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Prediction of College Students' Physical Fitness Based on K-Means Clustering and SVR

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In today's modern society, the physical fitness of college students is gradually declining. In this paper, a prediction model for college students' physical fitness is established, in which support vector regression (SVR) and k-means clustering are combined together for the prediction of college students' fitness. Firstly, the physical measurement data of college students are classified according to gender and class characteristics. Then, the k-means clustering method is used to classify the physical measurement data of college students. Next, the physical characteristics of college students are extracted by SVR to establish the prediction model of physical indicators, and the model for predicting college students' fitness can be obtained after scoring their physical fitness levels. Finally, based on college physical test data of students at a university in China, the prediction results show that the method has high predictive accuracy compared to other methods.

Keywords: Prediction technology, College students physical fitness, K-means clustering; SVR.

1. INTRODUCTION

With the continuous decline of teenagers' physical fitness, Miller and Fry (2018) have proposed that the country begin to attach importance to sports and health-promoting activities. Because many students do not seem capable of taking appropriate measures to maintain or improve their own physical fitness, schools should vigorously promote physical education and the health education. Jin et al. (2018) have proposed that through physical education and health education, schools can raise students' awareness of the importance of physical exercise and improving their physical fitness. In the whole educational program, the prediction of physical fitness plays a leading role. An accurate prediction of students' physical fitness can enable a school to determine the future trend of students' fitness in advance. Hence, McLester et al. (2017) have proposed that appropriate and effective physical fitness exercises can be formulated in time.

At present, prediction technology is used in various fields and can be divided into two categories. The first one is time series modelling, which is based on statistical learning. The other method is to establish the prediction model of constitution mechanism. By analyzing the relationship between the data features, Mingoia et al. (2017) proposed that the data features which are related to the results of physical fitness are mined. The machine learning method was used to establish the mechanism model of all the characteristics and physical fitness results (Han, Biao et al. (2018). Through data analysis, the former is mostly suitable for time series modelling, and the machine modelling method is suitable for physical fitness prediction. In this paper, the latter will be used to build a prediction model for college students' physical test data.

The physical fitness of students, and its perceived decline, has been playing a guiding role in physical education. Up to now, there has been a great deal of research in this area with corresponding results. Through the measurement of physical activity behaviour, Lemoyne and Valois (2014) have proposed that TPB variables and body self-concept. The structural equation model was used for statistical analysis, and showed that the gap between intention and physical activity had increased. Taking the perspective of gender and race (white, black), Penkal and Kurdek (2007) explored

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college students' dissatisfaction with various aspects of their bodies and their anxiety about their physical appearance. The multidimensional risk model was constructed to study college students' body dissatisfaction. Lundgren and Thompson (2004) have explored correlations between fear of negative physical appearance and measures of social system anxiety, body image, eating attitudes, and mood. A method for evaluating and predicting adolescent body image, dietary attitude and mood is proposed. Considering the influence of gender, family history, exercise status and other factors, Cox and Mayhew (1997) analyzed factors such as social physical anxiety, gender, body fat (% fat) using a stepwise multiple regression method to predict eating behaviour disorders. Moreover, these methods are based on the psychological behaviour of adolescents to predict the physical conditions of adolescents. However, the more advanced prediction algorithms are not used. In recent years, Cao et al. (2014) have proposed more mature algorithms that include support vector machines, artificial neural networks, extreme learning machines, etc. At present, college students constitute the majority of youth. In addition, there are many physical test data of college students in colleges and universities, which can achieve more objective physical prediction of college students. Therefore, this paper proposes a new method for predicting the physical fitness of college students by combining k-means and SVR.

SVR is known for its good generalization ability. By establishing a minimum risk structure, Al-Shehri et al. (2017) proposed that small errors can still be obtained in the face of small sample problems. The algorithm uses the nonlinear function to map the low-dimensional sample points to the high-dimensional characterization space, and then conducts linear regression in the high-latitude characterization space. Cheng (2017) proposed that the prediction model obtained by using this algorithm has the advantage of being highly accurate. In addition, the physical data of college students are diverse, and gender, region and other differences will also have a great impact on the prediction results. Therefore, the k-means algorithm should be adopted to cluster the physical test data of college students. Data with similar physical conditions are grouped together for analysis.

Based on the above discussions, a method for predicting college students' physical fitness is proposed. The correlation analysis of the characteristics of each body measurement index is carried out to obtain the feature set with larger correlation. SVR is able to map small samples with high precision. The prediction model was established for the body measurement data after cluster analysis (Sang-Bing Tsai et al., 2014). The prediction model for college students' physical fitness using college students' physical test data is established. This prediction model is more objective and plays a positive role in guiding the teaching of physical education courses in colleges and universities.

The rest of the paper is organized as follows: In Section 2, the clustering analysis of college students sports test data based on K-Means is proposed. The prediction model of college students sports test data based on SVR is developed in Section 3. In Section 4, simulation results are presented to illustrate the effectiveness and usefulness of the proposed prediction model. Finally, Section 5 presents the conclusions.

