Hindawi
Journal of Sensors
Volume 2024, Article ID 9845151, 1 page
https://doi.org/10.1155/2024/9845151

Retraction

Retracted: Prediction and Analysis of College Sports Test Scores Based on Computational Intelligence

Journal of Sensors

Received 23 January 2024; Accepted 23 January 2024; Published 24 January 2024

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] P. Cui, "Prediction and Analysis of College Sports Test Scores Based on Computational Intelligence," *Journal of Sensors*, vol. 2022, Article ID 4070030, 10 pages, 2022.

Hindawi
Journal of Sensors
Volume 2022, Article ID 4070030, 10 pages
https://doi.org/10.1155/2022/4070030

Research Article

Prediction and Analysis of College Sports Test Scores Based on Computational Intelligence

Pengtao Cui

Shaoxing University Yuanpei College, Shaoxing, Zhejiang 312000, China

Correspondence should be addressed to Pengtao Cui; cuipt@usx.edu.cn

Received 17 April 2022; Revised 4 July 2022; Accepted 15 July 2022; Published 24 August 2022

Academic Editor: Yuan Li

Nowadays, colleges and universities are paying more and more attention to the physical condition of students. Many schools set up physical education courses to exercise students and improve their physical quality. They also conduct physical examinations every semester to test students' conditions. In order to ensure more accurate sports results, this paper uses optimization of the neural group particle group model method to forecast the physical culture test scores of the investigated students. In addition, to guarantee accuracy the particle swarm optimization neural network model method, we compare the GXD method and the LM method with our method. It has the advantage of high precision, optimal prediction effect, strong versatility, higher recall rate, stronger antinoise performance, and wider application range. The article compares the neural network model method for particle swarm optimization with the GXD way and the LM way to ensure precision the neural network model method for particle swarm optimization.

1. Introduction

A raw good training technology based on a hybrid neural network has been trained and tested by the actual results of football match from the Italian A series. Finally, the results of the model are compared with other statistical prediction models. The results indicate that the new model is more accurate, so that the efficiency of all teams offers a better assessment [1]. By using the method of the document, logical analysis, and statistical data, the article analyzes and studies the 2012 ranking of tennis players who joined the 12th total game and predicts the distribution of tennis medals for the 12th total game [2]. We use video computer technology to build motion and analysis detection systems using RGB cameras and depth educational models. It can be identified from the RGB image, follow the overall assessment, and retour data in real time. RGB images are processed in two subsystems: human detection system and performance analysis system. The human detection system is used to detect a gesture with the user, and the performance analysis system is intended to return feedback from the details of the user gesture. The result of the system is satisfactory: in a human detection system, overall accuracy can reach more than 99%, which means that nearly four activities can be accurately classified. In the case of performance analysis systems, the results and details can be returned based on small differences in levels CM. The delay of the entire system is in milliseconds, which means that the system can bet the detection and analysis of real-time. Golf driving is used as an example to illustrate how the system works. Moreover, the system can promote other sports [3] in the research to survey various physical characteristics of successful archery and provide main attributes that help the results of high archery. In this study, 32 arms from arches from different arched students participated. Perform standard physical fitness tests and note the last recording result, multivariate primary analysis techniques (PCA), layered agglomeration analysis, and discriminatory analysis (DA). VARIMAX-rotated PCA represents two variables with 12 and 2 variators (VF). Standard, backward, and forward stepwise reach classes from 14 predictors with 74.2%, 96.7%, and 93.6% accuracies, appropriately. The results of the current investigation can help in assigning arched athletes in accordance with their bodily characteristics [4].

