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Research Article

Application of Machine Learning and Digital Information Technology in Volleyball

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Since the 1980s, machine learning has attracted extensive attention in the field of artificial intelligence. Following the expert system, it opened a precedent for the application of machine learning in the field of artificial intelligence and became one of the important topics of artificial intelligence. However, in the field of volleyball, the application of machine learning and information technology in volleyball is extremely limited. Volleyball has not developed widely in society nor has it become a common event in people's daily life. Therefore, the development of volleyball in China lags behind. Unlike other sports, volleyball requires both strong skills and playing tactics. While taking into account the technical and tactical aspects, the requirements for the comprehensive quality and learning ability of both sides of the teaching are relatively strict. If the application of modern information technology is neglected, it may affect the teaching effect of volleyball and hinder the long-term spread of volleyball. The article starts with the serving, landing, and blocking of two groups of volleyball players with different sports levels. Through the application of machine learning and digital information technology in volleyball, as well as the use of artificial neural networks and genetic algorithms, the reaction time and accuracy of judging serving, landing, and blocking are improved, and specific application strategies are further proposed. According to the influence of athletes of different levels on the cognition of volleyball landing points, it can be seen that there are three parts that account for 40% of the allocation.

1. Introduction

Although volleyball has developed rapidly in various countries and obtained many improvements and innovations, the rules have become more reasonable and scientific, the technology has become more standardized, and the development of volleyball has been unprecedentedly improved, but it still lacks the support of information technology. However, compared to football and basketball, the popularity of volleyball is relatively weak. As a confrontation project, volleyball requires each player to cooperate with each other to block, smash, defend, and respond; any part of the athlete's body can touch the volleyball, but they cannot land on the ball and hit the ball continuously during the game. For competitions, there is no time limit and no limit on the number of times. Volleyball requires comprehensive and sophisticated technology with its own unique characteristics.

The application of machine learning and digital information technology to volleyball can improve the accuracy of volleyball players hitting and blocking the ball. Applying machine learning and information technology to volleyball can observe the response and accuracy of players in different serving styles and provide an important theoretical basis for future volleyball training. Therefore, it is of great practical significance to prevent the injury of athletes in sports and prolong the sports years of athletes.

Machine learning and digital information technology are used not only in volleyball, but also in other fields. Using machine learning and combining the characteristics of artificial neural network and genetic algorithms can optimize and improve motion features and improve the accuracy and efficiency of digital processing and classification of motion information. It can provide certain help for different types of sports.

2. Related Work

Broecker et al. believe that the state-of-the-art machine learning techniques promise to be a powerful tool in statistical mechanics, as they can distinguish different phases of matter in an automated way. They demonstrated that convolutional neural networks (CNNs) can be optimized for quantum multifermion systems to correctly identify and localize quantum phase transitions in such systems. It turned out that this QMC + machine learning approach is even applicable to systems that exhibit severe fermion sign problems. In this case, traditional methods of extracting information from Green's functions (e.g., in the form of isochronous correlation functions) fail [1]. Coley et al., in 5x cross validation, trained models to specify primary product ranking 1 in 71.8% of cases, 3 in cases ranking ≤86.7%, and 5 in cases ranking ≤90.8% of deaths. Combining traditional reaction templates and machine learning, it is possible to predict organic reaction products in silicon using open-source data from the patent literature [2]. Given and Willson used a constructivist grounded theory approach to examine the research practices of humanities scholars, including their use of various resources and digital technologies. Through in-depth research, several themes emerged related to the role of technology in shaping the research practice of humanities scholars. The various digital technologies used by humanities scholars support traditional ways of working within their disciplines and create potential for new academic practices [3]. Gijsbert suggested that the challenge for experts is to extend their skills and abilities into leadership roles. To increase their leadership contributions, it is recommended to utilize a joint approach that integrates professional organizations with academia and policy-relevant healthcare organizations. And along with the diagnostics or information technology industries, a partnership approach is being used in education and training in healthcare [4]. Voyant et al. outline the method for predicting solar radiation using machine learning methods. Although many papers describe methods such as neural networks or support vector regression, predicting the output power of a Solar System is necessary for a well-functioning grid or for optimal management of the energy flux of a Solar System [5]. Tavakkoli-Moghaddam et al. proposed a genetic algorithm (GA) to solve the redundancy allocation problem for series-parallel systems. When a single subsystem can choose a redundancy strategy, most solutions to the general redundancy allocation problem assume that the redundancy strategy for each subsystem is predetermined and fixed. In general, active redundancy has received more attention in the past. However, in practice, in a particular system design, active redundancy and cold standby redundancy can be used. The choice of the redundant policy becomes an additional decision variable. Therefore, the problem is to choose the optimal redundancy strategy, components, and redundancy level for each subsystem to maximize the system reliability under system-level constraints. This is an NP-hard problem. Due to its complexity, it is difficult to solve it optimally using traditional optimization tools. It proves that genetic algorithm is an effective method to solve this kind of problem. Finally, the calculation results of a typical scenario are given and the robustness of the algorithm is discussed [6]. Lamperti et al. provide fairly accurate proxies for real models using machine learning proxies obtained by the

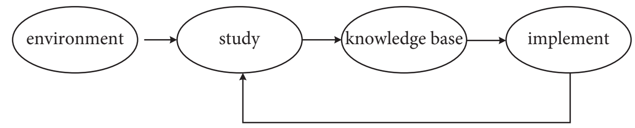

Figure 1: Basic composition of the learning system.

proposed iterative learning process and significantly reduce the computational time required for large-scale parameter space exploration and calibration [7]. The above research contents have great reference value for this paper. However, the time span of relevant studies is not large and the cases are relatively few, which may lead to inaccurate final results.

3. The State of the Art in Machine Learning

Definition. Machine learning is the study of computer programs that can self-improve their processing performance based on experience. Machine learning algorithms have been proven to be useful in many application domains [8]. In the field of data mining, they have a fairly high acuity for data mining. They can mine and analyze valuable rules from a large number of databases, for example, analyzing treatment results from patient databases, or obtaining general patterns of credit loans from financial data.

