Research Article

Evaluation of Children’s Physical Fitness Index and Prediction of Health Risk Trend Based on BP Neural Network Algorithm

Renle Wu¹ and Siyu Zhang²

¹College of Physical Education, Jinggangshan University, Ji’An, Jiangxi 343009, China
²General Graduate School, Sangmyung University, Seoul 03016, Republic of Korea

Correspondence should be addressed to Siyu Zhang; 9920100056@jgsu.edu.cn

Received 28 March 2022; Revised 15 April 2022; Accepted 25 April 2022; Published 9 May 2022

Academic Editor: Zhiguo Qu

Copyright © 2022 Renle Wu and Siyu Zhang. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

On the basis of literature review and expert interview, this study constructs the indexes of health fitness evaluation, obtains the difference of the indexes before and after the 15-week health fitness intervention, and establishes the health risk trend predictive equation based on BP neural network algorithm. The results of the study are as follows: after 15 weeks of health fitness intervention, there were significant differences in body fat rate, waist circumference, and waist-to-hip ratio (P < 0.01). There were significant differences in maximal oxygen uptake, 12-minute running distance, one-minute sit-ups, push-ups, standing long jump, pull-ups, and sitting forward flexion (P < 0.05). Body fat percentage, maximal oxygen uptake, forward bending in sitting position, and standing long jump can be used to evaluate the level of children’s physical fitness. In conclusion, after 15 weeks of health and fitness intervention course, the children’s health and fitness were improved. Health and Physical Fitness Intervention Curriculum can be promoted in schools so that more children can benefit from it. And the health risk trend prediction model based on BP neural network algorithm has a certain validity.

1. Introduction

Physical fitness refers to the ability of an individual’s body to cope with daily high-intensity work without fatigue, to have additional physical strength to enjoy life, and to cope with sudden stress and other changes [1, 2]. It first appeared in the United States in the 1950s of the 20th century; it is a compulsory test for recruits in the army, used to evaluate the body’s ability to adapt to the changes of sports, life, work, and complex environment. At present, health fitness evaluation and intervention are mainly used to prevent and solve those hidden risk factors which may cause disease and to intervene in the risk through certain exercise methods, so that the body can develop healthily in good way [3, 4]. After consulting the data, it is found that scholars and physical fitness experts majoring in physiology in Europe and America mainly divide healthy physical fitness into four aspects: cardiopulmonary endurance, strength and strength endurance, flexibility, and body composition [5, 6]. According to the evaluation criteria of these four aspects, there are seven commonly used indicators of body composition: BMI, height, weight, body fat rate, waist circumference, hip circumference, and waist hip ratio. There are two indexes of cardiopulmonary endurance, including maximum oxygen uptake and 12-minute running. Strength and strength endurance have four indexes, including pull-up, sit-ups, push-ups, and standing long jump. There is one index of flexibility, and most of them use sitting body flexion [7, 8].

Reference [9] proposed a deep learning-based psychosis risk prediction method. The deep collaborative filtering algorithm is studied to preprocess massive feature data, build a high-order nonlinear interaction model between patient features and health implicit features, and estimate the similarity between health implicit features by using the implicit feedback algorithm. The confidence of the feature vector is calculated by the backpropagation algorithm, learn the health implicit features from the training data set, and construct the target label and the evaluation index system of psychosis risk prediction in order to achieve more efficient and accurate personalized psychosis risk prediction.
algorithm. Reference [10] conducted a cross-sectional analysis of 415 children aged 8.47 ± 0.36 years in 14 schools in Granada, Spain. HRQOL results were assessed using an effective and reliable KINDL-R questionnaire covering six life dimensions, and children’s physical health was assessed using the Alpha Health Test Combination. Reference [11] evaluated the health and physical health-related biomarkers of young gymnasts, as well as the benefits of regular gymnastics practice in primary school. The study included 90 children, 49 of whom (mean age 9.5 years) had practiced rhythmic gymnastics for at least 2 years, averaging 6 hours per week, and a control group of 41 children (mean age 8.9 years). The participants completed the Alpha Fit fitness test combination (BMI, % fat, grip strength, standing long jump, 4 × 10 m shuttle run test, and 20 m multistage fitness test). Calculate the percentile score of each test result. The height, weight, BMI, and fat percentage of male and female gymnasts were significantly lower than those of the control group (p < 0.20). The body fat of all gymnasts is within the normal range. Reference [12] used pre- and post-quasi-experimental design and control group to evaluate school-based intervention. Schools from poor communities are oversampled. The intervention consisted of 9 sessions of 58 activities lasting between 9 and 13 hours, and the intensive intervention consisted of 2 sessions of 8 activities lasting between 3 and 4 hours. They are multilevel (individual, family, and school) and multicomponent (classroom, sports activities, and family).