Fast search and control over attitude changes; a method for designing a multimedia model is suggested. In the physical model and the kinematic model of the body, they quickly distinguish information about location and attitude information about the human body. Multimedia image analysis and intelligent control of the process that simulates the training of human traffic analyze the parameters of spatial traffic planning limits to achieve changes in attitude, which achieves optimal controls for sports training and sports planning. The simulation results show that the design based on the multimedia simulation of the computer is checked, and the error prediction of the traffic control parameters is low, and the ability to be the multimedia sport training model is stronger, and the effect of sports training has improved. In addition, simulation results will verify the efficiency of the internet [5]. Continuous development of computer and graphic technology, mode and image processing technology, and intelligent video tech techniques combine these related technologies and set image descriptions and supervision between images. Intelligent video analysis technology is widely used as in military and economic sectors. During the badminton training, when the trainer explains the behavior of the player, the video will be played and analyzed [6]. Machine learning (ML) is an intelligent approach to classification and prediction. This paper provides a detailed analysis of the M1 literature, focusing on the application of artificial neural networks (ANNs) in predicting traffic outcomes, as well as learning methods, data sources, appropriate model evaluation methods, and challenge-specific methods for predicting certain motion outcomes [7]. The main goal of this study is to build an intelligent mathematical model to predict the sports achievement of pole jumping in men; the method of the study consists of using five variables as the input to the neural network, which is the pathway of speed (m/sec in front distance 05 m closest and 05 m closest, maximum speed in the last 5 m total approach distance 30 m, conversion factor ratio of horizontal speed to vertical speed, conversion factor ratio of horizontal speed to vertical speed, and fist height at full pole long above); these are variables that are considered independent, while the correlated variables are the predictions that predict achievement (final height achieved by jumpers) as output. The neural network architecture is represented by three layers; the first layer is an input layer with five variables, and one layer is hidden and contains a node, while the last layer is an output layer representing the result of the prediction of athletic achievement male weight jumps [8]. The submission of recurrent neural networks (RNN) is learned in the prediction of sports outcomes of athletes in the Internet of Things (Internet of Things) environment. Specifically, the 3000 m slope enzymes and the corresponding outcomes of athletes were analyzed with RNN. Next model prediction of performance of athletes with 3000 M slope enzymes is determined by different algorithms, where IOT technology is used to predict and analyze the relationship between physical parameters and the efficiency of athletes [9]. Three algorithms of combined prediction of a gray model and neural network: GM-NN1: first, the original sports performance dataset is used to derive the error sequence using the MG (1, 1) model, and then, to get error sequence prediction, build a neural network to train error sequence regression. This new model uses a neural network to correct the error predicted by the GM model (1, 1), GM-NN2: this model uses some datasets for original traffic performance to make a set of universal data models (1, 1) and build a nervous network. The original data define a nonlinear relationship between the adjustment values; the resulting network estimated prediction trends for a group of generic (1, 1) models on partial data and achieved better results in sports achievement prediction [10]. By analyzing the students' vital indices as measured by their weight, height, and waist, this paper uses principal component regression analysis to set up a linear model for predicting exercise outcomes at 50 and 800 meters. In this way, it assists students to improve exercise results during their daily exercise [11]. Using physical testing methods, research has shown that although slightly more than the 2011 test results, men and women experience very large differences in physical life shape, physical function, body mass, and overall assessment that should draw attention. According to the "IT Public Plan for Reform of teaching sports university," the corresponding countermeasures were implemented to improve, the Western University Sport Sports Plan Reform of the course was set up. In 2013, the "IT College Sports Club" was implemented to provide theoretical reference [12]. Contributing to be a literature by developing a regression model that offers football results, we use prediction accuracy measures and wagering simulations to evaluate model performance. The model developed may equal or exceed the results of existing statistical models with a similar structure. Taken together, these results suggest that public odds for multiple soccer matches invested are slightly less effective, but these low performance does not cause the revenue of the statistical gambling algorithm. The results also show that the results of the historic alliance are the most important components in the statistical model of football forecasts and completed the moderate accuracy of these components and other data [13]. Prediction accuracy of various methods such as prediction markets and selection evaluates the ability to systematically produce the market and subtitles to produce the profit on the game market. We have introduced empirical results of the 678-837 study of the German Premiere Association game. The forecast market and the chance of plants are also applied to predictive accuracy, but both methods are very complicated [14]. Machine leather algorithm are accustomed to build models to predict physical student performance. The particle group optimization algorithm is used to select model parameters. This model applies to modeling physical properties and forecasts of specific universities. Application results show that the machine's algorithm can eliminate the learning of the shortcomings of traditional models and improve the effect of prognosis in sports activities, and the predicted results can lead to reforms of university sports [15].

2. College Sports Test Scores

2.1. Current Situation of College Sports Test Scores. At present, the physical quality of students is declining year by year, and the current exercise situation is not satisfactory: only 34.2% of the students exercise regularly, and most of the students do not exercise often, and their consciousness is weak. Boys perform better than girls on sports tests and, in different classes, have higher minimum scores than others. The intensity of exercise awareness, exercise time, and exercise frequency are not ideal and cannot produce good exercise effects. There are differences between male and female students and students of different grades. Because most students lack sports and choose to stay in dormitories most of the time, it can be seen from the results of college sports tests that most of the indicators are declining year by year, getting lower year by year.

The physical fitness of college students is declining year by year, and the current situation of physical exercise is also unsatisfactory. Only 34.2% of the students regularly participate in exercise, and most of the students rarely exercise, and they are not conscious of physical exercise. College students' physical exercise awareness intensity, exercise time, and exercise frequency are not ideal, and they cannot achieve good results of physical exercise. It can be seen from the results of college sports tests that most of the indicators are declining year by year, getting lower year by year.

2.2. Problems Existing in College Sports Testing. First of all, the evaluation of students' physical education performance largely relies on the evaluation of athletic ability, in order to systematically obtain sufficient information on students' personal physical fitness and learning achievements and to evaluate the degree of students' achievement of teaching goals. Physical education: there is no doubt that it is reasonable to use examinations as an important means of evaluating students' learning outcomes, but the problem is that the current examination form, content, and evaluation criteria are too monotonous and difficult to be comprehensive and accurate. Individual training subjects to measure: second, the understanding of the objectives of higher education physical education courses is not clear enough or incomplete; it only emphasizes the evaluation of explicit factors such as physical fitness, sports technology, and skills, while ignoring the coordinated development of hidden factors such as psychology and group relations, thus forming an evaluation process. Physical and mental separation, lack of awareness of the relationship between the purpose of diagnosis, and the purpose of physical education result in a certain degree of disconnection between the two. Third, theory and practice are the two most basic assessment elements to measure students' quality and performance. If only focus on practice and ignore theory in the process of talent training, only mechanical technology can be used to train robots. In quality education, special emphasis is placed on cultivating students' innovative ability. Talking about innovation without theoretical guidance can only be a slogan. Without mastering theoretical knowledge, students' development space will be limited. Participation in sports activities will inevitably lead to blindness and sometimes unnecessary physical and mental harm. Fourth, the purpose and function of the evaluation of students' academic performance are not clear, which leads to the use of summative evaluation as the main evaluation method for evaluating academic performance, which has obvious drawbacks.

