AN INTELLIGENT SYSTEM FOR EXERCISE PLANNING AND PHYSICAL ACTIVITY RECOGNITION USING MOBILE TECHNOLOGIES

A DOCTOR OF PHILOSOPHY (PhD) THESIS

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by

GÜLER KALEM

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AN INTELLIGENT SYSTEM FOR EXERCISE PLANNING AND PHYSICAL ACTIVITY RECOGNITION USING MOBILE TECHNOLOGIES

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Approval of the Graduate School of Natural and Applied Sciences, Atılım University.

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Prof. Dr. Ali Kara

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Doctor of Philosophy.

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Prof. Dr. Ali Yazıcı

Head of Department

This is to certify that we have read the thesis "An Intelligent System for Exercise Planning and Physical Activity Recognition Using Mobile Technologies" submitted by "Güler KALEM" and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Doctor of Philosophy.

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I declare and guarantee that all data, knowledge and information in this document has been obtained, processed and presented in accordance with academic rules and ethical conduct. Based on these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

GÜLER KALEM

ABSTRACT

AN INTELLIGENT SYSTEM FOR EXERCISE PLANNING AND PHYSICAL ACTIVITY RECOGNITION USING MOBILE TECHNOLOGIES

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Intelligent guidance in the healthcare domain using mobile technologies is an important development since users can benefit from the individual exercise plans that are specifically designed for their purpose, demographic information and health background. Furthermore, with the system continuously tracking their activities, the users are motivated and guided to complete their daily specified exercises. The developed system determines the specific exercise program suitable to the user with case-based reasoning. With the help of the accelerometer and gyroscope facilities of a mobile phone, users' activities are recognized and classified using KNN (K-Nearest Neighbors) algorithm. Based on their individual exercise routine and the performed activities in the current day, the rest of the exercises are calculated and presented to the user as a message to guide and encourage them. For the evaluation, the system is tested by users, and a questionnaire is conducted. The results show that the system is found to be beneficial and effective by all the participants.

Keywords: Mobile technology, healthcare, classification, activity recognition, intelligent system, case-based reasoning, Multiclass SVM (Support Vector Machines), KNN (K-Nearest Neighbors), LDA **(**Linear Discriminant Analysis**)**

ÖZ

MOBİL TEKNOLOJİLERİN KULLANILMASIYLA AKILLI BİR EGZERSİS PLANLAMA VE FİZİKSEL AKTİVİTE TANIMA SİSTEMİ

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Mobil teknolojilerin kullanılmasıyla sağlık alanında akıllı rehberlik, kullanıcıların amaçları, demografik bilgileri ve sağlık durumlarına göre özel olarak tasarlanmış olan bireysel egzersiz planlarından fayda sağlamaları açısından önemli bir gelişmedir. Ayrıca, sistemin sürekli olarak fiziksel aktivitelerini izlemesiyle, kullanıcılar motive olurlar ve belirlenen günlük egzersizlerini tamamlamaya yönlendirilirler. Geliştirilen sistem, vaka tabanlı çıkarım ile kullanıcı için uygun olan kişiye özgü egzersiz programını belirler. Cep telefonunun ivmeölçer ve jiroskop özelliklerinin yardımıyla, kullanıcıların fiziksel aktiviteleri KNN (K-En Yakın Komşu) algoritması kullanılarak algılanır ve sınıflandırılır. Egzersizlerin kalan kısımları, kullanıcılar için belirlenen bireysel egzersiz rutinleri ve gerçekleştirilen aktivitelere dayanarak hesaplanır ve kullanıcıyı yönlendirmek ve teşvik etmek için mesaj olarak sunulur. Değerlendirme için, sistem kullanıcılar tarafından test edilmiş ve anket uygulanmıştır. Sonuçlar, tüm katılımcıların sistemin faydalı ve etkin olduğunu düşündüğünü göstermektedir.

Anahtar Kelimeler: Mobil teknoloji, sağlık hizmeti, sınıflandırma, aktivite tanıma, akıllı sistem, vaka tabanlı çıkarım, Çok Sınıflı SVM (Destek Vektör Makineleri), KNN (K-En Yakın Komşu), LDA **(**Doğrusal Diskriminant Analizi**)**

To My Lovely Family, who encouraged and supported me throughout this process…

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LIST OF ABBREVIATIONS

ACC	-	Accelerometer
ANN	-	Artificial Neural Networks
BMI	-	Body Mass Index
CBR	-	Case-Based Reasoning
CGM	-	Continuous Glucose Monitoring
CLT	-	Central Limit Theorem
ECG	-	Electrocardiographs
FFT	-	Fast Fourier Transform
GPS	-	Global Positioning System
GUI	-	Graphical User Interface
GYR	-	Gyroscope
HMM	-	Hidden Markov Model
IBC	-	Intelligent Biomedical Clothing
IDE	-	Integrated Development Environment
KNN	-	K-Nearest Neighbors
LDA	-	Linear Discriminant Analysis
LIF	-	Less Important Feature
MOPET	-	Mobile Personal Trainer
PC	-	Personal Computer
PCA	-	Principal Component Analysis

PDA	-	Personal Digital Assistants
SMS	-	Short Message Service
SVM	-	Support Vector Machines
VIF	-	Very Important Feature

CHAPTER 1

INTRODUCTION

With the increase of the usage of mobile devices in recent years, new solutions in the vast area of healthcare emerge which include mobile technologies to fulfill requirements or suggest better solutions to existing problems. Attractive advantages of wireless technology accelerated the rapid development of mobile applications. Similar to other sectors, in the healthcare industry, mobile applications can provide better personalized healthcare, disease management and services for patients and their relatives, as well as presenting a more useful and flexible way of communicating among physicians and patients.

The main goal of this research is to develop an intelligent system which offers exercises suitable to the user, then provides guidance according to his/her purpose by performing physical activity recognition. In the study, data was collected from participants via the accelerometer and gyroscope components of a mobile phone to classify the different exercise activities; such as regular walking, quick walking and running. Offering an exercise plan is achieved with a reasoning method which is developed according to the advice of three professional physical trainers, by considering the user's demographic information such as age, height, weight, gender, existence of a health problem and the purpose of using this system. The system is executed to collect the data of the user's activity behavior along with durations of the activities during the day, with the help of the accelerometer and gyroscope properties of a mobile phone in order to guide and motivate the user to perform the rest of the specified activities for that day.

This research and the end product is expected to be useful for different types of users such as users who wish to lose weight or who wish to pursue an active lifestyle. In addition, the proposed system is expected to be helpful in disease management and treatments such as the treatment of high cholesterol, osteoporosis, etc. which requires patients to walk regularly.

1.1. Research Problem

The existing mobile applications implement step counting, activity tracking, tracking the route the user has created and measuring pace, distance and time. These applications generally have limited capability in terms of offering advice to the users. They offer guidance to all the users in a standard way. For example, since everyone should walk 10,000 steps every day for their health, the steps that the user has taken is traced during the day by the application, and an alert is issued about the number of steps left to reach his/her goal for that day. With these systems, all users are motivated to improve their progress in walking regularly or running from beginner level to higher level day by day with the help of the alert mechanisms. Yet, according to our investigation, in all of these applications the guidance provided are standard to all types of users regardless of their age, gender, height, weight, state of health or purpose.

1.1.1. Statement of the Problem

Healthcare consumers prefer to use medical mobile applications to have more control over their disease management or wellness. In addition, healthcare providers have a tendency to use medical mobile applications in order to obtain clinical information more efficiently and correctly from the user.

The investigation of the most popular mobile applications in the market according to the customer ratings have shown that none of them offer an intelligent system to the users. According to our evaluation, all of these systems offer the same package to all users, disregarding their individual characteristics. Since guiding the users individually should be an important part of such applications to achieve better results, the main goal of this research is to develop an intelligent system that offers suitable exercises based on individual characteristics and track the progress of the users to provide guidance.

As stated above, the main objective of this developed system is to offer users appropriate exercises according to their needs based on their demographic information. To track the execution of the suggested exercise, physical activities are recorded continuously by a mobile device such as a cell phone that works in the background mode. The system relies on device’s sensors and processing capabilities to estimate significant movements. Sensors collect data with the help of the accelerometer which is a device that senses changes in speed along its axis and the gyroscope which is a device containing a rotating wheel attached to a stable axis which allows the wheel to maintain its absolute direction regardless of the movement of the surrounding parts.

The suggested exercises are planned according to the needs of users' different characteristics, and have to be determined conforming with the adaptive rules using case-based reasoning. These rules are determined by consulting three professional physical trainers for different types of users with different attributes and purposes.

As stated before, the main goal of the system is to help patients who suffer from excess weight, or an illness such as hypertension (high blood pressure) to shorten their recovery period. Additionally, for the users who take care of their wellness, this system will motivate them to follow their exercise plan continuously.

The research questions of the study are as follows:

1. Can a mobile application provide a suitable exercise routine to a user based on demographic information, purpose of using this system and health background?

2. Can a mobile application track the progress of the user in the execution of a recommended exercise routine using activity recognition?

Hopefully, with such an intelligent mobile system that guides and motivates a user to exercise and follows up with its recommendations, more people will choose a more active lifestyle and therefore improve their health.

1.2. Organization of the Thesis

The organization of the thesis is as follows:

Chapter 2 provides the literature review about the thesis. Additionally, a background information about current mobile applications in the healthcare domain with some examples are provided. Moreover, this chapter gives related information about the approaches used for activity recognition and reasoning systems.

Chapter 3 presents information about the design and implementation of the system, the integration of the modules and the technical specifications of the system.

In Chapter 4, the activity recognition implementation of the application is presented. The experiments, results and the performance comparisons of tested classification methods and validation techniques are presented.

In Chapter 5, implementation of the reasoning is described. The cases and their corresponding solutions, the calculation process and the similarity measure are also presented.

Chapter 6 includes the evaluation of the overall system supported by a questionnaire and the results.

Chapter 7 concludes the thesis with suggestions and also provides the limitations of the study along with possible future work.

CHAPTER 2

LITERATURE SURVEY

2.1. The Utilization of Mobile Devices in Healthcare

The development of technology has increased the usage of mobile devices, and as a result, individuals and companies try to develop new mobile applications to help people in their daily lives. Since human factor is the main focus in the healthcare area, and since people's satisfaction is of utmost importance, the new technological changes can be used in healthcare with the overall objective of ensuring a higher quality of life (Kalem and Turhan, 2015-A; Shoaib et. al., 2015; Mosa et. al., 2012).

In the last years, many healthcare organizations and companies have evolved their plans to develop new healthcare models such as context-aware systems for patients (Chen and Kotz, 2000; Hong et. al., 2009). The reason for this is the dramatically rising healthcare costs, followed by the increasing population of aged people in the society as well as to improve the quality of healthcare. At this stage, disease management issues are being heavily emphasized, and patient's self-care efforts are significant for the populations (Fish and Richardson, 2013).

With an improved quality of life expectancy, stakeholders interest in disease management or self-management and programs for reducing health care costs and improving quality of life as well as patient/user satisfaction, is increasing (Denning et. al., 2009). Additionally, with the fast developmental changes in the sensors and the improvements of the mobile technologies, the technological development periods of 3-4 years are reduced to 6-8 months, and there is also a significant reduction in cost as well (Atluri et. al., 2015).

The development of mobile technologies steered both the manufacturers to compete with the existing firms, and the solution developers to produce new and talented applications using mobile technologies (Price and Summers, 2006; Dee et. al., 2005). In the healthcare environment, using mobile technologies and mobile devices have proven to be effective (Kalem and Turhan, 2015-A). While developing such applications, patient requirements and the level of patient acceptance of technology on their health care and disease management should be considered (Siau and Shen, 2000). It is a must to balance the cost of deployment, the use of device and fulfillment of patients' requirements.

The acceleration of medical applications and the increase in the usage of mobile devices in all areas of people's life have convinced the healthcare professionals such as physicians and nursing staff to use the applications in mobile technology is discussed by Scordo et. al. (2003) and by Lapinsky (2007).

A summary of some of the recent studies presenting literature reviews in this area is given as follows. Stevens et. al. (2015) have conducted a study of review aiming to examine the range of applications available on the market and the prevalence of healthcare professional input. In the study of Kumar et. al. (2013), they bring three concepts together; namely, a) evaluating assessments; b) evaluating interventions; and c) reshaping evidence generation using mHealth, and review the evaluation standards, discuss future possibilities, and set a grand goal for the emerging field of mHealth research. In the first part of Georga et. al.'s (2014) study, they review the state of the art in wearable medical devices for monitoring and controlling blood glucose levels with special emphasis on Continuous Glucose Monitoring (CGM) devices and insulin pumps. The second part of the study discusses mobile self-management support interventions in diabetes care, additionally they state that the advances in mobile computing and wireless communications have enabled the development of efficient mobile applications for self-monitoring diabetes, providing feedback. Furthermore, in the study by Mizouni et. al. (2014), they suggested a novel framework to build context aware and adaptive mobile applications. Han et. al. (2014) also suggested a context-dependent search engine that represents user context in a knowledge-based context model, and implemented in a hierarchical structure with granularity information. Another rare type of study belongs to Conroy et. al.

(2014) in which, the behavior change techniques represented in online descriptions of top-ranked applications are characterized for physical activity.

In the clinical area, there are applications that have been developed, used and tested; and valuable and acceptable results have been reached most of the time. These applications are reviewed and examined, and their advantages and disadvantages from different points of view are presented in the next section.

2.2. The Example Applications in the Healthcare

The recent studies for mobile applications in the healthcare domain are given as a summary. In the research of Azhar and Dhillon (2016), they have reviewed the influencing factors of the effective use of mHealth applications for self-care. In a study by Cojocarlu et. al. (2013) the design and implementation of a novel wireless electrocardiography device that is expected to be user-friendly, low cost and low power consumer, and has a high degree of interconnectivity with terminals such as smartphone, laptops and tablets, is presented. In the study of Azar et. al. (2013), the aim is the evaluation of diet/nutrition and anthropometric tracking application based on incorporation of features consistent with theories of behavior change.

In their study, Patrick et. al. (2014) aim to review the clinical trial of a two-year weight control intervention for young adults deployed by social and mobile media. An adaptive intervention is used for the patterns of usage of the system and user feedback which is better than standard intervention similar to our intelligent system, but the measures of body mass index, sedentary behaviour, physical activity, etc. are performed only in six-month periods. The results are promising since all participants have been recruited.

Burke et. al. (2016) have a study which aims to identify self-monitoring diet only using a PDA (Personal Digital Assistant) with daily feedback, and the results show that it was superior to using a paper diary on weight loss and maintenance. As it is observed in this study, the usage of mobile device such as PDA help during weight loss. In this study, the participants receive standard behavioral treatment for losing weight. However, it would be more helpful if personalized treatments would be offered according to participants' specifications.

Abbas et. al. (2015) conducted the study of evaluating the effect of mobile phone Short Message Service (SMS) on glycemic control in type 2 diabetes in Saudi patients. The standard messages are prepared by specialist in diabetes and diabetic educators to increase the level of awareness. This shows the different approaches to including mobile phones for a healthier life for diabetic patients. As a result of this study, significant improvement of patients' knowledge have been observed, in addition, the patients' blood glucose levels have improved.

Moreover, there are some recent studies related to activity recognition as summarized below. Arifoglu and Bouchachia (2017) has a study of activity recognition and abnormal behaviour detection for elderly people who suffer from dementia. Erdaş et. al. (2016), have studied three possible feature sets; time-domain, frequency domain and wavelet-domain statistics, and their combinations to represent motion signals obtained from accelerometer reads worn on the chest through a mobile phone. Ihianle et. al. (2016) suggested a topic model process to recognize activities and activity-object patterns from the interactions of low level state-change sensors. In another study, Chetty et. al. (2015), have suggested a novel data analytic scheme for intelligent activity recognition using smartphone based on information theory based feature ranking algorithm and classifiers based on random forests, ensemble learning and lazy learning. Imtiaz et. al. (2015), proposed a novel approach towards the recognition of human activity using spectral domain feature extraction. The study by Bayat et. al. (2014) shows outputs of the recognition of human physical activities of certain types using a mobile phone with only accelerometer data. In another study by Ayu et. al. (2012) the classification of human activities (walking, sitting, standing, jumping, jogging) and comparison of the performances of different classification algorithms is performed. In the research by Suarez et. al. (2015), a new method is presented to improve the recognition accuracy of physical activities by using only the accelerometer data. Bhattacharya et. al. (2014) in their research, propose a sparse-coding framework in ubiquitous and mobile computing that alleviates the fundamental problems of supervised learning approaches for activity recognition. In another study, (Abdallah et. al., 2015), for activity recognition, the researchers suggest a novel phone-based dynamic recognition framework with evolving data streams. Moreover, Kaghyan and Sarukhanyan, (2013) introduce an approach which allows human activity recognition using smartphone's acceleration and positioning sensors.

Additionally, in the study of Reddy et. al. (2010), the transportation modes of individuals were differentiated such as walking, running, biking, motorized transport or the stationary position of an individual using mobile phones which is a study of activity classification only.

Similar studies exist such as Miluzzo et. al. (2008) which performs activity classification for walking, running and still position with the help of accelerometer data without offering anything to the user. Another study by Zheng et. al. (2008) again performed only activity classification of walking, biking and motorized transportation using GPS (Global Positioning System) data. Furthermore, Sohn et. al. (2006) has the classification study of walking, motorized transportation and still position of the user with a mobile phone. As stated before in all of these studies only activity classification is performed, but in our study in addition to activity classification, an intelligent exercise recommendation system is implemented for different type of users with different demographic information.

ITAREPS (Information Technology Aided Relapse Prevention Programme in Schizophrenia) (Španiel et. al., 2008) is a program which helps in the prevention of schizophrenia using information technology and for this aim, a mobile phone based telemedicine solution is provided. With the help of the home telemonitoring system by a PC to mobile phone SMS (Short Message Service) platform that recognizes prodromal symptoms of relapse, the system warns to take the action before hospitalization process which is both costly and stressful for both the patient and his/her family.

As another application, during the management of asthma (Ryan et. al, 2005) peak flow monitoring is widely recommended and used. This is an observational study using handheld electronic peak flow meter monitoring and mobile phone technology. Patients with the age ranges of 12 to 55 requiring treatment with regular inhaled steroids and bronchodilators were recruited from nine general practices. As a total of 74% of the patients have reported that the system has helped to improve their ability to manage their symptoms. The most attractive features of the telemedicine system were the increased awareness and information about asthma, improved ability to monitor and control the condition with the feedback screens on the mobile phone and ease of use.

The usage of mobile phone technology for recording and gathering asthma data (Cleland, Caldow and Ryan, 2007) is another important study in this field. In this study, a qualitative interview study with a purposeful sample of 10 patients with asthma and two research staff were conducted. The patients' diary information was collected twice a day with an electronic peak flow meter linked to a mobile phone with an interactive screen to record current asthma symptoms and recorded information is stored in a server. Both the patients and the research staff believed that mobile phone technology would be helpful in clinical practice. Similarly, in another research by Cornelius and Gordon (2008), mobile technologies main uses were seen as identifying poor manage more quickly and facilitating communication with healthcare professionals without the need of face-to-face consultation and there was a high degree of acceptability by both patients and staff.

As another application, the IBC (Intelligent Biomedical Clothing) for wellness and for disease management (Lymberis and Olsson, 2003) was reported as a revolution in the clinical area in 2003 which also shows the promising value of using technological improvements in the medical area in those years. The developmental growths in microsystems and nanotechnologies as well as in information processing and communication technologies allow miniaturization and non-invasive smart monitoring of both physiological and physical data. With the multidisciplinary point of view, research in textile fibers, biomedical sensors, and wireless technology and mobile telecommunications is integrated together with telemedicine. This integration aims to develop IBCs that could open the way to support personalized control of health and disease management at any time needed. For many purposes such as health monitoring, disease prevention and control, rehabilitation, and sports medicine, IBC can offer wearable non-obtrusive telemedicine platform for individualized services that is readily accessible with good quality.

