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Retraction

Retracted: Optimizing the Training Mode of Swimmers Based on Deep Learning and Data Mining Technology

Wireless Communications and Mobile Computing

This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 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] S. Liu and S. Sun, "Optimizing the Training Mode of Swimmers Based on Deep Learning and Data Mining Technology," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1694833, 12 pages, 2022.

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Research Article

Optimizing the Training Mode of Swimmers Based on Deep Learning and Data Mining Technology

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Data mining is the most popular research direction of information science nowadays. It revolves around all the data and continuously excavates some of the potentially valuable data information. This information has great application value. This is a dynamic and interactive process. Deep learning is an important branch of machine learning, and the introduction of deep learning theory has promoted the development of artificial intelligence. Swimming is a rather special sport. From the perspective of special characteristics, the body is in an unstable state during swimming, there is no fixed fulcrum, and it is necessary to fight against water resistance in the water. In the case of maintaining the best streamlined and reducing resistance as much as possible, through the power forward movement method brought by rowing and kicking, the training of swimming-specific strength is also unique to the project. In this study, the application of deep learning and data mining technology to the optimization of swimming athletes' training mode is proposed, and algorithms such as neural network and support vector machine are expounded. This paper adopts two different training methods. That is, the experimental group adopts functional training. The control group used traditional training to compare the special performance of the two groups of athletes before and after physical training. In this way, we can understand the changes of traditional training and functional training on the performance of swimmers, compare the methods of the two groups of athletes and provide swimmers with more scientific and effective training methods. The experimental results of this paper show that through the data mining technology experiment, the main item test scores of the two groups of subjects before and after the experiment were $p = 0.004$, which was less than 0.01, showing a very significant difference. This shows that the use of deep learning and data mining technology has a very significant effect on swimming athletes in training to improve performance.

1. Introduction

The wave of artificial intelligence is sweeping the world. Artificial intelligence technology represented by machine learning is changing our lives. Machine learning is a technology that uses algorithms to analyze large amounts of data and learn from the data and complete tasks in the learning of the data. Deep learning is a further development based on machine learning algorithms. Compared with machine learning, the simulation of human brain mechanism by deep learning is more similar to human intelligence. Data mining is a technique for discovering useful information and tacit knowledge from large amounts of structured and unstructured data. This information is potentially valuable. Users can be interested, understand, apply, and decision support. They can bring benefits to businesses and governments, and they can also seek breakthroughs in scientific research.

Swimming is a speed-based physical activity. Its aquatic background and human motion output method have high requirements on the physical reserves and technical requirements of athletes. But in fact, the basic physical training method for swimming is relatively simple. Most youth swimming basic training is still carried out according to the traditional basic physical training method. The training

concept is outdated, and the training method is backward. Therefore, how to use advanced physical function training ideas and methods to help swimmers better carry out scientific, orderly, and efficient basic physical training safety is an important proposition to be solved urgently in the current swimming theory circle.

The innovation of this paper lies in (1) using data mining technology and deep learning to study the optimization of the training mode of swimmers; (2) it is innovative and practical.

2. Related Work

Deep learning and data mining technologies have been widely and deeply applied in various industries. More and more scholars use data mining and deep learning methods for research. Due to the rapid growth of internet users, security plays an important role in this internet world. In the past, many researchers have developed various intrusion detection systems that utilize data mining techniques to identify and detect intruders. However, existing systems cannot achieve sufficient detection accuracy when using data mining. To this end, Riyaz and Ganapathy proposed a new intrusion detection system to provide security for data communication by effectively identifying and detecting intruders in wireless networks. Here, Riyaz and Ganapathy propose a new feature selection algorithm called feature selection algorithm based on conditional random fields and linear correlation coefficients. It is characterized by selecting the largest contribution and classifying it using existing convolutional neural networks [1]. Considering that the high recognition rate of deep learning requires the support of a large amount of data, Zhang et al.'s research aims to propose an insulation fault recognition method based on a small dataset convolutional neural network (CNN). Due to the chaotic characteristics of partial discharge (PD) signals, the chaotic characteristics are obtained by equivalently transforming the partial discharge signals per unit power frequency cycle through phase space reconstruction. This method can realize the partial discharge identification of small data sets, which makes up for the deficiency of the partial discharge identification method based on CNN [2]. Person reidentification aims to match specific persons with nonoverlapping cameras. This is an important but challenging task in video surveillance. Traditional methods mainly focus on feature construction or metric learning. Therefore, Wang et al. proposed some deep learning-based methods to jointly learn image features and similarity measures [3]. Operators of chemical techniques are often faced with the problem of determining the best intervention. The goal of Dorgo is to develop data-driven models by exploring causal relationships in industrial system alarm and event log databases. He proposed a sequence-to-sequence deep learning model to predict them [4]. The purpose of the Yu et al. research is to illustrate how open-ended response and emotionally expressive texts can be mined from student surveys to provide valuable information for improving student experience management (SEM). The concept of SEM for students draws on the concepts of customer experience management (CEM) and aims to continuously improve customer relationships by understanding the customer's point of view. To illustrate how text mining can be applied to SEM, Yu et al. discusses an example of a campus-wide survey conducted by Arizona State University [5]. There has been a clear trend in recent years to develop deeper and longer tunnels in order to meet increasing mining demands. Localization of microseismic events is critical for predicting and avoiding traditional mine disasters caused by high stress concentrations. The biggest difference between deep learning and traditional backpropagation training methods is that deep learning can automatically and independently learn the features of large amounts of data without human intervention. Using convolutional neural networks and deep learning techniques, Huang et al. proposed a method to identify the arrival time delay and hypocenter location of microseismic events in underground mines [6]. With the continuous growth of massive high-dimensional data, deep learning hashing techniques are widely used for approximate nearest neighbor search on large-scale datasets with their remarkable efficiency and retrieval performance. Feng et al. proposed a new supervised deep hashing method, called multigranularity feature learning hashing, for learning compact binary descriptors. Specifically, Feng et al. design an end-to-end trainable network to jointly learn feature representations and hash codes. One of the global flows and one of the local flows are responsible for learning feature representations at different granularities. A hash stream is used to encode multigranularity features into binary codes [7]. AI technology plays an important role in modern manufacturing, especially in the context of the Industry 4.0 paradigm. Zeba et al. conducts a visual and comprehensive study of the application of artificial intelligence in manufacturing. It turns out that the most important topics today are as follows: cyberphysical systems and smart manufacturing, deep learning and big data, and real-time scheduling algorithms [8]. However, the shortcomings of these studies are that the model construction is not scientific and reasonable enough, and the data still needs to be improved.

