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Optimizing Physical Education Learning Behavior Recognition Model and Teaching Strategy Adjustment Based on AdaBoost Algorithm

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Abstract With the deepening of the new curriculum reform, physical education is receiving more and more attention from the state and schools. Aiming at the learning data of physical education students, a physical education learning behavior recognition model based on Adaboost-BP neural network is proposed. The BP neural network is used as a weak predictor in MapReduce environment, and a strong predictor is constructed by the Adaboost algorithm combining the results of the weak predictor to recognize the physical education learning behavior. On this basis, the physical education teaching strategy is adjusted, and physical education stratified teaching based on the Adaboost-BP model is proposed, and the teaching experiment is implemented to evaluate its application effect.The Adaboost-BP model has a good effect of recognizing physical education learning behaviors, and the average error of the recognition error has an absolute value of 0.029 and a relative value of 3.79%, which is smaller than the comparative method.The model will The model identifies the physical education learning behaviors of 100 students into three categories: “excellent”, “moderate” and “poor”. After the adjustment of teaching strategies, the three categories of students were improved in all indicators of physical fitness, and in terms of course enjoyment, motivation, skill mastery, course content rationality, learning experience, etc., the Adaboost-BP model can realize the stratification of students' behaviors, and then guide the adjustment of learning behaviors and physical education courses, and promote the improvement of physical education teaching quality.

Index Terms AdaBoost, BP neural network, learning behavior recognition, teaching experiment, physical education teaching

I. Introduction

Traditional sports training methods often rely on the knowledge, experience and analytical judgment ability of the coach, and although this approach has its own unique features, there are certain limitations in terms of objectivity and accuracy [1], [2]. In the high-intensity, high-frequency modern sports training, how to quickly and accurately recognize the wrong movements of athletes and give timely feedback has become the key to improve the training effect and prevent sports injuries [3]. In recent years, with the rapid development of computer vision technology, image processing and machine learning algorithms can provide a brand new solution for the recognition of wrong movements in sports learning videos [4]. This image processing and machine learning algorithm first extracts the key information from the massive sports training videos, then analyzes the details of the athletes' behavioral movements, and finally identifies their erroneous movements in real time [5], [6]. This method can not only greatly improve the accuracy and efficiency of the recognition of erroneous movements, but also provide coaches with richer and more intuitive feedback data, which provides a basis for the development of more scientific and more teaching strategy adjustment [7].

Traditional methods of sports training behavior recognition are not only time-consuming and labor-intensive, but also susceptible to the subjective influence of the observer, resulting in inconsistent and inaccurate results in the recognition of erroneous training movements, and a great deal of research has been conducted by scholars in order to realize the automation and objectivity of the recognition of sports training behaviors [8]-[11]. Kumar, R and Kumar, S first extract spatial feature representations from video frames with hierarchical structure and high level of abstraction, then input these features into Recurrent Neural Networks (RNN), and finally, through the recurrent structure inside the RNN, the temporal dependencies between video frames are captured, which enables the modeling of the entire video sequence [12]. Host, K and Ivašić-Kos, M outlined the application of computer vision in action recognition (HAR) in sports, stating that the method can enhance the performance level of complex sports movements and can be used in daily sports training [13]. Jiang, H and Tsai, S. B used SMO (Sequential minimal optimization) algorithm to optimize the sports combination training action recognition model using three-stream convolutional neural network (CNN) deep learning framework and soft Vlad representation to improve the accuracy of sports action recognition [14]. Pham, Q. T et al. developed a real-time human movement recognition application for monitoring physical activity based on deep neural networks that includes nine common exercise movements and can recognize all physical activity behaviors in a dataset with very high accuracy and F1 scores [15]. Khan, A. M et al. applied Axivity device and Decision Tree Classifier algorithm to sports learning behavior recognition, which can accurately recognize basic sports training movements such as elliptical trainer, butterfly stroke, bench press, and pull down with 93% accuracy [16]. Although the above studies have achieved good sports learning behavior recognition accuracy, there are still some defects. For example, RNNs are prone to the problems of gradient vanishing and gradient explosion leading to the degradation of their ability to accurately capture temporal dependencies in time series, CNNs have high computational resource requirements when dealing with the existence of long duration videos with large data volume and complex processing, and the domain differences between deep neural network pre-trained models and specific tasks may lead to an incomplete matching of temporal feature representations with actions.