In addition, automated speech recognition (Gröschel et. al., 2004) for time recording in out-of-hospital emergency medicine is a medical treatment with emergency medical missions and for the resuscitation process. In this study, a software of the standard speech recognition was adapted and then installed on two separate computer systems. One of these computer systems was a stationary PC (Personal Computer) and the other one was a mobile pen-PC. With the results at hand, time recording with automated speech recognition seems to be possible when emergency medical conditions.

Furthermore, the NICHE pilot study (Faridi et. al., 2008) is about the assessment of the impact using mobile phone technology on type 2 diabetic patients' self-management. This study utilizes information technology, such as Internet and mobile phones to further improve the quality in diabetic care. In this study, the purpose was to examine the feasibility of utilizing the mobile technology to assist with diabetes in self-care in a clinical population as well as its impact on clinical outcomes. At the end of the study, with the results it is indicated that, the intervention had a positive impact on some of the clinical outcome and self-efficacy.

The FTA (the Few Touch Application) (Årsand et. al., 2012) is another study about diabetic patients. It provides support for patients who suffer from diabetes for their self-management using a diabetes diary with the help of a mobile phone. This tool has different useful opportunities such as transferring of blood glucose data automatically, food advice for the patient, and monitoring of physical activity, etc. This study is helpful since it provides personalized decision support for personalized health goals, with the automatic transfer of human physical activity, sending advice to motivate users, and the blood glucose data automatic transfer makes patients feel more confident themselves.

Another area where mobile technologies are used by patients very commonly is in headache disorders (Hundert et al, 2014). Mobile applications help patients by creating a headache diary and health care professionals try to give a name for the type of the headache problem.

Moreover, the role of mobile phone usage in the prevention and control of mental disorders (Proudfoot, 2013) is a promising study as well, because they are successfully deployed in the therapeutic situations, and have proven to be useful and motivational both for the patient and patient's relatives.

Since phone based interference has shown positive results (Krishna et. al., 2009; Guy et. al., 2011), and the applications that are used in the healthcare area are increasing by time (Kalem and Turhan, 2015-B; O'Reilly and Spruijt-Metz, 2013), the usage of cell/mobile phones and text messages, by offering suitable exercises to individuals, will increase user's health and quality of life. As it is known, many chronic diseases such as asthma, diabetes, and mental disorders become worse under inactive behaviours; encouraging these kinds of patients to do suitable exercises help them to overcome symptoms and manage their diseases more easily. It can be stated that, mobile applications provide better personalized healthcare, disease management and services to patients/users, and in the healthcare environment it is suitable to use mobile technology and mobile devices.

Analyzing the medical applications that are developed for smartphones, some studies are encountered which summarizes the applications that have already been developed (Liebert, 2010; Sherry and Ratzan, 2012; Chomutare et. al., 2011). Some of them have disadvantages such as cost, device/platform dependency, and poor user interface. Some of them are free but not even preferable, and some of them are not aimed for patients, they are developed for physician candidates, etc. Few of them are useful but in different areas rather than our scope, such as medical dictionary, medical calculator, displaying pill information and their images, etc. Up to this point, the existing mobile applications are reviewed and examined carefully considering their limitations, advantages and disadvantages, capabilities, etc. The research related to intelligent systems and the methodologies used are presented below.

In a study, a wearable system MOPET (Mobile Personal Trainer) was developed by Buttussi and Chittaro (2008) which provides better personalized training and motivation support for the users who are in the fitness domain. It is a physical fitness activity supervising system that is adapted to the user and the context. MOPET shows a location-aware map of the trail on the PDA (Personal Digital Assistant) screen, motivates the user telling his/her speed, and trains the user by showing and explaining how to perform the exercises in a correct and safe manner. As a continuation of this study, with a separate article (Buttussi et. al., 2009), a user generated fitness trail database by automatic creation is used in the system. After the user preferences are stored in this database, the recommendations to the users are given using collaborative filtering based algorithms based on user preferences and physical abilities.

Additionally, in the study by Oliver and Flores-Mangas (2006), the MPTrain system is described which is a mobile phone based system that uses automatic music selection to encourage the users to reach his/her exercise goals. This system has physiological sensors of accelerometer and ECG (electrocardiographs) connected to a mobile phone wirelessly. The system implements a learning algorithm to determine a mapping between the musical features like beat, volume, etc. and the user’s current exercise level automatically. Another feature of this system is the availability of a virtual race. For the aim of a fair competition, the system automatically matches the users based on similarity which is applied by using the k-Nearest Neighbours algorithm.

2.3. Approaches Used for Activity Recognition and Reasoning

The methodologies and techniques mostly used in activity tracking systems are presented below:

- *Support Vector Machines (SVM)* are supervised learning model with associated learning algorithms that analyzes the data and recognizes the patterns. It is used for classification and regression analysis. Detailed description is given in Chapter 4.

- The *k-Nearest Neighbors algorithm (KNN)* is a non-parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether KNN is used for classification or regression. In Chapter 4, detailed description is given.

- *Linear Discriminant Analysis (LDA)* is a classifier with a linear decision surface. It is a preferable method since it is inherently multiclass and has proven to work well in practice. More detailed description is given in Chapter 4.

- The *Collaborative Filtering Approach* is the process of filtering for information or patterns using the techniques that involve collaboration among multiple data sources, agents, etc.

- The *Naive Bayesian classifier* is a technique to construct the classifiers based on Bayes' theorem with independence assumptions between predictors.

- *Decision Tree* algorithm is used to build classification or regression models in the form of a tree structure. It breaks down a dataset into smaller subsets while at the same time an associated decision tree is incrementally developed.

- *Artificial Neural Networks (ANN)* are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown.

Additionally, the reasoning systems are presented below:

- *Rule-Based Reasoning systems* are used as a technique to store and manipulate knowledge in order to interpret information in a useful way based on specific rules.

- *Case-Based Reasoning systems* solve problems in a way similar to human thinking and are based on using existing data such as cases and experiences in a domain in order to generate a solution to the current problem. More detailed description about Case-Based Reasoning is given in Chapter 5.

- *Decompositional Reasoning systems* break the problem into smaller components similar to divide-and-conquer approach, analyze the smaller parts and fit them together, resulting in the whole system.

In the study by Martin et. al. (2013), it is stated that determining and logging the user's motion for an automated activity recognition system will enable a wide range of applications such as personal health, sports training, disease diagnosis and treatment, and child or aged people's care using lightweight classification techniques such as Naive Bayes, Decision Table and Decision Tree in mobile devices. In this study, it is pointed out that; processing the data inside or outside the mobile device affects the selection of the algorithm because some of the algorithms require more memory and computing capability. For example, Bayesian and Decision Tree algorithms are appropriate to use when the data is needed to be classified inside the mobile device. However, ANN (Artificial Neural Networks), rule based algorithms and SVM (Support Vector Machines) algorithms are appropriate to use when the data is needed to be processed outside the mobile device.

After a brief literature review, as the scope of this research, it is decided to develop an intelligent system for patients/users offering suitable exercises according to their needs within the consideration of their demographic information, and tracking their physical activity performances continuously to provide motivation and guidance to fulfill the suggested exercise plan.

Chapter 2 presents the literature review about the study including some of the current mobile applications in the healthcare domain with a brief introduction about the approaches in activity recognition and reasoning systems.

CHAPTER 3

DESIGN AND IMPLEMENTATION OF THE EXERCISE PLANNER SYSTEM

3.1. Design of the System

The modules and their interactions in the system are graphically shown in Figure 1.

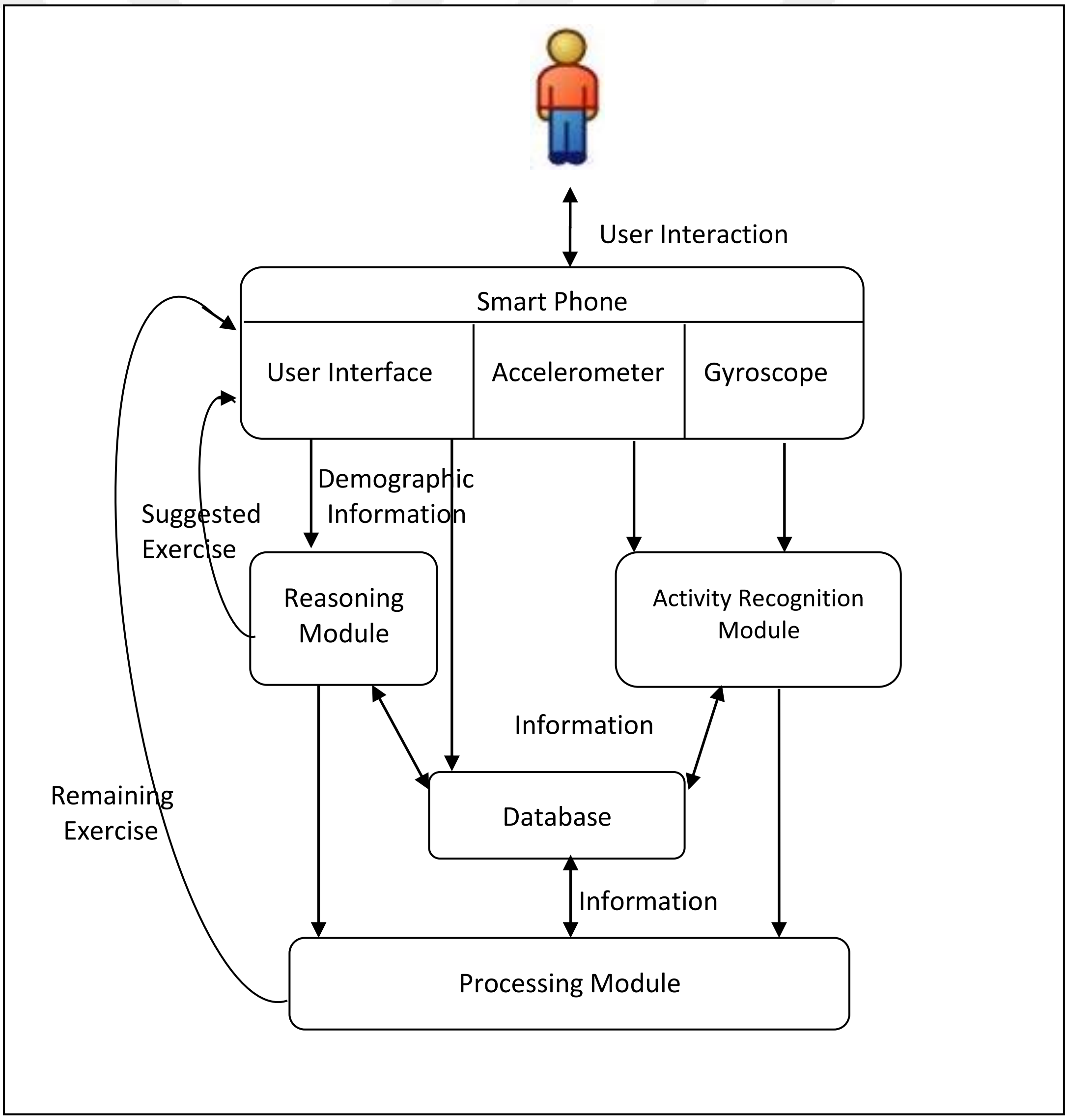

Figure 1. The design of the system

In this system, the user enters his/her demographic information; namely, age, height, weight, gender, health condition and purpose of using this system through the user interface of the mobile phone and this data is saved into the database. The demographic information is then sent to the Reasoning Module and data is processed for individual users to find a suitable exercise program based on the individual attributes of each of the user. The exercise plan with activities and durations are presented to the user with the user interface.

Then, with the help of the accelerometer and gyroscope features of the mobile phone, user's physical activity data is gathered and sent to the Activity Recognition Module, and user's activity data is also saved into the database. In this module, the user's physical activity tracking is implemented. While tracking the activity, the activity recognition is continuously executed while timing its duration and saved into the database for future use.

In the Processing Module, the tracked and recognized activities and their durations are compared against the offered exercise routine, and the user is guided on the remaining parts of the exercise plan for that day, or congratulated if he/she has finished the routine. During the day, if the suggested exercises are not completed, the user is warned with a message for motivational purposes to complete the remaining activities for each day in order to reach their objective. The parts of the exercises that remain are continuously updated by the Processing Module depending on the activity performances of the user during the day.

3.1.1. Research Methodology

In this study, after data collection, the data set is statistically analyzed where the findings are observable and quantifiable; consequently, this research follows the positivist methodology. Positivism[1] has accordance with the empiricist approach that knowledge depends on human experience as this study implies, and in addition this

[1] http://research-methodology.net/research-philosophy/positivism

study concentrates on facts as positivism requires (Easterbrook et. al., 2008; Recker, 2013).

3.2. Implementation of the System

The waterfall approach has been used in this study as the software process model. Since the waterfall model is a plan-driven model (Sommerville, 2015; Pfleeger and Atlee, 2009; Vliet, 2007), it includes separate and distinct phases of specification and development steps[2] (Berenbach, et. al, 2009; Bourque and Fairley, 2014; 2017; Pressman and Maxim, 2014) as given in Figure 2.

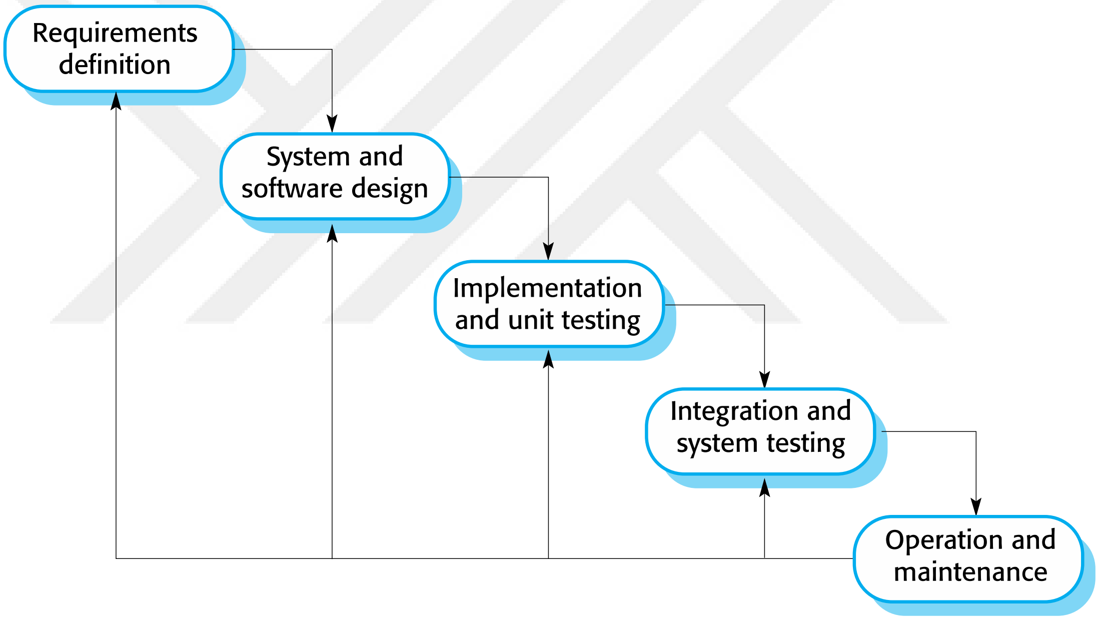

Figure 2. The Waterfall Model (Sommerville, 2015)

In the requirements definition phase, the real-life cases and corresponding real-life solutions to those cases are defined with the help of three professional physical trainers by considering the user's demographic information such as age, height, weight, gender, existence of a health problem and the purpose of using this system.

In the system and software design phase, the required modules, their input/outputs and the interaction between these modules are designed for this system.

[2] http://www.sei.cmu.edu

In the implementation and unit testing phase, the designed modules are implemented, such as the Reasoning Module which offers a suitable exercise routine to individuals according to their demographic information. The Activity Recognition Module continuously tracks the users' activities and the classification is performed for the implementation of activity recognition. The Processing Module receives the outputs of the Reasoning Module and the Activity Recognition Module as inputs and calculates the remaining exercises and their durations to communicate with the user for guidance and motivation. After the implementation of each module, unit testing is performed to ensure that each module works well separately.

In the integration and system testing phase, the separate modules are combined to construct the whole system. Then system is tested to check if the whole system works as planned after the integration of the separate modules. The last phase which is the operation and maintenance is left for future work.

Moreover, in this system different parts of the implementation are done in different modules such as the Reasoning Module, the Activity Recognition Module and the Processing Module. Dividing the system into different components provides high cohesion and low coupling and which are important in any software engineering application (Sommerville, 2015; Vliet, 2007). Each component/module performs its own responsibility and is not be affected by others achieving is high cohesion. All modules are connected to each other in a low coupled manner. This phenomenon is also important in the testing and maintenance steps of software engineering.

3.2.1. Integration of the System

In the Reasoning Module, the demographic information of the users are analyzed according to their specifications and a suitable exercise routine is offered. This is performed with the implementation of case-based reasoning. The defined real-life cases and solutions to those cases along with the implementation details are described in Chapter 5.

In the Activity Recognition Module, continuous activity tracking and the recognition are implemented. The best performance is achieved using KNN (K-Nearest Neighbors) algorithm as the classification method and applying Leave One Out Cross Validation technique for the validation. The performance rates and the detailed experiment results of the comparison of different classification methods along with different validation techniques are described in Chapter 4.

In the Processing Module, the offered exercise routine is received as an input from the Reasoning Module, and the tracked and recognized activities are gathered after the analysis of Activity Recognition Module, as an input. Then, both of those data are processed for each individual user to track the user performance regarding the suggested exercise. For this purpose, the integration of both systems are combined together with a prototype desktop implementation as a simulation of the mobile application.

3.2.2. Technical Specifications of the System

In this study, we have studied with real data which is collected from people using convenience sampling. The data collection is performed using a special software for gathering accelerometer and gyroscope data with a mobile phone, namely, Samsung Galaxy Note II, GT-N7100.

For the implementation of activity recognition, Matlab R2014a version is selected as a tool and, Matlab language is chosen since it has high performance while processing huge amounts of data which is described in Chapter 4 in detail.

For the implementation of the case-based reasoning system, C++ programming language is chosen. Since it is an object-oriented language, the different cases can easily be represented as objects. Dev-C++ 5.4.0 integrated development environment (IDE) is chosen for the implementation. The detailed information related to the implementation of case-based reasoning is described in Chapter 5.

Moreover, these two implementations are integrated using the C# language in Visual Studio as a desktop application. This is created as a simulation and prototype of a mobile application. The screen shot of the user interface is given below in Figure 3.