2.3. The Benefits of Computational Intelligence in the Predictions of the Results of Sports Tests. So as to implement the policy of the comprehensive development of morality, intelligence, and physique in universities and universities, the Ministry of Education of the People's Republic of China has issued the "Qualification Standards for College Students' Sports" for colleges and universities across the country. Students' sports performance is mainly divided into body type indicators, physical indicators, and sports quality. Body size is directly related to athletic performance. How to use the body shape index to predict sports performance not only has certain guiding significance for the role of teachers and students in teaching and daily exercise but also allows students to choose the appropriate body shape according to their physical fitness. The current state of the art in predicting student athletic performance is analyzed, and the reasons for the low prediction accuracy of current models are identified. An intelligent support vector machine is used to establish a student's sports performance prediction model, and the intelligent model is used to apply the model to college sports performance, modeling, and predicting characters. The intelligent algorithm can overcome the shortcomings of traditional models and improve the effect of predicting sports results. And predictive outcomes may lead to college sports reform.

Current research states forecast that indicate the execution of students who indicate the causes of low accuracy of predicting the current model. Calculate the intelligent machine for the support vector to determine a model prediction of the sporting efficiency of students, using intelligent models. Finally, the model applies to college sports results, Modeling and class prediction. The intelligent algorithm can overcome the shortcomings of traditional models and improve the effects of predicting a college sport efficiency, and the results of the forecasts can carry out a reform of the university sports disciplines.

2.4. Optimization of College Sports Test Scores. First, performance assessment is a significant section of physical education systems engineering and is intently involved to the personal interests of the students. The content and standards of the test should be as objective as possible, students should be assessed academically, and the classroom test prepared by teachers should be combined with the unified test at the classroom level, one-time, and continuous. Class exams, teaching, and exam drills by exam panels of teachers (classrooms) and classroom teachers who do not take class exams. Second, after the special courses are launched, the widely collected high-quality textbooks can be combined with the national physical exercise standard test. Among many projects of the same quality, several textbooks with lower technical requirements should be selected for use. The balance of textbooks, hours, and test standards is based on mathematical statistics, the correct selection of test standards, and the average score of qualitative categories dropped by 1 point to 50 points, which is in line with the national sports activities standard scoring method. For a small number of students with special difficulties in physical and physiological conditions, the relative performance assessment method should be used to evaluate their performance. The fourth is to strengthen the research on teaching methods and further improve the quality of education. The use of intelligent algorithms can conquer the defect of traditional models and improve the predictive effect of physical education outcomes in colleges and universities, and the prediction results can drive the reform of college sports disciplines.

3. Computational Intelligence Prediction Model for College Sports Test Scores

3.1. Neural Network Model for Particle Swarm Optimization

3.1.1. Neural Networks. The neural network is a multilayer feed-forward network, and one-way propagation generally falls on three or more layers. Here are the steps on how a neural network works:

In the first step, set a random nonzero number; its Vkl is relatively small, and set the weight coefficient of each layer to its range.

In the second step, the output sample is

$$A = (a_1, a_2 \cdots, a_m). \tag{1}$$

The corresponding expected output is

$$E = (e_1, e_2, \cdots, e_m). \tag{2}$$

The third step is to calculate the output of each layer and the kth neuron output in the hth layer as follows:

$$G_k^h = \sum V_{kl} A_k^{h-1}, \tag{3}$$

$$A_k^h = s\left(G_k^h\right). \tag{4}$$

Usually, Equations (3) and (4) will be represented by the Sigmoid function, as follows:

$$s(a) = \frac{1}{(1 - \exp(-a))}. \tag{5}$$

The fourth step is to evaluate the learning error d of each layer, in the output layer $h = n$,

$$f_k^n = A_k^n (1 - A_k^n)(A_k^n - E_k^n). \tag{6}$$

The other remaining layers exist:

$$f_k^h = A_k^h \left(1 - A_l^h\right) \sum V_k f_k^{h+1}. \tag{7}$$

The fifth step is to change the weight factor Vkl, as follows:

$$V_{kl}(p+1) = V_{kl} - q \cdot f_k^h \cdot A_l^{h-1}. \tag{8}$$

The sixth step is to determine if the calculated weight is coefficients of each tier can meet the request. If the requirements can be met, the calculations can be ended.

(1) Set a random nonzero number whose V_{kl} is relatively small, and set the weight coefficient of each layer to its range

(2) Output samples and corresponding expectations

(3) Calculate the output of each layer, and the output of the kth neuron in the h layer

(4) Evaluate the learning error d of each layer, and output each layer

(5) Correct the weight coefficient V_{kl}

(6) Define if the calculated weighting factors for each level meet the request. If the requirements can be met, the calculations can be aborted. Else, go back to step 3

3.1.2. Particle Swarm Optimization Method. The best answer for the current particle group optimization is gbestos, and the best explanation for the present group is gbestos. The fit performance depicting the advantages and disadvantages of a single particle is structured as follows:

$$\text{fitness} = \frac{1}{2N} \sum_{i=1}^{N} \sum_{j=1}^{D} \left(y_{ij} - t_{ij}\right)^2. \tag{9}$$

The primary random explanation of the particle swarm majorization way repeatedly iterates to discovery the optimal answer, and the particle follows two extreme worth in each iteration to guarantee that the particle itself can be renewed. The two extreme worth are t_{Best} and u_{Best} separately, the best explanation found by the particle itself is t_{Best}, and the optimal solution found by the whole population is u_{Best}. The particle location and velocity are updated by these two extreme worth using Equations (10) and (11). ω represents the speed of the particle; present represents the position of the particle itself; x_1 and x_2 represent the learning factor; y_1 and y_2 represent a random number between (0, 1).

$$\omega = \omega + x_1 \times y_1 \times (t_{\text{Best}} - \text{present}) + x_2 \times y_2 \times (u_{\text{Best}} - \text{present}), \tag{10}$$

$$\text{present} = \text{present} + \omega. \tag{11}$$

The first particle on the right edge of the velocity Equation (10) has no memory capacity and is random. It will search for a new region and has a powerful global majorization ability. But, in functional claims, it is essential to perform an entire finding to enhance the rate of search astringent and then use local search to obtain a more precise solution. σ represents the inertia weight. The larger the value of σ, the stronger the global search ability of the particle swarm optimization method, and vice versa.