In a study by Schapire, R. E, the weights were utilized to transform in real time according to the error, which led to the proposal of the AdaBoost algorithm, which improves the performance of the Boosting algorithm as well as solves the problems encountered in real situations [17]. AdaBoost algorithm is able to extract the original features and filter out a small number of features that are most meaningful for recognition, this method is able to reduce the amount of computation in the recognition process and thus improve the speed of recognition by selecting effective sample data for recognition among a large number of sample features by AdaBoost algorithm [18], [19]. Ji, X et al. selected the most discriminative features from the training data based on the AdaBoost algorithm to reduce the computational complexity of recognition and indirectly improve the accuracy of action recognition [20]. Liu, L et al. constructed an action recognition feature selection method based on AdaBoost algorithm, which achieved good accuracy in multiple action recognition datasets using Simple Plain Bayes Nearest Neighbor (NBNN) classifier [21]. Lin, X et al. proposed a new transfer learning framework TrAdaBoost by improving the AdaBoost algorithm and achieved high action recognition efficiency with some generalization in complex background environments [22]. Liao, X et al. conducted a systematic study on adolescents' physical education learning behaviors using Kinect motion capture technology and proposed an adaptive weighted AdaBoost algorithm improved based on the crawfish optimization algorithm for physical education teaching behavior classification [23]. Although related scholars have achieved good results in the research of AdaBoost algorithm for sports action recognition, it still has not solved the limitations of AdaBoost's sensitivity to outliers that are easy to fall into the phenomenon of overfitting, and the high computational complexity that leads to long training time. Therefore, further research is needed.

The study addresses the shortcomings of BP neural network model in practical application, and uses Adaboost algorithm to optimize and construct Adaboost-BP sports learning behavior recognition model, which organically combines Adaboost algorithm and BP neural network algorithm, using BP neural network as a weak predictor, and combining the outputs of multiple BP neural networks by Adaboost algorithm to construct a Strong predictor. The learning data of students in the School of Physical Education of a comprehensive university is collected as the experimental dataset, and the recognition accuracy of the Adaboost-BP model in this paper is explored by comparing the prediction errors of different models. At the same time, the learning behavior data of 100 students were randomly selected, and the Adaboost-BP model was used to identify them, and the sample students were divided into three types of learning states: "excellent", "medium" and "poor". Subsequently, based on the recognition effect of the Adaboost-BP model, the optimization strategy of physical education stratified teaching is proposed, and the strategy is used in actual teaching. The teaching effect of the physical education stratified teaching strategy was examined by comparing the physical measurement data before and after the experiment and analyzing the questionnaire survey.

II. Sports learning behavior recognition model based on Adaboost-BP

In this paper, on the basis of BP neural network, AdaBoost algorithm is used for optimization, and Adaboost-BP sports learning behavior recognition model is proposed. Using sports learning behavior data, it classifies students' learning state and realizes the dynamic planning of students on their own state and the dynamic detection of administrators on students' state.

II. A.BP neural network model

II. A. 1) BP neural network node design

In this paper, a three-layer neural network structure is used in constructing the sports learning behavior recognition model, which is designed as follows:

(1) Input layer

The online learning behavior feature data obtained above are used as the input variables of the model, including the number of logins X1, the duration of stay X2, the number of media types that have been viewed X3, the number of times the assignments have been submitted X4, the scoring of the assignments X5, the number of times the quizzes have been participated in X6, the number of times the resources have been uploaded X7, the number of times the resources have been browsed X8, the number of times the resources have been downloaded X9, the number of times the discussions and speeches have been made X10, and the time of online communication with the 11 feature items . Therefore, the number of nodes in this layer is set to 11.

(2) Implicit layer

The hidden layer abstracts the data from the input layer, making the predicted value more similar to the expected value. At the same time, the number of neurons in the hidden layer determines the recognition and prediction effect of the established neural network model to a certain extent. In most cases, the number of neurons is determined empirically. If the number of selected nodes is too large, it will lead to an increase in the model training complexity, resulting in overfitting, resulting in a lack of generalization ability of the model, and if the number of selected nodes is too small, it will make the model's accuracy relatively lower, and fail to achieve the expected results. The formula is shown below:

$$h=\sqrt{p+q}+a \tag{1}$$

$$h=\log_2 p \tag{2}$$

$$h=\sqrt{pq} \tag{3}$$

where p denotes the number of nodes in the input layer, h denotes the number of nodes in the hidden layer, q denotes the number of nodes in the output layer, and a is a regulating constant, which takes the value of a constant in the range between [1, 10]. According to the above formula, combined with the experimental results and the actual situation, under the goal that the model can both achieve the expected results and ensure a relatively compact structure, this paper finally determines the number of neurons in the hidden layer as 11.