In order to accurately test children’s physical fitness, find out the index suitable for children’s physical fitness in our country, and set up the discriminant equation through these indexes, so as to evaluate and predict the children and health risks that need intervention of physical fitness, this paper puts forward the evaluation of children’s physical fitness index and prediction of health risk trend based on BP neural network algorithm and constructs the prediction model of health risk trend based on BP neural network algorithm, so as to provide help for improving the overall level of children’s physical fitness in our country.

2. Evaluation of Children’s Physical Fitness Index

2.1. Research Object. The main research object was the evaluation index of children’s health and physical fitness. In view of the premise of discriminant function analysis method, the sample size must be more than 10~20 times of the number of independent variables, and the dependent variables are independent and have no commonality. The degree of factors affecting the health and physical fitness of young students varies in various regions, such as lifestyle, schoolwork burden, family economic level, and eating habits; in order not to repeat too much in this study, only 14 independent variables in common in four aspects are selected as children’s physical fitness indicators. 40 children participated in the experimental test. According to the constituent elements of health and physical fitness, the dependent variables are divided into four aspects. Therefore, it can be considered that the dependent variables involved in this study are independent and have no commonality, and the experimental sample size required by the independent variables basically meets the statistical requirements.

2.2. Research Methods. In the research process, this article uses the literature material law, and the experimental method carries on the research. Among them, the method of documentation refers to consult the Web of Science database of China Periodical Network and Foreign Periodical Network to retrieve the relevant documents published at home and abroad from 2010 to 2020. On the basis of careful reading and analysis of the obtained papers, the results of previous studies on health fitness were summarized to ensure the forward-looking and novelty of this study. The experimental method refers to 40 randomly selected 8th grade students (20 male and 20 female each, without obvious cardiopulmonary, brain, organ diseases, and movement disorders), including 20 in the experimental group and 20 in the control group. Warm up for 10 to 15 minutes before the test. During the test, the subjects stopped the test immediately after feeling unwell. Tsinghua Tongfang BCA~3D Body Fat Analyzer, GMCS~IIA Seat Forward Bend Tester, Casio stop-watch, and tape measure were used as testing equipment. SPSS21.0 is mainly used to process and analyze the data. When P < 0.01, there is a significant difference between the two samples. When P < 0.05, there is a significant difference between the two samples.

2.3. Research Process. Before the test, the required materials prepared in advance will be strictly disinfected, and the testers will demonstrate and explain the test methods, so as to promote the subjects to complete each test item quickly and effectively.

(1) For example, the body composition and body weight of the test subjects are measured by the electrical impedance test (body composition and body weight) method of the Korean standing board, and then, the body composition of the test subjects is measured by the electrical impedance test (body composition and body weight) method of the Korean standing board, including the basic body composition and body weight of the test subjects. After entering the test procedure, the subjects are required to hold the electrode with both hands and separate their arms naturally. After confirming that the measurement is ready, press the test switch for test, and finally, send the test results to the computer and print the test report. Note: changes in body position, body fluid, diet, and special physiological periods or pathological states will cause errors. Therefore, vigorous exercise is not allowed within 24 hours before the test. Before the test, fasting, diet, and water should be avoided. The tested personnel should strictly follow the test requirements to reduce errors.

(2) Cardiopulmonary function indicators: including vital capacity, maximum oxygen uptake, heart rate at rest, and blood pressure. Description of test instruments used: Guoyu high-precision digital display vital capacity tester (model: second-generation function enhanced), power bicycle Monark (model:
ergomedic839e Sweden), heart rate tester (model: polar T34), HSH intelligent speaking arm full-automatic electronic sphygmomanometer (model: hk-807), disposable blowing mouth nose clip, etc.

(3) The flexibility of lower limbs and upper limbs is described by gymnastic instruments, such as the flexibility of lower limbs and the flexibility of upper limbs. Test method: upper limb (shoulder) flexibility test: stand naturally, hold the gymnastics stick with fixed distance with both hands, lift it forward and turn the shoulder backward, and measure the distance from the lower earlobe to the upper arm in parallel with a tape measure.

