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Research Article

Analysis and Research on the Impact of Physical Exercise on Residents' Health Based on the Improved BP Neural Network Model

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With the rapid improvement of social economy and the enhancement of people's health awareness, it is necessary to make an in-depth analysis of the rationality of physical exercise and the physical quality of residents. Hence, this study aims to explore the algorithm optimization of the improved BP model to analyze the effect of exercise intervention on improving public sports effect. *K*-clustering and Levenberg–Marquardt algorithm were used to construct an improved BP neural network model to determine the sample clustering center, as well as the weight and threshold of the indicators, so as to optimize the analysis algorithm of improving public sports effect. MATLAB simulation shows that under the target error conditions of 0.01, 0.005, 0.001, and 0.0001, the target error rate and iteration times of the improved BP model are better than the standard BP model, and the time consumption is shorter, which can be conducive to more accurately analyzing the changes of improving public sports effect under exercise intervention. Therefore, the improved BP model can effectively solve the problems of data clustering and result error rate adjustment in the process of improving public sports effect analysis and improve the analysis speed and accuracy.

1. Introduction

As important evaluation content in exercise intervention, improving public sports effect is the guarantee of exercise effect and affects the continuous exercise. In this case, it is of great practical significance to construct a reasonable evaluation model of improving public sports effect and correctly predict the situation of exercise intervention to ensure the sports effect of patients and reduce sports injury. During the course of empirical research on exercise intervention abroad, it has experienced the development process from the establishment of univariate model to multivariate model, from general model to single-phase exercise model. The influence of physical exercise on residents' physical quality has the characteristics of persistence and intensification, so it is necessary to carry out physical exercise reasonably. How to do physical exercise better has become the focus of research at present. Compared with other methods, BP neural network algorithm is intelligent, can realize the analysis of massive data, and is suitable for physical exercise and the study of residents' physical fitness.

2. Literature Review

The research of exercise intervention model in China began in the late 1990s. Akifumi used statistical judgment analysis [1], Gaojie used logistic regression analysis [2], Isao used principal component analysis [3], and Isao et al. used artificial neural network [4] to establish the metabolic effect prediction model for exercise intervention. However, the prediction of improving public sports effect related to exercise intervention is rarely involved. Due to the great difference of exercise intervention between patients with different physical fitness and obvious individual characteristics, the accuracy of prediction using general model is bound to be affected. The standard BP neural network model is the main algorithm of improving public sports effect analysis, but its speed is slow, its accuracy is low, it is unable to accurately determine the cluster number and center point of sample data, and the hidden layer weight and threshold value lack effective adjustment. Some scholars suggest that the neural network model should be improved by integrating classification, clustering, and chaos algorithm to improve the calculation accuracy of the neural network model. Some scholars believe that the combination of various algorithms can comprehensively analyze the effect of physical exercise and reduce the influence of secondary influencing factors on residents' physical fitness. In addition, physical exercise involves many contents and presents a massive development trend. The fusion of various algorithms can improve the processing capacity of single data, shorten the calculation time of residents' physical fitness, and provide more accurate measures for relevant departments. The research results in recent years are shown in Figure 1.

Through the above analysis, we can see that physical exercise for residents' physical fitness research has become a hotspot and has a rapid development trend. Therefore, it is of great practical significance to strengthen the research on physical exercise and analyze its influence on residents' physical quality. In this paper, the BP neural network model is improved, which can more accurately determine the amount and center of clustering and iteratively adjust the hidden layer weight and threshold value, so as to improve the accuracy and speed of improving public sports effect rate analysis. From the current domestic actual situation, most of the data are studies on improving the effect of public sports, but there are few data on sports interventions for research subjects, it is difficult to obtain modeling data, and exercise intervention caused more disease. Therefore, this paper takes exercise intervention as the research object, uses the artificial neural network algorithm to study the improvement of public sports effect of exercise intervention from an empirical point of view, and intends to establish a set of scientific and practical analysis model for improving public sports effect rate.

3. Algorithm

3.1. BP Neural Network Description. Artificial neural network is a nonlinear system which is widely connected by a large number of neurons similar to the natural neural system to simulate the way of thinking of human brain. It has the characteristics of self-organization, self-adaptation, self-learning, and so on. At the same time, it has the advantages of easy learning and influence and has a unique function in dealing with the relationship between variables that affect each other, restrict each other, and have complex cross-effects and effects. It shows its superiority in the modeling of complex system and achieves good application effect in prediction and evaluation. Improving public sports effect in the process of intervention is affected by many factors, but the functional relationship of each factor is difficult to define, which belongs to a complex nonlinear system problem. Therefore, artificial neural network can be used to predict

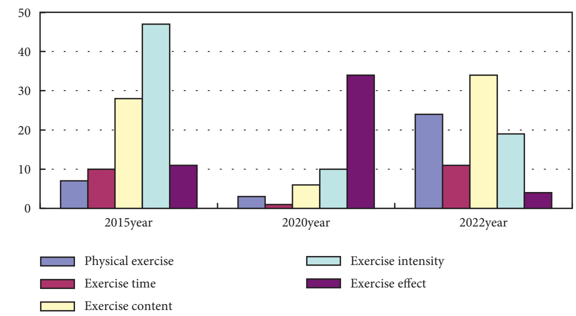

Figure 1: Research situation of physical exercise.

improving public sports effect. BP network is one of the most widely used network types in ANN technology. Compared with the traditional statistical analysis model, BP network has better fault tolerance and adaptability and is most suitable for prediction, classification, and evaluation. In this paper, the backpropagation algorithm of BP neural network is used to study the improvement of public sports effect, and it is realized by MATLAB. The first layer of the network model is the input layer, the middle layer is the hidden layer, and the third layer is the output layer. The results show that the artificial neural network algorithm based on improving public sports effect index information is an effective algorithm for enterprise improving public sports effect prediction. The prediction of improving public sports effect based on artificial neural network uses nonlinear function to better fit the data, which realizes the innovation of the algorithm. In the future research, we will try to introduce indicators and non-motion indicators (clinical medical indicators, historical records, etc.) to build a more comprehensive variable group. At the same time, we will further study how to build a self-learning evaluation system for improving public sports effect under exercise intervention based on neural network, so as to improve the applicability of improving public sports effect prediction.

