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ORIGINAL

Research on application of deep learning in competitive sports training

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Abstract

Objective: In order to improve the effect of competitive sports training, this paper applies deep learning to competitive sports training. In order to improve the feature recognition ability based on view deep learning, this paper proposes a structure-aware CNN joint learning framework to carry out effective feature fusion, and then input it to the Softmax classifier to realize the structure recognition and shape classification of the 3D model. Moreover, this paper combines the improved algorithm to construct a competitive sports training system based on deep learning. The data related to the training information integration analysis platform system is all realized through the access database management system, and the data involved in each module is managed in the form of a table in the database. Finally, this paper combines experimental analysis to analyze the performance of the system in this paper. The experimental results show that the competitive sports training system based on deep learning proposed in this paper is very effective.

Keywords. deep learning, competitive sports, training, model

1. INTRODUCTION

The process of competitive sports training is the process of continuously improving the competitive ability of competitive sports athletes, so that they have considerable strength, and then they can play out in the competition through participating in the competition. The breakthrough and integrated development of digital technologies such as big data, Internet of Things, mobile Internet, and cloud computing have profoundly changed people's work, life and thinking patterns. Moreover, it provides us with favorable conditions for in-depth understanding of the laws of competitive sports training and accelerating the datamation, objectivity and refinement of the training process. The future development direction of competitive sports training is the organic integration and coordinated development of physical stamina, skills and mental abilities, so as to achieve an overall improvement in the competitive strength of competitive sports athletes. This requires rapid acquisition of data information, construction of data collection, and real-time analysis and batch processing of data information. For this reason, we proposed the construction of a digital competitive strength platform (Aso, Hwang, & Koike, 2021).

The main line of scientific training is carried out around the law of load-fatigue-adaptation. Traditional small-volume data analysis is like a blind person touching the elephant, it is difficult to grasp the full picture of the data, and it lacks horizontal comparison and vertical tracking. In the process of competitive sports training, it is impossible to accurately quantify and comprehensively analyze factors such as the training load, fatigue level, competitive sports performance, and injury risk of competitive sports athletes. This makes it impossible for coaches and scientific researchers to diagnose, evaluate and monitor the training process and the status of competitive sports athletes in a timely manner (Azhand, Rabe, Müller, Sattler, & Heimann-Steinert, 2021). With the development of science and technology and the continuous understanding of training laws, scientific training concepts and training methods are constantly updated and upgraded, relatively "independent" or "closed" training modes can no longer meet the requirements of scientific training. The brand-new "digital +" training model has become an inevitable trend in the development of contemporary scientific training. The construction of a digital competitive strength platform is an important measure to accelerate the digitization, objectification and refinement of competitive sports training, and to continuously improve the level of scientific training and the competitive strength of competitive sports athletes (Bakshi, Sheikh, Ansari, Sharma, & Naik, 2021).

At present, science and technology help competitive sports have become the consensus of the sports world. With the development of digital training concepts and intelligent testing technology, technological assistance has fully entered the era of information and data. Data such as physical fitness, function, skills, psychology, injury, fatigue, form, etc., play an increasingly important role in supporting training, and the accumulation of data is also growing (XU, TASAKA, & YAMAGUCHI, 2021). However, in specific operations, there are problems such as weak research and development of intelligent and digital training equipment, low compatibility, complex training and monitoring data collection process, data loss, data fragmentation, and data fragmentation. This has led to a decline in the efficiency of related data storage, management and use, making training monitoring not scientific and precise, and affecting the implementation of scientific and technological assistance. In the process of promoting science and technology to help prepare for competitions, scientifically constructing a digital monitoring system and giving full play to the role of big data have become important means to promote science and technology to assist competitive sports. The digital competitive strength platform integrates and automates data collection through APIs. Moreover, it aggregates, stores, counts, analyzes and visualizes various data originally scattered in various equipment and special coaches, physical coaches, scientific research personnel, medical personnel, and anti-doping personnel. In addition, it comprehensively monitors competitive sports training through multiple data comprehensive views, which effectively improves the level of technology-assisted competitive sports (Zarkeshev & Csiszár, 2019).

In traditional competitive sports training, coaches, scientific researchers, medical personnel, etc., analyze and organize relevant data according to the division of labor, and finally generate reports to report to management personnel. Due to the inconvenient format of related training monitoring data and records, asymmetry in information, and unsystematic data management, problems such as inconvenient query, inconvenient storage, unintuitive analysis, and opaque data are caused. This not only consumes a lot of energy of coaches, scientific researchers and medical staff, but also makes managers unable to effectively control the quality of training and monitor the effects of training. This is not only inefficient, but there are too many links in the process of collaboration, which is error-prone and affects the arrangement and execution of the overall training plan. The digital competitive strength platform can liberate a large number of human resources, and at the same time improve the efficiency of data flow in training, and greatly save management costs. Close cooperation in many aspects will help relevant personnel provide timely feedback on the competitive status of competitive sports athletes, and provide targeted guidance and adjustments to them. Competitive sports training is under data management throughout the whole process, which improves the management staff's control over the quality of training.