2. CLUSTERING ANALYSIS OF COLLEGE STUDENTS SPORTS TEST DATA BASED ON K-MEANS

2.1 Principle of K-Means Algorithm

The data on college students' physical tests contain a lot of potential information, which is of great significance in predicting the physical fitness of college students. K-means is a clustering analysis method for a group of data based on the principle of the closest distance from the data centre, which can cluster data of the same class and improve the accuracy of prediction. The k-means method involves dividing the given sample set into k clusters according to the distance between samples. The algorithm flow is:

Step 1. The elbow rule is adopted to solve the k value in the k-means algorithm. When the sum of the squared errors (SSE) of all clustering samples reaches the minimum, the corresponding k is the clustering number that needs to be determined.

$$SSE = \sum_{i=1}^{k} \sum_{p \in C_i} |p - m_i|^2 \tag{1}$$

where C_i is the ith cluster. p is sample point. m_i is the centre. SSE is the clustering error of all samples.

Step 2. K samples were randomly selected from dataset $D = \{x_1, x_2, \cdots, x_m\}$, which is used as the initial k centroid vectors.

$$\{m_1, m_2, \cdots, m_k\} \tag{2}$$

Step 3. For $n = 1, 2, \cdots, N$,

1) The initial cluster of C is divided into $C_t = \oslash, t = 1, 2 \cdots, k$.
2) For $i = 1, 2, \cdots, m$, the distance d_{ij} between sample x_i and each center of mass vector $\mu_j (j = 1, 2, \cdots, k)$ is calculated. Mark x_i as category λ_i for the smallest d_{ij}

$$d_{ij} = \|x_i - m_j\|_2^2 \tag{3}$$

3) In this paper, the new center of mass m_j is recalculated for all samles in $C_j (j = 1, 2, \cdots, k)$.

$$m_j = \frac{1}{|C_j|} \sum_{x \in C_j} x \tag{4}$$

4) If all k centroid vectors are unchanged, go to step 4.

Step 4. Output cluster partition $C = \{C_1, C_2, \cdots, C_k\}$

2.2 Sports Test Data Analysis

Zhang and Guo (2017) have determined that the physical test dataset of college students contains characteristic information such as birthplace, gender, nationality, class and age, etc. Hence, much of the physical test data of college students need to be classified according to these characteristics. The application of shallow level data mining can improve to improving the accuracy of the prediction of college students' physical measurement data. Now the k-means algorithm is adopted to cluster the physical measurement data of students at a certain college in China.

The prediction of college students' test data is based on machine learning. Therefore, Pearson correlation coefficient analysis of the physical characteristics of college students is a very simple and effective method, which makes the method of predicting college students' physical fitness more accurate. Al-Shehri et al. (2017) have proposed that Pearson correlation coefficient is shown by

$$\rho_{X,Y} = \frac{\operatorname{cov}(X, Y)}{\sigma_X \bullet \sigma_Y} = \frac{E(X - \mu_X) \bullet (Y - \mu_Y)}{\sigma_X \bullet \sigma_Y} \tag{5}$$

where $\operatorname{cov}(X, Y)$ is the covariance of sample vectors X and Y, σ_X and σ_Y are the mean of sample vector X and Y respectively.

Therefore, Leasure, et al. (2015) proposed that the correlation coefficient analysis be carried out on the feature vector of physical test data after classification. Therefore, the correlation analysis is carried out between the feature vector of physical test data in college students' fourth year, and the corresponding feature vector of physical test data in the previous three years.

Remark 1 It should be pointed out that the k-means clustering method has a more comprehensive and fuller effect than the traditional classification method based on gender, region and other characteristics. Furthermore, by analyzing the Pearson correlation coefficient between variables, useful information in variables can be mined more accurately, giving the final prediction results greater accuracy.

3. PREDICTION OF COLLEGE STUDENTS PHYSICAL FITNESS BASED ON K-MEANS AND SVR

3.1 Principle of SVR

Support vector regression (SVR) was proposed in 1996 and, to date, has been used in various field. The basic expression of SVR is

$$f(x) = w \bullet x + b \tag{6}$$

On this basis, $\in$ loss deviation is introduced, and then Eq. (2) can be represented as

$$\min_{w,b} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m} l_{\in}[f(x_i) - y_i] \tag{7}$$

where C is the regularization constant; $l_{\in}$ is $\in$ insensitive loss function

$$l_{\in} = \begin{cases} 0, |z| \leq \in \\ |z| - \in, |z| > \in \end{cases} \tag{8}$$

where $|z| = |f(x_i) - y_i|$, the relaxation variables ξ_i and ζ_i are introduced, and equation (3) can be rewritten as

$$\min_{w,b,\xi_i,\zeta_i} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \zeta_i) \tag{9}$$