The larger the worth of σ, the stronger the entire find power of the particle swarm optimization method; the lower the worth of σ, the weaker the entire find power of particle swarm optimization method.

$$\omega = \sigma \times \omega + x_1 \times y_1 \times (t_{\text{Best}} - \text{present}) + x_2 \times y_2 \times (u_{\text{Best}} - \text{present}), \tag{12}$$

$$\text{present} = \text{present} + \omega. \tag{13}$$

Advantage:

(1) It can deal with some traditional methods that cannot be dealt with

Shortcoming:

(1) Not very good on some points

(2) Coding network weights and selecting genetic operators are sometimes difficult

3.1.3. Correct the Variance and Weight of the Web. When optimizing a neural network with particle swarm optimization methods, optimization is necessary in two parameters, variance σ_i $(i = 1, 2, \cdots, h)$ of neural network basis function and the weight $V_0, V_1, \cdots, V_K$, and the dimensions of the two parameters are the same as the network structure. Correlation, uniformly encode the weights and variances of the neural network, and a set of the weights and variation of neural networks are depicted by the particle. Taking the root mean square error as the fitness function, it can reflect the approximation error of the particle. a is the overall count of specimens; y_1^i and y_2^i are actual produced worth and the nervous net forecast value, respectively. The healthy worth of the particle is as follows:

$$\text{RMSE}(i) = \sqrt{\frac{1}{a}\sum_{j=1}^{a}\left(y_1^i - y_2^i\right)^2}. \tag{14}$$

3.2. Prediction Model of Sports Achievements of the University. Modeling of university sports results with nervous net model for particle swarm optimization. Optimization of neural network models using a swarm of particles for modeling of sports performance in colleges and universities, assuming that the initial performance time series is as follows:

$$A^{(0)}(p) = \left\{a^{(0)}(1), a^{(0)}(2), \cdots, a^{(0)}(m)\right\}, \tag{15}$$

$$B^{(0)}(p) = \left\{b^{(0)}(1), b^{(0)}(2), \cdots, b^{(0)}(m)\right\}. \tag{16}$$

Taking the first-order differential operation formula (14), formula (17) is obtained as the first-order differential sequence:

$$A^{(1)}(p) = \left\{a^{(1)}(1), a^{(1)}(2), \cdots, a^{(1)}(m)\right\}. \tag{17}$$

Table 1: Prediction results of college students' sports performance.

Iterations/time	Prediction error	Convergence time (s)
100	0.032	4.2
200	0.039	2.9
300	0.042	5.1
400	0.049	5.6
500	0.053	6
600	0.056	6.2
700	0.061	6.7
800	0.063	7.1
900	0.069	7.8
1000	0.072	8.1

In the first-order mean surgery formula (16), the first-order mean sequence is obtained as

$$B^{(1)}(p) = \left\{b^{(1)}(1), b^{(1)}(2), \cdots, b^{(1)}(m)\right\}. \tag{18}$$

The prediction model is established by formula (6), c and parameters, such as

$$\frac{fa^{(1)}}{fp} = ca^1 = \lambda. \tag{19}$$

Solving Equation (19), the albino differential equation predicting sports results colleges and universities is obtained, such as

$$\hat{a}^1(h+1) = \left(a^{(0)}(1) - \frac{\lambda}{c}\right)d^{-ch} + \frac{\lambda}{c}(h = 1, 2, 3, \cdots, m). \tag{20}$$

Using the neural network description formula (20), the nervous net parameters are gained by practice in the light of the key in and produce specimen data, and the best target shining upon the formula (20) is blanket.

4. Prediction and Analysis of College Sports Test Scores Based on Computational Intelligence

Taking the 1000-meter long-distance running performance of 50 freshmen in a university as the experimental object, after many calculations and analysis, the data truly reflects the students' sports trends. The neural network used in this method has 3 input nodes, 1 output node, and 10 hidden units. The population of the particle swarm optimization method is $m = 40$, the initial inertial mass value is 1, and the inertial mass is reduced to 0.5. The number of iterations gradually increases the values of af, $x1$, and $x2$ which are all equal to 3, and [-19.19] is the link weight change interval. The iteration stops when the number of iterations reaches the maximum value.

4.1. This Paper Method. A neural network model was used to optimize the particle swarm to predict the performance of

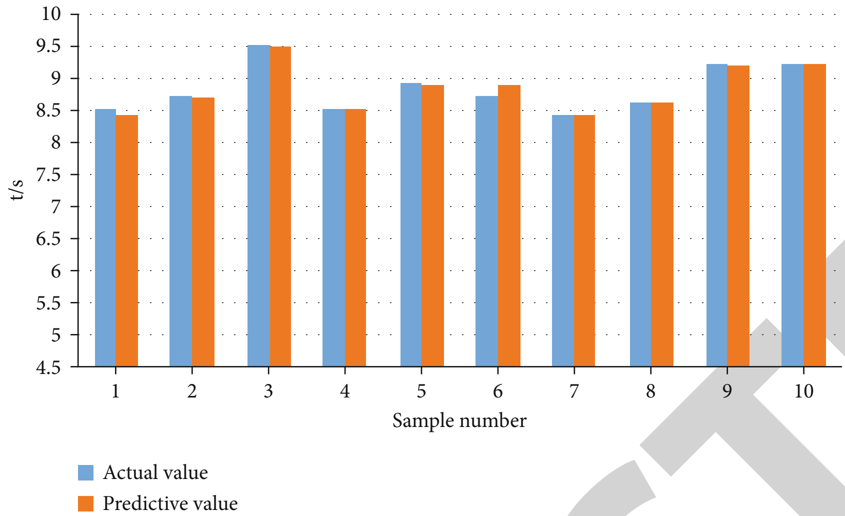

Figure 1: Comparison of predicted and actual results.

