IOP Conf. Series: Materials Science and Engineering **884** (2020) 012002 doi:10.1088/1757-899X/884/1/012002

Investigation of Multiparameter Trends and Anthropometric Measurements for Cardiorespiratory Fitness Assessment Among UTM Staff

Latha Nair Muralitharan, Wan Nor Syuhada Wan Zahari, Nor Aziyatul Izni Mohd Rosli, Norjihada Izzah Ismail, MB Malarvili[1] and Mohammed Rafiq Abdul Kadir

[1]*School of Biomedical Engineering & Health Sciences,*
Faculty of Engineering, Universiti Teknologi Malaysia, 81310, Skudai, Johor Bahru, Johor, Malaysia

E-mail: malarvili@biomedical.utm.my

Abstract. Cardiorespiratory fitness (CRF) is known to reduce metabolic-related diseases like cardiovascular diseases (CVD), obesity, hypertension, and type II diabetes. On the other hand, the gold standard to measure CRF is by measuring maximal oxygen consumption, VO2 max over the years. This study is performed to identify parameters that influence CRF without solely relying on invasive features such as VO2 max. A number of 31 UTM staff aged between 30 and 40 years old have participated in this study with 17 female subjects and 14 male subjects. Anthropometric measurements are obtained by direct measurement and body composition analysis using a body composition monitor. Multiparameter trend measurements were obtained from vital sign monitors at rest. Single feature analysis was performed in terms of accuracy, specificity and sensitivity to identify which feature influences CRF the most. The features collected are body mass index (BMI), body fat (BF), muscle mass (MM), bone density (BD), waist circumference (WC), resting heart rate (RHR), resting systolic blood pressure (RSBP), forced expiratory volume in one second (FEV1), and recovery trend heart rate (RecHR). Next, all these features were validated using Naïve Bayes (NB) and Decision Tree (DT) classifiers. Finally, six features which are BF, BM, BD, RHR, RSBP and FEV1, with accuracy more than 70% were selected and identified as the features which influence CRF of UTM staff.

1. Introduction

Physical fitness is defined as a set of attributes that some individual has which can be related to the ability to perform physical activity. Physical fitness assessment includes body composition, cardiorespiratory fitness (CRF), muscular endurance and muscular flexibility [1]. CRF has been assessed by measuring maximal oxygen consumption (VO_2 max) over the years during performing exhausting work either by treadmill exercises or bicycle ergometer. Then VO_2 max will be expressed as liter/min (L/min), or mL/kg/min [2]. The metabolic equivalent (METs) can be calculated from this expression to represent energy cost expended as multiples of resting metabolic rate [3]. Till this very day, the gold standard to measure CRF is by measuring VO_2 max [4,5].

[1] malarvili@biomedical.utm.my

Physical activity can be a marker of health-related fitness. Hence, low physical inactivity will lead to a low fitness level, thus contributing to health-related risks such as cardiovascular disease (CVD), diabetes mellitus (DM), and osteoporosis [6]. Despite the awareness regarding this matter, the physical activity trend has been reported to decrease in Malaysia, and generally lower among women compared to men [7]. One of the factors that said to contribute to this trend is due to rapid urbanization [8]. Physical activity without fitness test more or less like doing something without a purpose, as mentioned by, physical fitness can measure objectively the physical activity, as it is only a behaviour [9].

Estimated cardiorespiratory fitness (CRFe) can be done by obtaining several parameter trends as required in the respective equation for estimation of the CRF. Hence, for CRFe with maximal exercise, the parameter that usually used is treadmill time with workload exertion for maximum effort. However, despite the numerous equations developed, there will still be errors in the estimation of the VO_2 max [10]. Moreover, anthropometric measurements are being used widely to estimate body composition, fat distribution, and calculating body mass index, but rarely used to estimate cardiorespiratory fitness. It is shown that the body proportions obtained from anthropometric measurements have some association with physical fitness across gender. Some anthropometric measurement can be calculated as ratios and can be used for physical fitness tests [11].

Nowadays, there is a lack of data reflected to CRF. VO_2 max is still the gold standard used to calculate CRF among participants and there is no optimal approach to observe CRF in clinical environments as well as fitness assessment [10]. From the studies done, it can be seen that there are only some studies performed anthropometric measurement to observe the association with fitness which includes spirometry measurements. Hence, this study is focussing on identifying features that will influence CRF the most. A number of features will be measured from UTM staff, and collected data will be used to identify features that influence CRF.