Basic Structure. Machine learning specializes in how computers simulate or realize human learning behaviors to acquire new knowledge or skills, and to reorganize existing knowledge structures to continuously improve their performance [9]. According to the definition of machine learning, we can build a learning system structure model, as shown in Figure 1.

The learning system is mainly composed of four parts: environment, learning, knowledge reserve, and execution. The environment interacts with the outside world to provide beneficial information for the learning part. The evaluation of the information provided by the environment to the system includes two aspects: information level and information quality. The level and quality of information in the environment are the first factor affecting the design of the learning system. The learning process processes the information extracted from the environment. The processed information becomes the knowledge reserve. Finally, the information obtained from the feedback in the whole process is fed back to the learning process [10]. At the same time, a structure that can repeatedly memorize and renovate knowledge is necessary for the entire learning system. Test the knowledge learned, acquire new knowledge, and apply the knowledge to practice, so that the entire system is continuously upgraded and evolved [11].

The environment is like the integration of external information. It acts as a work object in the whole link and is the source of external information. The learning link, as the core link, is connected with the environmental part. It mainly integrates, summarizes, and analyzes the learned information, improves or supplements the information database, and strengthens the efficiency of the system to complete tasks. Execution is mainly to perform systematic learning tasks and feed the information gained in this process of learning back. Finally, the evaluation of the system is completed to guide the next work [12]. The complexity of the task depends on whether a single concept or multiple concepts are required to perform the task, and the way to perform the task is determined by one or more steps.

The main methods of machine learning are as follows.

3.1. Artificial Neural Network Method. A neural network is a set of connected input/output units. Each connection has a weight, and each neuron represents an output. By learning for each input or output unit, the corresponding weights are adjusted. After completing this stage, the corresponding predicted value is obtained according to the input value of the sample [13]. Neurons are the basic units that make up a neural network. It is generally a multi-input, single-output nonlinear element. In a neural network, there are many factors that affect neurons. For example, input signals and other factors within the neuron have a deep impact on the neuron. Therefore, in artificial neuron input modeling, bias is often used to input an input signal with a fixed value. Such input signals are sometimes also called threshold or gated neuron models [14] (as shown in Figure 2). The output vector of the neuron model can be expressed as

$$A = f\left(\sum_{i=1}^{w} t_{1,j} \bullet p_i + h\right). \quad (1)$$

The influence of hidden neurons on motion samples is described by the error expression:

$$\mathrm{wxx} = \frac{1}{2wT}\sum_{T=1}^{T}\sum_{j=0}^{w=1}\left(r_{j,t} - y_{j,t}\right)^2. \quad (2)$$

Among them, T represents the number of samples, w is the number of neurons in the output layer, r is the sample output, and y is the model output.

According to the artificial neuron model, a fixed input component is used to activate the function. The bias is added to $W * P$, and the input component of the process is a fixed constant 1 that can be used as a weight. In the field of neural networks, bias plays an important role. It not only moves left and right on the function graph but also increases the reliability of the problem solving [15].

BP neural network algorithm can be said to be a continuous nonlinear optimization function learning method. The transformation is performed by input and output, and iterative operations are used to solve the weight problem in the negative gradient descent algorithm [16]. BP algorithm is a gradient descent search method with slow convergence speed. It is easy to fall into the local extreme points of the error function. For a large search space, multipeak and nondifferentiable functions often cannot effectively search the global minimum points. The process of the BP network learning algorithm is shown in Figure 3.

Input layer, output layer, and hidden layer are the three basic structures of BP neural network, as shown in Figure 4. The BP neural network adopts the method of error

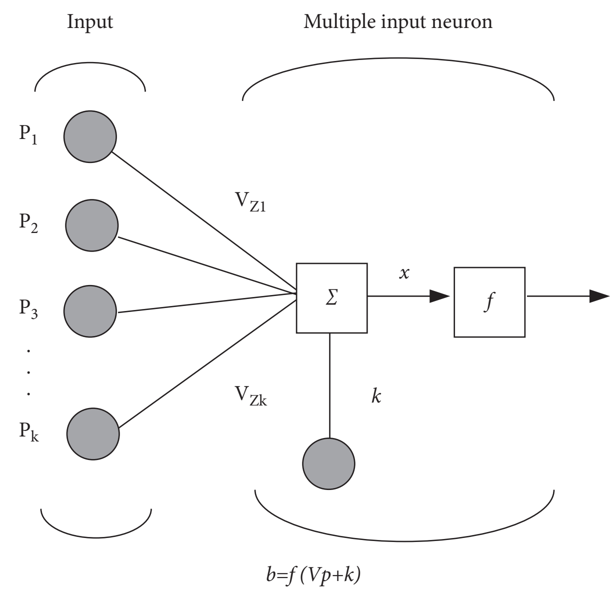

FIGURE 2: Artificial neuron model.

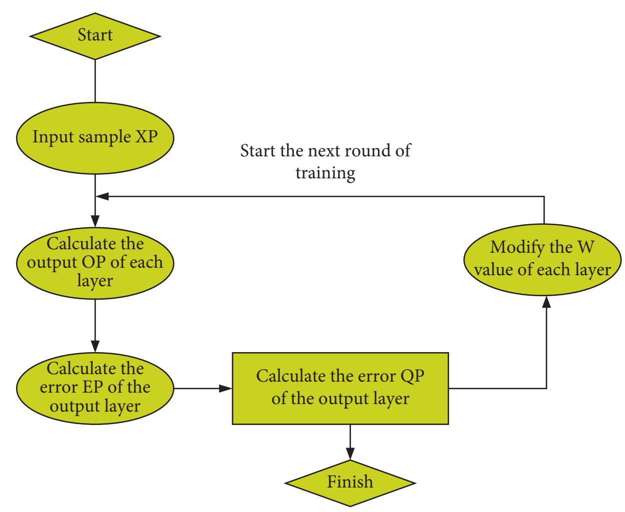

FIGURE 3: Flowchart of BP neural network algorithm.