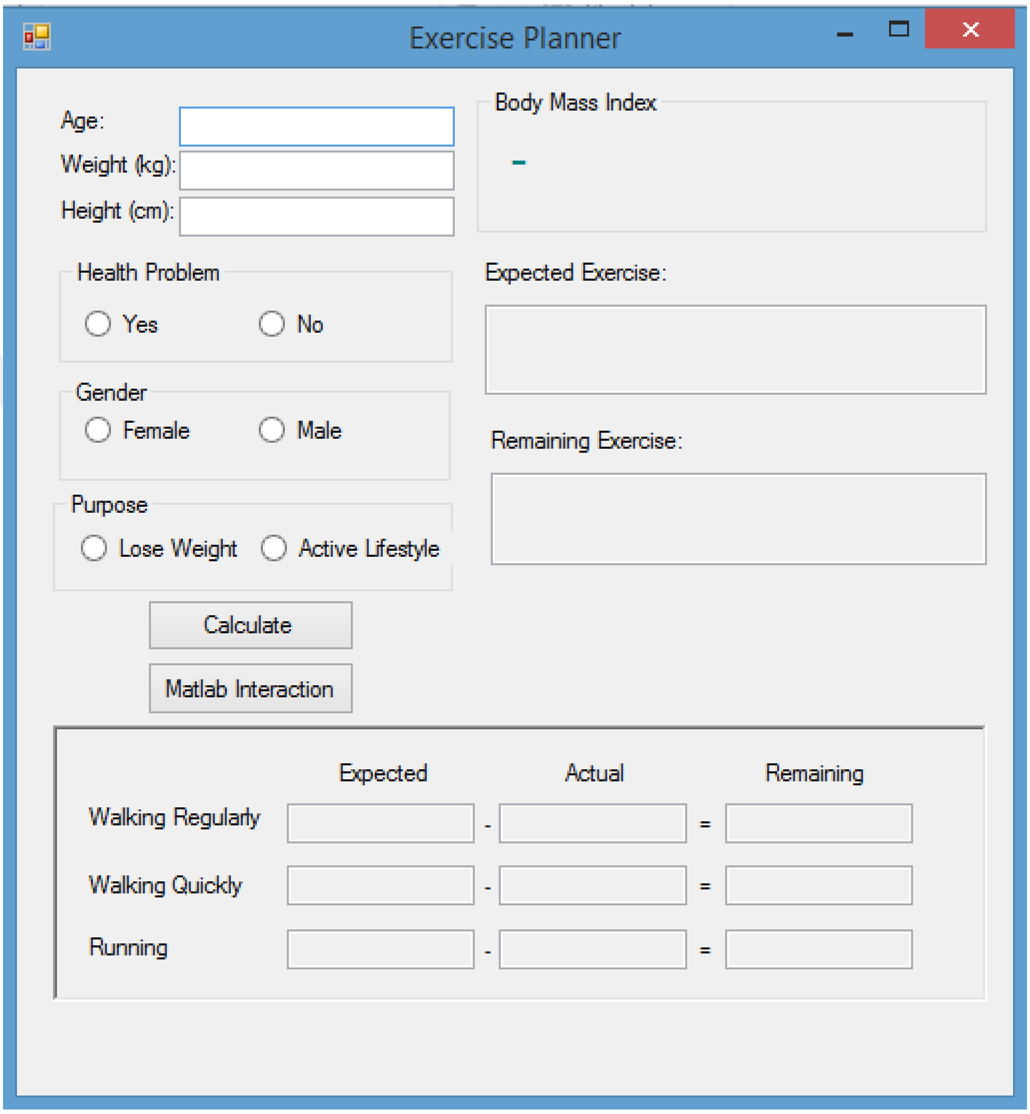

Figure 3. The User Interface of the Exercise Planner

The details of the developed user interface and the related screen shots are presented in Chapter 6.

Chapter 3 provides information about the design and implementation of the system along with the research methodology. The integration of each of the modules and the technical specifications of the system are also presented.

CHAPTER 4

ACTIVITY RECOGNITION

In the following section, retrieving data through sensors using the accelerometer and gyroscope properties of a mobile device that is implemented in the Activity Recognition Module will be described. Then, the test results of three classification methods along with three validation techniques and the selection of the best performances to be utilized in this system are presented.

The activity recognition procedure can be shown schematically as given below in Figure 4.

Figure 4. The Activity Recognition Procedure (Ayu et. al., 2012)

4.1. Data Collection

Data is collected from a group of 111 female and male participations, with the age range of 7 to 53. In addition, volunteers' demographic information is recorded, such as gender, height that varies from 110 cm to 192 cm, and weight that varies from 22 kg to 109 kg. In this study, the participations were selected using convenience sampling. In addition, all other necessary contact information is collected such as name, activity date, e-mail address, telephone number, etc. so that all volunteers are reachable if needed.

The data is collected using a special software aimed to collect this type of data with a mobile phone, namely, Samsung Galaxy Note II, GT-N7100. A subset of the information recorded is shown in Table 1 below.

Table 1. Example of Participant Information

Volunteer No	Code	ID	Activity Type	Name Surname	Birthdate	Gender	Height (cm)	Weight (kg)	Telephone Number	e-mail	Activity Date
5	24	242	Walking Regularly	x x	3.7.1988	M	190	90	kk	a@a	22.7.2015
		243	Walking Quickly								
		244	Running								
6	25	252	Walking Regularly	y y	7.3.1990	M	182	69	mm	b@b	22.7.2015
		256	Walking Quickly								
		258	Running								
7	26	262	Walking Regularly	z z	31.5.1986	F	159	57	nn	c@c	22.7.2015
		263	Walking Quickly								
		264	Running								
8	27	272	Walking Regularly	t t	27.1.1981	F	158	66	pp	d@d	22.7.2015
		273	Walking Quickly								
		274	Running								
9	28	282	Walking Regularly	h h	14.10.1976	M	180	77	rr	e@e	23.7.2015
		283	Walking Quickly								
		284	Running								

All volunteers are numbered from 1 to 111 in the *Volunteer No* column. A *Code* number has been assigned to each of the volunteers in a separate column. Then three different numbers (2: walking regularly, 3: walking quickly and 4: running) were appended to the code numbers, and this way, the *ID* numbers are created and used as primary keys to specify each volunteer's different activities, namely, walking regularly, walking quickly and running. If a volunteer was unable to finish the labeled activity successfully, then a consequent number was appended to create a new id number for the new recording, and the volunteer was requested to perform the same activity again, and this process was repeated until a successful activity recording was achieved. For this reason, some of the volunteer's id numbers are not consecutively coded like 242-243-244, instead, they have been coded as 252-256-258. This means that, the volunteer coded 25, has performed walking regularly once and received an id for walking regularly as 252, then repeated quick walking activity 4 times where the last record was accepted as a successful activity and received an id number 256 for quick walking, then repeated the running activity twice and received an id number 258 for running.

The specifications of the data is as follows; from 111 different volunteers, and from each volunteer, a total of 6 minutes of activity data were gathered which includes:

- walking regularly for 2 minutes
- walking quickly for 2 minutes
- running for 2 minutes

Activities were performed both indoors and outdoors, generally during the afternoon, and two hours after lunch. In addition, participations have performed the exercises on similar paths, and in similar weather conditions in order not to affect the activity records. Data were collected in consecutive 7 days, and weather conditions and the record dates are given in Table 2.

Table 2. Data Record Dates and Weather Conditions

Activity Date	Weather Condition	Daytime Temperature Highest	Daytime Temperature Lowest
21.07.2015 - Tuesday	Sunny	36 °C	12 °C
22.07.2015 - Wednesday	Sunny	34 °C	13 °C
23.07.2015 - Thursday	Sunny	35 °C	13 °C
24.07.2015 - Friday	Sunny	37 °C	14 °C
25.07.2015 - Saturday	Sunny	38 °C	17 °C
26.07.2015 - Sunday	Few Clouds	35 °C	16 °C
27.07.2015 - Monday	Few Clouds	35 °C	16 °C

While gathering data from 111 people, some problems were encountered. These problems and the solution proposals are described below;

- While the activity is being done, the volunteer unintentionally touches the turn-off button of the application, causing the application to stop. Then, the activity must be restarted from the beginning which tires the volunteer and consumes time unnecessarily. However, changing the application in order to operate at the background mode will solve the problem.
- If the activity is completed and the application has stopped in a normal manner, then the code number of the last volunteer remains on the form. The volunteer unintentionally touches the start button of the application, then the application starts again and it begins to record the new data inside exactly the same file that has the same code number. But, this happens while the activity is not being done, so wrong data is recorded onto the correct data. Then the activity must be repeated from the beginning again. For this problem, two solutions are proposed. First one is, after the activity is finished and the program stops, an empty form can be returned to the screen. The second solution is, if there is a record with the same name, another naming convention can be used for the new recording.

- From time to time, the recorded data is not saved to the file, or sometimes it only records half of the data or less. Activity should be repeated, or a new volunteer should be found. No solution can be proposed for this problem.

Due to such problems, some volunteers' problematic data (dirty data) have been eliminated, and as a result, 100 different volunteers' data have been analyzed.

4.2. Data Analysis

After collecting the data, all files were analyzed in a lengthy process since there are 111 different people's activity records, which are saved in different categories such as ACC (accelerometer) data file, GYR (gyroscope) data file, etc. In addition, those categorized data files are repeated for each activity of walking regularly, walking quickly and running. As a result, there are more than 666 (= 111 * 3 activities * 2 types of data) different data files. Before the actual analysis, the data have been cleaned and grouped together for each different category.

In order to perform the feature extraction, all data are read and stored into matrices. Matlab program is selected as a tool since it has high performance while processing huge amounts of matrices. At this stage, many problems have been faced, such as some of the file's recordings were less than 2 minutes duration which had to be discarded, etc. As a result, 100 volunteers' 600 (= 100 * 3 activities * 2 types of data) different data files have been analyzed.

In each of the data files, there are x, y and z coordinate data separated by a delimiter. The sampling frequency of 50 Hz is used and in 1 second, 50 lines of each of the coordinates are recorded to a data file. Since each activity is performed for 2 minutes (120 seconds), there are approximately 6.000 (= 50 lines * 120 seconds) lines of coordinate data in each file for each person's individual activity. A small part of a data file is given as an example in Figure 5.

```
2.0590134#0.54587793#0.54587793
0.69910693#0.057460785#0.057460785
0.11492169#0.06703758#0.06703758
0.93852705#0.8331821#0.8331821
0.7757214#0.7661443#0.7661443
1.3503298#2.0111299#2.0111299
4.098873#2.8155813#2.8155813
2.5953145#3.064578#3.064578
0.81402826#2.0494366#2.0494366
0.6129155#2.5665846#2.5665846
1.2545614#3.677494#3.677494
1.130063#3.8786068#3.8786068
1.8100166#4.625599#4.625599
3.4955344#2.173936#2.173936
6.6079965#8.0924015#8.0924015
. . .
. . .
. . .
0.10534486#0.17238283#0.17238283
0.7661446#0.9768343#0.9768343
0.019153655#1.0151415#1.0151415
0.21068972#1.0055642#1.0055642
1.0630256#0.708683#0.708683
```

6000 lines

Figure 5. Small Part of a Data File

There are approximately 6.000 lines of data for one activity's accelerometer data and also 6.000 lines of data for one activity's gyroscope data, so in total, there exist 36.000 (= 6.000 * 3 activities * 2 types of data) data lines for each person. This means that 3.600.000 (= 36.000 * 100 people) data lines have been recorded for 100 volunteers’ activity.

4.2.1. Feature Extraction

In order to implement feature extraction, each data file is read with sets of 50 lines and to each of these data sets, the features of maximum, minimum, average and some other functions are applied, and the results are recorded into a new matrix. This process is done using raw accelerometer and gyroscope data separately and then combined together. This is done because, while recording the raw data, the sampling frequency of 50 Hz is used, which means that, at each second, 50 lines of data have been recorded to the data file, and activity recognition and analysis are done for one second each time which is an optimum time as stated in Reddy's study (2010).

Different sets and combinations of features are used and tested separately for this data set (Bao and Intille, 2004; Jain et. al., 2000; Rasekh et. al., 2011; Reddy et. al., 2010). These features are listed below;

- mean,
- maximum,
- minimum,
- variance,
- standard deviation,
- entropy,
- mode (most frequent values),
- median,
- correlation,
- covariance,
- percentile of the data which are smaller than 25,
- percentile of the data which are smaller than 75,
- energy (sum of the squared discrete Fast Fourier Transform (FFT) component magnitudes of the signal),
- maximum frequency,
- number of peaks,
- taking differences of some of the above features, such as, (mean-median), (maximum-minimum), (standard deviation-mean), etc.

For each of the x, y, z coordinate axes, the above features are implemented in the following ways;

- powers of each axes one by one (x^2, y^2, z^2),
- powers together ($x^2+y^2+z^2$)
- powers with pairwise combinations (x^2+y^2, x^2+z^2, y^2+z^2),
- by just using x, y, z axes without any computation one by one (x, y, z), etc.

All these combinations are used to find and extract the usefulness of these features for this data set (Bao and Intille, 2004).

As a result of all the combinations of the above features, a total of 210 features are created and tested with different classification methods and validation techniques to achieve the best correct percentage result classification for three different activities. Related classification methods and validation techniques are explained in detail in the next two sections.

For this data set, in order to find the best possible feature subset selection of these 210 features, the Exhaustive Search is applied until 3rd degree. Exhaustive Search (Nievergelt, 2000) is a general problem solving technique that systematically enumerates all possible candidates for the solution and checks whether each candidate satisfies the problem's statement.

Since there are too many features, it is not possible to finish all possibilities for all degrees with Exhaustive Search which may take years using today's technology, and is therefore computationally infeasible. Instead, the Exhaustive Search with 3rd degree is applied which lasts approximately 14 days, and the results are evaluated. Results and the selected feature sets are explained in detail in the Results of Experiments section.

4.2.2. Classification

In order to correctly classify three activities of walking regularly, walking quickly and running with an acceptable performance, the features are extracted and different classification methods are tested.

According to the literature (Jain et. al., 2000; Miluzzo, 2008; Ravi et. al., 2005; Reddy et. al., 2010; Zhang, 2010; Kalem and Turhan, 2016), the following classification methods are used effectively to classify different groups of activities;

- KNN (K-Nearest Neighbors)
- LDA (Linear Discriminant Analysis)
- SVM (Support Vector Machines)

KNN algorithm works in a manner that, when a new item appears to be classified, k number of nearest neighbors are found, and the new item is included in the group with more number of neighbors.

LDA algorithm is an advanced coordinate transformation technique of Principal Component Analysis (PCA), aiming to find a new coordinate system by minimizing the ratio of (distribution within a class)/(distribution among classes) with more than one class. While doing this, the data groups' statistical distribution properties such as average and standard deviation are checked, and a covariance matrix is generated.

SVM algorithm has a logic that classifies two separate groups by drawing a linear or nonlinear line between these groups, so when a new item comes, this algorithm calculates the distances to find the largest one.

Since SVM is used to separate two classes and in this study there are three different classes to be differentiated, Multiclass SVM with One-Against-All is used for the classification of the three classes (Tapkın et. al., 2015; Sharan and Moir, 2015; Kumar and Gopal, 2011).

As shown in the Results of Experiments section, all of these methods are tested, and based on the results, an acceptable performance is achieved using KNN method. Then the data set is tested by applying different k values of the KNN algorithm to reach a better performance. For the k value of the KNN method, it is better to use an odd number since KNN would check the most number of neighbors. In accordance with this idea from 1 to 61, all odd numbers are tested and the corresponding performances are recorded in Table 3 below.

Table 3. K Values of KNN Method and Respective Performances

k value of KNN method	Performance %
k=1	98.08
k=3	98.65
k=5	97.57
k=7	97.85
k=9	98.31
k=11	98.47
k=13	98.64
k=15	97.96
k=17	98.05
k=19	97.90
k=21	97.84
k=23	97.66
k=25	97.76
k=27	97.85
k=29	97.83
k=31	97.72
k=33	97.67
k=35	97.62
k=37	97.52
k=39	97.63
k=41	97.58
k=43	97.44
k=45	97.48
k=47	97.56
k=49	97.51
k=51	97.51
k=53	97.45
k=55	97.44
k=57	97.48
k=59	97.31
k=61	97.26

The graphical representation of Table 3 is given in Figure 6.

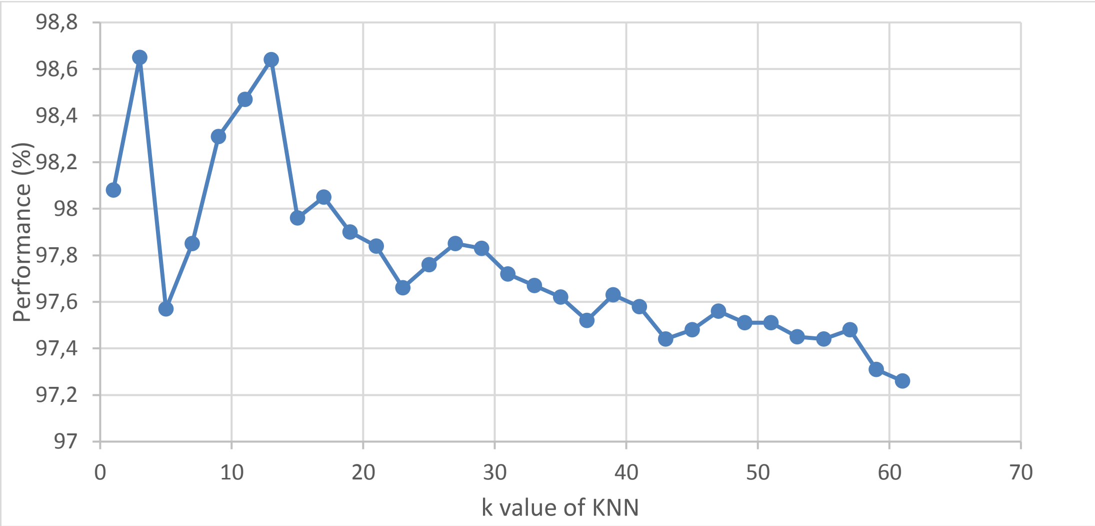

Figure 6. The Graphical Representation of K Values of KNN Method and Performances

According to the performances of different k values of KNN method, the k value is selected as 3. The combinations of each of the classification methods along with each validation technique tested are explained in the Results of Experiments section in detail.

4.2.3. Validation

With the extracted features, different classification methods are applied and during this process, different validation techniques are tested with different combinations. According to the literature (Camacho, 2014; Jain et. al., 2000; Sun et. al., 2010; Kalem and Turhan, 2016), the most widely used and effective validation techniques in the area of activity recognition are listed below;

- K-fold Cross Validation with the k value of 2
- K-fold Cross Validation with the k value of 10
- Leave One Out Cross Validation

Generally, the idea behind the validation techniques is feeding a part of the data to the system for training, then testing the system using the rest of the data. This process is repeated continuously until each part of the data is used as a training data set and in the following runs used as a test data set with different set of combinations.

K-fold Cross Validation (Camacho and Ferrer, 2014; Jain et. al., 2000) is a technique for estimating the performance of a classifier. It is a way to improve over the holdout method. The data set is divided into k subsets, and then the Holdout Method, explained below, is repeated k times. At each iteration, one of the k subsets is used as the test set and the other k-1 subsets are combined to form a training set. Then the average error across all k trials is calculated. The advantage of this method is how the data is divided is less important. Every data point gets to be in a training set k-1 times, and gets to be in a test set exactly once. As the k value is increased, the variance of the resulting estimate is reduced. This method has a disadvantage that the training algorithm has to be rerun from scratch k times, which means it takes k times as much computation to make an evaluation. This method's variant can be used which is to randomly divide the data into a test and training set k different times. By doing this, it gives an advantage where you can independently choose how large each test set is and how many trials you average over.

In the Holdout Method (Jain et. al., 2000; Kohavi, 1995), data set is separated into two, called the testing and training sets. The approximator function fits a function using only the training set. Then the approximator function is asked to predict the output values for the data in the testing set. The errors it produces are accumulated as before to give the mean absolute test set error, and it is used to evaluate the model.

Leave One Out Cross Validation (Jain et. al., 2000) technique leaves one value for the test data and uses the rest of the data set as training sets. This process is repeated until each one of the data values are used as test data, continuously.

In the K-fold technique, if the k value is selected as 2, then it is called 2-fold; if the k value is selected as 10, then it is called 10-fold. K-fold Cross Validation technique with the k value of 10 works in a manner where, 90% percentage of the data is used for training and 10% percentage of the data is used for testing. This algorithm is done iteratively 10 times, and because in each iteration, a different 10% percentage is tested, it will trace all data, iteratively. The experiment results with different combinations using this method are detailed at the Results of Experiments section.

In this study, all three validation techniques described above are applied and according to the experiment results, better performance is achieved using Leave One Out Cross Validation technique.

4.2.4. Results of Experiments

Experiments are performed in two different ways. In the first one, a group based calculation is done on the whole data set with different variations. In the second group, person-based calculations are performed.

4.2.4.1. Group Based Results

Data is collected from 111 different volunteers' three different activities as stated in the previous section. Since some of the volunteers' data are not recorded correctly or due to other problems, data set number is reduced to 100 people.