(3) Output layer

The main research goal of this paper is to monitor physical learning behavior, and the final output of the prediction model is learning enthusiasm Y1, knowledge point mastery Y2 and analysis ability to solve practical problems Y3, so the number of neurons in the output layer is 3. In this paper, these three qualitative indicators are quantified, and the values range from 0 to 1, divided into three levels, [0.8,1] means "excellent", [0.5,0.8) means "medium", and [0,0.5) means "poor".

II. A. 2) BP neural network parameterization

(1) Determine the initial weights

The first step in constructing a BP neural network is to initialize the weights to achieve a decrease in the error function along the gradient during the iteration process. The initial size of the weight values will affect the convergence speed of the neural network and the accuracy of the model to a certain extent. Throughout the network, it is desired that the input values converge to 0 after one transformation, which enables the activation function to adjust the weights well. When the initial weights are given the same value at the beginning stage, it will make the model keep the weight values equal during the learning process, so this paper sets a random function to generate a set of random numbers between [0,0.5].

(2) Learning rate

Whether the choice of the learning rate is reasonable is related to the stability of the neural network, if the learning rate is too large, it will make the weights change a larger amplitude, the convergence speed is relatively fast, but it will cause the system oscillation phenomenon, so that the overall convergence of the model is not good. If the learning rate is small, it will make the model convergence speed slower, the training time is too long, affecting the overall efficiency of the algorithm. The current selection of the learning rate is mainly based on experience, and there is no reasonable explanation and derivation, the general selection range is set in the interval of [0.01,0.8]. In this paper, the selection is based on ensuring the stability of the whole system, and tend to use a smaller learning rate, the final selection of the learning rate is 0.2.

(3) Activation function

The main role of the activation function is to further abstract the input data, most often used in the hidden layer, so that the neural network can adapt to nonlinear problems, such as the sigmoid function, tanh function, ReLU function, P-ReLU function, ELU function and so on. In this paper, the more commonly used sigmoid function is selected.

II. A. 3) Learning behavior recognition model construction

The main idea of sports learning behavior recognition model construction is to build a neural network structure model, train the model by sports learning behavior feature data, and then use the model to achieve learning behavior recognition and output predicted learning behaviors after the end of training. The specific steps are shown below.

Step1: Extract the online learning behavior features, and select the feature values with higher correlation factor with sports learning.

Step2: Normalize the feature values and divide the sample set into training set and test set in the ratio of 3:1 using random selection.

Step3: Initialize the network structure model, and train the model by training set data.

Step4: Model training is completed.

Step5: According to the data of students' learning behavior, after normalization, input it into the sports learning behavior recognition model to obtain the predicted sports learning behavior.

II. B.Adaboost-BP neural network algorithm

II. B. 1) Algorithmic steps

Through the deficiencies of the BP neural network model in practical applications, this paper proposes corresponding improvement measures. The combination of Adaboost algorithm and BP neural network is used to establish the model, and the BP neural network is used as a weak learner to optimize and improve the traditional BP neural network, which is easy to fall into the problem of local minima and low prediction accuracy, so as to achieve the effect of improving the model's prediction accuracy and generalization ability. The execution steps of the algorithm are:

(1) Initialize the distribution weights of the sample data and the BP neural network. The distribution weights of the sample data $D_i(i)=\frac{1}{m}$, m is the number of training samples.

Determine the structure of the BP neural network, the number of nodes in the input layer is determined according to the dimension of the sample features, the number of output layers is determined according to the dimension of the output results, and the number of nodes in the hidden layer is determined by the following formula:

$$n_h=\sqrt{n_i+n_o}+\alpha \tag{4}$$

where n_i,n_o,n_h denote the number of nodes in the input, output and hidden layers of the BP neural network, respectively, and α is a random number between [0, 1].

Initial weights and thresholds of the BP neural network are initialized to random numbers between [0, 1].

(2) Individual BP neural network weak predictor prediction. Train the BP neural networks and calculate the prediction error and ε_t for the prediction sequence $g(t)$ based on the output of each neural network:

$$\varepsilon_i=\sum_{i=1}^{m}D_i(i) \quad g_i(x_i)\neq y_i \quad i=1,2,\cdots,m \tag{5}$$

where $g_i(x_i)$ is the prediction result of the BP neural network and y_i is the desired prediction result.