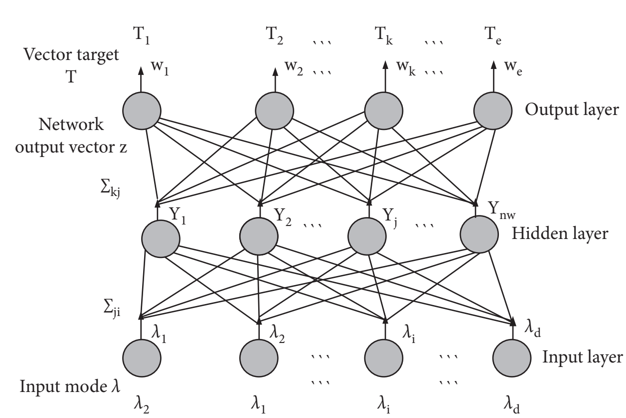

FIGURE 4: Three-layer BP neural network topology.

backpropagation to reduce the error. However, it has the weakness of small limitations, requires a lot of structure and learning parameters, and is easy to fall into local optimum [17].

According to each motion sample information $(F_x, E_x)(x = 1, 2, \ldots b)$, where F_x is the input and E_x is the corresponding output, the following operations are performed:

(1) Put the value of F_x into the unit layer; it can get

$$k_i = f\left(\sum_{i=1}^{b} V_{it}a_i + \theta_t\right), \text{Among them, } t = 1, 2, \ldots, n, \tag{3}$$

where f is a function of type S:

$$f(X) = \left(1 + e^{-w}\right)^{-1}. \tag{4}$$

(2) Then, get the activation value of the output layer:

$$e_j = f\left(\sum_{t=1}^{b} V_{tj} + R_j\right), j = 1, 2, \ldots, y. \tag{5}$$

(3) Calculate the generalization error of the previous unit layer:

$$g_j = f_j\left(1 - f_j\right)\left(f_j^{'} - f_j\right), j = 1, 2, \ldots, y. \tag{6}$$

(4) Then, get the error of (2) unit layer relative to g:

$$h_j = f_j\left(1 - c_j\right)\sum_{x=1}^{1} V_{jx} \bullet g_x, j = 1, 2, \ldots n. \tag{7}$$

This formula propagates the error from (3) to (4) unit layer.

(5) Adjust the connection weight from the second unit to the third unit, where β is the learning rate $(0 < \beta < 1)$; it can get

$$\Delta V_{tj} = \beta q_j \bullet h_t, j = 1, 2, \ldots, n; t = 1, 2, \ldots y. \tag{8}$$

(6) Adjust the threshold value of the third unit; it can get

$$\Delta R_x = \beta \bullet g_j, x = 1, 2, \ldots, y; 0 < \beta < 1. \tag{9}$$

(7) Adjust the connection weight of the first and second layers to get

$$\Delta V_{ti} = \alpha a_i \bullet h_r, r = 1, 2, \ldots, n; i = 1, 2, \ldots, m; 0 < \alpha < 1. \tag{10}$$

(8) Adjust the threshold value of the second unit to get

$$\Delta \theta_j = \alpha \bullet h_j. \tag{11}$$

Among them, $j = 1, 2, \ldots, n; 0 < \alpha < 1$.

3.2. Genetic Algorithm. First, a regular initial population is established, which is randomly generated. According to Darwin's principle of survival of the fittest, the groups that best fit the rules form new groups and offspring. The offspring establish a new population based on genetic manipulation [18]. Genetic operation is the operation of simulating biological genes. Its task is to impose certain operations on individuals according to their fitness and use genetic operations to optimize the solution of the problem generation by generation and approach the optimal solution. Each rule in the P population has a threshold that belongs to P until the population P completes the transformation. The standard genetic operation process is shown in Figure 5.

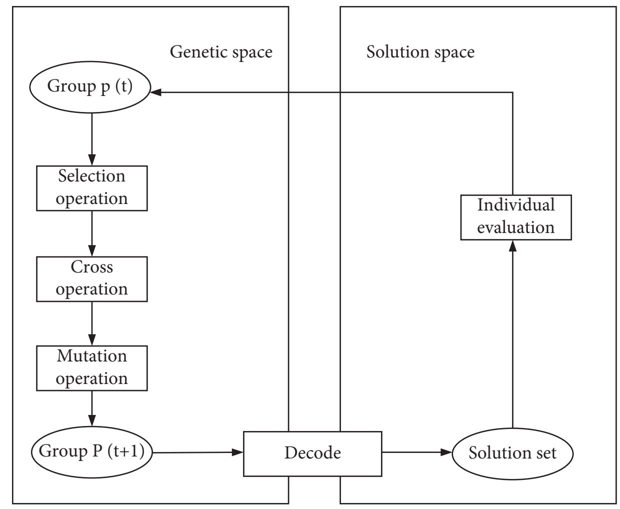

Figure 5: Schematic diagram of the standard genetic algorithm operation process.

The feature selection method can not only greatly select effective features but also reduce the dimension of feature space. It also further improves the accuracy of digital information processing and classification [19]. Firstly, the feature space of volleyball motion information is reduced in dimension by the feature selection metric method, and a feature subset with relatively low dimension is obtained. The 2χ-statistic (CHI) algorithm is used to quickly and efficiently perform the first feature selection on a large feature space [20]. χ's function is to balance imperceptibility and robustness. The larger the Chi value, the more the identification information related to the category C contained in feature t. The greater the correlation between features and categories, the more useful the identification information. Then, the second dimension reduction is performed by the method of the feature selection process of the genetic algorithm. To find the global optimal solution in the optimal feature subset, the schematic diagram is shown in Figure 6. Combining the advantages of volleyball's passing and jumping technology, it intercepts the net, improves the self-screening of the secondary ball, and changes the offensive rhythm.

