ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

Msc THESIS

Fatih Mehmet TAŞ

PREDICTION OF MAXIMUM MUSCULAR ENDURANCE TIME INVOLVING FOUR STABILIZATION EXERCISE ASSESSMENTS USING MACHINE LEARNING METHODS

DEPARTMENT OF COMPUTER ENGINEERING

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

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ABSTRACT

Msc THESIS

PREDICTION OF MAXIMUM MUSCULAR ENDURANCE TIME INVOLVING FOUR STABILIZATION EXERCISES ASSESSMENTS USING MACHINE LEARNING METHODS

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The muscular endurance time is viewed an important component influencing the performance of athletes in various sport branches, such as cycling, rowing, cross-country skiing, swimming and running. Due to several drawbacks of direct measurement, researchers need alternative ways to determine maximum muscular endurance time. The aim of this thesis is to build new models for predicting the maximum endurance time using demographic variables (age, gender, height, weight and body mass index), submaximal data (rating of perceived exertion) and machine learning methods including support vector machines (SVM), multilayer perceptron (MLP), generalized regression neural network (GRNN), radial basis function (RBF) and single decision tree (SDT). The root mean square error (*RMSE*) and multiple correlation coefficient (*R*) have been used for assesing the performance of prediction models. The results suggest that SVM is a viable method for maximum endurance time prediction with an acceptable accuracy.

Key words: Machine Learning, Endurance Time, Prediction

ÖZ

YÜKSEK LİSANS TEZİ

MAKINE ÖĞRENME YÖNTEMLERINI KULLANARAK DÖRT STABİLİZASYON EGZERSİZLERİNİ İÇEREN MAKSİMUM DAYANIKLILIK SÜRESİNİN TAHMİNLENMESİ

Fatih Mehmet TAŞ

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
BİLGİSAYAR MÜHENDİSLİĞİ ANABİLİM DALI

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Kas dayanıklılık süresi, bisiklete binme, kürek çekme, kros kayağı, yüzme ve koşma gibi çeşitli spor dallarındaki sporcuların performansını etkileyen önemli bir bileşen olarak görülmektedir. Doğrudan ölçümün bazı dezavantajları nedeniyle, araştırmacılar maksimum kas dayanıklılık süresini belirlemek için alternatif yollara ihtiyaç duyarlar. Bu tezin amacı, demografik değişkenler (yaş, cinsiyet, boy, kilo ve vücut kitle indeksi), submaksimal veriler (algılanan güç değerlendirmesi) ve makine öğrenme yöntemlerinden Destek Vektör Makine (SVM), Çok Katmanlı Algılayıcı (MLP), Genelleştirilmiş Sınıflandırma Sinir Ağı (GRNN), Radyal Temel Fonksiyon (RBF) ve Tek Karar Ağacı (SDT) yöntemlerini kullanarak maksimum dayanıklılık süresini tahmin etmek için yeni modeller oluşturmaktır. Tahmin modellerinin performansının değerlendirilmesinde kök ortalama kare hatası (RMSE) ve çoklu korelasyon katsayısı (R) kullanılmıştır. Sonuçlar SVM'nin kabul edilebilir bir doğrulukla maksimum dayanıklılık süresi tahmini için uygulanabilir bir yöntem olduğunu göstermektedir.

Anahtar Kelimeler: Makine Öğrenme, Dayanıklılık Süresi, Tahmin

GENİŞLETİLMİŞ ÖZET

Kas vücuda şekil veren, iskelet ve iç organların doğru hareket etmesini sağlayan yapılardır. Kaslar liflerin bir araya gelerek oluşturdukları demetlerdir. En önemli özelliği ise kemikleri birbirine bağlayan ve oldukça sağlam olmasını sağlayan güçlü yapıya sahiplerdir. Gün içinde yapılabilecek tüm vücut hareketlerinde, eklemler ve kemiklerle birlikte hareket etmemiz sağlarlar. Kas dayanıklılığı, belli bir zamanda, aralıksız kas gücünün veya kuvvetini kullanılabilme kapasitesidir. Kas kuvveti, iyi ve diri bir vücut duruşunun sağlanması; kas dayanıklılığı ise, iyi ve diri vücut duruşunun sürekliliğinin sağlanması için gereklidir. Ayrıca özellikle atletlerin, yapmış oldukları spor dallarında başarılı sonuçlar elde edebilmeleri için yüksek seviyede bir kas gücüne ve dayanıklılık sürelerinin fazla olması önemlidir.

Günümüzde kasların maksimum dayanıklılık süresinin doğrudan ölçülebilmesi adına çeşitli teknikler uygulanmaktadır. Bu tekniklerle gerçeğe yakın sonuçlar elde edilebilmesine rağmen bu yöntemlerin belirli zorlukları ve sınırlamaları vardır. Örneğin bu ölçümler için kullanılan egzersiz tipleri uzun sürmekle birlikte oldukça maliyetlidirler. Ayrıca bu yolla yapılan ölçümlerin kalabalık test grupları üzerinde uygulanması oldukça zordur. Bununla birlikte bu teknikler yardımıyla doğru sonuçlar elde edilebilmesi için profesyonel olarak eğitilmiş personeller ve uzun zaman dilimleri gerekmektedir. Bu koşullar altında, araştırmacılar direkt ölçüm yöntemlerinin yerine makine öğrenmesi metodları kullanılarak dayanıklılık süresinin tahmin edilebilmesini sağlamayı önermişlerdir. Bu konuda bazı çalışmalar yapılmıştır. Ancak bu çalışmalar, kullanılan makine öğrenmesi metodu sayısı ile ilgili kısıtlamalar içermektedir. Bu kısıtlamalar, tahmin modellerinde kullanılan her bir tahmin değişkenine ait performansın ayrıntılı bir şekilde kavranmasını engellemiştir. Bu sebepten dolayı maksimum dayanıklılık süresinin ölçümünde kullanılan tahmin değişkenlerinin sonuca etkilerinin kapsamlı bir şekilde kavranabilmesi için daha yeni ve fazla sayıda tahmin modeli üreten çalışmaların yürütülmesine ihtiyaç duyulmuştur.

Bu çalışmanın temel amacı, profesyonel olarak sporla ilgilenen sporcuların kas dayanıkılık sürelerinin; Destek Vektör Makineleri (Support Vector Machines, SVM), Çok Katmanlı Algılayıcılar (Multilayer Perceptron, MLP), Genelleştirilmiş Sınıflandırma Sinirsel Ağ (GRNN),Radyal Temel Fonksiyon (Radial Basis Function, RBF), ve Tekli Karar Ağaçları (Single Decision Tree, SDT) kullanılarak daha yeni ve kapsamlı tahmin modelleri oluşturulmasıdır. Kas dayanıklılık süresi Cinsiyet (Gender), Yaş (Age), Boy (Height), Ağırlık (Weight), Vücut Kitle İndeksi (Body Mass Index, BMI) ve Algılanan Egzersiz Süresi (Perceived Exertion Time, RPE) olmak üzere 6 adet bilimsel olarak ilgili tahmin değişkeninden yararlanılarak tahmin edilmiştir. Bu tez çalışmasında kullanılan veri seti, 80 adet atlete ait bilgileri içermektedir. 10-fold Cross Validation yönteminin kullanılmasıyla tahmin modellerine ait genel hata oranları hesaplanmıştır. Tahmin hatalarının hesaplanması için Ortalama Hata Kareleri Toplamı Karekökü (Root Mean Square Error, *RMSE*) ve Çoklu Korelasyon Katsayısı (Multiple Correlation Coefficient, R) değerleri kullanılmıştır.

Bu çalışmalardan elde edilen sonuçlara göre SVM tabanlı tahmin modelleri GRNN, MLP, RBF ve SDT tabanlı tahmin modellerine kıyasla daha yüksek performans sağlanmıştır. Bir başka deyişle, kas dayanıklılık süresinin tahmin edilmesinde SVM tabanlı modellerde en düşük *RMSE* değerleri bulunmuştur. Daha ayrıntılı olarak, SVM tabanlı modeller ile tahmini sonucunda *RMSE* değerleri ortalama olarak sağ yan köprü egzersiz tipinde 10.425Nm, sol yan köprü egzersiz tipinde 10.99 Nm, omurga uzantısı egzersiz tipinde 13.09 Nm ve son olarak plank egzersiz tipinde 18.15Nm şeklindedir. Bunun yanı sıra, tahmin değişkeni olarak her bir egzersiz tipinde boy ve ağırlık yerine BMI kullanılarak oluşturulan SVM tabanlı tahmin modelleri daha düşük RMSE değerlerine sahipken, aynı şekilde yaş tahmin değişkeni eklendiğinde ise boy ve ağırlık yerine BMI kullanılması SVM tabanlı tahmin modellerinde daha düşük değerlerin elde edilmesini sağlamıştır.

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LIST OF ABBREVIATIONS

MLP	: Multi-Layer Perceptrons
RBF	: Radial Basis Function
GRNN	: General Regression Neural Network
SVM	: Support Vector Machines
SDT	: Single Decision Tree
MLR	: Multiple Linear Regression
DTF	: Decision Tree Forest
RMSE	: Root Mean Square Errors
R	: Multiple Correlation Coefficient
RPE	: Perceived Exertion Time
W	: Weight
G	: Gender
H	: Height
BMI	: Body Mass Index
A	: Age
SEE	: Standard Error of Estimation
ERM	: Empirical Risk Minimization
SRM	: Structural Risk Minimization

1. INTRODUCTION

1.1. Overview of Muscular Endurance Time

The muscular endurance time provides a convenient means to assess muscle fatigue resistance and is viewed an important component influencing the performance of athletes in various sport branches, such as cycling, rowing, cross-country skiing, swimming and running. Although endurance time can accurately be measured by conducting isometric contraction exercise tests, many individuals are unaccustomed to holding an isometric contraction for an extended period of time. Also, these tests can be overly demanding, time consuming, and even risky for certain populations. For special populations and patients, tests of maximal physical exertion may not be feasible. In these populations, submaximal estimates are indicated to reduce the risk of injury or exacerbation of symptoms. Biering-Sorensen documented the association between lower scores of back muscle endurance and the occurrence of Low Back Trouble (LBT) (Biering-Sorensen, 1984).

