ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

**MSc THESIS**

**Erman AKTÜRK**

# PREDICTON OF MAXIMAL OXYGEN UPTAKE USING MACHINE LEARNING METHODS COMBINED WITH FEATURE SELECTION

**DEPARTMENT OF COMPUTER ENGINEERING**

**ADANA, 2014**

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on 18/08/2014

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# ABSTRACT

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Supervisor : Assoc. Prof. Dr. M. Fatih AKAY
Year: 2014, Pages: 97
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: Asst. Prof. Dr. Zehan KESİLMİŞ

Maximal oxygen uptake ($VO_2$max) refers to the maximum amount of oxygen that an individual can utilize during intense or maximal exercise. Although numerous studies exist to predict $VO_2$max, to date, no study has attempted to apply machine learning methods combined with feature selection algorithms to identify the discriminative features for prediction of $VO_2$max. The purpose of this thesis is to develop new $VO_2$max prediction models using Support Vector Machines (SVM) and Multilayer Perceptron (MLP) combined with feature selection algorithms. Two feature selection algorithms, Relief-F and Correlation-based Feature Selection (CFS), have been considered. By applying Relief-F on the full data sets, the ranking of the features have been obtained. Dimensionality of data sets is reduced by removing the feature with the lowest score at a time before being passed on to the regression method. CFS has been used separately on the full data sets to find out the best subset of features. Using 10-fold cross validation on four different data sets, the performance of prediction models has been evaluated by calculating their multiple correlation coefficients ($R$'s) and standart error of estimates ($SEE$'s). The results show that SVM-based $VO_2$max prediction models perform better (i.e. yield lower $SEE$'s and higher $R$'s) than the prediction models developed by other regression methods.

**Key Words**: Support Vector Machines, Multilayer Perceptron, Maximal Oxygen Uptake

## ÖZ

### YÜKSEK LİSANS TEZİ

### NİTELİK SEÇME İLE BİRLEŞTİRİLMİŞ MAKİNA ÖĞRENME YÖNTEMLERİ KULLANILARAK MAKSİMUM OKSİJEN TÜKETİMİNİN TAHMİNİ

**Erman AKTÜRK**

**ÇUKUROVA ÜNİVERSİTESİ**
**FEN BİLİMLERİ ENSTİTÜSÜ**
**BİLGİSAYAR MÜHENDİSLİĞİ ANABİLİM DALI**

Danışman : Doç. Dr. M. Fatih AKAY
Yıl: 2014, Sayfa: 97
Jüri : Doç. Dr. Ramazan ÇOBAN
: Yrd. Doç. Dr. Zehan KESİLMİŞ

Maksimal oksijen tüketimi ($VO_2$max), bireyin yoğun ve maksimal egzersiz sırasında kullandığı maksimum oksijen miktarını ifade eder. $VO_2$max'ı tahmin etmek için bir çok çalışma yapılmış olmasına rağmen, şu ana kadar hiç bir çalışmada $VO_2$max tahmini için ayırt edici niteliklerin belirlenmesinde nitelik seçme algoritmaları ile birleştirilmiş makine öğrenme yöntemlerinin uygulanması konusu yer almamaktadır. Bu tezin amacı, nitelik seçme algoritmaları ile birleştirilmiş Destek Vektör Makineleri (SVM) ve Çok Katmanlı Algılayıcı (MLP) kullanarak yeni $VO_2$max tahmin modelleri geliştirmektir. Relief-F ve Korelasyon-tabanlı Nitelik Seçme (CFS) algoritmaları kullanılmıştır. Tüm veri setleri üzerinde Relief-F uygulayarak, niteliklerin sıralaması elde edilmiştir. Her defasında en düşük skora sahip nitelik elenerek, veri setinin boyutu küçültülmüştür. Ayrı olarak, tüm veri setleri üzerinde CFS kullanılarak en iyi nitelikleri barındıran alt kümeler seçilmiştir. Dört farklı veri seti üzerinde 10 katlı çapraz doğrulama kullanılarak, tahmin modellerini performansı çoklu korelasyon katsayısı (*R*) ve standart tahmin hatası (*SEE*) hesaplanarak belirlenmiştir. Elde edilen sonuçlara göre, SVM tabanlı $VO_2$max tahmin modellerinin diğer regresyon yöntemleri ile geliştirilen modellere göre daha iyi performans (daha düşük *SEE* ve daha yüksek *R*) gösterdiği görülmüştür.

**Anahtar Kelimeler:** Destek Vektör Makineleri, Çok Katmanlı Algılayıcı, Maksimal Oksijen Tüketimi

## DEDICATION

***... to my wife Birgün***

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| | | |
|---|---|---|
| 3MWD | : | 3-Minute Walk Distance |
| ACSM | : | American College of Sports Medicine |
| AD | : | Accelerometer Data |
| AHR | : | After Heart Rate |
| ANN | : | Artificial Neural Network |
| AOD | : | Accumulated Oxygen Deficit |
| ARC | : | Anaerobic Rowing Capacity |
| BF | : | Body Fat |
| BF% | : | Percent Body Fat |
| BIA | : | Bioelectrical Impedance Analysis |
| BM | : | Body Mass |
| BMI | : | Body Mass Index |
| BSA | : | Body Surface Area |
| BYU | : | Brigham Young University |
| CFS | : | Correlation-Based Feature Selection |
| CRF | : | Cardiorespiratory Fitness |
| CV | : | Critical Velocity |
| EX | : | Exercise |
| FEV1 | : | Forced Expiratory Volume |
| GRNN | : | Generalized Regression Neural Networks |
| GXT | : | Graded Exercise Test |
| HR | : | Heart Rate |
| HR3 | : | Exercise Heart Rate At The End Of 1.5 Mile |
| LoPAR | : | Self-Report Physical Activity Assessment |
| LPA | : | Leisure-time Physical Activity |

| | | |
|---|---|---|
| L-PA | : | Leisure-time Physical Activity |
| MAX-GRD | : | Maximal Grade |
| MAX-HR | : | Maximal Heart Rate |
| MAX-RPE | : | Maximal Rating of Perceived Exertion |
| MAX-Time | : | Maximal Exercise Time |
| MFANN | : | Multilayer Feed-Forward Artificial Neural Networks |
| MIN3 | : | Elapsed Exercise Time At The End Of 1.5 Mile |
| MLP | : | Multilayer Perceptron |
| MLR | : | Multi Linear Regression |
| MPH | : | Speed |
| MVPA | : | Moderate to Vigorous Physical Activity |
| N-Ex | : | Non-Exercise |
| PA | : | Physical Activity |
| PACER | : | Progressive Aerobic Cardiovascular Endurance Run |
| PA-R | : | Physical Activity Rating |
| PAR-Q | : | Physical Activity Readiness Questionnaire |
| PARS | : | Physical Activity Rating Score |
| PASS | : | NASA Physical Activity Status Scale |
| PFA | : | Perceived Functional Ability |
| PFI | : | Physical Fitness Index |
| PHR15 | : | 15-Second Post-Exercise Heart Rate |
| PHR60 | : | 60-Second Post-Exercise Heart Rate |
| PRPE 15 | : | Power At RPE 15 |
| PO | : | Power Output |
| R | : | Multiple Correlation Coefficient |
| RER | : | Respiratory Exchange Ratio |
| RPC | : | Rating of Perceived Capacity |

| | | |
|---|---|---|
| RPE | : | Rating of Perceived Exertion |
| SC | : | Step Count |
| SD | : | Standard Deviation |
| SEE | : | Standard Error of Estimation |
| SM | : | Skeletal Muscle |
| SMAT | : | Skating Multistage Aerobic Test |
| SM-GRD | : | Submaximal Grade |
| SM-HR | : | Submaximal Heart Rate |
| SM-MPH | : | Submaximal Speed |
| SM-RPE | : | Submaximal Rating of Perceived Exertion |
| SM-Stage | : | Submaximal Treadmill Stage |
| SRT | : | Shuttle Run Test |
| SVM | : | Support Vector Machine |
| SVR | : | Support Vector Regression |
| $VO_2$ | : | Oxygen Consumption |
| $VO_2max$ | : | Maximum Oxygen Uptake |
| $VO_2max$-set1 | : | Maximum Oxygen Uptake – Data Set 1 |
| $VO_2max$-set2 | : | Maximum Oxygen Uptake – Data Set 2 |
| $VO_2max$-set3 | : | Maximum Oxygen Uptake – Data Set 3 |
| $VO_2max$-set4 | : | Maximum Oxygen Uptake – Data Set 4 |
| VPA | : | Vigorous Physical Activity |
| VPA | : | Vigorous Physical Activity |
| VSAQ | : | Veterans Specific Activity Questionnaire |
| WC | : | Waist Circumference |
| W-PA | : | Work-related Physical Activity |
| WR | : | Work Rate |

# 1. INTRODUCTION

## 1.1. Definition of Maximal Oxygen Uptake

During endurance exercise, increasing exercise intensity increases $VO_2$. If the intensity of exercise continues to increase, a point of maximal exertion is reached. $VO_2$ at this stage of maximal exertion is called $VO_2$max. It is the maximum volume of oxygen that body is capable of consuming and converting to energy for working muscles. $VO_2$max is considered to be the gold standard by which cardiorespiratory fitness level can be measured.

A person who is fit, would have a higher $VO_2$max than someone who is less fit. However, it is important to understand that if a person has a larger $VO_2$max than others, it does not necessarily mean that person could beat them in, for example, a marathon race. What it means is that the body is more able to absorb and use oxygen to generate energy for the muscles, and this will certainly give an edge, but what a person is actually capable of doing with that energy depends on many other factors (for instance, the mechanical efficiency with which a person runs at a given speed) (Shamsi et al., 2011).

Table 1.1. Female and male normative data for $VO_2$max (values in ml/kg/min) (Achten, and Jeukendrup, 2003)

| Gender | Age | Very Poor | Poor | Fair | Good | Excellent | Superior |
|---|---|---|---|---|---|---|---|
| Female | 13-19 | <25.0 | 25.0 - 30.9 | 31.0 - 34.9 | 35.0 - 38.9 | 39.0 - 41.9 | >41.9 |
| | 20-29 | <23.6 | 23.6 - 28.9 | 29.0 - 32.9 | 33.0 - 36.9 | 37.0 - 41.0 | >41.0 |
| | 30-39 | <22.8 | 22.8 - 26.9 | 27.0 - 31.4 | 31.5 - 35.6 | 35.7 - 40.0 | >40.0 |
| | 40-49 | <21.0 | 21.0 - 24.4 | 24.5 - 28.9 | 29.0 - 32.8 | 32.9 - 36.9 | >36.9 |
| | 50-59 | <20.2 | 20.2 - 22.7 | 22.8 - 26.9 | 27.0 - 31.4 | 31.5 - 35.7 | >35.7 |
| | 60+ | <17.5 | 17.5 - 20.1 | 20.2 - 24.4 | 24.5 - 30.2 | 30.3 - 31.4 | >31.4 |
| Male | 13-19 | <35.0 | 35.0 - 38.3 | 38.4 - 45.1 | 45.2 - 50.9 | 51.0 - 55.9 | >55.9 |
| | 20-29 | <33.0 | 33.0 - 36.4 | 36.5 - 42.4 | 42.5 - 46.4 | 46.5 - 52.4 | >52.4 |
| | 30-39 | <31.5 | 31.5 - 35.4 | 35.5 - 40.9 | 41.0 - 44.9 | 45.0 - 49.4 | >49.4 |
| | 40-49 | <30.2 | 30.2 - 33.5 | 33.6 - 38.9 | 39.0 - 43.7 | 43.8 - 48.0 | >48.0 |
| | 50-59 | <26.1 | 26.1 - 30.9 | 31.0 - 35.7 | 35.8 - 40.9 | 41.0 - 45.3 | >45.3 |
| | 60+ | <20.5 | 20.5 - 26.0 | 26.1 - 32.2 | 32.3 - 36.4 | 36.5 - 44.2 | >44.2 |

Table 1.1 shows normative data for the $VO_2$max assessment and comprises of the following grades: Very Poor, Poor, Fair, Good, Excellent and Superior.

### 1.2. Assessing Maximal Oxygen Uptake

Cardiorespiratory fitness is known to be an objective, reproducible measure that reflects the functional consequences of physical training and recent physical activity habits, and is a powerful predictor of chronic disease morbidity and mortality. Prospective observational studies have shown that low cardiorespiratory fitness is strongly associated with the risk for developing coronary heart disease, hypertension, type 2 diabetes mellitus, and metabolic syndrome as well as mortality from cardiovascular disease, cancer, and all causes of mortality. Hence, cardiorespiratory fitness has been suggested to be included in the European Health Monitoring System for the adult population, National Health and Nutrition Examination Survey in the United States, and the Exercise and Physical Activity Reference for Health Promotion 2006 in Japan, in which the recommended reference value for $VO_2$max to prevent lifestyle-related disease was reported. Although cardiorespiratory fitness is an important health indicator, cardiorespiratory fitness assessment is usually not performed in many health care settings because of the absence of feasible and practical assessment methods (Cao et al., 2009).

There are a variety of choices when it comes to performing a $VO_2$max test and the type of test that will be chosen often depends on who is being tested and where. When testing an individual, exercise or Monarc bikes, treadmills, and steps are the most common methods used, while the beep test is a popular choice when training sports teams.

Two treadmill tests that are commonly used are the Balke Protocol and the Bruce Protocol. Both tests involve a subject on the treadmill with increasing speed, grade or both. These tests are effective in estimating $VO_2$max without using too much time, effort or equipment. Using these tests, the subject walks or runs, and factors including grade and speed are changed. With the Balke test the grade is changed every minute with a constant speed until the subject can no longer perform. The final time is recorded and then put into an equation to estimate $VO_2$max (Chavda et al., 2013).

The most common option for fitness testing in a gym is bike tests. Most gyms will offer the choice of an exercise bike with built in fitness test such as the LifeCycle bike (the best option for older adults, or for someone who is obese, or very unfit) or a Monarc bike. The Monarc bike is designed specifically for fitness testing and has a weight attached to the wheel. This weight is adjusted every 3 minutes to increase the work load while the volunteer is exercising and the way in which heart rate responds helps to determine fitness level (Cao et al., 2010).

Personal trainers who don't work in a gym, prefer walking test. In this test, heart rate is recorded as volunteer walks for a set distance (normally 1.6 kms) and the time it takes is also noted. Heart rate and the time it takes to walk the distance is then used to determine fitness level. One of the advantages of this test is that volunteer can instantly see that his (her) fitness has improved at the next test by the time it takes to walk the distance (Nes et al., 2011).

A popular home testing method and often used by schools, the step test combines the height of the step with the number of steps that volunteer completes in one minute, to calculate fitness level. As with the walking tests, volunteer can instantly tell if his (her) fitness has improved at his (her) next test by how many steps he (she) is able to do (Chatterjee et al., 2005).

Popular with sporting clubs and other organizations, the beep test requires participants to run between two markers set 20 meters apart and is known as a multi-stage test. The athlete or client is required to run between the two markers, starting when the beep sounds and arrive at the other end before the beep is heard again. As the test progresses, the beeps sound closer together, making it necessary to run faster as an athlete is getting tired, just to keep up. Once the athlete misses two beeps in a row (i.e. cannot reach the marker before the beep sounds) they need to stop and the last staged noted is the equivalent of their fitness level (Chatterjee et al., 2008).

### 1.3. Measurement of Maximal Oxygen Uptake

$VO_2$ is essentially the difference between the amount of oxygen that a person inspires and the amount of oxygen that he expires. Therefore, to accurately determine someone's $VO_2$ it is necessary to know the volume of air that he inspires and the percentage of oxygen in the inspired and expired air. Sophisticated laboratory equipment is required to make these measurements while a subject performs a gradual progression to maximal physical exertion (generally this is done on a treadmill). Once maximal exertion is reached (i.e. the subject cannot work any harder) $VO_2$ will, after a slight delay, be observed to plateau. The highest measured $VO_2$ at this plateau stage represents the subject's $VO_2max$.

Results for $VO_2$ measurements are generally displayed in $L \bullet min^{-1}$ (i.e. liters per minute, representing the volume of oxygen consumed by the entire body each minute) or, to account for differences in total body mass, in $mL \bullet kg^{-1} \bullet min^{-1}$ (i.e. milliliters per kilogram per minute, representing the volume of oxygen consumed each minute per kilogram of the body mass).

The direct measurement of $VO_2max$ is the criterion measure, or "gold standard", of aerobic capacity where the participant undergoes a maximal exercise test on a cycle ergo meter or treadmill and oxygen consumption is measured directly, which is the most accurate method (Shamsi et al., 2011).

The ‘‘gold standard’’ for assessing $VO_2max$ is to undertake gas analyses while the client performs a maximal exercise test to exhaustion. This technique was pioneered by Hill and Lupton in 1923 (Hill and Lupton, 1923). Since that time, technological advances have facilitated the procedure and improved the accuracy of measurement, but the basic concept of exercising a client to the point of maximal effort, where a plateau may exist in oxygen consumption despite an increased workload, remains the same.

A $VO_2max$ test with gas analyses requires expensive equipment, trained personnel, and a highly motivated client. Because this is not always practical or possible, numerous prediction equations have been developed to estimate $VO_2max$ without the need for expensive gas analysis systems (Waddoups et al., 2008).

### 1.4. $VO_2$max Estimation Models

Due to the disadvantages of the direct measurement of $VO_2$max, several $VO_2$max estimation models have been developed. There are three common ways to predict $VO_2$max for an individual. $VO_2$max can be estimated with maximal, submaximal tests or non-exercise tests.

Submaximal tests indirectly estimate $VO_2$max using submaximal exercise variables and are most often performed on a treadmill, although they can be performed on an ergometer or a track. Use of a treadmill as a mode of submaximal exercise testing is effective because (a) treadmills are readily available in laboratories and fitness facilities; (b) jogging is a popular form of exercise, and treadmills are often used as a training modality; (c) treadmill protocols are easy to administer and control; and (d) individualized jogging programs can be based on the results of the treadmill jogging test. Submaximal tests are faster, safer, and cheaper to administer than maximal tests. In addition, submaximal exercise testing provides the administrator an opportunity to observe responses to exercise and to teach participants about selection of an appropriate intensity of exercise. However, submaximal tests have been found to be less accurate than maximal tests yet more accurate than the non-exercise tests (Akay et al., 2011).

Other methods that do not require exercise are also available to predict $VO_2$max. Without the need to perform a maximal or submaximal exercise test, non-exercise regression equations provide a convenient estimate of $VO_2$max. This approach is inexpensive, time-efficient, and realistic for large groups. Age, gender, BMI, BF%, PA-R and PFA are common non-exercise predictor variables. The PA-R question allows participants to self-report their level of physical activity during the past six months. The response to the PA-R question is the PA-R score (range = 0–10). The PFA includes simple questions which ask individuals to rate their ability to exercise at a comfortable pace for 1 and 3 miles (Akay et al., 2012). The disadvantage of non-exercise prediction model is that non-exercise tests depend upon the truthful self-report of activity and cannot be used when the individuals have an interest in the results, giving them a reason to falsify the self-reported activity levels (Akay et al., 2010).

In some studies, it was also shown that exercise and non-exercise variables could be combined to develop hybrid $VO_2$max estimation models. (George et al., 2009).

### 1.5. Feature Selection

Feature selection is an important issue in pattern recognition and machine learning which helps us to focus the attention of a classification algorithm on those features that are the most relevant to predict the class. Theoretically, if the full statistical distribution were known, using more features could improve results. However, in practical a large number of features as the input of induction algorithms may turn them inefficient as memory and time consumers. Besides, irrelevant features may confuse algorithms leading to reach false conclusions, and hence producing even worse results. So it is of fundamental importance to select the relevant and necessary features in the preprocessing step. Obviously, the advantages of using feature selection may be improving understandability and lowering cost of data acquisition and handling. Because of all these advantages, feature selection has attracted much attention within the machine learning, artificial intelligent and data mining communities (Sun et al., 2011).

### 1.6. Motivation, Purpose and Contributions of This Thesis

As discussed before, although direct measurement of $VO_2$max is the most reliable method, it has also several limitations. Because of these drawbacks, numerous $VO_2$max prediction models have been developed by using exercise and non-exercise variables. Most of these models have been developed by MLR. In recent years, Akay et. al (Akay et al., 2013) have shown that machine learning methods such as SVM and MLP perform better than MLR-based $VO_2$max prediction models.

The purpose of this thesis is to develop new $VO_2$max prediction models using SVM and MLP combined with feature selection algorithms. Two feature selection algorithms (Relief-F and CFS) have been considered. By applying Relief-F on the full data sets, the ranking of the features have been obtained. Dimensionality of data sets is reduced by removing the feature with the lowest score at a time before being passed on to the regression method. CFS has been used separately on the full data sets to find out the best subset of features. $VO_2$max prediction models have been developed using 4 different data sets. Using 10-fold cross validation, the performance of prediction models has been evaluated by calculating their *R*'s and *SEE*'s. For comparison purposes, MLR-based prediction models have also been developed.

The main contributions of this thesis are as follows:

- To the best of our knowledge, this is first study in literature that develops $VO_2$max prediction models using machine learning methods combined with feature selection algorithms.
- By using different regression and feature selection methods, this thesis allows to rank the applied methods for predicting $VO_2$max.
- Integrating feature selection algorithms into regression methods, this study yields discriminating the useful and redundant features for $VO_2$max prediction. In other words, this study shows that in certain models, $VO_2$max can be predicted with less error using less number of features.
- Development of different prediction models (non-exercise, submaximal and models) by using 4 different data sets considerably increases the reliability of the presented results.

### 1.7. Overview of Datasets

Four different dataset were used in this thesis:

**$VO_2$max-set1:** The subjects include 100 (50 females and 50 males) healthy volunteers ranging in age from 18 to 65 years. All subjects were recruited from the Y-Be-Fit Wellness Program at BYU and employees from the LDS Hospital in Salt

Lake City, Utah. Prior to exercise testing, all subjects completed a PAR-Q and signed an informed consent document that was approved by the BYU Institutional Review Board for Human Subjects. Subjects' height and body mass were measured and recorded using a stadiometer and balance beam scale, respectively. Instructions about the maximal graded exercise test were given to all subjects prior to testing.

The dataset includes non-exercise variables (gender, age, PFA, BMI and PA-R), maximal exercise test variables (MAX-HR, MAX-GRD and MAX-RPE) and submaximal exercise test variables (SM-HR, SM-GRD and SM-RPE).

**$VO_2$max-set2:** One hundred twenty six participants (81 males and 45 females), classified as ''low risk" according to ACSM risk stratification and aged from 17 to 40 years, were included in this study. Before exercise testing, all participants received a detailed explanation about the goal and the clinical implications of this investigation. All participants read and signed an informed consent form approved by the Brigham Young University's institutional review board and completed a pre-exercise test-ing screening questionnaire.

This dataset contains N-Ex variables (gender, age, BM, BMI and height) and submaximal test variables (SM-HR and SM-MPH).

**$VO_2$max-set3:** The subjects included 439 (229 females, 210 males) "apparently healthy" volunteers ranging in age from 20 to 79 years. All subjects were recruited from the Amherst and Worcester, Massachusetts, communities. The investigation was explained in detail before each subject signed an informed consent document in accord with University of Massachusetts Human Subjects Committee/Amherst guidelines. Each subject was screened for cardiovascular and orthopedic contraindications to brisk walking. Subjects taking medication known to affect HR and blood pressure responses to exercise were not tested. Resting HR, blood pressure, and 12-lead electrocardiograms were examined in all subjects over the age of 40 by a physician before testing. The physician was also present at maximal treadmill testing for subjects over the age of 40 years.