The rules of the genetic algorithm can perform the survival of the fittest operation on individuals: individuals with high fitness have a high probability of being inherited into the next generation; individuals with low fitness have a low probability of being inherited into the next-generation population [21]. The probability of each individual being

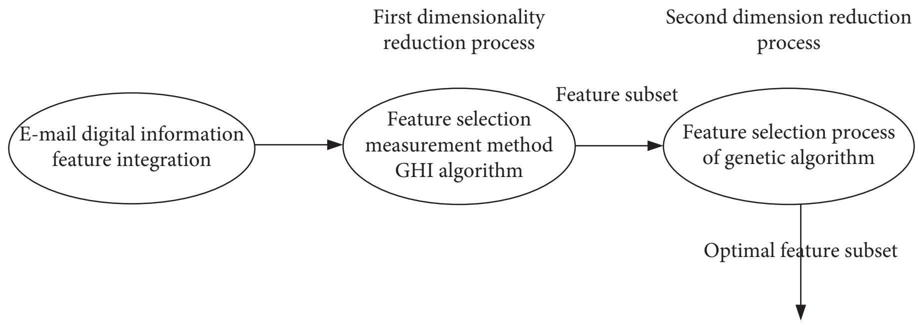

Figure 6: Schematic diagram of the feature selection method combining genetic algorithm and feature selection metrics.

selected is proportional to its fitness. The specific operation can be seen in the following formula:

$$Q(C_i) = \frac{f(C_i)}{\sum_{i=1}^{x} f(C_i)}, i = 1, 2, \ldots, n. \tag{12}$$

Among them, $Q(C_i)$ represents the probability of the *i-th* individual being selected. $f(C_i)$ represents the fitness function value of the *i-th* individual. n represents the number of individuals. Specific steps are as follows:

(i) Calculate the size of the fitness of each individual in the group
(ii) Calculate the probability of each individual being inherited into the next generation according to the formula
(iii) Calculate the cumulative probability of each individual based on the calculated probability of each individual being inherited into the next-generation population
(iv) Generate a random number in the [0,1] interval
(v) Select the corresponding individual according to the generated random number
(vi) Repeat the selection until enough individuals are selected. Here, the method that the next generation retains 10% of the individuals of the parents is adopted.

(1) Genetic Code. The crux of the encoding problem is to make the encoding represent the solution space of all possible subsets of a given feature set [22]. Assuming that W features need to be selected from a total of N feature sets ($W \leq H$), then a binary string of length H (chromosome) composed of "0" and "1" can be used to represent feasible feature combinations. "1" for any bit i of the chromosome (i is a natural number not greater than N) indicates that the i-th feature in the feature set is selected. "0" means that the feature is not selected. Clearly, the number of "1"s in the chromosomes that characterize feasible feature combinations is W.

(2) Generation of the Initial Population. The size of the initial population is generally between 50 and 100. A random method is used to select an initial group, and each individual selects an individual in {0,1} with equal probability according to the actual situation.

(3) Determination of Fitness Function. The choice of fitness function is of great significance to the optimization performance and speed of the genetic algorithm. In the heritage algorithm, a quantitative criterion is needed to measure the feature combination classification ability of each individual in the feature group:

$$f(x) = W_c - W_b. \tag{13}$$

The distance between classes is calculated as follows:

$$\begin{aligned} W_b &= \left[\left(v_i + v_j\right)\left(v_i + v_j\right)^T\right]^{1/2}, \\ v_i &= F\left[x_i\right], v_j = F\left[x_j\right]. \end{aligned} \tag{14}$$

Among them, x_i, x_j are the eigenvectors represented by the eigenvectors obtained by the first dimensionality reduction of the feature selection metric CHI method through the coding of individuals in the population. v_i, v_j are the mean eigenvectors, respectively.

Intraclass distance is calculated as follows:

$$\begin{aligned} W_b = {} & \frac{1}{n_i}\sum_{i=1}^{n_i}\left[\left(x_i - v_i\right)\left(x_i - v_i\right)^T\right]^{1/2} \\ & + \frac{1}{n_j}\sum_{j=1}^{n_j}\left[\left(x_j - v_j\right)\left(x_j - v_j\right)^T\right]^{1/2}. \end{aligned} \tag{15}$$

Among them, n_i, n_j is the sample size, respectively.

(4) Genetic Algorithm Termination Rule. The feature space is first encoded. A certain number of features are selected from the feature set to form the initial feature group [23]. The termination condition of the genetic algorithm is that the algorithm finds the lowest standard solution, reaches a fixed number of generations, and reaches the allocated budget. Among them, several feature items form a genetic individual coding string. Several individual coding strings form the initial population. An individual code is a possible optimal subset of features. The fitness value of each genetic individual in the population and the average fitness of the population are calculated. Finally, the optimal genetic operation is carried out, and the next-generation population is obtained through selection, crossover, and mutation operations; the genetic algorithm termination rule is used to judge whether the genetic algorithm feature selection process is over. If the

