Application of Training Load Prediction Model based on Improved BP Neural Network in Sports Training of Athletes

Lin Liu[1]
Department of Physical Education
Guilin Medical University, Guilin, 541004, China

Guannan Sheng[2]*
Faculty of Basic Medical Sciences
Guilin Medical University, Guilin, 541004, China

***Abstract*—With the enhancement of data mining technology, competitive sports informatization has become an inevitable development trend. It has become a common phenomenon to use data mining technology to help athletes train scientifically, assist coaches in rational decision-making, and improve team competitiveness. In competitive sports, cyclists' adaptation to training has a complex relationship with their physical performance. In order to explore the correlation between data and provide better training data for athletes, this study proposes a load prediction model based on BP neural network (Back propagation, BP). Considering the local convergence and random assignment of traditional BP model, an adaptive genetic algorithm with improved selection operator is used to determine the initial weights and thresholds of BP neural network to improve the accuracy of the prediction model. The experimental results show that the improved adaptive genetic algorithm improves the overall optimization ability of the BP neural network, the improved BP neural network model has good stability in the convergence process, and the algorithm can search for better weight thresholds. Compared with the basic BP neural network prediction model, the accuracy of the optimized prediction model is increased by 11.86%, and the average error value is reduced by 26.21%, which is a guide to improve the training effect of the cycling team's competitive sports.**

Keywords*—BP neural network; adaptive genetic algorithm; selection operator; training load

I. Introduction

In competitive sports, effective and scientific training is an important means to improve the performance of athletes. Athletes dedicate most of their professional training to improving fitness, competitiveness and self-confidence [1]. In particular, the physical fitness testing and evaluation of professional athletes, as well as the analysis of physiological and biochemical indicators, are of great significance for understanding the athlete's endurance, current physical fitness, and the scientificity and effectiveness of training interventions [2]. However, the traditional physical fitness index evaluation of athletes is mainly based on manual evaluation, and the accuracy is poor. Data mining is an interdisciplinary technique that can be used to analyze data and gain insights into specific problems [3]. Applying data mining technology to cycling, by analyzing the correlation between a series of physiological and biochemical indicators of cyclists, athletic ability indicators and athletes' training load levels, a cyclist training load prediction model is established , which not only helps coaches and athletes evaluate them in advance training readiness, while also assisting in training analysis and decision-making [4]. This study uses the information collected by the International Cycling Federation to develop a training load prediction model based on BP neural network. Since the BP neural network is nonlinear and easily trapped in local minima, this study uses an optimized adaptive genetic algorithm to determine the optimal initial weights and thresholds of the BP neural network to solve the problems associated with randomly assigning values [5]. Therefore, it is expected that the rationality of the training plan will be evaluated in advance to prevent adverse consequences for athletes due to unreasonable training plans. The research content can better ensure the safety and effect of athletes' training, and promote the progress of sports evaluation methods.

II. Related Works

Artificial Neural Network is an intelligent method for processing nonlinear relational data [6]. Due to its good adaptability, good nonlinear mapping and robustness, it is widely used in image processing, image recognition and other fields [7]. The BP network algorithm is simple, easy to implement, small in computation and good in parallelism. It is one of the most widely used and mature neural network algorithms. Because the fastest descending backpropagation method in the BP neural network is to correct the weights based on the negative gradient of the error function, it leads to problems such as low learning efficiency, slow convergence, and easy to fall into local miniaturization. [8]. Scholars at home and abroad have carried out the following researches on the shortcomings of BP neural network; Wu Jie and others. A BP network based on the improved particle swarm optimization algorithm is proposed. By adjusting the adaptability of the learning factor, the convergence speed of the BP neural network and the performance of the global optimal solution are improved. The simulation results show that the improved particle algorithm is better than the standard BP algorithm and particle swarm algorithm [9]. In order to improve the classification accuracy of ECG signals, Wang Li et al. the BP neural network is optimized using an additional momentum adaptive learning rate adjustment algorithm. The simulation results show that the improved BP neural network has better classification and recognition ability, and the accuracy rate of the whole sample classification is 98.4%. The optimization algorithm has fast convergence speed and high classification accuracy, which is helpful for the detection and diagnosis of heart disease [10]. Zhang D's team proposed that increasing the number of sample locations for training the BP network can improve the accuracy, and as the number of sample locations increases, the rate at which the fitting error decreases will decrease. The simulation results show that increasing the number of sample locations for training the BP neural network can improve the accuracy, and the fitting error decline rate decreases with the increase of the number of sample locations [11]. According to Cy A et al. the problem that BP neural network is easy to fall into the local minimum is solved. The empirical results show that the improved genetic algorithm is better than the traditional genetic algorithm in terms of convergence speed and prediction accuracy [12].