(3) Calculate the weights α_t of the predicted sequence:

$$\alpha_t=\frac{1}{2}\ln(\frac{1-\varepsilon_t}{\varepsilon_t}) \tag{6}$$

(4) Adjust the weights of the sample:

$$D_{t+1}(i)=\frac{D_t(i)}{B_t}\times\exp[-\alpha_t y_i g_t(x_i)] \quad i=1,2,\cdots,m \tag{7}$$

where B_t is the normalization factor, which serves to make the sum of weights remain 1 when the proportion of weights is constant.

(5) Construct the strong prediction function. Combine T sets of weak prediction functions $f(g_t,\alpha_t)$ obtained after T rounds of training to obtain the strong prediction function $h(x)$:

$$h(x)=sign[\sum_{t=1}^{r}\alpha_t\cdot f(g_t,\alpha_t)] \tag{8}$$

II. B. 2) Modeling

According to the online learning methods often adopted by learners and combined with the current status of online education, the sports learning behavior recognition model based on parallel Adaboost-BP neural network proposed in this paper is shown in Fig. 1.

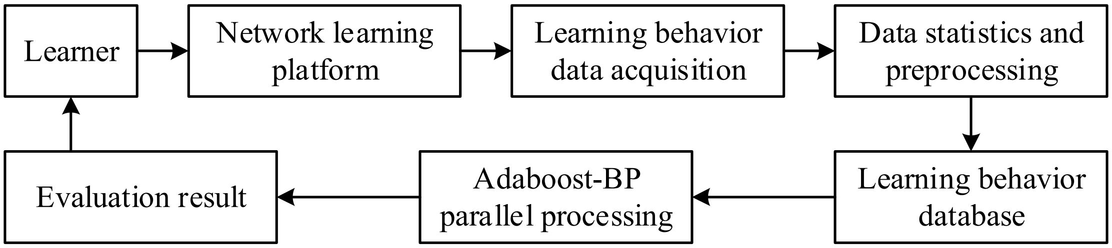

Figure 1: Physical learning behavior recognition model

Based on the parallel Adaboost-BP neural network online learning behavior recognition model for large-scale sports, based on the collected characteristics of learners' online learning behaviors, the MapReduce parallel programming model is used under the Hadoop platform to realize parallel processing and realize the automatic recognition of online learning behaviors. The specific steps are:

(1) Determine the topology of the model. In this paper, 11 BP neural networks are used as weak predictors, and for each BP neural network, since the inputs are x_1 to x_{11} 11 features of online learning behaviors, and the outputs are y_1 to y_3 3 evaluation indicators.

(2) Determine the learning sample data and normalize the data according to equation (9):

$$r_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{9}$$

where x_i is the sample eigenvalue, $x_{\max}, x_{\min}$ are the maximum and minimum values of the corresponding features in the sample space, respectively, and r_i is the eigenvalue after normalization.

(3) Parallel training of Adaboost-BP neural network. According to the parallel Adaboost-BP algorithm proposed in this paper, build a Hadoop cluster, continuously update the connection weights, repeatedly correct the error, train the network, and combine the output results of each network.

(4) Evaluation prediction. Use the trained network structure to predict the learning behavior of online learners and feedback the results to the learners.

II. C. Experimental results and analysis

II. C. 1) Evaluation indicators

The evaluation metric used in this paper for the sports learning behavior recognition model is the Mean Square Error (MSE).The MSE is a convenient metric used to measure the mean error and is often used to measure the model fit.The value of the MSE describes the mean of the summed variance of the predicted values corresponding to the target values.The smaller the value, the better the model fit to the data. The formula is expressed as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\alpha(y_i - \hat{y}_i)^2 \tag{10}$$

where n is the number of data samples, y_i is the expected value, y_i is the value of the data fitted to the model, and $\alpha > 0$.

II. C. 2) Data sets

The data object used in this paper is the online learning behavioral data of the students of the School of Physical Education of a comprehensive university, from which 500 sets of data were selected for experimental exploration. Out of the 500 sets of data, 400 sets of behavioral data are taken as training data and 100 sets as test data. And BP neural network as well as GA-BP neural network are used as comparison algorithms, aiming to explore the effect of Adaboost optimized BP neural network for sports learning behavior prediction.

