Research Article

Accuracy Analysis of Sports Performance Prediction Based on BP Neural Network Intelligent Algorithm

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With the increasing attention and popularity of competitive sports, the continuous progress of artificial intelligence, and deep learning theory, people’s sports performance prediction technology for professional athletes or sports students is also developing. Accurate and effective prediction can help athletes and students to carry out more targeted training, so as to further improve their performance. BP neural network (BPNN) is a multilayer feedforward neural network (NN). Therefore, based on the BPNN algorithm, this work conducts a deep research on the prediction of sports performance. First of all, this work uses the three-layer structure of BPNN to design the algorithm and then selects the weight, oxygen saturation, systolic and diastolic blood pressure, the previous best score, the worst score in the past period, and the average score of one week before the examination as the feature vector of the input sample. The students’ scores of two classes of physical education major in a university are selected as the prediction objects, and the time period of students’ relevant information data is selected from September 2018 to December 2018. The quantity of hidden units is calculated to be 15 by training. After the successful construction of BPNN sports performance estimation method, the PSO search approach is utilized to enhance the BPNN sports performance prediction model. Finally, the relationship between the two classes’ performance and the students’ performance is analyzed. 49% of the total number of times the error of class A was predicted to be 0, and the number of times that the error of class B was 0 was 50%, 58%, and 75%, respectively. There is no strong linear correlation between sports performance and body weight, but a high correlation systolic, pulse pressure, and plasma oxygen levels. This shows that the BPNN sports prediction model established in this work has high accuracy in predicting sports performance.

1. Introduction

1.1. Background Significance. Sports achievement is not only related to the honor of athletes’ career but also an intuitive reflection of sports skills. The prediction of sports performance is very important for athletes and coaches. It can provide data support for the development of scientific sports training programs. Artificial NN can deal with messy information very well [1]. An artificial NN is a computing system that mimics the NN of the human brain. Although not very efficient, they behave in roughly the same way. Especially BPNN, which has an excellent capacity to forecast, has seen extensive application in the forecasting industry. BPNN is a multilayer feedforward NN, and its main characteristics are as follows: the signal is forward propagated, and the error is back propagated. This work gives a new idea and direction for the research of sports achievement prediction, which has practical significance.

1.2. Related Work. BPNN has been widely used, and there are many related research results, aiming at the six-degrees-of-freedom joint angles challenge for the UR3 rover. Jiang et al. studied a back propagation (BP) NN algorithm based on particle swarm optimization (PSO), which overcomes some shortcomings of BPNN. The UR3 cobot is a small collaborative tabletop robot ideal for applications such as light assembly work and automated workbenches [2]. His
research on the convergence rate of the algorithm is not good enough. Determine the distance between two objects or calculate the area or volume, without learning how to read a tape or ruler reading [3]. According to the characteristics of the software defined network (SDN), Liu et al. proposes a technique for detecting DDoS attacks that combines PSO-BPNN with extended volatility and uses the generalized entropy method to predict traffic on switches. DDoS refers to distributed denial of service attacks, which can forge the source IP address during the attack [4]. His research in the algorithm learning training, the selected training samples, and test samples are not suitable, not a very good training algorithm. Liao uses the ARIMA model to predict the linear theme of the series and then uses the BPNN model to estimate its nonlinear residual and combines them to form a combined model to predict the RMB exchange rate [5]. Although their research and application of BPNN are insufficient, they provide a very important reference for the study of this work.

1.3. Innovative Points in This Paper. To accurately predict sports performance and provide scientific data support for the formulation of efficient sports training program, this work makes a deep research on the construction of sports performance prediction model. The innovations of this study are as follows: (1) by improving the inertia weight, boundary value and initialization, and using the PSO search method, the resolution speed and optimization ability of the BPNN algorithm are optimized. (2) The successful BPNN model for predicting sports is used to predict the youngsters’ athletic accomplishments majoring in physical education and the relationship between sports performance and body weight. Analysis is done on the blood pressure readings at the systolic and diastolic levels.

