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Research Article

Teaching Method Design of Tennis Baseline Stroke Technique Relying on Neural Network Learning Algorithm

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Tennis is an important sporting event. In China, the number of people who study and participate in tennis can be said to be quite large, but there are not many people who insist on playing tennis in the end. Some coaches and tennis groups have come up with a number of different teaching styles in order to keep tennis players going. Its main features are as follows: To cultivate students' interest in learning, the sequence of strokes in tennis is used for teaching. Although tennis has no special requirements for the physical condition of the athlete, tennis is a relatively difficult sport to master. What is lacking at present is more effective and simpler teaching methods, so training should be carried out in a targeted manner in the tennis baseline stroke technique. In order to make the tennis baseline stroke teaching more intuitive and easy to learn, this paper applies the neural network learning algorithm to the research and analysis of the tennis baseline stroke technique and proposes the core technology of the tennis baseline stroke technique. On this basis, the key techniques of tennis baseline stroke technique are discussed. Based on this, a basic model based on deep convolutional neural network is proposed. The experimental results show that the forehand scores of the three throwing methods in the experimental group are 6.47 and 7.28, respectively, which is better than the control group. The three throwing methods are self-throwing, close throwing, and long throwing. It shows that the teaching method in this paper can greatly improve the students' tennis baseline hitting skills.

1. Introduction

In recent years, due to the excellent performance of tennis of China in the world, more and more people have invested in tennis, which has promoted the promotion of tennis in China. While tennis is growing in numbers, few are able to continue their careers, or continue their careers, after finishing training. However, the students who practice on the tennis court fail to improve their tennis skills due to various technical mistakes or simply not training in accordance with the basic tennis movements. Many trainers and teachers have big problems with their demonstration moves and teaching methods. Therefore, it is very necessary to design the teaching method of tennis baseline stroke technique in the teaching of tennis baseline stroke technique.

Regarding the tennis baseline stroke technique, relevant scientists have done the following research. Hit speed is one of the fundamental factors in competitive tennis performance. The purpose of the Terraza-Rebollo study was to determine the effect of two strength training methods on tennis hitting speed. In a period of 8 weeks, the first group did an extra workout with an overload. The second group did additional training with a medicine ball and an elastic band. The third group conducted only technical-tactical training. They all trained for 3 days per week. It can be seen that a greater improvement in service speed was in the SC group. Group L improved the speed of throwing medicine balls, although there was no shift in hitting speed [1]. The purpose of the Filipcic study was to determine step-by-step times in four sets of moves in three categories of tennis players. The subjects were divided into three groups: male and female adolescents and male professional tennis players. In both matches, all matches were recorded with two fixed cameras. For each shot, the time between the point of impact on the opponent's shot and the player's step was measured. Players responded faster on the first serve than on the second serve. On a return serve, the reaction time was lower after the second serve [2]. Many aerial sports have spacer programs. The report of Amrani described a pilot approach to a spacer program following rotator cuff surgery for a female tennis player. The recorded matches were used to obtain the necessary data. Athlete workload was estimated by calculating the total game volume. Based on an individual's preinjury performance, a sport-specific interval hitting program can play a key role in the rehabilitation of tennis players from common musculoskeletal injuries [3]. The main problem of these studies is that the teaching effect is not obvious enough, so this paper introduces a neural network learning algorithm.

The following research results are currently available for neural network learning algorithms. Patra described a genetic algorithm based on neural networks. This algorithm is used to combine genetic algorithms, machine learning, and high-throughput computation or experimentation to discover materials with extreme properties without preexisting data. Predictions from step-by-step constructed artificial neural networks are used to bias the evolution of genetic algorithms and fitness assessments through direct simulations or experiments. The algorithm was tested against several standard optimization problems and polymer design problems and demonstrated to match the efficiency and reproducibility of standard methods. Usually, it can exceed these methods [4]. Cheng and Liu mainly introduced the most widely used spiking neuron model, and analyzed two types of neural networks, feedforward, and recursive, giving a more systematic elaboration. This study introduced new algorithms based on gradient descent, STDP, and spike train convolution rules. This study presented some case studies of spiking neural networks and neuromorphic processors in various national brain programs [5]. To achieve its better problem-solving performance, Gao et al. used six learning algorithms, including biogeography-based optimization, particle swarm optimization, genetic algorithm, ant colony optimization, evolutionary strategy, and population-based incremental learning to train it. By using the Taguchi experimental design method, the optimal combination of its user-defined parameters was systematically investigated. The results showed that the proposed learning algorithm is effective and promising for training DNMs, thereby making DNMs more powerful in solving classification, approximation and prediction problems [6]. The aim of Badaoui was to develop a mathematical model based on MLP artificial neural network to predict general meteorological parameters, especially moisture. In order to choose the optimal structure of the MLP neural network, several statistical criteria such as mean squared error, mean absolute percentage error, information criterion, mean absolute error, and correlation coefficient were used. The results of MLP artificial neural network were discussed and compared with mixed logistic regression (MLR) traditional methods. The MLP method showed a very strong ability in predicting relative humidity [7]. Liu et al. analyzed the human activity recognition (HAR) algorithm using a convolutional neural network that automatically extracts features [8]. In this paper, a neural network learning algorithm is introduced in order to improve the improvement effect of the tennis baseline stroke technique.

