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Research Article

An Analysis Method of Exercise Load in Physical Training Based on Radial Basis Neural Network Model

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In the training process of professional athletes, to optimize the training plan and make the athletes play the best competitive state at a special time point, it is usually achieved by controlling the training load and active and effective recovery process. For the general public, daily exercise is mainly for physical fitness and physical rehabilitation. Whether it is a professional athlete or the general public, there are times when injuries occur during sports. The appropriate degree of exercise load varies from person to person. According to different sports, people's exercise suitability is also different. Therefore, it is meaningful to analyze and monitor the exercise load of the athlete during exercise. This paper proposes to use radial basis neural network (RBFNN) in the analysis of sports f-load of athletes. RBFNN is a kind of neural network that relies on error backpropagation for parameter adjustment, and its convergence speed is slow. When the data dimension is large and the amount of data is large, it will affect the classification accuracy of the data. For this reason, this paper integrates the gray wolf optimization algorithm (GWO) and RBFNN, and applies GWO to the initial value determination of weights and thresholds, which can effectively reduce the adjustment range of parameters and improve the accuracy of data classification. The model can more accurately analyze the exercise load state of athletes during exercise. The experimental results show that the high-quality heart rate data can be classified based on the model used in this paper, so that the exercise load state can be correctly judged. This has a good reference value for the analysis of exercise load during sports training and the next monitoring.

1. Introduction

How to assess appropriate exercise load during human exercise has long been a topic of interest in the field of sports science research [1]. To begin with, in the training process for professional athletes, optimizing the training plan so that the athletes can play in the best competitive state at a specific time point is usually accomplished by controlling the training load and active and effective recovery process. Although the final performance of athletes is related to their physical and psychological ability factors in the sports process, the ability gap between elite athletes is shrinking as information science advances. As a result, athletes must devote more time and energy to navigating these minor differences. Coaches must develop a more reasonable training plan and effectively evaluate the athletes' daily training load to understand the athletes' overall state [2]. The likelihood of sudden death during exercise is low for the general fitness crowd. Excessive load or a sudden increase in exercise load during exercise, on the other hand, has been shown in studies to cause accidental injury to the body and greatly increase the risk of cardiovascular disease. A small load, on the other hand, does not stimulate the body and cannot achieve the effect of body exercise. As a result, whether for professional athletes or the general public, the body can only produce a good adaptive response to improve sports performance or achieve the effect of physical fitness through long-term appropriate load stimulation [3]. As a result, scientific and effective evaluation of exercise load has become an important task of sports science research in the process of developing a training or exercise plan.

At present, the analysis methods and means of exercise load during exercise are continuously updated. Initially, exercise load assessment was performed through the athletes training log as well as a questionnaire. Questions recorded and surveyed were primarily athletes' self-reported feelings of fatigue. The follow-up gradually developed into an analysis method based on physiological indicators in the laboratory. Physiological indicators mainly include blood lactate, maximum oxygen uptake, heart rate, and so on. The most primitive training logs and questionnaires are relatively subjective and are greatly affected by factors such as individual differences and the subjectivity of athletes, so the analysis results are not very accurate. On the other hand, the exercise load analysis method based on physiological indicators has significantly improved in the analysis accuracy. However, the problem is that the athletes must be monitored in real time during the entire training cycle to adjust the exercise load and training content [4]. This will bring some inconvenience to the athlete. For example, the collection of blood samples is inconvenient and invasive, so sampling and monitoring are cumbersome. Combined with expensive monitoring equipment, it is an urgent problem to construct a reliable, easy-to-use, noninvasive and nonintrusive method to assess exercise load [5].