A number of previous studies have employed various independent variables to accurately predict various dependent variables (such as cardiorespiratory fitness, maximum oxygen uptake etc.). Common demographic independent variables included age, gender, body mass or BMI. In terms of estimating exercise difficulty, RPE scores have been commonly employed as an independent variable. In terms of estimating fitness level and physical activity levels, ratings of perceived ability and perceived physical activity levels have been quantified using brief questionnaires. (George and et al., 1993, George and et al., 2007, Neilsen and et al., 2010, Mooney and et al., 2011, Borg, 1982, Faulkner and et al., 2007, Bradshow and et al., 2007, George and et al. 2007)

1.2. Motivation and Purpose of this Thesis

As stated in the previous section, direct measurement of maximum endurance time comes with several difficulties. Therefore, the related research community is interested to provide alternative ways to determine the endurance time. One possible way is to collect ratings of RPE data during isometric exercise tests, which is an individual's evaluation of fatigue based on a scale from 0 to 10 that can serve as an indirect predictor of endurance time. Relevant demographic data can be combined with the times to reach desired RPE scores to develop maximum endurance time prediction models.

The purpose of this thesis is to generate several new regression models that can accurately predict maximum endurance times involving four common core stabilization exercises using SVM, MLP, GRNN, SDT and RBF and also investigate the effect of predictor variables on maximum endurance time prediction.

1.3. Literature Review

McGill et al. developed a battery of exercises to assess the maximal muscular endurance of several core exercises (Mcgill and et al., 1999). In this study, normative data were outlined to document mean maximal endurance times for the side plank-right-side, side plank-left-side static spinal flexion, and static spinal extension in healthy participants aged between 20 and 26 years.

To the best of our knowledge, there exist only a few studies in literature to predict maximum endurance time involving core stabilization exercises.

In (Tolley and et. al., 2015), authors used MLR to predict maximal endurance time. Submaximal endurance tests using RPE values provide relatively accurate predictions of maximum muscular endurance involving core stabilization exercise assessments. The time to reach an RPE score of 8 (RPE-8) reduced mean maximal exercise time by about 10-60 seconds across the 5 core assessments, which decreases the cumulative spinal load during testing. The times to reach an

RPE-4 to RPE-7 decreased the overall length of the tests even more, but were less accurate in predictive accuracy.

In (Abut and et. al., 2015) , authors used SVM, DTF and RBF to predict maximal endurance times. These methods were used only on the side plank-right-side exercise. SVM-based prediction models gave the lowest SEE and highest Multiple R values by using gender, BMI and RPE-8. The worst prediction performance was obtained by using age, BMI and RPE-4.

In (Akay and et. al., 2017) , authors used MFANN, GRNN, RBF and SDT to predict maximal endurance times. These methods were used only on the left-side bridge exercise. MFANN-based prediction models gave the lowest SEE and highest Multiple R values by using gender, age, BMI, RPE-7 and RPE-8.

In (George and et. al., 2018) , authors used MLR to predict maximal endurance times. This methods were used plank, right-side bridge, left-side bridge and back extension exercise types. Submaximal protocols based on elapsed time to reach RPE8 provide strength and conditioning professionals relatively accurate univariate regression equation estimates of maximal core muscle endurance time and offer a viable submaximal alternative to maximal capacity testing when time efficiency.

1.4. Contributions of the Thesis

The main differences between this research proposal and the studies from related literatere can be summarized as follows:

- This is the first study that develops comprehensive maximum endurance time prediction models for four different core stabilization exercise types using machine learning methods.
- Using four different exercise types with different combinations of predictor variables will enable us to create more detailed prediction models. More specifically, 640 different prediction models have been developed,

however due to space limitations only the best performing 32 models have been presented in this thesis.

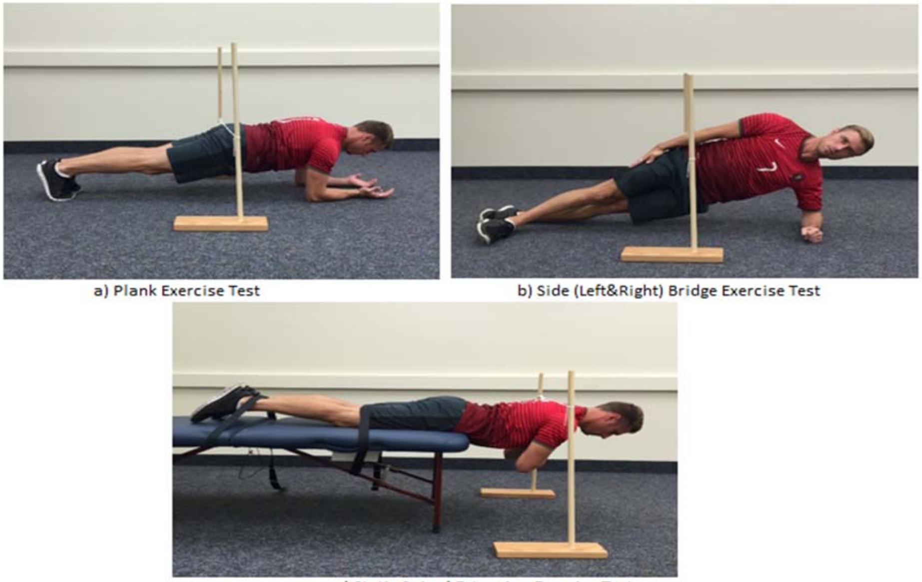
1.5. Overview of the Dataset

The dataset includes 80 healthy college-aged individuals. Participants were randomly assigned to perform the following core stabilization assessments: Plank, Side Bridge (right-side), Side Bridge (left-side) and Static Spinal Extension. These positions are shown in Figure 1.1.

Plank exercise test: The subject lies on the test bench and a pushup position, with forearms on the floor and the elbows directly under the shoulders. He maintains a neutral neck and spine and holds a perfect plank position with no flexion or extension of the spine or hips.

Side Bridge (right-side&left-side) exercise test: The subject lies on the test bench and with the side plank position, the elbow directly under the shoulder. He staggers the feet, with the top foot in front of the bottom foot and rests the opposite arm along the torso/hip. He creates a straight plank from the nose, sternum, navel, and feet with no sagging or hiking of hips, and no rotation of the upper body.

Static Spinal Extension exercise test: The subject lies on a soft table and straps the subject's thighs and ankles to the table top. He crosses the arms over the chest and maintains a perfect plank with the ear in a straight line with the hip joint, with no extension or flexion of the away from a neutral spine.



a) Plank Exercise Test

b) Side (Left&Right) Bridge Exercise Test

c) Static Spinal Extension Exercise Test

Figure 1.1. Exercise types

Participants were instructed to hold each exercise stabilization position for a maximal endurance time, while maintaining perfect form, and then to rest for a minimum of 5 minutes between tests. Assessments were terminated when participants could no longer maintain perfect form. A test administrator recorded participants' RPE (10-point scale) every 5 seconds throughout each assessment. After each test, maximal exercise time (total seconds) was recorded, along with the elapsed time to reach an RPE of 4, 5, 6, 7, and 8. Table 1.1. through Table 1.4. show statistical information regarding the four datasets.

Table 1.1. Statistics of the left-side bridge exercise test

Variables	Mean	Std. Dev.	Minimum	Maximum
Gender	0.49	0.5	0	1
Age (Year)	22.9	1.9	18	28
Height (cm)	173.6	173.6	157.48	198.12
Weight (kg)	72.78	14.37	52.16	136.08
BMI (kg/cm$^{2)}$	24.02	3.22	19.89	38.72
RPE-4	9.94	11.49	5	60
RPE-5	16.38	17.43	5	80
RPE-6	28.5	22.81	5	100
RPE-7	41.31	24.02	5	110
RPE-8	50.69	24.88	5	120
Time (second)	70.52	28.52	10.02	139.8

Table 1.2. Statistics of the plank exercise test

Variables	Mean	Std. Dev.	Minimum	Maximum
Gender	0.48	0.5	0	1
Age (Year)	22.7	1.93	18	28
Height (cm)	173.43	9.71	157.48	198.12
Weight (kg)	72.79	14.62	52.3	136.1
BMI (kg/cm$^{2)}$	24.06	3.27	19.89	38.72
RPE-4	18.05	20.51	5	85
RPE-5	32.34	30.03	5	120
RPE-6	53.70	38.81	5	155
RPE-7	71.23	43.3	5	175
RPE-8	86.36	44.36	10	205
Time (second)	119.93	52.46	15	250.02

Table 1.3. Statistics of the right-side bridge exercise test

Variables	Mean	Std. Dev.	Minimum	Maximum
Gender	0.5	0.5	0	1
Age (Year)	22.69	1.9	18	28
Height (cm)	173.6	9.57	157.48	193.12
Weight (kg)	72.79	14.62	52.3	136.1
BMI (kg/cm$^{2)}$	24.06	3.27	19.89	38.72
RPE-4	8.88	9.58	5	55
RPE-5	16.5	18.08	5	95
RPE-6	31.94	23.62	5	130
RPE-7	44.94	24.97	5	145
RPE-8	55.81	26.64	5	160
Time (second)	75.56	29.48	15	184.98

Table 1.4. Statistics of the spinal extension exercise test

Variables	Mean	Std. Dev.	Minimum	Maximum
Gender	0.49	0.5	0	1
Age (Year)	22.69	1.9	18	28
Height (cm)	173.6	9.57	157.48	193.12
Weight (kg)	72.79	14.62	52.3	136.1
BMI (kg/cm$^{2)}$	24.06	3.27	19.89	38.72
RPE-4	12.50	14.73	5	75
RPE-5	24.88	23.28	5	85
RPE-6	42.06	31.44	5	110
RPE-7	60.31	33.84	5	140
RPE-8	73.81	35.66	5	150
Time (second)	97.67	38.81	15	180

2. OVERVIEW OF METHODS

2.1. Support Vector Machines

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

2.1.1. Linear SVM

We are given the training data $(x_i, y_i), (i = 1, ..., \ell)$, where x is a d-dimensional input vector with $x \in \Re^d$ and the output vector is $y \in \Re$. (2.1.) shows the linear regression model (Vapnik, 2000):

$$f(x) = \langle \omega, x \rangle + b, \qquad \omega, x \in \Re^d, \; b \in \Re, \tag{2.1.}$$

In (2.1.1.1), the target function is denoted by $f(x)$ and $\langle .,. \rangle$ represents the dot product in $\Re^d$.