II. C. 3) Comparative experimental analysis

In order to analyze the predicted values of different neural network algorithms for the samples, Figure 2 shows the output values of each model in the test samples. Comparatively, the BP neural network, which was improved by the Adaboost optimization algorithm, predicted more closely to the expectation. Further exploring the sports learning behavior recognition accuracy of the individual models, Figure 3 plots the error of each model against the expected value on the test sample. The Adaboost-improved model clearly has a lower error, and the error value is more close to 0, with an error in the range of 0 to 0.051, while the BP neural network and the GA-BP neural network have an error range of 0.003 to 0.171 and 0.004 to 0.258, respectively.

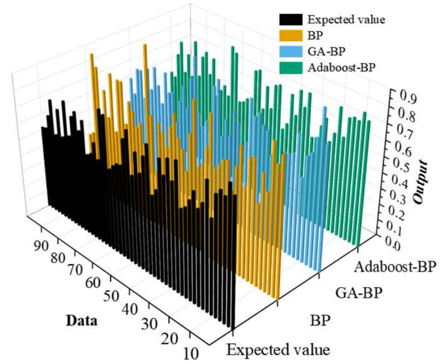

Figure 2: Comparison of output values of different models

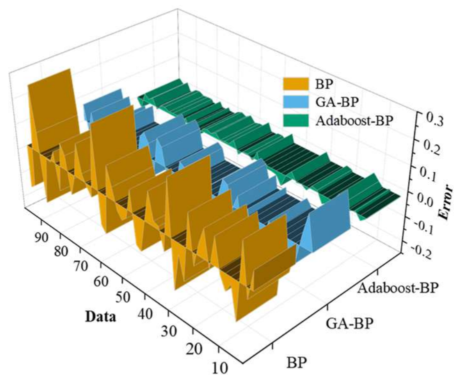

Figure 3: The error of each model on the test sample

Figure 4 shows the convergence process of Adaboost-BP neural network. In it, the mean square error is used as the evaluation index of the model. The dataset is divided into a training set and a test set, and for each training, the model derives an error value, verifies whether it meets the end conditions according to the set conditions, or determines whether the current error value is stabilized after several iterations, and if the error is no longer lower or higher, the model stops training to prevent overfitting. It can be seen that the best validation performance is reached after the 6th iteration, after which the curve tends to flatten and the network begins to converge, at which time the MSE values of the training set, validation set, and test set are 0.0055, 0.0002, and 0.0103, respectively.

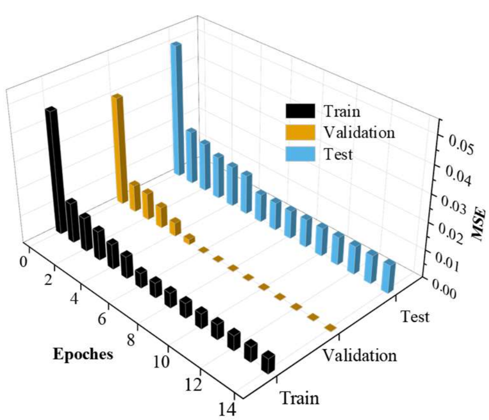

Figure 4: The convergence of the Adaboost-BP neural network

The mean error values and relative values of the prediction results are shown in Table 1. In order to facilitate the simplicity of subsequent data analysis, the expected values of sports learning behaviors were normalized. The average absolute error value of sports learning behavior identification was reduced from 0.223 to 0.157 for the BP neural network improved based on genetic algorithm, and the average absolute error value of prediction for sports learning behavior identification was reduced to 0.029 for the BP neural network improved based on Adaboost algorithm.The relative value of the average error of prediction of sports learning behavior was also reduced from 30.51% to 3.79% for the initial BP neural network. 30.51% to 3.79%, which is a more obvious improvement of the neural network prediction results.

Both PSOBP algorithm and SC-ISSABP algorithm have the effect of improving the performance of BP neural network, under the same dataset, the absolute value of sports learning behavior recognition error is reduced by 0.059 and 0.077 respectively, and the relative value of the average error is reduced by 8.99% and 11.25%.SC-ISSABP algorithm compared to PSOBP algorithm.Adaboost-BP algorithm compared to SC-ISSABP algorithm reduced the absolute value of prediction error by 0.117 and the relative value of average prediction error by 15.47%.