2. Neural Network and Intelligent Algorithm

2.1. Neural Network

2.1.1. Neurons and Activation Function. Supposing n input signals, $a_1, a_2, \ldots, a_n$, and the corresponding weight is $r_1, r_2, \ldots, r_n$ [6], the input vector $A$ and the corresponding connection weight vector $R$ are shown in

$$A = (a_1, a_2, \ldots, a_n),$$

$$R = (r_1, r_2, \ldots, r_n).$$

The weighted sum of the input signals obtained by the neuron is represented by net, as follows:

$$\text{net} = \sum a_n r_n.$$ (3)

The activation function can realize the corresponding function of neurons, and the corresponding output can be obtained through calculation after receiving input. An artificial NN’s perceptron, which runs on the neurons, is in charge of translating the input from the receptors to the outcome. There are four common activation functions: hyperbolic tangent, S-type, piecewise linear, and threshold function [7]. The threshold function includes step function and sgn function, whose expressions are shown in

$$f(a) = \begin{cases} 
1, & \text{if } a \geq 0, \\
0, & \text{if } a < 0,
\end{cases}$$ (4)

$$\text{sgn}(a) = \begin{cases} 
1, & \text{if } a \geq 0, \\
-1, & \text{if } a < 0.
\end{cases}$$ (5)

The expressions of hyperbolic tangent, S-type, and piecewise linear function are shown in

$$f(a) = \begin{cases} 
a, & \text{if } a \leq 1, \\
1, & \text{if } a \geq 1,
\end{cases}$$ (6)

$$f(a) = \frac{1}{1 + \exp(-a)}$$ (7)

$$f(a) = \frac{e^a - e^{-a}}{e^a + e^{-a}}.$$ (8)

2.1.2. The Structure of NN. There are three kinds of layered NNs: simple feedforward network, without feedback loop. Only the information from the preceding layer is received by each layer, which then processes the information in the hidden units before sending it to the output units [8]. The direction of information processing is unidirectional forward [9, 10]. The feedback of feedforward network’s signal transmission can from the output layer to the input layer, and from the input layer to the output layer as well [11, 12]. Like the simple feedforward network, the inner interconnected feedforward network can only process the signal forward in one direction and has no feedback loop [13, 14].

Any two neurons in the interconnected NN can be connected with each other to form a fully interconnected network. Signals are transmitted repeatedly between neurons, and the state of the network is constantly changing. The initial signal state of this kind of NN needs several changes to reach equilibrium. According to the degree of interconnection, interconnected NNs can be divided into interconnected, locally interconnected, and sparsely connected [15]. In the interconnected network structure, there may be a connection path between any two nodes, so interconnection, local interconnection, and sparse connection are to subdivide the interconnection network according to the degree of connection of nodes in the network.

2.1.3. Learning Method of NN. Network topology and connection weight determine the function of artificial NN [16, 17]. In the training of NN, many samples and expectations should be input into the NN, the training and feedback should be carried out according to certain learning rules, the connection weights and thresholds of the NN should be adjusted constantly, and finally, the results should be output [18].
The learning methods of NN include supervised learning, unsupervised learning, and hierarchical learning [19, 20]. Supervised learning can be regarded as the original prediction model. It uses basic data training, inputs the data that needs to be predicted, and obtains the prediction results (whether continuous or discrete), then performs unsupervised learning, processes a bunch of data, performs data clustering according to their similarity, and finally performs hierarchical learning. There is a large amount of information for tutor learning. Besides inputting training samples, we also need to give the corresponding ideal output value. In this learning mode, the NN will produce output for each input. The actual output is compared with the ideal value to determine whether to continue learning and adjust the weight according to its error value.

Unsupervised learning does not need goals, and its weight parameters are automatically adjusted according to the network structure and learning rules, and the specific way given is determined by the specific network. Hierarchical learning needs less information, and it does not need to provide the expected output, but provides the approximate accuracy level of the actual output.