2. Related work

The development of machine learning can be divided into two parts: shallow learning and deep learning. Shallow learning includes machine learning algorithms such as support vector machines, random forests, conditional random fields, and neural networks (Colyer, 2018). Shallow learning algorithms usually contain one or two layers of nonlinear transformations and perform well on restricted simple problems. However, shallow learning has the shortcomings of insufficient representation and modeling capabilities, and cannot be effectively processed when facing complex application scenarios such as speech processing and visual images. Neural network is a flexible machine learning algorithm. By adding network layers, the network can obtain stronger modeling capabilities and feature representation capabilities. However, neural network models with too many network layers have problems such as difficulty in training and easy over-fitting (Díaz, Laamarti, & El Saddik, 2021). Therefore, before the introduction of deep learning, traditional shallow learning algorithms have always been the mainstream algorithms in the field of artificial intelligence. For example, support vector machines were once the most popular machine learning algorithm in the field of artificial intelligence (Ershadi-Nasab, Noury, Kasaei, & Sanaei, 2018). Deep learning has become the main research direction in the field of machine learning, and has been widely used in speech recognition, computer vision, image enhancement, visualization and other fields (Gu, Wang, Jiang, & Hwang, 2019). Deep learning establishes a neural connection structure that simulates the human brain, which is composed of multiple layers of non-linear computing units. The output of the lower layer unit is used as the input of the higher layer unit, and the data characteristics are described hierarchically through multiple transformation stages to obtain the data Essential representation (Hua, Li, & Liu, 2020). Compared with "shallow learning" methods such as support vector machines, perceptrons, and decision trees, deep learning models have more levels of non-linear operations, so they are also called deep learning (M. Li, Zhou, & Liu, 2019). Deep learning is to transform the original data layer by layer to realize the transformation of the data from the original data space to the new feature space, thereby automatically learning the hierarchical features of the data. These feature representations can be used to complete tasks such as classification, regression, and feature visualization (Z. Li, Bao, Liu, & Jiacheng, 2020). Compared with shallow learning, deep learning can learn more abstract concepts and fit more complex functions. In addition, deep learning can build complex models with fewer parameters. For example, a function can be expressed concisely with a k-layer structure, while an exponential number of parameters are required to express the function with a K1 layer structure. Therefore, compared with Deep learning is more suitable for building complex models. In addition, shallow learning is prone to insufficient generalization capabilities, while deep learning can express more complex functions with fewer parameters, has better generalization capabilities, and is suitable for processing more complex tasks (Liu, Li, & Hua, 2018). Deep learning, with its powerful feature representation ability and function modeling ability, has well alleviated the problems of insufficient generalization ability and dimensionality disaster of traditional shallow machine learning algorithms (McNally, Wong, & McPhee, 2018).

Literature (Mehta et al., 2017) proposes a machine that can simulate human perception. As the basis of neural and support vector machines, the perceptron opened the first climax of neural network research. Literature (Nasr et al., 2020) analyzes and proves that the perceptron can only solve linearly separable problems, but cannot deal with non-linear and contingency problems. People hope to solve the problem of linear inseparability by adding hidden layers to form a multi-layer perceptron, but there is no method that can effectively train the hidden layer network parameters. Limited by the theoretical level and technical conditions at the time, the research of artificial neural networks fell into Low tide. The literature (X. Nie, Feng, Xing, Xiao, & Yan, 2018) studied the incentive method of visual information in the cerebral cortex, and proposed the concept of receptive field. Literature (Y. Nie, Lee, Yoon, & Park, 2019) proposed a hierarchical neural network model based on the receptive field. This model obtains each layer from the local area of the upper layer through the convolution kernel with shared weights. Literature (Y. Nie et al., 2019) proposed a network parameter training method for multi-layer perceptrons with non-linear continuous transformation functions, that is, back propagation algorithm (BP). Compared with the perceptron, the neural network with the added hidden layer can build more complex mathematical models, and can transform the data more flexibly to obtain richer expression capabilities. The network updates the network parameters through the backpropagation algorithm, and the residual value is transferred layer by layer from the output layer to the input layer, and the error sensitivity (residual value) on each neuron is calculated, so as to obtain the cost objective function relative to each weight. The gradient of (network parameters) realizes the update of network parameters. However, the increase in the number of neural network layers also brings some new problems. For non-convex objective loss function solutions, it is easy to fall into the local optimum, and the global optimum cannot be obtained through the backpropagation algorithm (Sárándi, Linder, Arras, & Leibe, 2020).

3. Feature recognition of sports training based on deep learning

This paper makes full use of the advantages of the BoF model and uses optimized multi-scale heat kernel signature (HKS) to construct distinctive geometric shape descriptors.

HKS describes the optimal basis of a smooth function on a given manifold. It has multi-scale features and can reveal rich local geometric information. It describes the heat conduction on the surface with respect to time. The thermal kernel formula is (Szűcs & Tamás, 2018):

$$K_t\left(x,x\right)=\sum_{i=0}^{m}\exp\left(-\lambda_i t\right)\phi_i^2\left(x\right) \tag{1}$$

It is usually defined by the first m eigenvalues and eigenvector ϕ_i of the Laplace-Beltrami operator (LBO) in the discrete space. It can be seen that the thermal core feature of the three-dimensional model is represented by intercepting the LBO feature vector of any dimension. However, improper feature vector interception tends to reduce the ability of feature representation. In order to reduce the loss of the HKS feature extraction process, this paper uses principal component analysis (PCA) and discrete thermal kernel formulas to construct the optimal representation of the feature embedding space and model space, which effectively improves the representation ability of the LBO embedding space[20].

$$\begin{cases} M=\left(1-\mu\right)AXX^{T}A=\mu\tilde{W}_h^{-1} \\ W_h=\dfrac{1}{4\pi t^2}e^{\frac{d\left(v_i,v_j\right)}{4t}} \end{cases} \tag{2}$$

Among them, the first part is the PCA model space mapping, A is the diagonal matrix, A_{ii} is the sum of the area of all triangles sharing vertex x, and X is the matrix of vertices. The second part represents the feature embedding space. W_h is the similarity matrix, and $d\left(v_i,v_j\right)$ represents the geodesic line between any pair of mesh vertices. Through the singular value decomposition matrix $M=Q\wedge Q^T$, the optimized eigenvalue diagonal matrix ^ and the orthogonal eigenvalue matrix Q are obtained.

In order to evaluate the representation ability of the optimized feature space, a reconstruction error is introduced:

$$E_M = \arg\min_{\hat{D}} \left\| X - \hat{D} \right\|_F \tag{3}$$

Among them, $\widehat{D} = Q_m Q_m^T X$ is the model reconstructed based on the previous feature orthogonal basis.

Figure 1 compares the standard LBO characteristics. From the feature visualization and the model results reconstructed based on the first m = 100 feature vectors, it can be seen that the feature vector optimized in this paper has strong structural discrimination, and effectively reduces the feature loss and improves the feature representation ability.

