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Research Article

Parameter Optimization and State Evaluation of Basketball Teaching Based on BPNN

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BPNN is a multi-layer network with forward and backward error algorithms. It is currently the most widely used NN. Especially when it is applied to the basketball teaching scene, it can improve the research on the parameter optimization and state evaluation of the BP neural network in the teaching scene. This paper is mainly to study how to optimize the parameters of basketball teaching scene to improve the teaching effect and to evaluate the state. This paper improves the BPNN technology to study the basketball teaching scene and then proposes a genetic algorithm on the basis of the BPNN. It optimizes the parameters of basketball teaching scene through genetic algorithm and then analyzes the experimental data. The experimental results of this paper show that the BPNN is not as good as the BPNN based on the genetic algorithm in optimizing the parameters of the basketball teaching scene. The BPNN based on genetic algorithm has a successful recognition rate of more than 93% for basketball dribbling and shooting, which is 7-8% higher than that of the BPNN.

1. Introduction

1.1. Background. With the development of basketball, the game has become more intense and confrontational, the use of defense against offense is more effective, the personal defense is more fierce, and the offense of the offensive players is suppressed. This requires basketball players to have comprehensive offensive skills; at the same time, the transition speed between offense and defense is fast, and the technology is connected quickly. Due to the diversity and complexity of motor skills and the limitations of class schedules, how to complete the teaching plan with high quality and efficiency is a huge problem for education teachers. Compared with other more independent sports with fewer participants, basketball is a combination of entertainment, teamwork, competition, and fun. It is a sport for people to exercise and relax in their spare time. Basketball can be described as a "good medicine" that people can apply in modern life. Its own characteristics and attributes determine that basketball can improve physical fitness and promote people's health. It can also improve the mental endurance of athletes and the will to bear hardships and stand hard work through its own group nature, confrontation, and competition, which effectively promotes the mental health of the public.

1.2. Significance. The traditional physical education teaching method mostly adopts the fixed practice method. In the training of the physical education class, students are allowed to repeatedly practice the same movement skills. This practice method is more common in the practice of a single action program. This practice method of practicing the same movement in a fixed manner enables students to learn a certain independent technical movement without being disturbed when practicing a single motor skill, which is relatively beneficial to the improvement of the practice effect. However, in a physical education class, when students need to practice multiple movement skills in more than two different movement programs, due to the difference in the difficulty of motor skills and the low acceptance of the skills learned by students, the repeated practice used in the fixed practice may not necessarily achieve satisfactory results. Therefore, it is very important to improve BPNN-related technologies.

1.3. Innovation. This paper mainly conducts a lot of research on the parameter optimization and state evaluation of basketball teaching scene based on BPNN technology and analyzes the problem through comparison. The innovation of the article is as follows: (1) this article has made a lot of explanations on the BPNN and introduced the difference between the two kinds of NNs. (2) In this paper, the parameters of BPNN are optimized by genetic algorithm, and then the differences between them are compared and analyzed.

2. Related Work

Today, researchers have researched BPNN technology. Among them, He F combines the advantages of artificial intelligence technology and BPNN to develop a new breakthrough prediction method. He also conducted simulations and field tests of the method to verify its performance [1]. Pan proposed a method for calculating the importance of complex input attributes based on BPNN. He also established a BPNN model for calculating the importance of attributes by studying the number of nodes, network layers, learning strategies, and learning factors in the NN [2]. Sun et al. present a new technique for micro-gap electro-assisted laser machining. He built an optimization model using the improved BPNN algorithm [3]. Li et al. proposed a new method combining chaotic algorithm and genetic algorithm (CGA) to optimize the initial weights and thresholds of BPNN [4]. Zeng et al. proposed an optimized rollover warning control strategy for BPNN for hydraulic wheel hub motor hybrid heavy trucks [5]. But the feasibility is not very high.

There are also some researchers who have studied parameter optimization and state evaluation. Among them, Carneiro et al. investigated parameter optimization of multiscale descriptors for shape analysis of medical image datasets. He optimized the scale parameter for normalized multiscale bending energy descriptors through a simulated annealing metaheuristic [6]. Tamimi et al. presented the evaluation of feature values and parameter selection in classifiers using different optimization algorithms [7]. Wang investigated the parameter optimization based on the grain shadow motion estimation algorithm for the ignition process [8]. Tiryaki et al. investigated performance evaluation in terms of predicting the mechanical properties of impregnated wood based on teaching-based optimization and traditional regression techniques [9]. But the cost of their research is relatively high.

