Research Article

Application of Feature Selection Based on Elastic Network and Random Forest in the Evaluation of Sports Effects

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With the rapid development of data mining and machine-learning technology and the outbreak of big sports data mining development challenges, sports data mining cannot simply use data statistical methods such as how to combine machine learning and data mining technology for effective mining and analysis of sports data, to provide useful advice for public physical exercise, and this is an urgent need to study. It is a kind of efficient sports data mining study through the feature selection algorithm. Around the difficult problems existing in the study of sports effect, given the limitations of existing data sets and traditional research methods, this paper starts from the data mining algorithm, builds the sports effect evaluation database, based on feature selection idea, using elastic network algorithm, random forest algorithm, and the influence of sports on the effect of physical indicators. The evaluation algorithm introduces machine learning algorithm and feature selection algorithm to guide the sports effect evaluation research. When studying the evaluation problem of sports effect, according to the constructed sports effect evaluation database, elastic network algorithm is added to regularize, optimize, and realize feature selection. When selecting the characteristics of different sports ability, using information gains indicators to rank the importance of characteristics, which can scientifically and accurately obtain the influence degree of sports on different physical indicators, make the physical fitness research more scientific, and can reveal the effect of sports as far as possible. Experimental results show that the selected features and ground-truth have good accuracy, good evaluation performance, and high accuracy compared with the baseline method.

1. Introduction

With the rapid development of Internet technology, the data from various industries show an explosive accumulation trend. The explosion of data in education, medical care, science, and finance has promoted the development of data mining and other related technologies in the era of big data. It can be seen that big data plays an important role in the process of national development, and the development and research of big data-related technologies are the needs of the current era and the focus of all walks of life [1].

Sports data is an important part of big data resources. The mining and analysis of sports data can effectively understand the impact of sports on human body and sports efficacy. With the rapid development of data mining and machine learning technology, the outbreak of big data sports has brought challenges to sports data mining development, and the existing sports data mining methods mainly focus on the extraction and construction of effective basic sports data features, and also use statistical methods to analyze the study of sports data. However, with the rapid development of data mining and machine learning technology, sports data mining cannot simply use data statistical methods such as how to combine machine learning and data mining technology for sports data mining and analysis, to provide useful advice for public physical exercise, which is an urgent need to study. Sports data mining is an important direction and application of big data analysis. It is a kind of efficient sports data mining study through the feature selection algorithm. Feature selection is done from the attribute set that is effective for system optimization [2]. These features can make the system classification effect more accurate, the process plays a role in ensuring the classification accuracy, and the feature
selection can improve the model learning performance, which is a crucial step in pattern recognition [3].

Based on this background, in order to realize the application of sports big data in sports effect evaluation, this paper proposes an algorithm combining elastic network and random forest to select the features of sports big data, and study and evaluate several types of sports effects. The full text is divided into four sections. Section 1 introduces the research background and research necessity, Section 2 the arrangement of the paper and random forest, Section 3 introduces the theory and modeling process of the elastic network and random forest, and Section 4 analyzes the importance of different types of sports, giving specific guidance for sports training.

2. State-of-the-Art

In many existing studies at home and abroad, many research methods use statistical analysis, such as statistical mean, standard deviation, and simple correlation coefficient method. When there is a correlation between the index characteristics, the simple correlation coefficient method is applied to study only the influence relationship between the two indicators, but not the influence of different factors. The research results are not comprehensive. At the same time, the physical fitness data is mainly the national physical fitness monitoring bulletin, investigation report, etc. Mostly in cross-sectional data, which cannot show the individual differences, the correlation is not significant, and cannot comprehensively study the situation of sports effect. Good data mining and feature selection technology are rarely used and less is used to study the impact of sports on physical index data. In relevant studies at home and abroad, Yu and others applied ID3 algorithm to decision tree to analyze the test data of handgrip strength and muscle strength, determined the root nodes of different test index parameters, and obtained the indicators that can scientifically evaluate human muscle strength [4]. Liu proposed an optimized random forest algorithm, using artificial swarm to optimize the classifier. The model can identify human motion patterns, which can get a relatively high classification accuracy [5]. Moreover, some work uses statistical methods to study the effect of physical fitness from sports data.