### 2.2. BPNN Learning Algorithm

#### 2.2.1. Model Structure of BPNN

The back propagation (BP) NN learns and trains by changing per layer’s weight matrix and criteria so that the predicted output of the network can continuously approach the expected output [21, 22].

The typical BPNN has three or multilayer structure, which includes the input layer, one or more hidden units, and the output layer. Typically, the cells within the buried layer activate in an S-type manner. The hidden layer connects the input and output and plays a decisive role.

Suppose there is an \(N\)-layer NN with sample \(X\) in the input layer. The input sum of neuron \(i\) in layer \(g\) is \(V_{ig}\), the output is \(X_{ig}\), \(Q_{ij}\) is the weight coefficient, and \(f\) is the activation function. Then, the relationship between the variables is shown in

\[
X_{ig} = f(V_{ig}),
\]

\[
V_{ig} = \sum Q_{ij}X_{j}^{g-1}.
\]

#### 2.2.2. Calculation Steps of BPNN

The calculation steps of the BPNN algorithm are generally divided into six steps: first, network initialization—determine the connection weight of each layer of the network, threshold, the number of network training, given the learning rate, error accuracy, and neuron activation function and input the training samples and the relative expected value.

Then, the sample pairs are selected in order from the sample set for training. Suppose that the input sample is \(x_n\). The hidden layer’s link value with the input layer is \(u_{ij}\), and the threshold value of the hidden layer unit is \(s_j\); then, the output value of each hidden layer cell is calculated:

\[
y_j = f\left(\sum_{i=1}^{n} u_{ij}x_i - s_j\right).
\]

The threshold value in the neuron model is written into the connection weight, so that \(u_{ij} = -s_j, x_0 = -1\). Formula (11) can be transformed into

\[
y_j = f\left(\sum_{i=0}^{n} u_{ij}x_i\right).
\]

The outcome for every unit in the layer, including \(Z\) in between the concealed layer, and the cell cutoff \(s\) of the output units are used in the third phase to compute the output of every cell in the output units. The calculation formula is

\[
O_k = f\left(\sum_{j=1}^{m} z_{kj}y_j - s_k\right).
\]

Similarly, let \(z_{0k} = -s_k\) and \(y_0 = -1\); formula (13) be changed into

\[
O_k = f\left(\sum_{j=0}^{m} z_{jk}y_j\right).
\]

Calculating the gap between the observed and predicted output values and determining if it is smaller than the previous orbital radius constituted the required action. If it is less, return to step two and choose the subsequent sample to carry out the training. Fault away will be used if it is more, and the weight will be changed to lessen the discrepancy. The weight correction of output layer is

\[
\Delta z_{ij} = -\mu \frac{\partial E}{\partial z_{ij}} = -\mu \frac{\partial E}{\partial net_k} \cdot \frac{\partial net_k}{\partial z_{ij}}.
\]

#### 2.2.3. Performance Analysis of BPNN Algorithm

Firstly, the convergence speed of the BPNN algorithm is slow because the selection of algorithm parameters may not be appropriate. A convergence of a sequence \(x_n\) to a means that, for any open set containing a, there is always a large enough \(N\) so that the tail after the array \(x_n\) term is fully contained within that open set. Another reason is the limitation of the algorithm itself. The error surface of the algorithm has a flat area, and the error gradient changes little. Even if the weight is adjusted, the error will decline slowly.

Secondly, the quantity of hidden neurons of connections inside this layer is hard to assess in BPNN. Without specific theory, we can only obtain approximate conclusions through experience or specific experiments. This has brought an indelible negative impact on the accuracy of BPNN algorithm.

