ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

PhD THESIS

Mustafa AÇIKKAR

DEVELOPING VO_2max PREDICTION MODELS FROM NON-EXERCISE, SUBMAXIMAL EXERCISE AND HYBRID TESTS USING MACHINE LEARNING METHODS

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Doctor of Philosophy by the board of jury on 6/9/2015.

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ABSTRACT

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Maximum oxygen uptake (VO_2max) is defined as the maximum ability to transport and consume oxygen during strenuous endurance exercise and is considered the single best measure of cardiorespiratory fitness (CRF). The purpose of this thesis is to develop VO_2max prediction models by using non-exercise, submaximal and hybrid variables by using Support Vector Machines (SVM), Multi-layer Feed-forward Artificial Neural Networks (MFANN) and Multiple Linear Regression (MLR) on different data sets. 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 standard error of estimates (SEE's). The results show that SVM-based VO_2max prediction models perform better (i.e. yield lower *SEE*'s and higher *R*'s) than the prediction models developed by MFANN and MLR. We also propose a new approach based on the elimination of irrelevant samples during the training phase for improving the performance of SVM and MFANN models for prediction of VO_2max. The performance of the proposed approach has been compared with the two widely used outlier detection algorithms. The results show that the improved SVM-based and MFANN-based VO_2max prediction models yield noticeable decrements in error rates compared to that of regular and outlier-based SVM and MFANN VO_2max prediction models.

Key Words: Support Vector Machines, Multi-Layer Feed-Forward Artificial Neural Networks, Maximal Oxygen Uptake

ÖZ

DOKTORA TEZİ

MAKİNE ÖĞRENME YÖNTEMLERİ KULLANILARAK EGZERSİZE DAYALI OLMAYAN, SUBMAKSİMAL VE HİBRİT TEST DEĞİŞKENLERİNDEN VO_2max TAHMİN MODELLERİNİN GELİŞTİRİLMESİ

Mustafa AÇIKKAR

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
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Maksimal oksijen tüketimi (VO_2max), şiddetli dayanıklılık egzersizi esnasında azami oksijen taşıma ve tüketme yeteneği olarak tanımlanır ve kalp-solunum (kardiyorespiratuvar) uygunluğunu ölçmenin tek ve en iyi yöntemi olarak kabul edilir. Bu tezin amacı farklı veri setleri ile submaksimal, egzersize dayalı olmayan ve hibrit değişkenleri kullanarak Destek Vektör Makineleri (DVM), Çok-Katmanlı İleri-Beslemeli Yapay Sinir Ağları (YSA) ve Çoklu Doğrusal Regresyon (ÇDR) ile VO_2max tahmin modelleri geliştirmektir. Dört farklı veri seti üzerinde, 10-katlı çapraz doğrulama kullanılarak, tahmin modellerinin performansları Çoklu Korelasyon Katsayısı (*R*) ve Standart Tahmin Hatası (*STH*) hesaplanarak elde edilmiştir. Sonuçlar, DVM-tabanlı VO_2max tahmin modellerinin YSA ve ÇDR-tabanlı tahmin modellerine göre daha başarılı olduğunu göstermiştir. Ayrıca bu tezde, DVM ve YSA-tabanlı VO_2max tahmin modellerinin performansını arttırmak için yeni bir yaklaşım önerilmiştir. Veri eksiltme olarak adlandırılan bu yaklaşım uyumsuz satırların öğrenme veri setinden öğrenme aşamasında çıkarılmasına dayalıdır. Önerilen yaklaşımın performansı yaygın olarak kullanılan iki farklı aykırı değer algılama algoritması ile karşılaştırılmıştır. Geliştirilmiş DVM ve YSA-tabanlı VO_2max tahmin modelleri, normal ve aykırı değerleri algılama algoritması tabanlı DVM ve YSA-tabanlı VO_2max tahmin modelleri ile karşılaştırıldığında hata oranlarında fark edilebilir düzeyde bir azalma ortaya çıkmıştır.

Anahtar Kelimeler: Destek Vektör Makineleri, Çok Katmanlı İleri Beslemeli Yapay Sinir Ağları, Maksimal Oksijen Tüketimi

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LIST OF ABBREVIATIONS

AC	:	Level of Physical Activity
ACSM	:	American College of Sports Medicine
ANN	:	Artificial Neural Network
BF%	:	Body Fat Percent
BIA	:	Bioelectrical Impedance Analysis
BM	:	Body Mass
BMI	:	Body Mass Index
CCN		Cascade Correlation Network
CRF	:	Cardiorespiratory Fitness
CPET	:	Cardiopulmonary Exercise Testing
ERM	:	Empirical Risk Minimization
GEP		Gene Expression Programming
GMDH		Group Method of Data Handling
GRNN		Generalized Regression Neural Networks
GXT	:	Graded Exercise Test
HR	:	Heart Rate
HR1	:	Exercise Heart Rate At The End of 0.5 Mile
HR2	:	Exercise Heart Rate At The End of 1.0 Mile
HR3	:	Exercise Heart Rate At The End of 1.5 Mile
IQR		Interquartile Range
Lo-PAR	:	Self-Report Physical Activity Assessment
L-PA	:	Leisure-time Physical Activity
MFANN	:	Multi-layer Feed-Forward Artificial Neural Networks
MIN1	:	Elapsed Exercise Time At The End of 0.5 Mile
MIN2	:	Elapsed Exercise Time At The End of 1.0 Mile
MIN3	:	Elapsed Exercise Time At The End of 1.5 Mile

MLR	:	Multi Linear Regression
MST	:	20 Meter Multistage Shuttle Run Test
MVPA	:	Moderate to Vigorous Physical Activity
PA	:	Physical Activity
PACER	:	Progressive Aerobic Cardiovascular Endurance Run
PAR	:	Physical Activity Rating
PARS	:	Physical Activity Rating Score
PFA	:	Perceived Functional Ability
PFI	:	Physical Fitness Index
PHR15	:	15-Second Post-Exercise Heart Rate
PHR60	:	60-Second Post-Exercise Heart Rate
Q1		First Quartile (Lower Quartile)
Q2		Second Quartile (Median)
Q3		Third Quartile (Upper Quartile)
R	:	Multiple Correlation Coefficient
RER	:	Respiratory Exchange Ratio
RPC	:	Rating of Perceived Capacity
RPE	:	Rating of Perceived Exertion
SC	:	Step Count
SD	:	Standard Deviation
SDT		Single Decision Tree
SEE	:	Standard Error of Estimation
SM-HR	:	Submaximal Heart Rate
SM-Speed	:	Submaximal Speed
SM-Stage	:	Submaximal Treadmill Stage
SRM	:	Structural Risk Minimization
SRT	:	20 m Shuttle Run Test
SVM	:	Support Vector Machine

SVR	:	Support Vector Regression
TB		Tree Boost
TMJ	:	Treadmill Jogging
VO_2	:	Oxygen Consumption
VO_2max	:	Maximum Oxygen Uptake
VPA	:	Vigorous Physical Activity
VSAQ	:	Veterans Specific Activity Questionnaire
W-PA	:	Work-related Physical Activity

1. INTRODUCTION

1.1. What Is VO_2max?

Maximal oxygen uptake (VO_2max) is defined as the maximum amount of oxygen that a person can use during maximal exercise and is known as the most accurate indicator of cardiorespiratory fitness (CRF) (George et al., 2009). The knowledge of VO_2max can be used for different purposes including determining of endurance capacity of athletes, evaluating the effects of training programs, and estimating the health risks of individuals (Akalan et al., 2008; Leibetseder et al., 2002; Sanada et al., 2007). The direct measurement of VO_2max during a maximal graded exercise test (GXT) is accepted as the most accurate method for the assessment of aerobic power.

All the body cells need oxygen especially for aerobic energy processes. Muscles use most of the oxygen uptaken and the amount depends on whether the body is resting or exercising. It is well known that the oxygen consumption will increase with an increment in exercise intensity. Muscle cells are not active when the body is resting, which yields low oxygen consumption. On the contrary, the requirement for oxygen increases as the body starts exercising. Many factors including age, gender, genetics and training play an important role for an individual's VO_2max value.

The duration of an intense exercise that a subject can withstand is directly related to his/her VO_2max value. Table 1.1 shows compared VO_2max values of a person (both for untrained case and trained for 8 weeks) with an athlete (training for several years). A pre-determined ratio of VO_2max can serve for explaining running speed (for instance, Table 1.1 shows 75% of VO_2max). It is clearly seen from Table 1.1 that the athlete has higher VO_2max, which enables him/her to run at a faster speed for a given ratio of VO_2max. Also, it can be concluded by using the data given in Table 1.1 that VO_2max can be improved by training.

Table 1.1. Normative data for VO_2max (values in ml•kg^{-1}•min^{-1}).

	Untrained	**Trained for 8 weeks**	**Athlete**
VO_2max	45	54	70
75%VO_2max	34	41	53
Running pace (mph) at 75% VO_2max	5,7	7.0	9.2

1.2. Measuring VO_2max

Performance laboratories, health clinics or hospitals are convenient locations for measuring VO_2max. Expired air must be determined in the volumes of oxygen and carbon dioxide for measuring VO_2. Expired air can be collected using a specialized system including a 2-way valve, which conveys air using a hose to a metabolic system containing sensors of oxygen and carbon dioxide. This procedure can be carried out at rest or during exercise; however for an accurate measurement of VO_2max, it is essential that the subject must be exercising around his or her aerobic capacity. Cycle ergometer or treadmill graded exercise tests (GXT) are commonly used for accurate measurement of VO_2max.

1.3. Exercise Testing Protocols

Several cycle ergometer or treadmill maximal exercise test protocols exist. The difference among the protocols is related with the work rate applied. Popular maximal exercise test protocols are progressive incremental exercise protocol, multistage exercise protocol, constant work rate protocol and discontinuous protocol. (ATS and ACCP, 2003).

1.3.1. Maximal Incremental Cycle Ergometer Protocols

Clinics and laboratories usually use this protocol. Diagnostic data can be acquired as the work rate increases progressively. In this protocol, it is customary to start the incremental portion of exercise with unloaded pedaling and increase the

work rate at a constant rate. In order for a cycle exercise test to be efficient, the following conditions must be satisfied:

1. The rest period must be 3 minutes.
2. The rest period must be followed by unloaded pedaling for 3 minutes.
3. The unloaded pedaling phase must be followed by the incremental phase until the subject gets exhausted or the supervisor stops the test.

Computer-based cycle ergometers use the ramp protocol, in which the work rate increases continuously. In general, there is a limit for the amount of total increment per minute, which is 5 to 25 W/minute. It has been reported that the results of 1 minute test and the ramp protocol give comparable values for metabolic and cardiopulmonary (ATS and ACCP, 2003).

1.3.2. Maximal Incremental Treadmill Protocols.

As in the case of cycle ergometer test, an incremental protocol is also used on a treadmill. The exercise can start with a speed of 0.6–1.0 mph. Speed and/or grade can then be increased at regular intervals in order to increase the work rate.

For more functional subjects, the Bruce protocol may be preferred. Bruce protocol is not convenient for the patients who have severe cardiac disease as these patients cannot handle the work rate of the first stage as well as the increments in the protocol. Alternatively, a modified version of the Naughton protocol, which is less demanding in terms of the work rate in the first stage and increments as compared to Bruce protocol, can used for these patients. However, both protocols have the same disadvantage, which is the length of the increment (3 minutes). Balke protocol is ideal for cardiopulmonary measurements. In Balke protocol, the speed is held constant (3.3 mph) and the grade of the treadmill increases by 1% every minute. The goal of all these protocols is to increase the applied work rate at a constant pace.

Other incremental treadmill protocols that combine speed and grade such as the standardized exponential exercise protocol has been used in patients having

pulmonary disease. For the standardized exponential exercise protocol, in order to reach a 15% increase in work rate, either the treadmill speed or the elevation is increased at each stage. People having different body masses can be evaluated with the same protocol. It has been reported that the use of the standardized exponential exercise protocol over the other well-known protocols does not show any clear advantage for cardiopulmonary exercise testing (CPET) (ATS and ACCP, 2003).

There exist several disadvantages of maximal exercise tests. First of all, expensive laboratory equipment and trained staff are required to perform a maximal exercise test. Secondly, some subjects including older and higher risk people may not be able to complete maximal exercise tests since these tests require doing exercise until the subject gets exhausted. Thirdly, it is not feasible to apply maximal exercise tests for all subjects when the number of subjects is large. (Hunn et al. 2002; Leibetseder et al., 2002). The limitations of direct measurement have led to the development of various regression models based on non-exercise or submaximal exercise tests for predicting VO_2max. VO_2max prediction equations provide a simple way of assessing a sophisticated measurement by using variables that can be measured easily.

Submaximal tests indirectly predict VO_2max using submaximal exercise variables (grade, heart rate (HR), speed and exercise time) along with physiological variables (age, gender, body mass index (BMI), weight, height and percentage of body fat). Submaximal tests are usually performed on a treadmill, an ergometer or a track. Common submaximal test protocols involve walking, jogging, and running on indoor/outdoor tracks or treadmills, cycling on ergometers, bench stepping, or performing the 20m shuttle run (George et al., 2009). Submaximal tests are faster, safer, and cheaper to administer than maximal tests and also provide the administrator with an opportunity to observe responses to exercise and to teach participants about selection of an appropriate intensity of exercise.

Non-exercise prediction equations employ questionnaire data (perceived functional ability (PFA) and physical ability rating (PAR)) in conjunction with other variables such as gender, age, height, weight and BMI to predict VO_2max. Non-exercise prediction models are easy to administer for large populations and do not

require expensive equipment and exercise testing. On the other hand, the dependence of the subject's own answers to questionnaires can affect the validity of the scores given by the subjects, which in turn suggests that non-exercise models should be used with caution when the subject has an interest in the results. (Chatterjee et al., 2006; Hunn et al., 2002; McComb et al., 2006).

The questionnaire data includes a subject's responses to PFA and PAR questions. The PFA questionnaire include questions about the coverage of one and a three mile distance by walking, jogging or running without becoming overly exhausted. There are two sections in the PFA questionnaire and the responses to each section are summed up to find the final PFA score, which is in the range of 2 – 26. The level of physical activity during the previous six months is the focus of the PAR questionnaire. PAR score is defined as the response to the PAR question (range = 0 – 10).

Figure 1.1 and Figure 1.2 show a sample modified PAR and PFA questionnaire, respectively (Akay et. al., 2009).

Select the number that best describes your overall level of physical activity for the previous 6 months:

0 = avoid walking or exertion; e.g., always use elevator, drive when possible instead of walking

1 = **light activity:** walk for pleasure, routinely use stairs, occasionally exercise sufficiently to cause heavy breathing or perspiration

2 = **moderate activity:** 10 to 60 minutes per week of moderate activity; such as golf, horseback riding, calisthenics, table tennis, bowling, weight lifting, yard work, cleaning house, walking for exercise

3 = **moderate activity:** over 1 hour per week of moderate activity as described above

4 = **vigorous activity:** run less than 1 mile per week or spend less than 30 minutes per week in comparable activity such as running or jogging, lap swimming, cycling, rowing, aerobics, skipping rope, running in place, or engaging in vigorous aerobic-type activity such as soccer, basketball, tennis, racquetball, or handball

5 = **vigorous activity:** run 1 mile to less than 5 miles per week or spend 30 minutes to less than 60 minutes per week in comparable physical activity as described above

6 = **vigorous activity:** run 5 miles to less than 10 miles per week or spend 1 hour to less than 3 hours per week in comparable physical activity as described above

7 = **vigorous activity:** run 10 miles to less than 15 miles per week or spend 3 hours to less than 6 hours per week in comparable physical activity as described above

8 = **vigorous activity:** run 15 miles to less than 20 miles per week or spend 6 hours to less than 7 hours per week in comparable physical activity as described above

9 = **vigorous activity:** run 20 to 25 miles per week or spend 7 to 8 hours per week in comparable physical activity as described above

10 = **vigorous activity:** run over 25 miles per week or spend over 8 hours per week in comparable physical activity as described above

Figure 1.1. Modified PAR questionnaire

Suppose you were going to exercise continuously on an indoor track for **1 mile**. Which exercise pace is just right for you — not too easy and not too hard?

Circle the appropriate number (any number, 1 to 7).

1. Walking at a *slow* place (18 minutes per mile or more)
2. Walking at a *medium* pace (16 minutes per mile)
3. Walking at a *fast* pace (14 minutes per mile)
4. Jogging at a *slow* pace (12 minutes per mile)
5. Jogging at a *medium* pace (10 minutes per mile)
6. Jogging at a *fast* pace (8 minutes per mile)
7. Running at a *fast* pace (7 minutes per mile)

How fast could you cover a distance of **3-miles** and NOT become breathless or overly fatigued? Be realistic.

Circle the appropriate number (any number, 1 to 7).

1.I could walk the entire distance at a *slow* pace (18 minutes per mile or more)
2. I could walk the entire distance at a *medium* pace (16 minutes per mile)
3. I could walk the entire distance at a *fast* pace (14 minutes per mile)
4. I could jog the entire distance at a *slow* pace (12 minutes per mile)
5. I could jog the entire distance at a *medium* pace (10 minutes per mile)
6. I could jog the entire distance at a *fast* pace (8 minutes per mile)
7. I could run the entire distance at a *fast* pace (7 minutes per mile or less)

Figure 1.2. PFA questionnaire

1.4. Overview of Data sets

In this thesis four different data sets (VO_2max-set-1, VO_2max-set-2, VO_2max-set-3 and VO_2max-set-4) have been used to develop VO_2max prediction models. VO_2max-set-1, VO_2max-set-2 and VO_2max-set-4 were obtained from James D. George, Department of Exercise Sciences Brigham, Young University, Provo,

UT. VO_2max-set-3 was obtained from Daniel P. Heil, Department of Exercise Sciences, University of Massachusetts, Amherst, MA.

VO_2max-set-1: The data set includes data of 185 college students (115 males and 70 females), aged from 18 to 26 years. The data set contains 10 predictor variables which are gender, age, weight, height, submaximal times (MIN1, MIN2 and MIN3) and heart rates (HR1, HR2 and HR3).

VO_2max-set-2: The data set includes data of 410 participants (255 males and 155 females), aged from 18 to 40 years. Subjects were selected from three different states (Utah, Illinois and Texas) of USA. The data set contains 6 predictor variables which are gender, age, weight, height, submaximal speed (SM-Speed) and heart rate (SM-HR).

VO_2max-set-3: The data set includes data of 440 subjects (210 males and 230 females), aged from 20 to 79 years. All subjects were recruited from the Massachusetts, USA. The data set contains 7 predictor variables which are gender, age, weight, height, body fat percent (BF%), lean body mass (LBM) and level of physical activity (AC).

VO_2max-set-4: The data set includes data of 100 healthy subjects (50 males and 50 females), aged from 18 to 65 years. Employees of the LDS Hospital in Salt Lake City and people from the Y-Be-Fit Wellness Program at Brigham Young University were selected for this data set. The data set contains 9 predictor variables which are gender, age, weight, height, PFA score, PAR score, submaximal speed, heart rate and stage (SM-Speed, SM-HR, SM-Stage).

The VO_2max measurement process for all the data sets was follows: A computer-based system was used for computing, averaging and printing the VO_2 and respiratory exchange ratio (RER) every 15 seconds. At the end of each stage of the maximal test, HR and RPE score of each subject were recorded. Also, TrueMax 2400 measurement system was used to collect the gases. As the end of the maximal test approached, the arithmetic average of the highest four consecutive 15-second scores was used to calculate VO_2max.

VO_2max was considered valid if at least two of the criteria given below have been satisfied (ACSM, 2012; Howley et al., 1995):

1. HR_{max} within 15 beats of age predicted HR_{max} (220 – age)
2. Maximal RER ≥ 1.10
3. No increase in VO_2 although work load increases

Descriptive statistics of the data sets is given in Table 1.2. through Table 1.5.

Table 1.2. Descriptive statistics of VO_2max-set-1

Variables	**Mean ± Standard Deviation**
Age (year)	22.422 ± 3.398
Weight (kg)	74.03 ± 15.427
Height (m)	1.756 ± 0.101
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_2max ($ml \bullet kg^{-1} \bullet min^{-1}$)	46.607 ± 5.923

Table 1.3. Descriptive statistics of VO_2max-set-2

Variables	**Mean ± Standard Deviation**
Age (year)	25.529 ± 5.835
Weight (kg)	71.76 ± 13.388
Height (m)	1.743 ± 0.087
SM-HR (bpm)	157.044 ± 13.982
SM-Speed (mph)	5.706 ± 0.674
VO_2max ($ml \bullet kg^{-1} \bullet min^{-1}$)	46.974 ± 6.169

Table 1.4. Descriptive statistics of VO_2max-set-3

Variables	**Mean ± Standard Deviation**
Age (year)	46.602 ± 16.661
Weight (kg)	72.851 ± 14.808
Height (m)	1.688 ± 0.011
BF%	23.397 ± 8.442
LBM	55.684 ± 12.308
AC	4.466 ± 2.044
VO_2max ($ml \bullet kg^{-1} \bullet min^{-1}$)	38.617 ± 10.375

Table 1.5. Descriptive statistics of VO_2max-set-4

Variables	**Mean ± Standard Deviation**
Age (year)	36.23 ± 13.223
Weight (kg)	74.86 ± 15.291
Height (m)	1.717 ± 0.089
SM-Speed(mph)	5.248 ± 1.013
SM-HR (bpm)	147.73 ± 12.357
SM-Stage	2.11 ± 0.49
PFA	14.75 ± 4.831
PAR	4.83 ± 2.252
VO_2max ($ml \bullet kg^{-1} \bullet min^{-1}$)	41.387 ± 9.145

1.5. Motivation and Purpose of This Thesis

The drawbacks of the past VO_2max prediction studies, which are summarized in Section 2, are summarized below:

1. All studies applied regression methods directly without trying to improve the performance of the methods.
2. Most of the VO_2max prediction models based on MLR did not present cross-validation results, which raises a question about the generalizability of the prediction models.
3. All studies used a single data set, the drawback of which is the generalizability of the presented results.

4. Only a few studies attempted to compare the performance of different regression methods for prediction of VO_2max using different data sets.
5. Although the number of subjects used in most of the studies is relevant, the variety of the subjects is limited in the sense that all the subjects are selected from the same region.
6. The scope of VO_2max prediction models is limited in most of the studies. Most of the studies concentrated on either submaximal or non-exercise models only. Hybrid models were developed in a few studies only.

The purpose of this thesis is to develop VO_2max prediction models by using non-exercise, submaximal and hybrid variables, and employing machine learning methods. Namely, we have used non-linear SVM and MFANN to build VO_2max prediction models. Several submaximal, non-exercise and hybrid VO_2max prediction models have been developed using four different data sets. The performance of the models has been evaluated by calculating the *SEE*'s and *R*'s of the test data. The results of all developed models have been compared with each other and with the ones that have been obtained from MLR. The results show that SVM-based VO_2max prediction models are more accurate (i.e. yield higher *R*'s and lower *SEE*'s) than the prediction models developed by MFANN and MLR.

We also propose a new approach for improving the performance of SVM and MFANN for prediction of VO_2max. Our approach is based on the elimination of irrelevant samples from the training data during the training phase by taking into account the absolute prediction errors of each sample. The samples that have prediction error values higher than a specified threshold have been removed to form a new training data. The performance of the proposed approach has been compared with the two widely used outlier detection algorithms including Z-score and Grubbs' test. It is shown that the improved SVM-based and MFANN-based VO_2max prediction models yield noticeable decrements in error rates compared to that of regular and outlier-based SVM and MFANN VO_2max prediction models.

2. PREVIOUS WORKS

In literature, a lot of VO_2max estimation models have been developed by using maximal, submaximal, non-exercise and hybrid variables that will be described in this section.

2.1. Studies on Submaximal Regression Models to Estimate VO_2max

For college students, Larsen et al. (2002) developed a VO_2max equation from a 1.5 mile submaximal test involving walking, jogging, or running. The data set included data of 101 subjects with 52 men and 47 women. Each subject completed two 1.5-mile submaximal tests and a maximal graded exercise test. Subjects were asked to reach an RPE of 13 and maintain a steady speed throughout each 1.5-mile test. MLR was used to develop the VO_2max prediction, which resulted in R = 0.86 and SEE = 3.37 ml•kg^{-1}•min^{-1}. Another regression equation using the HR predictor variable has also been developed. The reported values of R and SEE for the second equation was 0.90 and 2.87 ml•kg^{-1}•min^{-1}, respectively. The reported results suggested that VO_2max could be predicted with an easy-to-administer submaximal test and without using HR_{max}. Therefore, the developed equations can satisfy the needs of people with different fitness levels.

Dalleck et al. (2006) used an elliptical cross-trainer test for developing a VO_2max prediction equation. The data set included data of 54 healthy subjects with 25 men and 29 women. The data set was randomly split into two groups, namely a sample group with 40 subjects and a cross-validation group including 14 subjects. The elliptical cross-trainer submaximal and maximal VO_2max test were completed by the participants on the same day. A 15-minute rest period separated the two tests. In the original sample group, stepwise MLR was used for developing a VO_2max prediction formula. The cross-validation group was used in order to test the accuracy of the developed VO_2max equation. After observing similar values of R^2 for both groups, the data in both groups were combined to form a final prediction equation. The reported values of r, R^2 and SEE were 0.86, 0.732 and 3.91, respectively. T-tests

were applied to show insignificant differences between actual and predicted VO_2max. The authors concluded that the developed VO_2max equation along with the protocol explained in the paper can be safely used for accurate predictions of VO_2max.

McComb et al. (2006) used a water running protocol for developing a VO_2max prediction equation. The data set included 32 subjects (aged between 18 and 24 years). Each subject performed skin fold assessment, a maximal VO_2max treadmill test (Bruce protocol) and a 6 min submaximal water running test. MLR based VO_2max prediction equation has been developed, which includes the predictor variables BF%, height, weight, gender, and HR. The authors concluded that the variance in VO_2max has been considerably explained by the predictor variable BF%. The reported values of *r* and *SEE* were -0.87 and, 3.27 respectively. The explained variance in VO_2max was not affected by the other predictor variables.

In Faulkneret al. (2007), the authors tried to determine whether or not gender and daily activity effected the validity of VO_2max prediction obtained from the values of submaximal HR and RPE. The data set included 27 men and 18 women, who completed two GXTs to determine VO_2max. Hierarchical MLR analysis showed that inclusion of HR together with RPE score explained additional variance in VO_2max (2%). The results also revealed that for RPE values of 13 and 15, VO_2max was significantly correlated with power output for both men and women. For men, the inclusion of age predicted HRmax improved the accuracy of VO_2max prediction. The same was not observed for women. According to the results given by the study, the submaximal GXT is an efficient protocol for determining VO_2max of both men and women.

Liu and Lin (2007) analyzed the validity of HR parameters related with the 3-minute step test used for predicting VO_2max. The data set included 31 college students, whose VO_2max was determined by the Bruce protocol. Participants performed three step tests, the step heights of which are 30, 35 and 40 cm, respectively, were applied on the subjects. After conducting the step test, 15-second post-exercise heart rate (PHR15), 60-second post-exercise heart rate (PHR60) and physical fitness index (PFI) of the participants have been determined and these have

been shown to be correlated with measured VO_2max obtained. The difference between predicted and measured VO_2max was evaluated using linear regression with an alpha level of 0.05. Among all the developed prediction models, the best reported values of *r* and *SEE* were 0.50 and 2.94, respectively.

In order to estimate VO_2max in fit adults, (Vehrs et al., 2007) developed a single-stage submaximal treadmill jogging (TMJ) protocol. The data set included data of 400 subjects (250 men and 150 women), aged between 18 and 40 years. VO_2max values of the participants were measured using a maximal GXT. MLR based VO_2max prediction equation including the predictor variables gender, age, body mass, HR, and speed has been developed. The reported values of *R* and *SEE* were 0.91 and 2.52, respectively. It was concluded that MLR based VO_2max prediction model depending on the TMJ protocol is an effective approach to predict VO_2max of healthy adults.

Waddoups et al. (2008) conducted a submaximal test on 34 participants (aged from 18 to 55 years) to analyze if VO_2max can be predicted using low and high ends of the specified HR range. Low-intensity as well as high-intensity exercises were completed by each participant, which has shown significant difference between predictions of VO_2max. The low-intensity exercise generated lower VO_2max values than the actual ones while high-intensity exercise yielded higher VO_2max values than the actual ones.

Akalan et al. (2008) investigated the effect of HR responses to submaximal exercise. It was claimed that the errors in prediction of VO_2max were highly correlated with the individual differences in HR responses. Therefore, these differences had to be decremented in order to obtain more precise VO_2max predictions. In the study, a data set of 8 trained healthy subjects were used. The subjects first completed a self-report physical activity assessment (Lo-PAR). A modified YMCA protocol, which includes with 4-minute stages, and a ramp submaximal protocol were then applied on the subjects. The test was terminated when the subjects reach 80% of the age-predicted HR_{max}. Exercise and five-minute recovery HR data were collected. MLR based prediction models have been developed with an $R = 0.867$ and $SEE = 4.23$ ml•kg^{-1}•min^{-1}.

Castro- Piñero et al. (2009) tried to assess the validity of Cureton's equation for predicting VO_2max by using one-mile run/walk test. The data set included data of 66 trained children aging from 8 to17 years. The participants performed both a maximal exercise test until exhaustion and a one-mile run/walk test. VO_2max was estimated using Cureton's formula. Bland and Altman method was used to show the agreement between measured and predicted VO_2max. The reported values of *R* and *SEE* were 0.70 and 3 $ml \bullet kg^{-1} \bullet min^{-1}$, respectively. A positive relationship between the measured and predicted VO_2max difference has been reported. The authors concluded that VO_2max is underestimated by Cureton's formula for trained children having high VO_2max.

A submaximal test using a cycle ergometer and a continuous exercise protocol was applied in (Lambrick et al., 2009) for low-fit women to assess their VO_2max using HR and RPE. The data set had 11 women and their RPE was determined with a continuous test to volitional exhaustion. Strong correlation has been reported between measured and predicted VO_2max. It was concluded that VO_2max of healthy low-fit women can be accurately predicted using HR and RPE values gathered from the submaximal exercise test.

In Vema et al. (2009), the authors showed that a submaximal step-up test using the HR variable can be an alternative method for direct measurement of VO_2max. The data set included data of 60 university sportsmen from India. One mile run walk test, 3 Minute step up-test and Peak flow meter were applied on the subjects. Brat's formula was used to calculate VO_2max. A strong correlation has been shown between the HR value after the step up test and VO_2max. However, the correlation between peak flow performance and VO_2max was insignificant. Multi linear regression method was used to build a VO_2max prediction model from the pulse rate obtained after the step up test. The *SEE* of the prediction model was 1.81, which proved that step up test is an efficient was to estimate VO_2max.

Multiple linear regression VO_2max prediction model using both exercise and non-exercise data has been developed in Nielson et al. (2010). The data set included 105 college students, who completed both a maximal GXT and a submaximal cycle ergometer test. For the submaximal test, subjects were required to achieve a steady-

state HR equal to at least 70% of age-predicted HR_{max} (220-age). As for the maximal test, subjects exercised until volitional fatigue. Steady-state HR and ending work rate has been measured as part of the submaximal exercise protocol whereas body mass (BM), PFA and PAR scores were used as non-exercise data. The developed multiple linear regression based prediction equation showed that VO_2max can be safely predicted for college students using both exercise and non-exercise data.

Billinger et al. (2012) used a total body recumbent stepper for VO_2max estimation in order to analyze the performance of the YMCA submaximal exercise test protocol. The data set included 110 subjects who satisfied the criteria for participation and had minimal cardiovascular disease risk. Bruce protocol utilizing a motorized treadmill has been used in the maximal exercise test. A metabolic measurement system has been adopted for measuring oxygen uptake and analyzing expired gases. Subjects performed a submaximal exercise test after 1-5 days of maximal exercise testing. The protocol required to maintain a pace of 100 steps per minute. Also, the grade of the treadmill increased every 3 min. The maximal test continued until fatigue, or 85% of maximal heart rate (HR_{max}) was achieved. The performance and accuracy of VO_2max prediction equation, which included five variables, has been evaluated by using cross-validation. The presented *SEE* and *R* values were 4.09 and 0.92, respectively.

Açıkkar et al. (2012) tried that developing ANN based models to predict VO_2max from submaximal endurance exercise test. The exercise test is varying distances (0.5 mile, 1.0 mile, and 1.5 mile) involving walking, jogging, or running. A maximum GXT and a submaximal 1.5 mile endurance test were completed successfully by College students. 7 different ANN based VO_2max prediction models have been developed. 10-fold cross validation performed to data set. According to their study, for the best model, *SEE* and *R* values were 2.21 and 0.89, respectively.

Açıkkar and Akay (2013) proposed a new approach for improving the performance of SVM on regression. The performance of presented approach was assessed by applying it on a maximum oxygen uptake (VO_2max) data set, which has gender, age, BMI, exercise time and HR as predictor variables and VO_2max as target variable. Several models have been developed by using combination of the predictor

variables. Performance metrics *R* and *SEE* have been used to assess the performance of all prediction models. The results show that their approach is able to decrease the *SEE* of the models by 8.64% and increase the *R* of the models by 5.42% on the average. The best presented *SEE* and *R* values were 2.74 and 0.93, respectively.

Akay et al. (2014a) tried that developing SVM based models to predict VO_2max from submaximal endurance exercise test involving walking, jogging, or running. This exercise test completed at varying distances with 0.5 mile, 1.0 mile, and 1.5 mile. Participants successfully completed a submaximal endurance test and a maximum GXT. 21 different MLR based and SVM based VO_2max prediction models have been developed. The results have shown that SVM-based prediction models are more accurate than MLR-based prediction models. According to results, for the best SVM-based prediction model, *SEE* and *R* values were 2.90 and 0.87, respectively.

The purpose of study (Akay et al., 2014b) was to develop ANN-based models to predict VO_2max from a single stage submaximal exercise test involving walking, jogging or running. The data set includes data of 185 subjects and the input variables of the data set are gender, age, height, weight, exercise time (MIN1, MIN2 and MIN3) and heart rate (HR1, HR2 and HR3) at varying distances. 21 different ANN-based VO_2max prediction models have been developed by using combinations of the input variables. The results of ANN-based models are also compared with the ones obtained by MLR and it is shown that ANN-based models have better performance than MLR-based models average (6.59% on the average). The ANN model including the variables gender, age, height, weight, MIN3 and HR3 yields the lowest *SEE* (3.13 $ml \bullet kg^{-1} \bullet min^{-1}$).

The scope of Abut et al. (2015a) was to develop submaximal models for predicting the VO_2max of healthy subjects aged between 18 and 26 years. Machine learning methods used to develop the prediction models include Cascade Correlation Network (CCN), Gene Expression Programming (GEP) and Single Decision Tree (SDT). In order to form the training data set, 185 participants successfully completed a submaximal endurance exercise at varying distances involving walking, jogging or running. Using 10-fold cross validation on the data set, *SEE*'s, and *R*'s of the models

have been calculated. The results suggest that CCN-based models yield lower *SEE*'s and higher *R*'s than GEP and SDT-based models for predicting VO_2max. The CCN-based prediction model, which includes the variables gender, age, height, weight, MIN3 and HR3 gives the lowest *SEE* (2.69 ml•kg^{-1}•min^{-1}) and the highest *R* (0.89).

The purpose of study (Abut et al., 2015a) was to analyze the effects of BMI and location variables on the prediction of VO_2max using SVM. The data set includes 410 (250 men and 150 women) participants from three different locations, aged from 18 to 40 years. The performance of the models has been presented using *R* and *SEE*. The results show that, in general, inclusion of BMI in VO_2max models causes a negative effect whereas the inclusion of location variable has negligible effect on prediction accuracy. For comparison purposes, VO_2max prediction models based on TB (Tree Boost) and SDT have also been developed. The SVM based model containing the predictor variables age, gender, weight, height, HR and speed gives the highest *R* (0.77) and the lowest *SEE* (2.90 ml•kg^{-1}•min^{-1}) for prediction of VO_2max.

Yıldız and Akay (2015) developed VO_2max prediction models with four different machine learning methods. These methods were TB, DTF, GEP and SDT. The predictor variables which are gender, age, weight, height, treadmill speed, heart rate and stage used to develop prediction models. The performances of the prediction models have been conducted by calculating *SEE* and *R* and using 10-fold cross validation. The TB-based model containing the predictor variables gender, age, weight, height and treadmill speed gives the highest *R* (0.89) and the lowest *SEE* (4.16 ml•kg^{-1}•min^{-1}) for prediction of VO_2max.

Table 2.1. summarizes important studies that used submaximal variables to predict VO_2max.

Table 2.1. Overview of submaximal regression models for predicting VO_2max

Study	Predictor Variables	Method	R	SEE
Swank et al. (2001)	Age, BM, BMI, HR, RER	Stepwise MLR	0.95	4.46
Larsen et al. (2002)	G, BM, Exercise Time, HR (2 Models)	MLR	0.86-0.90	3.37-2.87
Dalleck et al. (2006)	G, Age, HR, BM	MLR	0.86	3.91
McComb et al. (2006)	G, Height, BM, BF, HR	MLR	0.89	3.31
Faulkner et al. (2007)	HR, RPE	MLR	0.69	7.75
Liu and Lin (2007)	PHR15, PHR60, PFI	LR	0.50	2.94
Vehrs et al. (2007)	G, Age, BM, MPH, HR	MLR	0.91	2.52
Waddoups et al. (2008)	G, Age, Height, BM, BMI, HR, RPE	Simple LR	0.78	5.70
Akalan et al. (2008)	G, BM, W/min, Delta Recovery HR, Recovery HR, Lo-PAR	MLR	0.94	4.23
Castro-Piñero et al. (2009)	Meter	MLR	0.68	3.00
Lambrick et al. (2009)	HR, RPE	LR	0.88	3.42
Vema et al. (2009)	HR	MLR	0.94	1.81
Akay et al. (2010)	Age, BM, MPH, HR	ANN	0.95	1.80
Nielson et al. (2010)	G, BM, HR, WR, PFA	MLR	0.91	3.36
Reis et al. (2010)	Meter	LR	0.95	4.85
Billinger et al. (2012)	G, Age, Height, Watt, HR	LR	0.92	4.09
Açıkkar et al. (2012)	G, Age, BMI, MIN1, MIN2, MIN3, HR1, HR2, HR3 (7 Models)	ANN	0.84-0.89	2.56-2.21
Açıkkar and Akay (2013)	G, Age, BMI, Time, HR (3 Models)	SVM	0.89-0.93	3.62-2.74
Akay et al. (2014a)	G, Age, H, W, MIN1, MIN2, MIN3, HR1, HR2, HR3 (21 Models)	SVM, MLR	0.60-0.87	5.09-2.90
Akay et al. (2014b)	G, Age, H, W, MIN1, MIN2, MIN3, HR1, HR2, HR3 (21 Models)	MLP	-	4.71-3.13
Abut et al. (2015)	G, Age, H, W, MIN1, MIN2, MIN3, HR1, HR2, HR3 (7 Models)	CCN, GEP, SDT	0.68-0.89	4.36-2.69
Genç et al. (2015)	G, Age, BMI, Location, HR, Speed (12 Models)	SVM, TB, SDT	0.47-0.77	4.45-2.90
Yıldız and Akay (2015)	G, Age, H, W, Stage, HR, Speed (7 Models)	TB, DTF, GEP, SDT	0.68-0.89	6.70-4.16

G, gender; **HR**, heart rate; **BM**, body mass; **H**, Height; **W**, Weight; **RER**, respiratory exchange ratio; **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; **Lo-PAR**, self-report physical activity assessment; **WR**, work rate; **PFA**, perceived functional ability.

2.2. Studies on Non-Exercise Regression Models to Estimate VO_2max

The purpose of the study in Bradshaw et al. (2005) was to develop a non-exercise VO_2max prediction equation using the predictor variables age, gender, BMI, PFA, and PAR. The data set included data of 100 subjects ranging in age 18 to 65 years. The subjects' VO_2max were measured using a maximal GXT. MLR was used to develop the prediction equation. Non-exercise prediction equation is generated by using MLR. The results revealed that PFA and PAR are effective non-exercise variables for prediction of VO_2max.

Skeletal muscle (SM) mass and stroke volume have been used in the study of Sanada et al. (2007) to develop VO_2max prediction models for Japanese young men. The data set included 60 subjects, who were randomly split into the development group and validation group. A treadmill running protocol has been used to measure VO_2max of the subjects and stepwise regression analysis was applied to get the VO_2max prediction equations in the development group. After applying the developed VO_2max prediction equations on the validation group, it turned out that the correlation between the measured and predicted VO_2max was significant. The results revealed that VO_2max prediction equations based on non-exercise variables SM mass and stroke volume can be accurate estimators of VO_2max in young Japanese adults.

Stahn et al. (2008) investigated whether or not inclusion of the bioelectrical impedance analysis (BIA), which is highly related to skeletal muscle mass and blood volume, as a predictor variable improves the performance of non-exercise VO_2max equations. VO_2max, anthropometry, self-reported PAR and BIA were collected in 115 men and women. MLR was used to develop the VO_2max prediction equations, which basically showed inclusion of BIA marginally improved the performance of VO_2max prediction models.

Cao et al. (2009a), using the PA predictor variable obtained from SC, developed a non-exercise VO_2max prediction formula for Japanese women. The data set included 189 subjects aged between 20 and 69 years. The formula included the predictor variables age, BMI, and SC. The prediction formula was developed by the

data of 87 subjects, whereas the same formula was validated using the data of 102 subjects. Subjects also completed a maximal VO_2max test on a bicycle ergometer. It was shown that VO_2max was correlated to SC after adjusting for BMI (kg/m^2) and age. The authors concluded that for Japanese women, SC is an efficient variable for prediction of VO_2max.

Cao et al. (2010) analyzed the effect of the physical activity (PA) variables for prediction of VO_2max in Japanese adult men. The data set included 129 subjects aged between 20 and 69 years. Subjects performed a maximal VO_2max exercise test using an incremental bicycle ergometer. For one week, daily step counts (SC) and the amount spent in moderate to vigorous PA (MVPA) and vigorous PA (VPA) of the subjects have been measured. Hierarchical MLR was applied to develop the VO_2max prediction models using non-exercise predictor variables including age, SC, VPA, and either BMI, or waist circumference. The performance of the prediction models has been assessed using cross-validation. After showing strong correlation between measured VO_2max and the non-exercise variables SC, MVPA, and VPA, the reported values of r were 0.58, 0.42 and 0.51, respectively. The authors concluded that the combination of SC with VPA, but not with MVPA, was efficient in estimating VO_2max variance.

Schembre and Riebe (2011) developed a VO_2max prediction equation using the results of physical activity questionnaire and sub-maximal exercise test. As a physical activity questionnaire, a well-known survey (The International Physical Activity Questionnaire) has been used. The data set included data of 80 college students, who completed both the International Physical Activity Questionnaire–Short Form and a maximal VO_2max exercise test. Multivariate regression was used in order to develop the prediction equation. The balance of gender was considered when creating the equation. The equation was developed on the data of 50 subjects and validated on the data of 30 subjects. It was shown that 43% of the variance in measured VO_2max was explained by the developed equation. The *SEE* was reported to be 5.45 $ml \bullet kg^{-1} \bullet min^{-1}$. Acceptable limits of error were observed for predicted VO_2max for 87% of the subjects.

Jang et al. (2012) developed a non-exercise VO_2max prediction formula for Korean adult employees and analyzed the effect of daily activity on VO_2max prediction. The data set included data of 217 subjects (113 men and 104 women), who were employees in small companies. Subjects showing symptoms of disease were not included in the study. Each subject completed both a maximal VO_2max exercise test and a self-report questionnaire. In order to develop the prediction equation for VO_2max, a statistical analysis has been carried out. The prediction equation includes non-exercise variables (leisure-time physical activity and work-related physical activity) and physical variables (age, gender and BMI). It was concluded that VO_2max could be predicted with reasonable rates using the work-related physical activity and the developed equation can be safely used for prediction of VO_2max of Korean employees.

Different methods for ending and starting speeds to design ramp protocols has been investigated by Silva et al (2012a). The data set that was used in the study included 117 subjects, who completed a maximal VO_2max test. The subjects also responded to different non-exercise questionnaires including Veterans Specific Activity Questionnaire (VSAQ), Rating of Perceived Capacity (RPC) and CRF Questionnaire. VO_2max estimation based on VSAQ showed significant differences (P<0.001) with measured VO_2max. Among the three non-exercise models, the CRF showed the best performance yielding the highest R and the lowest SEE. Similar results have been obtained between measured VO_2max and initial speeds from 50% – 60% VO_2max estimated by CRF. Starting at 50% VO_2max estimated by CRF, the identity line became more linear. It was concluded that CRF was an efficient was for defining the ending speed for ramp protocols.

Akay et al. (2014c) tried to develop non-exercise SVM-based VO_2max prediction models for healthy subjects aged between 18 and 65 years. In order to compare the performance of SVM-based VO_2max prediction models, MLR, and MLP prediction models have also been developed. The data set contains six predictor variables; age, gender, BMI, BF%, LBM, AC and VO_2max values of 126 subjects. 7 different VO_2max prediction models have been developed by using combinations of the input variables. 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. The results have shown that SVM models yield lower *SEE*'s than the other prediction methods. The SVM model including the variables age, gender, BMI, BF% and AC yields the lowest *SEE* (4.68 ml•kg^{-1}•min^{-1}) for prediction of VO_2max.

Akay et al. (2014d) aimed to compare the performance of different regression methods for VO_2max prediction. VO_2max prediction models based on non-exercise variables have been developed by using GMDH, GRNN and GEP methods. The data set includes measured VO_2max values of 439 individuals as well as the non-exercise test variables; age, gender, BMI, BF%, LBM and AC. 7 different VO_2max prediction models have been developed by using combinations of the input variables. 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. The results show that GRNN-based models yield the lowest *SEE*'s and GEP-based models yield the highest *SEE*'s for estimating VO_2max. Furthermore, the model including the predictor variables age, gender, BMI, BF%, and AC yields the lowest *SEE* (3.32 ml•kg-1•ml-1), whereas the model including the variables age, gender, BMI and LBM yields the highest *SEE* (7.03 ml•kg^{-1}•min^{-1}) for prediction of VO_2max. It was concluded that GRNN based non-exercise models can accurately predict VO_2max.

Genç and Akay (2015) conducted non-exercise models by using different machine learning methods for predicting the VO_2max. 100 healthy subjects aged from 18 to 65 years participated to the study. The data set contains measured VO_2max values of subjects as well as the predictor variables which are gender, age, weight height and questionnaire data. CCN, GMDH, DTF and SDT methods have been used for developing the prediction models. The performance of the prediction models has been evaluated by calculating their *R* and *SEE*. The results have shown that the CCN-based prediction model including the predictor variables age, gender, weight, height, PFA1, PFA2 and PAR yields the lowest *SEE* (3.73% ml•kg^{-1}•min^{-1}).

Table 2.2 summarizes important studies that used non-exercise variables to predict VO_2max.

Table 2.2. Overview of non-exercise regression models for predicting VO_2max

Study	Predictor Variables	Method	R	SEE
Jackson et al. (1990)	G, Age, PAR, fat	MLR	0.82	5.00
Bradshaw et al. (2005)	G, Age, BMI, PAR, PFA	MLR	0.91	3.63
Marks at al. (2007)	G, Age, BMI, PARS	Regression Analysis	0.78	5.60
Sanada et al. (2007)	BM, Stroke Volume	Stepwise MLR	0.85	0.39
Miyatani et al. (2008)	Age, BM, Height, BMI, Muscle Mass	MLR	0.75	5.70
Stahn et al. (2008)	G, Age, BM, Height, PAR, BIA	MLR	0.94	3.12
Akay et al. (2009)	G, Age, BMI, PFA, PAR	SVM, MFANN	0.91	3.23
Cao et al. (2009a)	Age, BMI, SC, MVPA, VPA (2 Models)	Hierarchical LR	0.75-0.86	4.33-2.98
Cao et al.(2009b)	Age, BC, SC, BMI, WC, MVPA, VPA (6 Models)	Hierarchical LR	0.80-0.86	3.51-2.98
Cao et al. (2010)	Age, BMI, SC, VPA	Hierarchical LR	0.86	3.90
Schembre et al. (2011)	G, Vigorous Activity	Stepwise MLR	0.65	5.45
Jang et al. (2012)	G, Age, BMI, Smoking, L-PA, W-PA	MLR	0.89	3.36
Silva et al. (2012a)	G, Age, VSAQ, RPC	LR	0.73	5.75
Açıkkar et al. (2013)	G, Age, BMI, PFA, PAR	SVM	0.93	3.23
Akay et al. (2014c)	G, Age, BMI, BF%, LBM, AC (7 Models)	MLR, SVM, MLP	-	5.75-4.68
Akay et al. (2014d)	G, Age, BMI, BF%, LBM, AC (7 Models)	GMDH, GRNN, GEP	-	7.03-3.32
Genç and Akay (2015)	G, Age, H, W, PFA1, PFA2 PAR (9 Models)	CNN, GMDH, DTF, SDT	0.70-0.91	6.45-3.73

G, gender; **BMI**, body mass index; **PAR**, physical activity rating; **PFA**, perceived functional ability; **fat**, percent body fat; **Freq**, frequency of strenuous exercise in 7-d period for a duration of 15 min or more; **PARS**, physical activity rating score; **BM**, body mass; **BIA**, bio electrical 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.

2.3. Studies on Maximal Regression Models to Estimate VO_2max

(Chatterjee et al., 2008) analyzed the applicability of the MST for Indian adult females. Cross over design was used for application of direct measurement. Repeatability was used for validation of the reported results. The data set included 32 female university students from. Subjects completed a maximal treadmill test using expired gas analysis for measurement of VO_2max. MST was used to estimate VO_2max. Statistical insignificance (p>0.10) was reported between the difference of the mean (SD) of measured VO_2max values and the predicted VO_2max values from MST.

The usage of the 20 m multistage shuttle run test (MST) for Nepalese adult females was analyzed by Chatterjee et al. (2010). The data set included 40 female college students. The subjects completed a maximal test in order to measure their VO_2max using expired gas analysis. No significance has been observed between the mean ±SD values of measured VO_2max and the predicted VO_2max from the MST (P>0.1). Maximal speed of the MST and predicted VO_2max have been shown to be highly correlated (r=0.94, P<0.01).

Bandyopadhyay (2011) analyzed whether the SRT test can be applied to Indian male college students for estimating their VO_2max. The data set included 84 college students. The data set was randomly split into two samples: study sample (54 students) and validation sample (30 students). Each subject completed a maximal test as well as an SRT, which were separated by 4 days. A significant correlation was found between the mean values of actual VO_2max and predicted VO_2max of the subjects in the study group (P<0.001). Limit of agreement analysis revealed Poor confidence level has been reported for application of SRT in this group of subjects. The predictor variables age, body mass, body height and speed have been used to predict VO_2max. Modified versions of VO_2max prediction equations based on MLR have been developed, which were shown to have small *SEE*'s, which in turn suggested that these equations can be used for the mentioned population for determining VO_2max.

In Mahar et al. (2011), Progressive Aerobic Cardiovascular Endurance Run (PACER) SRT was applied on the subjects aged between 10 and 16 years in order to develop and cross-validate maximal VO_2max prediction models. CR validation of the models has also been carried out. The data set included 244 subjects, who were randomly split into validation (n=174) and cross-validation (n=70) groups. The predictor variables PACER, BMI, gender and age have been used to develop VO_2max prediction models in the validation group. Classification of the prediction models was compared with classification by the criterion of measured VO_2max for evaluating the CR validity. The reported values of R and SEE for the Quadratic Model were 0.75 and 6.17 ml•kg^{-1}•min^{-1}. Similarly, the reported values of R and SEE for the Linear Model 2 were 0.74 and 6.29 ml•kg^{-1}•min^{-1}, respectively. It was concluded after cross-validation procedure that as compared to past PACER models, the Quadratic Model and Linear Model 2 developed in the study were slightly more accurate.

A new maximum aerobic power test for soccer players was developed by (Daros et al., 2012). The authors also developed an equation to predict VO_2max of the same subjects. The proposed test consists of applying progressive, continuous, and maximal speed running that covers 80 m, structured in a square, where the athletes performs up to exhaustion. The CD test of Yo-yo endurance type II was used to measure the speed of subjects in the field test. A maximal treadmill test was also applied on the subjects for comparison purposes. The data set included 24 soccer players. No significant difference between was observed between the treadmill test and the field test when it comes to determining VO_2max. Also, the authors showed that high correlation exists between VO_2max obtained from the field test and the distance covered (r=0.768; P<0.000). Similarly, high correlation was shown between VO_2max obtained from the field test and the maximum speed reached (r=0.737; P<0.000).

An ANN based formula was developed by Silva et al. (2012b) to predict VO_2max of young subjects from the 20 m shuttle run test (SRT). The data set included 193 subjects aged between 13 and 19 years. The VO_2max prediction equation included the predictor variables stage, gender, age, weight, and height. VO_2

and HR of the subjects were measured by using a portable gas analyzer. The authors also used cross-validation in order to show the generalizability the VO_2max prediction equation.

Machado et al. (2013) developed a VO_2max prediction formula for the boys aged between10 and 16 years old. The data set included data of 42 subjects. The subjects completed a maximal test on a treadmill, the initial speed of which was 9 km/h, until they became fatigue. MLR was used to develop the prediction equation. The reported values of *SEE* and *R* were 4.10 ml•kg^{-1}•min^{-1} 0.934, respectively. Based on the obtained results, the authors concluded that their formula is suitable for predicting VO_2max for the mentioned group of subjects.