The above expression can be solved by using the Lagrangian multiplier $u_i, \geq 0, \hat{u}_i \geq 0, \alpha_i \geq 0, \hat{\alpha}_i \geq 0$, the Lagrangian function is obtained

$$\begin{aligned} & f(x_i) - y_i \leq \in + \xi_i, \\ \text{s.t. } & y_i - f(x_i) \leq \in + \zeta_i, \\ & \xi_i \geq 0, \zeta_i \geq 0, i = 1, 2, \cdots m \end{aligned} \tag{10}$$

$$\begin{aligned} & L(w, b, \alpha, \hat{a}, \xi, \hat{\xi}, u, \hat{u}) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \hat{\xi}_i) - \\ & \sum_{i=1}^{m} u_i\xi_i - \sum_{i=1}^{m} u_i\zeta_i + \sum_{i=1}^{m} a_i[f(x_i) - y_i - \in - \xi_i] + \\ & \sum_{i=1}^{m} \hat{\alpha}_i[y_i - f(x_i) - \in - \hat{\zeta}_i] \end{aligned} \tag{11}$$

If the partial derivative of $L(w, b, \alpha, \hat{a}, \xi, \hat{\xi}, u, \hat{u})$ with respect to $w, b, \xi, \hat{\xi}_i$ is 0, we get

$$w = \sum_{i=1}^{m}(\hat{\alpha}_i - \alpha_i)x_i \tag{12}$$

$$\begin{cases} 0 = \sum_{i=1}^{m}(\hat{\alpha}_i - \alpha_i) \\ C = \alpha_i + u_i, C = \hat{\alpha}_i + \hat{u}_i \end{cases} \tag{13}$$

Substituting equations (7) and (8) into equation (6), SVR dual form can be obtained

$$\begin{aligned} & \max_{\hat{a},\alpha} \sum_{i=1}^{m} y_i\left(\hat{\alpha}_i - \alpha_i\right) - \in \left(\hat{\alpha}_i - \alpha_i\right) - \\ & \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}\left(\hat{\alpha}_i - \alpha_i\right)\left(\hat{\alpha}_j - \alpha_j\right)x_i^T x_j \\ & \text{s.t. } \sum_{i=1}^{n}\left(\hat{\alpha}_i - \alpha_i\right) = 0, 0 \leq \alpha_i, \hat{\alpha}_i \leq C \end{aligned} \tag{14}$$

The above process meets the Karush kuhn-tucker (KKT) condition and

$$\begin{cases} \alpha_i[f(x_i) - y_i - \in - \xi_i] = 0 \\ \hat{\alpha}_i[y_i - f(x_i) - \in - \hat{\zeta}_i] = 0 \\ \alpha_i\hat{\alpha}_i = 0, \xi_i\hat{\zeta}_i = 0 \\ (C - \alpha_i)\xi_i = 0, (C - \hat{\alpha}_i)\hat{\xi}_i = 0 \end{cases} \tag{15}$$

Under the condition of KKT, then

$$b = y_i + \in - \sum_{i=1}^{m}(\hat{\alpha}_i - \alpha_i)x_i^T x \tag{16}$$

$$f(x) = \sum_{i=1}^{m}(\hat{\alpha}_i - \alpha_i)x_i^T x + b \tag{17}$$

By introducing kernel function and integrating the Eqs. (7), (11) and (12), Eqs. (13) and (14) can be obtained.

$$w = \sum_{i=1}^{m} \left(\hat{\alpha}_i - \alpha_i\right) \varphi\left(x_i\right) \tag{18}$$

$$b = y_i + \in - \sum_{i=1}^{m} \left(\hat{\alpha}_i - \alpha_i\right) k\left(x, x_i\right) \tag{19}$$

$$f(x) = \sum_{i=1}^{m} \left(\hat{\alpha}_i - \alpha_i\right) k\left(x, x_i\right) + b \tag{20}$$

where $k(x, x_i) = \phi(x_i)^T \phi(x_j)$.

The selected kernel function is the radial basis kernel function

$$k\left(x_i, x_j\right) = \exp\left(-\frac{\left\|x_i - x_j\right\|^2}{\sigma^2}\right) = \exp\left(-g\left\|x_i - x_j\right\|^2\right) \tag{21}$$

where $g = \frac{1}{\sigma^2}$.

3.2 The Prediction Process of College Students' Physical Fitness Based on K-Means and SVR

Because the SVR can map two different relationships, it is used to determine the relationship between the input characteristics of the body test data and the body test data to be predicted. The input feature with a large Pearson correlation coefficient between the college students' physical measurement data and the output variables is taken as the input variable of the support vector regression model. The detailed algorithm flow is as follows:

1) Firstly, the physical test data of grade 14 students over four years of college are sorted out, and then the optimal clustering number k of the physical test data of college students is calculated using the elbow method.
2) Thee Pearson correlation coefficient between input and output variables of each type of data is calculated, and feature variables with correlation coefficient higher than 0.1 are taken as new input variables.
3) The input and output vectors are normalized. The training set and the test set are divided. The training samples of each kind of divided training set are trained by SVR algorithm.
4) The established SVR prediction model is used to predict the test set samples. The predicted values are normalized.
5) All kinds of body measurement prediction data are summarized. The predicted data are scored according to the school's scoring criteria, and the corresponding physical fitness level is obtained.