The work of the paper is organized as follows. Section 2 outlines method which includes (A) data recording (B) data acquisition and followed by performance analysis in section (C). The findings and discussion of the proposed method are presented in Section 3. Section 4 elucidates the conclusion of the present research.

2. Methodology

2.1 Data Acquisition

The study was done at Fitness Gym at School of Biomedical Engineering and Health Sciences (SKBSK), Universiti Teknologi Malaysia (UTM), Johor Bahru on 31 UTM staff aged 30 to 40 (17 female and 14 male) whom required to perform the physical fitness test. The participants' background of physical fitness and physical activity is unknown. The informed consent was obtained, where the participants agreed to be invited to the exercise session. The study was registered in National Medical Research Register (NMRR) and supported by research evaluation committee NIH (JPP-NIH) with NMRR ID: NMRR-19-1369-48241. The flow of the study approach was represented in Figure 1.

In this study, the flow of the study approach was started by acquiring data from submaximal exercise time (treadmill run) as shown in Figure 2 as well as anthropometric and multiparameter trend measurements. Next, Bruce estimation of VO_2 max in order to obtain Metabolic Equivalents (METs). Then, single feature analysis was performed using VO_2 max and data obtained from anthropometric and multiparameter trend measurements to identify optimal features which influences CRF.

IOP Conf. Series: Materials Science and Engineering **884** (2020) 012002 doi:10.1088/1757-899X/884/1/012002

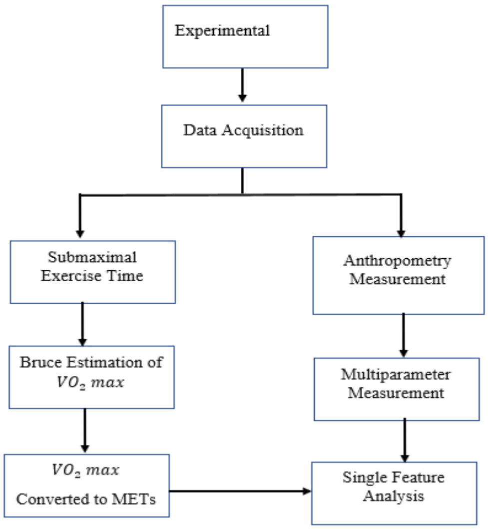

Figure 1. Flow of the study approach.

2.1.1 Multiparameter Trends

Before the cardiopulmonary exercise started, resting heart rate, resting blood pressure and lung capacity were recorded. These measurements were taken when participants in a relaxed state and sitting except for lung

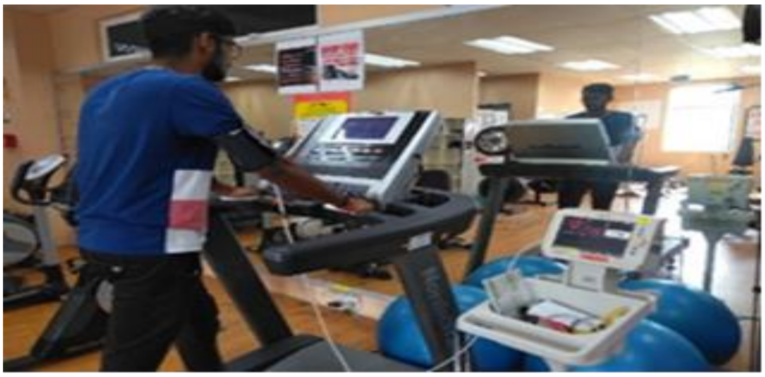

Figure 2. Submaximal exercise time measurement.

capacity to promote the best lung expansion. BP and HR were taken using digital sphygmomanometer after 10 minutes of rest [12]. Photo plethysmograph (PPG) was checked for accuracy by manual counting pulse over a minute before the experiment was started. Initial heart rate at rest was recorded as resting heart rate (RHR). Then, participants wore the PPG throughout the test to monitor continuously the HR. Data obtained during cardiopulmonary testing was summarized in Table 1.

