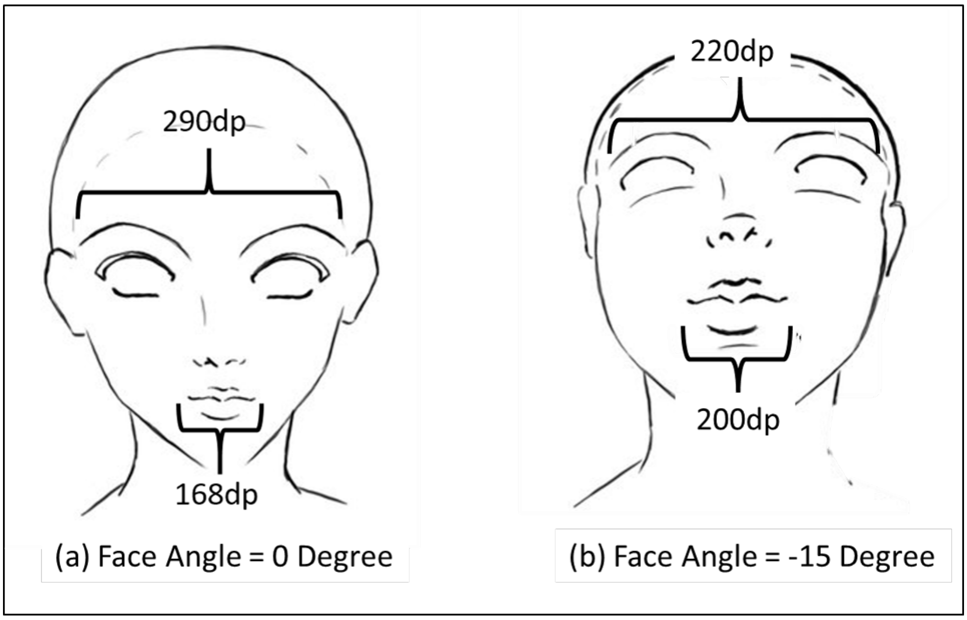


FIGURE 4.6: Example of different face ratios at different face angles

value, that is, every five percentages of face ratio change equals one degree of face angle change. The value 0.05 was obtained from an empirical study based on the data from a total of 100 images of four face angle values, $-15°$, $0°$, $15°$, and $30°$. If the face is pitching backward from the screen, the CFR will be less than the DFR. Therefore, the face angle will have a negative value. Conversely, if the face is pitching forward toward the smartphone screen, the CFR will be greater than the DFR. Therefore, the face angle will have a positive value. The unit of the face angle is in degrees. One of the benefits of using the face ratio when calculating the face angle is that it is scale invariant. The distance between the smartphone screen and the user's face does not affect the ratio because the widths of both the upper and lower parts of the face both change in the same direction. Therefore, the ratio remains the same.

$$FaceAngle = \frac{CFR - DFR}{0.05} \tag{4.1}$$

4.2.3 Smartphone tilt angle

One of the attributes we use to calculate the neck angle is the smartphone tilt angle. The system obtains the smartphone tilt angle value using a virtual sensor called the rotation vector sensor. The rotation vector sensor is a software-based sensor that consists of an accelerometer and a magnetic field sensor [86]. This sensor has been incorporated by Google into all Android-enabled devices. The angle can be obtained for all axes (X,Y, and Z); however, in our case, we are interested in the angle between the Y- and Z-axes. We can retrieve this value using the provided Android API.

4.2.4 Neck angle calculation

Our system calculates the neck angle using the two attributes that we mentioned earlier: the face angle and the smartphone tilt angle. A preliminary study of this calculation with only one sample human subject in 2015 [87] showed promising results. However, during that study, the quality of the device used to obtain the images and the coding technique needed several improvements. Therefore, in this study, we performed the calculation based on the same formula proposed in our previous study, but the results improved due to the optimization of the face feature detection attributes and the neck angle calculation attributes. Equation 2 shows the formula for calculating the neck angle, where $PhoneAngle$ is the phone tilt angle value obtained from the rotation vector sensor, $FaceAngle$ is the calculated face angle value mentioned in section 4.2.2, and the variable n represents the number of photos used in the calculation. In our case, OpenCV does not provide a constant result in the detection. Thus, the system calculates the neck angle on 30 sets of data (photos and sensor values) and average them. In doing so, it reduces the errors that might occur from false detection and other noise. The number 30, which is our n value, comes from the frame rate setting of the video obtained from the smartphone camera. Therefore, each averaged neck angle value represents one second of video. In general, the system calculates the neck angle 30 times in one second, but it will only record the final average value and use the value as the neck angle for that certain second. This approach is taken to reduce the variation as much as possible even if there are no or slight changes of the extracted face features between each frame. Thus, the averaged value of the neck angle, used to represent each second of the video, is more reliable than the neck angle calculated from a single frame of each second. Table 4.2 shows the example of neck angle calculation and its variation from one subject for 10 consecutive seconds in degrees. The table demonstrates the average, minimum, maximum, standard deviation, and variance of 30 neck angle values that were calculated in one second.

$$NeckAngle = \frac{\sum_{i=1}^{n}(PhoneAngle + FaceAngle)}{n} \tag{4.2}$$

4.2.5 Scenario

Figure 4.7 demonstrates all the possible scenarios of the calculation. Scenario 1 (Figure 4.7(a)) shows the situation where the face plane is perfectly parallel to the smartphone plane. In this case, we can conclude that the user's neck angle is equal to the smartphone tilt angle, which is the value obtained from the smartphone sensor. However, this situation rarely occurs in daily usage.

Figure 4.7(b) demonstrates the situation where the face plane is pitching backward away from the smartphone plane. In this case, the neck angle will be less than the smartphone tilt angle. Therefore, to correctly calculate the neck angle, we use the face angle value, as mentioned in section 4.2.2. The $FaceAngle$ for this situation will have a negative value. Therefore, after calculating the neck angle from the formula in Equation 2, the $NeckAngle$ value will be less than the $PhoneAngle$ value.

In the third scenario, as shown in Figure 4.7(C), the face plane is pitching forward toward the smartphone plane. Opposite to scenario 7(b), the calculated $FaceAngle$ will have a positive value. As a result, the calculation using Equation 2

Table 4.2: Example of calculated neck angle value from one subject over 10 consecutive seconds

Second No.	Average (degree)	Minimum (degree)	Maximum (degree)	Standard Deviation	Variance
1	35.71	32.13	39.40	1.91	3.66
2	34.75	30.30	39.40	2.03	4.12
3	36.21	34.73	38.67	1.15	1.32
4	29.49	25.45	33.98	2.24	5.02
5	20.94	19.10	25.11	2.20	4.84
6	23.42	17.25	26.51	2.41	5.80
7	21.06	18.13	26.46	2.04	4.16
8	21.59	18.10	26.82	1.97	3.88
9	21.13	18.38	27.47	2.19	4.80
10	22.36	18.62	26.69	2.13	4.54

will give a $NeckAngle$ value that is greater than the $PhoneAngle$. Figure 4.8 shows a sample image from the experiment where the system detects the face, eyes, and mouth and uses them to calculate the face angle and neck angle.

4.2.6 Neck angle classification

For this classification, we propose a classification method based on the neck angle in our prior study. This previous solution was solely based on the angle and did not consider other factors, such as the usage time. The classification based on the angle is the same, where the angle ranges were $0-15°$, $15-30°$, $30-45°$, $45-60°$, and more than $60°$. The classes are healthy, normal, slightly unhealthy, unhealthy, and very unhealthy for each respective angle range.

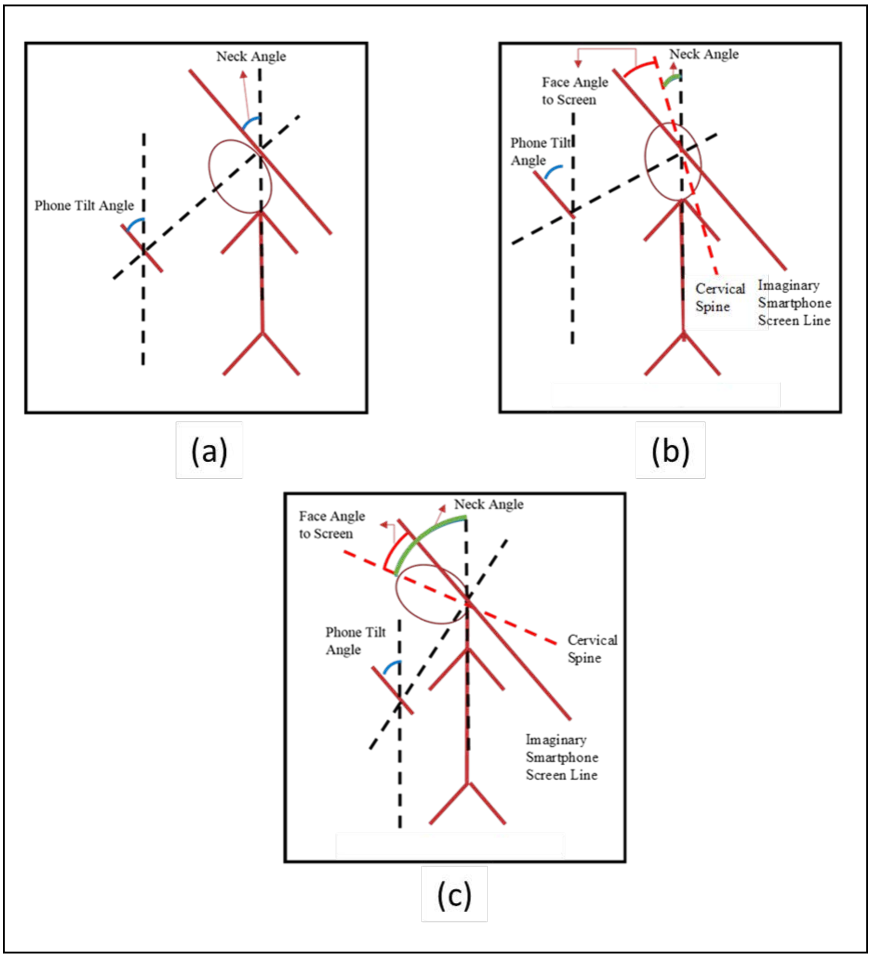


FIGURE 4.7: Three neck angle calculation scenarios

However, there is evidence that one of the causes of neck pain is related to prolonged smartphone usage[88]. Therefore, to make the classification more effective, the amount of usage time should also be considered. According to the recommendation in avoiding office syndrome[89], making a movement every 30 min could prevent severe pain in the back and neck. We make use of this recommendation in our classification by dividing the 30 min length into 5 periods, each period lasting 7.5 min. Longer usage times are unhealthy in the classification. The usage times are classified such that $0 - 7.5$ min is healthy, $7.5 - 15$ min is normal, $15 - 22.5$ min is slightly unhealthy, $22.5 - 30$ min is unhealthy, and more than 30 min is very unhealthy. The main purpose of this division was to provide ease of visualizing feedback to user, and

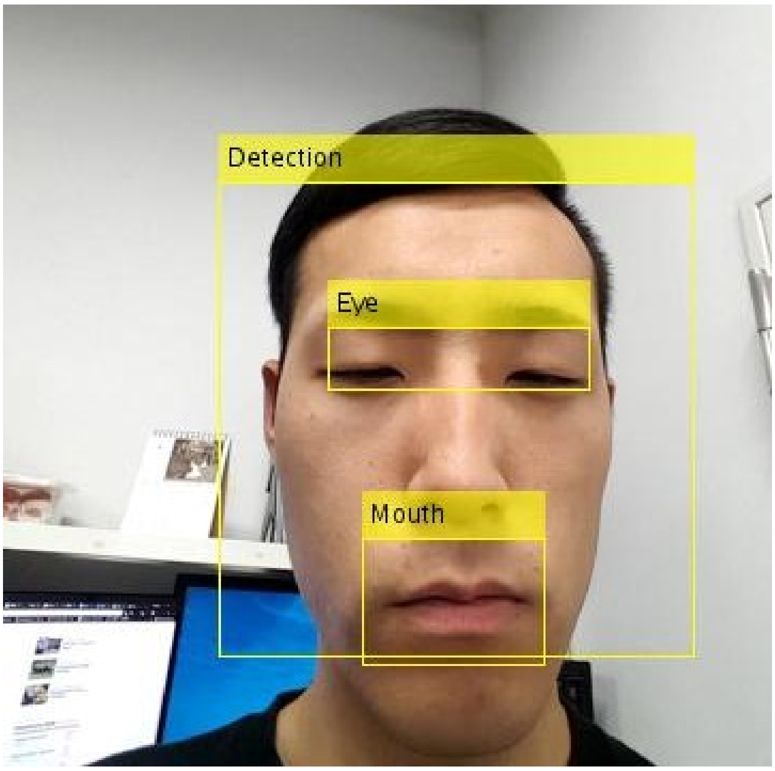


FIGURE 4.8: An example of image detection for the face, eyes, and mouth

the five periods of time division was to match the five classes while still presenting the fact that the less the user uses the smartphone, the less chance they would have for suffering from text neck syndrome.

We combined the two concepts of the classification, and Table 4.3 shows a classification diagram with both the angle and the usage time. The angle-based concept first classifies the neck posture; then, the result worsens based on the usage time, which is logged by the system at the start of the monitoring process. If the usage time is considered healthy, the result will remain the same, while if the usage duration is considered very unhealthy, the result will worsen by four steps to the very unhealthy class in all cases.

In addition, we consider that the user is using the smartphone when the system successfully detects face features and calculates the neck angle. Thus, if the neck angle is continuously detected, the system will constantly record the usage time and

TABLE 4.3: Prolonged usage classification diagram

Duration (Minutes) / Neck Angle (Degree)	0-7.5 Healthy	7.5-15 Normal	15-22.5 Slightly Unhealthy	22.5-30 Unhealthy	>30 Very Unhealthy
0-15 Healthy	Healthy	Normal	Slightly Unhealthy	Unhealthy	Very Unhealthy
15-30 Normal	Normal	Slightly Unhealthy	Unhealthy	Very Unhealthy	Very Unhealthy
30-45 Slightly Unhealthy	Slightly Unhealthy	Unhealthy	Very Unhealthy	Very Unhealthy	Very Unhealthy
45-60 Unhealthy	Unhealthy	Very Unhealthy	Very Unhealthy	Very Unhealthy	Very Unhealthy
>60 Very Unhealthy	Very Unhealthy	Very Unhealthy	Very Unhealthy	Very Unhealthy	Very Unhealthy

perform the classifications based on the pre-defined conditions given in Table 4.3. However, the system will stop recording when it cannot detect face features for neck angle calculation. In other words, the system assumes that when this happens, the user has looked away or making changes in the user's position. Thus, it will stop recording the usage time and the prolong usage duration will be reset to zero. In general, the limitation of this concept is that it cannot handle the position changes while the face features are still being detected, as this would require further devices for activity recognition.

4.3 Experiment

In this section, we discuss an experiment we conducted to validate the proposed algorithm. This section includes the design of the experiment, the evaluation method, the statistical analysis, and the experimental results.

4.3.1 Experiment design

We collected data from 30 human subjects, which consisted of 20 males and 10 females of six different nationalities. The age range of the subjects was between 20 and 31 years old. We informed all subjects of the experimental procedures and all subjects signed a consent form. The experiment was done in an office setting where the average brightness was 320 lux. This brightness level was also the recommended lighting condition for normal office and classroom[90].

The experiment process started after the subjects had signed the consent form. First, we collected a frontal face image with a camera; we used this picture to determine each individual subject's face ratio. Then, we placed two red sticker markers on the subject, one on the right tragus and the other on the large spinous process of the C7 vertebrae. We used these markers to determine the neck angle via the photogrammetric method, which we will discuss later in this paper. The tragus was easily visible, and the spinous process of the C7 vertebrae was located by running a hand along the back until reaching a large bump. Then, we asked the subject to sit with their back straight and look straight ahead without bending their neck forward. We used a camera to take a picture to measure the reference angle for the photogrammetric method, which we discuss in section 4.3.2.

The subject started the experiment by watching a one-minute long video on a smartphone in a neutral viewing position according to the subject's preference. During the video playback, the smartphone and the video camera recorded the video simultaneously. These two video sources were later used for the neck angle calculation and the evaluation, respectively. Lastly, we performed a statistical analysis on the obtained data.

4.3.2 Photogrammetric method

This method makes use of the neck angle measured from a side view photo of a person. This method has been proven to be reliable[91]; therefore, in this paper,

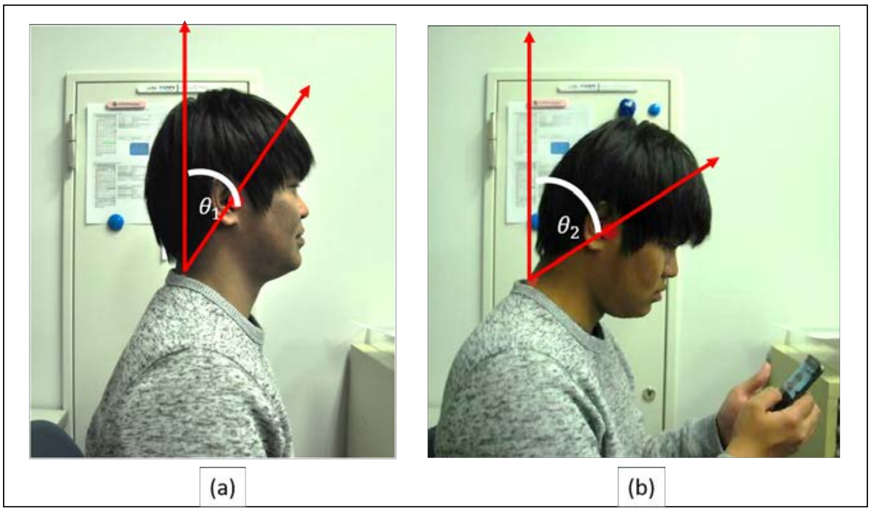


FIGURE 4.9: Example of a neck angle calculation by using the photogrammetric method

we used this method to validate the neck angle calculated from our smartphone monitoring system.