the subjects' movement. When the frequency of iterations is 100, the prediction mistake is the least, the prediction error is 0.032, and the convergence time is 4.2 s; when the frequency of iterations is 1000, the forecast error is the largest, the forecast error is 0.032, and the convergence time is 8.1 s. When the frequency of iterations is 200, the forecast error is 0.039, and the convergence time is 2.9 s; when the frequency of iterations is 300, the forecast error is 0.042, and the convergence time is 5.1 s; when the frequency of iterations is 400, the forecast error is 0.049, and the convergence time is 5.6 s; when the frequency r of iterations is 500, the forecast error is 0.053, and the convergence time is 6 s; when the iteration frequency is 600, the forecast error is 0.056, and the convergence time is 6.2 s; when the iteration frequency is 700, the forecast error is 0.061, and the convergence time is 6.7 s; when the frequency of iterations is 800, the forecast error is 0.063, and the convergence time is 7.1 s; when the frequency of iterations is 900, the forecast error is 0.069, and the convergence time is 7.8 s, as shown in Table 1.

10 students were randomly selected from the experimental subjects, and the particle swarm majorization nervous net method was formed to test comparison between the forecasted results and the actual values. There is no significant difference between the forecasted results obtained by this model and the actual values that are approximately equal. Actual value of sample 1 is 8.5 s, and the forecasted value is 8.4 s; the actual value of sample 2 is 8.7 s, and the predicted value is 8.68 s; the actual value of sample 3 is 8.5 s, and the predicted value is 8.49 s; the actual value of sample 4 is 8.49 s. The actual value of sample 5 is 8.9 s, and the predicted value is 8.88 s; the actual value of sample 6 is 8.7 s, and the predicted value is 8.89 s; the actual value of sample 7 is 8.4 s, and the predicted value is 8.89 s. The actual value of sample 8 is 8.6 s, and the predicted value is 8.6 s; the actual value of sample 9 is 9.2 s, and the predicted value is 9.19 s; the actual value of sample 10 is 9.2 s, and the predicted value is 9.2 s, as shown in Figure 1.

Table 2: Prediction results of college students' sports performance.

Iterations/time	Prediction error	Convergence time (s)
100	0.037	10.3
200	0.041	10.7
300	0.046	11.2
400	0.053	11.9
500	0.056	12.5
600	0.059	13.1
700	0.064	14.5
800	0.066	15.3
900	0.073	16.2
1000	0.078	17.6

4.2. GDX Method. Using the GDX method to predict the sports performance of the experimental subjects, when the frequency of iterations is 100, the forecast error is the smallest, the forecast error is 0.037, and the convergence time is 10.3 s; when the frequency of iterations is 1000, the forecast error is the largest, and the forecast error is 0.078, the convergence time is 17.6 s. When the frequency of iterations is 200, the forecast error is 0.041, and the convergence time is 10.7 s; when the frequency of iterations is 300, the forecast error is 0.046, and the convergence time is 11.2 s; when the frequency of iterations is 400, the forecast error is 0.053, and the convergence time is 11.9 s; when the frequency of iterations is 500, the forecast error is 0.056, and the convergence time is 12.5 s; when the frequency of iterations is 600, the forecast error is 0.059, and the convergence time is 13.1 s; when the frequency of iterations is 700 and when the frequency of iterations is 800, the forecast error is 0.066, and the convergence time is 15.3 s; when the frequency of iterations is 900, the forecast error is 0.073, and the convergence time is 16.2 s, as shown in Table 2.

10 students were randomly selected from the experimental subjects, and the GDX method was used to test the

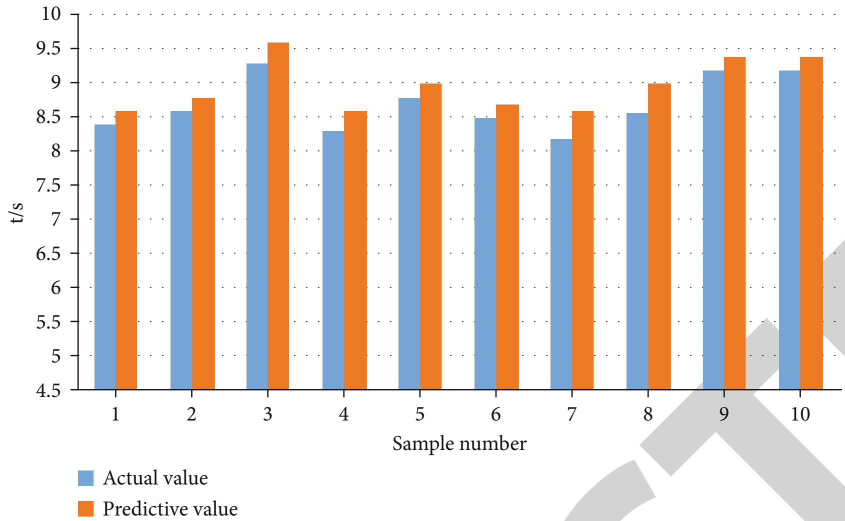

Figure 2: Comparison of predicted and actual results.