Table 1. Data extracted during cardiopulmonary testing.

Distance (m)	All	Female	Male
Number of Subjects	31	17	14
Age	32 ± 2.8	32.2 ± 2.6	31.9 ± 3.05
Treadmill Time (min)	11.7 ± 2.58	11.1 ± 1.89	12.4 ± 3.15
VO_2 max (ml.kg-1.min-1)	42 ± 10.17	40.6 ± 8.58	43.8 ± 11.90

IOP Conf. Series: Materials Science and Engineering **884** (2020) 012002 doi:10.1088/1757-899X/884/1/012002

According to Bruce submaximal test, submaximal effort can be reached when 85% of targeted heart rate is obtained. Maximal heart rate, according to the revisited study of age-maximal heart rate (MHR) can be calculated as 220 minus age according to Tanaka et al. (2001) then times 85% to get the submaximal heart rate [13].

Five minutes before starting the procedure, participants were asked to perform warm-up exercise. Participant ran on a treadmill at a designated speed and time. In this laboratory, the treadmill used was Wellness Alyn, model TMX 425 (See Figure 1). For the first three minutes, the treadmill was set at a speed of 1.6 km per hour (km/h) with 0% inclination for warm up on the treadmill and to allow participant to get used to the treadmill speed. The participant was not allowed to hold to hand rail throughout the test.

The treadmill was set at 5% inclination and speed of 2.5 km/h. Each stage shall be three minutes in duration, to achieve steady-state heart rate. Then speed was increased to four km/h with an inclination of 10%. If the targeted HR was not reached, speed was further increased to 6 km/h and then 8 km/h. If the heart rate difference increased between second and third minute > 6 beats per minute (bpm), it was not considered as a steady state. Upon 85% of MHR, the test was stopped and participant was asked to continue for recovery state about three to five minutes to cool down until respiration returned to normal or HR dropped below 100 bpm.

In order to ensure validity and reliability of the test, heart rate should exceed 110 beats per minute (bpm). If not, speed or inclination was adjusted. Blood pressure and heart rate were measured every minute until recovery time. Spirometry measurements were taken at the beginning of each stage. Time measured from beginning of running time until voluntary termination or upon reaching the 85% of MHR. From here, the VO_2 max was predicted by using the following equation [14]:

Men: VO_2 max,

$$14.8 - (1.379 \text{ x time}) + (0.451 \text{ x time2}) - (0.012 \text{ x time3}) \quad (1)$$

Women: VO_2 max,

$$4.38 \text{ (time)} - 3.90 \quad (2)$$

Note that time was in minutes, and seconds were expressed as a fraction of minute. Then, METs were calculated by dividing the VO_2 max with 3.5 mL/kg/min.

2.1.2 Anthropometric Measurements

Table 2 below shows the anthropometric measures extracted from the same staff.

Table 2. The description of anthropometric measurement procedure.

Measurements	Procedure
Standing and sitting height	Taking height during sitting with upright posture [15].
Weight	Measured using stadiometer.
Bio-impedance analysis	Measurement of body fat, body weight, body mass, muscle mass, bone density.
250Waist circumference	Measure waist girth at the midway between highest point from iliac crest and the lowest part of the ribcage according to WHO.
Chest circumference	Measure chest girth on the nipple line.
Bi-acromial width	Measurement of the width of the shoulder by measuring from acromian to acromian.

IOP Conf. Series: Materials Science and Engineering **884** (2020) 012002 doi:10.1088/1757-899X/884/1/012002

From anthropometric measurement above, body proportional ratios were calculated as shown in Table 3.

Table 3. Calculation of body proportion.

Proportional Ratios (%)	Calculation
Chest to Height (CHR)	Chest/ height x 100
Sitting-height-to-height (SHR)	Sitting height/height x 100
Waist to Height (WHR)	Waist/ height x 100