Considering multiple aspects to effectively evaluate the learning algorithm, the number of hidden units for sequential learning of the algorithm in this paper is 1044, the recognition accuracy of which is 88.2%, and the running time is 6.44 ms, which is better than the existing algorithm. Different hitting speeds were adjusted to test the students in the experimental group and the control group. The scores of the experimental group in sending the slow ball under the three throwing methods were 11.75, 10.12 and 13.52, respectively, which were better than those of the control group. The main innovations of this paper are as follows: For the teaching of tennis, this paper focuses on the analysis of the important technique of hitting the bottom line of tennis, which has not been studied by the predecessors. And this paper also designs the teaching method based on the characteristics of the neural network algorithm.

2. Teaching Method of Tennis Baseline Stroke Technique

In tennis, the bottom line hitting technique is the most commonly used technique in tennis technique, and it is also the most basic technique. In a sense, mastering basic skills is an important indicator to measure the level of students' tennis skills, and it is also the key to determine whether students can win the competition. As shown in Figure 1, the tennis baseline shot evaluation system is shown. The system compares the collected body movement data with standard scoring actions and scores according to the established scoring criteria.

Tennis is a competitive sport. Therefore, most people prefer to learn and master the essentials of various techniques in the game, rather than simple theoretical knowledge. A step-by-step approach based on everyday games is set against the backdrop of a real tennis match. From simple actions such as simple serving, positioning ball, and close ball, to complex situations such as rapid rotation, diagonal line, and volley ball, the player's skills can be gradually improved [9]. It gives full play to the interest of classroom teaching, which can not only improve students' interest in learning but also deepen students' understanding of classroom content, improving the quality and effect of classroom teaching [10]. In tennis teaching, teachers should fully mobilize the emotional needs of students, create a harmonious and positive learning environment, and improve the teaching effect of tennis.

In traditional tennis teaching, students often imitate the training of teachers and coaches and perform training repeatedly. Such training is not only tedious but also difficult to effectively test the training effect of students [11]. The game-style competition scene is adopted to allow students to better grasp the knowledge taught by the teacher in the practice which is not just a simple action but an overall strategy and decision. In practice, students can personally experience the power and feeling of the racket. This is a wonderful

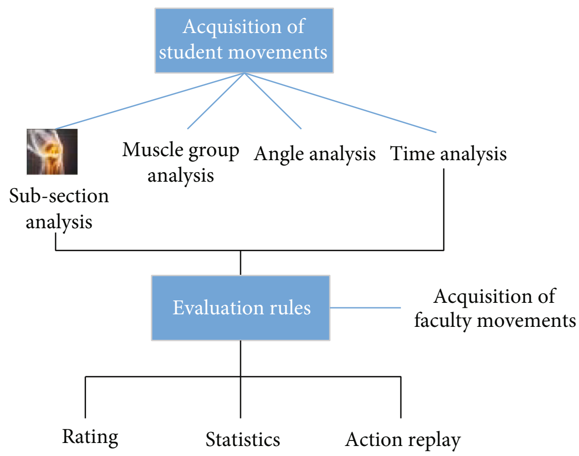

Figure 1: Tennis baseline shot evaluation system.

feeling. No matter how much the teacher says, the students cannot understand [12]. Successful experiences can spark a strong interest in tennis in students and continue to invest in their careers. The failure in the competition will also make the students realize their technical and tactical deficiencies and constantly improve themselves and their skills in training. Because of differences in factors such as age, gender, education level, and IQ of different students, teachers need to teach students according to their aptitude. The specific manifestations are different people, different teaching contents, and different educational methods.

For tennis players, agility, speed, and strength are the most important things. In tennis, because the speed, type, spin, and height of the opponent's ball are different, and it will happen on different courts, it is necessary to move quickly in all directions, constantly change directions, stop and start suddenly, and ensure the balance of the body and the efficient hitting at the same time [13]. Tennis is a fast sport, so agility is critical in tennis. High sensitivity can help athletes reach the hitting position quickly and smoothly, prepare in advance, and complete the technical action of hitting the ball relatively easily [14].

