ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

Noushin SHOKROLLAHI GHAHREMANLOU

PREDICTION OF MAXIMUM OXYGEN UPTAKE FROM MAXIMAL AND NON-EXERCISE VARIABLES USING MACHINE LEARNING METHODS

DEPARTMENT OF COMPUTER ENGINEERING

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ABSTRACT

MSc THESIS

PREDICTION OF MAXIMUM OXYGEN UPTAKE FROM MAXIMAL AND NON-EXERCISE VARIABLES USING MACHINE LEARNING METHODS

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The purpose of this thesis is to develop accurate VO_2max prediction models using maximal and N-Ex variables and show that the accuracy of maximal prediction models can be improved by adding N-Ex questionnaire predictor variables. Machine learning methods such as SVM, ANN, MLR and GRNN are used for developing VO_2max prediction models. Two different datasets are used for VO_2max prediction. Using 10-fold cross validation, the performance of the models are evaluated by calculating *R*'s and *SEE*'s. It is shown that adding questionnaire to ANN-based prediction models yields 4.25% to 10.81% increments in *R*'s and 27.53% to 35.59% decrements in *SEE*'s for the first dataset and 1.08% to 6.97% increments in *R*'s and 0.53% to 17.97% decrements in *SEE*'s for the second dataset. Also it is concluded that ANN-based prediction models are more accurate than GRNN-based, SVM-based and MLR-based prediction models.

Key Words: Machine learning, maximal oxygen uptake, prediction

.

ÖZ

YÜKSEK LİSANS TEZİ

MAKSİMAL VE EGZERSİZE BAĞLI OLMAYAN DEĞİŞKENLER KULLANARAK MAKSİMUM OKSİJEN ALIMININ MAKİNE ÖĞRENMESİ YÖNTEMLERİYLE TAHMİN EDİLMESİ

Noushin SHOKROLLAHI GHAHREMANLOU

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
BİLGİSAYAR MÜHENDİSLİĞİ ANABİLİM DALI

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: Yrd. Doç. Dr. Mustafa ORAL
: Doç. Dr. Ulus Çevik

Bu tezin amacı, maksimal ve egzersize bağlı olmayan değişkenler kullanarak doğru VO_2max tahmin modelleri geliştirmek ve maksimal tahmin modellerinin egzersize bağlı olmayan anket değişkenleriyle geliştirilebileceğini göstermektir. DVM, YSA, ÇDR ve GRSA gibi makine öğrenmesi yöntemleri, VO_2max tahmin modellerini geliştirmek için kullanılmıştır. VO_2max tahmin için iki değişik veri kümesi kullanılmıştır. Modellerin başarımını ölçmek amacıyla kullanılan *KK*ve *STH* değerleri 10 katlı çapraz doğrulama kullanarak hesaplanmıştır. Sonuçlar göstermiştir ki, YSA tabanlı maksimal tahmin modellerine anket sonuçlarını eklemek ilk veri kümesi için *KK* değerinde %4.25 ile %10.81 arasında artışa ve *STH* değerinde ise %27.53 ile %35.59 arasında bir düşüşe neden olmuştur. İkinci veri kümesinde ise *KK* değerinde %1.08 ile %6.97 arasında artış,*STH* değerinde ise %0.53 ile %17.97 arasında düşüş görülmüştür. Bununla birlikte YSA tabanlı tahmin modellerinin GRSA, DVM ve ÇDR tabanlı modellere göre daha doğru sonuçlar ürettiği gözlenmiştir.

Anahtar Kelimeler: Makine öğrenmesi,maksimum oksijenalımı, tahmin

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LIST OF ABBREVIATONS

ANN	: Artificial Neural Network
SVM	: Support Vector Machine
MLR	: Multiple Linear Regression
GRNN	: Generalized Regression Neural Network
VO_2max	: Maximal Oxygen Uptake
CRF	: Cardio Respiratory Fittness
SEE	: Standard Error of Estimation
R	: Correlation Coefficient
RBF	: Radial Basis Function
BMI	: Body Mass Index
HR	: Heart Rate
RER	: Respiratory Exchange Ratio
RPE	: Rating of Perceived Exertion
T	: Time
AC	: Activity Code
LBM	: Lean Body Mass
BF	: Body Fat
A	: Age
G	: Gender
GRD	: Grade
PFA	: Perceived Functional Ability
PA-R	: Physical Activity Rating
N-Ex	: Non-Exercise
DVM	: Destek Vektör Makineleri
YSA	: Yapay Sini Ağları
ÇDR	: Çoklu Doğrusal Regresyon
GRSA	: Genelleştirilmiş Regresyon Sinir Ağları
STH	: Standart Tahmin Hatası
KK	: Korelasyon Katsayısı

1. INTRODUCTION

1.1. What is VO_2max?

Maximum oxygen that human can consume during exercise in one minute is called maximal oxygen uptake (VO_2max) (Hill and Rowell, 1996). The term "VO_2" is derived from V-volume of O_2-oxygen. There is a point where exercise intensity can continue to increase without the associated rise in oxygen consumption. At this point oxygen consumption plateaus defines the VO_2max or an individual's maximal aerobic capacity. Either an absolute rate in liters of oxygen per minute (l/min) or a relative rate in milliliters of oxygen per kilogram of bodyweight per minute (ml/kg/min) can be used to express this volume (Kaminsky, 2005). The latter expression is often used to compare the performance of endurance sports athletes (Kaminsky, 2005). VO_2max is one indicator of an athlete's potential, while other data are better predictors of current endurance performance (Billat et al., 1999). Below is normative data for the VO_2max assessment and comprises of the following grades: Very Poor, Poor, Fair, Good, Excellent and Superior.

Table 1.1. Female Normative Data for VO_2max (values in ml/kg/min) (Achten, and Jeukendrup, 2003)

Age	Very Poor	Poor	Fair	Good	Excellent	Superior
13-19	<25.0	25.0 - 30.9	17.5 - 20.1	24.5 - 28.9	24.5 - 28.9	>41.9
20-20	<23.6	23.6 - 28.9	29.0 - 32.9	33.0 - 36.9	37.0 - 41.0	>41.0
30-39	<22.8	22.8 - 26.9	27.0 - 31.4	31.5 - 35.6	35.7 - 40.0	>40.0
40-49	<21	21.0 - 24.4	24.5 - 28.9	29.0 - 32.8	32.9 - 36.9	>36.9
50-59	<20.2	20.2 - 22.7	22.8 - 26.9	27.0 - 31.4	31.5 - 35.7	>35.7
60+	<17.5	17.5 - 20.1	20.2 - 24.4	24.5 - 30.2	30.3 - 31.4	>31.4

Table 1.2. Male Normative Data for VO_2max (values in ml/kg/min) (Achten, and Jeukendrup, 2003)

Age	Very Poor	Poor	Fair	Good	Excellent	Superior
13-19	<35.0	35.0 - 38.3	38.4 - 45.1	45.2 - 50.9	51.0 - 55.9	>55.9
20-20	<33.0	33.0 - 36.4	36.5 - 42.4	42.5 - 46.4	46.5 - 52.4	>52.4
30-39	<31.5	31.5 - 35.4	35.5 - 40.9	41.0 - 44.9	45.0 - 49.4	>49.4
40-49	<30.2	30.2 - 33.5	33.6 - 38.9	39.0 - 43.7	43.8 - 48.0	>48.0
50-59	<26.1	26.1 - 30.9	31.0 - 35.7	35.8 - 40.9	41.0 - 45.3	>45.3
60+	<20.5	20.5 - 26.0	26.1 - 32.2	32.3 - 36.4	36.5 - 44.2	>44.2

1.2. Why Measure VO_2max?

VO_2max gives an indication of a person's ability to provide essential fuel (oxygen) to working muscles, and the efficiency with which the muscles use this fuel to create movement. It is basically how well a person utilizes oxygen to create movement. Better breathing is the key in endurance events to go faster, reach higher, and be stronger. The idea of oxygen consumption being an accurate measure of the amount of energy that a person expends, and therefore the number of calories he (she) burns. VO_2max basically puts a value to this rate of energy expenditure. VO_2max represents the maximum value of energy expenditure that can be reached at full-out effort. The higher VO_2max, the greater oxygen consumption across all levels of effort.

1.3. Types of VO_2max Fitness Tests

There are a variety of choices when it comes to performing a VO_2max test and the type of test that will be chosen often depends on who is being tested and where. When testing an individual, exercise or Monarc bikes, treadmills, and steps are the most common methods used, while the beep test is a popular choice when training sports teams.

1.3.1. Bike Tests

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

1.3.2. Treadmill or Walking Tests

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

1.3.3. Step Tests

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

1.3.4. Beep Test

Popular with sporting clubs and other organizations, the beep test requires participants to run between two markers set 20 meters apart and is known as a multi-

stage test. The athlete or client is required to run between the two markers, starting when the beep sounds and arrive at the other end before the beep is heard again. As the test progresses, the beeps sound closer together, making it necessary to run faster as you are getting tired, just to keep up. Once the athlete misses two beeps in a row (i.e. cannot reach the marker before the beep sounds) they need to stop and the last staged noted is the equivalent of their fitness level.

1.4. How to Measure VO_2max?

Maximal fitness testing is one way to determine the maximum amount of oxygen consumed during exercise. To accurately measure VO_2max, an athlete would have to put forth a physical effort that would be in sufficient duration and intensity to fully tax their aerobic energy system. These tests can be either direct or indirect. To obtain the most accurate and direct results, the athletic testing would involve a graded treadmill or cycle test in which exercise intensity is progressively increased while measuring the ventilation and oxygen and carbon dioxide concentration of the inhaled and exhaled air via open-circuit spirometery. The subjects would be fitted with a respiratory mask, covering their mouth and nose, and would be connected to a cardiac monitoring device, in the beginning of the exam.

Prior to testing, all vital statistics would be taken to obtain baseline measurements including heart rate, resting respiration and blood pressure. The subjects would be encouraged to exercise to exhaustion during the test. Until maximum exertion is achieved the workload during the test would increase approximately every minute. During the assessment, a small (pinprick) blood sample is taken at regular intervals from either a finger or ear-lobe to test blood lactate concentrations. Essentially, as the athlete progresses to higher intensity during the test, the muscles need an increasing volume of oxygen, a process, which is continued until the supply of oxygen becomes limiting or the ability of the muscle to utilize oxygen is exceeded. There would be no further increase in oxygen uptake at this point. Again, intensity and heart rate response increase without the associated rise in oxygen consumption, once an athlete reaches their VO_2max, but this is not always

observed (Billat, and Koralsztein, 1996.; Carey and Richardson, 2003). To obtain recovery heart rate a two to three minute recovery time is always included. All data is recorded continuously throughout the test period and the test can be stopped by the subject at any time for whatever reason. The average total time for the tests are usually around 90 minutes, including time for a warm-up, the actual assessment, time for a cool down and an overview of the results. However, this can vary depending on the education of the athlete (Dabney, and Butler, 2006).

Direct measurement of VO_2max requires special, expensive equipment and requires the athlete to perform until maximal exertion has been reached (American College of Sports Medicine, 2000). Making submaximal tests are more attractive for many athletes because the time, performance, and equipment needed to perform maximal tests, are prohibitive for many athletes. Submaximal tests require less effort, time, and equipment, yet yield results that closely approximate VO_2max. Many choose the mile or mile-and-a-half run as the indicator of the aerobic fitness like, while many submaximal tests exist (Baechle and Earle, 2000; American College of Sports Medicine, 2000). The mile run and mile-and-a-half run tests are easy to administer (even to large groups) and require no special training or equipment. They are also relatively easy to score and interpret. These tests are generally viewed as adequate for purposes of general fitness testing while they yield estimates that are not as reliable as some of the other tests,. The YMCA cycle ergometer test and the Bruce submaximal treadmill test are more appropriate for those interested in more accurate estimates. However, not all athletes have proper training with either apparatus in order to perform at their best on these tests (Baechle and Earle, 2000). Typically, athletes perform these tests under the supervision of sports medicine specialists or personal trainers at local health clubs for a minimal charge, often already included with club membership.

Walking test where the Bruce Protocol is followed is the most common indirect test conducted to predict VO_2max values (Hill, and Timmis, 2002). The walking test that follows the Bruce Protocol would begin with a warm-up on the treadmill (Hill, and Timmis, 2002). The treadmill would then begin moving at an easy, comfortable pace of 2.7 km/hr at a gradient or incline of 10%. Every three

minutes, up to a point where the athlete feels unable to continue with the protocol, both the speed and the incline would increase. During this test, an exercise specialist would monitor the heart rate, blood pressure and rate of perceived exertion . The test would be terminated at the point where the athlete can no longer perform the exercise, this point would be their peak level of oxygen consumption. A two minute cool-down period would then begin to assess how quickly the cardiovascular system recovers. Since the Bruce Treadmill Test is known as an indirect test, it only estimates VO_2max using the following formulas (as opposed to direct tests that use gas analyzers to measure respired gases):

Men: $VO_2\text{max} = 14.8 - (1.379 * T) + (0.451 * T_2) - (0.012 * T_3)$
(1.1.)
Women: $VO_2\text{max} = 4.38 * T - 3.9$
(1.2.)

In both cases, T denotes the time in minutes spent on the treadmill. It is important to remember that 10 minutes and 45 seconds would be expressed as 10.75 minutes before the formula is used. By comparing past and present test results athletes can analyze their performances. A variety of exercise modes, including cycle ergometry, stepping and walking, and jogging or running on a treadmill or track, and prediction variables such as age, gender, body mass, exercise pace, and heart rate are used in these tests (Bruce, Kusumi, and Hosmer, 1973; Cooper, 1968; Kline et al., 1987).

Other methods that do not require exercise are also available to predict VO_2max. Without the need to perform a maximal or submaximal exercise test, non-exercise (N-Ex) regression equations provide a convenient estimate of CRF. This approach is inexpensive, time-efficient, and realistic for large groups. Age, gender, body mass index (BMI), percent body fat (BF), physical activity rating (PA-R) and perceived functional ability (PFA), are common N-Ex predictor variables. The PA-R questionnaire allows participants to self-report their level of physical activity during the past six months. The response to the PA-R questionnaire is the PA-R score (range = 0–10). The PFA includes simple questions which ask individuals to rate their

ability to exercise at a comfortable pace for 1 and 3 miles (Akay et. al., 2009). Figue 1.1 and Figure 1.2 show a sample PA-R and PFA questionnaire, repectively.

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 physical activity rating (PA-R) questionnaire (Akay et. al., 2009).

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 *mediu*m 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 *mediu*m 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 *mediu*m 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. Perceived functional ability (PFA) questionnaire. (Akay et. al., 2009).

1.5. Motivation and Purpose of This Study

The purpose of this thesis is to develop accurate VO_2max prediction models using maximal and N-Ex variables. Machine learning methods such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Multiple Linear Regression (MLR) and General Regression Neural Networks (GRNN) are used for

developing VO_2max prediction models. The performance of maximal prediction models are improved by including N-Ex variables in the models.

We use two different datasets that involve measured VO_2max values of individuals as well as the maximal test variables; heart rate , grade, RPE from treadmill test, RER, time and also non-exercise variables; gender, age, BMI, BF, LBM, responses to PFA, PA-R and AC questionnaires. Several different VO_2max prediction models are developed using 10-fold cross validation on the datasets. *SEE* and *R* values of the models are computed and it is shown that the performance of the VO_2max prediction model based on maximal and standard N-Ex variables are improved by adding questionnaire variables in the prediction model. Also, in this thesis, performance of the machine learning methods (ANN, SVM, GRNN and MLR) is compared for VO_2max prediction.

2. PREVIOUS WORKS

There are lots of studies that have used maximal, submaximal or N-Ex variables for VO_2max prediction, that will be described in this section.

2.1. Studies over Maximal Prediction Models

Froelicher et. al. (Froelicher et al., 1974) investigated the hypothesis that an individual's VO_2max can be realistically predicted by the maximal time achieved in the Balke treadmill protocol. The oxygen consumption in the final minute of exercise of 1025 healthy men who performed a maximal effort in the Balke protocol were linearly regressed on their maximal treadmill time using a least-squares fit technique. Their results for *SEE* and *R* were 4.26 and 0.72, respectively.

Foster et. al. (Foster et. al., 1984) had an investigation on 230 male patients. Individuals were categorized according to health status on the basis of having or not having cardiovascular disease (documented myocardial infarction, typical angina pectoris, or myocardial revascularization surgery). They used the time variable and tried to show nonlinear regression could produce more accurate results than linear regression for VO_2max prediction. *SEE* and *R* of their models were reported to be 3.35 and 0.97, respectively.

Patton et. al. (Patton et. al., 1982) used a maximal predictive cycle ergometer test for estimating VO_2max. The dataset contained 15 males and 12 females. The test consisted of pedaling a cycle ergometer (Monark) at 75 rev/min, beginning at an intensity of 37.5 watts and increasing this amount each minute until the subject could no longer maintain pedal rate. The highest work rate achieved was recorded as the end point of the test and used to construct regression equations to predict VO_2max. This was compared with two direct measures of VO_2max (an interrupted treadmill run and an interrupted cycle ergometer procedure at 60 rev/min) and with the submaximal predictive test. The *R* of their models was 0.85, however they did not report any results for *SEE*.

Storer et. al. (Storer et. al., 1990) used 116 females and 115 males, aged 20-70 years, sedentary, nonsmoking and apparently healthy subjects. They hypothesized that cycle ergometer VO_2max could be accurately predicted due to its more direct relationship with watts. Therefore, they developed an equation including the variables watts, weight and age. They reported that the *R* of their model was 0.94.

Jette et. al. (Jette et. al., 1976) investigated if VO_2max could be predicted from independent variables measured during the administration of the Canadian Home Fitness Test. They used 59 subjects between the ages of 15 and 74 years underwent the fitness test and a progressive exercise treadmill test for the direct determination of volitional VO_2max. Average oxygen cost of the last completed exercise stage, body weight, post exercise heart rate and age were the variables for their models. Their results indicated that VO_2max could be adequately predicted. *SEE* and *R* were reported to be 4.08 and 0.90, respectively.

Stickland et. al. (Stickland et. al., 2003) investigated the accuracy of the 20-m multi-stage shuttle run test to predict VO_2max in 60 men and 62 women young adults. Their models included only one variable called the last half-stage of the shuttle run completed. For men, the reported values of *SEE* and *R* were 4.07 and 0.88, respectively. For women, the reported values of *SEE* and *R* were 3.64 and 0.81, respectively.

Flouris et. al. (Flouris et. al., 2005) used the maximal attained speed from the 20-m shuttle run test to predict VO_2max of 110 healthy young males. *SEE* and *R* of their best model were reported to be 1.70 and 0.96, respectively.

Ruiz et. al. (Ruiz et. al., 2008) developed an artificial neural network (ANN) equation to estimate VO_2max from 20 m shuttle run test performance (stage), sex, age, weight, and height in 122 boys and 71 girls adolescents aged 13-19 years. The *SEE* and *R* of their model was reported to be 2.78 and 0.96, respectively.

Leger et. al. (Leger and Lambert, 1982) validated a maximal multistage 20-m shuttle run test for the prediction of VO_2max in 91 adults. Maximal speed was the only variable in their model. They hypothesized that the 20-m shuttle run test could be a valid and reliable test for the estimation of VO_2max. The presented *SEE* and *R*

values were 5.4 and 0.84, respectively.Table 2.1 summarizes the above studies that used maximal models to estimate VO_2max.

Table 2.1. Summary of maximal regression models to estimate VO_2max

Study	Ages	Predictor Variables	SEE	R
Frolicher et al. (1974)	20-53	Time	4.26	0.72
Foster et al. (1984)	-	Time1, Time2, Time3	3.35	0.97
Patton et al. (1982)	-	Watts	-	0.85
Storer et al. (1990)	20-70	Watts	212.0	0.94
Jette et al. (1976)	15-74	Heart Rate	4.08	0.9
Stickland et al. (2003)	-	Speed	3.64	0.81
Flouris et al. (2005)	-	Speed	1.7	0.96
Ruiz et al. (2008)	13-19	Stage, Speed, Time	2.78	0.96
Leger et al. (1982)	-	Speed	5.4	0.84

2.2. Studies over Non-Exercise Prediction Models

Bruce et. al. (Bruce, Kusumi, and Hosmer, 1973) measured VO_2max using an open circuit technique, during the last 2 to 4 minutes of a multistage treadmill test of maximal exercise in 151 men and 144 women of 29 to 73 years of age. Their prediction was highly correlated with duration of exercise by this standardized protocol. By regression equations they predicted average normal values for healthy persons from sex, activity status, and age. *SEE* and *R* of their study were reported to be 4.84 and 0. 81, respectively.

Jackson et al. (Jackson et al., 1990) in their study developed functional aerobic capacity prediction models without using exercise tests (N-Ex) and to compare the accuracy with Astrand single-stage submaximal prediction methods. The data of 2,009 subjects (9.7% female) were randomly divided into validation (N = 1,543) and cross-validation (N = 466) samples. The validation sample was used to develop two N-Ex models to estimate VO_2max. One model estimated percent fat from skinfolds (N-Ex %fat) and the other used body mass index (N-Ex BMI) to represent body composition. They proved that N-Ex models were more accurate than what was obtained from VO_2max estimated from the Astrand prediction models.

According to their reported results, values for *SEE* and *R* were 5 and 0.82, respectively.

Ainsworth et al. (Ainsworth et. al., 2004) determined the validity and reproducibility of the Physical Activity Index from the College Alumnus Questionnaire (PAI-CAQ) in 78 men and women of 21–59 years of age with a broad range of physical activity habits. The PAI-CAQ was computed as the sum of energy expended in stair climbing, walking, and sports and recreational physical activity recalled from the past week. Data were validated against measures of cardiorespiratory fitness, body fatness, motion detection, and physical activity records. All physical activities were recorded by participants for six 48-hour periods. Each day of the week, including weekends, were represented at least twice in the physical activity records. Age-adjusted correlation coefficients between like activities on the College Alumnus Questionnaire and physical activity records ranged from 0.25 to 0.65 in men and 0.28 to 0.86 in women. The presented *SEE* and *R* values were 4.46, 0.88, respectively.

Heil et al. (Heil et. al., 1995) developed a VO_2max prediction model derived from N-EX based predictors. VO_2max was measured using a walking treadmill protocol with 229 females and 210 males between 20 and 79 yr of age. They divided subjects into validation (V) (85% of total; N = 374) and cross-validation (CV) (15% of total; N = 65) groups. The V group was used to validate generalized and gender-specific models using stepwise multiple regression procedures with gender, age and age2, percent body fat, and a physical activity code (AC). Their study showed that generalized and gender-specific models were highly accurate relative to N-EX and exercise based models in the literature. Cross-validation procedures were used to evaluate model stability. Their reported values for *SEE* and *R* were 4.9 and 0.88, respectively.

George et al. (George, Stone, and Burkett, 1997) used self-reported N-EX predictor variables to develop VO_2max regression model. The VO_2max of 100 physically active college students (50 females, 50 males), aged 18 to 29 yr, was measured using a treadmill protocol and open circuit calorimetry. The questionnaire-based N-EX regression model developed in their study exceeded the accuracy of

previously developed N-EX regression models and was comparable to many exercise-based regression models in the literature. Their results suggested that a questionnaire-based N-EX regression model could provide a valid and convenient method for predicting VO_2max. Best *SEE* and *R* values of their study were 3.6 and 0.84, respectively.

Bradshaw et al. (Bradshaw et. al., 2005.) developed a regression equation to predict VO_2max based on N-EX data. All participants (N = 100), ages 18-65 years, successfully completed a maximal graded exercise test (GXT) to assess VO_2max. Multiple linear regression generated a N-EX prediction equation. Cross validation was used in their study. They proved that based on standardized beta-weights, the PFA variable was the most effective at predicting VO_2max followed by age, gender, BMI, and PA-R. They provided a N-EX regression model that yielded relatively accurate results and was a convenient way to predict VO_2max in adult men and women. Reported *SEE* and *R* values for their study were 3.63 and 0.91, respectively.

Akay et al. (Akay et. al., 2009) developed N-Ex VO_2max prediction models by using support vector regression (SVR) and multilayer feed forward neural networks (MFFNN). VO_2max values of 100 subjects (50 males and 50 females) measured using a maximal graded exercise test. The variables; gender, age, BMI, PFA to walk, jog or run given distances and PA-R were used to build two N-Ex prediction models. They used 10-fold cross validation on the dataset. They compared the results of SVR an MFFNN prediction models. Their best *SEE* and *R* were reported as 3.23 and 0.91, respectively. Table 2.2 summarizes the above studies that used N-Ex models to estimate VO_2max.

Table 2.2. Summary of N-Ex regression models to estimate VO_2max

Study	Ages	Predictor Variables	R	SEE
Bruce et al. (1973)	29-73	G, Age, PA-R, BM	0.81	4.84
Jackson et al. (1990)	18-70	G, Age, PA-R, fat	0.82	5.00
Ainsworth et al. (1992)	21-59	G, Age, Freq, BMI	0.88	4.46
Heil et al. (1995)	20-79	G, Age, PA-R, fat	0.88	4.90
George et al. (1997)	18-29	G, BMI, PA-R, PFA	0.84	3.60
Bradshaw et al. (2005)	18–65	G, Age, BMI, PA-R, PFA	0.91	3.63
M.F.Akay et al.(2009)	18–40	G, Age, BMI, PFA, PA-R	0.91	3.23

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

2.3. Studies over Submaximal Prediction Models

Ebbeling et al. (Ebbeling et. Al., 1991) developed an equation to estimate VO_2max based on a single submaximal stage of a treadmill walking test. Subjects (67 males, 72 females) aged 20-59 years completed 4-min stages at 0, 5, and 10% grades walking at a constant speed (2.0-4.5 mph) and then performed a VO_2max test. Heart rate and respiratory gas exchange variables were measured during the test. *SEE* and *R* of their models were reported to be 5.00 and 0.96, respectively.

Widrick et al. (Widrick, Ward, and Ebbeling, 1992) tried to determine whether a test developed to predict VO_2max during over-ground walking, was similarly valid as a predictor of peak VO_2 when administered during a 1-mile (1.61 km) treadmill walk. Treadmill walk time, mean heart rate over the last 2 full min of the walk test, age, and body mass were entered into two prediction equations. Their overall results indicated a highly significant linear relationship between observed peak VO_2 and predicted values. Their subjects were containing 75 females and 48 males aged 20-59 years. They reported *SEE* and *R* values as 5.26 and 0.91, respectively

Swank et al. (Swank et. Al., 2001) determined the reliability and validity of a branching treadmill protocol in predicting VO_2max. Thirty-seven, apparently healthy individuals (19 women and 18 men); volunteered to participate. On 2 separate testing days, each subject underwent maximal exercise testing using the protocol developed.

Stepwise regression analysis indicated that the percentage of age-predicted maximum heart rate (APMHR) achieved at stage 3, speed and grade at stage 3, and APMHR accounted for 89% of the variance in VO_2max. Their results indicated that health and fitness professionals could incorporate that protocol into their practices for the purpose of predicting VO_2max for their clients outside the laboratory environment. Furthermore, their results indicated that using the proposed regression model is reliable. *SEE* and *R* of their study were reported to be 4.46 and 0.95, respectively.

Larsen et al. (Larsen et. al., 2002) developed a submaximal, 1.5-mile endurance test for college-aged students using walking, jogging, or running exercise. College students (N = 101: 52 men, 47 women), ages 18-26 years, successfully completed the 1.5-mile test twice, and a maximal graded exercise test. Participants were instructed to achieve a "somewhat hard" exercise intensity (rating of perceived exertion = 13) and maintain a steady pace throughout each 1.5-mile test. They used multiple linear regression equations. They reported *SEE* and *R* values as, 2.87 and 0.9, respectively.

Dalleck et al. (Dalleck, Kravitz, and Robergs, 2006) developed an equation to predict VO_2max from a submaximal elliptical cross-trainer test. Fifty-four apparently healthy subjects (25 men and 29 women) participated in the study and were randomly assigned to an original sample group (n = 40) and a cross-validation group (n = 14). Each subject completed an elliptical cross-trainer submaximal (35-minute submaximal stages) and a VO_2max test on the same day, with a 15-minute rest period in between. Stepwise multiple regression analyses were used to develop an equation for estimating elliptical cross-trainer VO_2max from the data of the original sample group. The accuracy of the equation was tested by using data from the cross-validation group. Results indicated that the protocol and equation developed in their study could be used by exercise professionals to provide acceptably accurate estimates of VO_2max in non-laboratory-based settings. Reporetd *SEE* and *R* values were 3.91 and 0.86, respectively.

McComb et al. (McComb, Roh, and Williams, 2006) had a study to develop a prediction equation that could be used to estimate VO_2max from a submaximal water runningprotocol. Thirty-two volunteers (n =19 males, n = 13 females), ages 18

- 24 years, underwent the following testing procedures: (a) a 7-site skin fold assessment; (b) a land VO_2max running treadmill test, and (c) a 6 min water runing test. For the water running submaximal protocol, the participants were fitted with an Aqua Jogger Classic Uni-Sex Belt and a Polar Heart Rate Monitor, the participant's head, shoulders hips and feet were vertically aligned, using a modified running/bicycle motion. They used a regression model to predict VO_2max. They reported *SEE* and *R* values as 3.31 and 0.89, respectively.

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

Waddoups et al. (Waddoups et. al., 2008) determined if single-stage treadmill walking test correctly predicts VO_2max at the low (50% of maximum heart rate) and high (70% of maximum heart rate) ends of the specified heart rate range for males and females aged 18 - 55 years. In their study each of the 34 participants completed one low-intensity and one high-intensity trial. The two trials resulted in significantly different estimates of VO_2max (low-intensity trial and high-intensity trial). Their best results for *SEE* and *R* values reported as 5.7 and 0.78, respectively.

Akalan et al. (Akalan, Robergs, and Kravitz, 2008) hypothesized that a large proportion of the error of VO_2max prediction comes from individual differences in heart rate responses to submaximal exercise, and that if these differences could be decreased the accuracy of VO_2max prediction would increase. Eighty (43 male, 37 female) sedentary to highly trained, healthy volunteers first completed a self-report physical activity assessment (Lo-Par), and then performed a modified YMCA protocol with 4-minute stages, a second submaximal test involving an individualized

ramp submaximal protocol that was terminated at 80% of their cycle ergometer age-predicted maximum heart rate. Exercise and five-minute recovery heart rate data were collected. Multiple regression analysis was used to predict VO_2max. They reported *SEE* and *R* values as 4.23 and 0.94, respectively.

Akay et al. (Akay et. al., 2010) developed an accurate ANN-based model to predict maximal VO_2max of fit adults from a single stage submaximal treadmill jogging test. Participants (81 males and 45 females), aged from 17 to 40 years, successfully completed a maximal graded exercise test (GXT) to determine VO_2max. The variables; gender, age, body mass, steady-state heart rate and jogging speed are used to build the ANN prediction model. Compared with the results of the other prediction models in literature that were developed using Multiple Linear Regression Analysis, the reported values of *SEE* and *R* in thier study were considerably more accurate. They reported *SEE* and *R* values as 1.8 and 0.95, respectively. Table 2.3 summarizes the above studies that used submaximal models to estimate VO_2max.

Table 2.3. Summary of submaximal regression models to estimate VO_2max

Study	Ages	Predictor Variables	R	SEE
Ebbeling at al. (1991)	-	G, Age, HR, Walk speed	0.96	5.00
Widrick, Ward, and Ebbeling (1992)	20-59	G, Age, HR, Weight, Time	0.91	5.26
Swank et al. (2001)	18–43	Age, BM, BMI, HR, RER	0.95	4.46
Larsen et al. (2002)	18–27	G, BM, Exercise Time, HR	0.90	2.87
Dalleck et al. (2006)	20–49	G, Age, HR, BM	0.86	3.91
McComb et al. (2006)	18–56	G, Height, BM, BF, HR	0.89	3.31
Vehrs et al. (2007)	18-40	G, Age, BM, MPH, HR	0.91	2.52
Waddoups et al. (2008)	18–55	G, Age, Height, BM, BMI, HR, RPE	0.78	5.70
Akalan et al. (2008)	18–49	G, BM,W/min, HR, Recovery HR, LoPAR	0.94	4.23
M.F.Akay et al.(2010)	17-40	Age,BM, MPH,HR	0.95	1.80

G, gender; **BM**, body mass; **BMI**, body mass index; **HR**, heart rate; **RER**, respiratory exchange ratio; **RPE**, rating of perceived exertion; **LoPAR**, self-report physical activity assessment; **W/min** ,minutes that watt increase; **PFA**, perceived functional ability; **PA-R**, physical activity rating; **MPH**, speed.

There are several limitations of the studies in literature that focus on predicting VO_2max by using maximal variables. First of all, almost all of these studies used multiple linear regression for developing VO_2max prediction equations. Intelligent data processing techniques such as ANN's have been used in a few studies

only. Secondly, cross validation was not used in most of these studies, which raises a question about the reliability of the presented results. Thirdly, most of studies used maximal variables and standard N-Ex variables such as gender, age, weight and height. In other words, they did not consider including questionnaire type non-exercise variables in their VO_2max prediction models.

The purpose of this thesis is to develop accurate VO_2max prediction models using maximal and N-Ex variables. Machine learning methods such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Multiple Linear Regression (MLR) and General Regression Neural Networks (GRNN) will be used for developing VO_2max prediction models. The performance of maximal prediction models will be improved by including N-Ex variables in the models. The results of the developed models will be compared with the ones obtained from multiple linear regression analysis. It is believed that machine learning methods provide more accurate results for prediction of VO_2max.

3. MATERIAL AND METHODS

3.1. Artificial Neural Networks (ANN)

The human brain provides proof of the existence of massive neural networks that can succeed at those cognitive, perceptual, and control tasks in which humans are successful. The brain is capable of computationally demanding perceptual acts (e.g. recognition of faces, speech) and control activities (e.g. body movements and body functions). The advantage of the brain is its effective use of massive parallelism, the highly parallel computing structure, and the imprecise information-processing capability. The human brain is a collection of more than 10 billion interconnected neurons. Each neuron is a cell that uses biochemical reactions to receive, process, and transmit information. Treelike networks of nerve fibers called dendrites are connected to the cell body or soma, where the cell nucleus is located. Extending from the cell body is a single long fiber called the axon, which eventually branches into strands and substrands and are connected to other neurons through synaptic terminals or synapses. The transmission of signals from one neuron to another at synapses is a complex chemical process in which specific transmitter substances are released from the sending end of the junction. The effect is to raise or lower the electrical potential inside the body of the receiving cell. If the potential reaches a threshold, a pulse is sent down the axon and the cell is ‘fired’. ANN has been developed as generalizations of mathematical models of biological nervous systems. A first wave of interest in neural networks (also known as connectionist models or parallel distributed processing) emerged after the introduction of simplified neurons (McCulloch, and Pitts, 1943). The basic processing elements of neural networks are called artificial neurons, or simply neurons or nodes. In a simplified mathematical model of the neuron, the effects of the synapses are represented by connection weights that modulate the effect of the associated input signals, and the nonlinear characteristic exhibited by neurons is represented by a transfer function. The neuron impulse is then computed as the weighted sum of the input signals, transformed by the transfer function. The learning capability of an

artificial neuron is achieved by adjusting the weights in accordance to the chosen learning algorithm.

A typical artificial neuron and the modeling of a multilayered neural network are illustrated in Figure 3.1. Referring to Figure 3.1, the signal flow from inputs is considered to be unidirectional, which are indicated by arrows, as is a neuron's output signal flow (*O*). The neuron output signal *O* is given by the following relationship:

(3.1.)

