Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2017) 25: 2567 – 2582

doi:10.3906/elk-1603-304

Support vector machines for predicting the hamstring and quadriceps muscle strength of college-aged athletes

Mehmet Fatih AKAY[1,*], Fatih ABUT[1], Ebru ÇETİN[2], İmdat YARIM[2], Boubacar SOW[1]

[1]Department of Computer Engineering, Faculty of Engineering and Architecture, Çukurova University, Adana, Turkey

[2]College of Physical Education and Sport, Gazi University, Ankara, Turkey

Received: 29.03.2016 • **Accepted/Published Online:** 20.09.2016 • **Final Version:** 30.07.2017

Abstract: Hamstring and quadriceps muscles are essential for the performance of athletes in various sport branches. Hamstring muscles control running activities and stabilize the knee during turns or tackles, while quadriceps muscles play an important role in jumping and kicking. Although hamstring and quadriceps muscle strength in athletes can be accurately measured using isokinetic dynamometry, practical difficulties, such as the requirement of nonportable and costly equipment as well as a long period of measurement time, motivate the researcher to predict hamstring and quadriceps muscle strength using promising machine-learning methods. The purpose of this study is to build prediction models for estimating the hamstring and quadriceps muscle strength of college-aged athletes using a support vector machine (SVM). The data set included 75 athletes selected from the College of Physical Education and Sport, Gazi University, Turkey. The predictor variables of sex, age, height, weight, body mass index, and sport branch were utilized to build the hamstring and quadriceps muscle strength prediction models for various types of training methods. The generalization error of the prediction models was calculated by carrying out 10-fold cross-validation, and the prediction errors were evaluated using several performance metrics. For comparison purposes, prediction models based on a radial basis function neural network (RBFNN) and single decision tree (SDT) were also developed. The results reveal that the SVM-based hamstring and quadriceps strength prediction models significantly outperform the RBFNN-based and SDT-based models and can be safely utilized to produce predictions regarding new data with acceptable accuracy.

Key words: Support vector machine, radial basis function neural network, single decision tree, hamstring strength, quadriceps strength

1. Introduction

Muscular strength refers to the maximal amount of force that a muscle can apply against resistance in a single effort. The basic purpose of skeletal muscle is the creation of force, either to stabilize and balance the skeleton or to generate movement. Muscular strength is very critical and important for achieving a healthy and high-quality life. In addition to essential motoric parameters, such as endurance, speed, flexibility, and coordination, muscular strength is considered as a further fundamental parameter for athletes' success in their respective sports and is also assumed to be in close relation with each of these four parameters. For instance, trainings conducted for improving fast-running capability include not only speed practices but also muscle strength practices, as athletes' speediness is strongly dependent on their muscle strength [1]. Furthermore, monitoring the strength

*Correspondence: mfakay@cu.edu.tr

and stiffness of an athlete's musculature plays a crucial and important role in planning an appropriate training program, reaching expected levels of performance, avoiding injuries that stem from athletes' weakness, and determining suitable therapy programs to cure these injuries. Knowledge of strength parameters can even be used to gather knowledge in the field of rehabilitation and to develop appropriate treatment regimens. Well-known factors that can affect muscular strength include sex, age, and level of physical conditioning [2].

When recent research in the related literature is investigated, it is seen that athletes of various sport branches require high muscular performance to attain success. Two types of upper leg muscles, hamstring and quadriceps muscles, are especially related to the performance of athletes [3–5]. Quadriceps muscles play an important role in jumping and kicking, while hamstring muscles are found to control running activities and stabilize the knee during turns or tackles.

In the past decades, various techniques have been proposed for the direct measurement of hamstring and quadriceps muscle strength, including dynamometer tests [6], tensiometer tests [7], and isokinetic tests [8]. However, among these, isokinetic testing has become the most popular measurement technique in the field. The first devices conducting isokinetic tests were developed in the late 1960s and they have been indispensable for training and strength measurements of performance athletes ever since [9]. Isokinetic systems target specific muscles or muscle groups at various speeds and angle options and thus enable safe testing of muscle performance. Since isokinetic systems provide numeric measurements for muscle performance, today they are considered as the most preferred method for the rehabilitation of muscle injuries, injury follow-ups, and, most importantly, evaluation of athletes' performance [10].

The direct measurement of hamstring and quadriceps muscle strength in laboratory environments using advanced isometric devices leads to the most certain and accurate results. However, despite a high level of accuracy, the direct measurement of hamstring and quadriceps muscle strength is associated with several practical difficulties and limitations. First, the equipment required for conducting the measurements is highly expensive and not readily available. In particular, such measurement activities are frequently conducted within the scope of research projects in educational institutions or are provided as services in rehabilitation or health care facilities. Second, since those devices are bulky, they are not portable and their usage on the field is impossible. Portable devices, such as dynamometers, could be used on the field for strength measurement; however, they have notoriously limited utility [11]. Third, it is only possible to test one participant at a time and hence the practical application of direct measurement is not feasible for large populations. Finally, direct measurement via isokinetic devices requires expertise, detailed calculations, time-consuming practices, and interpretation of the data. Nevertheless, trainers on the field prefer directly administered, quick-resulting, and practical methods.

Because of these significant disadvantages and difficulties, it may be beneficial to predict rather than measure hamstring and quadriceps muscle strength. Although there are many studies [12–15] in the literature that directly measured hamstring and quadriceps muscle strength in laboratory environments using various test protocols, to the best of our knowledge, no study has ever attempted to predict them via promising machine-learning methods, which provide important tools for intelligent data analysis.

The purpose of this study is to build prediction models for estimating the hamstring and quadriceps muscle strength of college-aged athletes using a support vector machine (SVM). The data set included the data of 75 athletes from the College of Physical Education and Sport, Gazi University, Turkey. The hamstring and quadriceps muscle strength was predicted for various types of training methods by using several scientifically relevant predictor variables such as sex, age, height, weight, body mass index (BMI), and sport branch (SB),

which have previously been shown in the literature to correlate with hamstring and quadriceps muscle strength [16–18]. The generalization error of the prediction models was calculated by carrying out 10-fold cross-validation, and the prediction errors were computed using the root mean square errors (RMSEs), mean absolute errors (MAEs), mean absolute percentage errors (MAPEs), and multiple correlation coefficients (Rs). For comparison purposes, prediction models based on a radial basis function neural network (RBFNN) and single decision tree (SDT) have also been developed. The results have shown that the lowest RMSEs are obtained by the SVM-based models with 15.55 Nm and 24.17 Nm for prediction of hamstring and quadriceps muscle strength, respectively.