In tennis technical movements, the baseline stroke refers to the baseline forehand and backhand strokes. The baseline forehand and backhand skills are the most common basic skills and the first skills for beginners to master. In a tennis match, senior players often use their sharp forehand and backhand shots to create points to win the entire game [15]. Since the forehand service has been greatly improved in terms of stability, placement, rotation, speed, etc., it makes it more difficult for the opponent to return the ball, thereby enhancing the player's desire to attack. Therefore, the forehand and backhand play a crucial role at this stage. Because of the fast pace, many professional tennis players can hit the backhand from anywhere on the court. Players return the ball quickly, accurately and ruthlessly at a fast speed, forcing the opponent to take the initiative to drop points. This style of play, combined with good forehand and backhand technique, will give the upper hand on the court and make it easier to win games. In teaching, it is necessary to give full play to the subjective initiative and individuality of students and give full play to the individual characteristics of students in order to ensure that students are in the leading position in the learning of tennis skills and teachers and coaches only play a leading role.

Auxiliary exercises refer to the use of imitation, induction, assistance, and other means for the key parts of new movements to supplement the mental, quality, essentials, and other abilities that athletes lack in learning new movements. Practice has proved that auxiliary exercises are of great significance to the learning and mastering of new movements in physical education. Especially in the teaching of difficult movements, the use of auxiliary movements is indispensable, which often plays a key role in the learning and mastering of new technologies. Tennis is a sport dominated by net-separated confrontation skills, and the baseline forehand technique of tennis is the foundation of tennis skills. Its technical movements are complex, delicate, and relatively difficult, so it has great requirements on the physical fitness of athletes such as strength, speed, endurance, and sensitivity. It is often difficult for students to learn and master baseline tennis hitting techniques [16]. This can easily cause that many people's interest in it gradually decline in the learning process, or even give up learning. As shown in Figure 2, the motion capture function module of tennis shot evaluation is shown. This module captures the parameters of the player's batting action by using the catcher, extracts the time, angle, and speed and then transmits the collected data to the computer for further processing.

In tennis, batting evaluation are embodied in the differences from shallow to deep, from easy to difficult, and from simple to complex. According to where the ball falls, the ball played by the teacher can easily be caught by the students as long as it falls in a fixed position. That is, it is easy for students to find the target, but it is difficult if there is no fixed location [17]. From the perspective of tennis rotation, if the rotation of the tennis ball is strong, it is difficult to hit. If the rotation of the tennis ball is weak, then it is more likely to be hit. From the point of view of the friction between the ball and the net surface, if there is a lot of friction, it is not suitable to hit the ball. If there is no friction, it is much simpler. Because of the different distances between tennis balls and the net, beginners can easily grab the ball closest to the net without touching the ball that is too far from the net. From the perspective of the ball route, if the incoming ball route changes, it is not easy to hit the ball. On the contrary, if the incoming ball trajectory remains unchanged, it is easier to hit [18]. From the speed of tennis, if the ball is very fast, it is difficult to hit. Conversely, if the ball is not fast enough, it is more likely to be hit. Because the tennis ball has no contact with the floor, it is easier to hit after landing and bouncing, and it is more difficult to catch in the air.

Starting from the practice of hitting the ball without a racket and throwing the ball on the spot, by gradually increasing the distance of the ball tossing, the player's sense of movement of the ball is improved, and the good coordination between the racket swing and the hitting point is established. This design is the basic method of batting practice. It is recommended to use a multiball practice method during

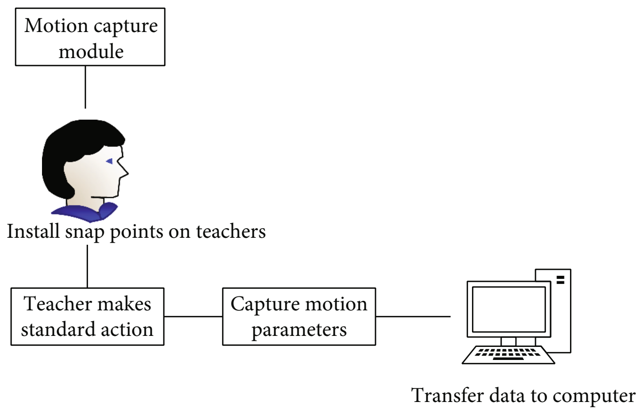

Figure 2: Motion capture function module.

practice and gradually improve the athlete's movements during practice. Feeling of the ball is quickly improved through a lot of hitting practice, and the connection between technique and the feeling of the ball can be found. At present, most coaches in college physical education classes do not adopt the design and method of multiball practice due to objective and subjective reasons, resulting in fewer opportunities for students in elective courses to practice. Ultimately, only a very small number of students master tennis skills. The bottom line exercises are as follows:

(1) Practice without the ball or with the auxiliary swing. The practice of swinging and hitting the ball without the ball is an important form and method of learning techniques, which can allow students to focus completely on the technique and ensure the standardization of the technique. Shooting without the ball can be a single split movement or a complete movement. Auxiliary action is an important form of experiencing or improving tennis baseline strokes. The usual method is to experience and master by throwing basketballs and medicine balls

(2) Practice of throwing and hitting the ball in place. At the beginning, the athlete completes the leading action, and the coach throws the ball vertically upward, so that the athlete can complete the swing and hit the ball. The athlete experiences the practice of swinging the racquet head upwards from the bottom of the hitting point, while looking for the hitting point. Grip and stance techniques can be taught and improved as player practices swinging and hitting the ball. With the improvement of the students' level, they are taught the technique of inducing the racket. At the same time, it should be noted that they should not only start from the sideways action to complete the lead and swing action but also learn the hitting technique, as well as find the hitting point

(3) Practice of tossing and hitting the ball in place after the cross moves. The coach moves the ball back and forth, left and right, asking the player to follow the coach sideways to complete the slap shot and find the hitting point. The coach should wait for the athlete to move in place, stop the movement of the ball, stand still in place, and then throw the ball vertically upwards, so that the athlete has enough time to react

(4) Practice of short forward tossing and hitting. A short distance is a distance of 3-4 meters where the coach throws the ball to the athlete. When throwing the ball, it needs to be careful not to throw the ball in the direction of the player's body. The landing point is about 1 meter before the baseline (to avoid throwing the ball under the students' feet). The height is moderate to the shoulders of the athlete. The frequency of throwing the ball should not be too fast. Starting from a short throw, it needs to be sure to pay attention to the movement of footsteps and the coordination of the lead shot. The athlete should be allowed to complete the lead-in action in the last two steps of the movement and swing the racket to hit the ball in a state of fixed footsteps, so as to experience, understand and master the rhythm of hitting the ball. The requirement of batting rhythm should run through the batting action from beginning to end, which is the key point to improve batting ability

At present, the teaching methods of tennis baseline stroke techniques generally have poor teaching effect. For this reason, this paper introduces a neural network learning algorithm. Logical thinking is reasoning on the basis of logical laws. First, the information is transformed into concepts and expressed in symbols. Then, logical reasoning is carried out according to the sequence of symbolic operations. This program can be written into a series of instructions, which are carried out by the computer. Deep learning is derived from artificial neural networks. In deep learning, deep convolutional neural network is a multilevel back-propagation artificial neural network, which is a multi-layer perceptron designed for recognizing shapes. Each layer of neurons is connected to the overlapping local field of view area of the previous layer network, while there is no connection between neurons in the same layer. The advantages of deep convolutional neural networks are as the followings: One is to minimize preprocessing as much as possible. Most of its inputs are raw data that has not been processed many times, and there is no precise mathematical expression between input and output. Its feature extraction is trained within the network, avoiding the subjectivity and limitations of manual feature extraction. The other is that the deep convolutional neural network is affected by the time-delay neural network.

The autoencoder assumes that the input is consistent with the output and trains the network to adjust the network parameters under this assumption. So, an autoencoder is a model that reproduces the input data as much as possible. The general process of the autoencoder is that the original input is fed forward to obtain data y, and the data z is obtained through feedback according to y. The error is as

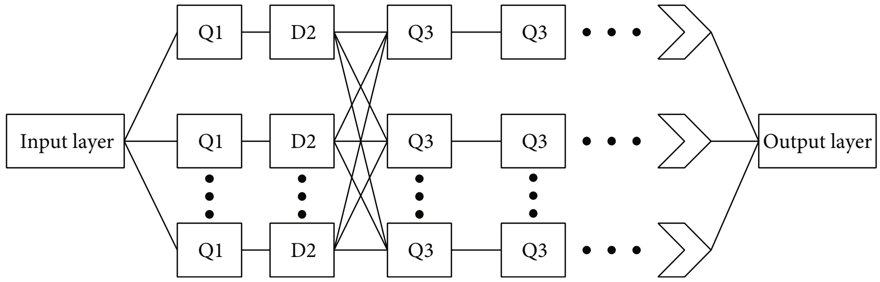

Figure 3: Deep convolutional neural network architecture.

small as possible through continuous iteration. In the process, the encoding and decoding of data are constrained by the same parameter matrix, in order to reduce the number of parameters and control the complexity of the model. In this process, unlabeled data is used to calculate the error update parameters, which belongs to the unsupervised learning model, and the sample features are extracted using a double-hidden layer structure similar to a neural network.