3.2. Determining the Input Index of the BMD Evaluation Model. Observation and prediction are very important work in the evaluation of mass sports index under exercise intervention. They play a very important role in the implementation, planning, and control of exercise intervention. Firstly, accurate prediction of improving public sports effect can help dispatchers arrange the start-up and shutdown of generator units economically and reasonably and arrange the rotating standby equipment reasonably, so as to minimize the power generation cost within the safe operation range of the system. Secondly, accurate observation and prediction must be the premise for energy exchange and reasonable observation and distribution among different systems. The observation of mass sports is a very complex problem, which involves many factors. It is not only closely related to the observation characteristics and power consumption structure of exercise intervention itself, but also closely related to the differences of regional economic development and weather. Improving public sports effect is a periodic nonstationary random process, including normal observation with relatively stable changes and observation with changes disturbed by random factors. In order to improve the accuracy and practicability of improving public sports effect prediction, people have done a lot of research work and put forward many models and algorithm of observation and prediction, such as time series algorithm and regression analysis algorithm. However, the relationship between observation and weather variables is not static but depends on the factors of space and time. Due to the limitation of its "knowledge bottleneck," expert system is still not very successful. Artificial neural network is considered as the most promising new algorithm for improving public sports effect prediction because it can continuously learn new knowledge, can deal with very complex nonlinear relationship, and has high robustness. Based on the analysis of the change rule of observation, this paper establishes a 24-hour observation model which is constructed separately according to the date type and effectively deals with the influencing factors. The example is predicted, and good results are obtained. In this study, the characteristic parameters related to exercise intervention and improving public sports effect were selected as input independent variables: chronic diseases chance x_1 (unit: none), expenditure on social and public health x_2 (unit: H), public sentiment improvement rate x_3 (unit: %), and observer chronic diseases chance/public sentiment improvement rate x_4. The value range and unit of the characteristic parameters of the independent variables are different and need to be standardized; the result is shown as the following formula:

$$\begin{cases} Z_{ij} = x_{ij} - \dfrac{\overline{x}_j}{\sqrt{s_{ij}}}, \\ \overline{x}_j = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} x_{ij}, \\ s_{ij} = \dfrac{1}{N-1}\displaystyle\sum_{i=1}^{N}\left(x_{ij} - \overline{x}_j\right)^2, \end{cases} \quad (1)$$

where M is the number of parameters, N is the number of samples, Z_{ij} is the amount of x_{ij} after treatment, $\overline{x}_j$ is the average of x_{ij}, and s_{ij} is the variance of x_{ij}.

3.3. Improved K-Means Algorithm. Throughout the published literature, there are several types of classification: ① the seven days of a week are divided into two types: working days and rest days; ② the week is divided into five types: Monday, Tuesday to Thursday, Friday, Saturday, and Sunday; ③ the seven days of a week are regarded as one type, with a total of seven types; the classification results are shown in Figure 2.

In this paper, we use the third mode of observation division, with each day as a different type. In the day before the prediction day, BMD was measured every other day (Masafumi [5]). A total of 24 groups of observation data were measured in one day. Since there is no sudden change between the adjacent points of the observation curve, the value at the later time must be related to the value at the previous time (unless there is a special case). Therefore, the real-time observation data of the previous day is taken as the sample data of the network (Isao et al. [6]). K-means algorithm is used to cluster according to the sum of squares error (Yu et al. [7]), and its similarity is Euclidean distance, but it has two shortcomings. On the one hand, it is necessary to set the number of categories K before the analysis; on the other hand, it is necessary to set the initial clustering center point before the subsequent clustering analysis. In view of the above shortcomings, this paper uses the contour coefficient S_t to determine the k value and then determines the initial clustering center by dividing the performance index equally P_E. S_t is shown as the following formula:

$$\begin{cases} S(i) = \dfrac{p(i) - q(i)}{\max\{q(i), p(i)\}}, \\ S_t = \dfrac{1}{N}\displaystyle\sum_{i=1}^{N} S(i), \end{cases} \quad (2)$$

where i is the average distance between any sample point, $q(i)$ is the point of i in the cluster, and $p(i)$ is the minimum distance between i and other points in the noncluster. At the same time, the mass sports index P_E is shown as the following formula:

$$P_E = \sqrt{\sum_{j=1}^{m} \omega_j\left(Z_{ij} - \min\left(Z_{ij}\right)\right)^2}, \quad i = 1, 2, \ldots, N. \quad (3)$$

Among them, ω_j is the weight of the jth characteristic parameter, the sum of which is 1, Z_{ij} is the cluster sample, $\min(Z_{ij})$ is the cluster center of sample i, and P_E is the Euclidean distance between the characteristic parameter vector of sample i and the minimum characteristic parameter vector which reflect the change trend of improving public sports effect rate. The initial cluster center can be determined by arranging the results in ascending order, and P_E was divided into k equal parts. In order to verify the accuracy of the above mathematical description, the data described by mathematics are fitted and analyzed, and the results are shown in Figure 3.

3.4. Improved BP Neural Network Model Construction. BP neural network realizes the mapping function from input to output, which can solve the complex nonlinear mapping problem. It has the self-learning ability and has been widely used in clinical medicine and sports. The BP neural network learning algorithm is mainly gradient descent algorithm, which can easily make the network fall into local minimum points, which can easily cause the network not to get the optimal solution at last. At the same time, the BP neural network learning algorithm is also improved in recent years; through the research of many experts and scholars, many improved BP algorithms have been proposed, such as adding