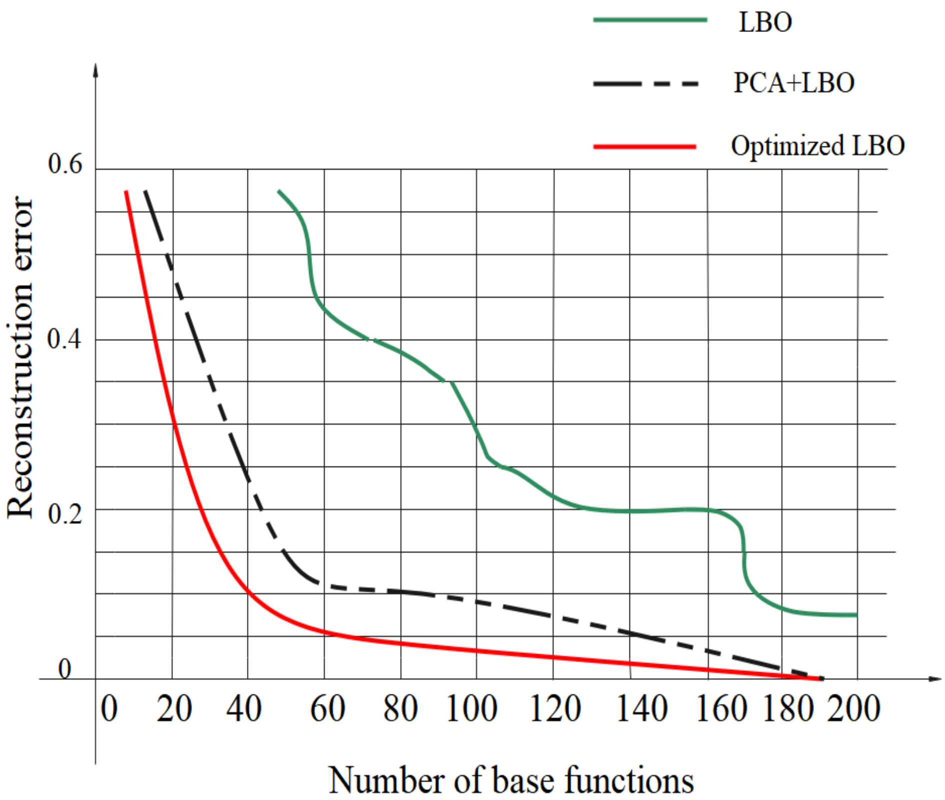


Figure 1. Feature distribution, reconstruction model and reconstruction error based on different LBO methods

Furthermore, based on the optimized eigenvalues and eigenvectors, we use the logarithmic interval $\left[t\ ln\ 1_{300}\ ln\ 1_{2_{max_{min}}}\right]$ to set the time parameter t and divide p = 100 time zones. Moreover, we select p eigenvalues and eigenvectors to generate p-dimensional optimized HKS feature representation.

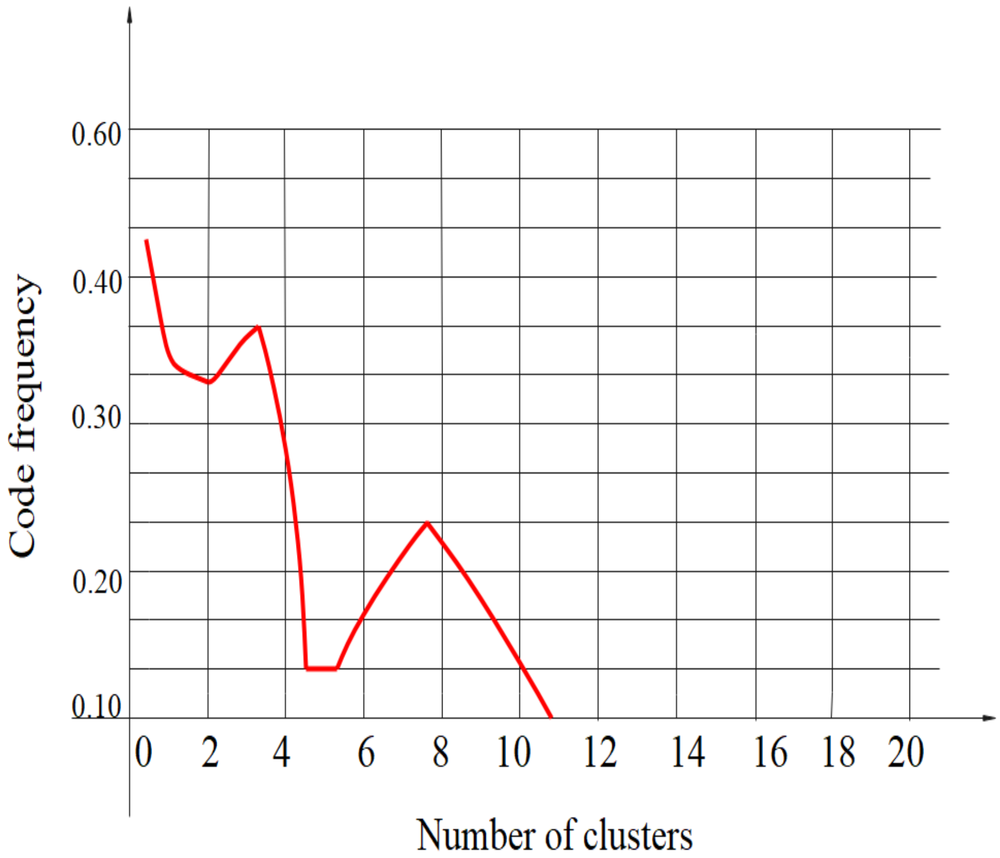
Therefore, any three-dimensional model M can be expressed as a geometric feature matrix $S_{HKS} = (s_1^h, s_2^h, \ldots, s_n^h)$, where s_i^h is the multi-scale thermonucleus descriptor of any vertex x_i, and n is the number of mesh vertices (Szűcs & Tamás, 2018).

This paper embeds the extracted low-level HKS geometric features into the vocabulary space. First, we use the unsupervised k-means method to cluster geometric features to generate k cluster centers (ie, codewords) to form a codebook. Second, we use the soft vector quantization (svQ) method. Each feature is mapped to the codebook through a soft allocation matrix for feature quantization, which is defined as:

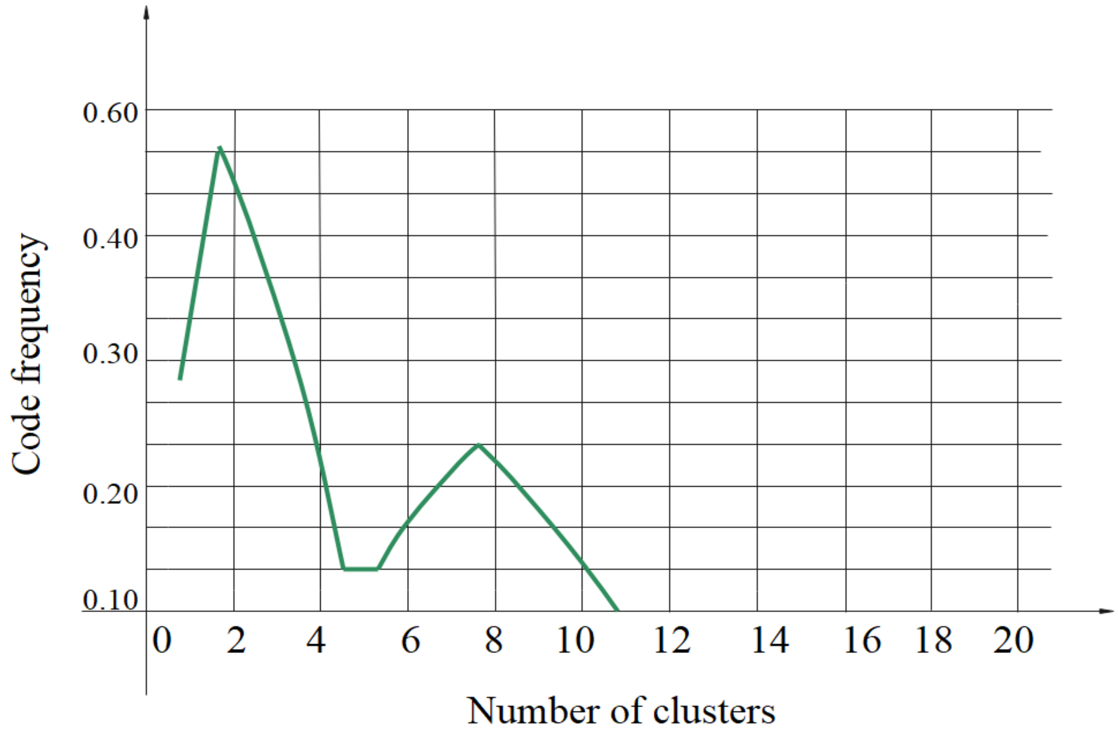
$$u_i = \frac{\exp\left(-\alpha \left\| s_i - v_t \right\|^2\right)}{\sum_{t=1}^{k} \exp\left(-\alpha \left\| s_i - v_t \right\|_2^2\right)} \qquad (4)$$

Among them, $|\cdot|_2^2$ represents the L2 norm, α is the smoothing parameter that controls the soft allocation, and $\alpha = 1/(8\eta^2)$. η represents the average value of cluster centers, and v_i represents k cluster centers. Each local descriptor s_i is mapped to a codebook for encoding, and a k×n-dimensional matrix U is constructed.

Figure 2 shows the extraction of geometric features HKS using the tiger model as an example. It embeds it into the vocabulary space through k=20 mean clustering, and finally obtains the frequency distribution of the codebook. Compared with the standard HKS-BoF results, the HKS-BoF features optimized in this paper have better regional internal recognition capabilities.



(a) Based on standard HSK features



(b) Optimized HSK features

Figure 2. HKS feature clustering and BoF feature distribution curve

However, BoF is limited to the statistics of local features, ignoring the spatial relationship of features. SA-BoF and GA-BoF introduce geodesic kernel function distance and biharmonic distance ideas to construct shape context information and generate a discriminative global BoF feature representation.

The distance of the geodesic kernel function is expressed as:

$$\begin{cases} g_{ij} = \sum_{x_j \in X} \sum_{x_j \in X} \phi_l(i)\phi_l(j)\exp\left(-k_{gd}\dfrac{g(x_i,x_j)}{\sigma_{gd}}\right) \\ F = UGU^T \end{cases} \quad (5)$$

Among them, the geodesic kernel function g_{ij} is the distribution information of geometric features constructed within a certain distance range, σ_{gd} represents the maximum geodesic distance between vertices, and k_{gd} is the attenuation rate of the distance.

Although the geodesic distance is equidistant and invariant, it has significant advantages in non-rigid three-dimensional shape matching and retrieval, but it is often sensitive to topological noise.

The biharmonic distance is not only robust to noise and topology changes, but also has global shape perception and smoothness.

$$\begin{cases} k_{ij} = \sum_{l=1}^{m} \frac{1}{\lambda_l^2} \left(\varphi_l(i) - \varphi_l(j) \right)^2 \\ F = UKU^T \end{cases} \tag{6}$$

The biharmonic distance k_{ij} is defined by the eigenvalue and eigenfunction of the LBO between any pair of mesh vertices v_i and v_j.

Figure 3 shows the example of David's human body model, which is based on the GA-BoF method and the SA-BoF method to construct the feature matrix representation. From its reconstructed error curve, it can be seen that the SA-BoF descriptor exhibits a stronger representation ability and a smaller error rate.