2. Data set generation

To create the ground-truth data set, 75 young athletes from the College of Physical Education and Sport of Gazi University were selected for the experiments. Four different protocols were applied to the athletes on different days. In particular, the protocols involved: (a) a light run for 5 min, referred to as classic training (CT); (b) a light run for 5 min, followed by active static stretching for 4 min, referred to as static training (ST); (c) a light run for 5 min and active static stretching for 4 min, followed by a rest for 5 min (ST-5MIN); and (d) a light run for 5 min and active static stretching for 4 min, followed by a rest for 15 min (ST-15MIN).

Subjects were requested to perform a warm-up exercise on a cycle ergometer at 55 $\pm$ 5 rpm for 5 min. The load of the warm-up exercise was adjusted to the subjects' heart rate, which had been previously recorded by a telemetric heart monitor (S810, Polar, Finland). During the warm-up period, the heart rate of the subjects was kept between 100 and 120 bpm.

After each warm-up exercise, the isokinetic strength of subjects was measured by fine-tuning the dynamometer settings according to the subjects' physical structure. The tests were performed in the sitting position, in such a way that subjects were fixed in a specific position on a chair with the help of tapes wrapping their abdomen and thighs. The chair settings involved the adjustment of the rotation degree and back angle, which were set to 40° and 85°, respectively. Dynamometer settings, on the other hand, required the adjustment of the tilt degree, rotation degree, and height, which were set to 0°, 40°, and 8 cm, respectively. Finally, the distance between the chair and the dynamometer was adjusted to 38 cm. During the tests, the subjects were requested to hold their arms on both sides of the chair, so that free movement of the arms was prevented and, at the same time, support was provided for the arms.

The isokinetic strength of all subjects' right upper leg hamstring and quadriceps muscles was measured with an isokinetic dynamometer (Isomed 2000, Germany) at 60°/s angular velocity. During isokinetic strength measurements, subjects were verbally supported with encouraging phrases to sustain and even improve their performance.

The created data set included the predictor variables of sex, age, height, weight, BMI, and SB, as well as the target variables of hamstring and quadriceps muscle strength. In more detail, hamstring and quadriceps muscle strength was measured using four different types of training methods, namely CT, ST, ST-5MIN, and ST-15MIN, which are referred to as hamstring-CT, hamstring-ST, hamstring-ST-5MIN, and hamstring-ST-15MIN and quadriceps-CT, quadriceps-ST, quadriceps-ST-5MIN, and quadriceps-ST-15MIN, respectively. Table 1 gives the minimum, maximum, mean, and standard deviation values for each predictor variable.

3. Prediction models

Three machine-learning methods, including the SVM, RBFNN, and SDT, were utilized to build the hamstring and quadriceps strength prediction models. The selection of these methods depended on several observations

Table 1. Descriptive statistics of predictor variables.

Predictor variable	Minimum	Maximum	Mean	Standard deviation
Sex (M/F)	0	1.00	0.35	0.48
Age (year)	19.00	38.00	21.78	3.06
Height (m)	1.57	2.02	1.71	0.07
Weight (kg)	45.00	93.00	62.04	11.27
BMI (kg/m^2)	16.45	26.31	21.05	2.57
SB	0	16.00	5.94	4.67

gained from the related literature. The SVM, in general, has been reported to be superior to other machine-learning methods, especially in the field of sport physiology [19–21]. The RBFNN is a popular artificial neural network (ANN)-based method that generally has a simpler structure and simpler learning methods than other ANN-based methods. It is considered as the main rival to the popular multilayer perceptron and has the merit of needing comparatively shorter training times. Finally, for the category of tree-structured methods, preference was given to SDT, due to fact that it often exhibits acceptable prediction performance despite negligible training times, which often are in the order of milliseconds.

Using the SVM, RBFNN, and SDT, hamstring and quadriceps muscle strength prediction models were developed in two categories. The first category of prediction models includes the predictor variables of sex, age, height, weight, and SB, whereas the second category of prediction models utilizes the same predictor variables, except that BMI is integrated instead of height and weight. The performance of the SVM-, RBFNN-, and SDT-based models was evaluated by using 10-fold cross validation and computing the values of RMSE, MAE, MAPE, and R, whose equations are given in Eqs. (1)–(4), respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y - Y')^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y - Y'| \tag{2}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y - Y'}{Y}\right| \tag{3}$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{n}(Y - Y')^2}{\sum_{i=1}^{n}\left(Y - \overline{Y}\right)^2}} \tag{4}$$

In Eqs. (1)–(4), 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. The RMSE, MAE, MAPE, and R metrics are the most widely used evaluation measures in the field of sport physiology. In addition, most studies related to the prediction of muscle strength utilize these metrics for performance and accuracy evaluations of prediction models. Particularly, RMSE measures the difference between predicted and measured values, which are squared and then averaged

over the number of total samples. In contrast to RMSE, MAE is less sensitive to occasional very large errors, because it does not square the errors in the calculation. MAPE is expressed in generic percentage terms. It is calculated as the average of the unsigned percentage error. Finally, the correlation coefficient R is a measure of the strength of the linear relationship between predicted and measured values.

The final values of the performance measures for every prediction model were obtained by averaging the values of performance measures for each fold of the 10-fold cross validation process.

3.1. SVM-based prediction models

The performance of an SVM model is affected by several parameters, including the value of C, the value of ε for the ε-insensitive loss function, kernel function type, and the selected parameters related to the kernel. There exists a trade-off between minimizing the complexity of the prediction model and the training error. The trade-off cost is related to the value of C.It is well known that the count of errors in the training phase increments with smaller values of C. On the other hand, a hard-margin SVM-like behavior is observed with a large C. The ε-insensitive loss function, proposed by Vapnik [22], is the most frequently used function to quantify the empirical risk and measure the quality of estimation. The value of ε affects the number of support vectors used to build the regression model. The bigger ε is, the fewer support vectors are selected. On the other hand, bigger ε-values result in flatter predictions. There are many different kernel functions, including the radial basis function (RBF), the polynomial function, and the sigmoid function. After experimenting with those different kernel functions, RBF was chosen in this study to develop the SVM-based prediction models, because the RMSEs obtained by using the RBF kernel were lower than those obtained by the utilization of other kernel functions. The RBF kernel function requires the regularization parameter gamma (γ) to be optimized. Intuitively, γ defines how far the influence of a single training example reaches, with low values meaning 'far' and high values meaning 'near'.