2.4. Results and Analysis

2.4.1. Composition of Physical Fitness. Healthy physical fitness is mainly composed of four parts as shown in Figure 1.

Figure 1 shows cardiopulmonary endurance, body composition, flexibility, and strength and strength endurance. This paper comprehensively analyzes the evaluation of indicators of health and physical fitness at home and abroad and determines 14 indicators that can represent the level of children's health and physical fitness through interviews with 4 experts in health and physical fitness. Height, weight, body fat ratio, waist circumference, hip circumference, waist hip ratio, and BMI represent body composition; 12-minute running performance and maximum oxygen uptake represent cardiopulmonary endurance; standing long jump, one-minute push-ups, and sit-ups represent strength and strength endurance; sitting forward flexion represents flexibility.

2.4.2. Operation and Practice of Health Fitness Intervention. According to the four constituent elements of health and physical fitness, the 15-week course is mainly set up with cardiopulmonary endurance, strength and strength endurance, and flexibility. Children in the intervention group are required to participate in a class every week. In addition, children in the intervention group are required to practice twice after class. The methods of extracurricular practice refer to the practice contents in the course. It is required to do a good job of self-supervision in the practice process and stop practicing immediately when they feel unwell.

2.4.3. Dietary Guidance and Evaluation in the Process of Health and Physical Fitness Intervention. A diet is of great significance for maintaining people's body shape and physical strength. In order to enable children to arrange their diet reasonably and regularly, a dietary guidance course shall be conducted before the intervention. In addition, two doctors majoring in nutrition were invited to conduct a retrospective statistical analysis of children's meals and snacks before and after the intervention and give reasonable suggestions to ensure the unity of dietary intake before and after the intervention. It is found in Table 1 that the subjects had increased in energy intake and carbohydrates and decreased in fat and carbohydrates after intervention, but there was no difference after paired t-test.

2.4.4. Experimental Results of Children's Body Shape. Table 2 shows the comparison of height indexes between male and female children before and after the experiment. It can be seen from Table 2 that children's height has increased to varying degrees, and the control group reflects their natural growth and development in adolescence. The experimental results show that the growth and development of the experimental group are greater than those of the control group, which can promote the growth of children's height.

Table 3 shows the comparison of the difference in body mass index between male and female children before and after the experiment.

It can be seen from Table 3 that the weight of boys in the experimental group before the experiment is lower than that of the control group, but there is no significant difference between the two. After the experiment, the weight of girls in the experimental group decreased, but the change was similar to that of boys. The results showed that the weight gain of the experimental group was lower than that of the control group. The results show that proper exercise can effectively inhibit overweight and promote children’s growth and healthy development of body fat rate.

2.4.5. Children's Physical Function Test Results. Table 4 shows the comparison of vital capacity indexes of male and female children before and after the experiment.

The results of pulmonary function test showed that there was almost no difference between the experimental group and the control group before the experiment. After the experiment, boys' vital capacity increased greatly, and girls' vital capacity also increased significantly. Because proper exercise requires teenagers to make use of the coordination and cooperation of lower limbs, trunk, and upper limbs, good ventilator energy can be formed through a period of training.

2.4.6. Experimental Results of Children's Physical Fitness. See Tables 5 and 6 for the comparison of physical quality of male and female children before and after the experiment.

It can be seen from Tables 5 and 6 that the sitting forward flexion value, standing long jump performance, and running performance of boys and girls in the experimental group have been significantly improved, indicating that appropriate sports training can effectively improve the muscle flexibility, muscle strength, and aerobic endurance of teenagers.

3. Health Risk Trend Prediction Model Based on BP Neural Network Algorithm

Based on the above obtained children's physical fitness index data, a health risk trend prediction model based on BP neural network algorithm [13, 14] is established, which is used as model input to realize children's health risk trend prediction.

3.1. Algorithm Initialization. In algorithm initialization, the specificity and correlation of rip are two important parts to
Table 1: Dietary intake before and after intervention.

| Index              | Before intervention | After intervention | P value |
|--------------------|---------------------|--------------------|---------|
| Energy intake (Kcal) | 2289.21 ± 459.14    | 2309.46 ± 430.15   | 0.598   |
| Fat (g)            | 50.17 ± 16.76       | 49.25 ± 17.21      | 0.421   |
| Carbohydrate (g)   | 349.16 ± 89.27      | 355.16 ± 89.20     | 0.338   |
| Protein (g)        | 65.13 ± 33.10       | 63.16 ± 33.17      | 0.205   |

Table 2: Comparison of height index differences between boys and girls before and after the experiment.

| Index               | Boy Experience group | Boy Control group | Girl Experience group | Girl Control group |
|---------------------|----------------------|-------------------|-----------------------|--------------------|
| Height (m)          | 0.01 ± 0.005         | 0.01 ± 0.005      | 0.01 ± 0.005          | 0.01 ± 0.005       |

where $M_j$ represents the correlation of each $j$ column of children’s physical fitness data. The smaller the $M$ is, the greater the correlation of the column matrix is, and the smaller the result error caused by noise interference is.