3. Deep Learning and Data Mining Technology

3.1. Deep Learning.
Deep learning techniques originated in neuroscience, also known as deep neural networks. Since current deep neural networks mainly use convolutional structures, deep neural networks are sometimes also referred to as deep convolutional neural networks [9].

3.1.1. Development History of Deep Learning.
Deep learning theory is developed from artificial neural network. The development of artificial neural network has experienced long-term exploration and unremitting efforts of several generations of scholars. People began to study neural networks very early. The perceptron model is a basic principle based on modern neural networks. It is a network model that can achieve classification and recognition functions through training and is a true neural network [10].

3.1.2. Deep Learning Network Model. Machine learning is a method of implementing artificial intelligence. Machine learning is the process of using algorithms to parse and train large amounts of data. Deep learning is an important branch of machine learning. The introduction of deep learning theory has promoted the development of artificial intelligence. Deep learning originated from perceptron-based artificial neural networks. After years of development, deep learning has made extraordinary achievements in image processing, speech recognition, and other fields, and a variety of deep learning models have also been born [11]. Now, the commonly used models of deep learning can be basically divided into two categories: unsupervised learning and supervised learning. Among them, unsupervised models mainly include autoencoders, restricted Boltzmann machines, and deep belief networks. Supervised learning mainly includes convolutional neural networks.

3.1.3. Autoencoder. An autoencoder is an unsupervised learning algorithm that employs a backpropagation algorithm. It is mainly used for high-dimensional complex data processing or feature extraction. The autoencoder is a three-layer neural network, the first and third layers are the input layer and the output layer, respectively, and the middle layer is the hidden layer for feature extraction on the data obtained by the first layer [12]. Figure 1 is the network structure of an autoencoder.

Autoencoders mainly consist of an encoder and a decoder that generates reconstructions. The encoder can be represented by function $D = F(x)$, and the decoder can be represented by function $S = J(D)$ [13]. The main function of the encoder is to extract features from the input data, and the function of the decoder is to restore the features extracted by the encoder to the original information.

Its related formula is as follows:

$$D_i = F(Qx_i + B),$$
$$\hat{x}_i = F\left(Q'x + A\right). \tag{1}$$

Among them, F represents the nonlinear activation function, which is generally a sigmoid function. Among them, $Q = \sum_{i=1}^{N} Q_{ij}x_i$ and $Q' = \sum_{i=1}^{M} Q_{ij}x_i$ are the weight matrices of the encoder and decoder, respectively. B and A are the biases of hidden layer D and input layer x, respectively. Due to the limited ability of a single-layer autoencoder to extract signal features, classifiers such as SVM and SoftMax are generally added to the autoencoder [14].

3.1.4. Restricted Boltzmann Machine. Restricted Boltzmann Machines are randomly generated random networks that learn probability distributions from an input dataset. The neurons of the restricted Boltzmann machine are random; that is, there are only two output states (active, inactive), which are usually represented by 0 and 1 in binary [15]. Restricted Boltzmann Machine (RBM) is evolved from Boltzmann Machine (BM) and is a special form of Boltzmann machine network (BM). A Boltzmann Machine (BM) is a stochastic recurrent neural network. Figure 2 is a model of a Boltzmann machine.

In Figure 2, the neurons of the Boltzmann Machine (BM) are interconnected. It is a fully connected network with strong unsupervised learning ability. But at the same time, the learning ability is strong because the neurons are fully connected; so, it takes a long time to train the Boltzmann machine, and its distribution is also difficult to obtain. Therefore, according to the network limitations of Boltzmann machines, the restricted Boltzmann machine (RBM) is derived. Its model is shown in Figure 3 [16].

It can be seen from Figure 3 that the neurons in the two layers of the restricted Boltzmann machine (RBM) are fully connected. However, neurons in the same layer are not connected and maintain an independent state, which is a simplified Boltzmann machine (BM) model [17]. A restricted Boltzmann machine is an energy-based model. From the above, the restricted Boltzmann machine is an unsupervised learning method, and the main purpose of the unsupervised learning method is to fit the input data as much as possible.