Building an efficient SVM model requires obtaining the optimal values of the three parameters C, ε, and γ. To this end, the grid search method has been used to determine the best values of the mentioned parameters. The idea behind a grid search is simple and it relies on a trial-and-error process. The values of the parameters are varied within a predefined range in the grid search, and the values of C, ε, and γ yielding the maximum prediction performance are selected. The limit values used for the grid search method were selected according to the recommendations made in [23]. Particularly, in [23] it was reported that trying exponentially growing sequences of C and γ is an effective way to determine the optimal values. Similarly, as proposed in .[24], the ε-values were chosen so that the percentage of support vectors in the respective SVM-based models is about 50% of the number of total samples. Table 2 lists the intervals for values of the utilized parameters for SVM-based prediction models.

Table 2. List of intervals for values of the utilized parameters for SVM-based prediction models.

Method	Parameter	Range
SVM	Cost (C)	[2^{-6} to 2^{16}]
	Epsilon (ε)	[0.01–150]
	Gamma (γ)	[2^{-10} to 2^{8}]

The flow chart of the SVM-based prediction model is shown in Figure 1. First, the data set was preprocessed using standardization so that the predictor variables had zero mean and unity variance. This process created new training and testing sets. The advantage of applying a standardization process is that the

predictor variables with high values get scaled. Hence, the computational power regarding creating the SVM prediction model was reduced. 10-fold cross-validation was applied to the data set to validate the models and improve the reliability of the presented results. Therefore, for each fold, the training data included 67 samples, whereas the test data included 8 samples. The optimal values of C, ε, and γ were found by implementing the grid search technique. These values were used for building the prediction model, which in turn was utilized for predicting the hamstring and quadriceps muscle strength values in the test set.

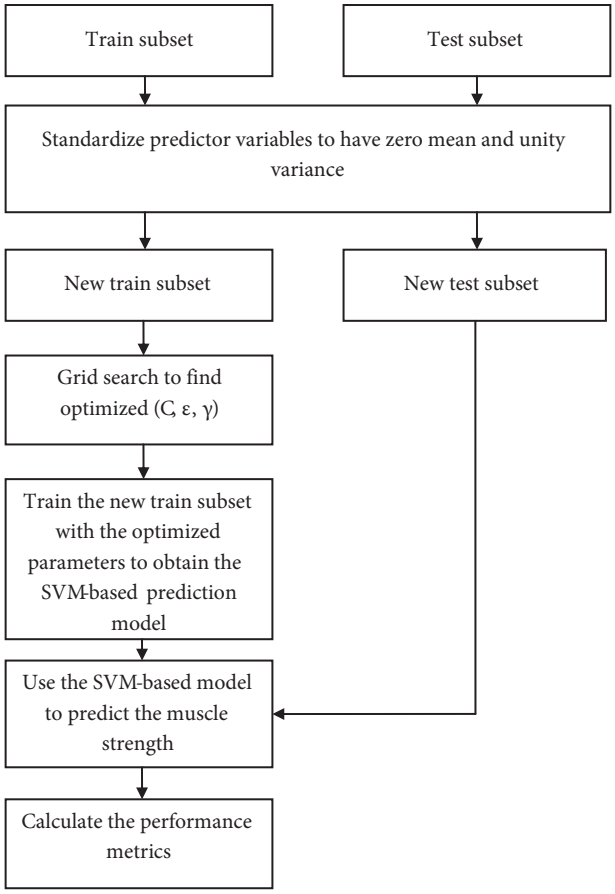

Figure 1. Flow chart of the SVM-based model for predicting the hamstring and quadriceps muscle strength for a single fold.

3.2. RBFNN- and SDT-based prediction models

RBFNNs are composed of a single hidden layer and a single output layer, which work faster compared to multilayer feedforward neural networks that have multiple hidden layers. One kernel function is associated with each hidden node in the RBFNN. The Gaussian function was used as a kernel function of the hidden nodes to develop the hamstring and quadriceps muscle strength prediction models.

Several steps were followed in building the RBFNN-based prediction model. First, after reading all the information from the data set, the network standardization of predictor variables is simulated and initialized. Then a new neuron is added to the RBFNN, and after adjusting the weight for the output layer, the error at the output of the network is computed. If the error is not acceptable, the RBFNN is enriched by inclusion of an additional neuron and then the error check is repeated. Otherwise, the performance of the network

for the test and training data is measured, and it is investigated whether the network exhibits satisfactory performance or not. In the event that the performance is not acceptable, the process reverts to the stage where an additional new neuron is added to the RBFNN and the acceptance checks of the error rates are repeated. The regularization parameter (λ), population size, radius of the RBFNN, and maximum number of neurons are the main parameters impacting the performance of an RBFNN-based model.

For a decision tree, the value of the target variable is predicted by using the values of the predictor variables to move through the tree until a leaf node is reached. The important parameters of the SDT-based prediction model are minimum rows in a node (i.e. a threshold value for the number of rows to fall after splitting), minimum size node to split (i.e. a threshold value for a node to be split), and maximum tree levels.

Table 3 shows the ranges of the utilized values of the parameters for the RBFNN- and SDT-based prediction models.

Table 3. List of intervals for values of the utilized parameters for RBFNN and SDT-based prediction models.

Method	Parameter	Range
RBFNN	Regularization parameter (λ)	[0.001–25]
	Population size	[200–350]
	Radius of the RBFNN	[0.001–400]
	Maximal number of neurons	[90–100]
SDT	Minimum rows in a node	[4–25]
	Minimum size node to split	[5–20]
	Maximum tree levels	[10–20]

4. Results and discussion

Tables 4 and 5 give the descriptive statistics of the measured and predicted target variables with and without BMI cases, respectively. Tables 6–13 show the training and validation results (i.e. the values of RMSE, MAE, MAPE, and R) for all prediction models that are used to predict the hamstring and quadriceps muscle strength for various training types. All following discussions refer to validation results, which are shown in Tables 10–13. However, the same observations also apply to the training results given in Tables 6–9.

In general, the results reveal that SVM-based prediction models yield the lowest RMSEs for the prediction of hamstring and quadriceps muscle strength, independently of which type of training method was applied to the participants. In particular, SVM-based models yield an average RMSE value of 17.20 Nm for the prediction of hamstring muscle strength and an average RMSE value of 26.29 Nm for the prediction of quadriceps muscle strength, respectively. The performance gain among the SVM-based models that yield the lowest and highest RMSEs is 17.46% for the prediction of hamstring muscle strength and 16.10% for the prediction of quadriceps muscle strength, respectively.