3. Optimization Method of Basketball Teaching Scene

3.1. BPNN Technology. Artificial neural network (ANN) is a kind of information processing that imitates some basic features of the NN of human brain. The basic idea is that it does not need to determine a mathematical formula for the functional relationship between input and output, but simply learns itself from the given data. It learns certain rules that a given input value will obtain the closest desired output value [10]. See Figure 1 for its origin.

An NN is a functional model consisting of neurons. Each neuron represents an output function. The memory of the ANN is the weighted value of the signal between the different connected neurons. The output value of the NN depends on the way the NN is connected, the size of the weights, and the activation function used. The neural network can imitate the structure of the human brain for information processing, and in the process of processing, it can continuously adjust its own weights and thresholds through self-learning of information. It makes the gap between the actual output value and the expected value smaller and smaller until the gap is within the given allowable range. The NN itself is usually a representation of a logical policy obtained by approximating an external algorithm or function. One of the neuron models is shown in Figure 2.

In the figure, $x1, x2, \ldots, xn$ represents the synaptic input of other neurons, respectively, and $w1, w2, \ldots, wn$ represents the corresponding synaptic connection strength between neurons, that is, the connection weight. y is the output, f is the excitation function, and θ is the threshold. The mathematical equations corresponding to neuron processes are described below.

The input vector is

$$X = [x1, x2, \ldots, xn]^T. \tag{1}$$

Row vector w indicates that the neuron's connection weight vector is

$$W = [w1, w2, \ldots, wn]. \tag{2}$$

The net input s to the neuron is

$$S = \sum w_i x_i + \theta. \tag{3}$$

After the net input is subjected to the transfer function, the output y of the neuron is obtained as

$$y = f(S). \tag{4}$$

If θ adopts the processing method of $x0 = 1$, the above formula can be expressed as

$$y = f(WX). \tag{5}$$

The BPNN is a multi-layer network with forward and backward error algorithms. It is currently the most widely used NN. Information processing is performed in the form of minimum mean square error learning, divided into forward and backward transfer. The actual values in the output layer are compared with the expected values. If the acceptable error range is exceeded, an error reversal process occurs. This error signal will be fed back to each neuron to change the weights to minimize the error [11]. This forward and backward error propagation is continuous, and the weights of neurons are continuously adjusted until the error between the expected value and the actual output reaches an

Figure 1: NN.

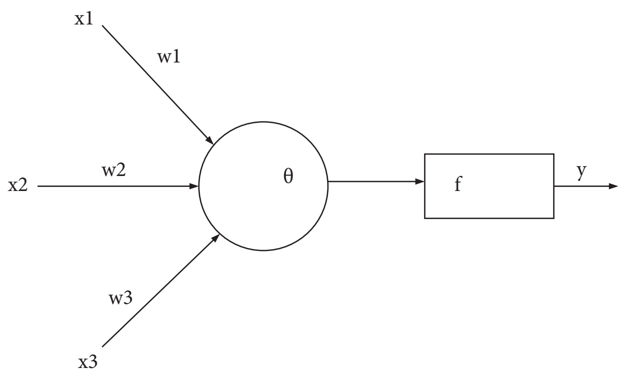

Figure 2: Neuron model.

acceptable value, the training is completed, and the estimation model is established. The ultimate goal of the BPNN learning algorithm is to globally approximate a highly fault-tolerant and generalizable optimization algorithm. The BPNN learning algorithm is implemented by continuously passing the signal forward and backward, changing the connection weights between layers until the error is minimized [12]. The learning process, also known as training, refers to the process of adjusting the free parameters of the neural network through the stimulation of the environment where the neural network is located, so that the neural network can respond to the external environment in a new way. The basic structure is shown in Figure 3.

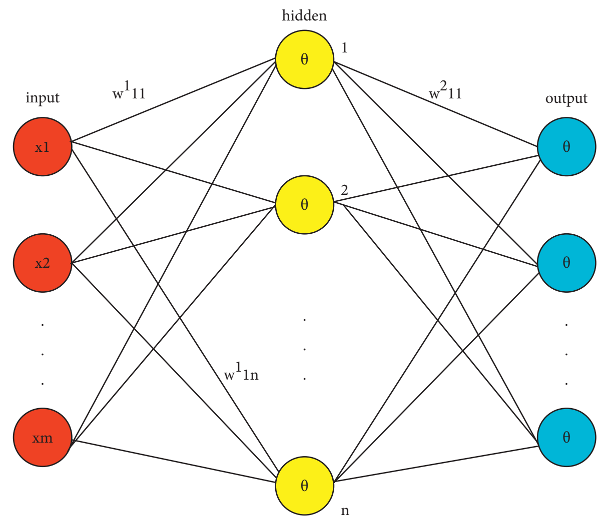

Figure 3: BPNN structure.

w_{ij}^1 represents the connection weight from the i-th node of the input layer to the jth node of the hidden layer; w_{ij}^2 represents the connection weight from the i-th node of the hidden layer to the jth node of the output layer; it uses 1 to represent the connection weight of the first layer and 2 to represent the connection weight of the second layer; θ represents the activation function of the hidden layer and the output layer. In its structure, s_j^1 represents the input of the jth node of the hidden layer, s_j^2 represents the input of the jth node of the output layer, $\overline{y}_j$ represents the output value, and y_j represents the expected value.