3.2. Selection of Support Set. The selection of support set is divided into two steps: one is to use the correlation maximization principle [17, 18] to obtain the maximum correlation value by comparing the results of correlation coefficients; the other is to use the regularization algorithm to find the corresponding index of correlation coefficients in the measurement matrix and store it in the index set [19, 20]. The following formula shall be met when the corresponding indexes of all correlation coefficients are entered into the index set:

$$|M(i)| \leq 2|M(j)|,$$

where $M(i)$ represents the correlation coefficient and $M(j)$ represents the corresponding index.

The key of the regularization algorithm is to eliminate the sparse noise of children’s physical fitness data from the measurement matrix [21], so as to obtain an index set with greater energy and better data. The children’s physical fitness data completes a denoising update, and the processed optimized data is stored in the support set. The advantage of this process is that after $N$ iterations, the support set with significant denoising effect and memory less than 2K can be obtained. However, the sparse noise carried by the children’s physical fitness data not selected into the support set is often greater than that carried by the children’s physical fitness data selected into the support set. In order to obtain the undisturbed original children’s physical fitness data, it is necessary to further denoise the missing data.

3.3. Threshold Setting and Optimization Algorithm. Set $\varepsilon_1$ and $\varepsilon_2$ thresholds in the measurement matrix, respectively. $\varepsilon_1$ is mainly responsible for limiting the number of iterations, and $\varepsilon_2$ is mainly responsible for stage threshold conversion. In order to obtain children’s physical fitness data with higher accuracy, it is necessary to compare the size of the two thresholds, strictly control the noise content according to the results, and finally achieve the effect of children’s physical fitness data reconstruction.
The optimization algorithm [22, 23] uses the method of stage transformation to denoise children’s fitness data one by one. In the iterative process, set the denoising model and screen and filter the non-denoised data. The processed children’s fitness data needs to be compared with the data in the support set. The closer the two results are to zero, the greater the gravity of the support set. The denoising data in the support set. The closer the two results are to zero, 

\[ x_i = \arg\min_{u} \| -\psi_{F_i} x + u \|_2, \quad r_i = -\psi_{F_i} x + u, \]  

where \( -\psi_{F_i} x + u \) represents the total amount of physical fitness data of children in the support set; \( -\psi_{F_i} x + u \) represents the index value of correlation coefficient; and \( x_i \) represents the reconstruction result of the original data of children’s physical fitness.

### 3.4. Prediction Model of Children’s Physical Fitness and Health Risk Based on Likelihood BP Algorithm

The likelihood BP algorithm simulates the evolution process of organisms; selects, crosses, and mutates the initial data from the two aspects of natural selection and development evolution; and finally produces data categories that can be integrated with the environment, so that the whole initial data can adapt to the environment and operate continuously [28, 29]. In this data category, the data individual that can best reflect the environmental fusion is called the optimal solution of likelihood BP algorithm. Therefore, the neural network combined with likelihood BP algorithm to encode, select, cross, and mutate children’s physical fitness data plays a vital role in the construction of prediction model.

#### 3.4.1. Coding

Binary coding [30, 31] and real coding are the most commonly used coding methods of likelihood BP algorithm. In the coding process, the coding object is mainly for the individual variables with feasible solutions, rather than the problem variables to be solved. Binary coding is simple to operate and conforms to the order of character arrangement from small to large, which easily realizes the crossover or variation of children’s physical fitness data. At the same time, the accuracy of binary coding is limited, and a longer

### Table 3: Comparison of weight index differences between boys and girls before and after the experiment.

| Index            | Experience group | Control group | Experience group | Control group |
|------------------|------------------|---------------|------------------|---------------|
| Weight (kg)      | 61.50 ± 7.60     | 61.75 ± 7.60  | 51.45 ± 5.65     | 51.50 ± 5.82  |