The dataset includes data of 439 subjects and the input variables of the dataset are gender, age, BMI, BF, MAX-RER, MAX-RPE, MAX-HR and MAX-Time.

**$VO_2$max-set4:** 185 apparently healthy college students (115 men and 70 women), aged 18 to 26 years, were recruited to participate in this study. Previous to any testing, all participants signed an informed consent document approved by the University Institutional Review Board and completed a brief PAR-Q to screen for possible cardiovascular contraindications.

The dataset of this study involves the independent predictors: gender, age, BMI, time and HR.

# 2. PREVIOUS WORKS

In the literature, lots of studies have been developed by using maximal, submaximal and non-exercise variables to $VO_2max$ prediction, that will be described in this section.

## 2.1. Maximal prediction models based studies

George et al. (George et al., 2007) developed an age-generalized regression model to predict $VO_2max$ based on a maximal treadmill GXT. Participants (N=100), ages 18–65 years, reached a maximal level of exertion during the GXT to assess $VO_2max$. That study provided a relatively accurate regression model to predict $VO_2max$ in relatively fit men and women, based on maximal exercise (treadmill speed and grade), biometric (BMI), and demographic (age and gender) data. *SEE* and *R* values of their model were 3.18 and 0.94, respectively.

Leone et al. (Leone et al., 2007) designed an on-ice test to predict $VO_2max$ in ice hockey players. 30 elite hockey players (age 14.7 ± 1.5 years) participated in this study. The oxygen uptake was assessed at submaximal and maximal velocities during an on-ice intermittent maximal multistage shuttle skate test with a 1-min/0.5-min work/rest ratio. The procedure consisted of skating back and forth on a distance of 45 m (stop and go) while following a pace fixed by an audible signal: initial velocity of 3.5 $m \cdot s^{-1}$ with increments of 0.2 $m \cdot s^{-1}$ every stage. The SMAT enabled the prediction of the $VO_2max$ from the maximal velocity variable. Their results for *SEE* and *R* were 3.01 and 0.97, respectively.

Chatterjee et al. (Chatterjee et al., 2008) validated the applicability of the 20-meter multi stage shuttle run test (20-m MST) in Indian adult female. For application of direct method cross over design was followed. For validity of the results repeatability was used. 32 female university students from three different universities of West Bengal, India were recruited for the study. Direct estimation of $VO_2max$ comprised treadmill exercise followed by expired gas analysis by scholander micro-gas analyzer whereas $VO_2max$ was indirectly predicted by the 20-m MST. For estimating $VO_2$max, maximal shuttle run speed was used in that model. They reported that *SEE* and *R* were 1.09 and 0.93, respectively.

Ruiz et. al. (Ruiz et al., 2008) developed an ANN equation to estimate $VO_2$max from 20 m shuttle run test performance (stage), sex, age, weight, and height in 122 boys and 71 girls adolescents aged 13-19 years. The *SEE* and *R* of their model was reported to be 2.78 and 0.96, respectively.

Chatterjee et al. (Chatterjee et al., 2010) validated the applicability of the 20-m MST in Nepalese adult females. Forty female college students from different colleges of Nepal were recruited for the study. Direct estimation of $VO_2$max comprised treadmill exercise followed by expired gas analysis by scholander micro-gas analyzer whereas $VO_2$max was indirectly predicted by the 20-m MST. Maximal shuttle run speed was used in the model to predict $VO_2$max. *SEE* and *R* were reported to be 0.53 and 0.94, respectively.

Tsiaras et al. (Tsiaras et al., 2010) developed and validated a $VO_2$max prediction equation from a treadmill running test in active male adolescents. Eighty-eight athletes performed a maximal exercise test on a treadmill to assess the actual $VO_2$max and a 20-m MST. A step-wise linear regression analysis and cross validation were used. Anthropométrie data, performance in 20-m MST and energy cost at submaximal speeds were used to predict $VO_2$max. The presented *SEE* and *R* values were 2.50 and 0.54, respectively.

Bandyopadhyay et. al. (Bandyopadhyay et. al., 2011) investigated validity of 20-m MST for estimation of $VO_2$max in male university students. Eighty four sedentary male university students of same socio-economic background were recruited from students of University of Calcutta, Kolkata, India to validate the applicability of 20 meter SRT for indirect estimation of $VO_2$max in young male sedentary university students of Kolkata, India. *SEE* and *R* of their best model were reported to be 1.38 and 0.94, respectively.

Mahar et al. (Mahar et al., 2011) developed and cross-validated regression models to estimate $VO_2$max from PACER 20-m shuttle run performance in boys and girls aged 10 –16 years. Several previously published PACER models were also cross-validated. PACER performance and $VO_2$max were assessed in a sample of 244 participants. The sample was randomly split into validation (n=174) and cross-validation (n=70) samples. The validation sample was used to develop the regression models to estimate $VO_2max$ from PACER, BMI, gender, and age. They indicated that *SEE* and *R* of their best model were 6.17 and 0.75, respectively.

Akay et al. (Akay et al., 2012) developed $VO_2max$ models by using different regression methods such as ANN's, SVR, GRNN's and MLR. The dataset included data of 439 subjects and the input variables of the dataset were gender, age, BMI, BF, RER, RPE, HR and time to exhaustion from treadmill test. For best model, they shown that *SEE* and *R* values were 3.73 and 0.91, respectively.

Daros et al. (Daros et al., 2012) developed a maximum aerobic power test and an equation to estimate $VO_2max$ for soccer athletes. The proposed test consisted of applying progressive, continuous, and maximal speed running that covers 80 m (1 lap), structured in a square (20m x 20m), where the athletes performs up to exhaustion. Two $VO_2max$ estimation equations were genareted by using simple linear regression analysis includes total distance and maximum speed variables. They reported the best values that *SEE* and *R* were 4.29 and 0.76, respectively.

Kendall et al. (Kendall et al., 2012) examined the relationship between the CV test and $VO_2max$ and developed a regression equation to predict $VO_2max$ based on the CV test in female collegiate rowers. Thirty-five female collegiate rowers performed 2 incremental $VO_2max$ tests to volitional exhaustion on a Concept II Model D rowing ergometer to determine $VO_2max$. After a 72-hour rest period, each rower completed 4 time trials at varying distances for the determination of CV and anaerobic rowing capacity. *SEE* and *R* of their study were reported to be 0.14 and 0.72, respectively.

Silva et al. (Silva et al., 2012) calculated and validated two models to estimate $VO_2max$ in Portuguese youths, aged 10-18 years, using a 20-meter SRT. Subjects (54 girls and 60 boys) were divided into estimation (n=91) and cross-validation (n=23) groups, and their $VO_2max$ was directly measured by wearing a portable gas analyzer during the SRT. MLR and ANN tests were carried out considering sex, age, height, weight, BMI and SRT stage as predictors of $VO_2max$. The reported *SEE* and *R* values were 4.90 and 0.84, respectively.

Aktürk et al. (Aktürk et al., 2013) developed $VO_2$max estimation models by using different regression methods such as MFANN's, SVR, GRNN's and MLR. The dataset included data of 439 subjects and the input variables of the dataset were gender, age, BMI, %BF, RER, RPE, HR and time to exhaustion from treadmill test. As best model values, *SEE* and *R* were reported to be 3.77 and 0.91, respectively.

Brown et al. (Brown et al., 2013) studied at a prediction equation for the estimation of cardiorespiratory fitness using an elliptical motion trainer. Fifty-nine subjects were randomly divided into a validation (VAL:n=39) or cross-validation (XVAL:n=20) group. $VO_2$max was measured via indirect calorimetry on an elliptical motion trainer for both groups. Subjects exercised at 150 strides·min-1 against a resistance of four and a crossramp of 8%. The resistance was increased every two minutes by two units until exhaustion. For the VAL group, a step wise regression analysis was used to predict $VO_2$max from resistance, MAX-HR, BMI, height and gender (female=0, male=1). They shown that *SEE* and *R* were 4.47 and 0.87, respectively.

Cao et al. (Cao et al., 2013) developed new $VO_2$max prediction models using a perceptually regulated 3MWD. $VO_2$max was measured with a maximal incremental cycle test in 283 Japanese adults. A 3-minute walk test was conducted at a self-regulated intensity corresponding to RPE 13. Three prediction models were developed by multiple regression to estimate $VO_2$max using data on gender, age, 3MWD, and either BMI, WC, or %BF. *SEE* and *R* values of their best model were 4.57 and 0.84, respectively.

Costa et al. (Costa et al., 2013) validated an equation to estimate the $VO_2$max of nonexpert adult swimmers. Participants were 22 nonexpert swimmers, male, aged between 18 and 30 years, divided into two subgroups: G1 – eleven swimmers for the $VO_2$max oximetry and modeling of the equation; and G2 – eleven swimmers for application of the equation modeled on G1 and verification of their validation. The test used was the adapted Progressive Swim Test, in which there occurs an increase in the intensity of the swim every two laps. Three different models were developed in their study. According to their reported results of best model, values for *SEE* and *R* were 7.20 and 0.80, respectively.

Koutlianos et al. (Koutlianos et al., 2013) assessed the indirect calculation of $VO_2$max using ACSM's equation for Bruce protocol in athletes of different sports and to compare with the directly measured; secondly to developed regression models predicting $VO_2$max in athletes. Fifty five male athletes of national and international level performed graded exercise test with direct measurement of $VO_2$ through ergospirometric device. Moreover, 3 equations were used for the indirect calculation of $VO_2$max: a) ACSM running equation, b) regression analysis model using enter

Table 2.1. Summary of maximal regression models to estimate $VO_2$max

| Study | Predictor Variables | SEE | R |
|---|---|---|---|
| George et. al. (2007) | G, Age, BMI, MPH, GR | 3.18 | 0.94 |
| Leone et al. (2007) | Velocity | 3.01 | 0.97 |
| Chatterjee et al. (2008) | Velocity | 1.09 | 0.93 |
| Ruiz et al. (2008) | G, Age, Height, BM, Stage | 2.78 | 0.96 |
| Chatterjee et al. (2009) | Velocity | 0.53 | 0.94 |
| Tsiaras et al. (2010) | Duration, BM | 2.50 | 0.54 |
| Bandyopadhyay (2011) | Age, BM, Height, Velocity | 1.38 | 0.94 |
| Mahar et al. (2011) | G, Age, BMI, PACER | 6.17 | 0.75 |
| Akay et al. (2012) | G, Age, BMI, BF, RER, RPE, Time | 3.73 | 0.91 |
| Daros et al. (2012) | Meter | 4.29 | 0.76 |
| Daros et al. (2012) | Velocity | 4.53 | 0.73 |
| Kendall et al. (2012) | CV, ARC | 0.14 | 0.72 |
| Silva et al. (2012) | G, Age, BM, Height, BMI, SR | 4.90 | 0.84 |
| Aktürk et al. (2013) | G, Age, BMI, BF, RER, Time | 3.77 | 0.91 |
| Brown et al. (2013) | G, Height, BMI, HR, Resistance | 4.47 | 0.87 |
| Cao et al. (2013) | G, Age, 3MWD, BMI | 5.26 | 0.78 |
| Cao et al. (2013) | G, Age, 3MWD, WC | 5.04 | 0.80 |
| Cao et al. (2013) | G, Age, 3MWD, %BF | 4.57 | 0.84 |
| Costa et al. (2013) | NLP | 7.91 | 0.74 |
| Costa et al. (2013) | NLP, BM | 7.57 | 0.77 |
| Costa et al. (2013) | NLP, BM, AHR | 7.21 | 0.80 |
| Koutlianos et al. (2013) | Age, BMI, Grade, Time | 6.11 | 0.64 |
| Koutlianos et al. (2013) | Age, Time | 6.18 | 0.61 |
| Machado et al. (2013) | BM, Velocity | 4.10 | 0.93 |

**G**, gender; **BMI**, body mass index; **MPH**, treadmill speed; **GR,** treadmill grade; **BM**, body mass; **PACER**, progressive aerobic cardiovascular endurance run; **SR**, shuttle run; **NLP**, number of laps performed; **AHR**, after heart rate; **BF**, body fat; **RER**, respiratory exchange ratio from treadmill test, **RPE**, self-reported rating of perceived exertion from treadmill test; **3MWD**, 3-minute walk distance; **WC**, waist circumference; **%BF**, body fat percentage; **HR**, heart rate; **CV**, critical velocity; **ARC**, anaerobic rowing capacity.

method and c) stepwise method based on the measured data of $VO_2$. Age, BMI, speed, grade and exercise time were used as independent variables. Best *SEE* and *R* values of their study were 6.11 and 0.64, respectively.

Machado and Denadai (Machado and Denadai, 2013) made a specific predictive equation to determine the $VO_2$max from boys aged 10-16 years-old. Forty-two boys underwent a treadmill running ergospirometric test, with the initial velocity set at 9 km/h, until voluntary exhaustion. *SEE* and *R* of their study were reported to be 4.10 and 0.93, respectively.

Table 2.1 summarizes the above studies that used maximal models to estimate $VO_2$max.

### 2.2. Non-exercise prediction models based studies

Bradshaw et al. (Bradshaw et al., 2005) developed a regression equation to predict $VO_2$max based on N-Ex data. All participants (N= 100), ages 18–65 years, successfully completed a maximal GXT to assess $VO_2$max. The N-Ex data collected just before the maximal GXT included the participant's age; gender; BMI; PFA to walk, jog, or run given distances; and current PA-R level. *SEE* and *R* of their study were reported to be 3.63 and 0.91, respectively.

Sanada et al. (Sanada et al., 2007) developed nonexercise models for predicting $VO_2$max using SM mass and cardiac dimensions and to investigate the validity of these equations in healthy Japanese young men. Sixty healthy Japanese men were randomly separated into two groups: 40 in the development group and 20 in the validation group. $VO_2$max during treadmill running was measured using an automated breath-by-breath mass spectrometry system. Stepwise regression analysis was applied to thigh SM mass and stroke volume for prediction of $VO_2$max in the development group, and these parameters were closely correlated with absolute measured $VO_2$max by multiple regression analysis. According to their reported results for best model, values for *SEE* and *R* were 0.39 and 0.85, respectively.

Miyatani et al. (Miyatani et al., 2008) determined and quantified the muscle mass required to maintain the $VO_2$max reference values in Japanese women. A total of 403 Japanese women aged 20–69 years were randomly allocated to either a validation or a cross-validation group. In the validation group, a multiple regression equation, which used a set of age and the percentage of muscle mass, as independent variables, was derived to estimate the $VO_2max$. After the equation was cross-validated, data from the two groups werepooled together to establish the final equation. The required percentage of muscle mass for each subject was recalculated by substituting the $VO_2max$ reference values and her age in the final equation. The presented *SEE* and *R* values were 5.70, 0.75, respectively.

Stahn et al. (Stahn et al., 2008) investigated the ability of whole-body and segmental multifrequency BIA to improve current nonexercise $VO_2max$ prediction models. Data for $VO_2max$, anthropometry, self-reported PA-R and BIA were collected in 115 men and women. MLR was used to develop the most parsimonious prediction model. Segmental BIA was not superior to whole-body measurements. Their reported values for *SEE* and *R* were 3.12 and 0.94, respectively.

Akay et al. (Akay et al., 2009) developed non-exercise (N-Ex) $VO_2max$ prediction models by using SVR and MFANN. $VO_2max$ values of 100 subjects (50 males and 50 females) were measured using a maximal GXT. The variables; gender, age, BMI, PFA) to walk, jog or run given distances and current PA-R are used to build two N-Ex prediction models. Using 10-fold cross validation on the dataset. They compared the results of SVR an MFANN prediction models. Reported *SEE* and *R* values for their study were 3.23 and 0.91, respectively.

Cao et al. (Cao et al., 2009a) developed a new non-exercise $VO_2max$ prediction model using a PA variable determined by pedometer-determined SC in Japanese women aged 20–69 years old. Eighty-seven and 102 subjects were used to develop the prediction model, and to validate the new model, respectively. $VO_2max$ was measured using a maximal incremental test on a bicycle ergometer. SC was significantly related to $VO_2max$ after adjusting for BMI and age. When the new prediction equation developed by multiple regression to estimate $VO_2max$ from age, BMI, and SC was applied to the validation group, predicted $VO_2max$ correlated well with measured $VO_2max$, suggesting that SC is a useful PA variable for non-exercise prediction of $VO_2$max Japanese women. Best *SEE* and *R* values of their study were 2.98 and 0.86, respectively.

Cao et al. (Cao et al., 2009b) investigated the use of the accelerometer-determined PA intensity variables as the objective PA variables for estimating VO2max in Japanese adult women. The subjects of this study were 148 Japanese women aged 20 to 69 yr. $VO_2$max was measured with a maximal incremental test on a bicycle ergometer. Daily SC and the amount spent in MVPA and VPA were measured using accelerometer-based activity monitors for 7 consecutive days. Using data of age, SC, MVPA, or VPA, and either BMI or WC, the nonexercise $VO_2$max prediction models were derived as BMI models MVPA, WC models MVPA, BMI models VPA, and WC models VPA, and cross-validated by using two separate cross-validation procedures. Reported *SEE* and *R* values for their best model were 2.98 and 0.86, respectively.

Suminski et al. (Suminski et al., 2009) examined the effects of smoking on both measured and predicted $VO_2$max. Indirect calorimetry was used to measure $VO_2$max in 2,749 men and women. Physical activity using the PASS, BMI and smoking (pack-y=packs-day*y of smoking) also were assessed. Pack-y groupings were Never (0 pack-y), Light (1-10), Moderate (11-20), and Heavy (>20). Multiple regression analysis was used to examine the effect of smoking on $VO_2$max predicted by PASS, age, BMI and gender. Their best *SEE* and *R* were reported as 4.85 and 0.80, respectively.

Cao et al. (Cao et al., 2010) investigated the use of the accelerometer-determined PA variables as the objective PA variables for estimating $VO_2$max in Japanese adult men. One hundred and twenty-seven Japanese adult men aged from 20 to 69 years were recruited as subjects of the present study. $VO_2$max was measured with a maximal incremental test on a bicycle ergometer. Daily SC and the amount spent in MVPA and VPA were measured using accelerometer-based activity monitors worn at the waist for seven consecutive days. The non-exercise models were derived using hierarchical linear regression analysis, and cross-validated using two separate cross-validation procedures. They reported that *SEE* and *R* values were 3.90 and 0.86, respectively.

Schembre and Riebe (Schembre and Riebe, 2011) develop and test a $VO_2max$ estimation equation derived from the International Physical Activity Questionnaire–Short Form. College-aged males and females (n=80) completed the International Physical Activity Questionnaire–Short Form and performed a maximal exercise test. The estimation equation was created with multivariate regression in a gender-balanced subsample of participants, equally representing five levels of fitness (n=50) and validated in the remaining participants (n=30). The resulting equation explained 43% of the variance in measured $VO_2max$. Estimated $VO_2max$ for 87% of individuals fell within acceptable limits of error observed with sub-maximal exercise testing (20% error). The International Physical Activity Questionnaire–Short Form can be used to successfully estimate $VO_2max$ as well as sub-maximal exercise tests. Development of other population-specific estimation equations is warranted. According the their models, best *SEE* and *R* were 5.45 and 0.65, respectively.

Jang et al. (Jang et al., 2012) determined whether work-related physical activity is a potential predictor of $VO_2max$, and to develop a $VO_2max$ equation using a non-exercise regression model for the cardiorespiratory fitness test in Korean adult workers. Study subjects were adult workers of small-sized companies in Korea. Subjects with history of disease such as hypertension, diabetes, asthma and angina were excluded. In total, 217 adult subjects (113 men of 21-55 years old and 104 women of 20-64 years old) were included. Self-report questionnaire survey was conducted on study subjects, and $VO_2max$ of each subject was measured with the exercise test. The statistical analysis was carried out to develop an equation for estimating $VO_2max$. The predictors for estimating $VO_2max$ included age, gender, BMI, smoking, leisure-time PA and the factors representing work-related physical activity. The work-related physical activity was identified to be a predictor of $VO_2max$. *SEE* and *R* of their best model were reported to be 3.36 and 0.89, respectively.

Shenoy et al. (Shenoy et al., 2012) developed a linear regression model to predict treadmill $VO_2max$ scores using non-exercise data. In this cross sectional study, one hundred twenty college-aged participants (60 male, 60 female) voluntarily participated and successfully completed a maximal GXT on a motorized treadmill to assess $VO_2$max. The maximal treadmill GXT required participants to exercise to volitional fatigue. Relevant N-Ex data included PFA score, PA-R score and BSA. Multiple linear regression generated the regression equation based model. The accuracy of the model was evaluated by conducting a cross-validation analysis (N=18). The presented *SEE* and *R* values were 0.42, 0.90, respectively.

Silva et al. (Silva et al., 2012) compared strategies to define final and initial speeds for designing ramp protocols. $VO_2$max was directly assessed in 117 subjects

Table 2.2. Summary of N-Ex regression models to estimate $VO_2$max

| Study | Predictor Variables | R | SEE |
|---|---|---|---|
| Bradshaw et al. (2005) | G, Age, BMI, PA-R, PFA | 0.91 | 3.63 |
| Sanada et al. (2007) | BM | 0.74 | 0.49 |
| Sanada et al. (2007) | BM, Stroke Volume | 0.85 | 0.39 |
| Miyatani et al. (2008) | Age, BM, Height, BMI, Muscle Mass | 0.75 | 5.70 |
| Stahn et al. (2008) | G, Age, BM, Height, PA-R, BIA | 0.94 | 3.12 |
| Akay et al. (2009) | G, Age, BMI, PFA, PA-R | 0.91 | 3.23 |
| Cao et al. (2009a) | Age, BMI, SC, MVPA, VPA | 0.86 | 2.98 |
| Cao et al. (2009a) | Age, BMI, SC | 0.75 | 4.33 |
| Cao et al.(2009b) | Age, BC, SC, BMI | 0.80 | 3.51 |
| Cao et al.(2009b) | Age, BC, SC, WC | 0.82 | 3.31 |
| Cao et al.(2009b) | Age, BC, SC, MVPA, BMI | 0.83 | 3.29 |
| Cao et al.(2009b) | Age, BC, SC, MVPA, WC | 0.85 | 3.14 |
| Cao et al.(2009b) | Age, BC, SC, VPA, BMI | 0.85 | 3.11 |
| Cao et al.(2009b) | Age, BC, SC, VPA, WC | 0.86 | 2.98 |
| Suminski et al. (2009) | G, Age, BMI, PASS | 0.80 | 4.85 |
| Cao et al. (2010) | Age, BMI, SC, VPA | 0.86 | 3.90 |
| Schembre et al. (2011) | G, Vigorous Activity | 0.65 | 5.45 |
| Jang et al. (2012) | G, Age, BMI, Smoking, L-PA, W-PA | 0.89 | 3.36 |
| Shenoy et al. (2012) | G, PFA, BSA | 0.90 | 0.42 |
| Silva et al. (2012) | G, Age, VSAQ, RPC | 0.73 | 5.75 |
| Açıkkar et al. (2013) | G, Age, BMI, PFA, PA-R | 0.93 | 3.23 |

**G**, gender; **BMI**, body mass index; **PA-R**, physical activity rating; **PFA**, perceived functional ability; **PARS**, physical activity rating score; **BM**, body mass; **BIA**, bioelectrical impedance analysis; **SC**, step count; **MVPA**, moderate to vigorous physical activity; **VPA**, vigorous physical activity, **L-PA**, leisure-time physical activity; **W-PA**, work-related physical activity; **VSAQ**, veterans specific activity questionnaire; **RPC**, rating of perceived capacity; **WC**, waist circumference; **PASS**, NASA Physical Activity Status Scale; **BSA**, body source area.