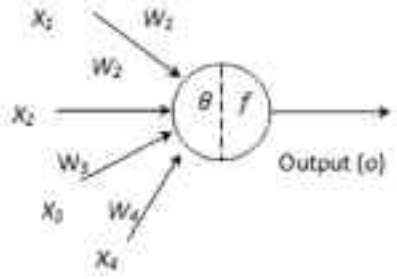
where *wj* is the weight vector, and the function *f(net)* is referred to as an activation (transfer) function. The variable *net* is defined as a scalar product of the weight and input vectors,

(3.2.)

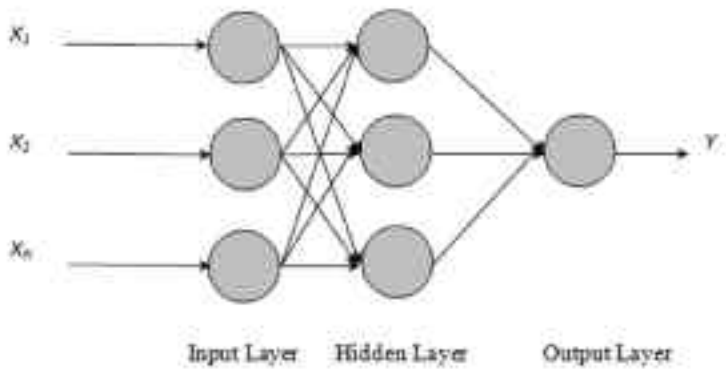
where *T* is the transpose of a matrix, and, in the simplest case, the output value *O* is computed as

(3.3.)

where θ is called the threshold level; and this type of node is called a linear threshold unit.



(a) Artificial neuron



(b) Multilayered artificial neural network

Figure 3.1. Architecture of an artificial neuron and a multilayered neural network.

3.1.1. Neural Networks Architectures

The basic architecture consists of three types of neuron layers: input, hidden, and output layers. In feed-forward networks, the signal flow is from input to output units, strictly in a feed-forward direction. The data processing can extend over multiple (layers of) units, but no feedback connections are present. Recurrent networks contain feedback connections. Contrary to feed-forward networks, the dynamical properties of the network are important. In some cases, the activation values of the units undergo a relaxation process such that the network will evolve to a stable state in which these activations do not change anymore. In other applications, the changes of the activation values of the output neurons are significant, such that the dynamical behavior constitutes the output of the network. There are several other neural network architectures (Elman network, adaptive resonance theory maps, competitive networks, etc.), depending on the properties and requirement of the application.

A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to train the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule. The learning situations in neural networks may be classified into three distinct sorts. These are supervised

learning, unsupervised learning, and reinforcement learning. In supervised learning, an input vector is presented at the inputs together with a set of desired responses, one for each node, at the output layer. A forward pass is done, and the errors or discrepancies between the desired and actual response for each node in the output layer are found. These are then used to determine weight changes in the net according to the prevailing learning rule. The term supervised originates from the fact that the desired signals on individual output nodes are provided by an external teacher.

The best-known examples of this technique occur in the backpropagation algorithm, the delta rule, and the perceptron rule. In unsupervised learning (or self-organization), a (output) unit is trained to respond to clusters of pattern within the input. In this paradigm, the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified; rather, the system must develop its own representation of the input stimuli. Reinforcement learning is learning what to do – how to map situations to actions – so as to maximize a numerical reward signal. The learner is not told which actions to take, as in most forms of machine learning, but instead must discover which actions yield the most reward by trying them. In the most interesting and challenging cases, actions may affect not only the immediate reward, but also the next situation and, through that, all subsequent rewards. These two characteristics, trial-and-error search and delayed reward are the two most important distinguishing features of reinforcement learning.

3.1.2. Hebbian Learning

The learning paradigms discussed above result in an adjustment of the weights of the connections between units, according to some modification rule. Perhaps the most influential work in connectionism's history is the contribution of Hebb (Hebb, 1949), where he presented a theory of behavior based, as much as possible, on the physiology of the nervous system. The most important concept to

emerge from Hebb's work was his formal statement (known as Hebb's postulate) of how learning could occur. Learning was based on the modification of synaptic connections between neurons. Specifically, when an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased. The principles underlying this statement have become known as Hebbian Learning. Virtually, most of the neural network learning techniques can be considered as a variant of the Hebbian learning rule. The basic idea is that if two neurons are active simultaneously, their interconnection must be strengthened. If we consider a single layer net, one of the interconnected neurons will be an input unit and one an output unit. If the data are represented in bipolar form, it is easy to express the desired weight update as

$$w_i(new) = w_i(old) + x_i o \tag{3.4.}$$

where *o* is the desired output for $i = 1$ to *n(*inputs*)*.

Unfortunately, plain Hebbian learning continually strengthens its weights without bound (unless the input data is properly normalized).

3.1.3. Perceptron Learning

The perceptron is a single layer neural network whose weights and biases could be trained to produce a correct target vector when presented with the corresponding input vector. The training technique used is called the perceptron learning rule. Perceptrons are especially suited for simple problems in pattern classification. Suppose we have a set of learning samples consisting of an input vector *x* and a desired output *d(k)*. For a classification task, the *d(k)* is usually +1 or −1. The perceptron-learning rule is very simple and can be stated as follows:

1. Start with random weights for the connections.
2. Select an input vector *x* from the set of training samples.

3. If output $y_k \neq d(k)$ (the perceptron gives an incorrect response), modify all connections *wi* according to: $\delta w_i = \eta(d_k - y_k)x_i$; ($\eta$ = learning rate).

4. Go back to step 2.

Note that the procedure is very similar to the Hebb rule; the only difference is that when the network responds correctly, no connection weights are modified.

3.1.4. Backpropagation Learning

The simple perceptron is just able to handle linearly separable or linearly independent problems. By taking the partial derivative of the error of the network with respect to each weight, we will learn a little about the direction the error of the network is moving. In fact, if we take the negative of this derivative (i.e. the rate change of the error as the value of the weight increases) and then proceed to add it to the weight, the error will decrease until it reaches a local minima. This makes sense because if the derivative is positive, this tells us that the error is increasing when the weight is increasing. The obvious thing to do then is to add a negative value to the weight and vice versa if the derivative is negative. Because the taking of these partial derivatives and then applying them to each of the weights takes place, starting from the output layer to hidden layer weights, then the hidden layer to input layer weights (as it turns out, this is necessary since changing these set of weights requires that we know the partial derivatives calculated in the layer downstream), this algorithm has been called the backpropagation algorithm.

A neural network can be trained in two different modes: online and batch modes. The number of weight updates of the two methods for the same number of data presentations is very different. The online method weight updates are computed for each input data sample, and the weights are modified after each sample. An alternative solution is to compute the weight update for each input sample, but store these values during one pass through the training set which is called an epoch. At the end of the epoch, all the contributions are added, and only then the weights will be updated with the composite value. This method adapts the weights with a cumulative

weight update, so it will follow the gradient more closely. It is called the batch-training mode.

Training basically involves feeding training samples as input vectors through a neural network, calculating the error of the output layer, and then adjusting the weights of the network to minimize the error.

3.2. Support Vector Machines (SVMs)

Support Vector learning is based on simple ideas which originated in statistical learning theory (Vapnik, 1998). The simplicity comes from the fact that Support Vector Machines (SVMs) apply a simple linear method to the data but in a high-dimensional feature space non-linearly related to the input space. Moreover, even though we can think of SVMs as a linear algorithm in a high-dimensional space, in practice, it does not involve any computations in that high-dimensional space. This simplicity combined with state of the art performance on many learning problems (classification and regression) has contributed to the popularity of the SVM.

SVMs use an implicit mapping Φ of the input data into a high-dimensional feature space defined by a kernel function, i.e., a function returning the inner product $(\Phi(x), \Phi(x'))$ between the images of two data points x, x' in the feature space. The learning then takes place in the feature space, and the data points only appear inside dot products with other points. This is often referred to as the "kernel trick" (Schölkopf, and Smola, 2002). More precisely, if a projection $\Phi: X \rightarrow H$ is used, the dot product $(\Phi(x), \Phi(x'))$ can be represented by a kernel function k

$$k(x, x') = \langle \Phi(x), \Phi(x') \rangle \tag{3.5.}$$

which is computationally simpler than explicitly projecting x and x' into the feature space H.

One interesting property of support vector machines and other kernel-based systems is that, once a valid kernel function has been selected, one can practically work in spaces of any dimension without any significant additional computational cost, since feature mapping is never effectively performed. In fact, one does not even need to know which features are being used.

Another advantage of SVMs and kernel methods is that one can design and use a kernel for a particular problem that could be applied directly to the data without the need for a feature extraction process. This is particularly important in problems where a lot of structure of the data is lost by the feature extraction process (e.g., text processing).

3.2.1. Classification

In classification, support vector machines separate the different classes of data by a hyperplane

$$\langle \mathbf{w}, \Phi(x) \rangle + b = 0 \tag{3.6.}$$

corresponding to the decision function

$$f(x) = \text{sign}(\langle \mathbf{w}, \Phi(x) \rangle + b) \tag{3.7.}$$

It can be shown that the optimal, in terms of classification performance, hyper-plane (Vapnik, 1998) is the one with the maximal margin of separation between the two classes. It can be constructed by solving a constrained quadratic optimization problem whose solution w has an expansion $\mathbf{w} = \sum_i \alpha_i \Phi(x_i)$ in terms of a subset of training patterns that lie on the margin. These training patterns, called support vectors, carry all relevant information about the classification problem. Omitting the details of the calculation, there is just one crucial property of the algorithm that we need to emphasize: both the quadratic programming problem and the final decision function depend only on dot products between patterns. This allows the use of the "kernel trick" and the generalization of this linear algorithm to the nonlinear case.

In the case of the L2-norm soft margin classification the primal optimization problem takes the form:

$$\begin{aligned} &\text{minimize} \quad t(\mathbf{w},\xi) = \frac{1}{2}\parallel \mathbf{w} \parallel^2 + \frac{C}{m}\sum_{i=1}^{m}\xi_i \\ &\text{subject to} \quad y_i(\langle \Phi(x_i), \mathbf{w}\rangle + b) \geq 1-\xi_i \quad (i=1,\dots,m) \\ &\qquad\qquad \xi_i \geq 0 \quad (i=1,\dots,m) \end{aligned} \tag{3.8.}$$

where m is the number of training patterns, and $y_i = \pm 1$. As in most kernel methods, the SVM solution **w** can be shown to have an expansion

$$\mathbf{w} = \sum_{i=1}^{m} \alpha_i\, y_i \Phi\,(x_i) \tag{3.9.}$$

where non-zero coefficients (support vectors) occur when a point (x_i, y_i) meets the constraint. The coefficients α_i are found by solving the following (dual) quadratic programming problem:

$$\begin{aligned} &\text{minimize} \quad W(\alpha) = \sum_{i=1}^{m}\alpha_i + \frac{1}{2}\sum_{i,j=1}^{m}\alpha_i\alpha_j y_i y_j\, k(x_i,x_j) \\ &\text{subject to} \quad 0 \leq \alpha_i \leq \frac{C}{m} \quad (i=1,\dots,m) \\ &\qquad\qquad \sum_{i=1}^{m}\alpha_i y_i = 0. \end{aligned} \tag{3.10.}$$

This is a typical quadratic problem of the form:

$$\begin{aligned} &\text{minimize} \quad c^T x + \frac{1}{2}x^T H x \\ &\text{subject to} \quad b \leq Ax \leq b + r \\ &\qquad\qquad l \leq x \leq u \end{aligned} \tag{3.11.}$$

where $H \in \mathbb{R}^{m\times m}$ with entries $H_{ij} = y_i y_j k(x_i, x_j)$, $C = (1,\dots,1) \in \mathbb{R}^m$, $u = (C,\dots,C) \in \mathbb{R}^m$, $l = (0,\dots,0) \in \mathbb{R}^m$, $A = (y_1,\dots,y_m) \in \mathbb{R}^m$, $b = 0$, $r = 0$. The cost parameter C of the SVM formulation in Equation 3.11 controls the penalty paid by

the SVM for miss-classifying a training point and thus the complexity of the prediction function. A high cost value *C* will force the SVM to create a complex enough prediction function to miss-classify as few training points as possible, while a lower cost parameter will lead to a simpler prediction function. Therefore, this type of SVM is usually called C-SVM.

Another formulation of the classification with a more intuitive hyperparameter than *C* is the ϑ-SVM (Schölkopf, Smola, Williamson, and Bartlett, 2000). The ϑ parameter has the interesting property of being an upper bound on the training error and a lower bound on the fraction of support vectors found in the data set, thus controlling the complexity of the classification function build by the SVM (see Appendix for details). For multi-class classification, mostly voting schemes such as one-against-one and one-against-all are used. In the one-against-all method k binary SVM classifiers are trained, where k is the number of classes, each trained to separate one class from the rest. The classifiers are then combined by comparing their decision values on a test data instance and labeling it according to the classifier with the highest decision value.

In the one-against-one classification method (also called pair wise classification (Knerr, Personnaz, and Dreyfus, 1990; Kreßel 1999), $\binom{k}{2}$ classifiers are constructed where each one is trained on data from two classes. Prediction is done by voting where each classifier gives a prediction and the class which is most frequently predicted wins ("Max Wins"). This method has been shown to produce robust results when used with SVMs (Hsu, and Lin, 2002a). Although this suggests a higher number of support vector machines to train the overall CPU time used is less compared to the one-against-all method since the problems are smaller and the SVM optimization problem scales super-linearly.

3.2.2. Regression

By using a different loss function called the _-insensitive loss function$\| y - f(x) \|_\epsilon = max\{0, \| y - f(x) \| - \epsilon\}$, SVMs can also perform regression. This loss

function ignores errors that are smaller than a certain threshold $\epsilon > 0$ thus creating a tube around the true output. The primal becomes:

$$\begin{aligned} &\text{minimize} && t(\boldsymbol{w}, \xi) = \frac{1}{2} \| w \|^2 + \frac{C}{m} \sum_{i=1}^{m} (\xi_i + \xi_i^*) \\ &\text{subject to} && (\langle \Phi(x_i), \mathbf{w} \rangle + b) - y_i \leq \epsilon - \xi_i \qquad (3.12.) \\ & && y_i - (\langle \Phi(x_i), \mathbf{w} \rangle + b) \leq \epsilon - \xi_i^* \qquad (3.13.) \\ & && \xi_i^* \geq 0 \qquad (i = 1, \dots, m) \end{aligned}$$

We can estimate the accuracy of SVM regression by computing the scale parameter of a
Laplacian distribution on the residuals $\zeta = y - f(x)$, where $f(x)$ is the estimated decision function.

3.2.3. Kernel functions

As seen before, the kernel functions return the inner product between two points in a suitable feature space, thus defining a notion of similarity, with little computational cost even in very high-dimensional spaces. Kernels commonly used with kernel methods and SVMs in particular include the following:

- the linear kernel implementing the simplest of all kernel functions

$$k(\mathrm{x}, \mathrm{x}') = \langle \mathrm{x}, \mathrm{x}' \rangle \qquad (3.14.)$$

- the Gaussian Radial Basis Function (RBF) kernel

$$k(\mathrm{x}, \mathrm{x}') = \exp(-\sigma \| \mathrm{x} - \mathrm{x}' \|^2) \qquad (3.15.)$$

- the polynomial kernel

$$k(\mathrm{x}, \mathrm{x}') = (scale. \langle \mathrm{x}, \mathrm{x}' \rangle + offset)^{degree} \qquad (3.16.)$$

- the hyperbolic tangent kernel

$$k(\mathrm{x},\mathrm{x}') = \tanh(scale.\langle \mathrm{x},\mathrm{x}'\rangle + offset) \quad (3.17.)$$

- the Bessel function of the first kind kernel

$$k(\mathrm{x},\mathrm{x}') = \frac{Bessel^{n}_{(\vartheta+1)}(\sigma\|\mathrm{x}-\mathrm{x}'\|)}{(\|\mathrm{x}-\mathrm{x}'\|)^{-n(\vartheta+1)}} \quad (3.18.)$$

- the Laplace Radial Basis Function (RBF) kernel
-

$$k(\mathrm{x},\mathrm{x}') = \exp(-\sigma \parallel \mathrm{x}-\mathrm{x}' \parallel) \quad (3.19.)$$

- the ANOVA radial basis kernel

$$k(\mathrm{x},\mathrm{x}') = (\sum_{k=1}^{n}\exp(-\sigma(x^k - x'^k)^2))^d \quad (3.20.)$$

- the linear splines kernel in one dimension

$$k(x,x') = 1 + xx'\min(x,x') - \frac{x+x'}{2}(\min(x,x'))^2 + \frac{(\min(x,x'))^3}{3} \quad (3.21.)$$

and for the multidimensional case $k(\mathrm{x},\mathrm{x}') = \prod_{k=1}^{n} k(x^k, x'^k)$.

The Gaussian and Laplace RBF and Bessel kernels are general-purpose kernels used when there is no prior knowledge about the data. The linear kernel is useful when dealing with large sparse data vectors as is usually the case in text categorization. The polynomial kernel is popular in image processing and the sigmoid kernel is mainly used as a proxy for neural networks. The splines and ANOVA RBF kernels typically perform well in regression problems.

3.3. Generalized Regression Neural Networks (GRNN's)

A GRNN is a variation of the radial basis neural networks, which is based on kernel regression networks (Celikoglu, 2006; Celikoglu, and Cigizoglu, 2007;

Cigizoglu, and Alp, 2005). A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function (Cigizoglu, and Alp, 2005). A GRNN consists of four layers, input layer, pattern layer, summation layer and output layer, as shown in Figure 3.2.

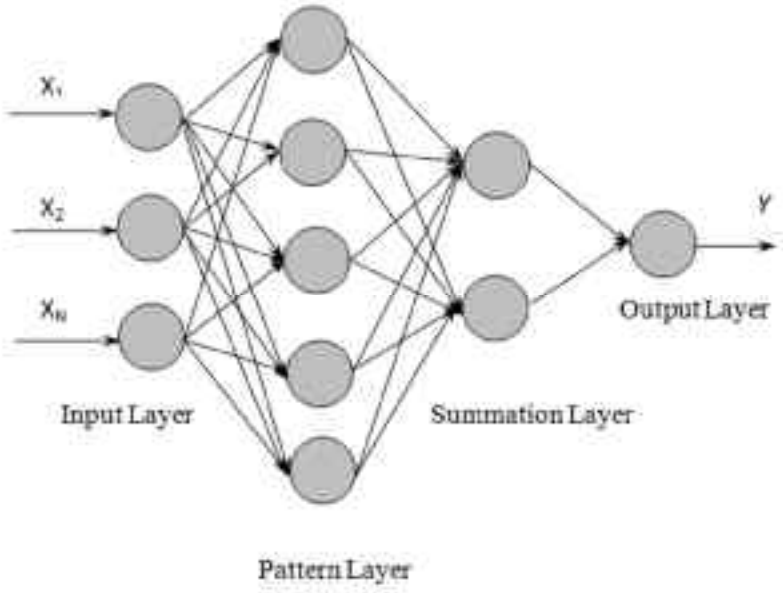


Figure 3.2. Architecture of GRNN.

The number of input units in input layer depends on the total number of the observation parameters. The first layer is connected to the pattern layer and in this layer each neuron presents a training pattern and its output. The pattern layer is connected to the summation layer. The summation layer has two different types of summation, which are a single division unit and summation units. The summation and output layer together perform a normalization of the output set. In training of network, radial basis and linear activation functions are used in hidden and output layers. Each pattern layer unit is connected to the two neurons in the summation layer, *S* and *D* summation neurons. *S* summation neuron computes the sum of weighted responses of the pattern layer. On the other hand, *D* summation neuron is used to calculate un-weighted outputs of pattern neurons. The output layer merely

divides the output of each *S*-summation neuron by that of each *D*-summation neuron, yielding the predicted value Y_i' to an unknown input vector *x* as (Kim et. al., 2004);

$$Y_i' = \frac{\sum_{i=1}^{n} y_i.\exp[-D(x,x_i)]}{\sum_{i=1}^{n} \exp[-D(x,x_i)]} \quad (3.22.)$$

$$D = \sum_{k=1}^{m} \left(\frac{x_i - x_{ik}}{\sigma}\right)^2 \quad (3.23.)$$

y_i is the weight connection between the i^{th} neuron in the pattern layer and the *S*-summation neuron, *n* is the number of the training patterns, *D* is the Gaussian function, *m* is the number of elements of an input vector, x_k and x_{ik} are the j^{th} element of *x* and x_i, respectively, σ is the spread parameter, whose optimal value is determined experimentally.

3.4. Multiple Linear Regression (MLR)

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

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

In multiple regression the basic model is the following:

$$y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip} + \varepsilon_i \quad (3.24.)$$

We assume that the error term ε_i is normally distributed, with mean 0 and standard deviation σ.

Here y_i is the output for unit or subject i and there are k input variables $X_{i1}, X_{i2}, \ldots, X_{ip}$. Often y_i is termed the dependent variable and the input variables $X_{i1}, X_{i2}, \ldots, X_{ip}$ are termed the independent variables. The latter can be continuous or nominal. However the term "independent" is a misnomer since the X's need not be independent of each other. Sometimes they are called the explanatory or predictor variables. Each of the input variables is associated with a regression coefficient $\beta_1, \beta_2, \ldots, \beta_k$. There is also an additive constant term β_0. These are the model parameters.

We can write the first section on the right-hand side of equation (3.24.) as

$$LP_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_k X_{ip}$$

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

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

3.4.1. Uses of Multiple Regression

1. To adjust the effects of an input variable on a continuous output variable for the effects of confounders. For example, to investigate the effect of diet on weight allowing for smoking habits. Here the dependent variable is the outcome from a clinical trial. The independent variables could be the two treatment groups

(as a 0/1 binary variable), smoking (as a continuous variable in numbers of packs per week) and baseline weight. The multiple regression model allows one to compare the outcome between groups, having adjusted for differences in baseline weight and smoking habit. This is also known as analysis of covariance.

2. To analyze the simultaneous effects of a number of categorical variables on an output variable. An alternative technique is the analysis of variance but the same results can be achieved using multiple regression.

3. To predict a value of an outcome, for given inputs. For example, an investigator might wish to predict the forced expiratory volume (*FEV*1) of a subject given age and height, so as to be able to calculate the observed *FEV*1 as a percentage of predicted, and to decide if the observed *FEV*1 is below, say, 80% of the predicted one.

3.5. Dataset Generation

Two different datasets are used in this thesis. Each dataset contains some input parameters and one output parameter (VO_2max). As will be described in the following sections, using different input parameters of datasets, different models are developed to predict VO_2max.

3.5.1. First DataSet

This dataset contains 100 subjects (50 females and 50 males), that are healthy volunteers ranging in age from 18 to 65 years. All subjects were recruited from the Y-Be-Fit Wellness Program at Brigham Young University (BYU) and employees from the LDS Hospital in Salt Lake City, Utah. During the exercise testing, a questionnaire (PA-R) and an informed consent document that was approved by the BYU Institutional Review Board for Human Subjects, were given all subjects to complete. Using a stadiometer and balance beam scale, volunteers' height and body mass were measured and recorded, respectively. Prior to testing, instructions about the maximal graded exercise test were given to all subjects. Subjects performed a

maximal graded exercise test using a modified version of the Arizona State University (ASU) maximal protocol (George, 1996), with only a slight change in the warm-up. The warm-up consisted of having subjects complete up to three 4-min stages and reach 75% of maximum heart rate (HR_{max}). During the first stage, subjects walked at a self-selected brisk pace, 4.8–6.4 km/h. If subjects progressed to the second stage, the speed was increased to a self-selected jogging pace between 4.8 and 6.4 km/h. If 75% of HR_{max} was not achieved by the end of the second stage, subjects continued to the third stage where the speed was increased to 9.6 km/h or greater. After the warm-up, while the test administrator explained the test procedures for the maximal graded exercise test and fit subjects with a mouthpiece and nose clip, subjects rested for approximately 5 min. As the necessary pace for the maximal graded exercise test the ending speed of the warm-up served. Thereafter, the grade was increased 1.5% each minute, while pace remained the same, and continued until subjects reached volitional fatigue and were no longer able to continue.

Metabolic gases were collected using the TrueMax 2400 metabolic measurement system during the maximal graded exercise test. Every 15s, the VO_2max and respiratory exchange ratio (RER) were computed, averaged, and printed by an online computer system. At the end of each stage, the subjects' exercise HR and RPE scores were recorded. If at least two of the following three criteria were met, VO_2max was considered valid:

1. HR_{max} within 15 beats of age predicted maximal heart rate.
2. RER equal to or greater than 1.10.
3. Plateau in VO_2max despite an increase in work load.

Subjects who failed to meet at least two of these criteria were dropped from the study. Prior to exercise testing subjects completed the PFA and a modified PA-R non-exercise questionnaire.

3.5.2. Second DataSet

The subjects included 439 (229 females, 210 males) "apparently healthy" volunteers ranging in age from 20 to 79 years. All subjects were recruited from the

Amherst and Worcester, Massachusetts, communities. The investigation was explained in detail before each subject signed an informed consent document in accord with University of Massachusetts Human Subjects Committee/Amherst guidelines. Each subject was screened for cardiovascular and orthopedic contraindications to brisk walking. Subjects taking medication known to affect HR and blood pressure responses to exercise were not tested. Resting HR, blood pressure, and 12-lead electrocardiograms were examined in all subjects over the age of 40 by a physician before testing. The physician was also present at maximal treadmill testing for subjects over the age of 40 years (Heil et. al. 1995).

All subjects successfully completed a maximal walking treadmill test. After having body mass and height measured, each subject assigned themselves a value between 0 and 7 which most accurately described their level of physical activity in the previous month. The treadmill protocol consisted of 4 minutes at a level grade, followed by 4 minutes at a 5% grade, and a 2.5% increase in grade every 2 minutes thereafter. Subjects were tested at the fastest comfortable walking speed they could handle (4.8 - 7.3 $km.h^{-1}$). Test termination occurred when subjects could not continue despite verbal encouragement by the lab technicians. Each subject's VO_2max was taken as the highest VO_2 value when at least two of three following test criteria were satisfied:

1. Leveling off VO_2 despite an increase in power output.
2. Maximal HR within 15 beats of age-predicted maximal HR (220-age).
3. RER $\geq$ 1.1.

5. CONCLUSSION

In this study, we use ANN, MLR,,GRNN and SVM to develop VO_2max prediction models by using maximal variables. We used two differnet datasets with different input variables. First dataset includes maximal variables heart rate, grade, self-reported RPE from treadmill test and non-exercise variables gender, age and BMI. Second dataset includes maximal variables heart rate, self-reported RPE from treadmill test, respiratory exchange ration (RER) and time to exhaustion from treadmill test and non-exercise variables gender, age, BMI, BF, LBM . We show that the accuracy of the VO_2max prediction models based on maximal and standard non-exercise variables can be improved by including questionnaire variables PFA, PA-R and AC in the models.

For the first dataset inclusion of PFA and PA-R in the prediction models yields 27.61% to 37.09% decrements in *SEE*'s and 5.55% to 11.49% increments in *R*'s of the models. For the second dataset inclusion of AC in the prediction models yields 1.08% to 6.97% increments in *R*'s and 0.53% to 17.97% decrements in *SEE*'s.

We use three groups of models that contain one, two and three maximal variables for first dataset and four grups of models that contain one, two, three and four maximal variables, for second dataset. The most accurate VO_2max prediction model for first dataset is the one that includes the variables gender, age, BMI, RPE, GRD and PFA. And the second dataset has two best VO_2max prediction models. The first one includes the variables gender, age, BMI, BF, RER, TIME and AC and the second one is the model that includes the variables gender, age, BMI, BF, RER, RPE, TIME and AC. According to the presented results, it is understandable that ANN performs better (i.e. higher *R* and lower *SEE*) than MLR, GRNN and SVM for prediction of VO_2max.

4. RESEARCH AND DISCUSSION

As described in Section 3, two datasets are used in this study. Using each of them several different VO_2max prediction models are developed. These models contain various combinations of input parameters. For each model VO_2max is predicted using ANN, MLR, GRNN and SVM. MATLAB 7.7.0.471 is used for creating some code snippets for ANN, MLR and GRNN methods. On the other hand, Weka 3.6's LibSvm library is used for SVM prediction.

The performance of ANN, MLR, GRNN and SVM models are evaluated by using 10-fold cross validation and calculating the *SEE* and *R*, whose formulas are given 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), Y is the measured VO_2max value, Y' is the predicted VO_2max value, $\bar{Y}$ is the mean of the measured values of VO_2max and N is the number of samples in a test subset. Using 10-fold cross validation, 10 training and 10 test sets are developed for each model. For ANN prediction method, the number of neurons in the hidden layer is changed from 1 to 10. Linear and Gaussian Radial Basis Function (RBF) kernel functions are used in SVM method.

28 and 84 VO_2max prediction models have been developed for first and second datasets, respectively. A tansigmoid activation function is used in the hidden layer and a pure linear activation function is used in the output layer of all ANN-based models. The network is trained using Levenberg-Marquardt (LM) algorithm. The inputs and outputs are normalized so that they have zero means and unity variance. The other important parameters of ANN models are the number of epochs (selected as 500) andthe learning rate (selected as 0.05). In order to assess the

performance of ANN-based VO_2max prediction models, GRNN-based, MLR-based and SVM-based prediction models have also been developed.

Table 4.1 shows the 28 models and variables that each model contains (for the first dataset). For ANN-based, MLR-based, GRNN-based and SVM-based VO_2max prediction models, the individual *SEE* and *R* values for each fold have been calculated and average values for each model are shown in Table 4.2 through Table 4.4. Table 4.2, Table 4.3 and Table 4.4 show the performance (in terms of *SEE* and *R*) of all VO_2max prediction models that include one maximal variable, two maximal variables and three maximal variables, respectively. Just like the first dataset, ANN-based, MLR-based, GRNN-based and SVM-based VO_2max prediction models are developed for the second dataset. Table 4.5 shows the 84 models and variables that each model contains. Table 4.6, Table 4.7, Table 4.8 and Table 4.9 show the performance (in terms of *SEE* and *R*) of all VO_2max prediction models that include one maximal variables, two maximal variable, three maximal variables and four maximal variables, respectively.

Table 4.1. Models that are developed for the first dataset.

Model#	Model Variables
1	G,A, BMI,RPE
2	G,A,BMI,HR
3	G,A,BMI,GRD
4	G,A,BMI,RPE,PA-R
5	G,A,BMI,HR,PA-R
6	G,A,BMI,GRD,PA-R
7	G,A,BMI,RPE,PFA
8	G,A,BMI,HR,PFA
9	G,A,BMI,GRD,PFA
10	G,A,BMI,RPE,PFA,PA-R
11	G,A,BMI,HR,PFA,PA-R
12	G,A,BMI,GRD,PFA,PA-R
13	G,A,BMI,GRD,HR
14	G,A,BMI,GRD,RPE
15	G,A,BMI,HR,RPE
16	G,A,BMI,GRD,HR,PA-R
17	G,A,BMI,GRD,RPE,PA-R
18	G,A,BMI,HR,RPE,PA-R
19	G,A,BMI,GRD,HR,PFA
20	G,A,BMI,RPE,GRD,PFA
21	G,A,BMI,RPE,HR,PFA
22	G,A,BMI,HR,GRD,PFA,PA-R
23	G,A,BMI,RPE,GRD,PFA,PA-R
24	G,A,BMI,RPE,HR,PFA,PA-R
25	G,A,BMI,HR,RPE,GRD
26	G,A,BMI,RPE,HR,GRD,PA-R
27	G,A,BMI,RPE,HR,GRD,PFA
28	Ge,A,BMI,HR,GRD,RPE,PFA,PA-R

BMI, body mass index; **HR**, heart rate; **RER**, respiratory exchange ratio; **RPE**, rating of perceived exertion; **GRD**, grade; **PFA**, perceived functional ability; **PA-R**, physical activity rating; **G**, gender; **A**, age;

Table 4.2. Results of ANN-based, MLR-based, GRNN-based and SVM-based models including one maximal variables (first dataset).

Model#	Regression Method									
	ANN		SVM				GRNN		MLR	
			Linear		RBF					
	SEE	R	SEE	R	SEE	R	SEE	R	SEE	R
1	3.72	0.86	0.56	0.73	5.51	0.75	7.07	0.46	5.44	0.65
2	3.59	0.86	5.70	0.74	5.57	0.76	6.68	0.55	5.43	0.65
3	3.15	0.89	5.11	0.77	5.09	0.79	6.77	0.5	5.09	0.72
4	2.63	0.93	4.32	0.84	4.22	0.86	6.96	0.51	4.30	0.81
5	2.73	0.92	4.39	0.81	4.37	0.81	6.16	0.65	4.28	0.81
6	2.65	0.93	4.53	0.81	4.40	0.82	6.45	0.62	4.26	0.82
7	2.39	0.93	3.83	0.88	3.80	0.89	5.47	0.71	3.80	0.86
8	2.35	0.94	3.85	0.89	3.70	0.90	4.82	0.76	3.77	0.86
9	2.28	0.95	4.01	0.86	3.99	0.86	5.39	0.73	3.75	0.86
0	2.34	0.93	3.54	0.88	3.47	0.88	5.59	0.70	3.82	0.86
11	2.23	0.94	3.77	0.89	3.72	0.89	4.88	0.76	3.77	0.86
12	2.28	0.94	4.01	0.84	3.96	0.85	5.48	0.72	3.73	0.87

Table 4.3. Results of ANN-based, MLR-based, GRNN-based and SVM-based models including two maximal variables (first dataset).

Model#	Regression Method									
	ANN		SVM				GRNN		MLR	
			Linear		RBF					
	SEE	R	SEE	R	SEE	R	SEE	R	SEE	R
13	3.20	0.89	5.15	0.72	5.10	0.73	6.72	0.55	5.04	0.74
14	3.30	0.88	5.09	0.79	5.01	0.79	6.91	0.57	5.13	0.71
15	3.54	0.87	5.70	0.74	5.61	0.75	7.28	0.55	5.48	0.64
16	2.64	0.93	4.60	0.81	4.56	0.81	5.91	0.67	4.28	0.82
17	2.63	0.93	4.62	0.80	4.50	0.81	6.47	0.62	4.34	0.81
18	2.78	0.92	4.48	0.82	4.42	0.82	6.18	0.66	4.28	0.82
19	2.29	0.94	3.80	0.87	3.77	0.87	4.96	0.77	3.76	0.87
20	2.20	0.95	3.88	0.86	3.83	0.87	5.40	0.73	3.82	0.86
21	2.28	0.95	3.83	0.89	3.79	0.89	4.88	0.76	3.82	0.86
22	2.25	0.95	3.81	0.86	3.77	0.87	4.96	0.76	3.73	0.87
23	2.19	0.95	3.94	0.86	3.91	0.86	5.47	0.72	3.81	0.86
24	2.29	0.94	3.82	0.89	3.87	0.89	4.87	0.76	3.83	0.85

Table 4.4. Results of ANN-based, MLR-based, GRNN-based and SVM-based models including three maximal variables (first dataset).

Model#	Regression Method									
	ANN		SVM				GRNN		MLR	
			Linear		RBF					
	SEE	R	SEE	R	SEE	R	SEE	R	SEE	R
25	3.16	0.90	5.15	0.73	5.09	0.74	6.86	0.62	5.05	0.73
26	2.54	0.94	4.67	0.8	4.51	0.8	5.93	0.67	4.35	0.82
27	2.29	0.94	3.99	0.85	3.92	0.86	4.97	0.77	3.82	0.86
28	2.20	0.95	3.87	0.89	3.80	0.89	4.97	0.76	3.80	0.86

Table 4.5. Models that are developed for the second dataset.