Deep learning is the application of neural networks in machine learning. Deep learning combines basic features to generate abstract high-level representations so as to find distributional features. On this basis, this paper proposes a deep convolutional neural network based on input layer, hidden layer, and output layer. The hidden layer is a repetitive structure that consists of multiple convolutional layers and a pooling layer (subsample layer). The middle input layer is the raw data without manual feature extraction. Multiple convolution kernels in the convolutional layer $Q1$ convolve the input data to generate corresponding convolution feature maps. The pooling layer $D2$ pools the feature map obtained by $Q1$ to generate the corresponding pooled feature map. $Q3$ and $S4$ repeat the steps of $Q1$ and $D2$, that is, this repeated step structure exists in the hidden layer of the deep convolutional neural network. The deep convolutional neural network uses the convolution and pooling settings to extract features from the data, so that the model has a good tolerance for deformed images that conform to distortion invariance. At the same time, the resolution of the feature image is reduced, and the number of feature maps is increased, so that it can obtain more feature data information. Finally, the full connection method is used to obtain the final output result. As shown in Figure 3, it is a deep convolutional neural network structure.

There are multiple feature maps in the convolutional layer, each feature map is composed of multiple neurons, and each neuron is locally connected to the previous layer feature map through a convolution kernel. In order to enhance the expressiveness of the convolutional layer of the deep convolutional neural network, K different filters are generally used in the convolutional layer to obtain K groups of different outputs, and each group of outputs shares the same performance filter. Using the filter as a feature extractor, then each set of outputs will be used as features after feature extraction.

Although the convolution of the convolutional layer can significantly reduce the number of connections, the number of output neurons in the convolutional layer does not significantly reduce. If the classifier is directly connected to the classifier after convolution, overfitting may easily occur due to the high dimension, so pooling in the deep convolutional neural network is essential. The formed pooling layer can greatly reduce the feature dimension and avoid overfitting. The definition of pooling is to analyze and count the characteristics of a certain area of the image to represent the overall characteristics of the entire area, and the area is called the pooling domain. In a deep convolutional neural network, the pooling layer follows the convolutional layer without changing the number of feature surfaces.

Compared with conventional pattern recognition methods, deep convolutional neural networks introduce a new weight allocation strategy in the convolutional layers. It can effectively reduce the parameters of the network and reduce the complexity of the network, thereby avoiding the problem of early overfitting. At the same time, the deep convolutional neural network introduces the pooling method in the network, which reduces the number of neurons and makes the model more robust. Meanwhile, the deep convolutional neural network has strong structural expansion ability, and the deep level can better reflect the better expression ability, which is suitable for complex classification problems. Due to the local connection, weight sharing and pooling characteristics of deep convolutional neural network, it can achieve translation, scaling, and deformation invariance within a certain range. The following are related algorithms for human action recognition based on deep convolutional neural networks:

$$g_t = g_{t-1} + Qh(m_t), \tag{1}$$

where g_t is the linear feedback transfer.

$$u_t = \mu\left(Q_{mu} m_t + X_{gu} g_{t-1} + j_u\right), \tag{2}$$

$$o_t = \mu\left(Q_{mo} + X_{go} g_{t-1} + j_o\right), \tag{3}$$

$$g_t = o_t \bullet \tan g(c_t), \tag{4}$$

where c_t is the memory unit, m_t is the time input, and μ is the nonlinear regression function.

$$n_t = Q_z z_t + j_z, \tag{5}$$

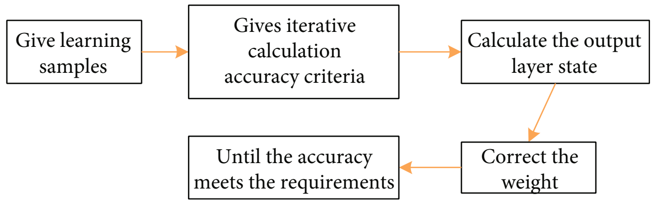

FIGURE 4: Neural network learning steps.

$$L(n_t = c) = \frac{\exp(n_t, c)}{\sum_{c'=C} \exp\left(n_t, c'\right)}, \tag{6}$$

where z_t is the output in the time series learning box and Q_z is the learning parameters for the classification layer.

$$g'_t = \tan g(Q_{mc} m_t + X(r_t \cdot g_{t-1})), \tag{7}$$

$$g_t = z_t \cdot g_{t-1} + (1 - z_t) \cdot g'_t, \tag{8}$$

where z is the update gate and r is the reset gate.

$$G_t(m, n, t) = \begin{cases} \varepsilon, \\ \max(0, G_\varepsilon(m, n, t-1)), \end{cases} \tag{9}$$

$$\delta(m, n, t) = \begin{cases} 1, \text{if } S(m, n, t) \geq \varphi, \\ 0, \end{cases} \tag{10}$$

where ε is the duration of the time period, t is the time, and φ is the preset parameters.