The structure of the prediction method of college students' physical fitness by SVR is shown in Fig. 1.

Remark 2 Support vector regression (SVR) was used to train college students' physical test data and predict their physical fitness, which is a more scientific and accurate means of predicting the physical data of college students compared with the traditional prediction method.

4. CASE STUDY

4.1 The Example Test

In order to prove the objectivity and reliability of the SVR-based method for the prediction of college students' physical fitness, the physical test data of college students at a university in Jiangsu, China is selected for simulation analysis. The physical education test data of grade 14 students at the university are selected as research samples. Weight, height, lung capacity, 50-meter run, long jump distance and sitting position forward flexion are used as the main variables in this study. The characteristics of the previous three years are taken as the input, and the characteristics of the fourth year are taken as the output to predict the sports test data of grade 14 college students in their senior year.

Firstly, the elbow method is used to obtain the optimal clustering number k of selected sports test data. SEE values are shown in Fig. 2 with different k. As can be seen from the figure, curvature is lowest when k is 5. Hence, 5 is the optimal clustering number to be aggregated.

The results of correlation analysis of the height, weight, lung capacity, 50-meter run, long jump distance and sitting position forward flexion sample data obtained by k-means clustering analysis of the sample data are shown in Figs. 3 to 8 respectively.

After the correlation analysis of sample data is completed, the new input vectors are determined by selecting variables with a correlation greater than 0.1. Then, SVR is used to train each kind of divided training sample, and the SVR model of each kind of sample data is obtained. The predicted values of college sports test data are obtained by substituting the test data of each category into the corresponding model. Finally, all kinds of data are integrated to obtain the prediction data of each measurement index. The height, weight, lung capacity, 50-meter run, long jump distance and sitting position forward flexion, six indicators of the predicted results are shown in Figs. 9 to 14 respectively.

4.2 Assessment of Predicted Results

To compare the prediction results of different methods, the following probabilistic prediction evaluation indicators are used:

1) Average absolute percentage error
2)

$$e = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{ttest(i) - ytest(i)}{y_{\mathrm{a}}} \right| \times 100\% \tag{22}$$

where N is the number of validation samples, $ttest(i)$ and $ytest(i)$ are the point predicted value and actual value of the ith validation sample, respectively; y_a is the installed capacity of wind motor.

The average absolute percentage error e of physical fitness prediction is calculated. Table 2 gives a comparison of the e values of the proposed method and two other existing methods.

In Table 2 above, the GM method has been used for comparison with our method, indicating the reliability of the proposed method.

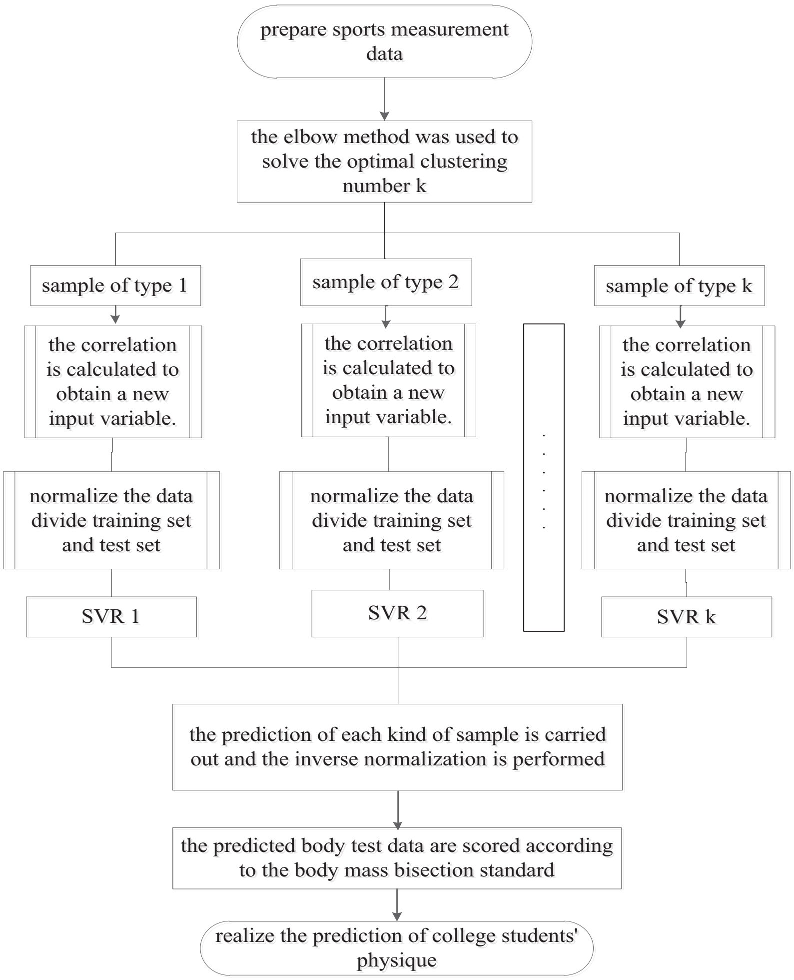

Figure 1 The flowchart of the college students' physical fitness prediction model