After the data cleaning process, a total of 210 features are extracted from the accelerometer data set and gyroscope data set, together. Then, different classification methods and validation techniques are applied to the data set with all possible combinations in order to recognize three different activities with the best possible performance result.

When KNN is applied for classification method on the 100 volunteers' data set, 80.61% performance is achieved using Leave One Out validation technique; 77.53% performance is achieved using 2-fold validation technique; and 77.34% performance is achieved using 10-fold validation technique. If LDA is applied as a classification method, this time 80.43% performance is achieved using Leave One Out validation technique; 78.02% performance is achieved using 10-fold validation technique; and

77.21% performance is achieved using 2-fold validation technique. The results are presented in Table 4.

If SVM is applied as a classification method, the program could not able to calculate the result since it gives an error message of "No convergence achieved within maximum number of iterations", which means that SVM cannot classify the activities since they are so similar to each other. All possible combinations of classification methods and validation techniques and their results are summarized in Table 4. These calculations are done by using both the accelerometer data set and the gyroscope data set.

Table 4. The Comparison of Classification and Validation of Three Activities

Number of volunteers	**Classification Method**	**Validation Technique (%)**		
		K-fold (2)	**K-fold (10)**	**Leave one out**
100 (ACC + GYR)	**KNN**	77.53	77.34	**80.61**
	LDA	77.21	78.02	80.43
	SVM	No convergence	No convergence	No convergence

In SVM, the maximum number of iterations is 15.000 as a default value, and with this data set, it could not converge. Then different iteration numbers are tried, and as a result it is seen that, using 45.000.000 number of iterations, it is still not able to converge with this data set. This shows a significant point that, this data set is too complicated to process because the activity groups are so similar, and the activities are very much dependent on the volunteer, since someone else's regular walking can be similar to another one's quick walking, and also someone's quick walking can be similar to another one's running, due to age, weight, gender, etc. Additionally, some of the volunteers performed the activities different than normal, because they know that the activities are recorded and someone is watching them. This problem affected the overall data set and all three activities are mixed together.

Because SVM was not able to converge with three activities, to see whether SVM converges when the number of activities are reduced, pairwise tests have been performed. In the pairwise tests, SVM was able to differentiate between the two activities. The results are summarized in Table 5-7 given below.

Activity classification is performed for only the activities of walking regularly and running, and as a data set, 100 volunteer's data recordings are used. Then, KNN is applied for classification and Leave One Out is used for validation, after that 96.91% performance is achieved. When LDA is applied for classification and 2-fold is used for validation, 94.20% performance is calculated. If SVM is applied as a classification and 10-fold is used for validation, then 98.68% performance is gained which are really high outputs that can be considered as acceptable percentages. All the calculations' results of different combinations of classification and validation techniques are summarized in Table 5 given below.

Table 5. The Comparison of Classification and Validation of Two Activities (Walking Regularly and Running)

Number of volunteers	**Classification Method**	**Validation Technique (%)**		
		K-fold (2)	**K-fold (10)**	**Leave one out**
100 (ACC + GYR)	**KNN**	96.11	96.03	96.91
	LDA	94.20	93.44	93.82
	SVM	98.19	**98.68**	98.25

In a similar manner, when the activity classification is performed for only the activities of quick walking and running, and 100 volunteer's data is used, 89.35% performance is achieved if KNN method is applied for classification and Leave One Out is used for validation. If LDA is applied for classification and 10-fold is used for validation, 90.17% performance is calculated. And if SVM is applied as a classification and Leave One Out is used for validation, then 90.46% performance is gained. All the results of calculations are listed in Table 6 given below.

As the performance results show, the activities of quick walking and running is less distinguished compared to the walking regularly and running activities, because some people's running activity were like jogging and consequently those running activities are accepted as quick walking by the program. So, person-based calculations would be more reliable for this kind of data set.

Table 6. The Comparison of Classification and Validation of Two Activities (Quick Walking and Running)

Number of volunteers	**Classification Method**	**Validation Technique (%)**		
		K-fold (2)	**K-fold (10)**	**Leave one out**
100 (ACC + GYR)	**KNN**	88.96	89.12	89.35
	LDA	89.30	90.17	89.72
	SVM	90.02	90.06	**90.46**

For only the activities of walking regularly and quick walking, similar calculations are done on 100 volunteers' data set. If KNN is applied for classification and Leave One Out is used for validation, 68.84% performance is calculated. If LDA is applied for classification and Leave One Out is used for validation, 68.56% performance is calculated. In addition, if SVM is applied as a classification and 10-fold is used for validation, then 76.07% performance is achieved. All the test results are summarized in Table 7 given below.

Similarly, when the performance results of the activities of walking regularly and quick walking are analyzed, it is obviously seen that it is very hard to distinguish regular walking and quick walking activities since it differs too much person to person. During data collection, it is already observed that some of the volunteers' regular walking activity were similar to quick walking activity. Repeatedly, person-based calculations would be much more reliable for this kind of data set.

Table 7. The Comparison of Classification and Validation of Two Activities (Walking Regularly and Quick Walking)

Number of volunteers	Classification Method	Validation Technique (%)		
		K-fold (2)	**K-fold (10)**	**Leave one out**
100 (ACC + GYR)	**KNN**	67.71	67.32	68.84
	LDA	68.24	68.09	68.56
	SVM	75.55	**76.07**	76.06

Up to now, all of the above calculations are done using both the accelerometer and gyroscope data set. In the next sections, each of these data sets are tested separately and the results are compared to each other. Afterwards, both the accelerometer and gyroscope data set are used together and tested again to compare the achieved results.

Since these three activities are too person dependent, the tests are repeated as person-based, and the achieved results are compared in the following sub-section.

4.2.4.2. Person-Based Results

When the calculations are done on the 100 volunteer data set in a person-based manner to distinguish all three activities, the accelerometer data and gyroscope data performances are calculated separately and then together, and important clues are extracted from this experiment.

With the accelerometer data, 90.05% performance is achieved if KNN is applied for classification and Leave One Out is used for validation. If LDA is applied for classification and 10-fold is used for validation, 86.43% performance is calculated. And if SVM is applied as a classification and 2-fold is used for validation, then 80.24% performance is achieved. The obtained results are summarized in Table 8 which is given below.

Table 8. The Comparison of Classification and Validation of Three Activities on Person-Based Results with Accelerometer Data

Number of volunteers	Classification Method	Validation Technique (%)		
		K-fold (2)	K-fold (10)	Leave one out
Person-based 100 (ACC)	**KNN**	88.68	89.14	**90.05**
	LDA	85.51	86.43	86.01
	SVM	No convergence	No convergence	No convergence

Next, with the gyroscope data, the same experiments are repeated, and 83.46% performance is achieved if KNN is applied for classification and Leave One Out is used for validation. If LDA is applied for classification and Leave One Out is used for validation, 83.01% performance is calculated. And if SVM is applied as a classification and Leave One Out is used for validation, then 78.12% performance is achieved. All test results are listed in Table 9 given below.

Table 9. The Comparison of Classification and Validation of Three Activities on Person-Based Results with Gyroscope Data

Number of volunteers	Classification Method	Validation Technique (%)		
		K-fold (2)	K-fold (10)	Leave one out
Person-based 100 (GYR)	**KNN**	82.03	81.79	**83.46**
	LDA	81.62	81.90	83.01
	SVM	No convergence	No convergence	No convergence

By using the accelerometer data and the gyroscope data together, the following results are achieved. 83.76% performance is achieved if KNN is applied for classification method and Leave One Out is used for validation technique. If LDA is applied for classification and Leave One Out is used for validation, 82.52% performance is gathered. If SVM is applied as a classification it is not able to converge . The results of experiments are listed in Table 10 given below.

Table 10. The Comparison of Classification and Validation of Three Activities on Person-Based Results with Accelerometer and Gyroscope Data

Number of volunteers	Classification Method	Validation Technique (%)		
		K-fold (2)	K-fold (10)	Leave one out
Person-based 100 (ACC + GYR)	**KNN**	83.01	83.55	**83.76**
	LDA	79.50	78.36	82.52
	SVM	No convergence	No convergence	No convergence

When the experiment results are examined in detail, it has been observed that, the accelerometer data performance is 90.05% and the gyroscope data performance is 83.46% at best. But if the accelerometer and the gyroscope data are used together, the expectation is that their combination would give higher results, but actually it is opposite of this case and it decreases the performance. The explanation of this performance decrease is; since the volunteers are expected to do the activities during a 2 minutes interval, some of the volunteers got tired and slowed down. Generally, these slow motion activities occurred during quick walking which is confused with regular walking, and during running which is confused with quick walking. Additionally, in this data set, the age range varies from 7 to 53 years old, which means that, while recording the running activity, a 7 year old child got tired and during the last minute, just walked instead of running.

Since a 7 year old child's activity speed and 25 year old young person's activity speed are far from each other, and similarly, a 53 year old person's activity speed is very different from a young person's activity speed, the disadvantages of such wide range of ages should be eliminated. Consequently, a subset is composed with similar age ranges from 17 to 30 years old, and this group includes 40 volunteers' data which is acceptable according to the Central Limit Theorem (Walpole et. al., 2013) that requires 30 samples for normal distribution. In the next section, performances of this subset are explained in detail.

Young subset

With the age range of 17 to 30, a young group of volunteers are selected and analyzed. There are 40 different volunteers' data in this group. The data set of 40 people is an acceptable number for a sample set according to the Central Limit Theorem (Walpole et. al., 2013) which states that there must be at least 30 samples to achieve the normal distribution. According to the Central Limit Theorem (CLT), regardless of, if the sampled population is finite or infinite, the sampled population's approximation for the mean for a given random sample of size n will generally be good if $n \geq 30$. Moreover, since the data set is not extremely skewed, it can also easily satisfy the normal approximation assumption set by the central limit theory, respectively.

With the accelerometer data, 92.49% performance is achieved if KNN is applied for classification and 10-fold is used for validation. If LDA is applied for classification and Leave One Out is used for validation, 90.94% performance is calculated. And if SVM is applied as a classification it could not converge. After the experiments, the obtained results are summarized in Table 11 given below.

Table 11. The Comparison of Classification and Validation of Three Activities on Person-Based Results with Accelerometer Data

Number of volunteers	**Classification Method**	**Validation Technique (%)**		
		K-fold (2)	**K-fold (10)**	**Leave one out**
Person-based 40 (ACC)	**KNN**	91.83	92.17	**92.49**
	LDA	90.42	90.16	90.94
	SVM	No convergence	No convergence	No convergence

With the gyroscope data set, 84.41% performance is achieved if KNN method is applied for classification and Leave One Out technique is used for validation. If LDA is applied for classification and Leave One Out is used for validation, 82.07%

performance is calculated. And if SVM is applied as a classification it could not converge. After the experiments, the obtained results are summarized in Table 12 which is given below.

Table 12. The Comparison of Classification and Validation of Three Activities on Person-Based Results with Gyroscope Data

Number of volunteers	**Classification Method**	**Validation Technique (%)**		
		K-fold (2)	**K-fold (10)**	**Leave one out**
Person-based 40 (GYR)	**KNN**	83.78	84.17	**84.41**
	LDA	80.78	81.55	82.07
	SVM	No convergence	No convergence	No convergence

When the accelerometer data and the gyroscope data are used together, the following results are achieved. 98.65% percentage is achieved if KNN method is applied for classification and Leave One Out technique is used for validation. If LDA is applied for classification and Leave One Out is used for validation, 96.96% performance is gathered. And if SVM is applied as a classification it is not able to converge. The experiment results are listed in Table 13 given below.

Table 13. The Comparison of Classification and Validation of Three Activities on Person-Based Results with Accelerometer and Gyroscope Data

Number of volunteers	**Classification Method**	**Validation Technique (%)**		
		K-fold (2)	**K-fold (10)**	**Leave one out**
Person-based 40 (ACC + GYR)	**KNN**	96.96	97.02	**98.65**
	LDA	95.01	95.21	96.96
	SVM	No convergence	No convergence	No convergence

As a result of the above experiments, when the age range is limited and person-based calculations are performed, it is seen that the results improve significantly with accelerometer data performance becoming 92.49% and the gyroscope data performance resulting in 84.41% as the best result. Also if the accelerometer and the gyroscope data are used together, a higher performance is achieved as 98.65%.

As the calculations are detailed in the previous section, without the limitation of the age range, the gyroscope data have decreased the performance of accelerometer data. But when a limited age range of people data is used, the gyroscope data have increased the performance of accelerometer data. This shows that, with similar aged people, the activities would be more distinguishable from each other.

Together with the accelerometer data set and the gyroscope data set, a total of 210 features are extracted and but this number of features are required to be decreased to an acceptable number by using Exhaustive Search. The Exhaustive Search with 3rd degree is applied to find the best possible feature subset selection among 210 features, and some different subsets including only 4 features are obtained such as;

- [mean, minimum, median, entropy],
- [mean, minimum, median, variance],
- [mean, minimum, maximum, (maximum-minimum)], and etc.

The performance of 98.65% is achieved only using 4 features of the given combinations instead of using all 210 features, and this decreases the time required to differentiate between three different activities, thereby increasing the performance of the whole system.

As a result of the calculations and observations, the KNN classification method with Leave One Out validation technique achieves better performance for the limited age group of data in a person-based calculation.

Chapter 4 presents the activity recognition implementation of the application. The experiments, comparisons, results and the selected classification and validation techniques are also provided in this chapter.

CHAPTER 5

REASONING

Reasoning[3,4] (Kowalski, 2009) is the process of deriving logical conclusions or inferences using given facts or some other intelligible information using logical techniques such as deduction and induction. There are many different types of reasoning systems, namely Case-Based Reasoning, Analogical Reasoning, Set-Based Reasoning, Decompositional Reasoning, Systemic Reasoning, etc. and they are not all mutually exclusive techniques where several of them have overlapping areas[5,6,7] (Kowalski, 2009).

Since the prospective users of our system can be categorized into different cases dependent on their demographic information, their purpose of using this system, and their medical background, among all the above mentioned reasoning systems, the most suitable one for this study is the Case-Based Reasoning system.

5.1. Case-Based Reasoning

Case-Based Reasoning (CBR) is an artificial intelligence technique (Richter and Weber, 2013) which is based on human problem solving. For every new problem, a solution is generated by recalling and adapting the solutions of similar existing

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[3] http://www.zeepedia.com/read.php?knowledge_representation_and_reasoning_artificial_intelligence&b=2&c=4
[4] http://web.itu.edu.tr/sonmez/lisans/dogus/come444/REASONING.pdf
[5] https://bittersweetend.word press.com /2012/11/17/what-are-the-different-types-of-reasoning
[6] http://changingminds.org/disciplines/argument/types_ reasoning/types_reasoning.htm
[7] http://library.royalroads.ca/writing-centre/writing/argumentation/building-argument/types-reasoning-deductive-vs-inductive

problems in the domain (Jalali and Leake, 2015). In other words, it is the act of providing solutions to problems by analyzing similarities with other problems based on pre-existing solutions (Aamodt, 1994). CBR uses analogical reasoning to infer solutions based on case histories. CBR systems are commonly used in customer/technical support and call center scenarios and have applications in fault diagnosis, industrial manufacturing, agriculture, medicine, law and many other areas[8,9,10] (Sauer, 2012).

A CBR system consists of four basic steps to generate a solution which is summarized in Figure 7.

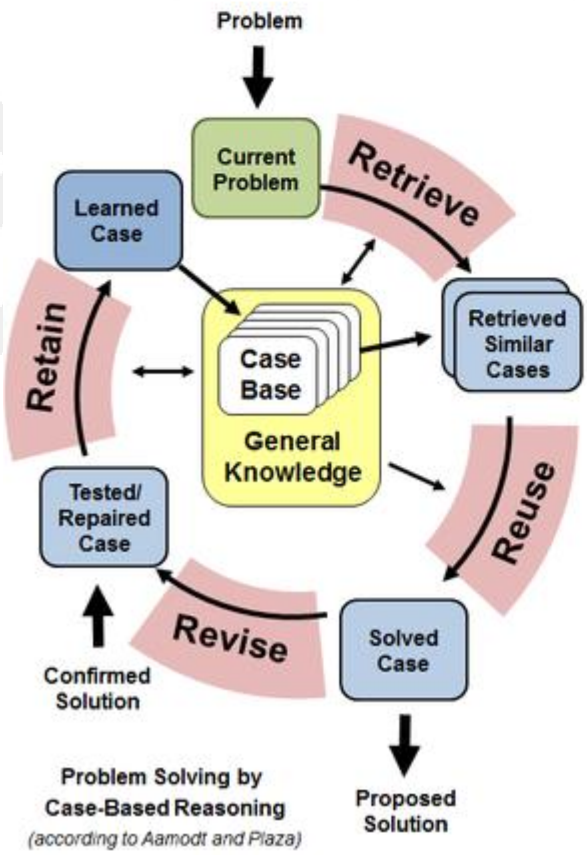

Figure 7. The CBR Cycle (Aamodt and Plaza, 1994)

[8] http://aitopics.org/topic/case-based-reasoning
[9] http://www.cs.indiana.edu/~leake/ papers/p-96-01_dir.html/paper.html
[10] http://www.iiia.csic.es/Projects/cbr

The descriptions of these steps are given below (Ontanon and Plaza, 2012);

- **Retrieve:** Retrieve from memory the most similar cases to solve the target problem.
- **Reuse:** Reuse the knowledge with the help of previous cases to map the solution.
- **Revise:** After having mapped the proposed solution to the target problem, test it in real life or environment and if necessary, revise the proposed solution.
- **Retain:** After the provided solution is generated, retain the resulting experience to be reusable for future problems as a new case.

5.2. Implementation of Case-Based Reasoning

In order to implement CBR for this system, at the beginning, different real-life cases and real-life solutions to these cases were defined. To define these cases and the corresponding solutions, three professional physical trainers were consulted. The physical trainers; Selvin Çiçek, Efe Can Rübendiz, and Semih Gökalp (personal information given in Appendix-A) were contacted to receive feedback about the different real-life cases and provide solutions to these cases. According to the acquired feedback, the prospective users of the system were categorized into different cases based on their demographic information, medical background and their purpose of using the system. After the categorization step, the solutions are constructed from the physical trainers' suggestions according to their experiences and knowledge for each different case.

While deciding on the cases and their corresponding solutions, the following features were taken into account:

- Age
- Gender
- Body Mass Index (BMI)
- Existence of a Health Problem
- Purpose of using this system

The prospective users enter the above listed features to the system using a Graphical User Interface (GUI), then the system decides on the solution using CBR and suggests an exercise routine. When the user enters his/her height and weight, and the BMI is calculated automatically.

According to the different types of features listed above, the data is structured/divided into various categories. Thus different cases and solutions to those cases are generated which are described in detail in the following sections.

Age Ranges

The age range is divided into 7 categories as given in Table 14. Since the sample data is collected from different type of users within the age range from 7 to 53, Table 14 intentionally represents age ranges within this range.

Table 14. Age Ranges

Age	Exercise
Less than or equal to 7	No regular/systematic exercise suggested
7 - 11	No regular/systematic exercise suggested
12 - 16	Exercise-a is suggested
17 - 30	Exercise-b is suggested
31 - 40	Exercise-c is suggested
41 - 53	Exercise-d is suggested
Above or equal to 54	No regular/systematic exercise suggested

If the prospective user's age is less than 12, or above 53, then no regular or systematic exercise is suggested without a doctor consultation to that user, because the data of the people whose ages are in these ranges can vary in a vast range.

However, if the age range is between 12 and 53, different types of exercises are suggested after analyzing their other demographic information.

Gender of Users

Exercise type and duration differs according to the gender information. Since males generally have more muscle than females, they generally burn 5% more energy than the opposite sex. In addition, in a normal day, males usually get more calories from nutrients than females, so they need to burn more calories. Accordingly, male exercises have longer durations than female exercises as given in Table 15.