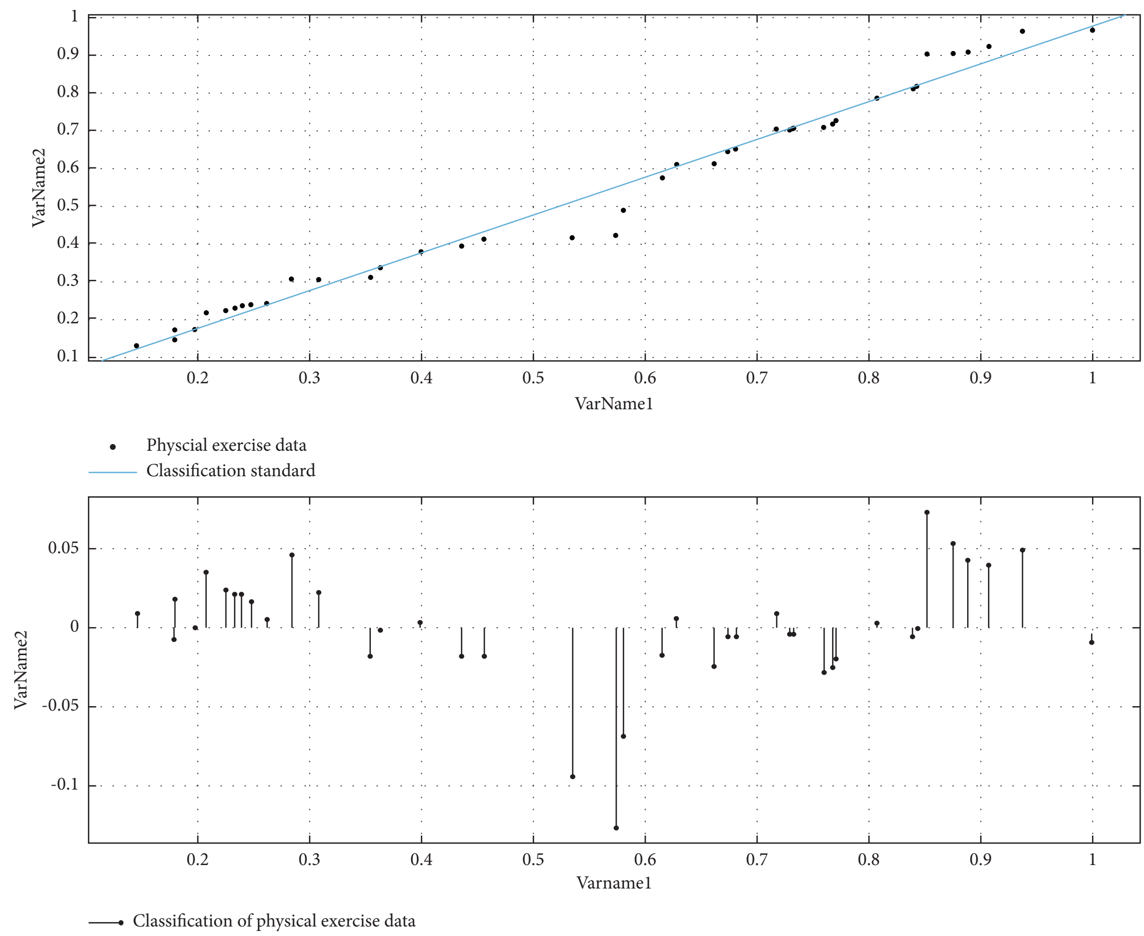

Figure 2: Classification of physical exercise.

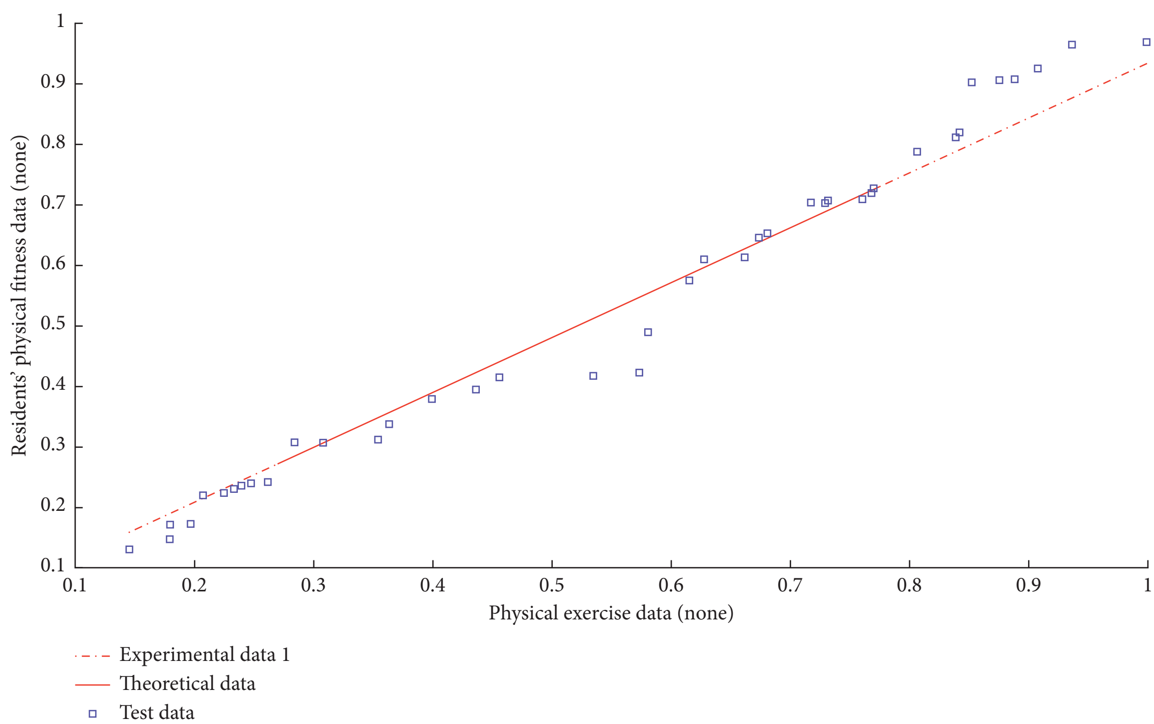

Figure 3: Test results of sample data.

momentum term, introducing inertia term, and L-M BP neural network algorithm.

First is the standard BP neural network model. Fuzzy neural network is the combination of fuzzy set and neural network, using the ability of fuzzy system to deal with uncertain information and the strong learning ability of neural network; the two complement each other and fuse each other. This paper introduces the combination of T-S model and artificial neural network, namely T-S neural network. The input and output signals of fuzzy system are expressed through the input and output nodes of the neural network model. The BP model is divided into input layer, hidden layer and output layer, hidden layer, and output layer (Iwamoto [8]); data analysis is completed by forward and backward signal propagation. In the process of back-propagation, the adjustment of the weights and thresholds of the neurons in the hidden layer directly affects whether the feedback error meets the requirements, so it is necessary to carry out adjustment, that is, multiple iterations.