A loss function should be defined for measuring the empirical risk. The ε-insensitive loss function, which is proposed by Vapnik (Vapnik, 2000), is the most frequently used function. (2.2.) defines the ε-insensitive loss function:

$$L_{\varepsilon}(y) = \begin{cases} 0 & \text{for } |f\ (x)\ -\ y| \leq \varepsilon \\ |\,f(x) - y| - \varepsilon & \text{otherwise} \end{cases} \tag{2.2.}$$

The optimization problem given in (2.3.) (Gunn, 1998) should be solved to find out the optimum values of $\overline{\omega}$ and $\overline{b}$

$$\min\ \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{\ell}(\xi_i^- + \xi_i^+) \tag{2.3.}$$

with constraints:

$$\begin{aligned} &\mathrm{y_i} - \langle \omega, x_i \rangle - b \leq \varepsilon + \xi_i^+, \\ &\langle \omega, x_i \rangle + b - \mathrm{y_i} \leq \varepsilon + \xi_i^+, \\ &\xi_i^+, \xi_i^- \geq 0, \quad \mathrm{i}=1,........,\ell \end{aligned} \tag{2.4.}$$

In (2.4.), there exists toleration for the deviations larger than ε and the tradeoff between the flatness of $f(x)$ is determined by C. The deviations from the ε -tube are represented by the slack variables ξ^- and ξ^+.

The dual optimization problem given in (2.5.)

$$\max_{\alpha,\alpha^*} -\frac{1}{2}\sum_{i=1}^{\ell}\sum_{j=1}^{\ell}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\langle x_i, x_j\rangle - \sum_{i=1}^{\ell} y_i(\alpha_i^* - \alpha_i) - \varepsilon\sum_{i=1}^{\ell}(\alpha_i^* + \alpha_i) \quad (2.5.)$$

with constraints:

$$0 \le \alpha_i, \alpha_i^* \le C, \qquad i = 1,\ldots,\ell \ ,$$
$$\sum_{i=1}^{\ell}(\alpha_i - \alpha_i^*) = 0 \quad (2.6.)$$

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

$$\bar{\omega} = \sum_{i=1}^{\ell}(\alpha_i^* - \alpha_i)x_i \quad ,$$
$$\bar{b} = -\frac{1}{2}\left\langle \bar{\omega}, (x_r + x_s)\right\rangle \ , \quad (2.7.)$$

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

2.1.2. Non-linear SVM

Nonlinear SVM can be constructed using a nonlinear mapping ϕ of the input space onto a higher dimension feature space. (2.8.) shows the nonlinear regression model

$$f(x) = \langle \omega, \phi(x)\rangle + b, \quad \omega, x \in \Re^{\mathrm{d}} \ , b \in \Re \ , \quad (2.8.)$$

where

$$\begin{aligned} &\bar{\omega} = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) \phi(x_i), \\ &\left\langle \omega, \bar{\phi}(x) \right\rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) \langle \phi(x_i), \phi(x) \rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(x_i, x), \\ &\bar{b} = -\frac{1}{2} \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*)(K(x_i, x_r) + K(x_i, x_s)) \end{aligned} \tag{2.9.}$$

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

After $\bar{b}$ is integrated into the kernel function, (2.9.) becomes:

$$\sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(x_i, x) \tag{2.10.}$$

Many different kernel functions including the RBF, the polynomial function and the sigmoid function exist. However; RBF, as defined in (2.11.) is the most commonly used Kernel function:

$$K(x, x') = \exp(-\frac{\|x - x'\|^2}{2\rho^2}). \tag{2.11.}$$

In (2.11.) the width of the RBF function is defined by ρ .

2.2. Multi-Layer Perceptron

MLP are organized in layers of neurons and implement a feed-forward processing chain. Following notations can be used for the layers and nodes of an MLP:

The network consists of L layers, with l=0 denoting the input layer and l=L denoting the output layer.

The notation for a single node is n_i^l $(1 \leq i \leq N^l)$, N^l being the number of nodes in layer l.

The activation of a network node depends on the strength of the input to that node with respect to threshold value. For notational convenience, the network thresholds are treated uniformly by adding an extra node with a fixed output of 1.0 to all but the output layer. This node – called the bias unit – is denoted n_0^l (for $\neq L$).

To allow for MLPs of arbitrary connectivity, it is useful to define a set of source nodes S_i^l and set of target nodes T_i^l for each node n_i^l. Given that node $m_j^m$is connected node n_i^l, n_j^m is a source node of n_i^l(i.e. $n_j^m \in S_i^l$) if m<l, but a target node of n_i^l (i.e. $n_j^m \in T_i^l$) if m>l. Set S_i^l is null for all input nodes (i.e. $S_i^0 = \emptyset$ for i =1,…,N0) and for all bias units (i.e. $S_i^0 = \emptyset$ for l =0,…,L-1); set $T_i^l$is null for all output nodes (i.e. $T_i^l = \emptyset$ for i =1,…,NL).

Network weights can be represented in terms of the nodes they connect; thus weight w_{ij}^{lm}connects nodes $n_j^m$and n_i^l with m<l (i.e. $n_j^m$is a source node of $n_i^l$and $n_i^l$is a target node of n_j^m). However, it will often be more convenient to consider weights in terms of the weight vector w comprising all W weights in the network, with a single weight denoted w_i(1 ≤ i ≤ W).

The number of nodes in the input and output layers of the MLP is determined by, respectively, the pattern size and the target size of the chosen training task. MLPs are typically trained using fixed training set of P training pairs, with each training pair comprising two real valued vectors – a pattern p_q(1≤ q ≤ P) and corresponding target (desired output) t_q. Individual pattern and target elements are denoted $p_{i,q}$ (1≤ i ≤ N0) and $t_{j,q}$ (1≤ j ≤ NL) respectively. The output $y_{i,q}^0$ of input node i is simply $p_{i,q}$ for pattern q (except for y_0^0 the fixed output of the bias unit). For non-input node n_i^l, the output is given by the weighted sum

$$a_{i,q}^l = \sum_{n_j^m \in S_i^l} w_{ij}^{lm}\, y_{j,q}^m,\ l > 0 \qquad (2.12.)$$

$$y_{i,q}^l = f\left(a_{i,q}^l\right),\ l > 0 \qquad (2.13.)$$

Where $a_{i,q}^l$ is the activation of node n_i^l for pattern q, and the squashing or activation function f(x) is both monotonic (i.e. non-decreasing) and continuously differentiable. By far the most commonly used squashing function is the sigmoid or logistic function

$$f(x) = \frac{1}{(1+e^{-x})} \qquad (2.14.)$$

Which compresses the output of each non-input node in the range [0,1]. The most popular alternative to the sigmoid is the hyperbolic tangent, f(x) = tanh(x), which gives a compressed range [-1, 1].

The layers between the input and output layers are known as hidden layers. The number of hidden layers and nodes has a major impact on MLP training: too few, and the network will be unable to learn the problem; too many, and the network may take excessively long to train and have poor generalization capabilities – a features as, but are not identical to, patterns in the training set. Upper and lower bounds on the number of hidden nodes required for an MLP to be capable of learning a given task have been established by Huang and Huang (1991), but optimal number of hidden nodes is much more difficult to determine.

2.3. Radial Basis Function

Network Architecture: RBF network includes several layers and the first layer has input neurons. These neurons feed the feature vectors into the network. The second one is the hidden layer that calculates the result of the basic functions. The last layer is the output layer that calculates a linear union of the basic functions. These kinds of networks have the general estimation property (Park and Sandberg, 1991). Simple structures of these networks give a decreasing for training time and make possible learning in stages.

$x \in R^n$ (a vector) is an input and f(x): $R^n \rightarrow$ R (a function) is an output estimated by using an RBF network:

$$f(x) = \sum_{i=1}^{N} w_i h_i\,(x) \tag{2.15.}$$

Where N represents the number of neurons and $h(x)$ is the radial basis function in the hidden layer. The typical radial basis function is taken to be Gaussian:

$$h_i(x) = exp\left(-\frac{(x-c)^2}{r^2}\right) \tag{2.16.}$$

The parameter c is the center vector and r is its radius.

Training: A two-step algorithm is usually used to train RBF. The first step requires the selection of the center vectors ci of the RBF functions in the hidden layer. Randomly sampled from some set of examples or K-means clustering can be used to accomplish the first step.

In the second step, the coefficients wi are fitted to the hidden layers output with respect to some transfer function. The least squares function is one of the commonly used transfer functions. Detailed information can be found in “Multivariable Functional Interpolation and Adaptive Networks”, (Broomhead D. S., 1988).

2.4. Single Decision Tree

Classification and prediction problems can be solved by decision trees, which are powerful data mining methodologies (Kantardzic, 2003). In general, a decision tree can be seen as a predictive model, whereas a tree structure represents a similar behavior to that of a flowchart. Target values can be obtained by decision trees by utilizing classification and analysis (Han et al., 2006).

The classification made by decision trees is based on sorting instances. The sorting is carried out by traversing the tree starting from the root node on top and ending at some intermediate leaf node. Classification of the instance is acheived by this process. There exist several popular tree-growing and tree-pruning algorithms. Quinlan's ID3 algorithm, its extended version C4.5 and C5.0 algorithms all utilize Greedy search methods for tree-growing and tree-pruning.