Table 15. Gender of Users

User's Information other than Gender	User's Gender	Offered Exercise
Age is between 17 and 30, BMI>normal, does not have any health problem, and wants to lose weight	Female	30 minutes Walking Regularly and 30 minutes Walking Quickly then 15 minutes Running
	Male	35 minutes Walking Regularly and 35 minutes Walking Quickly then 15 minutes Running

Ranges of BMI

The BMI range is divided into 5 different categories and the corresponding classification is given in Table 16.

Table 16. BMI Ranges

BMI	Classification
< = 15,5	Extremely Underweight
> 15,5 and < = 18,5	Underweight
> 18,5 and < = 25,0	Healthy Weight (Normal)
> 25,0 and < = 29,9	Overweight
> = 30,0	Obese

If the prospective user's BMI is less than or equal to 15,5 and if it is higher than or equal to 30,0 then no regular or systematic exercise is suggested without doctor consultation since these BMI values can indicate a risk in the user's health. However, for BMI value between 15,5 and 29,9, several different exercises are suggested after analyzing the user's other demographic information.

Existence of a Health Problem

In this system, the user is required to enter whether he/she has any type of a health problem. If the user inputs the existence of a health problem such as high or low blood pressure, heart related problems, diabetes, etc., only one type of standard exercise is suggested without checking his/her other demographic information as shown in Table 17. This standard exercise is suitable for all users who have a health problem, since it is the standard exercise for the heart and circulatory system.

Table 17. Existence of a Health Problem

Existence of a Health Problem	Offered Exercise
Yes	Standard Exercise: 30 minutes Walking Regularly or 30 minutes Walking Quickly
No	Exercise differs according to users' other information

For the type of users with no health problems, different types of exercises and durations are suggested by considering user's other demographic information.

Purpose of Using the System

The user is expected to enter his/her purpose of using this system. The system is designed for two different types of purposes: Lose Weight and Active Lifestyle. For the purpose of losing weight, the aim is to reduce BMI to the normal (healthy weight) range. To achieve this goal, suitable exercises are suggested. For the purpose of active lifestyle, it is aimed to maintain the user's existing state, and accordingly, the suitable exercises are suggested.

5.3. Combination of all Features

All of the features are analyzed one by one, and are combined together to define different cases and possibilities. Then, suggested solutions namely the exercise routines are constructed for each case for different types of purposes which are shown in Table 18 and Table 19.

Table 18 is generated for the purpose of losing weight and Table 19 for the purpose of active lifestyle. In both tables, each gender column is grouped into three different categories according to the BMI feature. Furthermore, each BMI sub-group column is grouped into two for the feature "existence of a health problem".

In Table 18, each cell represents four different features' combinations for the purpose of losing weight. Therefore, there are 48 different cases when the age category of 7 to 11 is excluded in Table 18. Similarly, Table 19 shows different combinations for the purpose of active lifestyle, and there are 48 different cases in that table as well. As a summary, for different categories of five different features, there are 96 (= 48 + 48) different cases in this study initially.

The abbreviations and signs used for activities of exercises are:

- W: Walking Regularly
- WQ: Walking Quickly
- R: Running
- the apostrophe (’): "minute time" duration
- the sign (/): "or" to denote an alternative

In Table 18 and Table 19, since each cell represents different types of cases, inside each cell a suggested exercise is written particularly for that case. For example, a user with following information:

- Gender: Female
- Age: 15
- BMI: Normal
- Health Status: No
- Purpose: Lose Weight

The exercise offered for that user is: 15’ WQ, 10’ R, 15’ WQ, 5’ W, meaning the user is required to do walk quickly for 15 minutes then run for 10 minutes and walk quickly for 15 minutes again, and finally walk regularly for 5 minutes.

As another example, a user with following information:

- Gender: Male
- Age: 36
- BMI: Normal
- Health Status: No
- Purpose: Active Lifestyle

The exercise offered for that user is: 20’ W/WQ, 20’ R, meaning the user is required to do walk regularly or walk quickly for 20 minutes, then run for 20 minutes.

Table 18. All Cases and Suggested Exercises for the Purpose of Losing Weight

AGE	FEMALE						MALE					
	BMI < normal		BMI = normal		BMI > normal		BMI < normal		BMI = normal		BMI > normal	
	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO
7-11	-	-	-	-	-	-	-	-	-	-	-	-
12-16	30’ W/WQ	15’ W/WQ 10’ R 5’ W	30’ W/WQ	15’ WQ 10’ R 15’ WQ 5’ W	30’ W/WQ	15’ W 15’ WQ	30’ W/WQ	20’ W/WQ 10’ R 5’ W	30’ W/WQ	15’ WQ 15’ R 15’ WQ 5’ W	30’ W/WQ	20’ W 20’ WQ
17-30	30’ W/WQ	20’ W 20’ WQ 10’ R	30’ W/WQ	15’ W/WQ 30’ R	30’ W/WQ	30’ W 30’ WQ 15’ R	30’ W/WQ	25’ W 25’ WQ 10’ R	30’ W/WQ	20’ W/WQ 30’ R	30’ W/WQ	35’ W 35’ WQ 15’ R
31-40	30’ W/WQ	20’ W 20’ WQ 10’ R	30’ W/WQ	20’ W/WQ 20’ R	30’ W/WQ	25’ W 25’ WQ 5’ R	30’ W/WQ	20’ W 20’ WQ 10’ R	30’ W/WQ	20’ W/WQ 20’ R	30’ W/WQ	25’ W 25’ WQ 5’ R
41-53	30’ W	30’ W 30’ WQ	30’ W	45’ W/WQ	30’ W	30’ W/WQ	30’ W/WQ	30’ W 30’ WQ	30’ W/WQ	45’ W/WQ	30’ W/WQ	30’ W/WQ

Table 19. All Cases and Suggested Exercises for the Purpose of Active Lifestyle

AGE	FEMALE						MALE					
	BMI < normal		BMI = normal		BMI < normal		BMI = normal		BMI < normal		BMI = normal	
	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO
7-11	-	-	-	-	-	-	-	-	-	-	-	-
12-16	30’ W/WQ	20’ W/WQ 10’ R	30’ W/WQ	20’ W/WQ 25’ R	30’ W/WQ	15’ W 15’ WQ	30’ W/WQ	20’ W/WQ 10’ R	30’ W/WQ	25’ W/WQ 30’ R	30’ W/WQ	20’ W/WQ 10’ R
17-30	30’ W/WQ	20’ W 20’ WQ 10’ R	30’ W/WQ	10’ W/WQ 20’ R	30’ W/WQ	25’ W 25’ WQ 15’ R	30’ W/WQ	25’ W 25’ WQ 10’ R	30’ W/WQ	15’ W/WQ 20’ R	30’ W/WQ	25’ W 30’ WQ 15’ R
31-40	30’ W/WQ	20’ W 20’ WQ 10’ R	30’ W/WQ	25’ W/WQ 20’ R	30’ W/WQ	25’ W 25’ WQ 5’ R	30’ W/WQ	20’ W 20’ WQ 10’ R	30’ W/WQ	20’ W/WQ 25’ R	30’ W/WQ	30’ W 30’ WQ 10’ R
41-53	30’ W	30’ W 30’ WQ	30’ W	45’ W/WQ	30’ W	30’ W/WQ	30’ W/WQ	30’ W 30’ WQ	30’ W/WQ	45’ W/WQ	30’ W/WQ	30’ W/WQ

Table 18 and Table 19 show all possible cases and offered exercise routines for each case. As stated before, there are a total of 96 (= 48 + 48) different cases for two of the purposes with various exercise suggestions.

But since the scope of this study is narrowed down for the young subset and covers only the users of ages within the range of 17 to 30, the tables and cases are shortened as shown in Table 20 and Table 21.

After discarding other age ranges, the number of cases are reduced to 24 (= 12 + 12) for two of the purposes. Moreover, since some of the offered exercises are similar to each other, there are a total of 11 (= 7 + 4) different solutions for all cases.

Table 20 and Table 21 show each case and offered exercise routines for the young subset, where case numbers and solutions (offered exercise routines) are noted down in each cell separately.

The abbreviations and their explanations/descriptions? used are;

- c: Case
- s: Solution

Case numbers and solution numbers are written in the beginning of each cell. For example, (c1-s1) represents case#1 and solution#1. Case#1 means that it is related with the type of user who is female with BMI which is less than normal and has a health problem and her aim is to lose weight. Solution#1 describes the suggested exercise of 30 minutes of walking regularly or walking quickly. Similarly, (c23-s1) has a meaning of case#23 and solution#1. Case#23 represents a male user with BMI value higher than normal and has a health problem with the purpose of having an active lifestyle. Then the same solution is offered which is solution#1 to that user also, because both of the users have a health problem and standard exercise is suggested for all users with health problems.

Table 20. Used Cases and Suggested Exercises for the Purpose of Losing Weight

AGE	FEMALE						MALE					
	BMI < normal		BMI = normal		BMI > normal		BMI < normal		BMI = normal		BMI > normal	
	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO
17-30	**(c1-s1)** 30’ W/WQ	**(c2-s2)** 20’ W 20’ WQ 10’ R	**(c3-s1)** 30’ W/WQ	**(c4-s3)** 15’ W/WQ 30’ R	**(c5-s1)** 30’ W/WQ	**(c6-s4)** 30’ W 30’ WQ 15’ R	**(c7-s1)** 30’ W/WQ	**(c8-s5)** 25’ W 25’ WQ 10’ R	**(c9-s1)** 30’ W/WQ	**(c10-s6)** 20’ W/WQ 30’ R	**(c11-s1)** 30’ W/WQ	**(c12-s7)** 35’ W 35’ WQ 15’ R

Table 21. Used Cases and Suggested Exercises for the Purpose of Active Lifestyle

AGE	FEMALE						MALE					
	BMI < normal		BMI = normal		BMI < normal		BMI = normal		BMI < normal		BMI = normal	
	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO	Health Problem YES	Health Problem NO
17-30	**(c13-s1)** 30’ W/WQ	**(c14-s2)** 20’ W 20’ WQ 10’ R	**(c15-s1)** 30’ W/WQ	**(c16-s8)** 10’ W/WQ 20’ R	**(c17-s1)** 30’ W/WQ	**(c18-s9)** 25’ W 25’ WQ 15’ R	**(c19-s1)** 30’ W/WQ	**(c20-s5)** 25’ W 25’ WQ 10’ R	**(c21-s1)** 30’ W/WQ	**c22-s10)** 15‘ W/WQ 20’ R	**(c23-s1)** 30’ W/WQ	**(c24-s11)** 25’ W 30’ WQ 15’ R

5.4. Calculation for Similarity Measures

For the implementation of case-based reasoning, all possible cases and provided solutions are constructed as described in the previous sections. For implementation, the C++ programming language is chosen and Dev-C++ 5.4.0 integrated development environment (IDE) is selected.

To represent each different case, a class is constructed and objects are created for each case from this class. All possible cases are written and stored in a text file as the simulation of a database for larger studies. In addition to the other required functions, a compare function is written to calculate the similarity value of the user entered data. Inside the compare function, there are criteria for the selection of features such as age, gender, BMI, medical background and purpose. For example, in order to decide on the age range or BMI range, for each of the ranges, the median is found and the difference is calculated with respect to that median value. The less the difference means a more similar feature.

According to the difference values, weights are defined between the values of 0 and 1 as shown in Tables 21-25 for all the features. For example; the value 0,2 means the difference between the current value and the median is large, which means that the input value is not similar to that case; accordingly, the weight is close to 0 value. However, the value 0,9 denotes that the difference is minimal, namely the user input is very similar to that case, thus the weight is close to 1. Therefore, fine-tuning is performed very carefully by testing all the cases with all possible input values, otherwise the useless solutions can match with a case which is an unexpected situation (Kar, Chakraborti and Ravindran, 2012; Ohana, 2012).

Table 22. Differences of Age Feature

Age Difference Lower Limit	Age Difference Upper Limit	Weight of Age
0	6	0.9
7	10	0.5
11	higher	0.1

Table 23. Differences of BMI Feature

BMI Difference Lower Limit	BMI Difference Upper Limit	Weight of BMI
lower	2.9	0.9
3.0	4.9	0.7
5.0	6.5	0.5
6.6	higher	0.1

Table 24. Selection of Gender Feature

Gender (Female/Male)	Weight of Gender
If equal	1.0
If not equal	0.0

Table 25. Selection of Health Problem Feature

Health Problem (Yes/No)	Weight of Health Problem
If equal	1.0
If not equal	0.0

Table 26. Selection of Purpose Feature

Purpose (Lose Weight / Active Lifestyle)	Weight of Purpose
If equal	1.0
If not equal	0.0

For the similarity calculation (Serrá, 2012; Villanueva, 2012), the above mentioned weights are multiplied with the corresponding features.

Additionally, features also have their own weights. For example; in this study, age and BMI features are selected as Very Important Feature (VIF), so their weights are higher than the other Less Important Features (LIF), gender, health problem and purpose. The decision of very important and less important ones are selected based on their ranges or categories. The features of gender, health problem and purpose have only two states; Female or Male for gender, Yes or No for health problem, and Lose Weight or Active Lifestyle for purpose. Because of this reason, they are categorized as less important feature and have less effect in the calculation. But the features of age and BMI have many ranges, consequently, they are selected as the very important feature which are more effective in the selection criteria as given in Table 27 and Table 28.

Table 27. Weights of Features

Feature	Weight
Very Important Feature	6
Less Important Feature	1

Table 28. Weights of Feature Categories

Feature Category	Weight
Age	6
Gender	1
BMI	6
Health Problem	1
Purpose	1

To calculate the similarity value, for each different case, the following formula is used, with the user input values;

$$S = \frac{\mathrm{VIF} * \mathrm{Wage} + \mathrm{VIF} * \mathrm{Wbmi} + \mathrm{LIF} * \mathrm{Wgender} + \mathrm{LIF} * \mathrm{WhealthPr} + \mathrm{LIF} * \mathrm{Waim}}{\sum_{m=0}^{1}(VIF_{\mathrm{m}}) + \sum_{n=0}^{2}(LIF_n)}$$

The abbreviations and their descriptions used in the above formula are;

- S: Similarity Measure
- VIF: Very Important Feature
- LIF: Less Important Feature
- Wage: weight of Age feature
- Wbmi: weight of BMI feature
- Wgender: weight of Gender feature
- WhealthPr: weight of existence of a Health Problem feature
- Waim: weight of Aim feature

In the above equation, the defined weights of features are multiplied with the corresponding features and added together, then the result is divided into the total of Very Important Feature and Less Important Feature for optimization. In the above formula, the result of all multiplications and summations are divided by 15 as a denominator of the fraction, because two very important features that have a weight of 6 are used (12 = 6 + 6), and three less important features that have a weight of 1 are used (3 = 1 + 1 + 1) in the numerator calculation. Therefore, as a total, of 15 (= 12 + 3) units of weighted features are used, and the summation is divided with this value for optimization. (15 = 6 + 6 + 1 + 1 + 1 = Total number of VIF and LIF weights).

The Similarity Measure (Sum of Weighted Sum / Sum of Weights) result is gathered and each calculation's result is compared with all cases' results in the same manner. When the maximum value is found, that case's solution is selected as the offered solution (McSherry, 2012).

The Compare Function compares two cases each time, and finds a similarity value for each case, then finds the maximum similarity value from a case, and returns the matched case as an object. One of the parameters inside that object is the solution parameter, so the offered exercise is presented to the user from the interface.

To summarize, when a new user starts using the system, the data inputted by the user will be mapped to the best suitable exercise plan based on the existing cases using CBR (Quijano-Sánchez et al, 2012-A; Quijano-Sánchez et al, 2012-B).

In Chapter 5, the implementation of the reasoning module is presented. The cases and their corresponding solutions, the process of calculation and the similarity measure are also provided in this chapter.

CHAPTER 6

EVALUATION

In this chapter, the evaluation results are discussed in detail. The validation according to the questionnaire results of the volunteers are examined briefly. The evaluation process is performed in two steps by the volunteers;

- Testing the system by inputting specific data
- Answering questions of the questionnaire

Then, according to the results of the questionnaire, the users' perception of the usability and effectiveness of the system are evaluated.

6.1. Testing the System

Convenience sampling is applied for the selection of volunteers in the 17 - 30 age range tested the system. The volunteers' age is limited with this range, because as it is stated at the Results of Experiments section, a young group of volunteers are selected and the analysis is done according to this Young Subset group of people. This age range is reflected to the participants of the evaluation also. 32 volunteers tested the system and this number of users is enough for a test set according to the Central Limit Theorem (Walpole et. al., 2013) which states that there must be at least 30 samples to achieve the normal distribution.

Before testing the system, a brief introduction about the system with its general purpose is presented to the volunteer. The volunteers are first requested to input his/her demographic information such as age, gender, height and weight data fields as seen on Figure 8.

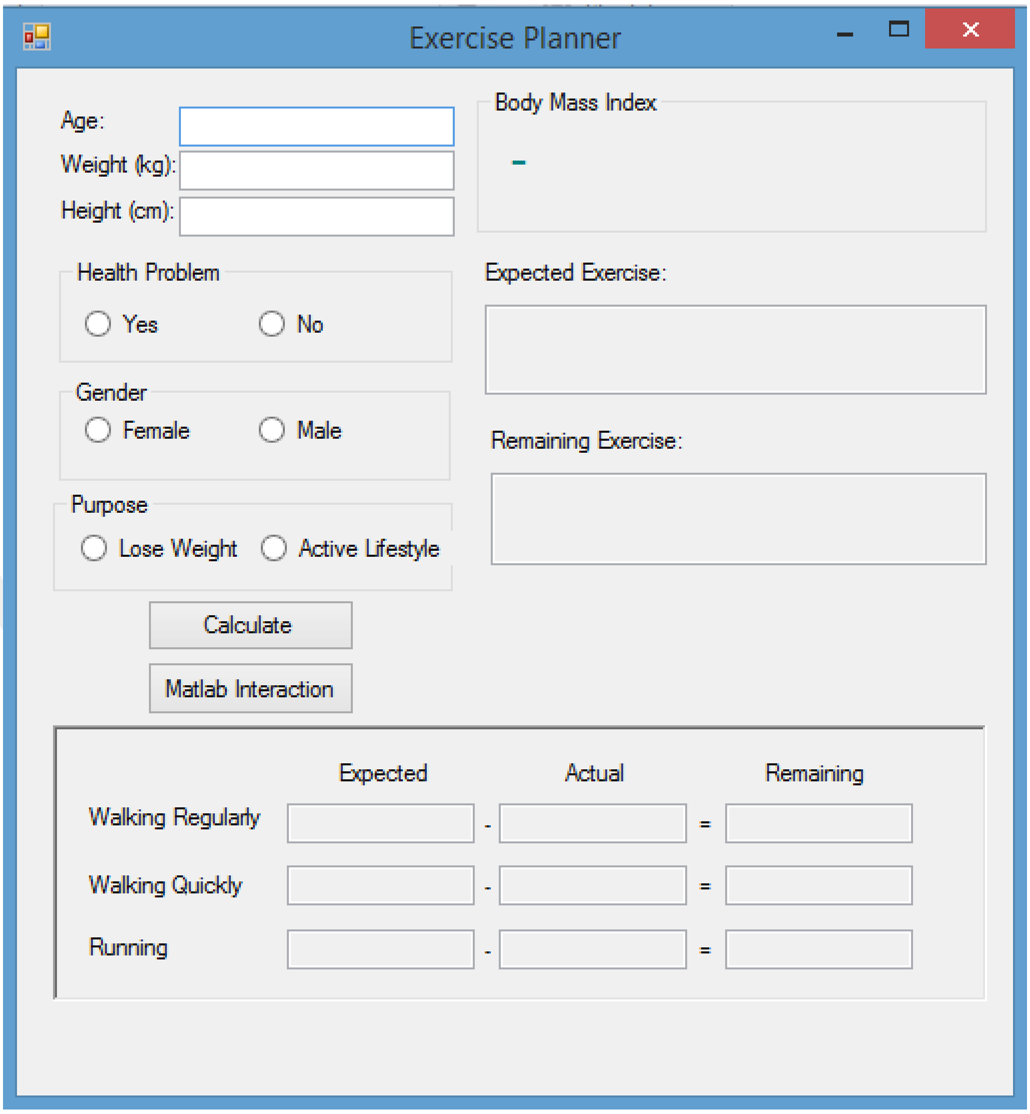

Figure 8. The User Interface of the Exercise Planner Desktop Application

Since the volunteers' demographic information is already known, this information is not asked again in the questionnaire. The Body Mass Index is calculated automatically by the system according to user's inputted weight and height.