The BP network has in-depth applications in many complex scenarios, and its application in athletes' training provides an important reference for the improvement of athletes' physical and mental fitness. Chen W et al. found that clothing fatigue will affect the effect of sports. At present, there is little research on sports clothing. Therefore, based on the theory of BP and surface electromyography, they predicted the fatigue of athletes and built a prediction model. Finally, the experiment found that the model can provide technical support for athletes' training and development [13]. Zhang Y. et al found that with the arrival of information technology, sports data is becoming more and more important. How to collect human motion data is the key, so based on neural network and density peak clustering algorithm, a motion data model is constructed. After experimental verification, compared with the traditional principal component dimensionality reduction method, the proposed scheme can obtain better feature data, and the effect is better [1, 4]. Li T et al. found that the intelligent sports management system is beneficial to improve the overall training effect of the players, so they built a sports posture recognition model based on BP, and analyzed the motion feature extraction and experimental results. The final experimental results show that this scheme has better performance than other sports management algorithms, providing important data reference for the development of athletes [15].

Based on the above literature research, BP network is competent in many complex environments, and scientific and effective sports training is the key to ensure the level of sports competition. BP network has outstanding advantages in the field of diagnosis and prediction. Applying it to the field of sports training will provide significant help for effective sports training and promote the development of information technology in the field of sports.

III. Construction of Training Load Prediction Model based on Improved BP Neural Network

A. Design of Training Load Prediction Model based on BP Neural Network

Training is an important daily activity for athletes. Appropriate training can improve their competitive performance, but too much training can lead to injuries, and too little training will not achieve the desired training effect [16]. In this study, a BP network was used to design a training load prediction model for cyclists, which was optimized by an improved adaptive genetic algorithm to evaluate whether the athlete's training plan was reasonable. In cycling training load prediction, the cyclist's load level should be predicted from the athlete's basic physiological and biochemical data, exercise level goals, and exercise content to determine whether the currently planned training load is appropriate. The research required analyzing and processing the data and selecting relevant metrics before building a model to predict the training load of cyclists. The filtered data is divided into a training set and a test set, and the test set data is used to test the accuracy and performance of the full training model in predicting the training load of athletes. For athlete training load prediction, the study selected 25 factors that have an impact on training load based on the recommendations of professional cycling coaches, as shown in Fig. 1.

Exponential differences between the filtered parts of the data, they must be normalized before feeding them into the BP neural network. The core of normalization is to project all data to the same interval after the algorithm has run. The formula for the Min-max normalization process is shown in Equation (1).

$$X = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

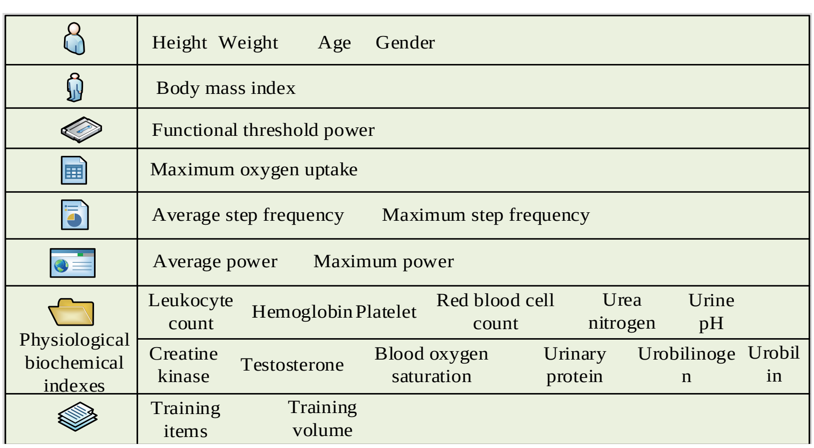

Fig. 1. Factors Affecting Athletes' Training Load.