### Table 4: Comparison of vital capacity indexes between boys and girls before and after the experiment.

| Index            | Experience group | Control group | Experience group | Control group |
|------------------|------------------|---------------|------------------|---------------|
| Vital capacity (ml) | 355.50 ± 208.08 | 105.75 ± 75.73 | 315.50 ± 230.17 | 103.95 ± 76.75 |

| \( P = 0.001 < 0.01 \) | \( P = 0.002 < 0.01 \) |

### Table 5: Comparison of physical fitness of boys before and after the experiment.

| Index                        | Experience group | Control group |
|------------------------------|------------------|---------------|
| Seat forward flexion (cm)    | 13.85            | 12.50         |
| Standing long jump (cm)      | 235              | 221           |
| 1000 meters (s)              | 280              | 288           |

### Table 6: Comparison of physical fitness of girls before and after the experiment.

| Index                        | Experience group | Control group |
|------------------------------|------------------|---------------|
| Seat forward flexion (cm)    | 15.1             | 13.2          |
| Standing long jump (cm)      | 167.5            | 161.1         |
| 800 meters (s)               | 245.0            | 245.4         |

### Table 7: Computer parameters required for experiment.

| Name                        | Parameter       |
|-----------------------------|-----------------|
| Resolving power             | 2K              |
| Graphics card               | RTX 2060        |
| Graphics card model         | GTX 1070        |
| CPU model                   | i7-8700K        |
| Memory                      | 16 G            |
| Display memory              | 8 G             |
| Operation storage space     | 64 bits         |
A binary string is needed to prolong the data, which makes the overall development of likelihood BP algorithm slow, which is an obvious disadvantage of binary coding. Real coding optimizes the defects of binary coding and makes up for its shortcomings to a certain extent. On the one hand, it improves the data accuracy; on the other hand, it reduces the complexity of data processing, speeds up the overall progress of the algorithm, and expands the search range.

After the children’s physical fitness data is input into the neural network, the fusion weight is obtained through the likelihood BP algorithm. Each fusion weight in the network is arranged into a long string in the order of large to small and left to right. Each unit data corresponds to a fusion weight, and the unit data before and after the long string has strong correlation.

3.4.2. Fitness Function. In the calculation process, the fitness function, as a landmark parameter, represents the evaluation of individual data on the overall adaptability. Therefore, it is a very important link of likelihood BP algorithm to reasonably design the fitness function to guide the overall data to evolve forward and find the optimal solution. Under normal circumstances, the fitness function evolves from the objective function, and the design of fitness function is different due to different problems to be solved. When the likelihood BP algorithm obtains the weights of the neural network, stabilize the correlation weights in a long string arranged neatly, and calculate the mean square error (MSE) of children’s physical fitness data output at this time [32, 33]. The fitness function formula obtained is as follows:

\[
\text{fitness} = \frac{1}{1 + \text{MSE}}, \\
\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (Y - y_i)^2,
\]

where fitness is the result of fitness function; MSE means mean square error; \(n\) represents the total amount of children’s physical fitness data; \((Y - y_i)^2\) represents the fusion weight string arranged by the neural network; and \(y_i\) represents the error result. When fitness gradually approaches 1, it can be considered that the error of fitness function is ignored.

3.4.3. Calculation Process: Selection, Crossover, and Variation. Likelihood BP algorithm uses selection operator and replication operator to calculate the overall data, simulates the principle of survival of the fittest in biological genetics, selects the optimal individual in the overall data, and transmits it to the offspring for cyclic calculation. The selection process includes roulette, serial number, elite, and other methods. The most basic and commonly used method is roulette selection. The probability of each individual being selected is inversely proportional to the result of fitness function. Assuming that the fitness function result of each individual in the overall data is \(f_{n}\), it can be calculated that the

| Training times | Proposed method | Reference [9] method | Reference [10] method |
|----------------|------------------|-----------------------|-----------------------|
|                | RMSE             | MAE                   | RMSE             | MAE                   | RMSE             | MAE                   |
| 1              | 0.46             | 0.16                  | 7.56             | 4.98                  | 8.99             | 9.32                  |
| 2              | 0.37             | 0.35                  | 8.32             | 4.33                  | 7.36             | 9.02                  |
| 3              | 0.12             | 0.22                  | 6.68             | 8.52                  | 8.32             | 8.66                  |
| Average        | 0.32             | 0.24                  | 7.52             | 3.10                  | 8.22             | 9.00                  |

Figure 2: Building data acquisition structure.

Table 8: Comparison of RMSE and MAE of prediction results of various models.
Figure 3: Comparison between prediction results of each model and actual values.