With the development of technology, researchers have found that the analysis of exercise load based on heart rate indicators meets the above needs. At present, many smart wearable devices can collect and monitor heart rate in real time. These sensing devices are inexpensive, easy to wear, and harmless to the body and can be purchased and used by both professional athletes and the general public. In terms of heart rate-based exercise compliance analysis, some studies have shown that the state of the autonomic nervous system can be monitored through post-exercise heart rate and other related indicators [4]. Other studies have shown that changes in exercise load can cause changes in the autonomic nervous system [6]. The above studies provide a more refined and comprehensive direction for the analysis of heart rate-based exercise load. To further accurately evaluate and analyze the exercise load, this paper uses an intelligent analysis model, that is, the radial basis neural network based on the gray wolf optimization algorithm (GWO-RBF), which is applied to the classification and identification of heart rate data during exercise. Based on the classification results, the state of exercise load is analyzed. The main work of this paper is as follows: (1) The importance of the analysis of exercise load to professional athletes and the general public; (2) An improved radial basis neural network is proposed for the analysis of exercise load. Specifically, the hybrid gray wolf optimization algorithm is integrated with the BP neural network, and the algorithm is applied to the determination of the initial values of weights and thresholds, which can effectively reduce the adjustment range of parameters and improve the classification accuracy of heart rate data. (3) To verify the performance of the proposed method, the experimental verification is carried out on the collected heart rate data set. The experimental results demonstrate the feasibility of the proposed method for solving exercise load analysis.

2. Relevant Knowledge

2.1. Definition of Heart Rate and Exercise Load. Heart rate is one of the most commonly used monitoring methods in both domestic and international sports training. By measuring the frequency of heartbeats, a linear relationship with exercise time, intensity, oxygen uptake, metabolism, and so on, is established to reflect the health status and exercise function of the human body. The load is controlled by the heart rate monitoring results, and the negative stimulation to the human body caused by the excessive load is avoided. Some researchers proposed as early as the mid-20th century that there is a linear relationship between heart rate and exercise intensity within a certain range. Some researchers have also confirmed that there is a strong relationship between maximum heart rate and maximum oxygen uptake. Resting heart rate, maximum heart rate, average heart rate, and heart rate recovery time are all common heart rate indicators. We can accurately assess the size of the exercise load using these indicators. Furthermore, heart rate variability can be used to track an athlete's recovery from fatigue (HRV). Many people regard HRV as a tool for measuring the body's response to training. HRV is a measure of the time difference between heartbeats that reflect the autonomic nervous system's function. As a result, it can accurately reflect body pressure. It is frequently used in athletic training to determine optimal training periods, monitor recovery status, and detect potential overtraining.

Exercise load refers to the physical load imposed on the human body, also known as an external load. The external load will lead to changes in human physiological functions. The load that human physiology can bear is called a physiological load, also known as an internal load. It is the physiological nature of physical exercise that the responsive changes in body function and structure are caused by appropriate external load stimuli. Load intensity is defined as the internal response caused by a certain amount of external load stimuli that the athlete's body is subjected to in a unit time or a continuous action. Some scholars divide exercise load into physiological, psychological, biochemical, and biomechanical loads according to the impact of exercise load on human function. Some scholars also divide exercise load into fitness load, teaching load, competition load, etc., according to the purpose of bearing load. The traditional training theory believes that exercise load is a kind of stimulus, which is composed of two factors: quantity and intensity. Load volume refers to the duration of the load and includes the total number of tasks performed during a single training exercise or series of exercises. Load intensity is the depth of stimulation to the body, such as the force value of a single exercise, the force of action, or the concentration of training workload at a certain time. Load volume and load intensity can promote the scientific level of sports training.

At present, people have begun to pay attention to physical fitness exercise, and national fitness has become a trend. All governments have pointed out that physical education and extracurricular exercises should be strengthened to promote physical and mental health and physical fitness of young people. The state requires that all school education should pay attention to the physical education of students and strengthen the physical exercise of students. Physical exercise means reaching a certain intensity of exercise. The exercise load that each individual can withstand is different. Exercise load will affect the quality of physical exercise to a large extent, so exercise load is an important indicator for judging exercise intensity and quality. Everyone's heart capacity is different, so based on people's heart rate data, sports activities with appropriate exercise load can be formulated.