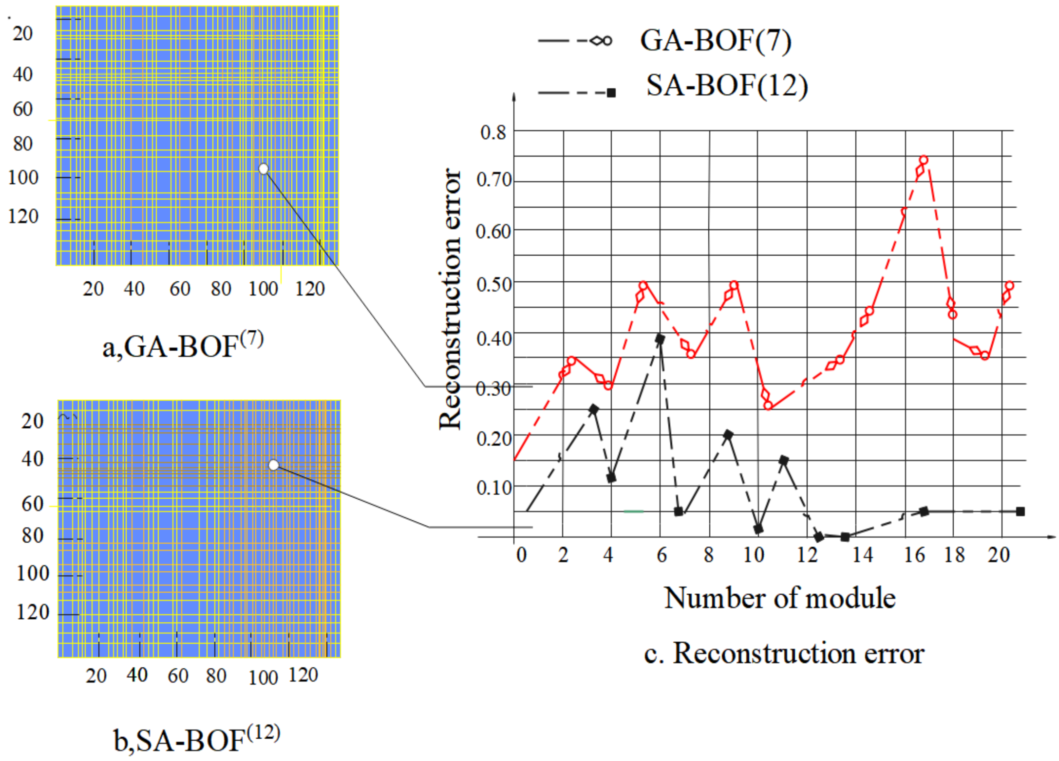


Figure 3. Representation of feature matrix constructed by different methods and reconstruction error

Therefore, this paper adopts dual harmonic distance, based on the optimized HKS-BoF feature, and effectively establishes an optimized BoF feature representation. Figure 4 shows the global BoF feature matrix constructed for the human body model in the SHREC2016 library. It can be seen that the BoF feature in this paper effectively reveals the geometric structure of non-rigid transformations and incomplete models, and has strong stability.

Although the BoF image effectively reveals the inherent geometric features of the model, it ignores the spatial structure information of the model to a certain extent, and lacks robustness to the model of large-scale topological transformation.

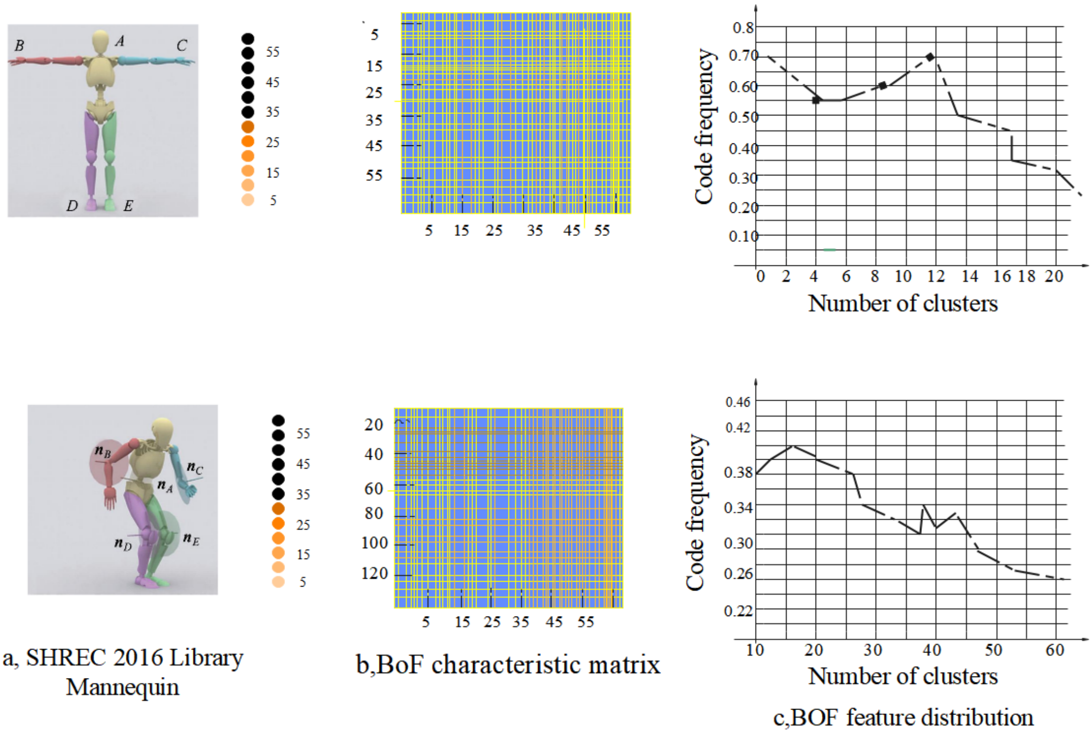


Figure 4. BoF characteristics and distribution based on global optimization

To effectively improve the structure recognition ability of deep features, this paper proposes a joint learning model based on convolutional neural networks.

Figure 5 inputs the generated BoF features into the CNN framework to learn the deep geometric structure of the model. At the same time, we build a view CNN framework to learn the spatial structure features of the model from multiple angle views, and then jointly optimize learning to generate structure-aware deep feature representations.

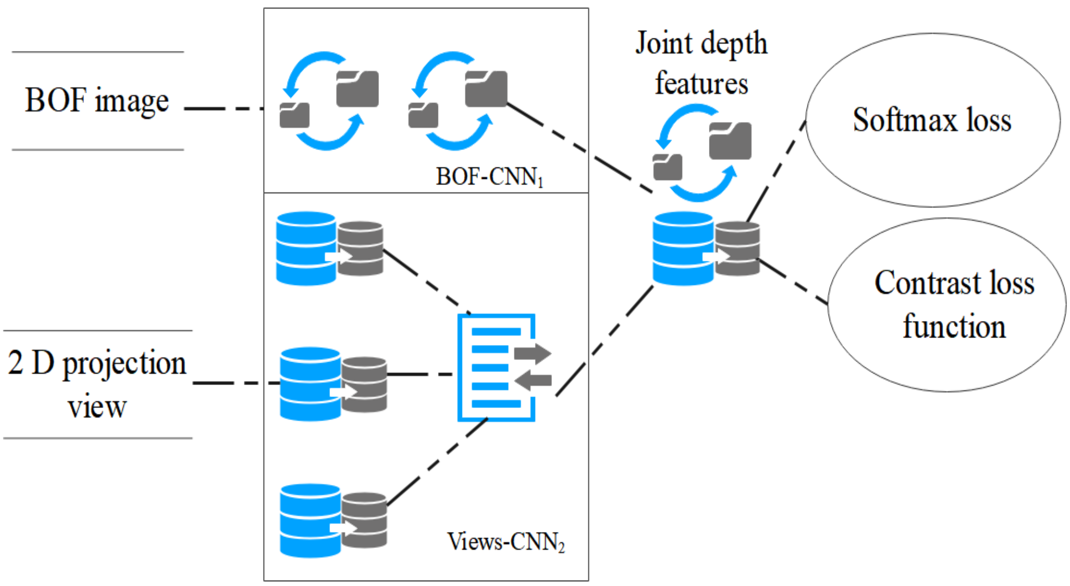


Figure 5. Structure-aware CNNs joint learning framework

The BoF convolutional learning model in this paper draws on the VGG-M structure, which mainly includes 5 convolutional layers and 2 fully connected layers. Each convolutional layer contains ReLU activation function and Max-Pooling operation. Among them, the convolution kernels of each convolution layer are sequentially set to 64, 128, 128, 512, and 512, and the size of all convolution kernels is 3×3 pixels. The final fully connected layer will generate 1024-dimensional feature vectors.