We recorded a video using a video camera, which was set up perpendicular to the subject. The video resolution was 640 x 480 pixels. The frame rate of the video was 24 frames per second. Nonetheless, to synchronize the video data with the video file from the smartphone, we considered the first frame of each second to be representative of the one-second window. We used this representative frame as data for the photogrammetric method and calculated the neck angle based on that data. Figure 4.9 shows an example of images used to calculate the neck angle using the photogrammetric method. Figure 4.9(a) shows an image of a subject sitting straight up; the angle θ_1 is used as the reference angle for this subject. Figure 4.9(b) shows an image of the subject while undergoing the experiment. The angle θ_2 is the angle measured by the photogrammetric method. To calculate the neck angle, we calculated the difference between the two angles, $\theta_2 - \theta_1$. Figure 4.10 shows the position of two red stickers that were used as a reference point for photogrammetric method. The result of this calculation was used later in a statistical analysis comparing these results with those obtained via the smartphone method.

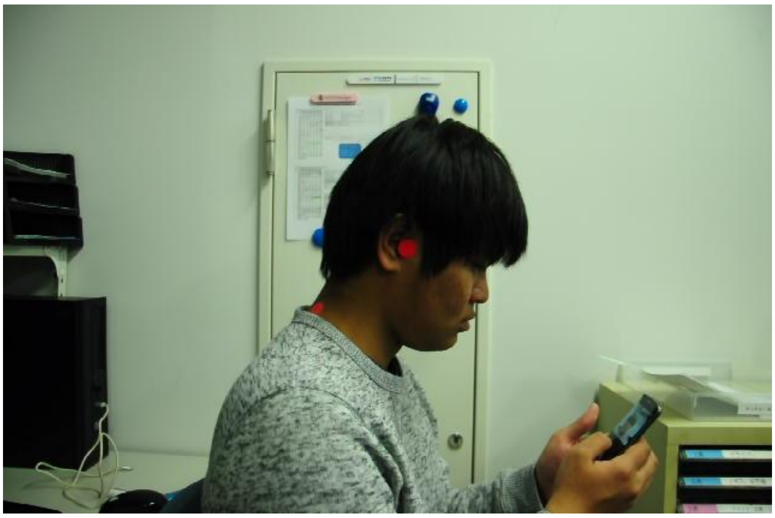


FIGURE 4.10: Positions of two red stickers for photogrammetric method for neck angle measurement

4.3.3 Statistical analysis

Using a total of 30 subjects, we collected 1,770 frames of data for both the smartphone application and the photogrammetric method. To verify that the results were reliable, we performed a paired sample t-test on the calculated neck angle from the smartphone system and the photogrammetric method to prove that there was no significant difference between the two methods. Equations 3 and 4 show the null hypothesis and the alternative hypothesis of this test where μ_1 and μ_2 in both Equations 3 and 4 represent the mean of the neck angles from the smartphone monitoring system and the photogrammetric method, respectively. The null hypothesis represents that the difference of the two mean values ($\mu_1 - \mu_2$) is equal to zero, and the alternative hypothesis represents the opposite. If the null hypothesis is not rejected, it means that the average difference of the neck angle from smartphone monitoring system and photogrammetric method is not big enough to be statistically significant.

$$H_0 : \mu_1 - \mu_2 = 0 \tag{4.3}$$

$$H_1 : \mu_1 - \mu_2 \neq 0 \tag{4.4}$$

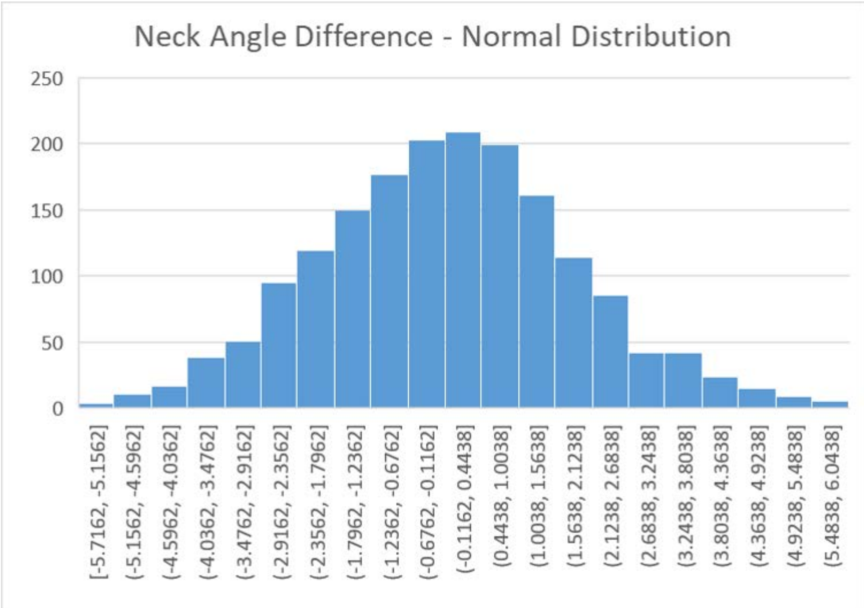


FIGURE 4.11: Normal distribution of the difference value from the two neck angle measurements

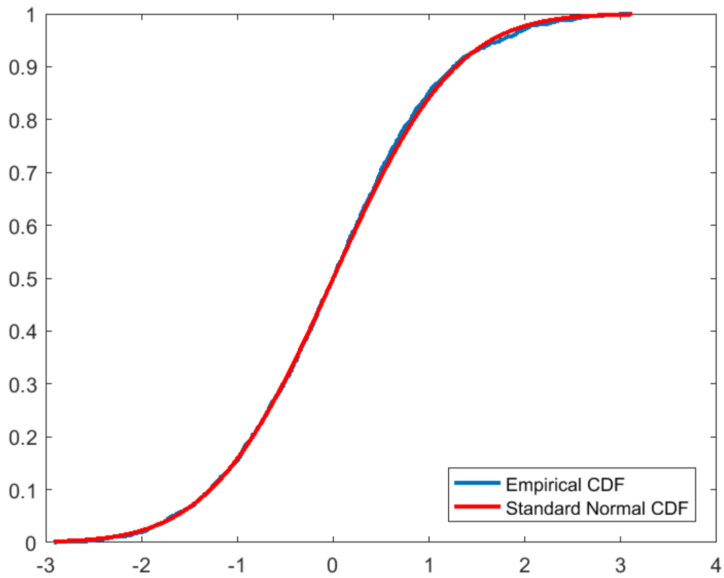


FIGURE 4.12: Kolmogorov-Smirnov test plot

To perform a paired sample t-test on these two sets of data, we calculated the difference between each frame of data. Figure 4.11 shows a histogram of the difference between the two methods in each frame of data. The data were assumed to be normally distributed, which was one of the prerequisites for performing the paired sample t-test. Therefore, we performed the Kolmogorov-Smirnov test on the data with a significance level (α) equal to 0.05. The p-value from the test was 0.798. Because the p-value was greater than the significance value, we concluded that the data were normally distributed. Figure 4.12 shows a graph of the test where the blue line represents the empirical cumulative distribution function and the red line represents standard normal cumulative distribution function.

TABLE 4.4: Descriptive statistical analysis of the data from the two measurement methods

Statistical Attributes	Photogrammetric Method	Smartphone Monitoring System
Mean	16.72	15.78
Median	15.94	16.29
Standard Deviation	7.25	7.29
Variance	52.65	53.15
Data Count	1,770	1,770

Table 4.4 shows the descriptive statistics of the two sets of data. The photogrammetric method calculated a mean neck angle from the 30 subjects of 16.72°, while the smartphone application calculated a mean of 15.78°. The standard deviations are 7.25° and 7.29° for photogrammetric method and the smartphone application, respectively.

Table 4.5 shows the result of a paired sample t-test on the two sets of data. Equation 5 shows the formula for calculating the t-value for the paired sample t-test where $\overline{d}$ is the mean difference of the two sets of data and $SE(\overline{d})$ is the standard error of the mean difference. The test was performed with a confidence level of

TABLE 4.5: T-test for two-paired sample mean results

Statistical Attributes	Value
Alpha	0.05
Population Mean of Difference ($\overline{d}$)	0.063
Standard Error of Mean Difference $SE(\overline{d})$	0.046
95% Confidence Interval	-0.154, 0.027
Degree of Freedom	1,769
Pearson Correlation	0.964
T-Value	-1.373
P-Value	0.170
T-Critical for Two-Tailed Analysis	-1.961, 1.961
Observation Count	1,770

95% ($\alpha = 0.05$). The degree of freedom for the test was 1,769. Therefore, the t-critical values for the two-tailed analysis were -1.961 and 1.961. The t-value for the analysis was -1.373 and the p-value was equal to 0.170, which was greater than the confidence level we set at 95% ($\alpha = 0.05$).

$$t = \frac{\overline{d}}{SE(\overline{d})} \tag{4.5}$$

4.3.4 Results

From the results, the t-value for the paired sample t-test is -1.373, which is between the t-critical values for the two-tailed analysis (-1.961 and 1.961). This leads us to accept the null hypothesis and conclude that the neck angle measured by the smartphone monitoring system has produced a result that is as accurate as the photogrammetric method at a confidence level of 95%. In other words, the paired sample t-test showed that the neck angle calculated would lie within the 95% confidence interval of mean difference, which was between $-0.154°$ and $0.027°$ of differences. Please note that during the experiment where we collected the data from the subjects with smartphone, the subjects were not required to look at the smartphone perpendicularly, instead, they were able to use the smartphone freely in their comfort position. As a result, the experiment showed that even with the subject did not maintain perpendicular eyesight to the smartphone, the system was capable of accurately calculating the neck angle where it showed no significant difference when compared to the result from photogrammetric method.

4.3.5 Demonstration

After the neck angle calculation was evaluated in the experiment, we performed as demonstration of the classification concept with a volunteer human subject. The subject was asked to use a smartphone for 30 minutes. The subject could move the phone freely to his comfort position as well as look away from the smartphone screen or take a short break within this 30 minutes period of experiment. As mentioned in section 4.2.6, the system tracked the usage time based on the detection of face features. Figure 4.13 shows the usage time of the subject over 30 minutes. The usage time increased as long as the system was capable of detecting face features and calculating neck angles. Then, the system stopped tracking the usage time when it failed to detect face features. As an example, the usage time was constantly increasing until the 15th minute mark, where it failed to detect the face features and with an assumption that the subject had stopped using the smartphone. As a result, the usage time was reset to zero and the system restarted the usage time tracking process when it successfully detected the face features again.

Figure 4.14 shows the calculated neck angle plotted together with the classification result where the primary vertical axis (left vertical axis) shows the neck angle in degree and the secondary vertical axis (right vertical axis) shows the class label (1=Healthy, 2=Normal, 3=Slightly Unhealthy, 4=Unhealthy, 5=Very Unhealthy). As a demonstration of the classification conditions mentioned in section 4.2.6, the classification process considered both usage time and neck angle. Previously, Figure

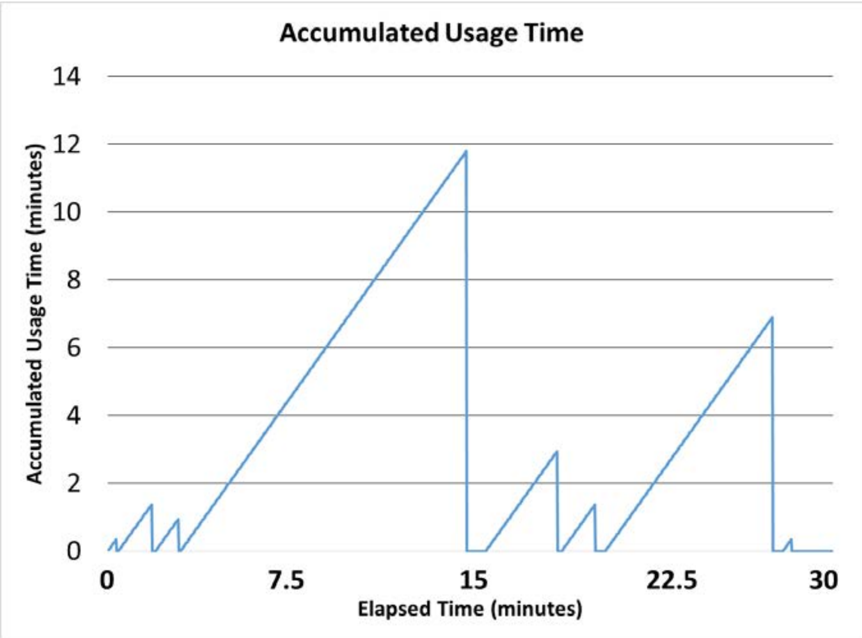


FIGURE 4.13: Usage time in minutes

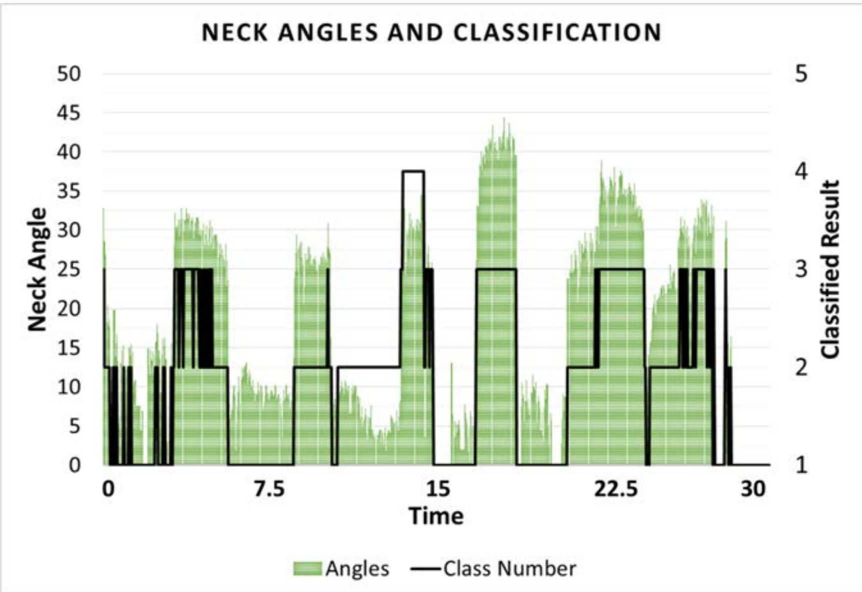


FIGURE 4.14: Neck angles and classification result using pre-defined conditions

4.13 shows that the tracked usage time at 15th minute was between 10 and 12 minutes. The neck angle calculated at the same point of time was between 30−35°. If the calculation were to be based on only neck angle, the result would be classified as 'Slightly Unhealthy', but Figure 4.14 shows that the classified result was labeled as 'Unhealthy' (4). This was because the usage time was between 7.5-15 minutes and the classification result will be worsen by one step based on classification conditions in Table 4.3. At other point of time where usage time was not more than 7.5 minutes, the classification was only based on neck angle

4.4 Discussion

In general, this system proposed a solution to prevent text neck syndrome which was a result from the excessive use of technology device like smartphone. In addition, person with text neck syndrome could consequently experience with severe headache and chronic diseases, which contribute to low well-being life. The system uses a combination of data from smartphone sensors and data from an image detection method to calculate the neck angle. The system calculates the neck angle based on those obtained values, which enables the system to give a high accuracy measurement even if the face plane is not parallel to the smartphone screen. Further, we set up an experiment to test the algorithm with a total of 30 human subjects, consisting of multiple nationalities and ages. The results from the paired sample t-test show that there is no significant difference in the neck angle between the smartphone monitoring system and the photogrammetric method. This supports our assumption and confirms that our proposed algorithm for the neck angle calculation is feasible. All in all, this system serves as a foundation for using technology approach to prevent and promote better well-being of a person. Further in chapter 5 and 6, more complicated and generic approaches for broader health-related issues are discussed and proposed.

4.5 Conclusion

In conclusion, this chapter provide the following contributions:

- This chapter proposed a solution to solve text neck syndrome by using smartphone and image processing technique along with the proposed neck angle calculation algorithm.
- This chapter proposed a classification rules where it considered both the neck angle and usage time. This help prevent and raise awareness for the text neck syndrome in both perspective.
- The results of this chapter is a foundation of developing a digital healthcare system that could cover bigger scope of well-being.