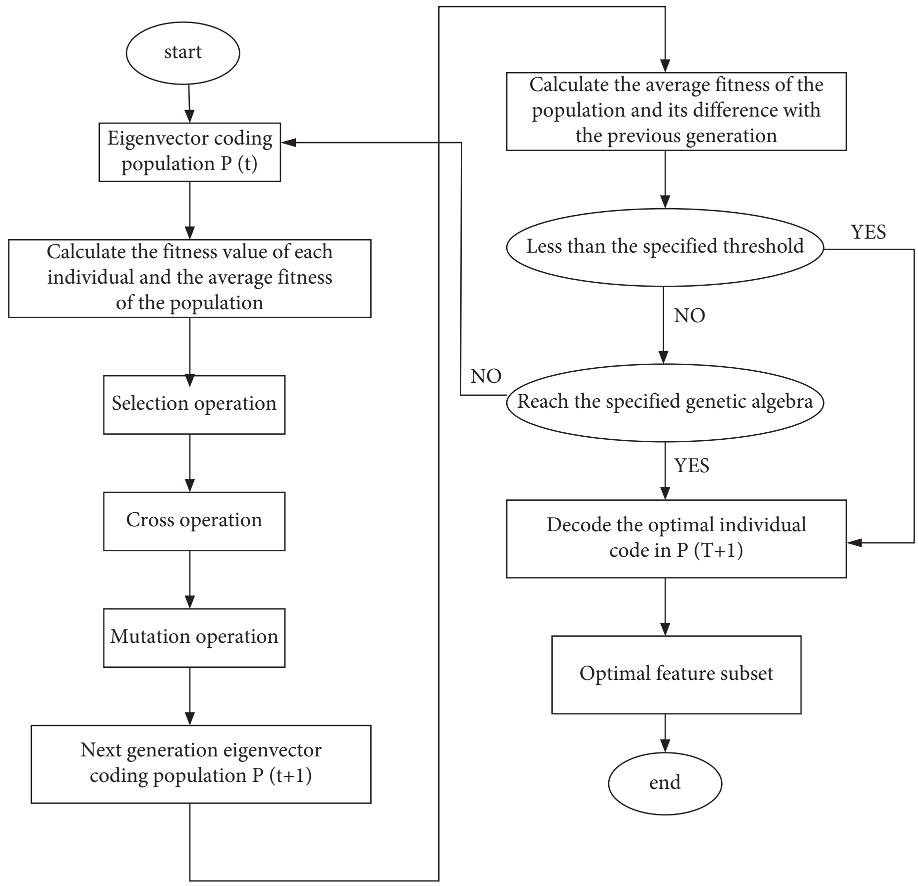

Figure 7: The flowchart of feature selection for the feature subset obtained by the feature selection metric by the genetic algorithm.

termination rule of the genetic algorithm is satisfied, the genetic individuals with the optimal characteristics are decoded and then combined to generate the optimal characteristic subset; if not, go to the second step to continue the genetic process. The flowchart is shown in Figure 7.

The weight of each feature item is calculated from the feature subset obtained by feature selection metric and two feature selections by genetic algorithm. Finally, the feature vector of mail digital information composed of feature items and weights is obtained. Through the feature selection method, the dimension of the high-dimensional vector of e-mail digital information can be reduced and a low-dimensional and better feature subset can be obtained. When selecting features according to a given feature selection measure, whether a feature can be selected only depends on the order of the corresponding measure of the feature in the set of corresponding measures of all features. This lays a solid foundation for the subsequent classification of digital information.

3.3. Clustering Algorithm. Clustering algorithms are relatively common machine learning algorithms. Their application is extensive. A clustering method is a process of dispersing the original data from a cluster to a series of data points. The algorithm starts with a given number of clusters K and then groups the data. Through continuous iterative optimization of the grouping, the clusters are finally obtained. The division of hierarchical clustering algorithm is based on the division of different objects into meaningful groups, so that the objects in the same group are similar, and the objects in different groups are not similar. K-means is the most common partition-based clustering algorithm. K-means is the most famous partition clustering algorithm. Because of its simplicity and efficiency, it has become the most widely used of all clustering algorithms. In Figure 8, an example of data clustering based on distance partitioning is given.

Hierarchical clustering algorithm is a kind of clustering algorithm. The main core content of the partitioned clustering algorithm is to divide a dataset containing N tuples or records into m groups. Each group is a cluster, $m < n$; hierarchical clustering method decomposes a given dataset hierarchically until certain conditions are met. Different from other algorithms, the hierarchical clustering algorithm builds a clustering tree according to the distance between different data. The leaf nodes of the tree are the respective raw data. Each nonleaf node in the tree is a collection of a series of original data, as shown in Figure 9.

3.4. Regression Analysis. The main object of regression analysis research is the statistical relationship between objective variables. It is based on a large number of experiments and observations on objective things, and it is a statistical method used to find statistical laws hidden in seemingly

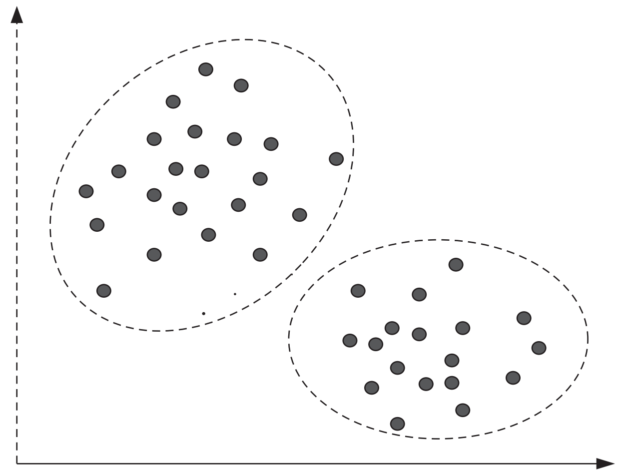

Figure 8: Example of data clustering based on distance partitioning.

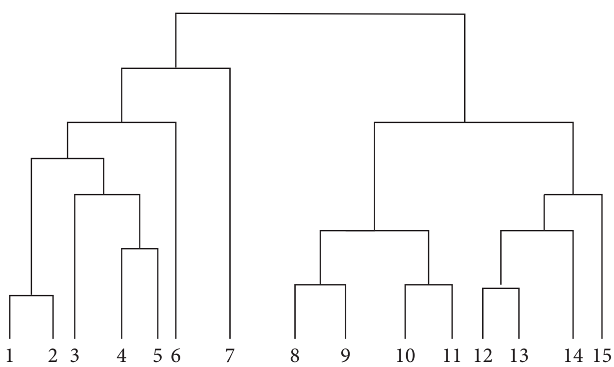

Figure 9: Example of hierarchical clustering.

uncertain phenomena. The application principle of regression analysis method is the least square method, which calculates the regression line that can best represent the relationship between business volume and mixed cost, to determine the method of fixed cost and variable cost in mixed cost.