In addition, the objective function of BPNN has minimal points. BPNN uses nonlinear activation function and considers global error. However, the existence of multiple minima will drop into the neighborhood limit throughout confluence. When learning for a certain time, the global error will not be reduced, but the accuracy of the algorithm has not reached the expected value.
2.3. Particle Swarm Optimization Algorithm

2.3.1. Particle Swarm Optimization Algorithm Flow. The PSO simulates the foraging behavior of birds. The optimal value of the problem to be optimized is regarded as the food that birds seek, and birds are regarded as particles with only speed and position. Particle target is to search in a certain space according to the requirements of the PSO algorithm and finally achieve or approach the best.

Suppose that there are \( m \) particles in the population in an \( N \)-dimensional target search space, the position of the \( i \)-th particle is \( \mathbf{D}_i = (d_{i1}, d_{i2}, \ldots, d_{iN}) \), and the velocity of the particle is \( \mathbf{V}_i = (v_{i1}, v_{i2}, \ldots, v_{iN}) \), where \( i = 1, 2, \ldots, m \). If the historical optimal position of the particle is \( H_{\text{best}} \) and the global optimal position is \( G_{\text{best}} \), then the particle’s velocity and position update are

\[
\mathbf{V}_i^{t+1} = \omega \mathbf{V}_i^t + s_1 r_1 (H_{\text{best}} - \mathbf{D}_i^t) + s_2 r_2 (G_{\text{best}} - \mathbf{D}_i^t),
\]

\[
\mathbf{D}_i^{t+1} = \mathbf{D}_i^t + \mathbf{V}_i^{t+1},
\]

where \( \omega \) is the inertia weight, \( e \) is the current number of iterations, \( s_1 \) and \( s_2 \) are the learning factors, and \( r_1 \) and \( r_2 \) are the random numbers between \([0, 1]\).

The flow of PSO is as follows. The item health value is determined before the optimizer is initiated. The second stage involves updating the object’s previous and world optimum values, determining if its velocity is inside or outside of the posted limit. The third step is to update the position of the particle and determine whether its position exceeds the constraint.

2.3.2. Advantages and Disadvantages of PSO Algorithm. PSO algorithm has the advantages of simple concept, less adjustment parameters, convenient implementation, fast convergence speed, and low requirements for computer configuration, so it has been applied in many practical engineering optimization fields. However, the PSO algorithm is not perfect, and there are still some shortcomings.

At present, the improvement of inertia weight can enhance the initial days of computer search’s worldwide search capability. But these improved strategies lack strict theoretical proof. Some algorithms will slow down the speed of particles in the late stage of search, leading to the particles in the population to the optimal solution position. The nation’s variety is increased within that means will be affected, and the search efficiency will be reduced, resulting in local optimization.

In the PSO algorithm, the parameter setting greatly affects the optimization results, and there is no specific parameter setting standard to solve the problem of different algorithms. In practical application, the improved PSO algorithm does not necessarily have good performance, but it often needs to be analyzed in combination with the specific situation of the problem.

When the improved particle PSO algorithm is used to solve the multimodal function problems, a multimodal function is a real-valued function that has multiple local maxima (peaks) in the considered interval. It often falls into the local optimum, and the particles cannot escape from the local optimal value in the search process and may be premature convergence. The convergence speed of the PSO algorithm cannot be improved when it reaches the specified solution precision, and both of them cannot be taken into account.

2.3.3. Improvement of PSO Algorithm. Based on the above analysis of the shortcomings of PSO algorithm, the improvement of PSO algorithm can start from improving the convergence speed and preventing falling into the local optimal value.