comparison between the forecasted results and the actual values. There is a significant difference between the forecasted results obtained by this model and the actual values. The actual value of sample 1 is 8.4 s, and the predicted value is 8.6 s; the actual value of sample 2 is 8.6 s, and the predicted value is 8.8 s; the actual value of sample 3 is 9.3 s, and the predicted value is 9.6 s; the actual value of sample 4 is 9.6 s. The actual value of sample 5 is 8.8 s, and the predicted value is 9.0 s; the actual value of sample 6 is 8.5 s, and the predicted value is 8.7 s; the actual value of sample 7 is 8.2 s, and the predicted value is 8.7 s. The actual value of sample 8 is 8.58 s, and the predicted value is 9.0 s; the actual value of sample 9 is 9.2 s, and the predicted value is 9.4 s; the actual value of sample 10 is 9.2 s, and the predicted value is 9.4 s, as shown in Figure 2

4.3. LM Method. The LM method is used to predict the sports performance of the experimental subjects. When the frequency of iterations is 100, the forecast error is the smallest, the forecast error is 0.043, and the convergence time is 15.3 s; when the frequency of iterations is 1000, the forecast error is the largest, and the forecast error is 0.087, and the convergence time is 24.5 s. When the frequency of iterations is 200, the forecast error is 0.047, and the convergence time is 16.5 s; when the frequency of iterations is 300, the forecast error is 0.056, and the convergence time is 17.2 s; when the frequency of iterations is 400, the forecast error is 0.059, and the convergence time is 18.9 s; when the frequency of iterations is 500, the forecast error is 0.067, and the convergence time is 19.2 s; when the frequency of iterations is 600, the forecast error is 0.071, and the convergence time is 20.2 s; when the frequency of iterations is 700 and when the frequency of iterations is 800, the forecast error is 0.079, and the convergence time is 22.2 s; when the frequency of iterations is 900, the forecast error is 0.082, and the convergence time is 23.6 s, as shown in Table 3.

10 students were randomly selected from the experimental subjects, and the LM method was used to test the comparison between the forecasted results and the actual values. There is a significant difference between the forecasted results obtained by this model and the actual values. The actual value of sample 1 is 8.5 s, and the predicted value is 8.2 s; the actual value of sample 2 is 8.6 s, and the predicted value is 8.5 s; the actual value of sample 3 is 9.4 s, and the predicted value is 9.2 s; the actual value of sample 4 is 9.2 s and 8.5 s, and the predicted value is 8.3 s; the actual value of sample 5 is 8.9 s, and the predicted value is 8.5 s; the actual value of sample 6 is 8.6 s, and the predicted value is 8.4 s; the actual value of sample 7 is 8.4 s, and the predicted value is 8.4 s. The actual value of sample 8 is 8.7 s, and the predicted value is 8.5 s; the actual value of sample 9 is 9.2 s, and the predicted value is 9.1 s; the actual value of sample 10 is 9.2 s, and the predicted value is 9.2 s, as shown in Figure 3.

Table 3: Prediction results of college students' sports performance.

Iterations/time	Prediction error	Convergence time (s)
100	0.043	15.3
200	0.047	16.5
300	0.056	17.2
400	0.059	18.9
500	0.067	19.2
600	0.071	20.2
700	0.076	21.8
800	0.079	22.2
900	0.082	23.6
1000	0.087	24.5

4.4. Comparison of This Method with GDX Method and LM Method. After comparing the prediction effect of the method in this paper with the GDX method and the LM method, it is necessary to verify the generality of predicting students' sports performance. These three methods are used to predict the average sports performance of 200 m sprint, 400 m sprint, 800 m sprint, long jump, high jump, and shot put.

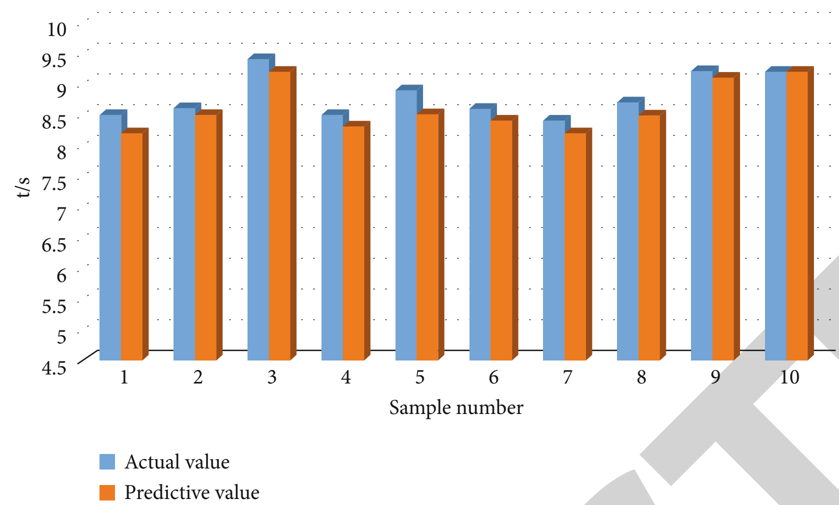

FIGURE 3: Comparison of predicted and actual results.