Additionally, the volunteer is requested to input two other data fields; namely, existence of a health problem and purpose of using this system. These two input data and the demographic information data fields are combined together, and used to calculate the user's matched group of case to generate an appropriate exercise plan according to that case.

As an example, the filled form of the Exercise Planner desktop application is shown in Figure 9. The user with the demographic information of a 17 year old male with the weight of 54 kg and height of 170 cm is used. He does not have a health problem and his purpose of using this system is to lose weight as seen in Figure 9.

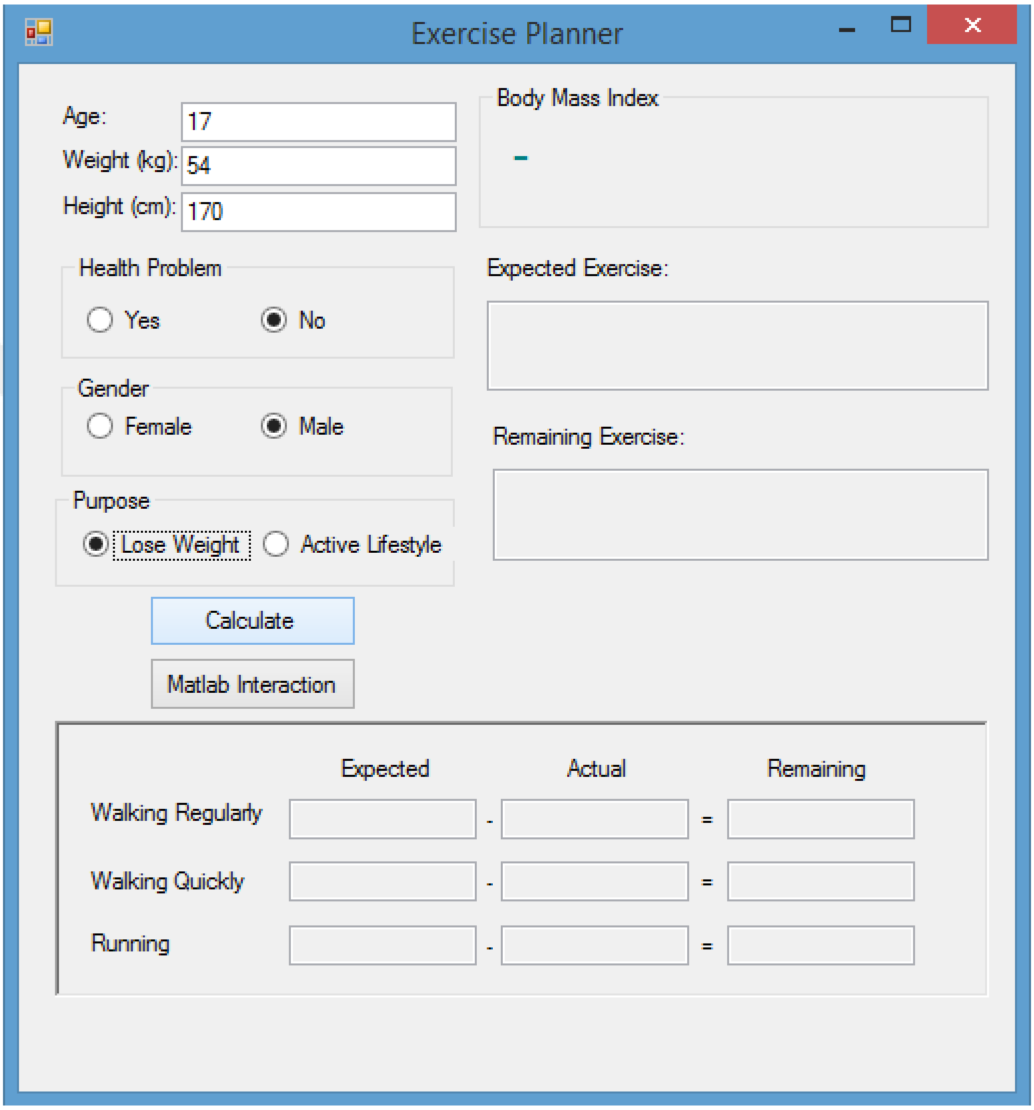

Figure 9. An Example of a Test Data

After entering this information to the interface, the user presses the Calculate button in order to see the advice where the system shows the matched case's solution number on the screen as seen in Figure 10.

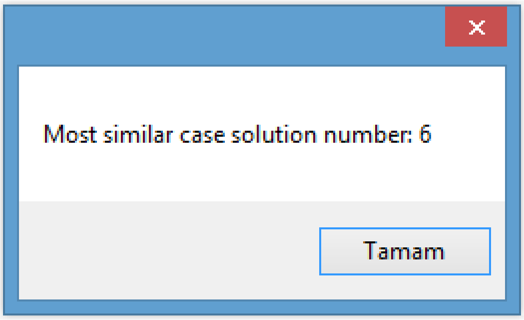

Figure 10. The Solution Number Screen Shot with the Example Data

Then the system calculates the Body Mass Index and shows the advice for each day according to the selected exercise plan which is shown as a solution on the Expected Exercise area on the screen. In addition, the expected values for each different activity is presented at the bottom part of the form as in Figure 11.

In order to validate the case-based reasoning system of this system, 64 different data sets are generated and tested to check whether each of the cases matches with the correct solution. Since fine-tuning is done in order to generate the correct solutions for each case, 100% performance is achieved for the case-based reasoning system validation. Table 29 which is given in Appendix-B shows each of the possible test case data as well as the solution number for each case.

Additionally, when the input data is entered by different volunteers it is also checked whether the correct cases and corresponding solutions are matched with the input data. All different test cases and solutions are correctly calculated by the system which shows that the case-based reasoning module of the implementation works properly for all cases.

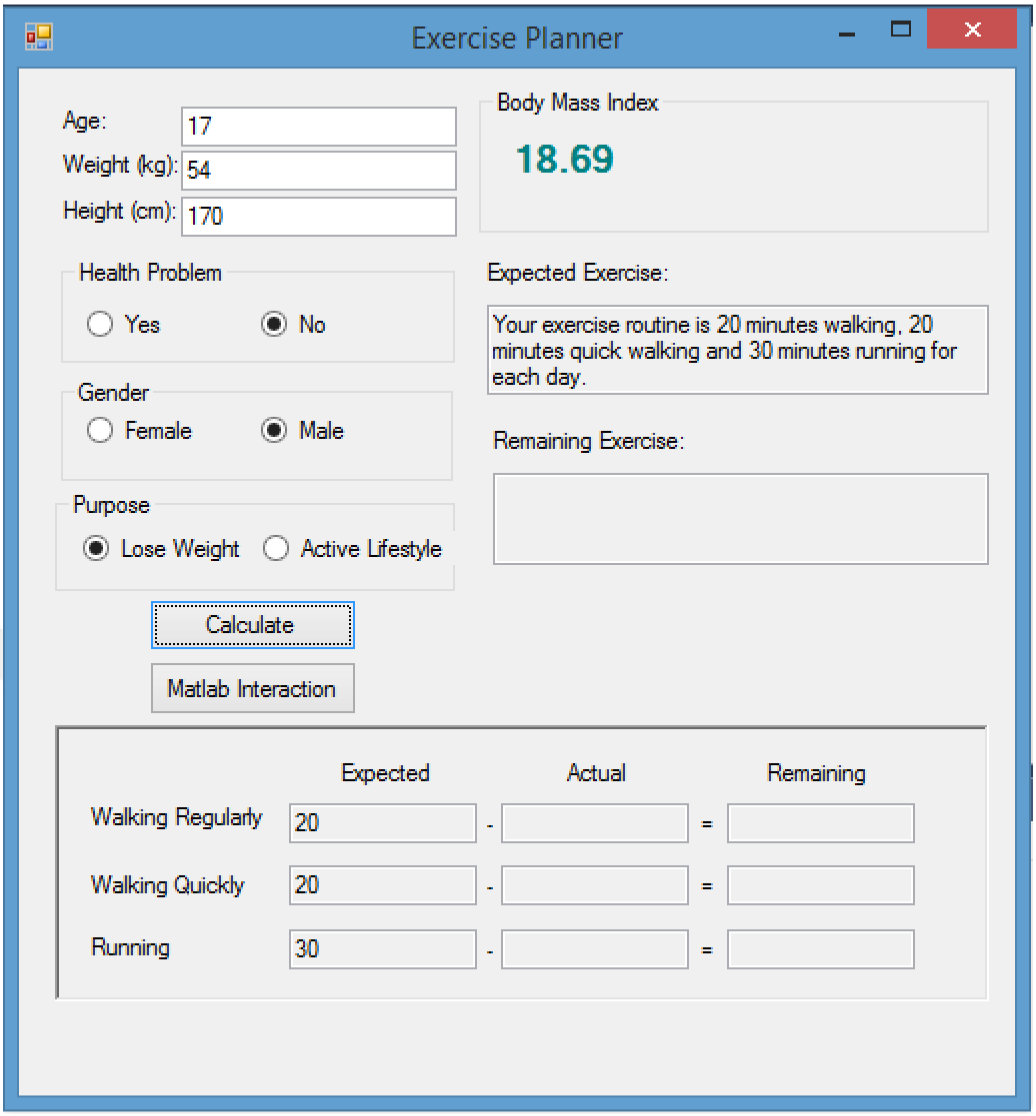

Figure 11. The Corresponding Advice Screen Shot with the Example Data

After this step, it is assumed that the user has done some activity and the data is recorded for that user. This part of the system is done as a simulation since the system is not implemented as a mobile application but as a desktop application, therefore, it was not possible to track the volunteers' activity data. Then, the Matlab Interaction button is activated to recognize the user's activities and the corresponding time for each activity as a simulation. The results of the Activity Recognition Module are shown as the actual values at the bottom part of the form for each different activity as seen in Figure 12.

Furthermore, for motivational purposes, the remaining exercise is reminded to the user after deducting the actual values from the expected values. The remaining activity which is required until the end of the day is shown as a motivation message at the Remaining Exercise box, and as the remaining values at the bottom part of the form for each different activity as seen below in Figure 12.

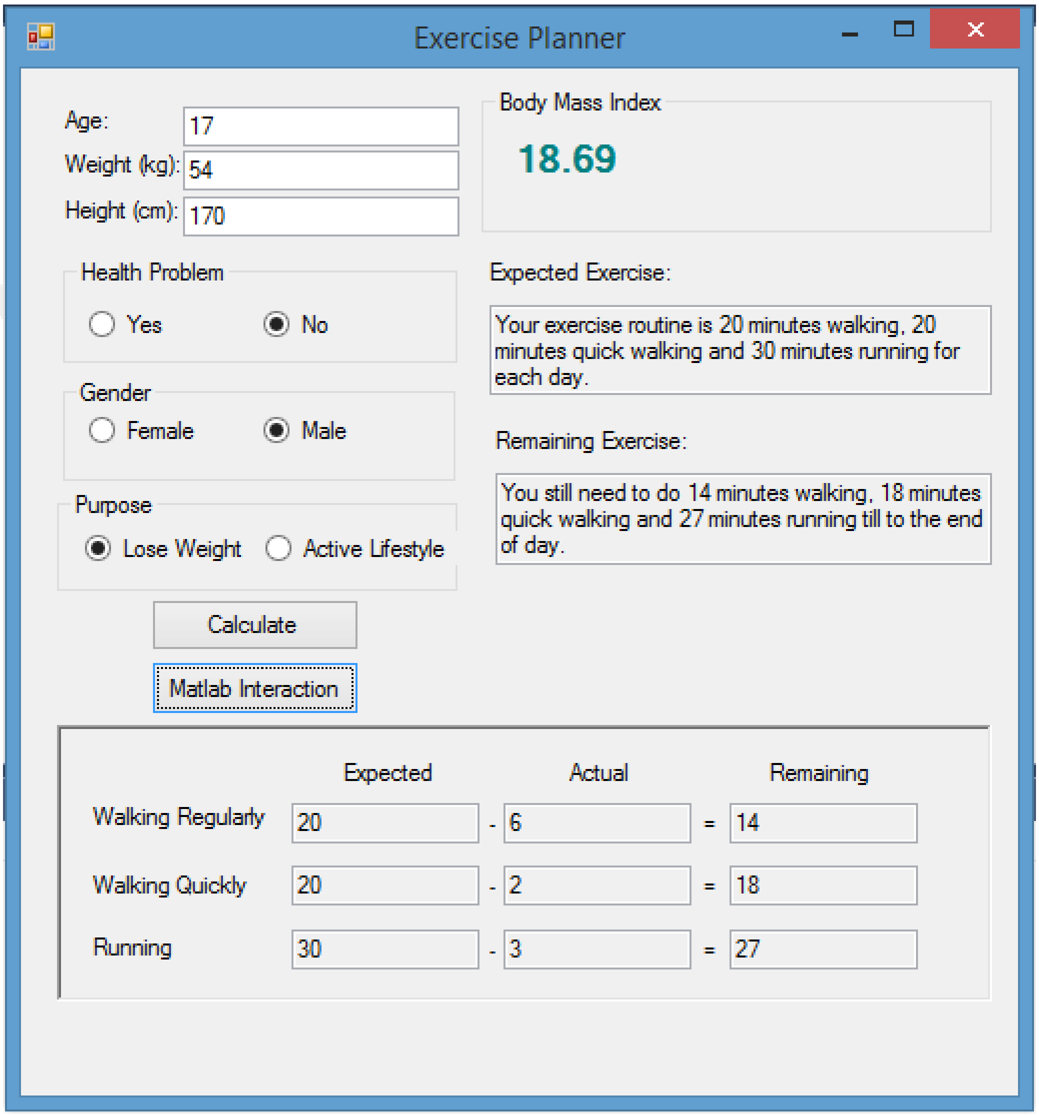

Figure 12. The Actual Activities and Remaining Exercises Screen Shot with the Example Data

6.2. Validation of the System

Each of the 32 volunteer users tested the system, afterwards a questionnaire was conducted to each of them in order to receive their opinions and evaluate the system performance.

6.2.1. The Questionnaire

The questionnaire can be seen below in Table 30.

Table 30. The Questionnaire of the Exercise Planner System

Exercise Planner Questionnaire					
Grade Distributions (1:Very Dissatisfied, 2: Dissatisfied, 3:Ok, 4: Satisfied, 5: Very Satisfied)	**1**	**2**	**3**	**4**	**5**
1- Did you find the system to be useful?					
2- Do you wish to use the system in your daily life?					
3- Will you suggest this system to your friends?					
4- Do you think that this system will help people lose weight?					
5- Do you think that this system will help people for their active lifestyle?					
6- Is the system user friendly?					
7- Is the system easy to use?					
8- Do you think that the system gives acceptable/correct advice?					
9- Do you think that the system motivates the people to complete the remaining exercise?					
10- Does the system work effectively?					
11- Does the system work efficiently?					
12- Give a grade for the overall satisfaction of the system?					

The survey questions are selected carefully to understand the user perception about the tested system. In order to let the user to reflect their idea clearly, all aspects of the system were evaluated in the questionnaire.

Each of the volunteer's grades for each of the questions in the questionnaire can be seen in Table 31 in Appendix-B. When the average values are calculated for each question out of 5,00, the following results are obtained shown in Table 32.

Table 32. The Average Values of Grading

Question Number	Averages
1	4,66
2	4,28
3	4,00
4	4,13
5	4,38
6	4,41
7	4,38
8	4,25
9	4,31
10	4,31
11	4,22
12	4,69
Total Avg:	**4,33**

According to the results of the 32 volunteer users of the Exercise Planner, all of the questions are satisfied according to user perception with at least a minimum average grade of 4,00/5,00. These results show that, all of the volunteers believe that the Exercise Planner System is an effective system to motivate people to exercise daily, and also to complete their exercises to reach their purpose.

The overall average of all the questions is 4,33/5,00, showing a high satisfaction rate for user perception.

Chapter 6 includes the evaluation of the whole system including the reasoning module and activity recognition module supported by a questionnaire and the results are presented.

CHAPTER 7

CONCLUSION

Technology is being improving day by day and changing our lives continuously. As an example, the usage of mobile devices has increased excessively in the recent years. To make people's life easier, mobile devices can be used in the healthcare area also. Mobile applications can provide better personalized healthcare, disease management and services for patients or individual users who take care of their personal healthcare.

The main goal of this research is to develop an intelligent system which offers exercises suitable to individual users according to their demographic information, purpose and existence of a health problem. Then, by tracking the user's physical activity during the day, the system provides guidance to complete the offered exercises in order to motivate and encourage the user. Since the existing applications do not exhibit any type of intelligence, this system contributes to research by providing intelligence in which users benefit by receiving individual exercise plans designed specifically for them.

With respect to the first research question, this study is able to provide a suitable exercise routine to a user based on his/her demographic information, purpose of using this system and health background.

With respect to the second research question, this study is able to track the progress of the user in the execution of a recommended exercise routine using activity recognition.

The developed system is expected to be useful for users who need to lose weight by following an exercise routine, and for people who take care of their personal health and wellness and wish to pursue an active lifestyle. Moreover, this system can also be useful for disease management and treatments. For example, treatment for high cholesterol, psychological disorders, diabetes and physiotherapy require patients to walk regularly.

Additionally, both healthy people and patients are considered as healthcare consumers, and today most healthcare consumers request mobile applications to be included into their daily life for their well-being. Moreover, the providers in the healthcare industry also are willing to provide more innovative applications.

In addition, using such kind of applications help to collect and store accurate data of users which are really important for this domain to help medical doctors or physical trainers to analyze correct data.

As discussed in the literature review, previous studies have used mobile technology in healthcare for weight control by checking user information once every six months, or monitoring user diets providing daily feedbacks.

However, in our system, personalized exercise plans are offered to each user depending on their specific information which promises better weight loss by providing continuous encouragement.

Moreover, in the study of Reddy et. al. (2010), the activity classification was performed a classification system consisting of a decision tree followed by a first-order discrete Hidden Markov Model (HMM), achieving a performance of 93.6% with the dataset of sixteen individuals. However, in our study, a performance of 98.65% with the data set of fourty individuals was achieved. Additionally, in Reddy's study the activities were walking, running, biking, motorized transport and the stationary position of an individual which are not similar to each other when compared to our study of similar activities which are harder to differentiate, namely, walking regularly, walking quickly and running.

In the study of Miluzzo et. al. (2008), three activities of walking, running and still position of the user were recognized using accelerometer, achieving the performance of 78% with eight users. Also, Zheng et. al. (2008) performed activity classification of walking, biking and motorized transportation using GPS data and the performance of 76% was achieved with sixty five users. In addition, Sohn et. al. (2006) performed the classification of walking, motorized transportation and still position of the user using a mobile phone and achieved a performance of 85% with three users. In these studies, only activity classifications are performed without offering any recommendation to the user. With the model that we have developed, we have achieved a much better performance of 98.65% in activity classification with the data set of fourty individuals along with offering an exercise routine that specifically meets the user needs and demographic information.

7.1. Limitations

Classifying the users' activities into only three groups is one of the limitations of this study, it can be enhanced to recognize more type of activities such as jumping, standing, riding a bicycle, etc. Another limitation is, since this system is a prototype, it is developed as a desktop application, and can be developed as a mobile application that works at the background mode of a mobile phone.