Then, assume that the connection weights have changed by Δw_{ij}, and then Δw_{ij} will have an impact on s_j. This results in s_j a change in Δs_j as well, then a $\Delta\theta(s_j)$, and finally an error of Δe at all output layers. Therefore, the adjustment of the weight will make the output result change, and the error is expressed by a continuous function. The calculation method of the minimum error is as follows:

$$L(e) = \frac{1}{2}\sum_{j=0}^{k}\left(\overline{y}_j - y_j\right)^2. \tag{6}$$

It uses stochastic gradient descent to find the gradient of weight w for $L(e)$ connection.

$$\frac{\partial L}{\partial w_{ij}^1} = \frac{\partial L}{\partial s_j^1}\cdot\frac{\partial s_j^1}{\partial w_{ij}^1}. \tag{7}$$

For

$$s_j^1 = \sum_{i=0}^{m} x_i \cdot w_{ij}^1. \tag{8}$$

So,

$$\frac{\partial L}{\partial w_{ij}^1} = \frac{\partial L}{\partial s_j^1}\cdot x_i. \tag{9}$$

It can then find $\partial L/\partial S_j^2$, and s_j^1 has an impact on the output vector, that is,

$$\frac{\partial L}{\partial s_j^1} = \sum_{i=1}^{k}\frac{\partial L}{\partial s_i^1}\cdot\frac{\partial s_i^1}{\partial s_j^1}. \tag{10}$$

For

$$\begin{aligned} s_i^2 &= \sum_{j=0}^{n}\theta\left(s_j^1\right)w_{ij}^2, \\ \frac{\partial s_i^2}{\partial s_j^1} &= w_{ij}^2\cdot\theta. \end{aligned} \tag{11}$$

According to the above two formulas, it can be obtained that

$$\frac{\partial L}{\partial s_j^1} = \sum_{i=1}^{k} \frac{\partial L}{\partial s_i^2} \cdot w_{ij}^2 \cdot \theta\left(s_j^1\right). \tag{12}$$

For the reverse transfer process of the BPNN, it means that nodes will get an error e. It takes e as the reverse input of the output layer, propagating the error toward the input layer, and the output layer δ is obtained first, i.e.,

$$\delta_j^1 = \sum_{i=1}^{k} \delta_i^2 \cdot w_{ij}^2 \cdot \theta\left(s_j^1\right). \tag{13}$$

The correction amount $\Delta w_{ij}^1, \Delta w_{ij}^2$ of the weight is proportional to the negative gradient direction of the error function; then,

$$\begin{aligned} \frac{\partial L}{\partial w_{ij}^1} &= \delta_j^1 \cdot x_i, \\ \frac{\partial L}{\partial w_{ij}^2} &= \delta_1^2 \cdot \theta\left(s_i^1\right). \end{aligned} \tag{14}$$

This leads to the correction

$$\begin{aligned} \Delta w_{ij}^1 &= \eta \delta_j^1 \cdot x_i, \\ \Delta w_{ij}^2 &= \eta \delta_i^2 \cdot \theta\left(s_i^1\right). \end{aligned} \tag{15}$$

And the weight for $t+1$ is

$$\begin{aligned} w_{ij}^1(t+1) &= w_{ij}^1(t) + \eta \delta_j^1 \cdot x_i, \\ w_{ij}^2(t+1) &= w_{ij}^2(t) + \eta \delta_i^2 \cdot \theta\left(s_i^1\right). \end{aligned} \tag{16}$$

$\eta = (0, 1)$ means the learning rate.

