Journal of Autonomous Intelligence (2024) Volume 7 Issue 3
doi: 10.32629/jai.v7i3.1439

ORIGINAL RESEARCH ARTICLE

Student sports data analysis and physical fitness evaluation based on convolutional neural networks

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ABSTRACT

In order to achieve the analysis of student sports data and physical fitness evaluation, the author proposes a method based on convolutional neural networks. A hybrid algorithm combining genetic algorithm and error backpropagation algorithm (BP) is used to train convolutional neural networks. The algorithm first uses genetic algorithm for global training, and then uses BP algorithm for local precise training. This overcomes the drawbacks of traditional BP networks such as long training time and frequent local atmospheric drift, and improves global circulation performance. A neural network model was established to display the relationship between the total physical activity score and multiple test scores of high school students by utilizing electrical networks to demonstrate the connectivity of the neural network. This model aims to evaluate the athletic performance of college students and compare the results with other experimental models. The results indicate that the neural network-based model for evaluating college student physical activity can reflect the differences in physical activity and scores among all students, making it a suitable standard for evaluating high school student physical activity. The fitting accuracy of deterministic neural network models is higher than that of multiple linear regression models, which means that neural network models better reflect the performance of the network. The accuracy of various indicators of student physical fitness and total score makes the model easy to operate, accurate to predict, and effective analysis is scientifically reasonable.

Keywords: college students; physical fitness; convolutional neural network; MATLAB program

ARTICLE INFO

Received: 15 November 2023
Accepted: 8 December 2023
Available online: 2 January 2024

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1. Introduction

With the development of society and the improvement of living standards, people's attention to health and physical fitness is becoming increasingly high. As an important group in society, the evaluation of students' physical fitness is of great significance for their health and development[1]. Traditional physical fitness assessment methods often require a large amount of manpower and material resources, and the results may be interfered by subjective factors. Therefore, a more scientific, objective, and efficient assessment method is needed.

In recent years, with the rapid development of artificial intelligence technology, Convolutional Neural Network (CNN) has achieved significant results in fields such as image processing and pattern recognition. CNN has the ability to automatically extract and learn image features, making it widely used in various fields. Sports data plays an important role in evaluating students' physical fitness. By analyzing and processing student sports data, more objective information can be obtained, which in turn can more accurately evaluate students' physical fitness[2].

Therefore, the study of student motion data analysis and physical fitness assessment based on convolutional neural networks has important theoretical and practical significance[3]. Through in-depth research and application of convolutional neural networks, automatic extraction, learning, and analysis of student motion data can be achieved, thereby more accurately evaluating students' physical fitness level and providing scientific basis for their healthy development. This study aims to explore and construct an efficient and accurate model using convolutional neural network technology to provide new methods and ideas for students' physical health assessment.

2. Literature review

Convolutional neural networks are a deep learning algorithm inspired by the human visual system. It can automatically extract features from raw data and extract and compress information through multiple convolutional and pooling layers.

Firstly, we need to collect students' exercise data. These data can be obtained through technologies such as intelligent wearable devices and motion sensors. For example, smart wristbands can record students' steps, heart rate, sleep and other information, and motion sensors can obtain students' running speed, long jump length and other data. These data will become inputs for the training of convolutional neural networks. Next, we need to construct a convolutional neural network model suitable for physical fitness assessment. During the training process, we can use existing physical fitness evaluation standards as labels, and through supervised learning, let the network learn how to accurately evaluate based on motion data[4].

After the training is completed, we can use this trained convolutional neural network model to evaluate the new student motion data. By inputting students' exercise data, the network can automatically extract features and provide corresponding physical fitness evaluation results. Compared with traditional evaluation methods, this convolutional neural network-based evaluation method has the following advantages:

Firstly, automation. Traditional physical fitness assessment methods require manual measurement and calculation, while convolutional neural network-based assessment methods can achieve automation, saving a lot of manpower and time[5].

Secondly, accuracy. Convolutional neural networks can learn features related to physical fitness from a large amount of data, making the evaluation results more accurate. Traditional evaluation methods are often influenced by subjective factors and prone to errors.