The multi-view learning framework follows the successful idea of MVCNNI23. First, the three-dimensional model is converted into a multi-angle projection image, and the parallel CNN framework is used to extract features from each view. Finally, it is merged into a unified deep feature representation through the View-Pooling operation

Finally, the intrinsic structure features output by BoF-CNN and the spatial structure features output by Views-CNN are effectively connected. Through the loss function, it is optimized to learn to generate information-rich structural features and input them into the Softmax classifier for shape recognition and classification.

In order to improve the learning performance of the CNN joint model and achieve the goals of maximizing the distance between classes and minimizing the distance between classes, this paper adopts cross-straight and contrast loss objective functions.

$$\begin{cases} \min(L) = \min(L_s + L_c) \\ L_c = \sum_{i=1}^{m/2} \left(\alpha D_W{}^2 + (1-\alpha) \max(T_r - D_W, 0)^2 \right) \end{cases} \tag{7}$$

In effectively improving the training optimization process of the learning model, L_s is the cross-loss function, L_c is the contrast loss function, m is the number of samples in the database, and c is the number of categories in the samples. D_W represents the L_2 norm of the paired shape features, and α represents the similarity between them. If they match, the similarity is set to 1, otherwise it is set to 0.T_r represents the distance between different types of shape features. For different features, this paper only considers the two Euclidean metrics 0 and T_r.

The contrast loss function L_c represents the matching degree of the pair of samples. It improves the cohesion of features by reducing the distance within the class. Good loss convergence will effectively reduce the amount of calculation and effectively improve the learning efficiency of the CNN framework.

4. Competitive sports training system based on deep learning

This system generally uses the user identity verification method. A modular development method is adopted in the realization of system functions, as shown in Figure 6.

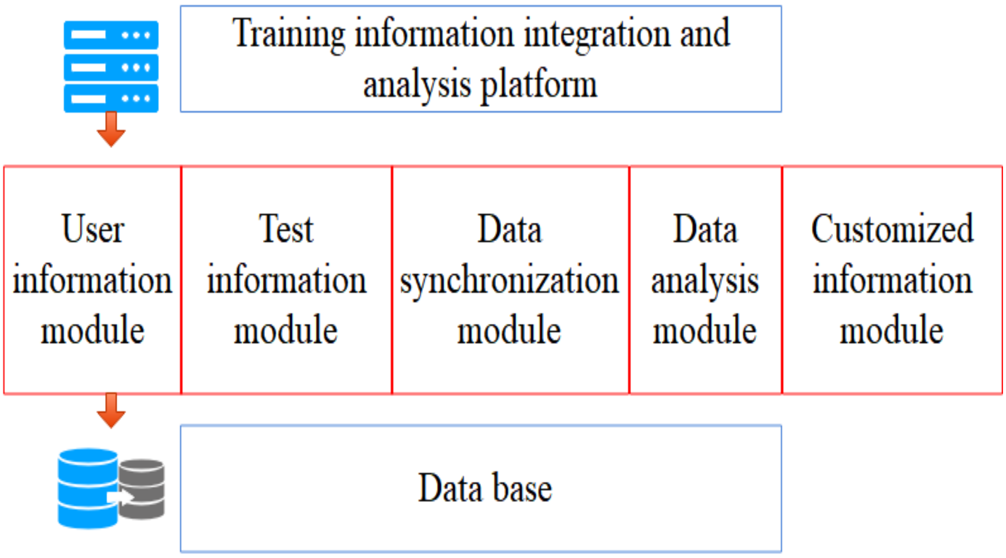


Figure 6. System module diagram

It centrally represents the dynamic characteristics of the system, data entry and data exit, interfaces with other programs, various operations, priorities, cycles, and special processing, as shown in Figure 7.

