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Retraction

Retracted: Application of Sports Clustering Deconstruction Based on Neural Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

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

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

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

References

[1] X. Ma, "Application of Sports Clustering Deconstruction Based on Neural Network," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 8203143, 9 pages, 2022.

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Research Article

Application of Sports Clustering Deconstruction Based on Neural Network

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Sports cluster analysis can mainly provide more teaching ideas for physical education. Teachers can make scientific and reasonable arrangements for the teaching plan according to the analyzed data results, so as to achieve better teaching purposes. However, due to various factors such as exercise time and course time conflict, this method cannot be widely used. The neural network had a good memory function, and it can be used to integrate physical education resources in sports. Then, a knowledge framework was formed by simulating a large number of human brain neuron structures, which can solve the problems existing in the motion cluster analysis to a certain extent. In this paper, the sports based on neural network is used to improve the problems existing in the practical teaching application of sports clustering analysis. A teaching system model based on motion recognition was established to improve motion cluster analysis and promote the implementation of data-based education. According to the experimental data obtained from the experimental test, people can know that the detection rate of the sports cluster analysis model is about 89.5%, and the average missed detection probability is about 5.5%.

1. Introduction

The implementation of quality education can further solve the shortcomings of the traditional education model, which is always centered on achievement. At the same time, this not only means to improve the teaching level and teaching quality of key schools, but also to provide more comprehensive quality talents for national development. Physical education is an indispensable subject in quality education. The types of sports are complex and diverse, and different intensities of sports have different requirements for physical fitness. Not every sport is suitable for students of every age. The application of sports cluster analysis in sports is mainly about the degree of application of sports in physical education, whether students are interested in the training programs carried out, and the improvement of students' comprehensive physical quality. Neural network technology is a distributed algorithm model based on animal neural network framework, which is designed to process data through computation. Its working principle is that by adjusting the weight between neurons, the value of the transfer function can be adjusted to control the weight threshold, so as to achieve the required accuracy. Neural network technology has developed rapidly in recent years because of its powerful data processing function, and its application range is also quite extensive. The application of neural network technology to sports teaching can better integrate physical education resources, make course teaching more interesting and vivid, and stimulate students' interest in sports. Also, it can help physical education teachers to choose sports that are more suitable for students' teaching.

Physical activity is indispensable for people's health in daily life, and the cluster analysis of sports has long been studied by international scholars. Kong used the model to identify and learn to analyze the TV golf course program and used the model to sense the teaching presence and learning effect of courses in different paths [1]. Kim studied the motivation of volunteers in sports events by cluster analysis and carried out a subdivision of the work of different volunteers in different events [2]. Kubo mainly discussed the conflict between school physical education and sports commercialization and used the method of cluster analysis to study the content of high school physical education from media platforms and journals [3]. Thornton used a cluster analysis method to study the influence of individual characteristics and background factors on training load and game performance in adult men's semi-professional basketball [4]. Behravan used a cluster analysis method to cluster the performance data of players in different games to find the role of players in football [5]. Most of the above studies lack the support of experimental data, and traditional clustering algorithms have inaccurate data identification to a certain extent and are not applied in combination with new technologies.

Neural network is a new technology and has been optimized and improved in a short period of time, so it is also a research hotspot of scholars. Goh used neural networks to model the feasibility of complex relationships between seismic and soil parameters and liquefaction potential [6]. Perna proposed a strategy for choosing the hidden layer size in a feedforward neural network model [7]. Segler proposed a model that can count computer language. The model mainly used neural network as a research method and drew the conclusion that the language characteristics obtained in computer language processing were related to the characteristics of the model that trained it [8]. Kohl proposed an interstellar object formation route that is not convincing in current astrochemical models and proposed an evolutionary neural network for strategic decision problems [9]. Holden proposed a real-time character control mechanism using a novel neural network architecture called phase function neural network [10]. He proposed a desired state estimator for guaranteed-uncertain-delay neural networks, mainly studying the robust state estimation problem of uncertain neural networks with time-varying delays [11]. Zhao discussed stochastic neural networks with time delays by constructing a suitable convergence theorem to ensure almost certain exponential stability of the network [12]. The above experiments have a lot of in-depth research on neural networks, but there is no related research on the clustering algorithm of sports, so such research is very necessary.

This paper mainly studies the physical cluster analysis of neural network technology in physical education. A cluster analysis technology system suitable for sports teaching is obtained by constructing a model, which mainly enhances the function of cluster analysis technology in processing data timeliness and accuracy.