Figure 4: Comparison of relative distribution error of each prediction model.
The sum of the fitness function results is \( S = \sum_{i=1}^{\text{pop-size}} f_i \), and \( t = 2, 3, \ldots \), pop-size is regarded as the range involved in the overall data. When pop-size, \( \sum_{i=1}^{t} f_i \) is output to obtain the selection interval:

\[
\left[ 0, \frac{f_1}{S} \right], \left[ \frac{f_1}{S}, \frac{f_1+f_2}{S} \right], \ldots, \left[ \sum_{i=1}^{t-1} \frac{f_i}{S}, \sum_{i=1}^{t} \frac{f_i}{S} \right], \ldots, \left[ \sum_{i=1}^{\text{pop-size}} \frac{f_i}{S}, 1 \right],
\]

(6)

where \( \sum_{i=1}^{t} f_i / S \) represents the optimal choice; \( [0, f_1 / S] \) represents the error of the optimal solution; \( f \) represents the winning probability of the individual in the bet selection; and \( (f_1 + f_2) \) represents the fitness function result. Following the basic operation of roulette selection, the winning individual randomly selects between pop-size and \( [0, 1] \). When \( \sum_{i=1}^{\text{pop-size}} f_i / S, 1 \) is output, the optimal solution appears and the selection is terminated.

The second operation in the likelihood BP algorithm is crossover, which simulates the gene recombination phenomenon of biological genetics [34, 35]; that is, a certain two groups of data mix the data characteristics into new individuals according to the principle of DNA exchange. Crossover operation can improve the retrieval ability of likelihood BP algorithm. In real-coded data samples, full probability crossover algorithm is usually adopted, and its expression is

\[
\left\{ \begin{array}{l}
P_{v1}^{r+1} = (1 - \alpha)P_{v2} + \alpha P_{v1}, \\
P_{v2}^{r+1} = (1 - \alpha)P_{v1} + \alpha P_{v2},
\end{array} \right.
\]

(7)

where when \( 1 > \alpha > 0 \), the crossresult meets the conditions required by the likelihood BP algorithm; \( P_{v1}^{r+1} \) and \( P_{v2}^{r+1} \) represent gene exchange and recombination between individuals in columns \( P_{v1}^r \) and \( P_{v2}^r \), respectively; and \( (1 - \alpha) \) represents the weight of the new individual after reorganization. In the calculation process, the value range of \( \alpha \) is uncertain, which can be selected in \( [0, 1] \) interval, or any data can be randomly selected in neural network.

The third operation in the likelihood BP algorithm is mutation, which simulates the phenomenon of biological genetic mutation and makes the data mutate randomly. The variant gene can exist in any data. After the recessive gene \( r \) is transformed into the dominant gene \( r' \), the data will complete the variation, and its expression is

\[
r = \alpha (r_{\text{max}} - r_{\text{min}}) + r_{\text{min}},
\]

(8)

where \( r_{\text{min}} \) and \( r_{\text{max}} \) represent the minimum probability and maximum probability of gene variation, respectively, and \( \alpha \) represents any number of \( [0, 1] \) interval.

After determining the coding method, fitness function, and several operation steps of selection, crossover, and mutation, the likelihood BP algorithm starts to work for
the purpose of constructing the prediction model. It should be noted that when the likelihood BP algorithm calculates the crossover probability \( P_c \) and mutation probability \( P_m \) for the neural network, the probability calculation results of \( P_c \) and \( P_m \) are closely related to the performance of the likelihood BP algorithm; that is, the performance of the likelihood BP algorithm is limited by the values of crossover probability and mutation probability. At the same time, the error rate of the output prediction model of the likelihood BP algorithm is increased. In order to improve the accuracy of the prediction model, it is necessary to add adaptive robust fault-tolerant control \([36]\) in the calculation process to ensure that \( P_c \) and \( P_m \) can eliminate the value limit and change with the change of fitness function. The individual data with high fitness function value takes \( P_c \) and \( P_m \) values with large range and low probability, and the individual data with low fitness function value takes \( P_c \) and \( P_m \) values with small range and high probability. The variation expressions of \( P_c \) and \( P_m \) are as follows:

\[
\begin{align*}
    P_c &= \begin{cases} 
        f_{avg} \leq f_c & P_{c\ max} = \frac{(P_{c\ max} - P_{c\ min})(f_c - f_{avg})}{(f_{avg} - f_{max})}, \\
        f_{avg} > f_c & P_{c\ max}
    \end{cases} \\
    P_m &= \begin{cases} 
        f_{avg} \leq f_m & P_{m\ max} = \frac{(P_{m\ max} - P_{m\ min})(f_m - f_{avg})}{(f_{max} - f_{avg})}, \\
        f_{avg} > f_m & P_{m\ max}
    \end{cases}
\end{align*}
\]

(9)

where \( P_{c\ max}, P_{c\ min}, P_{m\ max}, \) and \( P_{m\ min} \), respectively, represent the maximum crossover probability, minimum crossover probability, maximum mutation probability, and minimum mutation probability of the likelihood BP algorithm; \( f_{avg} \) represents the most active data in the data set to be mutated; \( f_{avg} \leq f \) represents the value range of fitness function value; \( f_{avg} > f \) represents the value range of crossover probability; \( f_{avg} \leq f \) represents the value range of variation probability; \( f_c \) represents the average crossover probability of the overall data; and \( f_m \) represents the average variation probability of the overall data.