2.2. Analysis Method of Exercise Load. In training science, exercise load is the cumulative stress of competition or training that an individual bears over a period of time [7]. According to the source of indicators for exercise load monitoring, exercise load has two classification forms: external load and internal load. The monitoring of external loads includes load monitoring based on on-site observation [8–10], GPS-based load monitoring [11–13], and video analysis-based load monitoring [14–16]. Internal load monitoring mainly includes load monitoring based on heart rate [17–19]; load monitoring based on blood, urine, and saliva components [20, 21]; load monitoring based on psychological questionnaires [22–24]; and load monitoring based on RPE scale [25–27]. Exercise load data collection was initially performed by recording training logs and filling out questionnaires. In contrast, training logs are much more frequent than questionnaires, basically at least once a day [28]. The data collected in this way are both a waste of energy and a waste of energy and have been criticized by people. A study in Reference [29] shows that 24% of trainers overestimate their training volume; 17% of trainers underestimate their training volume. It can be seen that this margin of error can seriously affect the training plan. Compared with collecting physiological index data to assess exercise load, using questionnaires to assess exercise load has lower reliability and validity [30]. Different questionnaires describe the questions in different styles, and different respondents have different understandings. In the process of filling out the questionnaire, some people will scribble randomly because they feel bored or impatient. All of these will affect the accuracy of the data collected by the questionnaire, resulting in a big difference between the final results and the actual situation. In conclusion, it is unreasonable to quantify exercise load during exercise based on training logs and questionnaires. With the development of science, such evaluation methods are gradually replaced by some objective physiological measurement indicators. Arguably, there is no "gold standard" for assessing exercise load [31].

3. Exercise Load Analysis Model

3.1. Grey Wolf Optimization Algorithm. GWO is an intelligent optimization algorithm that is widely used in a variety of fields due to its simple structure, fast convergence speed, and small number of parameters. The algorithm mimics the natural process of wolves hunting their prey. The three head wolves lead the gray wolf population in a continuous approach to the prey, culminating in an attack. The wolves are divided into four levels and have a strict hierarchy. Figure 1 depicts the hierarchical relationship:

Figure 1 depicts a pyramid shape. From top to bottom, there are four levels. The α wolf is the first level. The α wolf is the top leader of the wolf pack and the wolf with the best organizational and leadership skills. It is in charge of guiding the other wolves in decision-making, hunting plans, and food distribution. The second level is the β wolf, who is the α wolf's assistant and eventual successor. The β wolf is in charge of conveying the α wolf's orders and assisting the α wolf in making business decisions. The β wolf also serves as a conduit for the α wolf to communicate with the rest of the wolf pack. The δ wolf is the third level. It must carry out β and α wolves' orders and manage omega wolves. The δ wolf is the wolves' guardian, primarily in charge of keeping the wolves safe. The omega wolf is the fourth level. Omega wolves must obey orders and execute orders from their superiors, and they are an integral and important part of the wolf pack.

The gray wolf population moves according to the position of the first three rank wolves in the hierarchy shown in Figure 1 when hunting for prey. The gray wolf optimization algorithm abstracts the wolf pack's hunting, hierarchy, and movement rules into a mathematical model and abstracts the α, β, and δ wolves into three vectors representing the three wolves' current positions, respectively. Figure 2 depicts the hunting rules for the gray wolf population:

The hunt for wolves is divided into three stages:

3.1.1. Look for Prey. The wolves approach their prey gradually, and the position movement formulas are

$$H = \left|\mu \cdot X_p(t) - X(t)\right|, \tag{1}$$

$$X(t+1) = X_p(t) - \eta \cdot H. \tag{2}$$

Eq. (1) is the distance formula between the current wolf pack position and the prey position. In the formula, $X_p(t)$ is the position vector of the prey in t iterations. $X(t)$ is the position vector of the gray wolf population. μ is the coefficient, which the update formula is shown in Eq. (5). In the formula Eq. (2), η is the coefficient, and the updated formula of the coefficient is

$$\eta = 2\pi \cdot r_1 - \pi, \tag{3}$$

$$\pi = 2 - \frac{2t}{\text{maxiter}}, \tag{4}$$

$$\mu = 2r_2. \tag{5}$$

In Eq. (3) and Eq. (4), π is a coefficient that decreases linearly from 2 to 0, and Eq. (4) is the updated formula of π. Where *maxiter* is the maximum number of iterations. r, r_1, *and* r_2 are random numbers, and the value range is [0, 1].