(29±8 yrs) and estimated by three nonexercise models: (1) VSAQ; (2) RPC; (3) Questionnaire of CRF. Thirty seven subjects performed three additional tests. *SEE* and *R* values of their model were 5.75 and 0.73, respectively.

Açıkkar et al. (Açıkkar et al., 2013) developed N-Ex $VO_2$max prediction models by using SVR and MFANN. $VO_2$max values of 100 subjects were measured using a maximal graded exercise test. The variables; gender, age, BMI, PFA and PA-R were used to build two N-Ex prediction models. 10-fold cross validation were used on the datase. The best *SEE* and *R* were 3.23 and 0.93, respectively.

Table 2.2 summarizes the above studies that used N-Ex models to estimate $VO_2$max.

### 2.3. Submaximal prediction models based studies

Dalleck et al. (Dalleck et al., 2006) developed an equation to predict $VO_2$max from a submaximal elliptical cross-trainer test. Fifty-four apparently healthy subjects (25 men and 29 women) participated in the study and were randomly assigned to an original sample group (n=40) and a cross-validation group (n=14). Each subject completed an elliptical cross-trainer submaximal (3 5-minute submaximal stages) and a $VO_2$max test on the same day, with a 15-minuterest period in between. Stepwise multiple regression analyses were used to develop an equation for estimating elliptical crosstrainer $VO_2$max from the data of the original sample group. The accuracy of the equation was tested by using data from the cross-validation group. *SEE* and *R* of their model were reported to be 3.91 and 0.86, respectively.

McComb et al. (McComb et al., 2006) studied on developing a prediction equation that could be used to estimate $VO_2$max from a submaximal water running protocol. Thirty-two volunteers (n=19 males, n=13 females), ages 18–24 years, underwent the following testing procedures: (a) a 7-site skin fold assessment; (b) a land $VO_2$max running treadmill test; and (c) a 6 min water running test. For the water running submaximal protocol, the participants were fitted with an Aqua Jogger Classic Uni-Sex Belt and a Polar Heart Rate Monitor; the participants' head, shoulders, hips and feet were vertically aligned, using a modified running/bicycle motion. A regression model was used to predict $VO_2max$. The criterion variable, $VO_2max$, was measured using open-circuit calorimetry utilizing the Bruce Treadmill Protocol. Predictor variables included in the model were %BF, height, weight, gender, and heart rate following a 6 min water running protocol. They reported *SEE* and *R* values as 3.31 and 0.89, respectively.

Faulkner et al. (Faulkner et al., 2007) assessed whether the accuracy of predicting $VO_2max$ from SM-HR and RPE values was moderated by gender and habitual activity. In total, 27 men and 18 women completed two GXTs to determine $VO_2max$. *SEE* and *R* of their study were reported to be 7.75 and 0.69, respectively.

Liu et al. (Liu et al., 2007) evaluated the accuracy of three post-exercise HR parameters from a 3-minute step test used to estimate $VO_2max$. Thirty-one college male subjects had $VO_2max$ measured by the Bruce treadmill test. Subjects performed three step tests (24 ascents/min) with varying step heights of 30, 35 and 40 cm. Direct measurements of $VO_2max$ obtained from the treadmill test were correlated with a PHR15, PHR60 and PFI calculated after three different step test protocols. Linear regression analysis was used to determine the deviation of the estimated $VO_2max$ from the measured $VO_2max$. *SEE* and *R* of their study were reported to be 2.94 and 0.50, respectively.

Vehrs et al. (Vehrs et al., 2007) designed to develop a single-stage submaximal treadmill jogging test to predict $VO_2max$ in fit adults. Participants (N= 400; men= 250 and women=150), ages 18 to 40 years, successfully completed a maximal GXT at 1 of 3 laboratories to determine $VO_2max$. The test was completed during the first 2 stages of the GXT. Following 3 min of walking (Stage 1), participants achieved a steady-state HR while exercising at a comfortable self-selected submaximal jogging speed at level grade (Stage 2). Gender, age, BM, steady-state HR, and jogging speed (mph) were included as independent variables in the following MLR model to predict $VO_2max$. They reported *SEE* and *R* values as, 2.52 and 0.91, respectively.

Castro-Piñero et al. (Castro-Piñero et al., 2009) assessed the criterion-related validity of Cureton's equation for estimating $VO_2max$ from the one-mile run/walk test in endurance-trained children aged 8–17 years. Altogether, 66 physically active white children and adolescents (32 girls, 34 boys) completed a graded exercise test to volitional exhaustion and the one-mile run/walk test. Reported *SEE* and *R* values were 3.00 and 0.68, respectively.

Waddoups et al. (Waddoups et al., 2008) determined if this submaximal test correctly predicts $VO_2$max at the low (50% of maximum heart rate) and high (70% of maximum heart rate) ends of the specified heart rate range for males and females aged 18 – 55 years. Each of the 34 participants completed one low-intensity and one high-intensity trial. They reported *SEE* and *R* values as 5.70 and 0.78, respectively.

Akalan et al. (Akalan et al., 2008) hypothesized that a large proportion of the error of $VO_2$max prediction comes from individual differences in heart rate responses to submaximal exercise, and that if these differences could be decreased the accuracy of $VO_2$max prediction would increase. Eighty (43 male, 37 female) sedentary to highly trained, healthy volunteers first completed a Lo-Par, and then performed a modified YMCA protocol with 4-minute stages, a second submaximal test involving an individualized ramp submaximal protocol that was terminated at 80% of their cycle ergometer age-predicted maximum heart rate. Exercise and five-minute recovery heart rate data were collected. Multiple regression analysis was used to predict $VO_2$max. They reported *SEE* and *R* values as 4.23 and 0.94, respectively.

Lambrick et al. (Lambrick et al., 2009) assessed the utility of a single, continuous exercise protocol in facilitating accurate estimates of $VO_2$max from SM-HR and the RPE in healthy, low-fit women, during cycle ergometry. Eleven women estimated their RPE during a continuous test to volitional exhaustion (measured $VO_2$max). Individual gaseous exchange thresholds were determined retrospectively. Their reported *SEE* and *R* values are 3.42 and 0.88, respectively.

Coquart et al. (Coquart et al., 2010) developed a simple, convenient and indirect method for predicting $VO_2$max from a sub-maximal GXT, in obese women. Thirty obese women performed GXT to volitional exhaustion. During GXT, oxygen uptake and the PRPE 15 were measured, and $VO_2$max was determined. Following assessment of the relationships between $VO_2$max and PRPE 15, age, height and mass were made available in a stepwise multiple regression analysis with $VO_2$max as the dependent variable. They shown that *SEE* and *R* value were 0.16 and 0.83, respectively.

Reis et al. (Reis et al., 2010) investigated the AOD method in breaststroke swimming with the aims to assess the reliability of the oxygen uptake/ swimming velocity regression line and to quantify the precision of the AOD. Sixteen male swimmers performed two swimming tests in different days, with a 24-h recovery between tests: a graded swimming test and an all-out test. The all-out test was performed in one of two distances: 100 m (n=7) or 200 m (n=9). Values of *SEE* and *R* were 4.85 and 0.95, respectively.

Tierney et al. (Tierney et al., 2010) developed and validated graded submaximal and maximal stairmill protocols and to develop accurate maximal and submaximal equations to predict $VO_2max$ both the stairmill and Gerkin treadmill protocols. Fifty-four subjects, performed maximal graded exercise tests using both the stairmill and Gerkin treadmill protocols. Significant predictors of $VO_2max$ included BMI, time to completion for maximal protocols, and time to 85% of predicted maximal heart rate for submaximal protocols. Maximal prediction equations were more accurate on both the treadmill and stairmill than developed submaximal prediction equations for both the treadmill and stairmill. Both of the newly developed submaximal prediction equations more accurately predict $VO_2max$ than the current Gerkin equation. They indicated that *SEE* and *R* values of their best model were 4.85 and 0.70, respectively.

Akay et al. (Akay et al., 2011) developed an accurate ANN-based model to predict maximal $VO_2max$ of fit adults from a single stage submaximal treadmill jogging test. Participants (81 males and 45 females), aged from 17 to 40 years, successfully completed a maximal GXT to determine $VO_2max$. The variables; gender, age, body mass, steady-state heart rate and jogging speed are used to build the ANN prediction model. Compared with the results of the other prediction models in literature that were developed using Multiple Linear Regression Analysis, the reported values of *SEE* and *R* in thier study were considerably more accurate. They reported *SEE* and *R* values as 1.8 and 0.95, respectively.

Açıkkar et al. (Açıkkar et al., 2012) tried that developing ANN based models to predict $VO_2$max from submaximal endurance exercise at varying distances (0.5-mile, 1.0-mile, and 1.5-mile) involving walking, jogging, or running. College students, successfully completed a submaximal 1.5-mile endurance test and a maximum GXT. Relevant data are collected at the 0.5-mile mark, the 1.0-mile mark, and 1.5-mile mark. 7 different ANN based $VO_2$max prediction models have been developed. 10-fold cross validation performed to dataset. According to their study, for the best model, *SEE* and *R* values were 2.22 and 0.89, respectively.

Billinger et al. (Billinger et al., 2012) examined the ability of the YMCA submaximal exercise test protocol using a total body recumbent stepper to predict $VO_2$max. Out of 112 individuals initially screened, one-hundred ten individuals with low to moderate cardiovascular disease risk met the inclusion criteria for participation in the study. The maximal exercise test used a motorized treadmill and the Bruce or modified Bruce protocol. Oxygen uptake was measured and analyzed through collection of expired gases using a metabolic measurement system. The submaximal exercise test was performed at least 24 hours later but no more than 5 days post maximal exercise testing. Participants were instructed to keep a pace of 100 steps per minute and the resistance increase every 3 minutes according to the protocol until fatigue, or 85% of HR max was achieved. A cross validation study was also performed to determine the accuracy of the prediction equation. The presented *SEE* and *R* were 4.09, 0.92, respectively.

Tönis et al. (Tönis et al., 2012) identified parameters that can be used for estimating a subject's cardio-respiratory physical fitness level, expressed as $VO_2$max, from a combination of heart rate and accelerometer data. Data were gathered from 41 healthy subjects (23 male, 18 female) aged between 20 and 29 years. The measurement protocol consisted of a sub-maximal single stage treadmill walking test for $VO_2$max estimation followed by a walking test at two different speeds (4 and 5.5 $kmh^{-1}$) for parameter determination. The relation between measured heart rate and accelerometer output at different walking speeds was used to get an indication of exercise intensity and the corresponding heart rate at that intensity. Regression analysis was performed using general subject measures (age, gender, weight, length, BMI) and intercept and slope of the relation between heart rate and accelerometer output during walking as independent variables to estimate the $VO_2max$. They reported *SEE* and *R* values as 2.05 and 0.90, respectively.

Akay et al. (Akay et al., 2013) developed an accurate ANN-based model to $VO_2max$ of fit adults from a single stage submaximal treadmill jogging test. Participants (81 males and 45 females), aged from 17 to 40 years, successfully completed a maximal GXT to determine $VO_2max$. The variables; gender, age, body mass, steady-state heart rate and jogging speed are used to build the ANN prediction model. To increase accuracy, 10-fold cross validation was applied on the dataset. In their study, *SEE* and *R* were 1.80 and 0.93, respectively.

Table 2.3. Summary of submaximal regression models to estimate $VO_2max$

| Study | Predictor Variables | R | SEE |
|---|---|---|---|
| Dalleck et al. (2006) | G, Age, HR, BM | 0.86 | 3.91 |
| McComb et al. (2006) | G, Height, BM, BF, HR | 0.89 | 3.31 |
| Faulkner et al. (2007) | HR, RPE | 0.69 | 7.75 |
| Liu et al. (2007) | PHR15, PHR60, PFI | 0.50 | 2.94 |
| Vehrs et al. (2007) | G, Age, BM, MPH, HR | 0.91 | 2.52 |
| Castro-Piñero et al. (2008) | Meter | 0.68 | 3.00 |
| Waddoups et al. (2008) | G, Age, Height, BM, BMI, HR, RPE | 0.78 | 5.70 |
| Akalan et al. (2008) | G, BM, W/min, Delta Recovery HR, Recovery HR, LoPAR | 0.94 | 4.23 |
| Lambrick et al. (2009) | HR, RPE | 0.88 | 3.42 |
| Coquart et al. (2010) | Age, Power | 0.83 | 0.16 |
| Reis el al. (2010) | Meter | 0.95 | 4.85 |
| Tierney et al. (2010) | Age, BMI, HR | 0.70 | 4.85 |
| Akay et al. (2011) | Age, BM, MPH, HR | 0.95 | 1.80 |
| Açıkkar et al. (2012) | G, age, BMI, MIN3, HR3 | 0.89 | 2.22 |
| Billinger et al. (2012) | G, Age, Height, Watt, HR | 0.92 | 4.09 |
| Tönis et al. (2012) | G, Age, Height, BM, HR, AD | 0.90 | 2.05 |
| Akay et al. (2013) | G, Age, BM, HR, MPH | 0.93 | 1.80 |
| Ekblom-Bak et al. (2014) | G, Age, HR, PO | 0.91 | 0.30 |

**G**, gender; **HR**, heart rate; **BM**, body mass; **BF**, body fat; **RPE**, rating of perceived exertion; **PHR15**, 15-second post-exercise heart rate; **PHR60**, 60-second post-exercise heart rate; **PFI**, physical fitness index, **MPH**, speed; **BMI**, body mass index; **W/min** ,minutes that watt increase; **LoPAR**, self-report physical activity assessment; **WR**, work rate; **PFA**, perceived functional ability; **PO**, power output; **AD**, accelerometer data; **MIN3**, elapsed exercise time at the end of 1.5 mile; **HR3**, exercise heart rate at the end of 1.5 mile.

Ekblom-Bak et al. (Ekblom-Bak et al., 2014) created and evaluated a submaximal cycle ergometry test based on change in HR between a lower standard work rate and an individually chosen higher work rate. In a mixed population (n=143) with regard to sex (55% women), age (21–65 years), and activity status (inactive to highly active), a model included change in HR per unit change in power, sex, and age for the best estimate of $VO_2$max. The reported *SEE* and *R* values were 0.30 and 0.91, respectively.

Table 2.3 summarizes the above studies that used submaximal models to estimate $VO_2$max.

## 2.4. Hybrid prediction models based studies

George et al. (George et al., 2009) sought to develop a regression model to predict $VO_2$max based on submaximal treadmill EX and N-Ex data involving 116 participants, ages 18–65 years. The EX data included the participants' self-selected treadmill speed (at a level grade) when exercise heart rate first reached atleast 70% of predicted maximum heart rate (HRmax; 220 – age) by the end of any one of three 4-min consecutive stages involving walking (3.0–4.0 mph; Stage 1), jogging (4.1–6.0 mph; Stage 2), and running (> 6.0 mph; Stage 3). The N-Ex data included various demographic (age, gender), biometric (BM), and questionnaire (participants' PFA to walk, jog, orrun given distances, and their self-reported PA-R) information. All participants (n= 100) who completed the study requirements and successfully achieved a maximal level of exertion during a GXT to assess $VO_2$max. They shown *SEE* and *R* values as 3.09 and 0.94, respectively.

Akay et al. (Akay et al., 2010) studied on an ANN model based on both submaximal and non-exercise variables is developed to predict $VO_2$max of fit adults aged between 18 and 65 years. The predictor variables used in this study are gender, age, BMI, PAR, HR, and treadmill stage. The presented *SEE* and *R* were 2.01 and 0.96, respectively.

Nielson et al. (Nielson et al., 2010) developed a multiple linear regression model to predict treadmill $VO_2$max scores using both exercise and non-exercise data.

One hundred five college-aged participants (53 male, 52 female) successfully completed a submaximal cycle ergometer test and a maximal graded exercise test on a motorized treadmill. The submaximal cycle protocol required participants to achieve a steady-state heart rate equal to at least 70% of age-predicted maximum heart rate (220-age), while the maximal treadmill graded exercise test required participants to exercise to volitional fatigue. Relevant submaximal cycle ergometer test data included ending steady-state heart rate and ending workrate. Relevant non-exercise data included BM, PFA and PA-R. Their result was shown that *SEE* and *R* values were to be 3.36 and 0.91, respectively.

Akay et al. (Akay et al., 2011) reported that ANN and MLR models based on maximal and non-exercise variables were developed to predict $VO_2$max in healthy volunteers ranging in age from 18 to 65 years. The dataset included data of 100 subjects and the input variables of the dataset are gender, age, BMI, grade, self-reported RPE, HR, PFA and PA-R. The best *SEE* and *R* were 2.28 and 0.94, respectively.

Akay et al. (Akay et al., 2012) developed new MFANN-based $VO_2$max prediction models by using submaximal treadmill EX and N-Ex data. Using 10-fold cross validation on the dataset, *SEE* and *R* of the models were calculated. It was shown that the models including submaximal, standard nonexercise and questionnaire variables yield higher *R* and lower *SEE* than the ones including submaximal and standard nonexercise variables only. The results of ANN-based models were also compared with the ones obtained by MLR and it was shown that ANN-based models perform better than MLR-based models for predicting $VO_2$max. *SEE* and *R* values of their best model were 1.81 and 0.96, respectively.

Akay et al. (Akay et al., 2013) used multilayer feed-forward ANN to new $VO_2$max estimation models by using submaximal and N-Ex data. They pointed that the models including submaximal, standard N-Ex and questionnaire variables, *R* value increased, also, *SEE* value decreased. Their *SEE* and *R* values were 2.27 and 0.94, respectively.

Aktarla et al. (Aktarla et al., 2013) used ANN models based on maximal and N-Ex variables were developed to $VO_2$max the input variables of the dataset were gender, age, BMI, grade, self reported RPE from treadmill test, HR, PFA and PA-R. Their results suggested that the performance of $VO_2max$ prediction models based on maximal and standard N-Ex variables (i.e. gender, age, BMI etc) could be improved by including questionnaire variables (PFA and PA-R) in the models. The best model *SEE* and *R* value were 2.19 and 0.95, respectively.

Table 2.4 summarizes the above studies that used hybrid regression models to estimate $VO_2max$.

Table 2.4. Summary of hybrid regression models to estimate $VO_2max$

| Study | Predictor Variables | R | SEE |
|---|---|---|---|
| George et al. (2009) | G, Age, BM, MPH, PFA, PA-R | 0.94 | 3.09 |
| Akay et al. (2010) | G, Age, BMI, PA-R, HR, Stage | 0.96 | 2.01 |
| Nielson et al. (2010) | G, BM, HR, WR, PFA | 0.91 | 3.36 |
| Akay et al. (2011) | G, Age, BMI, GRD, PFA, PA-R | 0.94 | 2.28 |
| Akay et al. (2012) | G, Age, BMI, MPH, HR, PA-R, PFA | 0.96 | 1.81 |
| Akay et al. (2013) | G, Age, BMI, Stage, PA-R, PFA | 0.94 | 2.27 |
| Aktarla et al. (2013) | G, Age, BMI, RPE, GRD, PFA, PA-R | 0.95 | 2.19 |

**G**, gender; **BM**, body mass; **MPH**, speed; **PFA**, perceived functional ability; **PA-R**, self-reported level of physical activity; **BMI**, body mass index; **HR**, heart rate; **GRD**, grade; **RPE**, self-reported rating of perceived exertion from treadmill test.

### 2.5. Prediction models combined with feature selection based studies

Aktürk et al. (Aktürk et al., 2014) used MLP combined with a feature selection algorithm has been used to developed $VO_2max$ prediction models for healthy subjects ranging in age from 18 to 65 years. The models included the predictor variables age, gender, BMI, HR, RPE, RER and grade. Dimensionality of data set was reduced by one feature at a time before being passed on to the MLP. By using 10-fold cross-validation on the data set, the performance of the prediction models has been evaluated by calculating their *SEE*'s and *R*'s. They reported *SEE* and *R* values for best model as 4.63, 0.86, respectively.

Table 2.5 summarizes the above studies that used models to estimate $VO_2max$ combined with feature selection.

Table 2.5. Summary of models to estimate $VO_2$max combined with feature selection

| **Study** | **Predictor Variables** | **R** | **SEE** |
|---|---|---|---|
| Aktürk et al. (2014) | G, Age, BMI, HR, RER, Grade | 0.86 | 4.63 |

**G**, gender; **BMI**, body mass index; **HR**, heart rate; **RER**, respiratory exchange ratio.

There are several limitations of the studies in literature that focus on predicting $VO_2$max. First of all, almost all of these studies used multiple linear regression for developing $VO_2$max prediction equations. Intelligent data processing techniques such as ANN's have been used in a few studies only. Secondly, cross validation was not used in most of these studies, which raises a question about the reliability of the presented results. Thirdly, none of the studies applied feature selection algorithms to find out the most discriminative features for prediction of $VO_2$max.

# 3. OVERVIEW OF METHODS

## 3.1. Support Vector Machines

### A. Linear SVM's

Consider the problem of separating the set of training vectors belonging to two linearly separable classes,

$$(\mathbf{x}_i, y_i),\ \mathbf{x}_i \in R^n,\ y_i \in \{+1,-1\},\ i = 1,\ldots,n \tag{3.1.}$$

where $\mathbf{x}_i$ is a real-valued $n$-dimensional input vector and $y_i$ is a label that determines the class of $\mathbf{x}_i$. The SVM's employed for two-class problems are based on hyperplanes to separate the data. The hyperplane is determined by an orthogonal vector $\mathbf{w}$ and a bias $b$, which identifies the points that satisfy

$$\mathbf{w}.\mathbf{x} + b = 0. \tag{3.2.}$$

The parameters $\mathbf{w}$ and $b$ are constrained by

$$\min_i \left|\mathbf{w}.\mathbf{x}_i + b\right| \geq 1. \tag{3.3.}$$

The set of vectors is said to be separated by a hyperplane if it is separated without error and the distance between the closest vector to the hyperplane is maximal. Hence, a separating hyperplane in canonical form must satisfy the following constraints,

$$y_i\left(\mathbf{w}.\mathbf{x}_i + b\right) \geq 1,\ i = 1,2,\ldots,n. \tag{3.4.}$$

The distance $d_i$ of a point $\mathbf{x}_i$ from the hyperplane $(\mathbf{w}, b)$ is,

$$d_i = \frac{\left|\mathbf{w}.\mathbf{x}_i + b\right|}{\left\|\mathbf{w}\right\|}. \tag{3.5.}$$

The optimal hyperplane is given by maximizing the margin, $\rho$, subject to the constraints of (3.3.). The margin is given by

$$\rho = \frac{2}{\left\|\mathbf{w}\right\|}. \tag{3.6.}$$

Hence the hyperplane that optimally separates the data is the one that minimizes

$$\Phi(\mathbf{w}) = \frac{1}{2}(\mathbf{w}.\mathbf{w}). \tag{3.7.}$$

To consider how minimizing (3.7.) is equivalent to implementing the structural risk minimization principle, suppose the following bound holds,

$$\|\mathbf{w}\|^2 \le c. \tag{3.8.}$$

The VC dimension, $h$, of the set of canonical hyperplanes in *n*-dimensional space is bounded by,

$$h \le \min\left[\left(R^2 c\right), d\right] + 1 \tag{3.9.}$$

where $R$ is the radius of a hypersphere enclosing all training vectors. Hence minimizing (3.7.) is equivalent to minimizing an upper bound on the VC dimension.