Compared to the comparison algorithms, Adaboost-BP neural network has the smallest absolute value of error and relative value of mean error.WOA-BP uses whale algorithm to improve the BP neural network and reduces the prediction error by 0.091. The C-I-WOA-BP goes further, combining the chaotic mapping adaptive optimization with the whale algorithm to improve the BP neural network, the absolute value of the prediction error is reduced by 0.105, and the relative value of the average error is reduced by 12.81%. The experiment proves that the whale algorithm optimization BP neural network is able to effectively reduce the prediction error value. And the chaotic mapping adaptive algorithm can also effectively improve the performance of the WOA-BP algorithm.Adaboost-BP algorithm compared with the C-I-WOA-BP algorithm, the absolute value of the prediction error of the sports learning behaviors is reduced by 0.099, and the average relative error value is reduced by 13.91%.

Table 1: The average error value and relative value of the prediction result

Models	Average error absolute	Average error relative/%
BP	0.223	30.51%
PSOBP	0.164	21.52%
SC-ISSABP	0.146	19.26%
WOA-BP	0.142	19.53%
C-I-WOA-BP	0.128	17.70%
GA-BP	0.157	20.08%
Adaboost-BP	0.029	3.79%

II. C. 4) Learning Behavior Recognition

The physical education learning data of 100 students were selected from the collected data set, and the Adaboost-BP model was used to identify learning behaviors, and the learning behaviors of students in three dimensions, including learning enthusiasm Y1, knowledge point mastery Y2, and ability to analyze practical problems Y3, were output. The results of physical learning behavior recognition are shown in Figure 5, and the statistical results of the output indicators are shown in Table 2. In physical education, there were 24, 26 and 24 students with "excellent" learning enthusiasm Y1, knowledge point mastery Y2 and analytical ability to solve practical problems Y3, 40, 32 and 42 students with "medium" and 36, 42 and 34 students with "poor" respectively. The overall physical learning behavior of students was "excellent", "average" and "poor", accounting for 6%, 76% and 18%, respectively, and most of the students' physical learning behavior was at the medium level.

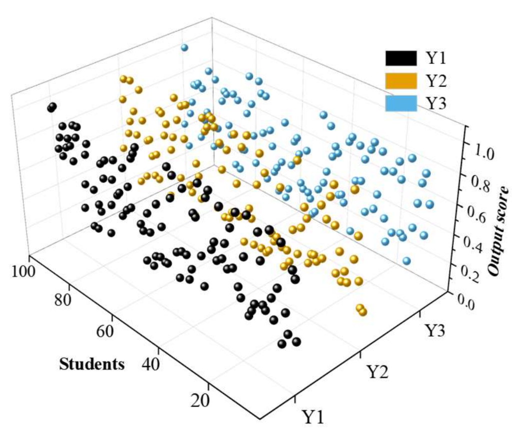

Figure 5: Identification of physical learning behavior

Table 2: Output index statistics

Output	[0.8,1]	[0.5,0.8)	[0,0.5)
Y1	24	40	36
Y2	26	32	42
Y3	24	42	34
Total score	6	76	18
Proportion	6%	76%	18%

III. Physical education teaching strategy adjustment

Through the previous analysis, the Adaboost-BP model constructed in this paper identifies students' physical education learning behaviors and divides students into groups of different levels. Based on this, physical education teaching strategies can be adjusted according to the results of the division of students' physical education learning behaviors, and more targeted stratified teaching can be carried out for students with different learning status.

III. A. Learning behavior stratification

Difference analysis combined with student stratification, the main body of teaching activities is the students, the teacher needs to play a guiding role in the teaching process, prompting the student teaching process is targeted, to avoid blind teaching. In this regard, teachers need to understand the different levels of students, analyze, objectively and accurately for different students to carry out targeted teaching. First of all, it is necessary to determine the criteria for student stratification, because students have individual differences, diversity and difficult to clearly define. The analysis of student differences includes: typological research and differential variable research. First, according to the different performance of different students in the learning process, the abstraction of the definition of similar students into one category, and give targeted teaching. Second, according to the actual classroom performance of students, the analysis of factors affecting the individual differentiation of students, and classified according to different situations, and teachers provide targeted teaching data. Students can be stratified using the sports learning behavior recognition model based on the Adaboost-BP model.

III. B. Personalized Guidance

Combining individualized instruction with tiered teaching means setting targeted teaching objectives on the premise of stratifying different types of students. The organic combination of individual guidance and stratified teaching is an important factor in promoting unified teaching. On the premise of stratified education in higher education sports, giving individual students guidance is of great significance to the development of students' specificity. In the traditional education model, the teacher pays more attention to the students with excellent academic performance, and pays serious attention to other students. High school sports stratified education, the teacher needs to fully do all the preparation before class, the students in the classroom may appear in a variety of situations to prepare. Secondly, the teacher should treat every student the same, avoiding the phenomenon of small cooking.