$$S(m, n, t) = |U(m, n, t) - U(m, n, t \pm \tau)|, \tag{11}$$

$$g_\theta(m) = \frac{1}{1 + e^{-\theta^T m}}, \tag{12}$$

were φ is the given difference threshold and $g_\theta(m)$ is the step function.

$$V(\theta) = -\frac{1}{a} \left[\sum_{u=1}^{a} n^{(t)} \log g_\theta\left(m^{(u)}\right) \right], \tag{13}$$

$$g_\theta\left(\mathrm{m}^{(u)}\right) = \frac{1}{\sum_{v=1}^{k} e^{\theta_v^T}}, \tag{14}$$

where k is the number of categories and $V(\theta)$ is the loss function.

$$V(Q, j) = \frac{1}{2} \sigma \|Q\|_F^2, \tag{15}$$

$$\|Q\|_F^2 = \sum_{p=1}^{P} \sum_{v=1}^{b} Q_{uv}^p, \tag{16}$$

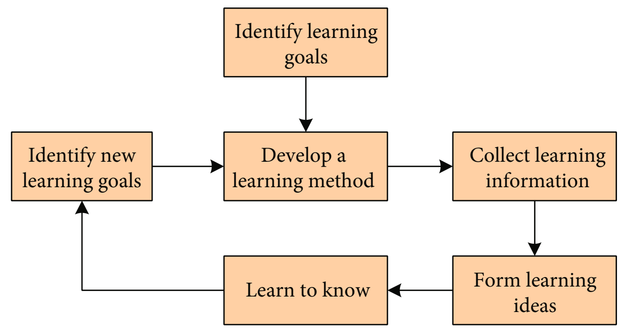

FIGURE 5: Basic steps to learn.

where Q is the weight matrix for each layer and j is the bias vector.

$$\alpha^{(p)} = \frac{\partial V(Q, j)}{\partial z^{(p)}}, \tag{17}$$

where $\alpha^{(p)}$ is an error term defined.

$$\tau'(m) = \tau(m)(1 - \tau(m)), \tag{18}$$

$$\tan g'(m) = 1 - (\tan g(m))^2, \tag{19}$$

$$\omega^{(p)} = f'_p(z^p)\omega^{p+1}, \tag{20}$$

where $\omega^{(p)}$ is the iterative formula and $\tau'(m)$ is the derivative of the function of the error term.

Figure 4 shows the neural network learning steps. The tennis teacher's batting action can be learned by using this learning step. After reaching a certain accuracy, the student's batting action can be detected, and the student's learning situation can be more accurately understood and adjusted.

3. Teaching Experiment of Tennis Bottom Line Batting Technique

3.1. Analysis of Neural Network Recognition Algorithm. In deep learning, deep convolutional neural network is a multilevel back-propagation artificial neural network, which is a multilayer perceptron designed for shape recognition. Each layer of neurons is connected to the overlapping local field of view area of the previous layer network, while there is no connection between neurons in the same layer. The basic steps of learning are shown in Figure 5.

In order to effectively evaluate the learning algorithm, multiple aspects such as scene type, viewing angle area,

Table 1: Learning algorithm effectiveness evaluation.

Algorithm model	LR	BP	This article
Number of hidden units for sequential learning	1012	524	1044
Recognition accuracy (%)	72.94	83.29	88.2
Running time (h)	8.4	10.2	6.44

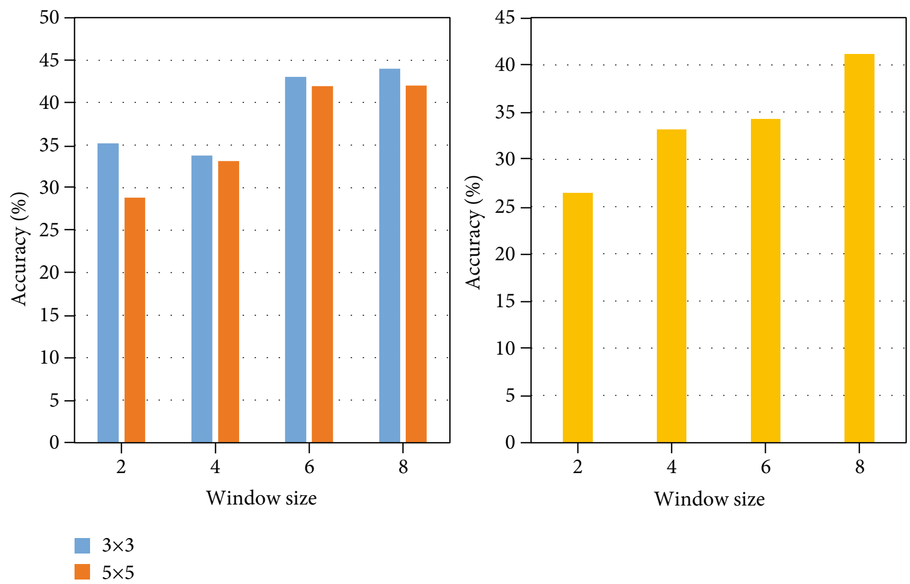

Figure 6: Action recognition segmentation accuracy comparison.