In Equation (1), x_i denote the current value of these data, $x_{\max}$ and $x_{\min}$ denote the maximum and minimum values of these data, respectively, which are uniformly distributed in a certain interval after normalization. The number of input and output layers is fixed at one layer, while the hidden layer can have multiple layers. The number of neurons in the input layer is determined by the dimension of the input signal, and the number of neurons in the output layer is defined by the problem to be solved. Function. Through the iterative alternation of these two processes, the connection weights and thresholds of the BP neural network are continuously optimized. Suppose there are m training samples X , x_1, x_2 , ... x_m , the expected output is t_1, t_2 , ... , t_m , the actual output is y_1, y_2 , ... , , There are y_m neurons in the hidden layer . s After the activation function is transformed, the expression of the output of the th neuron in the hidden layer is shown in formula (2). i

$$a_i = f\left(net_i\right) = f\left(\sum_{g=1}^{n} w_{ig} x_g - \theta_i\right) \tag{2}$$

In formula (2), f represents the activation function, represents the neuron in the output layer, represents g the weight factor g from neuron w_{ig} to neuron i , and represents θ_i the threshold of the neuron. The output of neurons in the output layer is shown in formula (3). g

$$y_g = f\left(\sum_{r=1}^{m} a_r w'_{gr} - \theta'_r\right) \tag{3}$$

In formula (3), w'_{gr} is the connection weight between the hidden layer and the output layer, which θ'_r represents the threshold of the neurons in the hidden layer. Let $net'_g = \sum_{r=1}^{m} a_r w'_{gr} - \theta'_r$, convert equation (3) to equation (4).

$$y_g = f\left(net'_g\right) \tag{4}$$

The error function is shown in equation (5).

$$E\left(w,\theta\right) = \frac{1}{2}\sum_{g=1}^{m}\left(t_g - y_g\right)^2 \tag{5}$$

Equation (6) can be derived from equations (3) and (5).

$$E = \frac{1}{2}\sum_{g=1}^{m}\left(t_g - y_g\right)^2 = \frac{1}{2}\sum_{g=1}^{m}\left(t_k - f\left(\sum_{r=1}^{m} a_r w'_{gr} - \theta'_r\right)\right)^2 \tag{6}$$

The output layer is shown in equation (7).

$$\frac{\partial E}{\partial net'_g} = \frac{\partial E}{\partial y_g}.\frac{\partial y_g}{\partial net'_g} = \frac{\partial E}{\partial y_g}.f'\left(net'_g\right) \tag{7}$$

The implicit layer is shown in Equation (8).

$$\frac{\partial E}{\partial net_i} = \frac{\partial E}{\partial a_i}.\frac{\partial a_i}{\partial net_i} = \frac{\partial E}{\partial a_i}.f'\left(net_i\right) \tag{8}$$

If the error between the desired output and the neural network is too large, gradient descent is used to correct the weights of the layers of the network. The adjustment amount of the weight between the hidden layer and the output layer is $\Delta w'_{gr}$ shown in formula (9).

$$\Delta w'_{gr} = -\eta\frac{\partial E}{\partial w'_{gr}} = -\eta\frac{\partial E}{\partial net'_g}.\frac{\partial net'_g}{\partial w'_r} = \eta\left(t_g - y_g\right).f'\left(net'_g\right).a_r \tag{9}$$

The amount of weight adjustment from the input layer to the hidden layer is Δw_{ig} shown in formula (10).

$$\Delta w_{ig} = -\eta\frac{\partial E}{\partial w_{ig}} = \eta\sum_{g=1}^{m}\left(t_g - y_g\right)f'\left(net'_g\right)w'_{ig}\,f'\left(net_i\right)x_j \tag{10}$$

Since both the activation functions of the input layer and the output layer use this function, the $Sigmoid$ sum Δw_{ig} transformation is shown in equation (11). $\Delta w'_{gr}$

$$\begin{cases}\Delta w_{ij} = \eta\left(\sum_{g=1}^{m}\left(t_g - y_g\right)y_g\left(1 - y_g\right)w'_{ig}\right)a_i\left(1 - a_i\right)x_j \\ \Delta w'_{gr} = \eta\left(t_g - y_g\right)y_g\left(1 - y_g\right)a_r\end{cases} \tag{11}$$

In order to build a model for predicting the training load of athletes, it is first necessary to define the structure and covariates of the BP neural network, that is, the number of layers of the BP neural network, the number of neurons, the data set processed, and the selection of initial weights and thresholds.