Model#	Model Variables	Model#	Model Variables	Model#	Model Variables
1	A,G,BMI,BF,HR	29	A,G,BMI,LBM,HR	57	A,G,BMI,BF,LBM,HR
2	A,G,BMI,BF,RER	30	A,G,BMI,LBM,RER	58	A,G,BMI,BF,LBM,RER
3	A,G,BMI,BF,RPE	31	A,G,BMI,LBM,RPE	59	A,G,BMI,BF,LBM,RPE
4	A,G,BMI,BF,T	32	A,G,BMI,LBM,T	60	A,G,BMI,BF,LBM,T
5	A,G,BMI,BF,AC,HR	33	A,G,BMI,LBM,AC,HR	61	A,G,BMI,BF,LBM,AC,HR
6	A,G,BMI,BF,AC,RER	34	A,G,BMI,LBM,AC,RER	62	A,G,BMI,BF,LBM,AC,RER
7	A,G,BMI,BF,AC,RPE	35	A,G,BMI,LBM,AC,RPE	63	A,G,BMI,BF,LBM,AC,RPE
8	A,G,BMI,BF,AC,T	36	A,G,BMI,LBM,AC,T	64	A,G,BMI,BF,LBM,AC,T
9	A,G,BMI,BF,HR,RER	37	A,G,BMI,LBM,HR,RER	65	A,G,BMI,BF,LBM,HR,RER
10	A,G,BMI,BF,HR,RPE	38	A,G,BMI,LBM,HR,RPE	66	A,G,BMI,BF,LBM,HR,RPE
11	A,G,BMI,BF,HR,T	39	A,G,BMI,LBM,HR,T	67	A,G,BMI,BF,LBM,HR,T
12	A,G,BMI,BF,RER, RPE	40	A,G,BMI,LBM,RER,RPE	68	A,G,BMI,BF,LBM,RER,RPE
13	A,G,BMI,BF,RER,T	41	A,G,BMI,LBM,RER,T	69	A,G,BMI,BF,LBM,RER,T
14	A,G,BMI,BF,RPE,T	42	A,G,BMI,LBM,RPE,T	70	A,G,BMI,BF,LBM,RPE,T
15	A,G,BMI,BF,AC,HR, RER	43	A,G,BMI,LBM,AC,HR, RER	71	A,G,BMI,BF,LBM,AC,HR, RER
16	A,G,BMI,BF,AC,HR, RPE	44	A,G,BMI,LBM,AC,HR, RPE	72	A,G,BMI,BF,LBM,AC,HR, RPE
17	A,G,BMI,BF,AC,HR,T	45	A,G,BMI,LBM,AC,HR,T	73	A,G,BMI,BF,LBM,AC,HR,T
18	A,G,BMI,BF,AC,RER, RPE	46	A,G,BMI,LBM,AC,RER, RPE	74	A,G,BMI,BF,LBM,AC,RER, RPE
19	A,G,BMI,BF,AC,RER, T	47	A,G,BMI,LBM,AC,RER,T	75	A,G,BMI,BF,LBM,AC,RER,T
20	A,G,BMI,BF,AC,RPE, T	48	A,G,BMI,LBM,AC,RPE,T	76	A,G,BMI,BF,LBM,AC,RPE,T
21	A,G,BMI,BF,HR,RER, RPE	49	A,G,BMI,LBM,HR,RER,R PE	77	A,G,BMI,BF,LBM,HR,RER, RPE
22	A,G,BMI,BF,HR,RER, T	50	A,G,BMI,LBM,HR,RER,T	78	A,G,BMI,BF,LBM,HR,RER,T
23	A,G,BMI,BF,RER,RP E,T	51	A,G,BMI,LBM,RER,RPE,T	79	A,G,BMI,BF,LBM,RER,RPE, T
24	A,G,BMI,BF,AC,HR, RER,RPE	52	A,G,BMI,LBM,AC,HR, RER,RPE	80	A,G,BMI,BF,LBM,AC,HR, RER,RPE
25	A,G,BMI,BF,AC,HR, RER,T	53	A,G,BMI,LBM,AC,HR, RER,T	81	A,G,BMI,BF,LBM,AC,HR, RER,T
26	A,G,BMI,BF,AC,RER, RPE,T	54	A,G,BMI,LBM,AC,RER, RPE,T	82	A,G,BMI,BF,LBM,AC,RER, RPE,T
27	A,G,BMI,BF,HR,RER, RPE,T	55	A, G, BMI, LBM, HR, RER, RPE, T	83	A,G,BMI,BF,LBM,HR,RER, RPE,T
28	A,G,BMI,BF,AC,HR, RER,T, RPE	56	A,G,BMI,LBM,AC,HR, RER, RPE,T	84	A,G,BMI,BF,LBM,AC,HR, RER, RPE,T

BMI, body mass index; **HR**, heart rate; **RER**, respiratory exchange ratio; **RPE**, rating of perceived exertion; **T**, time; **AC**, activity code; **LBM**, lean body mass; **BF**, body fat; **A**, age; **G**, gender;

Table 4.6. Results of second dataset including one maximal variable.

Model#	Regression Method									
	ANN		SVM				GRNN		MLR	
			Linear		RBF					
	SEE	R	SEE	R	SEE	R	SEE	R	SEE	R
1	4.78	0.84	5.61	0.77	5.22	0.81	5.88	0.75	6.00	0.65
2	4.49	0.86	5.62	0.77	4.92	0.83	5.63	0.77	5.99	0.66
3	4.79	0.84	5.62	0.77	5.23	0.81	5.62	0.77	5.89	0.67
4	3.85	0.90	4.61	0.85	4.32	0.87	5.03	0.82	4.67	0.81
5	4.23	0.88	5.08	0.82	4.64	0.85	5.70	0.76	5.08	0.79
6	4.10	0.89	5.12	0.82	4.56	0.86	5.31	0.80	5.27	0.77
7	4.31	0.88	5.09	0.82	4.82	0.84	5.35	0.79	5.22	0.78
8	3.65	0.91	4.36	0.87	4.09	0.88	4.81	0.84	4.43	0.83
29	5.28	0.80	6.12	0.73	5.88	0.76	6.77	0.63	6.96	0.54
30	4.83	0.84	6.12	0.73	5.54	0.79	6.41	0.68	6.83	0.56
31	5.18	0.81	6.07	0.74	5.80	0.77	6.42	0.68	6.80	0.57
32	4.05	0.89	4.88	0.84	4.51	0.86	5.26	0.80	5.06	0.78
33	4.51	0.86	5.39	0.80	5.10	0.82	6.54	0.67	5.75	0.73
34	4.38	0.87	5.41	0.80	5.03	0.83	6.02	0.73	5.84	0.72
35	4.58	0.86	5.42	0.80	5.06	0.82	6.08	0.72	5.84	0.72
36	3.79	0.91	4.44	0.87	4.23	0.88	5.07	0.82	4.75	0.81
57	4.81	0.84	5.62	0.77	5.25	0.81	5.71	0.77	5.98	0.65
58	4.50	0.86	5.62	0.77	4.89	0.83	5.39	0.80	5.93	0.67
59	4.78	0.84	5.63	0.77	5.23	0.81	5.39	0.79	5.84	0.68
60	3.91	0.90	4.64	0.86	4.34	0.87	4.90	0.83	4.73	0.81
61	4.30	0.87	5.06	0.82	4.71	0.85	5.71	0.77	5.06	0.79
62	4.11	0.89	5.07	0.82	4.57	0.85	5.23	0.81	5.22	0.78
63	4.33	0.87	5.09	0.82	4.88	0.84	5.24	0.81	5.17	0.79
64	3.69	0.91	4.32	0.83	4.07	0.89	4.80	0.84	4.48	0.83

Table 4.7. Results of second dataset including two maximal variables.

Model#	Regression Method									
	ANN		SVM				GRNN		MLR	
			Linear		RBF					
	SEE	R	SEE	R	SEE	R	SEE	R	SEE	R
9	4.47	0.86	5.60	0.77	4.80	0.84	5.87	0.75	5.87	0.68
10	4.78	0.84	5.56	0.78	5.22	0.81	5.86	0.75	5.81	0.69
11	3.88	0.90	4.60	0.85	4.35	0.87	5.45	0.79	4.66	0.81
12	4.54	0.86	5.60	0.76	4.88	0.83	5.62	0.77	5.84	0.68
13	3.77	0.91	4.76	0.84	4.19	0.88	5.03	0.82	4.60	0.82
14	3.90	0.90	4.57	0.85	4.31	0.87	5.08	0.81	4.63	0.82
15	4.03	0.89	5.23	0.82	4.53	0.86	5.66	0.77	5.02	0.80
16	4.33	0.87	5.08	0.82	4.75	0.84	5.65	0.77	5.00	0.80
17	3.64	0.91	4.30	0.87	4.09	0.88	5.26	0.80	4.33	0.84
18	4.16	0.88	5.09	0.82	4.56	0.85	5.35	0.79	5.20	0.78
19	3.55	0.92	4.36	0.87	3.59	0.89	4.81	0.84	4.39	0.84
20	3.67	0.91	4.34	0.87	4.09	0.89	4.85	0.83	4.41	0.84
37	4.88	0.83	6.12	0.73	5.33	0.80	6.77	0.63	6.76	0.58
38	5.23	0.81	6.09	0.74	5.77	0.77	6.77	0.63	6.75	0.57
39	4.06	0.89	4.76	0.84	4.56	0.86	5.90	0.74	5.06	0.78
40	4.89	0.83	6.25	0.74	6.03	0.79	6.42	0.68	6.69	0.59
41	3.97	0.89	4.78	0.84	4.42	0.87	5.26	0.80	4.96	0.78
42	4.01	0.89	4.75	0.86	4.56	0.86	5.25	0.80	5.02	0.78
43	4.31	0.87	5.38	0.80	4.86	0.83	6.54	0.67	5.65	0.74
44	4.62	0.86	5.39	0.80	5.06	0.83	6.54	0.67	5.69	0.74
45	3.77	0.90	4.40	0.87	4.32	0.87	5.77	0.76	4.67	0.82
46	4.41	0.87	5.43	0.80	4.95	0.83	6.08	0.72	5.79	0.73
47	3.68	0.91	4.44	0.87	4.13	0.88	5.07	0.82	4.70	0.81
48	3.78	0.90	4.47	0.86	4.24	0.88	5.08	0.82	4.74	0.81
65	4.45	0.86	5.61	0.77	4.85	0.83	5.71	0.77	4.99	0.80
66	4.75	0.85	5.57	0.78	5.28	0.81	5.70	0.77	4.98	0.80
67	3.93	0.90	4.63	0.85	4.35	0.87	5.33	0.80	4.37	0.84
68	4.47	0.86	5.61	0.78	4.89	0.83	5.39	0.79	5.77	0.69
69	3.75	0.91	4.62	0.85	4.12	0.88	4.90	0.83	4.66	0.81
70	3.89	0.90	4.61	0.86	4.36	0.87	4.92	0.77	4.68	0.81
71	4.10	0.89	5.06	0.82	4.44	0.86	5.59	0.78	4.99	0.80
72	4.24	0.88	5.05	0.82	4.71	0.84	5.60	0.78	4.98	0.80
73	3.60	0.91	4.28	0.87	3.95	0.89	5.23	0.81	4.37	0.84
74	4.14	0.88	5.10	0.82	4.61	0.85	5.24	0.81	5.15	0.79
75	3.60	0.91	4.31	0.87	3.87	0.89	4.80	0.84	4.45	0.83
76	3.71	0.91	4.33	0.87	4.09	0.89	4.81	0.84	4.45	0.83

Table 4.8. Results of second dataset including three maximal variables.

Model#	Regression Method									
	ANN		SVM				GRNN		MLR	
			Linear		RBF					
	SEE	R	SEE	R	SEE	R	SEE	R	SEE	R
21	4.50	0.86	4.36	0.87	4.10	0.88	5.85	0.75	5.72	0.70
22	3.77	0.91	4.67	0.85	4.12	0.88	5.40	0.79	4.57	0.82
23	3.73	0.91	4.60	0.85	4.12	0.89	5.05	0.82	4.57	0.82
24	4.11	0.88	5.06	0.82	4.44	0.86	5.65	0.77	4.90	0.81
25	3.55	0.92	4.29	0.87	3.90	0.89	5.26	0.80	4.27	0.85
26	3.55	0.92	4.34	0.87	3.95	0.89	4.85	0.83	4.38	0.84
49	4.87	0.83	6.07	0.74	5.39	0.80	6.77	0.63	6.62	0.60
50	3.99	0.89	4.75	0.85	4.34	0.87	5.90	0.74	4.94	0.79
51	3.87	0.90	4.75	0.85	4.45	0.87	5.25	0.80	4.94	0.79
52	4.39	0.87	5.39	0.80	4.84	0.84	6.54	0.67	5.61	0.75
53	3.65	0.91	4.40	0.87	4.15	0.88	5.77	0.76	4.60	0.82
54	3.70	0.91	4.46	0.86	4.16	0.88	5.08	0.82	4.69	0.81
77	4.42	0.87	5.55	0.78	4.91	0.84	5.70	0.77	5.60	0.70
78	3.78	0.91	4.57	0.85	4.10	0.88	5.33	0.80	4.63	0.82
79	3.77	0.91	4.60	0.86	4.14	0.88	4.92	0.83	4.63	0.82
80	4.08	0.89	5.03	0.82	4.48	0.86	5.58	0.78	4.93	0.81
81	3.60	0.91	4.27	0.87	3.90	0.89	5.23	0.81	4.32	0.84
82	3.75	0.91	4.33	0.87	3.94	0.89	4.82	0.84	4.43	0.83

Table 4.9. Results of second dataset including four maximal variables.

Model#	Regression Method									
	ANN		SVM				GRNN		MLR	
			Linear		RBF					
	SEE	R	SEE	R	SEE	R	SEE	R	SEE	R
27	4.34	0.87	4.58	0.85	4.06	0.98	5.39	0.79	4.54	0.82
28	3.56	0.92	4.28	0.87	3.91	0.89	5.25	0.80	4.26	0.85
55	3.95	0.90	4.75	0.85	4.26	0.88	5.91	0.74	4.92	0.79
56	3.73	0.91	4.39	0.87	4.12	0.88	5.77	0.76	4.60	0.82
83	3.75	0.91	4.57	0.86	4.07	0.89	5.33	0.80	4.60	0.82
84	3.57	0.91	4.28	0.87	3.90	0.89	5.24	0.81	4.30	0.84

Based on the presented results, the following discussions can be made:

1. For the first dataset:
    1. The ANN-based prediction models are more accurate than MLR-based, GRNN-based and SVM-based models. When we compare MLR-based models with GRNN-based models we can understand that MLR-based models are more accurate than GRNN-based models. Also if we compare

MLR-based models with SVM-based models, we can say that MLR-based models are usually more accurate than SVM-based models.

2. The accuracy of VO_2max prediction models based on maximal and standard N-Ex variables can be improved by including questionnaire variables in the models. Adding PA-R to ANN-based prediction models yields 4.25% to 7.52% increments in *R*'s and 15.87% to 29.30% decrements in *SEE*'s. Adding PFA to ANN-based prediction models yields 4.25% to 10.81% increments in *R*'s and 27.53% to 35.59% decrements in *SEE*'s. Adding both PA-R and PFA to ANN-based prediction models yields 5.31% to 8.15% increments in *R*'s and 27.61% to 37.88% decrements in *SEE*'s.
3. Between the questionnaire variables, PFA has a better effect than PA-R on the performance of all VO_2max prediction models. Including both PFA and PA-R in the prediction models yields comparable performance with the case of including just PFA in the models.
4. VO_2max prediction models that include a single maximal variable and questionnaire data yield comparable performance with the models that include more than one maximal variables and questionnaire data.
5. The best VO_2max prediction model is the ANN-based model #23. Also, ANN-based model #11, model #12, model #24 and model #28 give comparable performance with model #23.
6. If we compare SVM kernel functions, it is understandable that the RBF kernel function gives more accurate results than the linear kernel function.

2. For the second dataset:

1. The ANN-based prediction models are more accurate than MLR-based, GRNN-based and SVM-based models.
2. SVM-based VO_2max prediction models perform better than GRNN-based and MLR-based prediction models.
3. MLR-based VO_2max prediction models usually perform better than GRNN-based prediction models.

4. If we compare SVM kernel functions, it is understandable that the RBF kernel function gives more accurate results than the linear kernel function.
5. The accuracy of VO_2max prediction models based on maximal and standard N-Ex variables can be improved by including questionnaire variables in models. Adding activity code queationnaire (AC) to ANN-based prediction models yields 1.08% to 6.97% increments in *R*'s and 0.53% to 17.97% decrements in *SEE*'s.
6. Between the input variables, lean body mass (LBM) usually has a better effect than body fat (BF) on the performance of all VO_2max prediction models.
7. In general VO_2max prediction models that include two or three maximal variables and questionnaire data have better performance than the models that include one or four maximal variables and questionnaire data.
8. The best VO_2max prediction models are the ANN-based model #19 and model #25. Also, ANN-based model #28, and model #8 give comparable performance with the best models.

The scatter plots of the ANN-based VO_2max prediction models are shown in Figure 4.1 through Figure 4.112. The presented results together with the scatter plots of predicted versus measured VO_2max values prove the effectiveness of ANN's for prediction of VO_2max.

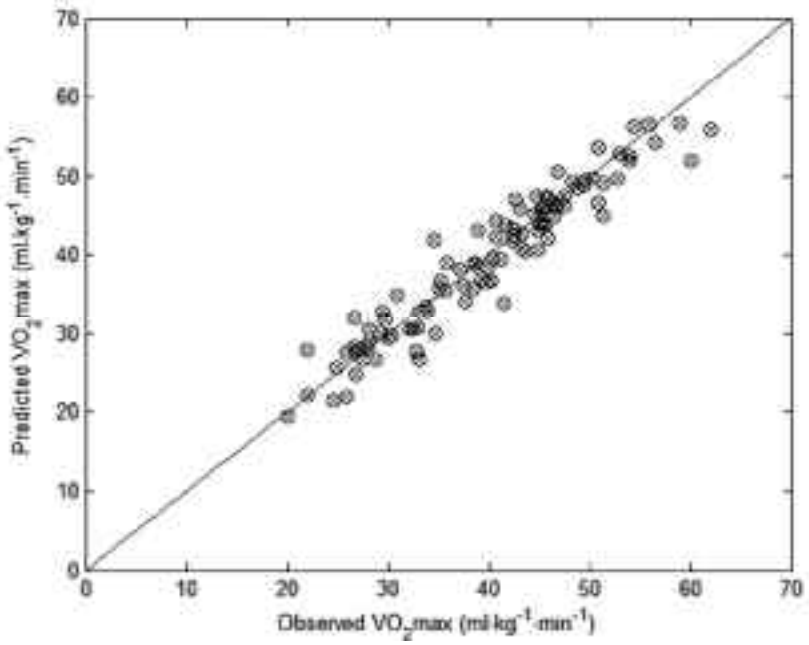


Figure 4.1. Predicted VO_2max versus measured VO_2max for the ANN-based model #1 of first dataset.

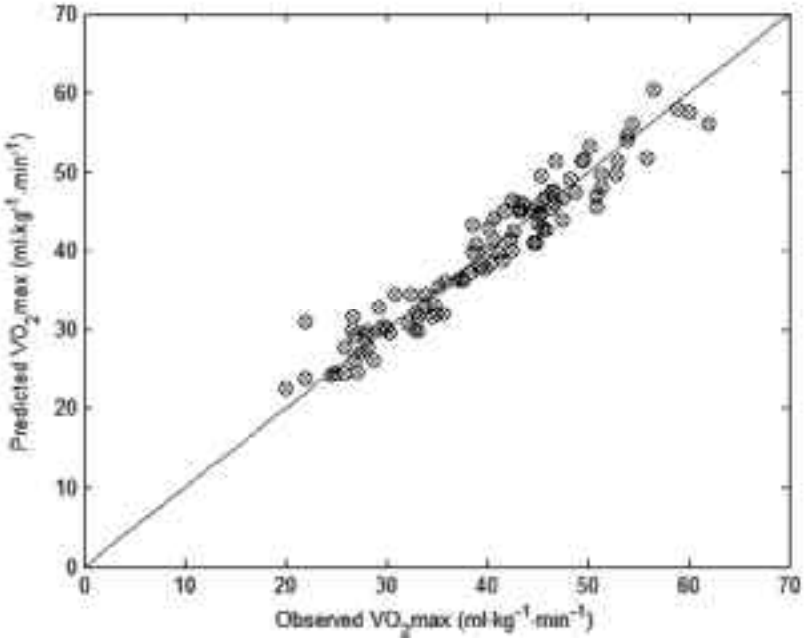


Figure 4.2. Predicted VO_2max versus measured VO_2max for the ANN-based model #2 of first dataset.

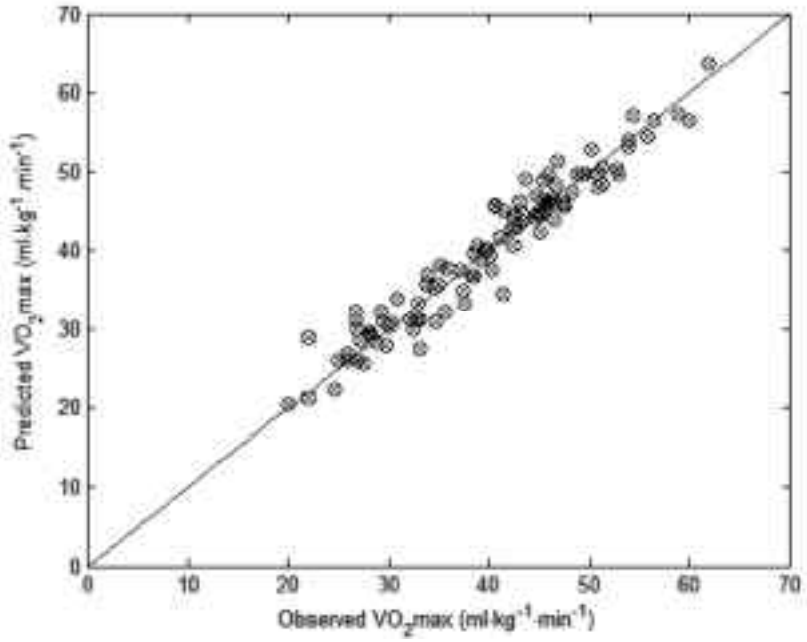


Figure 4.3. Predicted VO_2max versus measured VO_2max for the ANN-based model #3 of first dataset.

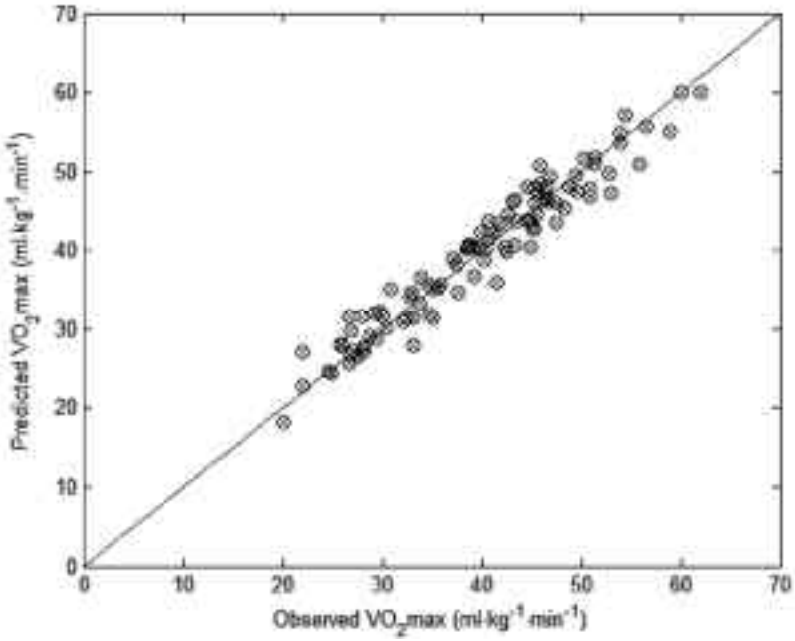


Figure 4.4. Predicted VO_2max versus measured VO_2max for the ANN-based model #4 of first dataset.

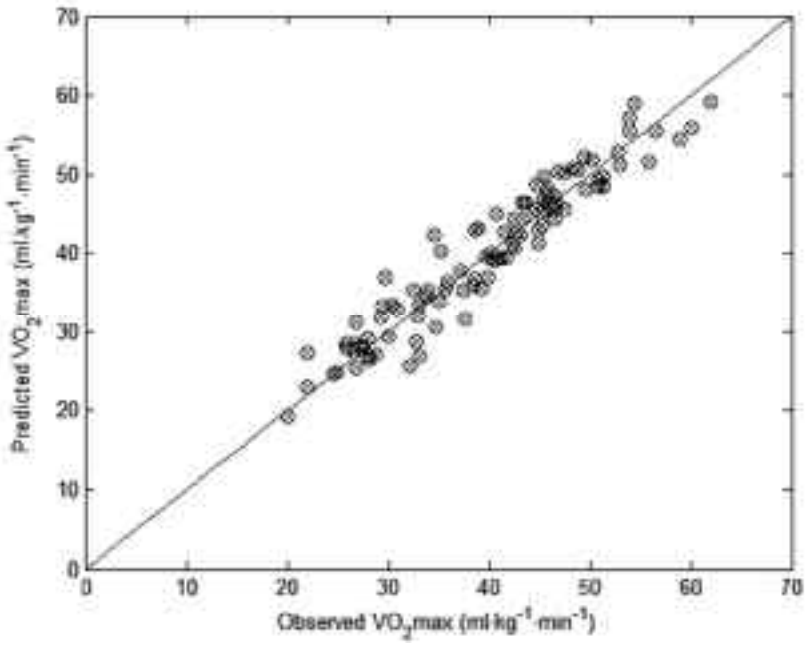


Figure 4.5. Predicted VO_2max versus measured VO_2max for the ANN-based model #5 of first dataset.

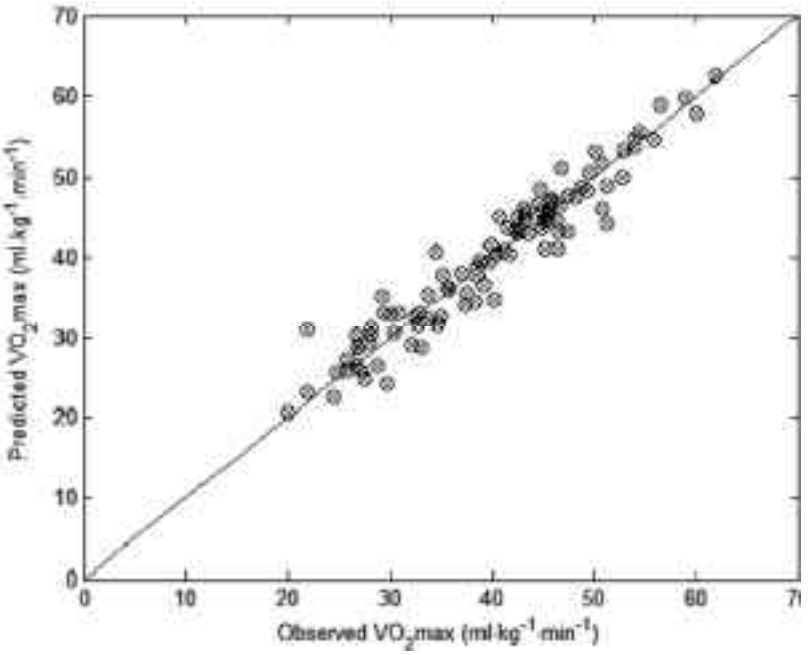


Figure 4.6. Predicted VO_2max versus measured VO_2max for the ANN-based model #6 of first dataset.

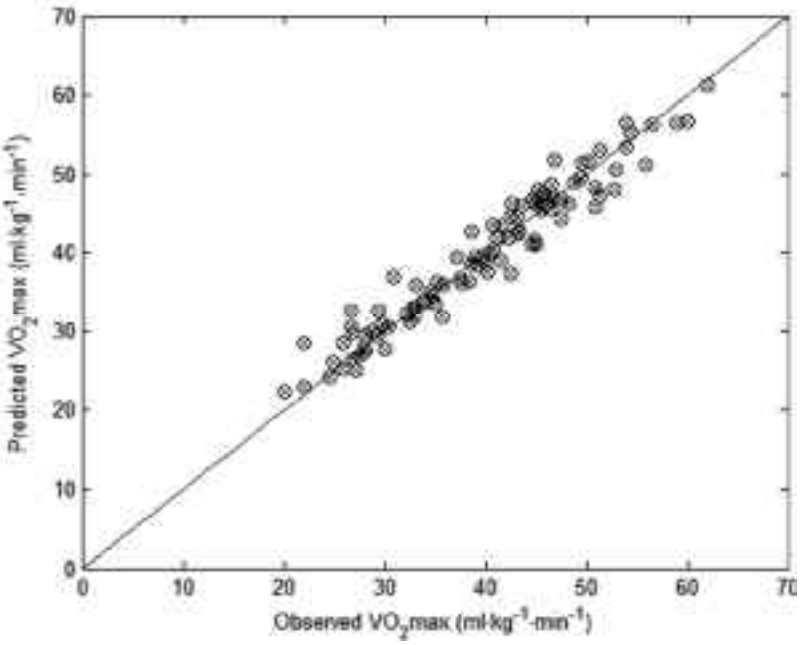


Figure 4.7. Predicted VO_2max versus measured VO_2max for the ANN-based model #7 of first dataset.

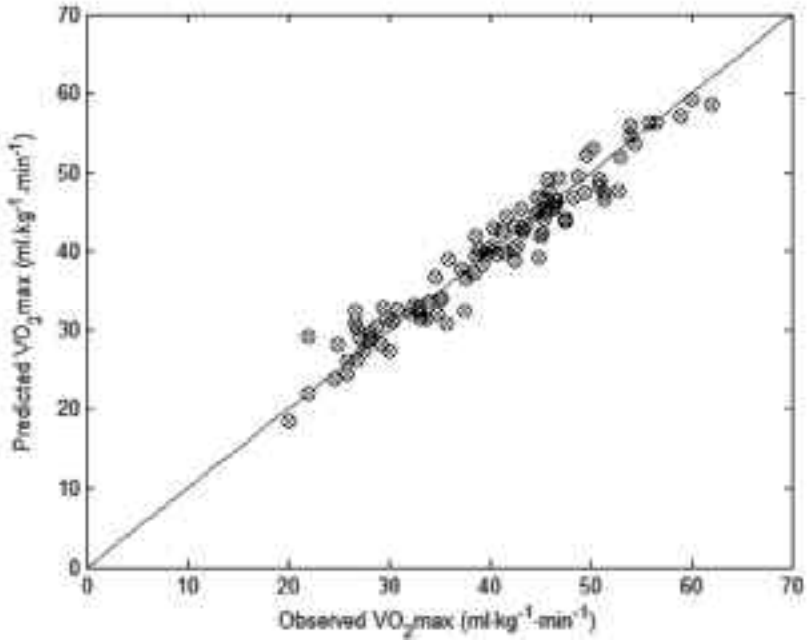


Figure 4.8. Predicted VO_2max versus measured VO_2max for the ANN-based model #8 of first dataset.

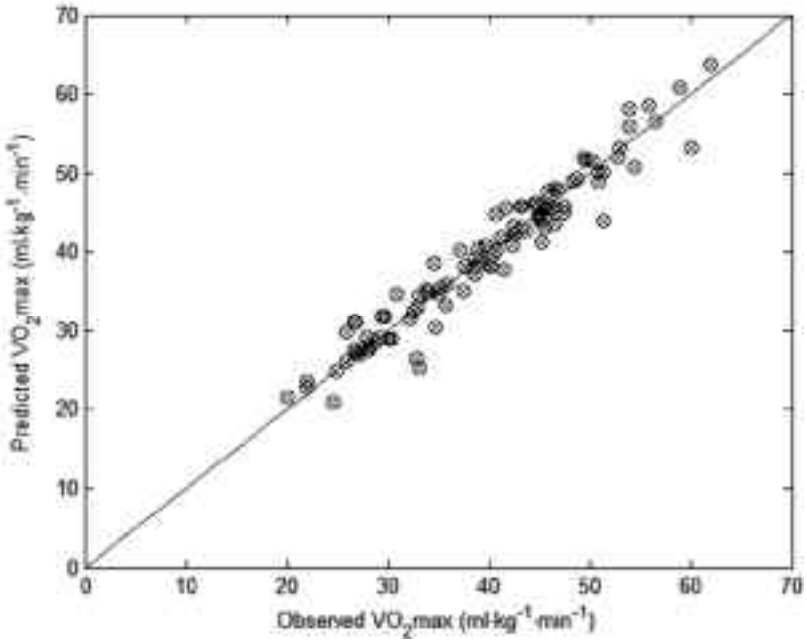


Figure 4.9. Predicted VO_2max versus measured VO_2max for the ANN-based model #9 of first dataset.

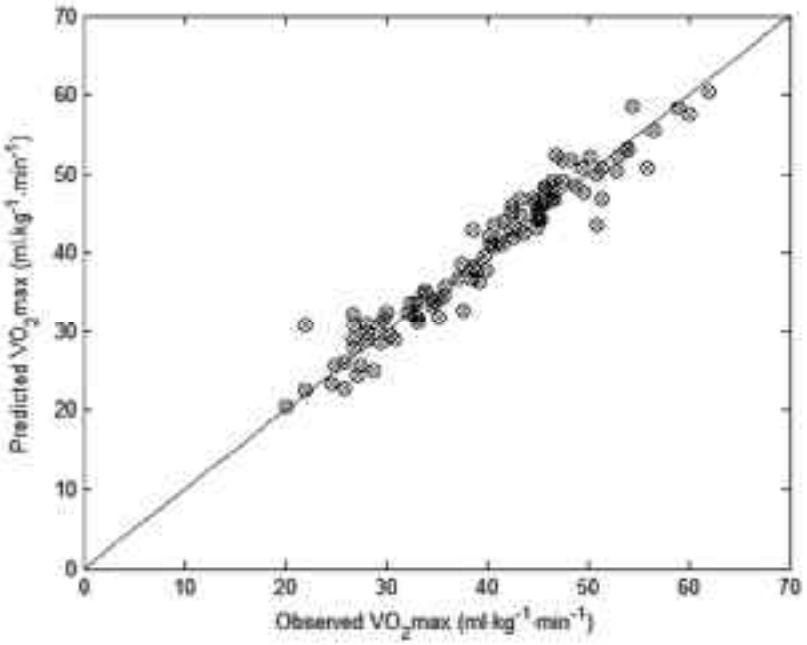


Figure 4.10. Predicted VO_2max versus measured VO_2max for the ANN-based model #10 of first dataset.