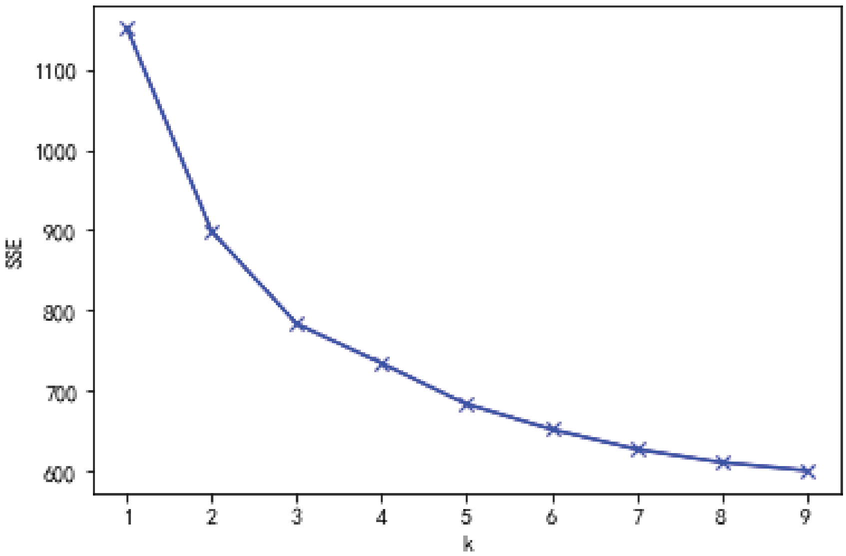

Figure 2 The flowchart for the college students' physical fitness prediction model

Table 1 Average absolute percentage error of prediction results.