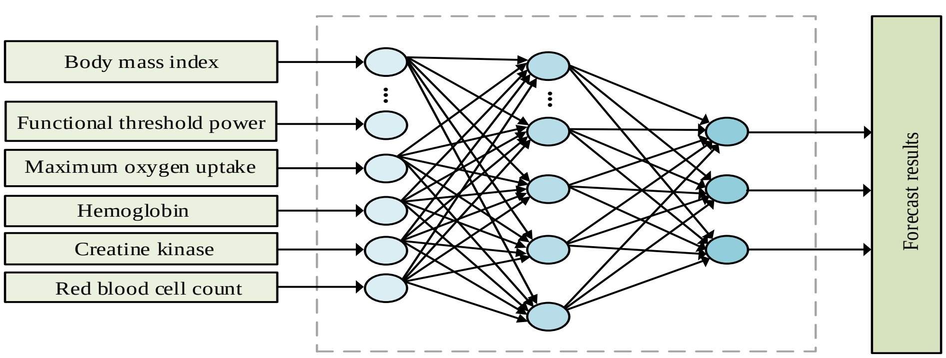

Fig. 2. The Topology of the Network Structure of the Training Load Prediction Model.

In Fig. 2, it can be seen that the structure of the BP neural network consists of an input layer, a hidden layer and an output layer, and the hidden layer can be composed of one or more layers. Since the three-layer BP neural network can approximate any continuous function in the closed interval, the basic three-layer hidden layer is selected as the basis for constructing the network prediction model. In the input layer, the input variables should not be highly correlated, and the input variables should significantly interfere with the output results.

Based on the above analysis of training load intervention factors, a total of 25 related factors were considered as input variables for the study, so the number of neurons in the input layer was set to 25. The prediction purpose of the model is to express the training load level of athletes through the training load results, which can be divided into too little training volume, moderate training volume and too much training volume. Therefore, the number of neurons in the output layer is determined to be three. The number of neurons in the hidden layer can be calculated according to formula (12), and then the optimal number of neurons in the hidden layer is determined by the trial and error method.

$$\begin{cases} n = \sqrt{ml} \\ n = \log_2 m \\ n = \sqrt{m+l} + a \end{cases} \tag{12}$$

In formula (12), n l and m represent the number of neurons in the hidden layer, the output layer and the input layer, respectively, which a is a constant and its value is in the interval $(1,10)$. Since $l = 3$, $m = 25$, the number of neurons in the hidden layer is in the range of [5, 15] above. Based on this, heuristics are applied to determine the number of neurons in the hidden layer. The number of neurons in the hidden layer is preset to five, and one neuron is added for each experiment. The prediction performance and convergence of the hidden layer with different numbers of neurons are compared in each experiment. The optimal number of neurons in the hidden layer is the final. The trial was determined to be 10.

B. Introducing an Improved Adaptive Genetic Algorithm to Optimize the BP Neural Network

Adaptive genetic algorithm is an improved genetic algorithm, which is characterized by automatically changing the probability of crossover and mutation based on chromosome fitness, reducing the possibility of crossover and mutation of individuals with high fitness, and improving the probability of crossover and mutation of somatic individuals, thereby increasing population diversity and retaining high-value chromosomes [17]. Since BP neural network is nonlinear, model convergence, occurrence of local minima and training time are closely related to the choice of initial weights and thresholds [18]. Initial weights and thresholds are usually randomly generated, and if not chosen properly, the network may not converge or may be constrained by local minima [19]. In order to better solve the random assignment problem of BP neural network, an improved adaptive genetic algorithm is used to find the optimal initial value and threshold of the network. Real encoding not only eliminates the need for decoding, but also facilitates the computation of genetic operations. Assuming a topological neuron network of 3-2-1, the number of weights and thresholds of the network used in the study is 293. In this neural network, the connection weights between the input and hidden layer neurons are W_{11}^1, W_{12}^1, W_{21}^1, W_{22}^1, W_{31}^1, , and W_{32}^1 the connection weights between the hidden layer and output layer neurons are W_{11}^2, W_{21}^2, between the hidden layer and output layer neurons The thresholds are θ_1, θ_2, θ_3. Both connection weights and thresholds are real numbers in the range 0 to 1. By ordering these weights and thresholds in order, $W_{11}^1 W_{12}^1 W_{21}^1 W_{22}^1 W_{31}^1 W_{32}^1 W_{11}^2 W_{21}^2 \theta_1 \theta_2 \theta_3$ real numbers can be encoded, and the resulting real numbers are chromosomes [20]. The BP neural network adjusts the weights and thresholds of the connections with the aim of minimizing the prediction error of the athlete's training load. The adaptive genetic algorithm applied in the study aims to find a set of weights and thresholds that minimize the prediction error, so the fitting function is negatively correlated with the sum of squares of the network output error, that is, the smaller the error, the greater the fit. The calculation of individual fitness is shown in Equation (13).