In contrast, for the prediction of hamstring muscle strength, the SDT-based prediction models show the worst performance. In particular, the SDT-based models for prediction of hamstring muscle strength yield an average RMSE value of 23.88 Nm. On the other hand, the RBFNN-based prediction models show the worst performance for prediction of quadriceps muscle strength. In particular, the RBFNN-based models for prediction of quadriceps muscle strength yield an average RMSE value of 29.64 Nm.

As compared to the RMSEs obtained by SDT-based prediction models, the average percentage decrement rates in RMSEs obtained by SVM-based prediction models are 12.74%, 12.33%, 23.31%, and 23.72% for the prediction of hamstring-CT, hamstring-ST, hamstring-ST-5MIN, and hamstring-ST-15MIN, respectively, and

Table 4. Descriptive statistics of the measured and predicted target variables (with BMI).

Target variable (Nm)	Minimum	Maximum	Mean	Standard deviation
Hamstring-CT (measured)	50.10	195.90	111.84	36.10
Hamstring-CT (predicted)	48.73	182.17	111.04	33.10
Hamstring-ST (measured)	61.20	197.70	111.61	36.44
Hamstring-ST (predicted)	61.59	190.74	109.21	32.44
Hamstring-ST-5MIN (measured)	56.70	202.20	112.59	36.53
Hamstring-ST-5MIN (predicted)	69.56	180.09	112.37	30.87
Hamstring-ST-15MIN (measured)	46.50	194.60	113.16	36.44
Hamstring-ST-15MIN (predicted)	60.52	187.77	112.74	32.79
Quadriceps-CT (measured)	72.20	285.20	154.77	54.80
Quadriceps-CT (predicted)	94.74	320.43	157.13	53.80
Quadriceps-ST (measured)	85.20	278.10	157.01	54.41
Quadriceps-ST (predicted)	91.90	288.37	156.43	46.33
Quadriceps-ST-5MIN (measured)	85.70	301.20	161.76	56.62
Quadriceps-ST-5MIN (predicted)	100.73	272.79	160.97	47.86
Quadriceps-ST-15MIN (measured)	83.40	280.20	157.88	51.95
Quadriceps-ST-15MIN (predicted)	96.68	255.82	158.31	44.91

Table 5. Descriptive statistics of the measured and predicted target variables (without BMI).

Target variable (Nm)	Minimum	Maximum	Mean	Standard deviation
Hamstring-CT (measured)	50.10	195.90	111.84	36.10
Hamstring-CT (predicted)	63.57	188.99	112.41	33.01
Hamstring-ST (measured)	61.20	197.70	111.61	36.44
Hamstring-ST (predicted)	55.22	278.20	112.33	37.98
Hamstring-ST-5MIN (measured)	56.70	202.20	112.59	36.53
Hamstring-ST-5MIN (predicted)	72.54	187.19	112.39	32.01
Hamstring-ST-15MIN (measured)	46.50	194.60	113.16	36.44
Hamstring-ST-15MIN (predicted)	71.42	196.82	114.31	32.67
Quadriceps-CT (measured)	72.20	285.20	154.77	54.80
Quadriceps-CT (predicted)	90.72	295.94	154.57	49.49
Quadriceps-ST (measured)	85.20	278.10	157.01	54.41
Quadriceps-ST (predicted)	91.13	310.28	156.49	47.95
Quadriceps-ST-5MIN (measured)	85.70	301.20	161.76	56.62
Quadriceps-ST-5MIN (predicted)	78.55	323.22	163.20	54.67
Quadriceps-ST-15MIN (measured)	83.40	280.20	157.88	51.95
Quadriceps-ST-15MIN (predicted)	93.46	281.59	158.03	48.41

4.24%, 9.18%, 6.35%, and 5.81% for the prediction of quadriceps-CT, quadriceps-ST, quadriceps-ST-5MIN, and quadriceps-ST-15MIN, respectively. Similarly, as compared to the RMSEs obtained by RBFNN-based prediction models, the average percentage decrement rates in RMSEs obtained by SVM-based prediction models are 22.83%, 23.24%, 29.80%, and 33.21% for the prediction of hamstring-CT, hamstring-ST, hamstring-ST-5MIN, and hamstring-ST-15MIN, respectively, and 11.39%, 12.00%, 10.94%, and 10.78% for the prediction of quadriceps-CT, quadriceps-ST, quadriceps-ST-5MIN, and quadriceps-ST-15MIN, respectively. Figures 2–5 illustrate the percentage decrement rates in RMSEs of hamstring and quadriceps muscle strength for SVM compared to RMSEs obtained by RBFNN and SDT.

Table 6. Averages of 10-fold training results for hamstring strength prediction models using various muscle-training types (with BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R	Training time (s)
CT	SVM	10.62	8.32	8.07	0.91	01.47
	SDT	18.92	14.71	13.90	0.72	00.20
	RBFNN	14.91	11.87	12.00	0.83	07.15
ST	SVM	11.19	9.03	8.70	0.89	01.40
	SDT	18.83	14.69	13.73	0.73	00.20
	RBFNN	13.72	10.07	9.49	0.88	06.19
ST-5MIN	SVM	12.30	8.75	8.57	0.89	02.54
	SDT	19.30	14.67	13.52	0.72	00.18
	RBFNN	13.24	10.10	9.46	0.87	10.00
ST-15MIN	SVM	13.91	11.00	10.76	0.85	01.40
	SDT	20.11	15.30	14.74	0.69	00.18
	RBFNN	14.90	10.75	11.18	0.83	11.50

Table 7. Averages of 10-fold training results for hamstring strength prediction models using various muscle-training types (without BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R	Training time (s)
CT	SVM	12.39	8.30	8.36	0.88	01.01
	SDT	14.07	10.65	10.79	0.85	00.19
	RBFNN	13.59	10.21	10.11	0.86	06.04
ST	SVM	11.69	8.01	7.87	0.91	01.11
	SDT	15.83	14.69	13.73	0.73	00.24
	RBFNN	13.37	9.99	9.46	0.86	10.67
ST-5MIN	SVM	13.66	8.21	8.11	0.86	01.11
	SDT	14.92	11.64	11.31	0.83	00.22
	RBFNN	14.07	9.90	9.47	0.85	08.20
ST-15MIN	SVM	13.67	10.18	10.42	0.86	05.51
	SDT	20.11	15.30	14.74	0.69	00.22
	RBFNN	14.24	9.76	10.40	0.85	07.38

In general, hamstring muscle strength prediction models yield lower RMSEs than quadriceps muscle strength prediction models, regardless of which regression method or training type was utilized. In particular, as compared to RMSEs of quadriceps muscle strength prediction models, the average percentage decrement rates in RMSEs for hamstring muscle strength prediction models are 34.56%, 28.60%, and 19.42% for SVM, RBFNN, and SDT, respectively.