Table 2: Main joint data sheet.

	Knee joint	Wrist joint	Shoulder joint	Elbow joint
Rotation angle (°)	9.2	7.2	20.4	32.7
Movement distance (cm)	12.1	14.5	28.3	51.2
Exercise time (ms)	538	567	435	578

illumination, background, and camera moving speed are fully considered. Table 1 shows the experimental comparison results.

It can be seen that the recognition accuracy of the algorithm in this paper is 88.2%, and the running time is 6.44 h, which improves the recognition accuracy of human actions and reduces the running time to a certain extent.

In addition to the space size of the convolution kernel, the size of the time dimension also affects the classification and recognition rate. When the time dimension is 3, the final classification and recognition accuracy rate is higher. As shown in Figure 6, the accuracy of action recognition segmentation is compared.

If the convolution kernel used is too large, the calculation amount of the convolution will also increase, and the computational complexity will be high. It can be seen from Figure 6 that the 3×3 convolutional network structure has the best effect, with the highest accuracy rate reaching 44%. The traditional recognition accuracy rate is about 30%, which is 14% lower than the algorithm in this paper.

Table 3: Batting performance test.

Group	Self-throwing ball	Close throw	Long throw ball
Test group	11.56	12.95	12.19
Control group	8.7	8.26	8.38
p	<0.01	<0.01	<0.01

The above neural network learning algorithm is used to identify the teacher's standard tennis baseline stroke. The main joint data table is shown in Table 2.

3.2. Analysis of the Teaching Effect of Tennis Bottom Line Hitting. The boys who had not received tennis training and who were in good physical condition voluntarily participated in the first grade of a middle school were selected as the survey objects and divided into the experimental group and the control group with the same number. The experimental group adopted the teaching method of this paper,

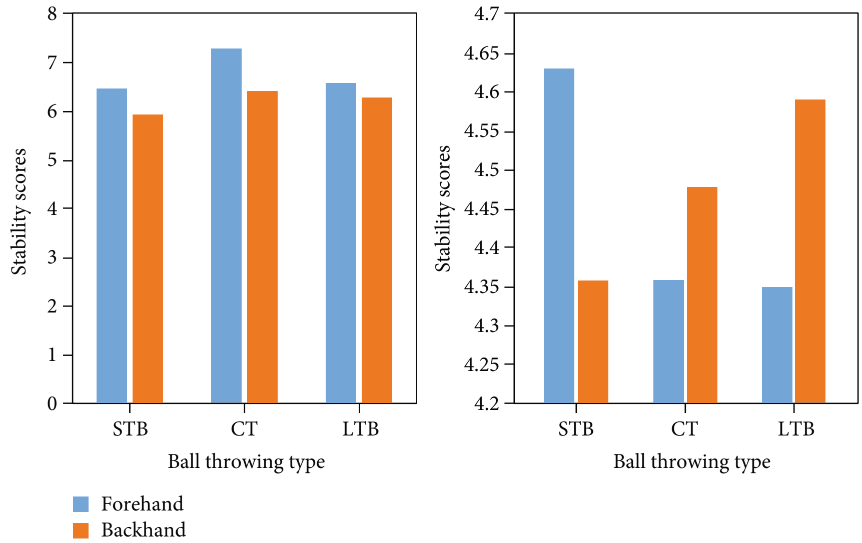

Figure 7: Bottom line ball striking stability test results.

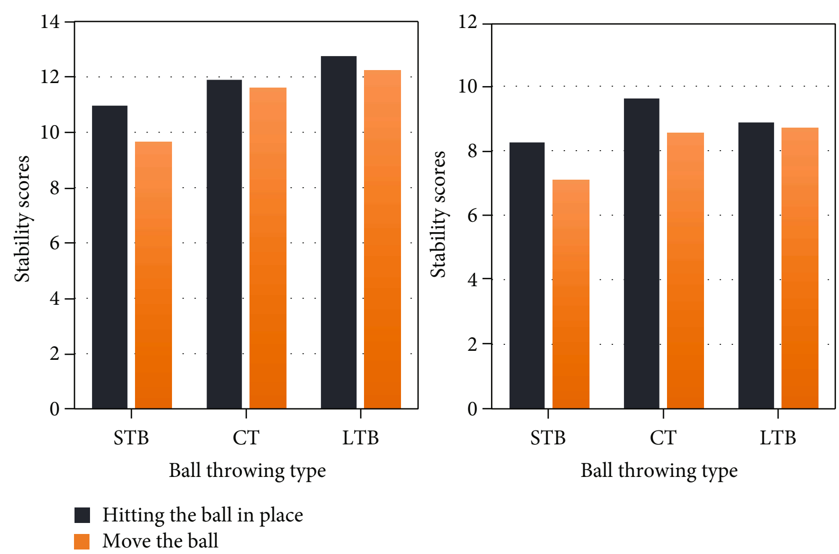

Figure 8: Batting position test results.