2. Construction Method of Sports Clustering Deconstruction Model Based on Neural Network

2.1. Sports Clustering Deconstruction Model. Cluster analysis is a clustering method that divides data into given requirements or rules according to a specific property [13]. In the cluster analysis, the label number of each object is unknown, and the data objects with high similarity are divided into clusters. The final result of the division is that the similarity between different clusters is the smallest, and the similarity within the same cluster is the highest. The application of cluster analysis in sports is mainly in the integration of physical education resources, and the clustering results are obtained by identifying body movements and extracting and analyzing the characteristics of the data. For example, in sprinting, striding and arm swing are two core movements in sprinting, and the speed of sprinting also depends to a large extent on these two core movements. The sports clustering analysis can extract and analyze the sprinters' arm movements and leg movements and then obtain a teaching model through clustering. Its schematic figure is shown in Figure 1.

The extraction and classification of data is to extract the sprinting action information in the underlying data, then use the classifier to mark the attributes of different information, and finally identify each action [14]. A sports cluster analysis model suitable for physical education teaching is constructed and can be classified to a certain extent. Among them, the determinant of the accuracy of the results obtained by the algorithm lies in the feature expression, and the most important part in the algorithm calculation and recognition is the feature extraction stage [15]. This stage is the most time-consuming stage, so the determinant of whether the action of sports is accurate or not lies in the process of feature extraction. This step is to decompose a complex nonlinear problem into multiple unit layers to form several learning units with independent weight functions and connection weight matrices. By learning the input signal and output signal and the corresponding parameters in the process of processing, the relationship between neurons and the relationship and interaction between them are determined, thus forming a complete sports cluster analysis model. Its structure figure is shown in Figure 2.

2.2. Clustering Deconstruction Algorithm. The data structures in cluster analysis are mainly data matrix and difference degree matrix [16]. The rows and columns in the data matrix represent "object-attribute," as shown in the following formula:

$$S = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \cdots & Y_{1,Q} \\ Y_{2,1} & Y_{2,2} & \cdots & Y_{2,Q} \\ \cdots & \cdots & \cdots & \cdots \\ Y_{Z,1} & Y_{Z,2} & \cdots & Y_{Z,Q} \end{bmatrix}. \tag{1}$$

The rows and columns of the dissimilarity matrix represent the same entity, which is an "object-object" structure. A certain calculation method is used to calculate the value of the feature difference degree between objects and store it in the form of a matrix:

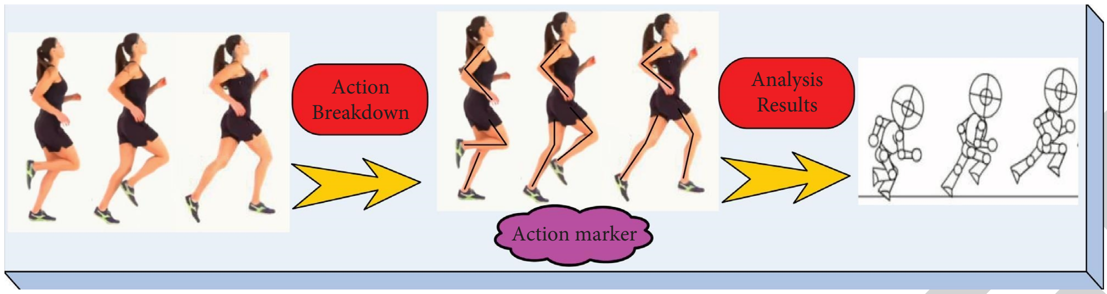

Figure 1: Schematic figure of sprinting cluster analysis.

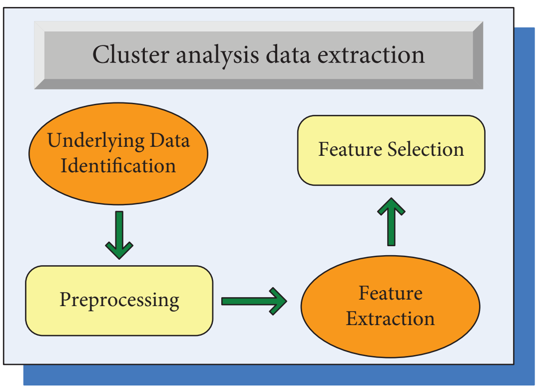

Figure 2: Schematic figure of cluster analysis model structure.

$$S = \begin{bmatrix} 0 & & & & \\ f_{(2,1)} & 0 & & & \\ f_{(3,1)} & f_{(2,1)} & 0 & & \\ \cdots & \cdots & \cdots & \cdots & \\ f_{(M,1)} & f_{(M,2)} & f_{(M,3)} & \cdots & 0 \end{bmatrix}. \quad (2)$$

An interval-scaled variable is a unit of measure that represents a continuous variable [17]. The choice of measurement unit determines the quality of the clustering results, so it is necessary to standardize the measurement values. The mean absolute deviation of $Z \times Q$-matrix normalization calculation is

Table 1: Binary variable data.