Four characteristics of BPNN data processing mode area s follows: (1) distributed storage. The BPNN stores the data in the network in a uniform distribution according to the information processing method of the virtual human brain; that is, the information is placed between each data transmission block. (2) Parallel processing. Because of its biology, information travels through neurons in the human brain which is much longer than taking a computer to process binary numbers. However, the human body reacts much faster than a computer and responds more accurately to postevent processing. This situation is due to the fact that the brain processes multiple events simultaneously [13]. BPNN is a mechanism that simulates the human brain to process information and can operate on multiple events at the same time, which improves computational efficiency. (3) It is fault-tolerant. The neurotransmission system of the human brain does not interrupt the transmission of complete information even if some cells die, and the brain can still function normally. BPNN also inherits this advantage. The complex connection of the units in the BP network ensures that even if there are small errors, they will not accumulate into the entire predicted result. It is also possible to correct the errors so that they meet the requirements of the network. (4) It has the functions of automatic learning, organization, and adaptation. The BPNN can make the data conform to the internal error of the network by changing error during the operation process and can automatically arrange reasonable limit values to adapt to the system. This can be seen as its innovative function, even beyond the user's initial expectations [14]. The flowchart of the BPNN is shown in Figure 4.

So far, the application degree of BPNN model is the highest. Four aspects of BP network applications are as follows: (1) function approximation: through the given input and output data, the network automatically trains a model and calculates a functional relationship, so that this relationship can approximately contain all the data. (2) Pattern recognition: the given irregular output data can reach a one-to-one correspondence with the original data through a certain network model. (3) Classification: through the existing output results and network model, the initial data are recombined according to a specific method in the opposite direction, and the properties of each combination are the same. (4) Data compression: it reduces the rank of prediction results for the convenience of data transmission and collection [15].

When using BPNN for recognition, the process can be divided into two phases, namely, the training and working phases of BPNN. The ultimate goal of the BP neural network learning algorithm is to make the global approximation an optimization algorithm with strong fault tolerance and generalization ability. Its principle and process are shown in Figure 5.

When using the BP neural network input data for training, the results calculated by the network cost function are passed backward through the neural network. This makes the neural network constantly modify its node thresholds and network weights, thereby reducing the thresholds and finally making them reach an acceptable range.

Based on the BPNN toolbox of MATLAB, the application field of MATLAB is the calculation of scientific research and practical work. It has the incomparable advantages of other software in the analysis of mathematical calculation and big data, and the input and output data are represented in the form of a matrix. At the same time, like some software, it can express the experimental results through the visualization window, and its image output function is still very powerful. Compared with other programming software, the biggest advantage of MATLAB is the simplicity of programming. It is mainly used in mathematics, but also in the fields of automatic monitoring, high simulation, signal classification management, information communication, and other fields [16]. The widespread use of MATLAB has led to continuous improvements in its functionality. Various toolboxes are applications developed for the main purpose of their usage requirements in a certain field. Therefore, the reason why the NN toolbox can be developed on the MATLAB platform is that people urgently need to use NNs quickly and accurately. The NN toolbox now contains a wealth of network models. These models have a variety of ways of using NNs, which can meet the application in real engineering practice. The BPNN used in this paper is one of

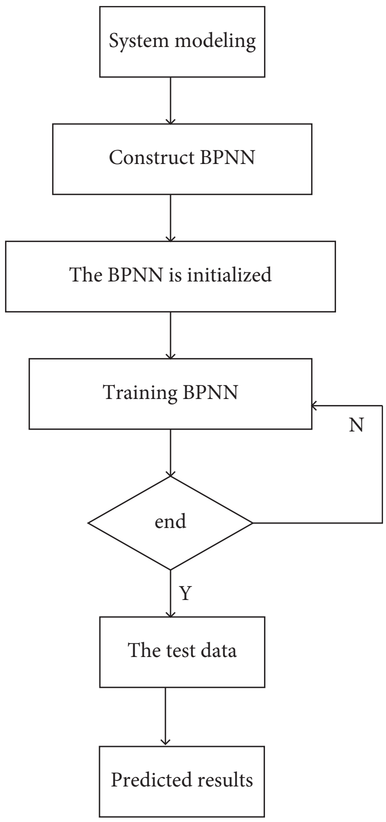

Figure 4: BPNN flowchart.