3.5. Information Gain. As a feature selection method, information gain (IG for short) has been widely used in the field of machine learning [20]. The information gain is not symmetrical and cannot be directly regarded as a measure or distance. It starts from the perspective of motion feature information. It selects the corresponding motion features according to the value of each feature. For feature z and document category x, information gain examines the frequency of documents that appear and do not appear in z to measure the information gain for x. The information gain $IG(z,x)$ of feature z for document category x is calculated as follows:

$$IG(z) = -\sum_{i=1}^{m} P(x_i)\log P(x_i) + P(z)\sum_{i=1}^{m} P\left(\frac{x_i}{z}\right) + P(\overline{z})\sum_{i=1}^{m} P\left(\frac{x_i}{\overline{z}}\right)\log P\left(\frac{x_i}{\overline{z}}\right). \tag{16}$$

Table 1: Basic information of experimental athletes.

	Second-grade athlete	Elective class
Number	12	12
Age	20.32 ± 1.71	20.63 ± 1.92
Height	1.86 ± 0.11	1.81 ± 0.08
Training years	6–8	1–2

The higher the IG value, the more concentrated the feature in the distribution, indicating that the feature is more prominent.

3.6. The Digital Information System Is Divided into Three Subsystems of Induction, Acquisition, Analysis, and Calculation. Among them, the sensing and acquisition are the hardware system of the DIS, and the analysis and calculation are the software system of the DIS.

The hardware of the whole system and its principle are mainly sensors. In a broad sense, a sensor (transducer/sensor) is a device that can convert physical or chemical quantities into electrical signals that are easy to use. The International Electrotechnical Committee (IEC) considers that a sensor is a precomponent in a measurement system. It converts input variables into measurable signals. Common sensors in life are pressure sensors in a kettle, optical sensors in mobile phone, digital cameras, force sensors in electronic scales, temperature sensors in electronic thermometer, and so on. Of course, there are many things related to sensors in life. The working principles of these sensors are more or less similar. For example, the controllable potential electrolysis sensor measures the concentration of the gas by measuring the gas to determine the current generated during the potential electrolysis. Most of the physics experiments in middle school can be collected by sensors. DIS can use different kinds of sensors and computers to accurately obtain experimental data. In addition to saving time, this also greatly improves the accuracy of the experimental results.

4. Experiment and Result Analysis of Volleyball Based on Machine Learning and Digital Information Technology

A total of 24 subjects in this experiment were divided into two groups with different exercise levels. The high-level group are the national second-level volleyball players, and the low-level group are the ordinary students of the special class of the sports college. There are 12 players in both groups.

The basic situation of the main athletes is shown in Table 1.

The volleyball players judge the response time and accuracy statistics of the serve landing point (as shown in Figure 10).

A T-test was performed on the accuracy of volleyball players in judging their landing points. The reaction time and accuracy test of the volleyball players watching different

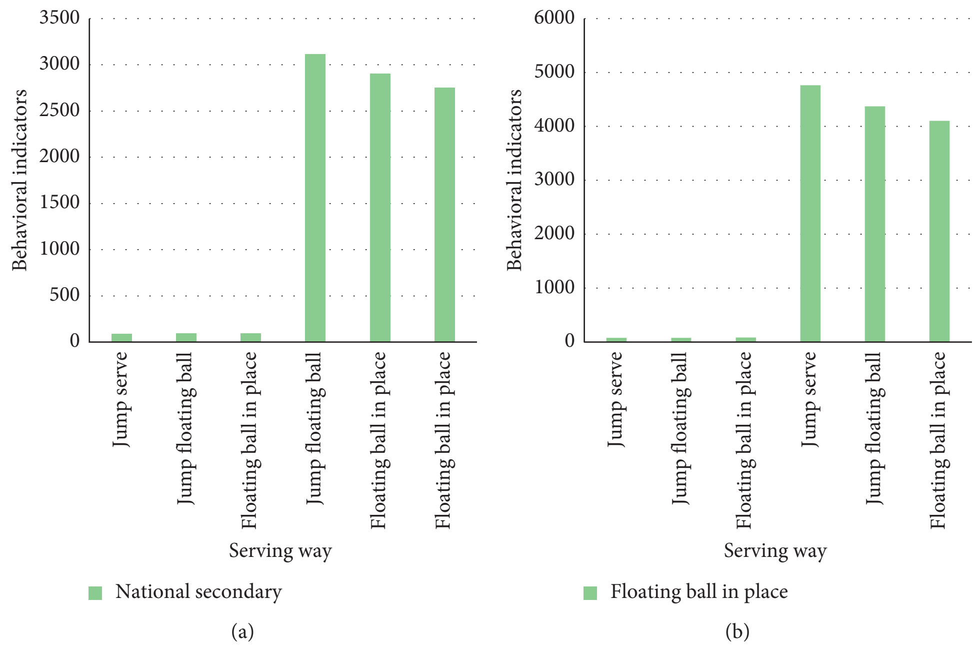

Figure 10: Athletes' behavioral indicators of serving prediction.

Table 2: The significance of accuracy comparison of volleyball players at different levels.

Main effect interaction	Freedom	F	P	Significance
Serving way	2	8.581	0.003	<0.01
Exercise level	1	11.022	0.001	<0.01
Serving way/exercise level	2	3.639	0.059	>0.05

serving styles were conducted according to the T-test when judging the landing point of the volleyball players (as shown in Table 2). It can be seen from the table that the main effect of the throwing method is significant ($F = 6.369$, $P = 0.013$). The main effect of exercise level was significant ($F = 4.103$, $P = 0.036$). There was no significant interaction between serving style and exercise level ($F = 1.537$, $P = 0.246$). After repeated tests, in different serving styles, the athletes' response to the floating ball was significantly shorter than that of the jumping ball ($P < 0.05$). The response time to the jumping ball was significantly shorter than that of the jumping serve ($P < 0.05$). This shows that the different serving styles of the players when judging the landing point of the ball have a significant impact on the players' reaction when judging the landing point. In terms of sports level, the reaction time of the students in the special class was significantly longer than that of the national second-level athletes.