2.2 Performance Analysis

Naïve Bayes is a method based on Bayes theory used widely in classification. The posterior class probability is a test data point can be derived based on class condition, density estimation and class prior probability. Then test data point can be derived and assigned to class with maximum posterior class probability. The main problem with this method is the class conditional density estimation due to uncertain data [16]. In probability theory, Bayes theorem relates the conditional and marginal probabilities of two random events. It is often used to compute posterior probabilities given observations. A technique for constructing such classifiers to employ Bayes' theorem to obtain the following equation [17]:

$$P(C_k|x) = \frac{P(x|C_k)\,P(C_k)}{\sum_{k'} P(x|C_{k'})P(C_{k'})} \tag{3}$$

A naive Bayes classifier assumes that the value of a particular feature of a class is unrelated to the value of any other feature [18]:

$$P(C_k|x) = \prod_{j=1}^{d} P(x^j|C_k) \tag{4}$$

Accuracy measured on the training set and accuracy as measured on unseen data (the test set) are often very different. In Machine Learning applications, training is set to be perfectly fitted, but performance on the test set to be very disappointing. Generally, the accepted method for estimation is to use the given data, in which all class memberships are known (assumed). Firstly, a substantial proportion (the training set) of the given data to train the procedure is used. This rule is then tested on the remaining data (the test set), and the results compared with the known classifications. The proportion correct in the test set is an unbiased estimate of the accuracy of the rule provided that the training set is randomly sampled from the given data [19].

$$Accuracy = \frac{\mathrm{TN+TP}}{\mathrm{TP+TN+FP+FN}} \tag{5}$$

Sensitivity is a test used to define the proportion of people with the disease who have positive results. If the test is applied to a hypothetical population, and eight of ten people with a certain disease is tested as positive, then the sensitivity of test is 80% [20]. Sensitivity only calculates for people with that disease, [21] which means the test shows good performance to identify disease when focussing only on those people with the disease. Test with 100% sensitivity identifies all patients with disease correctly. 80% sensitivity detects true positive values, whereas remaining 20% is undetected and this is known as the false negatives. High sensitivity is significant, especially in detecting serious but treatable diseases [22]. The formulation to sensitivity is:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives + False Negatives}} \tag{6}$$

IOP Conf. Series: Materials Science and Engineering **884** (2020) 012002 doi:10.1088/1757-899X/884/1/012002

Specificity of a test, on the other hand is the proportion of people without disease with negative results [20]. Specificity is only interested in calculating for those people without the disease. Thus, a test with 100% specificity identifies all patients without disease correctly. A test with 80% specificity reports 80 percent of patients without disease accurately, true negative and 20% patients without disease are falsely identified, false positive [22].

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}} \tag{7}$$

In order to reduce risk of overfitting with the large number of features, MATLAB and WEKA software were used to analyse single feature against the classification output. Two types of classifiers were used in this study, which are Naïve Bayes and Decision Tree (J48), in order to validate the results. Cross-validation with 10 folds was used prior to initiate each analysis [23]. Each of the features was classified and confusion matrix was obtained. From the confusion matrix, the performance of the classifier can be measured. The features with higher than 70% accuracy were selected and identified to influence cardiorespiratory fitness. There were several steps performed in order to obtain significant features.

3. Results and Discussion

All data were calculated in mean and standard deviation values and normalized as demonstrated in Table 4.

Table 4. Data extracted from the tests performed.

	All	Female	Male
Number of Subjects	31	17	14
Age	32 ± 2.8	32.2 ± 2.6	31.9 ± 3.05
BMI	24.7 ± 4.27	24.2 ± 4.4	25.3 ± 4.18
BF (%)	27.3 ± 8.66	31.6 ± 7.27	22.2 ± 7.45
MM (%)	44.2 ± 10.99	36.6 ± 6.83	53.4 ± 9.16
BD	2.6 ± 0.6	2.2 ± 0.46	3.0 ± 0.49
WC (cm)	80 ± 0.12	80 ± 0.11	90 ± 0.12
RHR (beat per min)	76.7 ± 9.41	77.7 ± 7.09	75.4 ± 12.18
RSBP (mmHg)	118.8 ± 15.95	113.5 ± 16.00	125.4 ±13.73
FEV_1 (L)	1.8 ± 0.63	1.5 ± 0.39	2.2 ± 0.69
RecHR (%)	25.0 ± 12.56	22.7 ± 10.77	27.8 ± 14.36
Treadmill Time (min)	11.7 ± 2.58	11.1 ± 1.89	12.4 ± 3.15
VO_2 max (ml.kg-1.min-1)	42 ± 10.17	40.6 ± 8.58	43.8 ± 11.90

Seventeen participants were female and fourteen were male with age between 30 and 39 years old. From Table 4, it can be seen that an overall mean BMI of participants is in a good range. However, male subjects demonstrated higher mean body mass index (BMI) which was slightly above normal level of 25. As for the percentage of body fat (BF), female participants demonstrated a higher percentage of BF as compared to the male participants which was about 10% difference. However, this range was acceptable as female normally has a higher fat composition compared to male.