After the above operations, the prediction model is finally established, and its expression is as follows:

\[
y = f^{(2)} \left( \sum_{j=1}^{l} \left( \sum_{i=1}^{m} w_{ji}^{(1)} x_i \right) w_{lj}^{(2)} f^{(1)} \right),
\]

(10)

where \( f^{(1)} \) and \( f^{(2)} \) represent the input and output of the neural network, respectively; \( w_{lj}^{(2)} \) represents the implicit parameters of the prediction model; \( \sum_{i=1}^{m} w_{ji}^{(1)} x_i \) represents the weight difference between the hidden layer and the visible layer of the prediction model.

4. Experiment and Analysis

In order to verify the overall effectiveness of the prediction method of the trend of physical fitness energy efficiency difference of regional donor children based on likelihood BP algorithm, it needs to be tested.

4.1. Experimental Environment. The code of simulation experiment is realized by MATLAB r2016a software platform. The hardware environment adopts an Intel Core i5-3570 model 3.4 GHz processor, 8 GB installed memory, and the operating system is 64-bit Windows 7 Ultimate.

The number of node neurons in the input layer, hidden layer, and output layer of BP neural network is set to 8, 18, and 2, respectively, so that the number of weights of BP neural network to be optimized is 180 and the threshold is 20, including 144 weights between the input layer and hidden layer and 36 weights between the output layer and hidden layer. Therefore, there are 200 optimization parameter indexes of BP neural network. In order to collect children’s physical fitness index data, prepare a computer. The parameter values of the computer are shown in Table 7.

Using the computer parameterized in Table 7, the data acquisition structure formed by connecting the server between each department and the total server is shown in Figure 2.

Using the data acquisition structure built in Figure 2, set the data acquisition cycle as one month; collect the children’s physical fitness index data for three months; mark the collected data as a fixed statistical cycle; process the collected data at the same time by using the reference \([9]\) deep learning method, the reference \([10]\) alpha health test method, and the proposed method; and compare the performance of the three prediction methods.

4.2. Result Analysis. The root mean square error (RMSE) and mean absolute error (MAE) of the output results of the three prediction models are compared. Random factors may interfere with the output results of the prediction model in the process of data training. While calculating the training error value of each prediction model, add the average value of calculation error to avoid affecting the evaluation of the prediction model and improve the stability of the output results. The comparison of RMSE, MAE, and average error of the output results of each model is shown in Table 8.

It can be seen from Table 8 that the RMSE, MAE, and average error of the prediction model of the proposed method are less than 0.5, which has obvious advantages in the three methods. The average values of RMSE, MAE, and error of the prediction model of reference \([9]\) method are not less than 3, and the average values of RMSE, MAE, and error of the prediction model of reference \([10]\) method are not less than 7. The above comparison shows that the error rate of the prediction model of the proposed method is low and the prediction performance is strong.

In the data set of children’s physical fitness indicators for 10 consecutive days, a total of 24 hours in one day is randomly selected as the actual change trend, which is compared with the output results obtained by the proposed
method, reference [9] method, and reference [10] method through the prediction model. The comparison between the actual value and the predicted value is shown in Figure 3.

It can be seen from Figure 3 that the prediction results of the above three prediction models for children’s health risks are significantly different. The prediction curve of the proposed method is almost consistent with the actual value curve, which meets the trend of unity. The prediction curve of reference [9] method and reference [10] method is quite different from the actual value curve, and any time node cannot be connected with the actual value, showing an overall deviation trend. Through the above comparison, it can be seen that the prediction trend of the proposed method is close to the actual value in unit time without significant deviation, and the change trend follows the actual change trend well at any time node. It is further verified that the prediction accuracy of the proposed method is high and the error rate is low.

Through in-depth analysis of the above prediction results, the percentage distribution of the prediction results of the proposed method, reference [9] method, and reference [10] method within different relative error ranges is shown in Figure 4.