The effect of sports mainly studies the influence of physical level. Sports to a large extent affect the change of physical level, further affect the physical health level, in which sports has become an important factor leading to the physical level. In the study of physical constitution, many scholars use the national monitoring data for analysis. Xu and Jiang used the adult body quality index (BMI) data obtained by Jiangsu Province national physical fitness monitoring in 2000 to analyze the impact of adult BMI index in Jiangsu province on physical fitness and health [6]. In 2007, HillsAP et al. discussed the causes of obesity, believing that physical activity and a healthy lifestyle are conducive to disease prevention and emphasizing that promoting children's active lifestyle and strengthening physical exercise can reduce childhood obesity [1]. In order to explore the changes in childhood cardiorespiratory health and BMI over time, in a series of uniform cross-sectional assessments of school children fitness decreased when BMI increased over 6 years, and even in lean children. Stratton et al. shows that public health measures to reduce obesity, such as increasing physical activity, may help to improve health levels for all children, not just overweight or obese children alone [7]. Jkman studied 11,407 data of adults aged 20–39 in the Shanghai National physical fitness monitoring database in 2005, and used the related rules and data mining technology to process and analyze 21 important physical indicators, function and quality of the research subjects, and obtain the relationship between physical indicators. The size of handgrip strength is related to vital capacity, which affects handgrip strength, longitudinal jump performance, and other indicators, and the relationship between handgrip strength and body balance ability and body obesity degree [8]. Ma and others studied the factors affecting the physical condition of students in the university, and proposed that the environment suitable for physical exercise seriously affects students “exercise, enhancing students” physical awareness affects the improvement of physical fitness, and family support affects the development of physical level [9]. Zhang et al. used the data of the 2014 National Physical Fitness Monitoring Bulletin to use statistical methods to study and analyze the physical fitness of the male teachers and staff of the school [10]. Zhou et al. used the questionnaire survey to collect different information of nearly 4,000 college students and studied and analyzed the influence of relationship between physical fitness level and lifestyle [11]. Feng et al. used the two years of physical test data of college students in this province to study and analyze the results of the questionnaire survey [12]. Mei et al. through literature review, comparative research, and mathematical statistics conducted descriptive analysis and one-way variance analysis of four physical fitness indicators: grip strength, sitting forward, one foot flexion, and response in Hebei Province [13].

From the analysis of a large number of research literature and results, it can be seen that the existing research data of sports effect evaluation technology are mainly derived from the national physical fitness monitoring report, questionnaire survey, and the data collected from various places. In addition, most of the data used are cross-section data, which cannot fully reflect the impact of sports on physical indicators. Moreover, the number of indicators in the data set is small, and the physical condition is not comprehensive. This paper starts with the research of data mining algorithm, in view of the limitations of existing data sets and traditional research methods, combined with the rapidly developing feature selection algorithm, database establishment, elastic network algorithm, random forest algorithm research, for the influence of sports effect on body indicators.

3. Methodology

3.1. SED Database Establishment. In the field of sports, data mining technology has developed rapidly, and sports data mining technology integrating new theories has been widely studied. Studying the effect of sports is a typical problem of
sports data mining. The essence of data mining is to obtain potentially useful information from algorithmic mining in a large amount of practical application data. Sports data mining is the application of data mining technology in the field of sports. Sports data mining technology is mainly used in physical education teaching, sports training monitoring, and sports information management, which involves image data, discrete data, and video data. There is no suitable public data set. Therefore, how to construct the representative sports data, and then realize the rapid and effective sports effect evaluation and research, is an urgent problem to be solved.

To study the sports effect evaluation method, the research team organized multiple objects for a period of time wrestling, competitive footprint, skills and modern school sports four types of sports training, and observe object training after more than 40 representative body forms, body functions, and physical quality of indicators, and physical indicators change as characteristic. First, the research team divided sports into five categories: wrestling, skills, competition, modern school sports, and no sports. The establishment of no sports, not a special sports test, is to reflect the impact of different sports on the physical indicators. The 785 students were test subjects with five sports categories, divided into five groups of different sports. Before physical training, the research team examined the physical indicators of each group, and the data were recorded as \( P \). During the physical training, each group will conduct the corresponding training for three months under the guidance of special personnel. The exercise cycle is three times a week, with 7 minutes of preparation, 30 minutes of exercise, and 3 minutes after work. The index data at the end of the final training session are recorded as \( P_f \). The team using height weight tester to measure height, weight index, sitting high tester sitting high index, using electronic acoustic metronome, electronic meter, spirometer, grip meter, and reaction tester instrument to measure the basic heart rate, heart work index, select reaction, and grip strength more than 40 body index data. Figure 1 shows the method of testing the heart rate index in it.