Finally, objectivity. The evaluation method based on convolutional neural networks is obtained by analyzing motion data, which is not affected by subjective factors and has high objectivity[6].

However, there are also some challenges in the physical fitness assessment method based on convolutional neural networks. Firstly, data preparation and annotation require a significant amount of time and effort. Secondly, network training requires a large amount of computing resources and time. In addition, due to the different physical fitness conditions of each student, the evaluation model needs to be optimized and adjusted for different groups. Chandler, L Examining the effect of feedback on health interventions on physical activity in college students. In this study, 430 undergraduates were randomly assigned to either the intervention or the control group. Physical fitness tests were given only to the intervention group. The survey will be carried out in four phases to evaluate the students' competence, independence, and motivation. The International Standard for Test-Retest measures the difference between those who take the test and those who don't. Compared to the control group, the group that received feedback on the physical fitness test had reduced depression (F (6848) = 2.33 p = 0.031) and ability (F (6488) = 3.81, p = 0.001)[7]. Wang et al. discussed computer vision design based solely on physical examination of pupils and data evaluation models.

In this paper, we focus on the motion detection algorithm. The CPU and the GPU are the key to the hardware configuration. In this model, a lot of parallelization algorithms can be provided by GPU, and the CPU is used to read and prepare data. The tester is in charge of sending commands and state messages, and managing all audio tests[8]. High Intensity Interval Training (HIIT) improves the maximal oxygen consumption, constitution, and health status of the elderly; however, its impact on older people remains controversial. Wu, Z. J. Assessing the effects of different exercise durations on lung health, body composition, physical health, and health-related outcomes in the elderly. In July 2020, four online databases (PubMed, Scopus, Medline, Web of Science) were searched to compare the effects of HIIT on health, metabolism, and cardiovascular disease in older people[9].

Assessing physical activity in college students is a comprehensive assessment of physical activity based on their physical fitness, physical activity, and physical ability. According to previous studies, most mathematical models related to the relationship between specific activities and physical activity in college students use the results of statistical models and various evaluation methods. However, statistical probabilities and multiple regression analyzes are greatly affected by the sample size of the test, and the predictions are incorrect. For this reason, the author used a neural network solution to solve the problem more accurately and improve the assessment of physical safety of students.

3. Methods

3.1. Basic theory of convolutional neural networks

An artificial neural network will simulate the type of work of a human neural network, which is a set of data generated by the structure and activity of neural networks in the brain. It is a large-scale, non-linear adaptive system that can perform complex tasks, consisting of multiple functional units called “neurons” connected in a convenient way[10].

When neuron j has n inputs (x_1, x_2, ..., x_n) and a single output (yj), the relationship between input and output can be expressed as:

$$\begin{cases} s_j = \sum_{i=1}^{n} w_{ij}x_i - \theta_j \\ y_j = f(s_j) \end{cases} \tag{1}$$

Among θ_j is the threshold, w_{ij} is the connection weight between neuron i and neuron j, and f () is the transfer function, or excitation function.

Among them, the fitness function F is obtained by the sum of the absolute error values e between the predicted output and the actual value.

$$\mathrm{F} = \mathrm{k}\left(\sum_{\mathrm{i}=1}^{\mathrm{n}} |\mathrm{y_i} - \mathrm{o_i}|\right) \tag{2}$$

In Equation 1, n is the number of network output nodes; y_i is the expected output of the i-th node of the BP neural network; O_i is the predicted output of the *i*-th node; K is a constant coefficient[11].

The hidden layer calculation function H is calculated based on the input vector X, output layer Y, and threshold a of the training sample, as shown in Equation (3).

$$H_j = f\left(\sum_{i=1}^{n} w_{ij}x_i = a_j\right) j = 1,2,\ldots,l \tag{3}$$

In Equation 3, l is the number of hidden layer nodes; f(x) is the hidden layer excitation function, and the function expression used by the author is

$$f(x) = \frac{1}{1 - e^{-x}} \tag{4}$$

1). Convolution layer

The features of the original input data are extracted through the convolution operation of this layer. The formula is shown in (5).

$$\mathrm{Con}\ vLay_j^l = g\left(\sum_{i \in M_j} I_i^{l-1} \otimes W_{i,j}^l + B_j^l\right) \tag{5}$$

Where: $g(*)$ represents the activation function; I_i^{l-1} is the input of layer $l-1$ to the j-th neuron; $W_{i,j}^l$ is the convolution nucleus between the neurons connected with layer $l-1$ and layer l; $\otimes$ is the convolution operation between connected neurons; B_j^l represents the offset parameter quantity.