The RMSEs of the prediction models for classic and static training have been found to be comparable, regardless of whether SVM, RBFNN, or SDT have been utilized for model development. On the other hand, there is no specific order between ST-5MIN and ST-15MIN, but the RMSEs related to ST-5MIN and ST-15MIN prediction models are always higher than those of CT and ST.

In general, using height and weight instead of BMI gives much lower RMSEs for the prediction of hamstring and quadriceps muscle strength, irrespective of whether SVM, RBFNN, or SDT has been used for model development, or which type of training method has been applied to the participants.

Table 8. Averages of 10-fold training results for quadriceps strength prediction models using various muscle-training types (with BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R	Training time (s)
CT	SVM	19.39	13.71	9.38	0.87	01.65
	SDT	24.68	18.52	12.71	0.79	00.18
	RBFNN	27.95	20.41	13.90	0.74	11.55
ST	SVM	18.53	14.73	10.18	0.88	01.50
	SDT	25.50	16.40	11.28	0.86	00.22
	RBFNN	27.07	21.52	14.20	0.75	10.71
ST-5MIN	SVM	21.83	16.54	10.59	0.85	01.57
	SDT	22.27	17.42	11.55	0.84	00.22
	RBFNN	24.67	15.39	9.73	0.84	11.58
ST-15MIN	SVM	12.50	9.11	6.24	0.94	04.42
	SDT	17.48	12.68	8.53	0.89	00.19
	RBFNN	22.62	18.77	12.41	0.77	09.19

Table 9. Averages of 10-fold training results for quadriceps strength prediction models using various muscle-training types (without BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R	Training time (s)
CT	SVM	18.45	13.02	9.01	0.88	05.39
	SDT	21.46	16.19	11.86	0.84	00.22
	RBFNN	21.70	14.49	9.76	0.84	09.56
ST	SVM	17.24	12.61	9.02	0.90	03.30
	SDT	20.61	18.54	12.78	0.81	00.20
	RBFNN	21.73	14.91	10.09	0.85	08.35
ST-5MIN	SVM	19.35	13.72	9.32	0.88	01.57
	SDT	22.66	17.01	10.91	0.84	00.23
	RBFNN	28.25	21.35	13.49	0.75	12.00
ST-15MIN	SVM	12.85	9.67	7.07	0.94	01.45
	SDT	22.44	15.11	9.73	0.81	00.20
	RBFNN	24.67	18.77	12.41	0.77	10.49

The Wilcoxon signed-rank test, the details of which are given in [25], has been applied to determine the statistical significance of SVM-based prediction results as well as the percentage decrement rates in the RMSEs of SVM-based models compared to the RMSEs of RBFNN- and SDT-based prediction models.

The Wilcoxon signed-rank test was applied to four different pair sets, including (SVM, RBFNN)$_H$, (SVM, SDT)$_H$, (SVM, RBFNN)$_Q$, and (SVM, RBFNN)$_Q$ pairs, which represent the corresponding SVM-, RBFNN-, and SDT-based RMSEs of hamstring and quadriceps muscle strength predictions. The sample size in each test case is eight ($n = 8$) and the two-sided level of significance, i.e. α, is set to 0.05. The test statistic for the Wilcoxon signed-rank test is W, defined as the smaller of $W+$ and $W-$, which are the sums of the positive and negative ranks, respectively. It is to be checked whether the observed test statistic W supports the null or research hypothesis. This check is performed using the critical value of W, which can be found using a predefined and well-known table of critical values. The calculated value of W in each case equals zero, and the critical value of W for $n = 8$ at $\alpha = 0.05$ is 3. Since W is less than the critical value, the null hypothesis is rejected, and it can be concluded that the performance gain obtained by SVM-based models compared to

Table 10. Averages of 10-fold validation results for hamstring strength prediction models using various muscle-training types (with BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R
CT	SVM	17.67	13.94	14.19	0.76
	RBFNN	20.50	15.21	14.99	0.67
	SDT	24.28	18.48	17.03	0.54
ST	SVM	17.39	13.89	13.39	0.77
	RBFNN	20.32	16.13	15.02	0.68
	SDT	24.15	17.83	16.64	0.55
ST-5MIN	SVM	18.84	14.61	14.65	0.73
	RBFNN	24.19	18.51	17.61	0.56
	SDT	26.26	18.96	18.48	0.48
ST-15MIN	SVM	18.30	14.19	14.66	0.74
	RBFNN	25.03	18.61	17.25	0.52
	SDT	28.63	21.07	20.47	0.37

Table 11. Averages of 10-fold validation results for hamstring strength prediction models using various muscle-training types (without BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R
CT	SVM	15.55	11.40	11.35	0.81
	RBFNN	17.60	12.73	12.41	0.76
	SDT	19.05	14.75	14.55	0.72
ST	SVM	15.75	12.38	11.93	0.81
	RBFNN	17.54	13.85	13.20	0.76
	SDT	19.31	14.95	13.95	0.72
ST-5MIN	SVM	17.17	13.64	13.35	0.78
	RBFNN	22.74	16.45	15.57	0.61
	SDT	25.01	18.75	18.26	0.52
ST-15MIN	SVM	16.99	12.37	13.20	0.78
	RBFNN	21.37	16.36	16.35	0.65
	SDT	24.38	17.55	17.24	0.55

Table 12. Averages of 10-fold validation results for quadriceps strength prediction models using various muscle-training types (with BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R
CT	SVM	27.21	20.86	14.42	0.75
	SDT	28.28	20.53	13.74	0.73
	RBFNN	30.93	23.30	16.07	0.68
ST	SVM	27.01	21.28	14.89	0.75
	SDT	29.95	23.23	15.63	0.69
	RBFNN	30.50	24.36	16.63	0.61
ST-5MIN	SVM	28.32	20.47	12.84	0.75
	SDT	30.17	22.05	13.83	0.71
	RBFNN	31.51	24.12	15.58	0.69
ST-15MIN	SVM	28.16	22.05	14.57	0.70
	SDT	30.55	22.11	15.25	0.65
	RBFNN	31.87	22.07	14.63	0.62

Table 13. Averages of 10-fold validation results for quadriceps strength prediction models using various muscle-training types (without BMI).