The experimental results found that, in different sports situations, the levels of two different levels of athletes are not the same. The reaction time of the students in the special class was inferior to that of the second-level athletes. This shows that elite athletes can capture and extract valuable information for them in different situations and make corresponding and accurate responses.

The weight of the network is generated according to the conventional method of generating the initial weight of the neural network. BP network contains the essence of neural network. Because of its simple structure and strong plasticity, it has been widely used. In particular, its learning algorithm with clear mathematical meaning and clear steps makes it have a wide application background. Any complete network weight is

$$M_i = \{F_i, X_i, \varpi_i, \theta_i, i = 1, 2, \ldots, P\}. \tag{17}$$

It means that there are P individuals here, and P represents a weight group, which is a group size. The connection weight of the input layer to the hidden layer is denoted by F_i. The connection weight of the hidden layer to the output value is denoted by V_i. The threshold of the hidden layer is denoted by ϖ_i. Denoted by θ_i is the threshold of the output layer.

The connection weight and threshold are defined by binary coding. Each weight and threshold are represented by 0 and 1. Then, the corresponding binary strings are concatenated to form a long gene chain . A chain code represents a set of connection weights and thresholds. Since the coding string is only a parameter string of the weight and threshold of a neural network, an interpretation operator is used as the research object of machine learning and digital information technology to realize the conversion function between coding and weight. Its conversion formula is

$$m_x(t,b,c) = m_{\min}(t,b,c) + \frac{\mathrm{bin}_x}{2^x - 1}\left[m_{\max}(t,b,c) - m_{\min}(t,b,c)\right]. \tag{18}$$

Among them, $\mathrm{bin}(t)$ is a binary integer represented by a $\int$-bit string. The variation range of the connection weight is

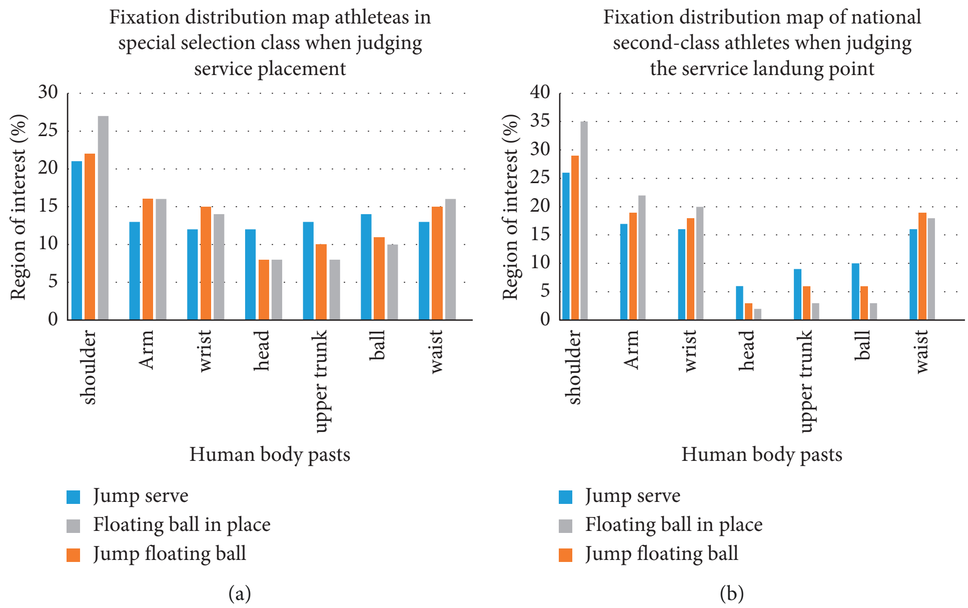

FIGURE 11: Comparison of gaze distribution when volleyball players judge where to serve.

TABLE 3: Descriptive statistics of various variables.

N		$M \pm SD$				
		Decision accuracy	Decision response time	Decision response time	Inhibition reaction time	Conversion cost
Second-grade athlete	37	0.49 ± 0.102	839.1 ± 245.785	0.7 ± 0.170	57.90 ± 69.704	317.91 ± 114.633
Students in special elective class	49	0.6 ± 0.095	837.0 ± 320.360	0.7 ± 0.156	49.12 ± 61.178	343.02 ± 132.046
Population	86	0.5 ± 0.119	837.9 ± 289.038	0.7 ± 0.161	52.90 ± 64.734	332.22 ± 124.773
t		-6.40^{**}	0.03	-0.16	0.62	-0.92

Note. ** representative $P < 0.01$.

denoted by $[m_{\max}(t, b, c) - m_{\min}(t, b, c)]$. Here, the length of the encoded string is set to 20, and the range of weights is $[-1, 1]$.

The sum of the squared errors between the network output value of the BP network and the expected output value can be expressed as a moderate function, and the error is used to test the performance of the network:

$$f = W - \sum_{i=1}^{N} (g_i - \widehat{g}_i)^2. \tag{19}$$

Among them, W is a constant. In the *i-th* sample, the expected output value is $\widehat{g}_i$, the actual output is g_i, and N represents the number of motion information samples.