Chapter 5

Smartphone Addiction Recognition and Stress Recognition Using IoT Sensors and Machine Learning Approach

5.1 Overview

This chapter discuss three systems that was developed to help raise awareness and prevent health-related issues of smartphone addiction and stress. For smartphone addiction, the system was developed to recognize the likelihood of having smartphone addiction syndrome from the smartphone usage data and physical activity. On the other hand, two systems were developed to recognized stress. The first system recognizes the stress level based on working behavior and working environment data, while the second system recognized the stress based on daily activity and heart rate data. All in all, these three systems used a survey based approach as a ground truth in system development, which was adopted and utilized further in the next chapter for well-being recognition system, and all of these systems have the same purpose in raising awareness to the health issue for better well-being.

5.2 Smartphone Addiction Recognition System

5.2.1 System Overview

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 [81]. As a result, a group of researchers has proposed a Next Generation e-Health Framework [92]. 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 5.1 shows the design of the proposed system architecture. We took the idea of dividing data mining tasks into layers from a prior work [93] 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

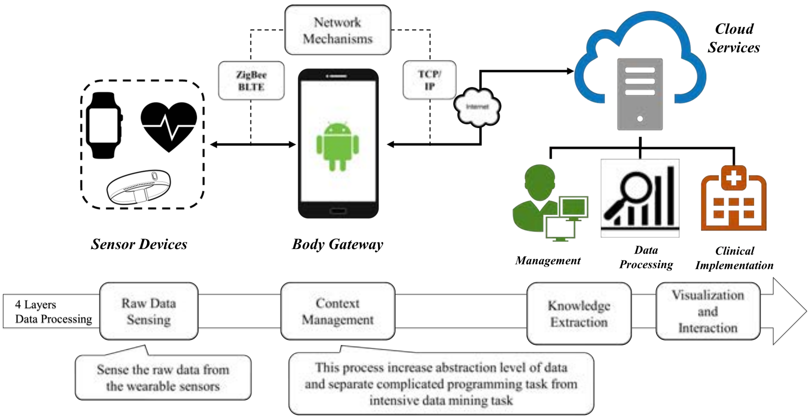


FIGURE 5.1: Overview of the proposed system architecture for healthcare system

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.

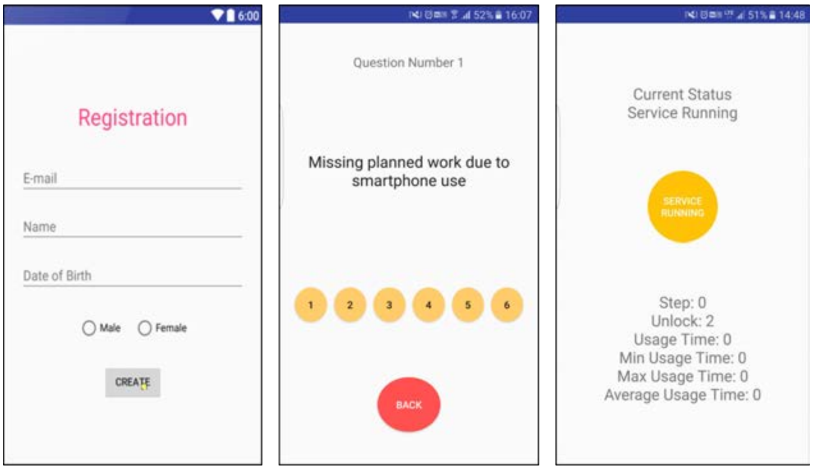


FIGURE 5.2: Three main page of the developed application

5.2.2 Smartphone addiction scale

Smartphone Addiction Scale (SAS) [94] 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.

5.2.3 Data collection application

For the development of smartphone addiction recoginition system, we developed an application to collect the data from the subjects. Figure 5.2 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.

5.2.4 Experiment design

We separated the experiment into three main stages. Figure 5.3 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 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.

5.2.5 Model training

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 section 5.2.3. 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.

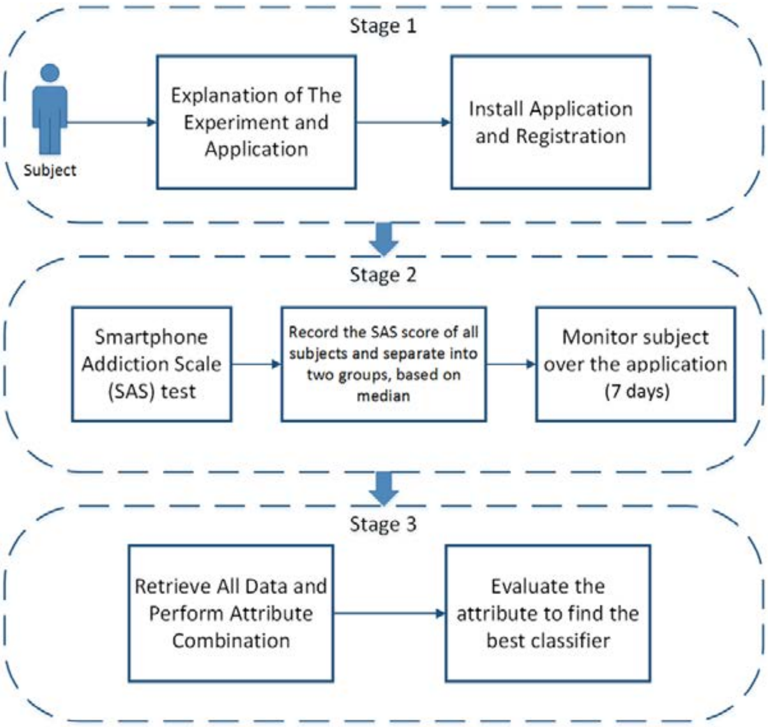


Figure 5.3: Overview of the experiment design

The application collected all the attributes mentioned earlier in the section 5.2.3. 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 minutes. Please note that, we set the period to 30 minutes 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 minutes or longer, as well.

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 minutes. 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.

5.2.6 Experiment and result

The 20 most accurate results of all attribute combinations are discussed in this section. Table 5.1 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 section 5.2.5.

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 5.2 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.

TABLE 5.1: 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 5.2: 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%

5.3 Stress recognition using IoT sensors for office monitoring

5.3.1 System overview and data collection

In order to collect data from the subject and use them for unsupervised learning, we designed and developed the data collection device from micro-controller boards and multiple sensors. Figure 5.4 shows the overview of the device. We used three force sensors for working behavior attributes. The force sensor embedded in seat cushion recognizes how often the subject change their posture from sitting to standing while the force sensor in the table mat recognizes the force applied to the table while working as well as the arm movement. The force sensor in the mouse pad recognizes the force applied during the mouse movement. By using force sensors, it was possible to detect the amount of force applied to each sensor which could relate to the amount of stress of each person. For the working environment attributes, we used humidity sensor, temperature sensor, and ambient light sensor to collect the data. All sensors are connected to micro-controller board. The board was configured to constantly retrieve the data from the sensors with 1000 milliseconds delay. At each retrieval of the data, the micro-controller board transmits the data to gateway. The gateway is responsible for preprocessing of the data which are used to calculate the attributes for clustering every 30 minutes. The 10 attributes calculated by the gateway are average table mat pressure, average mouse pad pressure, average humidity, average temperature, average ambient light, number of time for activity change between sitting and standing, average sitting time, average standing time, total sitting time, and total standing time.

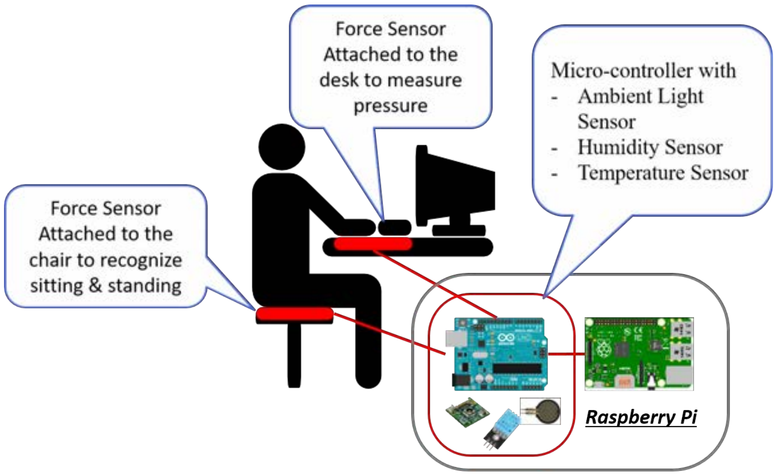


FIGURE 5.4: Overview of the data collection device

5.3.2 Perceive stress scale

PSS[53] is a 10 questions survey for assessing stress level of a person. The survey is used to assess the stress over the last month. The total score of the survey is 40, each question has a scale of zero to four. The score for the positively stated items are reversed before calculation (e.g. 0 = 4, 1 = 3, 2 = 2, 3 = 1, and 4 = 0). Score ranging from 0-13 is low stress, 14-26 is moderate stress, and 27 40 is high stress.

For our work, we used PSS to determine the stress level of each subject over the past month. The score was used later in the experiment in order to find the relationship between the subjects working behavior and their stress level.

5.3.3 PSS score calculation

We calculated the score of each subject PSS survey. The descriptive statistic of the score showed that the average PSS score of the 7 subjects were 18.86. When compare to the actual PSS score of each subject, 4 subjects have the PSS score higher than average and 3 subjects were lower than average.

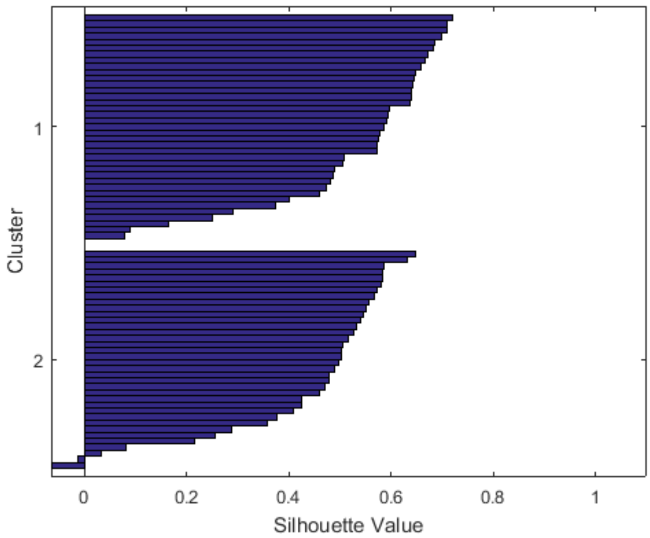


FIGURE 5.5: The silhouette result from k-means clustering

5.3.4 Unsupervised Learning

The data stored in the gateway database were the attributes mentioned in section 5.3.1. These attributes were of different units. Thus, we performed a rescaling to normalize them into the range between zero to one. The normalization is essential to the clustering process and the clustering algorithm relies on the distance between each instance. After that, we performed clustering on all 70 instances with k-means and hierarchical clustering algorithm. We set the number of cluster to 2, as we expected to show two clusters that represent working behavior related to either low or high stress.

Figure 5.5 shows the clustering result from k-means algorithm with silhouette value. The silhouette value was above 0.6 which means that the two clusters are well separated from each other.

Figure 5.6 shows the dendrogram from hierarchical clustering result. The cluster number was set to two where the result showed that the leaf node 30 was likely to be missed clustered to the other cluster as its height is very close to the root. The cophenetic correlation coefficient value was 0.726.

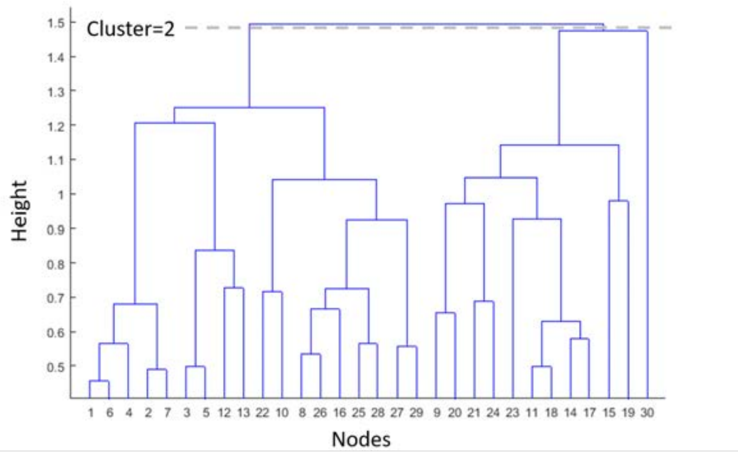


Figure 5.6: The silhouette result from k-means clustering

5.3.5 Working behavior analysis

Table 5.3 shows the clustering results when comparing with the instances from all subject. The number of instance represents how many instances from that subject belong to each cluster. The PSS score compared to mean represent the PSS score of each subject where 'High' classify the subject to have a higher PSS score than average and Low represents a lower PSS score than average. From a total instance of 70, 36 instances were determined as a member of cluster A for k-means algorithm and 34 instances for hierarchical algorithm. While the rest were determined to be in cluster B.

For cluster B, 34 and 36 instances were determined as members of cluster B for k-means and hierarchical algorithm respectively.

Regarding PSS score, subject 1, 3, and 7 had the PSS score that was classified as 'High'. The results show that the majority of instances from subject 1, 3, and 7 were clustered into cluster A for both algorithms. The instances from these subject equal to 81% of all instances for k-means clustering algorithm and 85% for hierarchical clustering algorithm, which was slightly higher than k-means. On the other hand, instances from subject 2, 4, 5, and 6, which had PSS score classified as 'Low', were clustered to cluster B at 97% for both k-means clustering algorithm

Table 5.3: Number of instances in each cluster

Subject	K-means Clustering (Number of Instances)		Hierarchical Clustering (Number of Instances)		PSS Score & Mean Comparison
	Cluster A	Cluster B	Cluster A	Cluster B	
1	10	0	10	0	High
2	0	10	0	10	High
3	10	0	9	1	High
4	1	9	1	9	High
5	3	7	3	7	High
6	3	7	1	9	High
7	9	1	10	0	High

and hierarchical clustering algorithm. However, as shown in subject 3, 4, 5, and 6, some instances from these subjects were clustered into the other cluster that does not represent the subjects PSS score.

Overall, cluster A represented working behavior that was related to high PSS score (higher stress), while the cluster B was related to low PSS score (lower stress).

Table 5.4 shows the characteristic of each cluster. For both algorithms, the results showed that in overall, the environmental attributes remain similar between the two clusters. However, for behavioral attributes, cluster A showed that average pressure on mouse pad, ambient light, and average total standing time are less than cluster B. While cluster B showed higher pressure on mouse pad, which could be referred to more movement on mouse pad, and higher activity change count as well as average total standing time. These characteristics pointed out the working behavior that was related to PSS score, where working behaviors in cluster A (higher stress) were likely to have less changes in activity. On the other hand, cluster B represent more active working behavior. The majority of the clusters members showed that

TABLE 5.4: Characteristic of the two clusters

Attributes (Average)	K-means Clustering		Hierarchical Clustering	
	Cluster A	Cluster B	Cluster A	Cluster B
Table Pressure	64.45	45.63	63.61	45.99
Mouse Pad Pressure	49.00	142.30	43.65	147.10
Humidity	59.17	61.19	58.89	61.55
Temperature (Celsius)	25.00	26.39	24.91	26.42
Ambient Light (Lux)	313.90	369.29	322.30	356.87
Total Sitting Time (Minutes)	27.34	7.79	27.54	8.43
Total Standing Time (Minutes)	2.82	22.36	2.61	21.72
Number of Activity Change	10	36	10	35

it was also related to the lower PSS score. As a result, cluster B represented the working behavior that led to lower stress level.

5.4 Stress recognition using activity tracker

5.4.1 System overview

Figure 5.7 shows the overview of the proposed system. This study designed the system according to the ETSI M2M architecture [81]. In this system, we divided the system into two main parts. The body area network consists of two main components, activity tracker and smartphone. The activity tracker serves as a sensor device that collects data from the user. The smartphone serves as a body area gateway. Its main task is to communicate and receive data from the activity tracker.

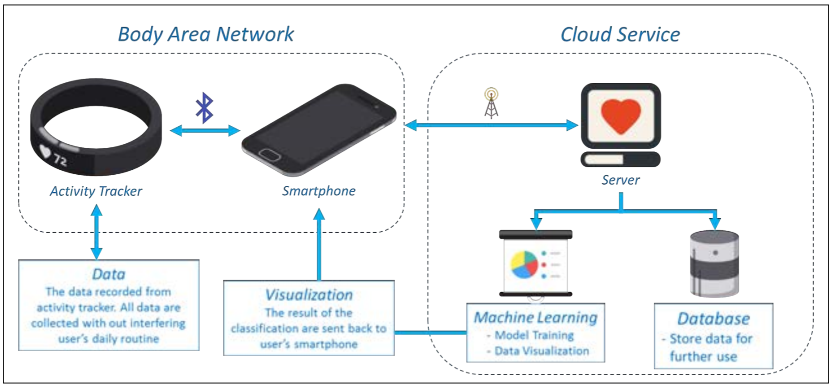


FIGURE 5.7: Overview of the daily stress recognition system

Then, it processes them before sending them to the cloud service using the Internet connection. Moreover, as an extension to this system, the use of body area gateway also enables the possibility of multiple sensor device implementation. As each device may not has Internet connectivity, the body area gateway can help gather the data, organize the data, and prepare the data before sending to cloud service. This reduces the traffic and bandwidth that is require between the devices and cloud service.