Relaxing the constraints of (3.4.) by introducing slack variables $\xi_i \ge 0,\ i = 1,2,...,n$, (3.4.) becomes

$$y_i.\left(\mathbf{w}.\mathbf{x}_i + b\right) \ge 1 - \xi_i,\ i = 1,2,...,n. \tag{3.10.}$$

In this case, the optimization problem becomes

$$\Phi(\mathbf{w},\xi) = \frac{1}{2}(\mathbf{w}.\mathbf{w}) + C\sum_{i=1}^{n}\xi_i \tag{3.11.}$$

with a user defined positive finite constant $C$. The solution to the optimization problem in (3.11.), under the constraints of (3.10.), could be obtained in the saddle point of Lagrangian function

$$L(\mathbf{w},b,\alpha,\xi,\gamma) = \frac{1}{2}(\mathbf{w}.\mathbf{w}) + C\sum_{i=1}^{n}\xi_i - \sum_{i=1}^{n}\alpha_i\left|y_i\left(\mathbf{w}.\mathbf{x}_i + b\right) - 1 + \xi_i\right| - \sum_{i=1}^{n}\gamma_i\xi_i \tag{3.12.}$$

where $\alpha_i \ge 0,\ \xi_i \ge 0, i = 1,2,...,n$ are the Lagrange multipliers. The Lagrangian function has to be minimized with respect to $\mathbf{w}$, $b$, and $\xi_i$. Classical Lagrangian duality enables the primal problem, (3.12.), to be transformed into its dual problem, which is easier to solve. The dual problem is given by,

$$\max_{\alpha}\left[\sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j\left(\mathbf{x}_i.\mathbf{x}_j\right)\right] \tag{3.13.}$$

with constraints

$$\sum_{i=1}^{n} \alpha_i y_i = 0,\ 0 \le \alpha_i \le C,\ i = 1,2,...,n. \tag{3.14.}$$

This is a classic quadratic optimization problem, for which there exists a unique solution. According to the Kuhn-Tucker theorem of optimization theory [16], the optimal solution satisfies

$$\alpha_i \left[ y_i \left( \mathbf{w}.\mathbf{x}_i + b \right) - 1 \right] = 0,\ i = 1,2,...,n. \tag{3.15.}$$

(3.15.) has non-zero Lagrange multipliers if and only if the points $\mathbf{x}_i$ satisfy

$$y_i \left( \mathbf{w}.\mathbf{x}_i + b \right) = 1. \tag{3.16.}$$

These points are termed support vectors (SV's). The hyperplane is determined by the SV's, which is a small subset of the training vectors. Hence if $\alpha_i^*$ is the non-zero optimal solution, the classifier function can be expressed as

$$f\left(\mathbf{x}\right) = \operatorname{sgn}\left\{ \sum_{i=1}^{n} \alpha_i^* y_i \left( \mathbf{x}_i.\mathbf{x} \right) + b^* \right\} \tag{3.17.}$$

where $b^*$ is the solution of (3.15.) for any non-zero $\alpha_i^*$.

**B. Non-linear SVM's**

When a linear boundary is inappropriate SVM's can map the input vector into a high dimensional feature space. By defining a non-linear mapping, the SVM's constructs an optimal separating hyperplane in this higher dimensional space. Usually non-linear mapping is defined as

$$\varphi(.) : R^n \to R^{nh}. \tag{3.18.}$$

In this case, optimal function (3.10.) becomes (3.19.) with the same constraints

$$\max_{\alpha} \left[ \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K\left( \mathbf{x}_i, \mathbf{x}_j \right) \right] \tag{3.19.}$$

where

$$K\left( \mathbf{x}_i, \mathbf{x}_j \right) = \left\{ \varphi\left( \mathbf{x}_i \right) . \varphi\left( \mathbf{x}_j \right) \right\} \tag{3.20.}$$

is the kernel function performing the non-linear mapping into feature space. The kernel function may be any of the symmetric functions that satisfy the Mercel conditions. The most commonly used functions are the Radial Basis Function (RBF)

$$K\left(\mathbf{x}_i, \mathbf{x}_j\right) = \exp\left\{ -\frac{\left|\mathbf{x}_i - \mathbf{x}_j\right|^2}{2\sigma^2} \right\} \tag{3.21.}$$

and the Polynomial Function

$$K\left(\mathbf{x}_i, \mathbf{x}_j\right) = \left(\mathbf{x}_i . \mathbf{x}_j + 1\right)^q, \ q = 1, 2, ... \tag{3.22.}$$

where the parameters $\sigma$ and $q$ in (3.21.) and (3.22.), respectively must be preset. The classifier function can then be defined as

$$f\left(\mathbf{x}\right) = \mathrm{sgn}\left\{ \sum_{i=1}^{n} \alpha_i^* y_i K\left(\mathbf{x}_i, \mathbf{x}\right) + b^* \right\} \tag{3.23.}$$

where $b^*$ is the solution of (3.24.) for any non-zero $\alpha_i^*$

$$\alpha_i \left[ y_i \left( \sum_{j=1}^{n} \alpha_j y_j K\left(\mathbf{x}_j, \mathbf{x}_i\right) + b \right) - 1 \right] = 0 \, . \tag{3.24.}$$

In summary, a non-linear mapping (3.18.) can be indirectly defined by a kernel function. The parameters $\sigma$ and $q$ affect how sparse and easily separable the data are in the expanded feature space, and consequently, they affect the complexity of the resulting SVM classifier and the training error rate. The parameter *C* also affects the model complexity. Currently, there is no indication, besides trial and error, on how to set *C*, to choose the best kernel function, and to set kernel parameters. In practice, a wide range of values have to be predicted for *C* and for the kernel parameters, and then the performance of the SVM classifier is estimated through for each of these values (and kernel functions) (Açıkkar et al., 2009).

### 3.2. Multilayer Perceptron

MLP's are computer programs designed to model the relationships between independent and dependent variables and are capable of modeling complex, non-linear relationships directly from the raw data. Unlike classical statistical techniques, such as response surface methodology, MLP's do not require the prior assumption of the nature of the relationships between input and output parameters, nor do they require the raw data to be transformed prior to model generation. Several neural network structures have been described. The most common architecture is the ultilayer perceptron. This network comprises an input and output layer of processing units termed nodes interconnected via one or more hidden layers. The number of nodes in the input and output layers is determined by the number of independent and dependent variables, respectively. The number of hidden layer nodes is defined by the user. Model development is achieved by a process of training in which the input parameters of a set of experimental records are presented to the input layer of the network. These data are then multiplied by a weighting factor and fed forward to the nodes of the first hidden layer. The weighted outputs from the input layer are summed and transformed by a transfer function. The resultant output is weighted and fed to the subsequent layer. The output(s) from the output layer comprise a prediction of the dependent variable(s) of the model. Comparison of the predicted properties with the observed properties of the formulation/process yields the prediction error from which a performance function (often the mean squared error) is derived. The performance function is used by a backpropagation training algorithm to adjust the weights applied at the connections between nodes in each layer. By iteratively presenting the training set to the network and adjusting the weight matrix, the performance function can be minimized. In this way, the network learns the

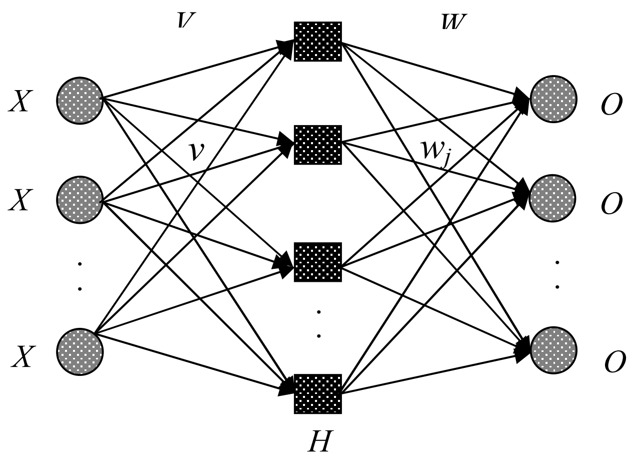


Figure 3.1. Concept of an multilayer perceptron

relationships between ingredients and properties and develops a model capable of predicting the properties of any formulation/process problem lying within the model space (Plumb et al., 2005).

Figure 3.1. shows a typical feed-forward MLP consiststing of several layers of neurons. $X_1,..,X_I$ denote inputs, $H_1,..,H_J$ denote hidden layer neurons, $O_1,..,O_K$ denote outputs, $V$ denotes input layer's weights and $W$ denotes hidden layer's weights. The first one (let it be layer 0) distributes the inputs to the input layer 1 with the input vector $X$. There is no processing in layer 0, it can be seen just as a sensory layer - each neuron receives just one component of the input (vector) $X$ which gets distributed, unchanged, to all neurons from the input layer. The last layer is the output layer which outputs the processed data; each output of individual output neurons being a component of the output vector $O$. The layer between the input one and the output one is the hidden layer $H$ (Akay et al., 2012).

### 3.3. Multiple Linear Regression

The multiple linear regression model is an extension of a simple linear regression model to incorporate two or more explanatory variable in a prediction equation for a response variable. Multiple regression modeling is now a mainstay of statistical analysis in most fields because of it's power and flexibility. It requires very little effort (and sometimes even less thought) to estimate very complicated models with large numbers of variables.

When we wish to model a continuous outcome variable, then an appropriate analysis is often multiple linear regression. For simple linear regression we have one continuous input variable. In multiple regression we generalize the method to more than one input variable and we will allow them to be continuous or categorical. Multiple regression is a generalization of the analysis of variance and analysis of covariance.

In multiple regression the basic model is the following:

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip} + \varepsilon_i \qquad (3.25.)$$

We assume that the error term $\varepsilon_i$ is normally distributed, with mean 0 and standard deviation $\sigma$. Here $y_i$ is the output for unit or subject $i$ and there are $k$ input variables $X_{i1}, X_{i2}, \dots, X_{ip}$. Often $y_i$ is termed the dependent variable and the input variables $X_{i1}, X_{i2}, \dots, X_{ip}$ are termed the independent variables. The latter can be continuous or nominal. However the term "independent" is a misnomer since the *X'*s need not be independent of each other. Sometimes they are called the explanatory or predictor variables. Each of the input variables is associated with a regression coefficient $\beta_1, \beta_2, \dots, \beta_k$. There is also an additive constant term $\beta_0$. These are the model parameters.

We can write the first section on the right-hand side of equation (3.25.) as

$$LP_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip} \qquad (3.26.)$$

where $LP_i$ is known as the *linear predictor* and is the value of $y_i$ predicted by the input variables. The difference $y_i - LP_i = \varepsilon_i$ is the error term.

The models are fitted by choosing estimates $b_0, b_1, \dots, b_p$, which minimize the sum of squares (SS) of the predicted error. These estimates are termed ordinary least squares estimates. Using these estimates we can calculate the fitted values $y_i^{fit}$, and the observed residuals $e_i = y_i - y_i^{fit}$. Here it is clear that the residuals estimate the error term (Draper and Smith, 1998).

Uses of multiple regression can be summarized as follows:

1. To adjust the effects of an input variable on a continuous output variable for the effects of confounders. For example, to investigate the effect of diet on weight allowing for smoking habits. Here the dependent variable is the outcome from a clinical trial. The independent variables could be the two treatment groups (as a 0/1 binary variable), smoking (as a continuous variable in numbers of packs per week) and baseline weight. The multiple regression model allows one to compare the outcome between groups, having adjusted for differences in baseline weight and smoking habit. This is also known as analysis of covariance.

2. To analyze the simultaneous effects of a number of categorical variables on an output variable. An alternative technique is the analysis of variance but the same results can be achieved using multiple regression.
3. To predict a value of an outcome, for given inputs. For example, an investigator might wish to predict the $FEV1$ of a subject given age and height, so as to be able to calculate the observed $FEV1$ as a percentage of predicted, and to decide if the observed $FEV1$ is below, say, 80% of the predicted one.

### 3.4. Relief-F Algorithm

A key idea of the original Relief algorithm (Kira and Rendell, 1992), given in figure 3.2., is to estimate the quality of attributes according to how well their values distinguish between instances that are near to each other. For that purpose, given a randomly selected instance $R_i$ (line 3), Relief searches for its two nearest neighbors: one from the same class, called nearest hit $H$, and the other from the different class, called nearest miss $M$ (line 4). It updates the quality estimation $W[A]$ for all attributes $A$ depending on their values for $R_i$, $M$, and $H$ (lines 5 and 6). If instances $R_i$ and $H$ have different values of the attribute $A$ then the attribute $A$

*Algorithm* Relief
*Input:* for each training instance a vector of attribute values and the class value
*Output:* the vector W of estimations of the qualities of attributes

1. set all weights $W[A] := 0.0$;
2. **for** i := 1 **to** $m$ **do begin**
3. randomly select an instance $R_i$;
4. find nearest hit $H$ and nearest miss $M$;
5. **for** $A$ := 1 **to** $a$ **do**
6. $W[A] := W[A] - \mathrm{diff}(A, R_i, H)/m + \mathrm{diff}(A, R_i, M)/m$;
7. **end**;

Figure 3.2. Pseudo code of the basic Relief algorithm.

separates two instances with the same class which is not desirable so we decrease the quality estimation $W[A]$. On the other hand if instances $R_i$ and $M$ have different values of the attribute $A$ then the attribute $A$ separates two instances with different class values which is desirable so we increase the quality estimation $W[A]$. The whole process is repeated for *m* times, where *m* is a user-defined parameter.

Function $\mathrm{diff}(A, I_1, I_2)$ calculates the difference between the values of the attribute $A$ for two instances $I_1$ and $I_2$. For nominal attributes it was originally defined as:

$$\mathrm{diff}(A, I_1, I_2) = \begin{Bmatrix} 0; value(A, I_1) = value(A, I_2) \\ 1; otherwise \end{Bmatrix} \tag{3.27.}$$

and for numerical attributes as:

$$\mathrm{diff}(A, I_1, I_2) = \frac{|value(A, I_1) - value(A, I_2)|}{\max(A) - \min(A)} \tag{3.28.}$$

*Algorithm* ReliefF
*Input:* for each training instance a vector of attribute values and the class value
*Output:* the vector W of estimations of the qualities of attributes

set all weights $W[A] := 0.0$;
**for** i := 1 **to** $m$ **do begin**
    randomly select an instance $R_i$;
    find $k$ nearest hits $H_j$;
    **for** each class $C \neq class(R_i)$ **do**
        from class $C$ find $k$ nearest misses $M_j(C)$;
**for** $A$ := 1 **to** a **do**
$W[A] := W[A] - \sum_{j=1}^{k} \mathrm{diff}(A, R_i, H_j)/(m \cdot k) +$
$\sum_{C \neq class(R_i)} [\frac{P(C)}{1 - P(class(R_i))} \sum_{j=1}^{k} \mathrm{diff}(A, R_i, M_j(C))]/(m \cdot k)$;
**end**;

Figure 3.3. Pseudo code of Relief-F algorithm.

The function diff is used also for calculating the distance between instances to find then nearest neighbors. The total distance is simply the sum of distances over all attributes (Manhattan distance).

The original Relief can deal with nominal and numerical attributes. However, it cannot deal with incomplete data and is limited to two-class problems. Its extension, which solves these and other problems, is called ReliefF.

The ReliefF (Relief-F) algorithm (Kononenki, 1994) (see figure 3.3.) is not limited to two class problems, is more robust and can deal with incomplete and noisy data. Similarly to Relief, ReliefF randomly selects an instance $R_i$ (line 3), but then searches for $k$ of its nearest neighbors from the same class, called nearest hits $H_j$ (line 4), and also $k$ nearest neighbors from each of the different classes, called nearest misses $M_j\left(C\right)$ (lines 5 and 6). It updates the quality estimation $W\left[A\right]$ for all attributes $A$ depending on their values for $R_i$, hits $H_j$ and misses $M_j\left(C\right)$ (lines 7, 8 and 9). The update formula is similar to that of Relief (lines 5 and 6 on figure 1), except that we average the contribution of all the hits and all the misses. The contribution for each class of the misses is weighted with the prior probability of that class $P(C)$ (estimated from the training set). Since we want the contributions of hits and misses in each step to be in [0,1] and also symmetric (we explain reasons for that below) we have to ensure that misses'probability weights sum to 1. As the class of hits is missing in the sum we have to divide each probability weight with factor $1-P\left(class\left(R_i\right)\right)$(which represents the sum of probabilities for the misses'classes). The process is repeated form times.

Selection of $k$ hits and misses is the basic difference to Relief and ensures greater robustness of the algorithm concerning noise. User-defined parameter $k$ controls the locality of the estimates. For most purposes it can be safely set to 10.

To deal with incomplete data we change the diff function. Missing values of attributes are treated probabilistically. We calculate the probability that two given instances have different values for given attribute conditioned over class value:

–if one instance (e.g., $I_1$) has unknown value:

$$\text{diff}\left(A,I_1,I_2\right)=1-P\left(value\left(A,I_2\right)\mid class\left(I_1\right)\right) \tag{3.29.}$$

–if both instances have unknown value:

$$\text{diff}\left(A,I_1,I_2\right)=1-\sum_{V}^{\#values(A)}\left(P\left(V\mid class\left(I_1\right)\right)\times P\left(V\mid class\left(I_2\right)\right)\right) \tag{3.30.}$$

Conditional probabilities are approximated with relative frequencies from the training set (Robnik-Šikonja and Kononenko, 2003).

### 3.5. Correlation-based Feature Selection

At the heart of the CFS algorithm is a heuristic for evaluating the worth or merit of a subset of features. This heuristic takes into account the usefulness of individual features for predicting the class label along with the level of intercorrelation among them. The hypothesis on which the heuristic is based can be stated:

*Good feature subsets contain features highly correlated with (predictive of ) the class, yet uncorrelated with (not predictive of ) each other.*

In test theory (Ghiselli, 1964), the same principle is used to design a composite test for predicting an external variable of interest. In this situation, the ”features" are individual tests which measure traits related to the variable of interest (class).

Equation 3.31. (Ghiselli, 1964) formalises the heuristic:

$$Merit_s=\frac{k\overline{r_{cf}}}{\sqrt{k+k\left(k-1\right)\overline{r_{ff}}}} \tag{3.31.}$$

Where $Merit_s$ is the heuristic “merit" of a feature subset $S$ containing $k$ features, $\overline{r_{cf}}$ is the mean feature class correlation ( $f\in S$ ), and $\overline{r_{ff}}$ is the average feature-feature intercorrelation. Equation 3.31. is, in fact, Pearson's correlation, where all variables have been standardised. The numerator can be thought of as giving an indication of how predictive of the class a group of features are; the denominator of how much redundancy there is among them. The heuristic handles irrelevant features as they will be poor predictors of the class. Redundant attributes are discriminated against as they will be highly correlated with one or more of the other features (Hall and Smith, 1999).

# 4. DATA SET GENERATION

Four different datasets were used in this thesis. Each dataset contains some input parameters and one output parameter ($VO_2$max). As will be described in the following sections, using different input parameters of datasets, different models are developed to predict $VO_2$max.

## 4.1. $VO_2$max-Set1

One hundred participants, 50 females and 50 males, aged 18-65 years will volunteer for this study. Thisstudy will recruit employees from the LDS Hospital and participants of the Brigham Young University Y-Be-Fit Program. Participants will be classified as either low risk or moderate risk according to ACSM (2000) guidelines. Low risk participants will be tested at BYU while moderate risk participants will be tested at the LDS Hospital. Participants will read and sign an informed consent document which contains written instructions explaining testing procedures, benefits, and risks of the test. Participants will also complete a PAR-Q and a non-exercise questionnaire. All participants will receive $25 compensation for their time and efforts. The study will be approved by the BYU Institutional Review Board for Human Subjects.

All participants will complete a maximal treadmill GXT. Prior to testing, participants will be instructed to wear comfortable clothing, acquire an adequate amount of sleep the night before the test (6-8 hours), and avoid exercise or strenuous physical activity the day of the test (ASCM, 2000). Participants will be instructed to drink plenty of fluids 24-hours prior to testing, and avoid food, tobacco, alcohol, and caffeine 3 hours before the test (ACSM).

Participants' height and body mass will be measured and recorded while wearing lightweight clothing and no shoes using a stadiometer and balance beam scale, respectively. Information pertaining to the maximal exercise test such as the electronic heart rate monitor, head-gear, mouth piece, nose-clip, and RPE scale (Borg, 1982) will be explained prior to testing.

Participants will perform a maximal GXT using a slightly modified version of the ASU maximal protocol (George, 1996). The maximal exercise test will begin with a 4-12 minute warm up on a treadmill at level ground. The warm up will consist of participants' completing up to three, four-minute stages until a steady state heart rate of 75% of age predicted heart rate max is achieved. During the first four-minute stage participants will walk at a brisk pace, 3-4 mph. If 75% of heart rate max is not achieved in this stage, participants will progress to the second stage,and speed will increase to a self-selected jogging pace between 4 and 6 mph. A third stage will be performed if heart rate criteria have not been met by the end of the second stage, and speed will increase to speeds of 6 mph or greater. Following the warm-up, participants will rest for approximately 5 minutes, while the test administrator explains the test procedures for the maximal GXT and fits participants with a mouthpiece and nose clip. The ending speed of the warm-up will serve as the necessary pace for the maximal GXT. Thereafter, the grade will increase 1.5% each minute, while pace remains the same, and continue until participants reach volitional fatigue and are no longer able to continue.

During the maximal GXT, metabolic gases will be collected using the TrueMax 2400 metabolic measurement system (Consentius Technologies, Sandy, UT). Participants' heart rate, $VO_2$, and RER will be averaged and analyzed by the computer every 15 seconds. The participants will give an RPE at the end of each stage to estimate the exercise intensity. $VO_2$max is considered valid when at least two of the following three criteria are met (ACSM, 2000; Howley et al., 1995):

1. Maximal heart rate within 15 beats of age predicted maximal heart rate.
2. Respiratory exchange ratio equal to or greater than 1.10.
3. Plateau in $VO_2$ despite an increase in work load.

Participants who failed to meet at least two of these criteria were dropped from the study (Howley et al., 1995).

The dataset includes non-exercise variables (gender, age, PFA, BMI and PA-R), maximal exercise test variables (MAX-HR, MAX-GRD and MAX-RPE) and submaximal exercise test variables (SM-HR, SM-GRD and SM-RPE).

### 4.2. $VO_2$max-Set2

Participants included 250 men and 150 women, aged 18 to 40 years-old from three university human performance laboratories in three different states participated in this study. Data from 122 subjects who participated in the original George et al. [R094] study were included in the present study. Prior to participation, all participants read and signed an informed consent form approved by the university=s institutional review board for human subjects and completed a preexercise testing screening questionnaire. All participants were classified as “low risk” according to the ACSM (2006) risk stratification.

All participants completed a maximal GXT to determine $VO_2$max. Participants were asked to refrain from strenuous exercise for 24 hr prior to testing and to arrive in the laboratory at least 3 hr after eating a meal. Height (cm) and BM (kg) were measured prior to performing the GXT. All GXTs were performed on a calibrated motorized treadmill. Oxygen consumption was measured during the GXT using a standard laboratory metabolic cart. Participants were fitted with a mouthpiece, two-way nonrebreathing valve (Hans Rudolf model 2700B, Kansas City, MO) and a nose clip so that expired gases could be measured. HR was continuously measured and recorded using an electronic HR monitor (Polar, Inc.) worn by the participant. During each stage of the GXT, participants reported a RPE using the 15-point scale (Noble et al., 1983).