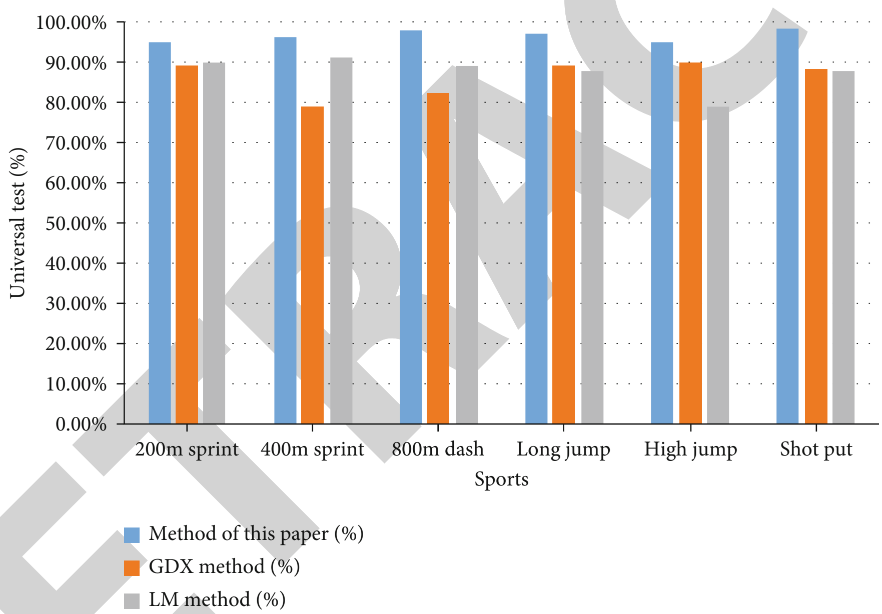

FIGURE 4: Universal test of college students' sports performance prediction.

Score prediction accuracy: looking at the figure below, you can see that the generality test of the method in this paper ranks first in sports, and the generality test results are above 95%. In the 200 m sprint, the generality test result of the method in this paper is 95.32%, the generality test result of the GDX method is 89.23%, and the generality test result of the LM method is 90.15%; the generality test result of GDX method is 78.99%, and the generality test result of LM method is 91.28%; in the 800 m long-distance running, the generality test result of this method is 98.36%, the generality test result of GDX method is 82.59%, and the generality test result of LM method is 98.36%. The result is 89.47%; in the long jump, the method generality test score in this document is 97.25%, and the method generality test score is 89.17%, and the generality test result of the LM method is 88.13%; in high school, the generality test result of the method in this paper is 95.36%, the generality test result of GDX method is 90.10%, and the generality test result of LM method is 79.18%; in shot put, the generality test result of this method is 98.75%, the generality test result of GDX method is 88.28%, and the generality test result of LM method is 95.36%. The sex test result was 88.19%, as shown in Figure 4.

As can be seen from the figure below, the particle swarm optimization nervous net method used in this paper has the highest recall rate, with a recall rate of 98.50%; the LM method has the lowest recall rate, with a recall rate of 92.3%; the GDX method has the highest recall rate. The completion rate ranks second with a recall rate of 94.60%, as shown in Figure 5.

So, to verify the antinoise effectiveness of the suggested way in predicting students' athletic performance, interference

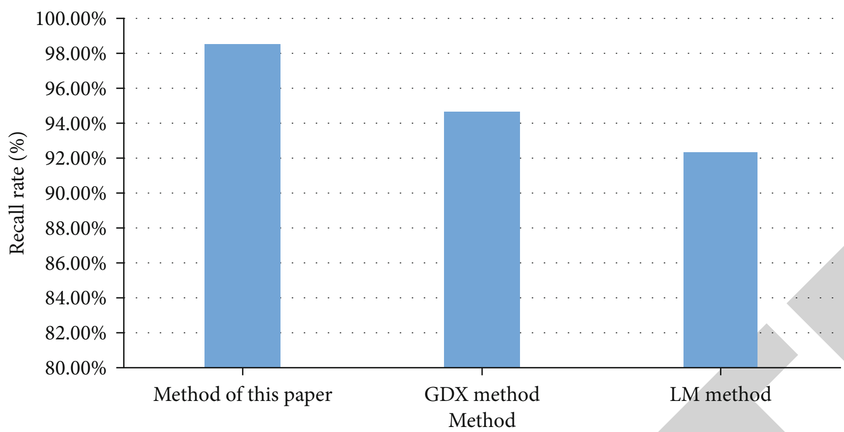

Figure 5: Comparison of the recall rate of college students' sports scores.

Table 4: SNR output results of different methods.

Method	This paper method/Db		GDX method/Db		LM method/dB	
Number of iterations	10	20	10	20	10	20
10	5.87	8.95	4.26	7.59	4.15	7.28
20	6.95	9.14	5.48	8.14	5.68	8.14
30	7.59	10.58	6.86	9.25	6.47	9.26
40	8.65	11.67	7.24	10.35	7.59	10.47
50	9.66	12.69	8.16	11.27	8.26	11.54
60	10.87	13.48	9.24	12.64	9.47	12.67
70	11.58	14.47	10.48	13.47	10.59	13.54
80	12.98	15.21	11.27	14.67	11.68	14.13
90	13.88	16.47	12.68	15.47	12.64	15.72
100	14.69	17.68	13.54	16.79	13.59	16.93
Average value	10.27	13.03	8.92	11.96	9.01	11.96

was added to the collected students' athletic show. In the 10th and 20th times of the method in this paper, the signal-to-noise ratio output of the method is higher than the other two methods; the signal-to-noise ratio output results are 10.27 dB and 13.03 dB, respectively. The 20th time SNR output results are 8.92 dB and 11.96 dB, respectively; the 10th and 20th time SNR output results of the LM method are 9.01 dB and 11.96 dB, respectively, as shown in Table 4.