For the cloud service, the first component, database, stores the data received from the body gateway. Moreover, the database stores personal information of the user and the classified data from the machine learning component. The machine learning component provides classification service, such as low or high stress level, and visualization to the user such that the visualization part provides feedback to user via the smartphone application. We conducted the experiment using a FitBit activity tracker. The tracker's heart rate sensor was proved to have no significant difference in sensing the heart rate compared to other famous trackers in the market [95]. First, all of the subjects were informed about the detail of the study as well as its purposes. Then, the subjects were asked to complete two surveys. The third survey was also given to them but they were asked to complete and return it the next day. Then, the data collection process started. After the data collection was completed on the next day, we prepared the data for model development, which was done when all data were received from every subject. Finally, we evaluated the model as discussed in section 5.4.7.

5.4.2 Surveys

This study used the perception survey as an evaluation method for the model. The surveys chosen for the study were to determine the overall stress level. The survey did not pointed out any stress from certain specific tragic event, such as loss of love ones, instead, it focused on overall perceived stress level.

Perceived Stress Scale

Perceived Stress Scale (PSS) [53] is one of the most widely used survey for measuring perception of stress. The survey consists of 10 questions, each one is a 5 point scale question (maximum score=40). The higher score results in a higher stress perceived by the subject over the past month.

General Self-Efficacy Scale

General Self-Efficacy Scale (GSE) [96] is a 10 questions 4 point scale survey (maximum score=40). The purpose of the survey is to measure the ability of a person in coping with problems and demands in the past month. It is widely used in stress related studies. The higher score represents the higher capability in handling the problems and demands.

General Survey

We developed the general survey that consisted of 5 questions. Each question related to the factor that affected stress levels, which were health [97], fatigue [98], nervous [99], workload [100], and mood [99]. The survey was a 5 point scale (maximum score=25). The total score represents the likelihood of experiencing stress where higher score represents higher possibility of stress. The general survey was completed during the day of the data collection where the morning part was completed during lunch and evening part was completed after they finished their work on that day. The purpose of this survey was that we wanted to examine the perceived stress of each day. While the PSS and GSE provided a stress level for the past month, the general survey could help to understand the stress level of each specific day.

5.4.3 Data collection

This study collected the data from a total of 10 subjects, including 6 males and 4 females aged between 20-26 years old. The subjects participated in the experiment were researchers and graduate students who worked between 6-10 hours per day. The subjects did not have any medical condition and they were not taking any kind of medicine during the experiment period. First, the instructor informed the subjects about the information of this data collection and experiment and gave them three surveys, as mentioned in section 5.4.2. Then, the data collection process start at night, where all subjects wore the activity trackers before sleep, and for the whole day of the next day. We collected the data from the subjects on their working day, where each subject had at least 6 working hours on the day. In total, we had 10 days of data from 10 subjects. The five types off data collected were number of steps, calories, sleep cycle, heart rate, and resting heart rate. In addition, we performed normality test on the collected data with Kolmogorov-Smirnov test. The null hypothesis for the test was that each type of data was normally distributed. The test at 5% significance level on all five types of data showed that it failed to reject the null hypothesis, and that the data came from a standard normal distribution.

5.4.4 Features extraction

From the total of 5 types of data, we extract a total of 17 features on 1-hour interval of collected data. The sleep cycle data were attached to each instance as it was recorded overnight.

5.4.5 Survey results

Every subject completed all three surveys and Table 5.5 shows the descriptive statistics of the three surveys' results. For the general survey, we calculated the mean from the two parts of the survey, which were morning and evening, and used it as the score. Please note that for GSE result, the higher score represented higher capability of handling problems and demands, which resulted in less stress. The maximum possible score of the surveys were 40, 40, and 25 respectively for PSS, GSE, and General Survey.

TABLE 5.5: Descriptive statistics of survey score

Survey	Mean	Standard Deviation	Maximum	Minimum
PSS	18.60	4.81	25.00	21.00
GSE	28.80	3.97	37.00	22.00
General Survey	10.45	2.20	14.00	7.00

From the results, we used the mean value of each survey as a separation mark to label the data instances from each subject. For PSS and general survey, the subjects with score above the mean of each survey were labeled as 'High' and those with score lower than the mean were labeled as 'Low' For GSE, the subjects with score higher than the mean were labeled as 'Low' and those with score lower than the mean were labeled as 'High'. Lastly, the combined label was based on the majority from the results of the three mentioned surveys. Please note that 'High' represents higher risk of stress based one each survey type and 'Low' represents lower risk of stress. Table 5.6 shows the survey score and labeled class of each subject.

TABLE 5.6: Survey score and label of all subjects for each survey type

Subject	PSS	GSE	General Survey	PSS Label	GSE Label	General Survey Label	Combined Label
1	18	27	11.00	Low	High	Low	Low
2	10	37	10.00	Low	Low	Low	Low
3	24	22	10.5	High	High	High	High
4	25	26	14.00	High	High	High	High
5	18	27	7.00	Low	High	Low	Low
6	19	28	12.50	High	High	High	High
7	24	29	13.00	High	Low	High	High
8	14	32	8.00	Low	Low	Low	Low
9	19	30	10.50	High	Low	High	High
10	15	30	10.00	Low	Low	Low	Low

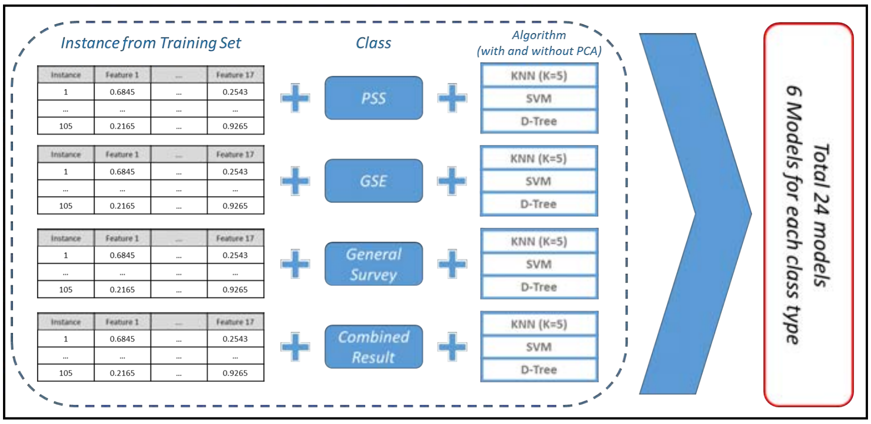


FIGURE 5.8: Model training process with 4 class types

5.4.6 Model training

We trained the model using three algorithms, including K-Nearest Neighbor (K=5), Support Vector Machine (SVM), and Decision Tree. The extracted features were preprocessed by mean normalization technique. Thus, all features were in the same scale. The data from each subject were randomly separated into training set and test set with the ratio of 80% to 20%. There were a total of 105 records in the training set and 25 records in the test set. First, we performed the training process using 5-fold cross validation on the training set. We trained the models to predict the stress using PSS, GSE, general survey, and combined result as the responses. Then, we performed training task using principal component analysis (PCA) on the same training set, classes, and algorithms. In total, we have trained 24 models, including 6 models for each response (PSS, GSE, general survey, and combined result). Figure 5.8 shows the modeling process with 4 class types.

5.4.7 Cross validation and test set

During the training process, we used K-fold cross validation (K=5) as a model validation technique. Figure 5.9 shows the results of the model from the training. The highest accuracy when trained using PSS as a class was 85.40% with decision tree algorithm without PCA. The highest accuracy for using GSE as a class was

96.30% with SVM algorithm without PCA. For using the general survey as a class, the highest achieved accuracy was 81.70% with SVM algorithm without PCA. Lastly, when the model was trained with a combined survey results, the highest accuracy was 84.10% with decision tree algorithm without PCA.

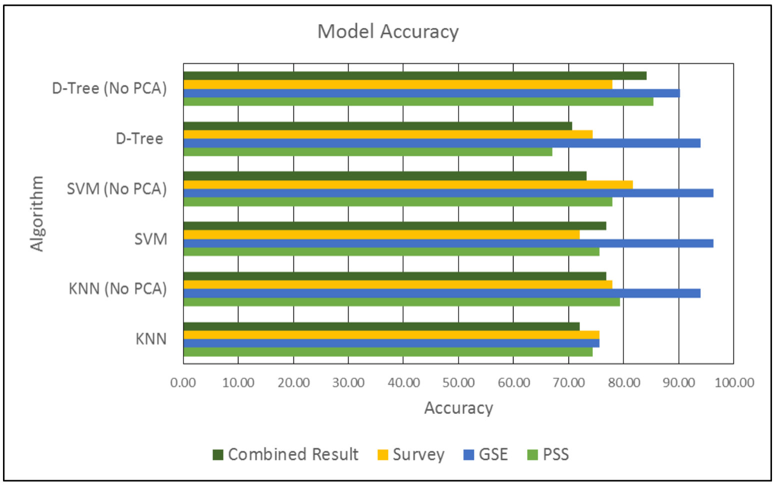


FIGURE 5.9: Accuracy of the model from the 5-fold cross validation

Then, we selected the better performer model of each algorithm, which was that without PCA, and applied them to the test set. In this process, the model predicted the test set based on its own class type. Figure 5.10 shows the accuracy of each model when predicting the test set of its class. In all class types, model with Decision Tree performed better with the accuracy of all models higher than 78.00%. For the model predicting the combined survey result, the accuracy was 78.95%. The worst performing model was a KNN model used to predict the stress based on PSS result, where the accuracy was at 57.90%.

5.5 Discussion

In this chapter, we presented a total of three systems to help promote better well-being. First, by preventing smartphone addiction, this leads to a prevention of

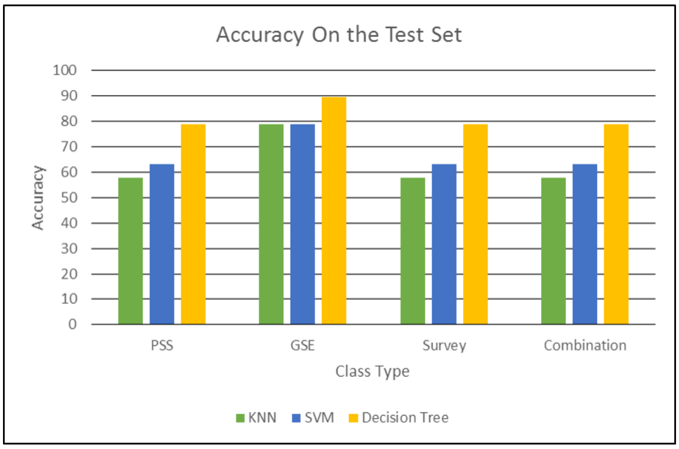


FIGURE 5.10: Accuracy of the models when applied on the test set

others physical syndromes, such as; text neck and CVS, as well. Moreover, as presented in chapter 2, smartphone addiction is likely to cause stress and other mental conditions. The developed system for recognizing smartphone addiction achieved as high as 78.74% in accuracy. This system clearly demonstrated two possibilities. First, the combination of smartphone usage data and physical activity can be used for recognizing the likelihood of smartphone addiction. Second, the survey based approach where surveys' results were used as a ground truth data can be efficiently utilize for such recognition system.

The second system was developed in the same survey based approach. However, the system was focusing on recognizing stress level instead of smartphone addiction. In other word, by recognizing the stress level from the working behavior was an foundation to recognizing well-being level as stress is one of the major component in reflecting users' well-being. In addition, this could help prevent other syndromes that have link to stress as well. The system demonstrated the used of IoT devices and sensors in data collection where it collected both working behavior data and working environment data. Instead of using survey results' as a ground truth information for labeling data, the unsupervised learning technique was performed to group the data into two clusters, representing either high or low level of stress. Then, each clusters was examined and the characteristic of each cluster represent the different working behavior. In general, the results of this cluster can be utilize further to develop a feedback system where the users would be able to aware of there own behavior, whether they are in a lower stress level cluster or higher stress cluster.

The final system was an extension to the second system. From the stationary IoT sensors that can collect only working behavior data, the system adopted an activity tracker, which can also collect heart rate data from the subjects. The use of activity tracker showed the possibility of monitoring the subject for 24 hours per day. Moreover, vital data like heart rate and sleep, which affect stress level directly, can also be collected through this activity tracker. The system demonstrated the used of multiple surveys in order to recognize the stress level from multiple dimension. The multi-dimension well-being recognition system is an important problem and this approach showed the possibility of doing so. Finally, the highest accuracy achieved in the training process was 84.10%.

Overall, this chapter demonstrated multiple approaches and contributions. First, all three systems adopted the survey approach to develop a recognition system while one of the system used multi-surveys to demonstrated multi-dimensional well-being recognition system, this will be further discussed in chapter 6. Secondly, all of the systems demonstrated the used of IoT devices along with either smartphone or gateway device (according to ETSI architecture [101]) to collect data and extract meaningful information. Thirdly, this chapter started from addressing the smaller concern like smartphone addiction and successfully recognize the likelihood of having the condition, then the next system addressed a larger scope where the stress recognition was presented. The approach slowly move from a smaller scope to a bigger scope where the system could cover more factors, more complete, and eventually, could help prevent and promote a better well-being. Finally, the techniques used in these three system were evaluated and improved for the implementation in the final well-being recognition system.

5.6 Conclusion

In conclusion, this chapter provide the following contributions:

- This chapter proposed a system to detect smartphone addiction, which it help promote a better well-being by raising awareness in smartphone-related syndromes.
- This chapter used unsupervised learning technique to pointed out the different behaviors of two subject groups with different stress levels. This demonstrated that it is possible to recognize the stress with behavior-related data.
- This chapter proposed the stress recognition model with integration of devices. Beside from demonstrating the possibility of developing the machine learning model, it also demonstrated the possibilities of integrating multiple devices to cover as much features as possible, which allow the model to reflect more aspect of users' behaviors.
- All studies in this chapter proposed the system development method using surveys to assess users health condition, namely smartphone addiction and stress, where it was later further used for development of well-being recognition system.

Chapter 6

Real-Time Well-Being Monitoring with Visualization

6.1 Overview

This chapter demonstrated two systems that were developed for the final goal of well-being recognition. The first system works as a foundation to the second system where more data sources were taken into consideration. This chapter also discussed how the system trained the machine learning model for multidimensional well-being recognition using multiple type of surveys.

6.2 Well-being recognition using video detection

The key components of the proposed system are based on M2M and IoT architecture[81]. Figure 6.1 shows the overview of the system and its components. In this study, we use web camera as a sensing device for the workstation area where it is connected to the micro-controller board. The R-Pi acted as a gateway to the system. The gateway is one of the essential component, as it helps reduce the workload on the server side by performing simple data pre-processing tasks. On the cloud services component, the server handles various tasks, which include data storage, daily behavior extraction using deep learning, and classification using the trained model. The results of the classification can be sent to the user's terminals. This feedback acts as a part of decision support system for user as it helps raise awareness regarding their working behavior and well-being. The ideal goal of the system is to provide a real-time feedback to the user regarding there behavior, where the system can provide the feedback based on the summary of tracking data. Nonetheless, in this study, we demonstrate the preliminary experiment using a summary of data on a daily basis.

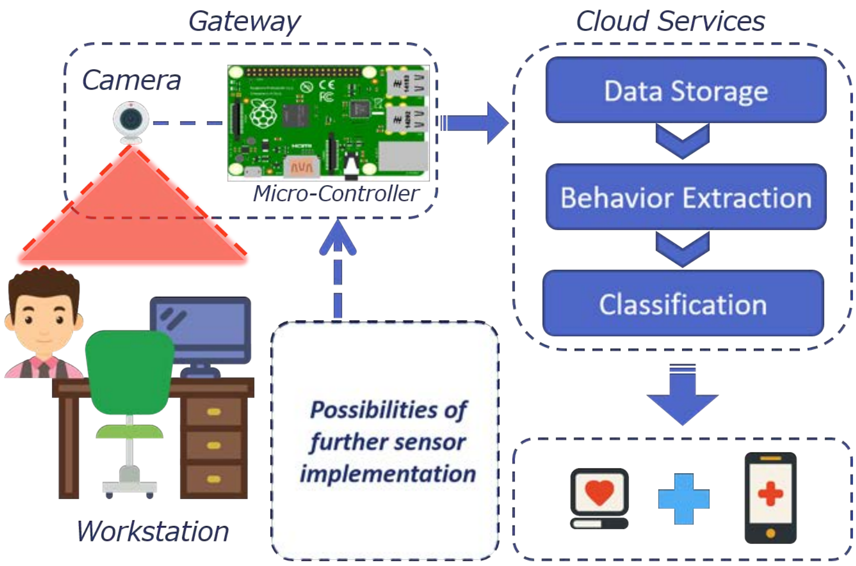


FIGURE 6.1: System overview of proposed daily stress and mood recognition system

Figure 6.2 shows the overall experiment procedures of this study. We conducted the experiment by implementing a web camera with 120 degrees viewing angle in full HD resolution as a device for data collection. The subjects were informed before the experiment about its purposes and the consent forms were given and signed by all subjects. The surveys, which we later discuss in this section 6.2.1, were given to the subjects and we gave them the instructions on how to complete the survey. The monitoring process started and lasted for a total of 60 days. We used the data only on the day where the subjects were present at the workstation and had completed the survey. Later, we performed behavior extraction by using body and hand detector that was trained with deep learning algorithm. The training process of the image detectors is discussed in section 6.2.2. Finally, we trained the classification model with the extracted behavior data. Details of the algorithms used in training of classification model are later discussed in section 6.2.3 and section 6.2.4.