Table 2.3 summarizes important studies that used maximal variables to predict VO_2max.

Table 2.3. Overview of maximal regression models for predicting VO_2max

Study	Predictor Variables	Method	R	SEE
Leone et al. (2007)	Velocity	MLR	0.96	3.16
Chatterjee et al. (2008)	Velocity	LR	0.93	1.09
Chatterjee et al. (2010)	Velocity	LR	0.94	0.53
Bandyopadhyay (2011)	Age, BM, Height, Velocity	MLR	0.94	1.38
Mahar et al. (2011)	G, Age, BMI, PACER	MLR	0.75	6.17
Daros et al. (2012)	Meter	Simple LR	0.76	4.29
Daros et al. (2012)	Velocity	Simple LR	0.73	4.53
Silva et al. (2012b)	G, Age, BM, Height, BMI, SR	LR	0.86	5.00
Costa et al. (2013)	NLP, BM, AHR	Simple LR	0.74-0.80	7.91-7.21
Machado et al. (2013)	BM, Velocity	MLR	0.93	4.10

BM, body mass; **G**, gender; **BMI**, body mass index; **PACER**, progressive aerobic cardiovascular endurance run; **SR**, shuttle run; **NLP**, number of laps performed; **AHR**, after heart rate.

2.4. Studies on Hybrid Regression Models to Estimate VO_2max

George et al. (2009) develop a VO_2max prediction equation using the combination of submaximal and non-exercise variables. The data set included 100 subjects aged from 18 to 65 years. The submaximal data consisted of subjects' self-selected speed when exercise HR first reached at least 70% of predicted HR_{max} by the end of any one of three 4-min consecutive stages involving walking, jogging, and running whereas the non-exercise variables consisted of age, gender, BM, PFA and PAR. VO_2max of the subjects were measured successfully during a GXT when they achieved a maximal level of exertion. They have reported *SEE* and *R* values as 3.09 and 0.94, respectively.

Akay et al. (2010) studied on an ANN model based on both submaximal and non-exercise variables is developed to predict VO_2max 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.

Exercise and non-exercise data have been used together in Nielson et al. (2010) for developing a VO_2max prediction equation using MLR. The data set

included 105 college students (53 males and 52 females), who completed a submaximal cycle ergometer test and a maximal graded exercise test. The submaximal cycle protocol required participants to achieve a steady-state HR equal to at least 70% of age-predicted HR_{max}, while the maximal treadmill graded exercise test required participants to exercise to volitional fatigue. Submaximal predictor variables included ending steady-state HR and ending work rate whereas non-exercise variables included BM, PFA and PAR. Their result showed that *SEE* and *R* values were to be 3.36 and 0.91, respectively.

Akay et al. (2012) developed MFANN-based VO_2max prediction models by using submaximal treadmill exercise and non-exercise data. Using 10-fold cross validation on the data sets, performance metrics *R* and *SEE* was used to assess the performance of all prediction models. It was shown that the models including submaximal, standard non-exercise and questionnaire variables yield higher *R* and lower *SEE* than the ones including submaximal and standard non-exercise 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_2max. *SEE* and *R* values of their best model were 1.81 and 0.96, respectively.

Akay et al. (2013) used MFANN to develop VO_2max estimation models by using submaximal and non-exercise data. They pointed that the models including submaximal, standard non-exercise 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. (2013) used ANN models based on maximal and non-exercise variables were developed to VO_2max the input variables of the data set were gender, age, BMI, grade, self-reported RPE from treadmill test, HR, PFA and PAR. Their results suggested that the performance of VO_2max prediction models based on maximal and standard non-exercise variables (i.e. gender, age, BMI etc.) could be improved by including questionnaire variables (PFA and PAR) in the models. The best model *SEE* and *R* value were 2.19 and 0.95, respectively.

In Akay et al. (2014e), authors investigated the effect of questionnaire variables on the prediction of VO_2max by using SVM and compared the results with

those obtained by MLR. Two types of questionnaire variables are considered. PFA questions are designed to determine how fast participants believe they could walk, jog, or run one mile distance (PFA1) and a three mile distance (PFA2) without becoming overly breathless or tired. The responses to the PFA1 and PFA2 questions are the PFA1 and PFA2 scores, respectively. PAR question allows participants to judge their level of physical activity during the past six months. The response to the PAR question is the PAR score. 24 different VO_2max prediction models have been developed. Predictor variables of the data sets were gender, age, weight, height, ending speed, heart rate and the three questionnaire variables PFA1, PFA2 and PAR. By using 10-fold cross-validation, the performance of the prediction models in each category has been thoroughly evaluated by calculating their *SEE*'s and *R*'s. The results have shown that the model including the predictor variables gender, age, weight, height, ending speed, PFA1 and PAR yields the lowest *SEE* (3.25 $ml \bullet kg^{-1} \bullet min^{-1}$) whereas the model including the variables gender, age, weight, height, heart rate and PFA2 yields the highest *SEE* (7.22 $ml \bullet kg^{-1} \bullet min^{-1}$) for prediction of VO_2max.

Table 2.4 summarizes important studies that used hybrid variables to predict VO_2max.

Table 2.4. Overview of hybrid regression models for predicting VO_2max

Study	**Predictor Variables**	**Method**	**R**	**SEE**
George et al. (2009)	G, Age, BM, MPH, PFA, PAR	MLR	0.94	3.09
Akay et al. (2010)	G, Age, BMI, PAR, HR, Stage	ANN	0.96	2.01
Nielson et al. (2010)	G, BM, HR, WR, PFA	MLR	0.91	3.36
Akay et al. (2012)	G, Age, BMI, MPH, HR, PAR, PFA	ANN	0.96	1.81
Akay et al. (2013)	G, Age, BMI, Stage, PAR, PFA	ANN	0.94	2.27
Aktarla et al. (2013)	G, Age, BMI, RPE, GRD, PFA, PAR	ANN	0.95	2.19
Akay et al. (2014e)	G, Age, W, H, HR, PAR, PFA1, PFA2 (24 Models)	SVM, MLR	-	7.22-3.25

G, gender; **BM**, body mass; **MPH**, speed; **PFA**, perceived functional ability; **PAR**, 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.

3. OVERVIEW OF METHODS

3.1. Support Vector Machines

SVM are one of the most promising statistical learning methods for classification and regression. (Vapnik, 1995) developed the principles of SVM. Since then, SVM have gained enormous popularity owing to the fact that SVM have due to many effective features, and providing good performance. Instead of the empirical risk minimization (ERM) principle, which is used by artificial neural networks, structural risk minimization (SRM) has been adopted in SVM (Gunn et al., 1997). The error in the training set is minimized in the ERM, whereas the expected risk is minimized in SRM. The generalization ability, which is one of the main aims of statistical learning, of SVM comes from this difference. Although SVM were originally designed to solve classification problems, they have been lately restructured to solve regression problems (Vapnik et al., 1997).

3.1.1. Linear SVM

We are given the training data $(x_i, y_i), (i = 1, ..., \ell)$, where x is a d-dimensional input vector with $x \in \Re^d$ and the output vector is $y \in \Re$. (3.1.) shows the linear regression model (Vapnik, 2000):

$$f(x) = \langle \omega, x \rangle + b, \qquad \omega, x \in \Re^d, \; b \in \Re, \tag{3.1.}$$

In (3.1.), the target function is denoted by $f(x)$ and $\langle .,. \rangle$ represents the dot product in $\Re^d$.

A loss function should be defined for measuring the empirical risk. The ε-insensitive loss function, which is proposed by Vapnik (Vapnik, 2000), is the most frequently used function. (3.2.) defines the ε-insensitive loss function:

$$L_\varepsilon(y)=\begin{cases}0 & \text{for } |f\ (x)\ -\ y| \le \varepsilon \\ |f(x)-y|-\varepsilon & \text{otherwise}\end{cases} \tag{3.2.}$$

The optimization problem given in (3.3.) (Gunn, 1998) should be solved to find out the optimum values of $\bar{\omega}$ and $\bar{b}$

$$\min\ \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{\ell}(\xi_i^- + \xi_i^+) \tag{3.3.}$$

with constraints:

$$\begin{aligned} &y_i - \langle \omega, x_i \rangle - b \le \varepsilon + \xi_i^+, \\ &\langle \omega, x_i \rangle + b - y_i \le \varepsilon + \xi_i^+, \\ &\xi_i^+, \xi_i^- \ge 0, \quad i=1,.....,\ell \end{aligned} \tag{3.4.}$$

In (3.4.), there exists toleration for the deviations larger than ε and the tradeoff between the flatness of $f(x)$ is determined by *C*. The deviations from the ε-tube are represented by the slack variables ξ^- and ξ^+.

The dual optimization problem given in (3.5.)

$$\max_{\alpha,\alpha^*} -\frac{1}{2}\sum_{i=1}^{\ell}\sum_{j=1}^{\ell}(\alpha_i^*-\alpha_i)(\alpha_j^*-\alpha_j)\langle x_i, x_j\rangle - \sum_{i=1}^{\ell} y_i(\alpha_i^*-\alpha_i) - \varepsilon\sum_{i=1}^{\ell}(\alpha_i^*+\alpha_i) \tag{3.5.}$$

with constraints:

$$\begin{aligned} &0 \le \alpha_i, \alpha_i^* \le C, \quad i=1,...,\ell\ , \\ &\sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*) = 0 \end{aligned} \tag{3.6.}$$

has to be solved, which in turn gives the optimum values of the Lagrange multipliers α and α^*, while $\bar{\omega}$ and $\bar{b}$ are given by

$$\bar{\omega} = \sum_{i=1}^{\ell} (\alpha_i^* - \alpha_i) x_i \quad ,$$
$$\bar{b} = -\frac{1}{2} \left\langle \bar{\omega}, (x_r + x_s) \right\rangle \ , \tag{3.7.}$$

where x_r and x_s are support vectors (Gunn, 1998).

3.1.2. Nonlinear SVM

Nonlinear SVM can be constructed using a nonlinear mapping ϕ of the input space onto a higher dimension feature space. (3.8.) shows the nonlinear regression model

$$f(x) = \langle \omega, \phi(x) \rangle + b, \quad \omega, x \in \Re^{\mathrm{d}} \ , \ b \in \Re \ , \tag{3.8.}$$

where

$$\bar{\omega} = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) \phi(x_i),$$
$$\left\langle \omega, \bar{\phi}(x) \right\rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) \langle \phi(x_i), \phi(x) \rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(x_i, x),$$
$$\bar{b} = -\frac{1}{2} \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) (K(x_i, x_r) + K(x_i, x_s)) \tag{3.9.}$$

the support vectors are represented by x_r and x_s . A Kernel function *K* satisfying Mercer's conditions has been used to explain dot products (Vapnik, 2000).

After $\bar{b}$ is integrated into the kernel function, (3.8.) becomes:

$$\sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*)K(x_i, x) \tag{3.10.}$$

Many different kernel functions including the radial basis function (RBF), the polynomial function and the sigmoid function exist. However; RBF, as defined in (3.11.) is the most commonly used Kernel function:

$$K(x, x') = \exp(-\frac{\|x - x'\|^2}{2\rho^2}). \tag{3.11.}$$

In (3.11) the width of the RBF function is defined by ρ.

3.2. Multi-Layer Feed-Forward Artificial Neural Network

Several problems in different fields including control, function approximation, pattern recognition and associative memory (Rumelhart and McClelland, 1986; Kohonen, 1988; Haykin, 1994) can be solved by the biologically inspired intelligent systems called Artificial Neural Networks (ANN's). ANN's are comprised of many simple processors interconnected by many interconnection networks. The use of ANN's provides the following advantages: learning ability, generalization ability, fault tolerance, input–output mapping, low energy consumption, nonlinearity, distributed representation and computation (Haykin, 1994).

Multi-layer feed-forward ANN's including one input layer, one output layer, and some hidden layers are one of the most useful and popular structures. The back propagation algorithm that relies on minimization of a convenient cost function is used for training the MFANN (Hristev, 1998; Kröse and Smagt, 1996).

ANN's can be classified in two groups (i.e. feed-forward neural networks (FNN) and recurrent networks) based on the connection structure. (Jain et al., 1996). These networks are trained using different learning algorithms.

A typical MFANN is shown Figure 3.1. A general L-layer FNN consists of three layers, which are input layer, hidden layer and output layer, respectively. The layers are connected in a feed-forward style. There are no connections between the neurons of the same layer. Also, there is no feedback in the network structure (Jain et al., 1996). In Figure 3.1, the inputs are donated by $x_1, \dots, x_I$, the neurons of the hidden layer are donated by $y_1, \dots, y_J$, and the outputs are denoted by $o_1, \dots, o_K$. The weights in the input layer are shown by *V* whereas the weights in the hidden layer are shown by *W*.

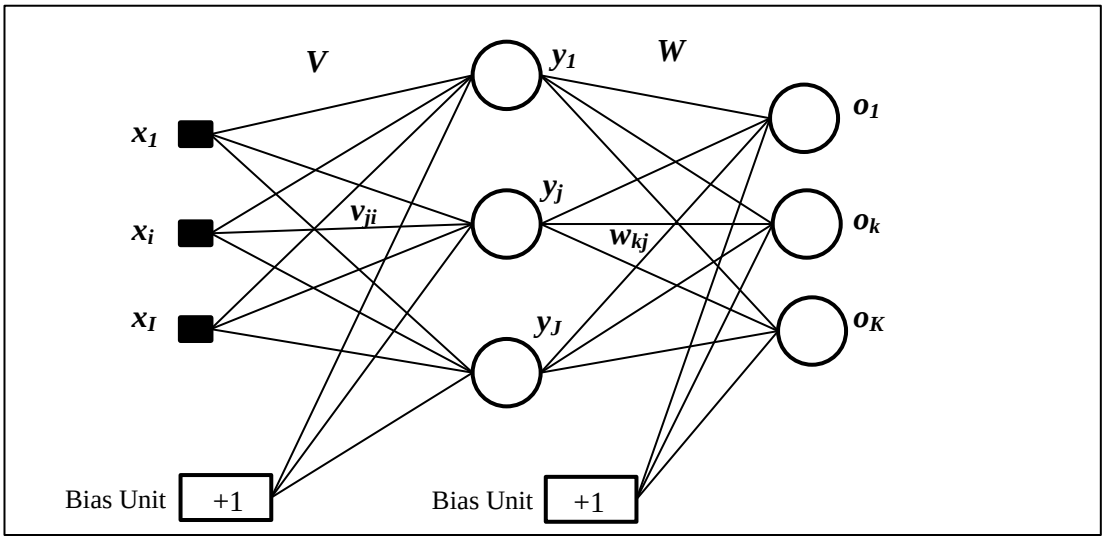

Figure 3.1. A typical MFANN structure.

The most commonly used training method for the MFANN is the back-propagation, which is basically used to determine the final weights of network. (Jain et al., 1996). In the back-propagation algorithm, the error calculated in the output layer neurons is back-propagated to the hidden layer using the gradient-descent method for minimizing the squared-error cost function in neurons according to the formula given in (3.12.)

$$E_p = \frac{1}{2}\sum_{k=1}^{K}\left(d_{kp} - o_{kp}\right)^2 + E_p. \quad (3.12.)$$

In (3.12.), the count of training patterns is given by *p*, *o* is the real output, the term E_p corresponds to the sum of the squared errors of the cost function and *d* represents the desired output matrix with size of *K*, o is actual output and. Different training functions including Quasi-Newton, Fletcher–Reeves and Levenberg–Marquardt can be used for back propagation.

3.3. Multiple Linear Regression

Multiple Linear Regression (MLR), due to its flexibility and power, is frequently used in statistical analysis. MLR is an extension of simple linear regression model in such a way that MLR uses two or more dependent variables in a prediction formula to estimate a desired variable. Even with complicated regression models including a large number of variables, MLR requires little effort to generate predictions.

MLR is appropriate when the target variable is continuous. Simple linear regression has a single continuous input variable, whereas MLR has more than one input variable, which can be either continuous or categorical.

(3.13.) shows the basic equation used in MLR:

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip} + \varepsilon_i \quad (3.13.)$$

The main assumption in (3.13) is that ε_i has a Gaussian distribution, which has a mean of 0 and a standard deviation of σ. In (3.13.), y_i shows the output of unit *i* and $X_{i1}, X_{i2}, \ldots, X_{ip}$ denote the *k* input variables. The output variable, which can be continuous or nominal, is known as dependent variable whereas the input variables are known as independent variables. For the input variables, the term "independent" can be misleading since the *X*'s can depend on each other. The input variables are

sometimes called predictor variables. Regression coefficients $\beta_1, \beta_2, \dots, \beta_k$ are used along with each input variable. β_0 is an additive constant.

The right-hand side of (3.13.) can be written as

$$LP_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip}. \quad (3.14.)$$

In (3.14.), LP_i is defined as the *linear predictor*, which represents the value of y_i estimated by the input variables. The error term is given by $y_i - LP_i = \varepsilon_i$.

The estimates, $b_0, b_1, \dots, b_p$, (known as ordinary least squares estimates) which minimize the sum of squares (SS) in the estimated error, are chosen in order to fit the models. The observed residuals $e_i = y_i - y_i^{fit}$ and fitted values y_i^{fit} can be calculated using these estimates. (Draper and Smith, 1998).

3.4. Cross Validation

The generalization of VO_2max prediction models has been satisfied using cross validation. The original data set is randomly split into *k* subsets in the case of *k*-fold cross validation. The training data is formed using *k - 1* subsets whereas the rest of the data is used as the validation data. This procedure is carried out exactly *k* times (known as the folds) so that the validation data includes every *k* subsets. The final performance measure is obtained by averaging or combining the results of each fold.

3.5. Outlier Detection Algorithms

3.5.1. Z-score

Z-score (standard score) indicates how many standard deviations an element is far from the mean (Seo, 2002). The formula for calculating the Z-score is given below:

$$Z = \frac{Y - \bar{Y}}{S} \tag{3.15.}$$

where Z is the Z-score, Y is the value of the element, $\bar{Y}$ is the mean, and S is the standard deviation.

3.5.2. Grubbs' Test

Grubbs' test (Grubbs, 1969) is used to check normally distributed data for outliers which have largest absolute deviation from the mean. Two-sided Grubbs' test statistic is defined as:

$$G = \frac{|Y - \bar{Y}|}{S} \tag{3.16.}$$

where $\bar{Y}$ and S denotes mean and standard deviation, respectively. For Grubbs' test, the critical value is calculated as

$$C = \frac{N-1}{\sqrt{N}} \sqrt{\frac{t^2_{(\alpha/2N,N-2)}}{N-2+t^2_{(\alpha/2N,N-2)}}} \tag{3.17.}$$

where N is number of elements and $t^2_{(\alpha/2N,N-2)}$ is the critical value of the *t*-distribution. In (3.17.), $\alpha/2N$ and $N-2$ show the significance level and degrees of freedom, respectively.

If the result of the test statistic G is greater than or equal to the critical value C, the corresponding value is confirmed as an outlier.

3.5.3. Box-Plot

In descriptive statistics, box-plot is a convenient way to show graphical representation of dispersion of the data through their quartiles (Seo, 2002).

The first quartile, also named as lower quartile (Q1), is equal to the 25th percentile of the data. The second quartile (Q2) or median of a data set is equal to the 50th percentile of the data. The third quartile, called upper quartile (Q3), is equal to the 75th percentile of the data. Interquartile range (IQR) is determined as Q3 – Q1. The upper and lower limits are fixed to the distance 1.5 times IQR (shown in Figure 3.2.). Any corresponding value outside these limits is accepted a potential outlier. A box-plot can be used even if data are not normally distributed because it bounds up with the median of the data and not the mean of the data.

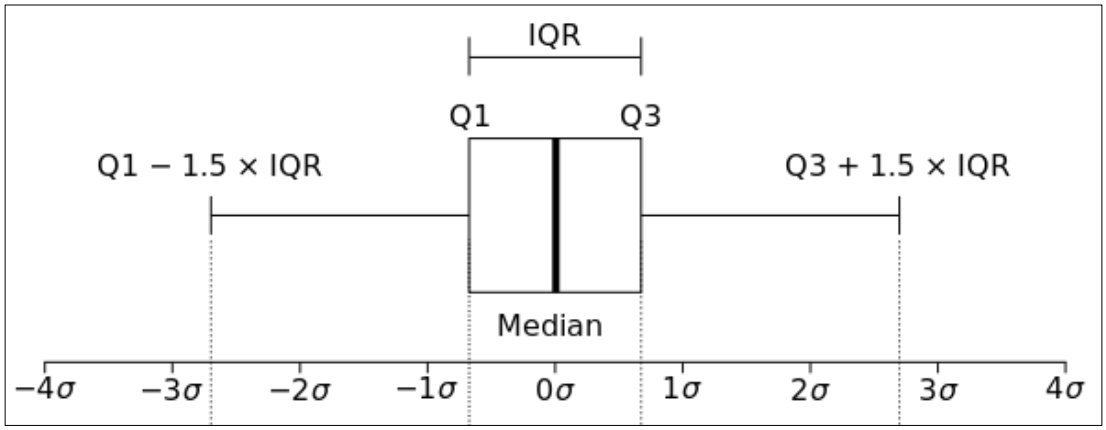

Figure 3.2. Box-plot with IQR for normally distributed data.

3.5.4. Walsh's Test

Walsh's test (EPA, 2006) is used for detecting multiple outliers in a large data set that is not required to be normally distributed. This test will detect outliers that are both much smaller and much larger than the rest of the data. It requires at least 60 samples to be performed at a significant level of 0.1 and at least 220 samples to be performed at a significant level of 0.05.

The *N* data values are ordered from smallest to largest. To detect the number of possible outliers *k*, following values must be computed:

$$c = ceil\left(\sqrt{2N}\right), \qquad r = k + c, \qquad b^2 = 1/\alpha\,, \qquad a = \frac{1 + b\sqrt{(c - b^2)/(c - 1)}}{c - b^2 - 1}$$

where *ceil* represents rounding the value to the next largest integer and α is level of significance.

The following conditions must be satisfied to detect a sample as an outlier.

$$X_k - (1 + a)X_{k+1} + aX_r < 0 \tag{3.18.}$$

$$X_{n+1-k} - (1 + a)X_{n-k} + aX_{n+1-r} > 0 \tag{3.19.}$$

In (3.18.), if the inequality is satisfied then k smallest data points are accepted as outliers with an α level of significance. Similarly, in (3.19.), if the inequality is satisfied then k largest data points are accepted as outliers with an α level of significance.

4. RESULTS AND DISCUSSION

The performance of the MLR, SVM and MFANN models have been assessed by applying 10-fold cross validation and calculating the values of the performance metrics *SEE* and *R*. S*EE* and *R* are defined in (4.1.) and (4.2.), respectively.

$$SEE = \sqrt{\frac{\sum(Y-Y')^2}{N}} \tag{4.1.}$$

$$R = \sqrt{1 - \frac{\sum(Y-Y')^2}{\sum(Y-\bar{Y})^2}} \tag{4.2.}$$

In (4.1.) and (4.2.), the target value is defined by Y, the estimated value is given by Y', the mean of the target values is represented with $\bar{Y}$ and the count of subjects in the testing set is given by N .

Table 4.1.through Table 4.4.show the prediction models for VO_2max and the predictor variables that each model contains.

Table 4.1. Overview of VO_2max prediction models along with the predictor variables for VO_2max-set-1.

Models*	**Predictor Variables**
Model 1	Gender, Age, Height, Weight, MIN1, HR1, MIN2, HR2, MIN3, HR3
Model 2	Gender, Age, Height, Weight, MIN1, HR1, MIN2, HR2
Model 3	Gender, Age, Height, Weight, MIN1, HR1, MIN3, HR3
Model 4	Gender, Age, Height, Weight, MIN2, HR2, MIN3, HR3
Model 5	Gender, Age, Height, Weight, MIN1, HR1
Model 6	Gender, Age, Height, Weight, MIN2, HR2
Model 7	Gender, Age, Height, Weight, MIN3, HR3
Model 8	Gender, Age, Height, Weight, MIN1, MIN2, MIN3
Model 9	Gender, Age, Height, Weight, MIN1, MIN2
Model 10	Gender, Age, Height, Weight, MIN1, MIN3
Model 11	Gender, Age, Height, Weight, MIN2, MIN3
Model 12	Gender, Age, Height, Weight, MIN1
Model 13	Gender, Age, Height, Weight, MIN2
Model 14	Gender, Age, Height, Weight, MIN3
Model 15	Gender, Age, Height, Weight, HR1, HR2, HR3
Model 16	Gender, Age, Height, Weight, HR1, HR2
Model 17	Gender, Age, Height, Weight, HR1, HR3
Model 18	Gender, Age, Height, Weight, HR2, HR3
Model 19	Gender, Age, Height, Weight, HR1
Model 20	Gender, Age, Height, Weight, HR2
Model 21	Gender, Age, Height, Weight, HR3

*These models also appear in Akay et.al. (2014b) and have been included for completeness and comparison purposes.

Table 4.2. Overview of VO_2max prediction models along with the predictor variables for VO_2max-set-2.

Models	**Predictor Variables**
Model 22	Gender, Age, Height, Weight, SM-Speed, SM-HR
Model 23	Gender, Age, Height, Weight, SM-Speed
Model 24	Gender, Age, Height, Weight, SM-HR

Table 4.3. Overview of VO_2max prediction models along with the predictor variables for VO_2max-set-3.

Models	**Predictor Variables**
Model 25	Gender, Age, Height, Weight, BF%, LBM, AC
Model 26	Gender, Age, Height, Weight, BF%, LBM
Model 27	Gender, Age, Height, Weight, BF%, AC
Model 28	Gender, Age, Height, Weight, LBM, AC
Model 29	Gender, Age, Height, Weight, BF%
Model 30	Gender, Age, Height, Weight, LBM
Model 31	Gender, Age, Height, Weight, AC

Table 4.4. Overview of VO_2max prediction models along with the predictor variables for VO_2max-set-4.

Models	**Predictor Variables**
Model 32	Gender, Age, Height, Weight, SM-Speed, SM-HR, SM-Stage, PFA, PAR
Model 33	Gender, Age, Height, Weight, SM-HR, SM-Stage, PFA, PAR
Model 34	Gender, Age, Height, Weight, SM-Speed, SM-Stage, PFA, PAR
Model 35	Gender, Age, Height, Weight, SM-Speed, SM-HR, PFA, PAR
Model 36	Gender, Age, Height, Weight, SM-Speed, SM-HR, SM-Stage, PAR
Model 37	Gender, Age, Height, Weight, SM-Speed, SM-HR, SM-Stage, PFA
Model 38	Gender, Age, Height, Weight, SM-Stage, PFA, PAR
Model 39	Gender, Age, Height, Weight, SM-Speed, PFA, PAR
Model 40	Gender, Age, Height, Weight, SM-Speed, SM-HR, PAR
Model 41	Gender, Age, Height, Weight, SM-Speed, SM-HR, SM-Stage
Model 42	Gender, Age, Height, Weight, SM-HR, PFA, PAR
Model 43	Gender, Age, Height, Weight, SM-HR, SM-Stage, PAR
Model 44	Gender, Age, Height, Weight, SM-HR, SM-Stage, PFA
Model 45	Gender, Age, Height, Weight, SM-Speed, SM-Stage, PAR
Model 46	Gender, Age, Height, Weight, SM-Speed, SM-Stage, PFA
Model 47	Gender, Age, Height, Weight, SM-Speed, SM-HR, PFA
Model 48	Gender, Age, Height, Weight, SM-Speed, SM-HR
Model 49	Gender, Age, Height, Weight, SM-Speed, SM-Stage
Model 50	Gender, Age, Height, Weight, SM-Speed, PFA
Model 51	Gender, Age, Height, Weight, SM-Speed, PAR
Model 52	Gender, Age, Height, Weight, SM-HR, SM-Stage
Model 53	Gender, Age, Height, Weight, SM-HR, PFA
Model 54	Gender, Age, Height, Weight, SM-HR, PAR
Model 55	Gender, Age, Height, Weight, SM-Stage, PFA
Model 56	Gender, Age, Height, Weight, SM-Stage, PAR
Model 57	Gender, Age, Height, Weight, PFA, PAR
Model 58	Gender, Age, Height, Weight, SM-Speed
Model 59	Gender, Age, Height, Weight, SM-HR
Model 60	Gender, Age, Height, Weight, SM-Stage
Model 61	Gender, Age, Height, Weight, PFA
Model 62	Gender, Age, Height, Weight, PAR

4.1 SVM Model for Predicting VO_2max

The performance of a SVM prediction model is effected by several parameters including the values of *C* and *ε*, kernel function type and the parameters selected related to the kernel. There exists tradeoff between minimizing the complexity of the prediction model and the training error. The tradeoff cost is related with the value of the *C*. It is well known that the count of errors in the training phase increments with smaller values of *C*. On the other hand, a hard-margin SVM like behavior is seen for higher values of *C*. The value of *ε* is also important in the sense that not only the width of the *ε*-insensitive zone is controlled by *ε* but also the count of support vectors is determined by *ε*. More support vectors yielding more complex prediction models appear as the value of *ε* is decreased (Ji and Wang, 2007). In this thesis, SVM based VO_2max prediction models have been developed using one of the most commonly used kernel functions names as the RBF kernel, which requires the parameter *γ* to be optimized.

Building an efficient SVM regression model requires to get the best values of the parameters *C*, *ε* and *γ*. Hence, one needs an effective search algorithm to find the best values of these parameters. This process is required in order to minimize the error in the test data. There exists many techniques, which include genetic algorithm (Friedrichs and Igel, 2005), particle swarm optimization (Guo et al., 2006), grid search (Hsu et al., 2003), grid search and cross validation, to find the best values of the mentioned parameters. Grid search is mostly used for medium-scaled regression problems. The idea behind grid search is simple and relies on a trial-and-error process. The values of the parameters are varied within a pre-defined range in grid search and the triple yielding the maximum performance is selected. The performance can be represented using several metrics including the minimization of root mean square error, the maximization of correlation coefficient or mean absolute error. The problem of generalization can be overcome using cross validation. The original data set is randomly split into k subsets in the case of *k* fold cross validation. The training data is formed using *k - 1* subsets whereas the rest of the data is used as the validation data. This procedure is carried out exactly *k* times (known as the folds)

so that the validation data includes every *k* subsets. The final performance measure is obtained by averaging or combining the results of each fold.

The flow chart of the SVM-based VO_2max prediction model is shown in Figure 4.1. Firstly, the data set is preprocessed using standardization so that the predictor variables and the target variable have zero mean and unit variance. This process created new train and test sets. The advantage of applying the standardization process is that the predictor variables with high values get scaled hence the computational power regarding creating the SVM prediction model is reduced. 10-fold cross validation has been applied on the data set to overcome the problem of generalization and improve the reliability of the presented results. The optimal values of the C, ε and γ have been found implementing grid search along with. The root mean square error is used as the performance metric for 5-fold cross validation. The triple yielding the lowest value of the root mean square error has been selected for building the prediction model, which in turn is utilized for predicting VO_2max values in the test set.

Table 4.5. shows the range of the values of the SVM model parameters.

Table 4.5. SVM Model parameters and parameter values.

Parameter	**Min Value**	**Max Value**	**Values in Between Min and Max Value**
C	2^{-6}	2^{16}	2^n, n = -6,…,16, (except n = 0)
ε	2^{-10}	2^{8}	2^n, n = -10,…,8, (except n = 0)
γ	2^{-12}	2^{6}	2^n, n = -12,…,6, (except n = 0)

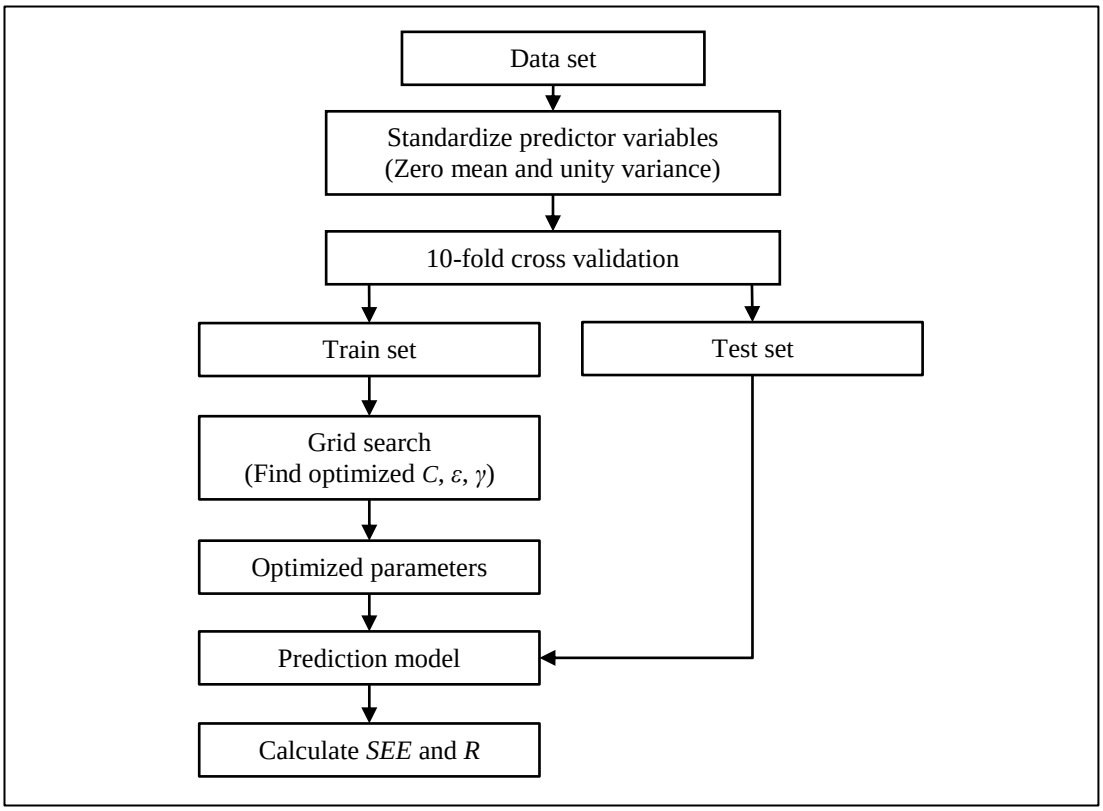

Figure 4.1. Flow chart of the SVM-based model for predicting VO_2max

4.2. MFANN Model for Predicting VO_2max

MFANN utilizing the back propagation algorithm has been implemented for developing VO_2max prediction models. Many factors including preprocessing, the number of hidden layers, the type of activation functions used in the hidden and output layers, the number of hidden layer neurons, the values of the learning rate, momentum and epoch count effect the performance of a MFANN based prediction model. There is a tradeoff between using less or more neurons in the hidden layer. Using less neuron may lead to missing information, whereas using more neurons increases the model complexity, which in turn yields a costly converge to a local minimum. (Haykin, 1994). In general, no specific principle exists to find the optimum number of neurons in the hidden layer. The optimum number of neurons in the hidden layer varies from one problem to the other at hand.

The inputs and outputs are normalized so that they have zero mean and unity variance. The tansigmoid activation function is used in the hidden layers whereas the

pure-linear activation function is used in the output layers. The Levenberg–Marquardt algorithm is utilized for training the network. In all MFANN models, number of epochs is set to 5000 by default.

Table 4.6. shows the range of the values of the MFANN model parameters.

Table 4.6. MFANN Model parameters and parameter values.

Parameter	**Min Value**	**Max Value**	**Step**
Number of neurons in the hidden layer	2	20	1
Learning rate (η)	0.05	0.5	0.05
Momentum (α)	0.1	0.5	0.1

Table 4.7. through Table 4.10. show the *R* and *SEE* values for VO_2max prediction models using MLR, SVM and MFANN regression methods on the VO_2max-set-1, VO_2max-set-2, VO_2max-set-3 and VO_2max-set-4, respectively.

Table 4.7. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2max-set-1.

Models	**MLR**		**MFANN**		**SVM**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 1	0.75	4.34	0.79	3.99	0.80	3.57
Model 2	0.86	4.12	0.79	3.85	0.81	3.49
Model 3	0.79	3.84	0.82	3.58	0.83	3.32
Model 4	0.82	3.52	0.84	3.26	0.87	2.96
Model 5	0.75	4.08	0.80	3.73	0.81	3.46
Model 6	0.80	3.62	0.80	3.40	0.83	3.29
Model 7	0.86	3.25	0.86	3.14	0.87	2.91
Model 8	0.76	4.11	0.79	3.79	0.81	3.49
Model 9	0.77	3.97	0.79	3.70	0.81	3.46
Model 10	0.78	3.83	0.81	3.56	0.83	3.32
Model 11	0.77	3.88	0.80	3.62	0.83	3.33
Model 12	0.77	3.89	0.80	3.66	0.81	3.46
Model 13	0.78	3.81	0.81	3.55	0.83	3.31
Model 14	0.80	3.62	0.83	3.39	0.83	3.28
Model 15	0.60	5.09	0.68	4.71	0.71	4.15
Model 16	0.66	4.57	0.71	4.36	0.72	4.08
Model 17	0.63	4.79	0.70	4.53	0.71	4.13
Model 18	0.64	4.78	0.70	4.38	0.72	4.13
Model 19	0.66	4.55	0.71	4.26	0.73	4.03
Model 20	0.68	4.47	0.72	4.21	0.73	4.03
Model 21	0.66	4.55	0.71	4.27	0.73	4.07

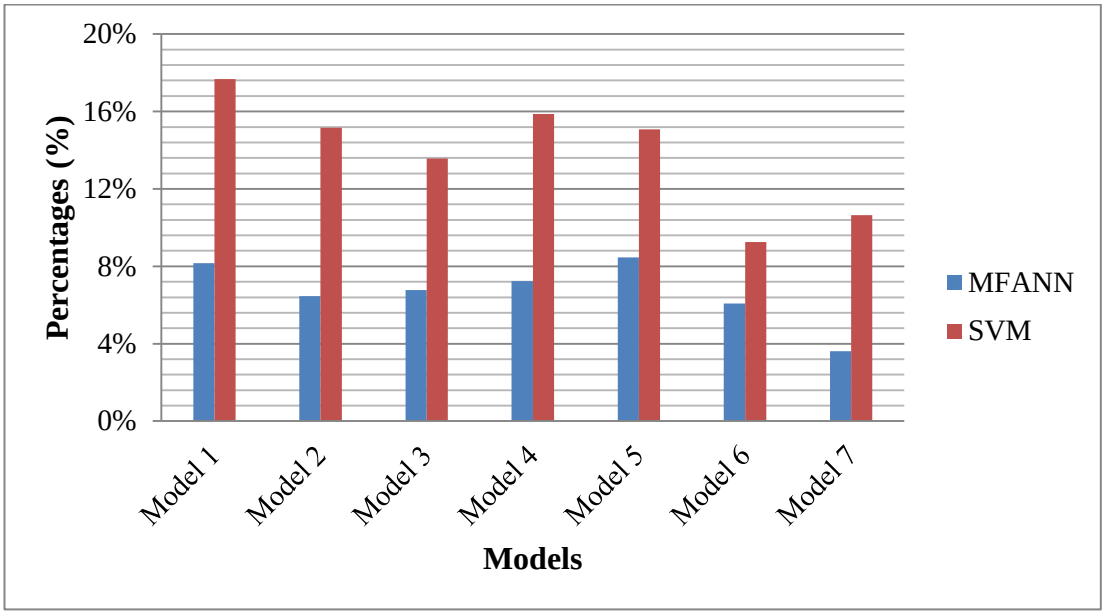

Figure 4.2. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-1 (Models 1-7)

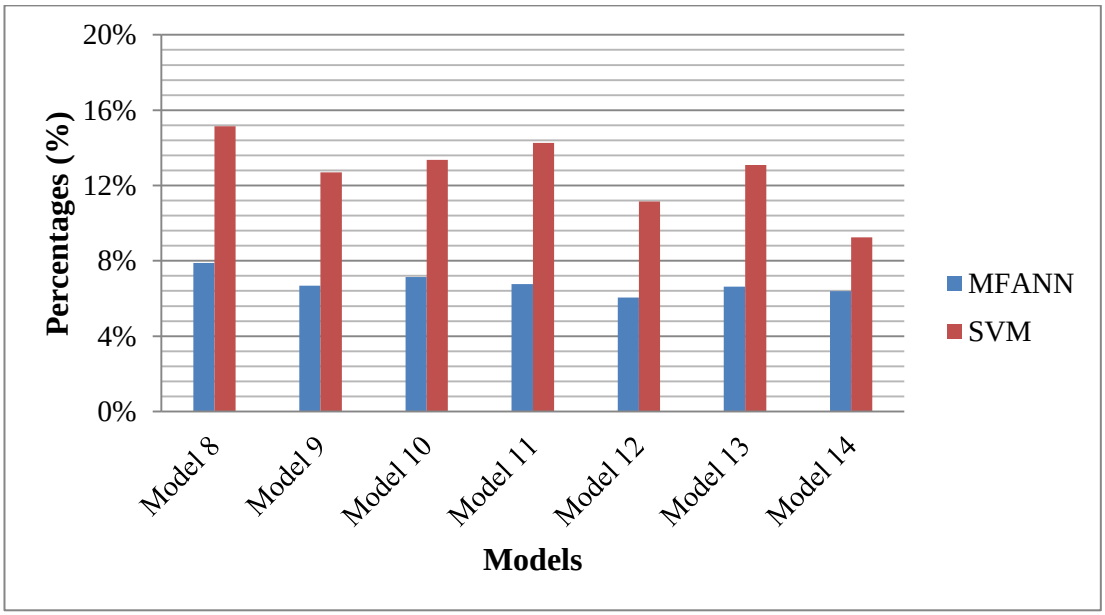

Figure 4.3. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-1 (Models 8-14)

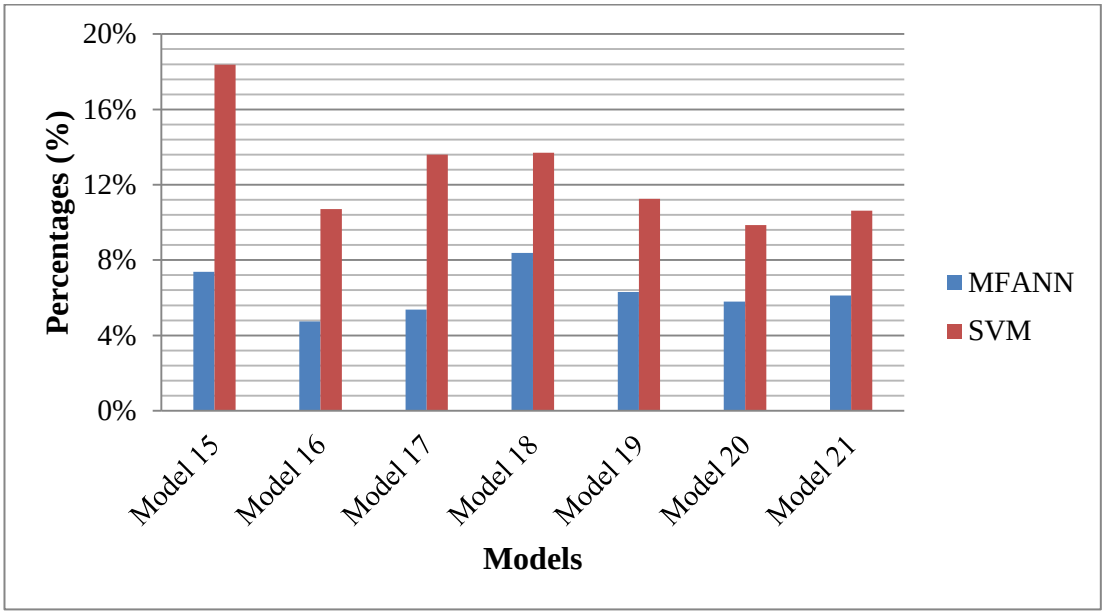

Figure 4.4. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-1 (Models 15-21)

Table 4.8. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2max-set-2.

Models	**MLR**		**MFANN**		**SVM**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 22	0.83	3.48	0.84	3.42	0.84	3.30
Model 23	0.76	4.02	0.77	3.95	0.79	3.82
Model 24	0.75	4.08	0.70	4.01	0.76	3.97

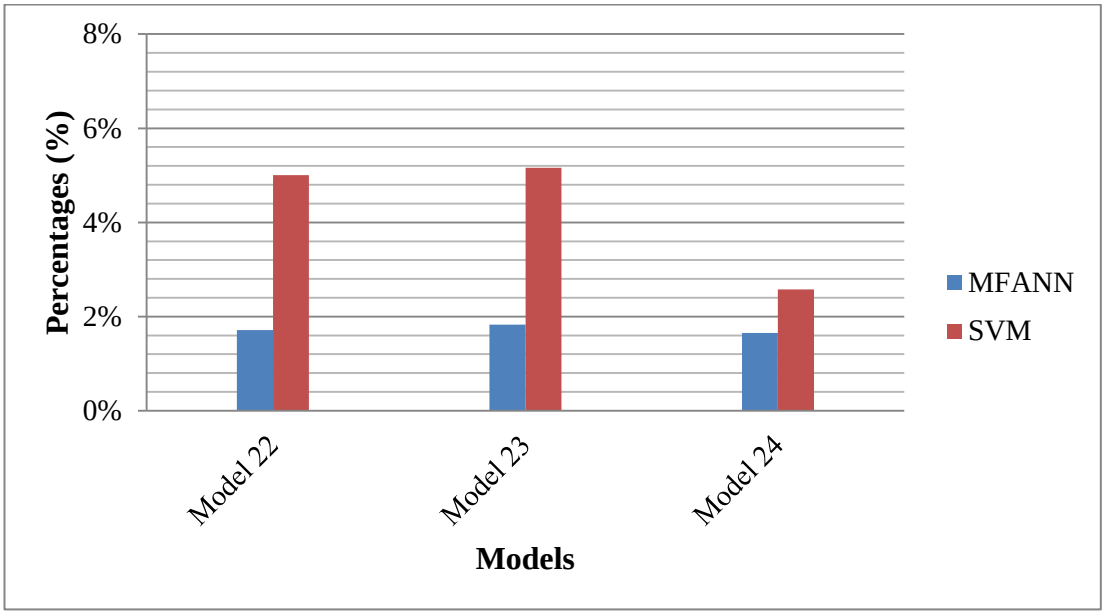

Figure 4.5. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-2 (Models 22-24)

Table 4.9. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2max-set-3.

Models	**MLR**		**MFANN**		**SVM**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 25	0.87	5.26	0.87	5.16	0.88	4.95
Model 26	0.84	6.05	0.84	5.62	0.86	5.30
Model 27	0.87	5.11	0.88	4.96	0.89	4.80
Model 28	0.85	5.46	0.86	5.32	0.87	5.20
Model 29	0.84	5.77	0.85	5.54	0.87	5.20
Model 30	0.80	6.33	0.81	6.10	0.84	5.69
Model 31	0.85	5.44	0.86	5.27	0.87	5.08

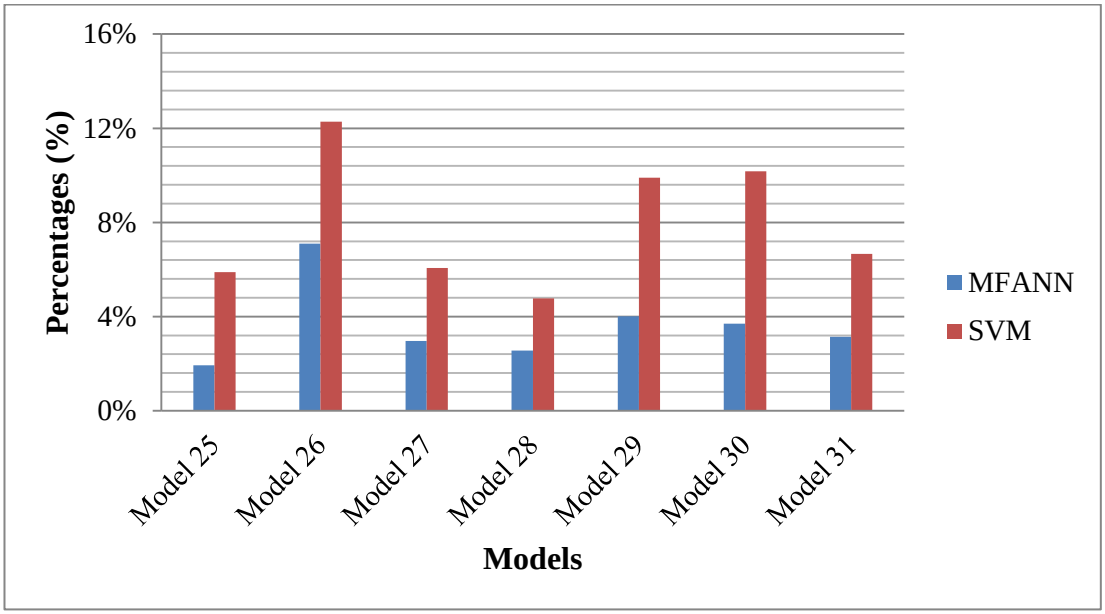

Figure 4.6. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-3 (Models 25-31)

Table 4.10. *R* and *SEE* values for VO_2max prediction models using different regression methods on the VO_2max-set-4.