In contrast to that, muscle mass (MM) percentage of the male subjects are usually higher which is close to 40%. Meanwhile, female subjects should be close to 30% of their body weight. In this study, the MM of male subjects is 53.4%, while female subjects have a muscle mass of 36.6%. It was also observed from Table 4 that bone density (BD) showed higher values in male as compared to female. According to World Health Organization (WHO), waist circumference for females should be less than 80 cm and less than 110 cm for males [24]. There were two female participants exceeding the normal range for waist circumference, but as for the male participants, waist circumference measurements were within the normal range.

As for the resting heart rate (RHR), it was observed that female participants have slightly higher RHR which is 77.7 (bpm) as compared to male participants which is 75.4 (bpm). Although the difference in RHR was not very high, the standard deviation for male participants was still larger than female and this could be due to small sample size. From the obtained results for forced expiratory volume in one second (FEV_1), male participants have a higher expiration as compared to female participants, 1.5 litres and 2.2 litres respectively. On the other hand, the percentage of recovery heart rate (RecHR) for male participants seems to be higher than female participants, which means time taken by women to reach a normal heart rate after the exercise was longer than male participants.

The treadmill time depicted that male participants lasted longer in a treadmill run as compared to female participants where male participants last for an average of 12.4 minutes whereas female participants lasted for an average of 11.1 minutes. Finally, results in maximal oxygen consumption (VO_2 max) revealed that male participants have better maximal oxygen consumption as compared to female participants at 43.8 mL.kg-1.min-1 and 40.6 mL.kg-1.min-1 respectively. Absolute values of VO_2 max are typically 40-60 % higher in men than in women, where males have a VO_2 max of approximately 3.5 litres/minute (absolute) and 45 mL/kg/min (relative) whereas females have a VO_2 max of approximately 2.0 litres/minute (absolute) and 38 mL/kg/min (relative) [25]. Overall, Table 4 shows that male participants are physically more active as compared to female participants and this may be due to the lifestyles of female participants.

Feature classification was performed with WEKA as it can provide confusion matrix as well as identify correct and incorrect classified data. These features were classified with Naïve Bayes and Decision Tree separately and the results were shown in Table 5. Out of nine features, six features (bolded) were identified to have more than 70% accuracy.

Table 5. Feature classification.

	Naïve Bayes	Decision Tree	Naïve Bayes	Decision Tree	Naïve Bayes	Decision Tree
	Accuracy (%)		Sensitivity (%)		Specificity (%)	
BMI	64.5	51.6	76.7	77.4	88.0	0.0
BF	71.0	74.2	77.4	77.4	0.0	0.0
MM	83.9	80.6	77.4	82.3	0.0	50.0
BD	80.6	80.6	79.3	75.9	50.0	0.0
WC	64.5	35.5	77.4	77.4	0.0	0.0
RHR	71.0	61.3	77.4	77.4	0.0	0.0
RSBP	58.1	74.2	80.0	75.0	33.0	70.0
FEV_1	74.2	74.2	75.9	77.4	88.0	78.0

Table 5 shows the difference in accuracy, sensitivity and specificity between Naïve Bayes and decision tree classifier for single feature classification. MATLAB software was used to train data against METS to observe which feature has higher accuracy. In terms of accuracy, the Naïve Bayes classifier was seen to have slightly higher values as compared to a decision tree. As for the overall sensitivity percentage, Naïve Bayes showed slightly higher sensitivity as compared to a decision tree. Naïve Bayes was more accurate because the classifier assumes that there are no dependencies among features or attributes, that is why this classifier is ideal for simple computations [26].