Without knowing the exact distribution of the input data, the neural network will have difficulty learning. And since any probability distribution can be transformed into an energy-based model, an energy function needs to be defined for it. For a given set of states (g, k), the following energy function can be defined:

$$R_\theta(g,k) = -\sum_{i=1}^{n_g} s_i g_i - \sum_{j=1}^{n_k} l_j k_j - \sum_{i=1}^{n_g}\sum_{j=1}^{n_k} k_j h_{j,i} g_i. \tag{2}$$

According to the energy function defined by formula (2), the joint probability distribution of the following states (g, k) can be given:

$$V_\theta(g,k) = \frac{1}{C_\theta} e^{-R_\theta(g,k)}. \tag{3}$$

Among them, $V_\theta(g,k)$ is the Boltzmann function, and C_θ is the normalization factor, also known as the partition function [18]. Among them,

$$C_\theta = \sum_{g,k} e^{-R_\theta(g,k)}. \tag{4}$$

For practical problems, we usually use the likelihood function derivation formula. The edge probability distribution function $V_\theta(g)$ of the visible layer k can be obtained, that is, the likelihood function:

$$V_\theta(g) = \sum_k V_\theta(g,k) = \frac{1}{C_\theta} \sum_k e^{-R_\theta(g,k)}. \tag{5}$$

Correspondingly, the marginal distribution of hidden layer g can be obtained:

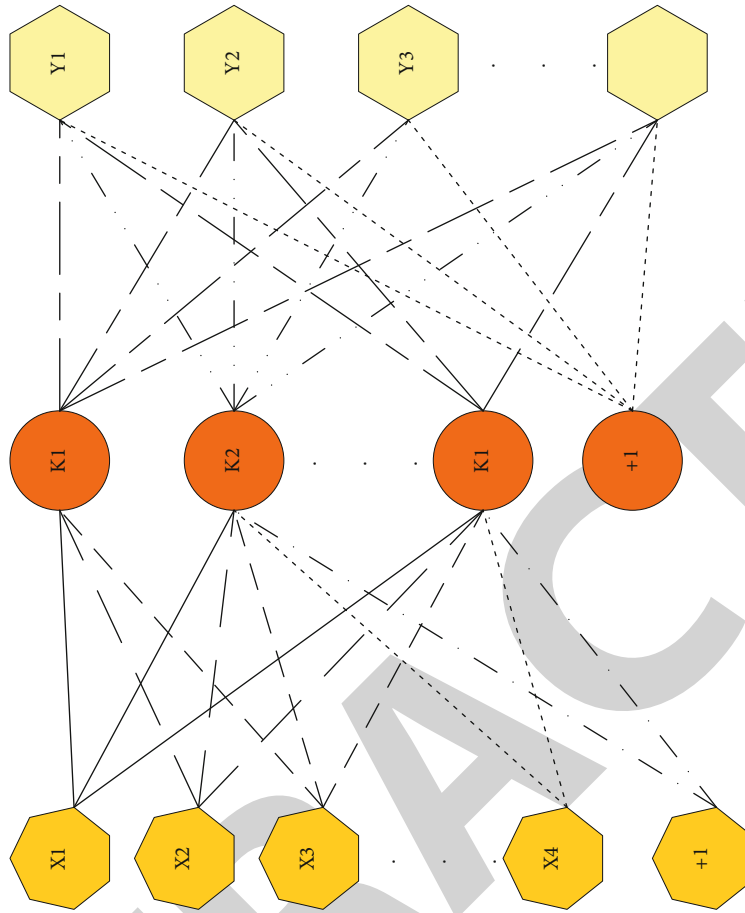$$V_\theta(g) = \sum_k V_\theta(g,k) = \frac{1}{C_\theta} \sum_g e^{-R_\theta(g,k)}. \tag{6}$$

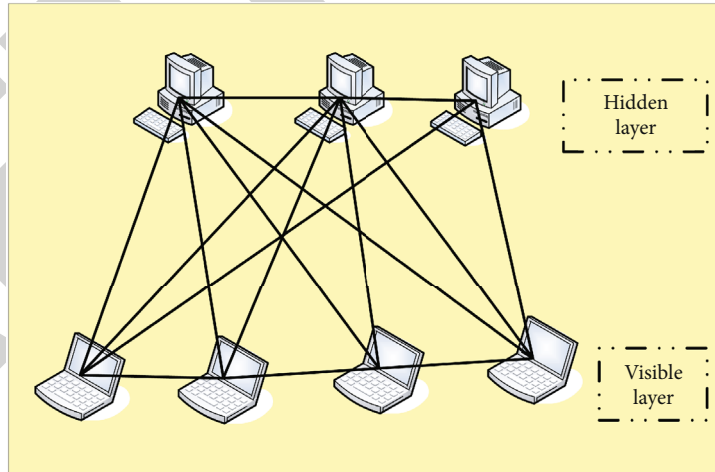Figure 1: Network model diagram of the autoencoder.

Figure 2: BM network diagram.

After the training samples are determined, the RBM needs to be learned [19]. The typical learning methods of RBM mainly include Gibbs sampling (Gibbs sampling) algorithm and contrastive divergence (CD) algorithm.