Another limitation is the limited age group, since this system is implemented for the young subset of users to achieve better performances for the activity recognition, and this can be applied to all users regardless of their age.

Additionally, for the validation of the system, feedback from companies' working in this domain can be collected.

Moreover, since this system is developed as a prototype and generated as a desktop application rather than a mobile application, while testing the system with the volunteers, their real exercise activities could not be collected, and was done as a simulation.

7.2. Future Work

For future work, heart rate measurement or blood pressure can be incorporated into the system. In addition, music and rhythm can be added to increase or decrease user's tempo since they can require a motivation to change from walking regularly to walking quickly or to running or vice versa, as well as to encourage them to continue with the activity. Additionally, a multi-language system can also be developed to be helpful for a wider range of users.

In addition, other available sensors in mobile phones can be used such as GPS which can be included in the study to track the position of the user. Moreover, to give the comments/advices to the user orally, a microphone can be attached to the system.

Moreover, different types of classification methods can also be tested with this data set to compare their performances such as K-means which is a promising algorithm while working on the physical activity data set both for giving high performance and taking a shorter time period for analysis. Finally, such a mobile application can be applied to another area other than healthcare, such as security, entertainment or detecting/analyzing the environment, such as when the mobile phone is not answered an automatic text message can be sent to the caller such as "driving right now", or "running right now", etc.

REFERENCES

Aamodt, A. and Plaza, E. (1994). Case-Based Reasoning: Foundational Issues, Methodological Variations, and System Approaches. *AI Communications. IOS Press, Vol. 7 (1),* (pp. 39-59).

Abbas, B. B., Fares, A. A., Jabbari, M., Dali, A. E. and Orifi, F. A. (2015). Effect of Mobile Phone Short Text Messages on Glycemic Control in Type 2 Diabetes. International Journal of Endocrinol Metab. 2015 January; 13(1): e18791. DOI: 10.5812/ijem.18791.

Abdallah, Z. S., Gaber, M. M., Srinivasan, B. and Krishnaswamy, S. (2015). Adaptive mobile activity recognition system with evolving data streams. *Neurocomputing 150 (2015),* (pp. 304-317). http://dx.doi.org/10.1016/j.neucom. 2014.09.074.

Arifoglu, D. and Bouchachia, A. (2017). Activity Recognition and Abnormal Behaviour Detection with Recurrent Neural Networks. *The 14th International Conference on Mobile Systems and Pervasive Computing (MobiSPC 2017), Procedia Computer Science 110 (2017),* (pp. 86-93). 10.1016/j.procs.2017.06.121.

Årsand, E., Frøisland, D. H., Skrøvseth, S. O., Chomutare, T., Tatara, N., Hartvigsen, G., and Tufano, J. T. (2012). Mobile Health Applications to Assist Patients with Diabetes: Lessons Learned and Design Implications. *Journal of Diabetes Science and Technology, vol. 6, Issue 5,* Diabetes Technology Society.

Atluri, V., Rao, S., Rajah, T., Schneider, J., Thibaut, M., Varanasi, S., and Velamoor, S. (April 2015). Unlocking digital health: Opportunities for the mobile value chain. *Telecommunications, Media, and Technology*. Url: www.mckinsey.com, date of visit: 05.11.2015.

Ayu, M. A., Ismail, S. A., Matin, A. F. A. and Mantoro, T. (2012). A comparison study of classifier algorithms for mobile-phone’s accelerometer based activity recognition. *International Symposium on Robotics and Intelligent Sensors 2012 (IRIS 2012), Procedia Engineering 41 (2012),* (pp. 224 - 229). DOI: 10.1016/j.proeng. 2012.07.166

Azar, K. M. J., Lesser, L. I., Laing, B. Y., Stephens, J., Aurora, M. S., Burke, L. E., Palaniappan, L. P. (2013). Mobile Applications for Weight Management, Theory-Based Content Analysis. *American Journal of Preventive Medicine, Published by Elsevier Inc., Am J Prev Med 2013;45(5)*: (pp. 583-589). http://dx.doi.org/10.1016/j. amepre.2013.07. 005

Azhar, F. A. B. and Dhillon, J. S. (2016). A Systematic Review of Factors Influencing the Effective Use of mHealth Apps for Self-care. *3rd International Conference On Computer And Information Sciences (ICCOINS),* (pp. 191-196). DOI: 978-1-5090-2549-7/16.

Bao, L. and Intille, S. S. (2004). Activity Recognition from User-Annotated Acceleration Data. *A. Ferscha and F. Mattern (Eds.): PERVASIVE 2004, LNCS 3001*, (pp. 1-17), Springer-Verlag Berlin Heidelberg 2004.

Bayat, A., Pomplun, M. and Tran, D. A. (2014). A Study on Human Activity Recognition Using A ccelerometer Data from Smartphones. *The 11th International Conference on Mobile Systems and Pervasive Computing, Procedia Computer Science 34 (2014),* (pp. 450-457). DOI: 10.1016/j.procs.2014.07.009.

Berenbach B., Paulish D. J., Kazmeier J. and Rudorfer A. (2009). Software & Systems Requirements Engineering: In Practice, Mc Graw Hill.

Bhattacharya, S., Nurmi, P., Hammerla, N. and Plötz, T. (2014). Using unlabeled data in a sparse-coding framework for human activity recognition. *Pervasive and Mobile Computing 15 (2014),* (pp. 242-262). http://dx.doi.org/10.1016/j.pmcj. 2014.05.006.

Bourque P. and Fairley R.E. (2014). Guide to the Software Engineering Body of Knowledge (SWEBOK). IEEE Computer Society.

Burke, L. E., Styn, M. A., Sereika, S. M., Conroy, M. B., Ye, L., Glanz, K., Sevick, M. A. and Ewing, L. J. (2012). Using mHealth Technology to Enhance Self-Monitoring for Weight Loss A Randomized Trial. *American Journal of Preventive Medicine, Published by Elsevier Inc, Am J Prev Med 2012;43(1)*: (pp. 20-26). http://dx.doi.org/10.1016/j.amepre.2012.03.016.

Buttussi, F., and Chittaro, L. (2008). MOPET: A context-aware and user-adaptive wearable system for fitness training. *Artificial Intelligence in Medicine, 42(2),* (pp. 153-163).

Buttussi, F., Chittaro, L., and Nadalutti, D. (2009). Filtering fitness trail content generated by mobile users. *Proceedings of the 17th International Conference on User Modelling Adaptation and Personalization (UMAP 2009),* Trento, Italy, (pp. 441-446).

Camacho, J., Ferrer, A. (2014). Cross-validation in PCA models with the element-wise k-fold (ekf) algorithm: Practical aspects. *Chemometrics and Intelligent Laboratory Systems, vol 131*, (pp. 37–50).

Chen, G and Kotz, D. (2000). A Survey of Context-Aware Mobile Computing Research. Dartmouth Computer Science Technical Report TR2000-381, Dartmouth College, Department of Computer Science, this research has been supported by DARPA contract F30602-98-2-0107, by DoD MURI contract F49620-97-1-03821, by Microsoft Research, and by Cisco Systems University Research Program.

Chetty, G., White, M., Akther, F. (2015). Smart Phone Based Data Mining For Human Activity Recognition. International Conference on Information and Communication Technologies (ICICT 2014), Procedia Computer Science 46 (2015), (pp. 1181-1187). DOI: 10.1016/j.procs.2015.01.031.

Chomutare, T., Fernandez-Luque, L., Arsand, E., Hartvigsen, G. (2011). Features of mobile diabetes applications: review of the literature and analysis of current applications compared against evidence-based guidelines, *J Med Internet Res*., 22;13(3):e65, doi: 10.2196/jmir.1874.

Cleland, J., Caldow, J., and Ryan, D. (2007). A qualitative study of the attitudes of patients and staff to the use of mobile phone technology for recording and gathering asthma data. *Journal of Telemedicine and Telecare, vol. 13 (2)*, (pp. 85-89).

Cojocarlu, L.-N., Dimian, M. and Prelipceanu, M. (2013). Developing a wireless electrocardiography device for mobile and at-home healthcare applications. *The 4th IEEE International Conference on E-Health and Bioengineering - EHB 2013*, 978-1-4799-2373-1/13.

Conroy, D. E., Yang, C-H. and Maher, J. P. (2014). Behavior Change Techniques in Top-Ranked Mobile Apps for Physical Activity. *American Journal of Preventive Medicine Published by Elsevier Inc. Am J Prev Med 2014;46(6)*: (pp. 649-652)

Cornelius, F. H., and Gordon, M. G. (2008). PDA Connections: Mobile Technology for Health Care Professionals. *Nurse Education Today, vol. 28,* (pp. 129-129).

Dee, C. R., Teolis, M., and Todd, A. D. (2005). Physicians' use of the personal digital assistant (PDA) in clinical decision making. *Journal of the Medical Library Association, vol. 93 (4)*, (pp. 480-486).

Denning, T., Andrew, A., Chaudhri, R., Hartung, C., Lester, J., Borriello, G., and Duncan, G. (2009). BALANCE: Towards a Usable Pervasive Wellness Application with Accurate Activity Inference. *Proceedings of the 10th IEEE Workshop on Mobile Computing Systems and Applications (HotMobile 2009); 2009: 5*. IEEE Computer Society Press, Los Alamitos, CA. DOI:10.1145/1514411.1514416.

Easterbrook, S., Singer, J., Storey, M. A. and Damian, D. (2008). Selecting Empirical Methods for Software Engineering Research. Guide to Advanced Empirical Software Engineering, (pp. 285-311), DOI: 10.1007/978-1-84800-044-5_11, Print ISBN: 978-1-84800-043-8, Online ISBN: 978-1-84800-044-5.

Erdaş, Ç. B., Atasoy, I., Açıcı, K. and Oğul, H. (2016). Integrating features for accelerometer-based activity recognition. *The 3rd International Symposium on Emerging Information, Communication and Networks (EICN 2016), Procedia Computer Science 98 (2016)*, (pp. 522-527). DOI: 10.1016/j.procs.2016.09.070

Faridi, Z., Liberti, L., Shuval, K., Northrup, V., Ali, A., and Katz, DL. (2008). Evaluating the impact of mobile phone technology on type 2 diabetic patients' self-management: the NICHE pilot study. *Journal of Evaluation Clinical Practice, vol. 14 (3)*, (pp. 465-469).

Fish and Richardson. (2013). Wireless Medical Technologies: Navigating Government Regulation in the New Medical Age. Final Regulatory White Paper Wireless Medical Technologies. Fish’s Regulatory & Government Affairs Group: Terry G. Mahn, Chair Washington, D.C.

Georga, E. I., Protopappas, V. C., Bellos, C. V. and Fotiadis, D. I. (2014), Wearable systems and mobile applications for diabetes disease management, *Health Technology (2014) 4*: (pp. 101-112). DOI: 10.1007/s12553-014-0082-y.

Gröschel, J., Philipp, F., Skonetzki, St., Genzwürker, H., Wetter, Th., and Ellinger, K. (2004). Automated speech recognition for time recording in out-of-hospital emergency medicine - an experimental approach. *Elsevier, Resuscitation, vol. 60*, (pp. 205-212).

Guy, R., Hocking, J., Wand, H., Stott, S., Ali, H., and Kaldor, J. (2011). How Effective Are Short Message Service Reminders at Increasing Clinic Attendance? A Meta-Analysis and Systematic Review. *Health Research and Educational Trust*, DOI:10.1111/j.1475-6773.2011.01342.x.

Han, J., Schmidtke, H. R., Xie, X. and Woo, W. (2014). Adaptive content recommendation for mobile users: Ordering recommendations using a hierarchical context model with granularity. Pervasive and Mobile Computing 13 (2014), (pp. 85-98). http://dx.doi.org/10.1016/j.pmcj.2013.11.002.

Hong, J.-Y., Suh, E.-H. and Kim, S.-J. (2009). Context-aware systems: A literature review and classification. *Expert Systems with Applications 36 (2009)*. (pp. 8509-8522). DOI: 10.1016/j.eswa.2008.10.071.

Hundert, A. S., Huguet, A., McGrath, P. J., Stinson, J. N., and Wheaton, M. (2014). Commercially Available Mobile Phone Headache Diary Apps: A Systematic Review. *JMIR Mhealth Uhealth. 2(3)*: e36. doi: 10.2196/mhealth.3452.

Ihianle, I. K., Naeem, U. and Tawil, A.-R. (2016). Recognition of Activities of Daily Living from Topic Model. *The 7th International Conference on Emerging Ubiquitous Systems and Pervasive Networks (EUSPN 2016), Procedia Computer Science 98 (2016),* (pp. 24-31). DOI: 10.1016/j.procs.2016.09.007.

Imtiaz, H., Mahbub, U., Schaefer, G., Zhu, S. Y.and Ahad, A. R. (2015). Human Action Recognition based on Spectral Domain Features. *19th International Conference on Knowledge Based and Intelligent Information and Engineering Systems, Procedia Computer Science 60 (2015)*, (pp. 430 - 437). DOI: 10.1016/j. procs.2015.08.161.

Jain, A. K., Duin, R. P. W. and Mao, J. (2000). Statistical Pattern Recognition: A Review. *IEEE Transactions on Pattern Analysis and Machine Intelligence, Volume: 22, Issue: 1*, (pp. 4-37). ISSN: 0162-8828, INSPEC Accession Number: 6525225, DOI: 10.1109/34.824819.

Jalali, V. and Leake, D. (2015). CBR Meets Big Data: A Case Study of Large-Scale Adaptation Rule Generation. *Proceedings of the Twenty-Third International Conference on Case-Based Reasoning, ICCBR-15*, Springer-Verlag, Berlin, 15 pages.

Kaghyan, S. and Sarukhanyan, H. (2013). Accelerometer and GPS Sensor Combination BasedSystem for Human Activity Recognition. *Ninth International Conference on Computer Science and Information Technologies, Revised Selected Papers*.

Kalem, G. and Turhan, Ç. (2015-A). Mobile Technology Applications in the Healthcare Industry for Disease Management and Wellness. *World Conference on Technology, Innovation and Entrepreneurship*, Procedia - Social and Behavioral Sciences, 195 (2015), (pp. 2014-2018), DOI: 10.1016/j.sbspro.2015.06.216.

Kalem, G. and Turhan, Ç. (2015-B). Sağlık Sektöründe Mobil Teknoloji Uygulamaları. *TBD 32. Ulusal Bilişim Kurultayı (BİLİŞİM' 2015)*, Ankara, (pp. 14-17). ISBN: 978-9944-5291-9-8.

Kalem, G. and Turhan, Ç. (2016). Fiziksel Aktivite Tanıma Sistemi. *TBD 33. Ulusal Bilişim Kurultayı (BİLİŞİM' 2016)*, Ankara, (pp. 49-54). Elektronik Kitap (Çevrim içi / Web tabanlı), ISBN: 978-605-82941-0-3.

Kar, D., Chakraborti, S. and Ravindran, B. (2012). Feature Weighting and Confidence Based Prediction for Case Based Reasoning Systems. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development*, LNCS 7466, (pp. 211–225), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Kohavi, R. (1995). A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *International Joint Conference on Articial Intelligence (IJCAI)*.

Kowalski, R. (2009). Reasoning with Conditionals in Artificial Intelligence. Department of Computing, Imperial College London.

Krishna, S., Boren, S. A., E. and Balas, A. (April 2009). Healthcare via Cell Phones: A Systematic Review. *TELEMEDICINE and e-HEALTH*, DOI: 10.1089/tmj.2008.0099, Mary Ann Liebert, Inc., vol. 15, no. 3.

Kumar, M. A., and Gopal, M. (2011). Reduced one-against-all method for multiclass SVM classification. *Expert Systems with Applications*, 2011, 38, (pp. 14238-14248), doi:10.1016/j.eswa.2011.04.237.

Kumar, S., Nilsen, W. J., Abernethy, A., Atienza, A., Patrick, K., Pavel, M., Riley, W. T., Shar, A., Spring, B., Spruijt-Metz, D., Hedeker, D., Honavar, V., Kravitz, R., Lefebvre, R. C., Mohr, D. C., Murphy, S. A., Quinn, C., Shusterman, V., Swendeman, D. (2013). Mobile Health Technology Evaluation, The mHealth Evidence Workshop. *American Journal of Preventive Medicine, Published by Elsevier Inc., 2013; 45(2)*: (pp. 228-236). http://dx.doi.org/10.1016/j.amepre.2013.03.017

Lapinsky, S. E. (2007). Mobile computing in critical care. *Elsevier, Journal of Critical Care, vol. 22*, (pp. 41-44).

Liebert, M. A. I. (January/February 2010). Medical Apps For Smartphones. *TELEMEDICINE and e-HEALTH*, DOI: 10.1089=tmj.2010.9999, vol. 16, no. 1.

Lymberis, A., and Olsson, S. (2003). Intelligent Biomedical Clothing for Personal Health and Disease Management: State of the Art and Future Vision. *Telemedicine Journal and e-Health, vol. 9*, number 4.

Martin, H., Bernardos, A. M., Iglesias, J., and Casar, J. R. (2013). Activity logging using lightweight classification techniques in mobile devices. *Pers Ubiquit Comput, 17:*, (pp. 675-695), DOI 10.1007/s00779-012-0515-4.

McSherry, D. (2012). A Lazy Learning Approach to Explaining Case-Based Reasoning Solutions. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development,* LNCS 7466, (pp. 241-254), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Miluzzo, E., Lane, N. D., Fodor, K., Peterson, R., Lu, H., Musolesi, M., Eisenman, S. B., Zheng, X. and Campbell A. T. (2008). Sensing Meets Mobile Social Networks: The Design, Implementation and Evaluation of the CenceMe Application. *SenSys'08, November 5-7, 2008*, Raleigh, North Carolina, USA. ACM 978-1-59593-990-6/08/11.

Mizouni, R., Matar, M. A., Mahmoud, Z. A., Alzahmi, S. and Salah, A. (2014). A framework for context-aware self-adaptive mobile applications SPL. *Expert Systems with Applications 41 (2014),* (pp. 7549-7564). http://dx.doi.org/10.1016/j.eswa.2014.05.049.

Mosa, A. S. M., Yoo, I. and Sheets, L. (2012). A Systematic Review of Healthcare Applications for Smartphones. *BMC Medical Informatics and Decision Making 2012, 12:67.* http://www.biomedcentral.com/1472-6947/12/67. DOI:10.1186/1472-6947-12-67.

Nievergelt, J. (2000). Exhaustive Search, Combinatorial Optimization and Enumeration: Exploring the Potential of Raw Computing Power. *V. Hlavac, K. G. Jeffery, and J. Wiedermann (Eds.): SOFSEM 2000, LNCS 1963,* (pp. 18-35). Springer-Verlag Berlin Heidelberg 2000.

O’Reilly, G. A. and Spruijt-Metz, D. (2013). Current mHealth Technologies for Physical Activity Assessment and Promotion. *American Journal of Preventive Medicine. Am. J. Prev. Med. 2013; 45 (4)*, (pp. 501–507).

Ohana, B., Delany, S. J., and Tierney, B. (2012). A Case-Based Approach to Cross Domain Sentiment Classification. Feature Weighting and Confidence Based Prediction for Case Based Reasoning Systems. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development,* LNCS 7466, (pp. 284-296), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Oliver, N., and Flores-Mangas, F. (2006). MPTrain: a mobile, music and physiology-based personal trainer. *Proceedings of the 8th Conference on Human Computer Interaction with Mobile Devices and Services*, Espoo, Finland, (pp. 21–28).

Ontanon, S., and Plaza, E. (2012). On Knowledge Transfer in Case-Based Inference. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development,* LNCS 7466, (pp. 312-326), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Patrick, K., Marshall, S. J., Davila, E. P., Kolodziejczyk, J. K., Fowler, J. H., Calfas, K. J., Huang, J. S., Rock, C. L., Griswold, W. G., Gupta, A., Merchant, G., Norman, G. J., Raab, F., Donohue, M. C., Fogg, B. J. and Robinson, T. N. (2014). Design and implementation of a randomized controlled social and mobile weight loss trial for young adults (project SMART). *Contemporary Clinical Trials 37 (2014)*, (pp. 10-18). http://dx.doi.org/10.1016/j.cct.2013.11.001.