The results were further classified into male and female to observe the sensitivity of data [20]. It was observed that the sensitivity for males were higher when using Naïve-Bayes classifier and sensitivity for female was higher when using decision tree classifier. This could be due to the number of female and male participants were imbalanced, as in 17 female and 14 male participants. Also, the sensitivity percentage for male were generally higher than women in both classifiers as from the METS calculated, male staff appears to be more fit as compared to women. Since sensitivity was defined as test with positive results, it showed a higher percentage for male because male staffs were more fit [20].

When looking at overall data specificity, it can be said that Naïve Bayes showed a higher percentage as compared to the decision tree classifier. Specificity was defined as a test with negative results [22]. The results in both classifiers were uncertain and this could be due to the number of unfit staffs were very less as compared to more fit staffs in UTM according to manually calculated METs.

From Table 5, it can be seen that Naïve-Bayes classifier has 70 % of accuracy as compared to decision tree classifier which was about 66.66 %. Since the difference between the two classifiers are not very high, this improved the accuracy of single feature classification since both classifiers provides about the same accuracy percentages for the selected features. Using one classifier may not produce an accurate output as it is not good enough which was why comparing two different classifiers produced optimal results. Moreover, both classifiers with almost the same accuracy help to justify feature accuracy percentages which influence cardiorespiratory fitness.

Thus, the single feature selection was done using the data accuracy from both Naïve Bayes and Decision Tree classifier. Since Naïve Bayes classifier is very simple and efficient as well as highly sensitive to feature selection, the study of feature selection was significant [27]. The multi-variate Bernoulli model was used by MATLAB software to perform Naïve Bayes classification. Then, the feature selection was done based on the assumption that the probability of occurrence of each feature was independent of the occurrence of each feature [27]. From Table 5, features with accuracy more than 70% were selected to proceed for further analysis. Table 5 shows the selected features in this study, which are RHR, RSBP, FEV_1, BF, BD and MM.

4. Conclusion

Anthropometric and multiparameter trend data were successfully collected from UTM staff and the results obtained were further filtered and used in classification to observe which feature influences CRF. From the analysis done, the comparison was implemented between two main classifiers which are Decision Tree and Naïve Bayes. From classification, the best single features which influence CRF are BF, BD, MM, RHR, RSBP, and FEV_1. The gold standard to determine CRF so far is using maximum oxygen uptake where the efficiency is still unclear in most studies. This is among the limitations in assessing CRF. Single feature analysis has been made by classifying each single feature against VO_2 max. Each classification performance has been observed to select the features that generates accuracy higher than 70%. At this stage, 6 optimal features that influences CRF were BF, BD, MM, RHR, RSBP and FEV_1. Many works have been carried out to obtain the exact method in assessing CRF accurately, although the association of it with cardiovascular disease has been proven in many studies.

Acknowledgement

This research is conducted as a part of the flagship grant of Fundamental Research Grant Scheme (FRGS), vote no. (R.J130000.7745.4F943), supported, by Ministry of Higher Education (MOHE) and also Universiti Teknologi Malaysia for providing the facilities and laboratory equipment for the completion of the research.

References

[1] Wilder R P, Greene J A, Winters K L, Long W B 3rd, Gubler K and Edlich R F 2006 Physical fitness assessment: an update. *J. Long Term Eff. Med. Implants* **16** 16193-204

[2] Cooper K H 1968 A Means of Assessing Maximal Oxygen Intake *JAMA* **203** 201-4

[3] Byrne N M, Hills A P, Hunter G R, Weinsier R L, Schutz Y, Nuala M, … and Roland L Metabolic equivalent : one size does not fit all. 2005 *J Appl. Physiol.* **99** 1112-9

[4] Laukkanen J A and Kurl S Cardiorespiratory Fitness and Physical Activity As Risk Predictors of Future Atherosclerotic Cardiovascular Diseases 2002 *Curr. Atheroscler. Rep.* **4** 468-76

[5] Kaminsky L A, Myers J and Arena R 2019 Determining Cardiorespiratory Fitness With Precision: Compendium of Findings From the FRIEND Registry *Prog Cardiovasc Dis.* **62** 76-82