Models	**MLR**		**MFANN**		**SVM**	
	R	***SEE***	***R***	***SEE***	***R***	***SEE***
Model 32	0.87	4.88	0.90	4.13	0.91	3.78
Model 33	0.82	5.47	0.86	4.93	0.87	4.51
Model 34	0.87	4.83	0.90	4.04	0.91	3.75
Model 35	0.87	4.85	0.90	4.05	0.91	3.75
Model 36	0.83	5.39	0.87	4.57	0.87	4.47
Model 37	0.73	6.69	0.79	6.41	0.80	5.71
Model 38	0.87	4.58	0.91	3.89	0.92	3.68
Model 39	0.89	4.36	0.92	3.72	0.93	3.48
Model 40	0.86	4.87	0.90	4.09	0.91	3.76
Model 41	0.72	6.83	0.78	6.47	0.76	5.89
Model 42	0.84	5.18	0.88	4.45	0.87	4.26
Model 43	0.82	5.50	0.86	5.05	0.87	4.43
Model 44	0.80	5.69	0.84	5.42	0.86	4.69
Model 45	0.86	4.82	0.90	3.99	0.91	3.73
Model 46	0.78	5.94	0.82	5.60	0.86	4.88
Model 47	0.77	6.17	0.84	5.86	0.84	5.13
Model 48	0.77	6.16	0.83	5.85	0.83	5.12
Model 49	0.76	6.14	0.82	5.78	0.84	5.04
Model 50	0.81	5.49	0.87	5.00	0.88	4.52
Model 51	0.89	4.31	0.92	3.68	0.93	3.45
Model 52	0.75	6.35	0.79	6.20	0.80	5.43
Model 53	0.80	5.62	0.84	5.30	0.86	4.63
Model 54	0.83	5.33	0.87	4.54	0.87	4.43
Model 55	0.82	5.29	0.88	4.49	0.88	4.29
Model 56	0.84	5.01	0.90	4.16	0.90	3.95
Model 57	0.87	4.53	0.91	3.89	0.92	3.66
Model 58	0.80	5.60	0.84	5.26	0.87	4.57
Model 59	0.76	6.25	0.81	6.04	0.81	5.38
Model 60	0.76	6.08	0.82	5.65	0.84	5.00
Model 61	0.82	5.25	0.88	4.46	0.88	4.28
Model 62	0.84	5.07	0.88	4.43	0.89	4.24

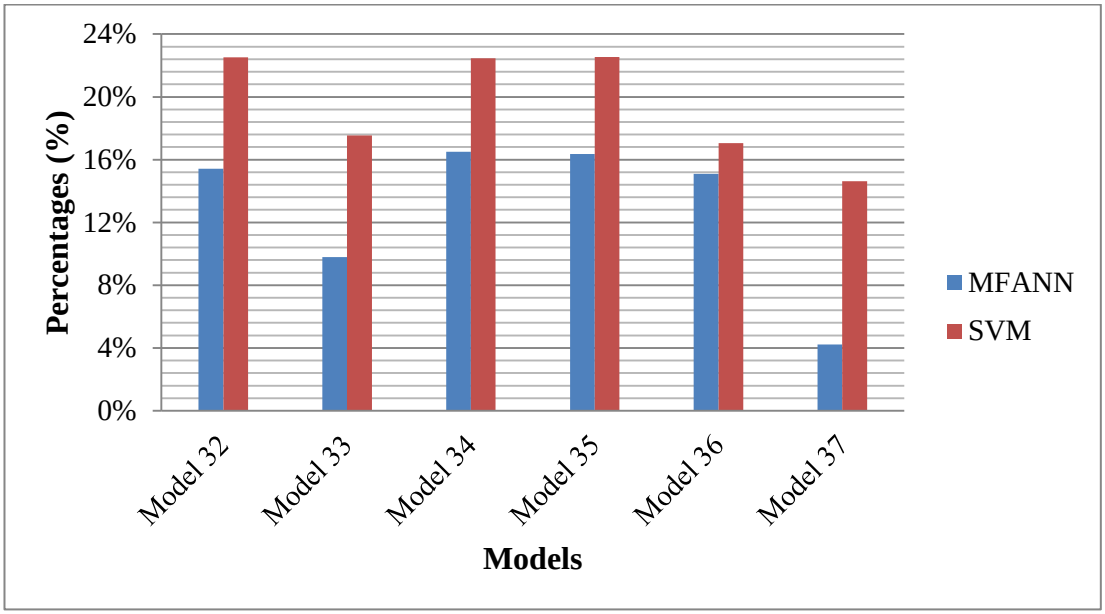

Figure 4.7. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-4 (Models 32-37)

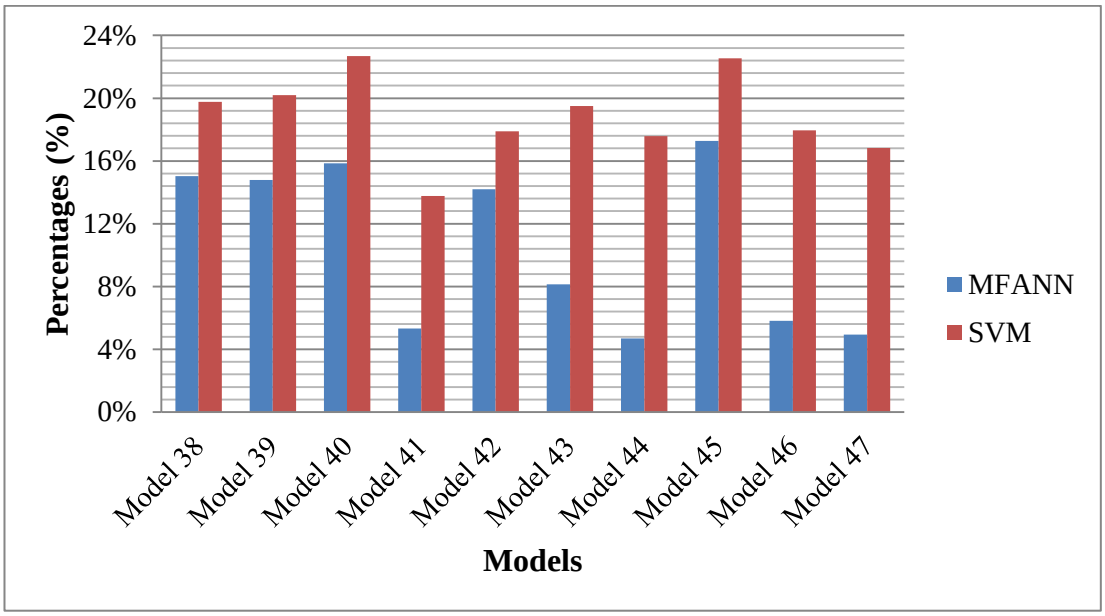

Figure 4.8. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-4 (Models 38-47)

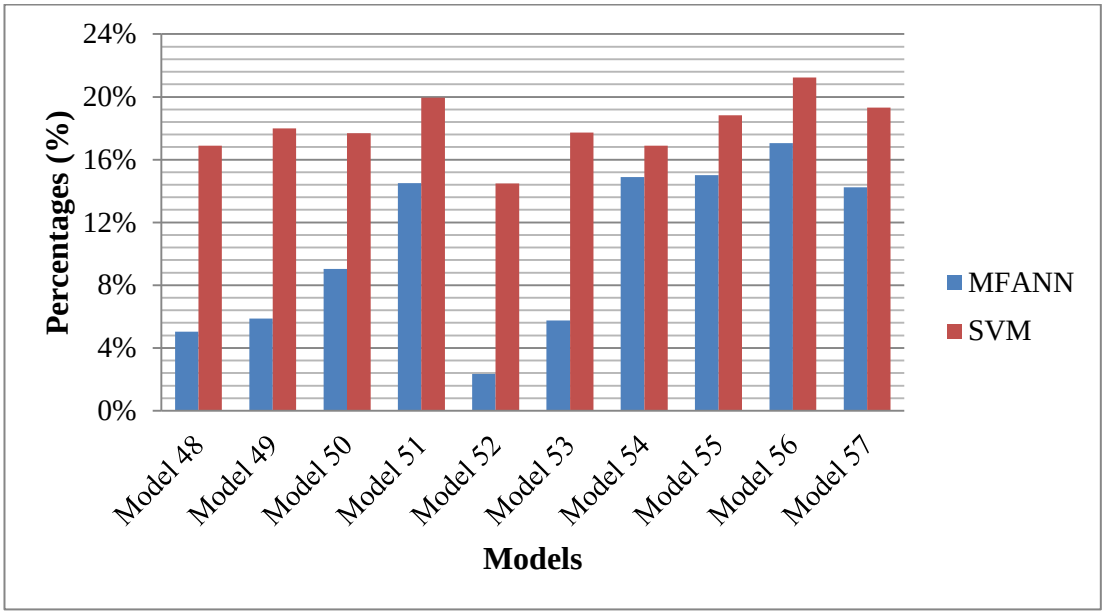

Figure 4.9. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-4 (Models 48-57)

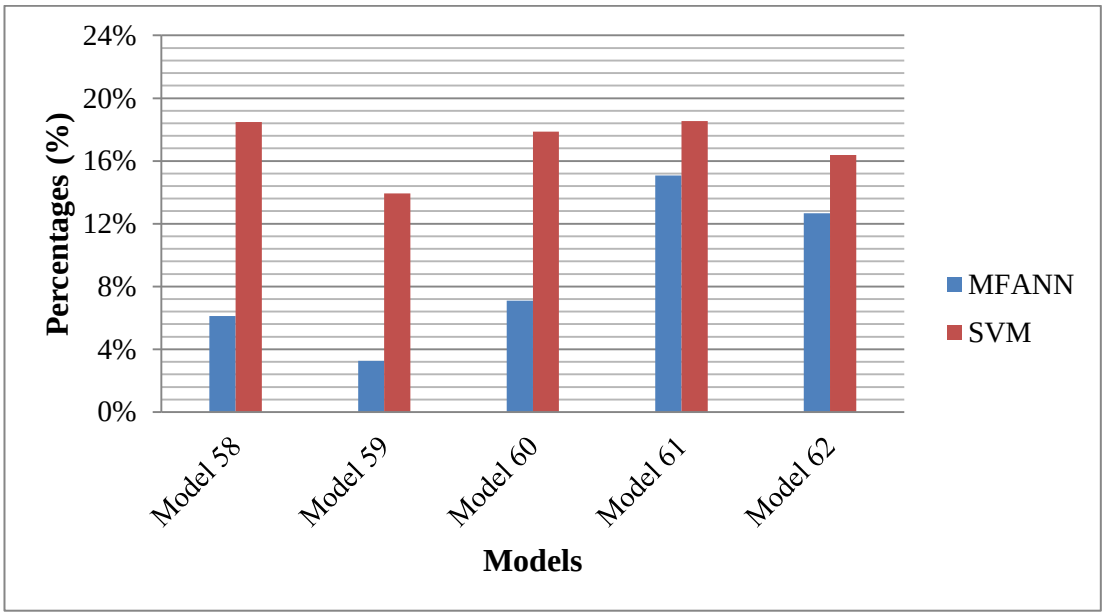

Figure 4.10. Percentage decrease rates in *SEE*'s of VO_2max for machine learning methods compared to *SEE*'s obtained by MLR on VO_2max-set-4 (Models 58-62)

4.3. Discussion on VO_2max-set-1 Results

1. SVM-based prediction models perform better than other models obtained by other regression methods. MFANN-based prediction models are more accurate than MLR-based models.
2. Model 7 including the submaximal predictor variables MIN3 and HR3 yields the lowest *SEE*'s (2.91, 3.14, 3.25) for SVM-based, MFANN-based and MLR-based prediction models whereas Model 15 including the submaximal predictor variables HR1, HR2 and HR3 yields the highest *SEE*'s (4.15, 4.71, 5.09) for SVM-based, MFANN-based and MLR-based prediction models.
3. The prediction model including the submaximal predictor variables (Model 4), MIN2, MIN3, HR2 and HR3, yields the second best performance for VO_2max prediction.
4. Among the prediction models including the MIN submaximal predictor variable only, the model including the MIN3 variable performs better than the other models.
5. Among the prediction models including the HR submaximal predictor variable only, although the *SEE*'s of all models are comparable to each other; the model including the HR2 variable performs better than the other models.
6. The ranking in the performance of the submaximal predictor variables for VO_2max prediction (from the highest to the lowest) is as follows: MIN3, MIN2, MIN1, HR2, HR1 and HR3.
7. Among the models including dual combinations of the MIN submaximal predictor variable, models including the MIN1 and MIN3 variables yield the lowest *SEE*'s. Additionally, the models including the MIN3 predictor variable gives lower *SEE*'s.
8. Among the models including dual combinations of the HR submaximal predictor variable, although the *SEE*'s of all models are comparable to each other; models including HR1 and HR2 yield the lowest *SEE*'s. Additionally, the models including the HR2 predictor variable gives lower *SEE*'s.

9. The *SEE*'s of prediction models including dual combinations of the submaximal predictor variable MIN are lower than that of the models including dual combinations of the submaximal predictor variable HR.
10. The *SEE*'s of prediction models including single submaximal predictor variables are lower than that of the models including dual combinations of submaximal predictor variables.
11. Among Models 5-7, Model 7 including MIN3 and HR3 yield the lowest *SEE*.
12. Among the models including dual combinations of the MIN-HR submaximal predictor variable, the model including MIN2, MIN3, HR2 and HR3 yields the lowest *SEE*'s.
13. Among all the prediction models including the MIN submaximal predictor variables, the model including the MIN1, MIN2 and MIN3 variables yields the highest *SEE*.
14. Among all the prediction models including the HR submaximal predictor variables, the model including the HR1, HR2 and HR3 variables yields the highest *SEE*.
15. Among all the prediction models including the MIN-HR submaximal predictor variables, the model including the MIN1, MIN2, MIN3, HR1, HR2 and HR3 variables yields the highest *SEE*.
16. For Model 7, the decrement rate in *SEE*'s between SVM-based and MLR-based prediction models is 10.46%. Also, for the same model, the decrement rate in *SEE*'s between SVM-based and MFANN-based prediction models is 7.32%.

4.4. Discussion on VO_2max-set-2 Results

1. SVM-based prediction models perform better than other models obtained by other regression methods. MFANN-based prediction models are more accurate than MLR-based models.
2. Model 22 including the submaximal predictor variables SM-Speed and SM-HR yields lower *SEE*'s (3.30, 3.42, 3.48) compared to the *SEE*'s of Model 23

(including the submaximal predictor variable SM-Speed only) and Model 24 (including the submaximal predictor variable SM-HR only).

3. For Model 22, the decrement rate in *SEE*'s between SVM-based and MLR-based prediction models is 5.00%. Also, for the same model, the decrement rate in *SEE*'s between SVM-based and MFANN-based prediction models is 3.35%.
4. The submaximal predictor variable SM-Speed has stronger effect than the submaximal predictor variable SM-HR for prediction of VO_2max.

4.5. Discussion on VO_2max-set-3 Results

1. The ranking in the performance of the regression methods for VO_2max prediction (from the best to the worst) is as follows: SVM, MFANN and MLR.
2. Model 27 including the non-exercise predictor variables BF% and AC yields the lowest *SEE*'s (4.80, 4.96, 5.11) for SVM-based, MFANN-based and MLR-based prediction models whereas Model 30 including the non-exercise predictor variable LBM yields the highest *SEE*'s (5.69, 6.10, 6.33) for SVM-based, MFANN-based and MLR-based prediction models.
3. The prediction model including all non-exercise predictor variables (i.e. AC, BF% and LBM) yields the second best performance for VO_2max prediction.
4. The ranking in the performance of the non-exercise predictor variables for VO_2max prediction (from the highest to the lowest) is as follows: AC, BF% and LBM.
5. Among the prediction models including two non-exercise predictor variables, the models having AC have lower *SEE*'s compared to the models without AC.
6. Since LBM is calculated by using weight and BF%, it has negative effect on VO_2max prediction.

7. The positive effect of the non-exercise predictor variable AC on VO_2max prediction is clearly seen from Table 4.7. as all the models including AC have lower *SEE*'s than the *SEE*'s of the other models.
8. For Model 27, the decrement rate in *SEE*'s between SVM-based and MLR-based prediction models is 6.06%. Also, for the same model, the decrement rate in *SEE*'s between SVM-based and MFANN-based prediction models is 3.19%.

4.6. Discussion on VO_2max-set-4 Results

1. The ranking in the performance of the regression methods for VO_2max prediction (from the best to the worst) is as follows: SVM, MFANN and MLR.
2. Model 51 including the hybrid predictor variables SM-Speed and PAR yields the lowest *SEE*'s (3.45, 3.68, 4.31) for SVM-based, MFANN-based and MLR-based prediction models whereas Model 41 including the submaximal predictor variables SM-Speed, SM-HR and SM-Stage yields the highest *SEE*'s (5.89, 6.47, 6.83) for SVM-based, MFANN-based and MLR-based prediction models.
3. The prediction model (Model 39) including the hybrid predictor variables, SM-Speed, PFA and PAR, yields the second best performance for VO_2max prediction.
4. Among the non-exercise predictor variables, PAR has the strongest effect for prediction of VO_2max. Similarly, among the submaximal predictor variables, SM-Speed has the strongest effect for prediction of VO_2max.
5. The ranking in the performance of the predictor variables for VO_2max prediction (from the highest to the lowest) is as follows: PAR, PFA, SM-Speed, SM-Stage and SM-HR.
6. Among the models including dual combinations of all hybrid predictor variables, the model including the SM-Speed and PAR variables yields the

lowest *SEE*'s whereas the model including the SM-Stage and SM-HR variables yields the highest *SEE*'s.

7. Among the models including triple combinations of all hybrid predictor variables, the model including the SM-Speed, PFA and PAR variables yields the lowest *SEE*'s whereas the model including the SM-Speed, SM-Stage and SM-HR variables yields the highest *SEE*'s.
8. Among the models including quadruple combinations of all hybrid predictor variables, the model including the SM-Speed, SM-Stage, PFA and PAR variables yields the lowest *SEE*'s whereas the model including the SM-Speed, SM-Stage, SM-HR and PFA variables yields the highest *SEE*'s.
9. Inclusion of non-exercise variables to the prediction models decreases the *SEE*'s.
10. The *SEE*'s of the prediction models including the non-exercise variables are always lower than the *SEE*'s of the models including submaximal variables.
11. For Model 51, the decrement rate in *SEE*'s between SVM-based and MLR-based prediction models is 19.94%. Also, for the same model, the decrement rate in *SEE*'s between SVM-based and MFANN-based prediction models is 6.37%.

Figure 4.11. through Figure 4.72. show the scatter plots of actual VO_2max vs. predicted VO_2max for all models (Models 1 to 62) using SVM on VO_2max-set-1, VO_2max-set-2, VO_2max-set-3 and VO_2max-set-4, respectively.

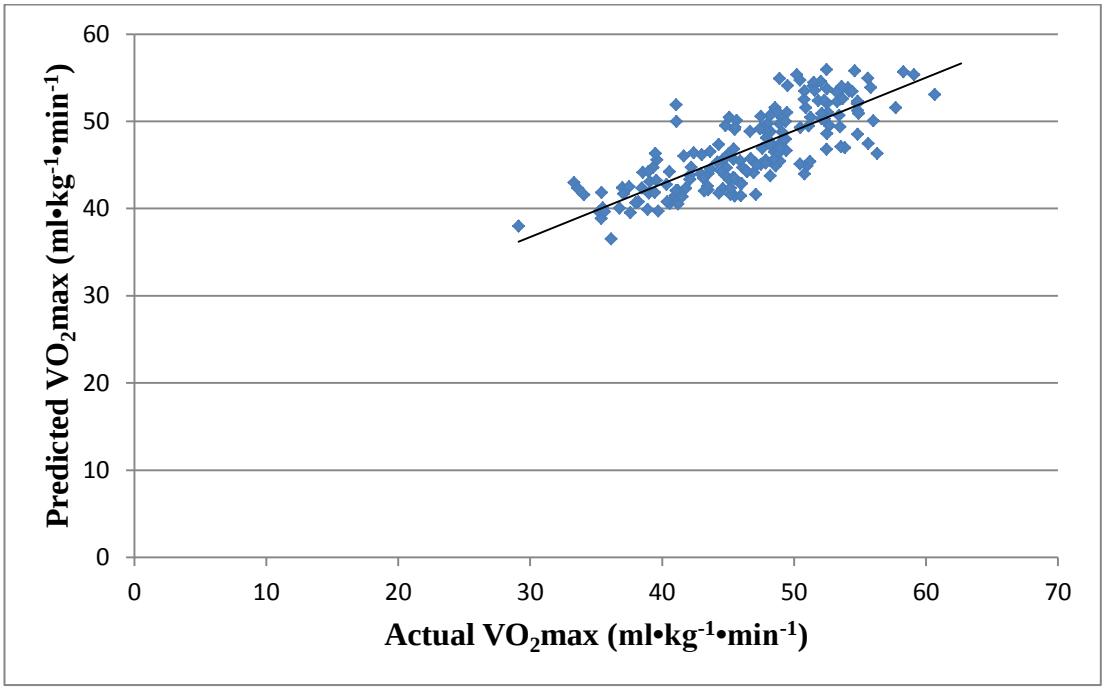

Figure 4.11. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 1 using SVM on VO_2max-set-1.

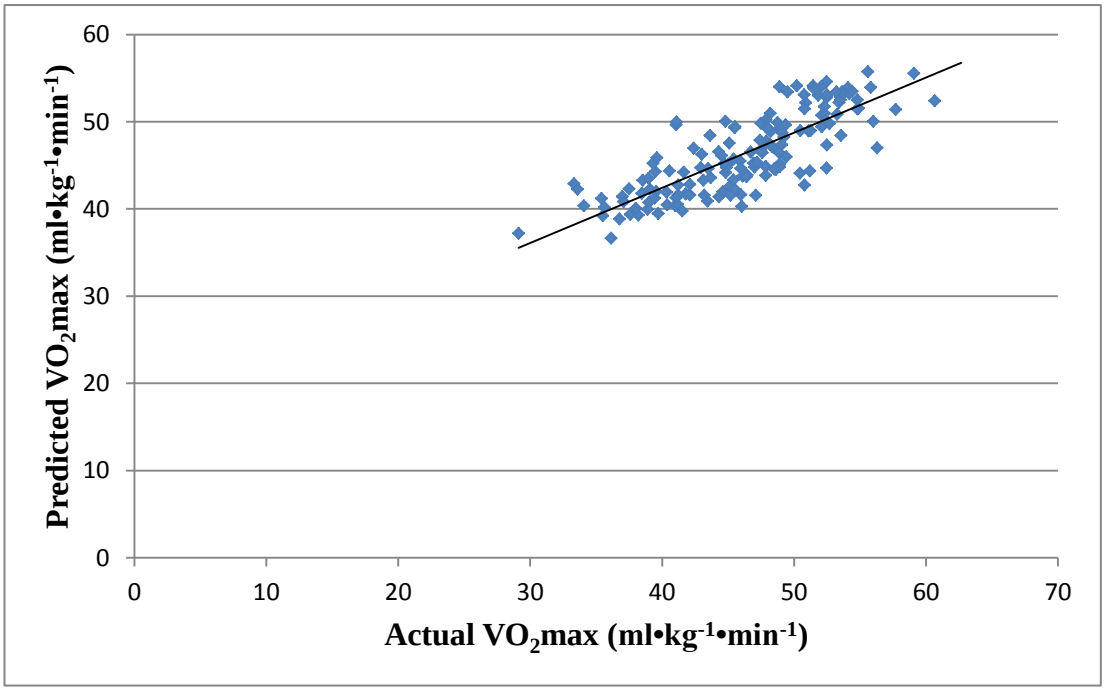

Figure 4.12. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 2 using SVM on VO_2max-set-1.

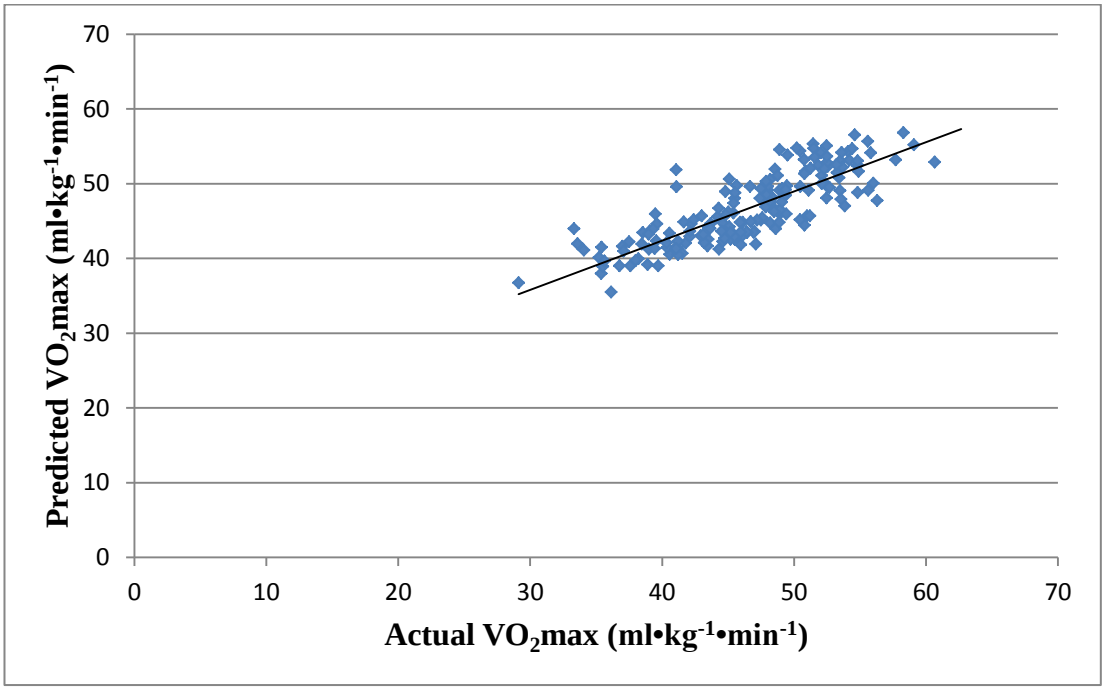

Figure 4.13. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 3 using SVM on VO_2max-set-1.

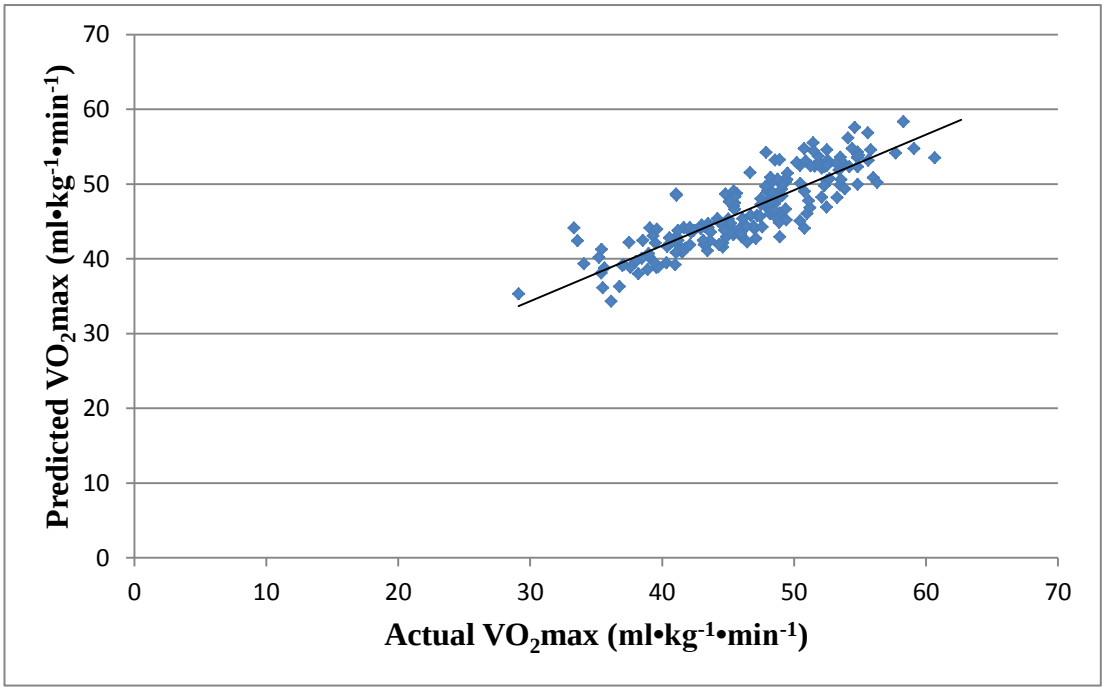

Figure 4.14. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 4 using SVM on VO_2max-set-1.

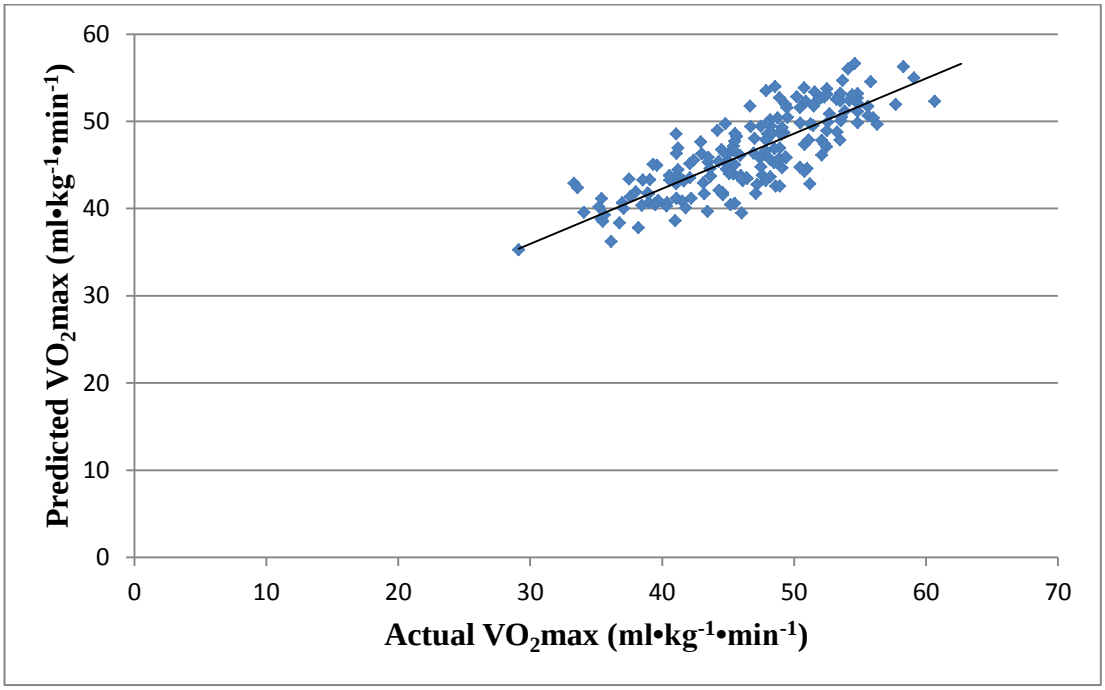

Figure 4.15. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 5 using SVM on VO_2max-set-1.

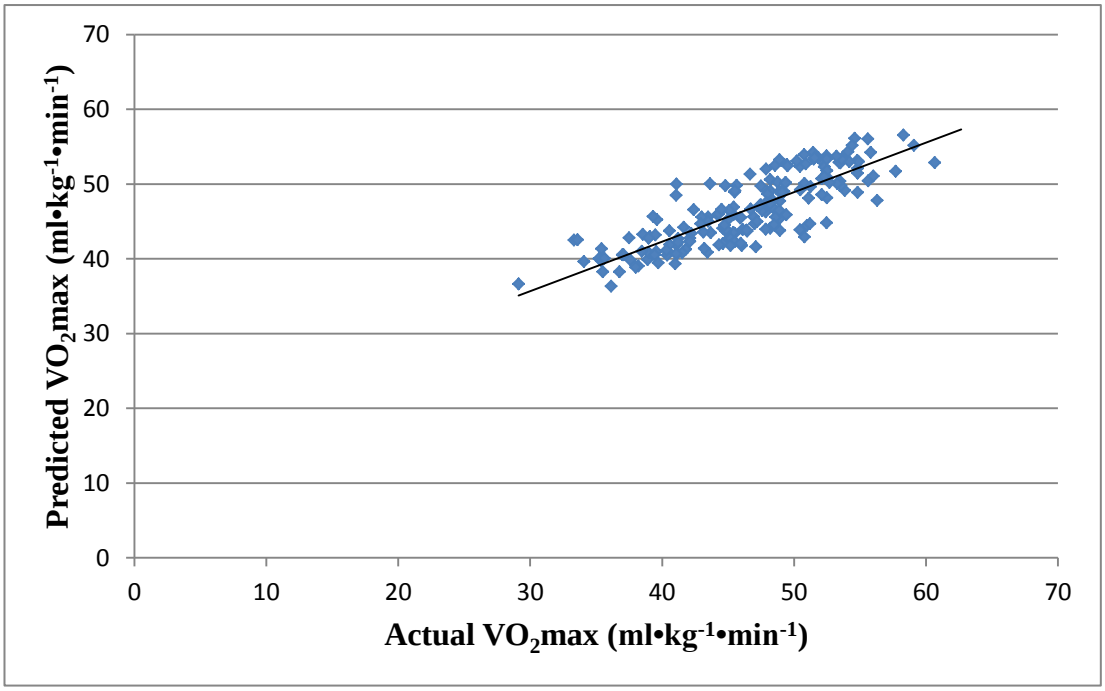

Figure 4.16. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 6 using SVM on VO_2max-set-1.

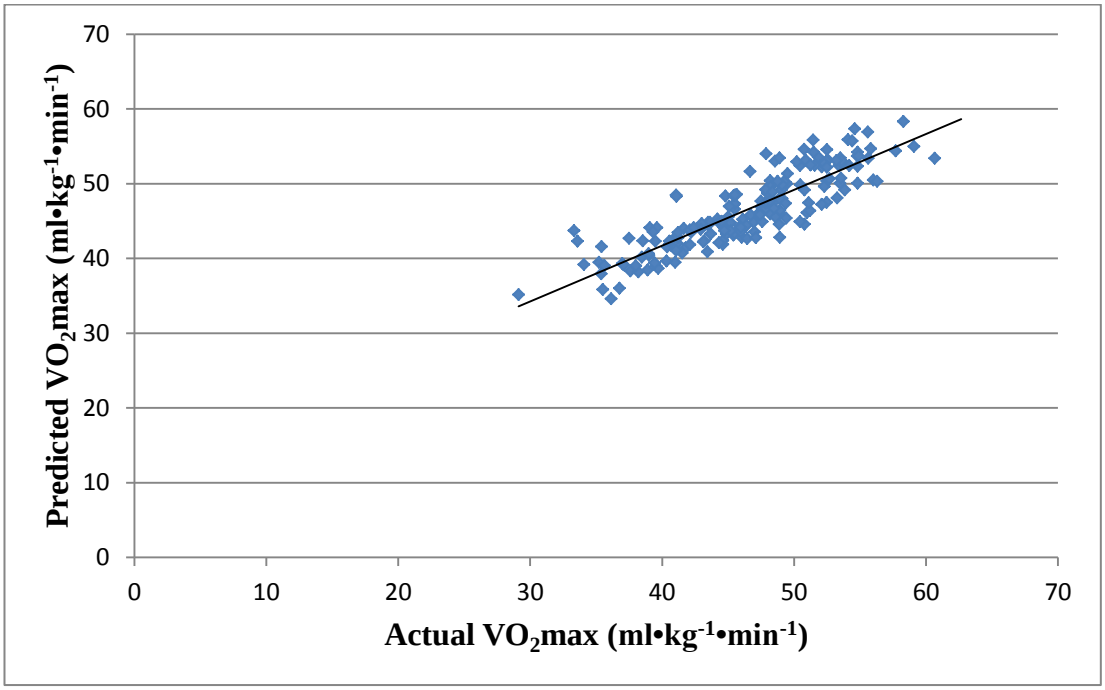

Figure 4.17. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 7 using SVM on VO_2max-set-1.

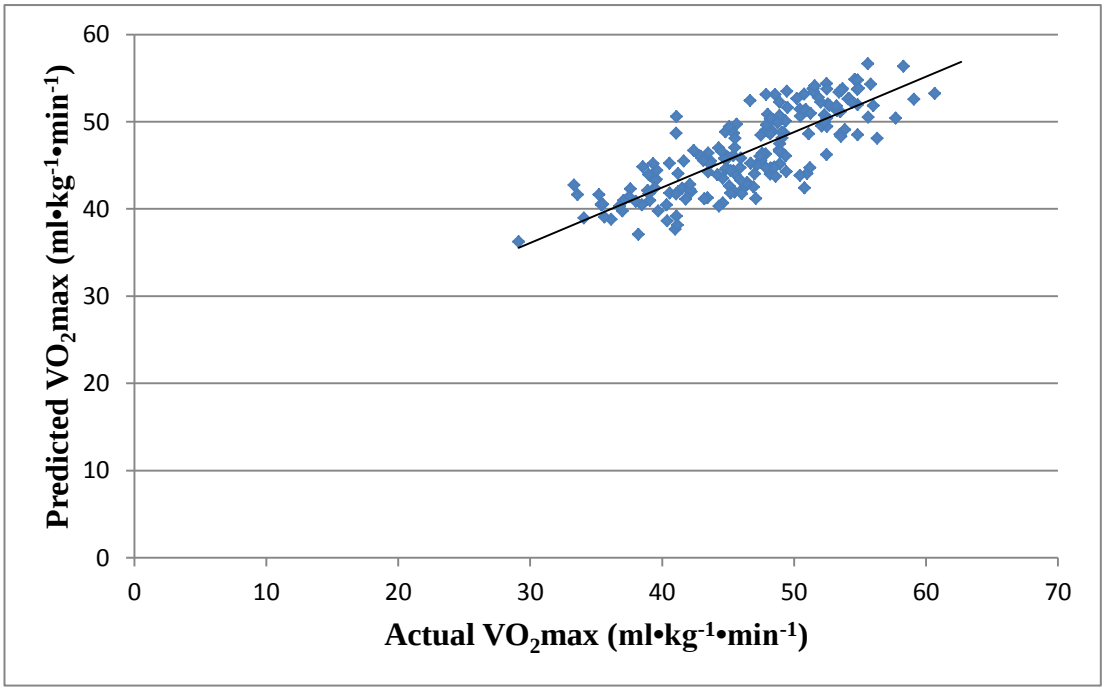

Figure 4.18. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 8 using SVM on VO_2max-set-1.

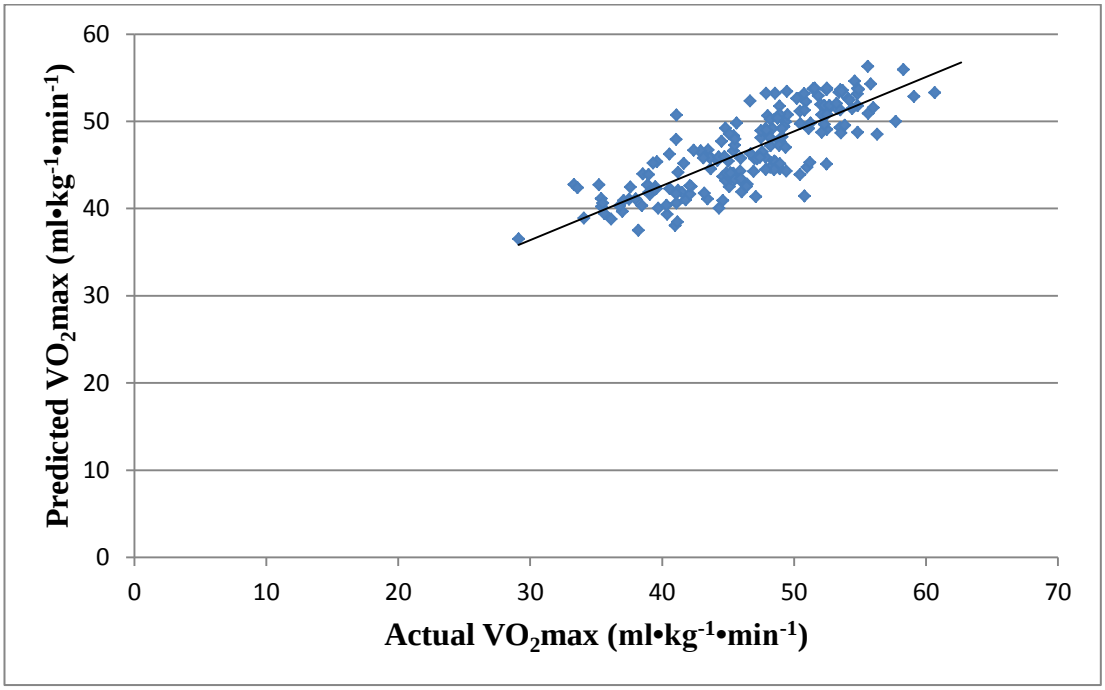

Figure 4.19. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 9 using SVM on VO_2max-set-1.

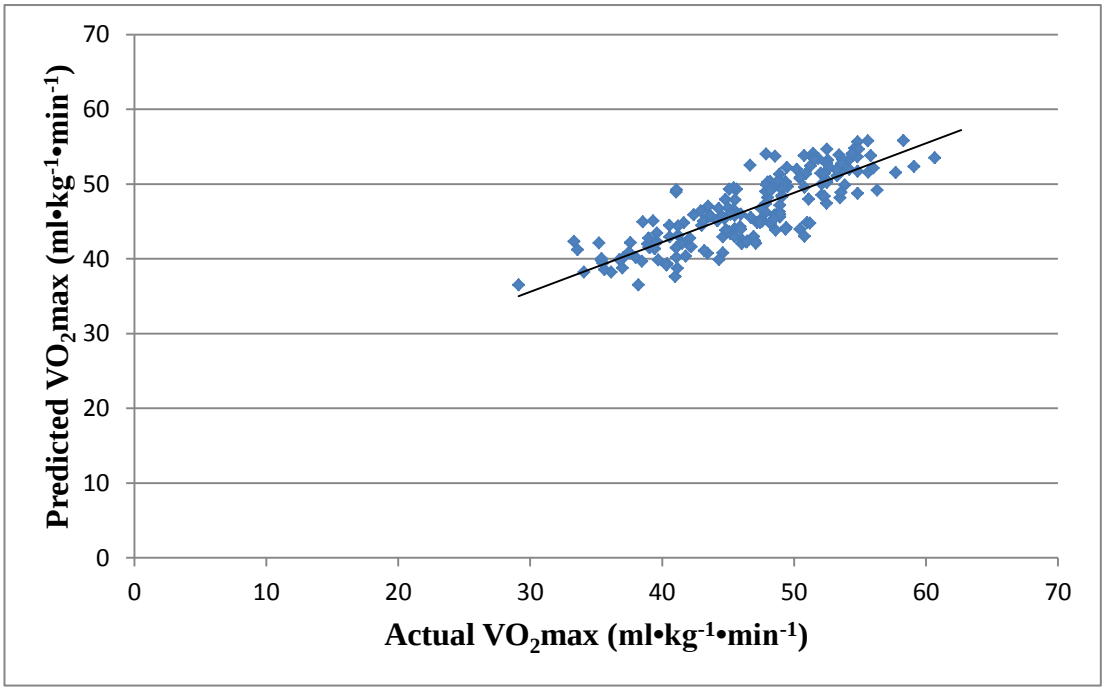

Figure 4.20. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 10 using SVM on VO_2max-set-1.

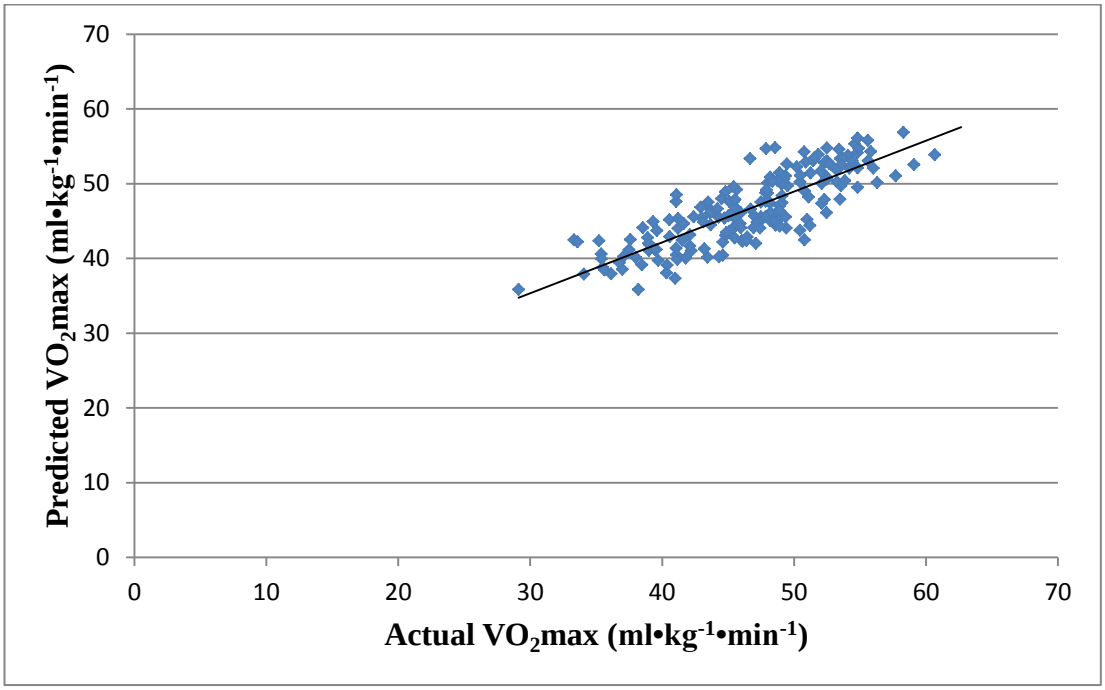

Figure 4.21. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 11 using SVM on VO_2max-set-1.

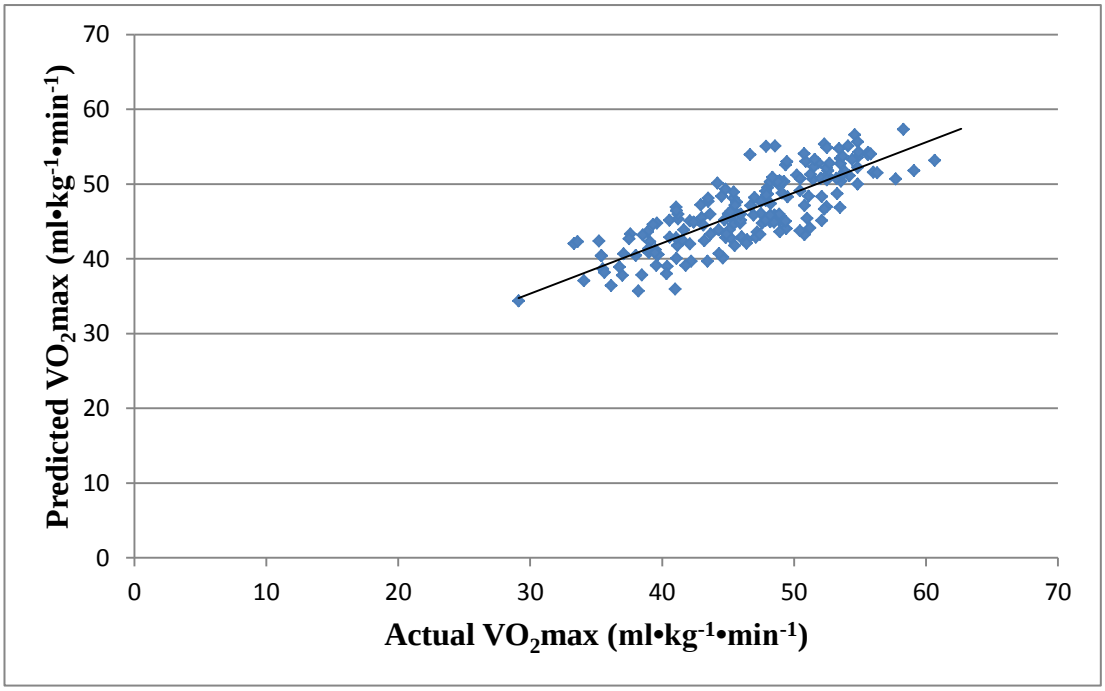

Figure 4.22. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 12 using SVM on VO_2max-set-1.

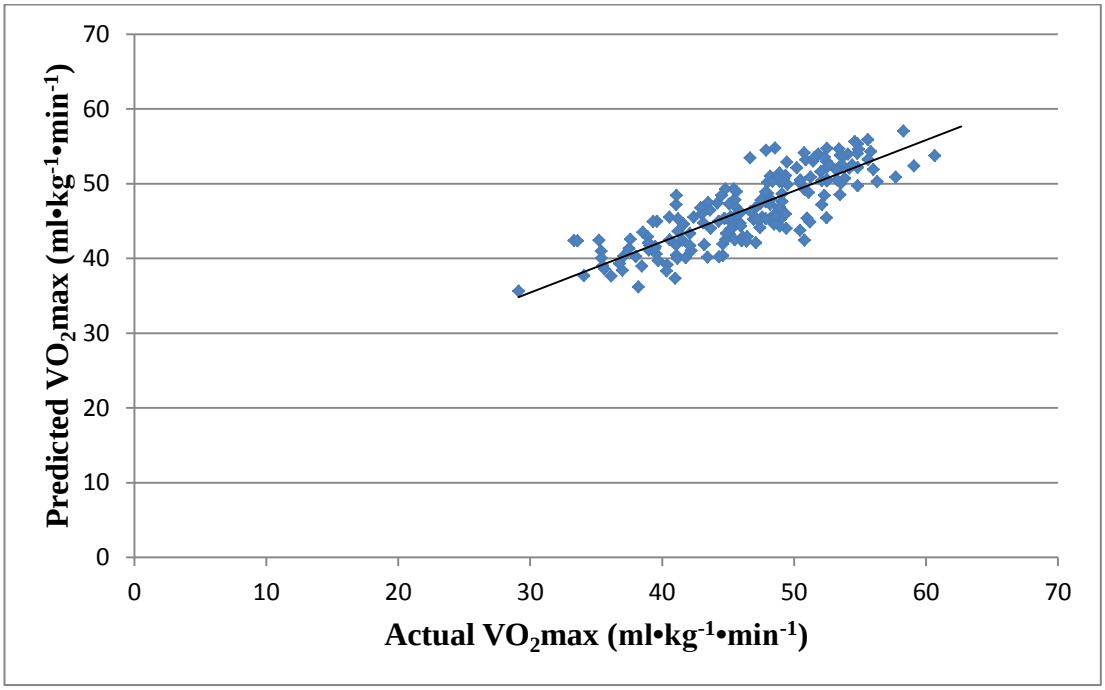

Figure 4.23. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 13 using SVM on VO_2max-set-1.

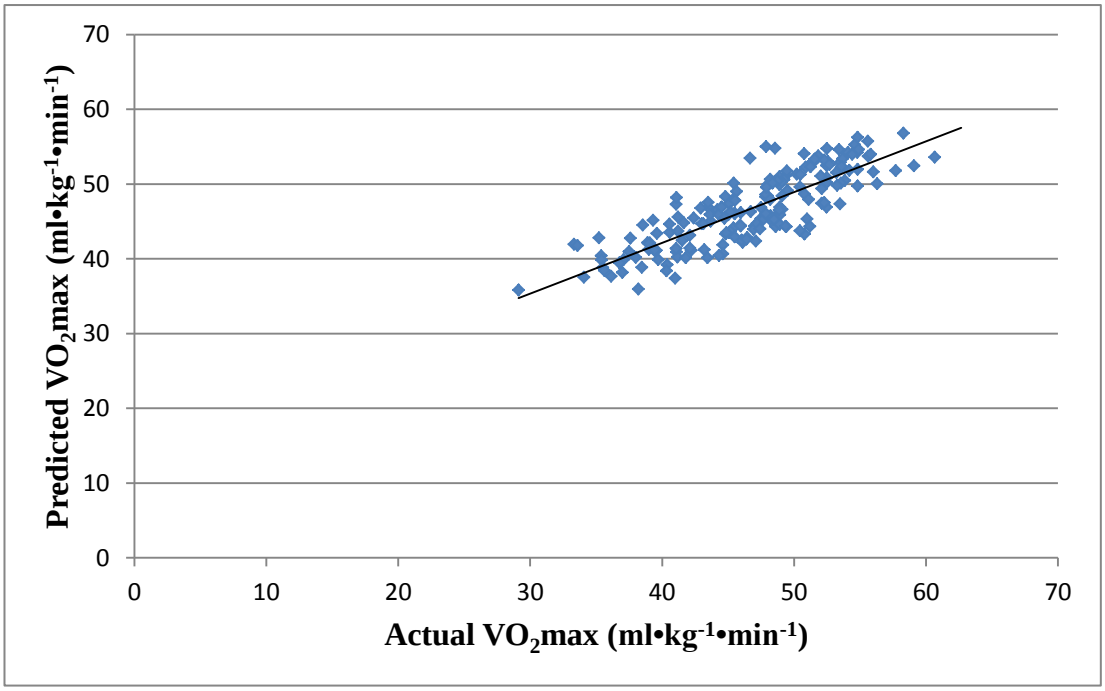

Figure 4.24. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 14 using SVM on VO_2max-set-1.

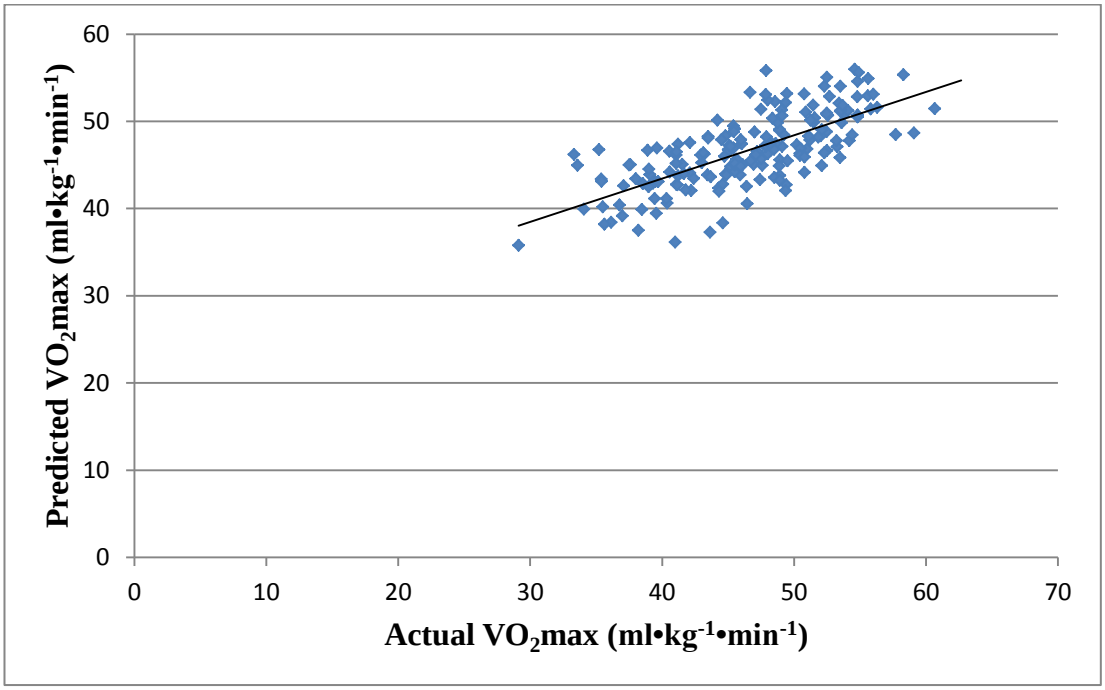

Figure 4.25. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 15 using SVM on VO_2max-set-1.

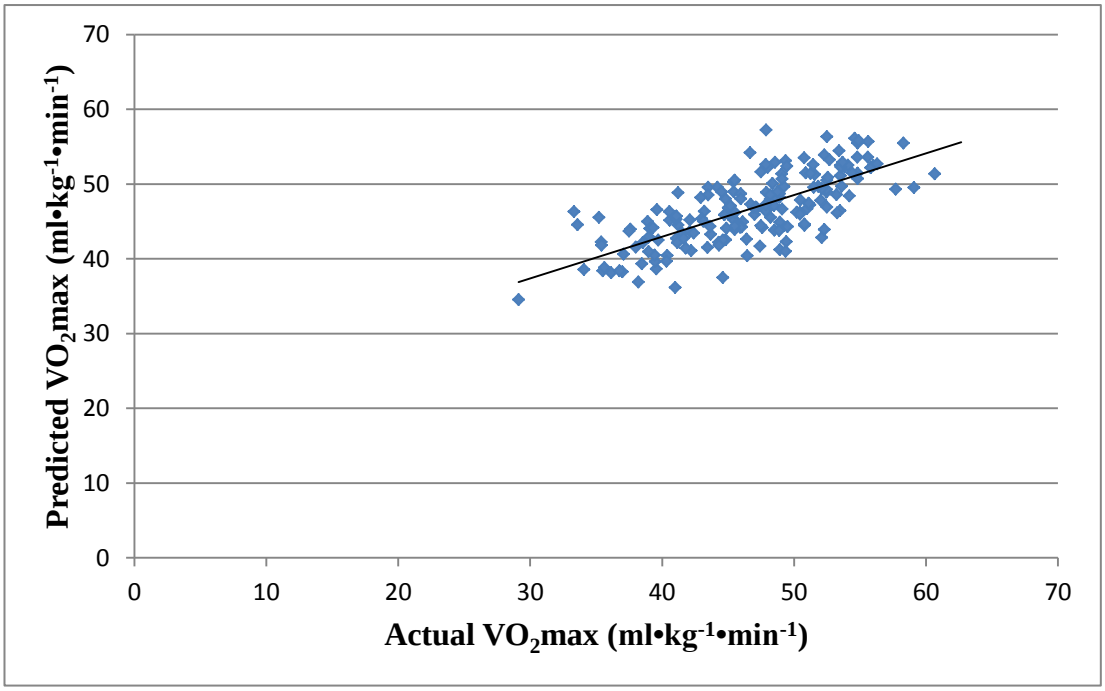

Figure 4.26. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 16 using SVM on VO_2max-set-1.