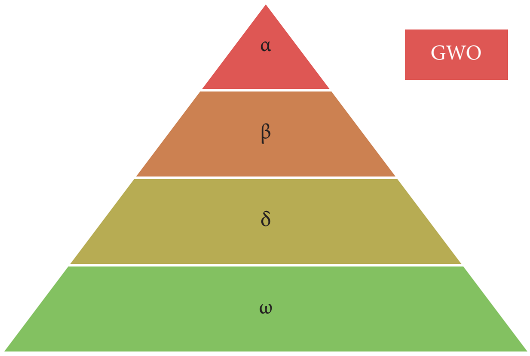

Figure 1: Wolves hierarchy.

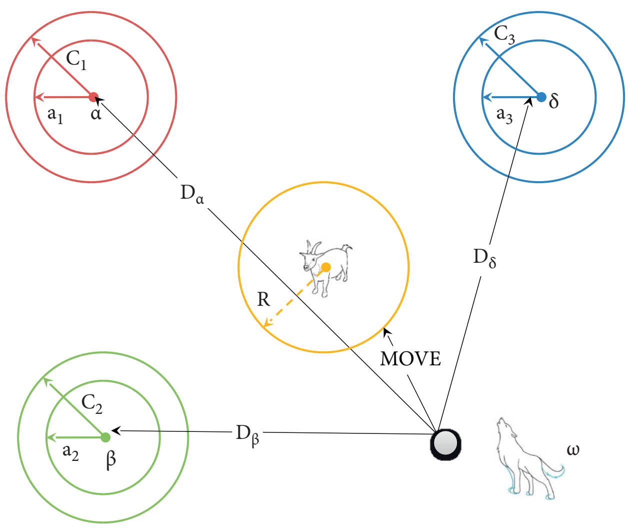

Figure 2: Gray wolf population hunting rules map.

3.1.2. Surrounding the Prey. The wolves move according to the positions of the three α wolves, β wolves, and δ wolves. The movement formula is shown in (6)–(12):

$$H_\alpha = \left|\mu_1 \cdot X_\alpha(t) - X(t)\right|, \tag{6}$$

$$H_\beta = \left|\mu_2 \cdot X_\beta(t) - X(t)\right|, \tag{7}$$

$$H_\delta = \left|\mu_3 \cdot X_\delta(t) - X(t)\right|, \tag{8}$$

$$X_1 = \left|X_\alpha(t) - \eta_1 H_\alpha\right|, \tag{9}$$

$$X_2 = \left|X_\beta(t) - \eta_2 H_\beta\right|, \tag{10}$$

$$X_3 = \left|X_\delta(t) - \eta_3 H_\delta\right|, \tag{11}$$

$$X(t+1) = \frac{1}{3}(X_1 + X_2 + X_3), \tag{12}$$

where α, β, and δ represent α wolf, β wolf, and δ wolf, respectively. $X_a(t)$, $X_\beta(t)$, and $X_\delta(t)$ are the position vectors of α wolf, β wolf, and δ wolf iteration t times, respectively. H_α, $H_{\beta,}$ and H_δ are the distances between the prey and the three wolves at t iterations. Eq. (12) represents the average position of the three ruthless wolves as the position of the wolves with $t+1$ times.

3.1.3. Attack the Prey. Typically, wolves attack their prey when it stops moving. It is known that the value range of π is between 0 and 2. η is constantly changing between $[-2\pi, 2\pi]$. When the value of η is $[-1, 1]$, according to Eq. (5), the next time the wolf pack position is updated, the wolf pack position will be between the current position and the prey. So when $|\eta| > 1$, the wolves will attack and start looking for new prey.

3.2. Selection of Radial Basis Function. Assuming that the input layer has n nodes, the input layer vector $X = \{x_1, x_2, \ldots, x_n\}$. The number of hidden layer neurons in RBFNN is h, and the activation function is $\varphi(x)$. There are k nodes in the output layer, then the output layer vector is $Y = \{y_1, y_2, \ldots, y_k\}$. Table 1 shows the commonly used radial basis functions.where ε is the radial base width and c is the center value. In this paper, the most commonly used Gaussian kernel function is selected as the radial basis function. The data are input to the hidden layer through the input layer, and after nonlinear transformation, it is output linearly through the output layer. The output results are as follows:

$$\begin{aligned} Y &= \sum_{j=1}^{h} w_j R_j(x), \quad j = 1, 2, 3, \ldots, h, \\ j &= 1, 2, 3, \ldots, h, \end{aligned} \tag{13}$$

where w_j is the weight.