[6] Wei M, Kampert J B, Barlow C E, Nichaman M Z, Gibbons L W, Paffenbarger R S Jr and Blair S N Relationship Between Low Cardiorespiratory Fitness and Mortality in Normal-Weight, Overweight, and Obese Men 1999 *JAMA* 1999 **282** 1547-53
[7] Hallal P C, Andersen L B, Bull F C, Guthold R, Haskell W, Ekelund U and Lancet Physical Activity Series Working Group Global physical activity levels: surveillance progress, pitfalls, and prospect 2002 *The Lancet* **380** 247-57
[8] Salamuddin N and Harun M T 2013 Physical Activity Index among Malaysian Youth Asian Social Science **9** 99-104.
[9] Blair S N, Kohl H W 3rd, Barlow C E, Gibbons L W and Macera C A Changes in Physical Fitness and All-Cause Mortality Prospective Study of Healthy and Unhealthy Men 1995 *JAMA* **273** 1093-8
[10] Ross R, Blair S N, Arena R, Church T S, Després J P, Franklin B A, … and Stroke Council 2016 Importance of Assessing Cardiorespiratory Fitness in Clinical Practice: A Case for Fitness as a Clinical *Circulation* **134** e653-99
[11] Radu L-E, Hazar F, and Puni A-R 2014 Anthropometric and Physical Fitness Characteristics of University Students *Procedia - Social and Behavioral Sciences* **149** 798-802.
[12] Moreira O C, Aparecida R, Oliveira R De and Doimo L A Anthropometric, cardiovascular and functional variables as indicators of health related physical fitness in university professors 2015 *Fisioterapia em Movimento* **28** 545-54
[13] Tanaka H, Monahan K D, and Seals D R Age-Predicted Maximal Heart Rate Revisited *J. Am. Coll. Cardiol.* **37** 153-6
[14] Peter J M and Carl F 2006 *Physiological Assessment of Human Fitness* (Champaign, US: Human Kinetics Publisher)
[15] Chan Y, Salem R M, Hsu Y H H, McMahon G, Pers T H, Vedantam S, … and Hirschhorn J N 2015 Genome-wide analysis of body proportion classifies height-associated variants by mechanism of action and implicates genes important for skeletal development. *Am. J. Hum. Genet.* **96** 695–-708
[16] Ren J, Lee S D, Chen X, Kao B, Cheng R and Cheung D Naive Bayes Classification of Uncertain Data 2009 *Ninth IEEE Int. Conf. Data Mining* 60703110 944-49
[17] Aggarwal C C, Member S and Yu P S 2009 A Survey of Uncertain Data Algorithms and Applications *IEEE Transactions On Knowledge Data Engineering* **21** 609-23
[18] Kriegel H and Pfeifle M 2005 Hierarchical Density-Based Clustering of Uncertain Data *Proc. Fifth IEEE Int. Conf. Data Mining* 689-692
[19] Michie E D, Spiegelhalter D J, and Taylor C C 1994 *Machine Learning, Neural and Statistical Classification* (US: Overseas Press)
[20] Akobeng, A K 2007 Understanding diagnostic tests 1: Sensitivity, specificity and predictive values *Acta. Paediatr.* **96** 338-41
[21] Wallace J M and Hobbs P V 2006 *Atmospheric Science: An Introductory Survey* (UK: Elsevier)
[22] Lalkhen A G and McCluskey A 2008 Clinical tests: sensitivity and specificity *Continuing Education in Anaesthesia Critical Care & Pain* **8** 221-23
[23] De Brabandere A, Op De Beéck T, Schütte K H, Meert W, Vanwanseele B and Davis J 2018 Data fusion of body-worn accelerometers and heart rate to predict VO 2max during submaximal running *PLoS One* **13** e0199509
[24] WHO Expert Consultation 2004 Appropriate body-mass index for Asian populations and its implications for policy and intervention strategies *The Lancet* **363** 157-63.
[25] Shephard R J, Allen C, Benade A J, Davies C T, Di Prampero P E, Hedman R, … and Simmons R 1968 The Maximum Oxygen Intake. An International Reference Standard of Cardiorespiratory Fitness *Bull. World Health Organ*. **38** 757-764
[26] Han J, Kamber M and Pei J 2001 Data Mining Concepts and Techniques ed M Kaufmann (UK: Elsevier) preface and chapter 1 pp 1-38

[27] Chen J, Huang H, Tian S, and Qu Y 2009 Feature selection for text classification with Naïve Bayes. Expert Systems with Applications *Expert Systems with Applications: Int. J.* **36** 5432-5.