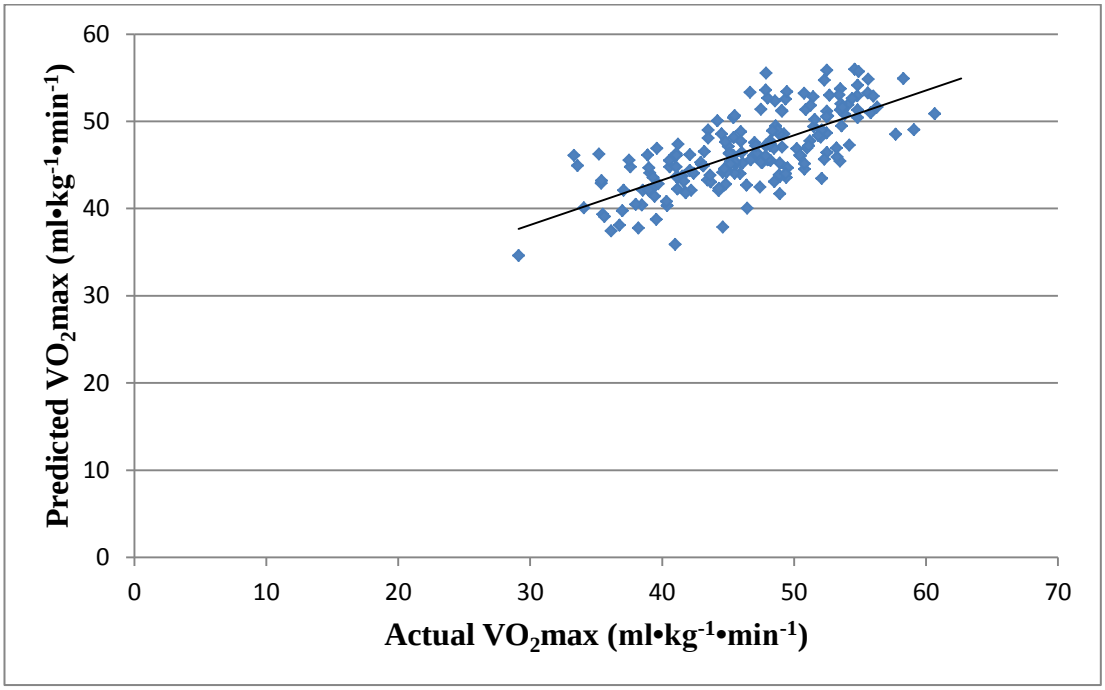

Figure 4.27. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 17 using SVM on VO_2max-set-1.

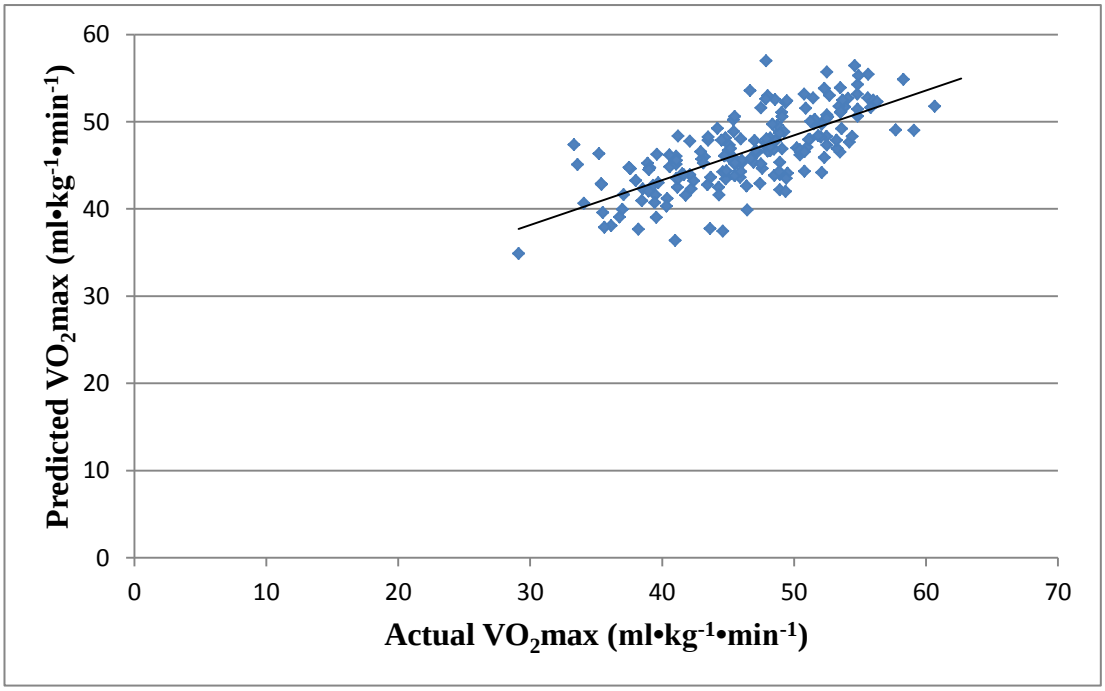

Figure 4.28. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 18 using SVM on VO_2max-set-1.

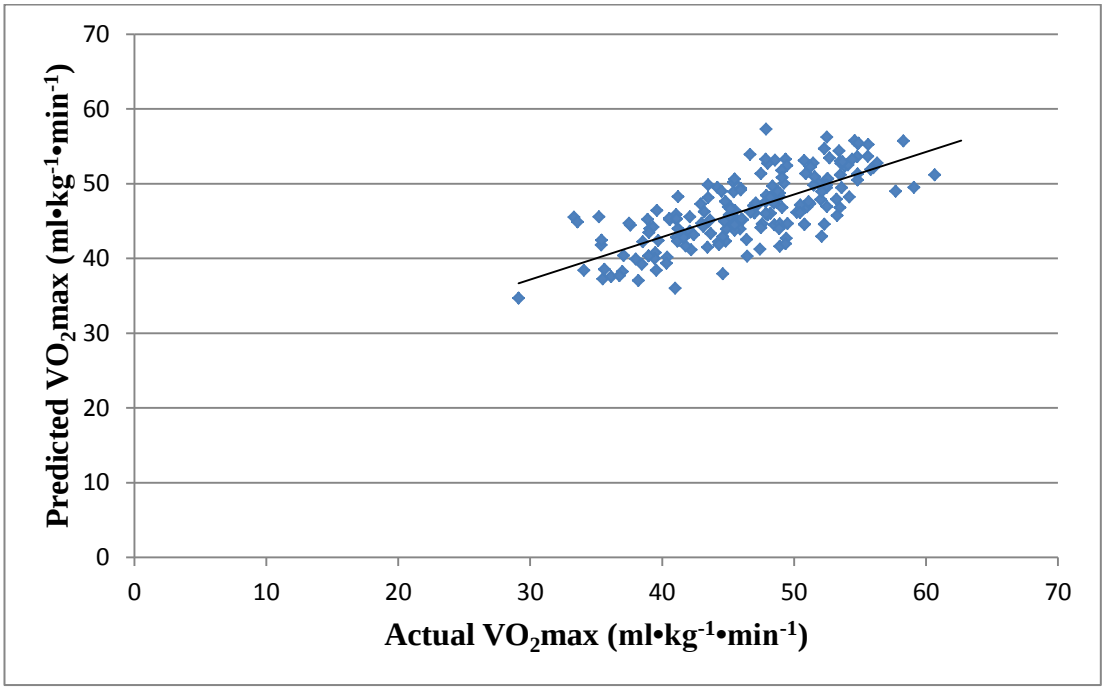

Figure 4.29. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 19 using SVM on VO_2max-set-1.

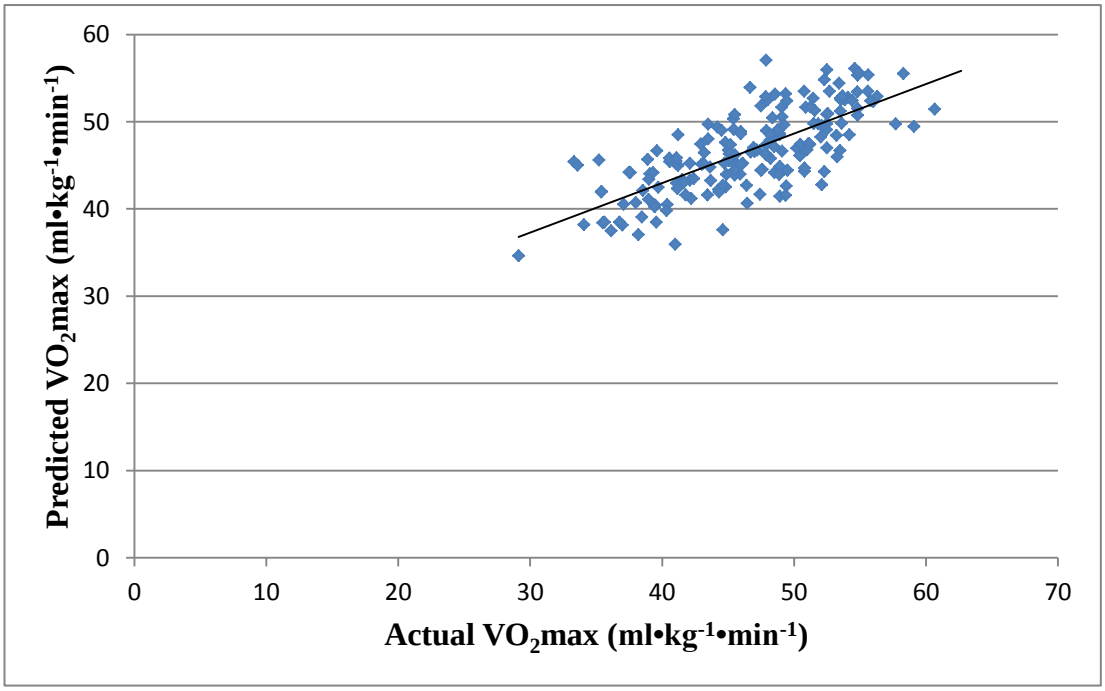

Figure 4.30. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 20 using SVM on VO_2max-set-1.

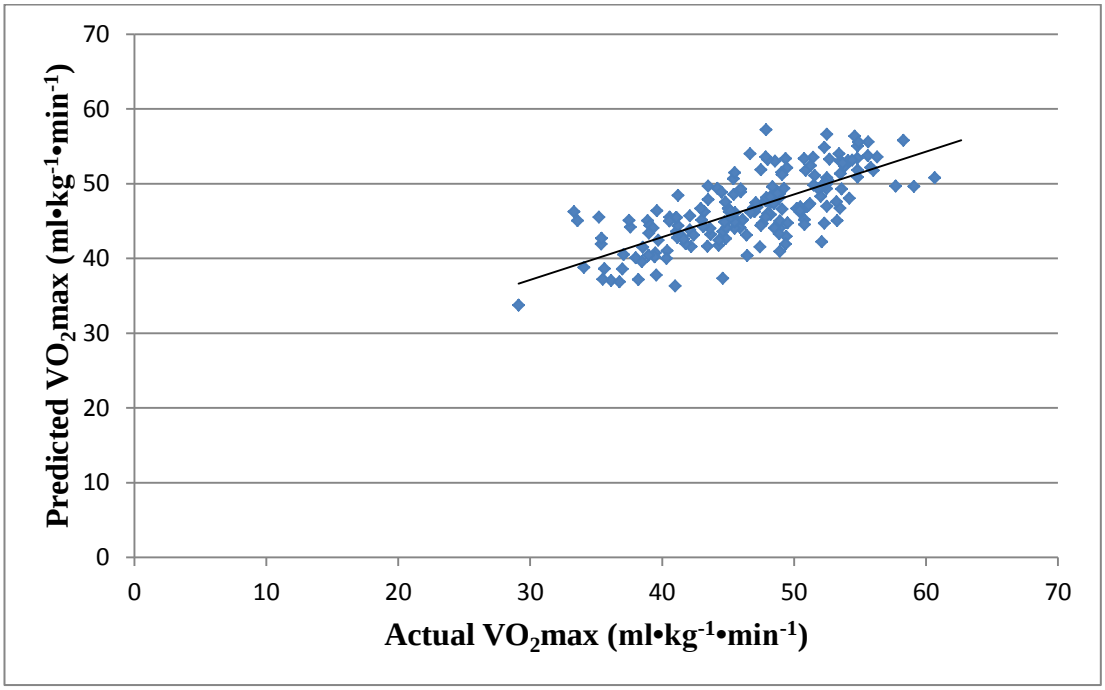

Figure 4.31. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 21 using SVM on VO_2max-set-1.

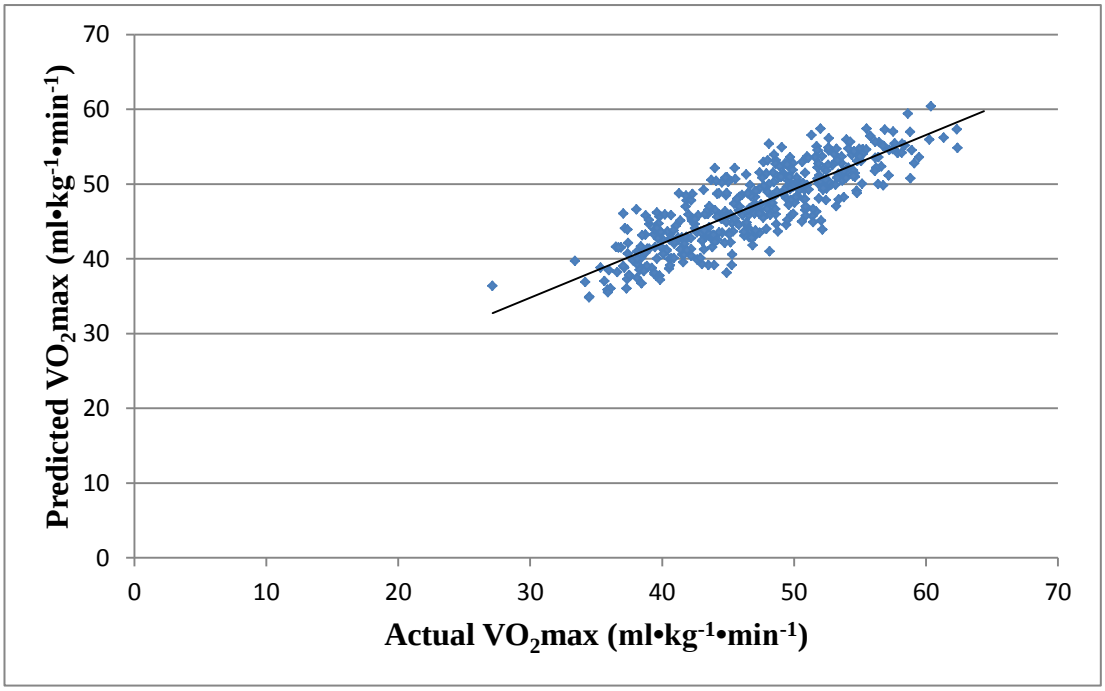

Figure 4.32. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 22 using SVM on VO_2max-set-2.

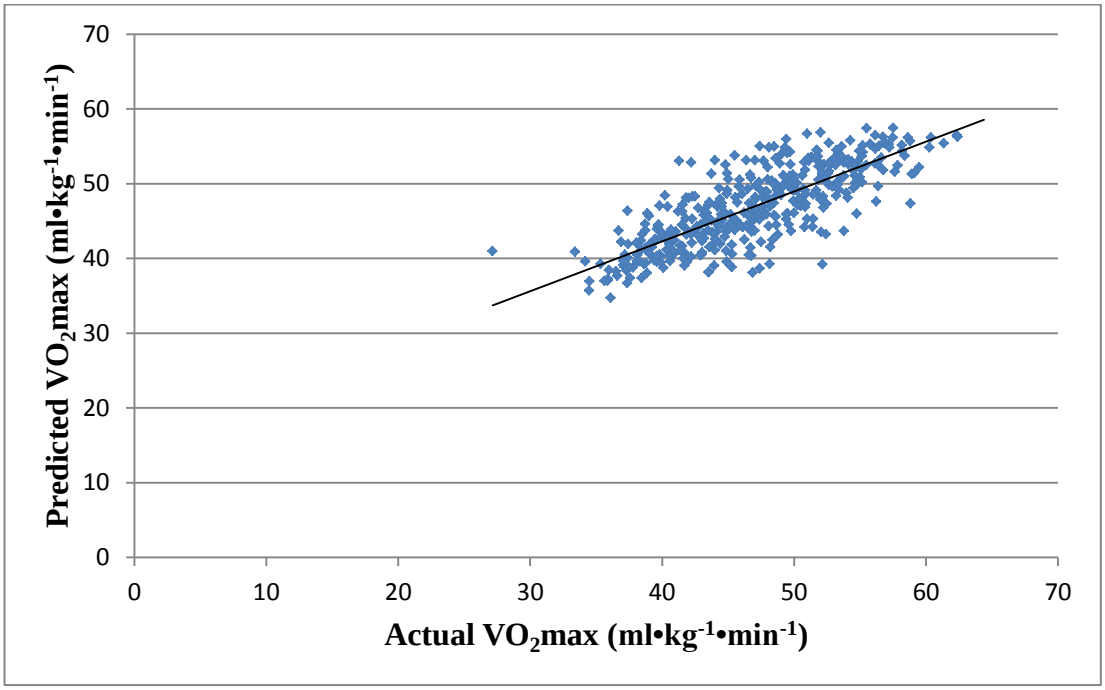

Figure 4.33. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 23 using SVM on VO_2max-set-2.

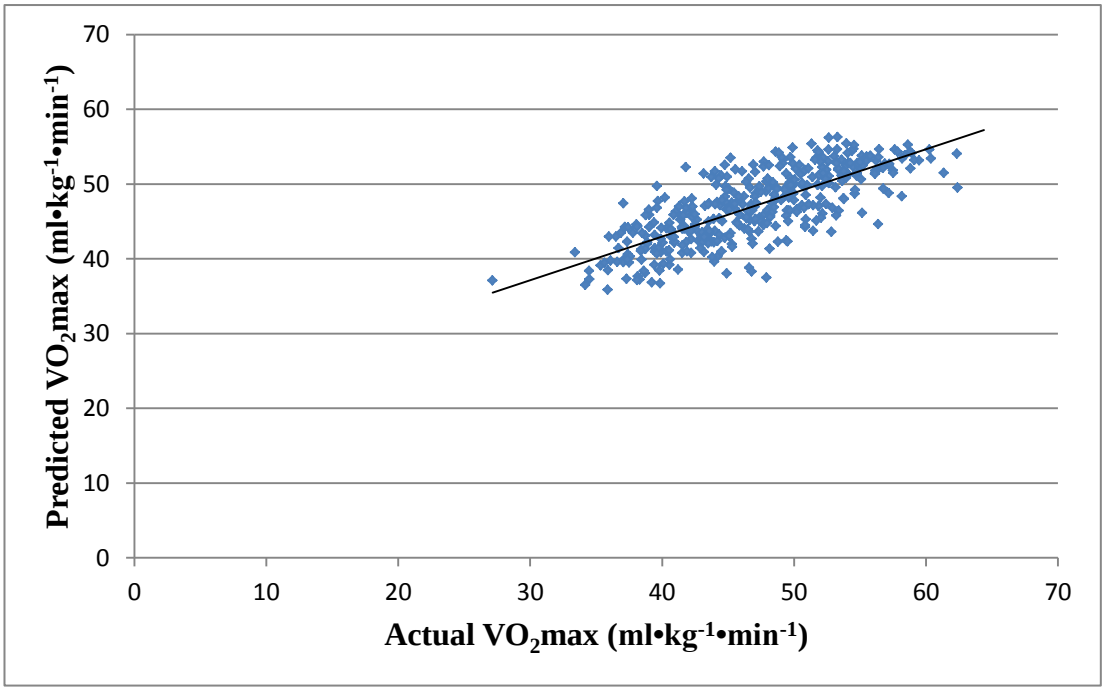

Figure 4.34. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 24 using SVM on VO_2max-set-2.

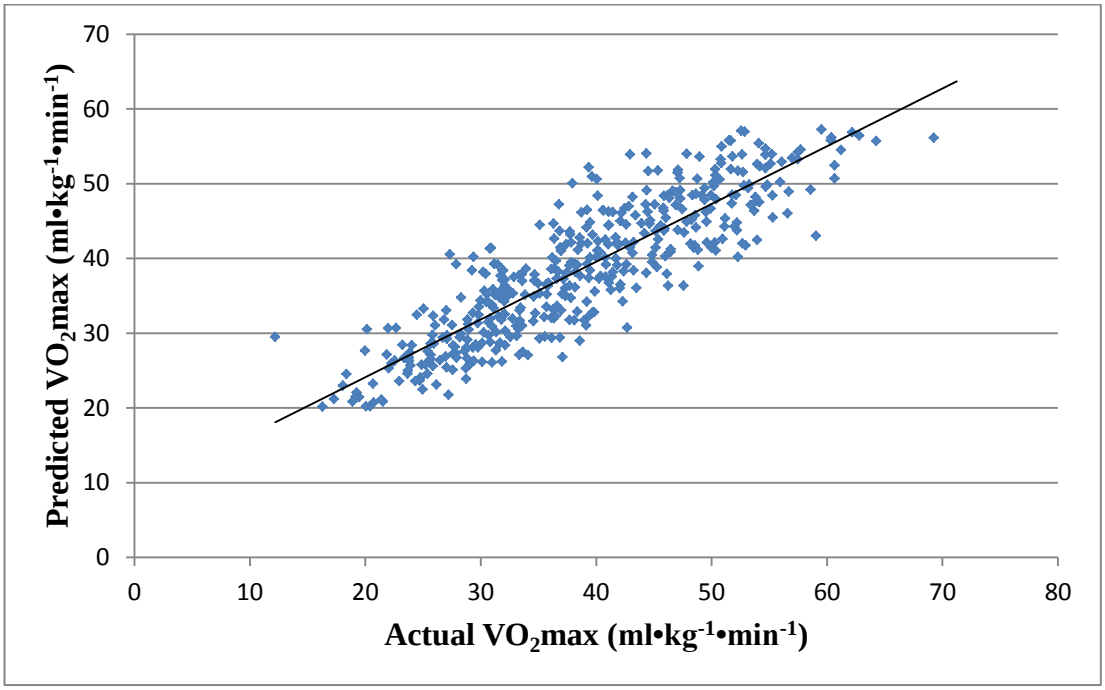

Figure 4.35. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 25 using SVM on VO_2max-set-3.

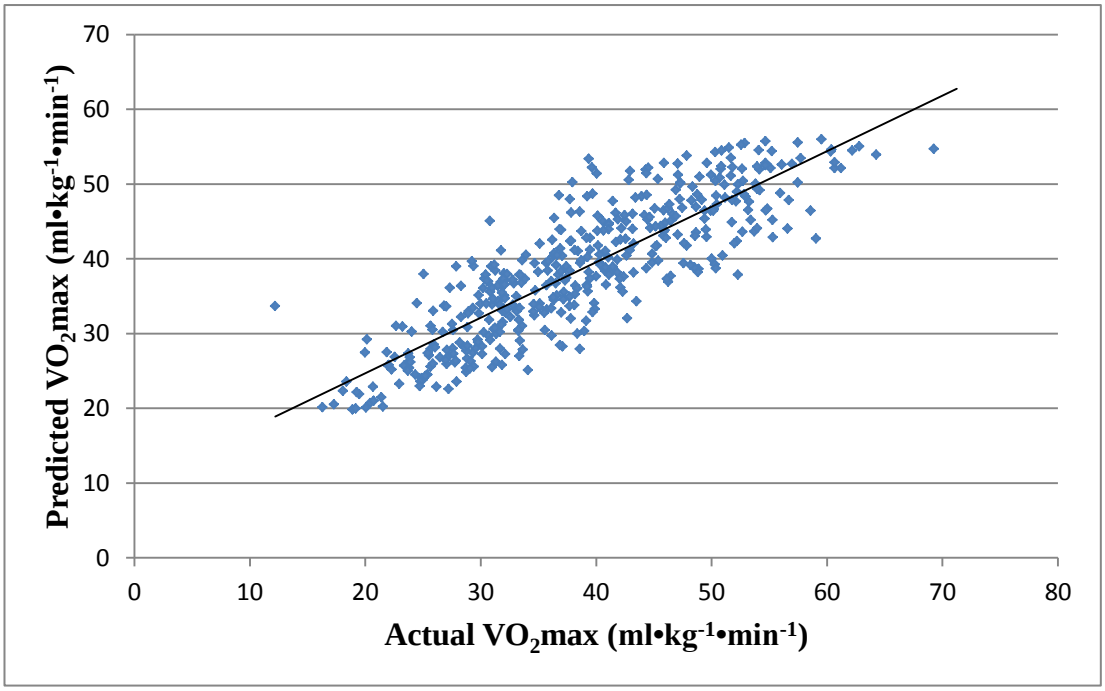

Figure 4.36. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 26 using SVM on VO_2max-set-3.

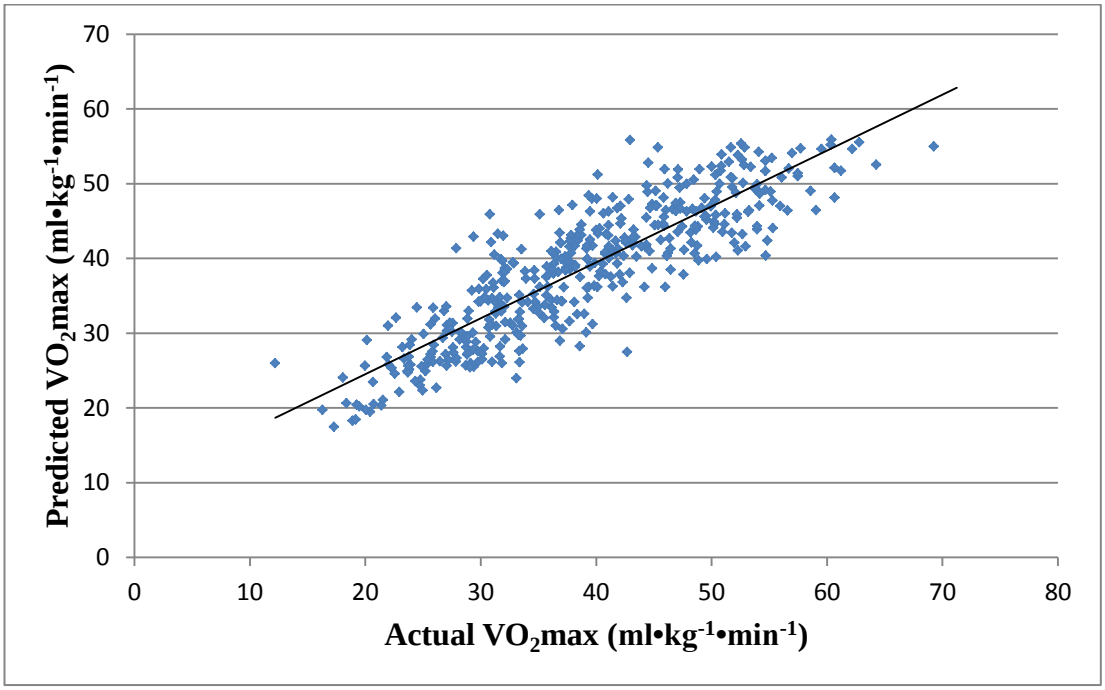

Figure 4.37. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 27 using SVM on VO_2max-set-3.

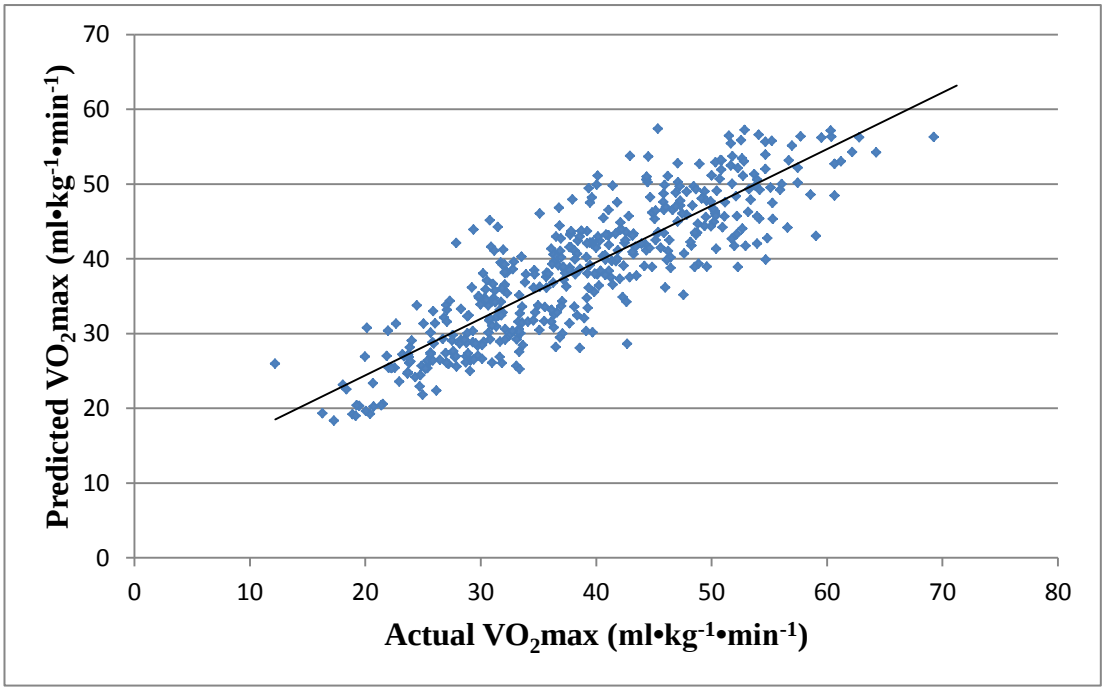

Figure 4.38. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 28 using SVM on VO_2max-set-3.

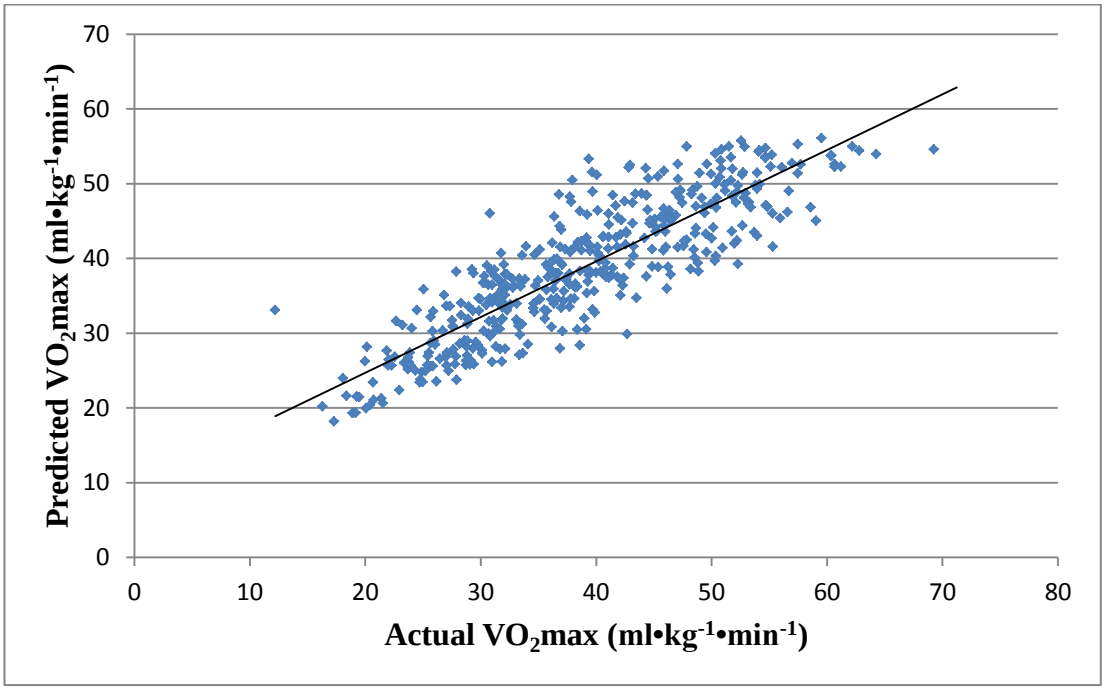

Figure 4.39. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 29 using SVM on VO_2max-set-3.

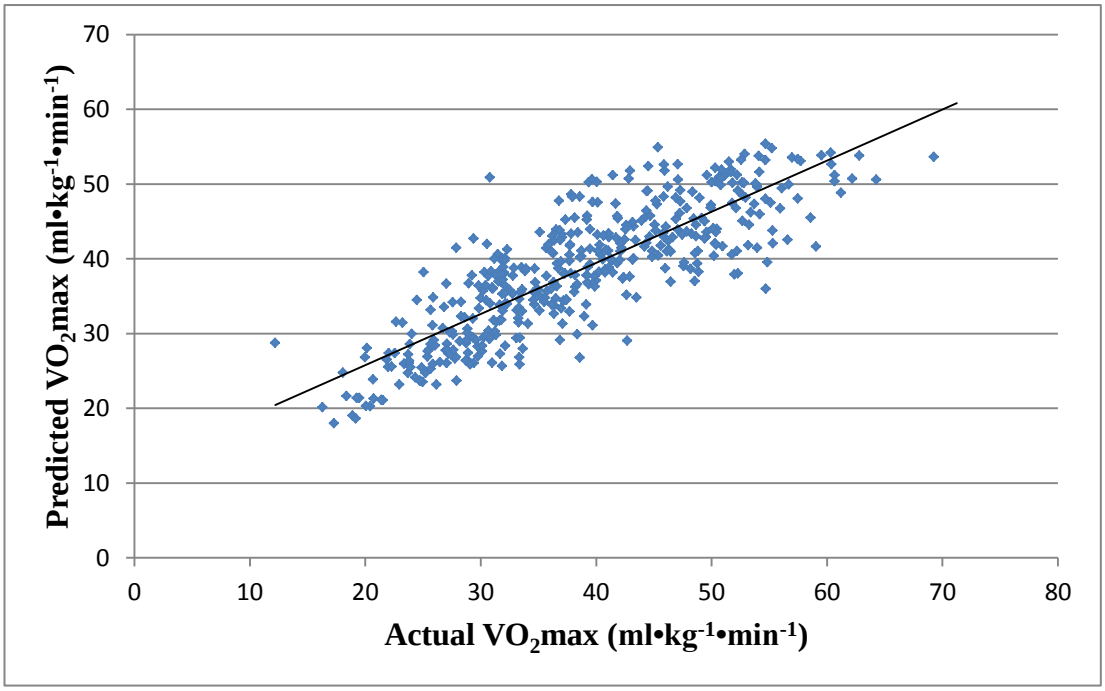

Figure 4.40. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 30 using SVM on VO_2max-set-3.

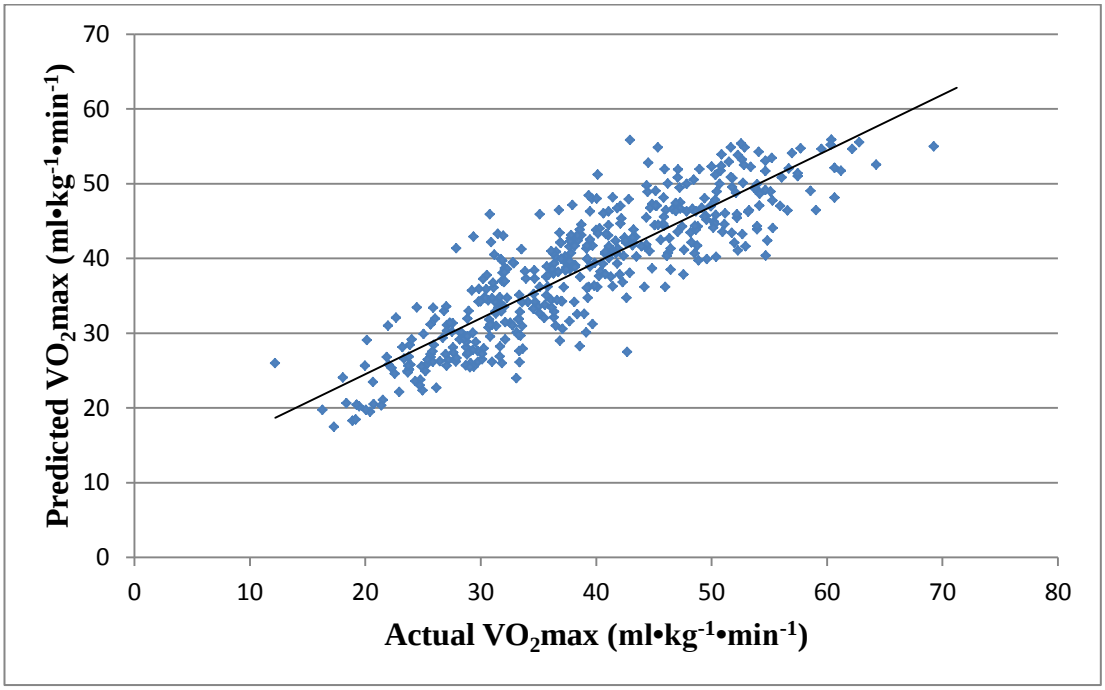

Figure 4.41. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 31 using SVM on VO_2max-set-3.

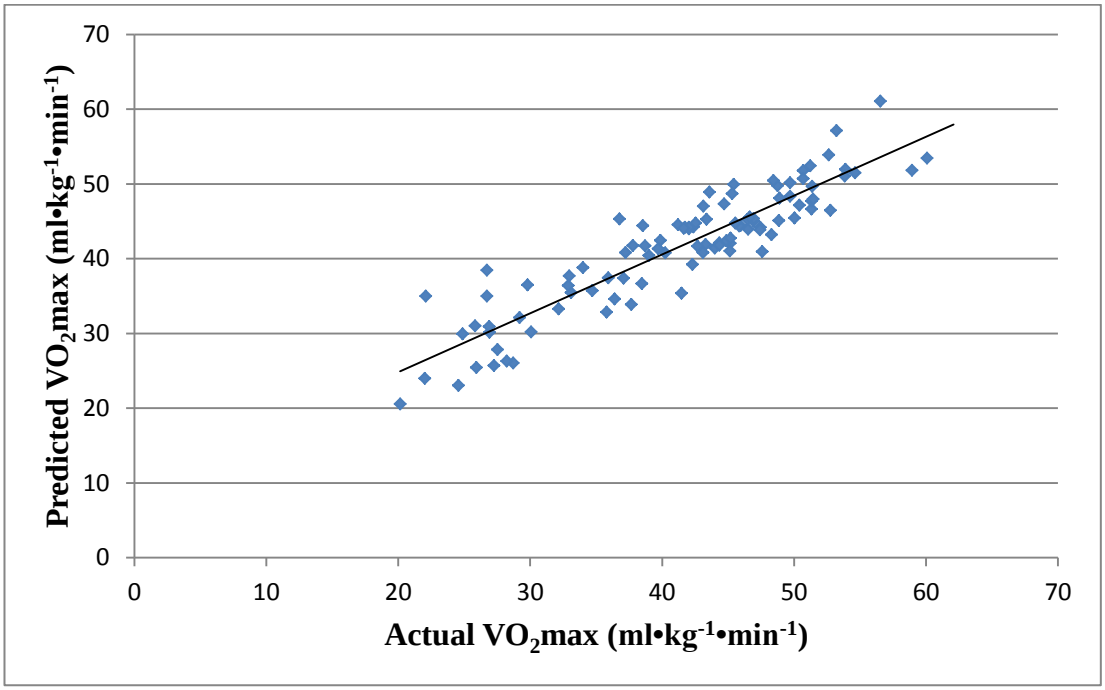

Figure 4.42. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 32 using SVM on VO_2max-set-4.

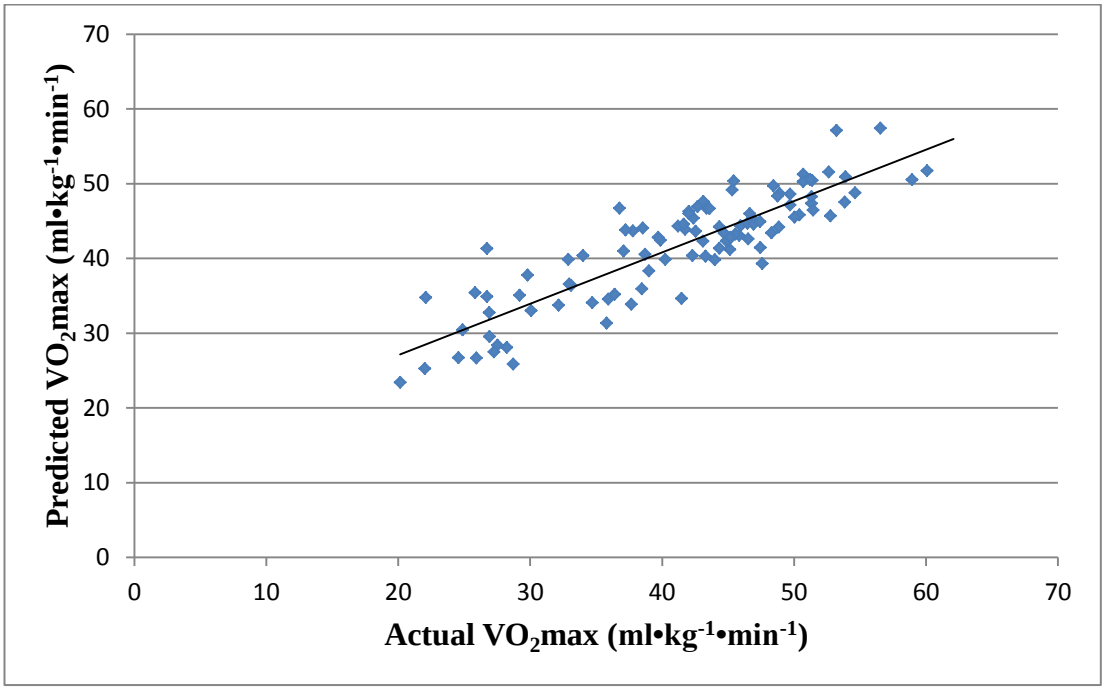

Figure 4.43. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 33 using SVM on VO_2max-set-4.

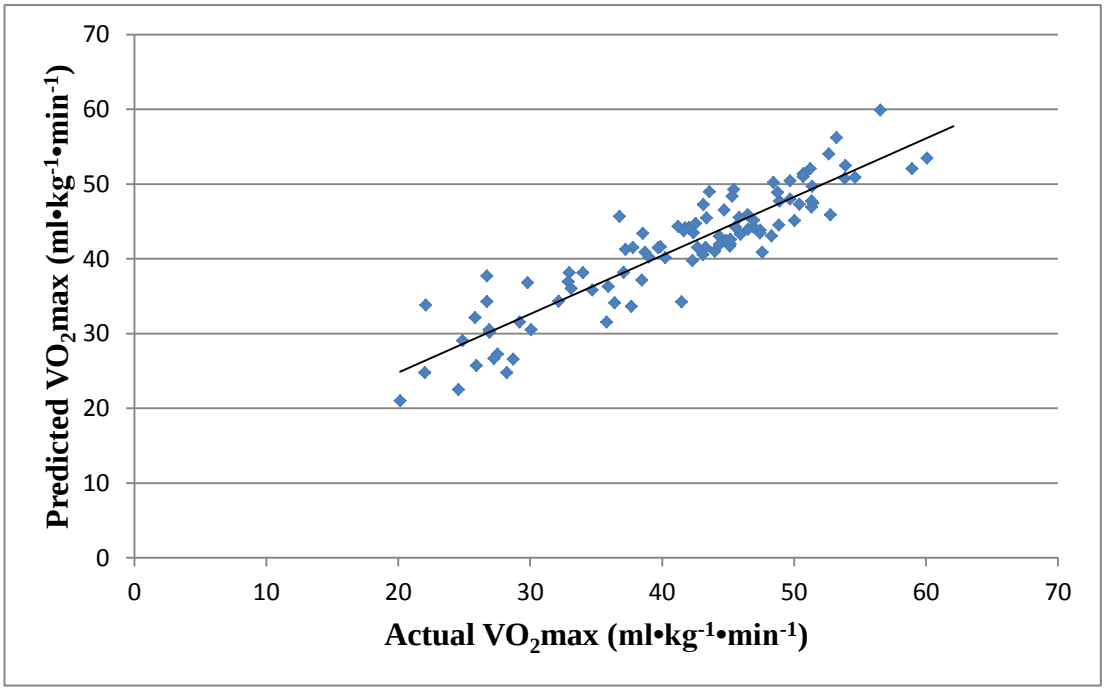

Figure 4.44. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 34 using SVM on VO_2max-set-4.

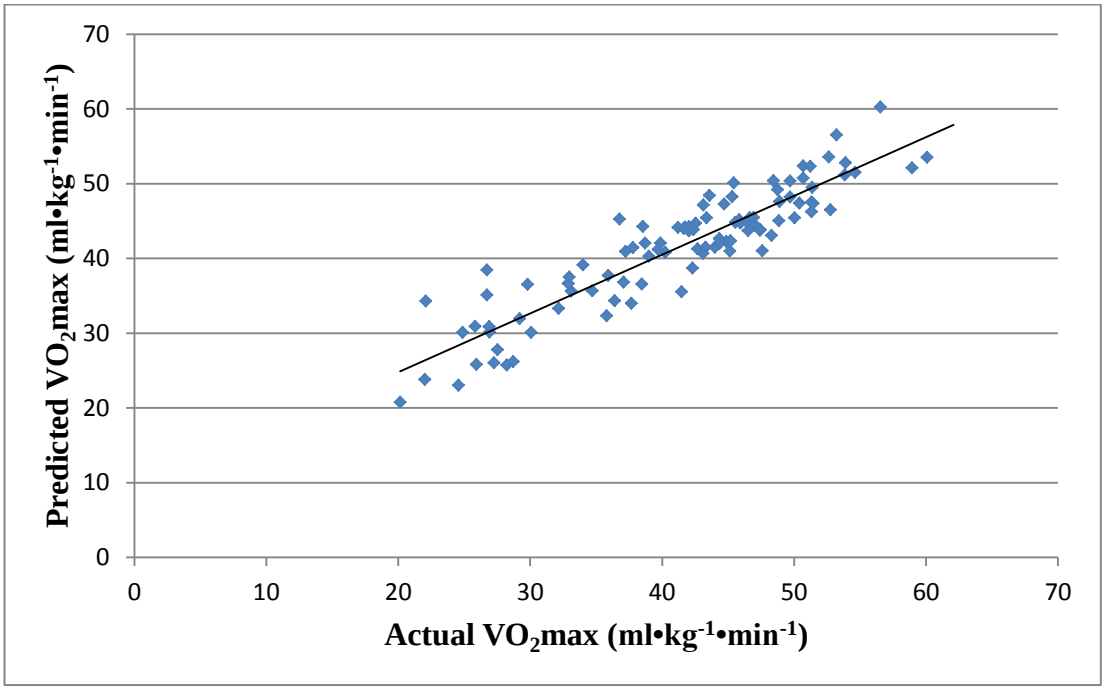

Figure 4.45. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 35 using SVM on VO_2max-set-4.

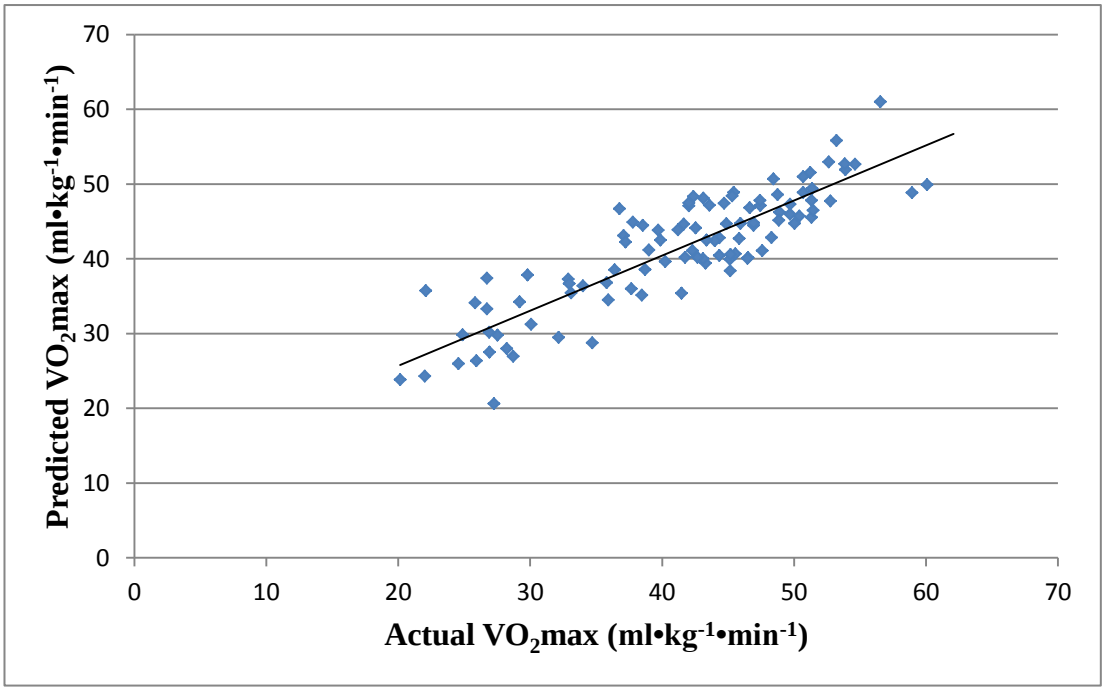

Figure 4.46. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 36 using SVM on VO_2max-set-4.

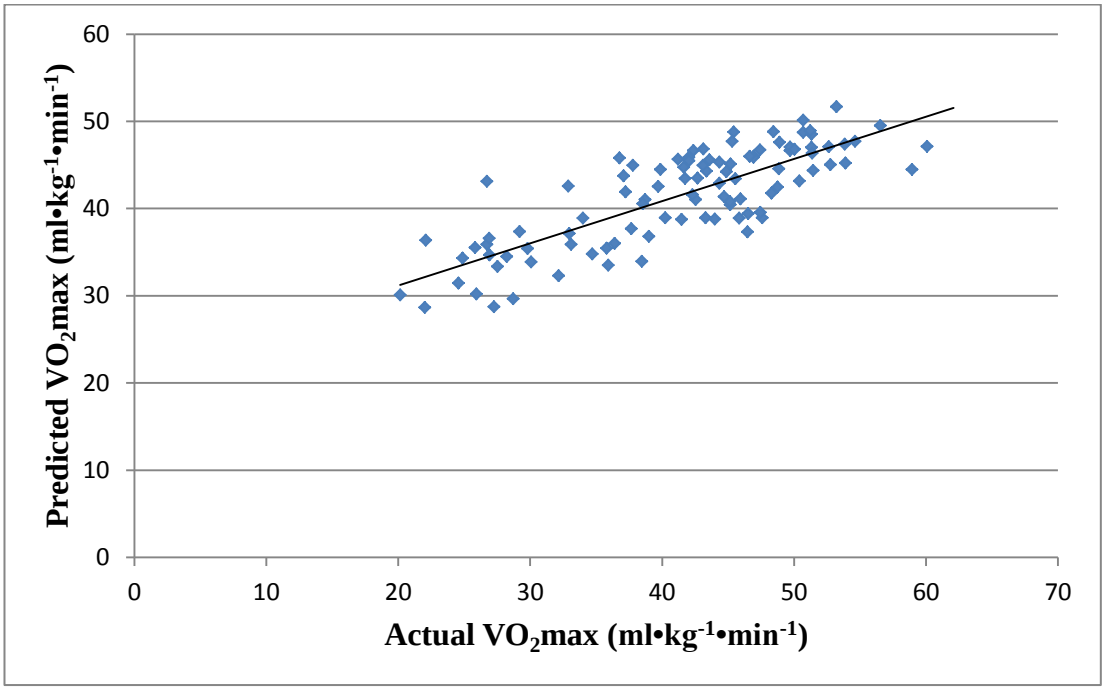

Figure 4.47. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 37 using SVM on VO_2max-set-4.