		Object j		
		1	2	Sum
Object i	1	x	y	$x+y$
	0	m	n	$m+n$
	Sum	$x+m$	$y+n$	Q

$$S_Q = \frac{1}{Z}\left(\left|Y_{1,Q} - n_Q\right| + \left|Y_{2,Q} - n_Q\right| + \cdots + \left|Y_{Z,Q} - n_Q\right|\right). \quad (3)$$

The standardized metric value is calculated as

$$X_{iQ} = \frac{Y_{iQ} - n_Q}{S_Q}. \quad (4)$$

Distance calculation is to obtain the similarity by calculating the gap between two data objects. There are three main methods:

(1) The Euclidean distance is expressed as

$$\left\{ f_{(i,j)} = \sqrt{\left|Y_{i,1} - Y_{j,1}\right|^2 + \left|Y_{i,2} - Y_{j,2}\right|^2 + \cdots + \left|Y_{i,Q} - Y_{j,Q}\right|^2} \quad i = \left(Y_{i,1}, Y_{i,2}, \cdots, Y_{i,Q}\right) j = \left(Y_{j,1}, Y_{j,2}, \cdots, Y_{j,Q}\right). \right. \quad (5)$$

(2) The Manhattan distance is expressed as

$$f_{i,j} = \left|Y_{i,1} - Y_{j,1}\right| + \left|Y_{i,2} - Y_{j,2}\right| + \cdots + \left|Y_{i,Q} - Y_{j,Q}\right|. \quad (6)$$

(3) The Minkowski distance is shown in the following formula:

$$f_{i,j} = \sqrt[n]{\left(\left|Y_{i,1} - Y_{j,1}\right|^n + \left|Y_{i,2} - Y_{j,2}\right|^n + \cdots + \left|Y_{i,Q} - Y_{j,Q}\right|^n\right)}. \quad (7)$$

For binary variables, the correlation coefficient between variables is calculated by correlation analysis [18]. The binary variable data are shown in Table 1:

When two variables have the same weight, it is called a symmetric binary variable, which can be used to evaluate the dissimilarity, as shown in formula (8):

$$f_{(i,j)} = \frac{y+m}{x+y+m+n}. \quad (8)$$

When the weight values of two variables are different, it is called an asymmetric binary variable, which can be used to evaluate the dissimilarity, as shown in formula (9):

$$f_{(i,j)} = \frac{y+m}{x+y+m}. \quad (9)$$

Standard variables are the generalization of binary variables:

$$f_{(i,j)} = \frac{Q - n}{Q}. \tag{10}$$

2.3. Sports Clustering Deconstruction Model Based on Neural Network. The neural network is actually a computational model through the processing of data information [19]. Its structure is similar to the human brain neuron network and a simple calculation model is built on the basis of this structure. Neuron is the most basic unit of a neural network. Its receiver is responsible for receiving information, and its output is responsible for transmitting information. Its structure is shown in Figure 3.

The output corresponding to the input value of the neuron is

$$S_{V,b}(y) = f\left(\sum_{i=1}^{3} V_i y_i + b\right). \tag{11}$$

The connection between each two neurons in the neural network represents the weight of the signal through this connection, that is, the network memory is formed, and each neuron represents a specific function called activation function or excitation function [20]. In order to enhance the expression of the neural network, a continuous nonlinear activation function is generally used because the continuous nonlinear activation function can be derived and can be solved by optimization.

The sigmoid function is shown in the following formula:

$$\sigma(y) = \frac{1}{1 + \exp(-y)}. \tag{12}$$

The Tanh function is shown in the following formula:

$$\mathrm{Tan}h(y) = \frac{e^{y} - e^{-y}}{e^{y} + e^{-y}}. \tag{13}$$

The two function figures are shown in Figure 4.

The neural network structure is the connection method of the network by each neuron, and its structure is the same as the neural network structure of the human brain [21]. It can also be divided into three layers: input layer, hidden layer, and output layer. These three correspond to the human brain neural network. The input layer corresponds to the receptive part, the hidden layer corresponds to the conduction part, and the output layer corresponds to the effect part. The neurons between layers and layers are connected to each other, and each connection will have a corresponding weight value. Its structure is shown in Figure 5.

The neural network adjusts the value of the transfer function by changing the weight relationship between neurons to control the threshold of the weight, so as to meet the required accuracy requirements [22]. After the neural network has performed the corresponding sample practice, if the input data and the training sample are the same data, regardless of whether the results are complete or accurate, the neural network can quickly obtain accurate judgment results through the data of the training samples.