Training type	Models	RMSE (Nm)	MAE	MAPE (%)	R
CT	SVM	24.17	17.61	12.01	0.80
	SDT	25.35	18.87	13.35	0.78
	RBFNN	27.07	20.26	14.14	0.75
ST	SVM	23.76	18.16	12.52	0.81
	SDT	25.97	20.25	13.58	0.79
	RBFNN	27.16	19.50	13.15	0.75
ST-5MIN	SVM	26.52	19.77	12.90	0.78
	SDT	28.38	21.38	13.51	0.75
	RBFNN	30.05	20.71	13.72	0.71
ST-15MIN	SVM	25.24	18.54	11.93	0.76
	SDT	26.24	19.82	12.93	0.74
	RBFNN	28.03	17.88	12.90	0.70

Table 14. z-scores and p-values for each pair of muscle-training type (with BMI).

Muscle-training type	z-score	p-value
Hamstring-CT	–0.38	0.70
Hamstring-ST	–0.55	0.58
Hamstring-ST-5MIN	–0.12	0.90
Hamstring-ST-15MIN	–0.41	0.68
Quadriceps-CT	–0.29	0.77
Quadriceps-ST	–0.03	0.98
Quadriceps-ST-5MIN	–0.20	0.84
Quadriceps-ST-15MIN	–0.06	0.95

Table 15. z-scores and p-values for each pair of muscle-training type (without BMI).

Muscle-training type	z-score	p-value
Hamstring-CT	–0.14	0.89
Hamstring-ST	–0.28	0.78
Hamstring-ST-5MIN	–0.21	0.83
Hamstring-ST-15MIN	–0.16	0.87
Quadriceps-CT	–0.42	0.67
Quadriceps-ST	–0.34	0.73
Quadriceps-ST-5MIN	–0.04	0.97
Quadriceps-ST-15MIN	–0.16	0.87

RBFNN- and SDT-based models is statistically significant at $\alpha = 0.05$, independently of whether hamstring or quadriceps muscle strength is predicted.

After investigating the performance gain of the SVM-based models, the Wilcoxon signed-rank test was also utilized to determine whether the differences between the measured and predicted values of hamstring and quadriceps muscle strength, obtained by SVM, are statistically significant or not. In this case, the value of n is set to 75 samples, whereas the two-sided level of significance, α, is again used as 0.05. Depending on the case considered, the minimum W values range from 1149 to 1237.5. Since the sample size is greater than 20, the

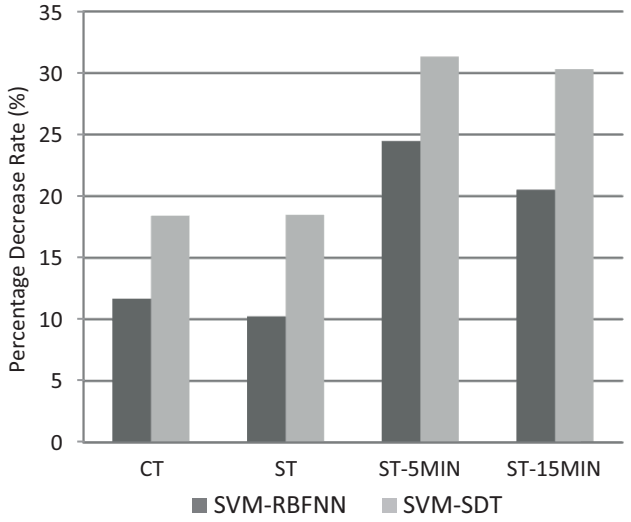

Figure 2. Percentage decrement rates in RMSEs of hamstring strength prediction with SVM compared to RMSEs obtained by RBFNN and SDT (without BMI).

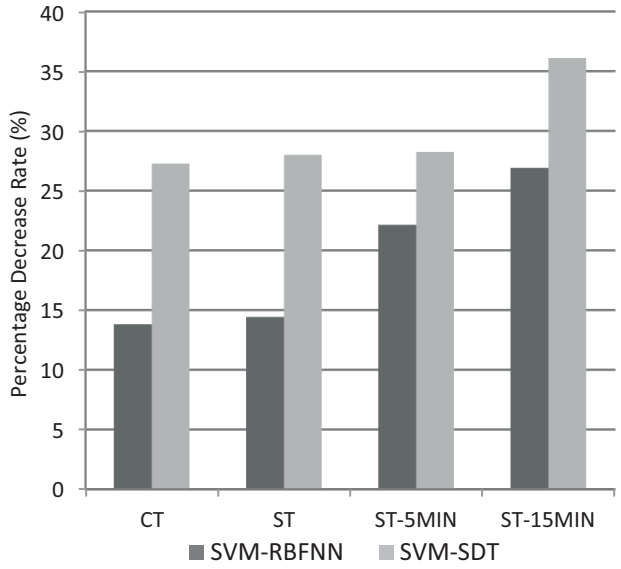

Figure 3. Percentage decrement rates in RMSEs of hamstring strength prediction with SVM compared to RMSEs obtained by RBFNN and SDT (with BMI).

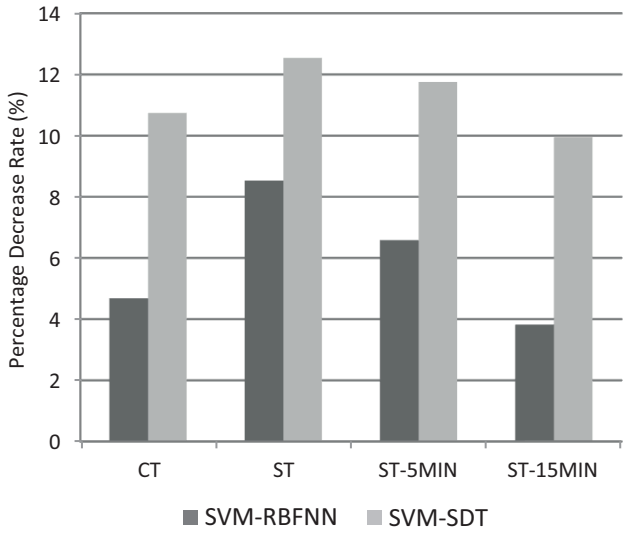

Figure 4. Percentage decrement rates in RMSEs of quadriceps strength prediction with SVM compared to RMSEs obtained by RBFNN and SDT (without BMI).