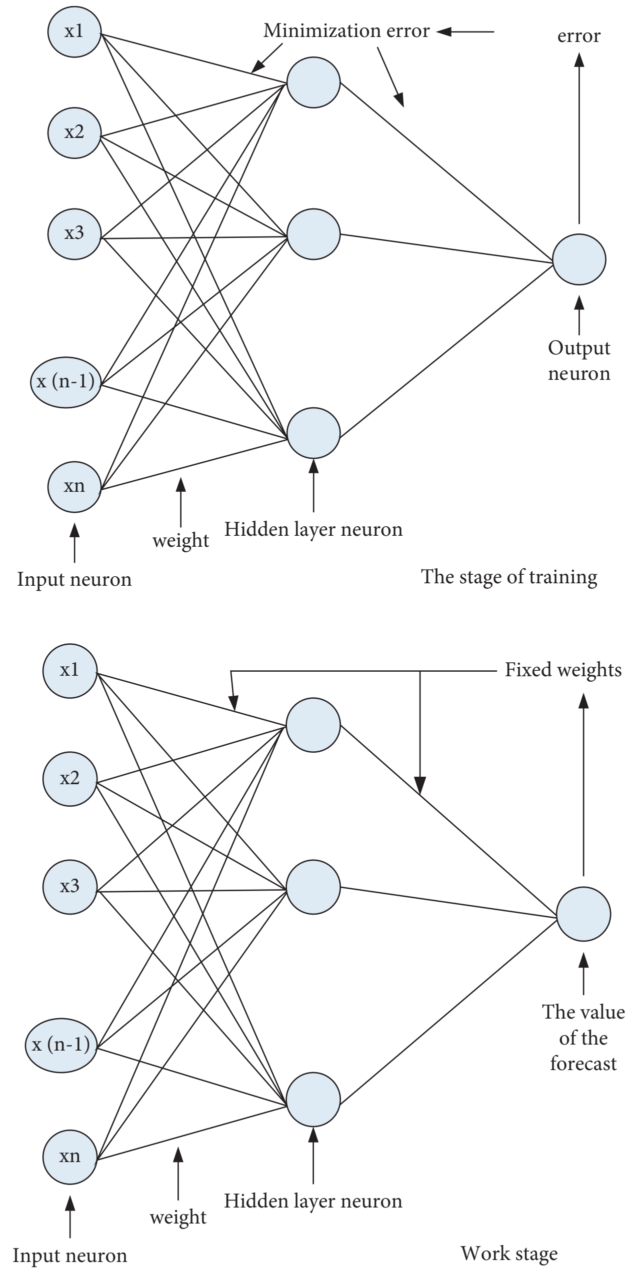

Figure 5: Training phase and working phase of BPNN.

them. The working principle of the NN toolbox is that developers first use the MATLAB language to compile all the functions used by the network and package them. When users need to use the network to predict data, they can directly select the appropriate function to use. In addition, the toolbox also contains a variety of classic weight functions of the correction network. When using the network training, it directly mutates the structure and content of the network and the required subcodes. Users can also directly call many learning algorithms in the NN toolbox according to the needs of the work [17]. The commonly used functions of BPNN are shown in Table 1.

Among them, the transfer function is the most important part of the BP network. Generally, the BP network adopts the sigmoid transfer function and the linear function, as shown in Figure 6.

The input interval of the function logsig is $(-\infty, \infty)$, and the output interval is $(0, 1)$; the input interval of the function tansig is $(-\infty, \infty)$, and the output interval is $(-1, 1)$; the input interval of the function purelin is $(-\infty, \infty)$, and the output interval is $(-\infty, \infty)$. In order to determine the best transfer function, it conducts the network with different transfer functions, records the training error of the network, and obtains the comparison table of network training errors under different training functions, as shown in Table 2.

It can be seen from Table 2 that when different transfer functions are selected for network training, the obtained network prediction errors are quite different, so choosing an appropriate transfer function will greatly improve the training network performance. As for the training function, the main function in the process of network training is to continuously adjust and correct the weights and thresholds of the entire network, and calculate the overall error through the performance function. The training is stopped when the calculated overall error is within the allowable range.

3.2. Basketball. This article mainly introduces the action of dribbling and shooting in basketball. According to the main characteristics of the existing dribble breakthrough technology in application, it classifies the breakthrough methods of dribble breakthrough technology from the following four aspects. It takes advantage of the change in speed to outpace the defender's dribble breakout. It takes advantage of a

Table 1: Common functions of BPNN.

Function types	The name of the function	Function uses
Forward network creation function	newef	Create a cascading forward network
	Newff	Create a forward BP network
The transfer function	logsig	Logarithm function of type S
	tansig	Tangent function of type S
	purelin	Purely linear function
Learning function	learngd	Learning function based on gradient descent method
	learngdm	Gradient descent momentum learning function
	mse	Mean square error function