Hypothesis influence sample is $x_r = (x_1, \ldots, x_m)^T$, hidden layer vector is $Y_r = (Y_1, \ldots, Y_n)^T$, output layer vector is $O_r = (o_1, \ldots, o_l)^T$, and expectation vector is $D_r = (d_1, \ldots, d_l)^T$. The weight between the input layer and the hidden layer is $w_{ij} = (i = 1, \ldots, m; j = 1, \ldots, n)$, and the threshold is $b_{ij} = (i = 1, \ldots, m; j = 1, \ldots, n)$; the weight between the hidden layer and the output layer is $w_{jk} = (j = 1, \ldots, n; k = 1, \ldots, l)$, and the threshold is $b_{jk} = (j = 1, \ldots, n; k = 1, \ldots, l)$. The forward propagation of BP neural network is shown as the following formula:

$$\begin{cases} y_j = f\left[\sum_{i=1}^{m}\left(w_{ij}x_i + b_{ij}\right)\right], & j = 1, \ldots, n, \\ o_k = f\left[\sum_{j=1}^{p}\left(w_{jk}y_i + b_{jk}\right)\right], & k = 1, \ldots, l. \end{cases} \tag{4}$$

The output error e is the distance between the output vector O and the expected vector p, and the analysis is shown as the following formula:

$$\begin{aligned} e &= \frac{1}{2}(D - O)^2 = \frac{1}{2}\sum_{k=1}^{l}\left(d_k - f\left[\sum_{j=1}^{p}\left(w_{jk}y_i + b_{jk}\right)\right]\right)^2 \\ &= \frac{1}{2}\sum_{k=1}^{l}\left(d_k - f\left[\sum_{j=1}^{p}\left(w_{jk}f\left[\sum_{i=1}^{m}\left(w_{ij}x_i + b_{ij}\right)\right] + b_{jk}\right)\right]\right)^2. \end{aligned} \tag{5}$$

Different input vectors get different output values, so that the group of weight coefficient values and thresholds held by the neural network are the correct internal representation of the network after adaptive learning. After repeated learning and influence, the network parameters corresponding to the minimum error are determined, and the influence is stopped. Once the neural network is trained, it can be used as an effective tool to predict improving public sports effect and make corresponding comprehensive judgment for different evaluation objects.

Secondly, the optimized BP neural network algorithm uses the minimum value of the reverse error function e (Yagishita [9]) in the propagation process to adjust the weights and thresholds in the BP model. The process is as follows. First, expand according to Taylor formula, $e[w(n+1)]$ which is shown as the following formula:

$$\begin{aligned} e[w(n+1)] &= e[w(n)] + g^T(n)\Delta w(n) \\ &\quad + 0.5\Delta w^T(n)A(n)\Delta w(n). \end{aligned} \tag{6}$$

Among them, $g(x)$ is the gradient vector and $A(x)$ is Hessian matrix.

If $\Delta w(n) = -A(n)^{-1}g(n)$, $e(w)$ takes the minimum value. In order to improve the speed of weight analysis, the Hessian matrix should be simplified to achieve approximate expression. Let $A = J^T J$ and $g = J^T e$ and get the simplified formula of (6); the result is shown as the following formula:

$$w(k+1) = w(k) - \left[J^T J + \mu I\right]^{-1} J^T e. \tag{7}$$

Under the condition of different influence objectives, BP neural network gets different analysis results. The error of influence target is inversely proportional to influence time and expected analysis accuracy.

Third is normalization of mass sports rate. Because the dimension of different index data is not the same, the neural network model will bring large system error without normalization. Therefore, considering the convergence problem of neural network influence and in order to facilitate the determination of the final evaluation value, the original index data of learning samples and test samples are normalized at the same time before network learning and influence, so as to eliminate the impact of different index dimensions and system errors. In this paper, the forward and backward propagation formulas are used to normalize the original index data to [0, 1]. Normalization processing can reduce the interference of other data with the analysis results (Makita [10]), map it to (0, 1) interval, and only save the variable relationship attributes between samples, as shown in formula (7) (Muschitz et al. [11]).

$$d_i' = \alpha\frac{d_i - d_{\min} + \beta}{d_{\max} - d_{\min} + \beta}. \tag{8}$$

Among them, d_i' and d_i are the values before and after normalization, and $d_{\max}$ and $d_{\min}$ are the maximum and minimum values of the sample. The transitive parameter approaches cannot reach 0 and 1, so when $d_i = d_{\max}$, $\alpha = 0.99$; when $d_i = d_{\min}$ and β is 0, a number close to 0 should be taken, that is, 0.01.

Fourth is error analysis of mass sports rate. The error of improving public sports effect under exercise intervention is divided into mean square error E_m and relative error percentage E_C. E_m is the error between the estimated value and the actual value, reflecting the overall error of the result; E_C is the error percentage of a single sample, as shown in the following formula:

$$\begin{cases} E_m = \dfrac{\left[\sum_{i=1}^{N-1} (d_i - o_i)^2\right]}{N-1}, \\ \\ E_C = \dfrac{o_i - d_i}{d_i} \times 100\%, \end{cases} \tag{9}$$

where n is a natural number.

3.5. Calculation Steps of the BP Neural Network Model. To study the influence of physical exercise on residents' physical quality, the fundamental idea is to analyze the content of physical exercise by using various strategies, and formulate influence programs with different intensity, strength, and endurance according to residents' quality. At the same time, through repeated iterative calculation, the complex analysis of physical exercise content is realized. The implementation steps of the impact analysis of residents' physical fitness in this paper are shown in Figure 4.

Step 1: determine the structure and complexity of physical exercise data, and determine the structure distribution of physical exercise content.

Step 2: initialize the physical exercise content, with influence index iteration times $n = 100$.

Step 3: build the fitness function. Randomly generate physical exercise data sets, select corresponding physical exercise strategies, and set standards w and degree of influence λ. Judge the normality of the data set and choose the best scheme.

Step 4: combine physical exercise strategies. The initial set is divided into subsets, and the fitness value is calculated to get the optimal result.

Step 5: iterate physical exercise content and influence effect. According to the change of physical exercise content, subsets' ally adjusts factor.

Step 6: optimize each physical exercise subset: after adjusting the physical exercise content, the g physical exercise scheme is calculated, and the optimal analysis is carried out with physical exercise

Step 7: judge whether the physical exercise content reaches the best match. If so, steps 1~5 are repeated; otherwise, the analysis will be stopped.

4. Results and Discussion

The BP neural network model used in this paper is solved by the function programming in the MATLAB neural network toolbox under the MATLAB environment. Before influencing the network, the weights and thresholds of the network must be initialized. The command will initialize the weights and thresholds of the network directly. In order to shorten the learning time of the neural network system and strive for the overall optimization, the gradient descent algorithm with momentum is used to train the BP network. The frequency *DF* is set as 10, the maximum influence times *me* is set as 2000, and the error index *eg* is set as 0.001 (Christian et al. [12]).

4.1. Sample Classification. Taking 102 exercisers as an example, the accuracy, convergence speed, and degree of the improved BP neural network algorithm were analyzed. Among them, the dependent variable is improving public sports effect rate D (%), and the independent variables are chronic diseases chance x_1 (unit: none), expenditure on social and public health x_2 (unit: h), public sentiment improvement rate x_3 (unit: %), and observer chronic diseases chance/public sentiment improvement rate x_4. The result is shown in Table 1.