Participants began the maximal GXT by walking at a self-selected brisk walking speed at level grade for 3 min. This was followed with jogging at a self-selected, submaximal jogging speed between 4.3 and 7.5 mph at level grade for 3 min or until a steady-state HR was achieved. Thereafter, the treadmill speed remained constant throughout the remaining stages of the exercise test; however, the grade was increased 1.5% each additional minute until the participant voluntarily terminated the test due to fatigue, despite verbal encouragement. The participant’s effort was considered maximal if physical signs suggestive of exhaustion were apparent and at least two of the following three criteria were met: a) maximal RER > 1.10, b) MAX-HR no less than 15 beats below age predicted MAX-HR, and c) leveling off of $VO_2$ despite an increase in workload (George, 1996; Larsen et al., 2002; Vehrs and Fellingham, 2006; Vehrs et al., 1998). The metabolic carts were configured to calculate and print $VO_2$ values every 15 s. Maximum $VO_2$ was defined as the highest 30-s average value, while MAX-HR was defined as the highest single HR value recorded during the GXT. The leveling off of $VO_2$ despite an increase in workload was defined as a change in $VO_2$ of less than ± 2 $mL \cong kg^{-1} \cong min^{-1}$ once $VO_2max$ was achieved (Vehrs et al., 2007).

This dataset contains N-Ex variables (gender, age, BM, BMI and height) and submaximal test variables (SM-HR and SM-MPH).

### 4.3. $VO_2$max-Set3

The subjects included 439 (229 females, 210 males) “apparently healthy” (ACSM, 1991) volunteers ranging in age from 20 to 79 yr. All subjects were recruited from the Amherst and Worcester, Massachusetts, communities. The investigation was explained in detail before each subject signed an informed consent document in accord with University of Massachusetts Medical School/Worcester and University of Massachusetts Human Subjects Committee/Amherst guidelines. Each subject was screened for cardiovascular and orthopedic contraindications to brisk walking. Subjects taking medication known to affect HR and blood pressure responses to exercise were not tested. Resting HR, blood pressure and 12-lead electrocardiograms were examined in all subjects over the age of 40 by a physician before testing. The physician was also present at maximal treadmill testing for subjects over the age of 40 yr.

All subjects successfully completed a maximal walking treadmill test. After having body mass and height measured, each subject assigned thhemselves a value between 0 and 7 which most accurately described their level of physical activity in the previous month. This is the same scale used by Jackson et al. (Jackson et al., 1990) and has been described elsewhere (Ross and Jackson, 1990). Subjects over the age of 40 were ECG monitored (standart 12 lead setup) during testing. Subjects between 20 and 39 yr of age were monitored with Vantage Heart Rate Monitors

(Polar CIC, Inc.). The treadmill protocol consisted of 4 min at a level grade, followed by 4 min at a 5% grade and a 2.5% increase in grade every 2 min thereafter. Subjects were tested at the fastest comfortable walking speed they could handle (4.8-7.3 km•$h^{-1}$). Test termination occurred when subjects could not continue despite verbal encouragement by the lab technicians. Each subject's $VO_{2peak}$ was taken as the highest $VO_2$ value when at least two of the three following criteria were satisfied: i) leveling of in $VO_2$ despite an increase in power output; ii) MAX-HR within 15 beats of age-predicted MAX-HR (220-age); and iii) RER $\geq$ 1.1. Previous experience in our laboratories with older populations (18) suggested that a ±15 beat range of age-predicted MAX-HR was better suited to older populations were larger interindividual differences in MAX-HR have been observed than in younger populations.

Oxygen consumption was determined using standart indirect calorimetry procudures. For approximately 60% of the sample, respiratory gas exchange was assessed with a Medgraphics CPX metabolic chart. The remaining 40% of the sample had expired gases continuously sampled from a 5-1 mixing chamber and analyzed for oxygen and carbon dioxide concentration via a computer based system (286 Leading Edge computer using VO2Plus Software from Exeter Research, Brentwood, NH) interfaced to Ametek oxygen (Model S-3AI) and carbon dioxide (Model CD-3A) analyzers. Inspired gas volumes were measured with a Rayfield Equipment dry gas meter. The computer system compiled information at 30-s intervals while HR was recorded at 1-min intervals. %BF was estimated using the Siri equation (Siri, 1961). Estimated body density was attained using the sum of three skinfold measures (Jackson, 1978; Jackson et al., 1980).

The dataset includes data of 439 subjects and the input variables of the dataset are gender, age, BMI, BF, MAX-RER, MAX-RPE, MAX-HR and MAX-Time.

### 4.4. $VO_2$max-Set4

185 apparently healthy college students (115 men and 70 women), aged 18 to 26 years, were recruited to participate in this study. Previous to any testing, all participants signed an informed consent document approved by the University Institutional Review Board and completed a brief PAR-Q to screen for possible cardiovascular contraindications.

Each participant completed a 1.5-mile endurance test and a maximal graded exercise test (each completed on different days). All participants were instructed to get sufficient sleep (6 to 8 hours) the previous night before testing and to avoid food, caffeine, tobacco products and alcohol for at least three hours prior to testing (ACSM, 2012). During the 1.5-mile test participants were instructed to sustain moderate exercise intensity throughout the entire test. To do this, participants were asked to attain a rating of perceived exertion (Borg, 1982) score of 13 and to satisfy the "talk test." The "talk test" is simple technique of monitoring respiratory rate in order to attain moderate exercise intensity. For example, the exercise should be difficult enough to elevate one's breathing rate, yet not so difficult that it prevents one from comfortably talking with a friend, if desired.

The 1.5-mile test was completed on a 229.7 m indoor track previously measured with a measurement wheel. The 1.5-mile distance required the completion of ten and a half laps. Each participant wore an electronic heart rate monitor and was asked to look at the heart rate display only when instructed. A test administrator recorded the elapsed exercise time and heart rate via the heart rate monitor which was read out loud to the researcher as the participant passed by the 0.5-mile, 1-mile, and 1.5-mile distances. At the end of the test, the ending rating of perceived exertion of each participant was recorded.

At least 24 hours after the 1.5-mile test (but not more than 7 days apart), participants completed a maximal graded exercise test in the laboratory. Upon entering the laboratory, participants' body mass was measured (with participants wearing light clothing and no shoes) using a standard physician's scale. In addition, body height was also measured (without shoes) using a wall-mounted stadiometer.

Participants performed the maximal graded exercise test using the Arizona State University maximal protocol (George, 1996). Before the maximal graded exercise test, a test administrator briefly summarized the procedures of the maximal test and fitted participants with an electronic heart rate monitor.

Additionally, participants were asked to wear the necessary head-gear, mouthpiece, and nose clip for the measurement of metabolic gasses during the maximal test. To warm-up for the maximal test participants began walking on the treadmill and then were instructed to continue walking briskly or to begin jogging/running at a comfortable pace for about 2-3 minutes. Following the warm-up, participants continued to exercise at this same self-selected pace (walking, jogging, or running) while the treadmill grade was increased 1.5% each minute. These progressive increases in grade continued until participants reached volitional fatigue, and were unable to continue despite verbal encouragement. After the maximal test, a brief 5-minute cool-down (walking at a slow pace) was completed.

The $VO_2$ and respiratory exchange ratio were computed, averaged, and printed by an on-line computer system every 15 seconds. During the maximal test, participants' exercise heart rate and rating of perceived exertion score were recorded at the end of each stage and metabolic gases were continuously collected using the TrueMax 2400 metabolic measurement system. $VO_2$max was calculated as the average of the highest four consecutive 15-second scores near the end of the maximal test. To accept a given $VO_2$max as valid, at least two of the following three criteria had to be met (ACSM, 2012; Howley et al., 1995):

1. Maximal heart rate within 15 beats of age predicted maximal heart rate (220 – age)

2. Maximal respiratory exchange ratio equal to or greater than 1.10

3. No increase in $VO_2$ despite an increase in work load

Participants who did not meet at least two of these criteria or who did not fully comply with the requirements of the study were not included in the statistical analysis.

The dataset of this study involves the independent predictors: Gender, age, BMI, time and HR.

Table 4.1. Descriptive statistics of $VO_2$max-set1

| **Variables** | **Mean ± Standard Deviation** |
|---|---|
| Gender | 0.5 ± 0.503 |
| Age (year) | 36.23 ± 13.223 |
| BM (kg) | 74.86 ± 15.291 |
| Height (m) | 1.717 ± 0.089 |
| BMI (kg/m$^2$) | 25.246 ± 4.005 |
| SM-MPH(mph) | 5.248 ± 1.013 |
| SM-HR (bpm) | 147.73 ± 12.357 |
| SM-RPE | 12.663 ± 1.699 |
| SM-Stage | 2.11 ± 0.49 |
| MAX-MPH (mph) | 5.313 ± 1.042 |
| MAX-HR (bpm) | 185.16 ± 13.19 |
| MAX-RPE | 19.01 ± 0.785 |
| MAX-GRD | 9.385 ± 2.712 |
| MAX-RER | 1.168 ± 0.052 |
| PFA | 14.75 ± 4.831 |
| PAR | 4.83 ± 2.252 |
| $VO_2$max (ml/kg/min) | 41.387 ± 9.145 |

Table 4.2. Descriptive statistics of $VO_2$max-set2

| **Variables** | **Mean ± Standard Deviation** |
|---|---|
| Gender | 0.622 ± 0.485 |
| Age (year) | 25.529 ± 5.835 |
| BM (kg) | 71.76 ± 13.388 |
| Height (m) | 1.743 ± 0.087 |
| BMI (kg/m$^2$ ) | 23.191 ± 4.181 |
| SM-HR (bpm) | 157.044 ± 13.982 |
| SM-MPH (mph) | 5.706 ± 0.674 |
| Location | 2.551 ± 1.215 |
| $VO_2$max (ml/kg/min) | 46.974 ± 6.169 |

Table 4.3. Descriptive statistics of $VO_2$max-set3

| **Variables** | **Mean ± Standard Deviation** |
|---|---|
| Gender | 0.523 ± 0.5 |
| Age (year) | 46.602 ± 16.661 |
| BM (kg) | 72.851 ± 14.808 |
| Height (m) | 1.688 ± 0.011 |
| BMI ($kg/m^2$ ) | 25.462 ± 4.106 |
| %BF | 23.397 ± 8.442 |
| AC | 4.466 ± 2.044 |
| MAX-HR (bpm) | 178.968 ± 15.596 |
| MAX-RER | 1.175 ± 0.069 |
| MAX-RPE | 18.292 ± 1.425 |
| MAX-Time (sec) | 16.162 ± 3.392 |
| $VO_2$max (ml/kg/min) | 38.617 ± 10.375 |

Table 4.4. Descriptive statistics of $VO_2$max-set4

| **Variables** | **Mean ± Standard Deviation** |
|---|---|
| Gender | 0.622 ± 0.486 |
| Age (year) | 22.422 ± 3.398 |
| BM (kg) | 74.03 ± 15.427 |
| Height (m) | 1.756 ± 0.101 |
| BMI ($kg/m^2$) | 23.838 ± 3.524 |
| MAX-HR (bpm) | 193.832 ± 8.347 |
| MAX-RER | 1.158 ± 0.048 |
| MIN1 (min) | 4.884 ± 1.382 |
| HR1 (bpm) | 165.719 ± 16.253 |
| MIN2 (min) | 9.726 ± 2.496 |
| HR2 (bpm) | 166.993 ± 26.564 |
| MIN3 (min) | 14.706 ± 3.566 |
| HR3 (bpm) | 171.476 ± 17.059 |
| $VO_2$max (ml/kg/min) | 46.607 ± 5.923 |

# 5. RESULTS AND DISCUSSION

As described in the previous section, four data sets have been used in this thesis. Using each data set, several maximal, submaximal and N-Ex $VO_2$max prediction models have been developed. These models contain various combinations of the predictor variables. For each model $VO_2$max has been predicted using SVM, MLP and MLR combined with Relief-F and CFS separately. Weka 3.6 and its LibSvm library have been used for developing prediction models.

The performance of SVM, MLP and MLR models have been evaluated by using 10-fold cross validation and calculating the *SEE* and *R*, whose formulas are given in (5.1.) and (5.2.), respectively,

$$SEE = \sqrt{\frac{\sum(Y-Y')^2}{N}} \tag{5.1.}$$

$$R = \sqrt{1-\frac{\sum(Y-Y')^2}{\sum(Y-\bar{Y})^2}} \tag{5.2.}$$

In formulas (5.1.) and (5.2.), $Y$ is the measured value, $Y'$ is the predicted value, $\bar{Y}$ is the mean of the measured values and $N$ is the number of samples in a test subset.

Table 5.1 through Table 5.8 show the maximal, submaximal and N-Ex prediction models for $VO_2$max and the predictor variables that each model contains.

Table 5.1. Overview of maximal $VO_2$max prediction models along with the predictor variables for $VO_2$max-set1 using Relief-F.

| **Models** | **Predictor Variables** |
|---|---|
| Model 1 | Gender, age, BMI, MAX-HR, MAX-GRD, MAX-RER, MAX-RPE |
| Model 2 | Gender, age, BMI, MAX-HR, MAX-GRD, MAX-RER |
| Model 3 | Gender, age, BMI, MAX-HR, MAX-GRD |
| Model 4 | Gender, age, BMI, MAX-HR |
| Model 5 | Gender, age, BMI |
| Model 6 | Gender, age |
| Model 7 | Gender |

Table 5.2. Overview of submaximal $VO_2$max prediction models along with the predictor variables for $VO_2$max-set1 using Relief-F.

| Models | Predictor Variables |
|---|---|
| Model 8 | SM-MPH, gender, SM-Stage, age, SM-HR, BMI, SM-RPE |
| Model 9 | SM-MPH, gender, SM-Stage, age, SM-HR, BMI |
| Model 10 | SM-MPH, gender, SM-Stage, age, SM-HR |
| Model 11 | SM-MPH, gender, SM-Stage, age |
| Model 12 | SM-MPH, gender, SM-Stage |
| Model 13 | SM-MPH, gender |
| Model 14 | SM-MPH |

Table 5.3. Overview of N-Ex $VO_2$max prediction models along with the predictor variables for $VO_2$max-set1 using Relief-F.

| Models | Predictor Variables |
|---|---|
| Model 15 | PFA, age, BMI, PAR, gender |
| Model 16 | PFA, age, BMI, PAR |
| Model 17 | PFA, age, BMI |
| Model 18 | PFA, age |
| Model 19 | PFA |

Table 5.4. Overview of submaximal $VO_2$max prediction models along with the predictor variables for $VO_2$max-set2 using Relief-F.

| Models | Predictor Variables |
|---|---|
| Model 20 | SM-MPH, gender, BMI, SM-HR, age, location |
| Model 21 | SM-MPH, gender, BMI, SM-HR, age |
| Model 22 | SM-MPH, gender, BMI, SM-HR |
| Model 23 | SM-MPH, gender, BMI |
| Model 24 | SM-MPH, gender |
| Model 25 | SM-MPH |

Table 5.5. Overview of maximal $VO_2$max prediction models along with the predictor variables for $VO_2$max-set3 using Relief-F.

| Models | Predictor Variables |
|---|---|
| Model 26 | MAX-Time, gender, age, BMI, MAX-HR, MAX-RER, MAX-RPE |
| Model 27 | MAX-Time, gender, age, BMI, MAX-HR, MAX-RER |
| Model 28 | MAX-Time, gender, age, BMI, MAX-HR |
| Model 29 | MAX-Time, gender, age, BMI |
| Model 30 | MAX-Time, gender, age |
| Model 31 | MAX-Time, gender |
| Model 32 | MAX-Time |

Table 5.6. Overview of N-Ex $VO_2max$ prediction models along with the predictor variables for $VO_2max$-set3 using Relief-F.

| Models | Predictor Variables |
|---|---|
| Model 33 | BF%, age, AC, gender, BMI |
| Model 34 | BF%, age, AC, gender |
| Model 35 | BF%, age, AC |
| Model 36 | BF%, age |
| Model 37 | BF% |

Table 5.7. Overview of maximal $VO_2max$ prediction models along with the predictor variables for $VO_2max$-set4 using Relief-F.

| Models | Predictor Variables |
|---|---|
| Model 38 | Gender, BMI, age, MAX-RER, MAX-HR |
| Model 39 | Gender, BMI, age, MAX-RER |
| Model 40 | Gender, BMI, age |
| Model 41 | Gender, BMI |
| Model 42 | Gender |

Table 5.8. Overview of submaximal $VO_2max$ prediction models along with the predictor variables for $VO_2max$-set4 using Relief-F.

| Models | Predictor Variables |
|---|---|
| Model 43 | Gender, min3, min2, min1, height, weight, BMI, hr2, hr3, hr1, age |
| Model 44 | Gender, min3, min2, min1, height, weight, BMI, hr2, hr3, hr1 |
| Model 45 | Gender, min3, min2, min1, height, weight, BMI, hr2, hr3 |
| Model 46 | Gender, min3, min2, min1, height, weight, BMI, hr2 |
| Model 47 | Gender, min3, min2, min1, height, weight, BMI |
| Model 48 | Gender, min3, min2, min1, height, weight |
| Model 49 | Gender, min3, min2, min1, height |
| Model 50 | Gender, min3, min2, min1 |
| Model 51 | Gender, min3, min2 |
| Model 52 | Gender, min3 |
| Model 53 | Gender |

By using the Relief-F attribute evaluator combined with ranker search method, the score of each attribute has been calculated and the attributes have been sorted in descending order according to their scores. Table 5.9 through Table 5.16 show the ReliEf-F scores of each attribute.

Table 5.9. Relief-F scores of the maximal attributes of $VO_2$max-set1

| **Variables** | **Score** |
|---|---|
| Gender | 0.05427 |
| Age (year) | 0.03435 |
| BMI (kg/m$^2$) | 0.01470 |
| MAX-HR (bpm) | 0.01075 |
| MAX-GRD | 0.00725 |
| MAX-RER | -0.00907 |
| MAX-RPE | -0.03924 |

Table 5.10. Relief-F scores of the submaximal attributes of $VO_2$max-set1

| **Variables** | **Score** |
|---|---|
| SM-MPH (mph) | 0.11794 |
| Gender | 0.05895 |
| SM-Stage | 0.03523 |
| Age (year) | 0.01333 |
| SM-HR (bpm) | -0.00601 |
| BMI (kg/m$^2$) | -0.01705 |
| SM-RPE | -0.02910 |

Table 5.11. Relief-F scores of the N-Ex attributes of $VO_2$max-set1

| **Variables** | **Score** |
|---|---|
| PFA | 0.02710 |
| Age (year) | 0.02570 |
| BMI (kg/m$^2$) | 0.01609 |
| PAR | 0.00752 |
| Gender | -0.00228 |

Table 5.12. Relief-F scores of the submaximal attributes of $VO_2$max-set2

| **Variables** | **Score** |
|---|---|
| SM-MPH (mph) | 0.06357 |
| Gender | 0.02526 |
| BMI (kg/m$^2$ ) | 0.01139 |
| SM-HR (bpm) | -0.00720 |
| Age (year) | -0.02612 |
| Location | -0.02622 |

Table 5.13. Relief-F scores of the maximal attributes of $VO_2$max-set3

| Variables | Score |
|---|---|
| MAX-Time (sec) | 0.10870 |
| Gender | 0.05080 |
| Age (year) | 0.02960 |
| BMI (kg/$m^2$ ) | -0.01900 |
| MAX-HR (bpm) | -0.02080 |
| MAX-RER | -0.02630 |
| MAX-RPE | -0.03540 |

Table 5.14. Relief-F scores of the N-Ex attributes of $VO_2$max-set3

| Variables | Score |
|---|---|
| %BF | 0.04080 |
| Age (year) | 0.02820 |
| AC | 0.02320 |
| Gender | 0.01330 |
| BMI (kg/$m^2$ ) | -0.02810 |

Table 5.15. Relief-F scores of the maximal attributes of $VO_2$max-set4

| Variables | Score |
|---|---|
| Gender | 0.04183 |
| BMI (kg/$m^2$) | 0.02593 |
| Age (year) | -0.00831 |
| MAX-RER | -0.01701 |
| MAX-HR (bpm) | -0.04229 |

Table 5.16. Relief-F scores of the submaximal attributes of $VO_2$max-set4

| Variables | Score |
|---|---|
| Gender | 0.06787 |
| MIN3 (min) | 0.06278 |
| MIN2 (min) | 0.03914 |
| MIN1 (min) | 0.03405 |
| Height (m) | 0.02641 |
| BM (kg) | 0.00692 |
| BMI (kg/$m^2$) | -0.00446 |
| HR2 (bpm) | -0.01229 |
| HR3 (bpm) | -0.01417 |
| HR1 (bpm) | -0.01831 |
| Age (year) | -0.02469 |

Table 5.17 shows the $VO_2$max prediction models obtained by CFS.

Table 5.17. Overview of $VO_2$max prediction models along with the predictor variables for $VO_2$max sets using CFS.

| Models | Predictor Variables |
|---|---|
| Model 54[1,a] | Gender, age, MAX-GRD, MAX-RER, BMI |
| Model 55[3,c] | BF%, age, AC, gender, BMI |
| Model 56[2,b] | Location, gender, SM-MPH, SM-HR |
| Model 57[3,a] | Age, gender, MAX-RPE, MAX-Time |
| Model 58[1,b] | Gender, age, SM-MPH |
| Model 59[1,c] | Gender, age, PFA |
| Model 60[4,b] | Gender, hr2, min3 |
| Model 61[4,a] | Gender, MAX-HR |

[1]: $VO_2$max-set1; [2]: $VO_2$max-set2; [3]: $VO_2$max-set3; [4]: $VO_2$max-set4; [a]: maximal; [b]: submaximal; [c]: N-Ex.

### 5.1. SVM model for predicting $VO_2$max

The type of kernel function, kernel function parameters, the value of $C$, and the value of $\varepsilon$ for the $\varepsilon$-insensitive loss function are the major components that affect the quality and performance of a SVM model. Parameter $C$ determines the tradeoff cost between minimizing the training error and minimizing model complexity. A small value for $C$ will increase the number of training errors, while a large $C$ will lead to a behavior similar to that of a hard-margin SVM. Parameter $\varepsilon$ controls the width of $\varepsilon$-insensitive zone. In addition, $\varepsilon$ determines the number of support vectors; smaller values of $\varepsilon$ may lead to more support vectors and result in a complex learning machine and vice versa. The kernel parameters define the nonlinear mapping from the input space to high-dimensional feature space (Ji et al., 2007). We chose to use the RBF kernel defined as $\exp\left\{-\gamma\left|\mathbf{x}_i-\mathbf{x}_j\right|^2\right\}$ for developing our SVM model. The parameter that should be optimized for the RBF kernel is the function parameter $\gamma$.