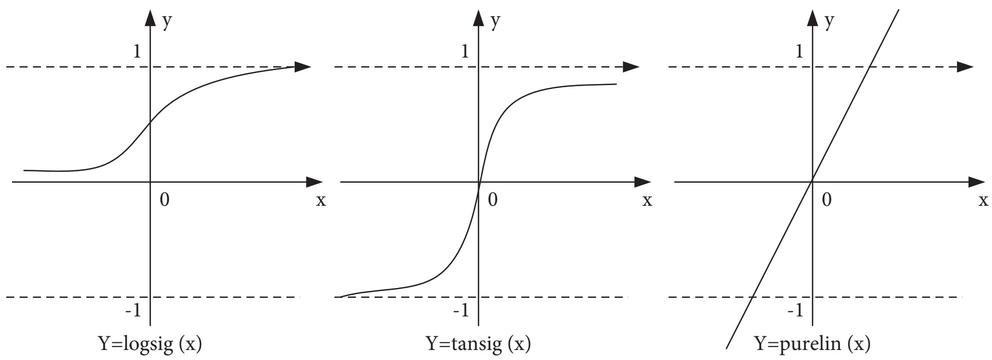

Figure 6: Transfer function diagram.

Table 2: Comparison of errors of different training functions.

Hidden layer function	Output layer function	Error percentage (%)	Mean square error
logsi	logsi	351.62	181.34
logsi	tansig	40.62	0.92
logsi	purelin	0.07	0.001
tansig	logsi	340.37	162.34
tansig	tansig	31.71	1.34
tansig	purelin	1.61	0.01
purelin	logsi	341.28	145.28
purelin	tansig	119.28	112.94
purelin	purelin	197.29	99.35

change in offensive direction to overtake a defender's dribble break. It utilizes the shaking of various body parts and deceptive fakes, etc., for dribble breakthrough fakes. It takes advantage of its super-strength and speed to push the defender's forced dribble break between moves. In practice, there are some dribbling breakthrough techniques that are nothing more than evolution or combination based on these four dribbling breakthrough methods [18, 19]. The action of dribbling is shown in Figure 7.

(1) Variable-speed dribble breakthrough. The attacker's dribble speed should be a combination of fast and slow dribbling. When changing the dribble breakthrough, it should make full use of the combination of the change of dribble rhythm and the change of dribble speed to disrupt the correct defensive position of the defender. (2) Change direction and dribble to break through. When changing direction to dribble and break through, the attacker has better control and coordination of his own body, and his footsteps should be flexible. It is necessary to use the three-axis dribbling technique of the shoulder, elbow, and wrist joints. (3) Fake dribble breakthrough. The fake dribbling breakthrough should use various swaying actions to confuse the defender, and it should be able to use the shaking of the body part to make the defender follow its transformation and then take the opportunity to use the instant space to break through. (4) Forcing the dribble breakthrough. It is necessary to rely on super-physical fitness to force dribble breakthroughs, and use strength and absolute speed to make breakthroughs [20].

The forward turn shooting technique is that when the offensive player has his back to the basket tube and the defender, after catching the ball, one foot is used as the pivot foot and the other foot is used as the turning foot, and the body turns in the direction of the turning toes. A shooting technique in which they brake and take off to complete the shot when they turn to the position facing the basket. There are three main processes in the forward turn shot. The rotation stage (stage 1) refers to the athlete bending his knees with his back to the basket to catch the ball, and the center of gravity of the body is slightly lowered. They put their hands

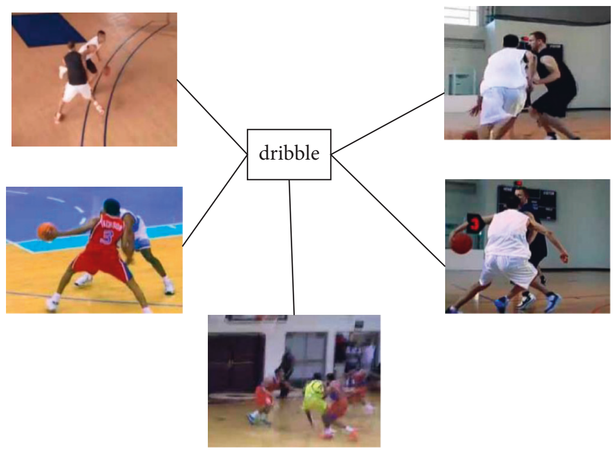

Figure 7: Dribbling action.

on the ball in front of their stomachs, turn their left foot, and start to leave the ground. Driven by the left foot, the left leg begins to turn clockwise with the right foot as the center and to the toe of the left foot. The braking stage (stage 2) is a stage after the athlete completes the rotation movement and before the take-off to complete the shooting action, which is between the rotation stage and the kick-off stage. The kick-off stage (stage 3) is the process in which the athlete pushes the soles of the feet on the ground until the feet leave the ground. At this stage, the first is the driving of the arms; after the arms reach a certain height, it is the extension of the trunk part and finally the extension of the lower limb joints.