The reasonable selection of parameters in the PSO algorithm plays an important role in the optimization ability. Through the dynamic adjustment of parameters, the parameters in the algorithm can be controlled relatively well. The contraction factor \( Q \) is introduced:

\[
Q = \frac{2}{2 - s - s^2 - 4s},
\]

where \( s = s_1 + s_2 \). The search ability of the algorithm is improved by enhancing the relationship between learning factor and inertia weight, and the convergence speed of the algorithm can be improved by properly adjusting the speed of particles. The time factor is added to the particle update formula, and the contraction factor and time factor are combined. The particle update formula is

\[
\begin{align*}
V_{ij}^{t+1} &= Q \left( V_{ij}^t + s_1 r_1 (H_{\text{best}} - D_{ij}^t) + s_2 r_2 (G_{\text{best}} - D_{ij}^t) \right), \\
D_{ij}^{t+1} &= D_{ij}^t + \text{time} \times V_{ij}^{t+1}.
\end{align*}
\]

In order to prevent the excessive concentration of particles and increase the active space of particles, the PSO algorithm can improve the optimization ability and avoid the emergence of local optimal value to a certain extent. The formula is as follows:

\[
\begin{align*}
\text{if fitness}_{\text{max}} (x) - \text{fitness}_{\text{min}} (x) < 1, \\
\text{if (fitness}_{\text{max}} (x) - \text{fitness}_{\text{min}} (x) < 1), \\
\text{pos} (x) &= \text{rand} (\text{time} - 1),
\end{align*}
\]

where \( \text{fitness} (x) \) is the fitness value of the particle \( x \) iteration and \( \text{pos} (x) \) is the distribution function of the particle swarm.

3. Construction Experiment of the Prediction Model of Sports Performance

3.1. Construction of the Sports Performance Prediction Model Based on BPNN

3.1.1. Design and Parameter Setting of BPNN. The design of BPNN needs to start with the determination of the number of layers, the number of neurons, activation function,
connection weight, and threshold. In this work, BPNN is used to design the algorithm. Its structure is shown in Figure 1.

The BPNN prediction model established in this study mainly aims at the performance prediction of sports major students. Considering the factors affecting the sports performance, the weight, blood oxygen saturation, systolic and diastolic blood pressure, the best score in the past, the worst score in the past period, and the average score of one week before the examination are selected as the feature vectors of the input samples.

There are 18 input layer neurons and 6 output values, and the range of hidden layer nodes is 10–20. Through training, the number of nodes in the hidden layer is 15, the number of learning times is 2500, the target error is 0.001, and the learning rate is 0.4. S-type function is used for activation function, and train SCG function is used for training function.

3.1.2. Selection of Experimental Sample Data. In order to verify the stability and practicability of the BPNN algorithm, this work selects the students’ scores of two classes of physical education major in a university as the prediction object so as to predict the sports performance of each student, arrange targeted training for it, and improve the performance. The number of students in class A and class B is 15 and 12, respectively. The selection period of students’ relevant information data is from September 2018 to December 2018. The results of the students in these two classes are relatively stable in the selected time period, which can accurately reflect the overall performance of each student and has good predictability.

Taking into account the correlation between the two classes before and after sports performance, the body weight, blood oxygen saturation, systolic and diastolic blood pressure, best score, worst score, and one-week average score of the two classes were taken as input samples. Students’ weight, blood oxygen saturation, systolic and diastolic blood pressure, best score, worst score, and average score of one week before the examination were taken as output samples on the eighth day, and then 100 training samples and 10 test samples were established.

3.2. PSO Algorithm Improved BPNN Sports Performance Prediction Model

3.2.1. Improvement of Inertia Weight. The inertia weight determines the inertia of particles to keep moving. Larger inertia weight can jump out of the local optimal solution, and smaller inertia weight is conducive to the enhancement of local optimization ability. In this work, the linear decreasing inertia weight method is selected. By setting the maximum and minimum inertia weight, the inertia weight is adjusted by combining the maximum iteration number and the current iteration number of the algorithm. The formula is as follows:

\[ \omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{t_{\text{max}}} \times t, \]  

where \( \omega_{\text{max}} \) and \( \omega_{\text{min}} \) are the maximum and minimum inertia weights, respectively, and \( t \) and \( t_{\text{max}} \) are the current iteration number and the maximum iteration number, respectively.

