Measuring Biosignals of Overweight and Obese Children for Real-time Feedback and Predicting Performance

Nurten Öksüz[1], Russa Biswas[1], Iaroslav Shcherbatyi[1], Wolfgang Maass[1, 2]

[1] Chair in Information and Service Systems, Department of Law and Economics, A5 4, Saarland University, 66123 Saarbrücken, Germany
[2] Deutsches Forschungszentrum für Künstliche Intelligenz (DFKI) GmbH, Campus D3 2, Stuhlsatzenhausweg 3, 66123 Saarbrücken, Germany

{nurten.oeksuez, iaroslav.shcherbatyi, wolfgang.maass}@iss.uni-saarland.de, biswasrussa@gmail.com, wolfgang.maass@dfki.de

Abstract. Child obesity is a serious problem in our modern world and shows an increase of 60% since 1990. Due to time and cost intensity of traditional therapy programs, scientists started to focus on IT-based interventions. Our paper focuses on measuring biosignals (e.g. heart rate) of obese children during fittest including different physical activities (e.g. running). We investigate whether it is possible to predict the performance of obese children during running test based on static (e.g. BMI) as well as dynamic (e.g. heart rate) parameters. Here, we focused on heart rate related parameters from the inverted U-shaped heart rate response of obese children during running test. For future research, we plan to consider physical activity (e.g. step count) of the children at home. Our approach is a NeuroIS service, which uses low-cost devices making prediction on an individual's future development and is also applicable to other domains (e.g. business information systems).

Keywords: heart rate · obesity · children · fitness · prediction

1 Introduction

Children obesity has become a serious problem in our modern world with an increasing trend. According to Ogden et al., the percentage of obese children aged 6-11 years in the United States increased from 7% in 1980 to 18% in 2012 [1]. Obese children and adolescents aged 12-19 years are more affected with an increase from 5% in 1980 to 21% in 2012 [1]. It has been observed that, besides psychological and physiological impacts, obesity has a lot of serious implications for the public and private healthcare sectors, e.g. dramatically increasing public health costs and obese children having risk factors for cardiovascular diseases [2,3]. Therefore, several efforts are needed to control the persistent epidemic of overweight and obesity [4]. Results of holistic therapy programs have shown positive effects on therapy outcomes of obese children [5,6,7,8]. However, these interventions are time and cost consuming for both the patients and physicians. To counteract this problem, scientists started to focus on IT-based interventions by using pervasive and smart technologies. There are several mobile solutions, which measure vital signs and use sensors for daily use to help controlling obesity [9,10,11]. While most of the existing solutions measure physical activity, there are few, which use methods from the NeuroIS field. These NeuroIS tools and methods can be used to create efficient time and cost saving solutions tailored to patients' individual needs. However, there are, to the best of the authors' knowledge, no papers focusing on NeuroIS solutions which make predictions on the performance (e.g. running, push-up, curl-up, trunk lift) of obese children based on static (e.g. BMI, age, gender) as well as dynamic (e.g. heart rate, skin conductance, blood pressure) parameters. The goal of this paper is to investigate whether the performance of obese children during running test can be predicted using static as well as dynamic parameters. In order to obtain the dynamic parameters, we conducted a fittest, which included a 6-minute running test. Several parameters including heart rate are measured during the fittest. In our study, we take *BMI* and *gender* as static parameters and *average heart rate* during the 6-minute running test as well as the *heart rate recovery* after the exercise as the dynamic parameters. We measured performance by counting the number of laps made during the 6-minute running test. The research question is as follows:

> *Is it feasible to predict the performance of overweight and obese children with the help of the static parameters BMI and gender as well as the dynamic parameters average heart rate during running test and heart rate recovery?*

2 State of the Art

2.1 Relationship of Body Mass Index and Fitness Level

Several study results indicate a relationship between the *Body Mass Index* (BMI) and the fitness of an individual [12,13,14,15]. The study of Joshi et al. with a sample size of n = 7000 school children doing a physical fitness assessment called *Fitnessgram* concludes that the fitness level of children having healthy BMIs is the highest, followed by those of overweight and obese children [12]. The results show that the higher the BMI, the less likely a child tends to be physically fit [12]. Physical fitness was measured by considering the number of exercises scored in the *healthy fitness zone* (HFZ) [12]. The study of Aires et al. also strengthen these results by finding out that obese children between 11-18 years old performed a decreased number of tests in the HFZ compared to the normal-weight children, indicating a reduced performance in both physical strength and cardiovascular fitness [15].