Due to some uncertainties, the data we obtain will not be available, such as duplicate values, missing values; so the data need to be preprocessed. Looking through the literature, we found that there is no standard and unified process for data preprocessing, which is generally related to the task itself. In addition, the attribute preprocessing steps are generally different for different datasets. The common processes of data preprocessing are the following: removing unique attributes, processing missing values, attribute coding, and data standardization. We mainly did the following several parts of the preprocessing. First, to remove unique attributes refers to the ID attributes in the data set, such as the "name" attribute in the obtained data, which cannot describe the distribution pattern of the sample, so we did a simple job of removing unique attributes. Second, for a small number of missing values in the processed data set, the missing values are completed. For example, the missing values of some boys in the same category are interpolated with the mean of other boys in the same grade.

Again, we process the attribute data that are the numerical data, and feature code, so the features, which are part of the attributes and form Boolean attributes, such as "one minute tennis"; we use the data before and after training, and set 0 for the boundary point, such that the positive attribute value is 1 and the negative attribute value is zero. Finally, the data is normalized, which is the scaling of the attributes of a sample to a specified range, and this study mainly sets the normal for the data difference between 0 and 1 before and after testing. Body form indicators include poor breathing, height, weight, sitting height, shoulder width, loose upper arm circumference, waist circumference, chest circumference, chest circumference, pelvic width, hip circumference, and body fat rate. Body function indicators include maximum oxygen intake, vital capacity, pulse pressure difference, heart function index, and base heart rate. Physical form indicators include one-minute tennis throwing, cross running, grip strength, 50 m sprint, standing rotation, sitting flexion, repeated, crossing, one minute sit-up, push-ups, back muscle strength, selective response, round run, horizontal fork, vertical jump, shoulder rotation and single foot standing. After data preprocessing steps such as data deletion, vacancy filling, and normalization, the database has 32 physical indicators.

3.2. Evaluation Technology of Sports Effect Based on Elastic Network. With the mining of massive electronic data, sports indicators, team development direction, other data enter the statistical analysis of athletics, and often face the problem of selecting the characteristics of high-dimensional variables. The regularization technology is widely cited in sports data mining. Regularization changes the weight of some feature attributes to zero, which is a typical method of model selection. Generally, regularization terms are added to the target optimization algorithm. The regularization term should be monotonically increasing about the model complexity, and the more complex the model, the higher the regularization value [14].

Regularization is a common technique for model optimization, which can reduce model complexity and solve over-fitting problems. The penalty term is added in the original objective function and provides regularization to the high complexity model to limit certain parameters in the loss function. Its mathematical expression form is as follows:

\[
\tilde{J}(w, X, y) = J(w, X, y) + \alpha \Omega(w).
\]

Here, \( X \) and \( y \) are training samples and labels, \( w \) is weight coefficient vector, \( J() \) is empirical risk, \( \Omega(w) \) is regularization term; coefficient control regularization degree. Different \( \Omega \) functions have different regularization effects. The commonly used \( \Omega \) function is \( L_1 \), the norm and \( L_2 \) normal number, the corresponding regularization is called \( L_1 \) Regularization and \( L_2 \) Regularization. The mathematical expressions are as follows:

\[
\tilde{J}(w, X, y) = J(w, X, y) + \lambda \|w\|_1, \\
\tilde{J}(w, X, y) = J(w, X, y) + \alpha \|w\|_2.
\]
Lasso regression can realize the function of attribute selection and compress the coefficient of attributes with little effect to 0. Although ridge regression also reduces the original coefficient of insignificant attributes to a certain extent, it will not compress the coefficient to 0. The final model still has all attributes and cannot play the role of attribute selection.

In 2006, Hui proposed the concept of elastic network algorithm. Elastic network algorithm is a multivariate pattern analysis method [15]. The method is able to choose a model with the best balance between the complexity and the degree of fit. The elastic network algorithm is a regularized regression method that combines Lasso regression and ridge regression; namely, it has the stability of feature selection and parameter estimation. In practice, the elastic network balances the advantages of Lasso regression and ridge regression; namely, it has the stability of ridge regression in the cyclic model. The underlying linear regression model is defined as follows:

\[ y = \sum_{j=0}^{d} \hat{\beta}_j x_j + \hat{\beta}_0 + \epsilon, \]  
\[ y = \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + L + x_d + \hat{\beta}_0. \]  