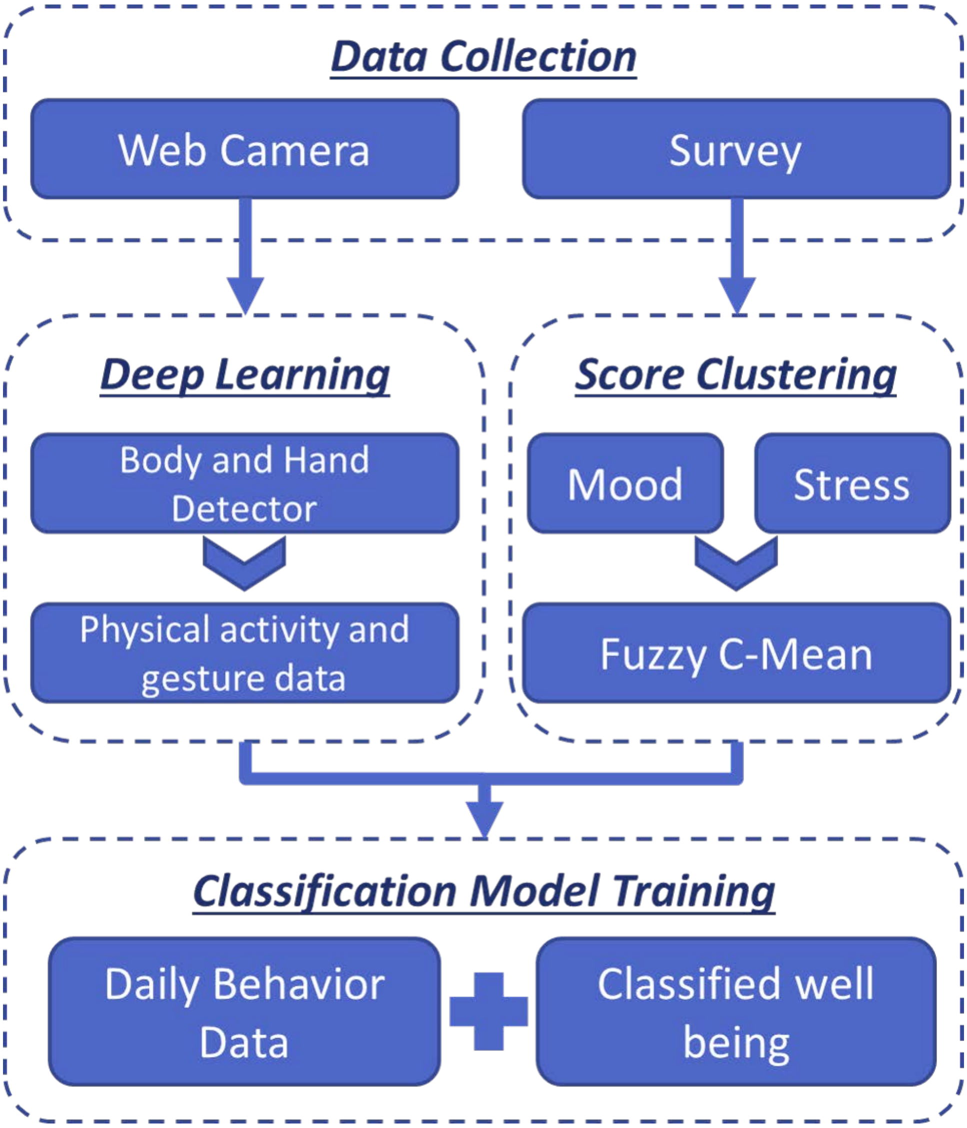


FIGURE 6.2: Overall experiment procedure of the study

6.2.1 Stress and mood surveys

This study used two surveys results to classify daily data into different levels of well-being. However, the study did not use the raw score from subjects as classes for classification. Instead, we performed fuzzy clustering on the survey scores to divide the scores into two groups where each group represented either higher or lower level of well-being. This technique is explained later in section 6.2.3. The following are the surveys used in this study:

Mood

The Positive and Negative Affect Schedule (PANAS) [102] is a 2-dimensions mood survey. The PANAS survey is a famous tool for assessing mood and it has been proved to be reliable, especially with short-term assessment. In general, the survey is capable of assessing the mood for 'right now' or 'today'. The instruction has to be clearly explained to the subject where 'right now' refers to feeling at the present moment and 'today' refer to the feeling for the whole day. In this study, the survey was used based on 'today' scope. The survey consists of 20 words, which are related to either positive or negative affect. The higher score on positive affect related words represents higher level of positive affect (PA). On the other hand, higher score on negative affect related words represents higher negative affect (NA) in the person's mood.

Stress

This study used the approach of recording the perceived stress level on a 100mm VAS where zero represented 'not at all stressful' and 100 represented 'as stressful as I can imagine'. The approach of using this kind of survey was also presented in a work by Gil, K. M. and others [103] for making daily record of stress and mood. The use of the perceive stress level also reflect the subjects' satisfaction level [80], which was pointed out as one of the major component in measuring well-being [70]. The checklists of daily stress assessment [104] were also presented to the subjects as a guideline for recording the stress level.

6.2.2 Image detection

To extract behavior of the two subjects, we used supervised learning approached to develop image detector models using a Faster Region-based Convolutional Neural Network (Faster R-CNN). Faster R-CNN [105] held an advantage to both Fast R-CNN and R-CNN by implementing the region proposal network (RPN) into the convolutional neural network (CNN). Thus, it avoided the bottleneck that may occur. We trained Faster R-CNN to detect two objects, body and hands. In this study, we recorded 10 days of video, with duration of one hour in each day, outside of the experiment period and used as a data set for training the model. We extracted 700 frames of video randomly and labeled the region of interest (ROI) for body and hands. Then, we split the data in to training set and test set with the ratio of 80:20. The Faster R-CNN model for body detection achieved the precision of 0.88 and the precision of hand detector was 0.75.

6.2.3 Survey results and fuzzy clustering

Table 6.1 shows a simple descriptive statistic of the results from two surveys of both subjects, where 'Overall' represents the descriptive statistic of survey results from both subjects combined. Please note that the two subjects have a noticeable differences in PA score and stress. This may be the results of either their overall workload, where subject A had higher overall overtime working hour than subject B. Thus, resulting in higher stress. Nonetheless, personal perception in filling out the survey also contributed to each person's scores. Please note that despite the scores shown in Table 6.1, all data were normalized before the clustering process.

To classify the survey results into clusters that represent either higher level or lower level of well-being, we used Fuzzy C-Means (FCM) [106] clustering algorithm. The advantage of the FCM is that it uses probability in calculation instead of using only distance. In our case, the survey score could be ambiguous as the score of a certain day may be closer to mean and could be easily classified into a wrong class. The clustering approach also helps us classify the data with multiple surveys. This

Table 6.1: Descriptive statistic of survey results from 2 subjects

	Mean	Maximum	Minimum
Subject A: PA	34.11	47	15
Subject A: NA	19.57	33	12
Subject A: Stress	61.17	90	40
Subject B: PA	26.16	33	20
Subject B: NA	20.11	30	13
Subject B: Stress	50.53	90	30
Overall: PA	29.31	47	15
Overall: NA	19.59	33	12
Overall: Stress	54.36	90	30

is because the statistical approach may be able to deal with one survey, but with three features from two surveys, the clustering approach is more suitable.

The clustering results are shown in Table 6.2. There are total of two clusters for each subject and the combined results. For Subject A, cluster one represents a higher level of well-being as the mean PA of the cluster is higher than the mean, while both NA and stress are lower than the overall mean of Subject A (as seen in Table 6.1). Cluster two of Subject A represents lower level of well-being as it shows a significantly lower PA and both NA and stress values are higher than overall mean of Subject A. The same characteristic is also presented in Subject B's clusters and overall results' clusters. The mean of each feature is slightly different among the data set (Subject A, Subject B, and Overall). As a result, we used the clustering results and data from Subject A to trained the personalized well-being recognition using only Subject A's data. Figure 6.3 shows a 3D plot of the 2 clusters where we perform FCM on the survey results from both subjects. The dots represent each data point, which were the survey result from each day from all subjects. The blue dots represent cluster 1 members and the red dots represent cluster 2 members.

TABLE 6.2: Mean of each feature in a cluster from each subject

	PA	NA	Stress
Subject A: Cluster 1	40.06	19.06	5.89
Subject A: Cluster 2	27.82	20.12	6.47
Subject B: Cluster 1	27.92	18.92	5.08
Subject B: Cluster 2	22.86	21.00	4.88
Overall: Cluster 1	33.84	18.16	5.16
Overall: Cluster 2	25.00	20.95	5.70

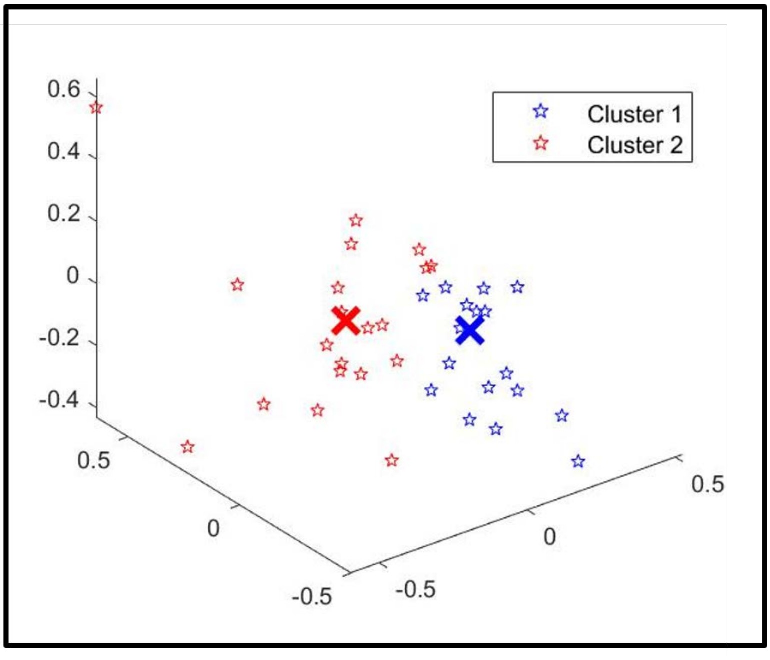


FIGURE 6.3: 3D plot of the clustering results using survey results from all subjects

6.2.4 Experiment and results

We conducted the experiment on two human subjects, one male and one female, with age of 25 and 26 respectively. Both subjects had their own workstation and their usual works did not require them to travel between places. The web camera continuously recorded the working behavior from the top view during day time. At the end of each day, subjects completed the surveys to record their mood and stress of that certain day. The total of monitoring period was 60 days. However, the data used were only from the days where the subjects presented at the workstation. The system extracted behavior from those days using the trained body and hand detector. In total, we had 44 days of data from Subject A (female subject) and 24 days of data from Subject B (male subject).

Daily Behavior Extraction

The image detectors detected both body and hands in the frame extracted from the video, and in this study, we extracted one frame per one second in each video. The detected body and hands were used to calculated the following behavior features: average of body movement, average of hand 1 and 2 movement, number of activity changes (activity change refer to a subject leave or comeback to his/her workstation), total time present at workstation, total time not present at workstation, and average time at workstation per one activity change. The window size of these calculations equaled to the total working time of the day for that subject. In total, there were 7 features from behavior extraction and all of the features were extracted on a daily basis. Each data point represented the behavior of the certain day, and the data points were labeled based on the survey score of that day, which we used FCM technique to separate the results into two classes as mentioned in section 6.2.3. Figure 6.4 shows a number of activity changes of each day over the 20-day period from both subjects.

Model Training

In addition to the daily behavior data, we also used daily weather as the features. This kind of psychological data was proved to have effects on a person's

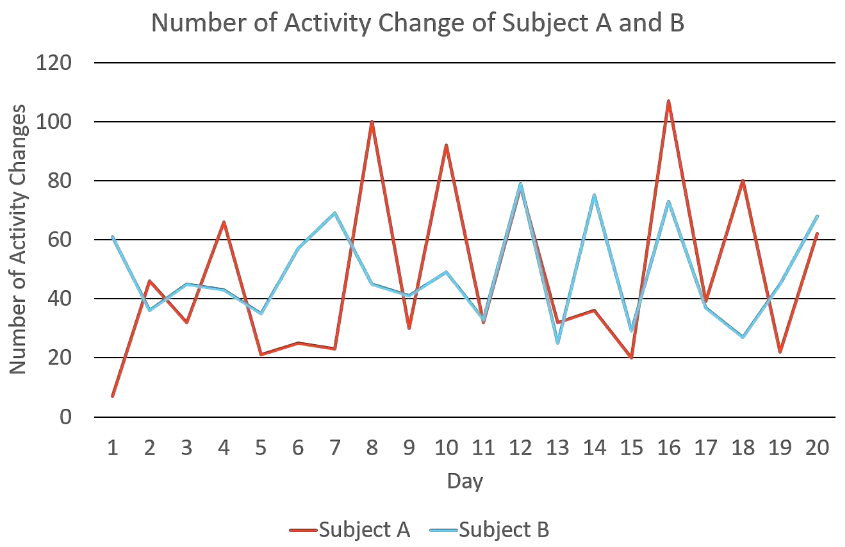


FIGURE 6.4: Example of number of activity change data from Subject A and Subject B during 20 days period of experiment

mood [107]. In general, the temperature has high effect on NA of a person. However, it is not necessary related to one specific rule and is usually based on the personality and preferences, as lower temperature may resulted in an increase of NA in one person while decreasing in another. We recorded the lowest and highest temperature of each day and attached them to the daily behavior data. Therefore, we had 7 features from behavior extraction and two features from weather data. Table 6.3 shows the example data from the 9 features for one single day from the experiment. We trained the model with the prepared dataset where 75% of dataset were used as a training set and 25% were used as a test set. The algorithms used for the training were the three algorithms, including KNN, SVM, and Decision Tree. All the data were normalized before the training process. In general, we trained the model on two bases: First, the generic model where we trained the model with data from both subjects. We used 24 days of data from Subject A and Subject B (total of 48 days of data). Second, the personalized model where we trained it with data from Subject A (total of 44 days of data). This approach demonstrated the possibility of training the recognition model for personalized well-being system. Please note that we did not train the personalized model for Subject B due to the small dataset from it.

Figure 6.5 shows the accuracy of the trained model.

TABLE 6.3: Example daily data of the 12 features used in the training process

	Subject A	Subject B
Average Body Movement (Dot pixels)	6.83	6.54
Average Hand 1 Movement (Dot pixels)	15.83	25.89
Average Hand 2 Movement (Dot pixels)	10.68	11.45
Number of Activity Change (Number of times)	16	33
Total Present Time (Minutes)	360.07	320.52
Total Away Time (Minutes)	31.86	42.38
Average Present Time per Activity Change (Minutes)	17.89	9.71
Lowest Temperature (Celsius)	19	19
Highest Temperature (Celsius)	29	29

For generic model, the highest accuracy was achieved with the SVM algorithms with 83% accuracy. The lowest accuracy for the generic model was from D-Tree algorithm where the accuracy was at 50%. For the personalized model based on data from Subject A, the highest accuracy were 91%, 72%, and 63% with SVM, KNN, and D-Tree, respectively. In general, SVM performed better in both types of model. This may also due to the fact that the classification problem was a binary classification.

Moreover, D-Tree performed poorly in both types of model, as it only achieved the highest accuracy of 63%. Lastly, the accuracy for the personalized model was slightly higher than the generic model and this suggested a good potential in developing a personalized recognition system to raise awareness for one's well-being.