3.2.2. Improvement of Boundary Value and Initialization. The size of velocity boundary determines the search ability of particles; the larger the value, the stronger the search ability, but it is easy to ignore the optimal value; the smaller the value, the stronger the local optimization ability. In this work, through the training of sports performance prediction model, the range of weight and bias value is extracted and multiplied by magnification, and the corresponding speed boundary is calculated. In this work, 16% is taken as the multiple to determine the boundary value of each part of the particle.

There are relatively large differences in the weight and threshold range of the BPNN sports performance prediction model, so it is necessary to initialize the particle weight and threshold difference, and the initialization boundary range is mainly in the range of weight and threshold. Adjust formula (17), introduce velocity factor \( \theta = 0.5 \), and update particle position formula as follows:

\[ D_{\text{new}}^{i+1} = D_{\text{new}}^i + \theta \times V_{\text{new}}^{i+1}. \]  

This formula enhances the inertia of particles and reduces the influence of velocity update on particles.

4. Discussion on Algorithm Performance and Result Prediction

The BPNN prediction model established in this study was trained. The body weight, blood oxygen saturation, systolic and diastolic blood pressure, best score, worst score, and average score of one week of students in class A and class B were taken as input samples. On the eighth day, body weight, oxygen saturation, systolic and diastolic blood pressure, best score, worst score, and average score of one week before the
examination were used as output samples to establish 100 training samples. The training results are given in Figure 2. As shown in Figure 2, the BPNN training results include 100 trainingsamples, and the trainingsamples are used for network training. In order to determine the number of nodes in the hidden layer, four processing schemes are proposed, and the number of nodes in the hidden layer is determined as 10–20. The minimum test root mean square error (RMSE) was obtained by training. In the figure, most of the average scores of class A is above 60, and the higher are even close to 80, indicating that the training results are good, while class B is obviously better, with the average training score basically over 75, and the highest is even close to 100, which may be because the overall physical quality of class B students is better.

As shown in Table 1, through training, when the number of nodes in the hidden layer is 15, the root mean square error of the test is the minimum, which is 2.893. When the number of nodes in the hidden layer is 12, the root mean square error is the largest, which is 6.208. With the change of the number of nodes in the hidden layer, the trend of root mean square error is as follows:

As shown in Figure 3, the most appropriate number of hidden layer nodes is 15, which can be used as the final parameter to build the NPNN sports performance prediction model.

4.1. Prediction Results

4.1.1. Class A Grade Forecast. Based on the data of the last week, this work forecasts the sports achievements of 15 students in class A and compares them with the actual sports achievements. Using the results of three different periods of time to predict, the full score of physical education score is 100, the predicted score is P1, P2, and P3, the actual score is R1, R2, and R3, respectively, and the difference is recorded as D1, D2, and D3.

As shown in Table 2, sometimes the predicted score is equal to the actual score, and the error is 0, and sometimes, there is a small error. The biggest error is 1.5, which is the difference between the predicted score and the actual score of A6 and A10 students. This work compares the change trend of the predicted and actual results of 15 students in class A. The results are as follows:

As shown in Figure 4, the students’ physical education performance has the characteristics of individuation, the best score is A3, and the predicted and actual scores of three times have exceeded 90 points. After the error is counted, the accuracy of the prediction model in predicting the grade of class A is calculated.

As shown in Figure 5, 49% of the total number of times the error of class A was predicted to be zero, and the three times of prediction accounted for 11%, 20%, and 18%, respectively. The absolute value of error is 0.5 in 40%, 1 in 7%, and only 4% in 1.5. This shows that the BPNN prediction model has higher accuracy in predicting the sports performance of class A.

4.1.2. Predicted Score of Class B. Based on the data of the last week, this work forecasts the physical education achievements of 12 students in class B. The prediction method is the same as that of class A.

As shown in Table 3, sometimes the biggest error between the predicted score and the actual score of class B is 1.5, which is the difference between the predicted score and the actual score of B5 and B7 students. The results are as follows:

As shown in Figure 6, the best score of class B is B2, and the predicted and actual scores of class B are all higher than 94 points. The worst score of class B is B7. The error was counted, and the accuracy of the prediction model in predicting the grade of class B was calculated.