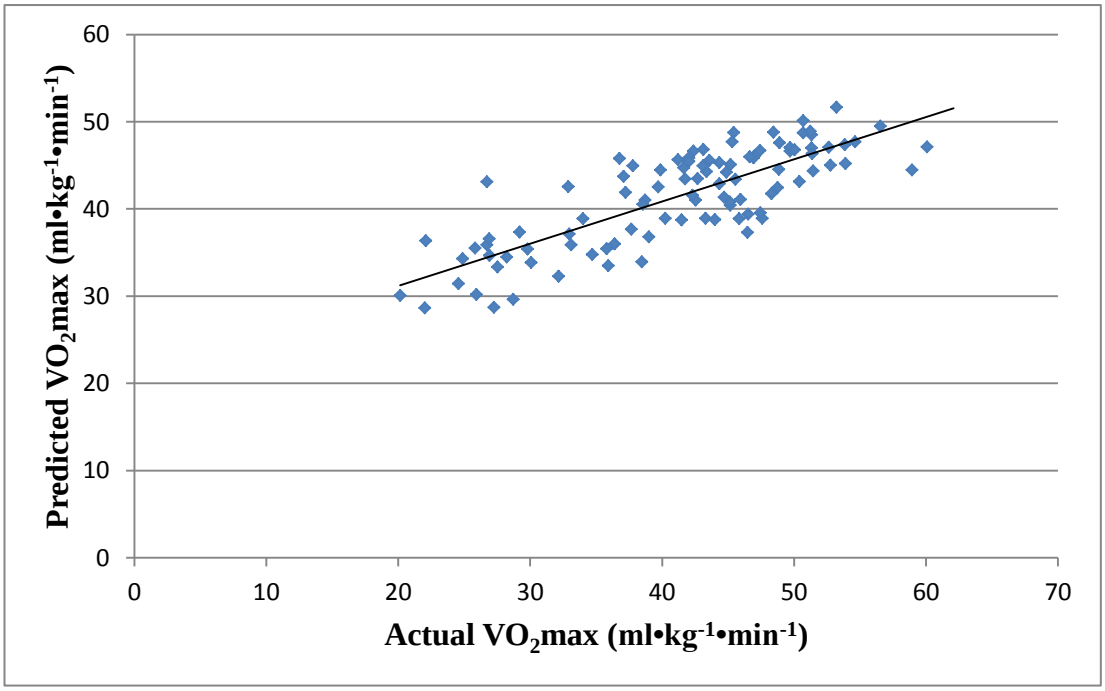

Figure 4.48. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 38 using SVM on VO_2max-set-4.

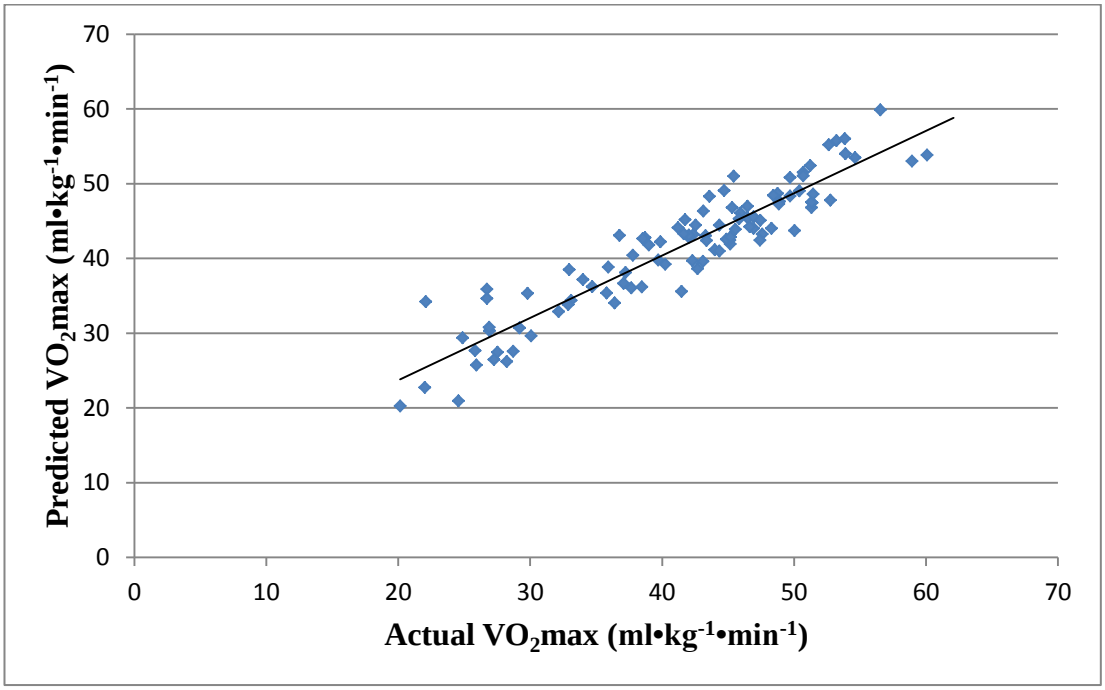

Figure 4.49. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 39 using SVM on VO_2max-set-4.

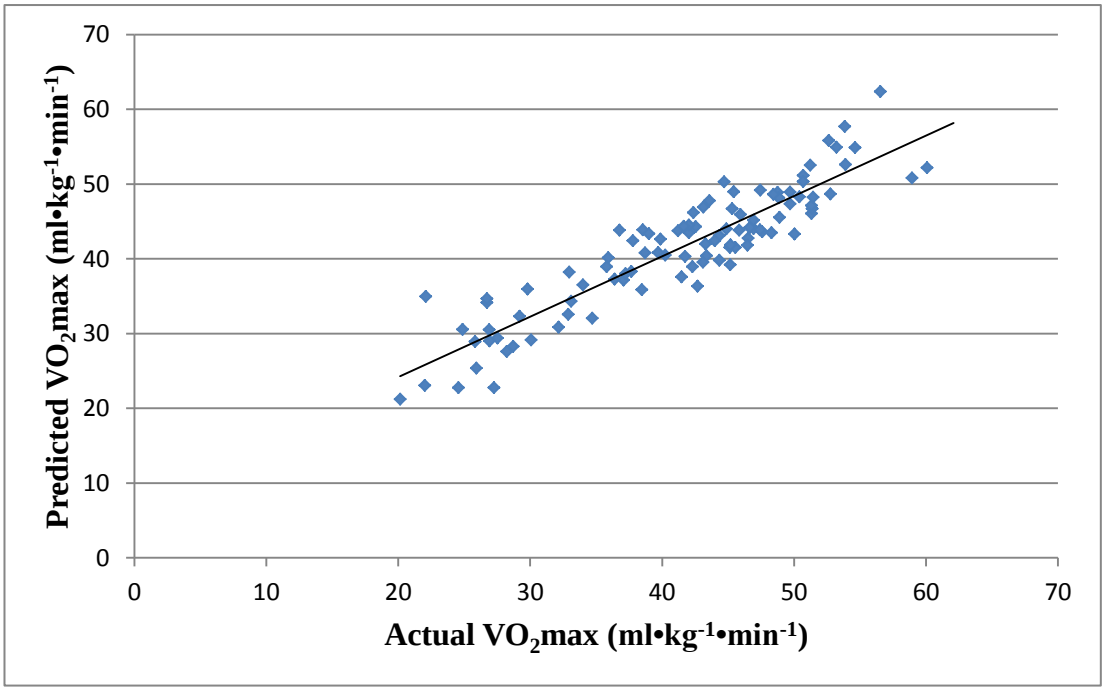

Figure 4.50. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 40 using SVM on VO_2max-set-4.

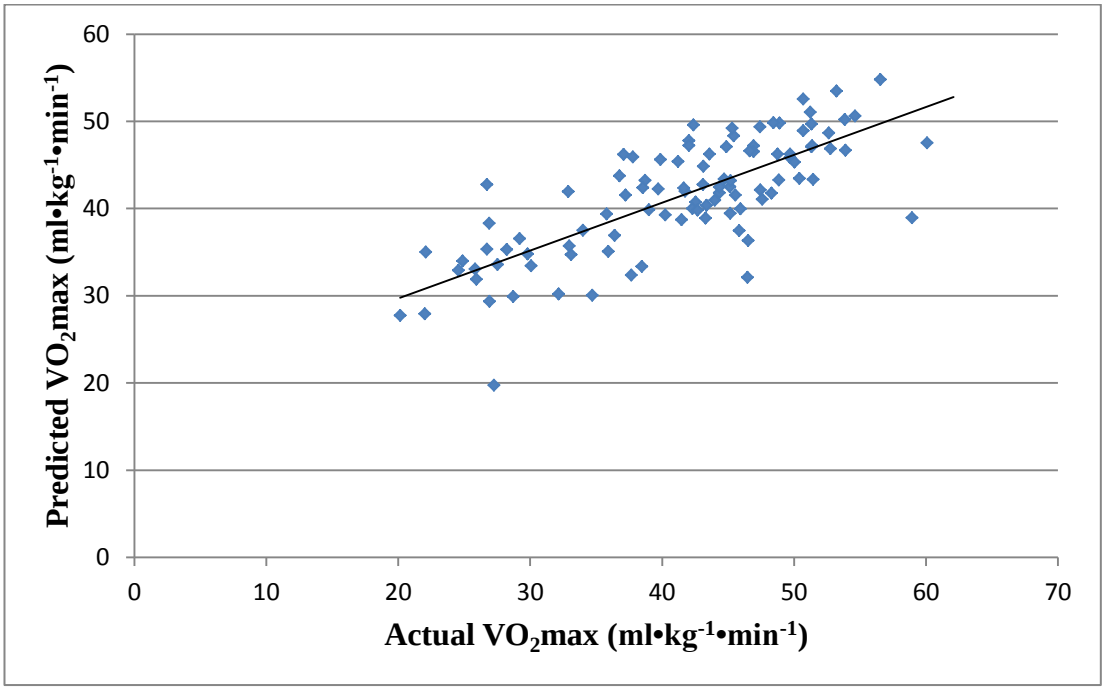

Figure 4.51. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 41 using SVM on VO_2max-set-4.

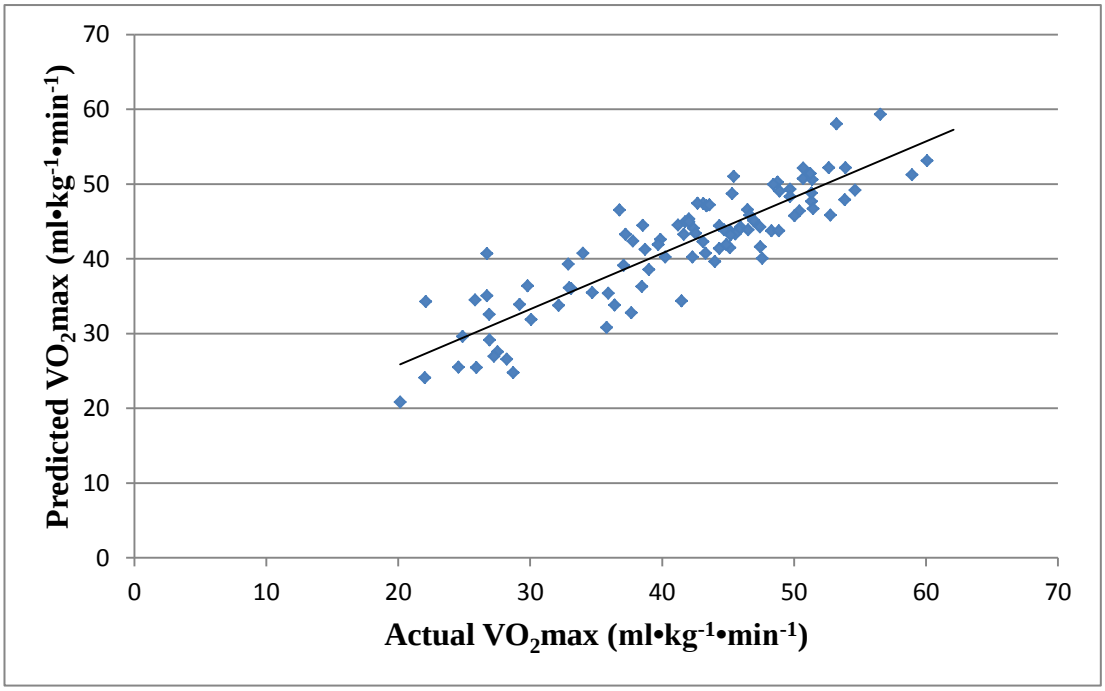

Figure 4.52. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 42 using SVM on VO_2max-set-4.

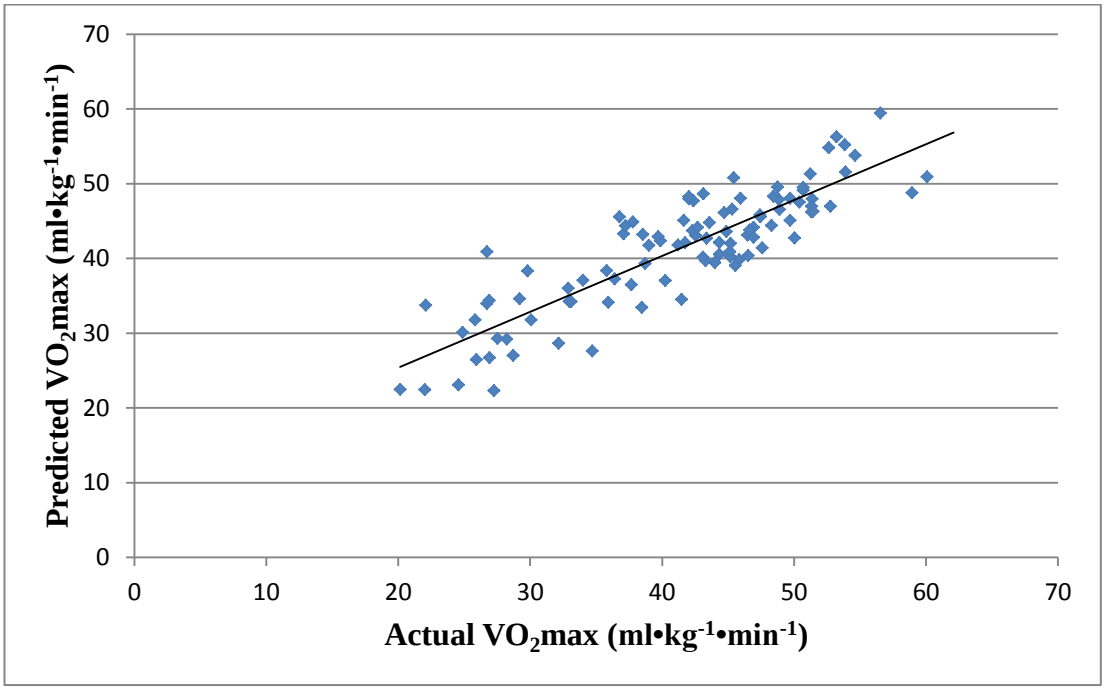

Figure 4.53. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 43 using SVM on VO_2max-set-4.

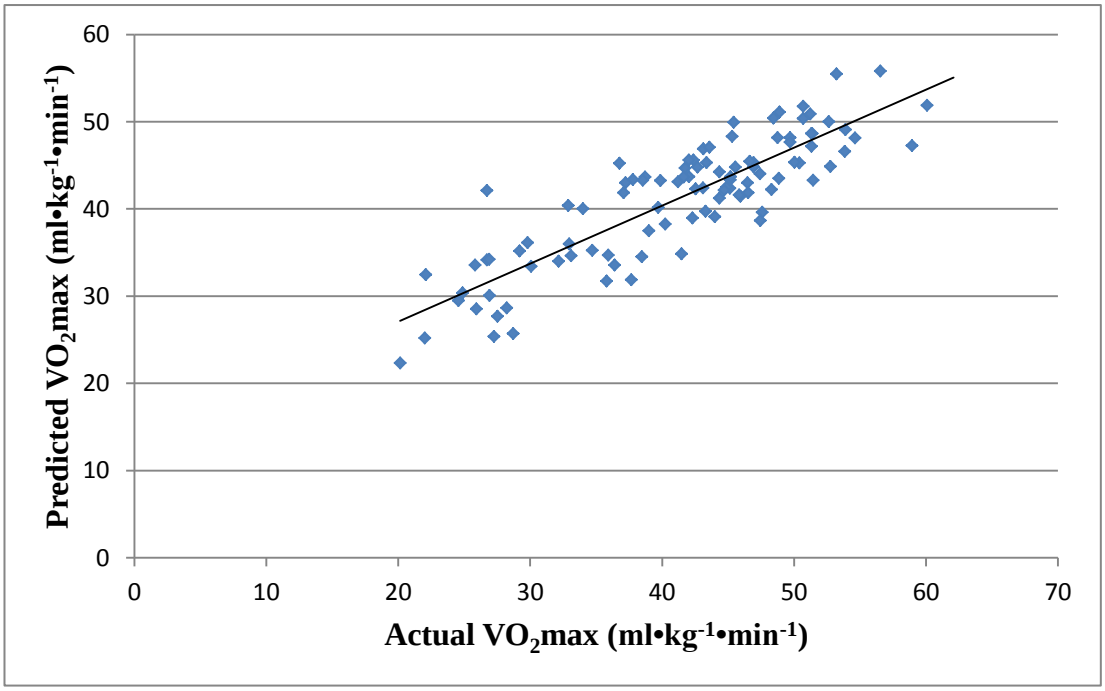

Figure 4.54. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 44 using SVM on VO_2max-set-4.

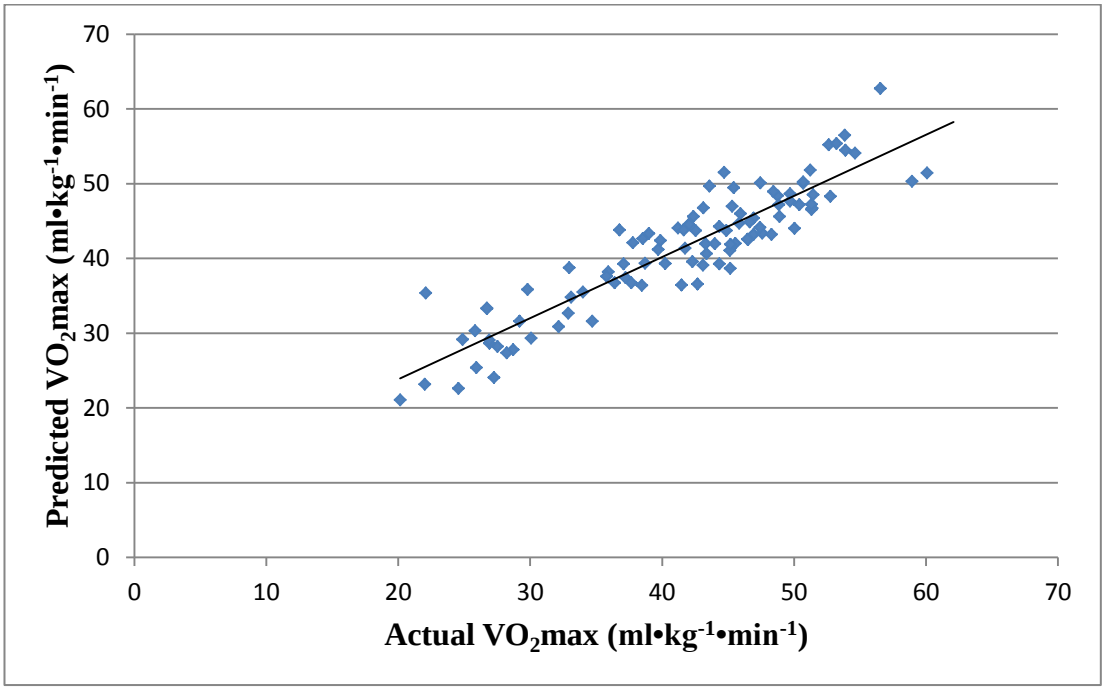

Figure 4.55. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 45 using SVM on VO_2max-set-4.

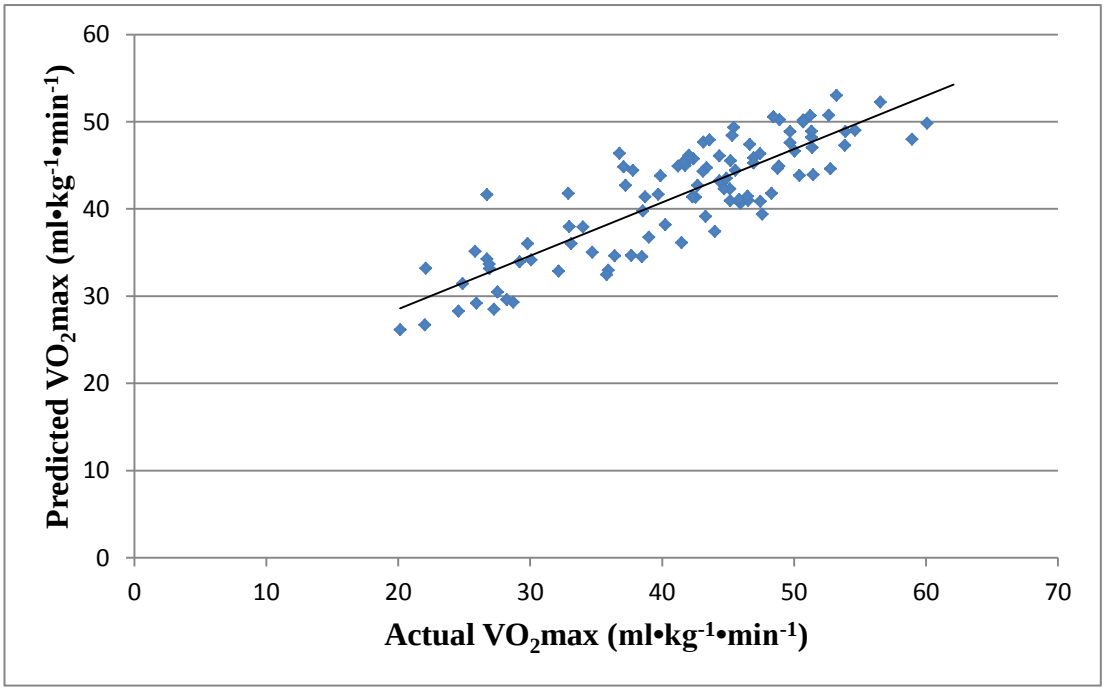

Figure 4.56. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 46 using SVM on VO_2max-set-4.

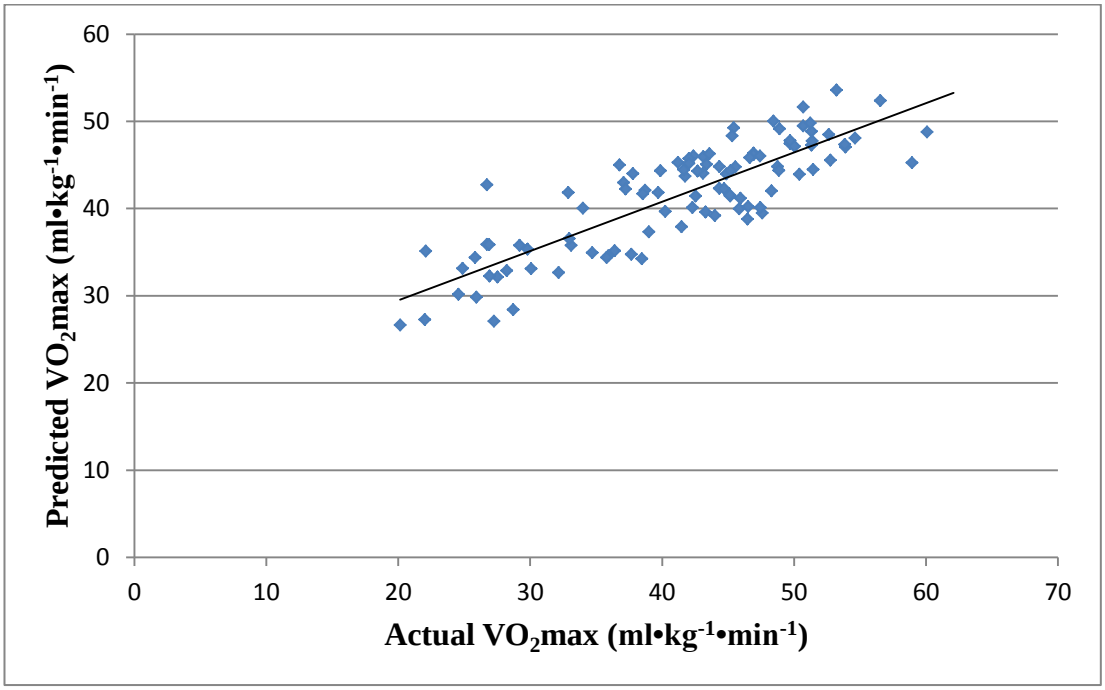

Figure 4.57. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 47 using SVM on VO_2max-set-4.

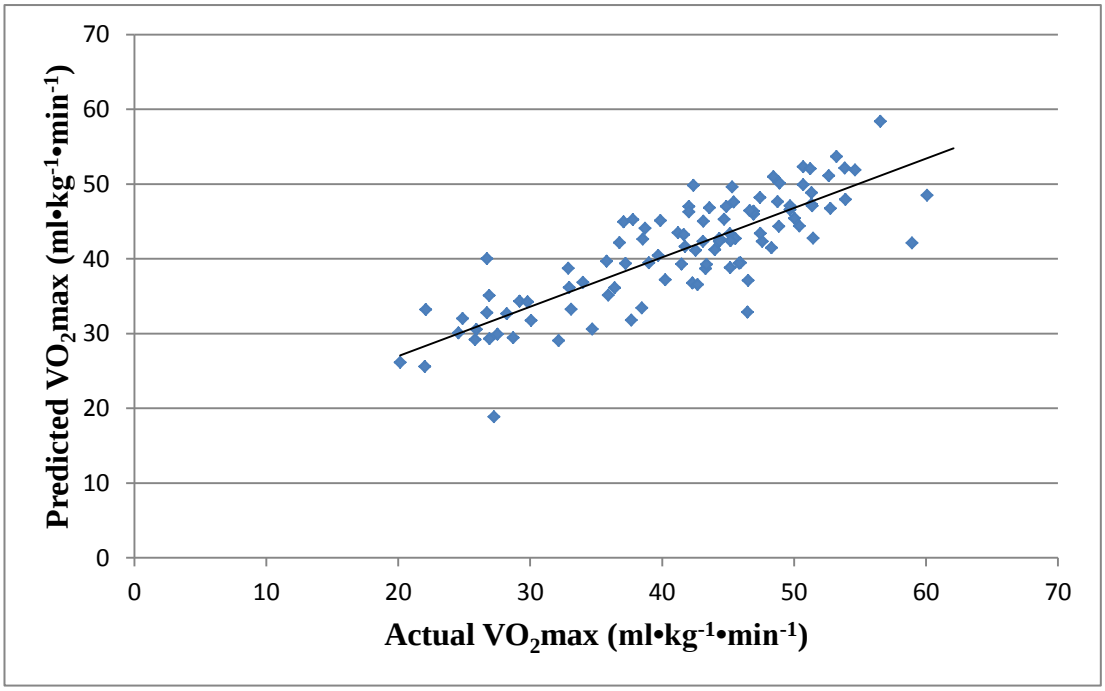

Figure 4.58. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 48 using SVM on VO_2max-set-4.

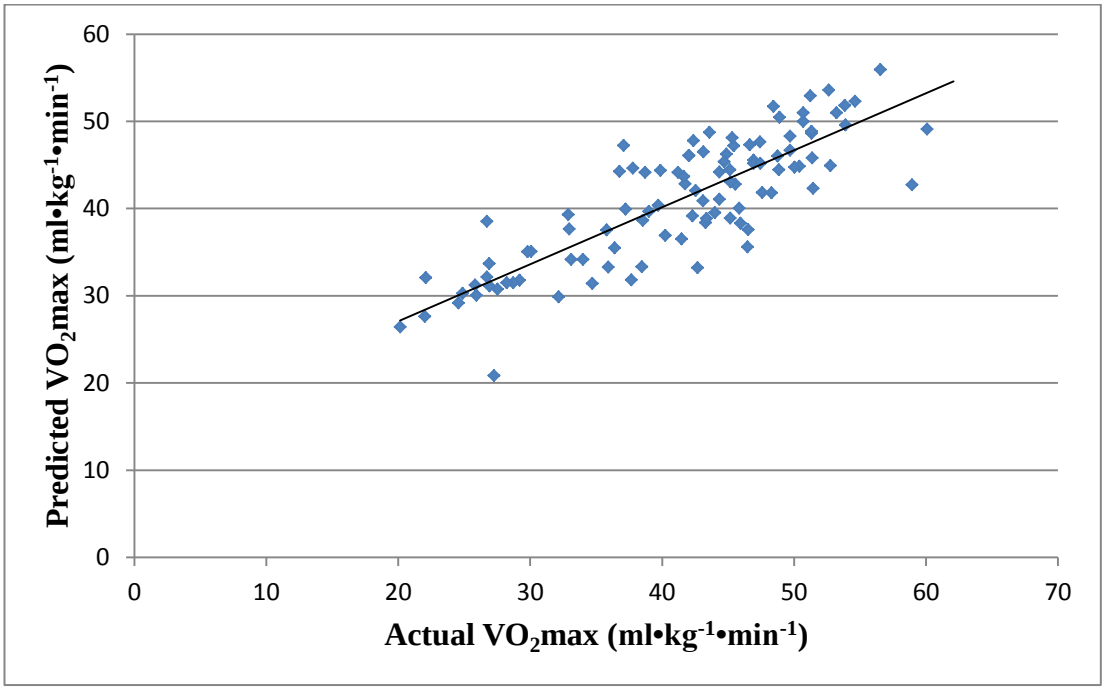

Figure 4.59. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 49 using SVM on VO_2max-set-4.

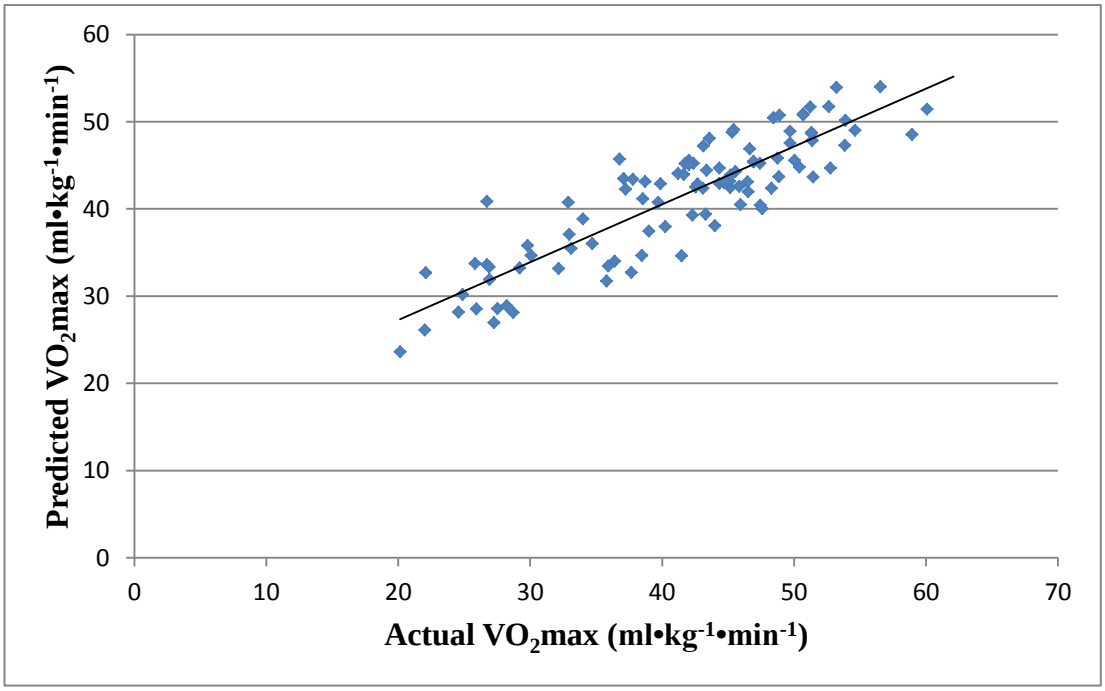

Figure 4.60. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 50 using SVM on VO_2max-set-4.

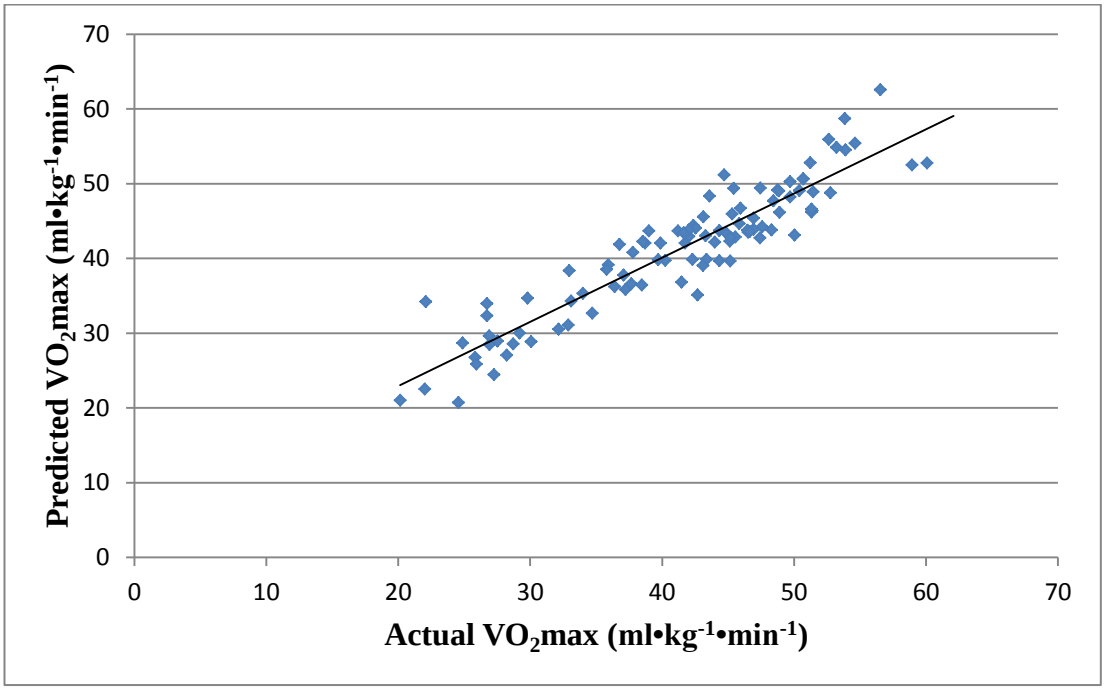

Figure 4.61. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 51 using SVM on VO_2max-set-4.

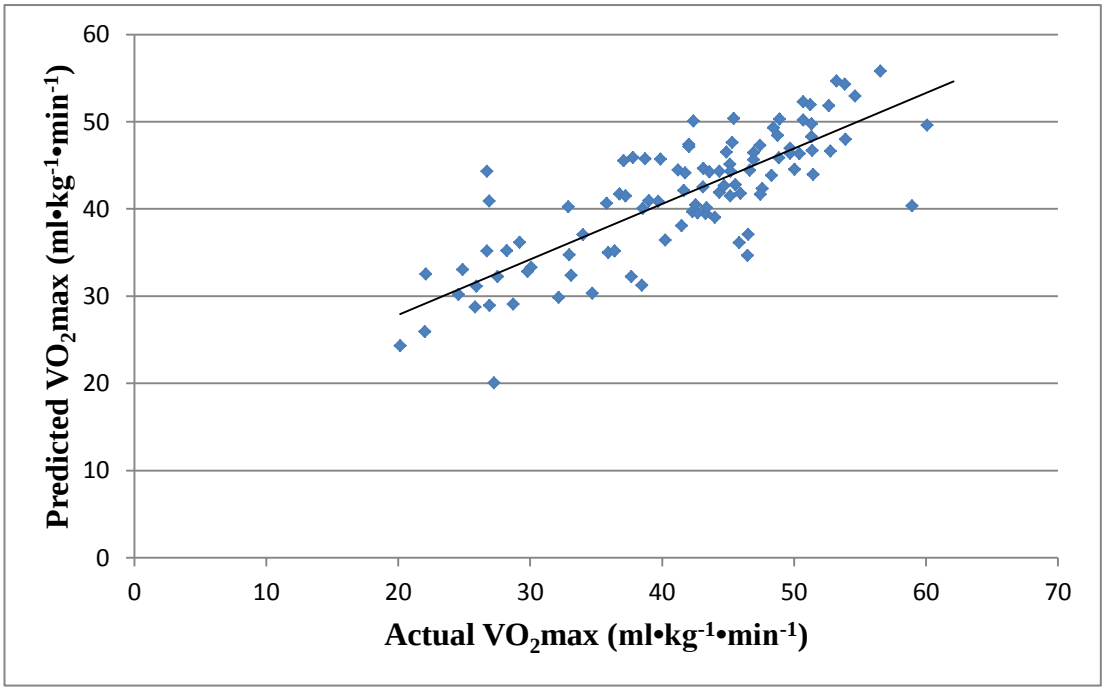

Figure 4.62. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 52 using SVM on VO_2max-set-4.

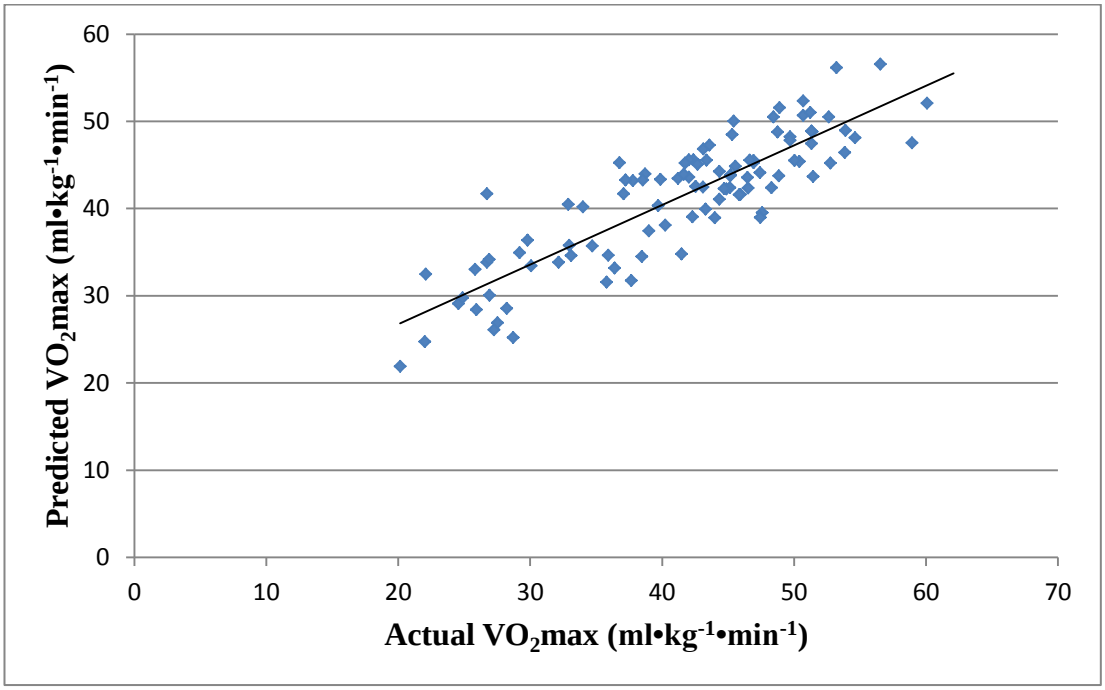

Figure 4.63. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 53 using SVM on VO_2max-set-4.

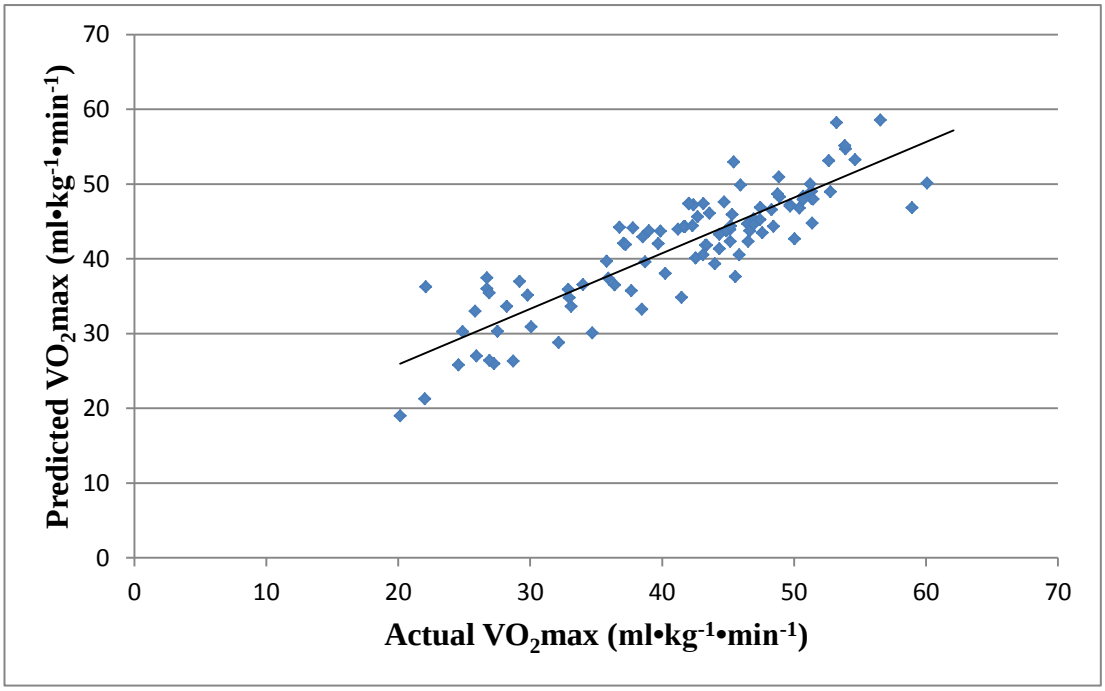

Figure 4.64. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 54 using SVM on VO_2max-set-4.

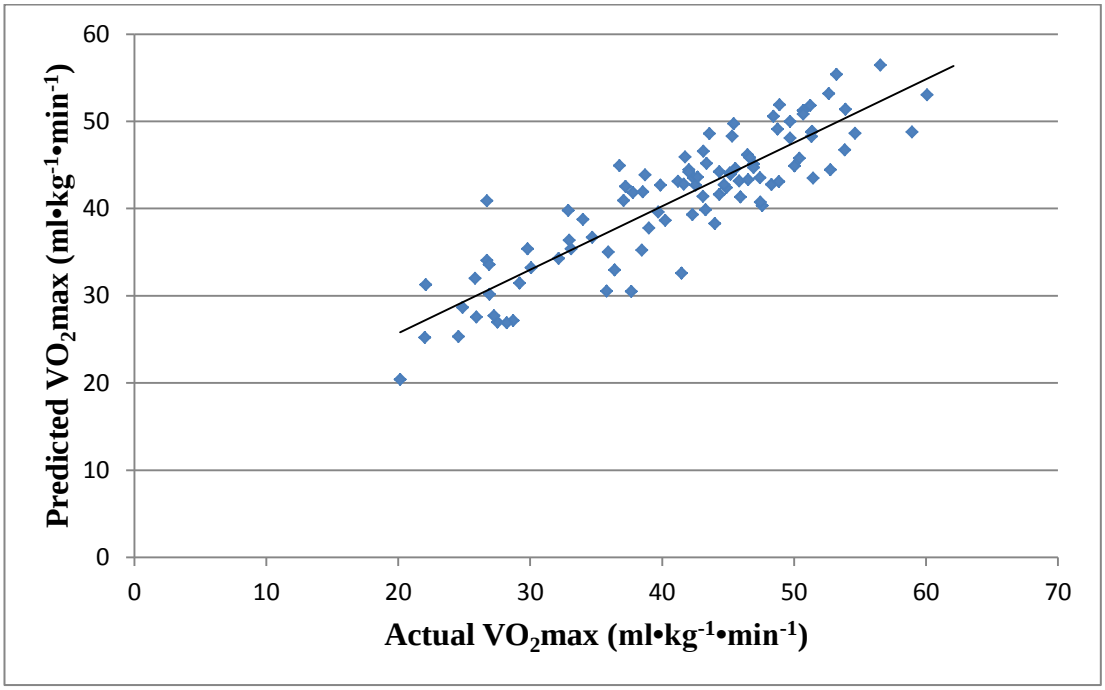

Figure 4.65. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 55 using SVM on VO_2max-set-4.

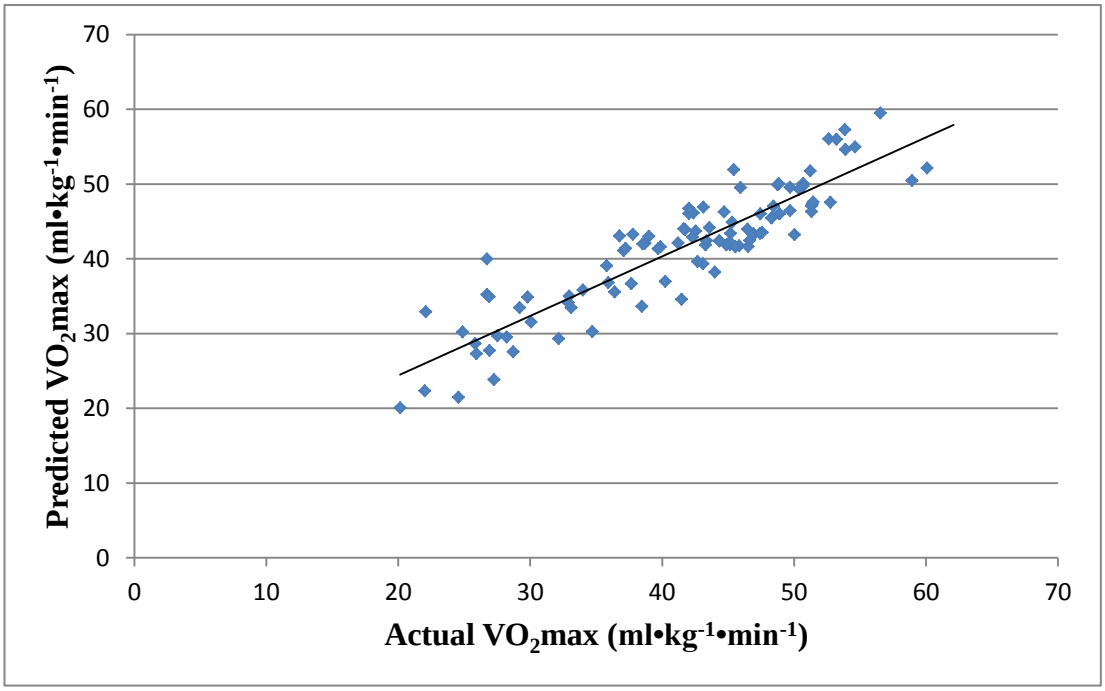

Figure 4.66. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 56 using SVM on VO_2max-set-4.

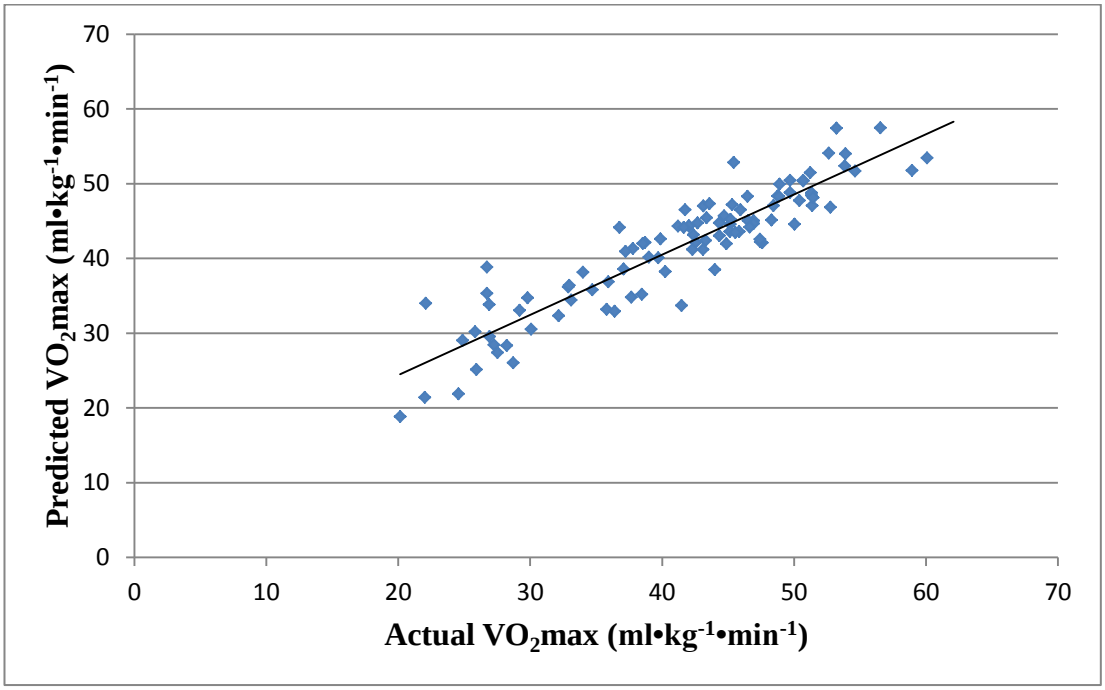

Figure 4.67. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 57 using SVM on VO_2max-set-4.

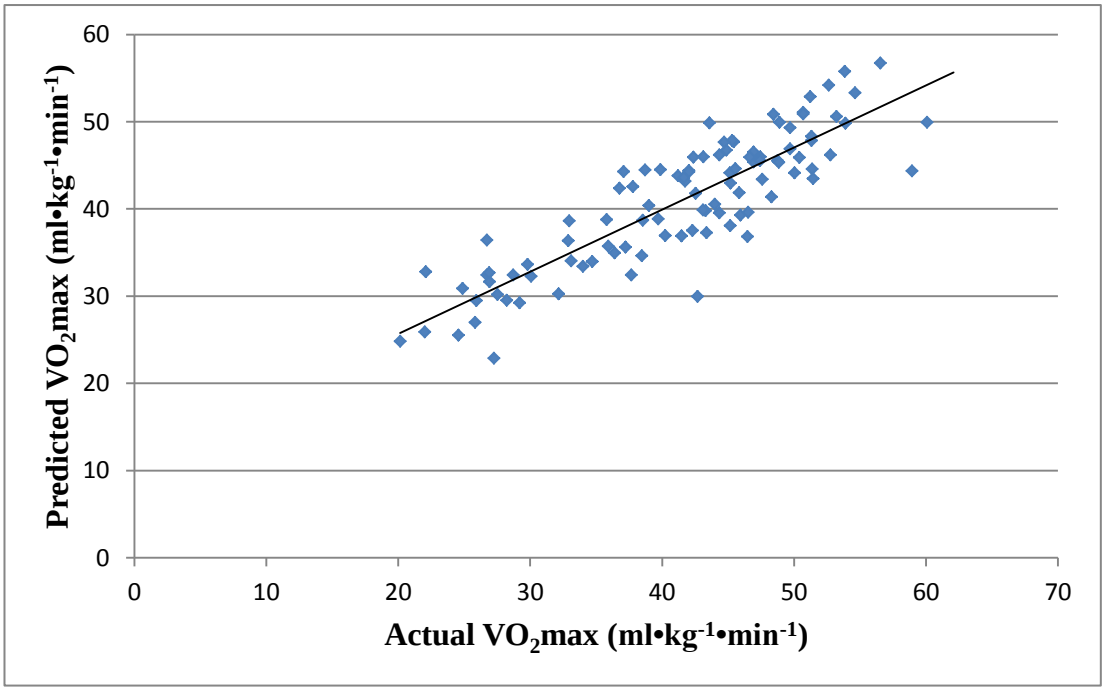

Figure 4.68. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 58 using SVM on VO_2max-set-4.

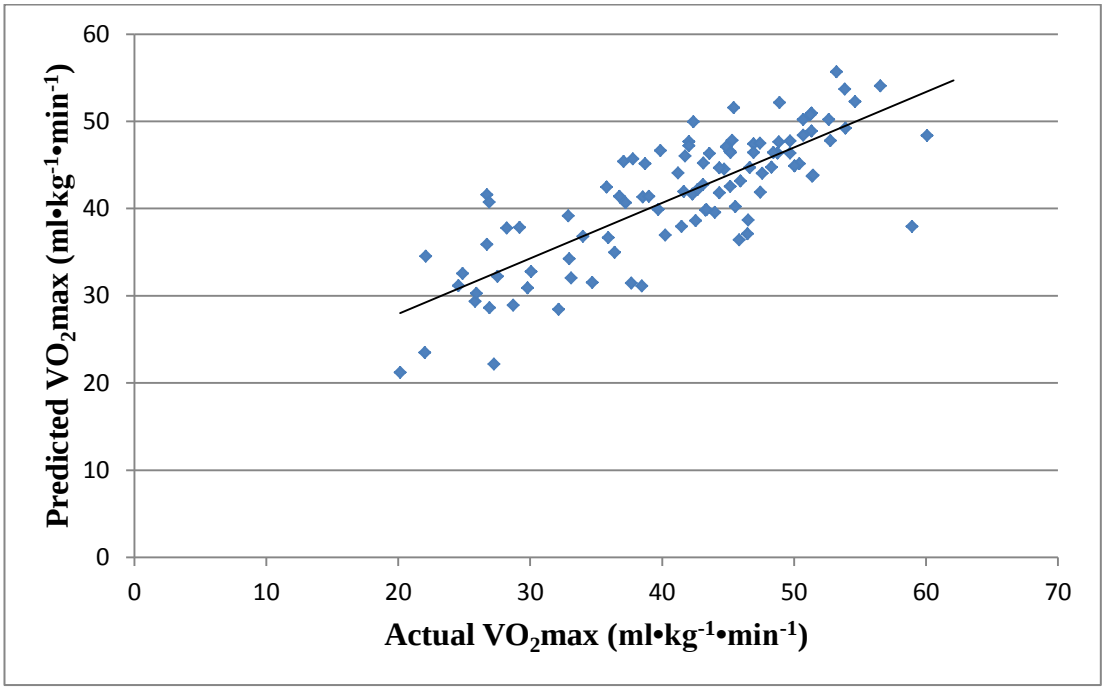

Figure 4.69. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 59 using SVM on VO_2max-set-4.