Given an input vector $Q_k = (c_{1,k}, c_{2,k}, \cdots, c_{m,k})$ and an output vector $T_k = (h_{1,k}, h_{2,k}, \cdots, h_{m,k})$. According to the input vector and the initialized weight V_{ij}, the calculation of the transfer process can be obtained:

$$\begin{aligned} h_j &= \sum_{i=1}^{m} V_{ij} c_i - \theta_j, \quad && j = 1, 2, \cdots, q, \\ b_j &= f(h_j), && j = 1, 2, \cdots, q. \end{aligned} \tag{14}$$

The output b_j weight of the hidden layer function is passed through the transfer function to obtain the result of the output layer, and the reflection is shown in the following formula:

$$\begin{cases} R_t = \sum_{j=1}^{q} W_{jt} b_j - \gamma_t, & t = 1, 2, \cdots, p, \\ A_t = f(R_t), & t = 1, 2, \cdots, p. \end{cases} \tag{15}$$

Then, through the output vector and reflection, the calculation error is

$$g_{tk} = (h_{tk} - A_t) * A_t * (1 - A_t), \quad t = 1, 2, \cdots, p. \tag{16}$$

According to the hidden layer output value b_j, weight W_{jt}, and output layer error g_{tk}, to calculate the back-propagation of the error, the error between the basic units is expressed as

$$u_{jk} = \left[\sum_{t=1}^{p} g_t * W_{jt}\right] * b_j * (1 - b_j), \quad j = 1, 2, \cdots, q, t = 1, 2, \cdots, p. \tag{17}$$

When the output value does not satisfy the error, return to formula (14) to recalculate until the basic unit error between samples meets the conditions. At this time, each layer performs the update and adjustment calculation of the weights and thresholds according to the output and error, as shown in the following formula:

$$\begin{cases} W_{jt}(m+1) = W_{jt}(m) + c * g_{tk} * b_j, \\ \gamma_t(m+1) = \gamma_t(m) + c * g_{tk}. \end{cases} \tag{18}$$

The weight threshold is updated and adjusted according to the error between the input vector and the basic neuron unit, as shown in the following formula:

$$\begin{cases} W_{ij}(m+1) = W_{ij}(m) + \beta * u_{jk} * c_{jk}, \\ \theta_j(m+1) = \theta_j(m) + \beta * u_{jk}. \end{cases} \tag{19}$$

In order to test the influence of the weight value on the experimental accuracy, the training data are selected to test the recognition accuracy of the model. The learning rate is the size of the update amplitude each time the value is updated, and the learning rate will affect the convergence speed of the parameters. The specific experimental conditions and parameters are shown in Table 2.

The learning rate is set to 0.001 according to the amount of experimental data in the actual experiment. According to the actual situation of the experimental hardware equipment and the size of the dataset, the attribute value is set to 32. In

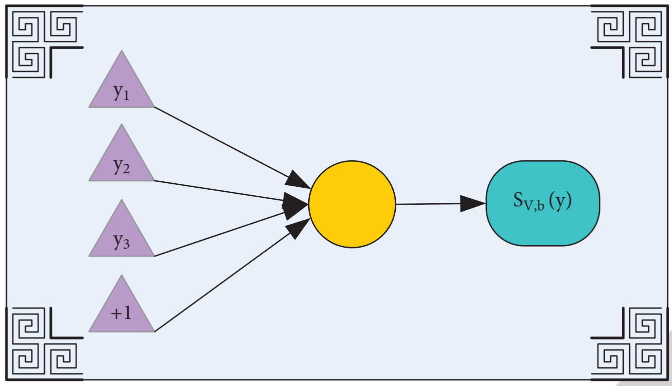

FIGURE 3: Schematic figure of neuron structure.

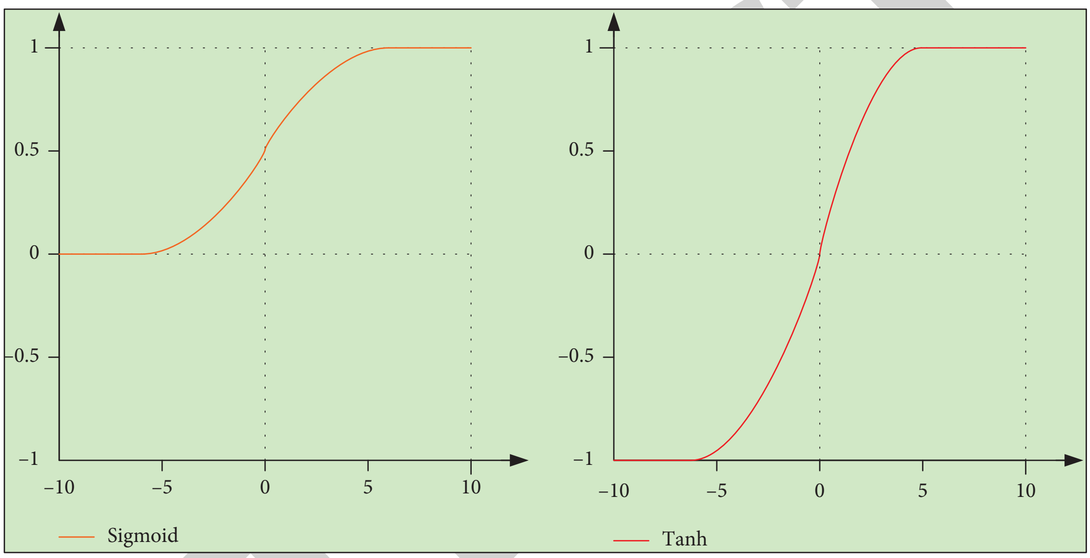

FIGURE 4: Figure of sigmoid and Tanh functions.