As shown in Figure 7, 50%, 58%, and 75% of the students predicted the grade of class B three times, and 33%, 17%, and 9% of them had absolute error of 0.5. This shows that the accuracy of the BPNN prediction model in predicting the sports performance of class B is also high.

4.2. Relationship between Performance and Each Feature Vector. This work uses the BPNN model to predict the results of the two classes and analyzes the relationship between the weight, oxygen saturation, systolic blood pressure, and diastolic blood pressure. Ten students were randomly selected from two classes and numbered S1–S10.

As shown in Table 4, the values of eigenvectors of 10 students are different even if they have the same situation. Each feature vector needs to be analyzed to determine the specific relationship between it and performance. First of all, the relationship between students’ weight and sports performance is analyzed.

As shown in Figure 8, the students whose weight is 65.8 kg have better physical performance than those who weigh 64.6 kg and 69.2 kg. This shows that there is no particularly strong linear correlation between students’ weight and sports performance. Then, it analyzes the relationship between the students’ blood oxygen saturation and sports performance.
As shown in Figure 9, when the students’ blood oxygen saturation is stable and high, their sports performance is also higher. Among them, the student with the highest score and the highest oxygen saturation was the same person, namely, S3 student. When the blood oxygen saturation of the students is lower than 94% of the normal value, their sports performance has become the lowest of all students, only 73 points. This shows that there is a strong correlation between blood oxygen saturation and sports performance. Finally, the relationship between the students’ systolic blood pressure and diastolic blood pressure and sports performance was analyzed.

As shown in Figure 10, the systolic blood pressure and diastolic blood pressure of the best achievers were 103.4 mm/Hg and 77.5 mm/Hg, respectively. The correlation between systolic blood pressure and diastolic blood pressure is high. When the systolic blood pressure is low and the diastolic blood pressure is high, it is easier for

| Table 1: Result of hidden layer node parameters. |
|-----------------------------------------------|
| **Input layer node** | **Output layer node** | **Training function** | **Hidden layer node** | **RMSE** |
| 1 | 18 | 6 | Trainscg | 10 | 5.112 |
| 2 | 18 | 6 | Trainscg | 11 | 4.381 |
| 3 | 18 | 6 | Trainscg | 12 | 6.208 |
| 4 | 18 | 6 | Trainscg | 13 | 3.717 |
| 5 | 18 | 6 | Trainscg | 14 | 5.014 |
| 6 | 18 | 6 | Trainscg | 15 | 2.893 |
| 7 | 18 | 6 | Trainscg | 16 | 5.711 |
| 8 | 18 | 6 | Trainscg | 17 | 5.032 |
| 9 | 18 | 6 | Trainscg | 18 | 4.916 |
| 10 | 18 | 6 | Trainscg | 19 | 4.158 |
| 11 | 18 | 6 | Trainscg | 20 | 5.062 |