$$F(x) = \frac{1}{E(x)+1} \tag{13}$$

In formula (13), x represents the current chromosome, which $E(x)$ is the sum of the squared errors of the network output generated by the BP neural network using the current weight-threshold combination represented by the chromosome. For population selection, the roulette method is widely used due to its simplicity and convenience. However, roulette is used to randomly select individuals based on their fitness relative to the ensemble, which may result in individuals with high fitness being ignored. Although the main purpose of the optimization strategy is to select the best individuals from the population, only starting from the best individuals and discarding the individuals with universal fitness will eventually lead to the problem of homogeneous population structure, which is prone to local convergence phenomenon. This study improves the selection operator by introducing an optimal conservation strategy based on a sorted list selection method. The population is first initialized by sorting the individuals in the population from the lowest fitness to the highest fitness and equally dividing the sorted individuals into four parts, as shown in Fig. 3, steps 1-3 for improving the selection operator.

As can be seen from Fig. 3, each segment was selected at a ratio of 0.4, 0.6, 0.8 and 1, resulting in individual numbers of 0.4*5=2, 0.6*5=3, 0.8*5=4 and 1*5= 5. Since six individuals were lost during the selection process, starting from paragraph four, one additional individual was randomly selected at a time, resulting in a final number of six individuals. Insert the selected individual to the end of the individual selected in step 5 to form a new population, steps 4-7 are shown in Fig. 4.

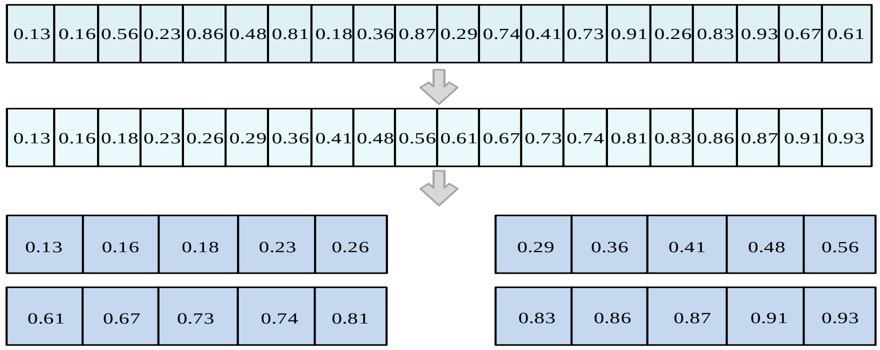

Fig. 3. Introduce the Best Preservation Strategy based on the Sorting List Selection Method to Improve the Selection Operator.

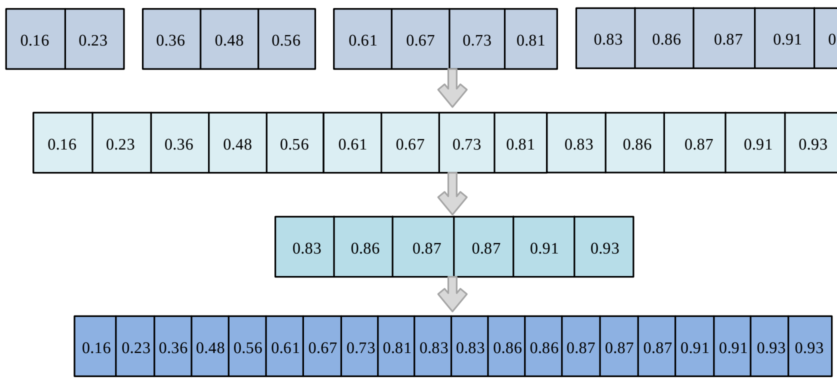

Fig. 4. Introduce the Best Preservation Strategy based on the Sorting List Selection Method to Improve the Selection Operator.