It is not known beforehand which $C$, $\varepsilon$ and $\gamma$ are the best for a given regression problem, therefore some sort of parameter search must be conducted. The purpose is to find optimized values of the triple ($C$, $\varepsilon$, $\gamma$) so that the regression model can predict testing data with minimum error. Many methods for selecting the optimal parameters have been proposed, for example, cross validation, grid search (Hsu et al., 2003), particle swarm optimization (Guo et al., 2006), genetic algorithm (Friedrichs and Igel, 2005), etc. For median-sized problems, the grid search method is an efficient method for finding the optimum values of $C$, $\varepsilon$ and $\gamma$. In grid search, the parameters are varied by fixed step-sizes through a range of values, and the performance of each set of parameters is measured and compared. When performing a search for optimal parameters, different criteria such as maximizing correlation coefficient, minimizing root mean squared error or mean absolute error can be used for determining the optimum function value. To improve the generalization ability, grid search can use a cross validation process. In $k$-fold cross validation, the original dataset is partitioned into $k$ subsets. Of the $k$ subsets, a single subset is retained as the validation data for testing the model, and the remaining $k-1$ subsets are used as training data. The cross validation process is then repeated $k$ times (the *folds*), with each of the $k$ subsets used exactly once as the validation data. The $k$ results from the folds then can be averaged (or combined) to produce a single estimation.

In this study, we use grid search together with 5-fold cross validation to determine the best values of $C$, $\varepsilon$ and $\gamma$. To guarantee that the prediction models developed by using SVM is valid and can be generalized for making new predictions regarding new data, the dataset is partitioned into training and independent test sets via a 10-fold cross validation. Figure 5.1 shows the flow chart of our SVM-based model for predicting $VO_2$max for a single fold.

Initially, by using the Relief-F attribute evaluator combined with ranker search method, the score of each attribute has been calculated and the attributes have been sorted in descending order according to their scores. Dimensionality of the data set is reduced by one feature at a time (the attribute with the lowest score is removed) before being passed on to the SVM. The train and test subsets are standardized to have zero mean and unit variance, so new train and test subsets are created. This process avoided predictor variables in greater numeric ranges dominate those in smaller numeric ranges and the computational difficulty associated with using larger numeric values. For each value of ($C$, $\varepsilon$, $\gamma$) triple, 5-fold cross validation is conducted on the new training subset and root mean squared errors of each prediction are calculated. The ($C$, $\varepsilon$, $\gamma$) triple that yields the lowest overall root mean squared error

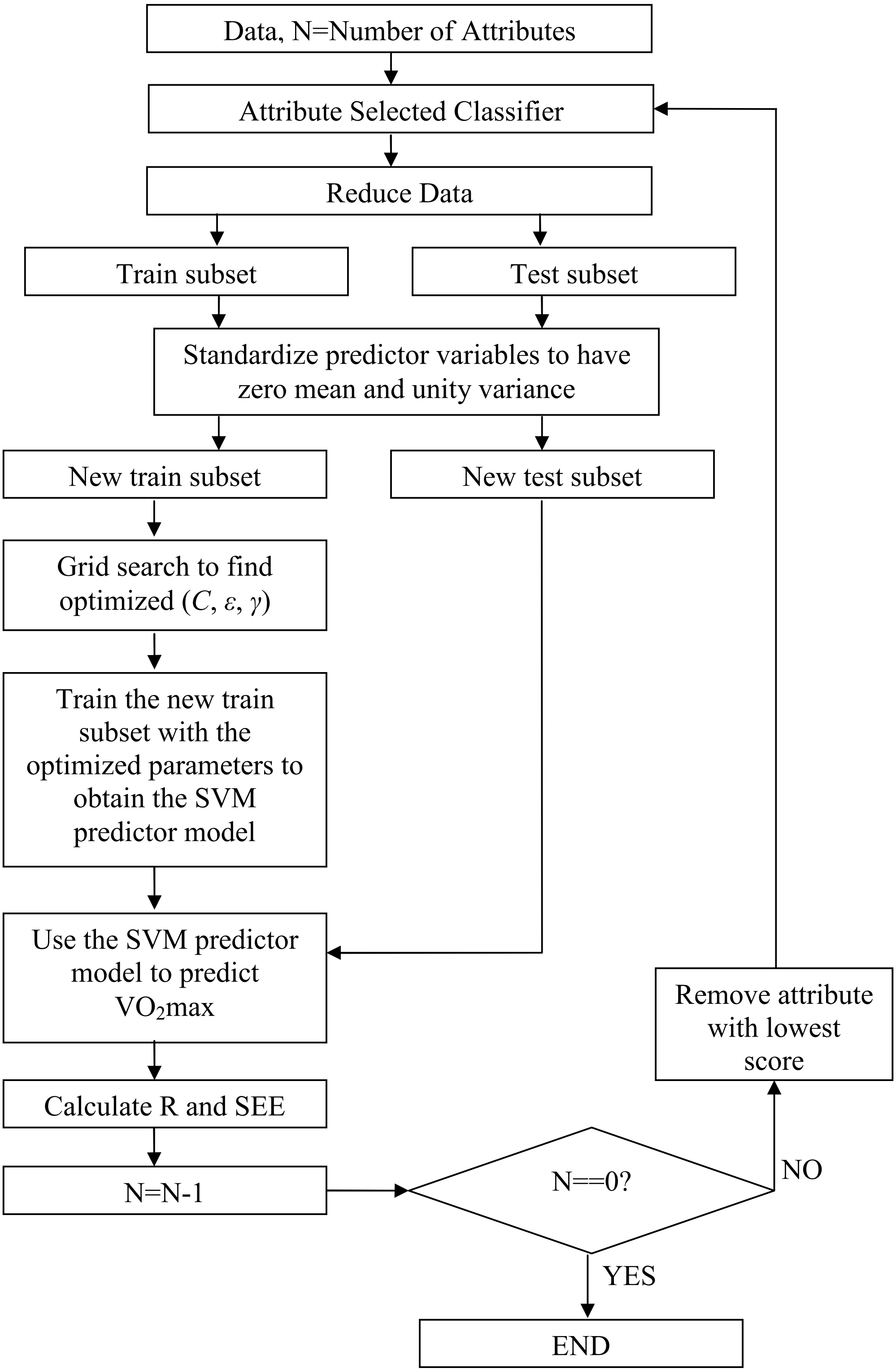


Figure 5.1. Flow chart of the SVM-based model for predicting $VO_2$max for a single fold

is chosen for training the train subset. The prediction model is developed after training subset is trained with the optimized values of $C$, $\varepsilon$ and $\gamma$. Lastly, the prediction model is used to estimate $VO_2$max value in the new test subset. The same procedure is repeated for the SVM combined with CFS.

### 5.2. MLP model for predicting $VO_2$max

Back-propagation MLP is used to develop models for prediction of $VO_2$max. The performance of an MLP depends on the number of hidden layers and the number of neurons in each hidden layer. The less neuron used, the less information will be obtained; in contrast, the local minimum may increase, and the network may converge to a local minimum mostly. Thus the network's precision will fall. However, there is not a rule in defining the number of neurons in a hidden layer. In general, the optimal number is empirically chosen based on the physical complexity of the problem.

The inputs and outputs are normalized so that they have zero mean and unity variance. Also, the inputs have been pre-processed by using the Principal Component Analysis (PCA) method to orthogonalize the components of the input vectors (so that they are uncorrelated with each other) and to order the resulting orthogonal components (principal components) so that those with the largest variation come first. The tansigmoid activation function is used in the hidden layers, the pure-linear activation function is used in the hidden layers, and the Levenberg-Marquardt algorithm is utilized for training the network. The other important parameters of the MLP models are the number of epochs (selected as 100), the learning rate and momentum.

Table 5.18. *R* and *SEE* values for maximal $VO_2$max prediction models using different regression methods combined with Relief-F on the $VO_2$max-set1.

| **Models** | **MLR** | | **MLP** | | **SVM** | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 1 | 0.68 | 7.40 | 0.71 | 7.06 | 0.68 | 6.81 |
| Model 2 | 0.68 | 7.34 | 0.68 | 7.02 | 0.70 | 6.80 |
| Model 3 | 0.72 | 6.60 | 0.71 | 6.56 | 0.74 | 6.26 |
| Model 4 | 0.71 | 6.57 | 0.71 | 6.54 | 0.74 | 6.10 |
| Model 5 | 0.64 | 7.12 | 0.65 | 6.97 | 0.67 | 6.70 |
| Model 6 | 0.54 | 7.81 | 0.61 | 7.52 | 0.63 | 7.12 |
| Model 7 | 0.31 | 8.95 | 0.35 | 8.56 | 0.46 | 8.08 |

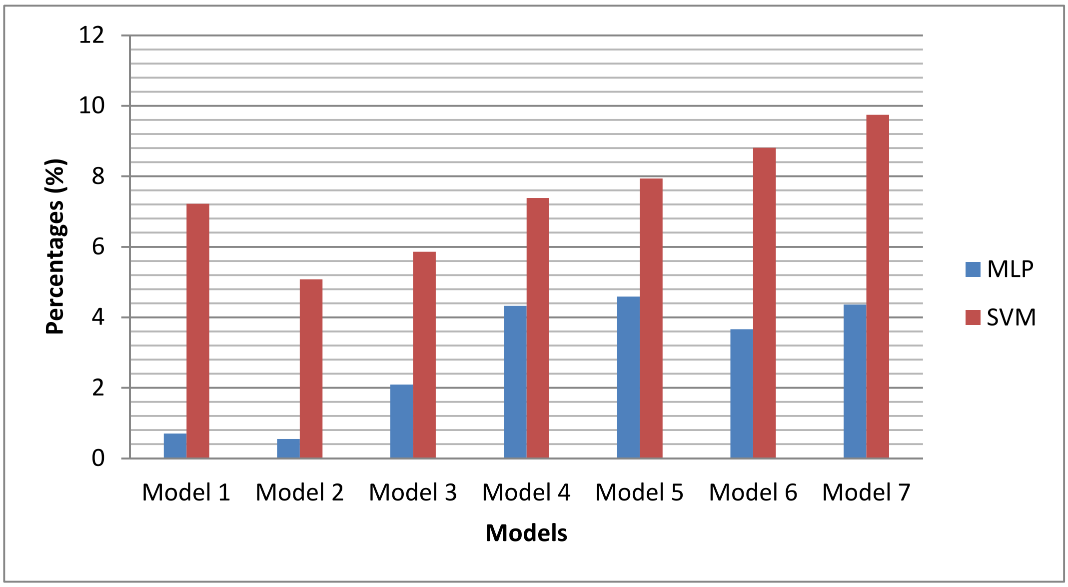


Figure 5.2. Percentage decrease rates in *SEE*'s of maximal $VO_2$max models for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined by Relief-F ($VO_2$max-set1)

Table 5.19. *R* and *SEE* values for submaximal $VO_2$max prediction models using different regression methods combined with Relief-F on the $VO_2$max-set1.

| **Models** | **MLR** | | **MLP** | | **SVM** | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 8 | 0.85 | 4.85 | 0.85 | 4.80 | 0.88 | 4.40 |
| Model 9 | 0.85 | 4.81 | 0.87 | 4.56 | 0.88 | 4.37 |
| Model 10 | 0.83 | 5.04 | 0.84 | 4.94 | 0.86 | 4.56 |
| Model 11 | 0.85 | 4.91 | 0.84 | 4.88 | 0.87 | 4.52 |
| Model 12 | 0.82 | 5.30 | 0.82 | 5.13 | 0.85 | 4.73 |
| Model 13 | 0.82 | 5.25 | 0.83 | 5.09 | 0.86 | 4.66 |
| Model 14 | 0.81 | 5.31 | 0.82 | 5.23 | 0.84 | 4.97 |

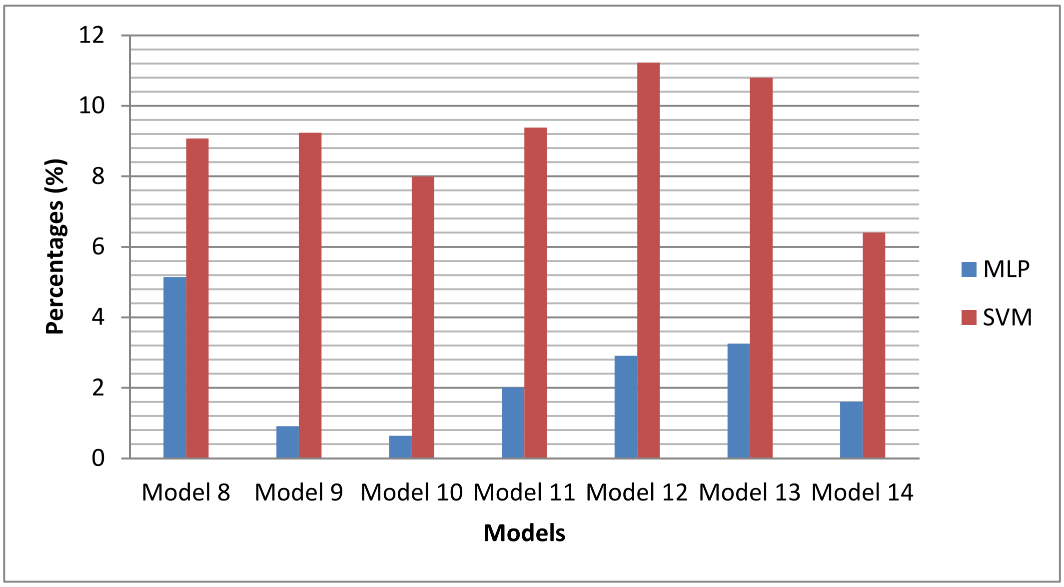


Figure 5.3. Percentage decrease rates in *SEE*'s of submaximal $VO_2$max for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined with Relief-F ($VO_2$max-set1)

Table 5.20. *R* and *SEE* values for N-Ex $VO_2max$ prediction models using different regression methods combined with Relief-F on the $VO_2max$-set1.

| **Models** | **MLR** | | **MLP** | | **SVM** | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 15 | 0.87 | 4.66 | 0.88 | 4.36 | 0.88 | 4.32 |
| Model 16 | 0.80 | 5.54 | 0.83 | 5.08 | 0.83 | 5.04 |
| Model 17 | 0.78 | 5.71 | 0.83 | 5.11 | 0.83 | 5.08 |
| Model 18 | 0.78 | 5.73 | 0.82 | 5.17 | 0.83 | 5.10 |
| Model 19 | 0.69 | 6.59 | 0.69 | 6.56 | 0.71 | 6.38 |

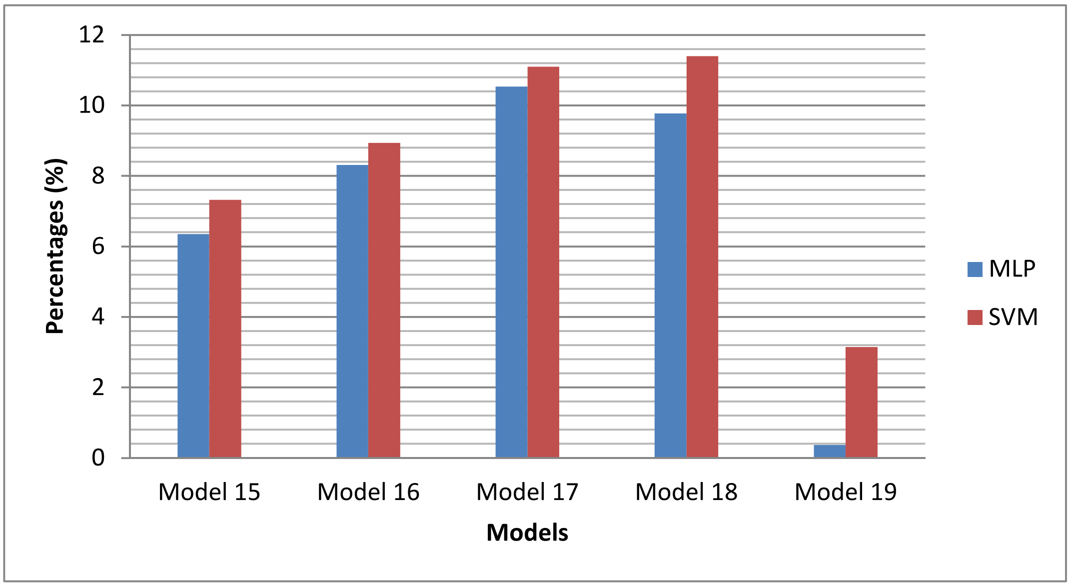


Figure 5.4. Percentage decrease rates in *SEE*'s of N-Ex $VO_2max$ for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined with Relief-F ($VO_2max$-set1)

Table 5.21. *R* and *SEE* values for submaximal $VO_2max$ prediction models using different regression methods combined with Relief-F on the $VO_2max$-set2.

| **Models** | **MLR** | | **MLP** | | **SVM** | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 20 | 0.83 | 3.46 | 0.84 | 3.34 | 0.85 | 3.26 |
| Model 21 | 0.83 | 3.40 | 0.84 | 3.31 | 0.85 | 3.21 |
| Model 22 | 0.79 | 3.78 | 0.82 | 3.53 | 0.83 | 3.48 |
| Model 23 | 0.77 | 3.93 | 0.78 | 3.89 | 0.79 | 3.81 |
| Model 24 | 0.68 | 4.50 | 0.73 | 4.24 | 0.76 | 4.02 |
| Model 25 | 0.38 | 5.71 | 0.65 | 4.67 | 0.67 | 4.56 |

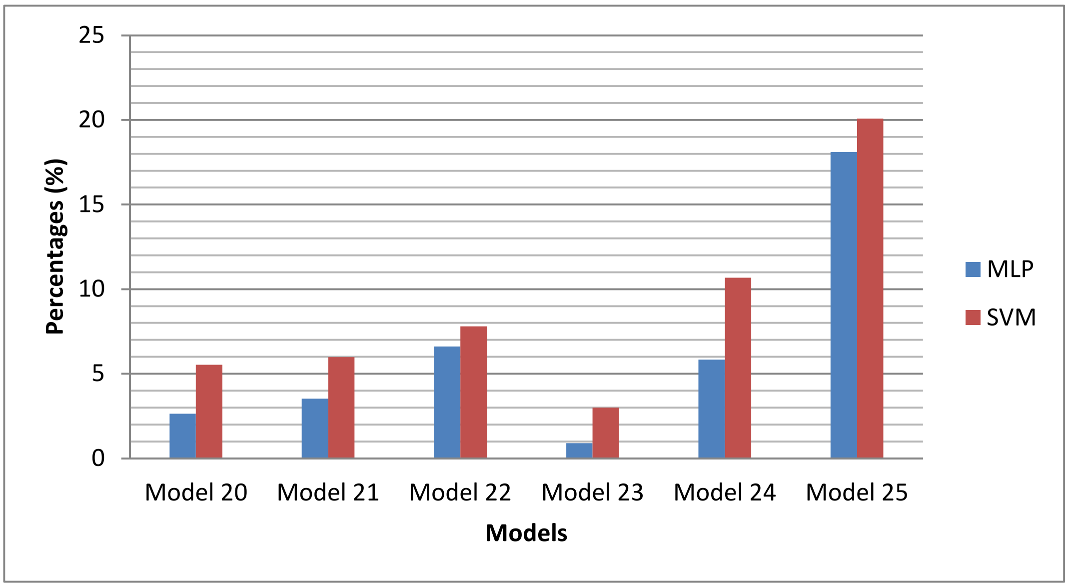


Figure 5.5. Percentage decrease rates in *SEE*'s of submaximal $VO_2max$ for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined with Relief-F ($VO_2max$-set2)

Table 5.22. *R* and *SEE* values for maximal $VO_2max$ prediction models using different regression methods combined with Relief-F on the $VO_2max$-set3.

| **Models** | **MLR** | | **MLP** | | **SVM** | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 26 | 0.89 | 4.89 | 0.89 | 4.75 | 0.89 | 4.71 |
| Model 27 | 0.88 | 4.89 | 0.89 | 4.66 | 0.90 | 4.60 |
| Model 28 | 0.89 | 4.77 | 0.90 | 4.62 | 0.90 | 4.58 |
| Model 29 | 0.88 | 5.01 | 0.88 | 4.96 | 0.89 | 4.79 |
| Model 30 | 0.83 | 5.84 | 0.87 | 5.08 | 0.89 | 4.84 |
| Model 31 | 0.79 | 6.36 | 0.84 | 5.68 | 0.84 | 5.61 |
| Model 32 | 0.76 | 6.75 | 0.76 | 6.56 | 0.78 | 6.55 |

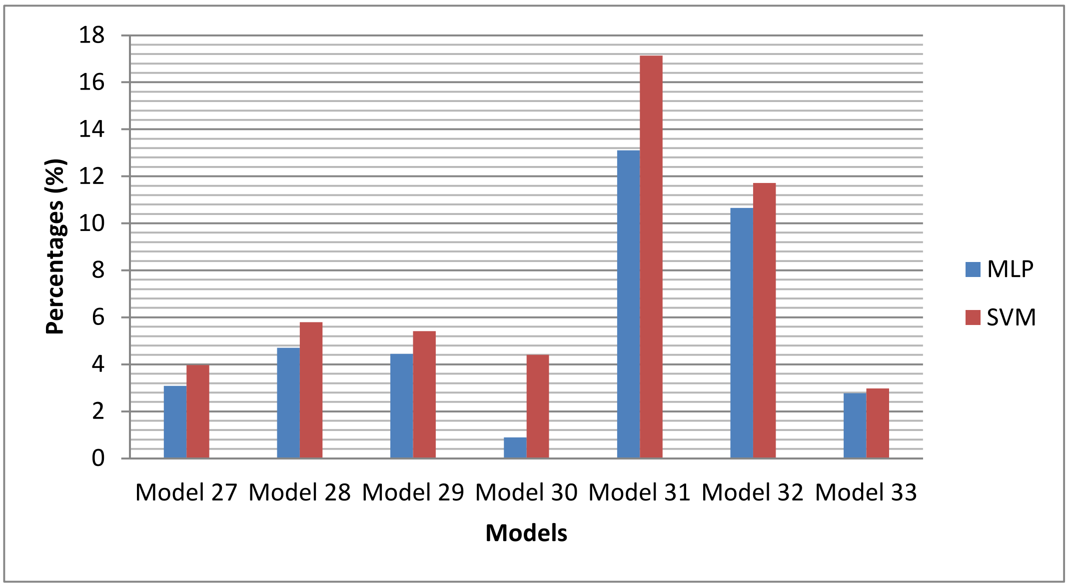


Figure 5.6. Percentage decrease rates in *SEE*'s of maximal $VO_2max$ for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined with Relief-F ($VO_2max$-set3)

Table 5.23. *R* and *SEE* values for N-Ex $VO_2$max prediction models using different regression methods combined with Relief-F on the $VO_2$max-set3.

| **Models** | **MLR** | | **MLP** | | **SVM** | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 33 | 0.87 | 5.11 | 0.88 | 4.89 | 0.89 | 4.80 |
| Model 34 | 0.85 | 5.53 | 0.88 | 5.01 | 0.88 | 4.87 |
| Model 35 | 0.80 | 6.23 | 0.86 | 5.21 | 0.88 | 5.00 |
| Model 36 | 0.70 | 7.35 | 0.82 | 5.99 | 0.84 | 5.69 |
| Model 37 | 0.60 | 8.28 | 0.75 | 6.81 | 0.76 | 6.69 |