The data in Table 1 shows a trend of centralization, and the overall clustering effect is good, which is suitable for corresponding analysis. We cluster the standardized 102 samples, then increase the number of clusters from 2 to 7, and calculate the contour coefficients under different K values. The result is shown in Table 2.

When the number of clusters is $k = 5$, the coefficient S_t is the largest, which indicates that the clustering effect of this class is the highest. Therefore, this paper selects $k = 5$ as the initial number of clusters and divides P_E into 5 equal parts. Then, the performance indexes are calculated and arranged in ascending order. The results show that the minimum value of P_E is 0.802, the maximum value is 10.232, and the value range is 0.8–10.2. Taking the center sample as the initial clustering center, K-means clustering analysis is carried out (Campos et al. [13]).

4.2. Analysis of the Influence of Residents' Physical Fitness. In order to further verify the performance of BP neural network algorithm, the physical quality indexes are analyzed, which are power, coordination, and strength results.

(1) For power judgment function, the result is shown as follows:

$$F(x) = \sum_{i=1} \frac{b_i^2}{n} \cdot \chi + \xi. \tag{10}$$

(2) For coordination judgment function, the result is shown as follows:

$$G(x) = \sum_{i=1} \frac{d_i^2}{n} \xrightarrow{+} \xi, \tag{11}$$

where $n \in [0, 100]$, i is n. Through the relevant parameters set, the total number of exercise content items is 100. The results of the functions are shown in Table 3.

From Table 3, we can see that the improvement of BP neural network algorithm is the best in terms of power, coordination, and strength, and the final result is also the best. Moreover, the overall influence of the improved BP

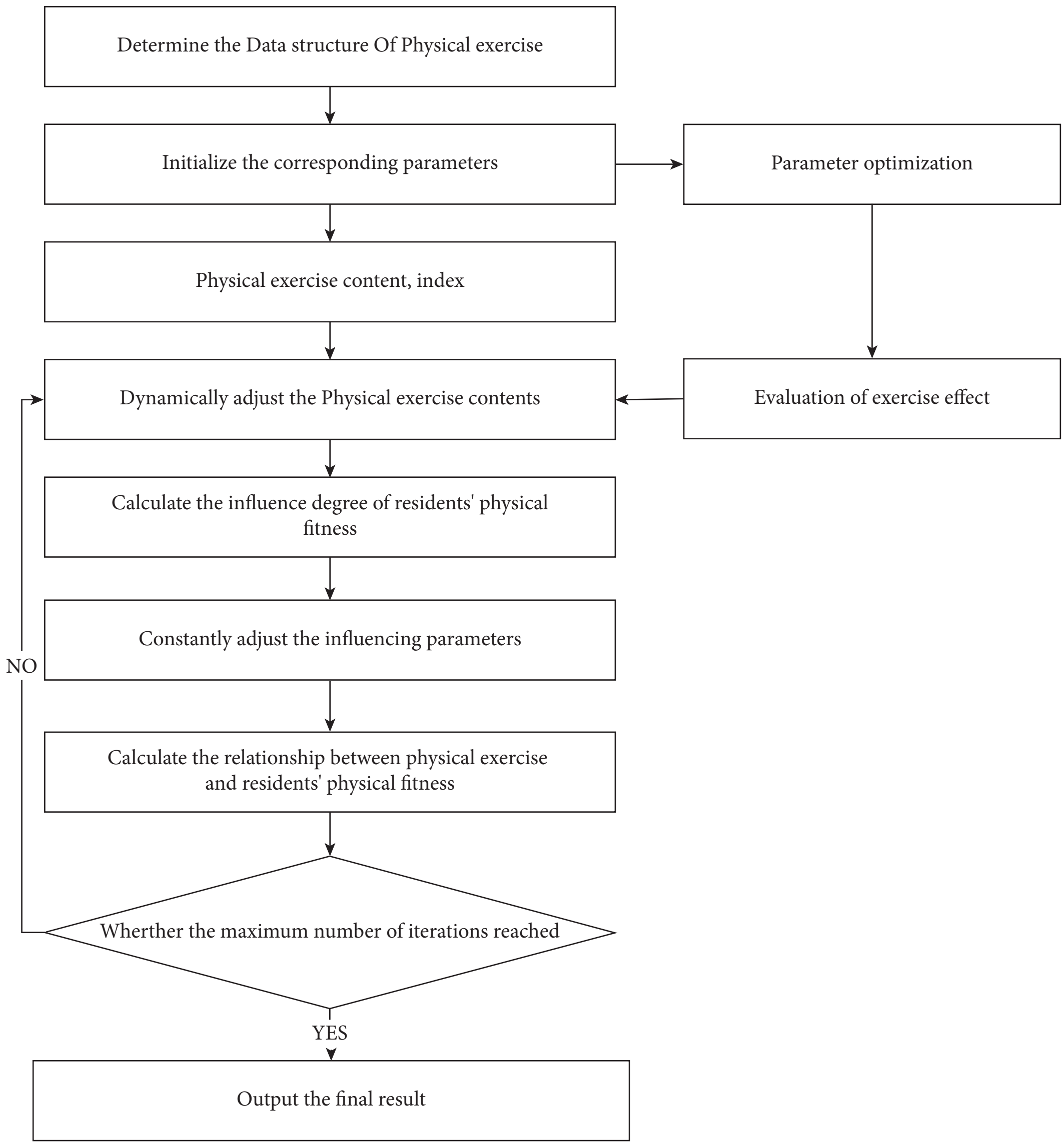

Figure 4: Steps of BP neural network.

Table 1: The sample clustering.

Category	Number of samples	Initial cluster center				P_E
		x_1	x_2	x_3	x_4	
1	63	92.22	5.56	94.44	106.67	2.78
2	12	95.56	2.22	103.33	94.44	1.78
3	41	95.56	4.00	91.11	103.33	1.11
4	18	13.33	3.00	98.89	94.44	2.44
5	43	12.00	3.11	92.22	90.00	1.43

Table 2: Profile coefficient S_t under different K values.

k value	S_t coefficient
2	0.11
3	0.56
4	1.44
5	0.21
6	0.38
7	0.44

neural network algorithm is above 92% (Zhang et al. [14]). For more concrete analysis, different sports contents are simulated to verify the effect of BP neural network, as shown in Figures 4 and 5.

From the analysis of Figure 5, it can be seen that BP neural network can accurately identify the improvement of residents' physical strength in analyzing physical exercise. The results show that the improvement process of residents' strength is a gradual process, and there is no significant change, which shows that the improvement of residents' physical strength accords with the physiological endurance of the body.