2.5. General Regression Neural Network

A GRNN includes four layers, the names of which are given in Figure 2.1. A typical GRNN architecture is illustrated in Fig. 2.1.

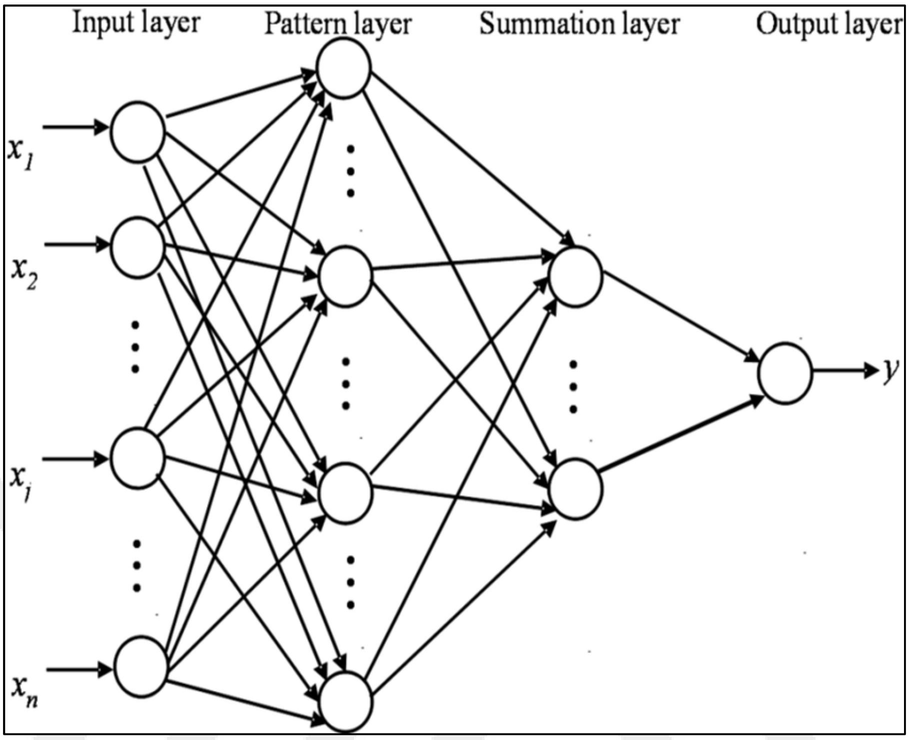


Figure 2.1. A typical GRNN architecture

Total number of features specifies the number of input structures. As shown in Figure 2.1, each layer is directly connected to next layer without having any feedback loops. The summation layer is comprised of a single division unit and summation units. A normalization of the output set is performed by both the summation and output layer.

GRNN can be considered as a technique to predict the joint pdf of x and y, when only a training set is given. Let f (x, y) represent the joint pdf of a vector random variable, x and a scalar random variable, y. In this case, the conditional expected value of y given X, is calculated by (2.17.).

$$E[y|X] = \frac{\int_{-\infty}^{\infty} y f(X,y) dy}{\int_{-\infty}^{\infty} f(X,y) dy} \tag{2.17.}$$

In case f (x, y) is not known, a sample of observations of x and y has to be used to predict f (x, y). Let f'(X, Y) given by (2.18.) be the probability estimator. f'(X, Y) includes sample values Xi and Yi of the random variables x and y. In (2.18.), n is the number of sample observations, σ is the width and p is the dimension of the vector variable x.

$$f'(X,Y) = \frac{1}{(2\pi)^{(p+1)/2}\sigma^{(+1)}}\frac{1}{n}\sum_{i=1}^{n} \exp[-\frac{(X-X^i)^T(X-X^i)}{2\sigma^2}]\exp[-\frac{(Y-Y^i)^2}{2\sigma^2}] \quad (2.18.)$$

The scalar function D_i^2 *is* given by (2.19.) and (2.20.) is obtained after carrying out the necessary integrations.

$$D_i^2 = (X - X^i)^T(X - X^i) \quad (2.19.)$$

$$Y'(X) = \frac{\sum_{i=1}^{n} Y^i \exp(-\frac{D_i^2}{2\sigma^2})}{\sum_{i=1}^{n} EXP(-\frac{D_i^2}{2\sigma^2})} \quad (2.20.)$$

It should be noted that the final equation given by (2.20.) is applicable to problems involving numerical data.

3. DEVELOPMENT OF PREDICTION MODELS

3.1. SVM Prediction Models

The selection of kernel type and the parameter C are the critical steps for the learning mechanism. The accuracy of the whole process also depends on these tasks. There is a tradeoff between reducing the error related to training and reducing the complexity of the model and this is stated by parameter C. A small value of C will increase a number of training errors and a large value of C will exhibit an attitude similar to that of a hard-margin SVM. The kernel parameters are important in the sense that they act as a bridge between the input space and the high-dimensional feature space (Ji and Wang, 2007). "ε" is the another important parameter for the SVM. It controls the width of insensitive zone and states the number of support vectors.

The optimal values of hyperparameters are usually found by grid search. That is, the values of the parameters are differentiated with a fixed step size through an interval of values and the performance of every combination is assessed using some performance measure. A cross-validation within the grid search can be utilized in order to develop the generalization capability of the SVM regression model. In the process of k-fold cross validation, the cross validation is recurred k times (this means k folds), with each of the k subsets utilized precisely once as the validation data. The k results from the folds then need to be associated to generate a single prediction.

RBF has been utilized as the kernel function. The intervals for the SVM parameters are as follows: [2-6 - 216] for C, [0.01 - 150] for ε and [2-8 - 28] for gamma.

3.2. MLP Prediction Models

The MLP architecture depends on the choice of the number of layers, the number of hidden nodes in each of these layers and the objective function. If the number of neurons that is utilized is not sufficient, less information will be acquired. On the contrary, the local minimum might enhance and the network might come close to a local minimum, hence the network's sensitivity will decrease. Nevertheless, there is not a strict regulation for detecting the number of neurons in a hidden layer. Generally, the optimal number is selected with trial and error based on the difficulty of the problem.

In the hidden layer of the MLP models, the tansigmoid function is utilized whereas in the output layer of MLP models, the pure linear function is used. LM algorithm is implemented to train the network.

Maximum iteration has been set to 10000 and the number of epochs is adjusted as 500. The intervals for the other MLP parameters are as follows: [2 - 20] for the number of neurons in the hidden layer, (0 - 1) for the learning rate, (0 - 1) for momentum and [2 - 20] for the number of convergence tries.

3.3. RBF Prediction Models

The performance of the RBF depends on numerous factor. The choice of basis function and shape parameter have a significant impact on the accuracy of an RBF. The decisions tremendously affect the accuracy and the numerical stability of the method utilized.

The intervals for the RBF parameters are as follows: [0.001 - 25] for the regularization parameter, [100 - 400] for the population size, [0.001 - 450] for the radius of RBF and [95 - 100] for the maximum number of neurons.

3.4. SDT Prediction Models

There are three important parameters that affect the performance of SDT-based prediction models. One of the parameters is known as the minimum rows in a node and the others are known as the minimum size node to split and maximum tree levels.

The intervals for the SDT parameters are as follows: [2-15] for the minimum size node to split, [2 - 25] for the minimum size in a node and [5 - 10] for the maximum tree levels.

3.5. GRNN Prediction Models

For a GRNN-based model, the minimum and maximum values for sigma, search step and the type of kernel function influences the performance of GRNN-based models.

Gaussian kernel function has been selected. The intervals for the GRNN parameters are as follows: [0.0001 - 11] for the minimum sigma, [1 - 65] for the maximum sigma and [1 - 80] for the search step.

4. RESULTS AND DISCUSSIONS

4.1. Approach of this Thesis

Using the combinations of predictor variables height, weight, gender, age, BMI and RPE4-8 four categories of endurance time prediction models have been created for four different stabilizitaion excercise types. The first category includes predictor variables gender, BMI and combination of the RPE-4 to RPE-8. In the second category predictor variables gender, height, weight and combination of the RPE-4 to RPE-8. In the third category predictor variables gender, age, height, weight and combination of the RPE-4 to RPE-8. In the fourth category predictor variables gender, age, BMI and combination of the RPE-4 to RPE-8. In order to evaluate the performance and the accuracy of the different models, the values of *RMSE* and *R* have been computed using 10-fold cross validation method. The equations of *RMSE* and *R* are given in (4.1.) and (4.2.) respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y - Y'\right)^2} \quad (4.1.)$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}\left(Y - Y'\right)^2}{\sum_{i=1}^{n}\left(Y - \overline{Y}\right)^2}} \quad (4.2.)$$

In (4.1.) and (4.2.), Y is the measured value, Y' is the predicted value, $\bar{Y}$ is the mean of the measured values and n is the number of samples in a test subset.

Table 4.1. through Table 4.4. show the prediction models variety for the SVM, GRNN, MLP, RBF and SDT and uses the four core stabilization excercise types respectively for the meximum endurance time prediction.