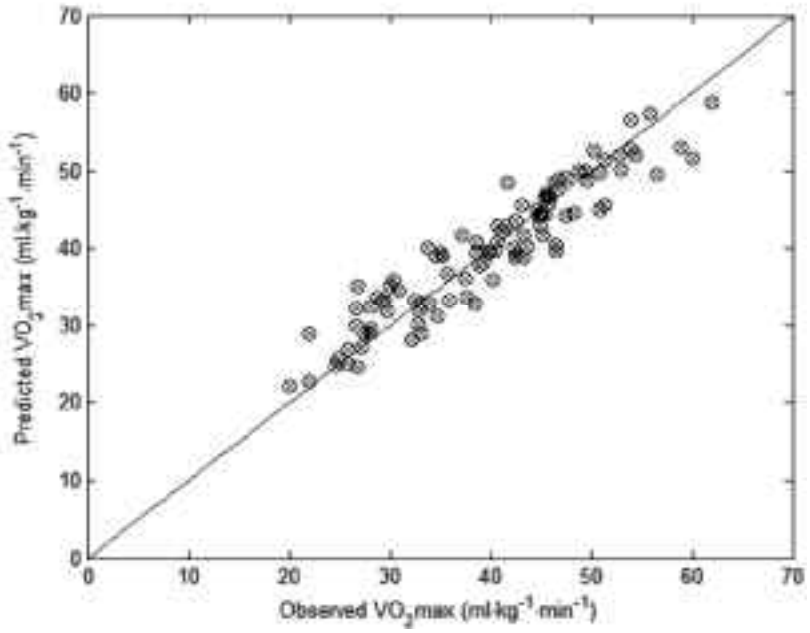


Figure 4.11. Predicted VO_2max versus measured VO_2max for the ANN-based model #11 of first dataset.

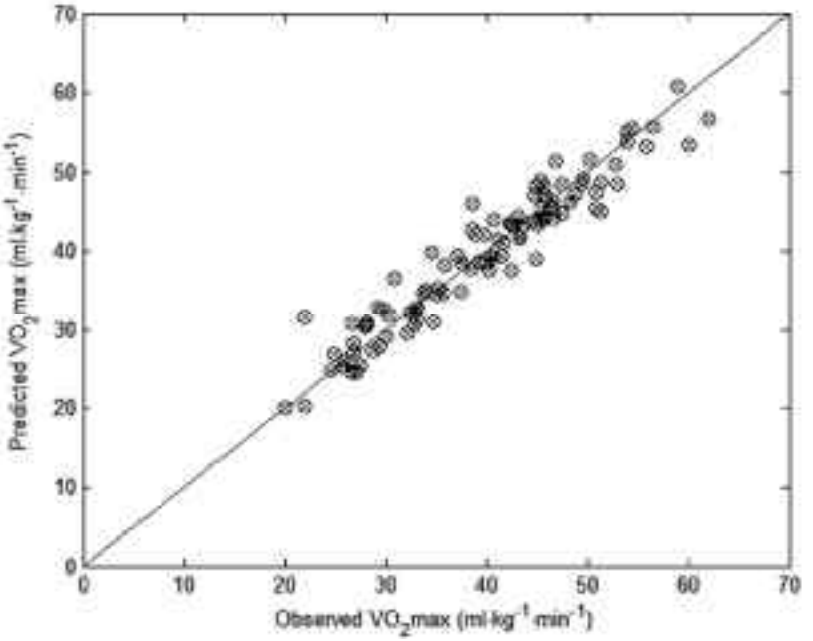


Figure 4.12. Predicted VO_2max versus measured VO_2max for the ANN-based model #12 of first dataset.

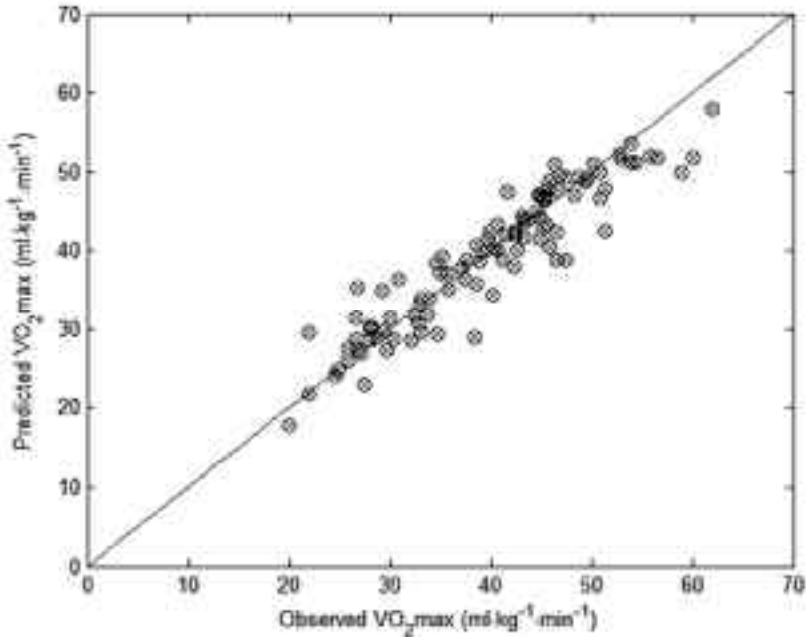


Figure 4.13. Predicted VO_2max versus measured VO_2max for the ANN-based model #13 of first dataset.

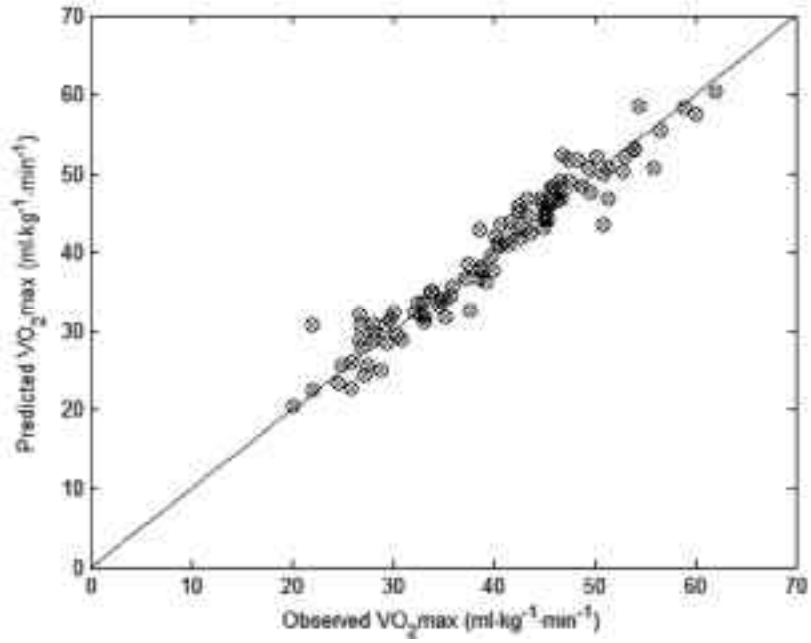


Figure 4.14. Predicted VO_2max versus measured VO_2max for the ANN-based model #14 of first dataset.

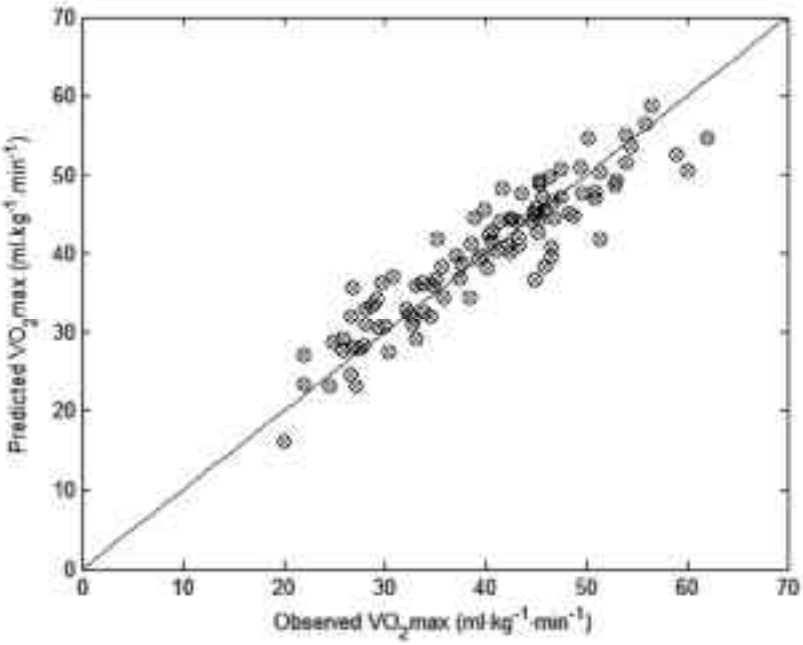


Figure 4.15. Predicted VO_2max versus measured VO_2max for the ANN-based model #15 of first dataset.

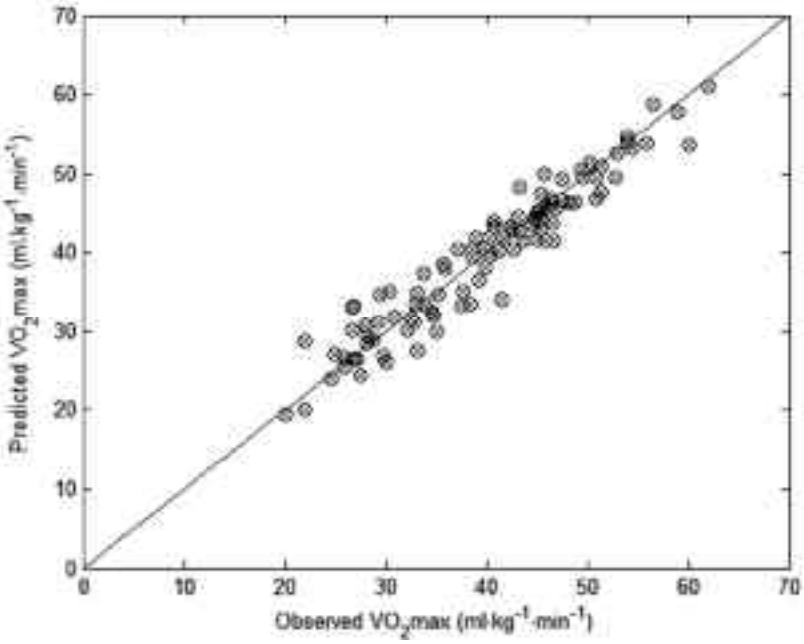


Figure 4.16. Predicted VO_2max versus measured VO_2max for the ANN-based model #16 of first dataset.

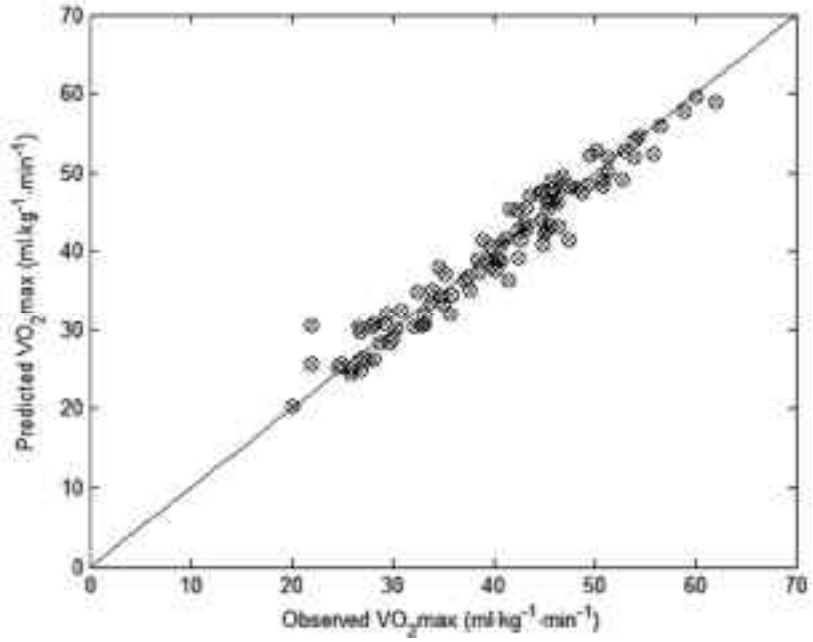


Figure 4.17. Predicted VO_2max versus measured VO_2max for the ANN-based model #17 of first dataset.

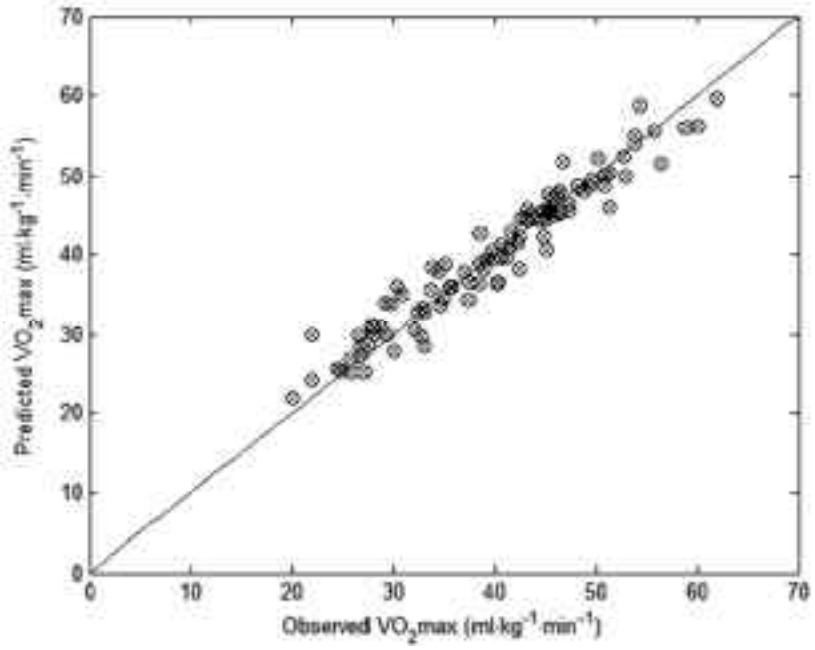


Figure 4.18. Predicted VO_2max versus measured VO_2max for the ANN-based model #18 of first dataset.

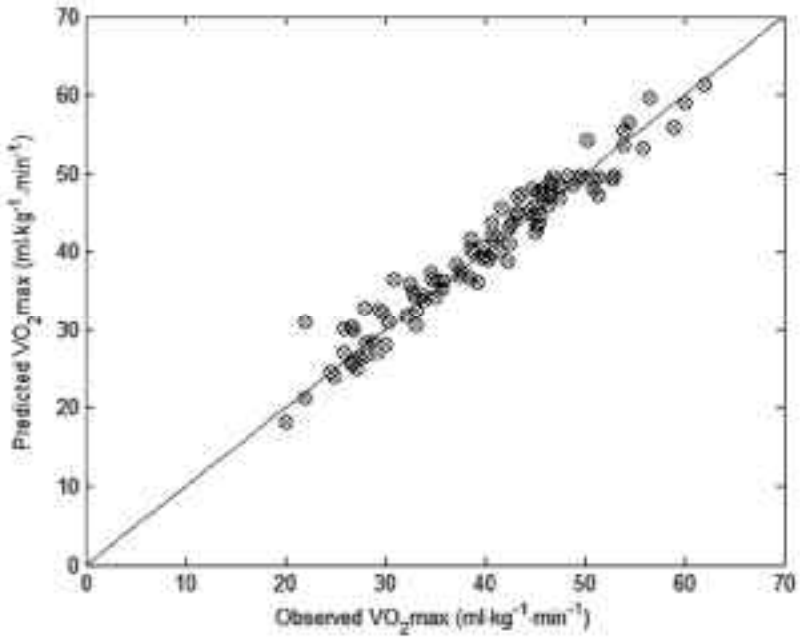


Figure 4.19. Predicted VO_2max versus measured VO_2max for the ANN-based model #19 of first dataset.

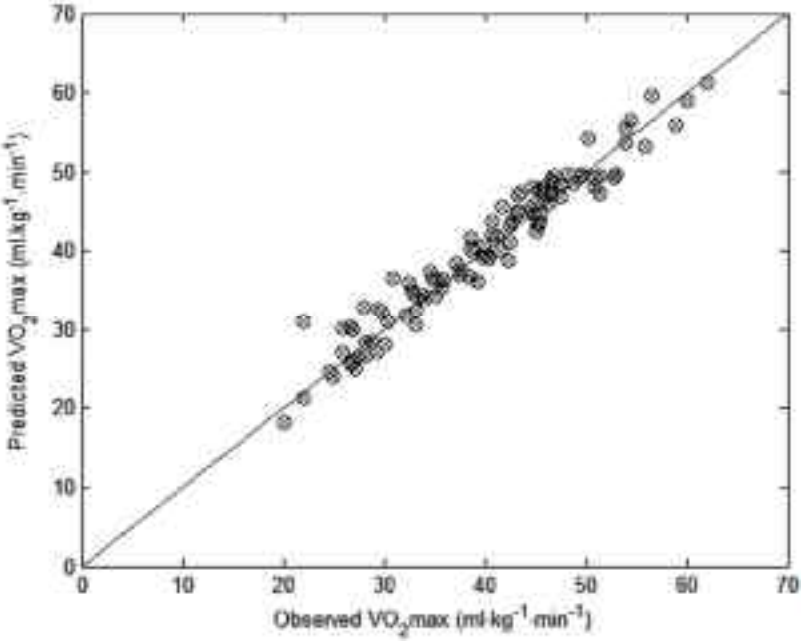


Figure 4.20. Predicted VO_2max versus measured VO_2max for the ANN-based model #20 of first dataset.

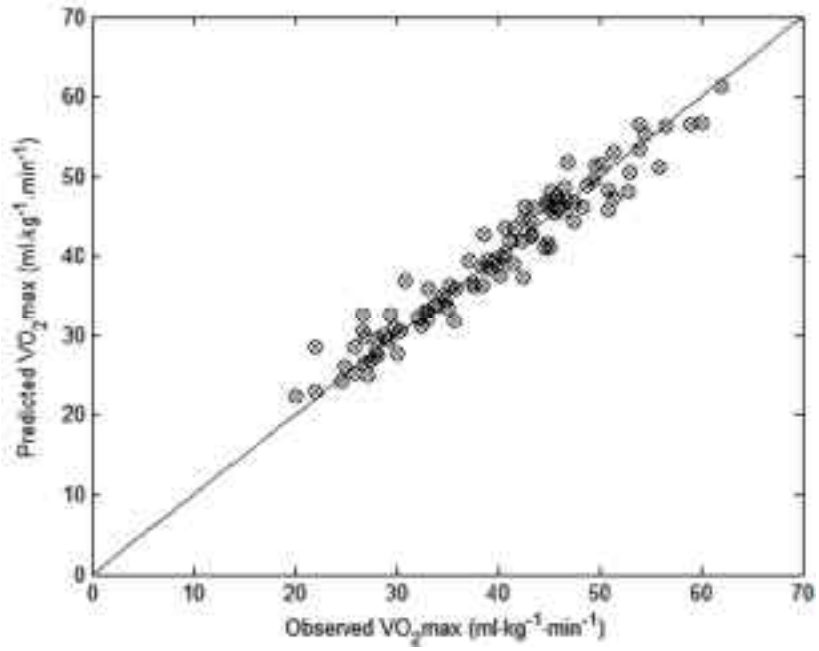


Figure 4.21. Predicted VO_2max versus measured VO_2max for the ANN-based model #21 of first dataset.

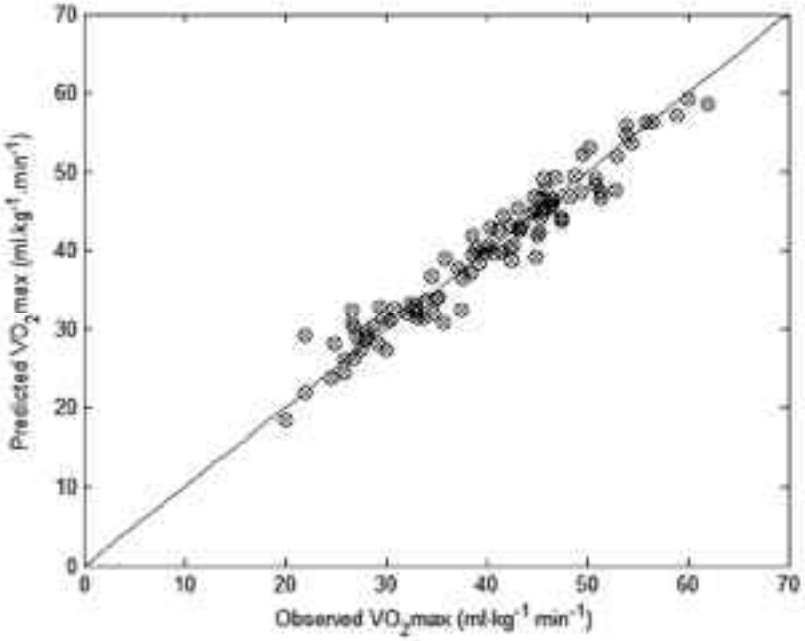


Figure 4.22. Predicted VO_2max versus measured VO_2max for the ANN-based model #22 of first dataset.

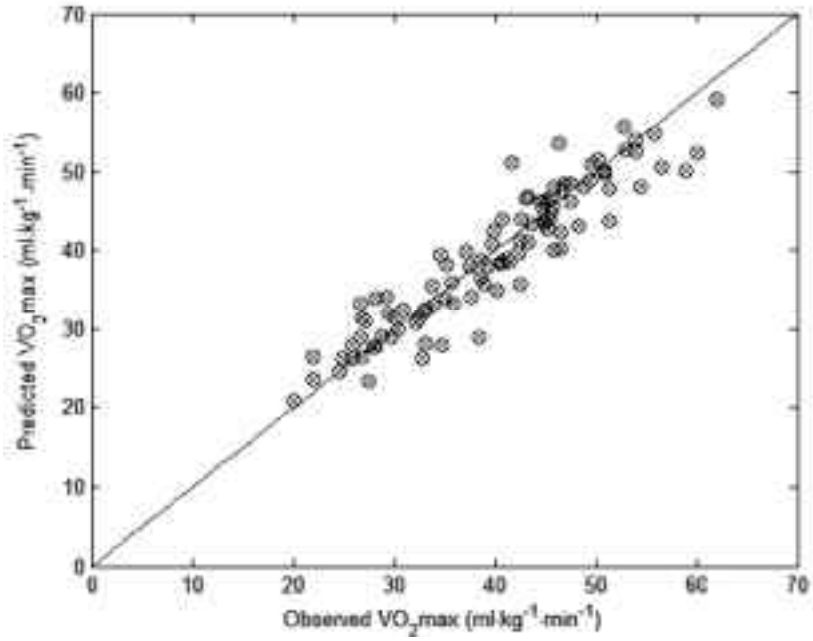


Figure 4.23. Predicted VO_2max versus measured VO_2max for the ANN-based model #23 of first dataset.

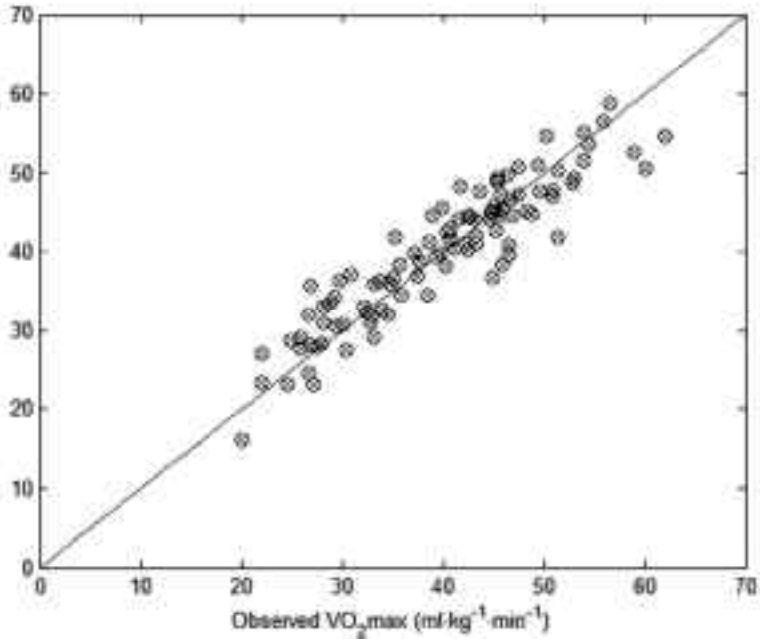


Figure 4.24. Predicted VO_2max versus measured VO_2max for the ANN-based model #24 of first dataset.

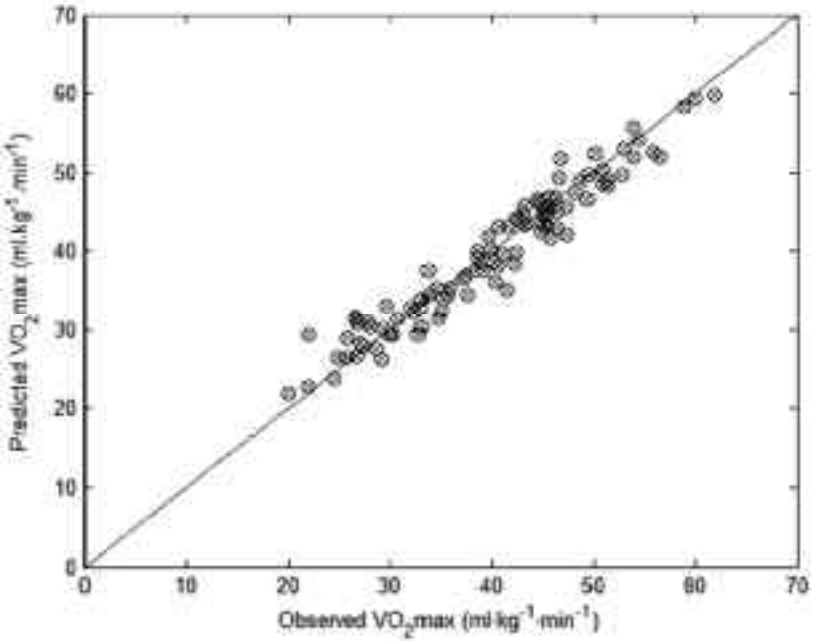


Figure 4.25. Predicted VO_2max versus measured VO_2max for the ANN-based model #25 of first dataset.

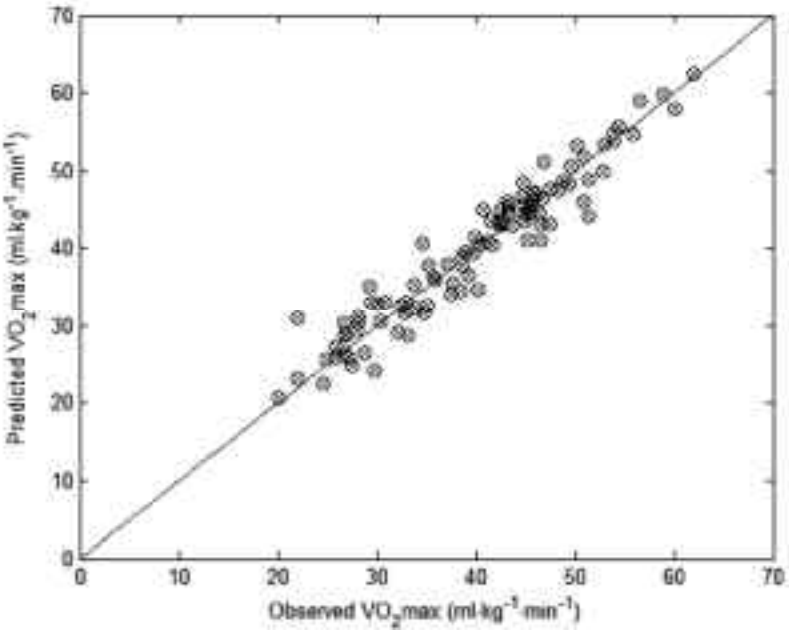


Figure 4.26. Predicted VO_2max versus measured VO_2max for the ANN-based model #26 of first dataset.

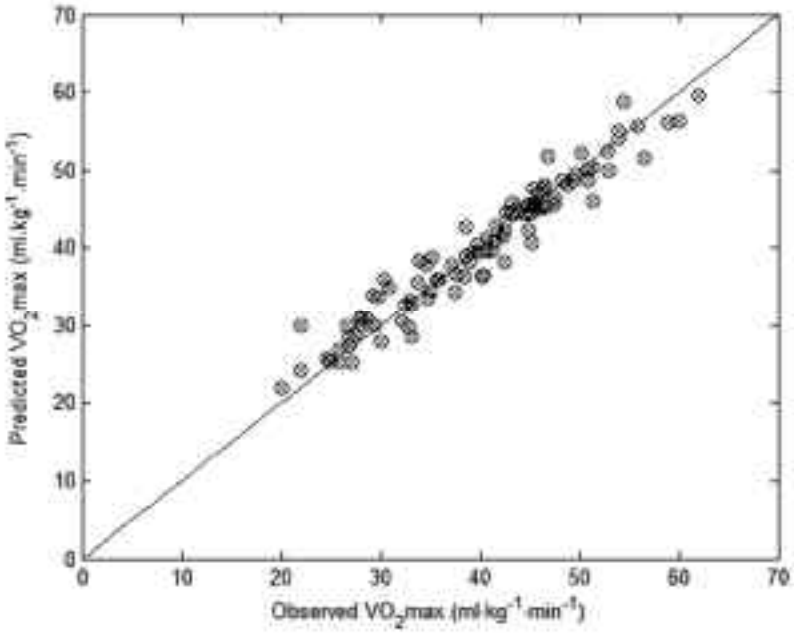


Figure 4.27. Predicted VO_2max versus measured VO_2max for the ANN-based model #27 of first dataset.

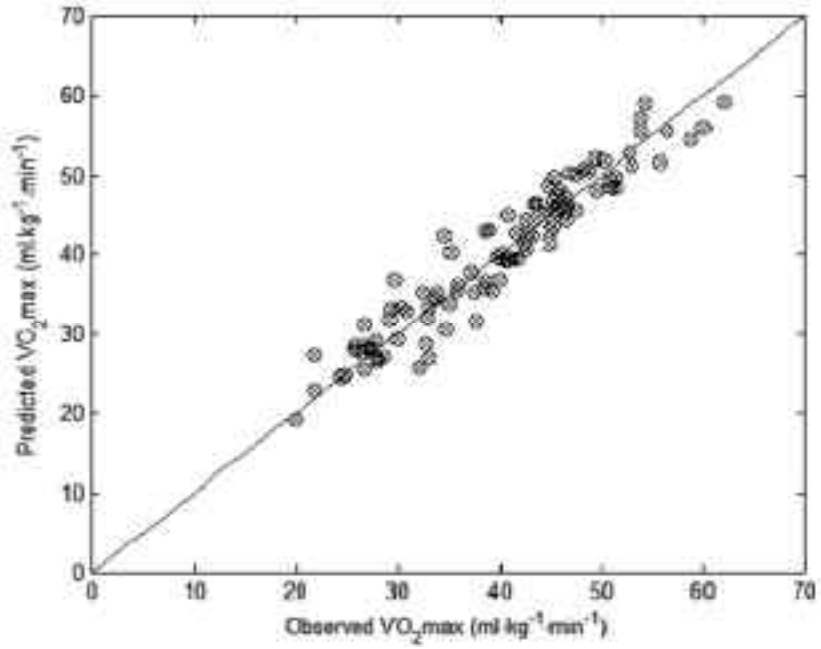


Figure 4.28. Predicted VO_2max versus measured VO_2max for the ANN-based model #28 of first dataset.

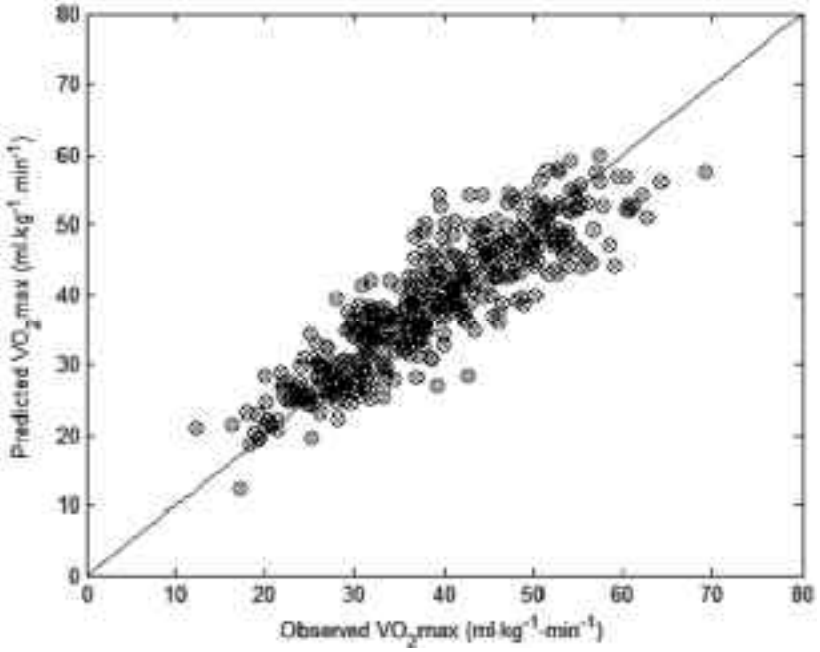


Figure 4.29. Predicted VO_2max versus measured VO_2max for the ANN-based model #1 of second dataset.

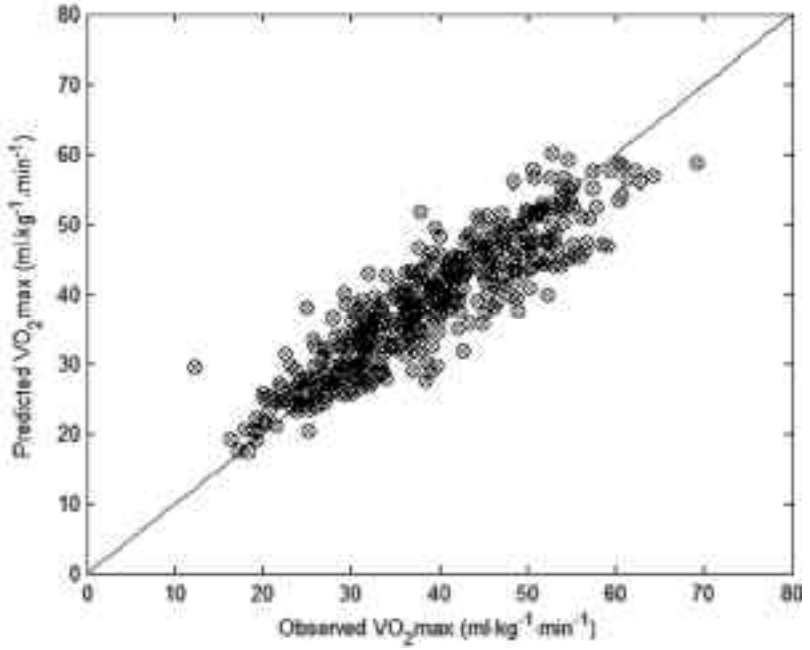


Figure 4.30. Predicted VO_2max versus measured VO_2max for the ANN-based model #2 of second dataset.