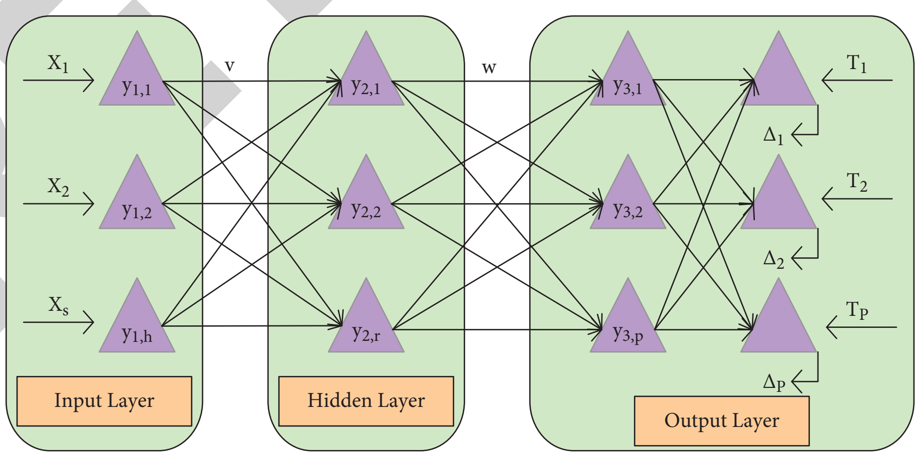

FIGURE 5: Schematic figure of neural network structure.

order to make the features more sparse and to a certain extent prevent the large amount of parameters generated by feature fusion from causing overfitting in network training, the output value is set to 0.1. The weights in the weighted feature fusion formulas are tested on the dataset, and the value with the highest accuracy is selected as the accurate value of the weight. The specific experimental results are shown in Figure 6.

Table 2: Experimental condition data.

Parameter	Numerical value
Learning rate	0.001
Attribute value	52
Output value	0.1

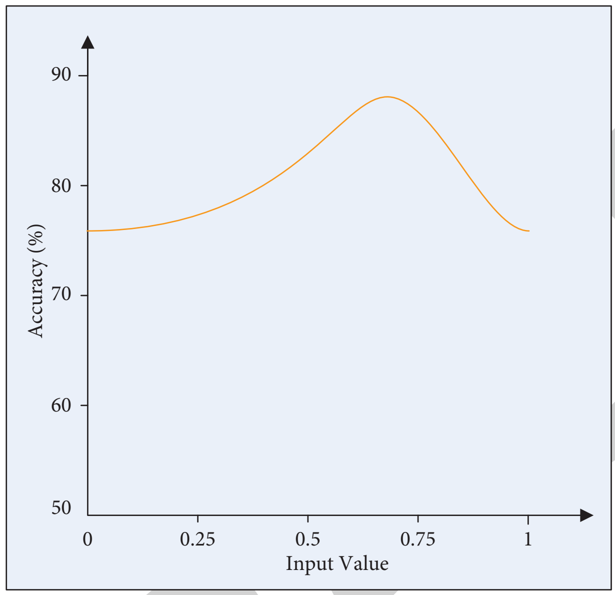

Figure 6: Line figure of weight value accuracy under different input values.

It can be seen from the analysis of the weight experiment results that when the weight of the input value is 0.7, the accuracy of the network algorithm is the highest, so the weight value is 0.7 in the next experiment. When the weights of the feature vectors are the same, the two features complement each other to reach a balanced state.

3. Experiment of Sports Clustering Deconstruction Model Based on Neural Network

To evaluate the model, conduct experiments on experimental samples of 5 kinds of sports teaching resources. Different numbers of experimental samples are taken for each sport, which are 50, 100, 150, and 200. The attribute values of each sample are 5, 10, 15, and 20. The specific experimental dataset is shown in Table 3.

In order to test the recognition performance of the model, the above experimental dataset is tested, and the functionality of the model is reflected by testing its sample detection rate and missed detection rate. The experimental results are shown in Figure 7.

The experimental results show that the detection rate of the model is about 89.5%, and the average missed detection probability is about 5.5%, which can achieve better functions. When the attribute values are different, the detection rate and missed detection rate of the model for different exercise types are also different. This is because the input values are different when the attribute values are different,

Table 3: Experimental dataset of sports teaching resources.