3.3. Parameter Optimization of BPNN by Genetic Algorithm. The running steps of the genetic algorithm are the process of simulating the laws of biological heredity [21, 22]. Its microscopic expression is a specific set of genes, but its expression in an individual is the difference between the characteristics and functions of the unit. Simply put, the difference of human blood type is determined by the chromosomes composed of genes that determine this characteristic in different arrangements [23]. So in the computer, the coding work is the process of transforming the external entities that can be sensed into abstract codes recognized by the computer [24, 25]. Because the operation requirements according to the gene encoding are very complicated, the current method is abbreviated, usually using a binary array. In each generation, the selection of new individuals depends on whether the fitness of all selected data falls within the specified range. In the process of selecting the next generation, it uses the crossover and mutation of chromosomes in genetics to calculate a new set of representative solutions. The set of numbers solved by this genetic program is like the evolution of nature, and it is closer to the actual value than the previous generation of data. The data generated in the last generation can be reverse-encoded to obtain the predicted solution closest to the actual value [26].

Table 3: Specific conditions of athletes.

Serial number	Age (years)	Height (cm)	Weight (kg)
1	24	188	87
2	23	192	83
3	23	187	92
4	25	195	79
5	27	193	88
6	23	189	80
7	24	196	91
8	22	201	90
9	24	191	93
10	25	185	96

4. Experiment and Analysis of Parameter Optimization and State Evaluation of Basketball Teaching Scene

4.1. Experiment Preparation. The 10 athletes participating in the experiment were numbered 1–10, and warm-up activities should be fully done before the experiment. After the preparatory activities are completed, it is time to start testing the action. Each person did 10 times for each dribbling action and shooting movement, and then used the recognition system of BPNN to judge the movement. It is evaluated experimentally, and the parameters are optimized using a genetic algorithm. It was studied with 10 high-level basketball players. The specific conditions of the athletes are shown in Table 3.

4.2. Specific Experimental Data. It uses two recognition systems of BPNN and BPNN optimized by genetic algorithm, respectively, to detect the movements of these 10 people and then record the relevant data. The number of successful identifications of various dribbling movements is shown in Figure 8.

It can be seen from the two graphs in Figure 8 that the range of the successful detection times of each dribbling action by the BPNN is between 7 and 9. The number of successful recognition of each dribbling action of the BPNN optimized by genetic algorithm is mostly in the range of 9-10. Obviously, the genetic algorithm has a great effect on the optimization of basketball motion parameters. The number of successful shots is shown in Figure 9.

It can be seen from Figure 9 that there is little difference in the detection of basketball movement between the two methods. Because of the shooting process, the basketball will be separated from the person for a long time, which can be well discriminated.

To sum up, it can be seen from the experimental data that the genetic algorithm in the BPNN technology has a great optimization effect on the parameters of the basketball teaching scene, especially in the difficult basketball game such as dribbling. In the recognition system of BPNN technology, the recognition of each dribbling action is below 90%. The recognition of fake dribble and forced dribble is even lower, between 80 and 85%. The BPNN technology optimized by genetic algorithm has greatly improved the