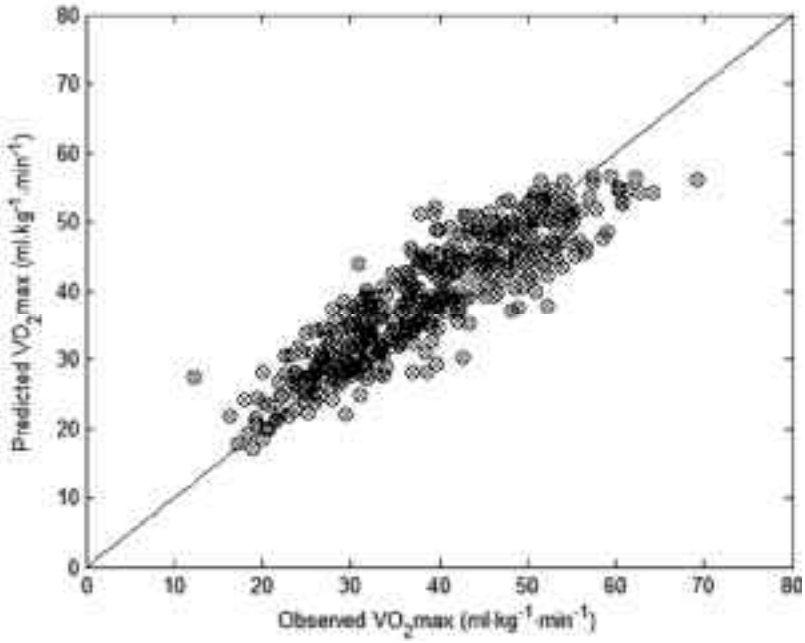


Figure 4.31. Predicted VO_2max versus measured VO_2max for the ANN-based model #3 of second dataset.

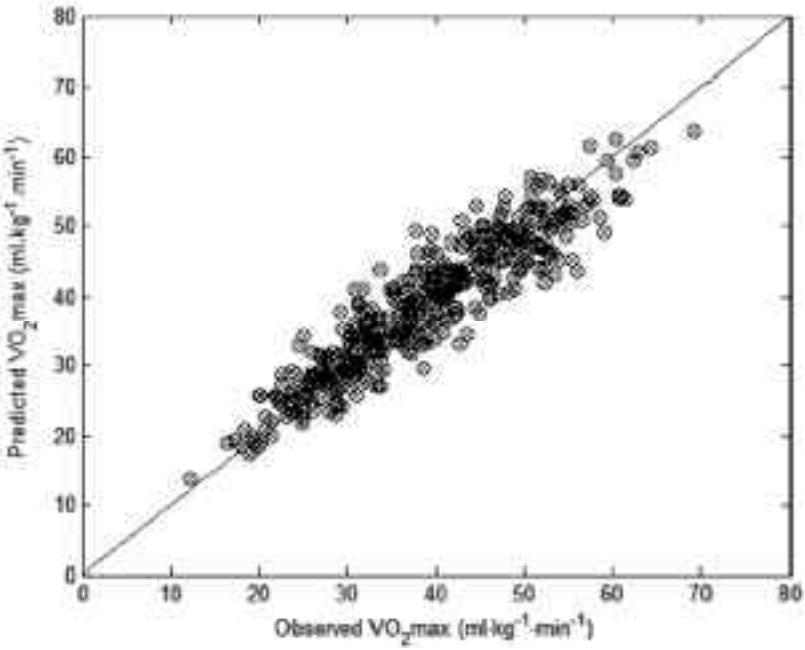


Figure 4.32. Predicted VO_2max versus measured VO_2max for the ANN-based model #4 of second dataset.

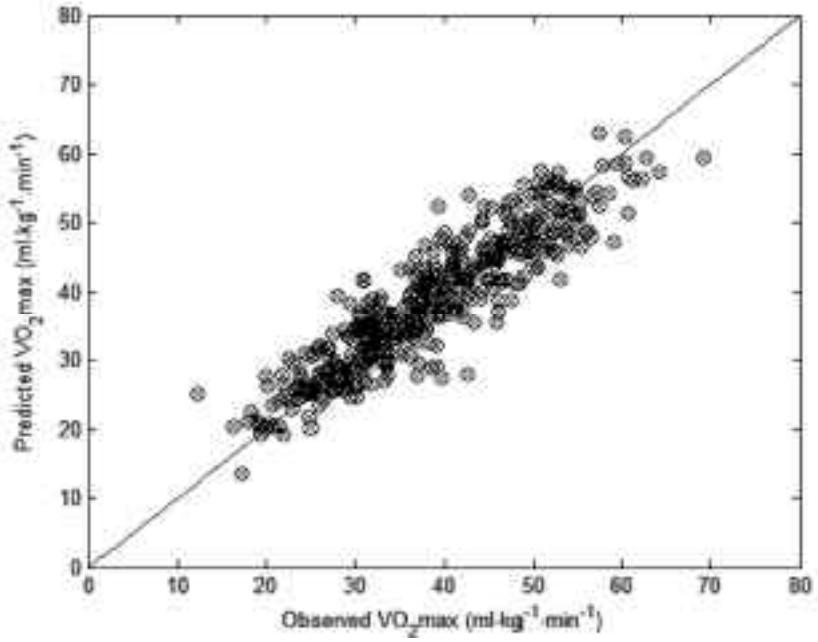


Figure 4.33. Predicted VO_2max versus measured VO_2max for the ANN-based model #5 of second dataset.

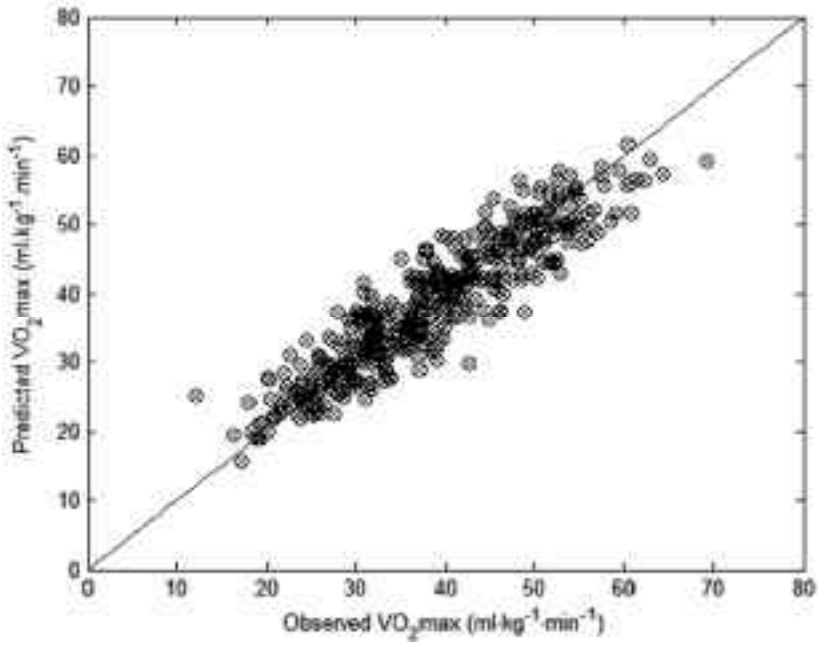


Figure 4.34. Predicted VO_2max versus measured VO_2max for the ANN-based model #6 of second dataset.

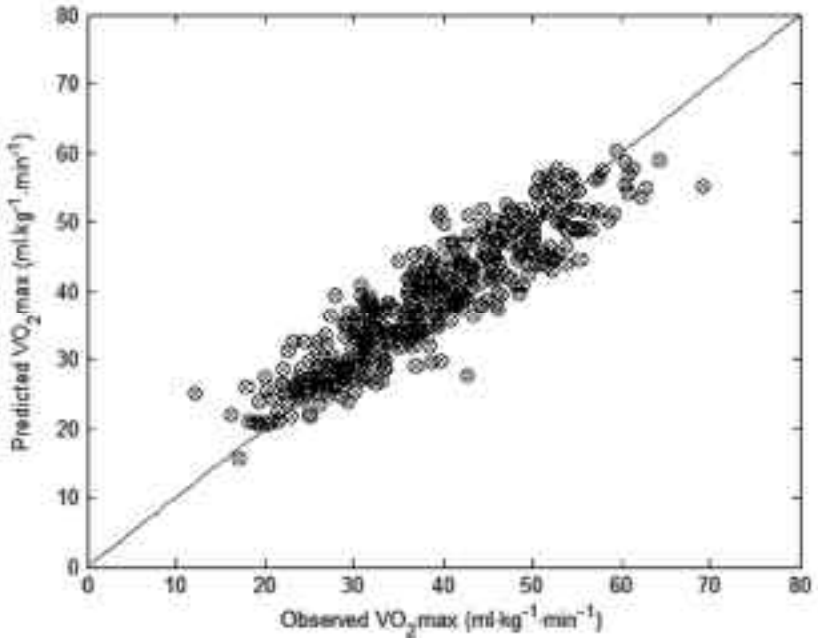


Figure 4.35. Predicted VO_2max versus measured VO_2max for the ANN-based model #7 of second dataset.

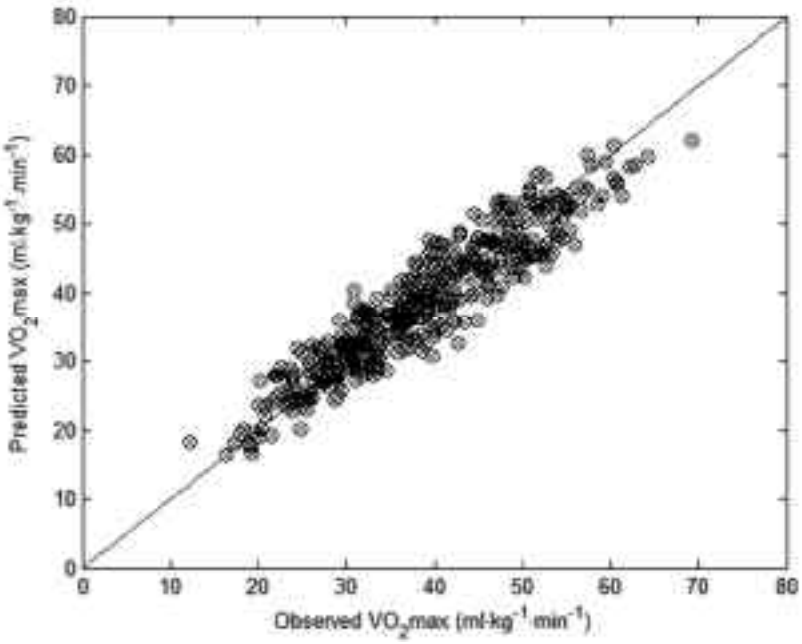


Figure 4.36. Predicted VO_2max versus measured VO_2max for the ANN-based model #8 of second dataset.

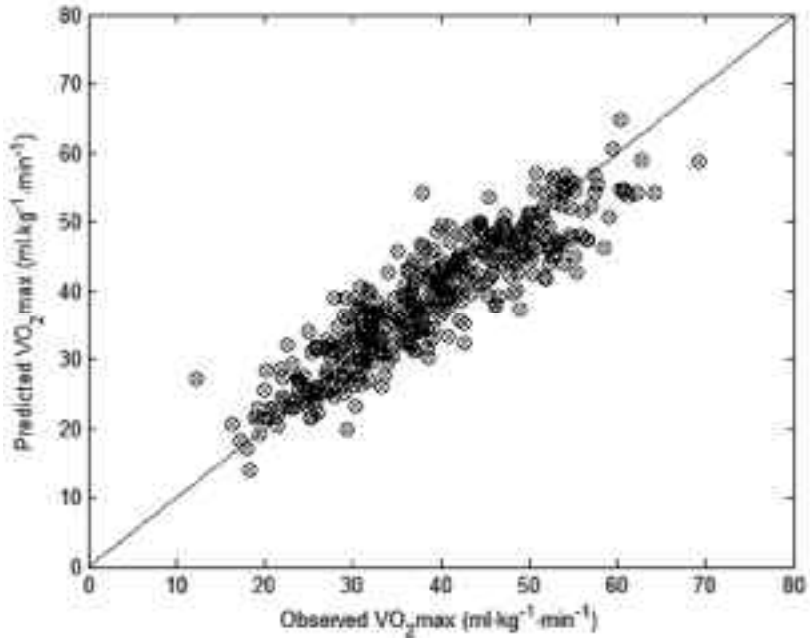


Figure 4.37. Predicted VO_2max versus measured VO_2max for the ANN-based model #9 of second dataset.

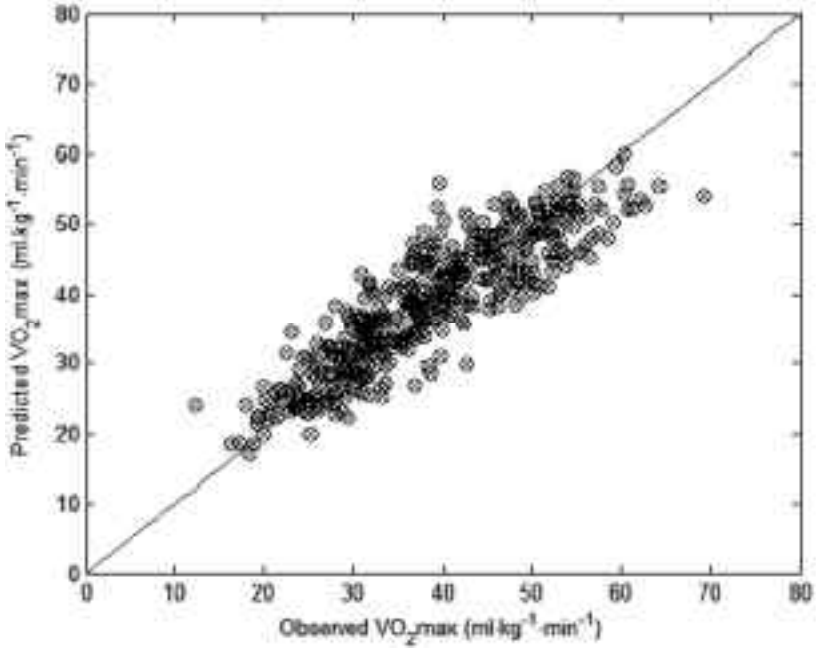


Figure 4.38. Predicted VO_2max versus measured VO_2max for the ANN-based model #10 of second dataset.

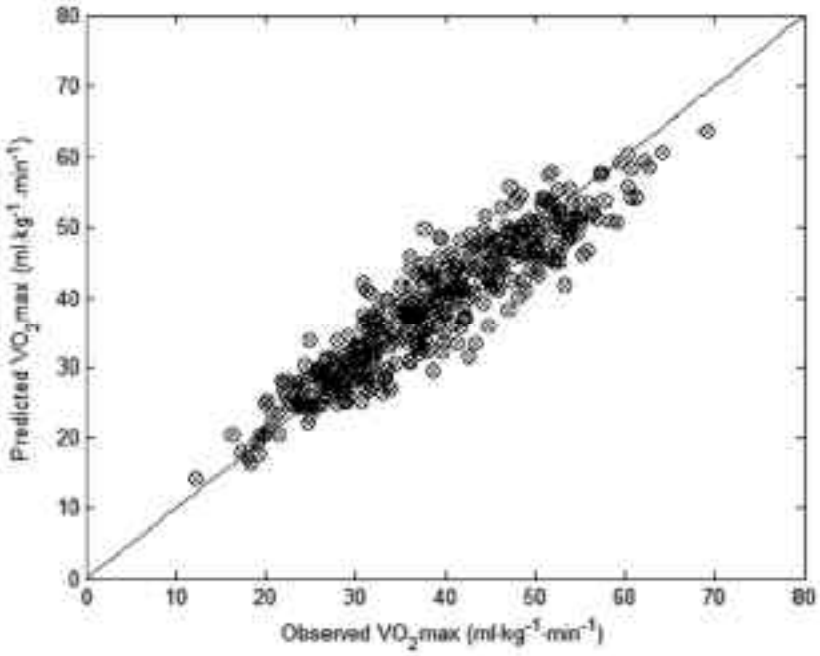


Figure 4.39. Predicted VO_2max versus measured VO_2max for the ANN-based model #11 of second dataset.

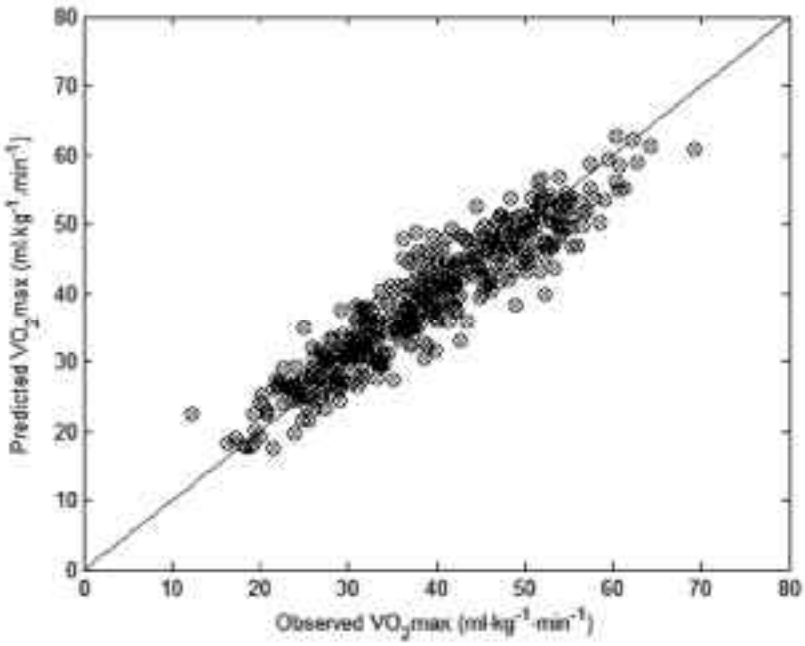


Figure 4.40. Predicted VO_2max versus measured VO_2max for the ANN-based model #12 of second dataset.

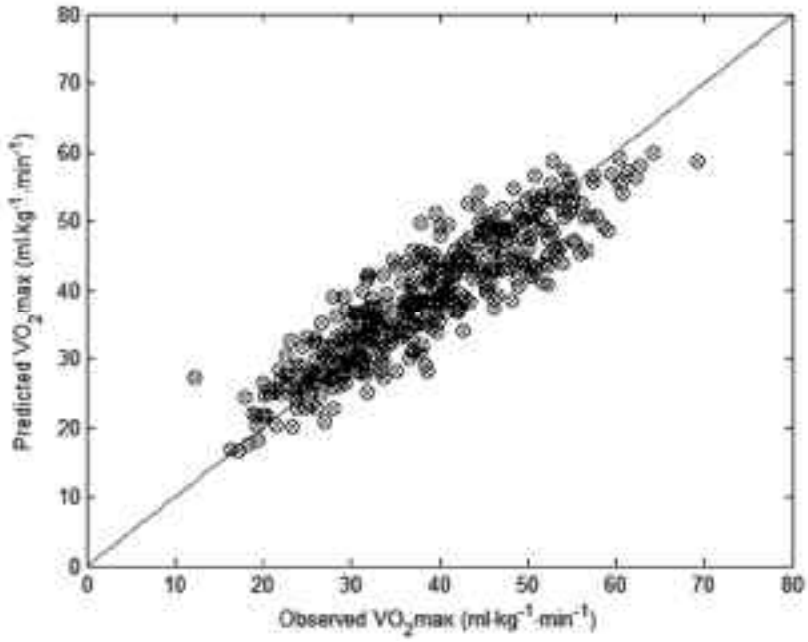


Figure 4.41. Predicted VO_2max versus measured VO_2max for the ANN-based model #13 of second dataset.

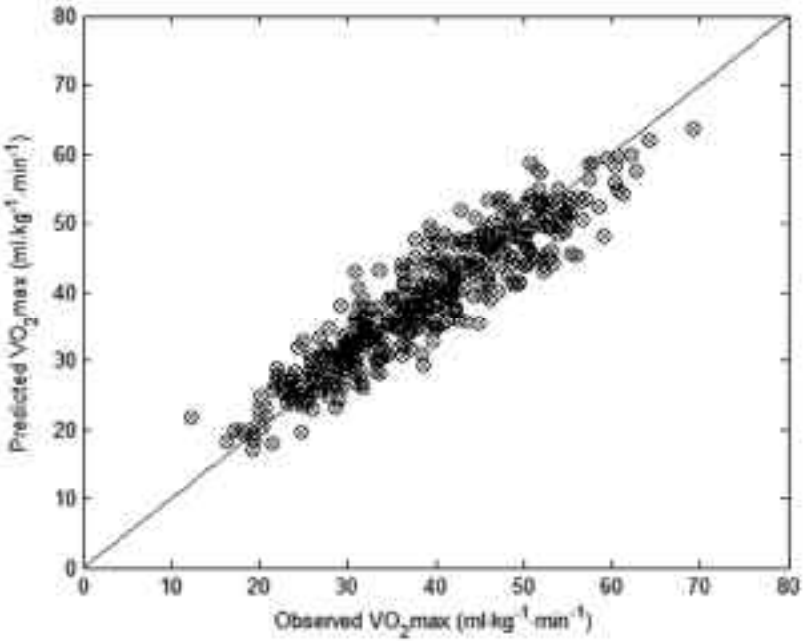


Figure 4.42. Predicted VO_2max versus measured VO_2max for the ANN-based model #14 of second dataset.

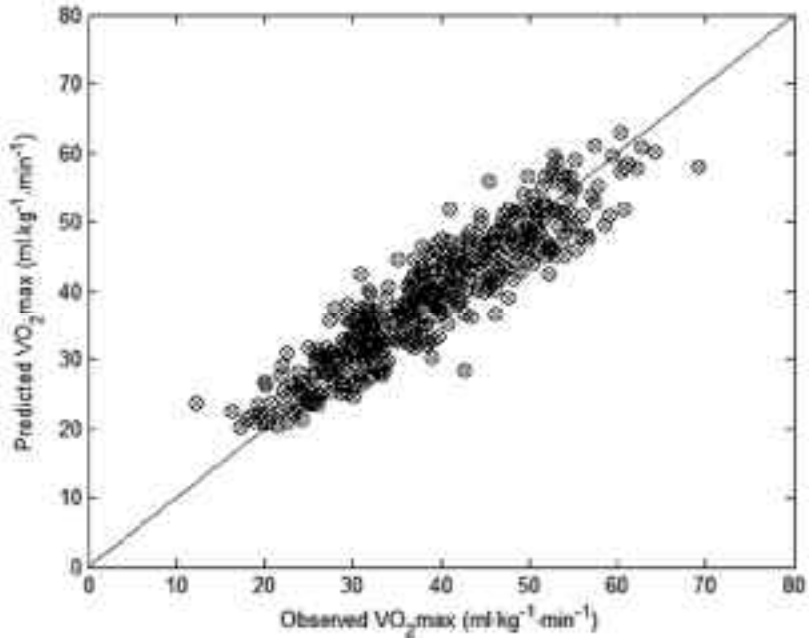


Figure 4.43. Predicted VO_2max versus measured VO_2max for the ANN-based model #15 of second dataset.

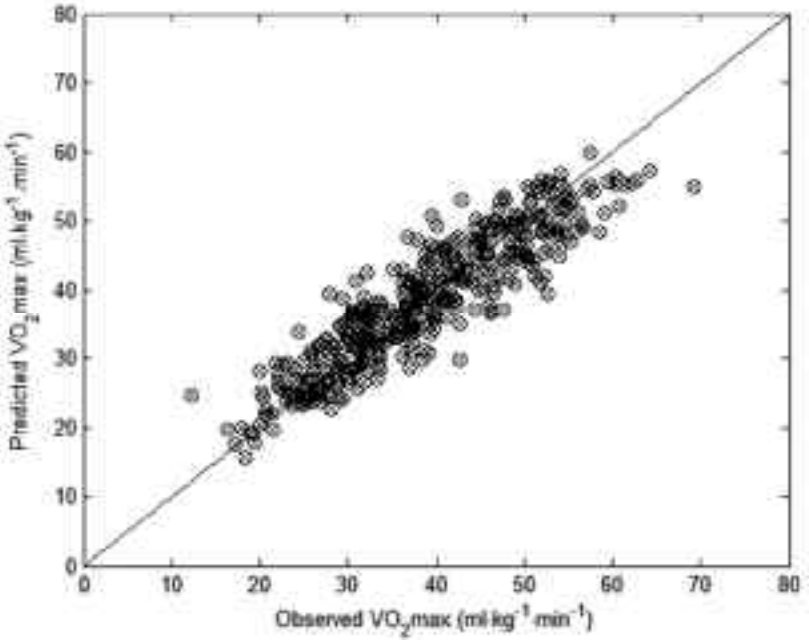


Figure 4.44. Predicted VO_2max versus measured VO_2max for the ANN-based model #16 of second dataset.

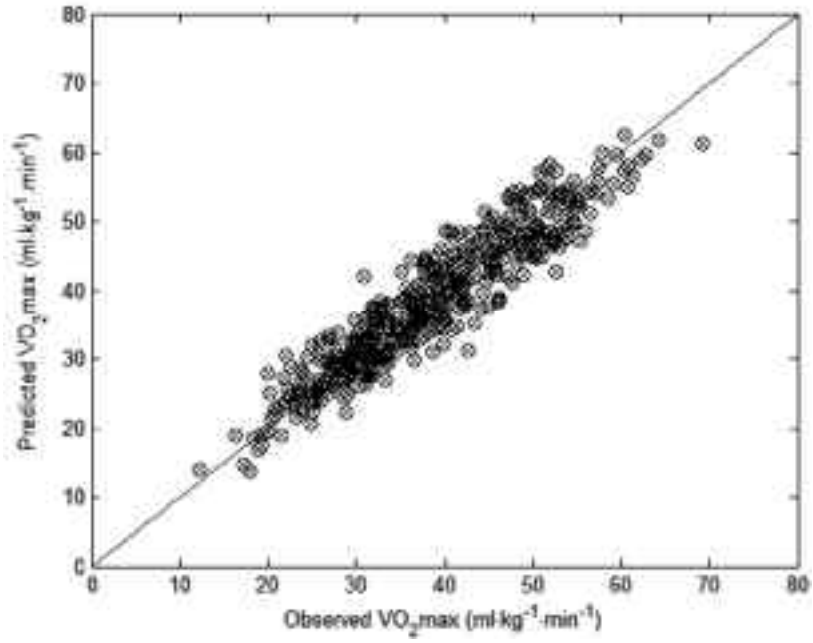


Figure 4.45. Predicted VO_2max versus measured VO_2max for the ANN-based model #17 of second dataset.

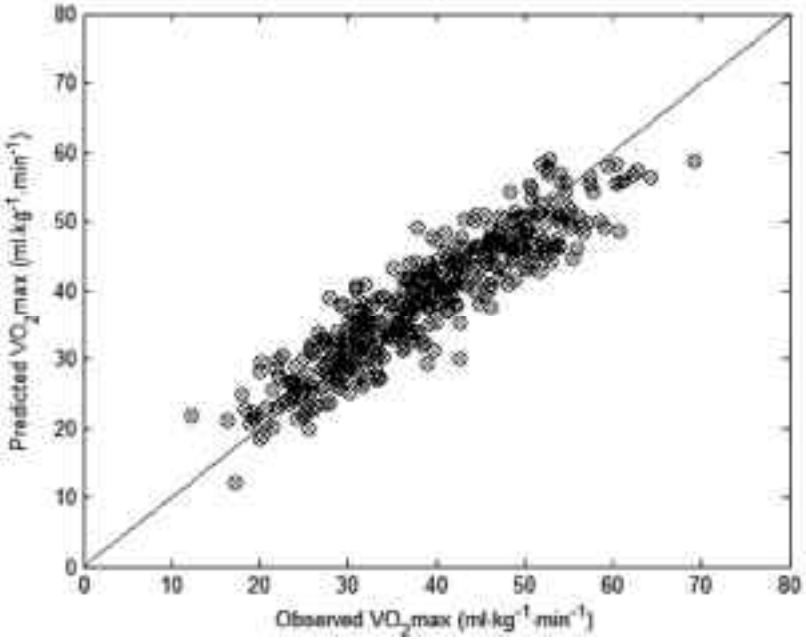


Figure 4.46. Predicted VO_2max versus measured VO_2max for the ANN-based model #18 of second dataset.

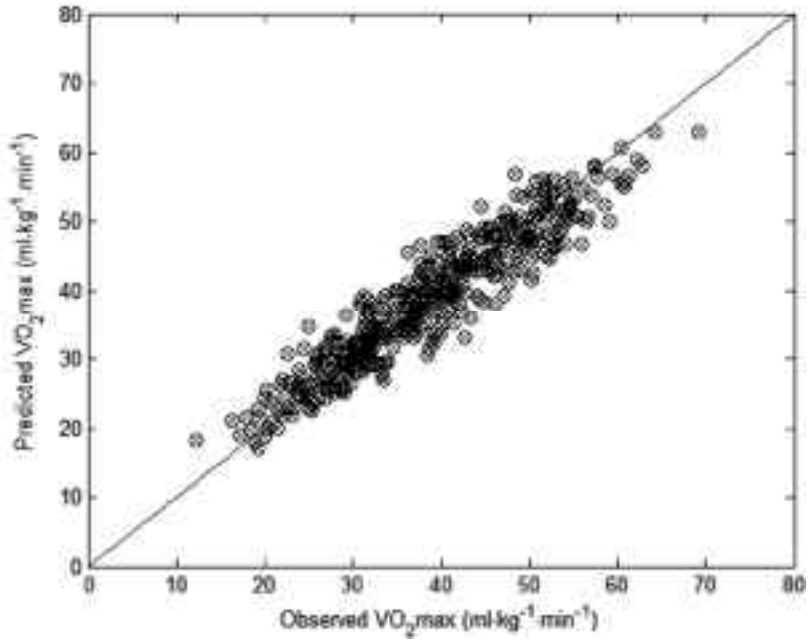


Figure 4.47. Predicted VO_2max versus measured VO_2max for the ANN-based model #19 of second dataset.

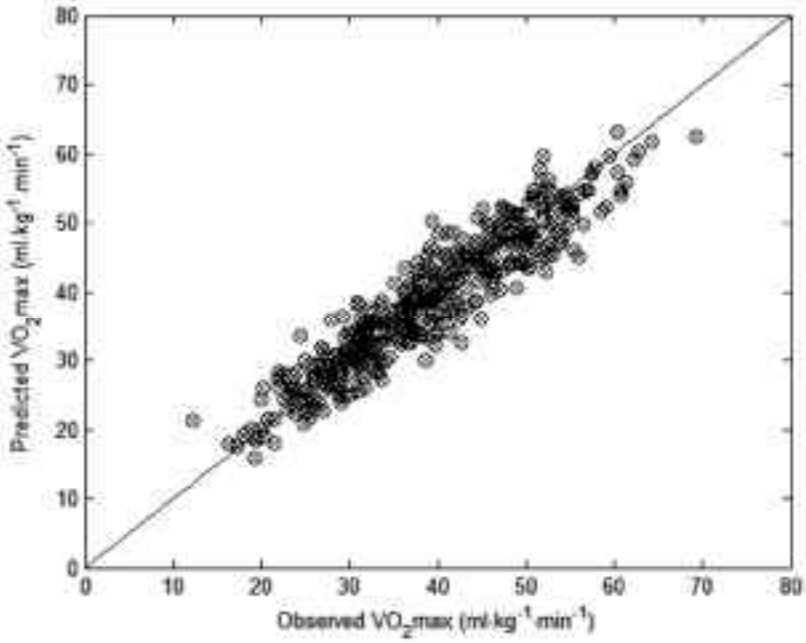


Figure 4.48. Predicted VO_2max versus measured VO_2max for the ANN-based model #20 of second dataset.

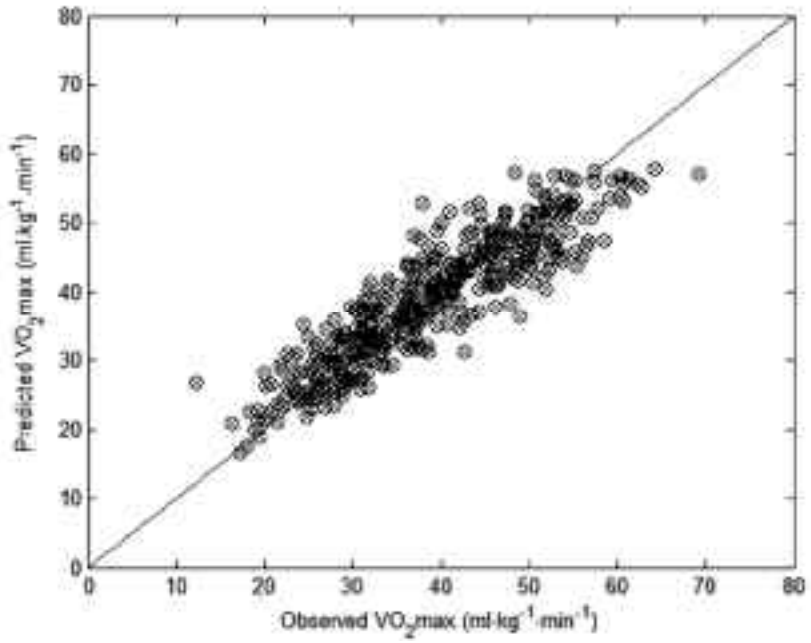


Figure 4.49. Predicted VO_2max versus measured VO_2max for the ANN-based model #21 of second dataset.

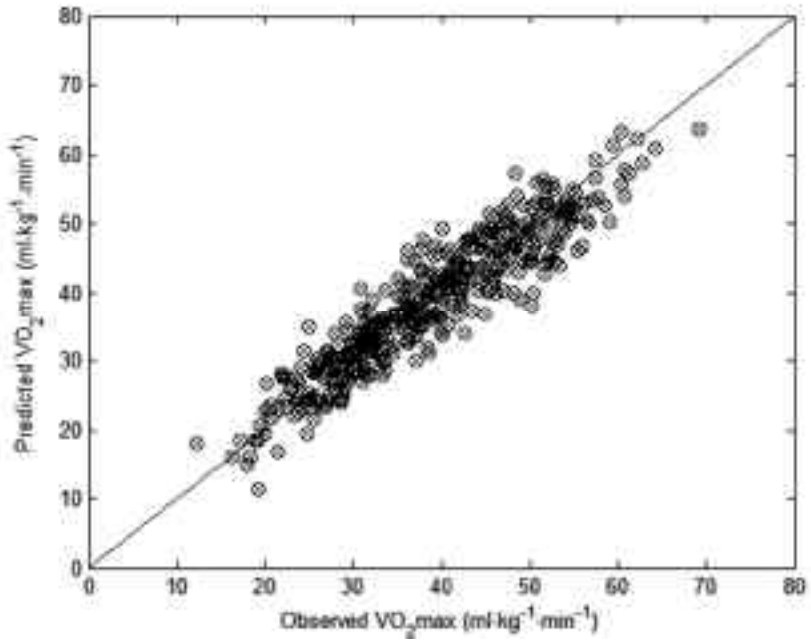


Figure 4.50. Predicted VO_2max versus measured VO_2max for the ANN-based model #22 of second dataset.

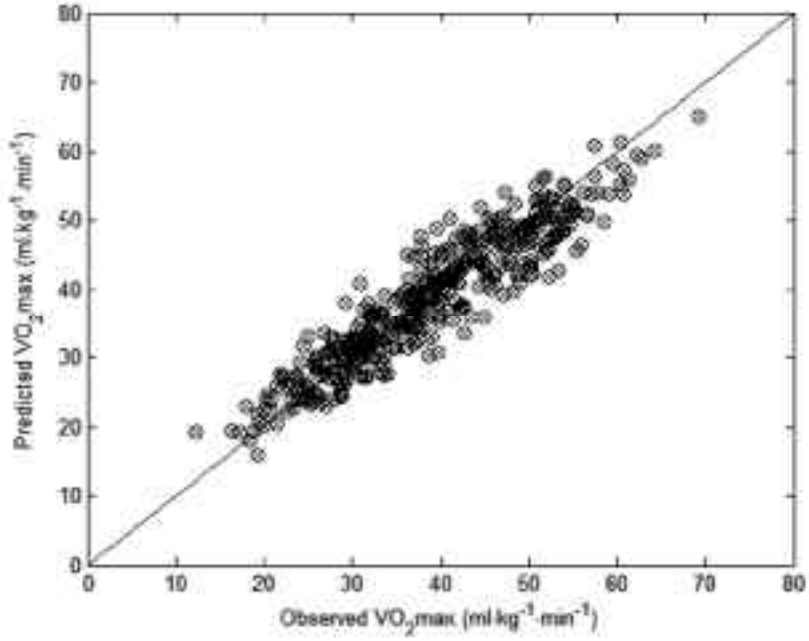


Figure 4.51. Predicted VO_2max versus measured VO_2max for the ANN-based model #23 of second dataset.