2.2 Heart Rate during and after Exercise and its Relationship to Fitness

Exercise heart rate as well as the post-exercise heart rate can give information about an individual's fitness level [16]. Physical activity or exercising elevates the heart rate for the duration of physical activity and slows it down during the cool down after the physical activity [17,18]. The fitter an individual is, the lower the heart rate will be during training, the lower it will be during cool down and the faster it will return to the pre-exercise level [16]. Repeating the test after a certain period of time will create a comparable set of results that can be used to detect changes of an individual's fitness [16]. The *heart rate recovery* (HRR) depends on, amongst others, the intensity of the exercise and the cardiorespiratory fitness of an individual [19,20]. Obese children and adolescents tend to have lower cardiorespiratory fitness and physical abilities when compared to normal-weight children and young adults, mainly due to increased effort required to carry the large amount of body fat and to move their larger body mass [21]. Furthermore, Singh et al. conducted a study using a maximal treadmill exercise to compare the HRR of normal-weight and overweight children [22]. The results show that children with higher BMI, especially those who are overweight, have slower 1-minute HRR after exercise [22].

2.3 Pervasive and Smart Technologies for controlling Obesity

There are several approaches, which focus on measuring vital signs and applying sensors to help controlling obesity. BALANCE is able to automatically calculate the calorie spent in the everyday activities by using inertial sensors, which is worn on the body. Nevertheless, the patient has to manually enter the calorie content of the single food items [9]. HealthAware uses GPS and accelerometer embedded in a smartphone to monitor activities and a camera to additionally analyze food items intake. The user needs to manually enter name of the single food items and the system will calculate the calorie based on the collected data [10]. UbiFit Garden uses classifiers trained to differentiate walking, running, and cycling using a stairs machine as well as an elliptical trainer by means of barometer and 3-d accelerometer to encourage physical activity [11]. TripleBeat is a NeuroIS service, which consists of accelerometer to measure movements during run as well as *Electrocardiogram* (ECG) sensors to monitor the heart rate [23]. ExerTrek monitors exercise as well as heart rate during exercise and gives real-time online feedback about the user's heart status and any occurring abnormalities. Furthermore, there are many commercial solutions (e.g. RunKeeper, Sportypal, and Runtastic PRO) available that track the activities of the users to help them losing weight.

3 Research Methodology

Our study is conducted at a Swiss children's hospital in St. Gallen in cooperation with four universities. In total, 20 children aged between 11 and 17 years with higher BMI values ($25<BMI<37$) participated in the fittest (7 female and 13 male). The participants have taken the fittest in a sports hall, which consisted of exercise elements of the Dordel Koch Fittest and the EuroFit Fitness Test. The fittest included a running test in the last 6 minutes. For every child, the number of laps was counted. Besides BMI, gender, number of steps and number of laps the children ran during the 6 min running test, the exercise heart rate (about 25 minutes) as well as the post-exercise heart rate (cool down period of 3 minutes) was measured. To measure the heart rate, the participants were equipped with a Scosche Rhythm+ heart rate monitor and a Samsung Galaxy S6 smartphone, in which the app *PathMate2* is installed. The app *PathMate2* collects the heart rate data from the heart rate monitor when the *Exercise Button* or the *Cool Down Button* is pressed and sends the data to the server, where the data is processed for further explorative and predictive analysis. Before the participants start the exercise, the *Exercise Button* was pressed to measure the initial heart rate as well as the heart rate during the exercise. Right after the exercise, the *Cool Down Button* was pressed to separately measure the heart rate of the participants during the cool down.

For the purpose of predictive analysis, we calculated the average heart rate during steady state as the *average heart rate* during the running test (see figure 1). Furthermore, the heart rate difference between the start of the cool down and the average of the last 10 values of the cool down is taken as the *heart rate recovery.*

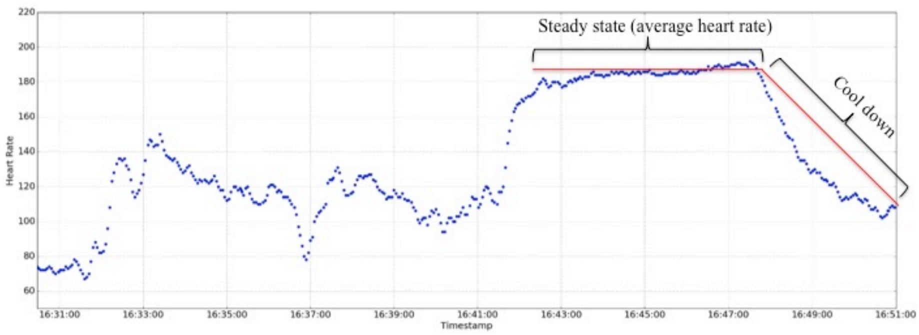

Fig. 1. Heart Rate during the Fittest

3 Results

We intend to predict the number of laps made during the 6-minute running test using the linear regression model Least Absolute Shrinking and Selection Operator (LASSO). The features used to train the model are *BMI, gender, average heart rate* during the running and *heart rate recovery*. We used k-fold cross validation with k=3 to select the best parameter (α) for the model. The data set is divided into train and test set using Leave One Out Cross Validation (LOOCV). Each data point (child) in the data set is used once as a test set (singleton) while the remaining data is used as the train set.

The results show that the average difference between the actual number of laps and the number of laps predicted by our model is 2.185 with an overall average error of 7.1%. Our model makes better prediction of the number of laps made during 6-minute running test compared to the constant value model (baseline method). The constant value model considers the average number of laps in the train set as the predicted number of laps for the test set. The Mean Squared Error (MSE) of our model (MSE = 6.892) is better than the MSE of the constant value model (MSE =10.052).