3.1.5. Deep Learning Network. Deep Belief Networks (DBNs) are a generative deep model. By training the weights between its neurons, it can make the entire neural network generate training data according to the maximum probability. RBM imitates the way the human brain processes information, and training each RBM is essentially learning the hidden features of the input data. The human brain relies on a large number of neurons and layers to process information. Therefore, the ability to process complex information
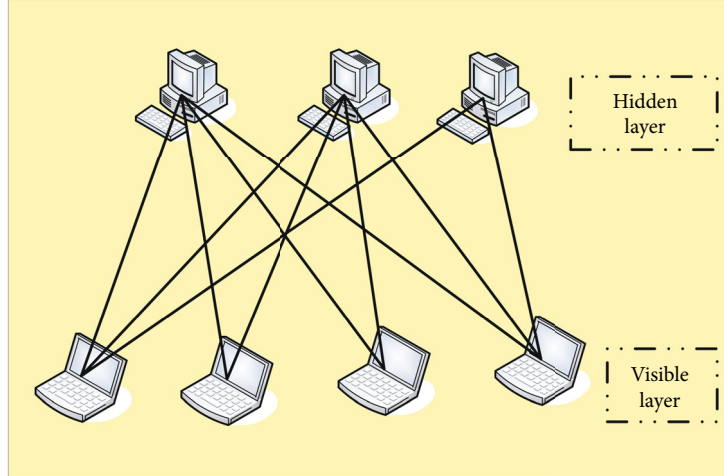
Figure 3: RBM network diagram.

appears stronger. This gives us a good inspiration, the network constructed by stacking multiple RBMs will become stronger, and the ability to extract feature information will be stronger. A deep belief network is such a neural network composed of stacks of multiple Restricted Boltzmann Machines (RBMs) [20]. Figure 4 shows the network structure of a typical deep belief network.

The quality of neural network training will affect the learning of features. In general, however, global optimization of DBNs with multiple hidden layers is currently very difficult. Generally, the network can only be optimized by layer-by-layer training, and the RBM model parameters of each layer are sequentially trained. The global DBNs are finally obtained through a greedy algorithm. The training process is mainly divided into a pretraining process and a fine-tuning process. The pretraining process is mainly to train the RBM of each layer in turn without supervision and input the parameters obtained after each layer of RBM training into the next layer of RBM network, and so on, until it is transmitted to the last layer. The fine-tuning process mainly uses the weight parameters obtained in the pretraining process as the initial weight. Then in this process, the BP back-propagation method is used for training. In this way, it is easier to obtain the weight parameters within the scope of the global optimal solution. Then, this will not get stuck in a local optimum [21].

3.1.6. Structure and Algorithm of Convolutional Neural Network. Convolutional neural networks (CNN) are a deep learning structure that combines artificial neural networks and deep learning networks. It is a special perceptron model specialized in recognizing two-dimensional images. CNN automatically extracts features of sample data by training weights in a supervised manner. Convolutional neural networks are a variant of MLP networks. Its model was influenced by the development of neurobiology [22]. Figure 5 is a simple convolutional neural network model.

As can be seen from Figure 5, unlike multilayer feedforward sensors, convolutional neural networks constrain the network structure by utilizing local connections in the receptive regions.

① Before training, use different small random numbers to initialize the ownership values of the convolutional neural network for supervised training. There are two stages to training a folded neural network:

(a) In the prepropagation stage, samples from the sample set are extracted, and X is input to the network. W is the weight of the network, and F is the mapping function. Pass the information from the input layer to the output layer through a one-step transformation and calculate the corresponding actual output:

$$O_P = F_n(\cdots(F_2(F_1(XW_1)W_2)\cdots)W_n. \tag{7}$$

(b) In the backtracking phase, calculate the difference between the actual output Op and the ideal output Yp

$$E_P = \frac{1}{2}\sum_j \left(Y_{pj} - O_{Pj}\right)^2. \tag{8}$$

The weight matrix is then adjusted in a way that minimizes the error.

② Activation function is as follows: the sigmoid function is a sigmoid function. Not only is it monotonically increasing but its inverse function is also monotonically increasing. Therefore, the sigmoid function is very suitable as a threshold function for neural networks. Its function value is between 0 and 1.

Its function analytic formula is
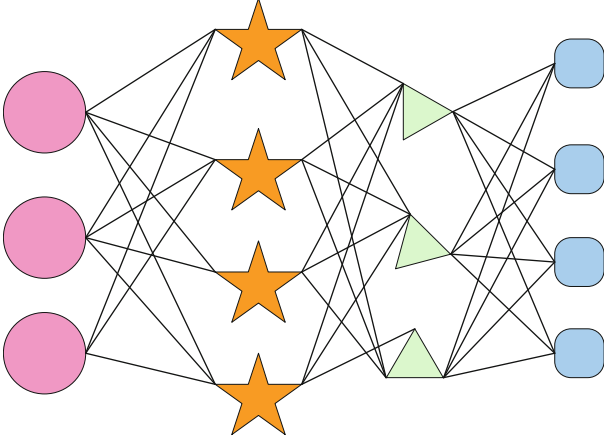
$$\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}. \tag{9}$$

FIGURE 4: Deep belief network structure.

The Tanh function output value can be scaled nonlinearly in the (-1, 1) range. This facilitates normalizing model features.

Its function analytic formula is

$$\tanh{(x)} = \frac{e^x - e^{-x}}{e^x + e^{-x}}. \tag{10}$$

3.2. Data Mining Technology. Data mining is a new information processing technology. It is a process of extracting, transforming, analyzing, processing or modeling a large number of data, and using the extracted key data to analyze, model, and predict. The main data mining tools used in this paper are as follows: neural network, support vector machine, and random forest. The data mining flow chart is shown in Figure 6.

3.2.1. Neural Network. A neural network is a complex mathematical model that simulates the organizational structure of the human nervous system. It is widely used in the field of machine learning and is used for complex modeling or fitting of input data and output data. It is a nonlinear modeling tool [23].