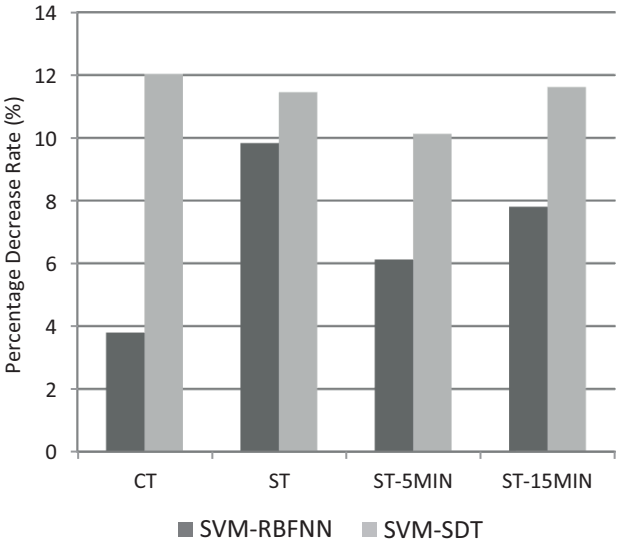

Figure 5. Percentage decrement rates in RMSEs of quadriceps strength prediction with SVM compared to RMSEs obtained by RBFNN and SDT (with BMI).

table of critical values for W cannot be utilized [26]. Alternatively, statistical analysis can be conducted using the normal distribution approximation. In this case, the required calculations for different cases yield z-scores ranging from –0.55 to –0.03, which in turn yield p-values in the range of 0.58 and 0.98 for $\alpha = 0.05$. All p-values are higher than α; therefore, the null hypothesis is accepted. In conclusion, the test results reveal that there is a statistically insignificant difference between measured and predicted values of SVM-based hamstring and quadriceps muscle strength prediction models. Tables 14 and 15 show z-scores and p-values for each pair of muscle-training type with and without BMI cases, respectively.

There are some indirectly related studies [27–30] in the literature that also predict other specific types of muscle strength, such as back extensor muscle strength or skeletal muscle strength, via multiple regression analysis. However, to the best of our knowledge, there is only a single study [31] in the literature that is directly associated with our work. This study utilizes various equations (which are not based on machine-learning algorithms) for predicting quadriceps muscle strength. As outlined below, there are several major differences between the current study and the study in [31]:

- In [31], empirical prediction equations with just two independent variables, including weight and repetitions to failure, were utilized. In contrast, the current study predicted both the hamstring and quadriceps muscle strength by using several predictor variables and promising machine-learning methods with intelligent data analysis capabilities. The effect of classic and static trainings on hamstring and quadriceps muscle strength prediction was also investigated. Thus, the research results presented in this study are more comprehensive.
- The study in [31] requires the subjects to complete a submaximal exercise test in order to generate the predictions. In contrast, the current study provides a significant benefit by proposing nonexercise-based prediction models that can be quickly applied to large populations without the need to perform any prior exercise tests.
- In [31], the number of subjects within the utilized data set is very limited and only includes a group of 18 homogeneous subjects with osteoarthritis of the knee joint. In contrast, this study utilizes a data set comprising 75 college-aged athletes, who are active in various sports branches.

Keeping these differences in mind, the performance of the models for prediction of quadriceps muscle strength, evaluated in both studies, has also been compared. The difficulty here was that both studies used different evaluation metrics with different units, which do not allow a direct comparison of the performances of the prediction models. In particular, in contrast to the current study, which used metrics including RMSE, MAE, MAPE, and R, the study in [31] used the typical error as the main performance evaluation criterion. Thus, to enable a comparison between the results of the two studies, the typical error values of the prediction models proposed in this study have also been calculated. In [31], it was reported that the values of the typical error range from 3.1 kg to 5.2 kg, whereas the values of typical error of SVM-based models in this study range from 3.9 Nm to 6.4 Nm. It is obvious that the lowest typical error values achieved in this study and those reported in [31] have different units; therefore, a direct comparison of the results of both studies is not feasible. However, significant advantages, such as nonexercise-based usage and applicability to a broader range of college-aged athletes, make the prediction models proposed in this study reasonable alternative solutions.

5. Conclusion and future work

In this study, 75 healthy young athletes from Gazi University, Turkey, were examined to determine the possibility of predicting hamstring and quadriceps muscle strength from sex, age, height, weight, BMI, and SB. Four different muscle training methods were used, including CT, ST, ST-5MIN, and ST-15MIN. The prediction models were developed based on the SVM, RBFNN, and SDT. For model validation, 10-fold cross-validation was conducted and the accuracy of the prediction models was evaluated by calculating the values of RMSE, MAE, MAPE, and R.

Several conclusions can be drawn from the results of this study. First, among the machine-learning methods, the SVM-based models exhibited the best performance with acceptable RMSEs, independently of

whether quadriceps or hamstring muscle strength had been predicted or which type of training method had been applied to the participants. Depending on the type of training method, hamstring muscle strength was predictable with RMSEs of 15.55–18.84 Nm, whereas the RMSEs of quadriceps muscle strength prediction varied from 23.76 Nm to 28.32 Nm, respectively. Second, the models built for the prediction of hamstring muscle strength give much lower RMSEs than the models developed for the prediction of quadriceps muscle strength, regardless of which regression method or training type has been utilized. Third, it has been shown that the CT and ST models for predicting hamstring and quadriceps muscle strength exhibit comparable performance and yield the lowest RMSEs. In contrast, the RMSEs of the ST-5MIN and ST-15MIN prediction models are higher than those of CT and ST prediction models. Finally, all prediction models that use height and weight instead of BMI, in addition to other predictor variables, lead to relatively lower RMSEs for each machine-learning method and training type.

This is the first major study that used intelligent regression methods for the prediction of hamstring and quadriceps muscle strength of the upper leg. Several research directions for future work are available for this prediction field. The prediction models proposed in this study can be developed into practical prediction applications that can serve as a feasible alternative solution to the direct measurement of hamstring and quadriceps muscle strength. Other candidate potential predictors of hamstring and quadriceps muscle strength, such as the length and width of the bone and leg fat-free mass, can be tested to investigate whether more accurate prediction models can be built. Finally, various feature selection algorithms can be applied to identify the relevant and irrelevant predictors among the set of candidate predictors of hamstring and quadriceps muscle strength.

References

[1] Di Michele R, Del Curto L, Merni F. Mechanical and metabolic responses during a high-intensity circuit training workout in competitive runners. J Sports Med Phys 2012; 52: 33-39.