Type of sport	Attribute value	Number of training
Basketball	15	50
Sprint	10	150
Football	5	100
Badminton	20	200
Long jump	20	200

and the detection of samples with more attribute values is more complicated. According to the experimental results of various sports types, the three sports types of sprint, badminton, and long jump have higher missed detection rates. This is because the attribute values of these 3 sports are higher, and the detection rate of the model decreases when the number of tests is larger.

In order to further test the clustering effect of the model on sports, the accuracy of the clustering effect of different numbers of five sports is tested, and the attribute values of these five sports are controlled to be equal. The specific experimental data are shown in Figure 8.

It can be seen from the experimental data that when the number of samples gradually increases and when the number of samples is 100, the accuracy of the model with the highest accuracy rate decreases, and when the sample dataset doubles, the accuracy of the model decreases linearly. When the number reaches about 800, the accuracy of the model almost reaches its peak and remains at about 76.5%. This also

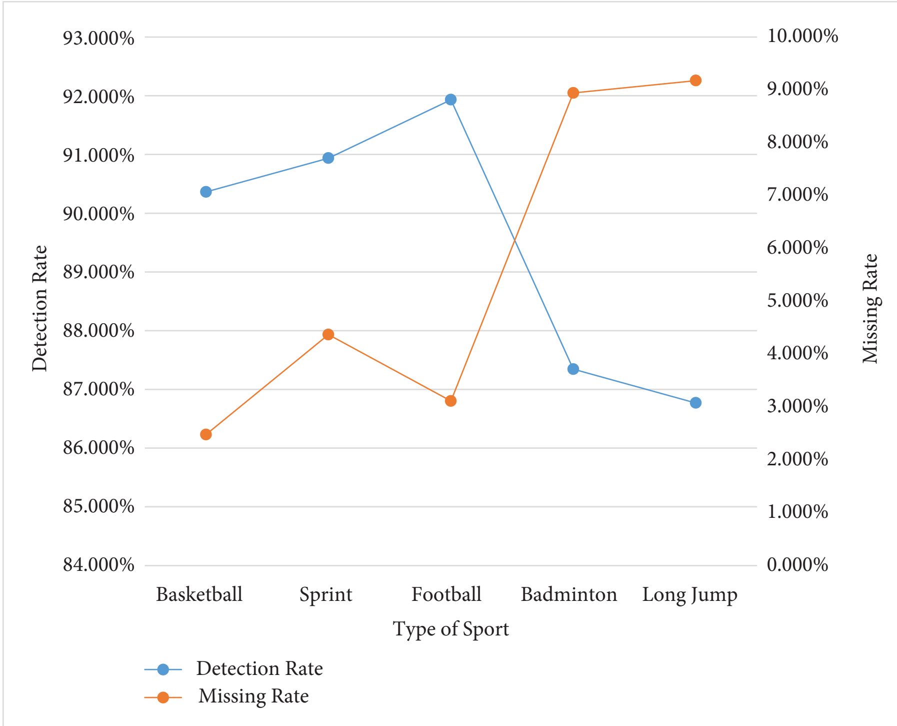

Figure 7: Line figure of detection rate and missed detection rate of different sports types.

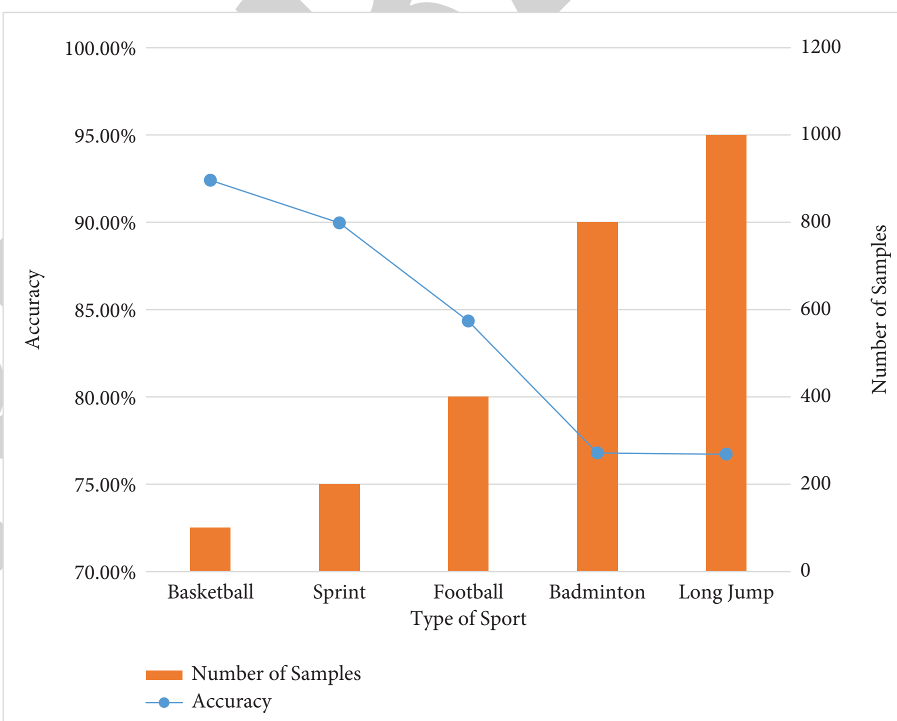

Figure 8: Accuracy of test results with different number of samples.