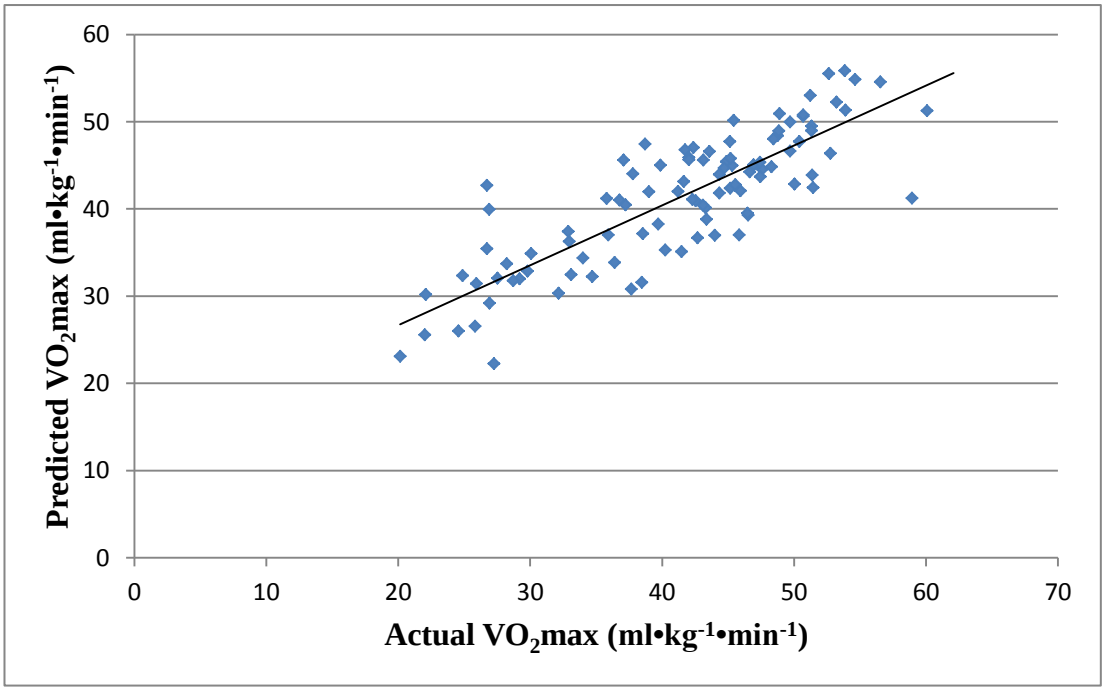

Figure 4.70. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 60 using SVM on VO_2max-set-4.

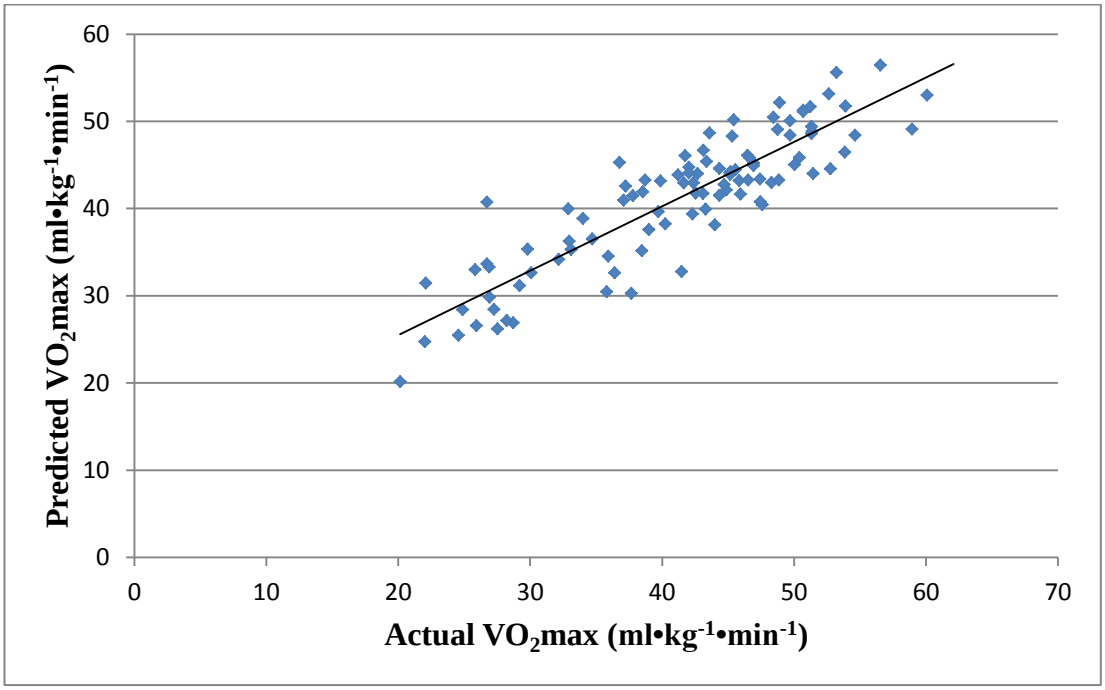

Figure 4.71. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 61 using SVM on VO_2max-set-4.

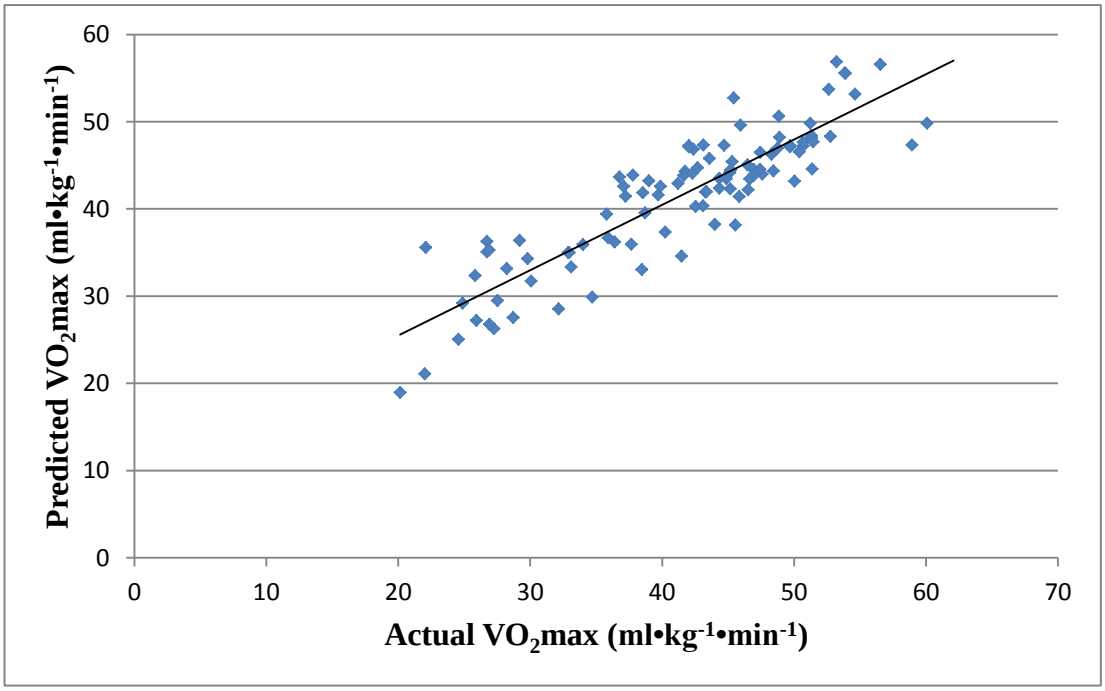

Figure 4.72. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 62 using SVM on VO_2max-set-4.

4.7. Performance Improvement of SVM-based and MFANN-based Models

In this section, we propose a new approach for improving the performance of SVM and MFANN models for VO_2max prediction. Figure 4.73. shows the flow chart of the improved SVM-based and MFANN-based models for predicting VO_2max. Initially, the data set is standardized to have zero mean and unit variance and splitted into train and test sets using a predetermined train/test split ratio. This standardization avoided predictor variables in greater numeric ranges dominate those in smaller numeric ranges and the computational difficulty associated with using larger numeric values.

5-fold cross validation is conducted on the training set to determine the optimized values of the parameters affecting the accuracy of the prediction models. More specifically, for the SVM-based prediction models, grid search has been applied to find the optimized values of *(C, ε, γ).* The overall root mean squared error is taken as a metric when deciding about the values of the optimized parameters. After experimenting with regular SVM-based prediction models, it has been shown that reducing the number of search steps in grid search does not make a significant increase in the *SEE* values. Also, it is well known that grid search is a time consuming process. Based on these two reasons, the range of the values of the parameters that are used to build improved SVM-based models (shown in Table 4.11.) differs from the ones that are used to build regular SVM-based models. Similarly, after experimenting with regular MFANN prediction models, the optimized value of the number of hidden layers turned out to be less than 10. Also, it did not make a big difference when the step size of the learning rate was changed as 0.1. Therefore, we used a different range and step size for the number of neurons in the hidden layer and learning rate, respectively (given in Table 4.12.) in developing the improved MFANN prediction models.

Table 4.11. SVM Model parameters and parameter values for proposed data reduction algorithm.

Parameter	**Min Value**	**Max Value**	**Values in Between Min and Max Value**
C	2^{-6}	2^{16}	2^{2n}, n = -3,…,8, (except n = 0)
ε	2^{-10}	2^{8}	2^{2n}, n = -5,…,4, (except n = 0)
γ	2^{-12}	2^{6}	2^{2n}, n = -6,…,3, (except n = 0)

Table 4.12. MFANN Model parameters and parameter values for proposed data reduction algorithm.

Parameter	**Min Value**	**Max Value**	**Step**
Number of neurons in the hidden layer	2	10	1
Learning rate (η)	0.1	0.5	0.1
Momentum (α)	0.1	0.5	0.1

The prediction model is developed after training subset is trained with the optimized parameters. Then, the prediction model is used to estimate VO_2max values in the new test subset. By using actual and predicted VO_2max values, absolute error of each sample is calculated. If absolute error is greater than the specified threshold value, related sample is marked to be removed from the test subset after the algorithm is executed. After trying several different threshold values, it has been concluded that ±15% of the actual value serves as the optimum in terms of the obtained *SEE* values. If the absolute error is greater than 15%, the related sample is marked to be removed from the training data.

At the end of the data reduction algorithm, the new reduced train set is obtained by removing the samples that have been marked during training. Then search algorithm is applied to the reduced train set to find optimized parameters for improved SVM-based and MFANN-based prediction models separately. After that the prediction model is developed with the optimized parameters. Finally, the performance of the model has been evaluated by calculating the *SEE*'s and *R*'s of the test set.

The above mentioned process is repeated 5 times in order to increase the reliability of the presented results and the average values of *SEE* and *R* have been reported.

The performance of the proposed approach has been compared with two outlier detection algorithms namely Z-score and Grubbs' test. For the Z-score, the outliers are detected based on the mean and standard deviation of the data as well as the threshold value used for the Z-score of the sample. In statistics, the so-called 68-95-99.7 rule (empirical rule) is used for indicating the threshold values; more precisely 68.27%, 95.45% and 99.73% of the values lie within one, two and three standard deviations of the mean, respectively. In our Z-score calculations on data sets, 9 different threshold values in between one and three standard deviations of the mean with step size of 0.25 have been used. Results showed that using 1.75 standard deviation as a threshold value yielded the lowest *SEE*'s and highest *R*'s for the prediction models. Therefore, we chose to use 1.75-standard deviation as threshold value in our Z-score calculations on the data sets for comparison purposes.

As for the Grubbs' test, the following values have been used as the significance level: 0.01, 0.05 and 0.1. When the significance level was set to 0.01, it was observed that no outliers were detected in any of the data sets. When the significance level was set to 0.05, the Grubbs' test performed similarly to the Z-score using two-standard deviation as a threshold value. Results showed that using 0.1 as a significance level yielded the lowest *SEE*'s and highest *R*'s for the prediction models. Therefore, we chose to use 0.1 as the value of the significance level.

Table 4.15. shows the percentage of the removed samples for the outlier detection algorithms, Z-score and Grubbs' test.

In addition to the above mentioned outlier detection algorithms, box-plot and Walsh outlier detection algorithms have also been applied on all data sets. For the box-plot algorithm, no outliers were detected in VO_2max-set-1, VO_2max-set-3 and VO_2max-set-4, whereas a single outlier was detected in VO_2max-set-2. For the Walsh algorithm, only one outlier was detected for both VO_2max-set-1 and VO_2max-set-2, two outliers were detected for VO_2max-set-3 and no outliers were detected for VO_2max-set-4. Detection of only a few outliers on the data sets did not make significant changes in the *SEE* values of the prediction models. Because of this reason, the box-plot and Walsh algorithms were not included as outlier detection algorithms for comparison purposes.

In addition to the outlier detection algorithms mentioned above, several other algorithms have been investigated in detail to see whether or not they can be included in this thesis. However, due to the reasons given in Table 4.13, Dixon's test, Rosner's test and Discordance test were not included in this study.

Table 4.13. Reasons for the disuse of some other outlier detection algorithms

Algorithm	**Reason for the disuse of the Algorithm**
Dixon's Test	Used when the sample size is between 3 and 25 observations and used for detecting a small number of outliers.
Rosner's Test	Used for detecting up to 10 outliers
Discordance Test	Used when the sample size is between 3 and 50 observations.

Below is a detailed comparison of the proposed data reduction algorithm and the outlier algorithms named as Z-score and Grubbs' test.

1. In the proposed data reduction algorithm, irrelevant sample determination is carried out during training phase whereas the same occurs before training in the outlier detection algorithms.
2. The proposed data reduction algorithm uses absolute errors between the predicted and actual values to determine irrelevant samples. Outlier detection algorithms use different statistical methods for the same purpose.
3. The proposed data reduction algorithm presents intelligent and dynamic elimination of irrelevant samples whereas outlier detection algorithms use static elimination for the same purpose.
4. The performance of the proposed data reduction algorithm depends highly on the selection of the value of the threshold. The performance of the Grubbs' test depends on the value of the significance level, degrees of freedom, mean, standard deviation and data set size whereas the performance of the Z-score depends on the mean, standard deviation and threshold value.
5. The proposed data reduction algorithm is more selective compared to the outlier detection algorithms. Table 4.14. and Table 4.15. show the percentage

of the removed samples for the proposed approach as well as the outlier detection algorithms.

6. The disadvantage of the proposed data reduction algorithm is that it is more time consuming than the outlier detection algorithms owing to the fact that irrelevant sample determination is carried out during training phase yielding double training for developing the prediction models.

To apply our new approach for improving the performance of SVM and MFANN models for VO_2max prediction, data sets (VO_2max-set-1, VO_2max-set-2, VO_2max-set-3 and VO_2max-set-4) have been splitted into train and test sets. For all data sets, 70% of the data is used for the train set and the rest of the data is used for the test set (Split70). Data sets are named as VO_2max-set-1-Split70, VO_2max-set-2-Split70, VO_2max-set-3-Split70 and VO_2max-set-4-Split70, respectively. Similarly, 80% of the data is used for the train set and the rest of the data is used for the test set (Split80). Data sets are named as VO_2max-set-1-Split80, VO_2max-set-2-Split80, VO_2max-set-3-Split80 and VO_2max-set-4-Split80, respectively. Then we applied regular, outlier-based and improved VO_2max prediction models using SVM and MFANN for all Split70 and Split80 sets and calculated the *SEE*'s and *R*'s of the test sets.

Table 4.14. Average percentage of the removed samples for improved MFANN-based and SVM-based models on Split70 sets and Split80 sets.

Method	**Data Set**	**Average Percentage of the Removed Samples for Split 70**	**Average Percentage of the Removed Samples for Split 80**
MFANN	VO_2max-set-1	11.3%	11.1%
	VO_2max-set-2	13.2%	14.8%
	VO_2max-set-3	15.1%	15.9%
	VO_2max-set-4	9.8%	10.1%
SVM	VO_2max-set-1	12.2%	11.8%
	VO_2max-set-2	14.2%	16.1%
	VO_2max-set-3	16.4%	16.9%
	VO_2max-set-4	10.5%	11.9%

Table 4.15. Percentage of the removed samples for outlier detection algorithms on data sets.

Algorithm	Parameter Value	Data Sets			
		VO_2max-set-1	**VO_2max-set-2**	**VO_2max-set-3**	**VO_2max-set-4**
Z-score	1	34.1%	37.1%	35.5%	35.0%
	1.25	22.2%	23.2%	23.9%	25.0%
	1.5	13.0%	13.4%	12.3%	16.0%
	1.75	7.6%	6.3%	6.6%	7.0%
	2	3.2%	2.7%	3.0%	4.0%
	2.25	1.1%	1.0%	1.1%	1.0%
	2.5	0.5%	0.5%	0.5%	No Outlier
	2.75	0.5%	0.1%	0.2%	No Outlier
	3	No Outlier	0.1%	No Outlier	No Outlier
Grubbs' Test	0.1	8.6%	8.2%	8.4%	10.0%
	0.05	3.7%	2.9%	3.4%	4.0%
	0.01	No Outlier	No Outlier	No Outlier	No Outlier

Table 4.16. through Table 4.23. show *SEE* and *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on VO_2max-set-1-Split70, VO_2max-set-2-Split70, VO_2max-set-3-Split70 and VO_2max-set-4-Split70, respectively.

Figure 4.74. through Figure 4.91. show the percentage decrease rates in *SEE*'s of outlier-based and improved SVM and MFANN prediction models compared to *SEE*'s obtained by regular SVM and MFANN prediction models on Split70 sets.

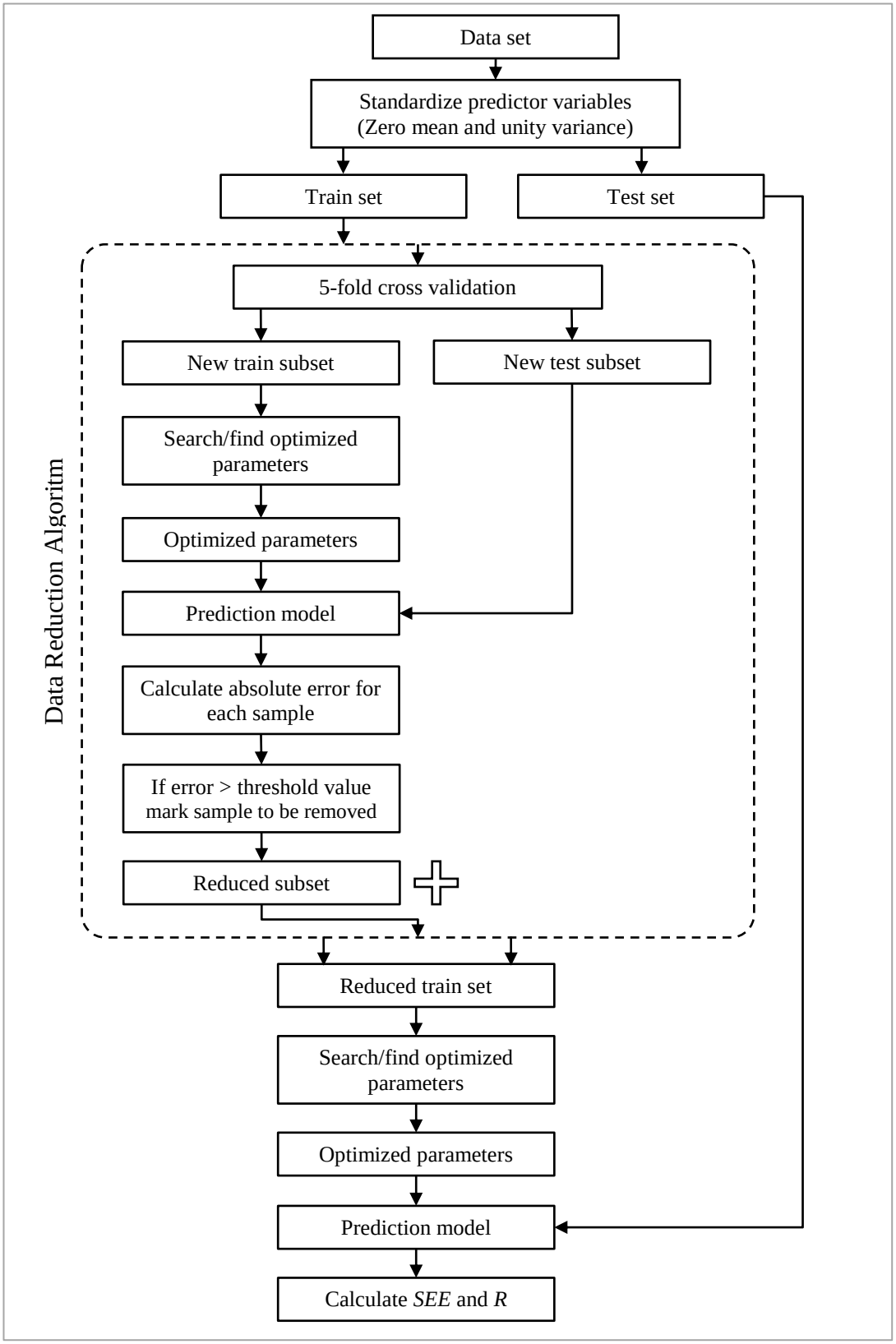

Figure 4.73. Flow chart of the improved SVM-based and MFANN-based models for predicting VO_2max

Table 4.16. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-1-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 1	4.02	3.95	3.94	3.79	3.79	3.70	3.67	3.37
Model 2	3.77	3.66	3.65	3.58	3.71	3.60	3.57	3.36
Model 3	3.58	3.50	3.47	3.45	3.45	3.36	3.36	3.12
Model 4	3.13	3.06	3.06	2.92	2.77	2.71	2.67	2.49
Model 5	3.79	3.70	3.72	3.64	3.67	3.59	3.57	3.18
Model 6	3.36	3.28	3.25	3.12	3.29	3.21	3.19	2.90
Model 7	3.00	2.94	2.91	2.82	2.73	2.67	2.62	2.40
Model 8	3.84	3.74	3.74	3.64	3.69	3.59	3.54	3.36
Model 9	3.78	3.72	3.69	3.51	3.66	3.54	3.52	3.30
Model 10	3.57	3.49	3.48	3.36	3.45	3.34	3.30	3.10
Model 11	3.68	3.61	3.59	3.48	3.47	3.37	3.37	3.15
Model 12	3.72	3.63	3.60	3.33	3.72	3.59	3.62	3.27
Model 13	3.53	3.45	3.43	3.30	3.44	3.32	3.29	3.01
Model 14	3.32	3.23	3.23	3.13	3.27	3.17	3.16	2.85
Model 15	4.74	4.65	4.62	4.57	4.48	4.35	4.30	4.09
Model 16	4.49	4.42	4.38	4.17	4.44	4.30	4.32	4.03
Model 17	4.54	4.45	4.44	4.35	4.47	4.34	4.28	3.99
Model 18	4.49	4.42	4.40	4.18	4.46	4.30	4.26	3.97
Model 19	4.44	4.34	4.33	4.19	4.40	4.27	4.29	3.98
Model 20	4.41	4.31	4.27	4.09	4.38	4.25	4.23	3.98
Model 21	4.44	4.31	4.30	4.17	4.42	4.27	4.24	4.01

Reg: Regular, **Imp**: Improved

Table 4.17. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-1-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 1	0.81	0.81	0.82	0.83	0.83	0.85	0.85	0.86
Model 2	0.84	0.84	0.84	0.86	0.85	0.85	0.86	0.88
Model 3	0.89	0.89	0.89	0.90	0.87	0.87	0.87	0.89
Model 4	0.91	0.91	0.91	0.92	0.92	0.92	0.92	0.94
Model 5	0.84	0.85	0.85	0.86	0.87	0.88	0.89	0.91
Model 6	0.87	0.88	0.88	0.88	0.89	0.89	0.89	0.92
Model 7	0.91	0.91	0.92	0.92	0.92	0.93	0.93	0.95
Model 8	0.87	0.88	0.88	0.89	0.86	0.87	0.87	0.89
Model 9	0.84	0.83	0.84	0.86	0.88	0.88	0.89	0.91
Model 10	0.88	0.88	0.88	0.90	0.88	0.89	0.89	0.90
Model 11	0.89	0.89	0.89	0.91	0.88	0.90	0.91	0.92
Model 12	0.85	0.86	0.87	0.87	0.85	0.85	0.86	0.88
Model 13	0.88	0.89	0.89	0.89	0.89	0.90	0.90	0.92
Model 14	0.89	0.90	0.90	0.91	0.89	0.90	0.90	0.91
Model 15	0.71	0.71	0.71	0.72	0.79	0.80	0.80	0.82
Model 16	0.76	0.76	0.76	0.77	0.77	0.78	0.78	0.80
Model 17	0.77	0.78	0.78	0.78	0.80	0.81	0.81	0.83
Model 18	0.75	0.75	0.76	0.77	0.77	0.77	0.77	0.79
Model 19	0.77	0.77	0.78	0.78	0.81	0.81	0.83	0.84
Model 20	0.77	0.76	0.77	0.79	0.77	0.78	0.78	0.80
Model 21	0.78	0.78	0.78	0.79	0.77	0.79	0.78	0.80

Reg: Regular, **Imp**: Improved

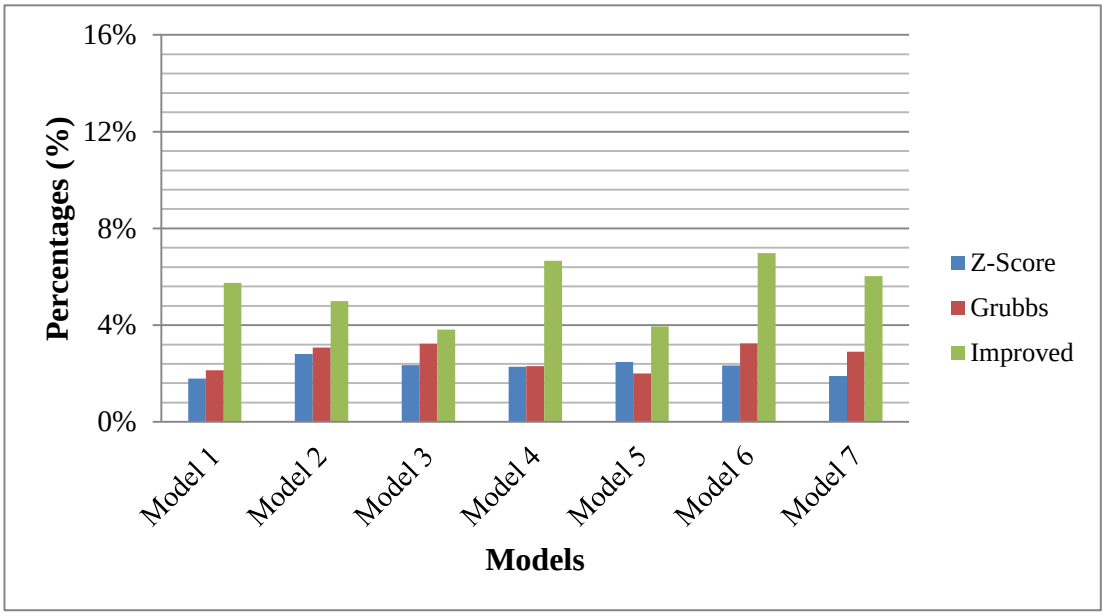

Figure 4.74. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-1-Split70 (Models 1-7)

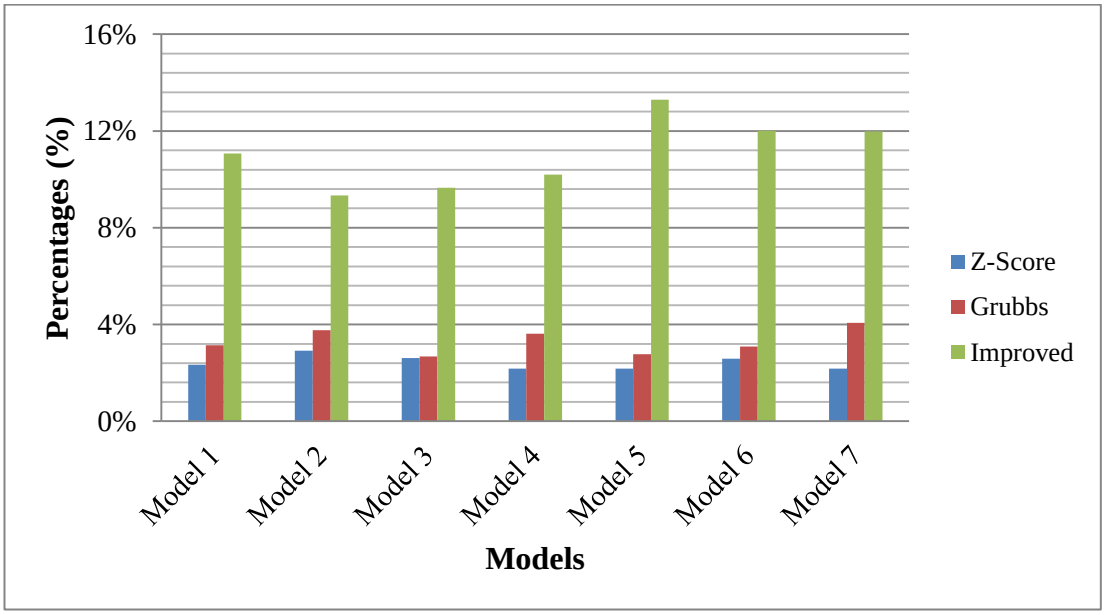

Figure 4.75. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-1-Split70 (Models 1-7)

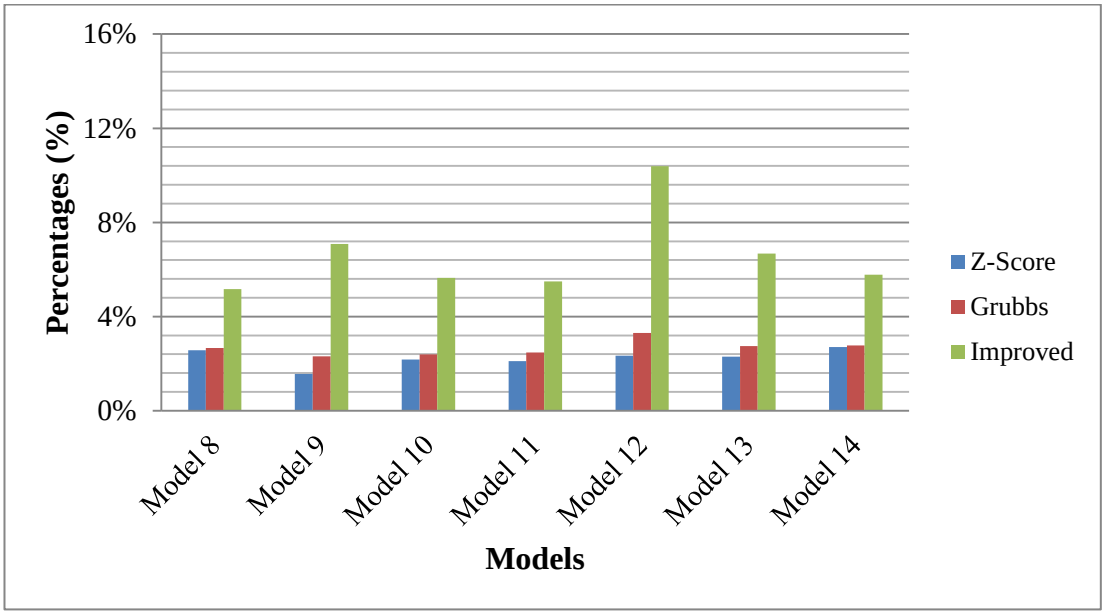

Figure 4.76. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-1-Split70 (Models 8-14)

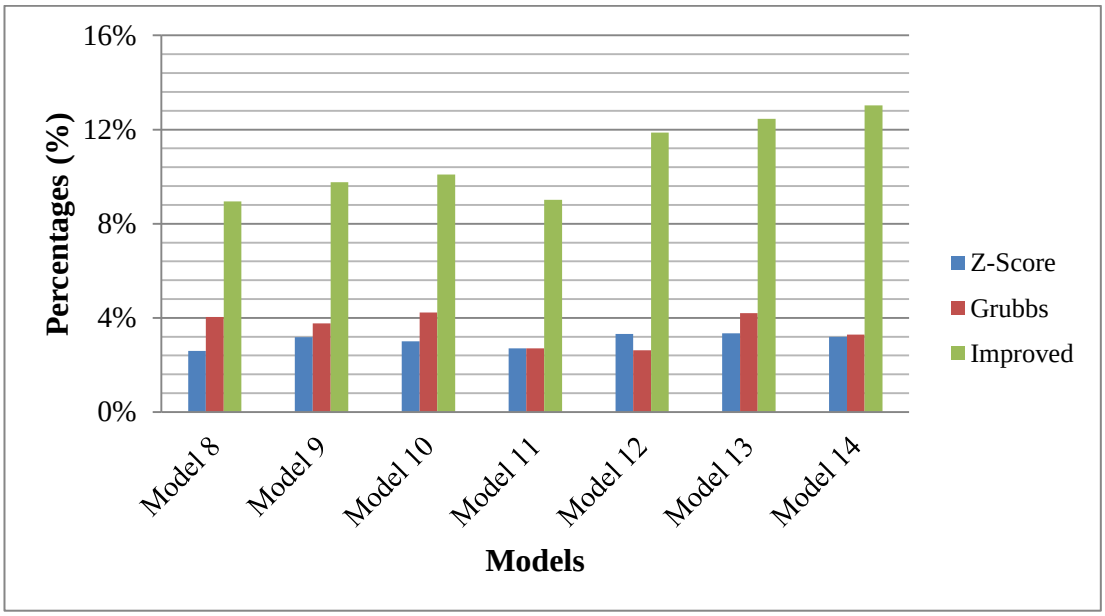

Figure 4.77. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction model on VO_2max-set-1-Split70 (Models 8-14)

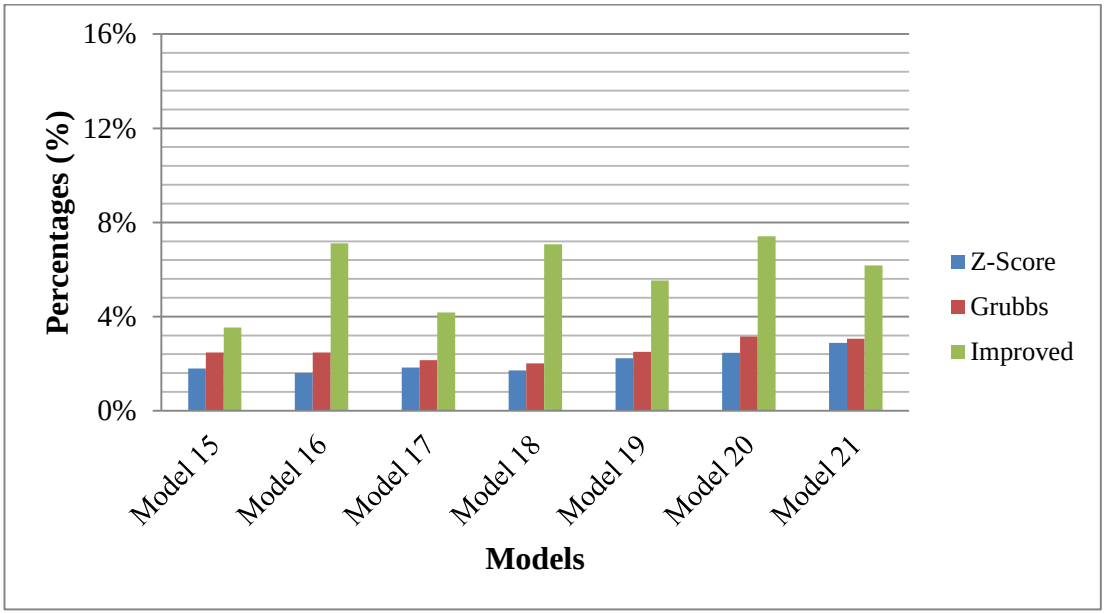

Figure 4.78. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-1-Split70 (Models 15-21)

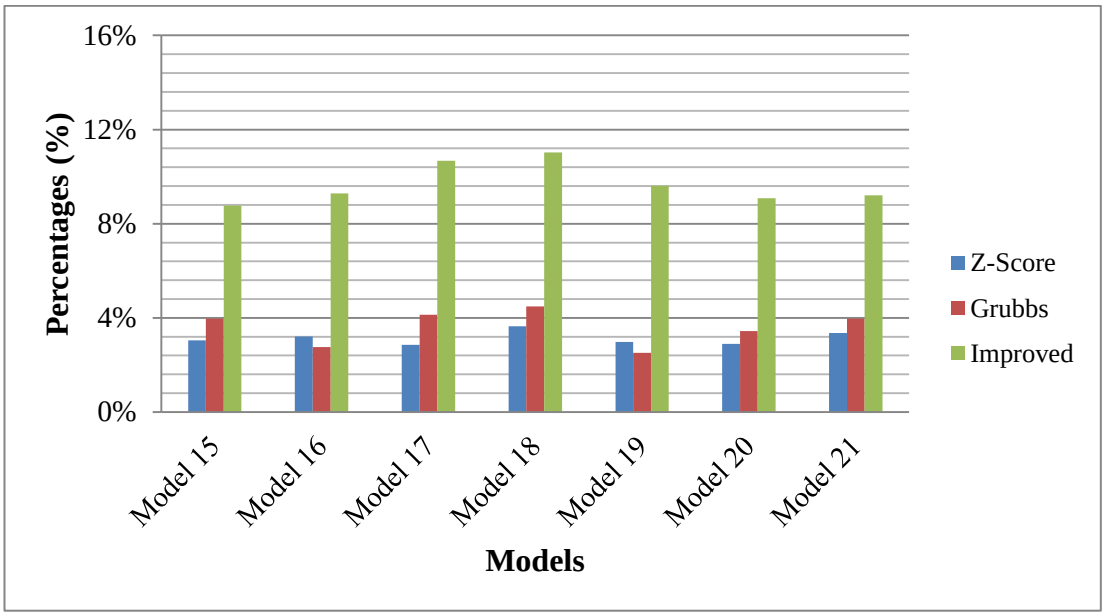

Figure 4.79. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-1-Split70 (Models 15-21)

Table 4.18. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-2-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 22	3.32	3.24	3.22	3.10	3.08	3.02	3.00	2.76
Model 23	3.53	3.45	3.43	3.38	3.47	3.31	3.28	3.08
Model 24	4.18	4.08	4.04	3.98	3.76	3.65	3.63	3.39

Reg: Regular, **Imp**: Improved

Table 4.19. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-2-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 22	0.84	0.85	0.85	0.86	0.86	0.87	0.87	0.89
Model 23	0.81	0.82	0.82	0.82	0.82	0.82	0.83	0.85
Model 24	0.72	0.73	0.73	0.74	0.78	0.77	0.78	0.82

Reg: Regular, **Imp**: Improved

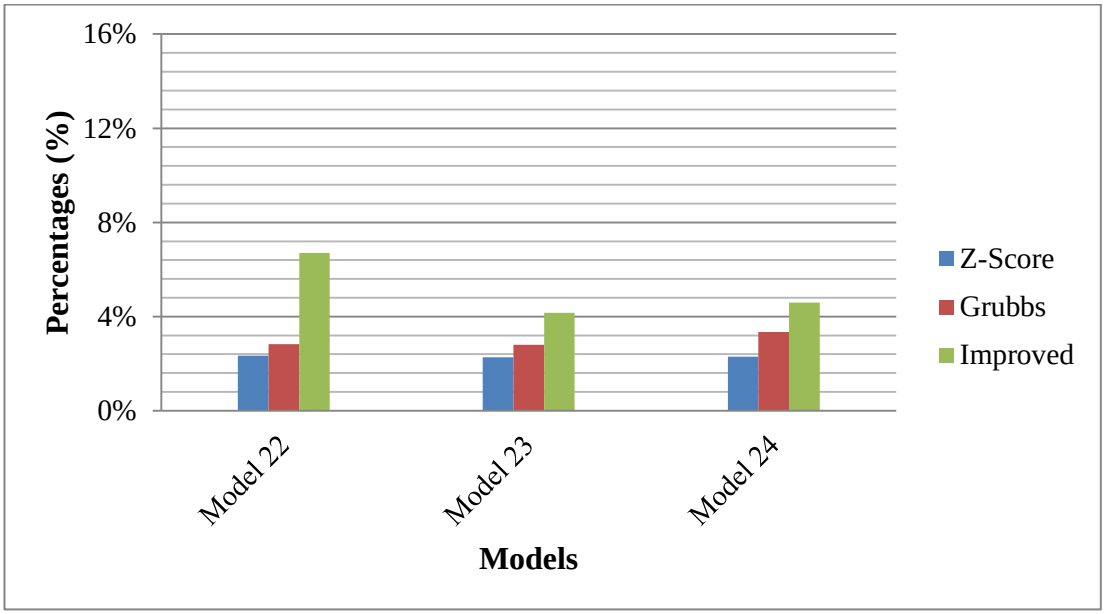

Figure 4.80. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-2-Split70 (Models 22-24)

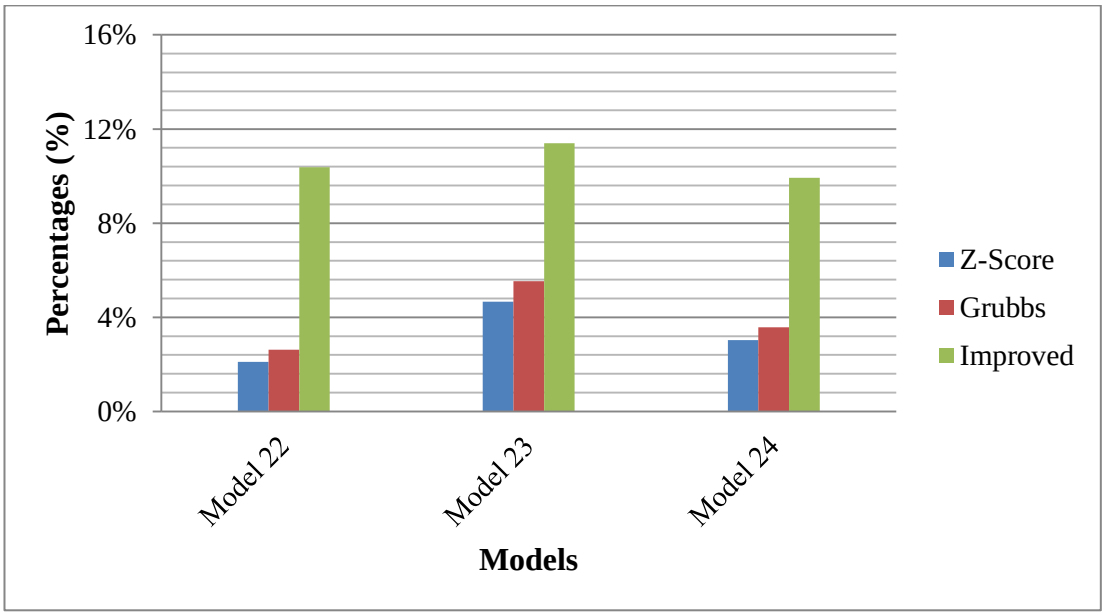

Figure 4.81. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-2-Split70 (Models 22-24)

Table 4.20. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-3-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 25	5.52	5.31	5.28	5.15	5.31	5.19	5.20	4.80
Model 26	6.22	5.98	5.97	5.86	5.79	5.56	5.46	5.21
Model 27	5.44	5.28	5.27	5.13	5.31	4.98	4.97	4.76
Model 28	5.98	5.81	5.77	5.50	5.77	5.50	5.40	5.15
Model 29	6.08	5.91	5.86	5.66	5.78	5.44	5.40	5.13
Model 30	6.58	6.41	6.33	6.25	6.37	6.01	5.95	5.51
Model 31	5.85	5.66	5.62	5.53	5.75	5.47	5.46	4.96

Reg: Regular, **Imp**: Improved

Table 4.21. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-3-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 25	0.87	0.87	0.88	0.88	0.87	0.88	0.89	0.92
Model 26	0.82	0.83	0.83	0.85	0.85	0.86	0.86	0.88
Model 27	0.87	0.88	0.89	0.89	0.87	0.87	0.88	0.90
Model 28	0.86	0.87	0.87	0.88	0.84	0.86	0.87	0.89
Model 29	0.85	0.85	0.85	0.87	0.85	0.84	0.85	0.87
Model 30	0.83	0.83	0.84	0.85	0.80	0.82	0.83	0.85
Model 31	0.85	0.86	0.87	0.88	0.84	0.85	0.86	0.89

Reg: Regular, **Imp**: Improved

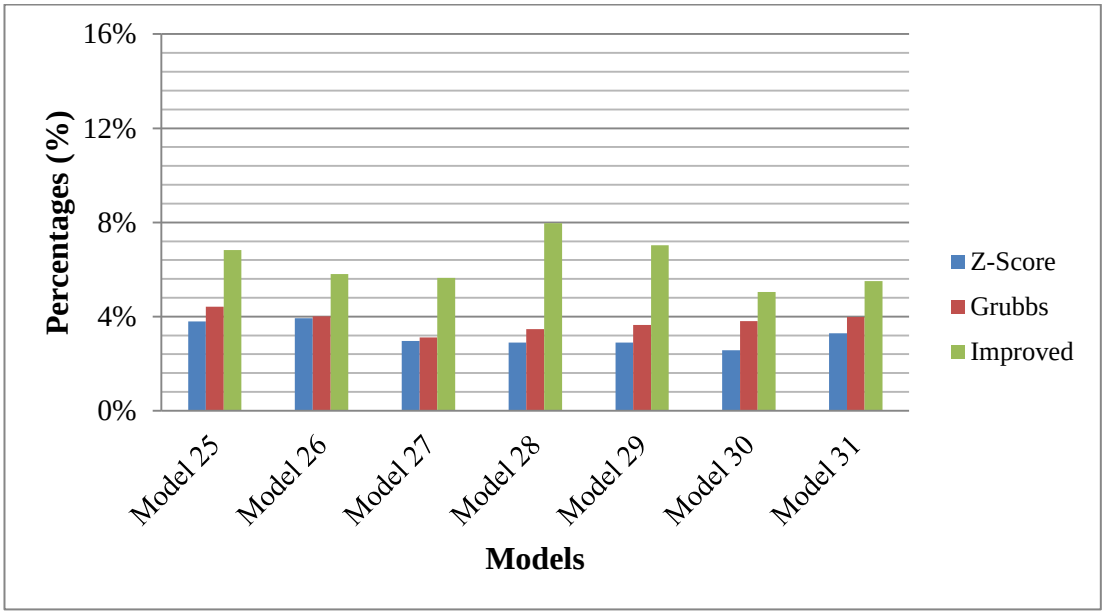

Figure 4.82. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-3-Split70 (Models 25-31)

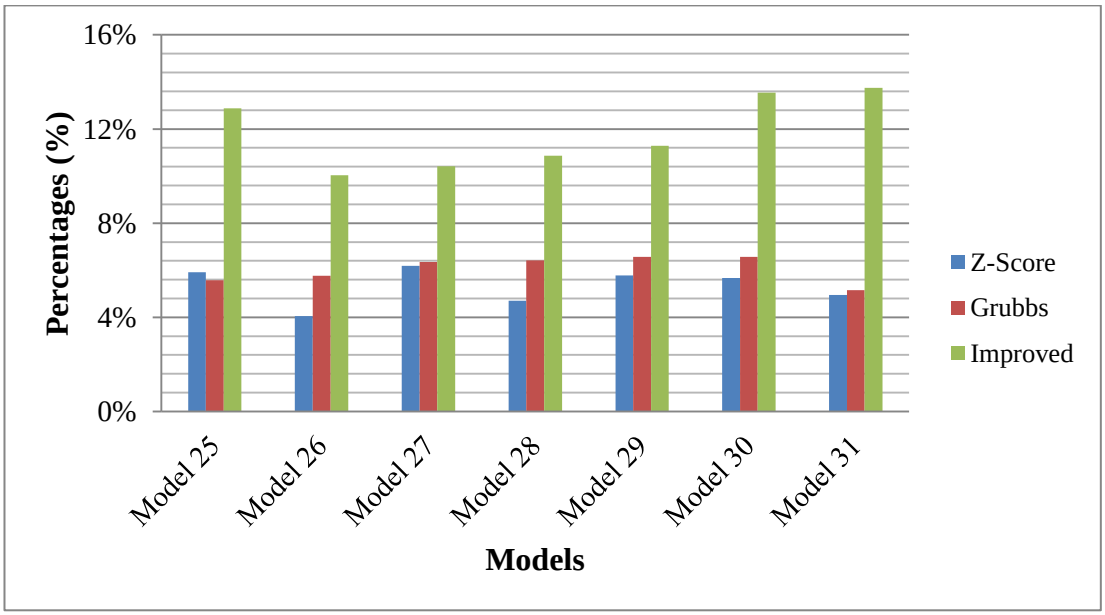

Figure 4.83. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-3-Split70 (Models 25-31)

Table 4.22. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-4-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 32	4.90	4.78	4.77	4.49	4.54	4.40	4.31	4.11
Model 33	5.96	5.80	5.76	5.66	5.39	5.21	5.16	4.61
Model 34	4.72	4.61	4.54	4.49	4.49	4.37	4.32	3.91
Model 35	4.76	4.63	4.63	4.53	4.50	4.29	4.23	3.87
Model 36	5.56	5.42	5.35	5.22	5.35	5.16	5.10	4.79
Model 37	7.51	7.35	7.26	6.88	6.99	6.78	6.73	6.15
Model 38	4.57	4.49	4.44	4.32	4.22	4.05	4.06	3.66
Model 39	4.47	4.38	4.33	4.12	4.19	4.08	3.96	3.59
Model 40	4.84	4.71	4.72	4.47	4.53	4.30	4.36	4.01
Model 41	7.86	7.65	7.58	7.43	7.01	6.65	6.61	6.24
Model 42	5.37	5.22	5.18	4.94	5.07	4.83	4.82	4.33
Model 43	6.13	6.03	5.91	5.63	5.44	5.16	5.11	4.86
Model 44	6.56	6.38	6.35	6.05	5.65	5.33	5.29	4.96
Model 45	4.67	4.59	4.53	4.37	4.48	4.29	4.21	3.84
Model 46	6.61	6.48	6.40	6.17	5.92	5.68	5.62	5.22
Model 47	7.05	6.85	6.79	6.63	6.38	6.16	6.13	5.74
Model 48	6.96	6.75	6.70	6.49	6.26	6.07	6.04	5.54
Model 49	6.86	6.67	6.59	6.52	6.18	5.87	5.95	5.48
Model 50	6.06	5.90	5.85	5.72	5.40	5.20	5.18	4.73
Model 51	4.43	4.32	4.27	4.11	4.17	4.04	4.00	3.56
Model 52	7.27	7.16	7.07	6.68	6.92	6.57	6.67	5.97
Model 53	6.40	6.25	6.21	5.95	5.58	5.30	5.22	4.85
Model 54	5.50	5.30	5.28	5.09	5.30	5.11	5.08	4.57
Model 55	5.44	5.33	5.29	5.13	5.18	5.05	4.95	4.64
Model 56	4.99	4.84	4.80	4.69	4.79	4.60	4.56	4.27
Model 57	4.55	4.42	4.37	4.27	4.25	4.16	4.10	3.59
Model 58	6.32	6.18	6.15	5.88	5.49	5.24	5.26	4.79
Model 59	7.16	6.97	6.98	6.71	6.88	6.52	6.44	6.01
Model 60	6.72	6.58	6.51	6.17	6.16	5.87	5.90	5.53
Model 61	5.40	5.25	5.23	5.07	5.12	4.89	4.93	4.49
Model 62	5.33	5.25	5.18	5.04	4.97	4.79	4.74	4.24