[2] Faigenbaum AD, Myer GD. Resistance training among young athletes: safety, efficacy and injury prevention effects. Br J Sports Med 2010; 44: 56-63.

[3] Aginsky J, Neophytou N, Charalambous T. Isokinetic hamstring and quadriceps muscle strength profiles of elite South African football players. Afr J Phys Heal Educ Recreat Danc 2015; 20: 1225-1236.

[4] Greco CC, Da Silva WL, Camarda SRA, Denadai BS. Rapid hamstrings/quadriceps strength capacity in professional soccer players with different conventional isokinetic muscle strength ratios. J Sports Sci Med 2012; 11: 418-422.

[5] Jordan MJ, Aagaard P, Herzog W. Rapid hamstrings/quadriceps strength in ACL-reconstructed elite Alpine ski racers. Med Sci Sports Exerc 2015; 47: 109-119.

[6] Ford-Smith CD, Wyman JF, Elswick RK, Fernandez T. Reliability of stationary dynamometer muscle strength testing in community-dwelling older adults. Arch Phys Med Rehabil 2001; 82: 1128-1132.

[7] Clarke HH. Comparison of instruments for recording muscle strength. Res Quart Am Assoc Heal Phys Educ Recreat 2013; 25: 398-411.

[8] Montgomery LC, Douglass LW, Deuster PA. Reliability of an isokinetic test of muscle strength and endurance. J Orthop Sports Phys Ther 1989; 10: 315-322.

[9] Tate CM, Williams GN, Barrance PJ, Buchanan TS. Lower extremity muscle morphology in young athletes: an MRI-based analysis. Med Sci Sports Exerc 2006; 38: 122-128.

[10] Manca A, Solinas G, Dragone D, Deriu F. Isokinetic testing of muscle performance: new concepts for strength assessment. Isokinet Exerc Sci 2015; 23: 69-75.

[11] Harman E. Principles of test selection and administration. In: Haff GG, Triplett NT, editors. Essentials of Strength Training and Conditioning. 4th ed. Champaign, IL, USA: Human Kinetics, 2008. pp. 238-247.

[12] Maayah MF, Al-Jarrah MD, El Zahrani SS, Alzahrani AH, Ahmedv ET, Abdelaziem AA, Lakshmanan G, Almawajdeh NA, Alsufiany MB, Asi YOM. Test-retest strength reliability of the Electronic Push/Pull Dynamometer (EPPD) in the measurement of the quadriceps and hamstring muscles on a new chair. Open J Intern Med 2012; 2: 123-128.

[13] Barber-Westin SD, Noyes FR, Galloway M. Jump-land characteristics and muscle strength development in young athletes: a gender comparison of 1140 athletes 9 to 17 years of age. Am J Sports Med 2006; 34: 375-384.

[14] Ferro E. Intra- and inter-reliability of lower extremity muscle strength measurements using a hand-held dynamometer with and without a stabilization strap. Int J Exerc Sci 2011; 2: 23.

[15] Kılınç BE, Kara A, Camur S, Oc Y, Celik H. Isokinetic dynamometer evaluation of the effects of early thigh diameter difference on thigh muscle strength in patients undergoing anterior cruciate ligament reconstruction with hamstring tendon graft. J Exerc Rehabil 2015; 11: 95-100.

[16] Lemmer JT, Hurlbut DE, Martel GF, Tracy BL, Ivey FM, Metter EJ, Fozard JL, Fleg JL, Hurley BF. Age and gender responses to strength training and detraining. Med Sci Sports Exerc 2000; 32: 1505-1512.

[17] Lindle RS, Metter EJ, Lynch NA, Fleg JL, Fozard JL, Tobin J, Roy TA, Hurley BF. Age and gender comparisons of muscle strength in 654 women and men aged 20–93 yr. J Appl Physiol 1997; 83: 1581-1587.

[18] Dervišević E, Hadžić V. Quadriceps and hamstrings strength in team sports: Basketball, football and volleyball. Isokinet Exerc Sci 2012; 20: 293-300.

[19] Akay MF, Abut F, Özçiloğlu M, Heil D. Identifying the discriminative predictors of upper body power of cross-country skiers using support vector machines combined with feature selection. Neural Comput Appl 2016; 27: 1785-1796.

[20] Abut F, Akay MF. Machine learning and statistical methods for the prediction of maximal oxygen uptake: recent advances. Med Device 2015; 8: 369-379.

[21] Acikkar M, Akay MF, Ozgunen KT, Aydin K, Kurdak SS. Support vector machines for aerobic fitness prediction of athletes. Expert Syst Appl 2009; 36: 3596-3602.

[22] Vapnik V. The Nature of Statistical Learning Theory. 2nd ed. New York, NY, USA: Springer, 2000.

[23] Hsu CW, Chang CC, Lin CJ. A Practical Guide to support Vector Classification. Taipei, Taiwan: National Taiwan University, 2003.

[24] Mattera D, Haykin S. Support vector machines for dynamic reconstruction of a chaotic system. In: Schölkopf B, Burges C, editors. Advances in Kernel Methods. Cambridge, MA, USA: MIT Press, 1999. pp. 211-241.

[25] Taheri SM, Hesamian G. A generalization of the Wilcoxon signed-rank test and its applications. Stat Pap 2012; 54: 457-470.

[26] Anaene Oyeka IC, Ebuh GU. Modified Wilcoxon signed-rank test. Open J Stat 2012; 2: 172-176.

[27] Tan S, Wang J, Liu S. Establishment of the prediction equations of 1RM skeletal muscle strength in 60- to 75-year-old Chinese men and women. J Aging Phys Act 2015; 23: 640-646.

[28] Muraki S, Fukumoto K, Fukuda O. Prediction of the muscle strength by the muscle thickness and hardness using ultrasound muscle hardness meter. Springerplus 2013; 2: 457.

[29] Maeda T, Oowatashi A, Kiyama R, Yoshida Y, Sakae K. Prediction of muscle strength using length and width of the bone. J Phys Ther Sci 2001; 13: 27-30.

[30] Mannion AF, Adams MA, Cooper RG, Dolan P. Prediction of maximal back muscle strength from indices of body mass and fat-free body mass. Rheumatology 1999; 38: 652-655.

[31] McNair PJ, Colvin M, Reid D. Predicting maximal strength of quadriceps from submaximal performance in individuals with knee joint osteoarthritis. Arthritis Care Res (Hoboken) 2011; 63: 216-222.