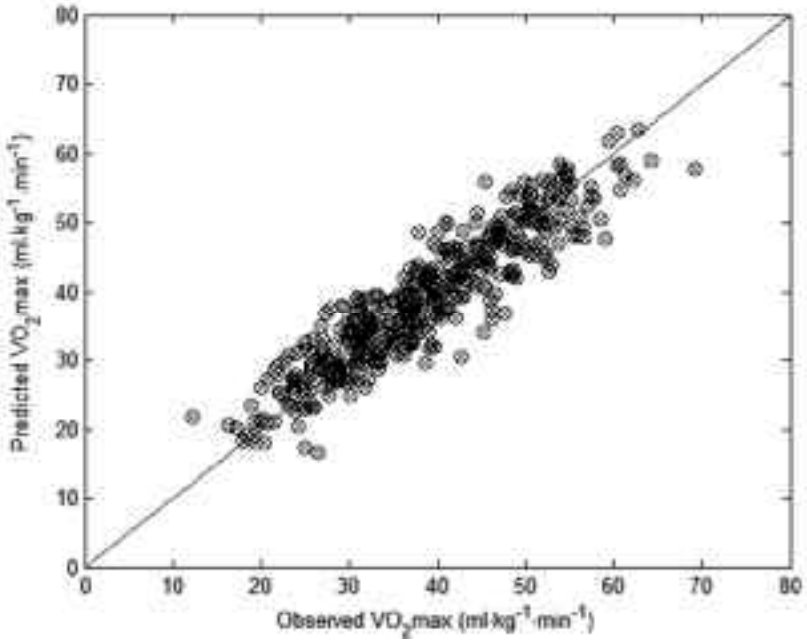


Figure 4.52. Predicted VO_2max versus measured VO_2max for the ANN-based model #24 of second dataset.

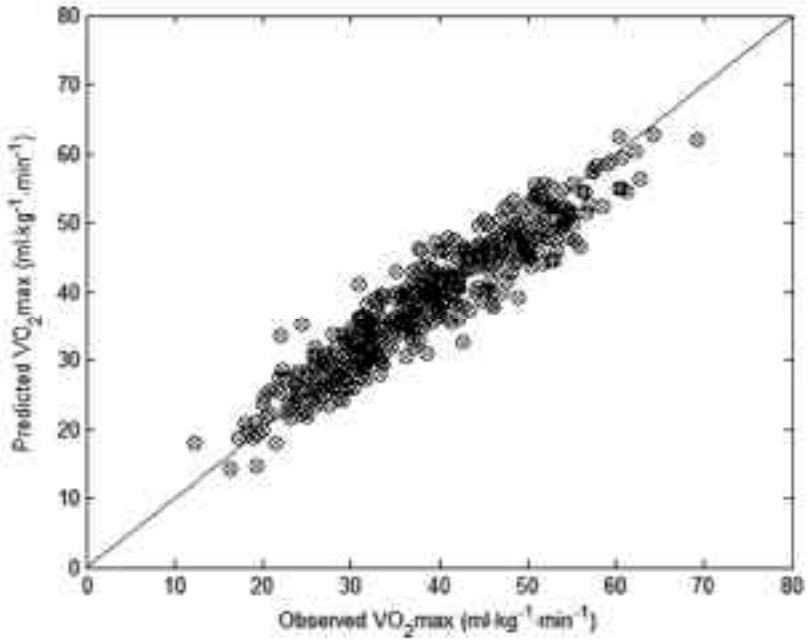


Figure 4.53. Predicted VO_2max versus measured VO_2max for the ANN-based model #25 of second dataset.

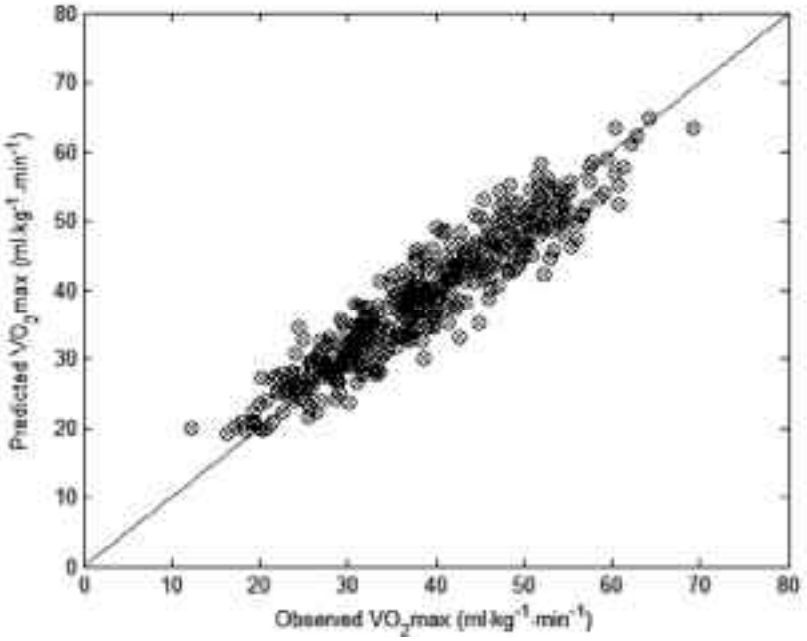


Figure 4.54. Predicted VO_2max versus measured VO_2max for the ANN-based model #26 of second dataset.

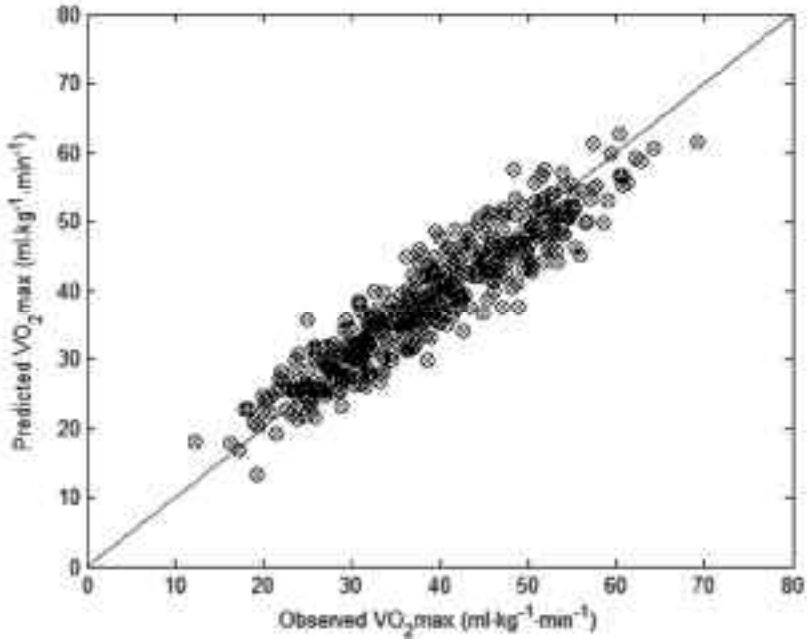


Figure 4.55. Predicted VO_2max versus measured VO_2max for the ANN-based model #27 of second dataset.

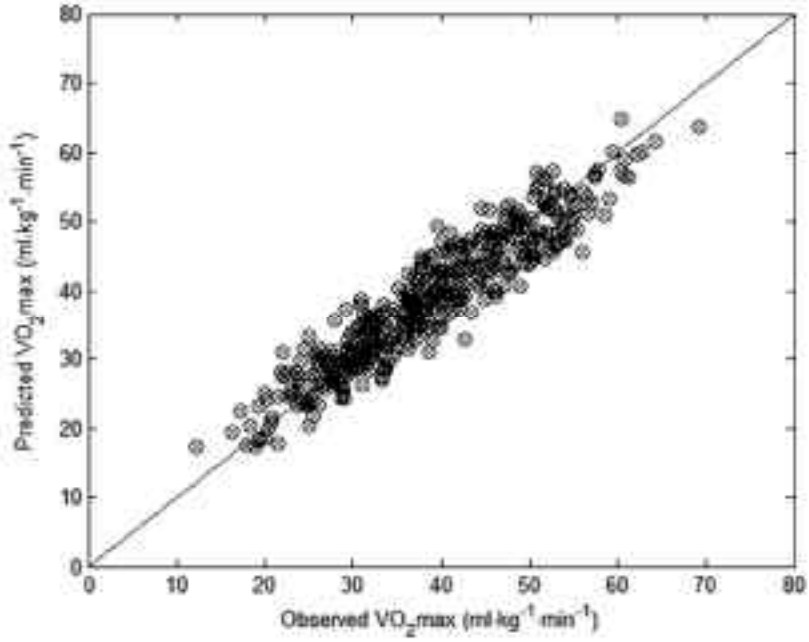


Figure 4.56. Predicted VO_2max versus measured VO_2max for the ANN-based model #28 of second dataset.

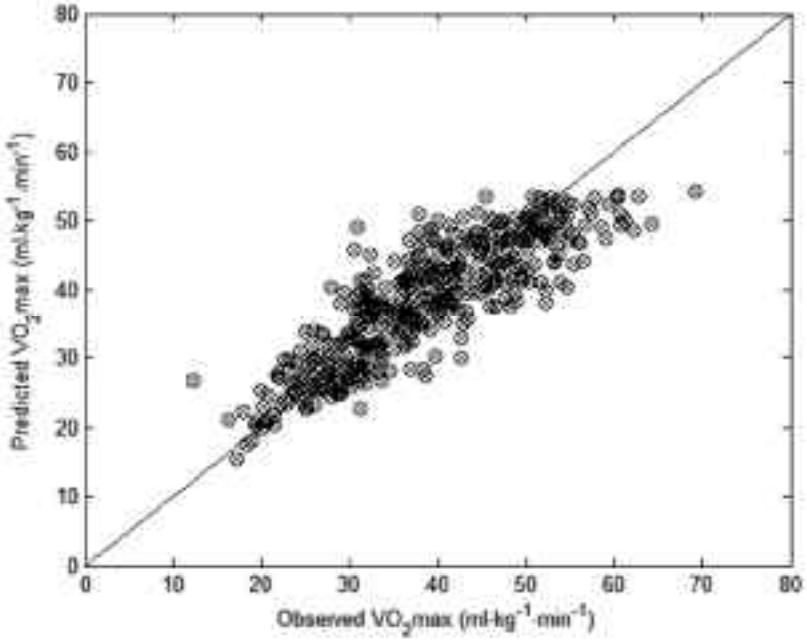


Figure 4.57. Predicted VO_2max versus measured VO_2max for the ANN-based model #29 of second dataset.

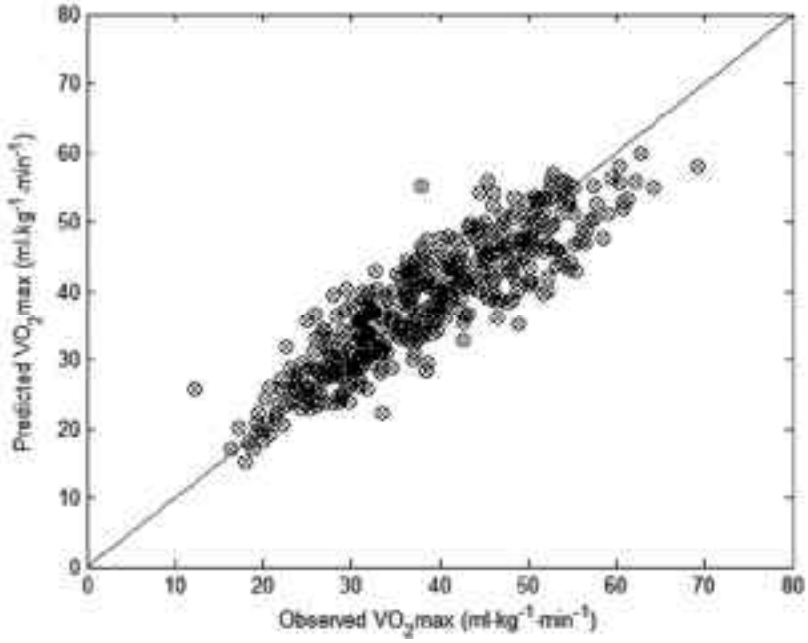


Figure 4.58. Predicted VO_2max versus measured VO_2max for the ANN-based model #30 of second dataset.

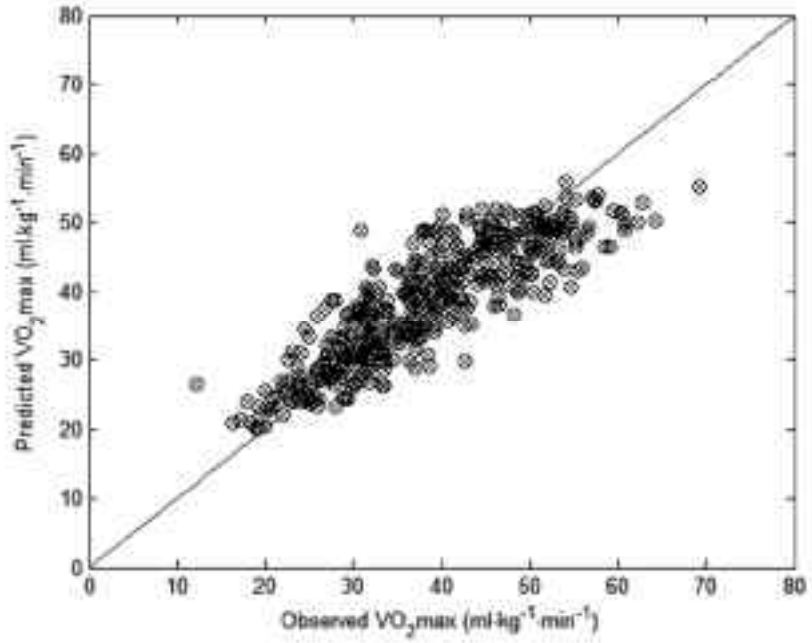


Figure 4.59. Predicted VO_2max versus measured VO_2max for the ANN-based model #31 of second dataset.

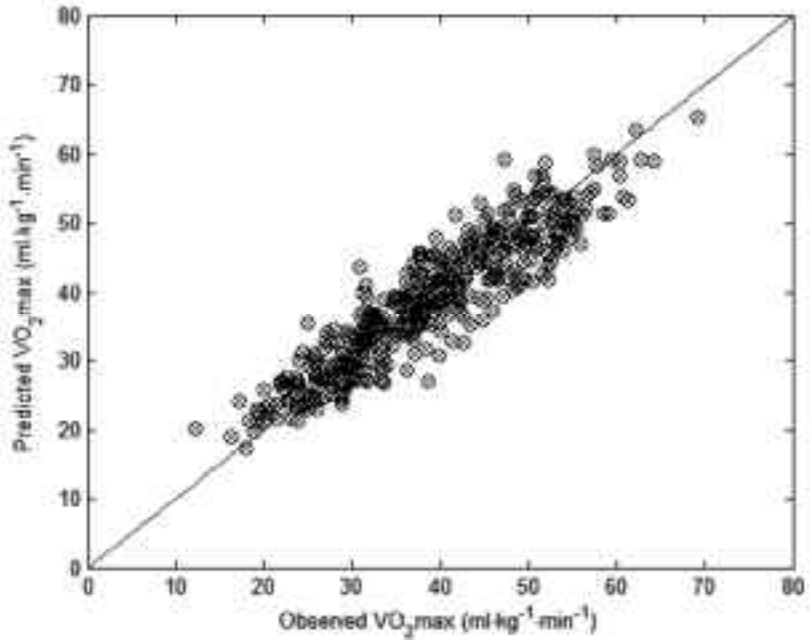


Figure 4.60. Predicted VO_2max versus measured VO_2max for the ANN-based model #32 of second dataset.

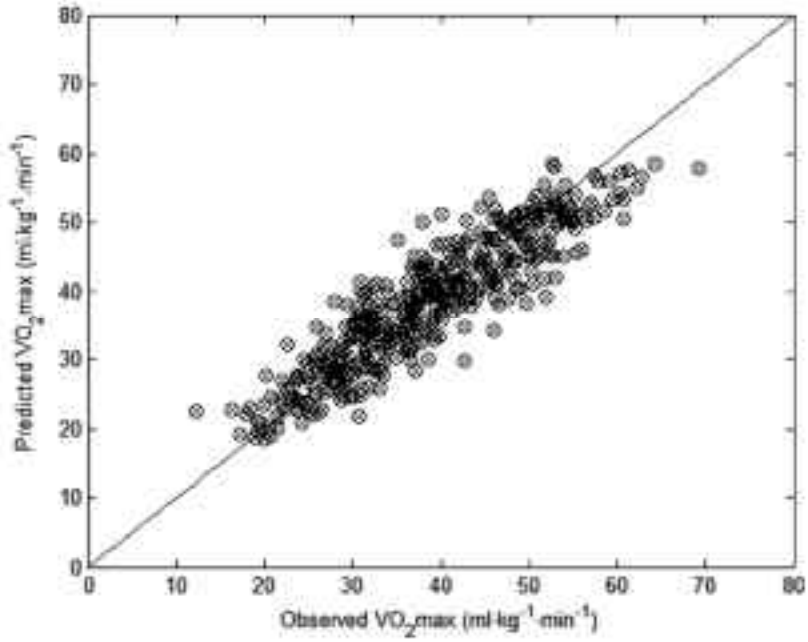


Figure 4.61. Predicted VO_2max versus measured VO_2max for the ANN-based model #33 of second dataset.

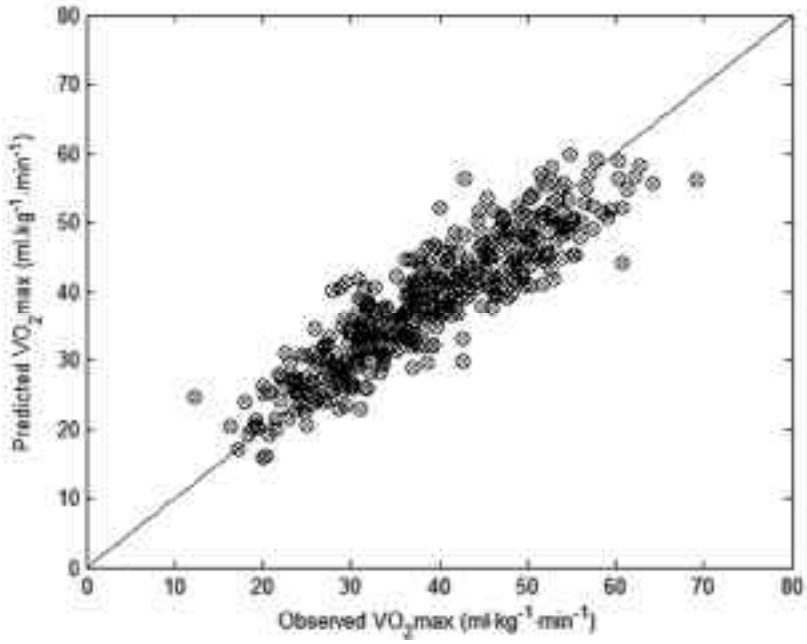


Figure 4.62. Predicted VO_2max versus measured VO_2max for the ANN-based model #34 of second dataset.

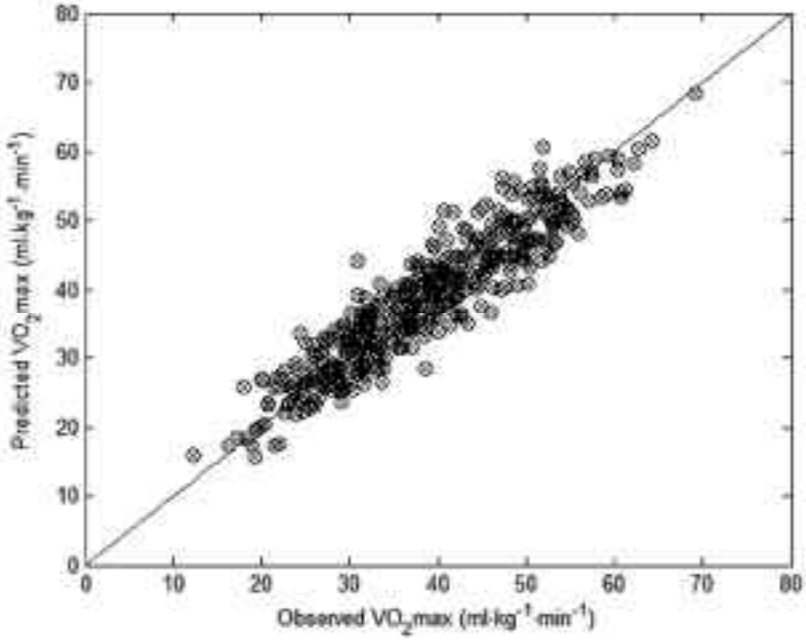


Figure 4.63. Predicted VO_2max versus measured VO_2max for the ANN-based model #35 of second dataset.

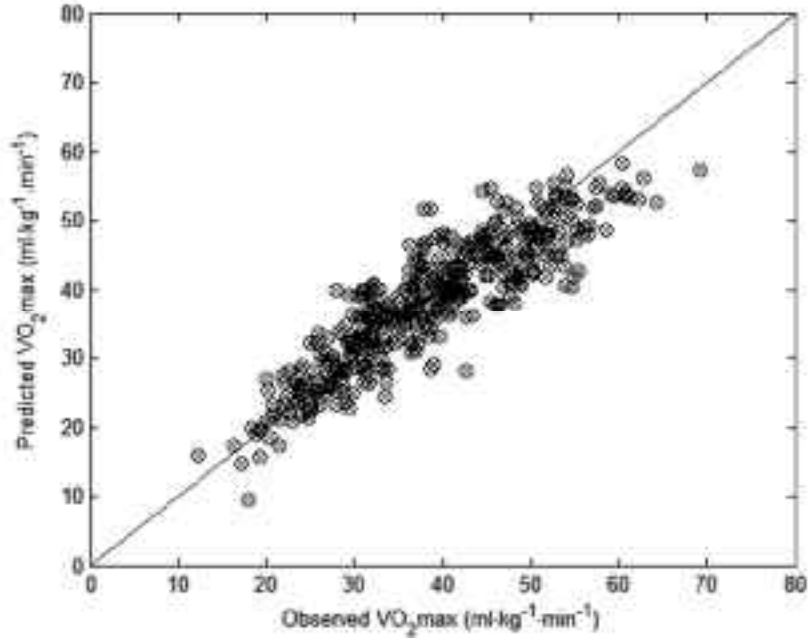


Figure 4.64. Predicted VO_2max versus measured VO_2max for the ANN-based model #36 of second dataset.

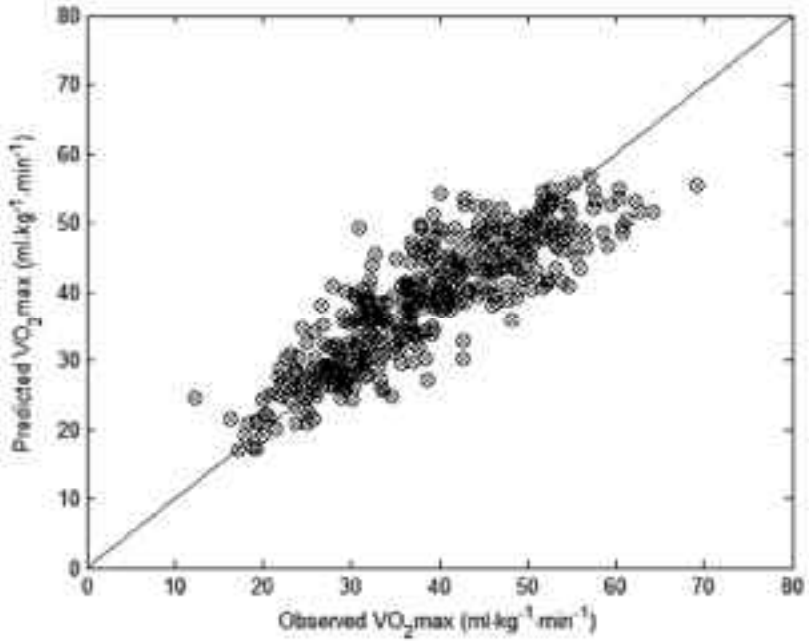


Figure 4.65. Predicted VO_2max versus measured VO_2max for the ANN-based model #37 of second dataset.

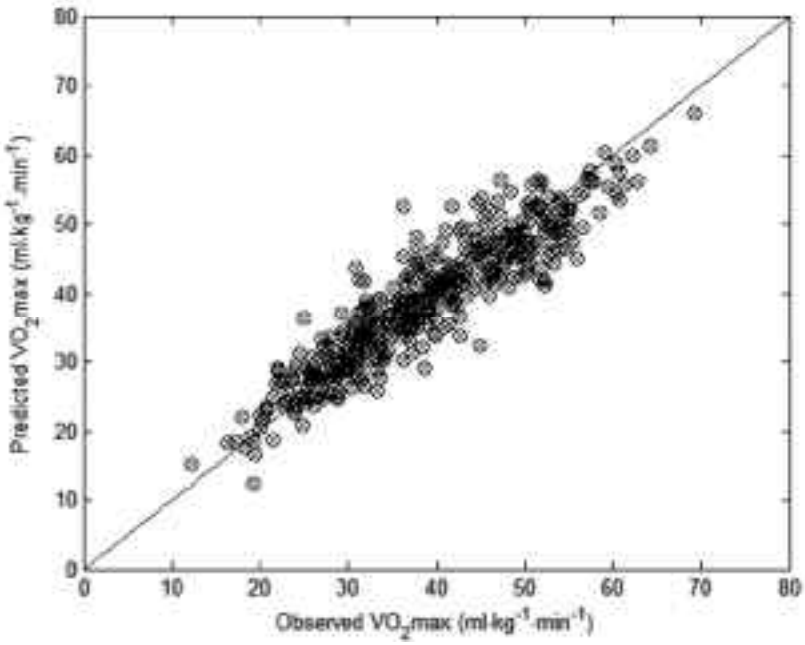


Figure 4.66. Predicted VO_2max versus measured VO_2max for the ANN-based model #38 of second dataset.

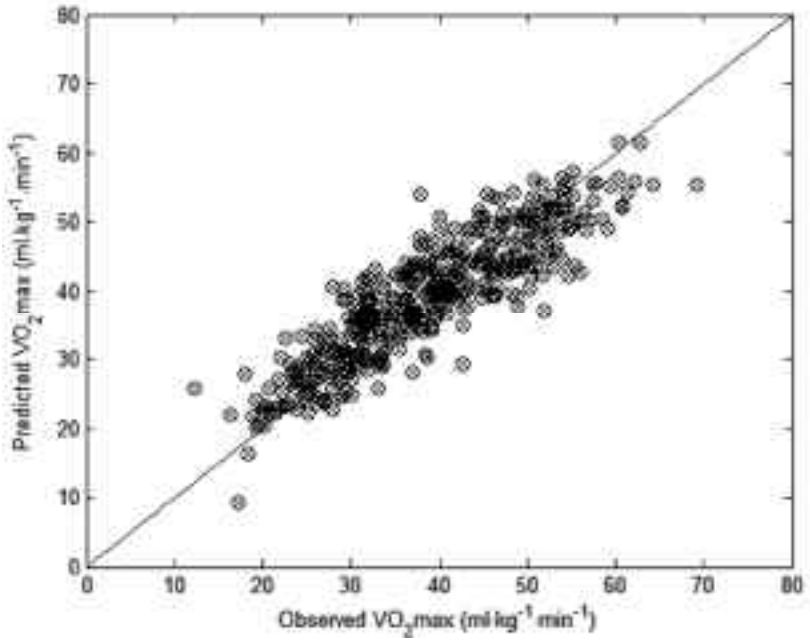


Figure 4.67. Predicted VO_2max versus measured VO_2max for the ANN-based model #39 of second dataset.

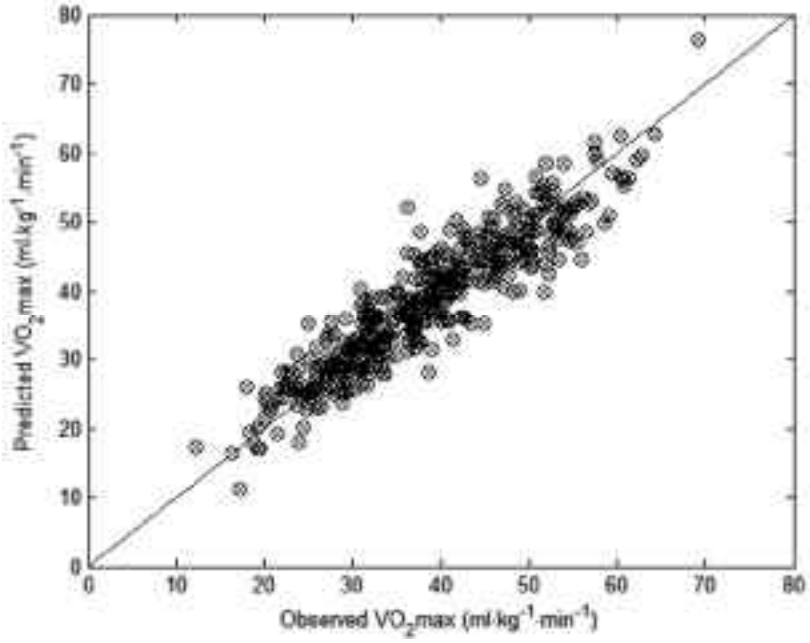


Figure 4.68. Predicted VO_2max versus measured VO_2max for the ANN-based model #40 of second dataset.

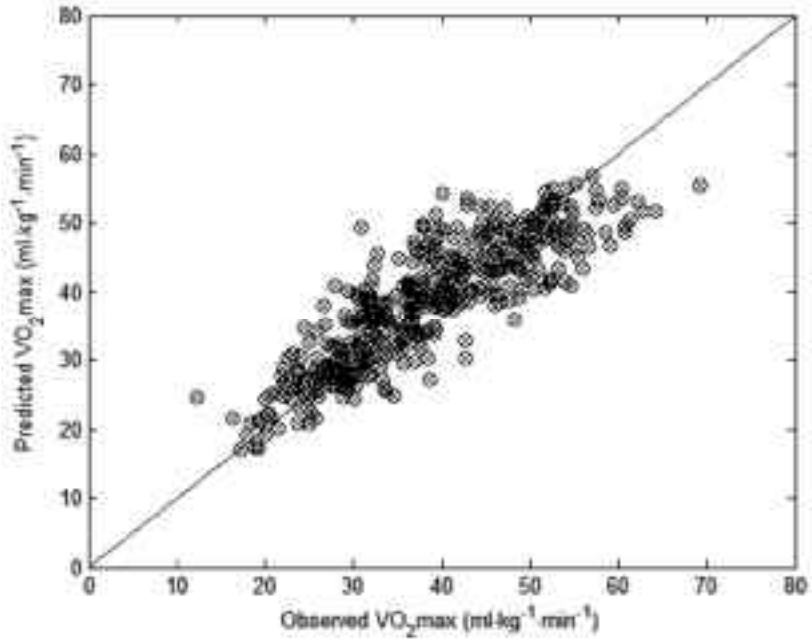


Figure 4.69. Predicted VO_2max versus measured VO_2max for the ANN-based model #41 of second dataset.

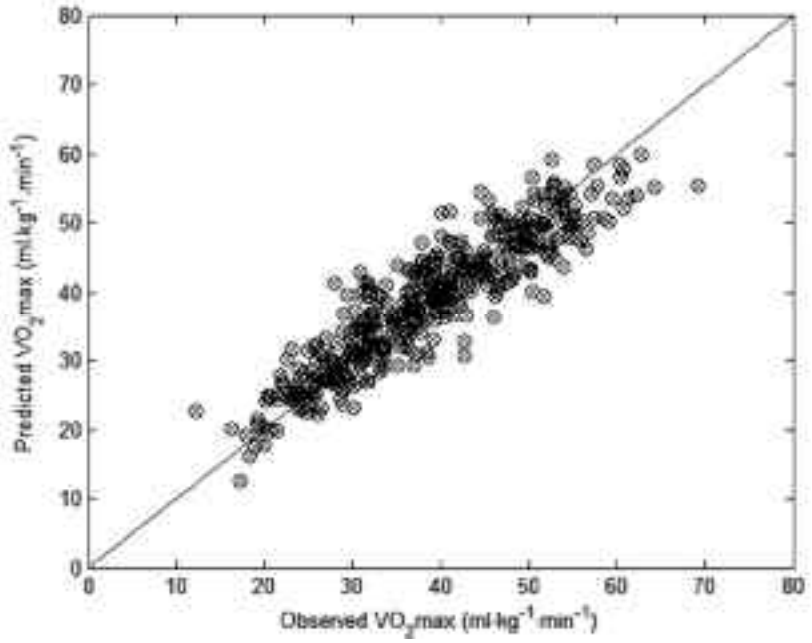


Figure 4.70. Predicted VO_2max versus measured VO_2max for the ANN-based model #42 of second dataset.

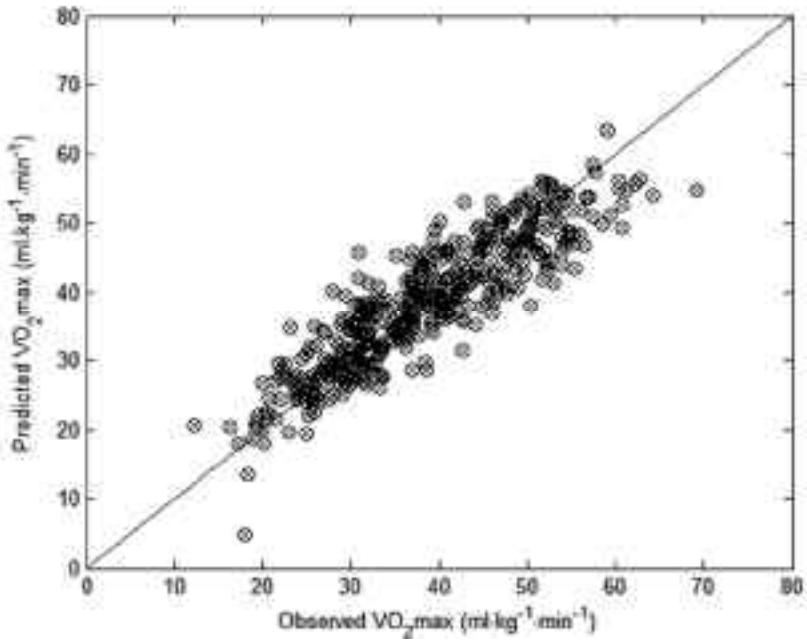


Figure 4.71. Predicted VO_2max versus measured VO_2max for the ANN-based model #43 of second dataset.