Reg: Regular, **Imp**: Improved

Table 4.23. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-4-Split70.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 32	0.87	0.87	0.87	0.88	0.89	0.90	0.90	0.93
Model 33	0.80	0.80	0.81	0.81	0.87	0.88	0.89	0.91
Model 34	0.87	0.88	0.88	0.89	0.90	0.90	0.91	0.93
Model 35	0.87	0.87	0.88	0.88	0.90	0.91	0.92	0.93
Model 36	0.82	0.83	0.83	0.84	0.84	0.85	0.85	0.87
Model 37	0.75	0.76	0.76	0.77	0.81	0.83	0.83	0.84
Model 38	0.89	0.90	0.90	0.91	0.91	0.91	0.91	0.95
Model 39	0.90	0.91	0.91	0.92	0.91	0.92	0.91	0.95
Model 40	0.88	0.89	0.88	0.90	0.89	0.89	0.90	0.93
Model 41	0.72	0.72	0.73	0.73	0.76	0.77	0.77	0.79
Model 42	0.85	0.86	0.87	0.88	0.90	0.91	0.91	0.93
Model 43	0.81	0.81	0.81	0.83	0.84	0.84	0.84	0.88
Model 44	0.78	0.78	0.78	0.79	0.86	0.87	0.87	0.88
Model 45	0.88	0.89	0.89	0.89	0.89	0.91	0.92	0.93
Model 46	0.78	0.78	0.80	0.80	0.85	0.85	0.85	0.87
Model 47	0.81	0.82	0.82	0.82	0.84	0.84	0.85	0.87
Model 48	0.79	0.79	0.79	0.80	0.78	0.78	0.79	0.81
Model 49	0.81	0.82	0.81	0.83	0.78	0.79	0.79	0.82
Model 50	0.83	0.84	0.84	0.85	0.88	0.89	0.89	0.90
Model 51	0.89	0.90	0.90	0.91	0.91	0.91	0.92	0.95
Model 52	0.79	0.79	0.80	0.80	0.71	0.72	0.72	0.74
Model 53	0.81	0.81	0.81	0.82	0.86	0.87	0.87	0.90
Model 54	0.84	0.84	0.84	0.85	0.85	0.86	0.86	0.88
Model 55	0.82	0.83	0.84	0.84	0.89	0.89	0.89	0.92
Model 56	0.88	0.88	0.88	0.89	0.88	0.90	0.90	0.92
Model 57	0.89	0.91	0.91	0.91	0.91	0.91	0.92	0.93
Model 58	0.80	0.80	0.80	0.82	0.84	0.84	0.85	0.88
Model 59	0.82	0.82	0.83	0.83	0.72	0.73	0.73	0.75
Model 60	0.78	0.79	0.79	0.80	0.78	0.80	0.79	0.80
Model 61	0.84	0.83	0.83	0.85	0.89	0.90	0.90	0.92
Model 62	0.86	0.86	0.86	0.88	0.87	0.88	0.88	0.90

Reg: Regular, **Imp**: Improved

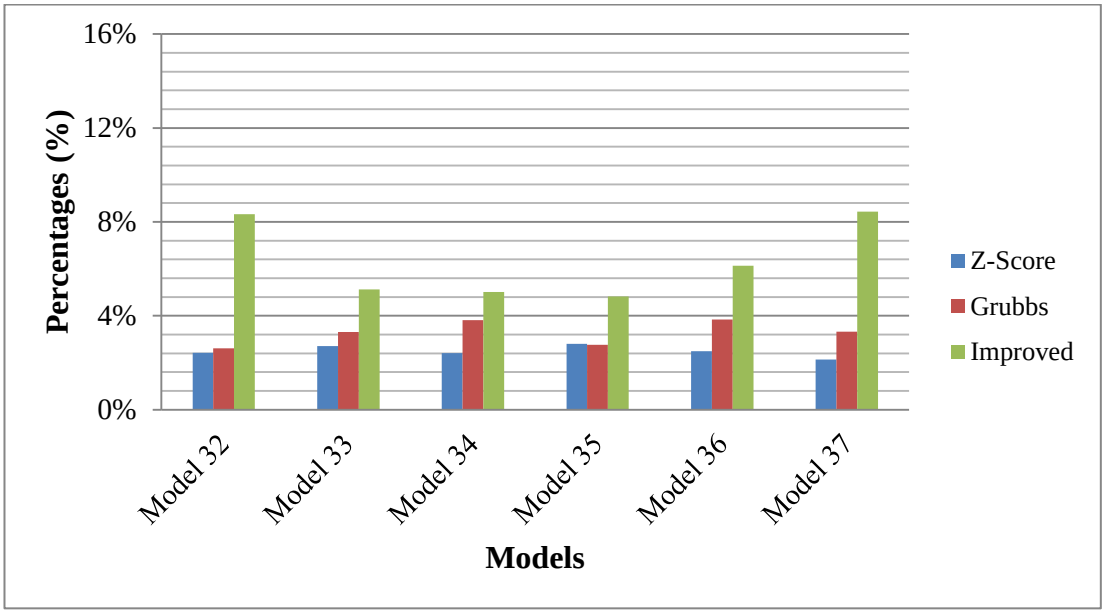

Figure 4.84. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split70 (Models 32-37)

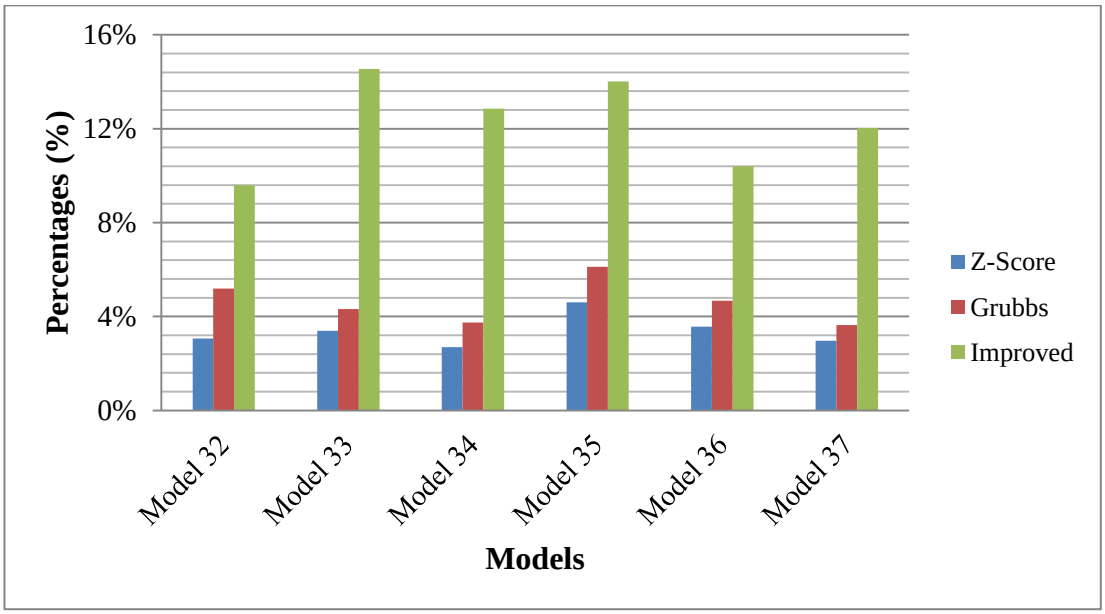

Figure 4.85. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split70 (Models 32-37)

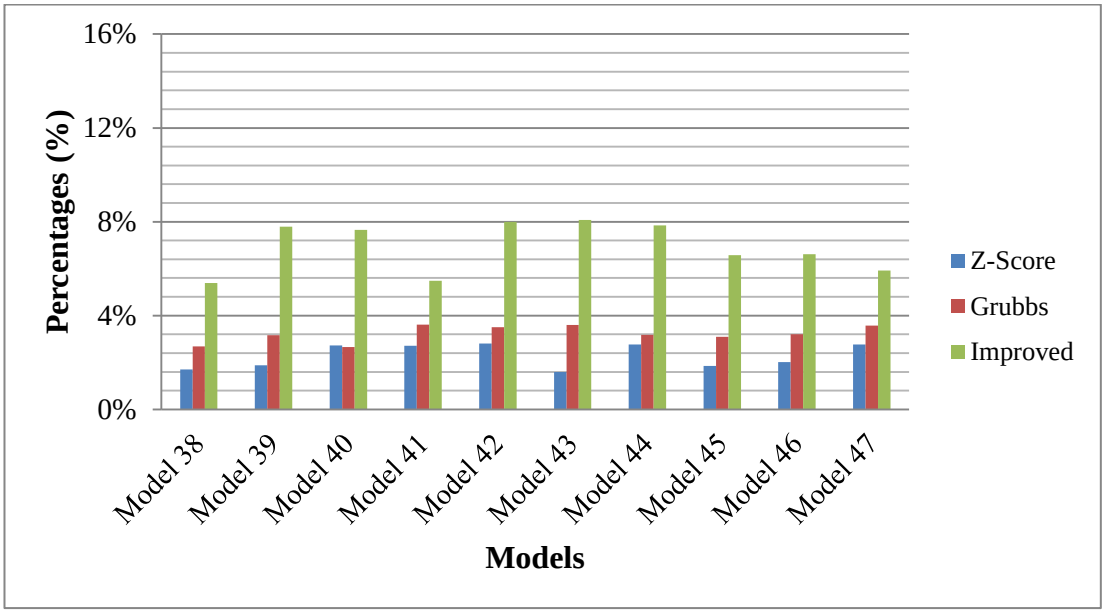

Figure 4.86. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split70 (Models 38-47)

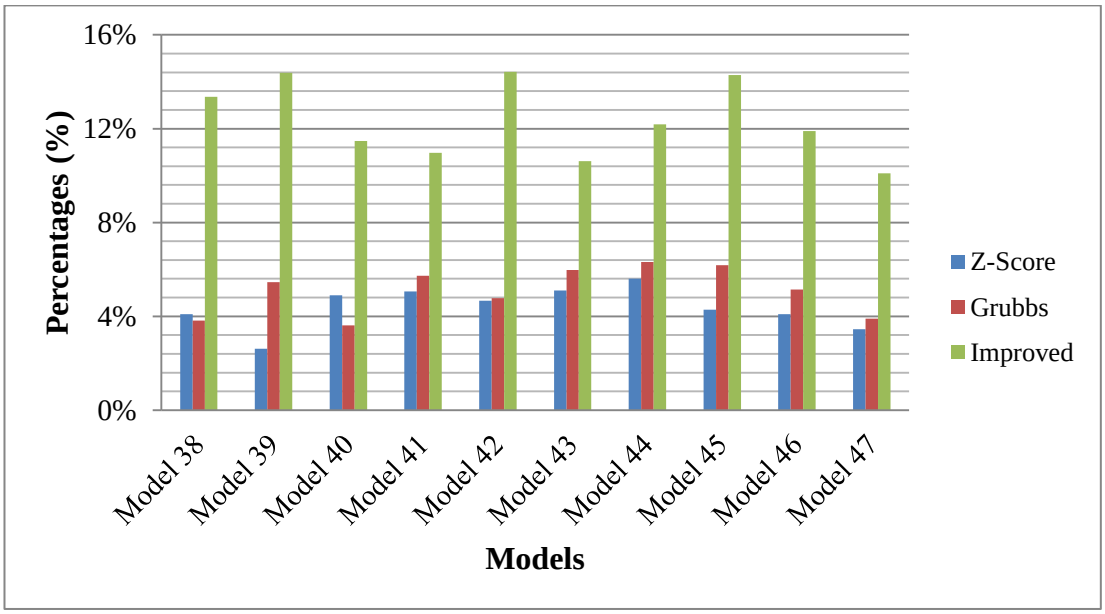

Figure 4.87. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split70 (Models 38-47)

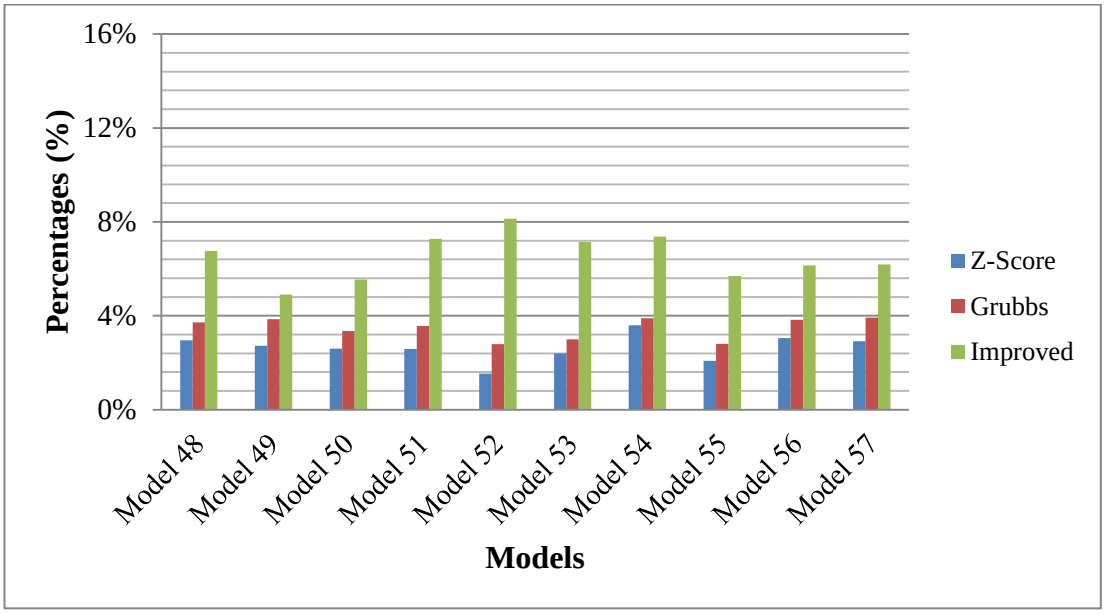

Figure 4.88. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split70 (Models 48-57)

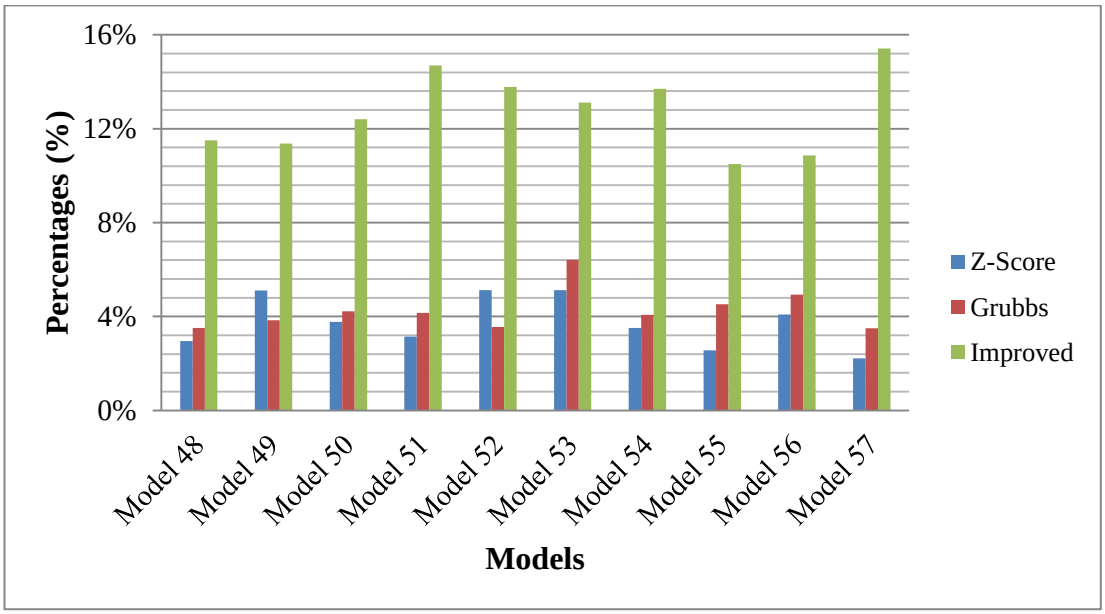

Figure 4.89. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split70 (Models 48-57)

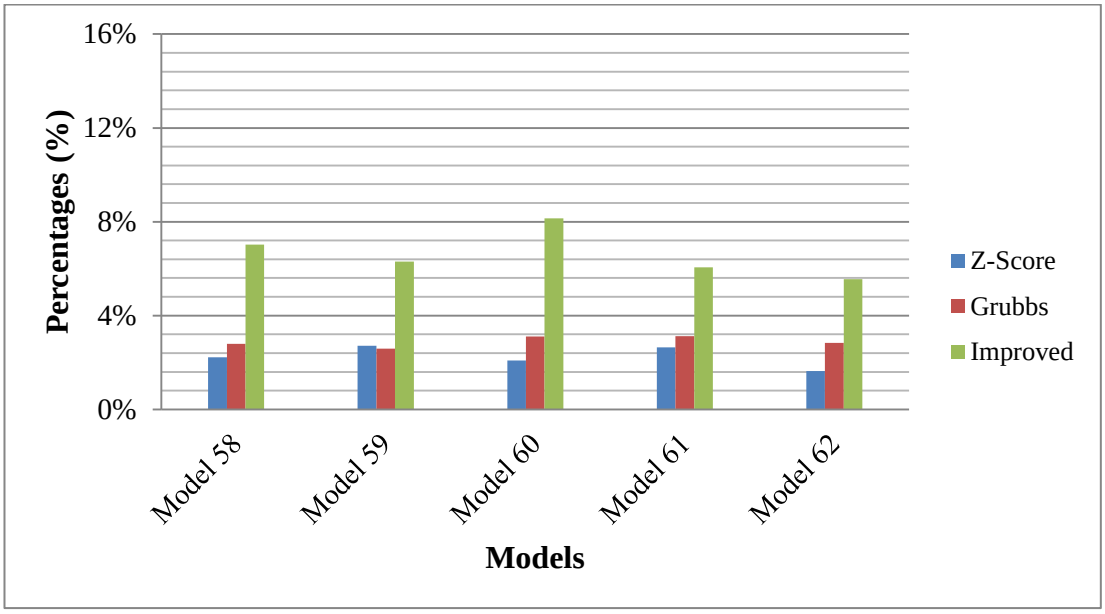

Figure 4.90. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split70 (Models 58-62)

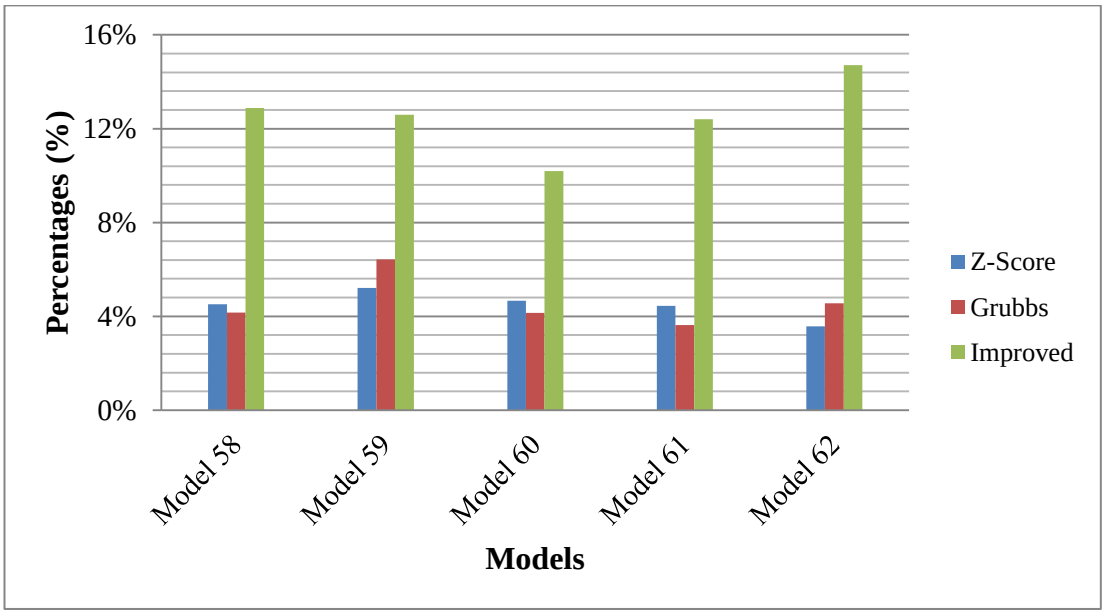

Figure 4.91. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split70 (Models 58-62)

Table 4.24. through Table 4.31. show *SEE* and *R* values for regular and improved VO_2max prediction models using SVM and MFANN on VO_2max-set-1-Split80, VO_2max-set-2-Split80, VO_2max-set-3-Split80 and VO_2max-set-4-Split80, respectively.

Figure 4.92. through Figure 4.109. show the percentage decrease rates in *SEE*'s of outlier-based and improved SVM and MFANN prediction models compared to *SEE*'s obtained by regular SVM and MFANN prediction models on Split80 sets.

Table 4.24. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-1-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 1	3.99	3.84	3.82	3.68	3.71	3.55	3.50	3.22
Model 2	3.75	3.65	3.61	3.36	3.71	3.57	3.55	3.03
Model 3	3.57	3.45	3.46	3.29	3.39	3.26	3.23	2.81
Model 4	3.16	3.05	3.05	2.93	2.71	2.64	2.59	2.31
Model 5	3.81	3.66	3.66	3.49	3.66	3.52	3.48	3.16
Model 6	3.29	3.19	3.18	3.03	3.23	3.07	3.11	2.83
Model 7	2.95	2.86	2.82	2.69	2.70	2.61	2.59	2.20
Model 8	3.88	3.74	3.70	3.58	3.70	3.59	3.54	3.25
Model 9	3.72	3.60	3.57	3.46	3.64	3.47	3.45	3.16
Model 10	3.58	3.47	3.43	3.20	3.37	3.21	3.18	2.92
Model 11	3.69	3.57	3.55	3.44	3.46	3.32	3.29	2.90
Model 12	3.66	3.53	3.53	3.31	3.70	3.58	3.55	3.02
Model 13	3.51	3.40	3.38	3.27	3.37	3.27	3.20	2.72
Model 14	3.28	3.19	3.14	2.94	3.27	3.18	3.11	2.71
Model 15	4.72	4.55	4.57	4.33	4.52	4.36	4.34	3.75
Model 16	4.40	4.26	4.23	4.11	4.39	4.22	4.14	3.70
Model 17	4.54	4.39	4.37	4.14	4.37	4.19	4.15	3.73
Model 18	4.43	4.30	4.24	4.01	4.41	4.30	4.20	3.78
Model 19	4.37	4.24	4.20	3.97	4.43	4.25	4.24	3.88
Model 20	4.31	4.14	4.17	3.97	4.35	4.14	4.12	3.82
Model 21	4.40	4.26	4.25	3.96	4.36	4.17	4.13	3.51

Reg: Regular, **Imp**: Improved

Table 4.25. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-1-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 1	0.82	0.81	0.82	0.84	0.84	0.85	0.85	0.88
Model 2	0.85	0.84	0.84	0.87	0.86	0.86	0.86	0.90
Model 3	0.89	0.89	0.89	0.92	0.87	0.87	0.88	0.90
Model 4	0.91	0.91	0.91	0.93	0.93	0.93	0.93	0.96
Model 5	0.85	0.85	0.85	0.87	0.88	0.87	0.88	0.91
Model 6	0.87	0.87	0.88	0.88	0.89	0.89	0.90	0.93
Model 7	0.92	0.92	0.92	0.93	0.93	0.94	0.93	0.96
Model 8	0.88	0.88	0.88	0.90	0.86	0.87	0.87	0.90
Model 9	0.85	0.85	0.84	0.87	0.89	0.89	0.90	0.92
Model 10	0.89	0.88	0.88	0.91	0.88	0.89	0.89	0.92
Model 11	0.89	0.89	0.89	0.91	0.89	0.89	0.89	0.93
Model 12	0.86	0.86	0.87	0.87	0.86	0.86	0.86	0.89
Model 13	0.89	0.89	0.89	0.91	0.89	0.90	0.91	0.94
Model 14	0.89	0.90	0.90	0.91	0.90	0.91	0.90	0.93
Model 15	0.71	0.71	0.71	0.72	0.77	0.80	0.80	0.80
Model 16	0.76	0.76	0.76	0.77	0.78	0.78	0.78	0.81
Model 17	0.78	0.78	0.78	0.79	0.80	0.80	0.80	0.83
Model 18	0.76	0.76	0.76	0.78	0.77	0.77	0.77	0.81
Model 19	0.77	0.77	0.78	0.79	0.81	0.82	0.83	0.85
Model 20	0.78	0.77	0.77	0.79	0.78	0.78	0.78	0.82
Model 21	0.78	0.78	0.78	0.79	0.77	0.78	0.78	0.81

Reg: Regular, **Imp**: Improved

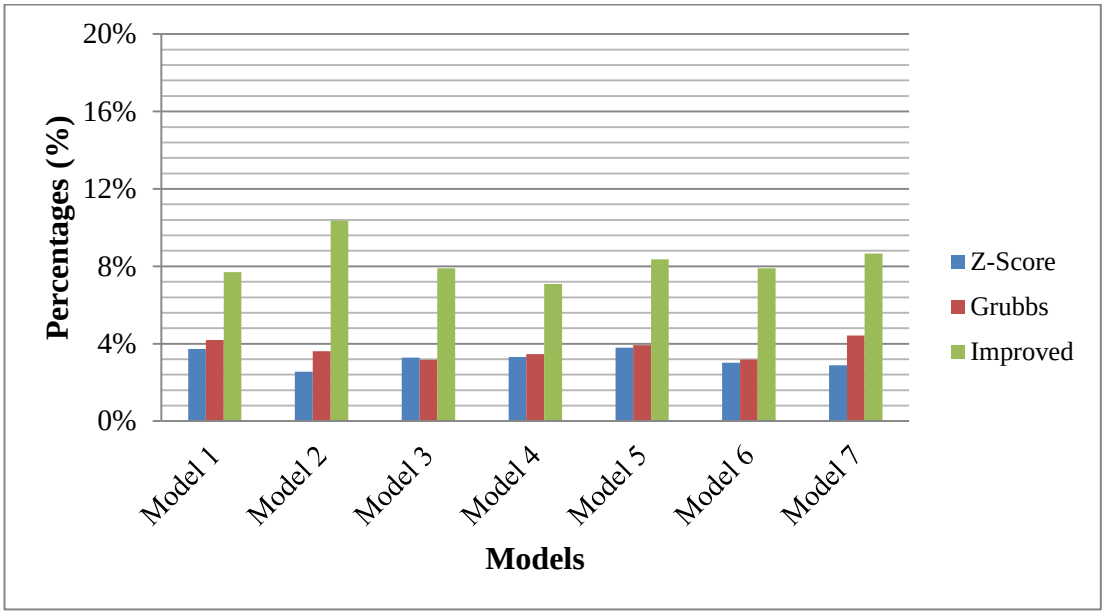

Figure 4.92. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-1-Split80 (Models 1-7)

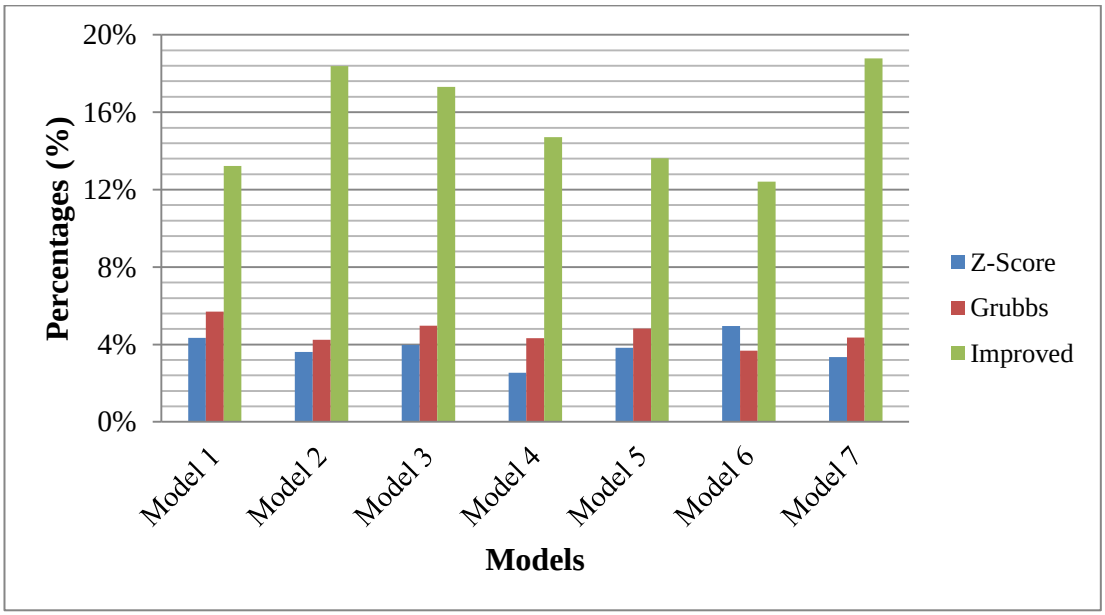

Figure 4.93. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-1-Split80 (Models 1-7)

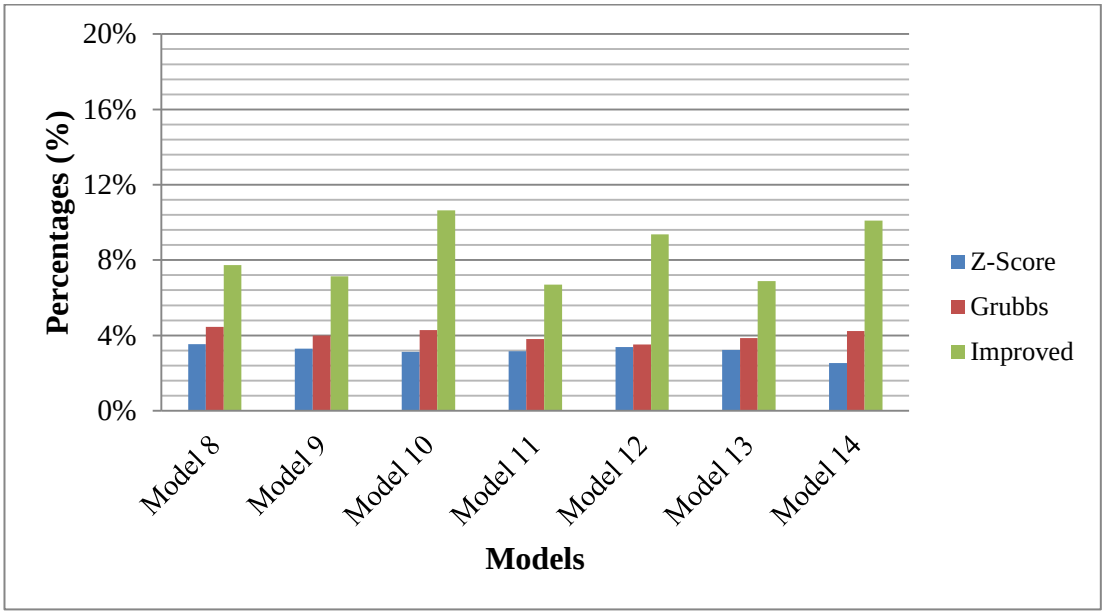

Figure 4.94. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-1-Split80 (Models 8-14)

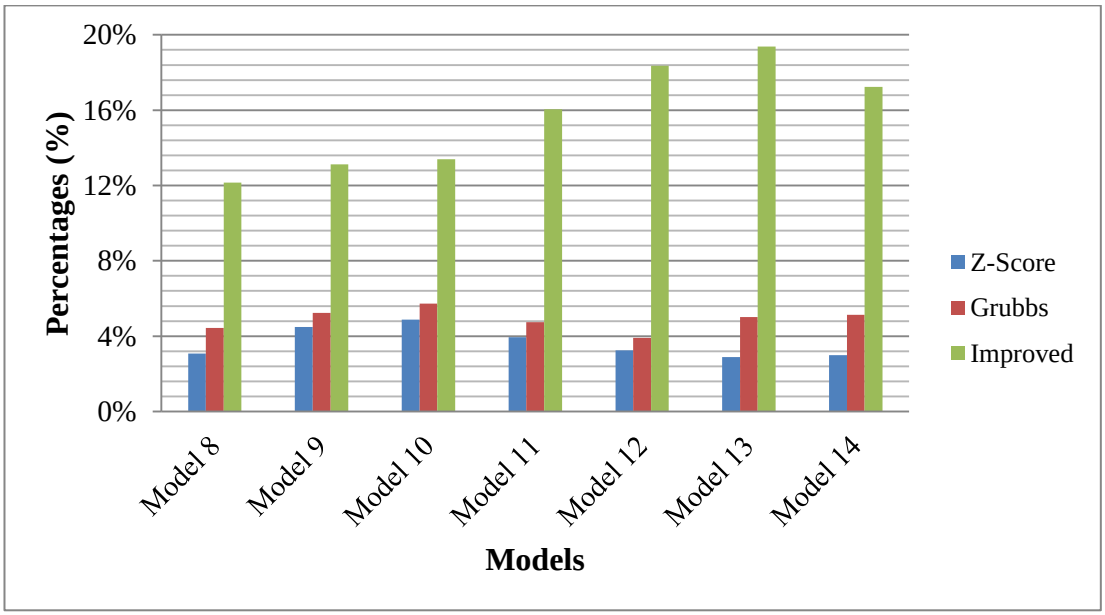

Figure 4.95. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-1-Split80 (Models 8-14)

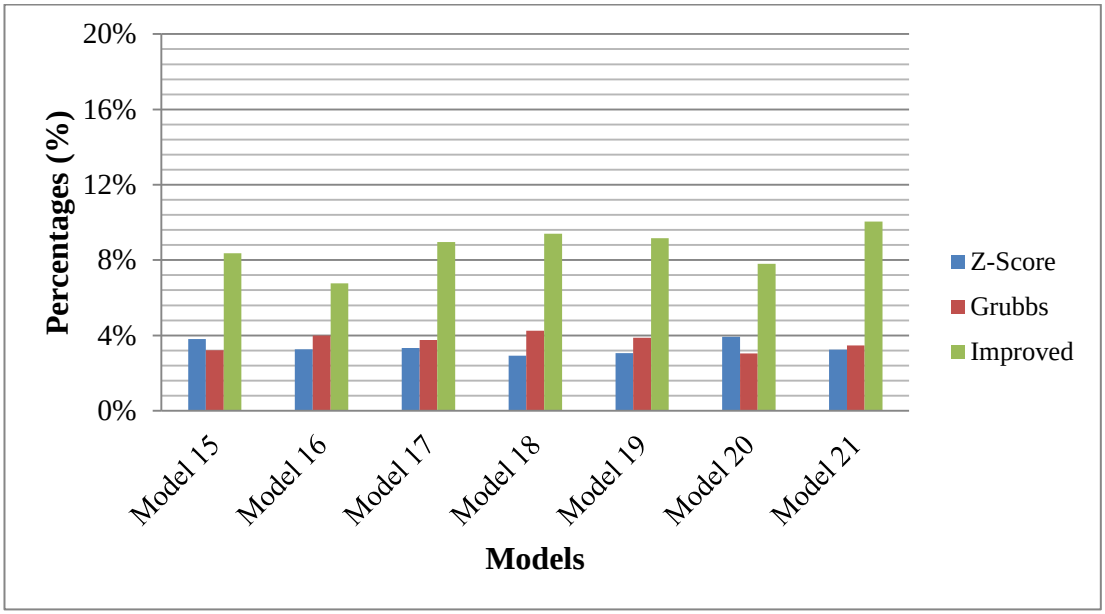

Figure 4.96. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-1-Split80 (Models 15-21)

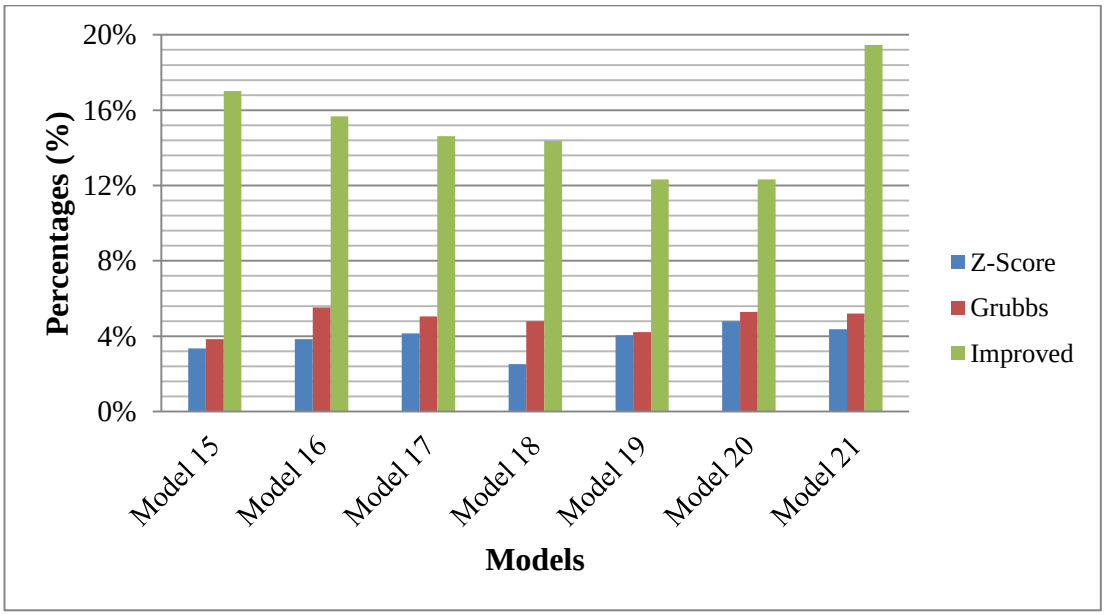

Figure 4.97. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-1-Split80 (Models 15-21)

Table 4.26. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-2-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 22	3.26	3.15	3.14	3.01	3.06	2.96	2.92	2.61
Model 23	3.49	3.41	3.39	3.23	3.42	3.30	3.28	2.95
Model 24	4.11	3.99	3.95	3.62	3.72	3.56	3.54	3.10

Reg: Regular, **Imp**: Improved

Table 4.27. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-2-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 22	0.85	0.85	0.85	0.86	0.87	0.86	0.86	0.89
Model 23	0.82	0.82	0.82	0.82	0.83	0.83	0.82	0.84
Model 24	0.73	0.73	0.73	0.74	0.78	0.78	0.78	0.80

Reg: Regular, **Imp**: Improved

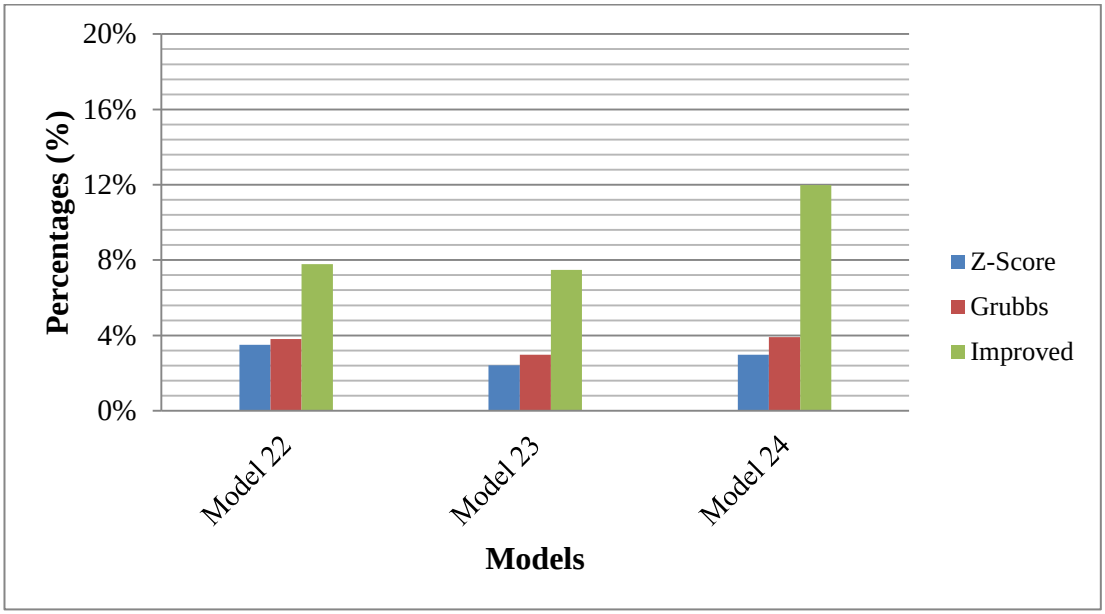

Figure 4.98. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-2-Split80 (Models 22-24)

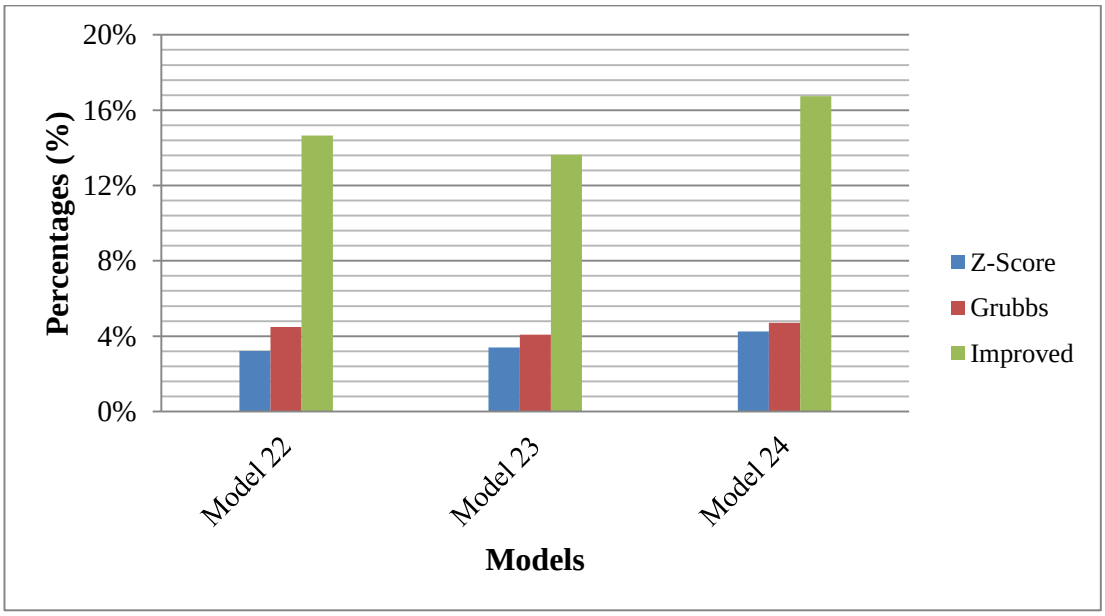

Figure 4.99. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-2-Split80 (Models 22-24)

Table 4.28. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-3-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 25	5.41	5.19	5.13	4.86	5.32	4.96	4.86	4.41
Model 26	6.02	5.75	5.70	5.45	5.70	5.28	5.21	4.66
Model 27	5.39	5.11	5.09	4.81	5.23	4.93	4.90	4.22
Model 28	5.81	5.52	5.53	5.22	5.65	5.28	5.20	4.61
Model 29	5.93	5.69	5.65	5.47	5.69	5.34	5.33	4.87
Model 30	6.43	6.17	6.12	5.74	6.28	5.85	5.75	5.05
Model 31	5.70	5.47	5.40	5.15	5.60	5.25	5.22	4.45

Reg: Regular, **Imp**: Improved

Table 4.29. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-3-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 25	0.88	0.88	0.88	0.90	0.89	0.88	0.89	0.92
Model 26	0.84	0.85	0.85	0.87	0.86	0.86	0.86	0.88
Model 27	0.88	0.88	0.89	0.91	0.88	0.89	0.88	0.92
Model 28	0.88	0.87	0.87	0.91	0.86	0.87	0.88	0.89
Model 29	0.86	0.85	0.86	0.89	0.86	0.86	0.86	0.89
Model 30	0.84	0.84	0.84	0.87	0.82	0.82	0.83	0.84
Model 31	0.87	0.88	0.88	0.89	0.86	0.86	0.86	0.89

Reg: Regular, **Imp**: Improved

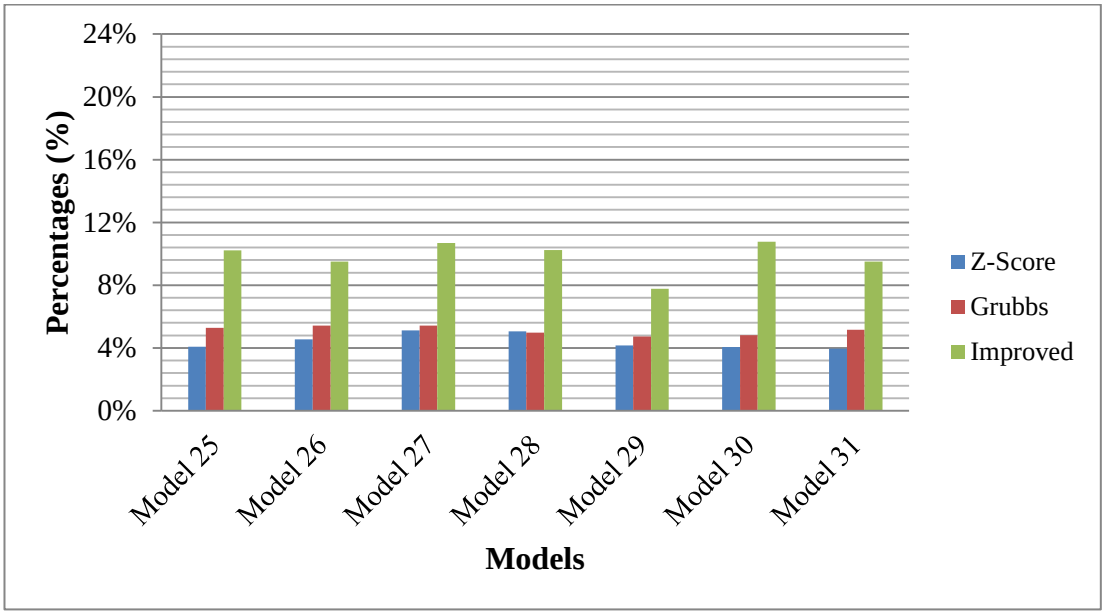

Figure 4.100. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-3-Split80 (Models 25-31)

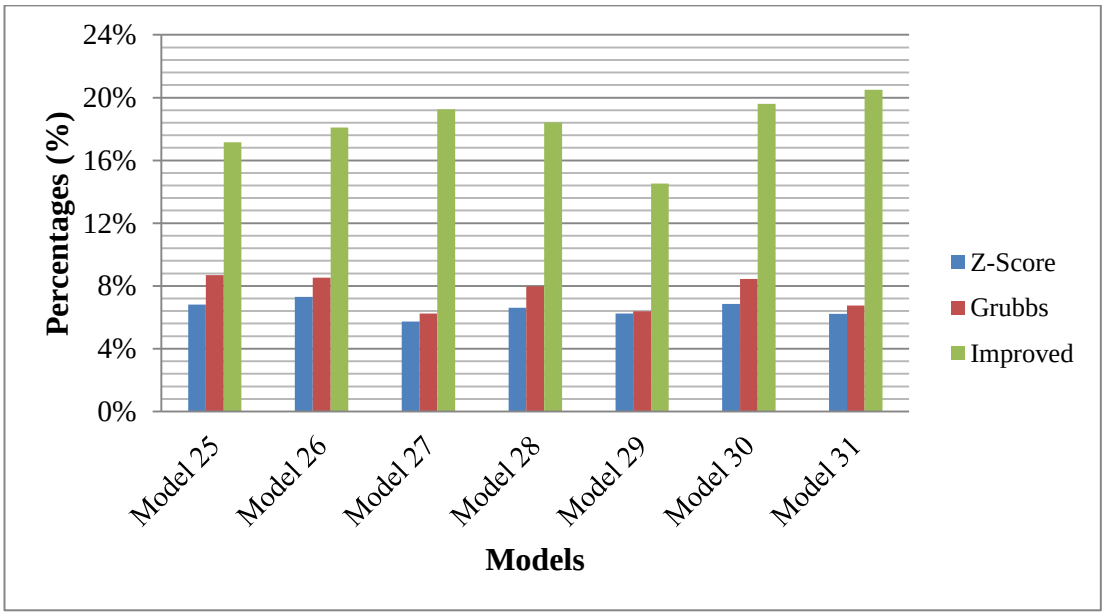

Figure 4.101. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-3-Split80 (Models 25-31)

Table 4.30. *SEE* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-4-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 32	4.88	4.74	4.68	4.38	4.52	4.20	4.15	3.78
Model 33	5.94	5.77	5.65	5.47	5.28	4.99	4.93	4.32
Model 34	4.71	4.57	4.56	4.21	4.38	4.16	4.11	3.55
Model 35	4.76	4.60	4.55	4.32	4.49	4.31	4.21	3.74
Model 36	5.50	5.33	5.27	4.90	5.27	4.99	4.89	4.49
Model 37	7.35	7.06	7.09	6.77	6.88	6.49	6.50	5.65
Model 38	4.56	4.42	4.39	4.11	4.25	4.07	3.98	3.44
Model 39	4.40	4.25	4.24	4.01	4.18	3.94	3.83	3.37
Model 40	4.84	4.68	4.64	4.38	4.42	4.19	4.18	3.53
Model 41	7.85	7.54	7.46	7.16	6.89	6.51	6.52	5.74
Model 42	5.37	5.20	5.14	4.95	5.03	4.75	4.64	4.35
Model 43	6.10	5.84	5.80	5.58	5.36	5.01	4.97	4.61
Model 44	6.49	6.30	6.27	5.87	5.51	5.16	5.09	4.68
Model 45	4.59	4.44	4.39	4.12	4.44	4.15	4.10	3.58
Model 46	6.47	6.25	6.22	5.93	5.87	5.54	5.45	4.68
Model 47	6.92	6.66	6.59	6.36	6.25	5.80	5.73	5.38
Model 48	6.84	6.60	6.60	6.13	6.16	5.65	5.66	5.08
Model 49	6.73	6.54	6.44	5.99	6.10	5.80	5.77	5.01
Model 50	6.04	5.83	5.75	5.40	5.32	5.10	5.03	4.21
Model 51	4.36	4.23	4.21	3.88	4.13	3.90	3.84	3.35
Model 52	7.20	6.88	6.84	6.39	6.79	6.40	6.29	5.88
Model 53	6.25	6.11	6.04	5.73	5.46	5.14	5.09	4.71
Model 54	5.36	5.21	5.20	4.86	5.05	4.84	4.70	4.15
Model 55	5.38	5.21	5.19	4.86	5.14	4.88	4.76	4.38
Model 56	4.91	4.75	4.67	4.38	4.73	4.38	4.36	4.08
Model 57	4.48	4.31	4.29	4.13	4.24	4.02	3.95	3.38
Model 58	6.20	5.92	5.90	5.72	5.47	5.15	5.09	4.69
Model 59	7.14	6.91	6.92	6.32	6.81	6.36	6.26	5.67
Model 60	6.71	6.47	6.39	6.13	6.00	5.67	5.67	4.89
Model 61	5.38	5.25	5.20	4.81	5.11	4.80	4.74	4.33
Model 62	5.22	5.05	5.06	4.76	4.86	4.57	4.58	4.19

Reg: Regular, **Imp**: Improved

Table 4.31. *R* values for regular, outlier-based and improved VO_2max prediction models using SVM and MFANN on the VO_2max-set-4-Split80.