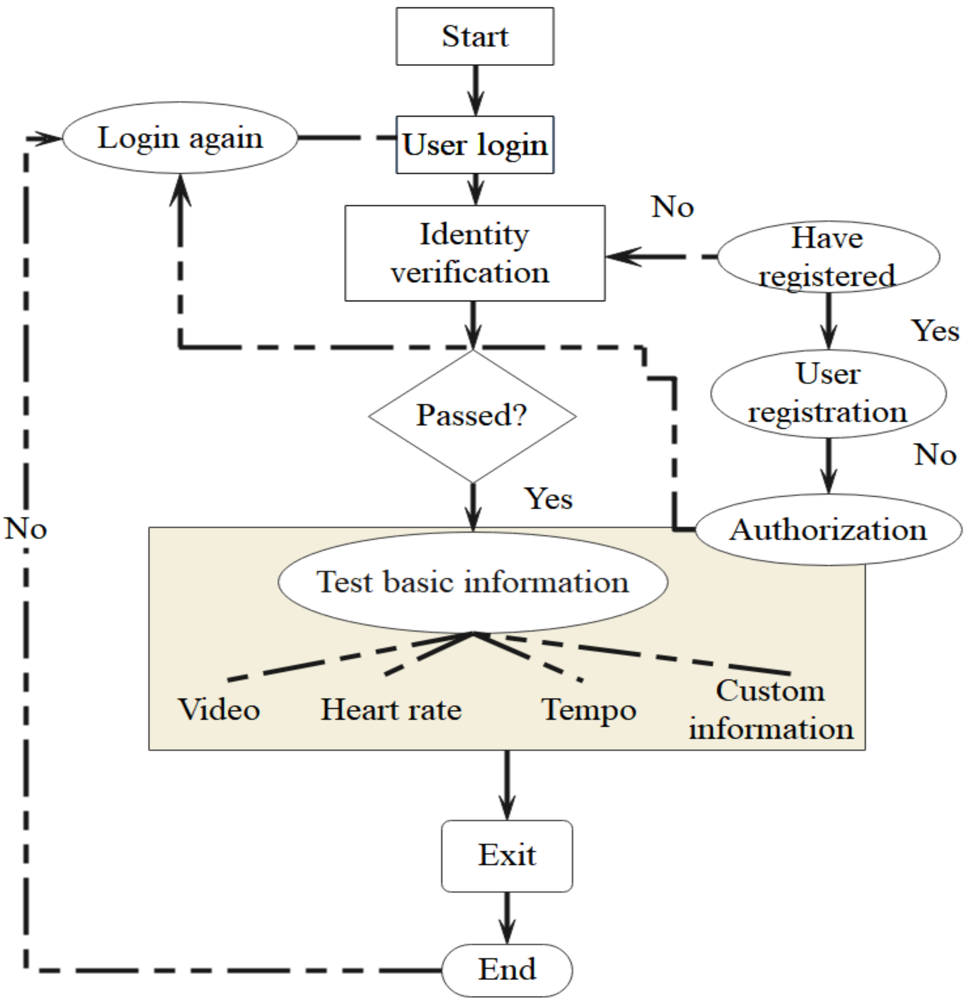


Figure 7. System logic flow chart

From the logical structure flow chart of the system and the process of training and competition, the relevant data of the system can be attributed to: user information, athlete information, video data, heart rate data, custom data, etc. Personnel information relates to character strings, numbers, etc., video data relates to video types, and heart rate data relates to time types. When the specific program is implemented, it is necessary to reasonably specify the data types supported by the database.

In the realization of the process function, the use of data items in the process can be expressed with the help of data structures such as arrays, sets, and linked lists. In the definition of the database structure, the length of the field is defined appropriately to prevent the situation of unsupported data overflow in the use of the system. At the same time, there are close connections between different tables in the database. Another point is the compatibility of the national kayaking team training information integration analysis platform system and the computer operating system. Therefore, the software environment that supports software operation must be considered during development. Current development is generally based on window-based object-oriented software development processes such as WINDOWS.

The data related to the training information integration analysis platform system is all realized through the access database management system, and the data involved in each module is managed in the form of a table in the database. If there is a requirement for sharing or mutual access between the table and the table, the data access interface is implemented when the table is defined. The national kayaking team training information integration analysis platform system must have a large flexible space for data sharing.

This is not only for each functional module, but also for the data between modules. Therefore, it is necessary to clarify the operation process of all functional modules in the entire process before the program is specifically written, and define appropriate access interfaces for the management of modules that require shared data.

The entire process management of the national canoe team training information integration analysis platform system involves a large amount of data in different formats. These data are not only large in volume, but also different types of unit data occupy different sizes of space. The national kayaking team training information integration analysis platform system must implement a graphical model of the process in terms of process monitoring, since it involves the realization and update of graphics.

Because the amount of calculation is very large, this puts a higher level of demand on the CPU of the PC or server. Only the graphical process management on a computer with a higher frequency is more visual and intuitive. Secondly, there is the issue of compatibility between the national canoeing team training information integration analysis platform system and the computer hardware, so the hardware environment that supports the software operation must be considered during development. Ensuring a seamless integration between the national canoeing team training information integration analysis platform system and the computer hardware is crucial necessitating a thorough evaluation of the hardware environment throughout the development process.

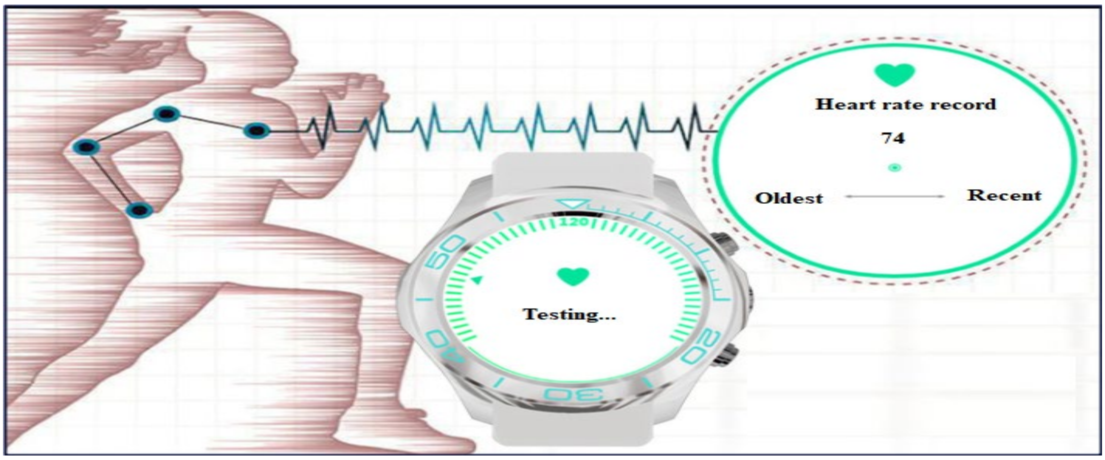


Figure 8. Schematic diagram of system simulation interface

On this basis, the application effect of deep learning in competitive sports training is verified, and the results are shown in Figure 9 below. From the cluster analysis in Figure 9, it can be seen that deep learning can effectively process relevant data in economic sports training.