2). Lower sampling layer

At the same time, adding the down sampling layer can also make the algorithm more robust for facial expression recognition under unrestricted conditions, and is not sensitive to the rotation or translation of expression images.

3). Full connection layer

The full connection layer is generally located after the convolution layer and the lower sampling layer in the convolution neural network. The main function of this layer is to map the facial expression features learned in the previous structure to the label space of the data set. The full connection layer can also be regarded as the convolution operation of a convolution kernel of a specific size. When connected behind the full connection layer, it is equivalent to a convolution kernel of 1×1 size; When connected to the convolution layer, it is equivalent to a convolution core of $h * w$ size, which performs global convolution operation on the output of the previous layer. The calculation process of the whole connection layer is shown in formula (6):

$$h_{w,b}(x) = f(W^T x + b) \tag{6}$$

Where: $f(*)$ is the activation function; x represents the input value of neuron; $h_{w,b}(x)$ is the output result after down sampling operation; $W^T x$ is the calculation parameter weight; b is the offset parameter.

4). Sofmax output layer

Softmax output layer can also be understood as the classification layer of convolutional neural network. This layer takes the expression feature vector extracted from the previous structure as the input, then each neuron will output a probability value between 0 and 1, respectively representing the probability corresponding to each expression, and the sum of these k values is 1. Among the k probability values, the expression category corresponding to the maximum value is selected as the final expression recognition result. The function expression of softmax output layer is shown in formula (7):

$$P(C_j = j \mid x) = \frac{e^{\theta_j^T x}}{\sum_{j=1}^{K} e^{\theta_j^T x}} \tag{7}$$

Where: $P(C_j = j \mid x)$ represents the probability that the x-th expression data belongs to the j-th expression category; θ_j^T is the model parameter; $\sum_{j=1}^{K} e^{\theta_j^T x}$ represents normalization processing, which aims to satisfy that the sum of probabilities of all categories is 1.

3.2. Convolutional neural network evaluation model for physical fitness of college students

3.2.1. Structural design of convolutional neural network based physical fitness evaluation model for college students

It has been theoretically proven that a convolutional neural network system with three layers (input layer, hidden layer, and output layer) can achieve any nonlinear mapping. Therefore, the physical fitness evaluation model for college students chose a three-layer convolutional neural network model with only one hidden layer, as shown in **Figure 1**.

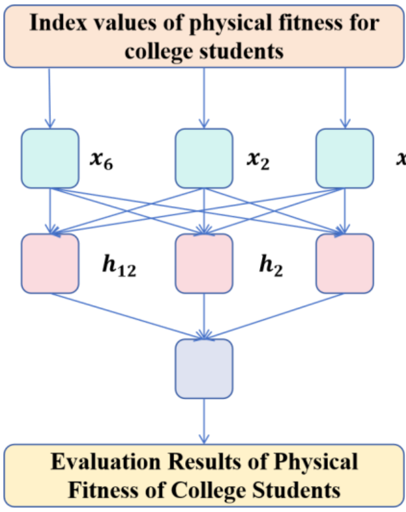

Figure 1. Structure of the Model of Physical Fitness Assessment based on Convolutional Neural Network.

The input layer of the evaluation model consists of six indicators: Height (x_1), weight (x_2), lung capacity (x_3), endurance performance (x_4), flexibility and strength performance (x_5), and speed and dexterity performance (x_6); The output layer only has one neuron y, which represents the total score of college students' physical fitness tests; According to empirical formula (5).

$$n_1 = \sqrt{n + m} + alpha \tag{8}$$

n_1 represents the number of neurons in the hidden layer, while n and m represent the number of neurons in the input and output layers, respectively, the αlpha is determined to be a constant between 1–10, and the number of neurons in the output layer is 12[12].