Table 4.1. Prediction models including age and BMI

Model No	**Predictor Variables**
1	Gender, Age, BMI, RPE-7, RPE-8
2	Gender, Age, BMI, RPE-6, RPE-7, RPE-8
3	Gender, Age, BMI, RPE-4, RPE-7, RPE-8
4	Gender, Age, BMI, RPE-4, RPE-6, RPE-7, RPE-8
5	Gender, Age, BMI, RPE-5, RPE-7, RPE-8
6	Gender, Age, BMI, RPE-5, RPE-6, RPE-7, RPE-8
7	Gender, Age, BMI, RPE-4, RPE-5, RPE-7, RPE-8
8	Gender, Age, BMI, RPE-4, RPE-5, RPE-6, RPE-7, RPE-8

Table 4.2. Prediction models including age, height and weight

Model No	**Predictor Variables**
9	Gender, Age, Height, Weight, RPE-7, RPE-8
10	Gender, Age, Height, Weight, RPE-6, RPE-7, RPE-8
11	Gender, Age, Height, Weight, RPE-4, RPE-7, RPE-8
12	Gender, Age, Height, Weight, RPE-4, RPE-6, RPE-7, RPE-8
13	Gender, Age, Height, Weight, RPE-5, RPE-7, RPE-8
14	Gender, Age, Height, Weight, RPE-5, RPE-6, RPE-7, RPE-8
15	Gender, Age, Height, Weight RPE-4, RPE-5, RPE-7, RPE-8
16	Gender, Age, Height, Weight, RPE-4, RPE-5, RPE-6, RPE-7, RPE-8

Table 4.3. Prediction models including BMI

Model No	**Predictor Variables**
17	Gender, BMI, RPE-7, RPE-8
18	Gender, BMI, RPE-6, RPE-7, RPE-8
19	Gender, BMI, RPE-4, RPE-7, RPE-8
20	Gender, BMI, RPE-4, RPE-6, RPE-7, RPE-8
21	Gender, BMI, RPE-5, RPE-7, RPE-8
22	Gender, BMI, RPE-5, RPE-6, RPE-7, RPE-8
23	Gender, BMI, RPE-4, RPE-5, RPE-7, RPE-8
24	Gender, BMI, RPE-4, RPE-5, RPE-6, RPE-7, RPE-8

Table 4.4. Prediction models including height and weight

Model No	**Predictor Variables**
25	Gender, Height, Weight, RPE-7, RPE-8
26	Gender, Height, Weight, RPE-6, RPE-7, RPE-8
27	Gender, Height, Weight, RPE-4, RPE-7, RPE-8
28	Gender, Height, Weight, RPE-4, RPE-6, RPE-7, RPE-8
29	Gender, Height, Weight, RPE-5, RPE-7, RPE-8
30	Gender, Height, Weight, RPE-5, RPE-6, RPE-7, RPE-8
31	Gender, Height, Weight, RPE-4, RPE-5, RPE-7, RPE-8
32	Gender, Height, Weight, RPE-4, RPE-5, RPE-6, RPE-7, RPE-8

4.2. Results

Table 4.5. through Table 4.12. show the results for prediction models of right-side bridge exercise type, Table 4.13. through Table 4.20. show the results for prediction models of left-side bridge exercises type, Table 4.21. through Table 4.28. show the results for prediction models of spinal extension exercises type, Table 4.29. through Table 4.36. show the results for prediction models of plank exercises type.

Table 4.5. RMSE's values for right-side bridge exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	11.03	12.12	12.77	15.45	16.07
2	11.45	12.57	12.96	15.73	16.52
3	11.73	12.82	13.54	15.79	16.76
4	11.88	13.34	14.51	16.11	16.91
5	12.12	13.59	15.31	16.32	17.07
6	12.36	13.99	16.15	16.30	17.20
7	12.47	14.10	16.12	16.34	17.30
8	12.61	14.44	16.68	16.78	17.95

Table 4.6. R's values for right-side bridge exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	0.86	0.83	0.81	0.72	0.70
2	0.85	0.82	0.79	0.71	0.68
3	0.84	0.81	0.79	0.71	0.67
4	0.83	0.79	0.75	0.70	0.67
5	0.83	0.78	0.73	0.69	0.66
6	0.82	0.77	0.70	0.69	0.65
7	0.82	0.77	0.68	0.68	0.64
8	0.81	0.76	0.66	0.67	0.63

Table 4.7. RMSE's values for right-side bridge exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	10.39	12.11	12.43	15.34	15.64
10	10.70	12.79	12.82	15.66	15.86
11	10.84	13.23	13.53	15.73	16.06
12	10.98	14.20	14.44	15.81	16.36
13	11.11	15.06	15.21	16.06	16.83
14	11.21	15.98	15.94	16.39	17.08
15	11.33	16.11	16.56	16.69	17.38
16	11.57	17.02	17.29	17.40	17.78

Table 4.8. R's values for right-side bridge exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	0.87	0.83	0.82	0.73	0.71
10	0.87	0.81	0.80	0.72	0.70
11	0.86	0.80	0.79	0.71	0.70
12	0.86	0.76	0.76	0.71	0.69
13	0.86	0.75	0.73	0.70	0.68
14	0.85	0.73	0.70	0.69	0.66
15	0.85	0.70	0.68	0.67	0.65
16	0.84	0.68	0.65	0.64	0.63

Table 4.9. RMSE's values for right-side bridge exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	10.46	12.10	12.43	15.45	15.54
18	10.80	12.49	12.90	15.71	15.87
19	10.90	12.81	13.63	15.81	16.19
20	11.00	13.18	13.89	16.11	16.24
21	11.03	13.50	14.26	16.20	16.45
22	11.04	13.61	14.51	16.40	16.49
23	11.15	13.66	14.95	16.56	16.84
24	11.30	14.04	15.13	16.63	17.09

Table 4.10. R's values for right-side bridge exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	0.87	0.83	0.82	0.72	0.71
18	0.86	0.82	0.80	0.72	0.71
19	0.86	0.81	0.78	0.71	0.70
20	0.86	0.80	0.78	0.70	0.69
21	0.85	0.79	0.76	0.69	0.68
22	0.85	0.78	0.76	0.69	0.68
23	0.85	0.78	0.75	0.68	0.67
24	0.85	0.77	0.74	0.68	0.66

Table 4.11. RMSE's values for right-side bridge exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	10.67	12.10	12.65	15.71	15.90
26	10.92	12.50	13.45	15.81	16.24
27	10.80	12.85	13.79	15.91	16.35
28	11.05	13.36	14.08	16.40	16.46
29	11.08	13.62	14.28	16.55	16.63
30	11.12	13.65	15.03	16.63	16.76
31	11.17	13.94	15.09	16.69	16.88
32	11.22	14.13	15.21	16.70	17.07

Table 4.12. R's values for right-side bridge exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	0.87	0.83	0.81	0.71	0.71
26	0.86	0.82	0.79	0.71	0.69
27	0.86	0.81	0.78	0.69	0.69
28	0.85	0.79	0.77	0.69	0.68
29	0.85	0.78	0.76	0.68	0.68
30	0.85	0.78	0.75	0.68	0.67
31	0.85	0.78	0.74	0.67	0.67
32	0.84	0.77	0.74	0.67	0.66

Table 4.13. RMSE's values for left-side bridge exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	11.35	11.43	11.66	12.89	13.55
2	11.54	11.66	11.79	13.08	13.65
3	11.65	11.78	11.95	13.18	13.76
4	11.73	11.85	12.03	13.54	13.94
5	11.82	12.07	12.16	13.74	14.12
6	12.01	12.15	12.20	14.04	14.27
7	12.28	12.34	12.54	14.33	14.42
8	12.36	12.50	12.69	14.46	14.61

Table 4.14. R's values for left-side bridge exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	0.84	0.83	0.83	0.79	0.77
2	0.83	0.82	0.82	0.79	0.77
3	0.82	0.82	0.82	0.78	0.76
4	0.82	0.81	0.81	0.77	0.76
5	0.81	0.81	0.81	0.76	0.75
6	0.81	0.80	0.80	0.75	0.75
7	0.81	0.80	0.80	0.75	0.74
8	0.80	0.79	0.79	0.74	0.74

Table 4.15. RMSE's values for left-side bridge exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	11.09	11.38	11.41	12.80	13.29
10	11.11	11.46	11.61	12.95	13.49
11	11.24	11.76	11.80	13.12	13.60
12	11.30	11.86	12.01	13.46	13.68
13	11.36	12.08	12.22	13.66	13.95
14	12.10	12.27	12.32	13.86	14.13
15	12.23	12.35	12.39	14.13	14.26
16	12.35	12.44	12.67	14.24	14.42

Table 4.16. R's values for left-side bridge exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	0.85	0.84	0.83	0.80	0.78
10	0.84	0.83	0.83	0.79	0.77
11	0.84	0.82	0.82	0.79	0.77
12	0.83	0.82	0.81	0.77	0.76
13	0.82	0.81	0.81	0.77	0.76
14	0.81	0.81	0.80	0.76	0.75
15	0.81	0.80	0.80	0.75	0.75
16	0.80	0.80	0.79	0.75	0.74

Table 4.17. RMSE's values for left-side bridge exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	10.63	10.77	11.00	12.22	12.68
18	10.75	10.98	11.10	12.51	12.82
19	11.08	11.16	11.32	12.96	13.12
20	11.32	11.48	11.55	13.38	13.49
21	11.44	11.65	11.91	13.56	13.66
22	11.63	11.95	12.11	13.66	13.76
23	12.02	12.22	12.51	13.76	14.02
24	12.16	12.33	12.54	13.86	14.09

Table 4.18. R's values for left-side bridge exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	0.86	0.86	0.85	0.81	0.80
18	0.85	0.85	0.85	0.81	0.80
19	0.85	0.84	0.84	0.79	0.79
20	0.84	0.84	0.83	0.78	0.77
21	0.83	0.83	0.82	0.77	0.77
22	0.82	0.82	0.82	0.77	0.76
23	0.82	0.81	0.81	0.76	0.76
24	0.82	0.81	0.80	0.76	0.75

Table 4.19. RMSE's values for left-side bridge exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	10.92	11.27	11.43	12.62	12.74
26	10.89	11.41	11.53	12.73	12.92
27	11.06	11.53	11.69	12.80	13.08
28	11.41	11.70	11.84	13.30	13.54
29	11.89	12.04	12.12	13.50	13.88
30	12.09	12.12	12.25	13.76	14.02
31	12.10	12.21	12.29	13.91	14.15
32	12.16	12.32	12.38	14.09	14.32

Table 4.20. R's values for left-side bridge exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	0.85	0.84	0.84	0.80	0.80
26	0.85	0.84	0.83	0.80	0.79
27	0.85	0.83	0.83	0.79	0.79
28	0.84	0.83	0.82	0.78	0.77
29	0.83	0.82	0.82	0.77	0.76
30	0.83	0.82	0.81	0.76	0.76
31	0.82	0.81	0.81	0.76	0.75
32	0.81	0.81	0.80	0.75	0.75