A neural network can gradually improve its performance by "learning" from examples and is an adaptive system. The neural network trains and models its relationship according to the input signal and output signal provided, just like simulating the human nervous system to respond to each stimulus, forming a memory law. In essence, artificial neural network is like the human nervous system, which is composed of a large number of neurons. We call this a simple information processing unit. Then, each processing unit is connected to each other through the weights formed by training, and finally, a distributed system is formed [24]. Each time new data is input, the weights formed by training are calculated and analyzed, and the final result is output. The connections inside the network can be systematically adjusted based on inputs and outputs, making it ideal for supervised learning. It is abstracted into a mathematical model, as shown in Figure 7.

In the figure, $X_1, X_2, \cdots, X_m$ represents the input signal, the symbol $V_1, V_2, \cdots, V_m$ represents the synaptic weight

of the m-th neuron, and Y represents the neuron output signal.

The perceptron introduced in Figure 7 has m inputs and one output. The perceptron first calculates the product of the input matrix X and the weight matrix V and then adds a bias X_m to the activation function F to calculate the output Y of the perceptron, namely,

$$Y = F(X \bullet V + X_m). \tag{11}$$

Among them, the activation function $F: R \longrightarrow R$, the expression can be simply expressed as

$$F(X) = \begin{cases} 0, X < 0, \\ 1, X \geq 0. \end{cases} \tag{12}$$

From the output of the activation function F, it can be known that the perceptron can only produce 0 or 1 output. Therefore, the perceptron can be used as a simple two-class classifier: the sample X to be classified is input into the perceptron, and the positive and negative categories of X are divided by the output of the perceptron.

Using the perceptron as a classifier is generally trained in the following way. First, the weight of the perceptron is randomly initialized, and then for each input sample (X_i, Y_i), the output $Y_i' = F(X_i \bullet W + X_m)$ of the perceptron is calculated, and if $Y_i' \neq Y_i$, the weight parameter of the perceptron is updated. This is repeated until the perceptron can classify all the samples correctly, and the update weight rules are as follows:

$$V \longleftarrow V_i + \Delta V_i. \tag{13}$$

Among them,

$$\Delta V_i = \eta \left(Y_i - Y_i' \right) \times X_i. \tag{14}$$

η is a learning rate in the perceptron training process, which is a relatively small nonnegative constant. It represents the adjustment range of each update of the neuron weight parameters. This formula proves that on the linearly separable problem, the above training method can make the perceptron converge in a limited time and reach the weight corresponding to the global minimum error. However, the perceptron composed of a single neuron has a simple structure and limited capabilities and can only solve linearly separable problems. For more complex nonlinear problems, the perceptron appears to be powerless. Therefore, a neural network composed of multiple perceptrons is produced to solve more complex nonlinear classification problems [25].

3.2.2. Support Vector Machine. A support vector machine (SVM) is one of the supervised machine learning methods. Its regression algorithm has been successfully applied to time series forecasting, nonlinear modeling and forecasting, etc. and has improved the usability and forecasting accuracy of the model. It can be viewed as a neural network with
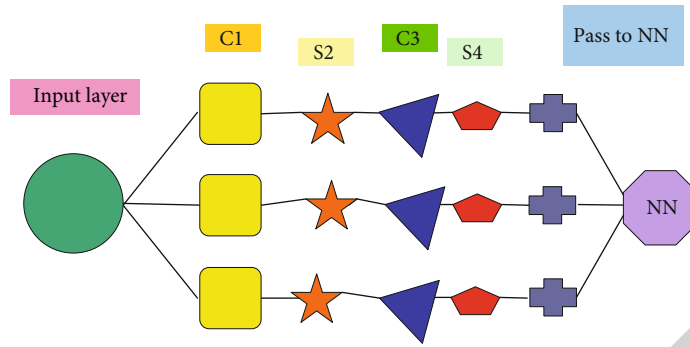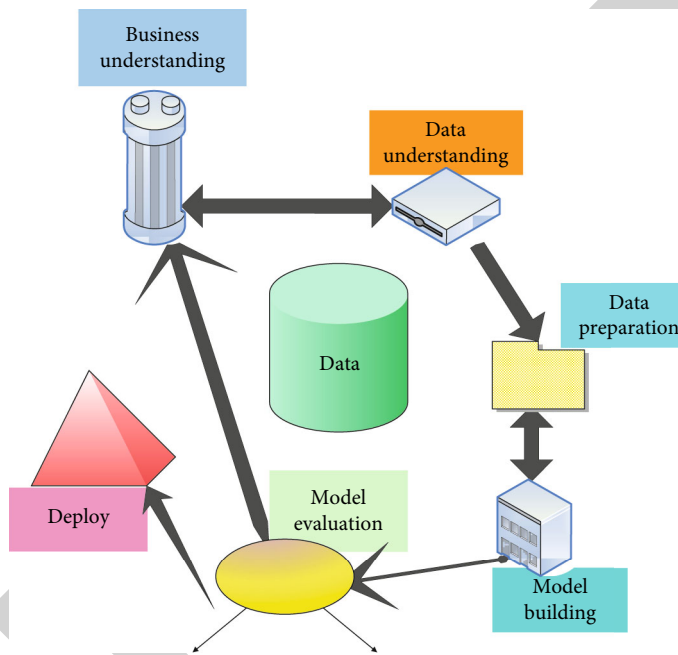
FIGURE 5: Convolutional neural network.
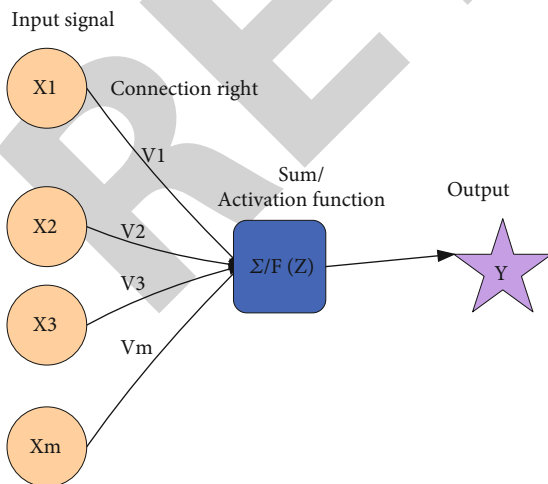

FIGURE 6: Data mining flowchart.