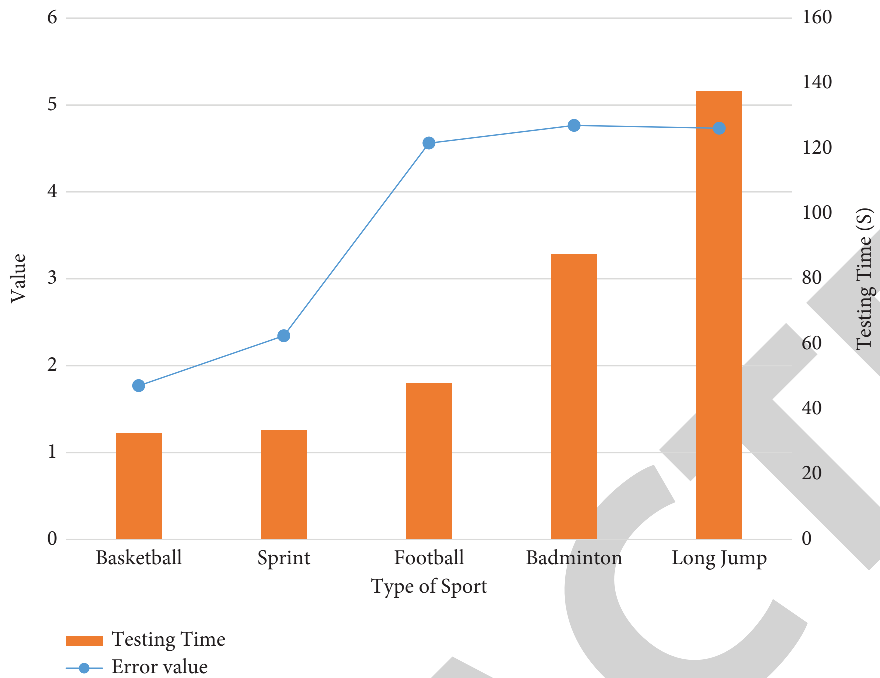

Figure 9: Comparison of error value and test time.

proves that the sample size affects the accuracy of the clustering effect of the model.

In order to further explore the influence of quantity on the accuracy of the model, the data statistics of the detection time and error value of the model for different data in the above experiments are carried out, and the results are shown in Figure 9.

It can be seen from the experimental results that when the number of experimental samples is low, the test time of the model is not much different, about 45 s or less. Experimental testing time increases with the number of samples, which shows that when the number of samples is large, the model needs to spend a lot of time to maintain the accuracy of the test. Moreover, when the number of test samples reaches a certain value, the error value of the test results of the model tends to be stable. When the number is about 400, the error of the model test is gradually stabilized, and the error is controlled at about 4.5.

4. Conclusions

The research content of this paper is the application of sports clustering analysis based on neural network. It mainly analyzes the clustering effect of sports and uses neural network to build a model. By building a model that can identify and accurately classify sports teaching resources, through the influence mechanism of the neural network and the influence of the weight value change on the model accuracy, the optimal experimental configuration is obtained to achieve a dynamic balance state. Then, use the model to test the detection rate, missed detection rate, error, and test time of sports test samples with different attributes and different numbers. Through the test results, it can be found that the detection rate of the model is about 89.5%, and the average missed detection probability is about 5.5%. Also, the test time is positively correlated with the sample size, and the test time becomes longer as the number increases. This shows that when the number is large, the model needs to spend a lot of time to maintain the accuracy of the test and reduce the error value of the cluster. From the overall results of the experiment, the neural network technology designed in this paper has a good performance for the sports clustering analysis model. The optimization, reform, and upgrading of education is the only way for a country to become more permanent. It is said that physical health is the foundation of all achievements. Paying attention to physical education can not only make students have a better physique but also promote children's mental health and provide great help for children to complete their studies well.

Data Availability

No data were used to support this study.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References

[1] J. Y. Kong, H.G. I. Lee, and S. M. Shin, "The causal model of perceived teaching presence, learning presence and learning effects of TV golf lesson program," *Korean Society for the Study of Physical Education*, vol. 22, no. 2, pp. 109–122, 2017.