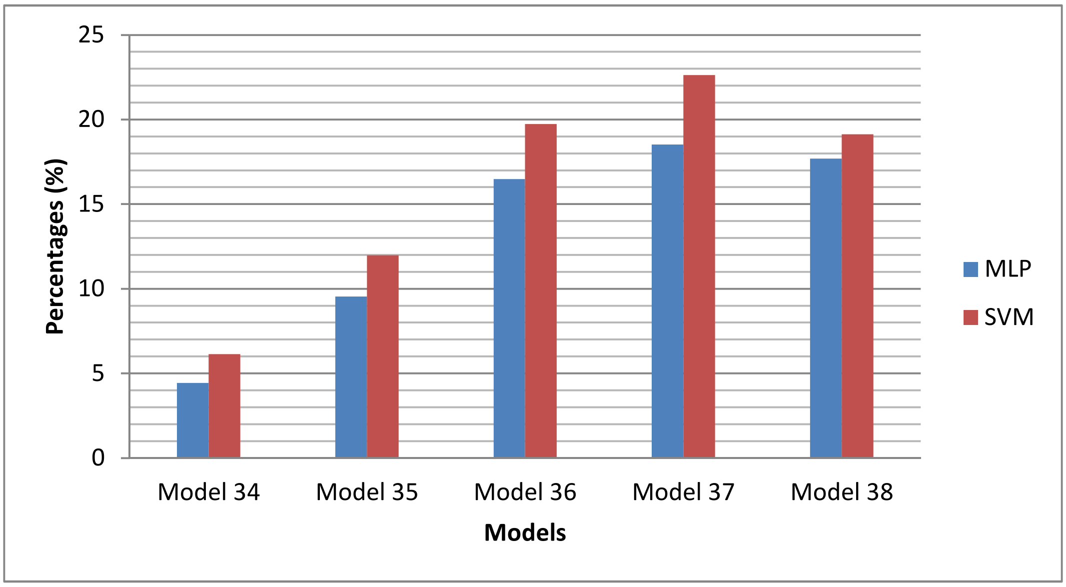


Figure 5.7. Percentage decrease rates in *SEE*'s of N-Ex $VO_2$max for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined with Relief-F ($VO_2$max-set3)

Table 5.24. *R* and *SEE* values for maximal $VO_2$max prediction models using different regression methods combined with Relief-F on the $VO_2$max-set4.

| **Models** | **MLR** | | **MLP** | | **SVM** | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 38 | 0.59 | 4.92 | 0.67 | 4.54 | 0.70 | 4.20 |
| Model 39 | 0.61 | 4.76 | 0.67 | 4.50 | 0.72 | 4.13 |
| Model 40 | 0.65 | 4.52 | 0.66 | 4.45 | 0.73 | 4.05 |
| Model 41 | 0.37 | 5.48 | 0.65 | 4.57 | 0.70 | 4.25 |
| Model 42 | 0.29 | 5.65 | 0.50 | 5.13 | 0.55 | 4.92 |

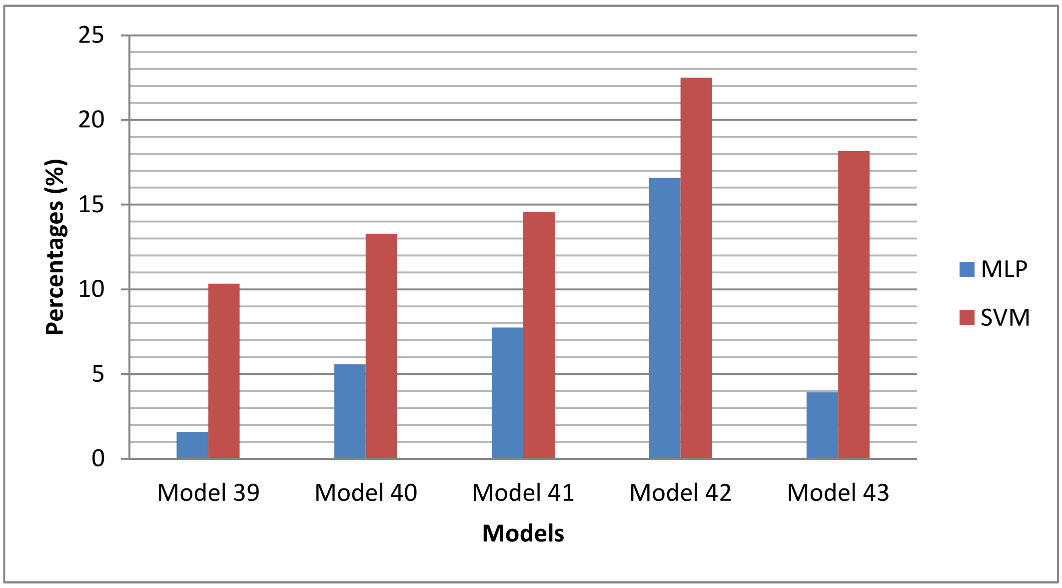


Figure 5.8. Percentage decrease rates in *SEE*'s of maximal $VO_2$max for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined with Relief-F ($VO_2$max-set4)

Table 5.25. *R* and *SEE* values for submaximal $VO_2max$ prediction models using different regression methods combined with Relief-F on the $VO_2max$-set4.

| Models | MLR | | MLP | | SVM | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 43 | 0.68 | 5.08 | 0.77 | 4.08 | 0.74 | 3.99 |
| Model 44 | 0.74 | 4.47 | 0.76 | 4.03 | 0.74 | 3.96 |
| Model 45 | 0.82 | 3.51 | 0.88 | 2.81 | 0.90 | 2.60 |
| Model 46 | 0.81 | 3.57 | 0.88 | 2.86 | 0.89 | 2.71 |
| Model 47 | 0.78 | 3.71 | 0.82 | 3.55 | 0.83 | 3.31 |
| Model 48 | 0.80 | 3.59 | 0.80 | 3.54 | 0.83 | 3.28 |
| Model 49 | 0.78 | 3.76 | 0.79 | 3.63 | 0.80 | 3.51 |
| Model 50 | 0.76 | 3.90 | 0.77 | 3.81 | 0.78 | 3.73 |
| Model 51 | 0.73 | 4.08 | 0.77 | 3.85 | 0.76 | 3.81 |
| Model 52 | 0.49 | 5.16 | 0.72 | 4.15 | 0.73 | 4.06 |
| Model 53 | 0.40 | 5.94 | 0.58 | 4.89 | 0.58 | 4.82 |

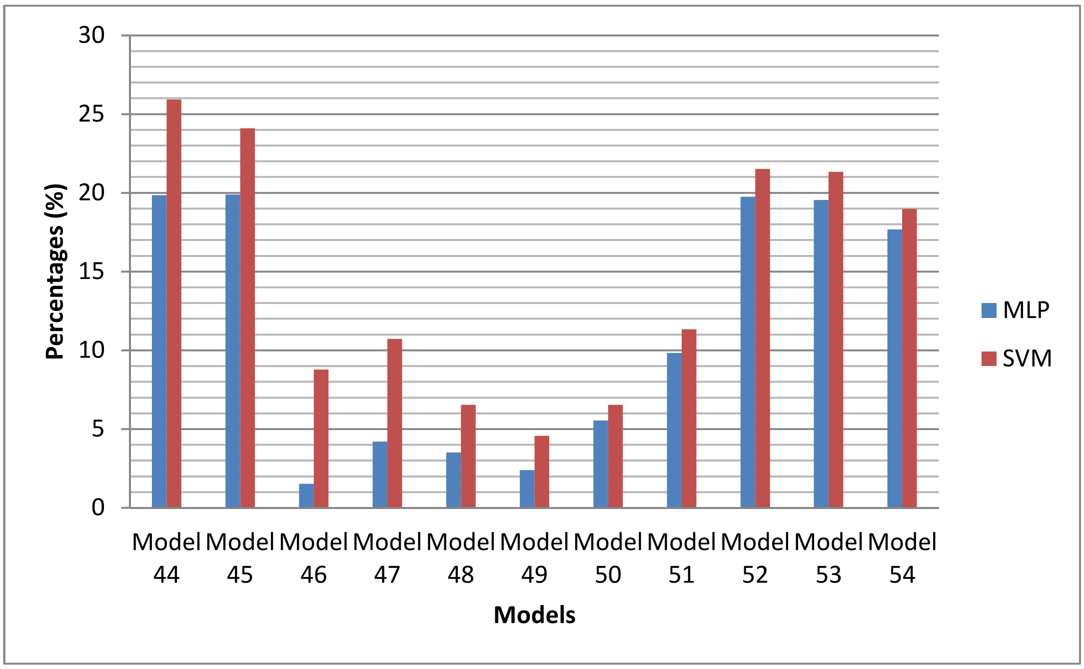


Figure 5.9. Percentage decrease rates in *SEE*'s of submaximal $VO_2max$ for machine learning methods combined with Relief-F compared to *SEE*'s obtained by MLR combined with Relief-F ($VO_2max$-set4)

Table 5.26. *R* and *SEE* values for $VO_2$max prediction models using different regression methods combined with CFS on the $VO_2$max sets.

| Models | MLR | | MLP | | SVM | |
|---|---|---|---|---|---|---|
| | ***R*** | ***SEE*** | ***R*** | ***SEE*** | ***R*** | ***SEE*** |
| Model 54[1,a] | 0.78 | 5.66 | 0.80 | 5.52 | 0.80 | 5.43 |
| Model 55[3,c] | 0.87 | 5.11 | 0.88 | 4.89 | 0.89 | 4.80 |
| Model 56[2,b] | 0.74 | 4.15 | 0.78 | 3.85 | 0.80 | 3.72 |
| Model 57[3,a] | 0.88 | 4.99 | 0.88 | 4.88 | 0.89 | 4.80 |
| Model 58[1,b] | 0.84 | 4.97 | 0.86 | 4.67 | 0.87 | 4.44 |
| Model 59[1,c] | 0.77 | 5.88 | 0.84 | 5.08 | 0.84 | 4.87 |
| Model 60[4,b] | 0.75 | 3.96 | 0.82 | 3.42 | 0.83 | 3.33 |
| Model 61[4,a] | 0.50 | 5.15 | 0.73 | 4.07 | 0.75 | 3.95 |

[1]: $VO_2$max-set1; [2]: $VO_2$max-set2; [3]: $VO_2$max-set3; [4]: $VO_2$max-set4; [a]: maximal; [b]: submaximal; [c]: N-Ex.

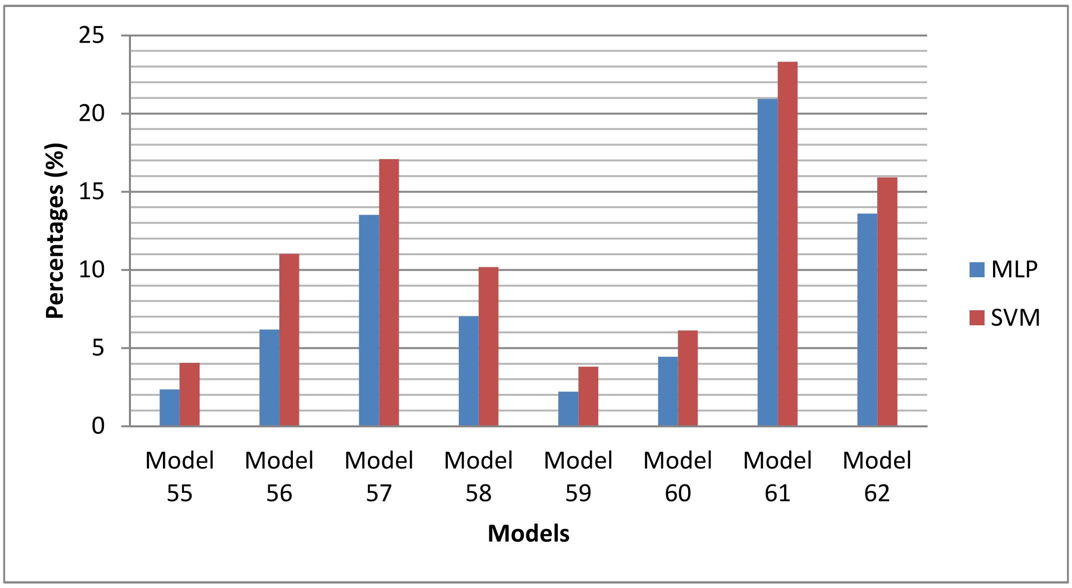


Figure 5.10. Percentage decrease rates in *SEE*'s of $VO_2$max for machine learning methods combined with CFS compared to *SEE*'s obtained by MLR combined with CFS ($VO_2$max sets)

### 5.3. Discussions on maximal $VO_2$max-set1 Results

- As can be seen from Table 5.9, gender has the highest score while MAX-RPE has the lowest one.
- The results from Table 5.18 show that SVM-based prediction models perform better than MLP-based prediction models. MLP-based prediction models are more accurate than MLR-based prediction models.
- Among the SVM-based, MLP-based, and MLR-based models, Model 4 including the predictor variables gender, age, BMI, MAX-HR has the lowest *SEE*'s (6.10 ml•kg$^{-1}$•min$^{-1}$, 6.54 ml•kg$^{-1}$•min$^{-1}$ ,and 6.57 ml•kg$^{-1}$•min$^{-1}$) and the highest *R*'s (0.74, 0.71, and 0.71), respectively.
- Between Model 1 including all attributes and Model 1, the decreasing rate in *SEE*'s is calculated as 10.41%, 7.34%, and 11.13% for SVM-based, MLP-based, and MLR-based prediction models, in the order given.
- Model 7, which has one predictor variable, gives the highest *SEE*'s (8.08 ml•kg$^{-1}$•min$^{-1}$, 8.56 ml•kg$^{-1}$•min$^{-1}$ ,and 8.95 ml•kg$^{-1}$•min$^{-1}$) for the SVM-based, MLP-based, and MLR-based prediction models, respectively.
- Among the $VO_2$max prediction models in Table 5.18, gender, age, and BMI attributes have the strongest effect on the performance of $VO_2$max prediction.

### 5.4. Discussions on submaximal $VO_2$max-set1 Results

- It can be noticed from Table 5.10 that the variable SM-MPH has the highest score whereas the variable SM-RPE has the lowest score.
- The outcomes from Table 5.19 indicate that SVM-based prediction models are more accurate *SEE*'s than MLP-based prediction models. MLP-based prediction models perform better than MLR-based prediction models.
- Among the SVM-based, MLP-based, and MLR-based models, Model 9 consisting of the variables, SM-MPH, gender, SM-Stage, age, SM-HR, and BMI gives the lowest *SEE*'s score (4.37 ml•kg$^{-1}$•min$^{-1}$, 4.56 ml•kg$^{-1}$•min$^{-1}$,

and 4.81 ml•kg$^{-1}$•min$^{-1}$) and the highest *R*'s (0.88, 0.87 and 0.85), respectively.

- Inclusion of SM-RPE to the best model in Table 5.19 yields higher *SEE*'s and lower *R*'s.
- It is clearly seen from Table 5.19 that the model including one variable has the highest *SEE*'s (4.97 ml•kg$^{-1}$•min$^{-1}$, 5.23 ml•kg$^{-1}$•min$^{-1}$, and 5.31 ml•kg$^{-1}$•min$^{-1}$) and lowest *R*'s (0.84, 0.82, and 0.81) for SVM-based, MLP-based, and MLR-based prediction models, respectively.

### 5.5. Discussions on N-Ex $VO_2$max-set1 Results

- It is easily seen from Table 5.11 that PFA has the highest score while gender has the lowest score.
- The results obtained from Table 5.20 represent SVM-based prediction models perform better than the prediction models obtained by other regression methods. MLP-based prediction models give more accurate *SEE*'s than MLR-based prediction models.
- From Table 5.20, it can be seen that Model 15, which has all attributes, PFA, age, BMI, PAR, and gender, has the lowest *SEE*'s (4.32 ml•kg$^{-1}$•min$^{-1}$, 4.36 ml•kg$^{-1}$•min$^{-1}$, and 4.66 ml•kg$^{-1}$•min$^{-1}$) and highest *R*'s (0.88, 0.88, and 0.87) whereas Model 19 including only one variable, gender, gives the highest *SEE*'s (6.38 ml•kg$^{-1}$•min$^{-1}$, 6.56 ml•kg$^{-1}$•min$^{-1}$, and 6.59 ml•kg$^{-1}$•min$^{-1}$) and lowest *R*'s (0.71, 0.69, and 0.69) for the SVM-based, MLP-based, and MLR-based models, respectively.
- Between Model 19, the worst model, and Model 15, the best model, 32.31%, 33.51%, and 29.26% decrements in *SEE*'s and 23.26%, 27.29%, and 25.91% increments in *R*'s for the SVM-based, MLP-based, and MLR-based prediction models have been obtained, respectively.
- Among the $VO_2$max prediction models in Table 5.20, questionare variables (i.e. PFA and PAR) have the strongest effect on the performance of $VO_2$max prediction.

### 5.6. Discussions on submaximal $VO_2$max-set2 Results

- It is clear from Table 5.12 that speed is the most effective attribute while the attribute location is the most ineffective one for prediction of $VO_2$max.
- As can be seen from Table 5.21, SVM-based prediction models give more accurate *SEE*'s than MLP-based prediction models while MLP-based prediction models perform better than MLR-based prediction models.
- Among the SVM-based, MLP-based, and MLR-based models, Model 21 with the attributes, speed, gender, BMI, SM-HR, and age, gives the lowest *SEE*'s (3.21 ml•kg$^{-1}$•min$^{-1}$, 3.31 ml•kg$^{-1}$•min$^{-1}$ ,and 3.40 ml•kg$^{-1}$•min$^{-1}$).
- By extraction of location, which has the lowest score in Table 5.4, from Model 20, the most accurate prediction model has been obtained.
- Model 25 with one variable has the highest *SEE*'s (4.56 ml•kg$^{-1}$•min$^{-1}$, 4.67 ml•kg$^{-1}$•min$^{-1}$ ,and 5.71 ml•kg$^{-1}$•min$^{-1}$) and lowest *R*'s (0.67, 0.65, and 0.38) for SVM-based, MLP-based, and MLR-based prediction models, in the order given.
- Decrements in *SEE*'s between Model 25 and Model 20 are 28.60%, 28.50%, and 39.31% for the SVM-based, MLP-based, and MLR-based prediction models, respectively.

### 5.7. Discussions on maximal $VO_2$max-set3 Results

- As indicated in Table 5.13, exercise time has the highest score but MAX-RPE has the lowest one. The model including the single predictor variable exercise time has the lowest *SEE* values in the Table 5.22.
- Table 5.22 shows that SVM-based $VO_2$max prediction models perform better than MLP-based and MLR-based prediction models. Similarly, MLP-based $VO_2$max prediction models have have better *SEE* values than MLR-based prediction models.
- When all models are examined, Model 28 including the predictor variables MAX-Time, gender, age, BMI, MAX-HR has the lowest *SEE*'s (4.58 ml•kg$^{-}$

$^{1}$•min$^{-1}$, 4.62 ml•kg$^{-1}$•min$^{-1}$ ,and 4.77 ml•kg$^{-1}$•min$^{-1}$) and the highest *R*'s (0.90, 0.90, and 0.89), for SVM-based, MLP-based and MLR-based models, respectively.

- When Model 28 and Model 26 are compared, inclusion of MAX-RER and MAX-RPE to the best model in Table 5.22 yields higher *SEE*'s and lower *R*'s.

**5.8. Discussions on N-Ex $VO_2$max-set3 Results**

- It is clear from Table 5.14 that BF% variable has the highest rank value. However, the models including only BF% have the lowest *SEE* values in Table 5.14.
- The outcomes from Table 5.6 show that the ranking of the performance models is as follows: SVM-based, MLP-based and MLR-based.
- Among the SVM-based, MLP-based, and MLR-based models, Model 33 including the predictor variables BF%, age, AC, gender, BMI has the lowest *SEE*'s (4.80 ml•kg$^{-1}$•min$^{-1}$, 4.89 ml•kg$^{-1}$•min$^{-1}$ ,and 5.11 ml•kg$^{-1}$•min$^{-1}$) and the highest *R*'s (0.89, 0.88, and 0.87), respectively.
- Model 37, which has one variable, gives the highest *SEE*'s (6.69 ml•kg$^{-1}$•min$^{-1}$, 6.81 ml•kg$^{-1}$•min$^{-1}$ ,and 8.28 ml•kg$^{-1}$•min$^{-1}$) for the SVM-based, MLP-based, and MLR-based prediction models, respectively.

**5.9. Discussions on maximal $VO_2$max-set4 Results**

- The results obtained from Table 5.15 present that gender has the highest score while HR-MAX has the lowest one. The model including the single variable gender has the highest *SEE'*s.
- In Table 5.24, for the SVM-based, MLP-based, and MLR-based models, Model 40 including the predictor variables gender, BMI, age has the lowest *SEE*'s (4.05 ml•kg$^{-1}$•min$^{-1}$, 4.45 ml•kg$^{-1}$•min$^{-1}$ ,and 4.52 ml•kg$^{-1}$•min$^{-1}$) and the highest *R*'s (0.73, 0.66, and 0.65), respectively.

- Adding MAX-RER and MAX-HR variables to Model 40, values of *SEE*'s and *R*'s improve for SVM-based, MLP-based, and MLR-based prediction models, in the order given.
- Among SVM-based, MLP-based and MLR-based prediction models, Model 42 which has one variable gives the worst *SEE*'s (9.42 ml•kg$^{-1}$•min$^{-1}$, 5.13 ml•kg$^{-1}$•min$^{-1}$, and 5.65 ml•kg$^{-1}$•min$^{-1}$) and *R*'s (0.55, 0.50, and 0.29), respectively.
- Among the models in Table 5.24, gender, age and BMI attributes yield increments in the performance of $VO_2$max prediction.

### 5.10. Discussions on submaximal $VO_2$max-set4 Results

- As can be seen from Table 5.16 gender has the highest score while age has the lowest one.
- SVM-based prediction models give more accurate *SEE*'s than MLP-based prediction models when MLP-based models comparatively give better *SEE*'s than MLR-based models.
- Among the SVM-based, MLP-based, and MLR-based models, Model 45 including the predictor variables gender, MIN3, MIN2, MIN1, height, weight, BMI, HR2, HR3 has the lowest *SEE*'s (2.60 ml•kg$^{-1}$•min$^{-1}$, 2.81 ml•kg$^{-1}$•min$^{-1}$, and 3.51 ml•kg$^{-1}$•min$^{-1}$) and the highest *R*'s (0.90, 0.88, and 0.82), in the order given.
- Between Model 43 including all attributes and Model 45 which has the lowest *SEE*'s, the decreasing rate in *SEE*'s is calculated as 34.82%, 31.01%, and 30.94% for SVM-based, MLP-based and MLR-based prediction models, respectively.
- Model 53 with one variable has the highest *SEE*'s (4.82 ml•kg$^{-1}$•min$^{-1}$, 4.89 ml•kg$^{-1}$•min$^{-1}$ ,and 5.94 ml•kg$^{-1}$•min$^{-1}$) and lowest *R*'s (058, 0.58, and 0.40) for SVM-based, MLP-based, and MLR-based prediction models, respectively.

- Decrements in *SEE*'s between Model 43 and Model 53 are 17.14%, 16.62%, and 14.97% for the SVM-based, MLP-based, and MLR-based prediction models, respectively.
- Among the $VO_2$max prediction models, the MIN attributes have the strongest effect on the performance of $VO_2$max prediction.