FIGURE 7: Neuron model.

hidden layers. Explain SVM from the perspective of neural network, as shown in Figure 8.

For the linearly separable case, the decision rule defined by the optimal hyperplane separating the binary decision classes gives the following formula in terms of support vectors:

$$G = \text{sign} \left(\sum_{i}^{N} g_i b_i (h \bullet h_i) + a \right). \tag{15}$$

Among them, G is the result. g_i is the class value of the training sample h_i, representing the inner product. Vector $h = (h_1, h_2, \cdots, h_n)$ corresponds to the input. Vector h_i and $i = 1, 2, \cdots, n$ are the support vector. In formula (2-1), a and b_i are parameters that determine the hyperplane.

For the nonlinear separable case, a higher-dimensional version of the formula is given as follows:

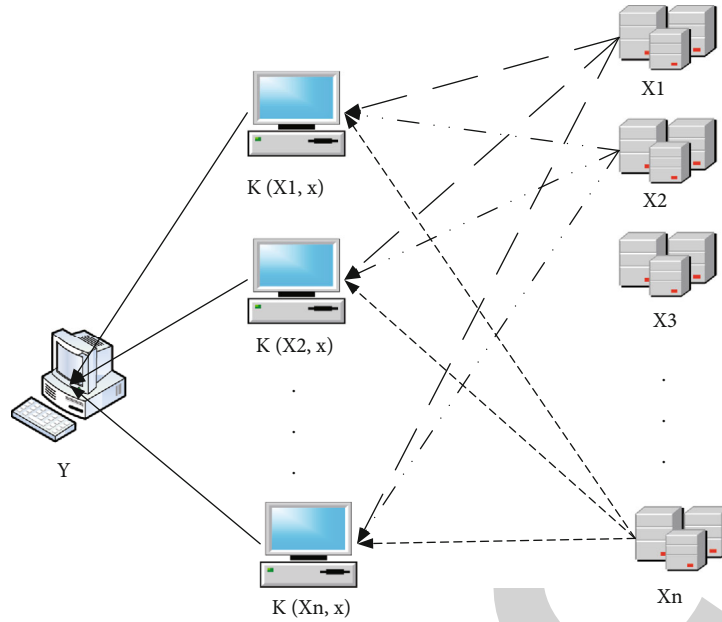$$G = \text{sign} \left(\sum_{i}^{N} g_i b_i D(h, h_i) + a \right). \tag{16}$$

FIGURE 8: Schematic diagram of the structure of the support vector machine.

For building decision rules, three common types of SVMs are given:

(1) Polynomial machine with kernel function is as follows:

$$D(h, h_i) = (h \bullet h_i + 1)^r. \tag{17}$$

Among them, r is the order of the polynomial kernel.

(2) Radial basis function machine with kernel function is as follows:

$$D(h, h_i) = \exp\left(\frac{-1}{\delta^2 (h - h_i)^2}\right). \tag{18}$$

Among them, δ is the bandwidth of the radial basis function kernel.

(3) Two-layer neural network machine with kernel function is as follows:

$$D(h, h_i) = F[(h \bullet h_i)] = \frac{1}{1 + \exp\left(v(h \bullet h_i) - b\right)}. \tag{19}$$

Among them, v and b are the parameters of the F-shaped function $F[(h \bullet h_i)]$ that satisfies the inequality $b \geq v$.

4. Experiment and Analysis on the Optimization of Training Mode for Swimmers

4.1. Changes in Test Scores of Subjects before and after the Data Mining Experiment. The test is of great significance to improve the level of exercise and practice and improve human functional defects and asymmetric movements. These functional deficits or asymmetries in movements can affect the effect of functional training. There are many advantages of testing, which can be summed up in the following aspects: (1) reduce the probability of sports injuries, (2) widely used in sports medicine, physical fitness, sports, and other fields; (3) provide a basis for coaches to formulate training plans for athletes themselves; (4) identify physical imbalances and deficiencies (to facilitate coaches and athletes to assess movements themselves); (5) check the weak links of the body with hooves and use simple exercises to correct the weak links and the balance of the body; and (6) enable athletes and coaches to detect potential physical defects and asymmetries early and reduce the probability of sports injuries and chronic injuries; all in all, testing is important. The test finds out the deficiencies of the body through the hoof and exercises to improve the body function and the function of each link and further improve the level of exercise, so as to achieve the best competitive state.

From Table 1, the FMS test results before and after the experiment are greater than 14 points, indicating that the athlete has better flexibility and stability. Swimmers generally have higher levels of flexibility, flexibility, and stability. The average score of all subjects in the FMS test results before the experiment was 18.05, and the average score in the test results after the experiment was 18.23. The improvement of the average score was mainly reflected in the experimental group. The test results of FMS in the control group

TABLE 1: FMS test scores before and after the experiment ($n = 26$).