It can be seen from Figure 4 that when the proposed method is used to predict the relative error, the proportion fluctuation of the error in different ranges is small, and the peak value of the overall error is no more than 15%, which shows that the prediction of the change trend of physical fitness energy efficiency for children by the proposed method is not disturbed by external factors, and the output result is stable. The error proportion of reference [9] method and reference [10] method fluctuates obviously in different ranges, and the peak error proportion of reference [9] method is not less than 25%, and the peak error proportion of reference [10] method is not less than 30%. Through the above comparison, it can be seen that there is a large gap between the method of reference [9] and the method of reference [10] and the proposed method, which reflects the stability and practicability of the proposed method.

Compare the model complexity of the proposed method, reference [9] method, and reference [10] method by using the time complexity (TC) value of model execution and the space complexity (SC) value of model execution. The comparison of the complexity of each model is shown in Figure 5.

As can be seen from Figure 5, the time complexity (TC) and space complexity (SC) of the proposed method do not exceed 100 s and 50 MB, respectively. The time complexity of reference [9] method and reference [10] method is more than 90 s, and the space complexity is more than 48 MB. Through the above comparison, it can be seen that the prediction model of the proposed method has low complexity, needs to occupy small computer memory, and has fast computer operation and processing speed, which reflects the highest efficiency and strongest performance of the proposed method.

Score and evaluate the proposed method, and select the four conditions of “helpful,” “think it is not helpful but helpful,” “little help,” and “no help” according to their own real experience, which are coded as 1, 2, 3, and 4 in turn. The statistical results are shown in Figure 6.

Among the 40 professional children who participated in the survey, 22 children thought that the prediction results of this paper were helpful for them to continue physical fitness training; 12 children thought that this method was not helpful, but it was actually very effective; 4 children thought that this method was not helpful; and 2 students thought that this method was not helpful. It can be seen from the analysis results that most of the experimenters believe that the health risk prediction results obtained by this method are effective, and only a few children disagree with the results. In general, the proposed prediction model has strong reference value.

The comprehensive analysis of the experimental results shows that the root mean square error and average absolute error of the method in this paper are lower, the model prediction results are basically consistent with the actual value curve, and the relative error of the model prediction results is less than 15%. The time complexity (TC) and space complexity (SC) of the model are no more than 100 s and 50 MB, respectively, and 22 children of the subjects think that the prediction results in this paper are helpful for them to continue physical fitness training.

5. Conclusion

In order to evaluate the teaching effect of children’s physical fitness, this paper presents the evaluation of children’s physical fitness index and prediction of health risk trend based on BP neural network. After a period of implementation of the Healthy Physical Fitness Intervention Course, the level of Healthy Physical Fitness of the interfered children was improved significantly. Therefore, the Health Fitness Intervention Curriculum can be promoted in schools, so that more children can benefit from it, so that children can better adapt to the study and life pressure.

Data Availability

The author can provide all the original data involved in the research.

Conflicts of Interest

The author indicate that there was no conflict of interest in the study.

References

[1] A. S. Babiuch, K. Oestervemb, A. Lipińska et al., “Differences in the level of physical fitness and mobility among older women with osteoporosis and healthy women—cross-sectional study,” Scientific Reports, vol. 11, no. 1, p. 14179, 2021.
[2] D. Vancampfort, S. Kimbowa, P. B. Ward, and J. Mugisha, “Physical activity, physical fitness and quality of life in outpatients with a psychotic disorder versus healthy matched controls in a low-income country[],” Schizophrenia Research, vol. 229, no. 3, pp. 1-2, 2021.
[3] C. Leduc, S. I. Giga, I. J. Fletcher, M. Young, and S. C. Dorman, “Participatory development process of two human dimension intervention programs to foster physical fitness and psychological health and well-being in wildland Firefighting,”
[34] M. S. Al-Duais, F. S. Mohamad, M. Mohamad, and M. N. Husen, "Enhancement processing time and accuracy training via significant parameters in the batch BP algorithm," *International Journal of Intelligent Systems and Applications*, vol. 12, no. 1, pp. 43–54, 2020.

[35] S. Panda and G. Panda, "Performance evaluation of a new BP algorithm for a modified artificial neural network," *Neural Processing Letters*, vol. 51, no. 2, pp. 1–21, 2020.

[36] A. A. Ladel, A. Benzaouia, R. Oulbib, and M. Ould-Sine, "Robust fault tolerant control of continuous-time switched systems: an LMI approach," *Nonlinear Analysis: Hybrid Systems*, vol. 39, no. 2, p. 100950, 2021.