Method	*e*
Our method	0.2162
GM	0.3115

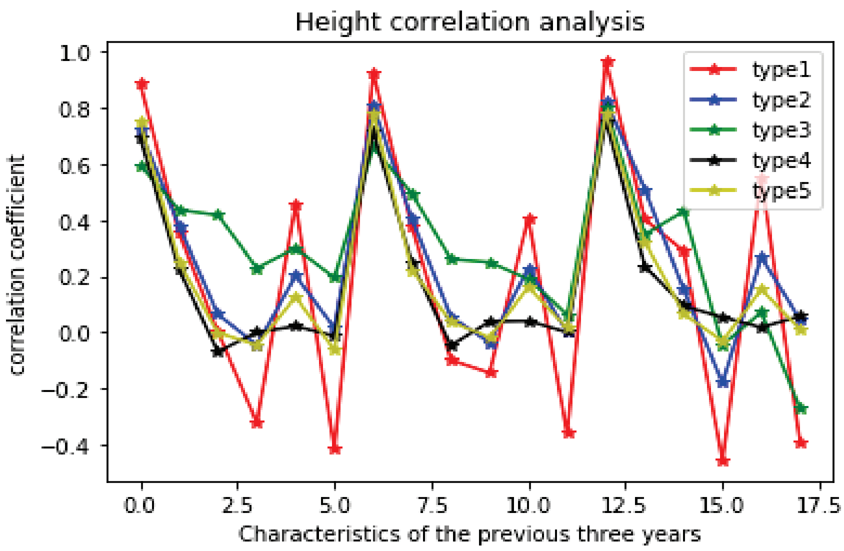

Figure 3 The correlation analysis of the height sample data

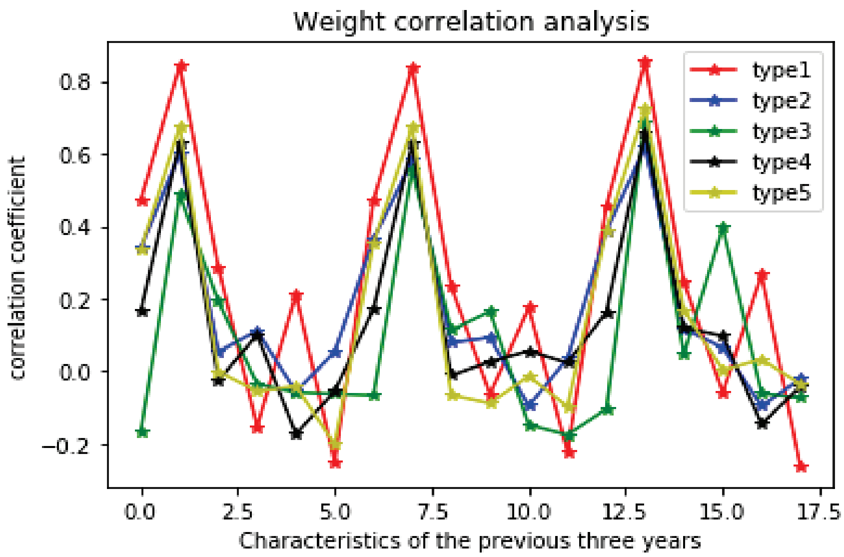

Figure 4 The correlation analysis of the weight sample data

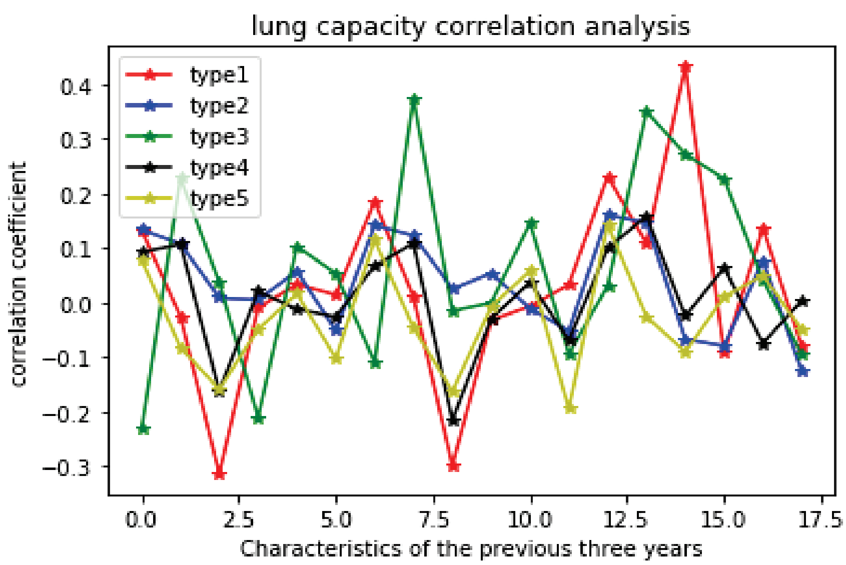

Figure 5 The correlation analysis of the lung capacity sample data