Table 4.21. RMSE's values for spinal extension exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	13.76	14.76	15.42	18.01	18.40
2	14.13	14.99	15.59	18.18	18.75
3	14.57	15.27	16.19	18.37	18.98
4	14.89	15.45	16.58	18.45	19.32
5	15.02	15.80	16.70	18.65	19.78
6	15.20	15.82	16.86	18.90	20.08
7	15.26	16.14	17.41	19.12	20.37
8	15.26	16.34	17.67	19.17	20.87

Table 4.22. R's values for spinal extension exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	0.88	0.85	0.84	0.78	0.77
2	0.87	0.85	0.83	0.77	0.76
3	0.86	0.84	0.82	0.77	0.75
4	0.85	0.84	0.82	0.76	0.75
5	0.85	0.83	0.81	0.75	0.74
6	0.84	0.83	0.80	0.75	0.74
7	0.84	0.82	0.80	0.75	0.73
8	0.83	0.82	0.79	0.74	0.73

Table 4.23. RMSE's values for spinal extension exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	13.56	14.60	15.24	18.00	18.18
10	14.11	14.89	15.69	18.16	18.39
11	14.34	15.08	16.14	18.31	18.75
12	14.55	15.37	16.24	18.42	18.96
13	14.73	15.43	16.32	18.50	19.32
14	14.87	15.65	16.66	18.60	19.75
15	15.07	15.89	16.20	18.92	20.08
16	15.17	16.27	16.23	19.17	20.37

Table 4.24. R's values for spinal extension exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	0.88	0.86	0.84	0.78	0.78
10	0.87	0.85	0.83	0.78	0.77
11	0.86	0.85	0.83	0.77	0.76
12	0.86	0.84	0.82	0.77	0.76
13	0.85	0.84	0.82	0.76	0.75
14	0.85	0.84	0.81	0.76	0.75
15	0.85	0.83	0.80	0.75	0.74
16	0.84	0.82	0.80	0.75	0.73

Table 4.25. RMSE's values for spinal extension exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	12.36	14.37	14.53	17.42	17.46
18	13.17	14.62	14.89	17.54	17.54
19	13.38	14.67	15.14	17.95	18.10
20	13.76	14.84	15.26	18.12	18.37
21	13.93	15.00	15.57	18.37	18.75
22	14.35	15.41	16.04	18.56	18.93
23	14.63	15.62	16.48	18.72	19.23
24	13.17	15.97	16.86	18.82	19.75

Table 4.26. R's values for spinal extension exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	0.90	0.86	0.86	0.80	0.79
18	0.88	0.86	0.85	0.79	0.79
19	0.88	0.86	0.85	0.79	0.78
20	0.87	0.85	0.84	0.78	0.77
21	0.87	0.85	0.84	0.78	0.76
22	0.86	0.84	0.83	0.77	0.76
23	0.86	0.84	0.82	0.76	0.75
24	0.88	0.83	0.81	0.76	0.75

Table 4.27. RMSE's values for spinal extension exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	12.69	14.53	14.62	17.83	17.98
26	13.46	14.75	14.99	17.97	18.10
27	14.01	14.81	15.30	18.32	18.37
28	14.36	15.07	15.73	18.42	18.75
29	14.40	15.37	15.97	18.60	18.93
30	14.42	15.51	16.29	18.70	19.23
31	14.48	15.65	16.51	19.09	19.75
32	14.52	16.18	16.82	19.12	20.08

Table 4.28. R's values for spinal extension exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	0.89	0.86	0.85	0.78	0.78
26	0.88	0.85	0.85	0.78	0.78
27	0.87	0.85	0.84	0.77	0.77
28	0.86	0.85	0.83	0.77	0.76
29	0.86	0.84	0.83	0.77	0.76
30	0.86	0.84	0.82	0.76	0.75
31	0.85	0.84	0.82	0.75	0.75
32	0.85	0.82	0.81	0.75	0.74

Table 4.29. RMSE's values for plank exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	18.61	19.16	19.44	23.00	23.17
2	19.09	19.39	19.78	23.02	24.12
3	19.42	19.63	20.23	24.03	24.32
4	19.71	20.07	20.78	24.14	25.03
5	20.28	20.17	21.39	24.33	25.34
6	20.72	20.33	21.50	25.03	25.72
7	21.09	20.44	21.58	25.38	26.24
8	21.60	20.74	21.65	25.64	26.67

Table 4.30. R's values for plank exercise prediction models (models 1-8)

Model No	SVM	GRNN	MLP	SDT	RBF
1	0.87	0.86	0.86	0.80	0.79
2	0.87	0.86	0.85	0.80	0.78
3	0.86	0.85	0.85	0.79	0.77
4	0.86	0.85	0.84	0.78	0.77
5	0.85	0.84	0.83	0.77	0.76
6	0.84	0.83	0.83	0.77	0.75
7	0.84	0.83	0.82	0.76	0.75
8	0.83	0.82	0.82	0.76	0.74

Table 4.31. RMSE's values for plank exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	18.23	18.65	19.05	22.74	23.08
10	18.42	19.04	19.44	23.02	23.21
11	19.19	19.54	19.78	23.12	24.25
12	19.45	19.69	20.23	24.03	24.32
13	19.78	20.07	20.78	24.25	25.21
14	19.94	20.12	21.39	24.43	25.68
15	20.53	20.29	21.51	25.10	25.78
16	20.72	20.39	21.58	25.46	26.12

Table 4.32. R's values for plank exercise prediction models (models 9-16)

Model No	SVM	GRNN	MLP	SDT	RBF
9	0.88	0.87	0.87	0.81	0.80
10	0.87	0.86	0.86	0.80	0.79
11	0.86	0.86	0.85	0.80	0.78
12	0.86	0.85	0.85	0.79	0.77
13	0.86	0.85	0.84	0.78	0.77
14	0.85	0.84	0.83	0.77	0.76
15	0.84	0.84	0.83	0.77	0.75
16	0.84	0.83	0.82	0.76	0.75

Table 4.33. RMSE's values for plank exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	17.58	17.96	18.31	21.52	22.26
18	17.95	18.38	18.63	21.92	22.60
19	18.22	18.64	19.10	22.87	23.18
20	18.42	19.15	19.41	23.09	23.54
21	19.08	19.46	19.73	23.53	24.25
22	19.38	19.63	20.21	23.98	24.43
23	19.69	19.75	20.77	24.17	25.21
24	19.89	19.94	21.33	24.43	25.64

Table 4.34. R's values for plank exercise prediction models (models 17-24)

Model No	SVM	GRNN	MLP	SDT	RBF
17	0.89	0.88	0.88	0.82	0.82
18	0.88	0.88	0.87	0.82	0.81
19	0.88	0.87	0.87	0.81	0.80
20	0.87	0.87	0.86	0.80	0.79
21	0.87	0.86	0.86	0.79	0.78
22	0.86	0.85	0.85	0.79	0.77
23	0.86	0.85	0.84	0.78	0.77
24	0.85	0.84	0.84	0.78	0.76

Table 4.35. RMSE's values for plank exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	18.18	18.39	18.62	21.93	22.61
26	18.43	18.65	19.11	22.87	23.19
27	19.09	19.08	19.44	23.10	23.21
28	19.36	19.20	19.75	23.54	24.24
29	19.53	19.64	20.21	24.03	24.38
30	19.88	20.02	20.78	24.25	25.21
31	20.06	20.12	21.35	24.43	25.64
32	20.24	20.29	21.50	25.04	25.78

Table 4.36. R's values for plank exercise prediction models (models 25-32)

Model No	SVM	GRNN	MLP	SDT	RBF
25	0.88	0.88	0.87	0.81	0.81
26	0.87	0.87	0.86	0.80	0.80
27	0.87	0.87	0.86	0.79	0.79
28	0.86	0.86	0.86	0.78	0.78
29	0.86	0.85	0.85	0.77	0.77
30	0.85	0.85	0.84	0.77	0.77
31	0.84	0.84	0.84	0.76	0.76
32	0.84	0.84	0.83	0.75	0.75

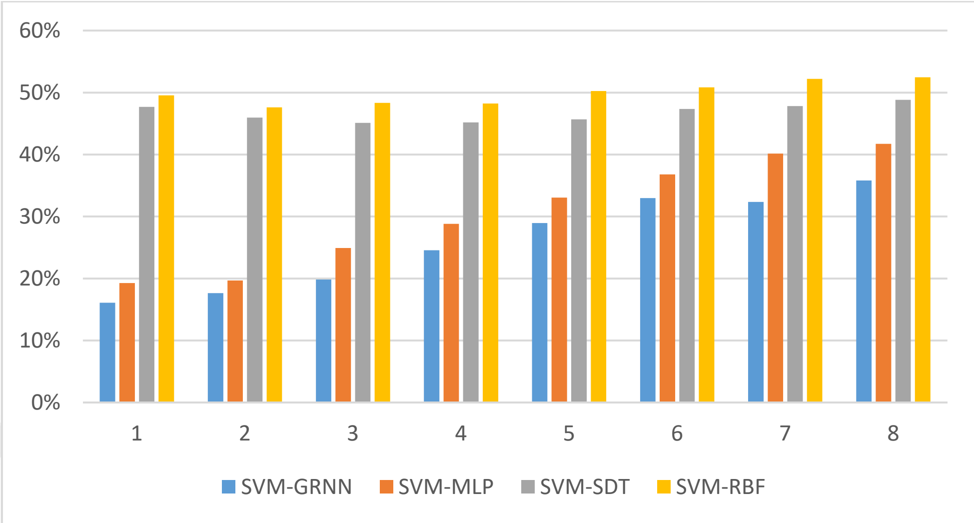


Figure 4.1. Average percentage decrease rates in RMSE's of right-side bridge excercise for SVM-based models compared to RMSE's obtained by the rest of other models