3.3. Determination of Parameters. In addition to selecting the kernel function, the leaves of three parameters must be determined when training the radial basis neural network model: the radial basis width, the weight w, and the center value c. These parameters have a significant impact on the neural network model's efficiency and final accuracy.

3.3.1. Base Width Radial. The radial basis width is shown in Eq. (14) because the radial basis function is a Gaussian kernel function:

$$\sigma_j = \frac{H_{\max}}{\sqrt{2h}} . j = 1, 2, 3, \ldots, h, \tag{14}$$

where $H_{\max}$ is the greatest possible distance between the centers.

3.3.2. Weights. RBFNN selects weights using the minimum mean square error method, and the weight update calculation formula is as follows:

$$w_{k,j}(t+1) = w_{k,j}(t) + \gamma \frac{e_k(t)}{\left\|z_n\right\|^2}, \tag{15}$$

Table 1: Radial basis functions.

Function name	Calculation formula
Gaussian function	$\varphi(X) = \exp[-XX^T/\varepsilon^2]$
Inverse multiple quadratic function	$\varphi(X) = \exp[-1/(XX^T+\varepsilon^2)^{1/2}]$
Reflected sigmoid function	$\varphi(X) = 1/(1+\exp[XX^T/\varepsilon^2])$
Gaussian kernel function	$\varphi(X) = \exp[-\|X-c_j\|^2/2\varepsilon_j^2], \quad j = 1,2,3,\ldots,h$

where n is the number of input data, Z is the input vector of the hidden layer, and γ is a constant and takes value in [0,2].

The central value c is given by the K-means algorithm, and the specific process is as follows:

3.3.3. Center Value. The central value c is given by the K-means algorithm, and the specific process is as follows:

Suppose a set of data $X = [X_1, X_2, \ldots, X_n]^T$. This set of data is divided into k categories, and the data center of each category is $C = [C_1, C_2, \ldots, C_k]^T$. The closest distance is $D_{\min}$, and the Euclidean distance is used as the judgment basis. The Euclidean distance formula is

$$\operatorname{dist}(X, D) = \sqrt{\sum_{i=1}^{n}\left(X_i^t - C_j^t\right)^2}, \quad (16)$$

where X_i^t is the ith dimension component of the mth data in the dataset, and C_j^t is the tth dimension component of the jth center of the central dataset.

If the value of $\operatorname{dist}(X, D)$ is less than the nearest distance Lmin, put this data into the category where the nth center data are located. After all the data are classified, the average value of each center point is taken as the center point C.

3.4. GWO-RBF Model. Because traditional RBFNN has difficult-to-determine parameters, it affects the model's classification accuracy and adaptability. So, in this paper, GWO is applied to RBFNN to solve the problems mentioned above. The GWO algorithm's main concept is based on the hunting process of the parent, offspring, and mutant gray wolf populations. This is the optimization process in the mathematical model, and the result is the optimal solution. The GWO optimization algorithm is used to adjust the weights and center values of RBFNN, which improves the model's classification accuracy.

First, encode the weights and center values, and edit these two parameters into a multidimensional vector. Then, adjust the vector through Eq. (4)–(12). The mean square error is used as the fitness function. The vector value corresponding to the minimum error is found as the weight and center value of RBFNN. The process of GWO-RBF is shown in Figure 3:

The algorithm execution steps are summarized in the algorithm flow chart as follows:

Step 1: Encode all parameters that need to be optimized, with the first t components representing weights and the remaining $t+1$ to $t+n$ representing central value parameters.