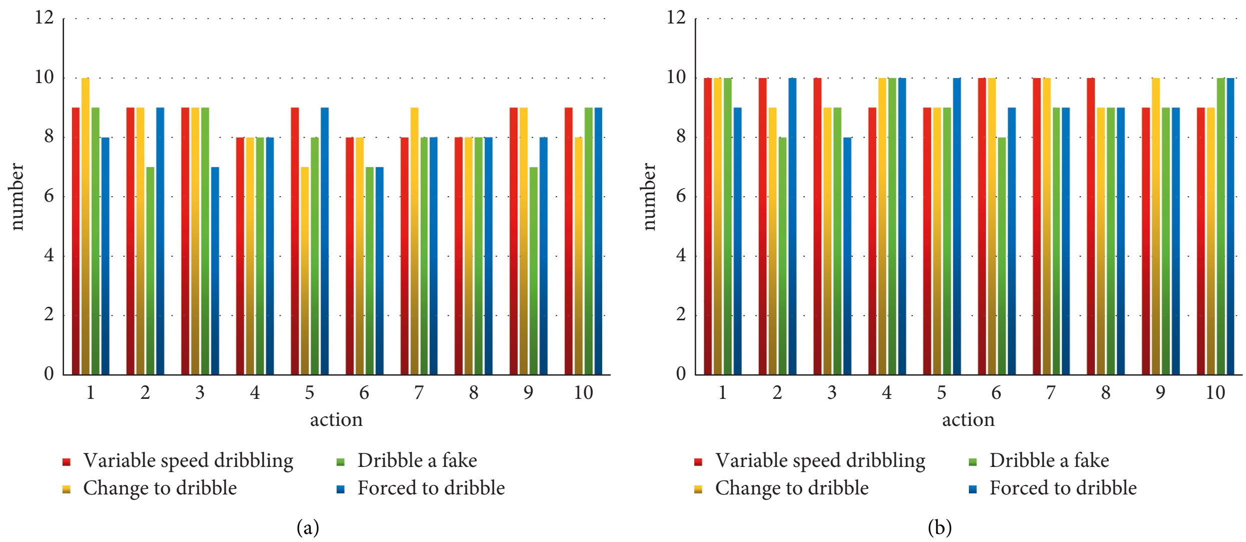

FIGURE 8: Number of successful recognitions for basketball dribbling motion detection. (a) BPNN detection of basketball dribbling motion, (b) BPNN optimized by genetic algorithm to detect basketball dribbling motion.

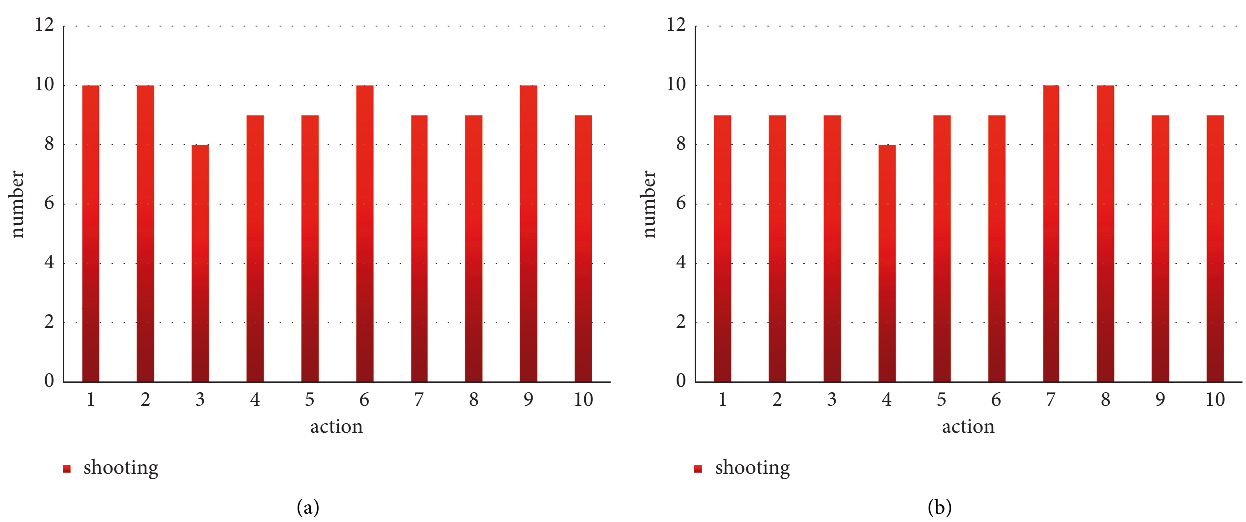

FIGURE 9: The number of successful recognition of basketball shooting motion detection. (a) BPNN for basketball shooting motion detection, (b) BPNN optimized by genetic algorithm to detect basketball shooting and dribbling motion.

recognition of basketball movement, all above 93%. Therefore, the genetic algorithm has a significant effect on parameter optimization of basketball teaching scenarios.

5. Discussion

This article mainly finds 10 male athletes who have many years of basketball experience, and let them perform ten times on the speed change dribble breakthrough, the change direction dribble breakthrough, the fake dribble breakthrough, the forced dribble breakthrough, and the shooting movement. It then uses the recognition system of the BPNN to identify their actions, observes how the BPNN works, then uses the genetic algorithm to optimize the system, then performs the same experiment, and finally compares and analyzes the experimental data. However, there are still some shortcomings in this paper. The experimental objects in this experiment are relatively small, and there may be some errors in the experimental data. In addition, this experiment only includes dribbling and shooting for 1 basketball movement, and some other professional movements are not analyzed and compared. But overall, it is still very convincing.

6. Conclusions

This paper compares basketball recognition between BPNN and BPNN optimized by genetic algorithm. The experimental results show that the BPNN optimized by the genetic algorithm has a great improvement on the basis of the BPNN. The number of successful identifications is between 9 and 10 times, and the success rate is over 93%. It shows that optimizing the parameters of the basketball teaching scene of the BPNN will greatly improve the teaching quality. In the future, researchers will conduct more researches on parameter optimization of basketball teaching scenarios to improve teaching.

Data Availability

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Conflicts of Interest

The author states that this article has no conflicts of interest.

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