The BP neural network model is an important psychological mechanism in cognitive processing. Executive function in this model plays a crucial role in motor decision-making. Through the statistics of the gaze distribution ratio of the volleyball players' served landing point judgment (as shown in Figure 11), the athletes have all points of the body that can obtain information, such as shoulders, arms, wrists, upper limbs, torso, head, ball, and waist. The data shows that the two groups of athletes have stronger cognition of shoulders, arms, and wrists and have the most gaze time. It shows that these three items are the main basis for athletes to judge where the tennis ball is. It can also be seen from the information in the figure that the national athletes pay more attention to these three parts than the athletes of the special class. In addition to this, the distribution of gaze to the ball, head, and upper torso was significantly less.

Attention must be paid to the athlete's subjective initiative to block, and in the process of practicing blocking skills, it is necessary to pay attention to the principle of gradual differentiation and the principle of overall coordination. It is also necessary to pay attention to various factors on the decision-making ability of volleyball players to block shots, recognize the shortcomings of athletes, and improve the refreshment function of athletes. The digital information system just supports the athlete's subjective position in the experiment, allowing the athlete to use the refresh function to respond to the decision in the interference situation. Descriptive data statistical analysis was performed on the study variables, and the differences in exercise levels were compared. The results are shown in Table 3.

Table 4: Correlation matrix of various variables.

	1	2	3	4	5	6
(1) Decision accuracy	1					
(2) Decision response time	−0.19	1				
(3) Decision response	0.13	−0.13	0.02	1		
(4) Inhibition reaction	−0.15	0.02	−0.07	−0.06	1	
(5) Conversion cost	−0.11	0.04	0.1	0.15	30**	1
(6) Exercise level	0.57**	0	1			

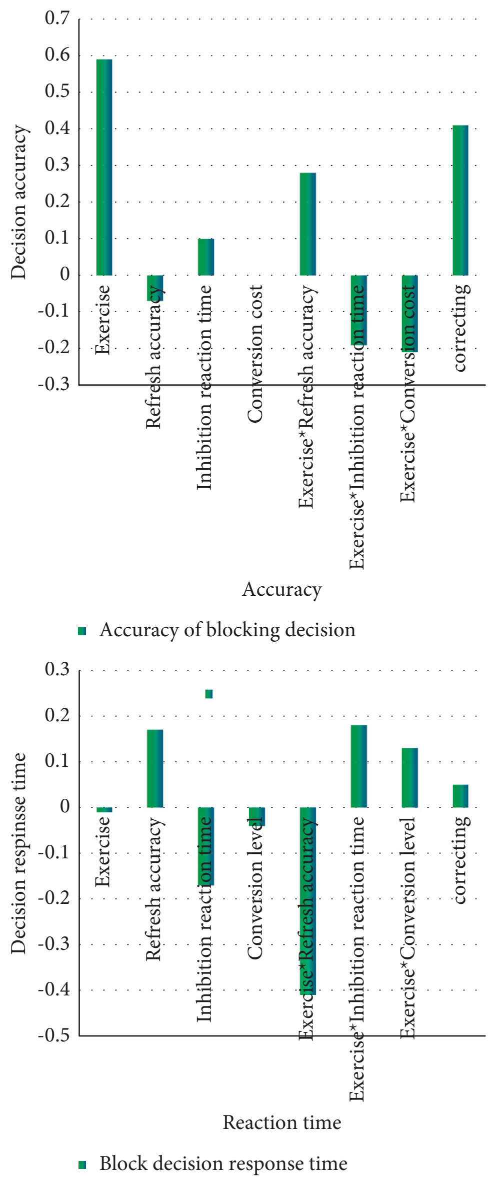

Figure 12: Comparison of regression analysis with block decision accuracy and reaction time variables.

The results showed that the correct rate of blocking decision-making of secondary volleyball players was significantly higher than that of selected volleyball players ($t = 6.40$, $df = 84$, $P < 0.05$); in the block decision reaction ($t = 0.03$, $df = 84$, $P = 0.97$), refresh correct rate ($t = -0.16$, $df = 84$, $P = 0.87$), inhibition reaction ($t = 0.62$, $df = 84$, $P = 0.54$), and the conversion cost ($t = -0.92$, $df = 84$, $P = 0.36$), there was no significant between-group difference in exercise level.

Correlation analysis was carried out on the variables of the study. The data showed that the sports level of the athletes had a great relationship with the decision-making accuracy, but the correlation with the decision-making response time was not significant, and the correlation with other variables was also not obvious. For second-level athletes, the refresh accuracy rate can intuitively and clearly predict the block decision accuracy rate. The higher the refresh accuracy rate, the higher the decision accuracy rate; for athletes in the low-level group, the refresh accuracy rate cannot predict the block decision accuracy rate. Comparing the two groups of athletes at different levels, it is obvious that the second-level athletes are more affected by the refresh function of decision-making accuracy, as shown in Table 4.

Regression analysis of blocking decision based on two sets of different variables is shown in Figure 12.

It can be seen from the figure that the block decision of the volleyball player by the refresh function is regulated by the sports level. Compared with high-level athletes and low-level athletes, the high-level athletes' block decision-making response was more affected by the refresh function. For low-level athletes, refresh accuracy does not predict the accuracy and response of their blocking decisions. The results all show that the national second-level long-distance mobilizers are better than the special class athletes in terms of blocking decision-making rate.

5. Discussion

In this article, through experimental comparison, we know that there are many methods of machine learning, which are widely used, and there are many methods that can act on volleyball. As an optimization search method, genetic algorithm has the characteristics of intelligence, process, robustness, and overall optimization. Through the application of artificial neural network and genetic algorithms in volleyball, this paper provides more effective methods for players to serve, land, and block volleyball and at the same time improves the players' prediction ability and accuracy.

6. Conclusions

This paper studies the impact of athletes' athletic level, decision-making accuracy, and decision-making response time, as well as the refreshment function and cognitive level of athletes on hitting, landing, and blocking during tennis. The higher the exercise level is, the less it is affected by other factors, the faster the reaction speed is, and the more accurate the judgment is. Executive function influences block decision-making in high-level volleyball players. Refresh, transform, and suppress functions play different roles in motor decision-making.

Data Availability

Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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