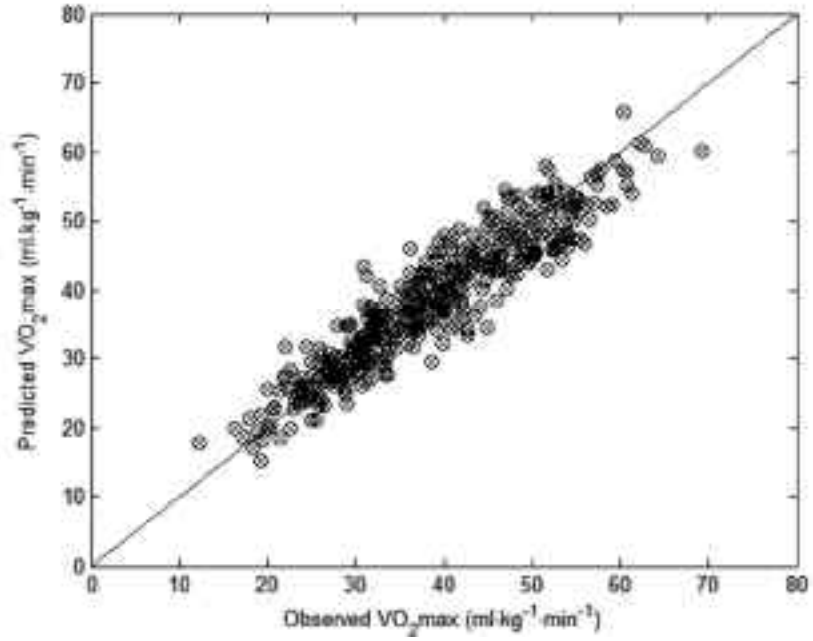


Figure 4.72. Predicted VO_2max versus measured VO_2max for the ANN-based model #44 of second dataset.

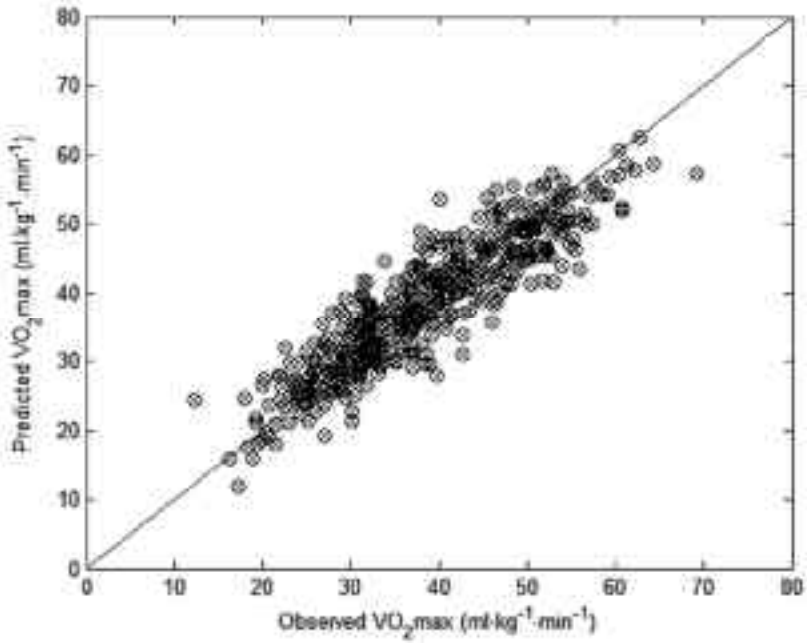


Figure 4.73. Predicted VO_2max versus measured VO_2max for the ANN-based model #45 of second dataset.

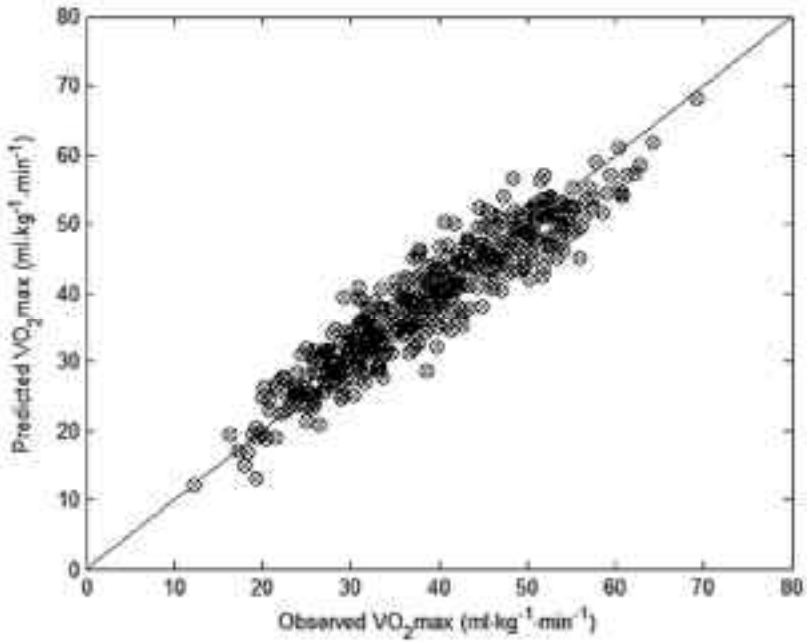


Figure 4.74. Predicted VO_2max versus measured VO_2max for the ANN-based model #46 of second dataset.

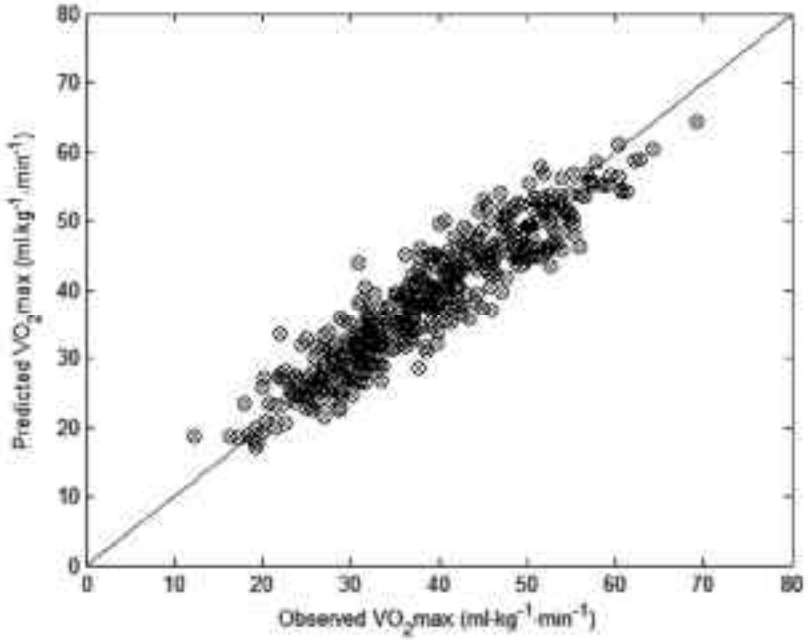


Figure 4.75. Predicted VO_2max versus measured VO_2max for the ANN-based model #47 of second dataset.

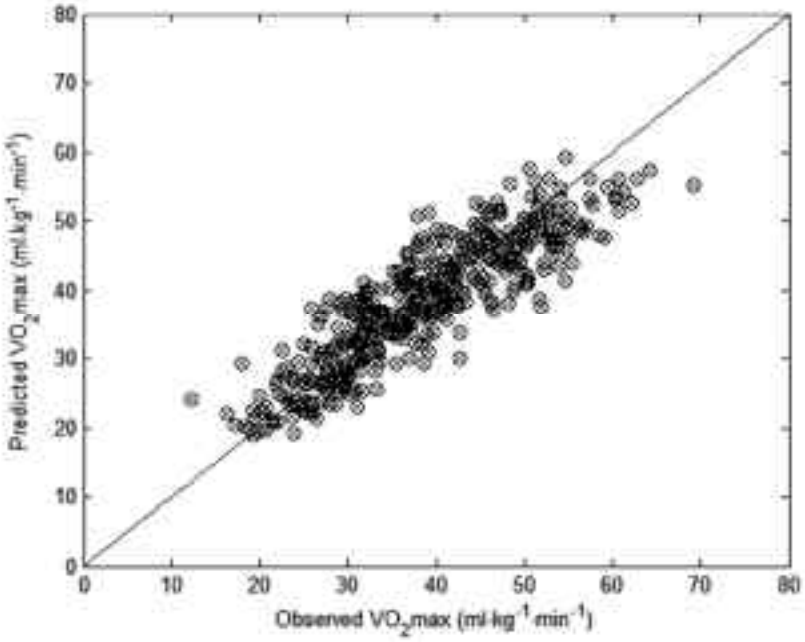


Figure 4.76. Predicted VO_2max versus measured VO_2max for the ANN-based model #48 of second dataset.

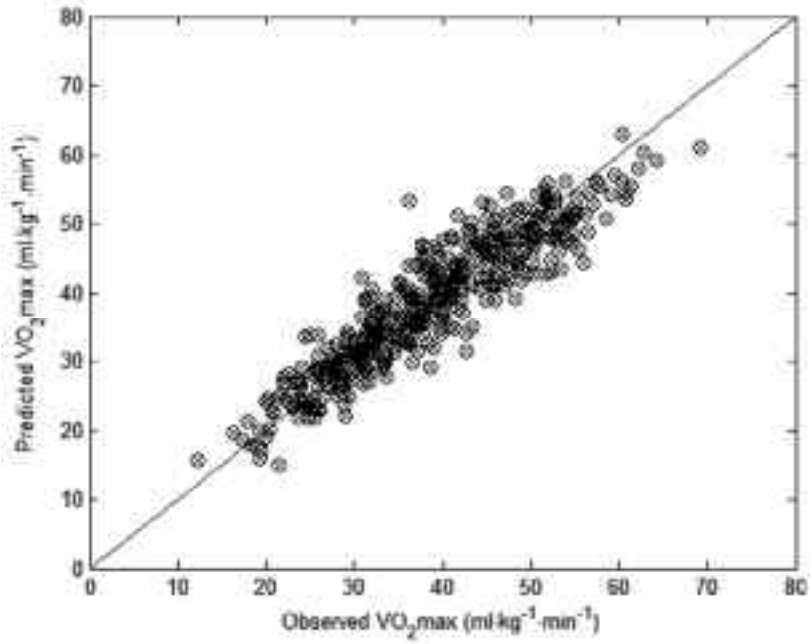


Figure 4.77. Predicted VO_2max versus measured VO_2max for the ANN-based model #49 of second dataset.

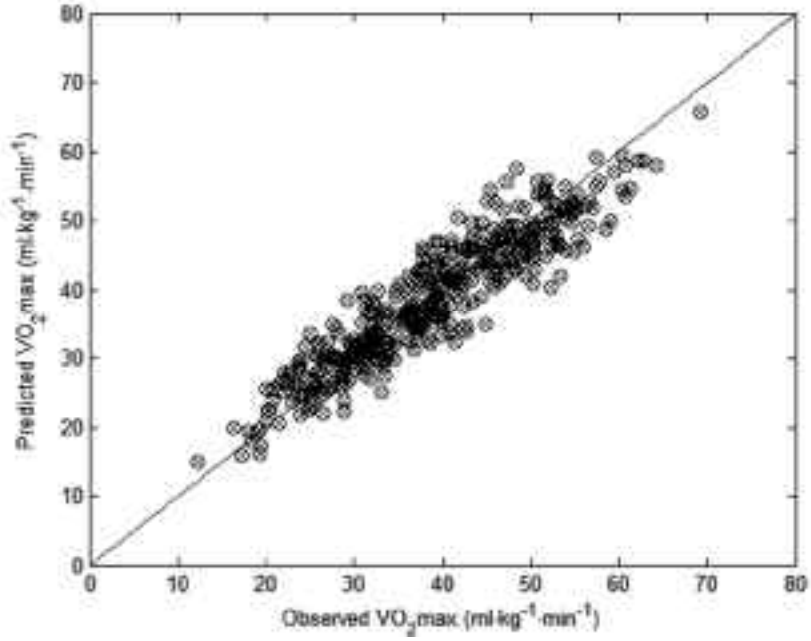


Figure 4.78. Predicted VO_2max versus measured VO_2max for the ANN-based model #50 of second dataset.

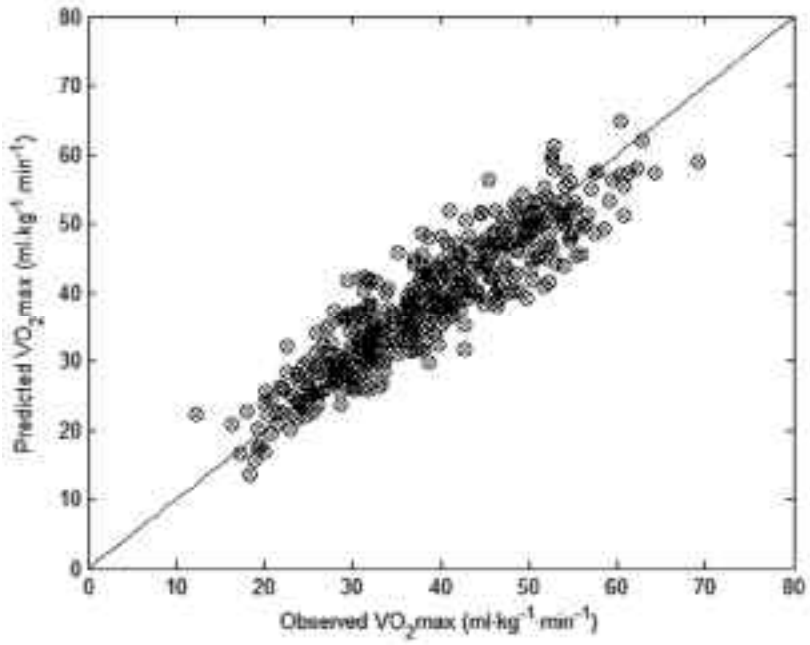


Figure 4.79. Predicted VO_2max versus measured VO_2max for the ANN-based model #51 of second dataset.

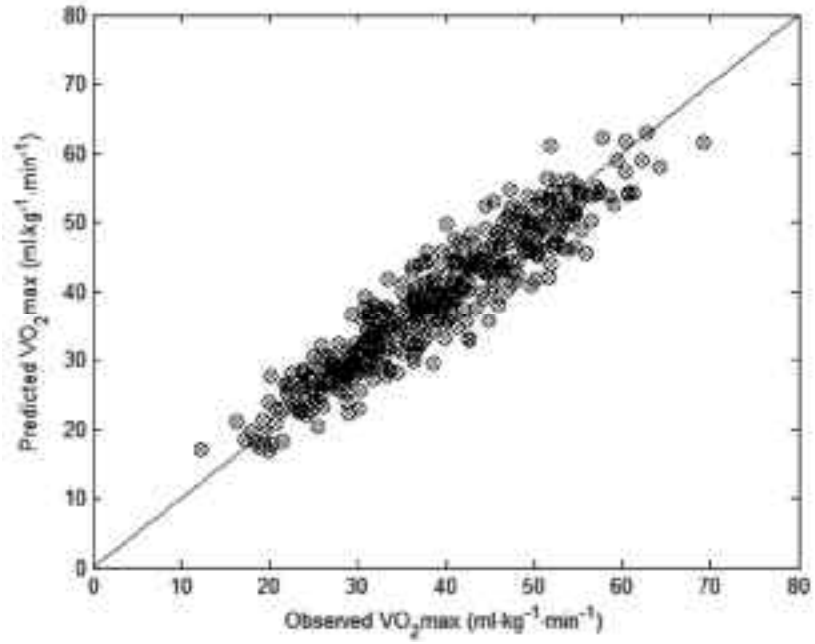


Figure 4.80. Predicted VO_2max versus measured VO_2max for the ANN-based model #52 of second dataset.

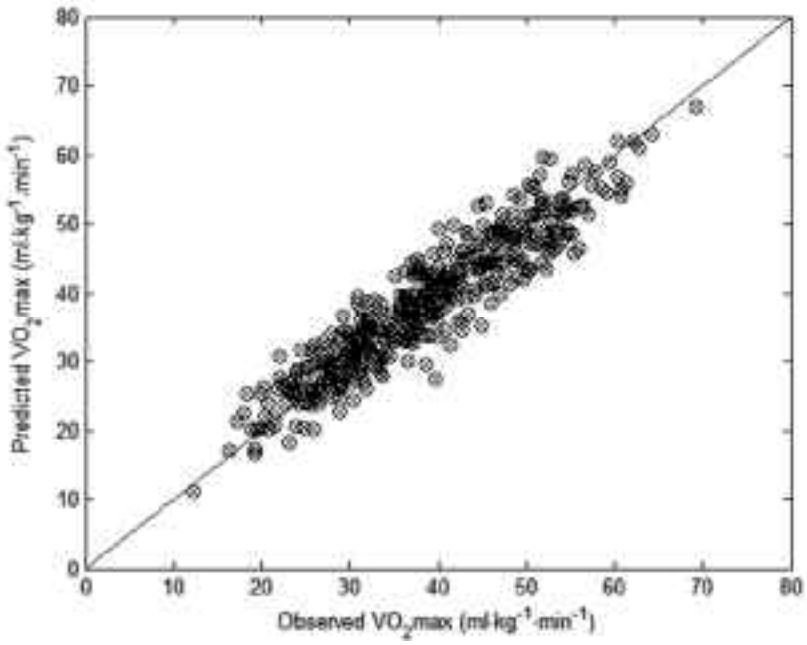


Figure 4.81. Predicted VO_2max versus measured VO_2max for the ANN-based model #53 of second dataset.

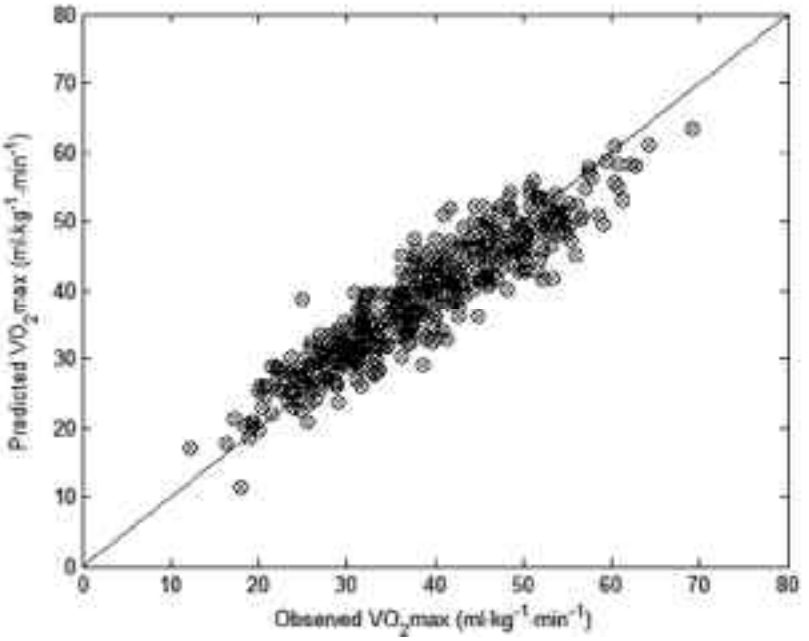


Figure 4.82. Predicted VO_2max versus measured VO_2max for the ANN-based model #54 of second dataset.

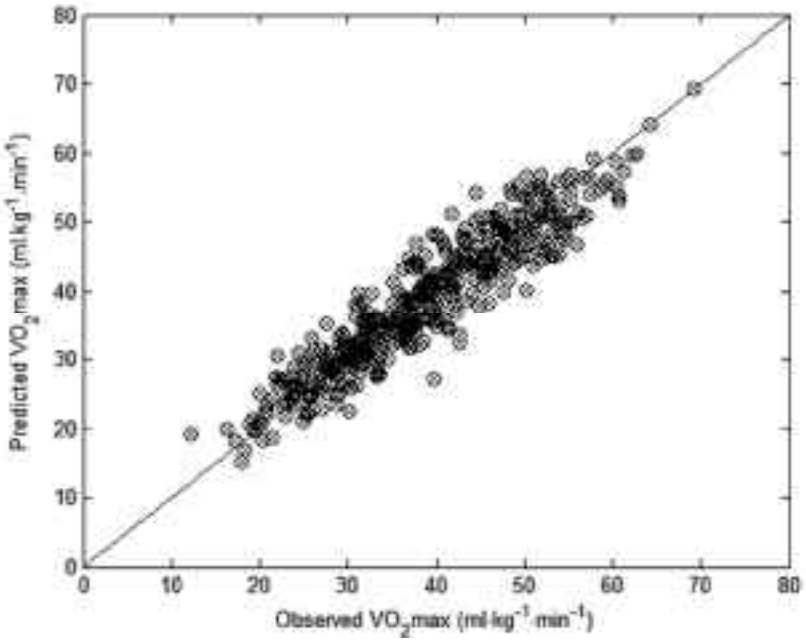


Figure 4.83. Predicted VO_2max versus measured VO_2max for the ANN-based model #55 of second dataset.

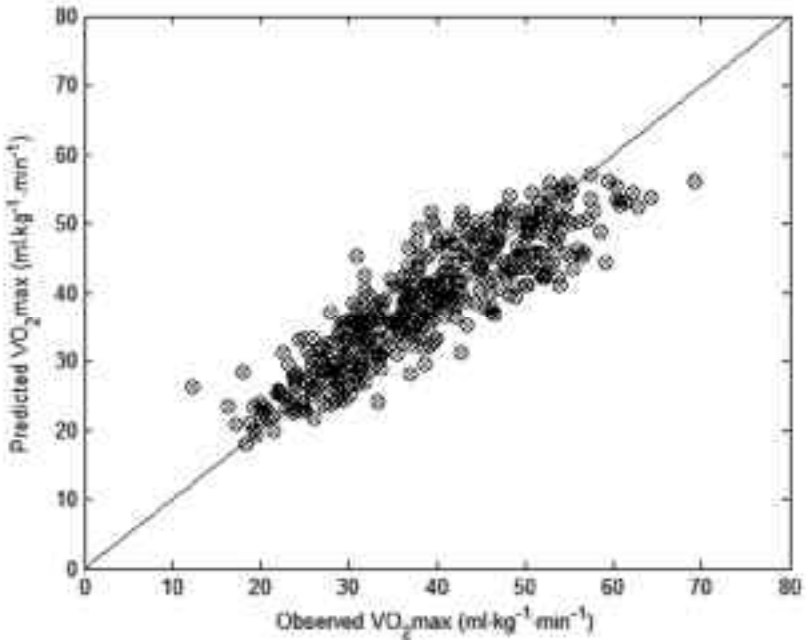


Figure 4.84. Predicted VO_2max versus measured VO_2max for the ANN-based model #56 of second dataset.

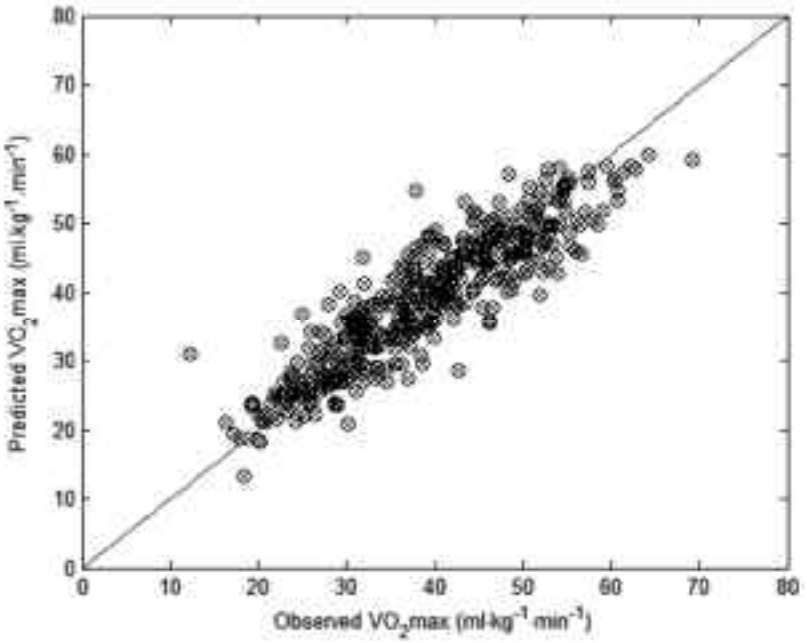


Figure 4.85. Predicted VO_2max versus measured VO_2max for the ANN-based model #57 of second dataset.

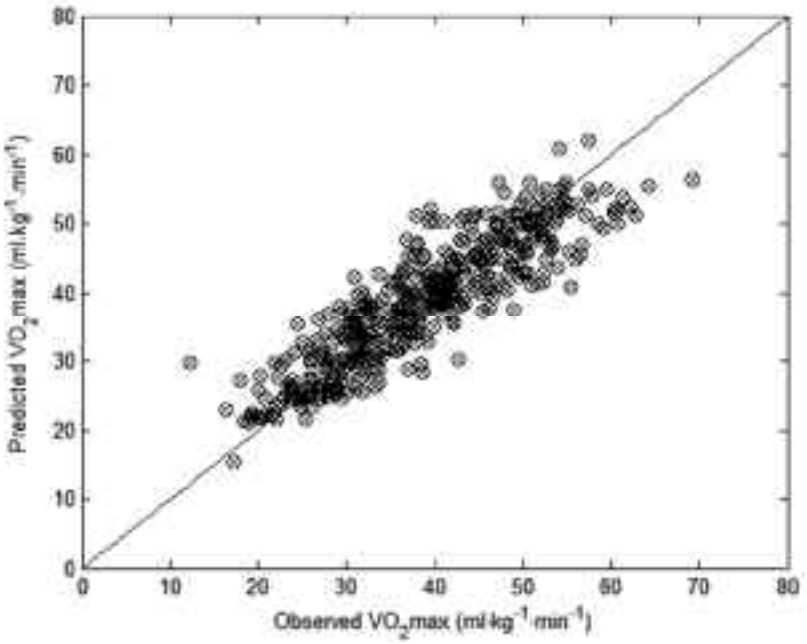


Figure 4.86. Predicted VO_2max versus measured VO_2max for the ANN-based model #58 of second dataset.

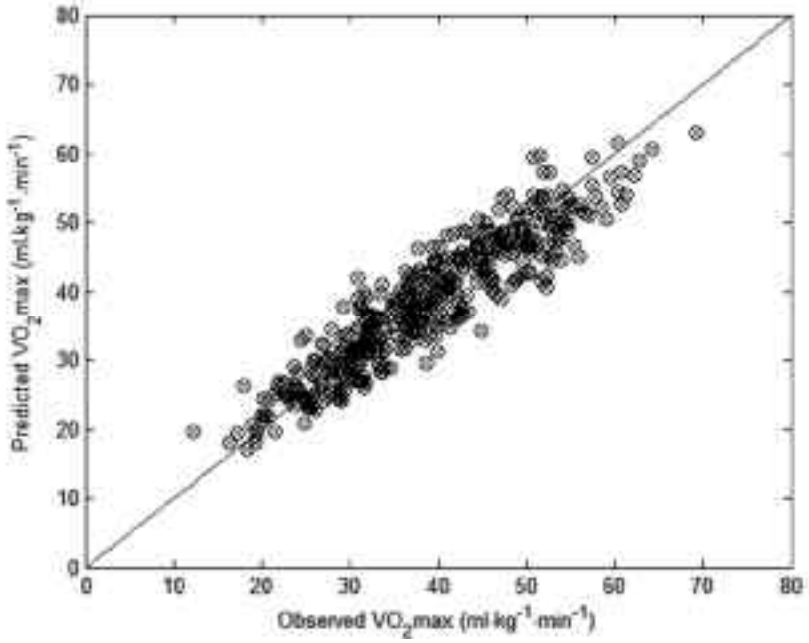


Figure 4.87. Predicted VO_2max versus measured VO_2max for the ANN-based model #59 of second dataset.

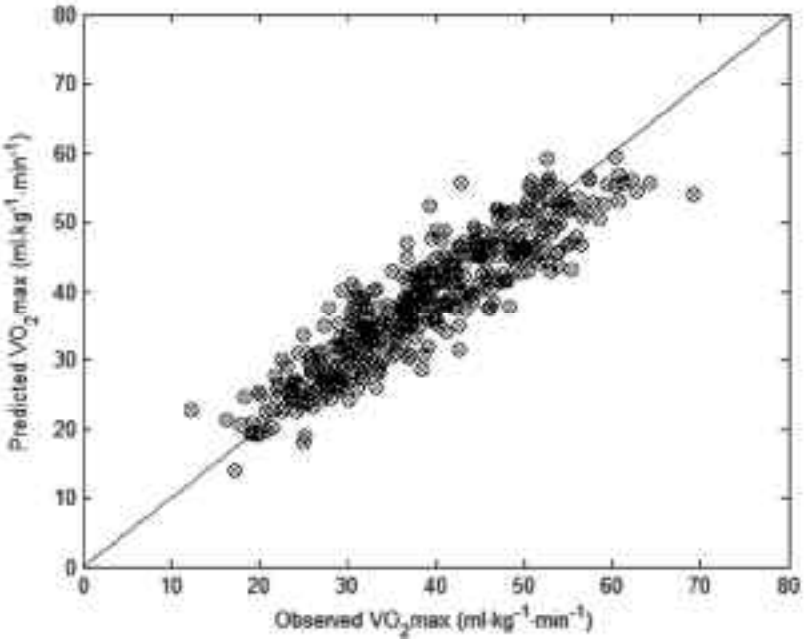


Figure 4.88. Predicted VO_2max versus measured VO_2max for the ANN-based model #60 of second dataset.

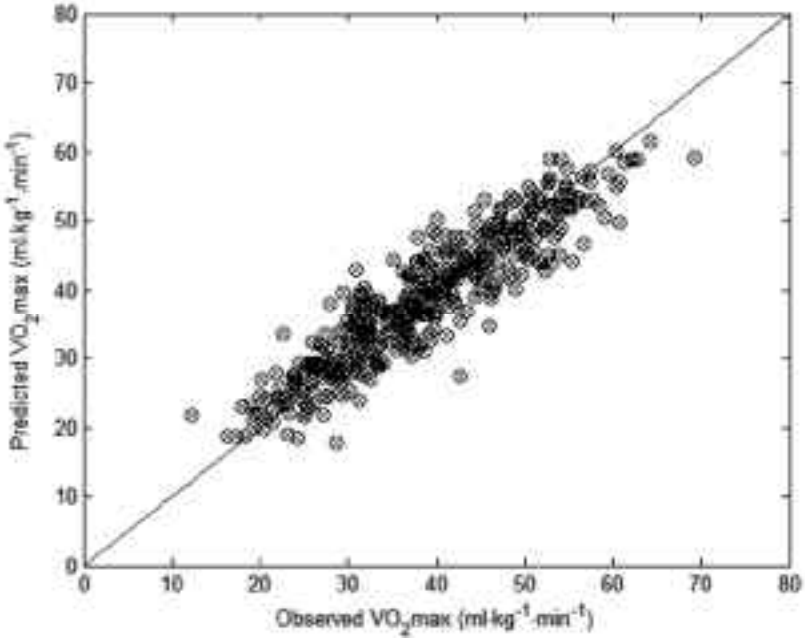


Figure 4.89. Predicted VO_2max versus measured VO_2max for the ANN-based model #61 of second dataset.

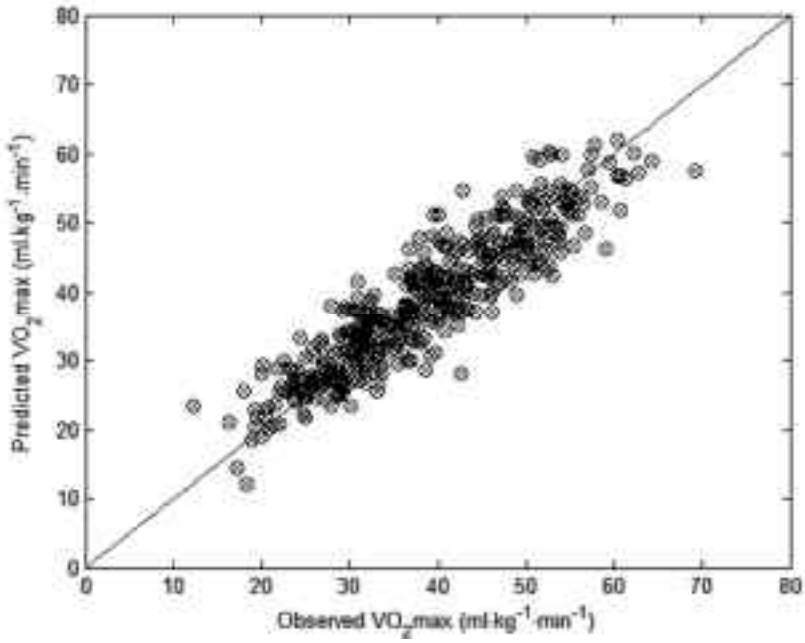


Figure 4.90. Predicted VO_2max versus measured VO_2max for the ANN-based model #62 of second dataset.

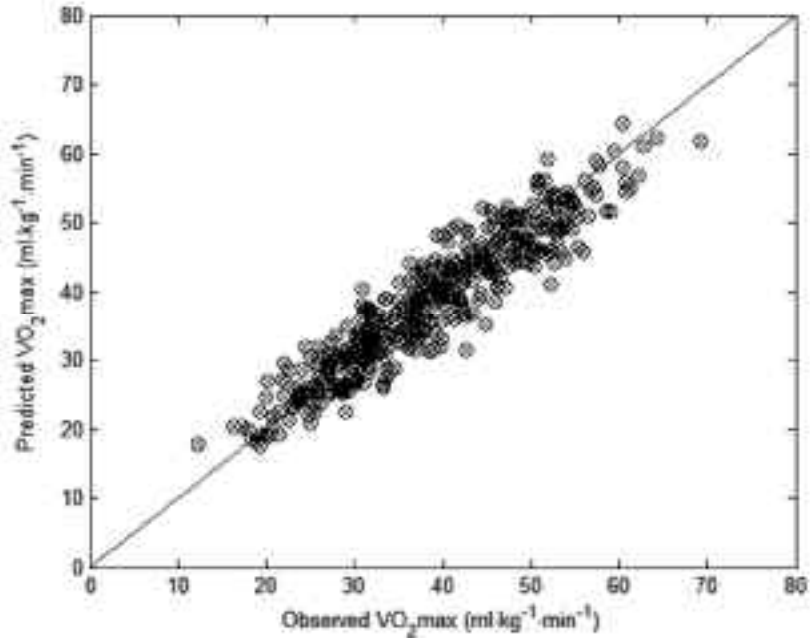


Figure 4.91. Predicted VO_2max versus measured VO_2max for the ANN-based model #63 of second dataset.

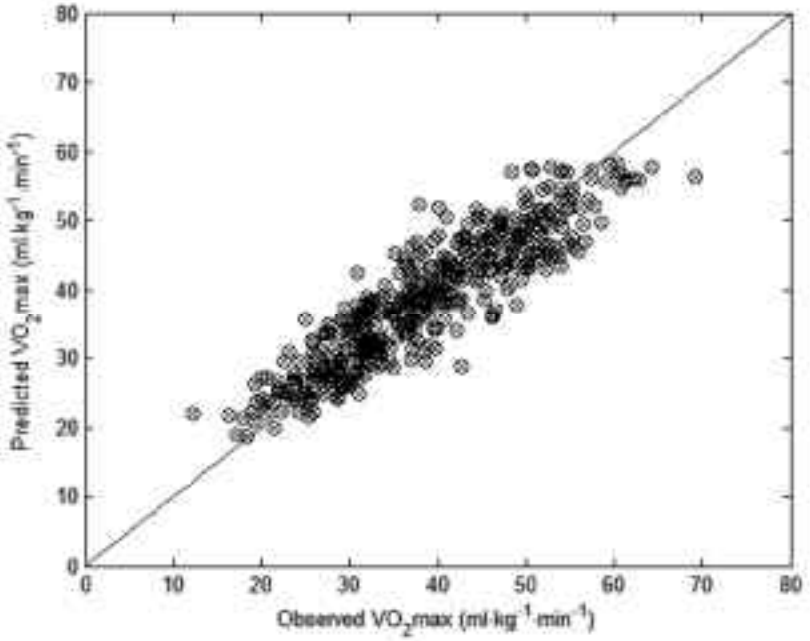


Figure 4.92. Predicted VO_2max versus measured VO_2max for the ANN-based model #64 of second dataset.