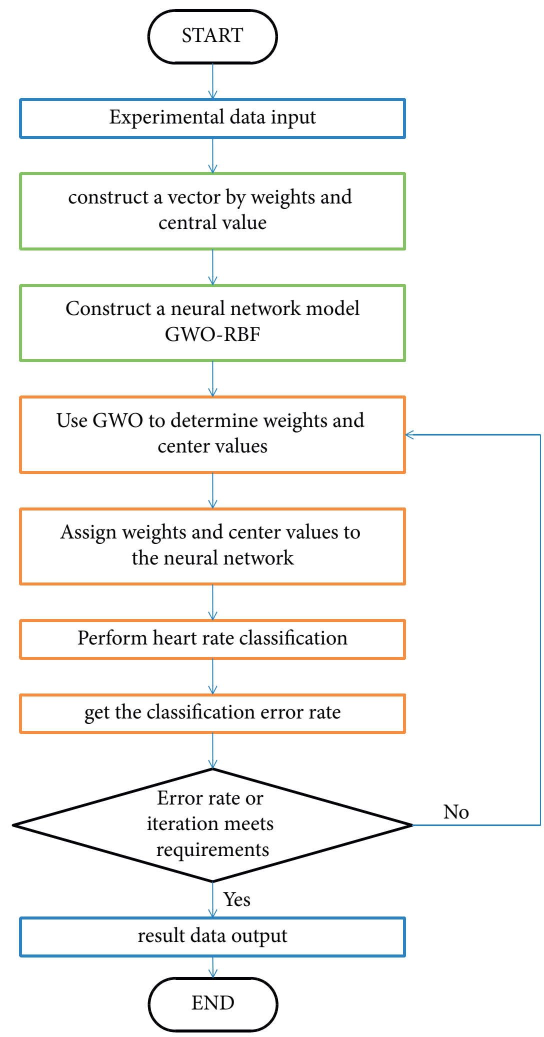

Figure 3: GWO-RBF process.

Step 2: Determine the RBFNN's structure. Determine the number of neurons in the input layer to be $t+n$, the number of neurons in the output layer to be 1, and the number of neurons in the hidden layer to be 1.

Step 3: Modify the value of wc following the GWO algorithm flow.

Step 4: Determine the fitness function value for each adjustment and use the mean square error as the fitness function.

Step 5: If the mean square error is less than 0.01 or the maximum number of iterations is 1000, the process is complete. Otherwise, return to step 3 to carry on with the execution.

Table 2: Questionnaire.

NO. 1 sport name:	Heart rate observations under different exercise intensities (bpm)		
	Mild	Generally	Severe
Test1			
Test2			
Test3			
NO. 2 sport name:	Heart rate observations under different exercise intensities (bpm)		
	Mild	Generally	Severe
Test1			
Test2			
Test3			
NO.3 sport name:	Heart rate observations under different exercise intensities (bpm)		
	Mild	Generally	Severe
Test1			
Test2			
Test3			
...			

Occupation	Age	Sex	Weight	Height

Table 3: Basic information of experimental subjects.

Object	College students		General athletic staff		Provincial athlete		National athlete	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Age(years)	20.12	±1.25	24	±2.36	17.23	±2.85	20.42	±3.68
Gender	Male:0.6	Female:0.4	Male:0.7	Female:0.3	Male:0.5	Female:0.5	Male:0.6	Female:0.4
Weight (Kg)	62.95	±3.54	59.76	±4.31	68.93	±4.90	71.31	±3.58
Height (cm)	173.02	±5.64	167.48	±6.34	176.93	±7.13	178.93	±6.53

4. Experimental Analysis

4.1. Experimental Design. To analyze the exercise load status of different objects during different sports, to better understand the exercise load that various groups can bear during sports training. First of all, this paper selects four types of objects: college students, general sports athletes, provincial athletes, and national athletes. Among them, there are 30 college students, 20 general sports personnel, 10 provincial athletes, and 5 national athletes. Second, collect the heart rate data of each subject when they are walking, jogging, fast running, sit-ups, playing badminton, and rowing. Finally, discrete wavelet transform and independent component analysis are selected as feature extraction methods, and Naive Bayes (NB), support vector machine (SVM), BP neural network(BPNN), and RBFNN are used as contrasting models.

Before collecting heart rate data, questionnaires were distributed to each experimental subject. The purpose was to understand the psychological feeling of each experimental subject's body under different exercise loads. The questionnaire is shown in Table 2:

After collecting the questionnaires of each subject, the basic information of the experimental subjects was obtained, as shown in Table 3.