| Table 2: Predicted and actual scores of class A. |
|-----------------------------------------------|
| **Student number** | **P1** | **R1** | **D1** | **P2** | **R2** | **D2** | **P3** | **R3** | **D3** |
| A1 | 83 | 84 | –1 | 85 | 85 | 0 | 85.5 | 85 | 0.5 |
| A2 | 79.5 | 79 | 0.5 | 83 | 82.5 | 0.5 | 80 | 80 | 0 |
| A3 | 91.5 | 92 | –0.5 | 92 | 92 | 0 | 94 | 93.5 | 0.5 |
| A4 | 82 | 82 | 0 | 85 | 85 | 0 | 84 | 84 | 0 |
| A5 | 78 | 78 | 0 | 81.5 | 82 | –0.5 | 80 | 80.5 | –0.5 |
| A6 | 81 | 80.5 | 0.5 | 83 | 84.5 | –1.5 | 84 | 84 | 0 |
| A7 | 88 | 88 | 0 | 90 | 89.5 | 0.5 | 89 | 89 | 0 |
| A8 | 71.5 | 72 | –0.5 | 73 | 73 | 0 | 72 | 72.5 | –0.5 |
| A9 | 84 | 84 | 0 | 84.5 | 84 | 0.5 | 84 | 84 | 0 |
| A10 | 90.5 | 90 | 0.5 | 91.5 | 91.5 | 0 | 92.5 | 91 | 1.5 |
| A11 | 93 | 93 | 0 | 92 | 92.5 | –0.5 | 91 | 91 | 0 |
| A12 | 87 | 88 | –1 | 89 | 89 | 0 | 90 | 90 | 0 |
| A13 | 83 | 83.5 | –0.5 | 85 | 85 | 0 | 84.5 | 83.5 | 0 |
| A14 | 91 | 90.5 | 0.5 | 93 | 93 | 0 | 90 | 90.5 | –0.5 |
| A15 | 88 | 88.5 | –1 | 89 | 88.5 | 0 | 91 | 91 | 0.5 |

*Figure 3: Root mean square error of the test under different hidden layer node parameters.*
students to achieve better results. To sum up, in order to improve students’ sports performance, it is necessary to pay attention to students’ blood oxygen saturation, systolic blood pressure, and diastolic blood pressure and adjust training methods and rest time according to these data.
Figure 6: Comparison of predicted and actual scores of class B in three times.

Figure 7: Prediction accuracy of class B.

Table 4: The relationship between sports performance and eigenvector.

| Student number | Weight (kg) | Blood oxygen saturation (%) | Systolic pressure | Diastolic pressure | Sports achievements |
|----------------|-------------|------------------------------|-------------------|-------------------|---------------------|
| S1             | 68.8        | 96.5                         | 108.2             | 72.2              | 88                  |
| S2             | 65.4        | 97.3                         | 108.7             | 73.6              | 89.5                |
| S3             | 62.3        | 98.6                         | 103.4             | 77.5              | 94.5                |
| S4             | 68.5        | 98.1                         | 104.5             | 77.1              | 93.5                |
| S5             | 60.9        | 97                           | 107.5             | 73                | 88                  |
| S6             | 62.5        | 97.5                         | 104.8             | 75                | 91                  |
| S7             | 67.7        | 93.8                         | 120.3             | 62.9              | 73                  |
| S8             | 69.2        | 95.7                         | 116.4             | 65.3              | 83                  |
| S9             | 64.6        | 94.1                         | 113.3             | 63.3              | 80                  |
| S10            | 65.8        | 97.4                         | 105.1             | 75.8              | 91                  |
Figure 8: Weight and sports performance.

Figure 9: Blood oxygen saturation and sports performance.

Figure 10: Systolic and diastolic blood pressure and sports performance.
5. Conclusions

BPNN has relatively strong nonlinear mapping ability, high self-learning and adaptability, good generalization, and fault tolerance. However, the convergence speed of the BPNN algorithm is slow, the number of hidden layers and the number of nodes in this layer are difficult to determine, and there are local minima in the objective function, so the accuracy of the algorithm is not easy to achieve the expected value.

PSO algorithm has the advantages of strong optimization ability, less adjustment parameters, and fast convergence speed, which can just make up for the shortcomings of the BPNN algorithm. Therefore, this work uses the PSO algorithm to optimize the convergence speed and optimization ability of the BPNN algorithm from the improvement of inertia weight, boundary value, and initialization. A BPNN model with fast convergence speed and strong optimization ability is obtained, which can effectively and accurately predict sports performance.

This investigation still has certain flaws because of the information and temporal gaps. For example, there are problems in the selection of training samples and test sample data, the sample data capacity is small, and there are certain differences between the sports performance of students and professional athletes. And, we will carry out the next phase of the research on the training of athletes and expand the sample size.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest with respect to the research, authorship, and/or publication of this article.

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