	Before experiment		Total	After the experiment		Total
	Experience group	Control group		Experience group	Control group	
17.5points	2	4	6	0	5	5
18 points	6	5	11	0	5	5
18.5points	5	4	9	12	3	15
19 points	0	0	0	1	0	1
Total	13	13	26	13	13	26

TABLE 2: Comparison of the differences between the special quality test indicators before and after the experiment ($n = 26$).

	M		SD		T	P
	Experience group	Control group	Experience group	Control group		
Stroke amplitude	0.069	-0.015	0.058	0.079	2.594	0.014
Stroke rate	0.068	-0.015	0.057	0.078	2.586	0.014
50 m freestyle results	-1.125	0.333	1.222	1.143	-2.652	0.011

before and after the experiment did not change and remained at the original level. In the experimental group, through functional training, the subjects who scored 18.5 points improved their scores on the trunk stability push-up test, which was two points before the experiment and three points after the experiment. However, the score for rotational stability did not improve and remained at the original high level.

4.2. Changes in Subjects' Special Qualities before and after the Experiment.
Stroke frequency (SR) and stroke range (DPS) are two important indicators that affect swimming speed. The two directly determine the athletic performance of the athlete: swimming speed (V) = stroke frequency (SR) * stroke range (DPS). Considering this relationship, improving swimming speed mainly includes the following ways: (1) keep the stroke range unchanged and increase the stroke frequency. (2) The stroke frequency remains unchanged, and the stroke range is increased. (3) The stroke frequency and stroke range are increased at the same time.

It can be seen from the data in Table 2 that after eight weeks of training, the stroke range of the experimental group has been slightly improved. The control group decreased slightly. That is to say, after functional training, the number of strokes required for the subjects in the experimental group to complete the 50-meter freestyle was reduced, and the number of strokes in the control group was slightly increased. $p = 0.014$ between the two groups, there is a significant difference. Compared with before the experiment, the stroke frequency of the experimental group increased, but the frequency of the control group decreased to a certain extent. A t-test value p less than 0.05 was considered significant between the two groups. After eight weeks of functional training in the experimental group, the athletes' stroke frequency and stroke range were significantly improved. It can be speculated that the experimental group's performance improved. In contrast, the frequency and magnitude of subjects in the control group decreased, resulting in lower final grades. Although there are many reasons for

this result, and there may be test error, this still explains the variation in the 50-meter freestyle performance shown in the table between the two groups. That is, after eight weeks of functional training, the experimental group's 50-meter freestyle performance improved, while the control group's performance decreased. This shows that through the intervention of functional training, the energy transfer efficiency of swimmers between the upper and lower limbs has been improved.

4.3. Changes in Subjects' Special Scores before and after the Experiment.
As can be seen from Figure 9, the performances of butterfly, backstroke, and breaststroke have been improved before and after the experiment in both the experimental group and the control group. In the experimental group, the subjects whose main item was butterfly stroke had an average improvement of 0.7 seconds before and after the experiment; the subjects whose main item was backstroke had an average improvement of 3.3 seconds before and after the experiment. Subjects whose main item was breaststroke improved their test scores by an average of 1.37 seconds before and after the experiment. Although the performance of the control group also improved, the magnitude was not as large as that of the experimental group. Before and after the experiment, the main item test scores of the two groups of subjects were $p = 0.004$, which was less than 0.01, showing a very significant difference. This shows that the introduction of functional training in the training of swimmers has a very significant effect on improving performance.