4.2. Experimental Data and Analysis. To analyze the abnormal situation of people's exercise load when they perform various sports, the collected heart rate data are classified and processed. The evaluation index is classification accuracy. Its calculation formula is calculated by dividing the number of pairs of samples by the total number of samples. Generally speaking, the higher the accuracy, the better the model. The classification results are shown in Table 4 and Figure 4.

It can be seen from the above experimental results that for the above five classification models, the experimental results obtained by the feature extraction method based on discrete wavelet transform are better than those based on independent component analysis. For the five classification models of NB, SVM, BPNN, RBFNN, and GWO-RBF, the classification accuracy obtained by discrete wavelet transform is improved by 0.0301, 0.0099, 0.0172, 0.0143, and 0.0174, respectively, based on the independent component analysis. From the perspective of model classification performance, the experimental results obtained by GWO-RBFNN are the best. This is because the model fuses GWO with RBFNN. GWO intelligent population algorithm is used to adjust the parameters of RBF neural network weight and center value, which improves the classification accuracy of RBF. Among the remaining classification models, RBFNN has the best experimental results, which shows that the network is suitable for the classification of heart rate data, which is one of the reasons why this model is selected as the basic model in this paper.

The classification results of each sample can be obtained through GWO-RBFNN. For the wrongly classified sample, it means that the sample is abnormal. At this time, it is necessary to pay attention to the state of the athlete, whether the exercise load carried out at this time is not suitable for

Table 4: Experimental results.

Feature extraction method\model	NB	SVM	BPNN	RBFNN	GWO-RBF
Discrete wavelet transform	0.7873	0.8052	0.7928	0.8132	0.8326
Independent component analysis	0.7643	0.7973	0.7794	0.8017	0.8184

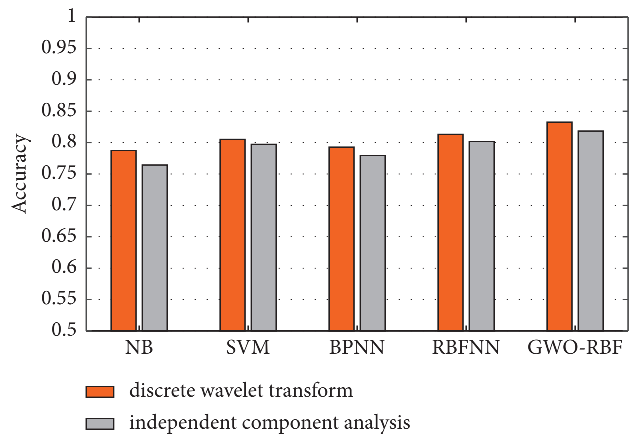

Figure 4: Comparison of experimental results.

the physical condition of the athlete. The significance of this study is to be able to judge whether the current exercise load of the athlete belongs to the normal and acceptable range of exercise load based on the heart rate data collected in real time. When the classification result is abnormal, it indicates that the state of the athlete is not good, and it is necessary to stop and check the physical state in time.

5. Conclusion

With the continuous evolution of the concept of exercise load, more scholars have begun to analyze the impact of exercise load on people's physical exercise process. Whether it is a professional athlete or the general public, it is meaningful to be able to understand their exercise load in real time and adjust their exercise plan in real time according to their characteristics. The monitoring and management of exercise load is a long-term and continuous matter. To improve the analysis efficiency of exercise load, this paper proposes a GWO-RBF model to apply the real-time heart rate collected during exercise. Compared with the traditional RBFNN, the model proposed in this paper applies the GWO optimization algorithm to the RBFNN and adjusts its weights and center values, thereby improving the classification accuracy of the RBFNN. The feasibility of this method is also verified by comparative experiments. In this paper, the exercise load analysis method based on the intelligent model abandons the disadvantages of the traditional questionnaire survey and other data collection methods. This approach makes the analysis of exercise load simpler and smarter. Exercise load analysis is the basis for exercise load monitoring and management, and the accuracy of its data is important. However, there are still some problems in this work. For example, the performance of the model depends heavily on the settings of the initial parameters and is sensitive to parameters. Moreover, the classification accuracy still needs to be improved, and it is best to reach 95% before it can be truly applied to the market.

Data Availability

The labeled data set used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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