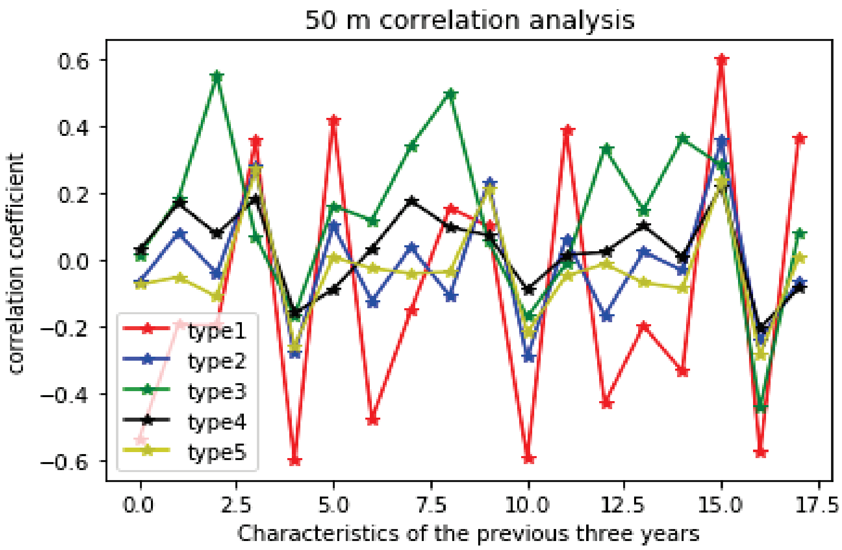

Figure 6 The correlation analysis of the 50-meter run sample data

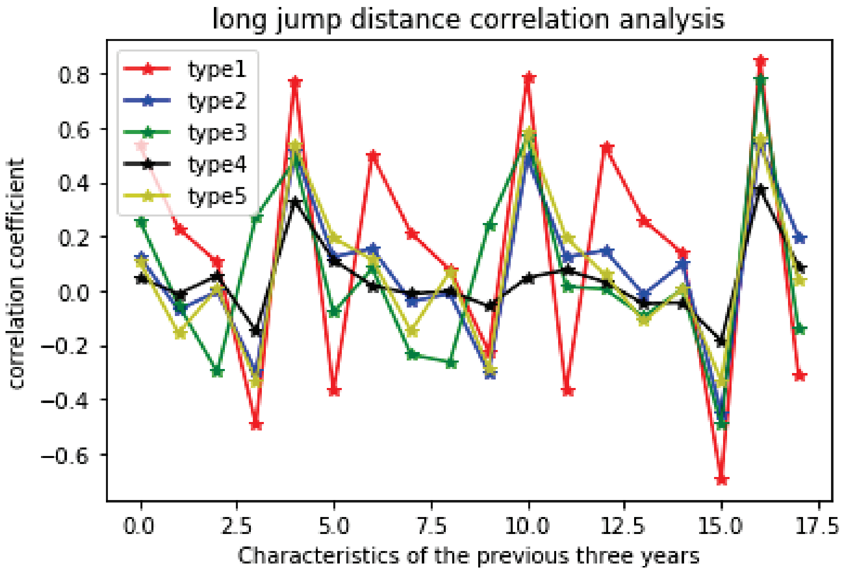

Figure 7 The correlation analysis of the long jump distance sample data

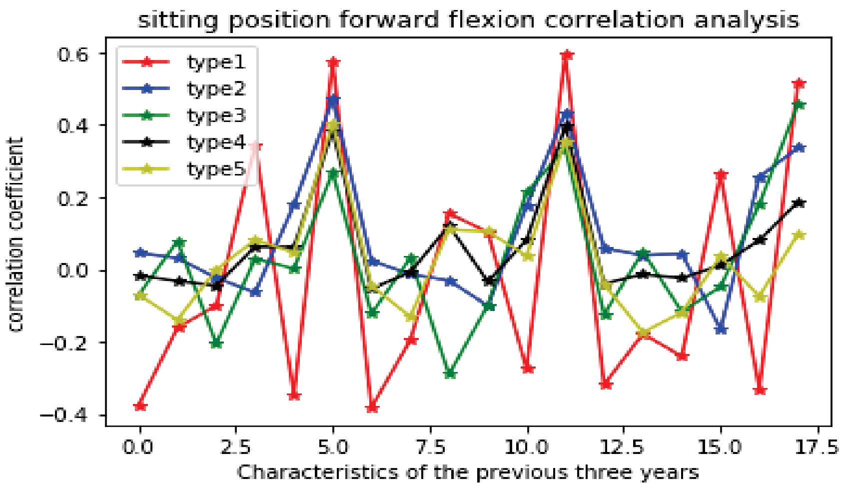

Figure 8 The correlation analysis of the sitting position forward flexion sample data