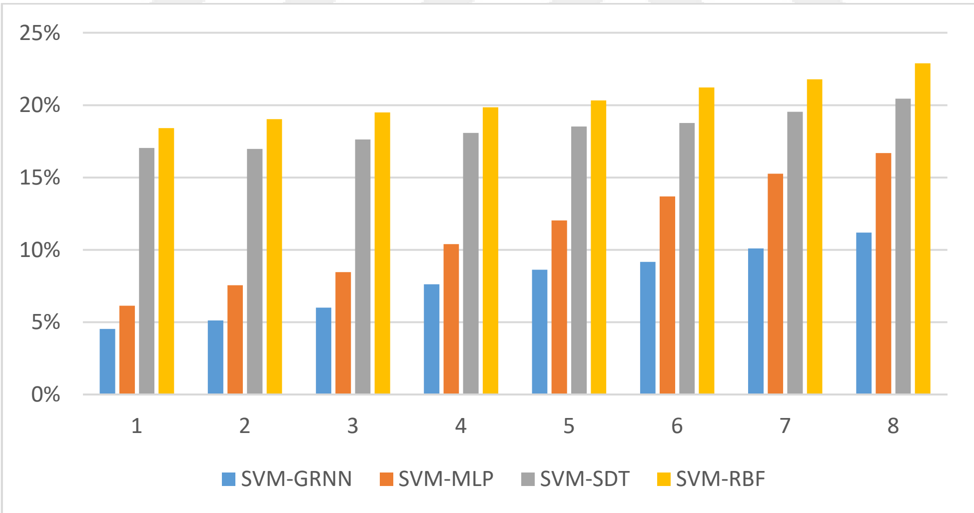


Figure 4.2. Average percentage decrease rates in R's of right-side bridge excercise for SVM-based models compared to R's obtained by the rest of other models

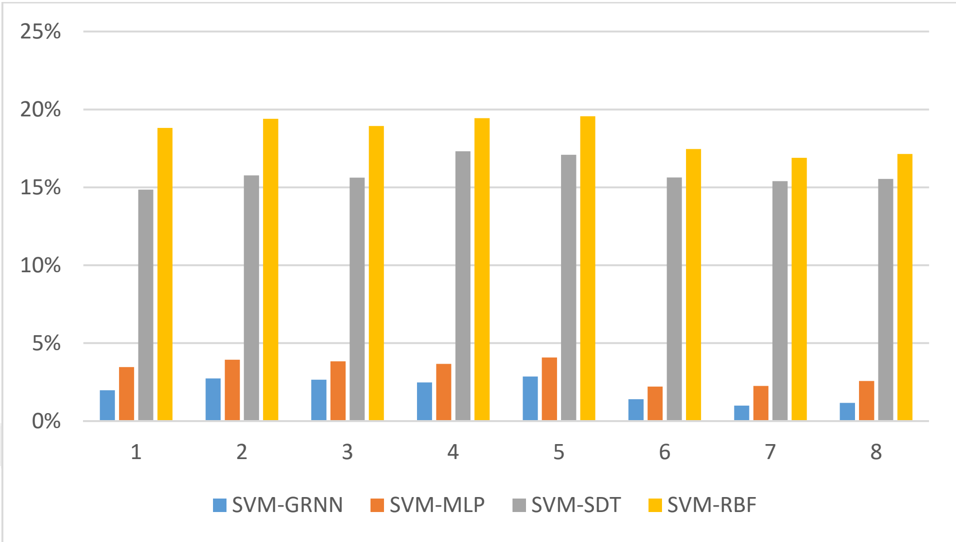


Figure 4.3. Average percentage decrease rates in RMSE's of left-side bridge excercise for SVM-based models compared to RMSE's obtained by the rest of other models

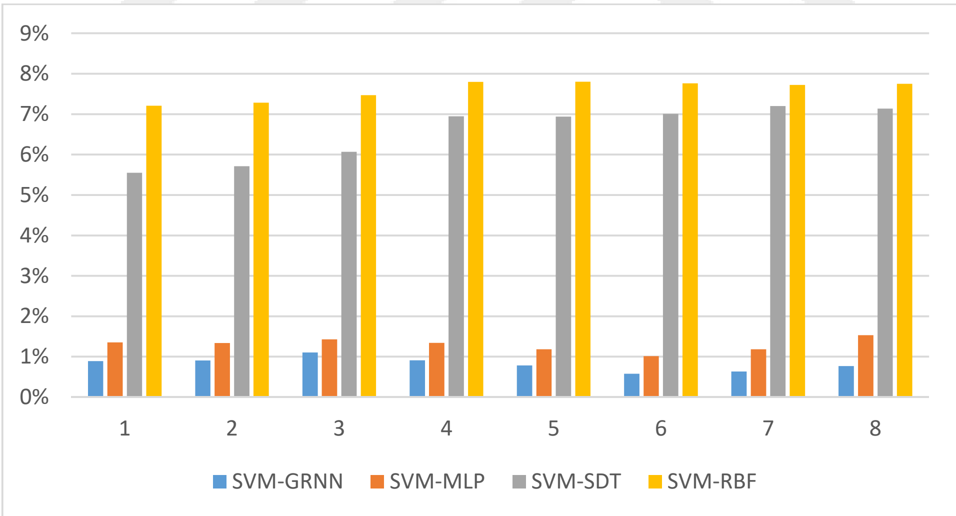


Figure 4.4. Average percentage decrease rates in R's of left-side bridge excercise for SVM-based models compared to R's obtained by the rest of other models

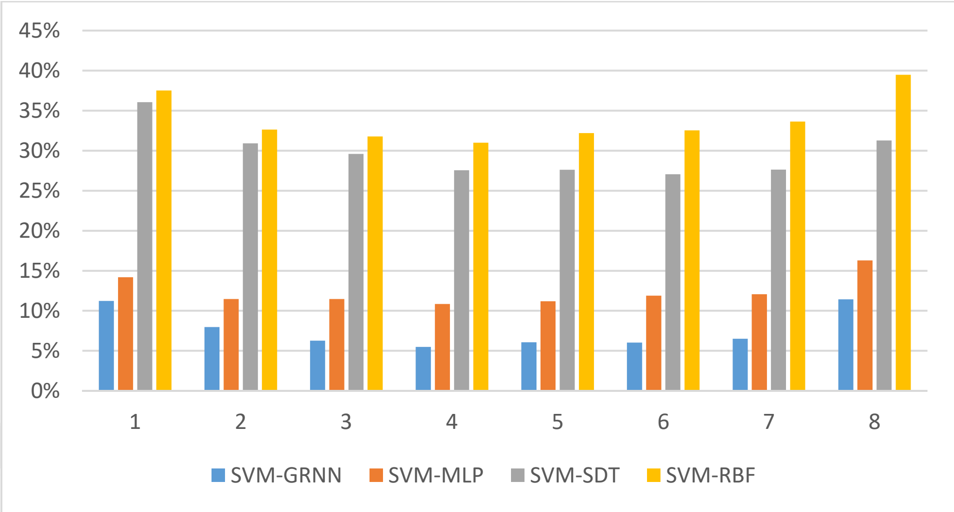


Figure 4.5. Average percentage decrease rates in RMSE's of spinal extension excercise for SVM-based models compared to RMSE's obtained by the rest of other models

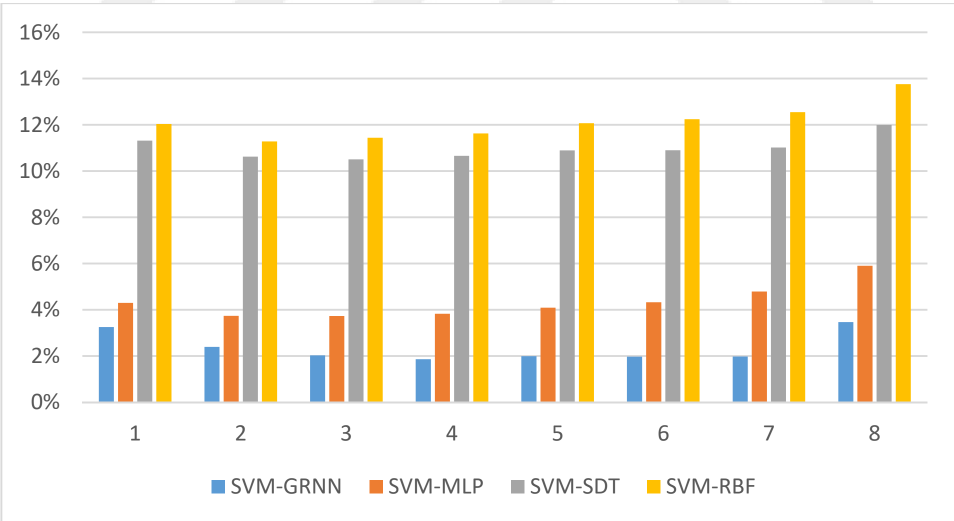


Figure 4.6. Average percentage decrease rates in R's of spinal extension excercise for SVM-based models compared to R's obtained by the rest of other models

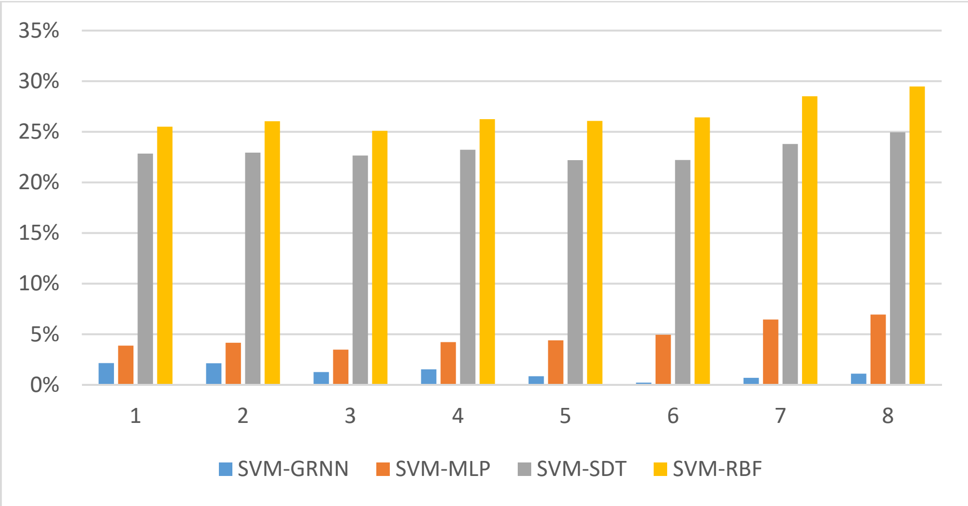


Figure 4.7 Average percentage decrease rates in RMSE's of plank excercise for SVM-based models compared to RMSE's obtained by the rest of other models