Using the sum of squares of residuals to derive ordinary least squares estimates, specific formulas are as follows:

\[ \beta = \arg \min \sum_{i=1}^{n} \left( y_i - \sum_{j=1}^{d} \beta_j x_{ij} \right)^2. \]  

The specific Lasso algorithm is to add a penalty to the above formula to get the formula:

\[ \hat{\beta} = \arg \min \sum_{i=1}^{n} \left( y_i - \sum_{j=1}^{d} \beta_j x_{ij} - \beta_0 \right)^2 + \lambda \sum_{j=1}^{d} |\beta_j|. \]  

Nonnegative tuning parameters can be increased to 0. When the parameter is equal to 0, these variables are deleted, thus selecting features. This compression generally improves the assessment accuracy under the bias-variance trade-off. For the basic linear regression model, the loss function of the elastic network algorithm is formulated as follows:

\[ J(w, X, y) = J(w, X, y) + \lambda \|w\|_1 + \frac{1 - a}{2} \epsilon \|w\|_2. \]  

\[ J(w, X, y) = J(w, X, y) + \lambda \|w\|_1 + \frac{1 - a}{2} \epsilon \|w\|_2. \]  

The \( \hat{\beta} \) in the formula represents the regularization parameter. Being able to find that the E-Net penalty adds a ridge regression penalty to the Lasso penalty, calculated as a weighted sum of the Lasso penalty and the ridge regression penalty. The parameters in the formula are responsible for regulating the sparsity of the model, and larger values...
indicate the sparser the model. The parameters are responsible for controlling the proportion of the Lasso penalty and the ridge regression penalty within the formula.

### 3.3. Evaluation Technique of Sports Effect Based on Random Forest

Random forest algorithm is a machine-learning algorithm commonly used for classification. Random forest is a classification method that integrates multiple decision trees to train, test, and predict sample datasets. Random forest algorithms are more acceptable, more accurate than neural networks, and operate faster to noisy and missing data. Therefore, random forest algorithms are more commonly used in data mining. In 2001, Hui combined the Bagging integrated learning theory with the random subspace method [16]. Integration is a divide and conquer strategy. The principle of integrated learning is to use a certain number of weak learning machines to form a strong learning machine, so that integrated learning can reduce variance and improve performance. A decision tree is a tree classifier in which each node of the tree structure selects the children of the optimal policy according to the sample features until the leaf node of the decision tree is reached so that each leaf node is a classification result [17]. A schematic representation of the random forest decision tree is shown in Figure 2.

Random forest is a supervised learning algorithm that has the ability to solve both classification and regression problems. Random forests consists of a certain number of decision trees, usually the larger the number of decision trees, the higher the accuracy of the random forest algorithm, and the stronger the robustness. Given a new input sample, in the classification problem, each tree is a result to the properties of this object, and we then save these classification results as voting and select the classification result with the highest votes as the final classification result for this random forest. In the regression problem, we can average the output of each decision tree to get the results, as shown in the Figure 3 for feature extraction using the random forest algorithm.

For the sports effect evaluation method research, the classification is based on the random forest algorithm, and the useful features are automatically selected during the classification process. Based on the advantages of the random forest algorithm, this algorithm representing the integrated feature selection method is particularly applicable in the evaluation of sports effect. Random forest is a classifier containing multiple decision trees. Therefore, for using the random forest method, the first step is to construct the decision tree. Decision tree is a basic classifier that generally divides features into two categories. The decision tree recursively selects the features to divide the dataset until it ends in two categories. In the process of classification, we use the information gain to test whether the features produce nodes, and the information gain can be expressed as follows:

\[
\text{Gain}(D, a) = \text{Ent}(D) - \sum_{v=1}^{V} \frac{D_v}{D} \text{Ent}(D_v).
\]  

Each time the decision tree is built, data are obtained by repeated sampling to train the decision tree, to evaluate the classification performance of the decision tree, and to calculate the prediction error rate of the model. For each decision tree, the corresponding out-of-bag data (OOB) is selected to calculate the prediction error rate, and noise interference is randomly added to the feature X of all

![Figure 2: Schematic representation of the random forest.](image-url)

![Figure 3: Flow chart of the random forest regression algorithm.](image-url)
samples of the out-of-bag data to calculate the out-of-bag data error again. Assuming \( N \) trees in the forest, the average of the \( N \) trees is calculated to indicate the importance of feature \( X \). Random noise is added to study the change in prediction error rate and select important features.