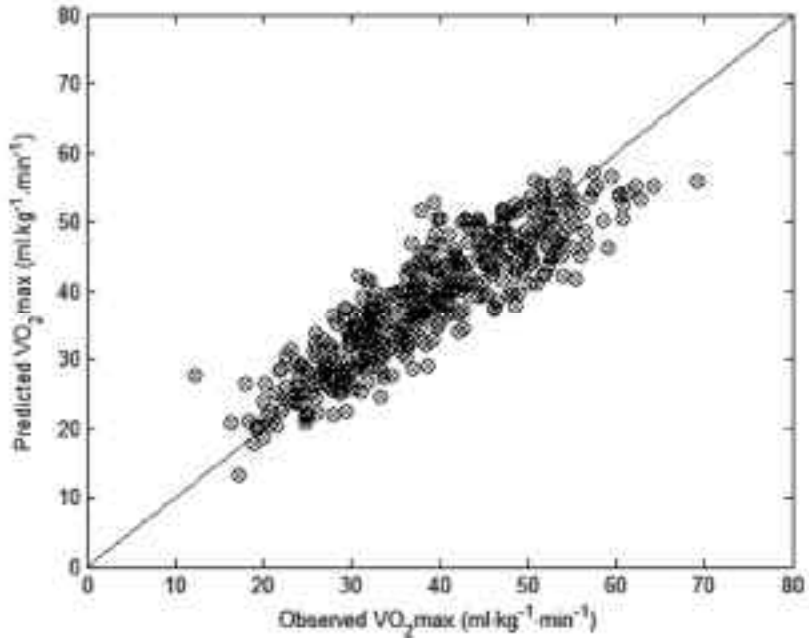


Figure 4.93. Predicted VO_2max versus measured VO_2max for the ANN-based model #65 of second dataset.

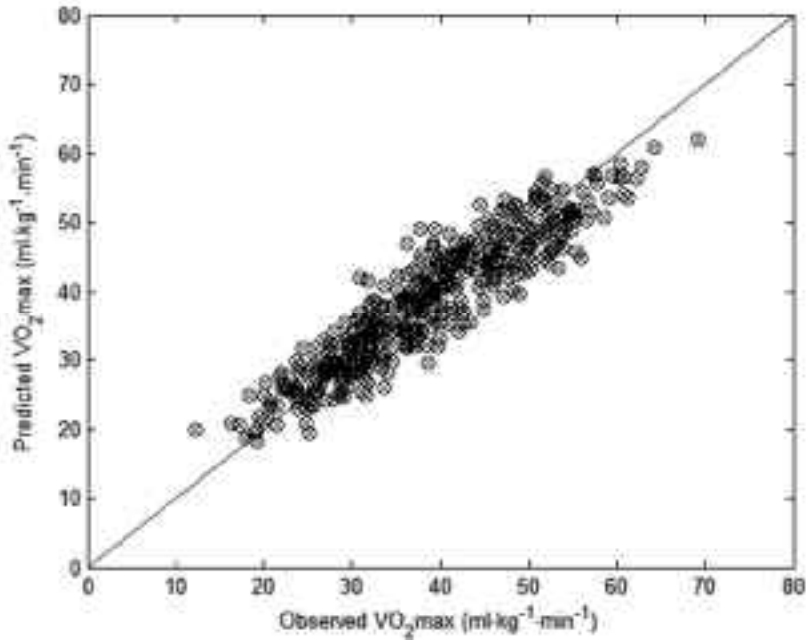


Figure 4.94. Predicted VO_2max versus measured VO_2max for the ANN-based model #66 of second dataset.

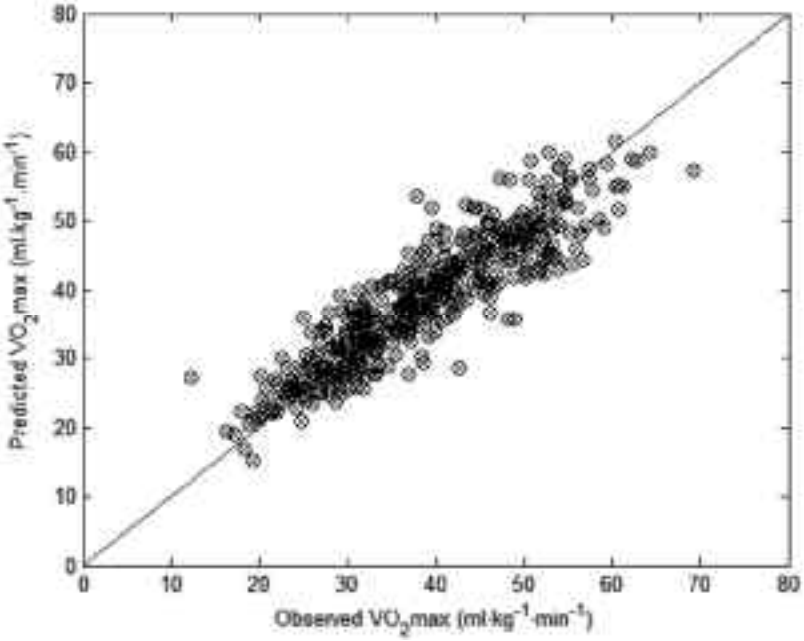


Figure 4.95. Predicted VO_2max versus measured VO_2max for the ANN-based model #67 of second dataset.

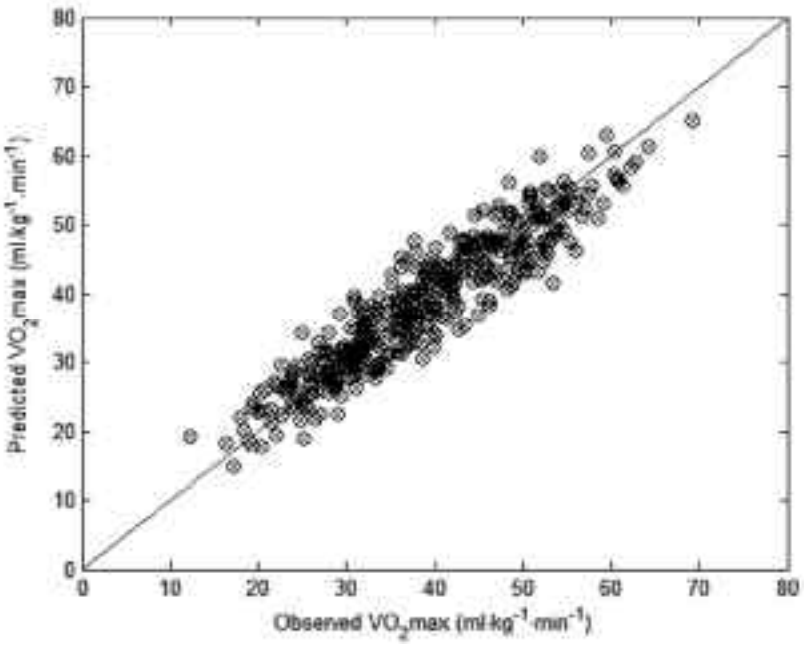


Figure 4.96. Predicted VO_2max versus measured VO_2max for the ANN-based model #68 of second dataset.

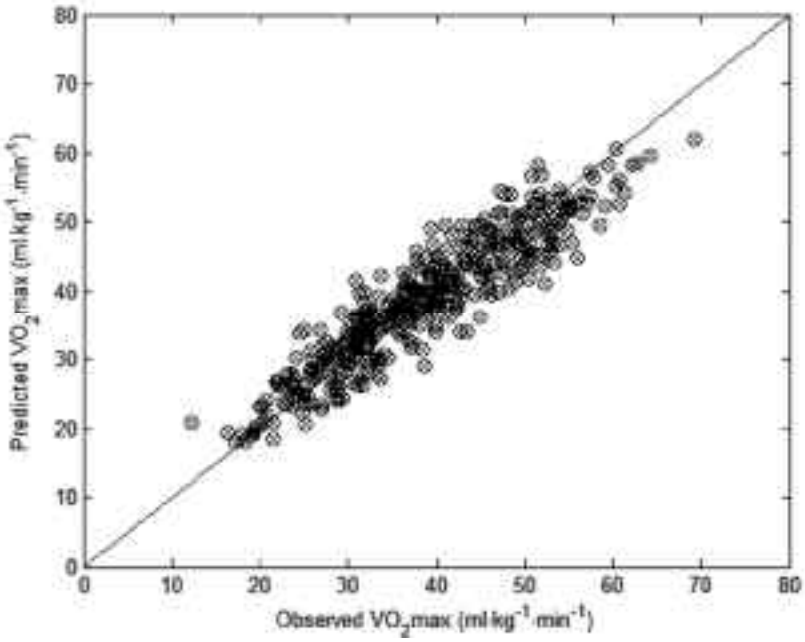


Figure 4.97. Predicted VO_2max versus measured VO_2max for the ANN-based model #69 of second dataset.

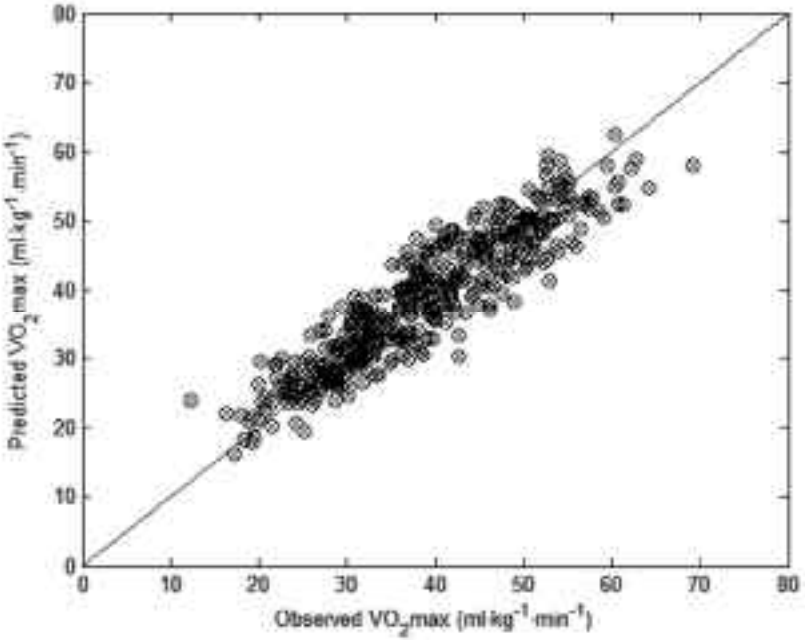


Figure 4.98. Predicted VO_2max versus measured VO_2max for the ANN-based model #70 of second dataset.

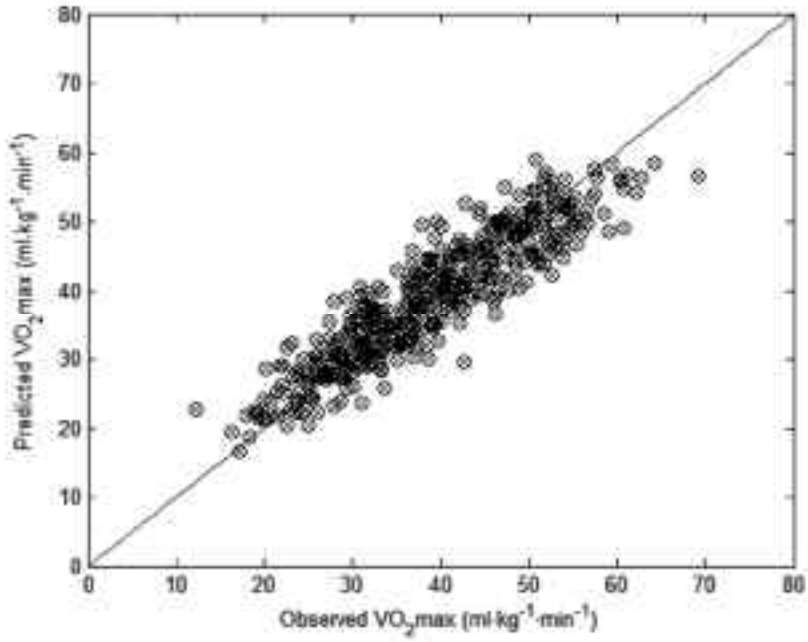


Figure 4.99. Predicted VO_2max versus measured VO_2max for the ANN-based model #71 of second dataset.

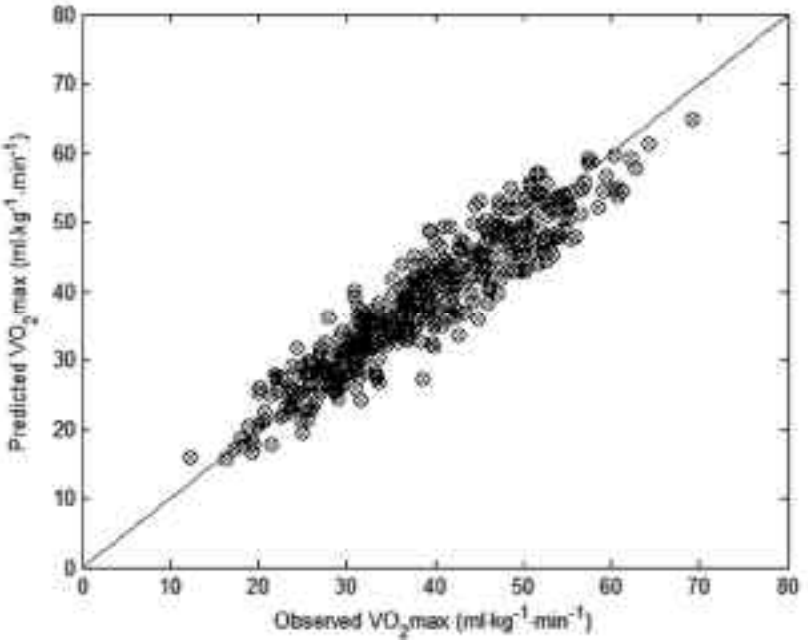


Figure 4.100. Predicted VO_2max versus measured VO_2max for the ANN-based model #72 of second dataset.

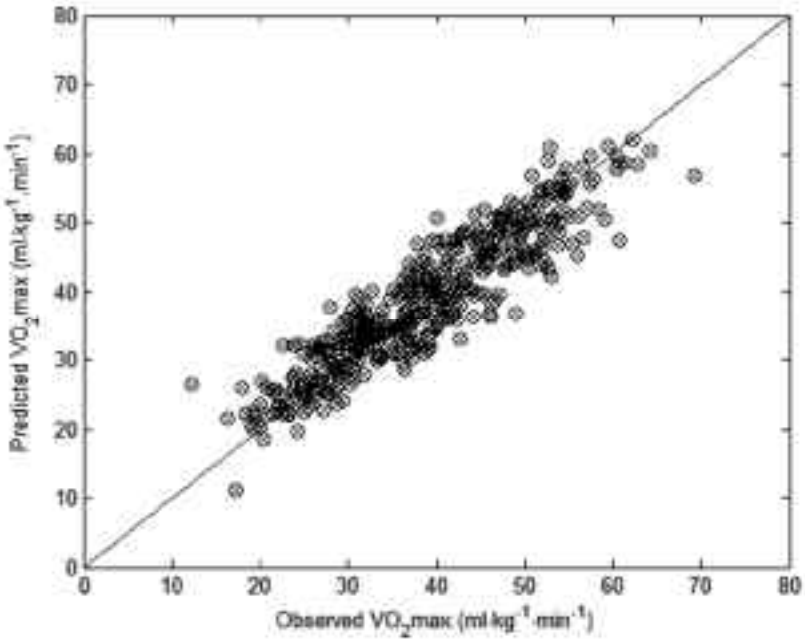


Figure 4.101. Predicted VO_2max versus measured VO_2max for the ANN-based model #73 of second dataset.

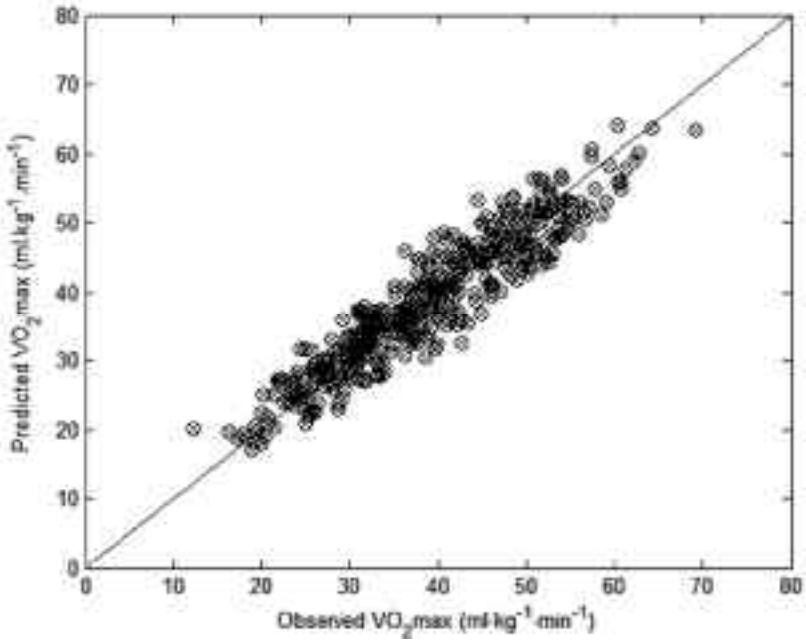


Figure 4.102. Predicted VO_2max versus measured VO_2max for the ANN-based model #74 of second dataset.

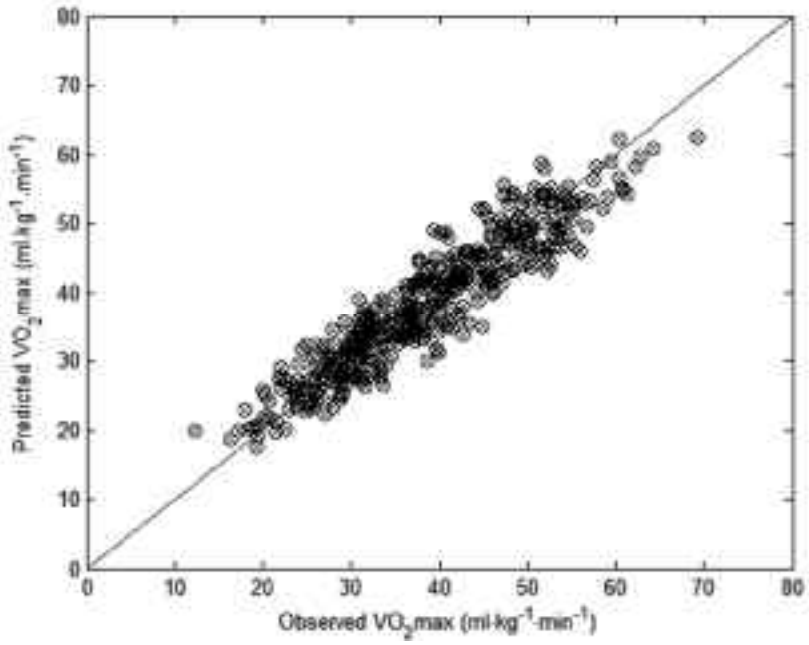


Figure 4.103. Predicted VO_2max versus measured VO_2max for the ANN-based model #75 of second dataset.

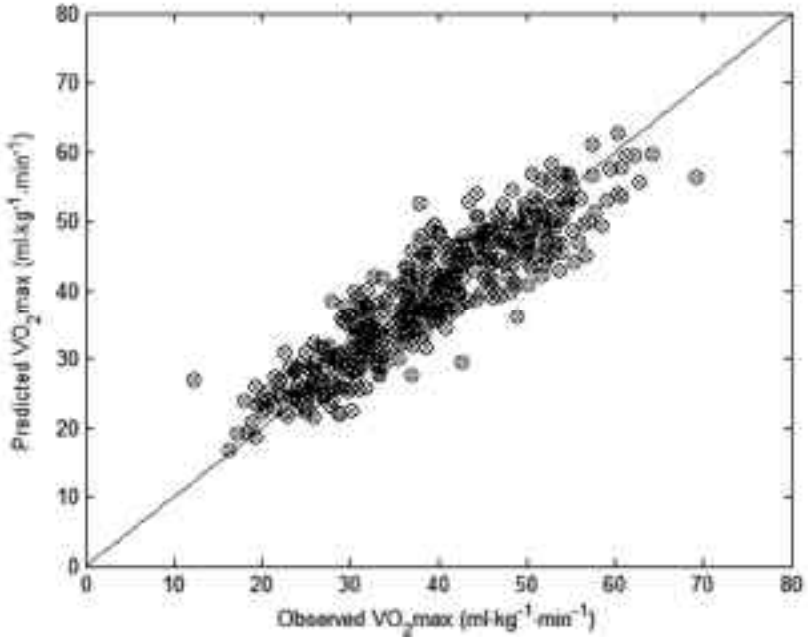


Figure 4.104. Predicted VO_2max versus measured VO_2max for the ANN-based model #76 of second dataset.

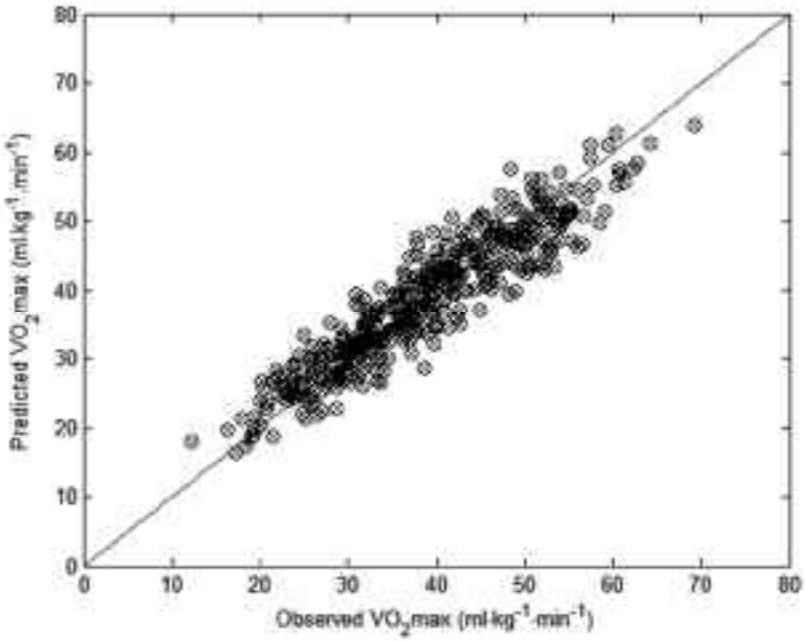


Figure 4.105. Predicted VO_2max versus measured VO_2max for the ANN-based model #77 of second dataset.

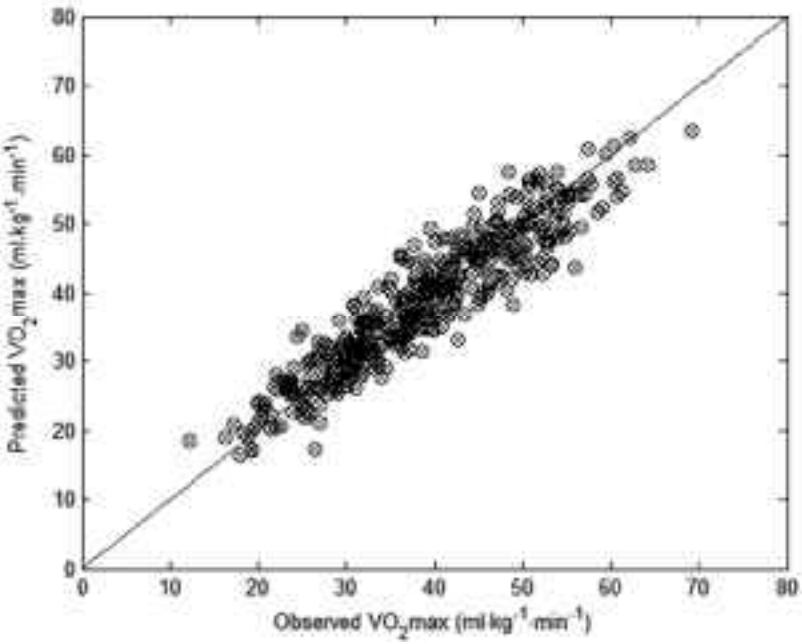


Figure 4.106. Predicted VO_2max versus measured VO_2max for the ANN-based model #78 of second dataset.

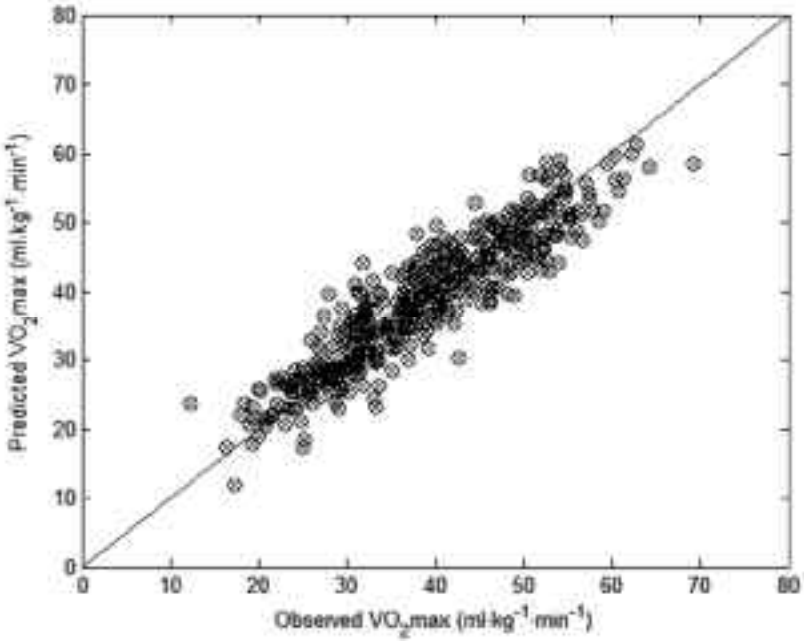


Figure 4.107. Predicted VO_2max versus measured VO_2max for the ANN-based model #79 of second dataset.

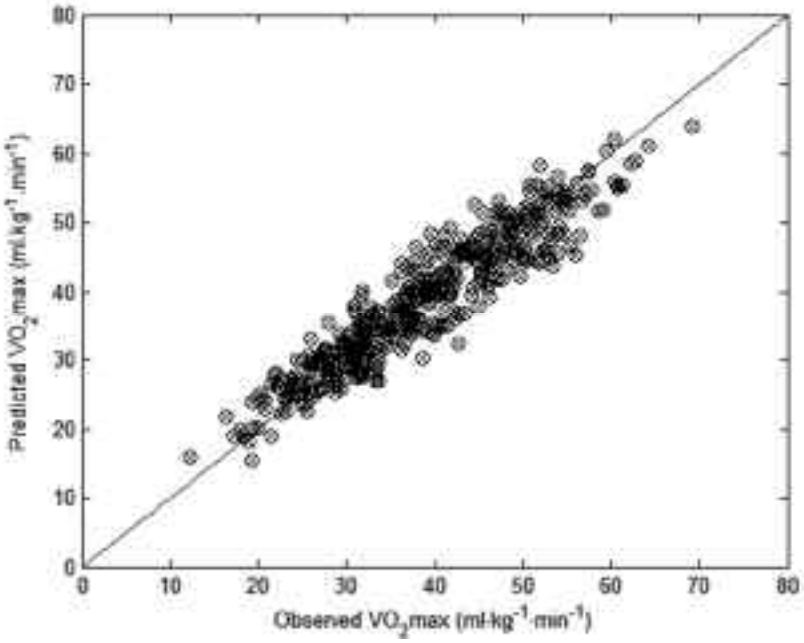


Figure 4.108. Predicted VO_2max versus measured VO_2max for the ANN-based model #80 of second dataset.

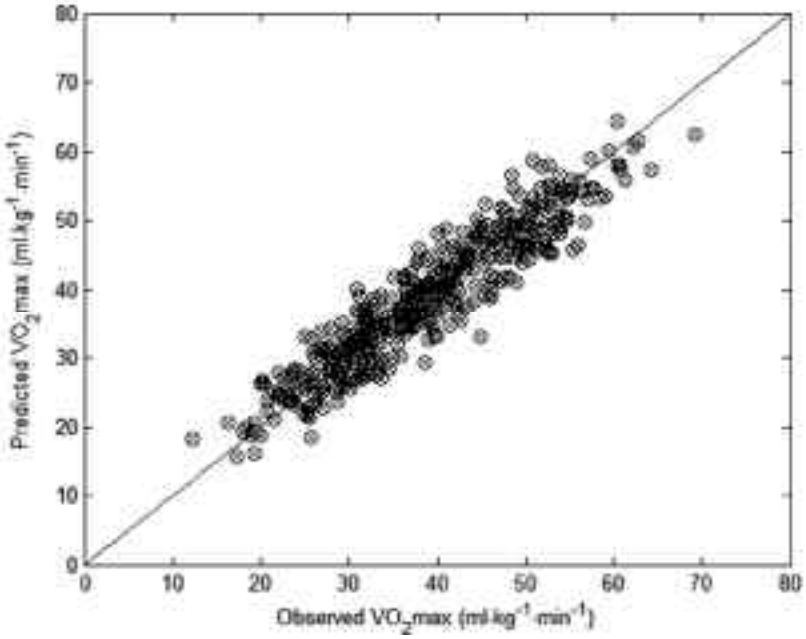


Figure 4.109. Predicted VO_2max versus measured VO_2max for the ANN-based model #81 of second dataset.

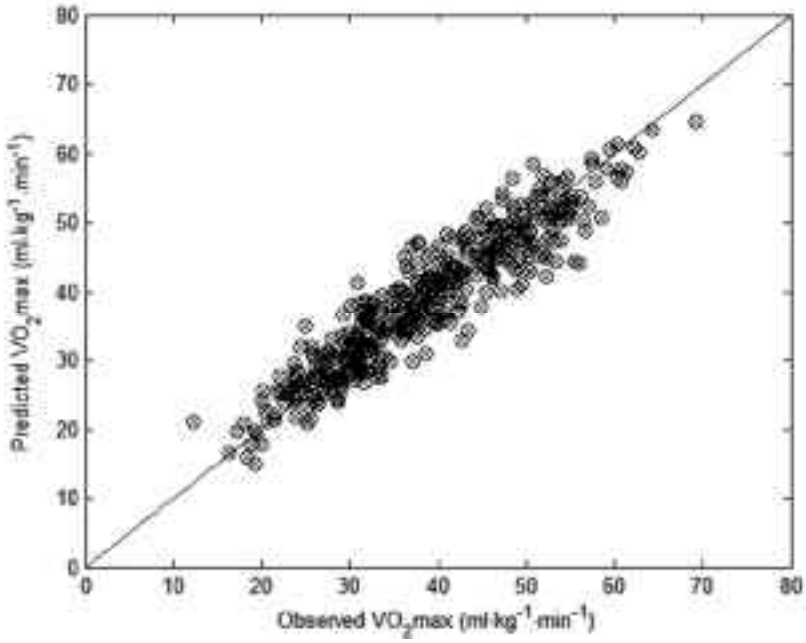


Figure 4.110. Predicted VO_2max versus measured VO_2max for the ANN-based model #82 of second dataset.

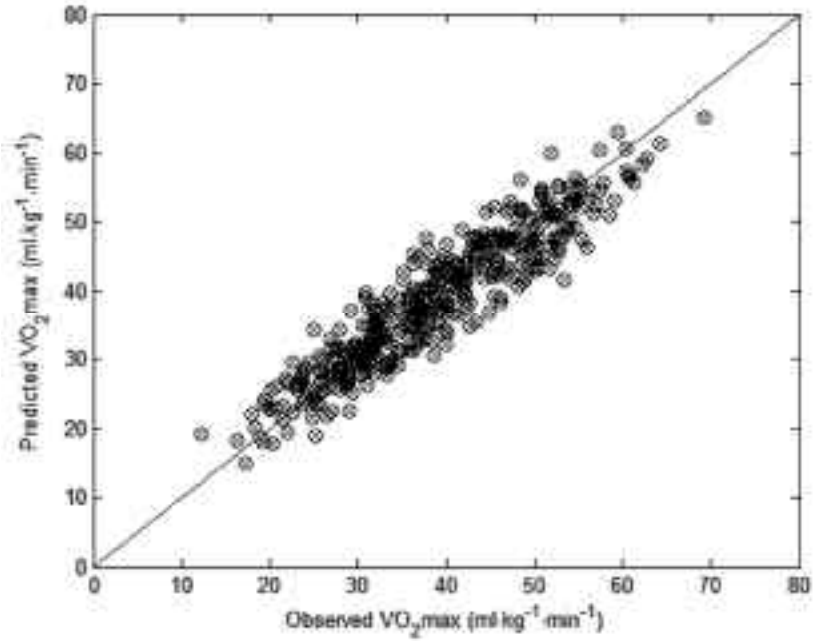


Figure 4.111. Predicted VO_2max versus measured VO_2max for the ANN-based model #83 of second dataset.

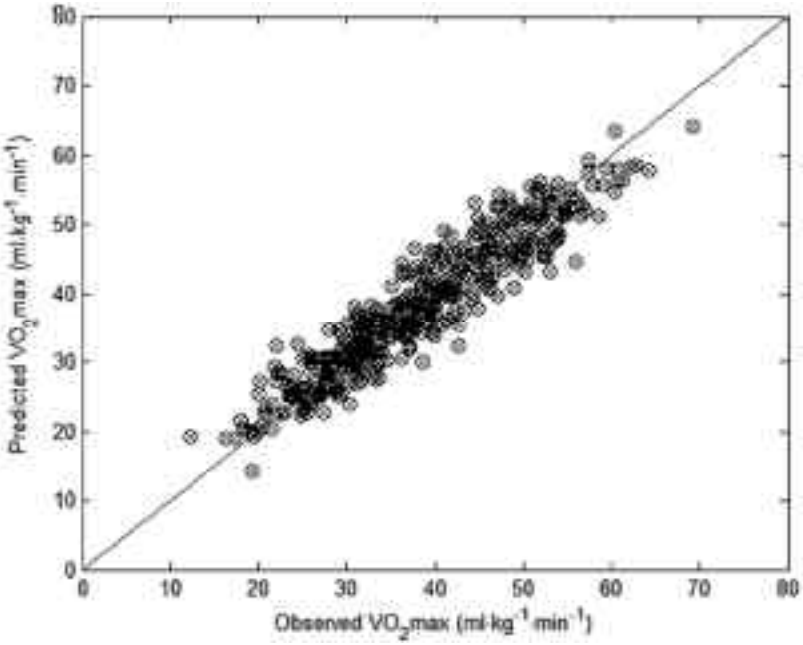


Figure 4.112. Predicted VO_2max versus measured VO_2max for the ANN-based model #84 of second dataset.

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