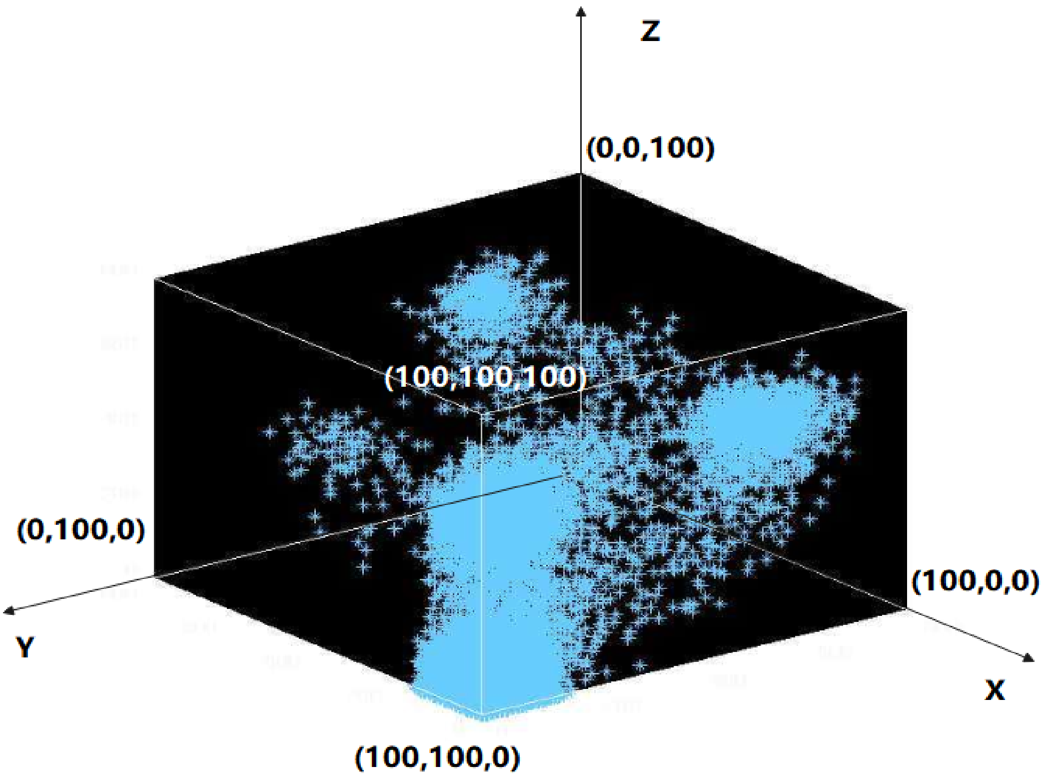


Figure 9. Clustering effect of deep learning in competitive sports training

In order to further study the effect of deep learning in economic sports training, the cluster effect analysis of multiple competitive sports is carried out, and the result shown in Figure 10 is obtained.

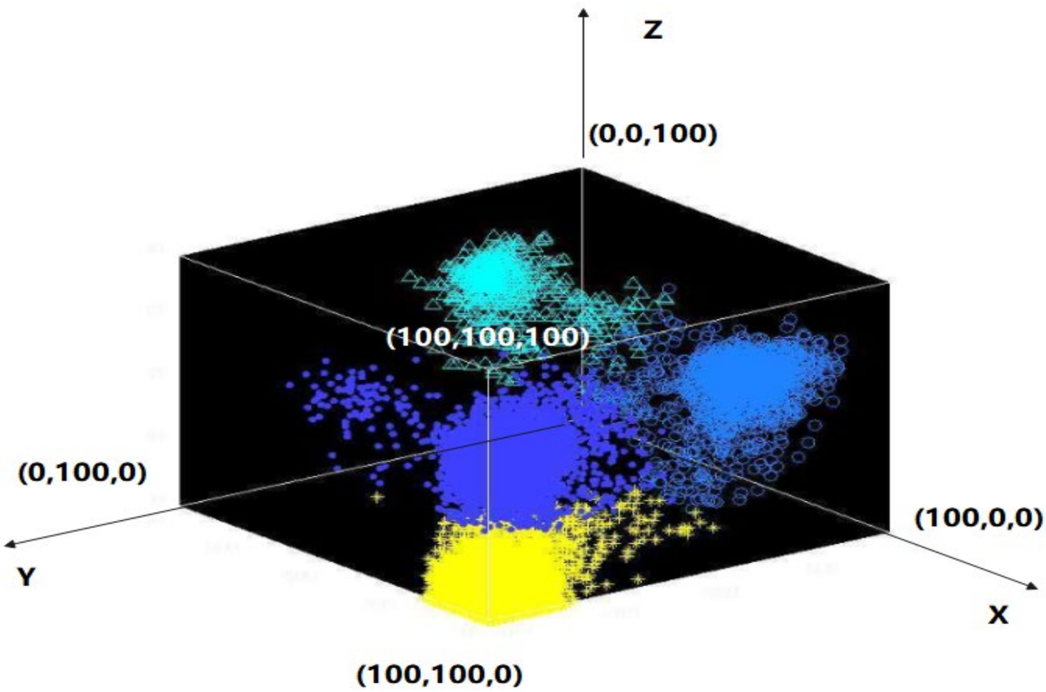


Figure 10. Application evaluation of deep learning in a variety of competitive sports training

On this basis, the training effect of the competitive sports system based on deep learning is evaluated, and the results shown in Table 1 below are obtained.

Table 1. Training effects of competitive sports training system based on deep learning

NO	Training effect	NO	Training effect	NO	Training effect
1	89.00	21	89.45	41	84.69
2	87.79	22	82.77	42	92.46
3	85.69	23	92.13	43	87.47
4	92.40	24	79.85	44	93.01
5	86.58	25	93.86	45	80.05
6	82.61	26	91.12	46	88.33
7	91.56	27	78.42	47	88.70
8	88.86	28	90.02	48	86.45
9	88.05	29	89.30	49	87.02
10	93.93	30	83.84	50	79.86
11	78.85	31	87.61	51	88.23
12	87.88	32	91.10	52	78.05
13	93.69	33	84.29	53	79.69
14	86.68	34	84.03	54	92.38
15	87.71	35	93.55	55	81.27
16	88.57	36	81.84	56	88.88
17	87.45	37	88.84	57	80.13
18	88.37	38	80.02	58	91.07
19	83.51	39	91.74	59	84.36
20	83.46	40	80.66	60	82.45

Through the above analysis, it can be seen that the training effect of the competitive sports training system based on deep learning proposed in this paper is very good.

5. Conclusion

The process of sports training is the process of continuously improving athletes' competitive ability, so that they have considerable strength, and then they participate in the competition and play out in the competition. The breakthrough and integrated development of digital technologies such as big data, Internet of Things, mobile Internet, and cloud computing have profoundly changed people's work, life and thinking patterns. Moreover, it provides us with favorable conditions for in-depth understanding of the laws of sports training and accelerating the digitization, objectification and refinement of the training process. The future development direction of sports training is the organic integration and coordinated development of physical stamina, skills and mental abilities, so as to realize the overall improvement of athletes' competitive strength. This requires the rapid acquisition of data and information, the construction of data collections, and the real-time analysis and batch processing of data and information. For this reason, we have proposed the construction of a digital competitive strength platform. This article combines deep learning to construct a competitive sports training system, and combines experimental analysis to analyze the performance of this system. It can be seen that the competitive sports training system based on deep learning proposed in this paper is very effective

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