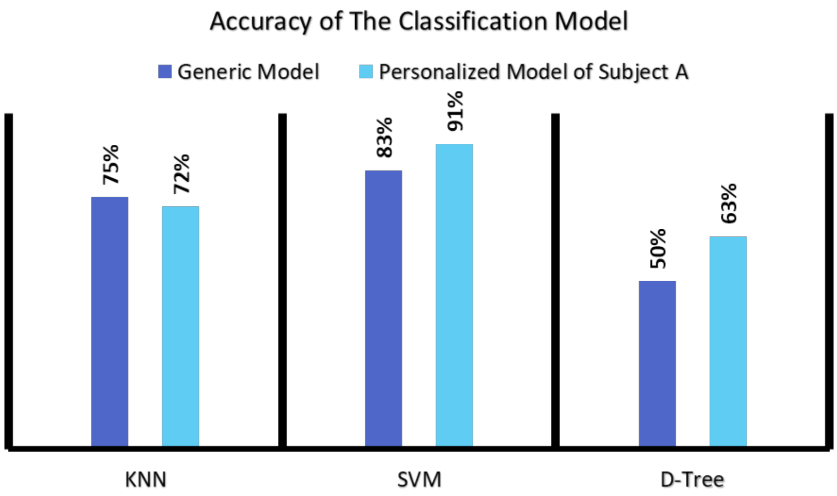


FIGURE 6.5: Accuracy of the classification models

6.3 Personal well-being recognition system

6.3.1 System overview

In order to make improvement to the system previously discussed in section 6.2, personal well-being recognition system was developed. Figure 6.6 shows the overview of the system. In this system, data was collected from multiple sources, more machine learning technique were used to extracted meaningful data for training of recognition model. From the figure, IoT sensors were used to collect the environment data features, which include humidity, temperature, ambient light, and voice activities. Activity tracker were used to collect physical activities data and sleep data. This was the replacement of video movement recognition from the previous system as it is a less intrusive method. Furthermore, through survey, daily commuting data and dietary were also collected and used as one of the features. The assessment of mood and stress level were done through surveys as same as the previous system and then FCM were used to cluster the result for labeling data. Visualization of the result were done in two manners, first, all data were monitored real-time and visualize through the web application with statistical comparison to the groups average. Second, the classification of well-being level was done on half-day basis and the result is visualized through the same web application as well. The detail of this visualization is further discussed in chapter 6.4

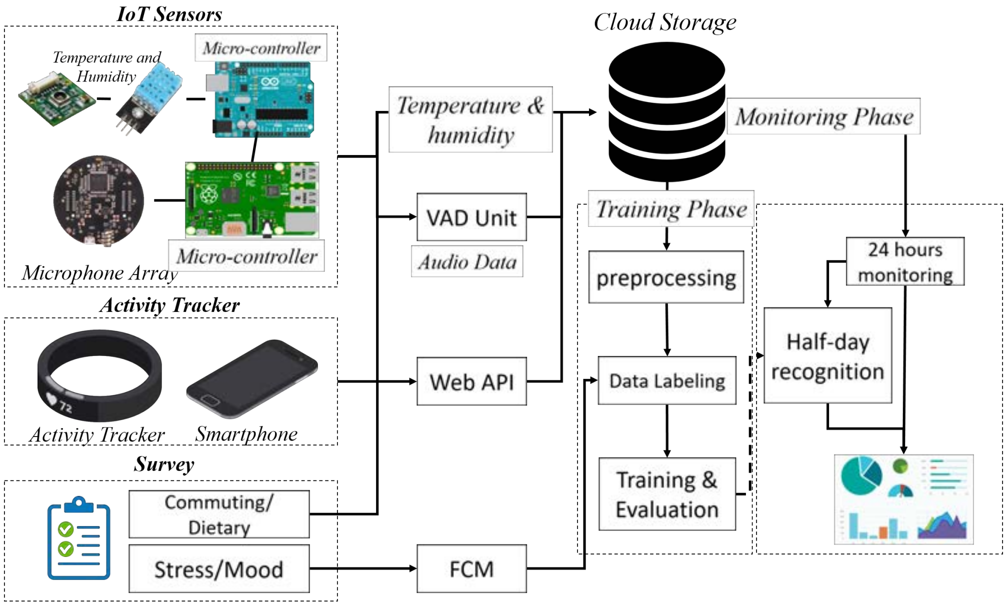


FIGURE 6.6: Overview of personal well-being recognition system

6.3.2 System requirement

As previously discussed in chapter 2, several key points were pointed out in designing persuasive system. This section summarize those key points and the system requirement for the personal well-being recognition system.

- **Reduction:** The system provide knowledge and feedback to users via the dashboard, in this way, the user requires less effort in changing their behavior.

- **Tunneling:** The mean for the action to change the behavior is provided in the system, where it will persuade users to change their behavior for a better well-being.
- **Tailoring:** The system shall provide a tailored data and visualization for each user group.
- **Personalization:** The system shall provide a personalized visualization based on the collected data, the recognition results, and users' behavior. In other word, each users' dashboard will be different.
- **Self-monitoring:** The system's dashboard shall provide a full self-monitoring capability to the users where they can keep track of their progress 24-hours a day.
- **Simulation:** The comparison between users' data to the users' average and to the high level of well-being group shall be presented to show the link between the cause and effects.

An consideration of rehearsal suggested in the key points was omitted as rehearsing or practicing for having high level of well-being would not make sense or feasible in this system. Other key points regarding to dialogue support for the users were also implemented as part of the system requirement where the system shall communicate with the users in a supportive way with consideration of praise, rewards, reminders, suggestion, similarity, liking, and social role.

All in all, the proposed system requirements were based on the idea of developing a successful persuasive system where it should achieve its goal in contributing to a better well-being level of users.

6.3.3 Data collection and features

General environment feature

From the work done in chapter 5.3, the system demonstrated the possibility of using simple IoT sensors in recognizing stress level in office environment. This system partially adopted the usage of those sensors. The sensors that were used in this system include ambient light sensor, temperature sensor, and humidity sensor. The assumption of using these sensors for recognizing well-being were also supported by, where the work pointed out that these factors affect the level of stress and mood in workplace. All of the sensors were connected to micro-controller board where it was connected to another micro-controller board, which acted as a gateway for the system. The data were retrieved on a 1000 milliseconds delay and preprocessed on the gateway before stored in the cloud storage. The features extracted from these sensors include average temperature, average ambient light, and average humidity.

Audio feature

In order for the system to realize the environment in the subjects workplace as much as possible, the system adopted the used of Voice Activity Detection (VAD) in data collection. The microphone array was used to collect the data through the micro-controller. However, it purpose was not meant for speech or voice recognition from the specific subject or person, but only for detecting presence of speech in order to determine the amount of interactions between people in the workplace. One reason that the system avoided adopting voice recognition or speech recognition was privacy concern. The audio was collected with mono channel and 16000 sample rate. Amount of speech were extracted in form of total duration. The system used WebRTC Voice Activity Detector [108] to detect the presence of speech in each audio files and keep track of total duration.

Activity tracker feature

The used of activity tracker were adopted from system in section 5.4. Difference from tracking activity using web camera in section 6.2, by using activity tracker, it allowed the system to track physical activities of the subject throughout the day, even when the subject is not presence at the workstation. Moreover, the activity tracker also provided the ability to collect vital data like sleep duration. In this system, two activity trackers, which were FitBit Alta HR and FitBit Flex 2 were used to collected data. Due to the limitation for FitBit Flex 2 features, heart rate data from FitBit Alta HR was not included as one of the features in training. All of the data were retrieved through the web API and stored in the cloud storage for preprocessing and training procedure. The features from the activity tracker include sleep duration, average step count per hour, max step count, average calories per hour, max calories, sedentary time, lightly active time, fairly active time, and very active time.

Commuting and dietary feature

Another new source of data for this system is through the survey. It was show that commuting time and dietary can affect mood and stress level of a person [19]. In order to collect these data, we developed a web survey and ask the subject to fill them out at the end of each day. The questions include commuting method and time to work, commuting method and time from work, calories intake for breakfast, calories intake for lunch, and calories intake for dinner. All of the information was used in training the recognition model.

6.3.4 Experiment and results

Experiment design

To demonstrate the accuracy of the model, this study conducted an experiment on total of 30 human subjects, including 18 males and 12 females. The age range of the subject were between 20 to 32 years old. The data were collected for 2 consecutive day from each subject. All of the subject were either researchers or graduate students who conduct research job daily with their own workstation in a laboratory. The flow of conducting the experiment is as follow: first, the participant was informed about the purpose and detail of this experiment, which include the monitoring device and data that will be collected, then, the subject signed the consent from to participate in this experiment. Next, the device was installed and setup for monitoring, this included setting up IoT sensors monitoring device at subject's workstation, setting up activity tracker device and explaining the survey questions to the subject. All of this processes were finished on the day before the day of monitoring. Thus, it is possible for the system to start collecting sleeping data from the activity tracker on that night. During the monitoring period, the subject completed the survey on a half-day basis (morning and evening), which include the data collection part and well-being assessment part. After the monitoring period, all data were stored in cloud storage, and was used later to build the well-being recognition model. Figure 6.7 shows the overall process of this experiment.

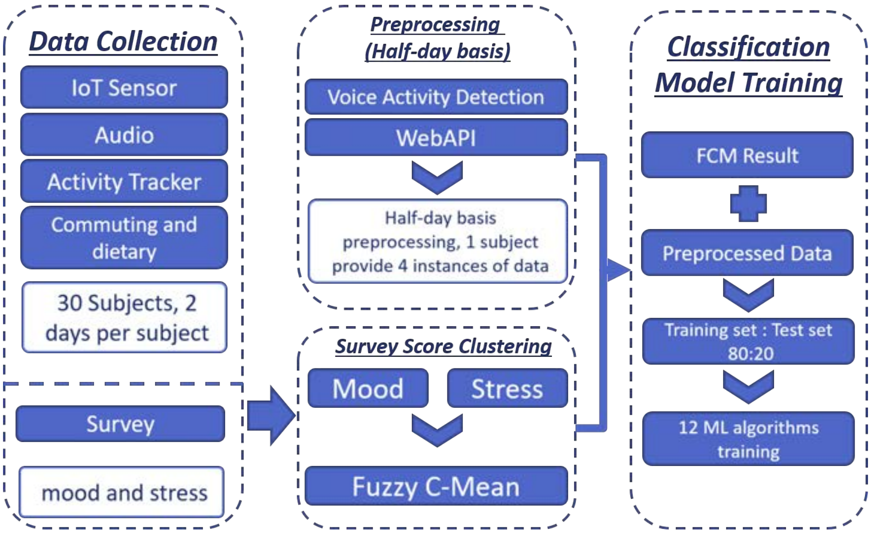


FIGURE 6.7: Overview of experiment process for training of well-being recognition model

Surveys and fuzzy c-means clustering

In the development of this system, we adopted the same surveys used in section 6.2, which were stress level, and PANAS. From this two surveys, we extracted three features, which are stress level, positive mood effects, and negative mood effects. All of this three features were fed into FCM algorithms to separate them into two clusters, where each cluster represent higher level of well-being and lower level of well-being in two dimensions well-being recognition (stress and mood). Table 6.4 shows the statistical results of the two clusters, where there are 58 data instances in cluster 1 and 62 instances in cluster 2. As presented in the table, cluster 1 represents higher level of well-being where average stress level is lower, average positive affect (PA) is higher, and average negative affect (NA) is lower. On the other hand, cluster 2 represent lower level of well-being with the opposite results to cluster 1.

Table 6.4: Average of stress level, positive affect level, and negative affect level of the two clusters

Cluster	Average Stress Level	Average PA Level	Average NA Level
Cluster 1	3.15	7.32	3.00
Cluster 2	6.09	4.09	5.95

Data preprocessing

In total, from the data collected (as mentioned in section 6.3.2), the system extracted a total of 18 features. Table 6.5 shows the features extracted. In this experiment, all data were handled on a half-day basis where morning data refer to data from 12.00 AM to 12.00 PM and evening data refers to data between 12.00 PM to 12.00 AM. The sleep data refers to the sleep duration of the day before certain monitoring data and was attached to each data instant of each day, both morning and afternoon data. For calories intake feature, the morning data used breakfast calories intake as the feature and evening data used the combination of lunch and dinner calories intake as the feature. From 20 subjects, we had a total of 80 instances of data, 4 periods from 2 days of monitoring from each subject. All data were normalized before being used in the model training step and each instance was labeled according to the result of the FCM clustering, which represent lower or higher level of well-being.

Model training

To train the model, we fed the preprocessed data into a total of 4 algorithms, KNN, SVM, Linear Discrimination, and Logistic Regression. For KNN and SVM in this experiment, we also performed the model training on different distance metric and kernel to find the best algorithm for the model. The distance metrics used for KNN were Euclidean and Cosine. Distance weights used for KNN were equal, inverse, and square inverse. Kernel functions used for SVM training were Linear, Gaussian, Quadratic, and Cubic. The data was split into training set and test set with the ration of 80:20. The training set were trained on a 5-fold cross validation. Figure 6.8 shows the accuracy of the final model on the test set.

Table 6.5: Extracted 18 features from multiple data sources

Data sources	Features
IoT Sensors	Temperature, Ambient light, Humidity
Audio	Duration of total speech presence (seconds)
Activity Tracker	Sleep duration, average step count per hour, max step count, average calories per hour, max calories, sedentary time, lightly active time, fairly active time, and very active time.
Commuting and dietary	Commuting time to work, commuting and time from work, calories intake for breakfast, calories intake for lunch, and calories intake for dinner

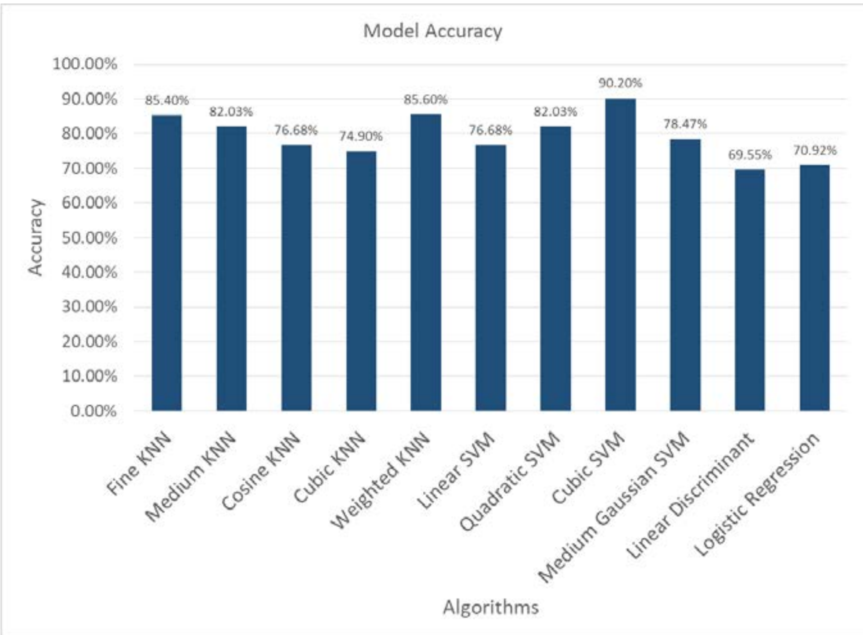


Figure 6.8: Accuracy results for well-being recognition models

From the figure, the results shows that the highest accuracy was from SVM algorithms with Cubic kernel where it achieved an accuracy of 90.20%. The second most accurate algorithms were wighted KNN (KNN with inverse distance weight) and Fine KNN (KNN with K=1) where they achieved the same accuracy of 85.60%.

The three worst performer algorithms were Cubic KNN, Logistic Regression, and Linear Discriminant with the accuracy of 74.90%, 71.40%, and 69.60% respectively.

In general, all model performed higher than 70%, which suggested that the collected data has contributed to the model training and that it can be used for training the multi-dimensional well-being recognition model. Furthermore, regarding the consideration of SVM kernel, in most cases, SVM with Gaussian kernel should outperform other kernel with the trade-off that it consume more resources in computation. However, in this study, the SVM with cubic kernel performed better than the one with Gaussian kernel in the test set accuracy (90.20% to 78.47%). This may due to the fact that the model was tested on an unseen test set and the model trained with Gaussian SVM was over-fitted during the training period due to small size of data set. On another perspective, considering the same cubic kernel being used for both KNN and SVM, but SVM with cubic still outperformed KNN. In this case, this may due to the fact that the nature of KNN was created for multi-class classification. KNN uses distance matrix to calculate the distance between each data point to the centroid of the class. However, the model may find it difficult and classify the data point into the wrong class if the distance of that data point to the classes' centroid are not significantly different. On the other hand, SVM tries to calculate the minimum optima for the classification. In another word, it try to draw the optimum line that can separate the data into two classes. Thus, it is mostly used for binary classes classification, which is the same situation of this study. All in all, with the collected data, the model trained with Cubic SVM was proved to be the most practical in recognizing well-being level.

Table 6.6 shows the model from each algorithms along with its accuracy, training time (in seconds), and prediction time (number of observation/second). Noticeably for Fine KNN, even though it achieved high accuracy but its training time was large and the number of observation per second is much less when compare to SVM-based algorithms. Cubic KNN, which achieved the highest accuracy, completed the training in 1.91 seconds and it capable of predicting up to 2500 observations per seconds. In other word, the system with same specification as this experiment system would be able to serve up to 150,000 observation per minute.

Table 6.6: Accuracy, training time, and prediction time of the trained models

Algorithms	Accuracy (%)	Training Time (Seconds)	Prediction Time (Observation/Second)
Fine KNN	85.40	7.23	1300
Medium KNN	82.03	2.35	1600
Cosine KNN	76.68	1.68	1900
Cubic KNN	74.90	1.91	2500
Weighted KNN	85.60	1.36	3000
Linear SVM	76.68	1.05	2700
Quadratic SVM	82.03	2.01	4000
Cubic SVM	90.20	1.83	4500
Gaussian SVM	78.47	3.56	4200
Linear Discriminant	69.55	1.41	1500
Logistic Regression	70.92	1.72	1300

6.4 Visualization

6.4.1 Visualization dashboard

In developing the visualization dashboard, all the challenges that were mentioned in chapter 2 were taken into consideration. This dashboard was developed to be modern, easy to understand, and providing a meaningful information to users. Moreover, the dashboard was developed on the idea that it must be able to work on cross-platform devices. Thus, even it is a web application, it is totally responsive and works on all kind of devices. Figure 6.9 shows an overview of the visualization dashboard web application. One of the main component here is display on the top of the dashboard, 'Your daily well-being results'. This component show the result of the data being classified into either higher or lower level of well-being using our trained model for multidimensional well-being recognition. This component represent the core contribution and novelty of this study where all data was taken into consideration to provide a meaningful information in an easy-to-understand manner back to users.