III. C. Combined process evaluation

Combining process evaluation with result evaluation, in the process of sports stratified teaching of college students, it is of great significance to formulate reasonable evaluation methods and standards for students' learning process and learning results to promote sports stratified teaching in colleges and universities. The development of stratified education evaluation standards and methods need to be combined with the differences in the level of students at all levels and the degree of progress, scientific and reasonable development, while trying to avoid speculative behavior caused by the difficulty of the assessment of the students cheating and other speculative behavior, to ensure that the evaluation results of the fairness and authenticity. In addition, there are differences in the teaching mode of students at different levels, and there are differences in the content of the knowledge they receive, so there are naturally different evaluation results. Therefore, we should not only focus on the evaluation results of the students' learning situation, but also combine the process evaluation with the evaluation results, so as to truly and objectively reflect the students' spiritual quality, learning level and learning integrity.

IV. Experiments in teaching physical education classification

Stratified teaching mode is to follow the syllabus on the basis of different students' physique and personality, appropriately divide the teaching content, cultivate students' active participation in physical education learning initiative consciousness, and promote the healthy development of students' physical and mental qualities, in order to comply with the law of development of contemporary physical education teaching. Based on the Adaboost-BP model, this paper adjusts and optimizes the teaching of physical education teaching strategies and proposes stratified teaching under the identification of students' behaviors. This chapter carries out the practical application of the proposed teaching strategy and explores its teaching effect.

IV. A. Subjects of study

The 100 students who used the Adaboost-BP model for sports learning behavior recognition in the previous paper were the experimental subjects. Among them, 6, 76 and 18 were identified as excellent, moderate and poor learning behaviors, respectively. According to the classification results, different physical education teaching strategies were implemented.

IV. B. Research methodology

IV. B. 1) Questionnaire method

Questionnaires were distributed to the selected 100 students and were tested for validity and reliability and the test results showed that the questionnaires were valid. A total of 100 questionnaires were distributed and 100 questionnaires were recovered with a recovery rate of 100%, of which 98 questionnaires were valid, with a validity rate of 98%.

IV. B. 2) Experimental methods

Referring to the Evaluation Standard of College Students' Physical Fitness Monitoring and Physical Measurement to evaluate the indicators of different categories of students, the feasibility and practicality of 16-week categorized teaching is verified through the physical indicators before and after the test.

IV. B. 3) Statistical processing

Excel 2016 was used to process the results, which were expressed as mean ± standard deviation, and T-tests were used before and after teaching, with significant differences expressed at $P < 0.05$ and highly significant differences at $P < 0.01$.

IV. C. Experimental results

The changes of physical indexes before and after the experiment of the students whose learning behaviors were identified as “excellent” are shown in Table 3, * indicates P<0.05 compared with the pre-exercise, ** indicates P<0.01 compared with the pre-exercise, the same as below. The height and weight of male and female college students whose learning behavior was identified as superior did not change much before and after the experiment, and the lung capacity was elevated in both male and female students, but it was not statistically significant. Seated body flexion was significantly higher before and after for both male and female students ($P < 0.05$), and grip strength was significantly higher for female students than before the physical education categorization teaching class ($P < 0.05$).

Table 3: Physical indicator changes before and after the experiment(excellent students)

Excellent students			Height/cm	Weight /kg	Lung capacity /mL	Preflexion /cm	Holding strength /kg
Boys (n=3)	Before	Mean	172.72	64.96	3260.72	5.57	32.64
		SD	3.06	5.33	11.42	1.36	2.32
	After	Mean	173.02	65.53	3558.21	6.79*	33.91
		SD	3.17	3.41	10.57	1.76	2.13
Girls(n=3)	Before	Mean	161.45	52.81	2370.88	11.09	20.56
		SD	3.45	3.15	14.56	4.25	4.57
	After	Mean	161.96	52.87	2539.12	13.04*	23.25*
		SD	3.49	3.33	12.11	5.24	2.26

The changes in body indexes before and after the experiment of the students whose learning behaviors were identified as “medium” are shown in Table 4. The height and weight of male and female college students did not change much before and after the experiment, and the lung capacity, sitting forward bending and grip strength all increased. Among them, the improvement in lung capacity and sitting forward bend was significant for male students, and the improvement in lung capacity, sitting forward bend and grip strength was significant for female students ($P < 0.05$).