The improved selection operator ensures population diversity by retaining the best individuals and selecting others according to their size. It is also easy to operate because only the fitness is calculated and the best individuals are selected by basic operations like sorting, grouping and insertion. In contrast, the roulette method is computationally intensive because it requires first calculating the fitness of individuals, then calculating the proportion of individual fitness, and then solving for the selection probability. Therefore, improving the selection operator can theoretically improve the selection and convergence ability of the network. New individuals are generated by performing adaptive genetic algorithm operations on crossover and mutation between populations. In order to construct individuals with higher fitness, in the process of crossover mutation operation, the individuals to be processed are selected according to the crossover mutation rate. The crossover rate is ρ_c shown in Equation (14).

$$\rho_c = \begin{cases} \rho_a - \dfrac{(\rho_a - \rho_b)(f - f_{avg})}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ \rho_a, f < f_{avg} \end{cases} \tag{14}$$

In equation (14), $\rho_a = 0.9$, $\rho_b = 0.6$. f represents the current individual fitness, $f_{\max}$ is the maximum fitness of all individuals in the population, and is f_{avg} the average fitness of all individuals in the population. The rate of change is ρ_m shown in equation (15).

$$\rho_m = \begin{cases} \rho_i - \dfrac{(\rho_i - \rho_j)(f_{\max} - f)}{f_{\max} - f_{avg}}, f \geq f_{avg} \\ \rho_i, f < f_{avg} \end{cases} \tag{15}$$

In equation (15), $\rho_i = 0.1$, $\rho_j = 0.001$. IAGABP is an optimized BP neural network algorithm based on an improved adaptive genetic algorithm. It is divided into a genetic algorithm part and a BP neural network part. The specific flowchart of the algorithm is shown in Fig. 5.

As shown in Fig. 5, in the genetic algorithm part, N chromosomes are randomly generated through real-value coding to form the initial population of the algorithm, and the fitness of the entire population is improved through continuous genetic operations until the algorithm terminates in the population after several generations. After the evolution in the BP neural network, the network structure and other parameters are solved first, and the optimal individual in the genetic algorithm is decomposed into a series of initial values and thresholds of the BP neural network. Finally, the network is weighted and thresholded using error backpropagation until the initial error of the network reaches the final state, which constitutes the final model of the BP neural network.

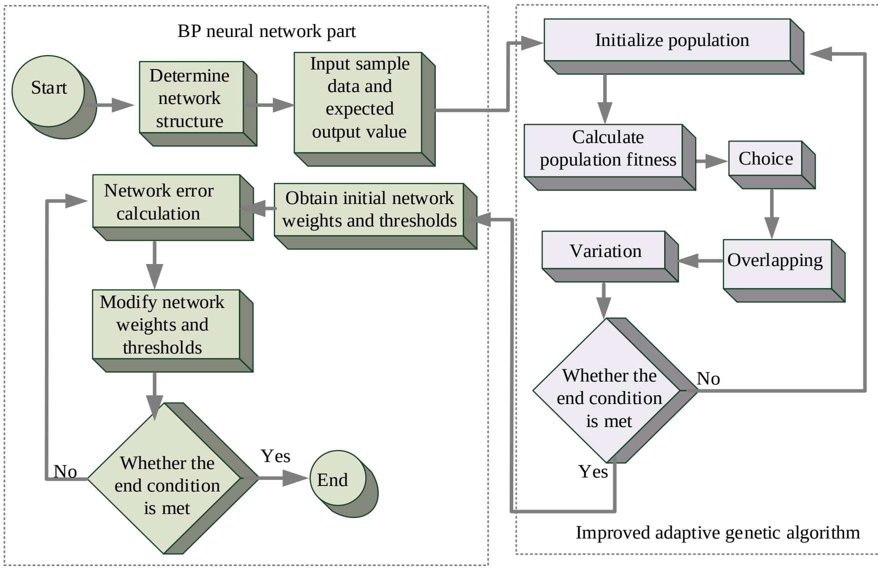

Fig. 5. BP Neural Network based on Improved Adaptive Genetic Algorithm.

IV. Four Prediction Performance Test of BP Neural Network Model based on Improved Adaptive Genetic Algorithm

An improved adaptive genetic algorithm was applied to a BP (Improved Adaptive Genetic Algorithm Back Propagation, IAGABP) neural network to create a predictive model of cyclist training load. The performance of the proposed optimization model is compared with the traditional BP neural network model and the traditional neural network model based on Adaptive Genetic Algorithm Back Propagation (AGABP). The topology of the BP neural network is set to 25-10-3, the target accuracy is 0.001, the maximum number of iterations is 1000, and the learning rate is 0.1. The initial population size of the genetic algorithm is 40, the maximum evolutionary generation is 25, and the prediction results are divided into overtraining, medium training and undertraining. The 5000 pieces of exercise training data recorded are selected as the training sample set, and the other 1985 pieces of training data are used as test samples. The comparison of the error accuracy between the BP neural network model and the IAGABP model is shown in Fig. 6(a), and the comparison of the fitness between the AGABP and IAGABP models is shown in Fig. 6(b).