Pfleeger, S. L. and Atlee, J.M. (2009). Software Engineering: Theory and Practice. Pearson, Fourth Edition, ISBN: 0136061699.

Pressman, R. S. and Maxim, B. R. (2014). Software Engineering: A Practitioner's Approach. McGraw Hill, Eighth Edition, ISBN: 0078022126.

Price, S., and Summers, R. (2006). Mobile healthcare in the home environment. *EMBS Annual International Conference*.

Proudfoot, J. (2013). The future is in our hands: The role of mobile phones in the prevention and management of mental disorders. *Australian & New Zealand Journal of Psychiatry 47(2)*, 111–113.

Quijano-Sánchez, L., Bridge, D., Díaz-Agudo, B., and Recio-García, J. A. (2012-A). Case-Based Aggregation of Preferences for Group Recommenders. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development,* LNCS 7466, (pp. 327-341), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Quijano-Sánchez, L., Bridge, D., Díaz-Agudo, B., and Recio-García, J. A. (2012-B). A Case-Based Solution to the Cold-Start Problem in Group Recommenders. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development,* LNCS 7466, (pp. 342-356), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Rasekh, A., Chen, C.A. and Lu, Y. (2011). Human Activity Recognition using Smartphone. *Texas A&M University, Cornell University Library*. arXiv:1401.8212 [cs.CY].

Ravi, N., Dandekar, N., Mysore, P., and Littman, M. L. (2005). Activity Recognition from Accelerometer Data. *American Association for Artificial Intelligence, IAAI-05*, (pp. 1541-1546). www.aaai.org.

Recker, J. (2013). Scientific Research in Information Systems. Progress in IS. *Queensland University of Technology*. ISBN 978-3-642-30047-9 ISBN 978-3-642-30048-6 (eBook), DOI 10.1007/978-3-642-30048-6, Springer Heidelberg New York Dordrecht London.

Reddy, S., Mun, M., Burke, J., Estrin, D., Hansen, M., and Srivastava, M. (February 2010). Using Mobile Phones to Determine Transportation Modes. *ACM Transactions on Sensor Networks, vol. 6, No. 2,* Article 13, ACM: 1550-4859/2010/02 - ART13, DOI: 10.1145/1689239.1689243, http://doi.acm.org/10.1145/1689239.1689243.

Richter, M. M., and Weber, R. O. (2013). Case-Based Reasoning - a textbook, Springer ISBN: 978-3-642-40166-4 (Print) 978-3-642-40167-1 (Online).

Ryan, D., Cobern, W., Wheeler, J., Price, D., and Tarassenko, L. (2005). Mobile phone technology in the management of asthma. *Journal of Telemedicine and Telecare*, *vol. 11 (1)*, (pp. 43-46).

Sauer, C. S., Hundt, A. and Roth-Berghofer, T. (2012). Explanation-Aware Design of Mobile myCBR-Based Applications. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development,* LNCS 7466, (pp. 399-413), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Scordo, K. A., Yeager, S., and Young, L. (2003). Use of personal digital assistants with acute care nurse practitioner students. *American Association of Critical-Care Nurses, vol. 14, (3),* (pp. 350-362).

Serrá, J., and Arcos, J. L. (2012). A Competitive Measure to Assess the Similarity between Two Time Series. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development,* LNCS 7466, (pp. 414-427), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Sharan, R. V., and Moir, T. J. (2015). Noise robust audio surveillance using reduced spectrogram image feature and one-against-all SVM. Neurocomputing 2015, 158. (pp. 90-99). http://dx.doi.org/10.1016/j.neucom.2015.02.001.

Sherry, J. M., and Ratzan, S. C. (2012). Measurement and Evaluation Outcomes for mHealth Communication: Don't We Have an App for That?. *Journal of Health Communication,* 17: (pp. 1-3), Taylor & Francis Group, LLC ISSN: 1081-0730 print/1087-0415 online DOI: 10.1080/10810730.2012.670563.

Shoaib, M., Bosch, S., Durmaz-Incel, O., Scholten, H., and Havinga, P. J. M. (2015). A Survey of Online Activity Recognition Using Mobile Phones. *Sensors 2015, 15*, (pp. 2059-2085), DOI: 10.3390/s150102059.

Siau, K., and Shen, Z. (2000). Mobile Healthcare Informatics. *Medical Informatics and the Internet in Medicine, vol. 31 (2),* (pp. 89-99).

Sohn, T., Varshavsky, A., Lamarca, A., Chen, M., Choudhury, T., Smith, I., Consolvo, S., Hightower, J., Griswold, W., and De Lara, E. (2006). Mobility detection using everyday GSM traces. *Lecture Notes in Computer Science*, vol. 4206, Springer-Verlag, Berlin, Germany, 212.

Sommerville, I. (2015). Software Engineering. Addison-Wesley, Tenth Edition, ISBN: 0133943038.

Španiel, F., Vohlídka, P., Hrdlička, J., Kožený, J., Novák, T., Motlová, L., Čermák, J., Bednařík, J., Novák, D., & Höschl, C. (2008). ITAREPS: Information Technology Aided Relapse Prevention Programme in Schizophrenia. *Science Direct, Schizophrenia Research, 98*, (pp. 312-317).

Stevens, D. J., McKenzie, K., Cui, H. W., Noble, J. G. and Turney, B. W. (2015). Smartphone apps for urolithiasis. Urolithiasis (2015) 43: (pp. 13-19), DOI: 10.1007/s00240-014-0738-0.

Suarez, I., Jahn, A., Anderson, C. and David, K. (2015). Improved Activity Recognition by Using Enriched Acceleration Data. *UBICOMP '15, SEPTEMBER 7-11, 2015, OSAKA, JAPAN, Session: People, Traces and Behaviors*, (pp. 1011-1015). ACM: 978-1-4503-3574-4/15/09, http://dx.doi.org/10.1145/2750858.2805844.

Sun, L., Zhang, D., Li, B., Guo, B. and Li, S. (2010). Activity Recognition on an Accelerometer Embedded Mobile Phone with Varying Positions and Orientations. *Ubiquitous Intelligence and Computing, Volume: 6406 of the series Lecture Notes in Computer Science, 7th International Conference, UIC 2010, Xi'an, China, Proceedings*, (pp. 548-562), DOI: 10.1007/978-3-642-16355-5_42, Print ISBN: 978-3-642-16354-8.

Tapkın, S., Şengöz, B., Şengül, G., Topal, A. and Özçelik, E. (2015). Estimation of Polypropylene Concentration of Modified Bitumen Images by Using k-NN and SVM Classifiers. *Journal of Computing in Civil Engineering*, 2015. 29, 5. (pp. 401-405), DOI : 10.1061 / (ASCE) CP . 1943 - 5487 . 0000353. ISSN : 0887 - 3801 / 04014055 (11).

Villanueva, B. S., and Sánchez-Marre, M. (2012). Case-Based Reasoning Applied to Textile Industry Processes. *20th International Conference, ICCBR 2012, Case-Based Reasoning Research and Development*, LNCS 7466, (pp. 428-442), Springer-Verlag Berlin Heidelberg. ISSN: 0302-9743, e-ISSN: 1611-3349, ISBN: 978-3-642-32985-2, e-ISBN: 978-3-642-32986-9, DOI: 10.1007/978-3-642-32986-9.

Vliet, Hans V. (2007). Software Engineering: Principles and Practive. Wiley.

Walpole, R. E., Myers, R. H., Myers, S. L., Ye, K. (2013). Essentials of Probability & Statistics for Engineering & Scientists. Pearson Education, International Edition, ISBN 10: 0-321-84584-6, ISBN 13: 978-0-321-84584-9, (pp. 165-167).

Zhang, S., McCullagh, P., Nugent, C. and Zheng, H. (2010). Activity Monitoring Using a Smart Phone's Accelerometer with Hierarchical Classification. *IEEE Computer Society, 2010 Sixth International Conference on Intelligent Environments*, 978-0-7695-4149-5/10, DOI: 10.1109/IE.2010.36.

Zheng, Y., Li, Q., Chen, Y., Xie, X., and Ma, W. (2008). Understanding mobility based on GPS data. *Ubiquitous Computing*. ACM New York, (pp. 312-321).

APPENDICES

1. APPENDIX-A:

Physical Trainers' Information

Selvin Çiçek:

Atılım Üniversitesi Spor Koordinatörü Yardımcısı Selvin Çiçek, Gazi Üniversitesi Beden Eğitimi ve Spor Yüksekokulu Antrenörlük Eğitimi Bölümü mezunu olup, Yüksek Lisans Eğitimi'ni Gazi Üniversitesi Sağlık Bilimleri Enstitüsü'nde Antrenman ve Hareket Bilimleri üzerine yapmıştır. Daha sonra Başkent Üniversitesi Eğitim Fakültesi'nden Pedagojik Formasyon Eğitimi tamamlayıp Beden Eğitimi Öğretmeni sertifikasını almıştır. Uzun yıllardır basketbol oynayan Selvin Çiçek halen lisanslı olarak basketbol oynamaya devam etmektedir. Ayrıca Basketbol antrenörlüğü yapmıştır, yüksek antrenördür.

Efe Can Rübendiz:

1990 doğumlu olan Efe Can Rübendiz Modern Pentatlon Milli Takım sporcusudur ve Pentatlon Türkiye Rekortmeni'dir. Atılım Üniversitesi Endüstri Mühendisliği Bölümü'nden 2012 yılında mezun olmuştur. Aynı bölümün yüksek lisans programından 2015 yılında mezun olmuştur.

TED Ankara Koleji, 22-23 Ekim 2010 yılında Adana'da yapılan Modern Pentatlon Federasyonu Yaz Biatlon Şampiyonasında 1. olmuştur. Ayrıca, 22.Ekim.2010 tarihinde Adana'da gerçekleşen ve Türkiye'de ilk defa yapılan “At Binme Testi'nde” sporcu Efe Can Rübendiz tam puan alarak, Uluslararası müsabakalarda ülkemizi temsil etme hakkını elde etmiştir.

Lise yıllarında yüzme takımında yer almıştır. Lisans eğitimi süresince içerisinde bulunduğu faaliyetler ve topluluklar şunlardır: IESC, Üniversitenin Yüzme, Eskrim, Atıcılık takımlarının kurulması faaliyetleri ve üniversitelerarası spor müsabaklarında temsil edilmesi. Yüksek Lisans eğitimi süresince ise; Üniversitenin Yüzme, Eskrim, Atıcılık takımlarının Antrenörlüğünü yapmıştır.

Efecan Rübendiz de Şanlıurfa'daki Üniversiteler Yüzme Şampiyonası'nda 100 metre kurbağalama kategorisinde 8. si, 200 metre serbest kategorisinde ise Türkiye 4. sü olmuştur. Ayrıca, Kara Harb Okulu'nda düzenlenen Üniversitelerarası Türkiye Atıcılık Şampiyonası'nda 10 metre havalı tabanca atışlarında 44 yarışmacı arasında 17.'lik derecesi almıştır.

Semih Gökalp:

1981 yılında Ankara Üniversitesi Veteriner Fakültesinde Spor Uzmanı olarak göreve başlamış ve daha sonra Ankara Üniversitesi bünyesinde öğretim görevlisi olarak çalışmasına devam etmiştir. Atılım Üniversitesi Spor Koordinatörlüğüne devam etmektedir, 1980 yılı 19 Mayıs Gençlik Spor Akademisi mezunu olup, Gazi Üniversitesi Kazaları Araştırma Enstitüsünde Acil Yardım ve Rehabilitasyon üzerine yüksek lisansını tamamlamıştır. Ayrıca, profesyonel olarak basketbol kariyerini milli takımda da yer alarak geliştirmiştir, uluslararası antrenör belgesine sahip olan Semih Gökalp çeşitli liglerde ve daha sonra Genç-Ümit Milli Takım antrenörlüğünü yapmıştır. Ankara Üniversitesi Spor Koordinatörlüğü görevlerini yaptıktan sonra 2006 yılında emekli olmuştur.

2. APPENDIX-B:

The Table of All Possible Test Cases and Generated Solutions

Table 29 presents all possible test cases and corresponding solutions to check the correctness of the case-based reasoning system.

Table 29. The Possible Cases and Solutions

Number of cases	Age	Weight	Height	BMI	Health Problem	Gender	Aim	Suggested Exercise / Solution	Case No	Status of BMI
1	17	40	1,70	13,8408	Y	F	W			extremely underweight
2	17	45	1,70	15,5709	Y	F	W	**s1**	**c1**	underweight
3	17	53	1,70	18,3391	Y	F	W	**s1**	**c1**	underweight
4	17	54	1,70	18,6851	Y	F	W	**s1**	**c3**	healthty weight
5	17	72	1,70	24,9135	Y	F	W	**s1**	**c3**	healthty weight
6	17	73	1,70	25,2595	Y	F	W	**s1**	**c5**	overweight
7	17	86	1,70	29,7578	Y	F	W	**s1**	**c5**	overweight
8	17	87	1,70	30,1038	Y	F	W			obese
9	17	40	1,70	13,8408	Y	M	W			extremely underweight
10	17	45	1,70	15,5709	Y	M	W	**s1**	**c7**	underweight
11	17	53	1,70	18,3391	Y	M	W	**s1**	**c7**	underweight
12	17	54	1,70	18,6851	Y	M	W	**s1**	**c9**	healthty weight
13	17	72	1,70	24,9135	Y	M	W	**s1**	**c9**	healthty weight
14	17	73	1,70	25,2595	Y	M	W	**s1**	**c11**	overweight
15	17	86	1,70	29,7578	Y	M	W	**s1**	**c11**	overweight
16	17	87	1,70	30,1038	Y	M	W			obese
17	17	40	1,70	13,8408	N	F	W			extremely underweight
18	17	45	1,70	15,5709	N	F	W	**s2**	**c2**	underweight
19	17	53	1,70	18,3391	N	F	W	**s2**	**c2**	underweight
20	17	54	1,70	18,6851	N	F	W	**s3**	**c4**	healthty weight
21	17	72	1,70	24,9135	N	F	W	**s3**	**c4**	healthty weight
22	17	73	1,70	25,2595	N	F	W	**s4**	**c6**	overweight
23	17	86	1,70	29,7578	N	F	W	**s4**	**c6**	overweight
24	17	87	1,70	30,1038	N	F	W			obese
25	17	40	1,70	13,8408	N	M	W			extremely underweight
26	17	45	1,70	15,5709	N	M	W	**s5**	**c8**	underweight

27	17	53	1,70	18,3391	N	M	W	**s5**	**c8**	underweight
28	17	54	1,70	18,6851	N	M	W	**s6**	**c10**	healthty weight
29	17	72	1,70	24,9135	N	M	W	**s6**	**c10**	healthty weight
30	17	73	1,70	25,2595	N	M	W	**s7**	**c12**	overweight
31	17	86	1,70	29,7578	N	M	W	**s7**	**c12**	overweight
32	17	87	1,70	30,1038	N	M	W			obese
33	17	40	1,70	13,8408	Y	F	S			extremely underweight
34	17	45	1,70	15,5709	Y	F	S	**s1**	**c13**	underweight
35	17	53	1,70	18,3391	Y	F	S	**s1**	**c13**	underweight
36	17	54	1,70	18,6851	Y	F	S	**s1**	**c15**	healthty weight
37	17	72	1,70	24,9135	Y	F	S	**s1**	**c15**	healthty weight
38	17	73	1,70	25,2595	Y	F	S	**s1**	**c17**	overweight
39	17	86	1,70	29,7578	Y	F	S	**s1**	**c17**	overweight
40	17	87	1,70	30,1038	Y	F	S			obese
41	17	40	1,70	13,8408	Y	M	S			extremely underweight
42	17	45	1,70	15,5709	Y	M	S	**s1**	**c19**	underweight
43	17	53	1,70	18,3391	Y	M	S	**s1**	**c19**	underweight
44	17	54	1,70	18,6851	Y	M	S	**s1**	**c21**	healthty weight
45	17	72	1,70	24,9135	Y	M	S	**s1**	**c21**	healthty weight
46	17	73	1,70	25,2595	Y	M	S	**s1**	**c23**	overweight
47	17	86	1,70	29,7578	Y	M	S	**s1**	**c23**	overweight
48	17	87	1,70	30,1038	Y	M	S			obese
49	17	40	1,70	13,8408	N	F	S			extremely underweight
50	17	45	1,70	15,5709	N	F	S	**s2**	**c14**	underweight
51	17	53	1,70	18,3391	N	F	S	**s2**	**c14**	underweight
52	17	54	1,70	18,6851	N	F	S	**s8**	**c16**	healthty weight
53	17	72	1,70	24,9135	N	F	S	**s8**	**c16**	healthty weight
54	17	73	1,70	25,2595	N	F	S	**s9**	**c18**	overweight
55	17	86	1,70	29,7578	N	F	S	**s9**	**c18**	overweight
56	17	87	1,70	30,1038	N	F	S			obese
57	17	40	1,70	13,8408	N	M	S			extremely underweight
58	17	45	1,70	15,5709	N	M	S	**s5**	**c20**	underweight
59	17	53	1,70	18,3391	N	M	S	**s5**	**c20**	underweight
60	17	54	1,70	18,6851	N	M	S	**s10**	**c22**	healthty weight
61	17	72	1,70	24,9135	N	M	S	**s10**	**c22**	healthty weight
62	17	73	1,70	25,2595	N	M	S	**s11**	**c24**	overweight
63	17	86	1,70	29,7578	N	M	S	**s11**	**c24**	overweight
64	17	87	1,70	30,1038	N	M	S			obese

The Questionnaire Grading Table

The grading table of the volunteers' are presented in Table 31.

Table 31. The Volunteers' Grading Table of the Exercise Planner System Questionnaire

	Question Number											
Volunteer Number	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	5	5	4	5	5	5	5	4	4	5	5	5
2	4	4	4	3	3	4	4	5	3	4	4	4
3	5	5	5	5	5	5	5	5	5	5	5	5
4	5	4	3	3	4	5	5	3	5	5	5	5
5	5	5	5	5	5	5	5	5	5	5	5	5
6	3	3	3	5	5	5	5	3	4	3	3	5
7	5	4	5	3	4	5	3	4	3	4	5	4
8	5	3	3	4	4	3	4	4	5	3	3	5
9	5	5	3	3	3	4	5	3	4	3	3	4
10	4	4	5	5	3	5	5	4	4	5	5	5
11	3	5	4	5	5	4	4	5	5	5	5	5
12	5	5	5	5	5	5	5	5	5	5	5	5
13	5	5	4	4	5	4	5	5	4	5	5	5
14	5	5	5	5	5	5	5	5	5	4	4	5
15	4	5	4	5	5	5	4	4	5	4	4	5
16	4	3	4	3	5	3	5	5	4	5	5	5
17	5	5	5	5	5	5	5	5	5	5	5	5
18	5	4	4	5	5	5	5	4	5	5	4	5
19	5	5	5	5	5	4	4	5	4	5	5	5
20	3	4	3	3	5	3	4	3	3	4	4	4
21	5	5	5	5	5	5	5	5	5	5	5	5
22	5	4	3	3	3	3	4	4	4	3	3	4
23	5	4	4	3	3	5	5	4	5	4	4	5
24	5	5	5	5	5	5	5	5	5	5	5	5
25	5	4	2	3	5	5	4	5	5	5	4	4
26	4	3	3	3	5	4	3	5	5	3	3	3
27	5	4	4	4	3	3	3	3	3	3	3	4
28	5	4	3	5	3	4	4	4	5	4	3	5

29	5	5	4	5	4	4	3	4	2	4	4	5
30	5	2	3	3	4	4	3	3	4	4	3	4
31	5	5	4	3	4	5	5	5	4	5	5	5
32	5	4	5	4	5	5	4	3	4	4	4	5