[2] E. Kim, L. Fredline, and G. Cuskelly, "Heterogeneity of sport event volunteer motivations: a segmentation approach," *Tourism Management*, vol. 68, pp. 375–386, 2018.

[3] K. Kubo and A. Sugimoto, "Conflict between education and business in high school Sports: Based on analysis of the

content of newspaper articles," *Journal of Japan Society of Sports Industry*, vol. 28, no. 2, pp. 177–187, 2018.

[4] C. Thornton, D. Sheffield, and A. Baird, "A longitudinal exploration of pain tolerance and participation in contact sports," *Scandinavian Journal of Pain*, vol. 16, no. 1, pp. 36–44, 2017.

[5] I. Behravan, S. H. Zahiri, S. M. Razavi, and R. Trasarti, "Finding roles of players in football using automatic particle swarm optimization-clustering algorithm," *Big Data*, vol. 7, no. 1, pp. 35–56, 2019.

[6] A. T. C. Goh, "Seismic liquefaction potential assessed by neural networks," *Environmental Earth Sciences*, vol. 76, no. 9, pp. 1467–1480, 2017.

[7] C. Perna and M. L. Rocca, "Designing neural networks for modeling biological data: a statistical perspective," *Mathematical Biosciences & Engineering Mbe*, vol. 11, no. 2, pp. 331–342, 2017.

[8] M. H. S. Segler, T. Kogej, C. Tyrchan, and M. P. Waller, "Generating focused molecule libraries for drug discovery with recurrent neural networks," *ACS Central Science*, vol. 4, no. 1, pp. 120–131, 2018.

[9] N. Kohl and R. Miikkulainen, "Evolving neural networks for strategic decision-making problems," *Annals of Surgical Oncology*, vol. 22, no. 3, pp. 326–337, 2018.

[10] D. Holden, T. Komura, and J. Saito, "Phase-functioned neural networks for character control," *ACM Transactions on Graphics*, vol. 36, no. 4, pp. 1–13, 2017.

[11] H. He, F. Gang, and C. Jinde, "Robust state estimation for uncertain neural networks with time-varying delay," *Journal of Jishou University (Natural Sciences Edition)*, vol. 19, no. 8, pp. 1329–1339, 2019.

[12] H. Zhao and D. Nan, "Dynamic analysis of stochastic Cohen–Grossberg neural networks with time delays," *Applied Mathematics and Computation*, vol. 183, no. 1, pp. 464–470, 2017.

[13] R. Falquina and C. Gallardo, "Development and application of a technique for projecting novel and disappearing climates using cluster analysis," *Atmospheric Research*, vol. 197, pp. 224–231, 2017.

[14] A. A. Liu, Y. T. Su, W. Z. Nie, and M. Kankanhalli, "Hierarchical clustering multi-task learning for joint human action grouping and recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 1, pp. 102–114, 2017.

[15] G. P. Adam and A. G. Monika, "Effect of feature extraction on automatic sleep stage classification by artificial neural network," *Metrology and Measurement Systems: Metrologia i Systemy Pomiarowe*, vol. 24, no. 2, pp. 229–240, 2017.

[16] J. Jokinen, T. Raty, and T. Lintonen, "Clustering structure analysis in time-series data with density-based clusterability measure," *IEEE/CAA Journal of Automatica Sinica*, vol. 6, no. 6, pp. 1332–1343, 2019.

[17] M. G. Borgelt, M. van Kreveld, M. Löffler et al., "Planar bichromatic minimum spanning trees," *Journal of Discrete Algorithms*, vol. 7, no. 4, pp. 469–478, 2009.

[18] T. G. Swart and J. H. Weber, "Binary variable-to-fixed length balancing scheme with simple encoding/decoding," *IEEE Communications Letters*, vol. 22, no. 10, pp. 1992–1995, 2018.

[19] H. Lu, L. Ehwerhemuepha, and C. Rakovski, "A comparative study on deep learning models for text classification of unstructured medical notes with various levels of class imbalance," *BMC Medical Research Methodology*, vol. 22, no. 1, pp. 181–196, 2022.

[20] L. Wanquan and X. Lixin, "A new recurrent neural network adaptive approach for host-gate way rate control protocol within intranets using atm abr service," *Journal of Industrial and Management Optimization*, vol. 1, no. 3, pp. 389–404, 2017.

[21] N. T. Luy, "Adaptive dynamic programming-based design of integrated neural network structure for cooperative control of multiple MIMO nonlinear systems," *Neurocomputing*, vol. 237, pp. 12–24, 2017.

[22] H. Braak and K. D. Tredici, "Neuropathological staging of brain pathology in sporadic Parkinson's disease: separating the wheat from the chaff," *Journal of Parkinson's Disease*, vol. 7, no. s1, pp. 71–85, 2017.