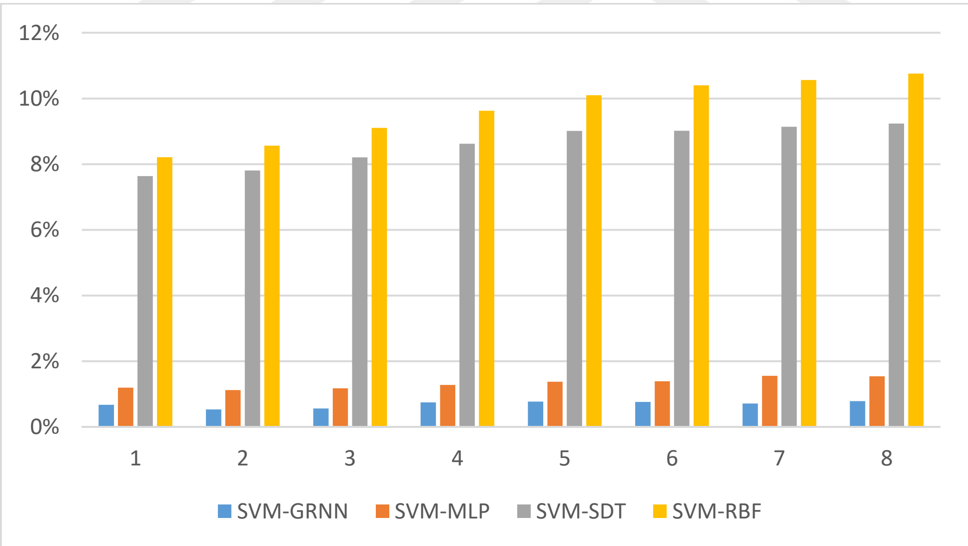


Figure 4.8. Average percentage decrease rates in R's of plank excercise for SVM-based models compared to R's obtained by the rest of other models

4.3. Discussion

The results obtained in this study reveal that SVM-based prediction models outperform GRNN-based, MLP-based, RBF-based and SDT-based prediction models. In other words SVM models show the highest accuracy for the prediction of maximum endurance time, regardless of which category of prediction models has been utilized or which endurance time exercise type has been applied to the participants. In more details:

- For the right-side bridge exercise, the range of percentage decrement rates of SVM-based prediction models with respect to prediction models based on other machine learning methods are as follows: 17.49% - 46.83% for GRNN, 20.94% - 54.55% for MLP, 51.81% - 63.83% for SDT and 53.84% - 68.59% for RBF.
- For the right-side bridge exercise, SVM-based prediction model including the predictor variables gender, age, height, weight, RPE-7 and RPE-8 shows the highest performance with an RMSE value of 10.38 second.
- For the right-side bridge exercise, RBF-based prediction model including the predictor variables gender, age, BMI, RPE-4,RPE-5, RPE-6, RPE-7, RPE-8 shows the worst performance with an RMSE value of 17.95 second.
- For the left-side bridge exercise, the range of percentage decrement rates of SVM-based prediction models with respect to prediction models based on other machine learning methods are as follows: 2.39% - 3.85% for GRNN, 4.19% - 5.51% for MLP, 17.96% - 23.34% for SDT, 22.75% - 26.45% for RBF.
- For the left-side bridge exercise, SVM-based prediction model including the predictor variables gender, BMI, RPE-7 and RPE-8 shows the highest performance with an RMSE value of 10.63 second.

- For the left-side bridge exercise, RBF-based prediction model including the predictor variables gender, age, BMI, RPE-4,RPE-5, RPE-6, RPE-7, RPE-8 shows the worst performance with an RMSE value of 14.61 second.
- For the spinal extension exercise, the range of percentage decrement rates of SVM-based prediction models with respect to prediction models based on other machine learning methods are as follows: 11.36% - 24.11% for GRNN, 21.58% - 34.37% for MLP, 57.05% - 66.02% for SDT, 61.41% - 83.34% for RBF.
- For the spinal extension exercise, SVM-based prediction model including the predictor variables gender, BMI, RPE-7 and RPE-8 shows the highest performance with an RMSE value of 12.35 second.
- For the spinal extension exercise, RBF-based prediction model including the predictor variables gender, age, BMI, RPE-4,RPE-5, RPE-6, RPE-7, RPE-8 shows the worst performance with an RMSE value of 20.87 second.
- For the plank exercise, the range of percentage decrement rates of SVM-based prediction models with respect to prediction models based on other machine learning methods are as follows: 2.78% - 7.27% for GRNN, 12.49% - 28.08% for MLP, 75.27% - 101.03% for SDT, 84.03% - 119.36% for RBF
- For the plank exercise, SVM-based prediction model including the predictor variables gender, BMI, RPE-7 and RPE-8 shows the highest performance with an RMSE value of 17.58 second.
- For plank exercise, RBF-based prediction model including the predictor variables gender, age, BMI, RPE-4,RPE-5, RPE-6, RPE-7, RPE-8 shows the worst performance with an RMSE value of 26.67 second.
- At the right-side bridge exercise type at the GRNN model the highest avarege value of RMSE was seen including gender, BMI variables. On the other hand the lowest avarege value of RMSE was seen including gender,

age, height, weight variables.

- At the right-side bridge exercise type at the MLP model the highest avarege value of RMSE was seen including gender, BMI variables. On the other hand the lowest avarege value of RMSE was seen including gender, age, height, weight variables.
- At the right-side bridge exercise type at the SDT model the highest avarege value of RMSE was seen including gender, age, BMI variables. On the other hand the lowest avarege value of RMSE was seen including gender, height, weight variables.
- At the right-side bridge exercise type at the RBF model the highest avarege value of RMSE was seen including gender, BMI variables. On the other hand the lowest avarege value of RMSE was seen including gender, age, BMI variables.
- At the left-side bridge exercise type at the GRNN model the highest avarege value of RMSE was seen including gender, BMI variables. On the other hand the lowest avarege value of RMSE was seen including gender, age, BMI variables.
- At the left-side bridge exercise type at the MLP model the highest avarege value of RMSE was seen including gender, height, weight variables. On the other hand the lowest avarege value of RMSE was seen including gender, BMI variables.
- At the left-side bridge exercise type at the SDT model the highest avarege value of RMSE was seen including gender, height, weight variables. On the other hand the lowest avarege value of RMSE was seen including gender, age, BMI variables.
- At the left-side bridge exercise type at the RBF model the highest avarege value of RMSE was seen including gender, BMI variables. On the other hand the lowest avarege value of RMSE was seen including gender, age,

BMI variables.

- At plank exercise type for all models which includes SVM, GRNN, MLP, SDT, RBF the highest avarege value of RMSE was seen including gender, BMI variables. On the other hand the lowest avarege value of RMSE was seen including gender, age, BMI variables.
- The ranking of machine learning methods in terms of performance from lowest *RMSE*'s to highest ones can be listed as SVM, GRNN, MLP, SDT and RBF for maximum endurance time prediction of which training type is used or which prediction model is considered.

5. CONCLUSION

The use of machine learning methods for the muscular endurance time prediction is relatively recent. However the results obtained especially in this thesis are clearly promising. In order to carry out this study, five main machine learning methods namely SVM, GRNN, MLP, RBF and SDT have been used to build the muscular endurance time prediction models. These prediction models are divided in four categories according to the number of predictor variables. Gender, age, weight, height, BMI and RPE-4, RPE-5, RPE-6, RPE-7, RPE-8 are the predictor variable used in this study. Predictor variable BMI has been used in place of weight and height for a certain number of prediction models. The dataset used for the muscular endurance time prediction included 80 healthy college-aged. Participants were randomly assigned to perform the following core stabilization assessments: Plank, Side Bridge (right-side), Side Bridge (left-side) and Static Spinal Extension.10-fold cross-validation has been used for the calculation of the generalization error of the prediction models. *RMSE*'s and *R*'s have been used for computing the prediction errors.

On the basis of the results obtained, several conclusions can be made on this study. Firstly, the results reveal that machine learning methods especially SVM can be used for estimating the muscular endurance time prediction with an acceptable accuracy. Secondly, SVM-based prediction models outperform the other regression methods utilized in this study, regardless of whether muscular endurance time is predicted; or which category of prediction models is used. The Average decrement rate in *RMSE*'s obtained by SVM-based prediction models varies between 2.78% and 119.36%. On the other hand, RBF exhibits the worst performance for the maximum endurance prediction. Thirdly, the prediction models of maximum endurance time yield lower *RMSE*'s when using the RPE-7 and RPE-8 prediction models.

While this thesis has revealed the potential of using machine learning methods to predict with accuracy the maximum endurance time prediction, many opportunities for improving and extending the result of this thesis remain. For instance, in order to determine discriminative features, feature selection algorithms such as F-scores can be employed. The combination of feature selection algorithms and machines learning methods can improve the future results. Others machines learning methods such as Tree Boost, Logistic Regression and Gene expression programming can be used for estimating the maximum endurance time prediction. Different muscle training methods and additional datasets that include more predictor variable such as the length, the thickness of the muscles can be explored to create more accurate model.

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