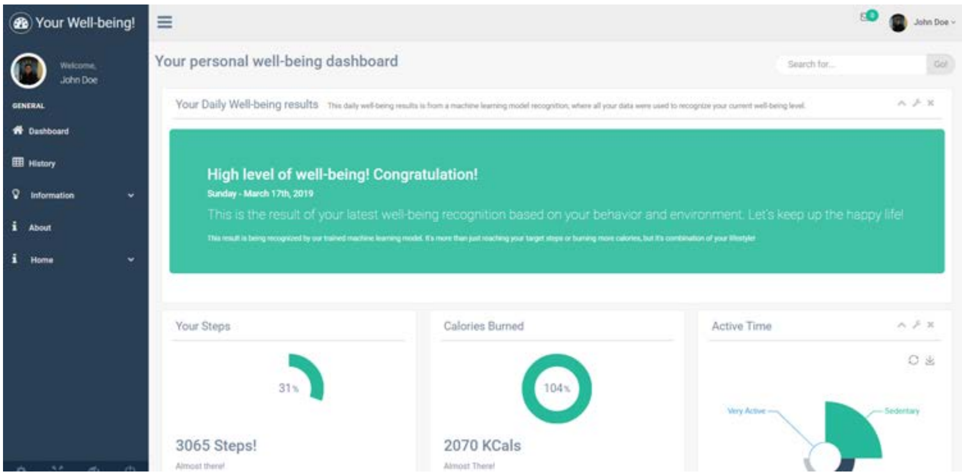


FIGURE 6.9: Overview of dashboard in visualization application

Figure 6.10 shows the three components that visualized calories burned, number of steps, and active time. This components show the data that was retrieved from the device in real-time. The 100% on calories burned and number of steps represent the recommendation level of each parameter. The 100% on active time component represents the total time up to the retrieval point. Figure 6.11 shows the environment features over the past 24-hours where the voice activity component shows the results from voice activity detection component on a 24 hours time-line basis. Figure 6.12 shows the visualization of sleep logs and calories burned/intake over the week.

Another important component is demonstrated in Figure 6.13. This component visualizes all data from user and average of data from the higher level of wellbeing data instances. This compare user's data to the goal that they should meet. The average of each data type was obtained by finding average of data in the dataset that were labeled as higher level of well-being. In general, this component aimed to encourage the user to meet the average of those who has good well-being.

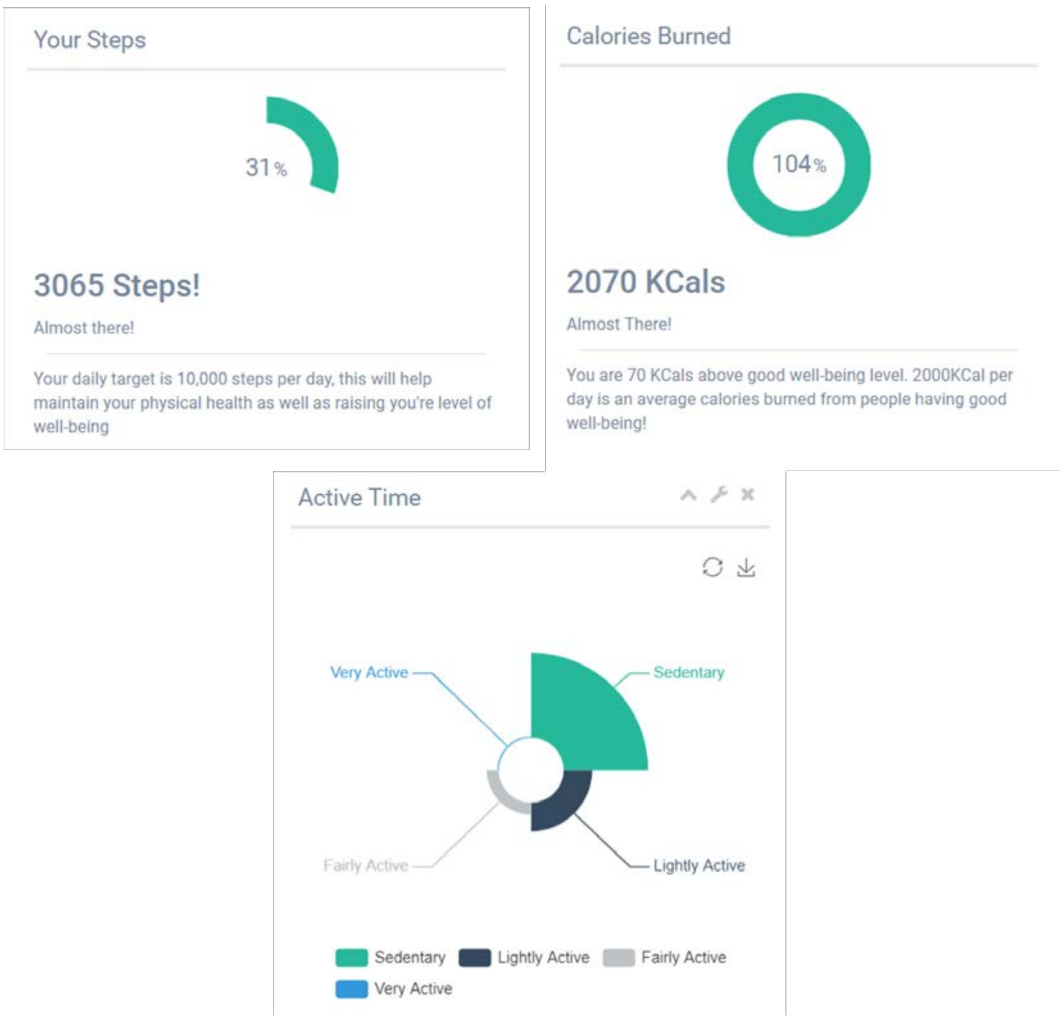


FIGURE 6.10: Visualization of calories burned, number of steps, and active time

6.4.2 User experience survey

In order to evaluate the proposed visualization dashboard, we adopted the User Experience Questionnaire (UEQ) [109] to measure the overall user's experience on the system. The questionnaire consists of 26 items, each item represents two opposite sides of that category, for example; annoying/enjoyable, creative/dull, and motivating/demotivating. Each item is scaled from -3 to 3 where -3 represents most negative answer, 0 neutral answer, and +3 the most positive answer. From the 26 items, the results can be grouped to represent 6 categories of user experience,

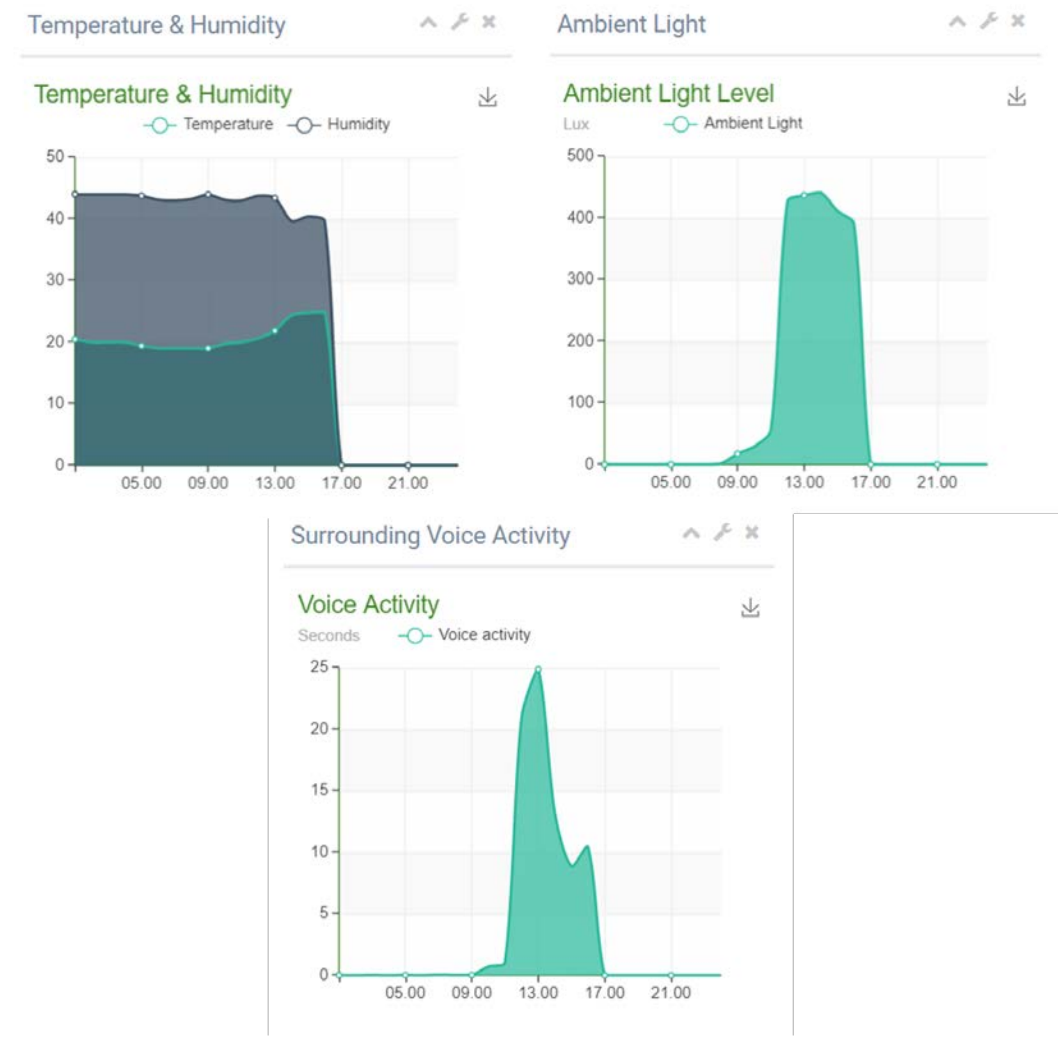


FIGURE 6.11: Visualization of environment data (temperature, humidity, ambient light, and voice activity)

which includes attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. We conduct the survey on 75 subjects, where 30 of the subjects were participants in the experiment for building the well-being recognition model.

Figure 6.14 shows the mean value of all 26 items. From the figure, it can be easily notice that in all items, the mean values were positive. For interpretation of the results, UEQ suggested that the values between -0.8 to 0.8 represent neutral evaluation, values $>$ 0.8 represent positive evaluation, and values $<$ -0.8

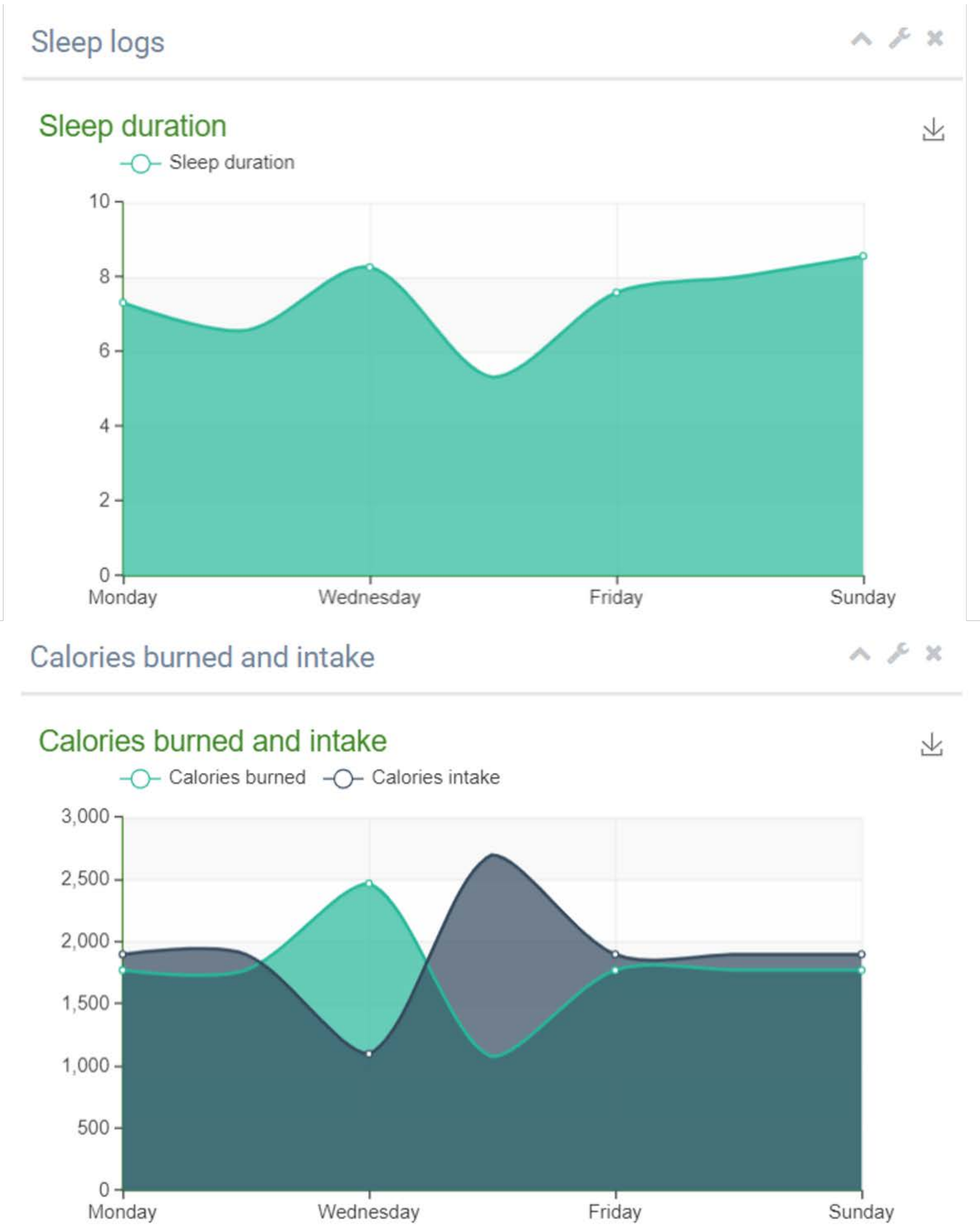


FIGURE 6.12: Visualization of sleep logs and calories burned/intake

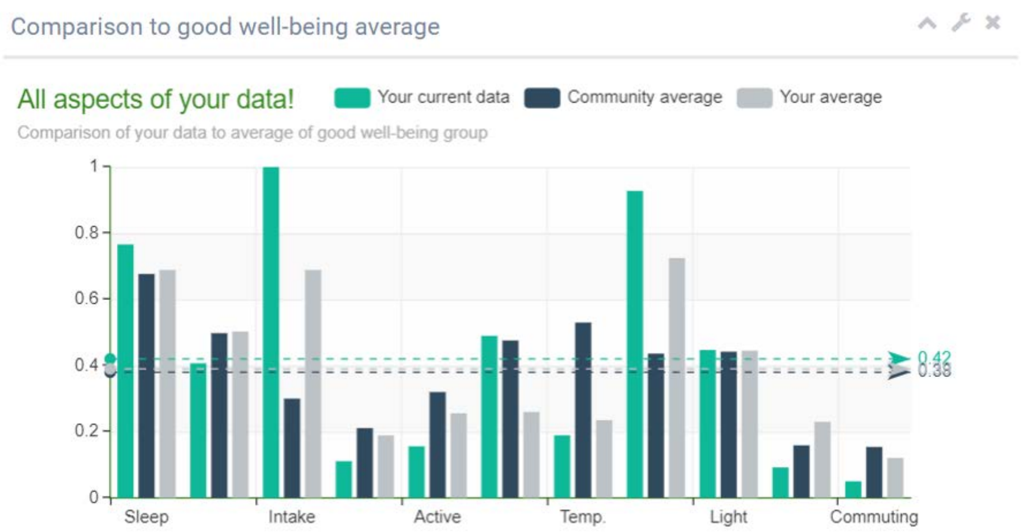


FIGURE 6.13: Comparison of user's data to the community's average

represents negative evaluation. The highest mean value was 2.1 in 'does not meet expectations/meets expectations' item. The lowest mean value was 0.5 in 'unpredictable/predictable' item, which lies in neutral evaluation range. In general, all items were in the positive evaluation range except for only three items, which were 'creative/dull', 'unpredictable/predictable', and 'conservative/innovative', that were in neutral evaluation range.