From Fig. 6(a), it can be seen that the IAGABP model achieves the target accuracy of 0.001 after about 480 iterations, while the BP network model achieves this target accuracy after about 1000 iterations. The IAGABP model exhibits significant advantages and stability in the convergence process. This is because the improved genetic algorithm can obtain better initial weights and thresholds, thereby reducing the time spent by the BP neural network in the process of finding the optimal solution. It can be seen from Figure 6(b) that the fitness of the AGABP model is still unstable after 15 generations of evolution, while the fitness curve of the IAGABP model is gradually stable after 14 generations. The optimal chromosome fitness of the IAGABP model is compared with that of AGABP. improved by 0.24. The results show that the group search performance of the adaptive genetic algorithm can be improved by improving the selection operator to obtain a better weight threshold.

In deep learning, the loss function curves of the three models trained on the dataset are shown in Fig. 7. The loss function of the AGABP model drops at the fastest speed, and after 20K training steps, its loss function drops rapidly to within 100. The curves of the AGABP model and the IAGABP model are basically the same, and the loss function fluctuates smoothly after 100K steps and remains in the range of 80-100. The loss function of the BP model decreases more slowly, within 120 after 60K steps, and the function value fluctuates between 100 and 110. To sum up, the curve of the IAGABP model is smooth and has good stability and accuracy. The precision-recall curves of the three models are shown in Fig. 8.

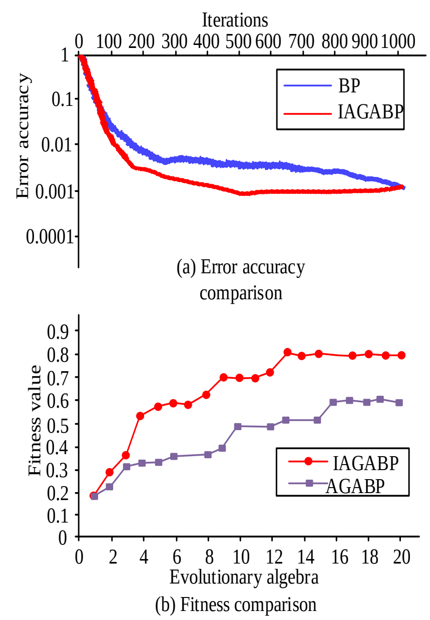

Fig. 6. Performance Test Comparison of Different Models.

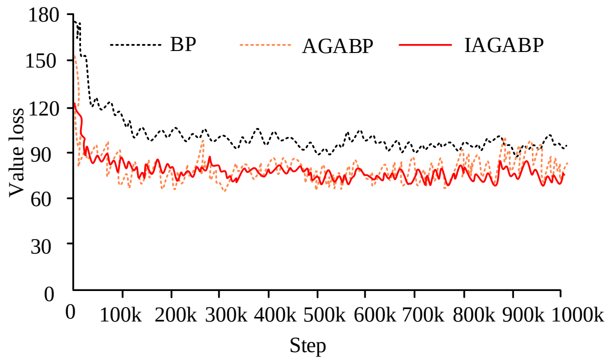

Fig. 7. Loss Functions for Different Models.

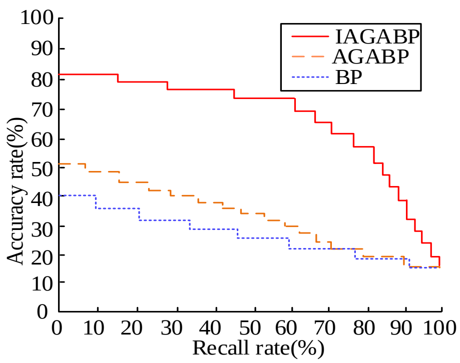

Fig. 8. Precision-Recall Curves for Different Models.

The precision-recall curve can be used to reflect the performance of the model on the task of retrieving similarity. It can be seen from Fig. 8 that the accuracy of the model decreases as the recall rate increases, in which the model IAGABP decreases at the slowest speed in the recall rate interval of 0-70%, and as can be seen from the figure, in this region the precision-recall curve of the model IAGABP is significantly larger than the other two models. This shows that the model IAGABP has the highest accuracy on the similarity search task on the same dataset. The prediction results of the three models based on 2486 test samples are shown in Fig. 9.