As can be seen from Figure 6, the optimal solution selection speed of the improved BP neural network algorithm is faster and more stable, which is better than that of the BP neural network algorithm 6 (Zhang et al. [15]). Therefore, the improved BP neural network algorithm performs better in the speed of combination strategy and the accuracy of combination strategy.

Table 3: Judgment results of different functions.

Function	Sports content	Content quantity	Number of policies	Optimization success degree	Degree of conformity with standards	Standard number
Power	Jumping	1	3.2	90.2 ± 0.21	95.1~98	1
	Swinging	2	7	92.3	92.6	2
	Throwing	2	4.1	95.7 ± 0.85	98.9	3
	Running	2	9.6	91.8	95.3~3.2	2
Coordination	Jumping	1	5	89.3 ± 0.75	94.7	3
	Swinging	4	4	85.7	96.8	1
	Throwing	3	3.8	92.4 ± 0.85	92.4	12
	Running	3	6	93.6	92.1~90.8	43

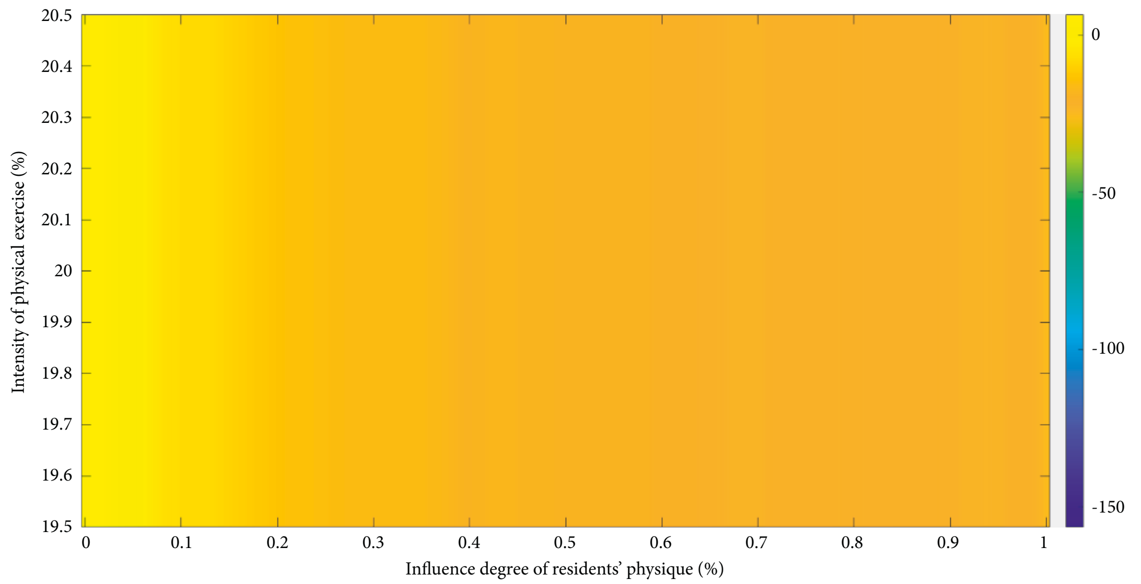

Figure 5: Power of BP neural network.

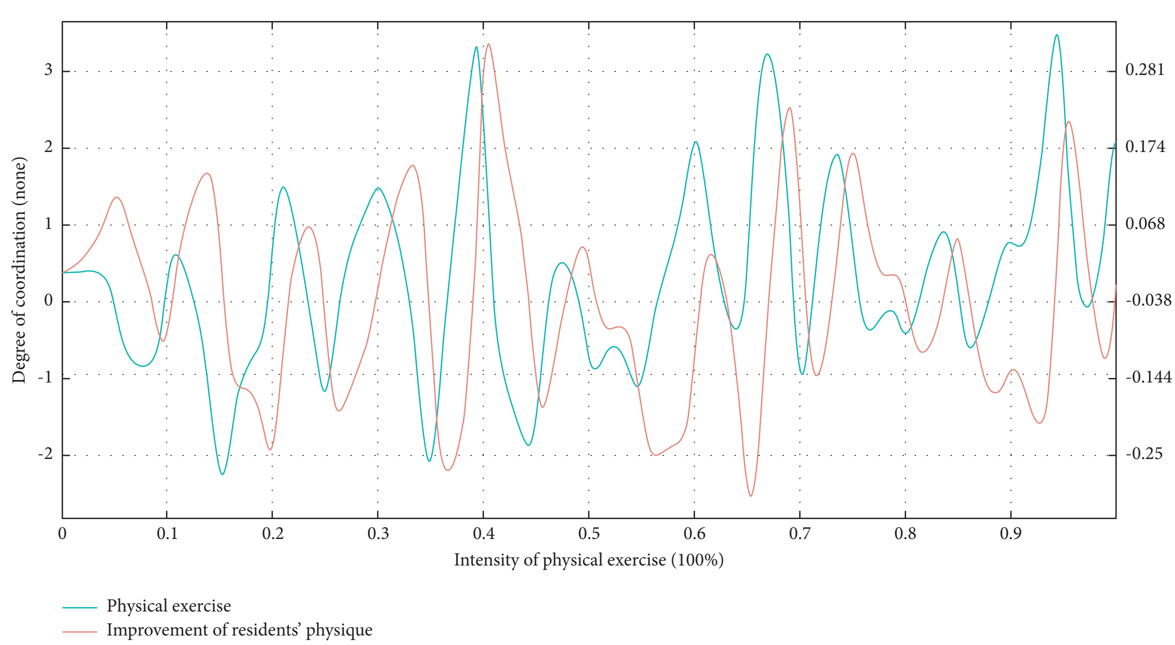

Figure 6: Coordination of BP neural network.

Table 4: Collection of the types and proportion of exercise content.

Group	Influence content	Influence score	Influence results
The BP neural network algorithm	Jumping	$2.3 \pm 0.12^*$	Significant impact
	Swinging	$1.2 \pm 0.13^*$	Significant impact
	Throwing	$8.1 \pm 0.27^*$	Significant impact
Standard statistical analysis method	Jumping	2.3 ± 0.72	General impact
	Swinging	0.9 ± 0.12	General impact
	Throwing	7.3 ± 0.21	General impact

Note. Compared with standard statistical analysis method, $^* P < 0.05$.

Table 5: Comparison of two BP models under different conditions.