Models	**MFANN**				**SVM**			
	Reg	**Z-score**	**Grubbs**	**Imp**	**Reg**	**Z-score**	**Grubbs**	**Imp**
Model 32	0.88	0.88	0.89	0.89	0.90	0.91	0.92	0.92
Model 33	0.82	0.82	0.82	0.83	0.88	0.88	0.89	0.90
Model 34	0.89	0.88	0.89	0.91	0.92	0.92	0.93	0.93
Model 35	0.89	0.89	0.89	0.91	0.92	0.91	0.93	0.95
Model 36	0.84	0.86	0.85	0.86	0.84	0.85	0.85	0.86
Model 37	0.76	0.76	0.77	0.78	0.82	0.83	0.82	0.84
Model 38	0.91	0.92	0.92	0.93	0.93	0.92	0.94	0.94
Model 39	0.91	0.91	0.92	0.92	0.92	0.91	0.92	0.94
Model 40	0.89	0.89	0.89	0.91	0.89	0.89	0.90	0.92
Model 41	0.73	0.73	0.74	0.75	0.77	0.77	0.78	0.79
Model 42	0.87	0.89	0.89	0.89	0.91	0.91	0.92	0.93
Model 43	0.82	0.82	0.82	0.84	0.85	0.86	0.86	0.88
Model 44	0.79	0.79	0.79	0.80	0.86	0.87	0.87	0.89
Model 45	0.89	0.89	0.89	0.91	0.89	0.90	0.91	0.92
Model 46	0.80	0.80	0.80	0.81	0.86	0.86	0.87	0.89
Model 47	0.82	0.82	0.83	0.84	0.85	0.85	0.86	0.87
Model 48	0.80	0.79	0.81	0.81	0.79	0.79	0.80	0.81
Model 49	0.82	0.82	0.83	0.84	0.80	0.79	0.81	0.81
Model 50	0.84	0.87	0.86	0.86	0.89	0.89	0.90	0.91
Model 51	0.91	0.91	0.92	0.93	0.91	0.93	0.92	0.95
Model 52	0.80	0.80	0.80	0.81	0.73	0.75	0.74	0.74
Model 53	0.82	0.82	0.83	0.84	0.88	0.88	0.89	0.90
Model 54	0.85	0.86	0.86	0.86	0.88	0.87	0.88	0.89
Model 55	0.84	0.84	0.84	0.85	0.91	0.91	0.91	0.93
Model 56	0.90	0.89	0.92	0.92	0.89	0.89	0.89	0.91
Model 57	0.91	0.92	0.92	0.93	0.91	0.92	0.92	0.94
Model 58	0.81	0.80	0.82	0.83	0.85	0.84	0.85	0.88
Model 59	0.84	0.84	0.84	0.85	0.73	0.74	0.74	0.75
Model 60	0.79	0.80	0.81	0.81	0.80	0.80	0.81	0.82
Model 61	0.86	0.86	0.86	0.87	0.90	0.90	0.91	0.93
Model 62	0.88	0.88	0.88	0.89	0.87	0.87	0.89	0.89

Reg: Regular, **Imp**: Improved

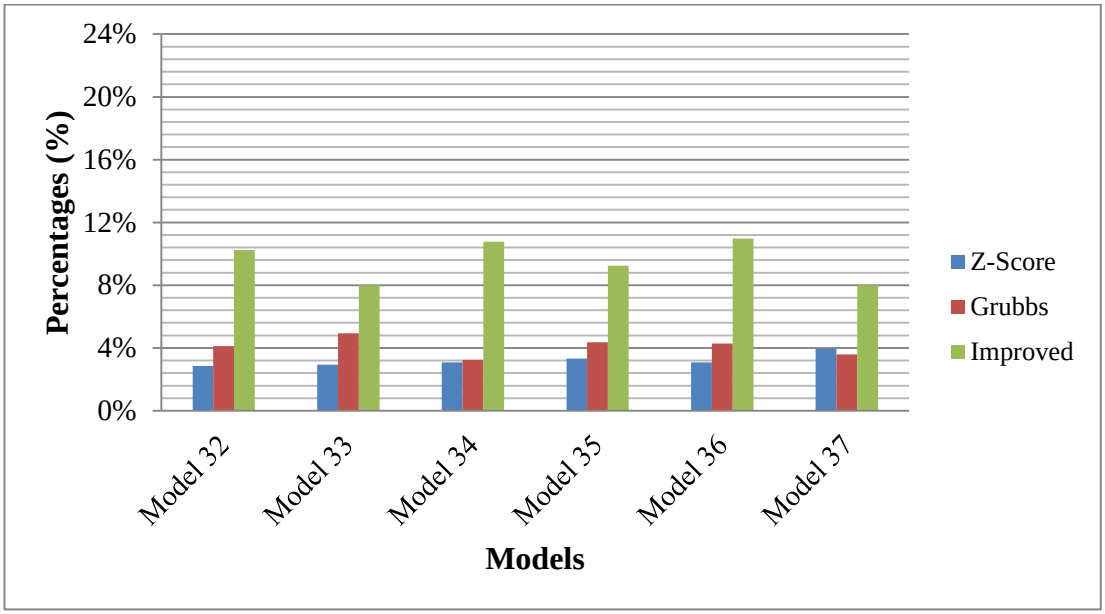

Figure 4.102. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split80 (Models 32-37)

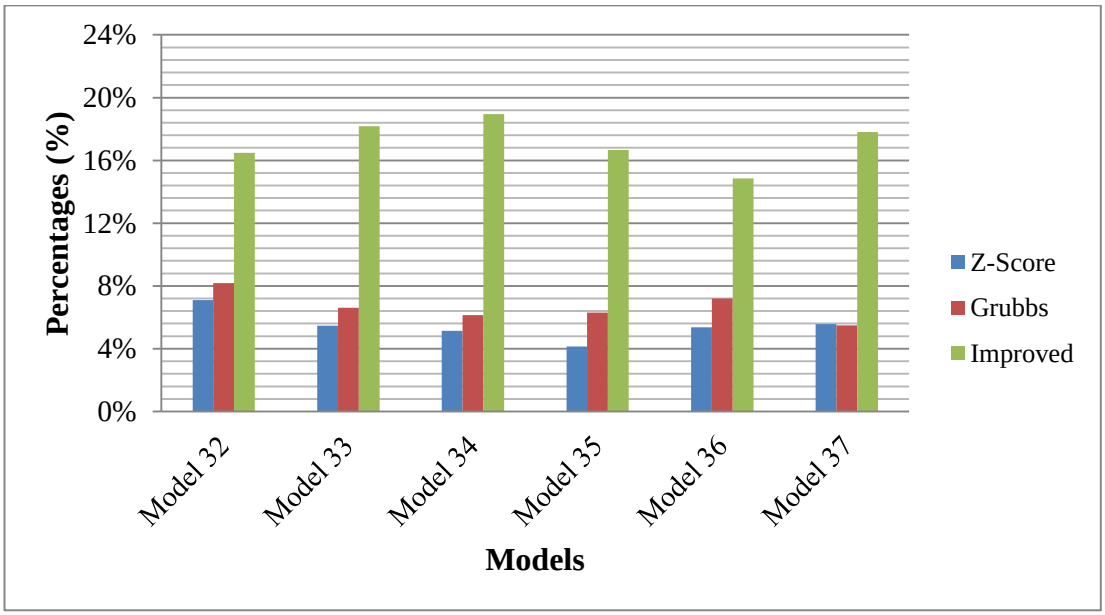

Figure 4.103. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split80 (Models 32-37)

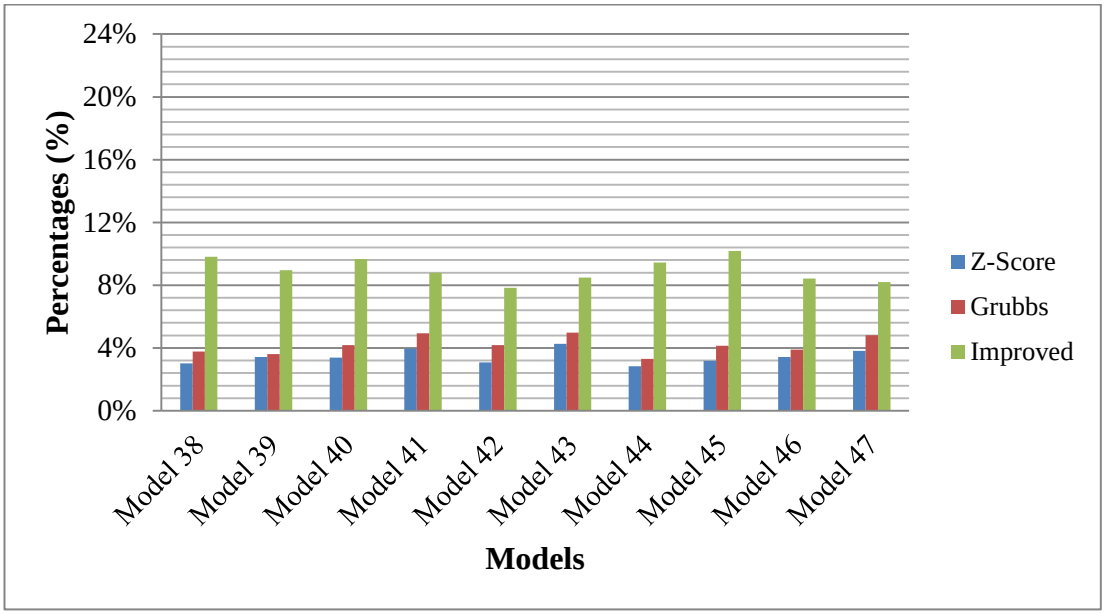

Figure 4.104. Percentage decrease rates in SEE's of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split80 (Models 38-47)

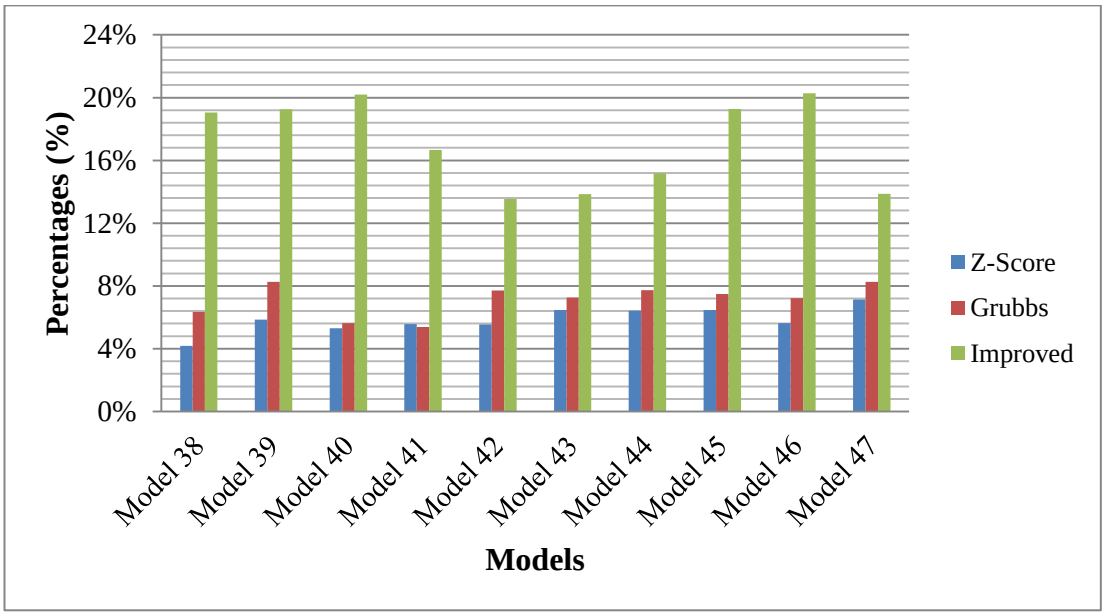

Figure 4.105. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split80 (Models 38-47)

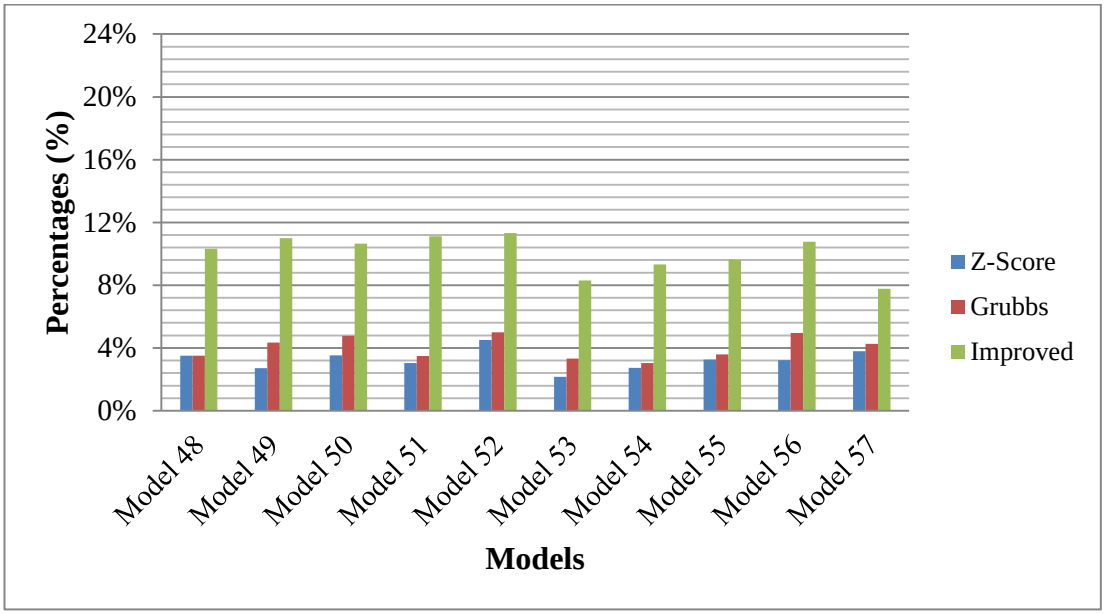

Figure 4.106. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split80 (Models 48-57)

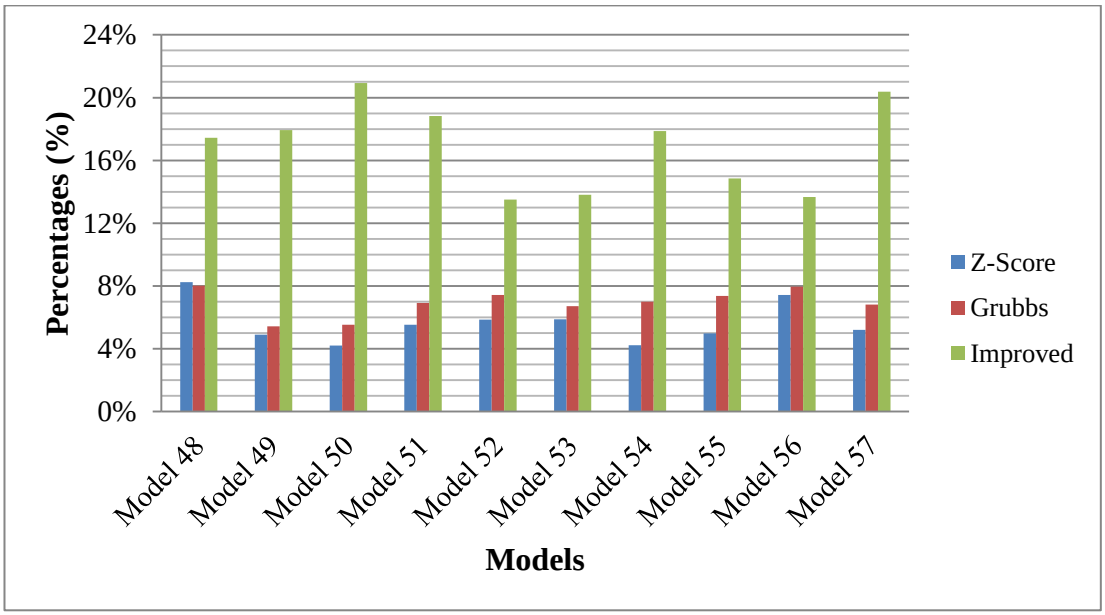

Figure 4.107. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split80 (Models 48-57)

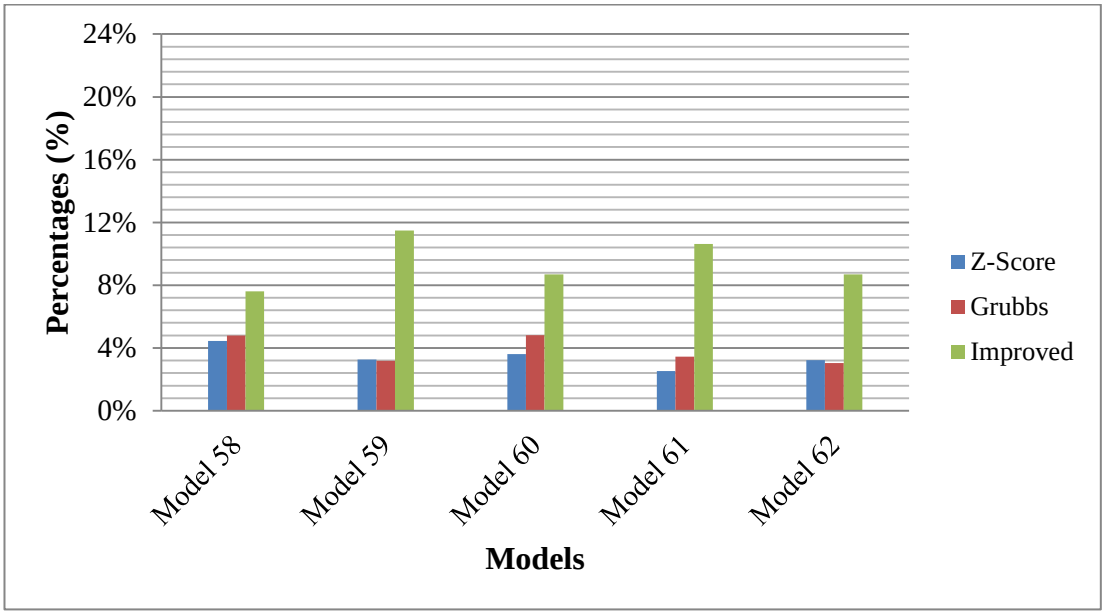

Figure 4.108. Percentage decrease rates in *SEE*'s of outlier-based and improved MFANN prediction models compared to *SEE*'s obtained by regular MFANN prediction models on VO_2max-set-4-Split80 (Models 58-62)

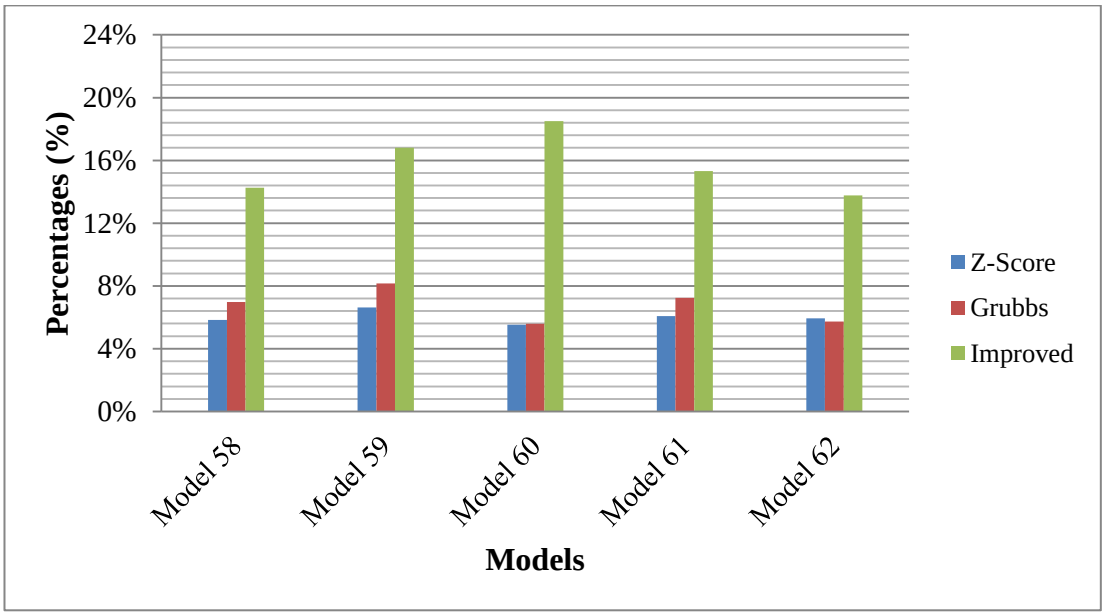

Figure 4.109. Percentage decrease rates in *SEE*'s of outlier-based and improved SVM prediction models compared to *SEE*'s obtained by regular SVM prediction models on VO_2max-set-4-Split80 (Models 58-62)

4.8. Discussion on General Results for Split70 and Split80 Sets

1. Improved MFANN-based prediction models perform better than regular MFANN-based models. The minimum and maximum decrement rates in *SEE*'s of the improved MFANN-based prediction models with respect to the *SEE*'s of the regular MFANN-based models are 3.54% and 11.98%, respectively.
2. Improved SVM-based prediction models perform better than regular SVM-based models. The minimum and maximum decrement rates in *SEE*'s of the improved SVM-based prediction models with respect to the *SEE*'s of the regular SVM-based models are 8.77% and 20.92%, respectively.
3. Regular SVM-based prediction models are more accurate than regular MFANN-based prediction models. The minimum and maximum decrement rates in *SEE*'s of the regular SVM-based prediction models with respect to the *SEE*'s of the regular MFANN-based models are 0.21% and 15.13%, respectively.
4. Improved SVM-based prediction models are more accurate than improved MFANN-based prediction models. The minimum and maximum decrement rates in *SEE*'s of the improved SVM-based prediction models with respect to the *SEE*'s of the improved MFANN-based models are 2.30% and 26.97%, respectively.
5. Training times of improved SVM-based and MFANN-based prediction models are higher than those of regular SVM-based and MFANN-based prediction models. The training times of the SVM models increase 53.1% on the average whereas the training times of the MFANN model increase 25.9% on the average after application of the improvement algorithms.

4.9. Discussion on Improved and Outlier-based Prediction Models

1. The results show that improved MFANN-based prediction models perform better than outlier-based MFANN-based models. The average decrement

rates in *SEE*'s of the outlier-based and improved MFANN-based prediction models as compared to the *SEE*'s of the regular MFANN models is given in Table 4.32.

2. The results show that improved SVM-based prediction models perform better than outlier-based SVM-based models. The average decrement rates in *SEE*'s of the outlier-based and improved SVM-based prediction models as compared to the *SEE*'s of the regular SVM models is given in Table 4.33.

Table 4.32. The average decrement rates in *SEE*'s of the outlier-based and improved MFANN-based models as compared to the *SEE*'s of the regular MFANN models on Split70 sets and Split80 sets.

Set	**Data set**	**Average Decrement Rates**		
		Z-score	**Grubbs' Test**	**Improved**
Split70 Sets	VO_2max-set-1	2.20%	2.64%	5.97%
	VO_2max-set-2	2.30%	2.99%	5.15%
	VO_2max-set-3	3.19%	3.78%	6.26%
	VO_2max-set-4	2.44%	3.26%	6.63%
Split80 Sets	VO_2max-set-1	3.26%	3.80%	8.43%
	VO_2max-set-2	2.96%	3.57%	9.08%
	VO_2max-set-3	4.43%	5.12%	9.82%
	VO_2max-set-4	3.33%	4.06%	9.49%

Table 4.33. The average decrement rates in *SEE*'s of the outlier-based and improved SVM-based models as compared to the *SEE*'s of the regular SVM models on Split70 sets and Split80 sets.

Set	**Data set**	**Average Decrement Rates**		
		Z-score	**Grubbs' Test**	**Improved**
Split70 Sets	VO_2max-set-1	2.87%	3.49%	10.49%
	VO_2max-set-2	3.27%	3.91%	10.57%
	VO_2max-set-3	5.32%	6.06%	11.83%
	VO_2max-set-4	4.01%	4.65%	12.49%
Split80 Sets	VO_2max-set-1	3.77%	4.77%	15.43%
	VO_2max-set-2	3.62%	4.42%	15.01%
	VO_2max-set-3	6.54%	7.57%	18.22%
	VO_2max-set-4	5.73%	6.91%	16,84%

4.10. Discussion on VO_2max-set-1-Split70 and VO_2max-set-1-Split80 Results

1. Model 7 including the submaximal predictor variables MIN3 and HR3 yields the lowest *SEE*'s (2.40, 2.73, 2.82, 3.00; 2.20, 2.70, 2.69, 2.95) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models whereas Model 15 including the submaximal predictor variables HR1, HR2 and HR3 yields the highest *SEE*'s (4.09, 4.48, 4.57, 4.74; 3.75, 4.52, 4.33, 4.72) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models on VO_2max-set-1-Split70 and VO_2max-set-1-Split80, respectively.
2. The prediction model including the submaximal predictor variables MIN2, MIN3, HR2 and HR3 (Model 4) yields the second best performance for regular and improved SVM and MFANN.
3. For the best model (Model 7), the decrement rates in *SEE*'s between improved SVM-based and regular SVM-based prediction models are 11.98% and 18.78%. Also, for the same model, the decrement rates in *SEE*'s between improved MFANN-based and regular MFANN-based prediction models are 6.03% and 8.66% on VO_2max-set-1-Split70 and VO_2max-set-1-Split80, respectively.
4. Among improved MFANN-based and regular MFANN-based prediction models, Model 12 has the highest decrement rate in *SEE*'s (10.40%). Also, Model 5 has the highest decrement rate in *SEE*'s (13.29%) among improved SVM-based and regular SVM-based prediction models on VO_2max-set-1-Split70.
5. Model 10 has highest decrement rate in *SEE*'s (10.64%) among improved MFANN-based and regular MFANN-based prediction models. Also, Model 21 has the highest decrement rate in *SEE*'s (19.47%) among improved SVM-based and regular SVM-based prediction models on VO_2max-set-1-Split80.

6. Average decrement rate in *SEE*'s for improved MFANN-based and SVM-based prediction models are 5.97%, 10.49% and 8.43%, 15.43% on VO_2max-set-1-Split70 and VO_2max-set-1-Split80, respectively.

4.11. Discussion on VO_2max-set-2-Split70 and VO_2max-set-2-Split80 Results

1. Model 22 including the submaximal predictor variables SM-Speed and SM-HR yields the lowest *SEE*'s (2.76, 3.08, 3.10, 3.32; 2.61, 3.06, 3.01, 3.26) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models whereas Model 24 including the submaximal predictor variable SM-HR only yields the highest *SEE*'s (3.39, 3.76, 3.98, 4.18; 3.10, 3.72, 3.62, 4.11) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models on VO_2max-set-2-Split70 and VO_2max-set-2-Split80, respectively.
2. The prediction model including the submaximal predictor variable HR-Speed only (Model 23) yields the second best performance for regular and improved SVM and MFANN.
3. For the best model (Model 22), the decrement rates in *SEE*'s between improved SVM-based and regular SVM-based prediction models are 10.37% and 14.65%. Also, for the same model, the decrement rates in *SEE*'s between improved MFANN-based and regular MFANN-based prediction models are 6.70% and 7.79% on VO_2max-set-2-Split70 and VO_2max-set-2-Split80, respectively.
4. Among improved MFANN-based and regular MFANN-based prediction models, Model 22 has the highest decrement rate in *SEE*'s (6.70%). Also, Model 23 has the highest decrement rate in *SEE*'s (11.40%) among improved SVM-based and regular SVM-based prediction models on VO_2max-set-2-Split70.
5. Model 24 has highest decrement rate in *SEE*'s (11.98%) among improved MFANN-based and regular MFANN-based prediction models. Also, the same model has the highest decrement rate in *SEE*'s (16.74%) among

improved SVM-based and regular SVM-based prediction models on VO_2max-set-2-Split80.

6. Average decrement rate in *SEE*'s for improved MFANN-based and SVM-based prediction models are 5.15%, 10.57% and 9.08%, 15.01% on VO_2max-set-2-Split70 and VO_2max-set-2-Split80, respectively.

4.12. Discussion on VO_2max-set-3-Split70 and VO_2max-set-3-Split80 Results

1. Model 27 including the non-exercise predictor variables BF% and AC yields the lowest *SEE*'s (4.76, 5.31, 5.13, 5.44; 4.22, 5.23, 4.81, 5.39) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models whereas Model 30 including the non-exercise predictor variable LBM only yields the highest *SEE*'s (5.51, 6.37, 6.25, 6.58; 5.05, 6.28, 5.74, 6.43) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models on VO_2max-set-3-Split70 and VO_2max-set-3-Split80, respectively.
2. The prediction model including the non-exercise predictor variables BF%, LBM and AC (Model 25) yields the second best performance for regular and improved SVM and MFANN.
3. For the best model (Model 27), the decrement rates in *SEE*'s between improved SVM-based and regular SVM-based prediction models are 10.42% and 19.25%. Also, for the same model, the decrement rates in *SEE*'s between improved MFANN-based and regular MFANN-based prediction models are 5.65% and 10.70% on VO_2max-set-3-Split70 and VO_2max-set-3-Split80, respectively.
4. Among improved MFANN-based and regular MFANN-based prediction models, Model 28 has the highest decrement rate in *SEE*'s (7.97%). Also, Model 31 has the highest decrement rate in *SEE*'s (13.75%) among improved SVM-based and regular SVM-based prediction models on VO_2max-set-3-Split70.

5. Model 30 has highest decrement rate in *SEE*'s (10.78%) among improved MFANN-based and regular MFANN-based prediction models. Also, Model 31 has the highest decrement rate in *SEE*'s (20.50%) among improved SVM-based and regular SVM-based prediction models on VO_2max-set-3-Split80.
6. Average decrement rate in *SEE*'s for improved MFANN-based and SVM-based prediction models are 6.26%, 11.83% and 9.82%, 18.22% on VO_2max-set-3-Split70 and VO_2max-set-3-Split80, respectively.

4.13. Discussion on VO_2max-set-4-Split70 and VO_2max-set-4-Split80 Results

1. Model 51 including the hybrid predictor variables SM-Speed and PAR yields the lowest *SEE*'s (3.56, 4.17, 4.11, 4.43; 3.35, 4.13, 3.88, 4.36) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models whereas Model 41 including the hybrid predictor variables SM-Speed, SM-HR and SM-Stage yields the highest *SEE*'s (6.24, 7.01, 7.43, 7.86; 5.74, 6.89, 7.16, 7.85) for improved SVM-based, regular SVM-based, improved MFANN-based and regular MFANN-based prediction models on VO_2max-set-4-Split70 and VO_2max-set-4-Split80, respectively.
2. The prediction model including the hybrid predictor variables SM-Speed, PFA and PAR (Model 39) yields the second best performance for regular and improved SVM and MFANN.
3. For the best model (Model 51), the decrement rates in *SEE*'s between improved SVM-based and regular SVM-based prediction models are 14.70% and 18.82%. Also, for the same model, the decrement rates in *SEE*'s between improved MFANN-based and regular MFANN-based prediction models are 7.28% and 11.11% on VO_2max-set-4-Split70 and VO_2max-set-4-Split80, respectively.
4. Among improved MFANN-based and regular MFANN-based prediction models, Model 37 has the highest decrement rate in *SEE*'s (8.44%). Also, Model 57 has the highest decrement rate in *SEE*'s (15.42%) among improved

SVM-based and regular SVM-based prediction models on VO_2max-set-4-Split70.

5. Model 59 has highest decrement rate in *SEE*'s (11.49%) among improved MFANN-based and regular MFANN-based prediction models. Also, Model 50 has the highest decrement rate in *SEE*'s (20.92%) among improved SVM-based and regular SVM-based prediction models on VO_2max-set-4-Split80.
6. Average decrement rate in *SEE*'s for improved MFANN-based and SVM-based prediction models are 6.63%, 12.49% and 9.49%, 16.84% on VO_2max-set-1-Split70 and VO_2max-set-4-Split80, respectively.

Figure 4.110. through Figure 4.113. show the scatter plots of actual VO_2max vs. predicted VO_2max for best models using improved SVM on VO_2max-set-1-Split70, VO_2max-set-2-Split70, VO_2max-set-3-Split70 and VO_2max-set-4-Split70, respectively.

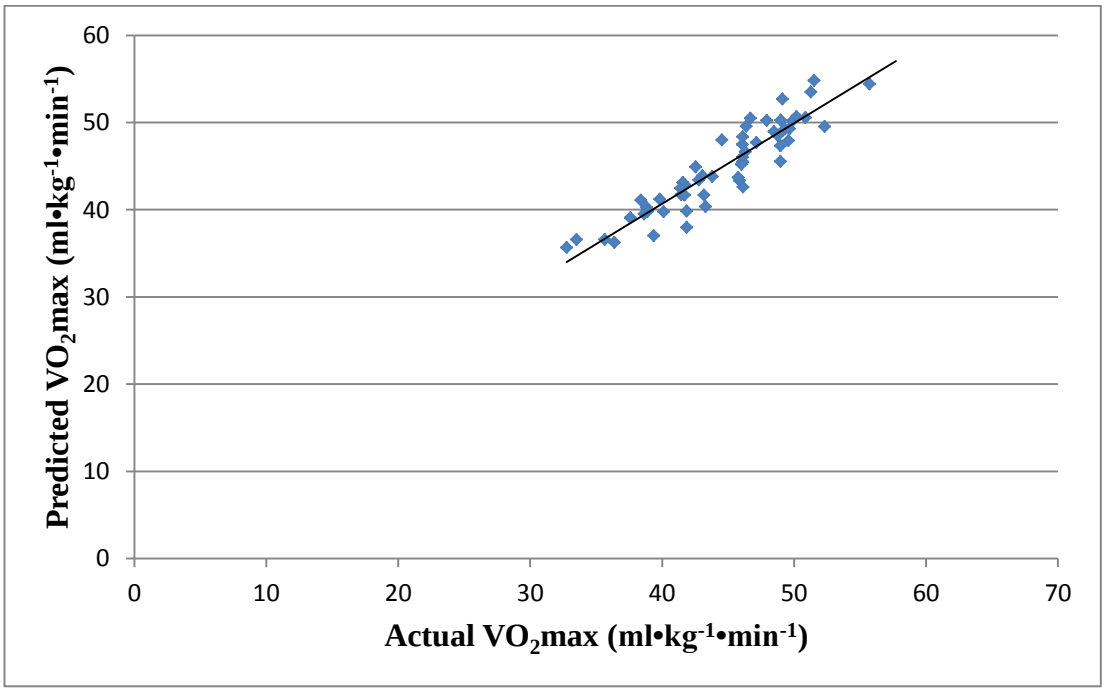

Figure 4.110. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 7 using improved SVM on VO_2max-set-1-Split70.

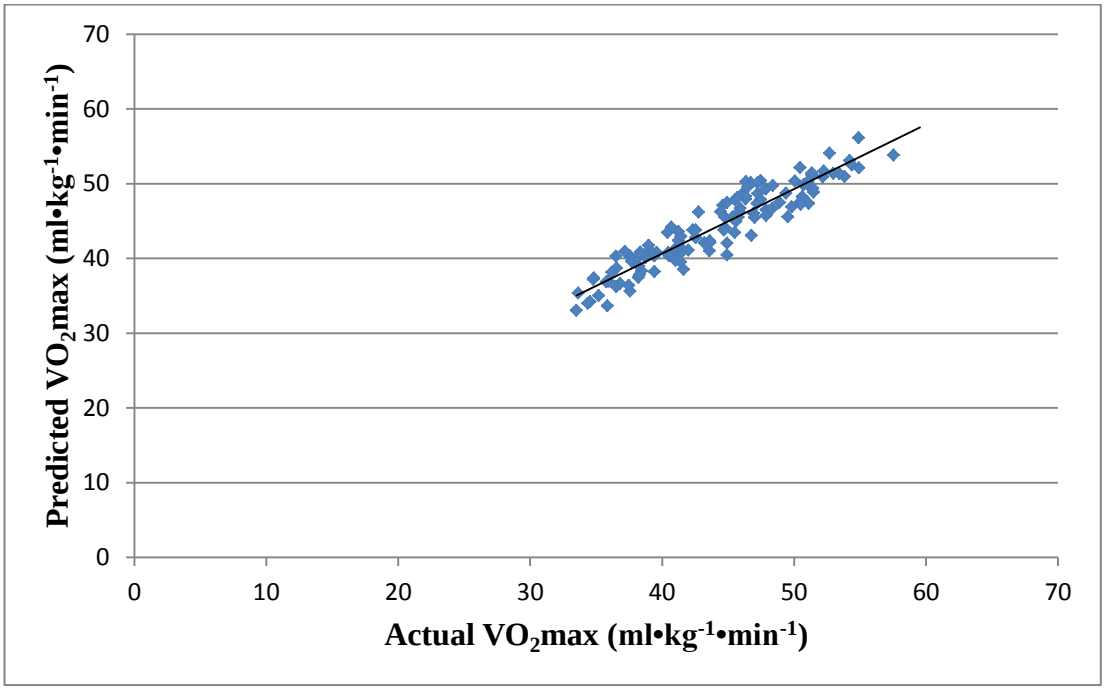

Figure 4. 111. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 22 using improved SVM on VO_2max-set-2-Split70.

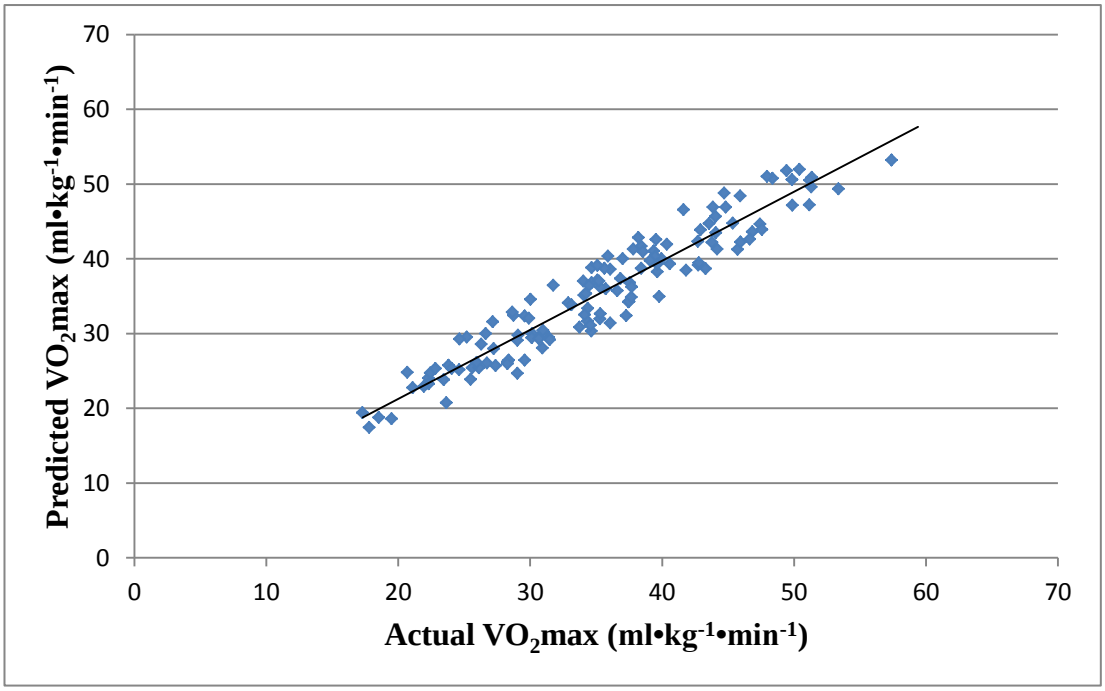

Figure 4.112. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 27 using improved SVM on VO_2max-set-3-Split70.

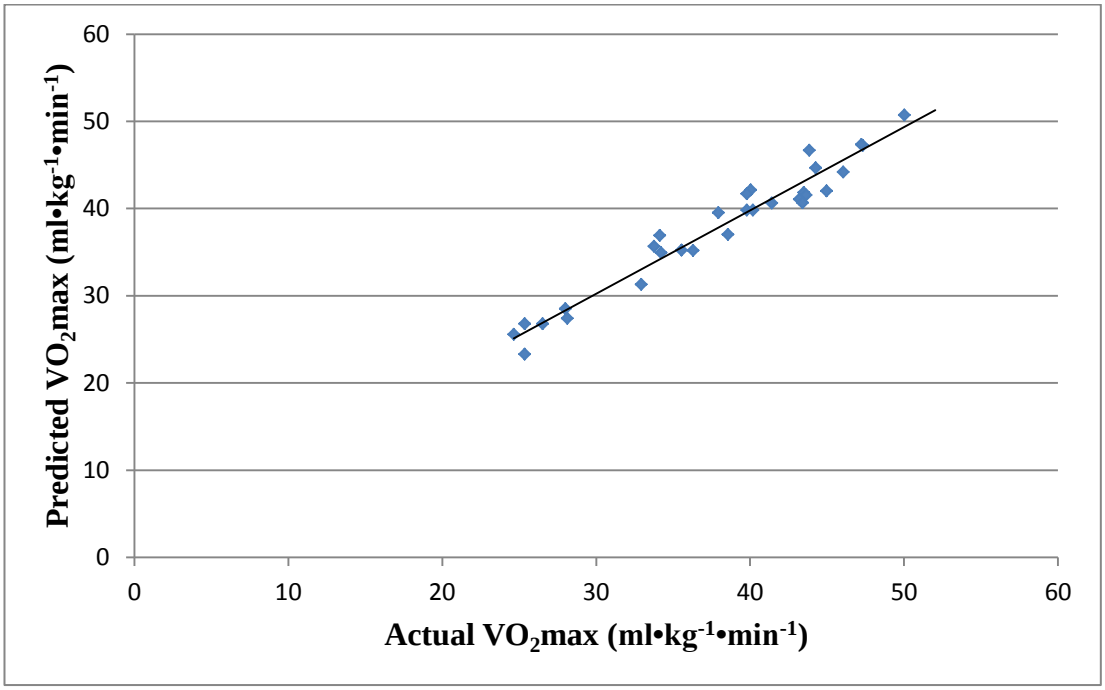

Figure 4.113. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 51 using improved SVM on VO_2max-set-4-Split70.

Figure 4.114. through Figure 4.117. show the scatter plots of actual VO_2max vs. predicted VO_2max for best models using improved SVM on VO_2max-set-1-Split80, VO_2max-set-2-Split80, VO_2max-set-3-Split80 and VO_2max-set-4-Split80, respectively.

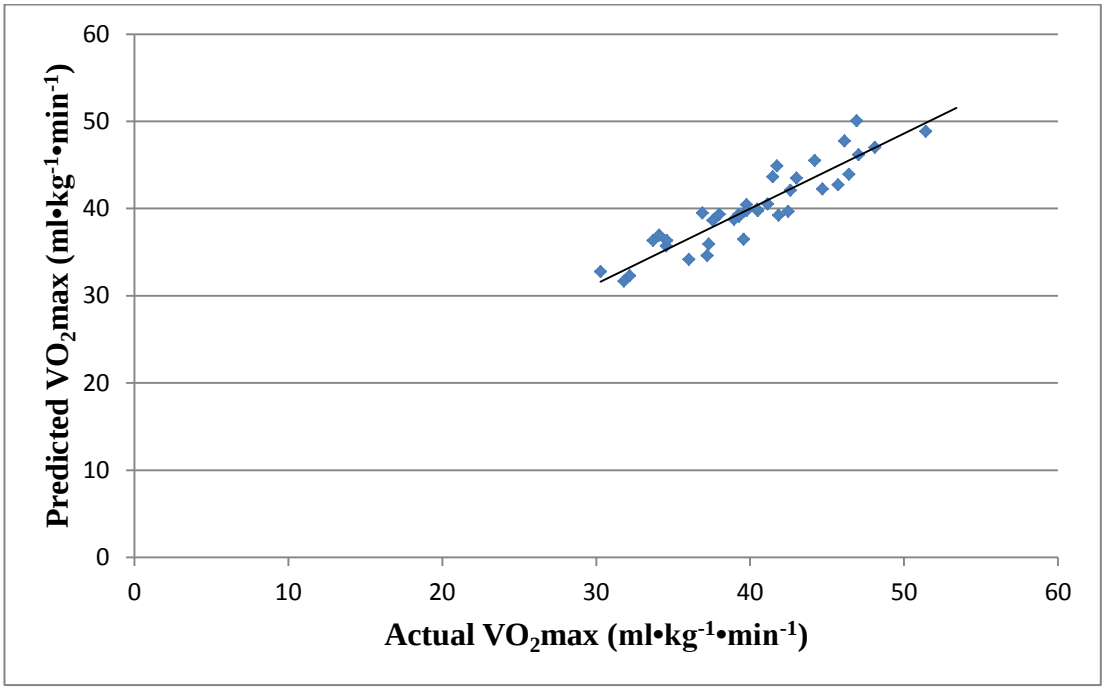

Figure 4.114. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 7 using improved SVM on VO_2max-set-1-Split80.

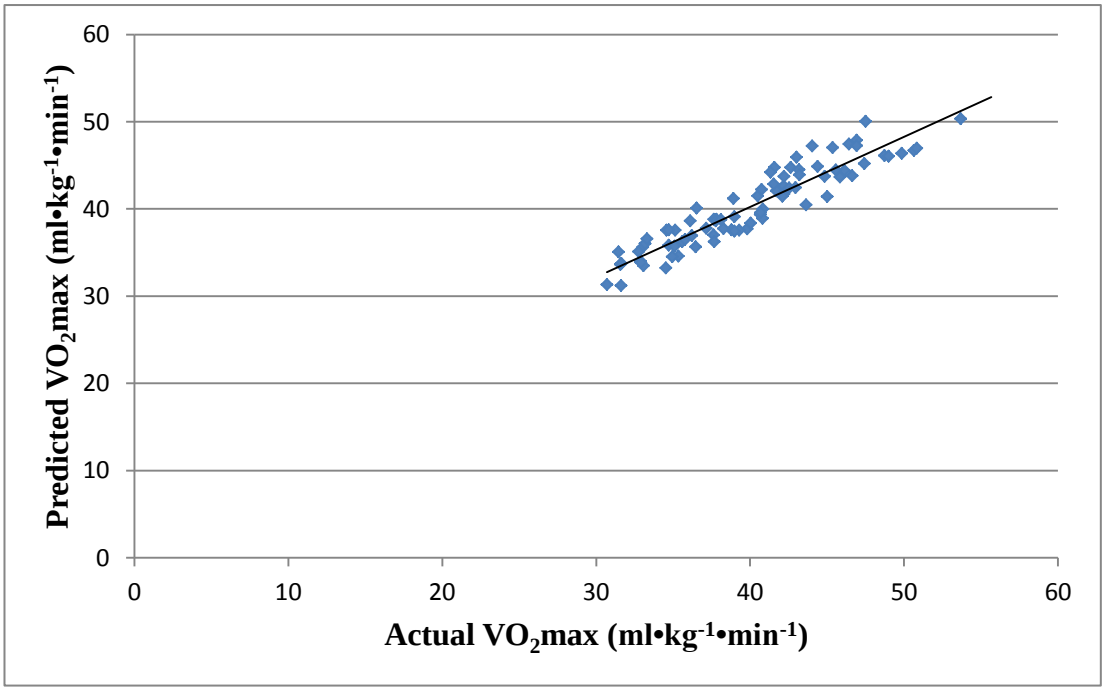

Figure 4.115. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 22 using improved SVM on VO_2max-set-2-Split80.

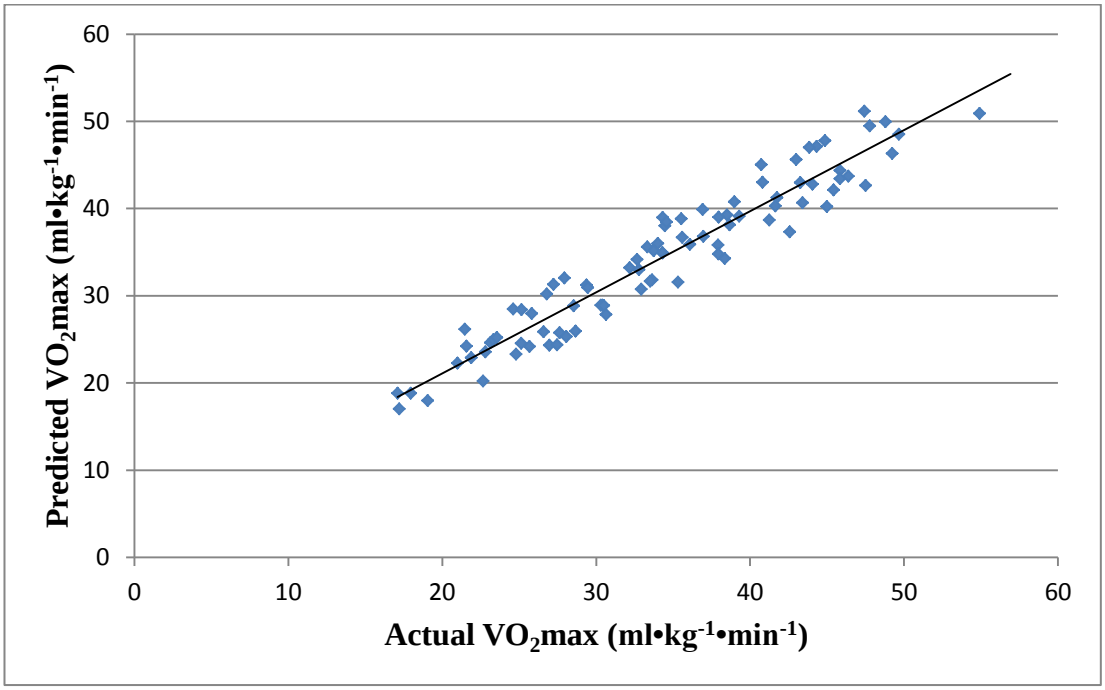

Figure 4.116. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 27 using improved SVM on VO_2max-set-3-Split80.

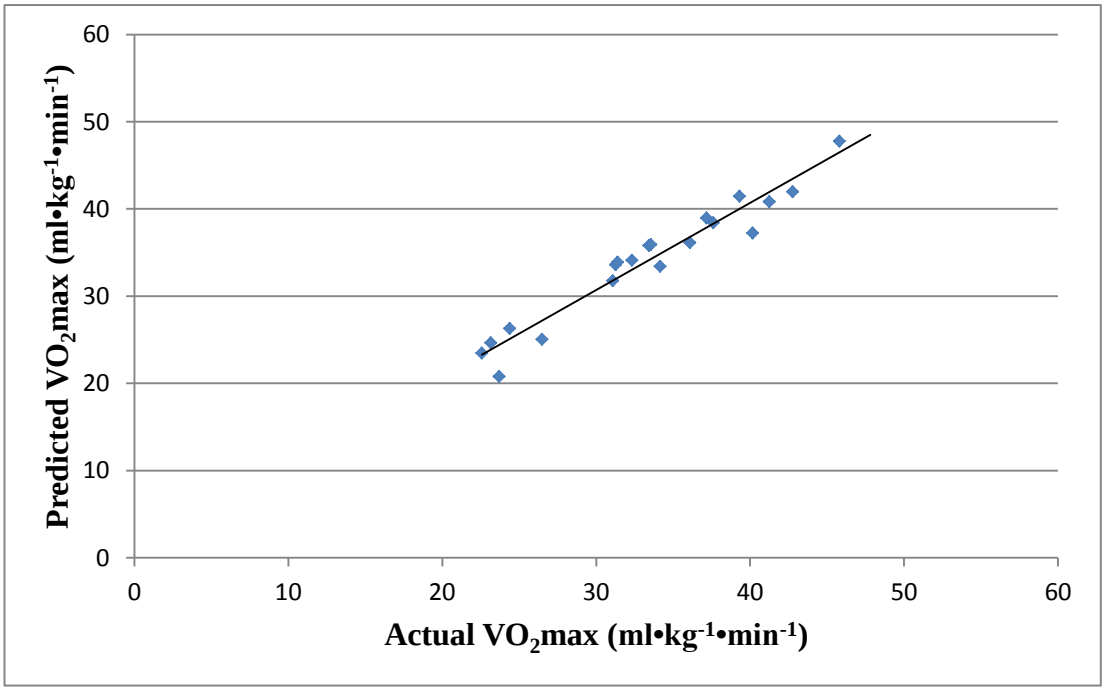

Figure 4.117. Scatter plot of actual VO_2max vs. predicted VO_2max for Model 51 using improved SVM on VO_2max-set-4-Split80.

5. CONCLUSION

In this thesis, several VO_2max prediction models have been developed by using non-exercise, submaximal and hybrid variables and employing SVM, MFANN and MLR regression methods on four different data sets. Using 10-fold cross validation on the data sets, performance metrics *R* and *SEE* have been used to assess the performance of all prediction models.

Considering the obtained results, one can conclude that SVM-based VO_2max prediction models are more accurate than the prediction models developed by MFANN and MLR. In other words, SVM-based VO_2max prediction models yield higher *R*'s and lower *SEE*'s. The ranking in the performance of the methods for prediction of VO_2max, in ascending order, is SVM, MFANN and MLR. Because of the non-linear characteristics of VO_2max, linear regression methods yielded higher *SEE*'s for prediction. On the other hand, MLR produced faster results compared to the other machine learning methods for prediction.

For VO_2max-set-3, among the prediction models including non-exercise predictor variables, the models including the non-exercise questionnaire variable AC have lower *SEE*'s compared to the models without AC. The *SEE*'s of the prediction models including the non-exercise questionnaire variables are always lower than the *SEE*'s of the models including submaximal variables. According to these results, it is clearly seen that the non-exercise questionnaire predictor variables have a positive effect on VO_2max prediction.

For VO_2max-set-4, among the models including hybrid predictor variables, inclusion of non-exercise variables to the prediction models decreases the *SEE*'s and among the non-exercise predictor variables, PAR has the strongest effect for prediction of VO_2max. Similarly, among the submaximal predictor variables, SM-Speed has the strongest effect for prediction of VO_2max. According to this determination, the models including the submaximal variable SM-Speed and non-exercise variable PAR yields the lowest *SEE*'s compared to all other hybrid models.

Also, a new approach for improving the performance of SVM and MFANN models for prediction of VO_2max has been proposed. As stated before, this data

reduction algorithm is based on the elimination of irrelevant samples from the training data by taking into account the absolute prediction errors of each sample. It is shown that improved SVM-based and MFANN-based VO_2max prediction models yield noticeable decrements in error rates compared to that of regular SVM-based and MFANN-based VO_2max prediction models. Additionally, the results on our new approach showed that improved SVM-based prediction models are more accurate than improved MFANN-based prediction models on all data sets.

On the other hand, training times of improved SVM-based and MFANN-based prediction models are higher than those of regular SVM-based and MFANN-based prediction models. In addition, average decrement rates in *SEE*'s of improved SVM-based and MFANN-based prediction models on Split80 sets are higher than improved SVM-based and MFANN-based prediction models on Split70 sets.

In the scope of this thesis, the performance of the proposed data reduction algorithm has been compared with two outlier detection algorithms including Z-score and Grubbs' test. It is shown that the improved SVM-based and MFANN-based VO_2max prediction models perform better than outlier-based SVM and MFANN VO_2max prediction models. In addition, the proposed data reduction algorithm is more selective compared to the outlier detection algorithms. The percentage of the removed samples of the proposed approach is higher than the percentage of the removed samples of the outlier detection algorithms.

Future work will include improving the performance of the data reduction algorithm. More specifically, adaptive threshold determination using intelligent techniques will be explored. In addition, this algorithm can be applied to solve different prediction problems than VO_2max.

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