Figure 6.15 shows the results of the UEQ questionnaire in 6 categories, which were calculated from the 26 items. The interpretation of the results is the same as of the 26 items' results. The items in each categories are as followed:

- **Attractiveness:** annoying/enjoyable, good/bad, unlikable/pleasing, unpleasant/pleasant, attractive/unattractive, friendly/unfriendly
- **Perspicuity:** not understandable/understandable, easy to learn/difficult to learn, complicated/easy, clear/confusing
- **Efficiency:** fast/slow, inefficient/efficient, impractical/practical, organized/-cluttered

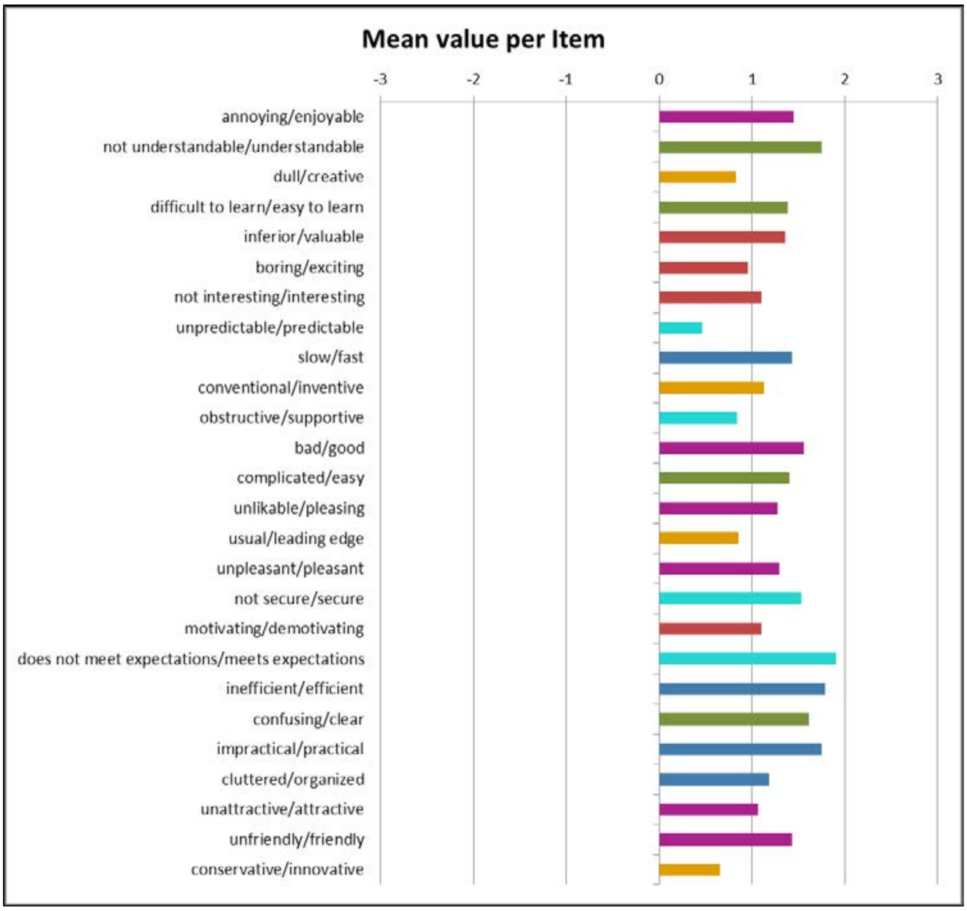


FIGURE 6.14: 26 items of UEQ along with its mean value from the responses

- **Dependability:** unpredictable/predictable, obstructive/supportive, secure/not secure
- **Stimulation:** valuable/inferior, boring/exciting, not interesting/interesting, motivating/demotivating
- **Novelty:** creative/dull, inventive/conventional, usual/leading edge, conservative/innovative

The scores were 1.35, 1.54, 1.54, 1.19, 1.13, and 0.87 for categories of attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty, respectively. In these six categories, all of them were considered to be in positive evaluation range. To emphasize the results, the score of items in perspicuity, which reflects on persuasive system, has relatively high results with 1.7, 1.4, 1.4, and 1.6 for not understandable/understandable, easy to learn/difficult to learn, complicated/easy, and clear/-confusing, respectively. In general, this questionnaire results showed that the

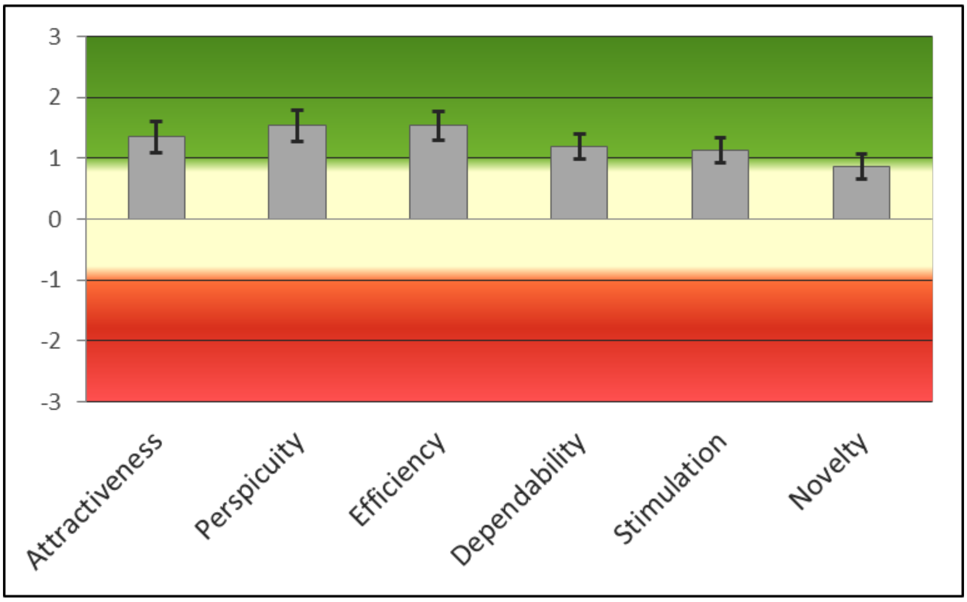


FIGURE 6.15: UEQ results in the six categories calculated from 26 questionnaire items

proposed visualization dashboard has a positive evaluation from users, which mean that user can understand the data being visualized easily and eventually, this will raise awareness in user's well-being level and help encourage the better behavior.

6.5 Discussion

In this chapter, two systems were developed to demonstrate the possibility of using multiple machine learning approach to recognize well-being level in multi-dimension, namely stress and mood. In the first part of this chapter, we discussed about the development of well-being recognition based on video working behavior using video recognition and image detection. The system considered the working behaviors, which mostly are body movement, during the working hours. This resulted in the recognition model with satisfying accuracy, where it achieved 83% on generic model (based on data from two subjects) and 91% on personalized model with data from one subject.

In the second part of this chapter, we improved the system and integrated more data source based on published research that show relation of each parameter to stress, positive affect, and negative affect. The system was also made to be available 24 hours with the use of activity tracker while being less intrusive by not using any personal recognition parameters (voice recognition or image recognition). The same approach of using unsupervised learning (FCM) in order to label the data for multi-dimension well-being recognition model training was the same as the first system. The data was also trained with multiple consideration to achieved the best accuracy on the result model. As a results, we achieved an improved model with higher accuracy where the highest accuracy was as high ass 90.20%

All in all, this chapter concluded the development of well-being recognition system in multi-dimension manner. All three major components for recognizing well-being, as suggested in chapter 2, were considered in the development of this final system. The system integrated multiple data sources where most of them has been proven in earlier system that they can contribute to the recognition model. The final approach of training the model was the result of improvements from the previous systems where all the previous systems have demonstrated the pros and cons for this final system to adopt and abandon. Finally, the visualization in the final stage demonstrated the absolute goal of this dissertation where it needs to provide feedback and raise awareness to users. The system is an alternative to the conventional methods for monitoring well-being, such as well-being diary. It demonstrated the use of techniques and technologies in proposing a solution to the issue in digital healthcare domain where it provide an easier solution for users to live a healthier life.

6.6 Conclusion

In conclusion, this chapter provide the following contributions:

- The first part of this chapter proposed a method to train recognition model by labeling the data with results from clustering survey results with FCM. This allow the recognition model to reflect the well-being in multi-dimension manner.
- This chapter proposed the multidimensional model to recognize the well-being level from multiple data sources. The final model achieved the accuracy of 90.20%
- The final system provides a visualization that achieved satisfying UEQ survey score where it can help users monitor their well-being level and raise their awareness.
- The final system proposed a solution that combined advantages of each studies, which resulted in the implementation of multiple data collection devices, model training techniques, and visualization development that provides 24-hours monitoring and recognition of well-being level.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

This study presented a behavior monitoring system using machine learning technique to promote better well-being level. In total, this study developed 8 systems, which addressed the problem from smaller scale to a larger scale. All of the systems that were developed led to the final system demonstrated in chapter 6, where it has the largest scope, compare to other system.

The implementation of using sensor data along with machine learning technique is presented in chapter 4 to demonstrate its possibility. The system provided a neck posture monitoring system, where the neck angle was accurately calculated from the results of image detection and sensor values. In chapter 5, the study presented an approach in implementing further machine learning technique to extract knowledge from the collected data. The result model from the system was able to accurately recognize the level of smartphone addiction and stress based on the collected data. The approach of using machine learning to develop a recognition model is then applied further in chapter 6 where this study presented a more generic system to recognize well-being level. Fuzzy clustering was another technique implemented to allow the system to consider the well-being from multiple aspect. The famous deep learning was implemented to perform tasks like object detection and voice activity detection. The used of deep learning allowed the model to be trained with more insight data. As a result, the trained model was able to accurately recognize the well-being level. Furthermore, chapter 6 also presented the visualization of the extracted knowledge as a tool for raising awareness in users where it demonstrated how the system achieved the goal of contribution to the society for a sustainable living and healthier life.

In summary, this dissertation provides the following contributions:

7.1.1 Major Contributions

1. The study demonstrated the result of machine learning model where it was trained and tested on the collected data to recognize the level of well-being. The accuracy was in a satisfaction level. This model showed the possibility of providing an autonomous system in recognizing well-being to raise awareness in users. The following findings support this contribution:

   1-I. Chapter 4: The study provided a neck angle calculation equation and classification rules where it can accurately calculate the neck angle that led to the neck posture monitoring system for promoting better smartphone usage behavior. The calculation was based on the used of data from smartphone sensors and image detection.

   1-II. Chapter 5: This study proposed a smartphone addiction recognition system where the model was trained based on the smartphone usage data. The system addressed the concern in smartphone addiction, which led to both physical syndromes and mental syndromes, and tackled the problem by using machine learning to raise awareness to users.

   1-III. Chapter 5: Stress recognition model was developed as a part of stress recognition system. This study demonstrated the possibility in using IoT sensors along with activity tracker in recognizing stress, where it trained the recognition model with multiple machine learning algorithms using collected data.

1-IV. Chapter 6: The multidimensional well-being recognition model was developed to reflect the users current well-being level from multiple data sources. The data collection was based on daily behavior data and the model achieved the highest accuracy of 90.20%

2. The study proposed a system where it implemented emerging technologies to provide services in medical application. The technologies range from data collection devices, system architecture, and software application. This also provided a service which is easier to use for users. The following are the findings that support this contributions:

   2-I. Chapter 4: The use of image processing and smartphone sensors were adopted to provide the neck posture recognition system.

   2-II. Chapter 5: Multiple devices were implemented to develop the smartphone addiction recognition system and stress recognition system. All of the devices aim to capture subjects' behavior information what can be use in model training.

   2-III. Chapter 6: The final system implemented multiple data source that can provide 24-hours of data collection and monitoring. Multiple techniques include: data preprocessing technique for real-time sensor data, image detection using deep learning and voice activity detection using deep learning were also implemented.

3. The study contribute to the society with a completed monitoring system where it is easier to keep track of their well-being level as well as their daily collected statistic data. This system provide information and knowledge to users with visualization dashboard where all the components are related to sustainable living, which can help raise the well-being level for a better. This was proven in the development of the dashboard. The full monitoring system also demonstrated how the result of development can be deliver to users in and raise the awareness of their well-being.

   3-I. Chapter 6: The result of the final machine learning model were used to developed the full system with application.

3-II. Chapter 6: This chapter developed a visualization dashboard to demonstrate the possibility of raising awareness in well-being. This provided the completeness to the system where users can reflect on their own well-being level.

3-III. Chapter 6: The chapter demonstrated how the system satisfied the system requirements, which was a guideline in developing a persuasive system. The satisfied the following requirements: reduction, tunneling, tailoring, personalization, self-monitoring, and simulation.

In conclusion, this dissertation's novelty lies in providing a complete well-being monitoring system to promote a healthier society, which was the final result of multiple studies that have been conducted. Figure 7.1 shows the final system that was developed in chapter 6. This system provide the complete system components regarding to IoT/M2M system, which include the basic of device for data collection, gateway data management, cloud storage and machine learning model, to the final client application. Beside from the technological side, the ultimate goal of this study was to provide and help create a society with sustainable living and higher level of well-being. The contribution of this study for this final goal can be considered as the most importance one of this study, as it proved that the technology can help raising the well-being level, which according to the research and studies from multiple physicians, will lead society to healthier and happier life.

7.2 Future works

In addition to this dissertation, there are several improvements that are possible to provide a better well-being monitoring system. First, with the emerging technology of fog computing [110], the possibility of implementing the approach for better real-time data analytic is possible. Fog computing uses the improved computing performance of IoT gateway to do data analytic tasks. With this approach, it delay the time takes to send all the data to the cloud and perform recognition tasks. It also provide the possibility of operating the system in without Internet connection.

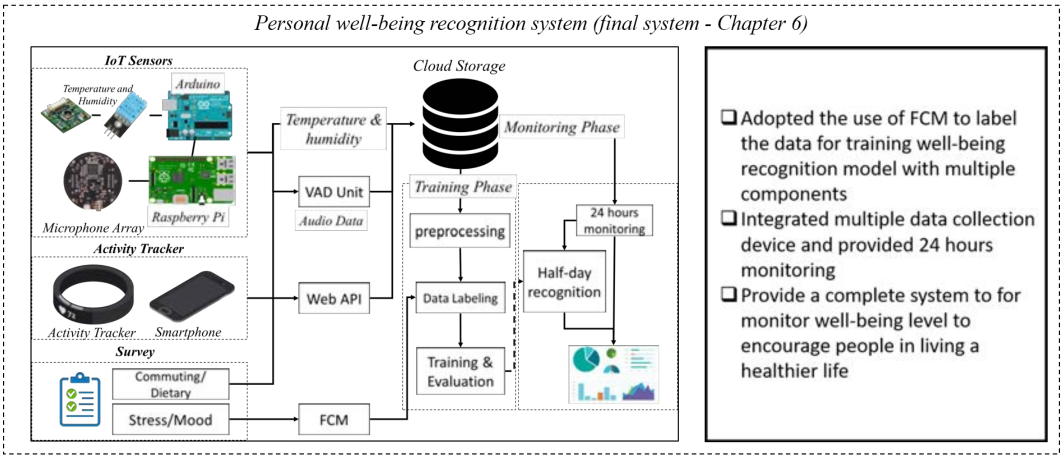


FIGURE 7.1: Overview of personal well-being recognition system and its components

Secondly, this system built the well-being recognition model based on famous machine learning algorithms, namely KNN, SVM, D-Tree, and Naive Bayes. For the future, there is possibility of improvement for a model to be built on deep learning algorithms. In order to do so, a large dataset need to be collected and establish. In other word, if the system is deployed and widely used, when there is enough data, it is possible to use them for training a deep learning recognition model where it will provide a better recognition result as well as possibility of a building a personalized healthcare system.

Finally, the connection technology is improving rapidly, and the launch of 5G in commercial market is within reach. This will improve the capability of data transmission enormously. In other words, it would be possible to collect more rich data, such as videos, images, and sound, for recognizing well-being level. The larger bandwidth that 5G technology provide would reduce time taken to send data over the network, either to the fog or cloud computing unit. Then, it would be up to the computing units to use those data and extract knowledge from them as much as possible.

All in all, this dissertation serves as a foundation to multi-dimensional well-being recognition system. Nonetheless, with the advancement of technologies and continuous development, the system could be improved into a more efficient better decision support system for raising awareness and encourage better well-being in the society.

Appendix A

List of Publications

A.1 International journal paper

[J.1] Worawat Lawanont, Masahiro Inoue, Pornchai Mongkolnam, and Chakarida Nukoolkit, 2018 "Neck Posture Monitoring System Based on Image Detection and Smartphone Sensors Using The Prolonged Usage Classification Concept" *IEEJ Transactions on Electrical and Electronic Engineering* Vol. 13, No. 10, pp. 1501-1510, 2018.

A.2 International conference papers (peer-reviewed)

[C.1] Worawat Lawanont, Masahiro Inoue, Taketoshi Yokemura, Pornchai Mongkolnam, and Chakarida Nukoolkit. "Daily Stress and Mood Recognition System Using Deep Learning and Fuzzy Clustering for Promoting Better Well-Being." *2019 IEEE International Conference on Consumer Electronics (ICCE)*, pp. 1-6. IEEE, 2019.

[C.2] Worawat Lawanont, Pornchai Mongkolnam, Chakarida Nukoolkit, and Masahiro Inoue. "Daily stress recognition system using activity tracker and smartphone based on physical activity and heart rate data." *International Conference on Intelligent Decision Technologies*, pp. 11-21. Springer, Cham, 2018.

[C.3] Worawat Lawanont, and Masahiro Inoue. "An unsupervised learning method for perceived stress level recognition based on office working behavior." *2018 International Conference on Electronics, Information, and Communication (ICEIC)*, pp. 1-4. IEEE, 2018.

[C.4] Worawat Lawanont, and Masahiro Inoue. "A development of classification model for smartphone addiction recognition system based on smartphone usage data." *International Conference on Intelligent Decision Technologies*, pp. 3-12. Springer, Cham, 2017.

[C.5] Worawat Lawanont and Masahiro Inoue. "A Development of Healthcare System Architecture with Customizability and Reusability for Smartphone Addiction Recognition System." *11th South East Asian Technical University Consortium Symposium (11th SEATUC)*, pp. 1-7, 2017

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