		0.01		0.001		0.0001	
		Improvement	Change	Improvement	Change	Improvement	Change
Iterations		72	1032	157	3032	423	7000
Mean square error		1.42	2.12	0.12	0.82	0.02	0.29
Under different mass sports indexes E_C (%)	<5	282 (23.5)	242 (20.1)	690 (53.5)	378 (31.5)	990 (82.5)	1139 (94.5)
	5–10	41 (3.4)	2 (2)	18 (1.8)	6 (0.5)	167 (13.9)	150 (12.5)
	10–20	214 (17.8)	262 (21.8)	109 (10.7)	139 (11.6)	18 (1.5)	52 (4.3)
	20–30	223 (18.6)	294 (24.5)	142 (13.9)	232 (19.3)	10 (0.8)	82 (6.8)
	>30	615 (51.7)	640 (53.2)	332 (32.7)	361 (30)	25 (2.5)	92 (7.7)

4.3. Overall Effect of BP Neural Network. Based on skipping rope, sprinting, push-ups, and other sports, this paper carries out BP xneural network of folk music, bel canto, popular music, and rock music and judges the overall effect of BP neural network for college students. The specific contents are shown in Table 4.

From Table 4, we can see that the influence scores and influence results of the observation group are better than those of the control group and the influence results are one grade higher than those of the control group (Yu et al. [16]).

4.4. Analysis of Mass Sports Rate by the Improved BP Model. The target errors of the improved BP neural network model were set to 0.01, 0.001, and 0.0001 (Wu et al. [17]), and the mass sports rate under different target errors was calculated. The results are shown in Table 5.

It can be seen from Table 5 that with the reduction of influence target error, the iterations of the standard BP neural network model are 500, 1000, and 1500, while the iterations of the improved BP neural network model are 72, 157, and 423, indicating that the analysis speed of the improved BP neural network model is better than that of the standard BP neural network model. In addition, under the target error conditions of 0.01, 0.001, and 0.0001, the relative error of the improved BP neural network model increased from 23.5% to 82.5%, the BMD index of >30% decreased from 51.7% to 2.5%, and the relative error of the standard BP neural network model increased from 20.1% to 94.3%, and the relative error of >30% decreased from 53.2% to 7.7% (Wang et al. [18]), indicating that the improved BP neural network model still maintains good convergence at 0.0001. Although the number of iterations of the two algorithms is the most at 0.0001, the time of the improved BP neural network model is 4 s, which is acceptable, while the time of the standard BP neural network model is 66 s. Therefore, the improved BP network model is better than the standard BP network model in the analysis accuracy and speed. The result is shown in Figure 7.

Through the analysis of the above simulation results, it can be concluded that although the prediction result of BP neural network has a small deviation from the actual value, the analysis of Figure 7 shows that the prediction value of the improved neural network has the same change trend as the actual value, while the change trend of the prediction value of BP neural network is not obvious compared with the actual value, and the deviation of the prediction result is large (Tan and Song [19]). At the same time, Figure 7 shows that the prediction accuracy of the improved neural network is higher than that of BP neural network. Therefore, the simulation results show that the improved fuzzy neural network can effectively predict improving public sports effect under exercise intervention and has high prediction accuracy (Qu et al. [20]). Therefore, in the future research, this paper will strengthen the research of physical exercise, especially the fitting analysis between data, and improve the accuracy of the analysis results.

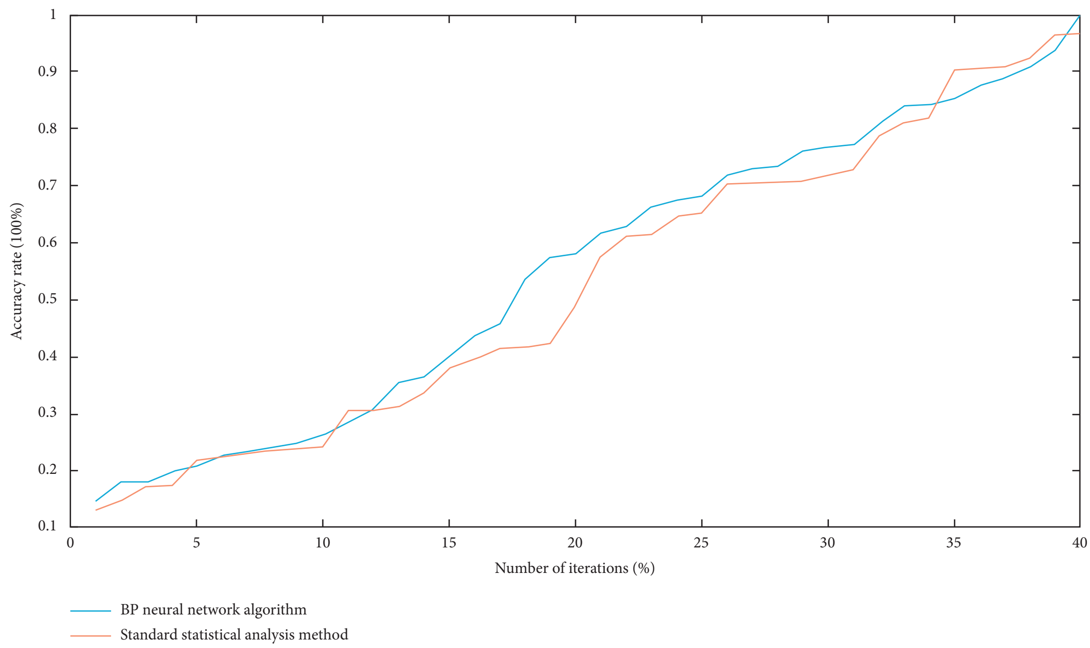

FIGURE 7: The accuracy comparison of different algorithms on residents' physical fitness.

5. Conclusion

The improved BP neural network model first determines the k value through the contour coefficient S_t, and P_E arranges the mass sports indexes under exercise intervention in ascending order, then divides them into different clusters by k, and takes the center sample of each class as the initial center point of this class (Lu et al. [21]). LM algorithm is used to calculate the minimum value of error function e in the process of backpropagation, and the weights and thresholds of standard BP neural network model are iteratively adjusted to improve the analysis accuracy. LM algorithm normalizes the input variables of BP neural network model and maps them to (0, 1) to improve the analysis speed (Liu et al. [22]). The algorithm verification results show that under the target error conditions of 0.01, 0.001, and 0.0001, the number of iterations of the improved BP neural network model increases from 72 to 423, E_C <5% from 24.8% to 94.3%, and E_C >10% from 51.7% to 2.5%, which are better than the standard BP neural network model (Li and Fan [23]). Therefore, BP neural network for the analysis of physical exercise is better, with the impact of residents' physical fitness analysis. However, the improved BP neural network model is still insufficient for the analysis of mass sports rate of sample objects; some samples will appear as E_C large abnormal samples, but in the overall sample analysis, the problem of abnormal samples is ignored, which is easy to affect the accuracy of mass sports rate analysis (Lei and Yin [24]).