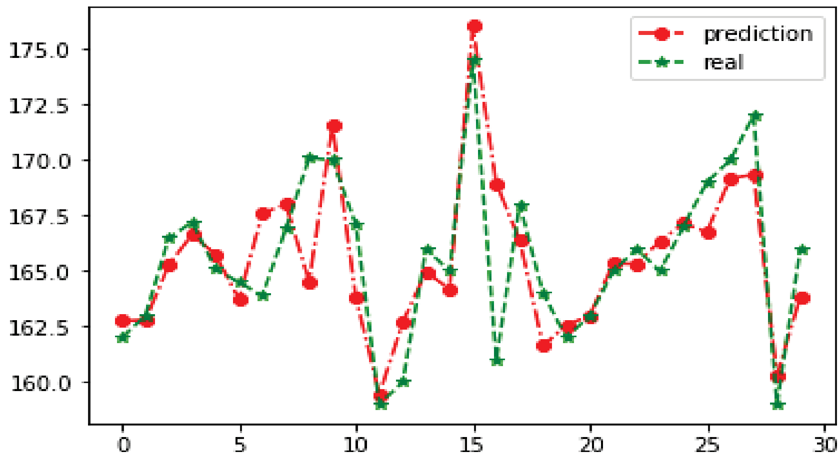

Figure 9 The prediction of height

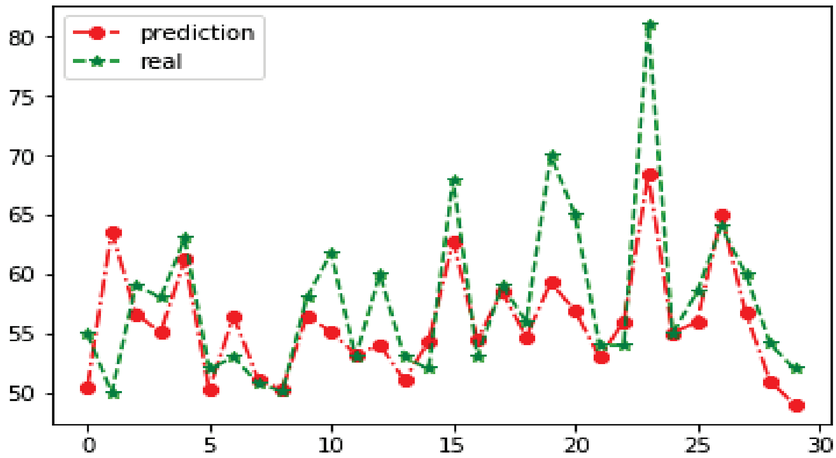

Figure 10 The prediction of weight

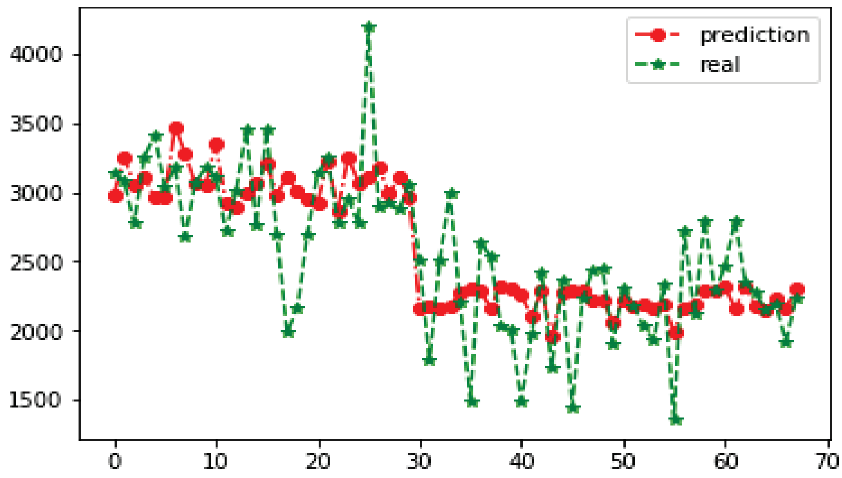

Figure 11 The prediction of lung capacity

5. CONCLUSION

In this paper, machine learning technology is combined with undergraduate physical fitness prediction. Moreover, k-means clustering and Pearson correlation coefficient are used to analyze and mine the potential correlations in the physical test data characteristics of college students. The maximum correlation feature information in physical fitness prediction was mined, and the support vector regression model was used to carry out high-dimensional mapping on the body measurement data of samples. This paper proposes a method for predicting college students' physical fitness, and through the prediction simulation of data in a university in Jiangsu province and comparison with other methods, the following conclusions are drawn:

1) SVR is used to process college students' body measurement data, which can well map a small number of samples in high dimensions, thus effectively addressing the deficiency

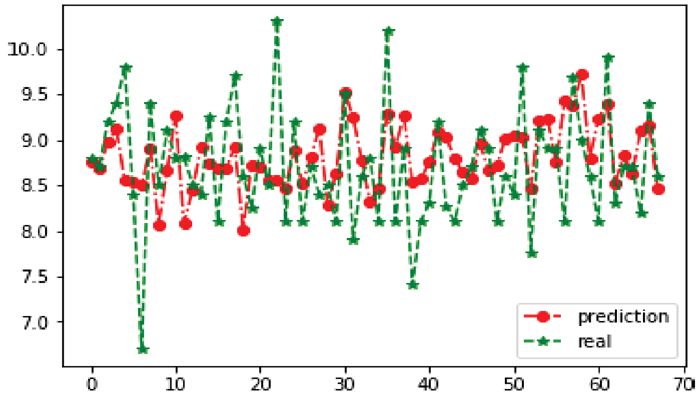

Figure 12 The prediction of 50-meter run

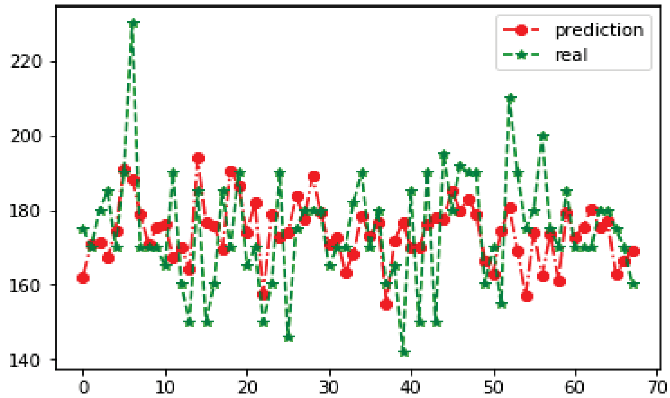

Figure 13 The prediction of long-jump distance

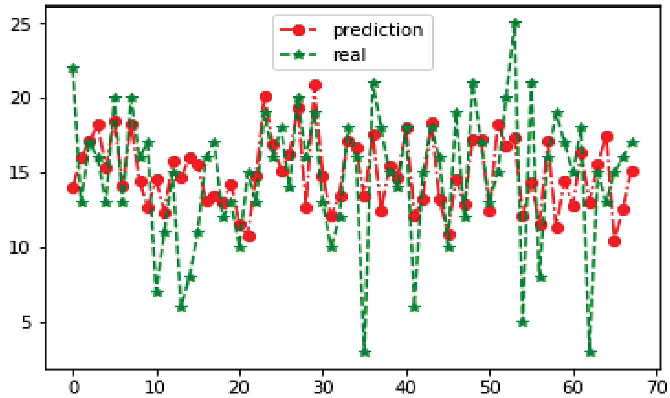

Figure 14 The prediction of sitting position forward flexion

of the prediction model for small samples, and improving the prediction ability of the model.

2) By using machine learning method to predict the single index of college students' physical test data, we can see the development trend of college students' physical fitness, which has important guiding significance for the arrangement of college sports.

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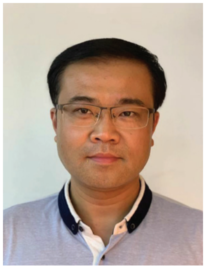

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