Each time, a certain proportion of features are eliminated, and the information gain is used to select a new attribute set \( a^* \), which can be expressed as follows:

\[
a^* = \arg \max_{a \in A} \text{Gain}(D, a) \tag{9}
\]

4. Result Analysis and Discussion

The data used in the experiment is the SED of the sports database, which details the establishment process and the data form in Section 3. The database was set to the training set and the test set with a ratio of 4:1. This paper mainly studies the influence of four types of sports on the indicators of the body, does sports data to obtain as positive, no sports data as negative, and compares the two kinds of data. The experiments in this review are divided into four groups: the first group of experiments are the indexes of the variance of the data.

Above, three baseline algorithms were used to compare the four experiments with the ground-truth data in the dataset. The experimental evaluation criterion in this paper is the accuracy of top@k, defined as the ratio at which the body indicator influence is obtained based on the algorithm that matches the real case ground-truth. The higher the accuracy is, the more effective the algorithm is. The accuracy rate (Precision) is calculated as follows:

\[
\text{Precision} = \frac{k}{n} \tag{10}
\]

where \( k \) represents the number of influence indicators consistent with ground-truth, and \( n \) represents the total number of indicators selected in ground-truth.

Combined with the idea of regularization, the elastic network method was used to rank the characteristics of the four types of sports effects, and found that the four types of sports have different effects on some indexes. Figure 4 gives the ranking of the influence degree of angular force movement, which shows that the greater influence are standing long jump, dorsal muscle strength, average grip strength, selection response time, and cardiac power index. In fact, wrestling exercises mainly exercise strength, and the experimental results are in line with cognition. We can also use the random forest algorithm, and the results are shown in Figure 5.

Different sports have different fitness effects, and research can choose according to the characteristics important for training different sports effect on different body indicators, and the same for different people who want to exercise different parts to improve the body ability, and can according to the evaluation results choose the corresponding exercise. It can also be seen from the
experimental results that different categories of sports have different exercise effects and affect different physical indicators. Sports cannot only help students improve their physical condition but also exercise their reaction power and strength. Two evaluation algorithms influence larger indicators and we know that the indicators of exercise are inconsistent, such as modern school sports body weight, standing long jump, lung capacity, and closed eye influence, but Ground-Truth did not specify the influence of these indicators; may be experts think these indicators do not have obvious variability, and it is worth exploring. Combining all sports together for evaluation yields four types of integrated sports feature indicator significance, as shown in Figure 6.

In order to verify the efficiency of the design model in realizing the assessment of sports skills, simulation analysis and SPSS statistical analysis software were conducted. According to the above simulation parameter setting, the sports skill ability evaluation is conducted, and using the big data analysis of sports skill ability evaluation, the big data mining results of sports skill ability evaluation are shown in Figure 7. The overall movement ability remained below the standard line, and decreased with the increase of iteration.

According to the data mining results of Figure 7, a statistical analysis model of sports skill ability evaluation was established, and the regular features of the information fusion of sports skill ability evaluation were analyzed, and
the sports skill ability evaluation was realized, and the comparison output of evaluation confidence was obtained as shown in Figure 8. Figure 8 shows that the confidence level of sports skill assessment was high.

5. Conclusions

Due to the outbreak of sports big data, sports data can not only be mined and analyzed by existing data sets using traditional methods, but also the evaluation of sports effect has been widely considered by relevant scholars. This paper starts with the study of data mining algorithm, considering the limitations of existing data sets and traditional research methods, and combining the rapidly developing feature selection algorithm. This paper proposes the elastic network algorithm and random forest algorithm to study the effect of sports and guide sports. The experimental results are consistent with the subjective cognition and judgment of sports experts. Compared with the baseline method, the classification results of the two algorithms are more accurate. In this regard, we can choose the corresponding type of exercise according to the skills we want to exercise according to the results of the exercise, and help guide the school physical education teachers in physical exercise. At the same time, we can also use our sports exercise effect evaluation method to evaluate the effect of the made exercise.

Most young people should always pay attention to physical health, not only clear the impact of all kinds of sports on the body, but also to be aware of where they need to improve physical health, through adjustment, construction, and adhere to active and healthy sports, choose suitable sports types.

Data Availability

The labeled datasets used to support the findings of this study are available from the corresponding author upon request.
Conflicts of Interest
The authors declare no conflicts of interest.

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