5. Discussion

Since the wave of artificial intelligence swept across, deep learning theory, as an important part of machine learning theory, has shown its infinite vitality. Deep learning theory was developed from artificial neural networks. After years of development, deep learning has produced many deep learning models suitable for various application scenarios.
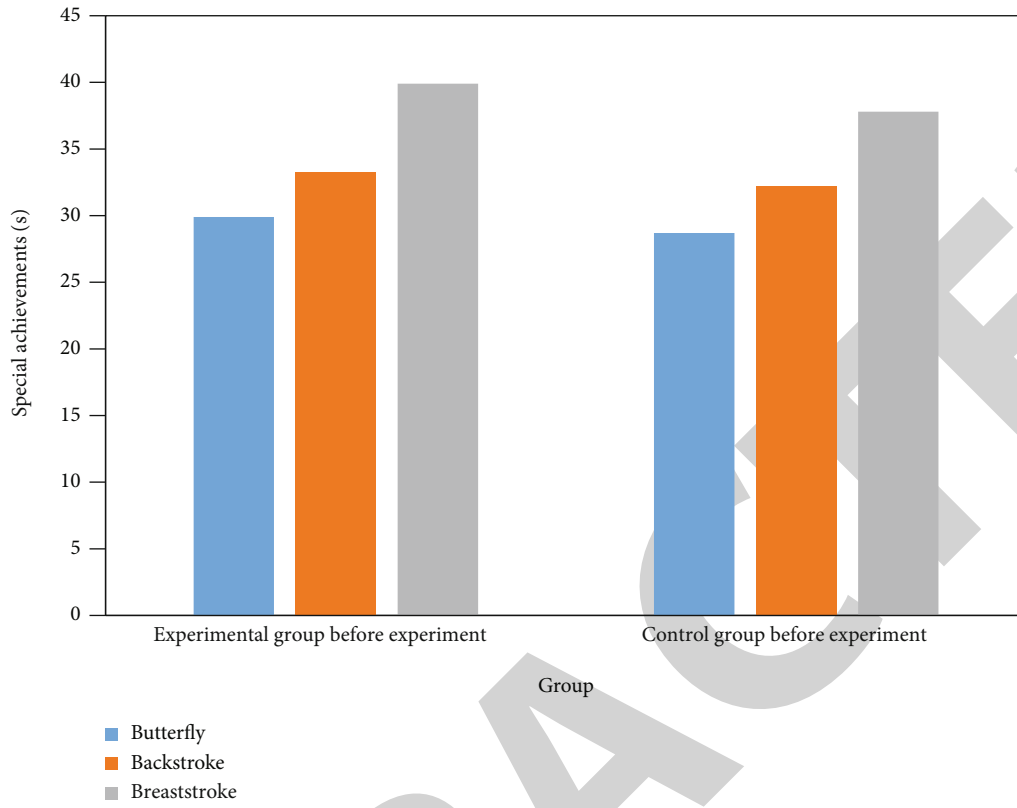
(a)
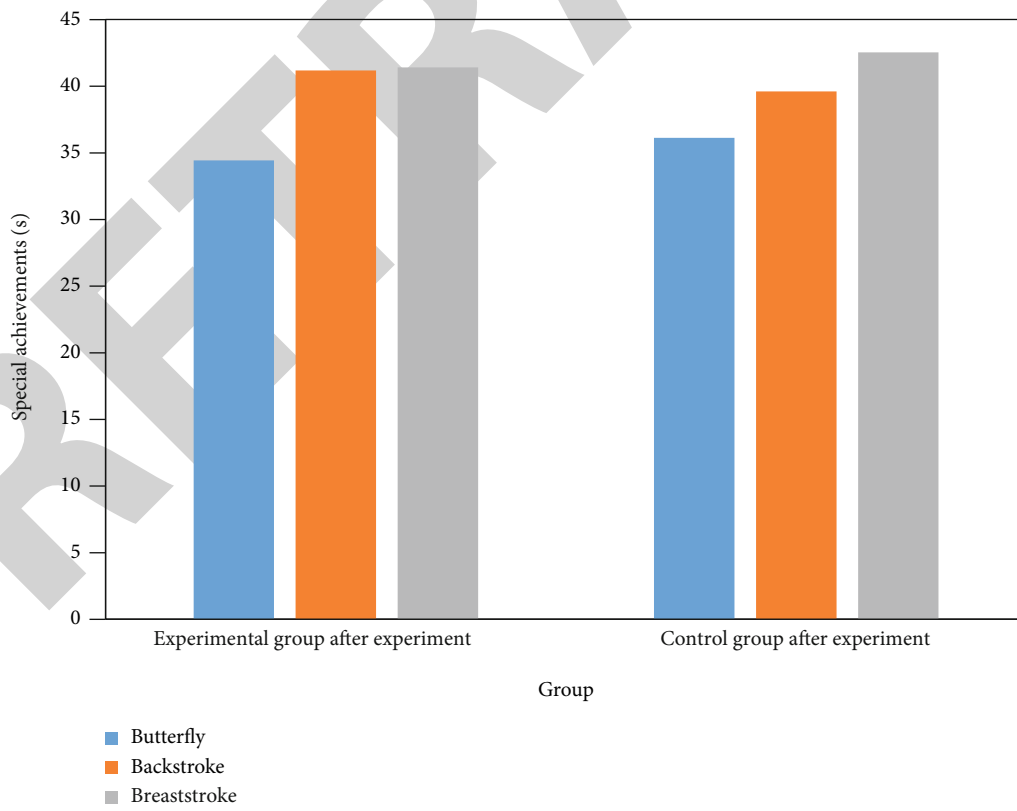
(b)

Figure 9: Schematic diagram of the comparison of special grades.

Competitive swimming has become the second largest event after the modern Olympic track and field competition. Its quality directly affects the total number of gold medals in the Olympic Games. Therefore, swimming is more and more valued by the country. Swimming has developed rapidly, and the training methods and training systems have been gradually improved and perfected in the rapid update. Competitive swimming is inseparable from special strength. Therefore, specific strength quality is one of the important reference factors for evaluating swimmers. Swimming is a cycle project, and the training of special strength should be diversified, rather than a single withdrawal training is enough.

Swimming is a racing event. The key to good results for athletes is "fast." The meaning of "fast" is to go through the whole process quickly. Swimmers mainly rely on anaerobic metabolism to provide energy in competition. Athletes in the 50-meter race mainly rely on the phosphate system for energy supply, and the athletes have strong explosive ability. Athletes in the 100-meter and 150-meter races mainly rely on glycolysis for energy, and the athletes have strong lactic acid tolerance. For swimming events of the same stroke and different distances, the shorter the distance, the higher the stroke frequency of the athlete. The longer the distance and the larger the stroke, the better the stroke economy of the athlete.

6. Conclusions

In this study, through data mining technology and deep learning, two different training methods were used for students in a swimming class. That is, the experimental group used functional training, while the control group used routine training. The two groups of subjects took special quality tests before and after fitness, the data were compared and analyzed, and the following conclusions were drawn: The physical quality of swimmers was generally improved significantly. In addition, the stroke frequency and stroke range of the athlete are also improved, the special quality of the athlete is greatly improved, and the performance of the swimmer is improved. However, there was a significant difference in the improvement in specific performance of the two groups of athletes between those who received functional training and those who received traditional training. There was a significant difference between the improvement of the subject's specific performance in the backstroke and the improvement of the subject's specific performance in the butterfly and breaststroke. Subjects in the backstroke improved even more.

Data Availability

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

Conflicts of Interest

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

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