Table 4: Physical indicator changes before and after the experiment(Medium students)

Excellent students			Height/cm	Weight /kg	Lung capacity /mL	Preflexion /cm	Holding strength /kg
Boys (n=40)	Before	Mean	170.21	65.36	2960.19	5.97	31.77
		SD	3.43	2.62	12.03	2.07	1.85
	After	Mean	170.75	65.55	3558.87*	6.38*	32.54
		SD	3.78	2.67	12.36	2.67	1.86
Girls(n=36)	Before	Mean	160.42	52.97	2071.04	11.19	20.37
		SD	2.34	2.93	12.07	1.65	1.29
	After	Mean	160.78	51.76	2339.83*	14.82*	23.94*
		SD	2.31	2.96	12.29	1.64	1.27

The changes of physical indicators before and after the experiment of the students whose learning behaviors were identified as “poor” are shown in Table 5. Lung capacity, seated forward bending and grip strength of both male and female students before and after the experiment showed significant differences at the 5% level, indicating that the physical indicators of both male and female students improved after the adjustment of physical education teaching strategies.

Table 5: Physical indicator changes before and after the experiment(Poor students)

Excellent students			Height/cm	Weight /kg	Lung capacity /mL	Preflexion /cm	Holding strength /kg
Boys (n=9)	Before	Mean	169.46	64.33	2873.14	5.86	30.58
		SD	3.32	1.44	10.25	2.64	2.56
	After	Mean	170.22	64.46	3496.97*	6.24*	32.18*
		SD	3.32	1.49	13.46	2.48	2.49
Girls(n=9)	Before	Mean	161.58	52.77	2018.64	10.46	20.09
		SD	1.76	3.14	12.83	1.74	2.51
	After	Mean	161.65	52.68	2290.04*	13.92*	23.35*
		SD	1.66	3.44	12.45	1.78	2.58

The non-physical indicators of this subject are related to students' enjoyment of physical education courses, learning motivation, skill mastery, rationality of course content, learning experience and other related contents. The evaluation results of non-physical indicators before and after the experiment are shown in Table 6. The experimental results show that students' enjoyment and learning motivation of physical education learning increased by 55% and 63% after the categorized teaching, and the aspects of motor skill mastery, course content rationality and learning experience were also recognized by the students, which increased by 60%, 68% and 65%, respectively. The overall optimization of students' physical education learning was achieved after the adjustment of physical education teaching strategies.

Table 6: The results of non-physical indicators before and after the experiment

Topic selection	Before experiment		After experiment		Difference/%
	Number	Proportion/%	Number	Proportion/%	Proportion/%
Course preference	10	8%	65	65%	55%
Learning initiative	17	15%	78	78%	63%
Skill master	12	12%	72	72%	60%
Content rationality	8	7%	75	75%	68%
Learning experience	11	9%	74	74%	65%

V. Conclusion

This paper uses the Adaboost algorithm to optimize the BP neural network to construct the sports learning behavior recognition model. And based on this model, it adjusts the physical education teaching strategy and puts forward the suggestion of physical education stratified teaching. Finally, it is applied to teaching practice, and the effect of the teaching strategy is evaluated through the comparison of students' physical measurement data and questionnaire survey. The experimental results show that compared with other methods, the Adaboost-BP model has the smallest error in the identification of sports learning behaviors, with the absolute and relative average errors of 0.029 and 3.79%, respectively, which are 0.194 and 26.72% lower than that of the BP model, and the identification of students' sports learning behaviors is more accurate. The 100 randomly selected students were identified as “excellent”, “moderate” and “poor” learning behaviors, accounting for 6%, 76% and 18% respectively. At the end of the experiment, students in all three categories showed improvement in lung capacity, seated forward bending and grip strength, with the most significant improvement in students with “poor” learning behaviors. At the same time, students' enjoyment of physical education courses, learning motivation, skill mastery, course content rationality, and learning experience also gained significant improvement, with improvement ranging from 55% to 68%%, indicating that the proposed Adaboost-BP-based physical education tiered teaching strategy has a facilitating effect on students' physical education learning. Physical education can not only improve the physical quality of students, but also improve the psychological quality of students, which is conducive to promoting the overall development of students. In high school physical education teaching, teachers can stratify students based on the physical education learning behavior identification model, and according to the differences in student teaching, giving each level of targeted education programs, to ensure that each level of students can give full play to their own strengths, and to promote the development of the quality of physical education teaching.

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