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] T. Akifumi, "The role of myokine irisin on improving public sports effect," *Journal of the Korea Society of Computer and Information*, vol. 24, no. 9, pp. 32-33, 2010.

[2] Z. Gaojie, "Effects of long-term physical exercise on mass sports and improving public sports effect in middle school girls," *International Journal of Education and Economics*, vol. 2, no. 2, pp. 32-33, 2019.

[3] N. Isao, "Evaluation of cartilage and improving public sports effect in collegiate athletes belonging to various sports clubs by analyzing type II collagen degradation and synthesis,and type I collagen degradation," *Juntendo Medical Journal*, vol. 64, no. 1, pp. 23–25, 2019.

[4] N. Isao, T. Akifumi, and Y. Masafumi, "Evaluation of cartilage and improving public sports effect in collegiate athletes belonging to various sports clubs by analyzing type II collagen degradation and synthesis, and type I collagen degradation; poster sessions-musculoskeletal system," *Juntendo Medical Journal*, vol. 64, no. 11, pp. 22-23, 2019.

[5] Y. Masafumi, "Effects of long-term aerobic exercise on body breaking force and serum improving public sports effect markers in ovariectomized mice," *Journal of the Korean*

Society of Living Environmental System, vol. 26, no. 1, pp. 32-33, 2019.

[6] N. Isao, T. Akifumi, and Y. Masafumi, "Evaluation of cartilage and improving public sports effect in collegiate athletes belonging to various sports clubs by analyzing type II collagen degradation and Synthesis,and type I collagen degradation," *Juntendo Medical Journal*, vol. 64, no. 1, pp. 32-33, 2018.

[7] L. H. Yu, L. Y. Xie, C. M. Liu, S. Yu, Y. X. Guo, and K. J. Yang, "Optimization of BP neural network model by chaotic krill herd algorithm," *Alexandria Engineering Journal*, vol. 61, no. 12, pp. 9769–9777, 2022.

[8] J. Iwamoto, "Calcium and improving public sports effect across women's life stages. Exercise and sport to increase body strength in accordance with female lifecycle," *Clinical Calcium*, vol. 27, no. 5, pp. 33-34, 2017.

[9] K. Yagishita, "Calcium and improving public sports effect across women's life stages. Stress fracture in female athletes," *Clinical Calcium*, vol. 27, no. 5, pp. 43-44, 2010.

[10] K. Makita, "Calcium and improving public sports effect across women's life stages. Nutritive therapy for improvement of body and calcium metabolism according to life stage in women," *Clinical Calcium*, vol. 27, no. 5, pp. 44–48, 2010.

[11] C. Muschitz, R. Kocijan, J. Haschka et al., "The impact of vitamin D, calcium, protein supplementation,and physical exercise on improving public sports effect after bariatric surgery: the BABS study," *Journal of Body and Mineral Research*, vol. 31, no. 3, pp. 44-45, 2016.

[12] M. Christian, K. Roland, H. Judith et al., "The impact of vitamin D, calcium, protein supplementation, and physical exercise on improving public sports effect after bariatric surgery: the BABS study," *Journal of Body and Mineral Research*, vol. 31, no. 3, pp. 45–48, 2016.

[13] R. M. S. Campos, M. T. de Mello, L. Tock et al., "Aerobic plus resistance influence improves improving public sports effect and inflammation in adolescents who are obese," *The Journal of Strength & Conditioning Research*, vol. 28, no. 3, pp. 44–46, 20104.

[14] J. G. Zhang, P. T. Li, X. Yin, S. Wang, and Y. G. Zhu, "Back analysis of surrounding rock parameters in pingdingshan mine based on BP neural network integrated mind evolutionary algorithm," *Mathematics*, vol. 10, no. 10, 2022.

[15] G. Zhang, B. T. Sun, W. Bai, and H. Y. Zhang, "Prediction of the yield performance and failure mode of RC columns under cyclic-load by PSO-BP neural network," *Buildings*, vol. 12, 2022.

[16] L. H. Yu, L. Y. Xie, C. M. Liu, S. Yu, Y. X. Guo, and K. J. Yang, "Optimization of BP neural network model by chaotic krill herd algorithm," *Alexandria Engineering Journal*, vol. 61, no. 12, pp. 9769–9777, 2022.

[17] Q. Wu, Y. Wang, Y. P. Wang et al., "Ablation state assessment of SF6 circuit breaker contacts based on BP neural network and mean impact value," *Energy Reports*, vol. 8, pp. 874–883, 2022.

[18] H. J. Wang, T. Jin, H. Wang, and D. Su, "Application of IEHO-BP neural network in forecasting building cooling and heating load," *Energy Reports*, vol. 8, pp. 455–465, 2022.

[19] X. F. Tan and M. F. Song, "Characteristics of physiological changes in athlete training based on the data mining algorithm," *Revista Brasileira de Medicina do Esporte*, vol. 28, no. 5, pp. 386–389, 2022.

[20] Y. Y. Qu, T. Yang, T. Li, Y. Zhan, and S. C. Fu, "Path tracking of underground mining boom roadheader combining BP neural network and state estimation," *Applied Sciences-Basel*, vol. 12, no. 10, 2022.

[21] X. P. Lu, X. X. Wang, X. J. Zhang, J. Wang, and Z. N. Yang, "Winter wheat leaf area index inversion by the genetic algorithms neural network model based on SAR data," *International Journal of Digital Earth*, vol. 15, no. 1, pp. 362–380, 2022.

[22] J. P. Liu, P. W. Hu, H. R. Xue, X. Pan, and C. Chen, "Prediction of milk protein content based on improved sparrow search algorithm and optimized back propagation neural network," *Spectroscopy Letters*, vol. 55, no. 4, pp. 229–239, 2022.

[23] S. J. Li and Z. Y. Fan, "Evaluation of urban green space landscape planning scheme based on PSO-BP neural network model," *Alexandria Engineering Journal*, vol. 61, no. 9, pp. 7141–7153, 2022.

[24] R. C. Lei and J. Yin, "Prediction method of energy consumption for high building based on LMBP neural network," *Energy Reports*, vol. 8, pp. 1236–1248, 2022.