and the control group adopted the traditional teaching method. The teaching last for one semester, and the two groups of students were tested at the end of the semester. The batting score test is shown in Table 3.

It can be seen that among the three types of throwing methods, the hitting scores of the experimental group are 11.56, 12.95, and 12.19, respectively, which are better than those of the control group, indicating that the teaching method in this paper is more effective in this regard.

As shown in Figure 7, the baseline hitting stability test results are shown. It can be seen from Figure 7 that the hitting stability of the experimental group is higher than that of the control group under the three throwing methods, and the forehand scores of the students in both groups are better than the backhand scores.

The effects of the two groups of students' downbatting under different batting methods were tested. Figure 8 shows the hitting position test results of the two teaching groups. It can be seen that the in situ hitting scores of the experimental group are 10.96, 11.89, and 12.75, respectively, which are higher than those of the experimental group and the control group, indicating that the teaching method in this paper is better.

Two groups of students were tested by adjusting for different hitting speeds. As shown in Figure 9, the performance comparison of delivery speed is shown.

It can be seen that the scores of the students in the experimental group in sending the fastball are 9.71, 7.38, and 12.14, which are lower than those in the slowball. However, compared with the control group, there is still a big

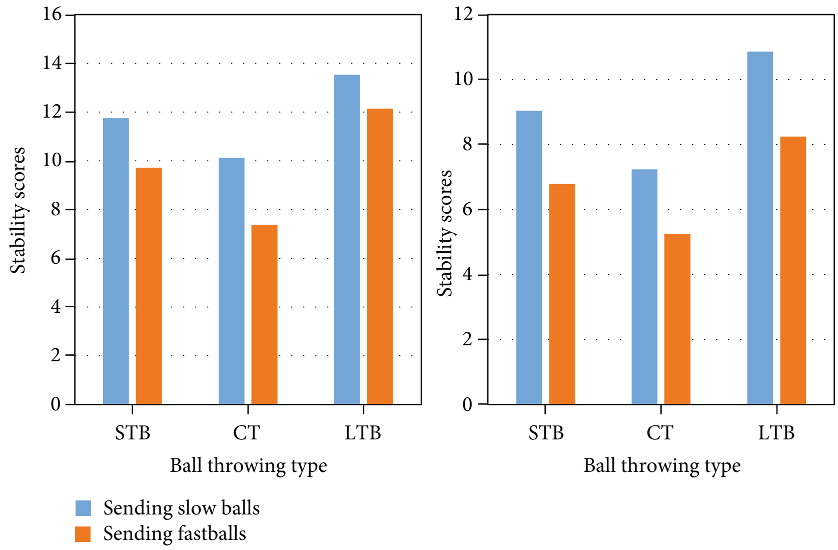

FIGURE 9: Comparison of ball delivery speed scores.

advantage. The bottom line area is far from the net, and the success rate of hitting the ball over the net is affected by many factors. The main task and goal of tennis learning for beginners is to hit the ball over the net. When they are not proficient in ball feel, hitting point, and power control, the farther it is away from the net, the more mistakes they will make. If they use slow tennis balls at this stage, the low bounce feature can reduce the number of missed shots.

4. Conclusions

In order for tennis beginners to learn tennis skills more effectively in a short time, a more effective teaching method is needed. In this paper, a neural network learning algorithm is introduced to capture the action recognition of teachers and students. Motion capture technology can obtain a large number of data such as kinematic technical parameters and physiological indicators of related technical movements. Through the statistics of its movement laws, it can provide scientific guidance for athletes to scientifically and effectively complete the expected training goals. The experimental group and the control group were set up to test the stability of the baseline batting, different batting speeds, and the performance of the baseline batting. The experimental results all prove that the teaching method of this paper can greatly improve the students' tennis baseline hitting skills. In this paper, the preliminary prediction research is carried out. In view of the limited data sources and academic level, there are inevitably some omissions in the research. In the current situation analysis stage, the analysis is not thorough enough, only showing the changes of relevant indicators, with a lack of internal judgment analysis. In the theoretical research stage, the grasp of the theory is not deep enough.

Data Availability

Data will be available on request.

Conflicts of Interest

There is no conflict of interest.

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