### 5.11. Discussions on CFS Results

- The results from Table 5.26 show that all $VO_2$max predicton models include the attribute "gender" while most prediction models have also the attribute "age".
- Among the SVM-based, MLP-based, and MLR-based models, Model 60 including the predictor variables gender, hr2, min3 has the lowest *SEE*'s (3.33 ml•kg$^{-1}$•min$^{-1}$, 3.42 ml•kg$^{-1}$•min$^{-1}$ ,and 3.96 ml•kg$^{-1}$•min$^{-1}$) while Model 54 having gender, age, MAX-GRD, MAX-RER and BMI give the highest *SEE*'s (5.43 ml•kg$^{-1}$•min$^{-1}$, 5.52 ml•kg$^{-1}$•min$^{-1}$ ,and 5.66 ml•kg$^{-1}$•min$^{-1}$), respectively.
- When the performance of CFS and Relief-F is compared for the maximal prediction models of $VO_2$max-set1, it is seen that the CFS-based model yields better performance than Relief-F-based models for all regression methods. The reductions in *SEE*'s of Relief-F-based models are 13.34%, 18.48%, and 16.07% for SVM-based, MLP-based and MLR-based models, respectively.
- When the performance of CFS and Relief-F is compared for the submaximal models of $VO_2$max-set1, it is seen that the CFS-based model yields better performance than Relief-F-based models for all regression models. The reductions in *SEE*'s of Relief-F-based models are 1.60%, 2.41%, and 3.33% for SVM-based, MLP-based and MLR-based models, respectively.
- When the performance of CFS and Relief-F is compared for the N-Ex models of $VO_2$max-set1, it is seen that the CFS-based model yields worse performance than Relief-F-based models for all regression models. The increments in *SEE*'s of Relief-F-based models are 12.73%, 16.51%, and 26.18% for SVM-based, MLP-based and MLR-based models, respectively.

- When the performance of CFS and Relief-F is compared for the submaximal models of $VO_2$max-set2, it is seen that the CFS-based model yields worse performance than Relief-F-based models for all regression models. The increments in *SEE*'s of Relief-F-based models are 6.90%, 9.07%, and 9.79% for SVM-based, MLP-based and MLR-based models, respectively.
- When the performance of CFS and Relief-F is compared for the maximal models of $VO_2$max-set3, it is seen that the CFS-based model yields worse performance than Relief-F-based models for all regression models. The increments in *SEE*'s of Relief-F-based models are 4.80%, 5.63%, and 4.61% for SVM-based, MLP-based and MLR-based models, respectively.
- When the performance of CFS and Relief-F is compared for the maximal models of $VO_2$max-set4, it is seen that the CFS-based model yields best performance than Relief-F-based models for SVM-based and MLP-based regression models. The reductions in *SEE*'s of Relief-F-based models are 2.53% and 9.34% for SVM-based and MLP-based models, respectively.
- When the performance of CFS and Relief-F is compared for the submaximal models of $VO_2$max-set4, it is seen that the CFS-based model yields worse performance than Relief-F-based models for all regression models. The increments in *SEE*'s of Relief-F-based models are 28.08%, 22.06%, and 12.82% for SVM-based, MLP-based and MLR-based models, respectively.

### 5.12. Discussions on General Results

- Using the Relief-F attribute evaluator, the gender has been ranked with the highest score in all submaximal sets. Age appears in all of the submaximal models.
- For maximal $VO_2$max prediction sets, the variables gender and age generally seem to be in top positions in the Relief-F rankings. Using a combination of the two variables significantly increases the performance of the models.

- For N-Ex $VO_2$max sets where age is used alone achieves the lowest performance within its group while its combination with gender increases the prediction performance.
- It is observed that the best prediction models in each category include the variables gender, age and BMI.
- For the best models in the submaximal sets, significant performance improvements have been observed when the variables SM-MPH and SM-HR have been used in combination.
- The best models obtained by Relief-F and CFS are different from each other. Exceptionally, in the N-Ex $VO_2$max group, the same models have been observed.
- When the group-based best models obtained by Relief-F are compared with the best models achieved by CFS, it can be observed that Relief-F exhibits much higher performance than CFS.
- Although Relief-F exhibits much higher performance, as compared to CFS, Relief-F-based models have used much more features. For example, when the N-Ex $VO_2$max-set1 is examined in more detail, it can be observed that Relief-F-based best prediction model has 5 features while CFS-based best prediction model contains 3 features.

Finally, below are given the scatter plots of actual vs. predicted $VO_2$max scores for each best model from the eight data sets using SVM.

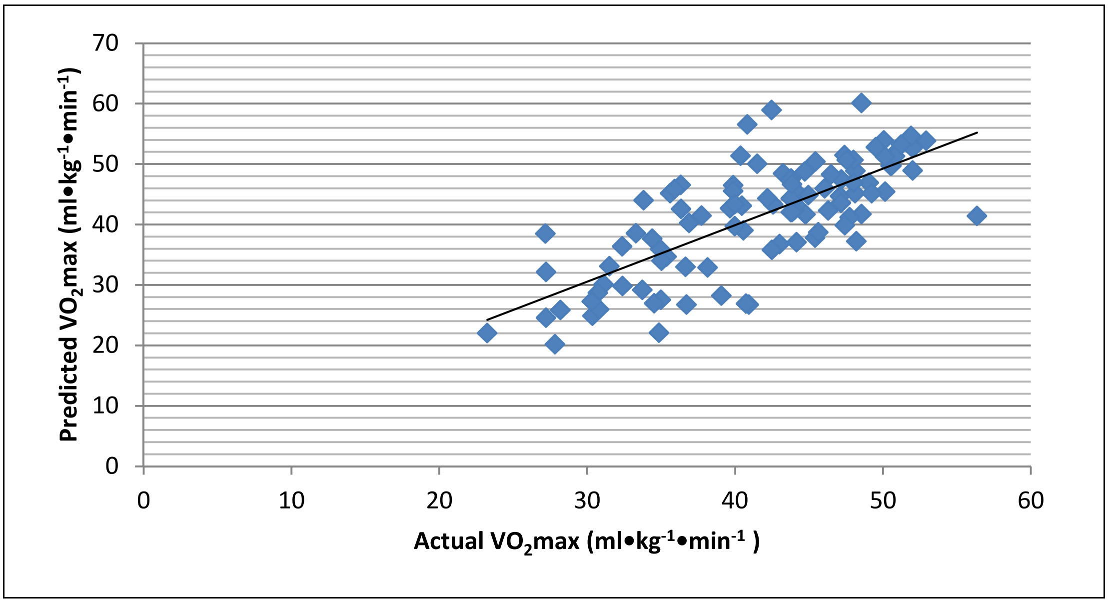


Figure 5.11. Scatter plot of actual $VO_2$max vs. predicted $VO_2$max for Model 4 using SVM.

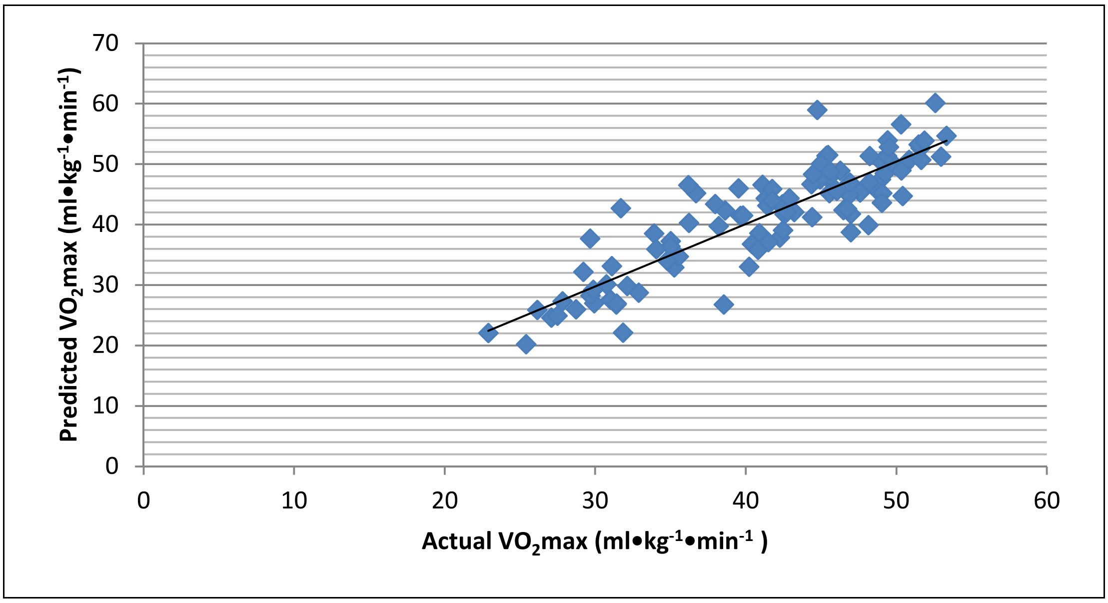


Figure 5.12. Scatter plot of actual $VO_2$max vs. predicted $VO_2$max for Model 9 using SVM.

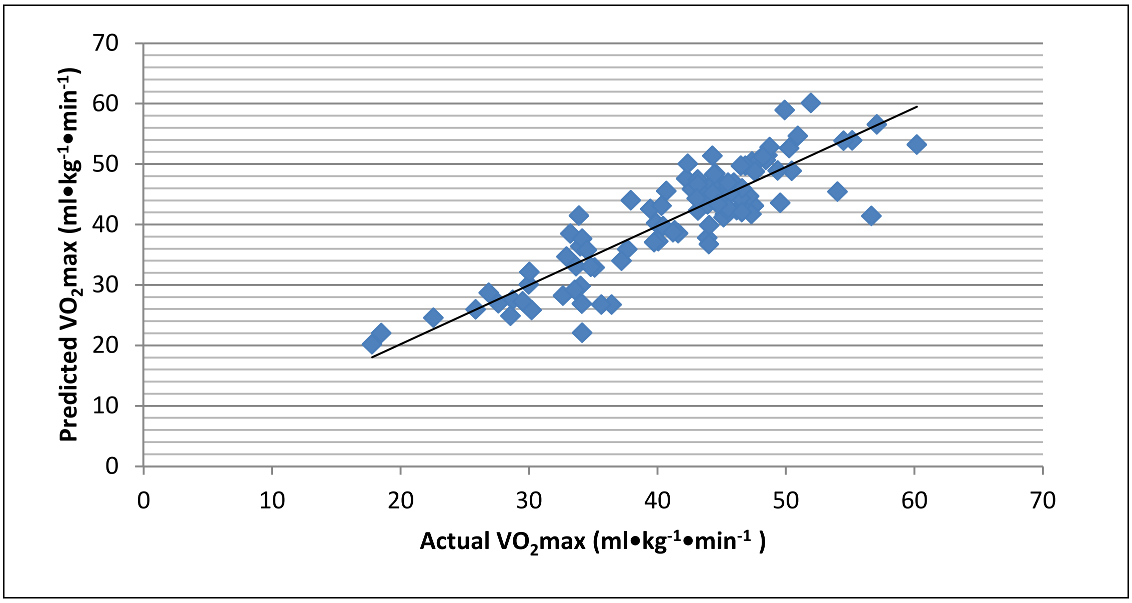


Figure 5.13. Scatter plot of actual $VO_2$max vs. predicted $VO_2$max for Model 15 using SVM.

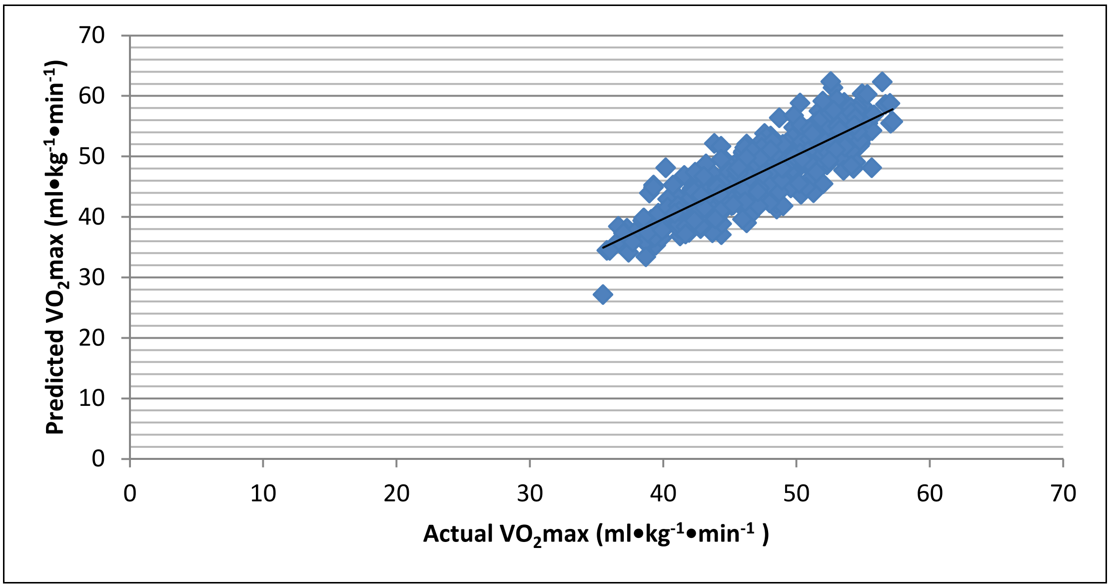


Figure 5.14. Scatter plot of actual $VO_2$max vs. predicted $VO_2$max for Model 21 using SVM.

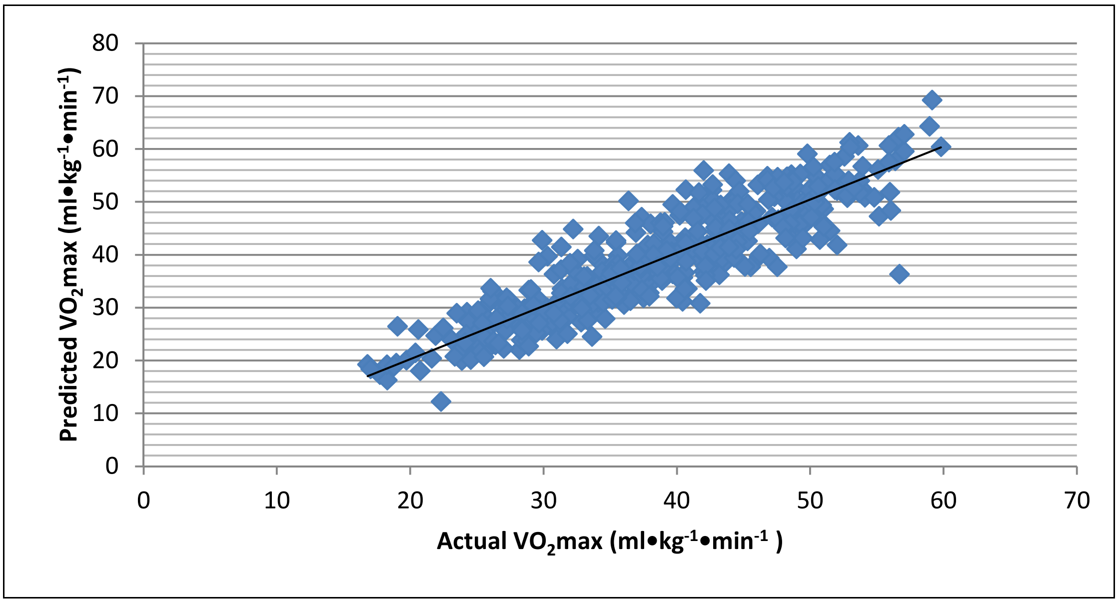


Figure 5.15. Scatter plot of actual $VO_2max$ vs. predicted $VO_2max$ for Model 28 using SVM.

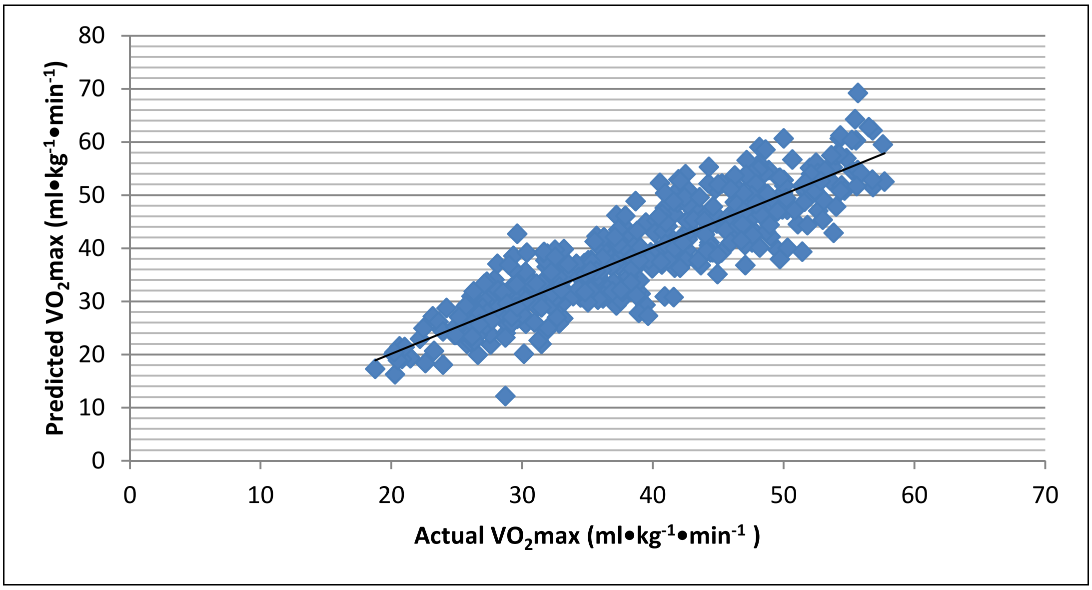


Figure 5.16. Scatter plot of actual $VO_2max$ vs. predicted $VO_2max$ for Model 33 using SVM.

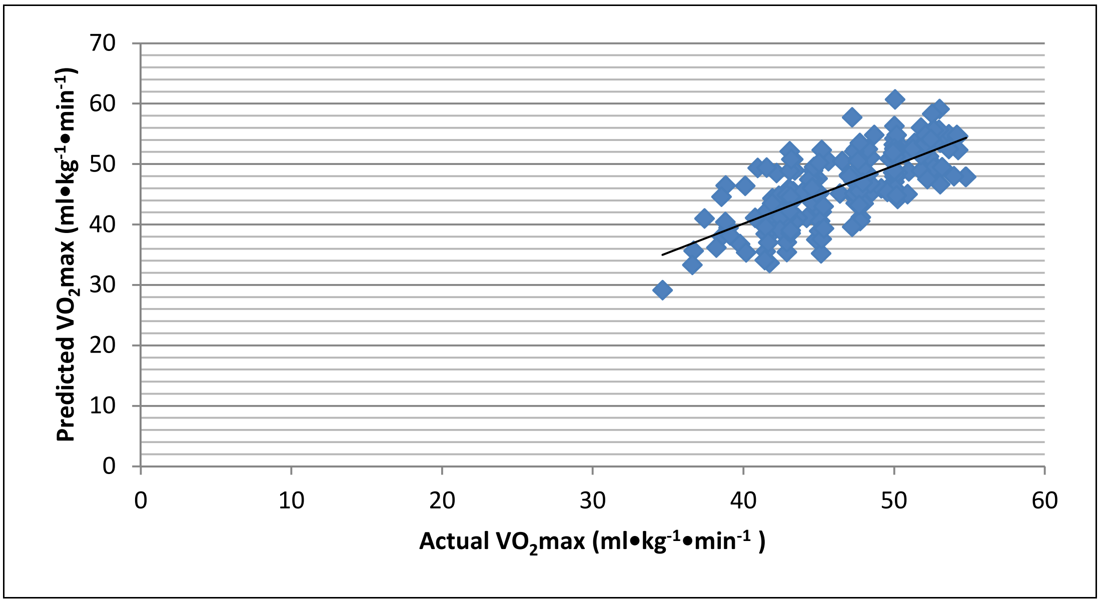


Figure 5.17. Scatter plot of actual $VO_2$max vs. predicted $VO_2$max for Model 40 using SVM.

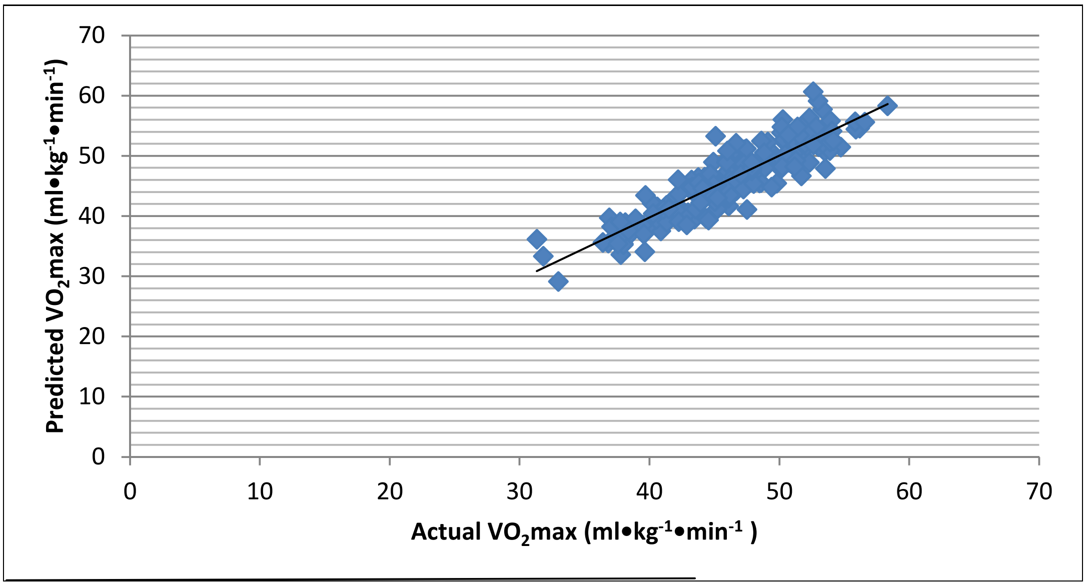


Figure 5.18. Scatter plot of actual $VO_2$max vs. predicted $VO_2$max for Model 45 using SVM.

# 6. CONCLUSION

In this thesis, several $VO_2$max prediction models have been developed using different data sets and combinations of the predictor variables such as protocol, age, gender, height, weight, BMI, HR and exercise time. Different regression methods (i.e. SVM, MLP and MLR) combined with feature selection algorithms (i.e. Relief-F and CFS) have been applied on the prediction models. By using 10-fold cross validation on the data sets, the performance of the models has been evaluated by calculating *R*'s and *SEE*'s. The results show that $VO_2$max can be predicted with reasonable error rates.

Considering the results obtained, one can reach several conclusions. First of all, SVM-based prediction models show better performance (i.e. higher *R* and lower *SEE*) than the models developed by other regression methods. The order of the regression methods for prediction of $VO_2$max, from the best to the worst, is SVM, MLP and MLR. Due to the non-linear characteristics of $VO_2$max, linear regression methods yield higher *SEE*'s for prediction. On the other hand, linear regression methods yield faster results for prediction.

By using different regression and feature selection methods, the features of the models have been ranked for $VO_2$max prediction. In more detail, this thesis shows that in certain models, $VO_2$max could be predicted with less error rates using less number of features. Although Relief-F-based models in general exhibit higher performance than the CFS-based ones for all regression models, they need many more features as compared to CFS-based models.

This is an initial study to show that $VO_2$max can be predicted using regression methods combined with feature selection. Future work can be performed in a number of different areas. Other regression methods such as generalized regression neural networks, radial basis function neural networks and tree-boosting can be used for prediction of $VO_2$max. Different feature selection algorithms can be combined with regression methods to identify the relevant and irrelevant features for prediction of $VO_2$max.

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## CURRICULUM VITAE

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