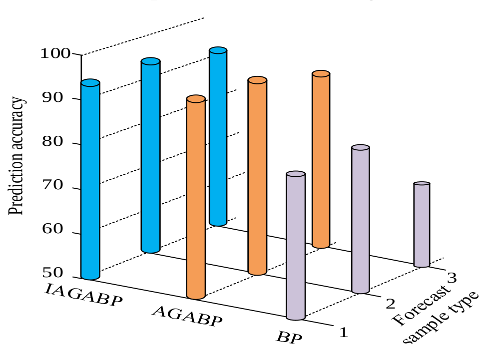

Fig. 9. Prediction Results of the Three Models.

The first type of prediction samples is the accuracy of a small number of trained test samples, the second is the accuracy of a moderately trained test sample, and the third is the accuracy of a large number of trained test samples. From the results in Fig. 9, it can be seen that the AGABP model improves the prediction accuracy by 9.55% compared with the BP neural network model. On the other hand, the IAGABP model with the improved selection operator is 2.31% more accurate than the AGABP model. This shows that the BP neural network optimized by the improved genetic algorithm is superior to the traditional BP neural network in terms of prediction accuracy and performance, and meets the requirements of athletes' training load prediction.

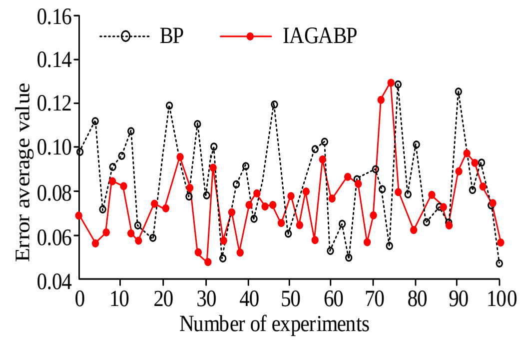

Fig. 10. Average Experimental Error.

In terms of fitting effect and prediction accuracy, the BP neural network based on the improved adaptive genetic algorithm has greatly improved the prediction accuracy. To further evaluate the predictive validity of the model proposed in the study, the study derives the average error of the model using 100 iterations, as shown in Fig. 10. It can be seen that the average error of IAGABP prediction is lower than that of BP neural network which is 0.0867, while the average error of BP neural network is 0.1175.

A comprehensive comparison of the above results shows that the improved IAGABP model has obvious improvements in error accuracy, model accuracy and prediction accuracy compared with the traditional BP model and the AGABP model. Compared with the traditional artificial exercise load index evaluation scheme, its innovation lies in that the IAGABP model is based on more advanced intelligent neural network technology, and performs secondary optimization on the basis of the traditional BP model, avoiding the local convergence of traditional BP and exercise monitoring data. The IAGABP model can realize real-time and effective detection of the physical and mental state data of athletes. At the same time, the relevant monitoring data will be analyzed and diagnosed through the network big data technology to provide athletes with more scientific physical training skills and opinions, avoid physical injuries to athletes, and improve the effect of sports training.

V. Conclusion

With the development of big data, many sports are using data mining technology to determine the relationship between athletes' training load and physical fitness, which provides new opportunities for the development of national cycling events. Competitive sports informatization has become an inevitable development trend. Since many factors intervening in the relationship between athletes' training load and physical fitness show nonlinear relationship, this study designed a training load prediction model based on BP neural network as the basic algorithm. In order to further improve the accuracy and convergence of the BP network prediction model, this study uses the adaptive genetic algorithm to optimize the initial value and threshold of the BP network, and improves the selection operator of the adaptive genetic algorithm. The results show that the BP neural network model based on the improved adaptive genetic algorithm has significant advantages and stability in the convergence process, and the algorithm can search for better weight thresholds. The accuracy rate of athletes' training load prediction is 95.76 %, the average error is 0.0867, which is 11.86% better than the standard BP neural network model, and the average error is 26.21% lower. This meets the requirements of athletes' training load prediction. This study can establish a scientific and reasonable bicycle training load prediction model based on the actual physical condition of non-professional groups, and provide an important reference for scientific sports training. However, there are also shortcomings in the research. Only the indicators of exercise routine training are considered, and the training environment, such as temperature and altitude, is not considered.

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