4 Discussion

The goal of this paper was to investigate the feasibility of predicting the performance of overweight and obese children by the number of laps made during a 6-minute running test using the static parameters *BMI* and *gender* as well as the dynamic parameters *average heart rate* during the running test and *heart rate recovery*. As mentioned above, the study of Joshi et al. concludes a casual relationship between the BMI and the fitness level of the children [12]. The fitness level of a specific child was measured in terms of performance during several exercises (e.g. push-up, curl-up, running). In our study, we measured performance by counting the number of laps made during a 6-minute running test. Furthermore, the heart rate recovery of children after exercise has a causal relationship with their fitness level (see Section 2.2). Therefore, in our predictive analysis study we included the static parameter BMI as well as the dynamic parameter *heart rate recovery* as features to predict the performance of the children during the running test. We also included *average heart rate* during the running test for the analysis since heart rate during the exercise is another dynamic parameter, which serves as an indicator of an individual's fitness level (see Section 2.2). The quantitative results as mentioned in Section 3 depicts that our method works better than the baseline method, which is the constant value model. Thus, our method provides a tentative prediction on the performance of the observed children. Despite the fact that the MSE of our model is better than that of the baseline method, the accuracy can still be improved. The accuracy of our model is influenced by several factors. First, our data set might be biased due to the fact that the study is done only on overweight and obese children. This implies that all the children in the data set exhibit almost similar health characteristics. Second, the data set is very small leading to chances of overtraining the model. To overcome it in the best possible way we used LOOCV to divide the data into train set and test set. Third, the children exerted themselves to different extents during the 6-minute running test. Nevertheless, despite of these drawbacks the linear model used in our study is capable of predicting the number of laps with an overall error of 7.1%.

5 Conclusion and Outlook

It can be concluded from our analysis that pre-exercise and post-exercise heart rate as well as BMI and gender can be leveraged to predict the number of laps made by the children during the running test. Therefore, low cost wearable devices along with predictive analysis methods allow predicting health conditions reducing the cost of the traditional therapy programs. In future work, we intend to focus on applying the method to a large data set including obese, overweight and normal children to improve the accuracy of prediction. Furthermore, we plan to use a standardized fitness test (e.g. treadmill running test) to provide all the children with the same fittest environment. However, taking other static (e.g. age) and dynamic parameters (e.g. blood pressure) into account can also lead to other interesting prediction. In future, similar predictive analysis methods could open up new areas of remote patient monitoring and interventions as well as other domains using low cost devices such as smartphones and smartwatches (see figure 2).

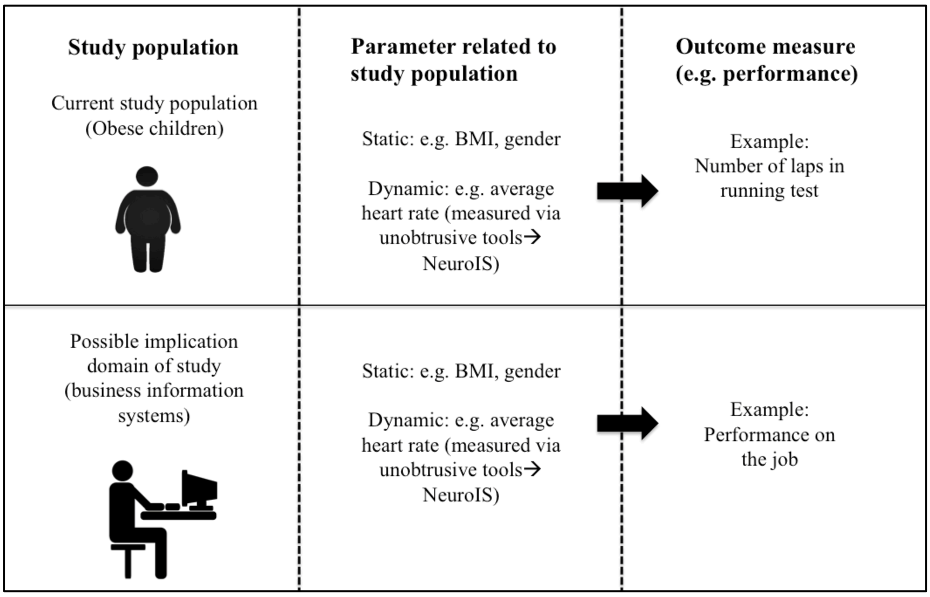

Fig. 2. Current and possible study population and predicted performance

For instance, this approach is not only interesting for child obesity, but also applicable to fields such as business information systems domain, since biosignals of employees on the job is a current topic. Kowatsch (2016) for example suggests measuring physiological arousal of employees on the job to detect a relationship between job strain and task performance [24]. For our purpose, measuring the heart rate of employees on the job to predict the task performance on the job could be the prime focus.

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