The utility of the sports show forecast method is evaluated by testing the performance of the three methods. The paper is mostly better than the performance of the other two methods in all aspects. In terms of convergence speed, the convergence speed of the method in this paper is fast, the speed of GDX method is medium, and the speed of LM method is slow; in terms of model structure, the structure of this method is simple, the structure of GDX method is medium, and the structure of LM method is medium; in terms of antinoise strength, the strength of the method in this paper is strong, the strength of the GDX method is medium, and the strength of the LM method is medium; in terms of data requirements, the requirements of the method in this paper are medium, the requirements of the GDX method are strong, and the requirements of the LM method are strong; in terms of accuracy, the method in this paper is strong, the GDX method is low, and LM method is low; in terms of scope, the method in this article is wider, the GDX method is medium, and the LM method is medium; in terms of development prospects, the method in this paper is large, and the GDX method is medium and is moderate, and the LM method is moderate, as shown in Table 5.

Table 5: Integrity performance comparison of different methods.

Performance	Method of this paper	GDX method	LM method
Convergence speed	Quick	Medium	Slow
Model structure	Simple	Medium	Medium
Antinoise strength	Powerful	Medium	Medium
Data request	Medium	High	High
Prediction accuracy	High	Low	Low
Scope of use	Wide	Medium	Medium
Prospects	Big	Medium	Medium

In this paper, the particle swarm majorization nervous net model method is used to predict the sports test results of the investigated people, to accurately forecast sports show; it can offer a trustworthy basis for analysis to formulate goals of physical education teaching. Compared to traditional methods, our method is characterized by a higher speed of convergence and lower error and more accurate prediction results for college students' sports performance and has higher antinoise performance and practicability.

5. Conclusion

The article uses a comparative method to predict and analyze the results of computational intelligence in physical education exams. The nervous net model way used in this paper for particle swarm optimization is more accurate than the GDX method and the LM method, the convergence speed is faster, and the antinoise strength is stronger. Through analysis, it is discovered that the predicted value is relatively shut to the real value; there is no significant difference between the two errors, indicating that the way proposed in this paper has the best application effect in predicting student athletic performance, and the neural network model particle swarm optimization method can be used to obtain college sports exam scores predict. Further improving the quality of education and using intelligent algorithms can conquer the defect of traditional models and improve the forecast effect of college sports show, and the forecast results can guide the reform of college sports disciplines. Simultaneously, it plays a leading part in teaching and daily practice for teachers and students, and students can also choose sports that suit them according to their physique.

Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declared that there are no conflicts of interest regarding this work.

References

[1] T. Cheng, D. Cui, Z. Fan, J. Zhou, and S. Lu, "A new model to forecast the results of matches based on hybrid neural networks in the soccer rating system," in *Proceedings Fifth International Conference on Computational Intelligence and Multimedia Applications*, pp. 308–313, Xi'an, China, September 2003.

[2] B. Jiang and Y. P. Wang, "A prediction and analysis of tennis medal distribution situation on the 12~ (th) national games," *Liaoning Sport Science and Technology*, vol. 2, no. 4, pp. 231–254, 2013.

[3] B. Zhang, C. Y. Chen, L. C. Chan, and W. Fok, "Intelligent sports performance scoring and analysis system based on deep learning network," in *2020 3rd International Conference on Artificial Intelligence and Big Data (ICAIBD)*, pp. 17–21, Chengdu, China, May 2020.

[4] Z. Taha, M. Haque, and R. M. Musa, "Intelligent prediction of suitable physical characteristics toward archery performance using multivariate techniques," *Journal of Global Pharma Technology*, vol. 9, no. 7, pp. 44–52, 2017.

[5] J. Dan, Y. Zheng, and J. Hu, "Research on sports training model based on intelligent data aggregation processing in internet of things," *Cluster Computing*, vol. 25, no. 1, pp. 727–734, 2022.

[6] L. I. Yunwei and S. Jiang, "Video analysis technology and its application in badminton sports training," *Journal of Physics: Conference Series*, vol. 4, no. 2, pp. 23–64, 2019.

[7] X. Li, "A machine learning framework for predicting sports results," *Techniques of Automation and Applications*, vol. 8, no. 6, pp. 21–64, 2019.

[8] E. S. Hussein, "Predicting the sporting achievement in the pole vault for men using artificial," *Neural Networks*, vol. 23, no. 11, pp. 221–236, 2020.

[9] J. Hou and Z. Tian, "Application of recurrent neural network in predicting athletes' sports achievement," *The Journal of Supercomputing*, vol. 78, no. 4, pp. 5507–5525, 2022.

[10] X. Zhang, "Combination of grey system and neural network based sports achievement forecasting algorithm," in *2017 International Conference on Applied Mathematics, Modelling and Statistics Application (AMMSA 2017)*, pp. 353–356, China, May 2017.

[11] X. M. Huang, "The forecast model of college students' sports results," *Journal of Shangluo Teachers College*, vol. 24, no. 5, pp. 23–56, 2005.

[12] X. J. Zhang and F. Wang, "It in 2012 college students physical health standard test results of the statistics and analysis," *Journal of Gansu Normal Colleges*, vol. 12, no. 3, pp. 121–452, 2013.

[13] V. Sillanpää and O. Heino, "Forecasting football match results - a study on modeling principles and efficiency of fixed-odds betting markets in football," 2013.

[14] M. Spann and B. Skiera, "Sports forecasting: a comparison of the forecast accuracy of prediction markets, betting odds and tipsters," *Journal of Forecasting*, vol. 28, no. 1, pp. 55–72, 2009.

[15] J. Wang, University S I, and University Z, "Machine learning based prediction and analysis of college sports performance," *Modern Electronics Technique*, vol. 6, no. 2, pp. 109–112, 2017.