3.2.2. Application example of convolutional neural network based physical fitness assessment model for college students

The research object of this study is: a total of 40 students in the ninth grade administrative class of compulsory education in a certain school, including 22 boys and 18 girls.

a) Analysis of the completion status of average heart rate and exercise density goals

This study monitored classroom teaching for 39 minutes, with a target heart rate of 120 beats per minute and a target exercise density of 50%. The monitoring results show that the average heart rate of the entire class is 153 beats per minute, and the proportion of achieving the target heart rate is 100%. The average exercise density of students is 80%, with 37 people achieving the goal and 3 people not achieving it. Among them, all male students completed the goal, while 15 female students completed the goal. The completion rate of students' goals is 94%, as shown in **Figure 2**.

The exercise load of middle school physical education classroom teaching is an average heart rate of 140–150 beats/min, with an expected intensity index of 1.7–1.9, and an expected exercise density of over 50%. However, in this class, the expected average heart rate is 130-150 beats/min, with a target heart rate of 120 beats/min, and an expected exercise density of over 75%. The actual measured average heart rate (153 beats/min) and exercise density of students are both (80%). Therefore, this class has achieved the prescribed expected goals[13].

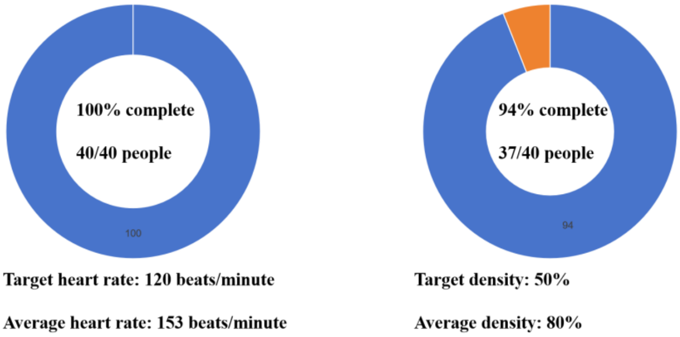

Figure 2. Analysis of the target completion of the average heart rate and exercise density.

b) Analysis of the distribution of exercise intensity

There are 26 people with an average heart rate between 140–160 beats per partition, accounting for 65.79% of the total class size. There are 9 people with an average heart rate above 160 beats per minute, accounting for 23.68% of the total class size. Among them, the average heart rate is the highest at 176 beats per minute and the lowest at 133 beats per minute, as shown in **Figure 3**.

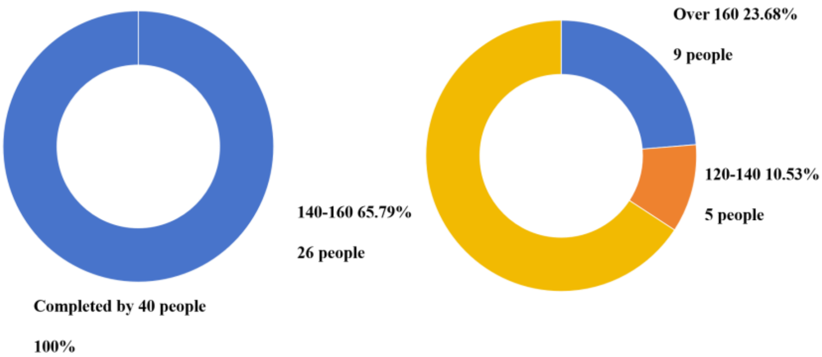

Figure 3. Analysis of exercise intensity distribution.

c) Analysis of exercise heart rate curve

The teaching duration of this class is 39 minutes, and the number of students tested is 40. The exercise heart rate curve shows that the basic average heart rate of the entire class is 105 beats per minute, as shown in **Figure 4**. Among them, dynamic physical fitness warm-up+ball training (4–5 minute interval), combination techniques of dribbling and passing during movement (11–12 minute interval), combination techniques of dribbling and passing during movement (16–21 minute interval), dribbling and passing during movement+bottom shot during movement (26–29 minute interval), and physical fitness+skill training (31-35 minute interval) all showed heart rate peaks. The average heart rate of the entire class reached 153 beats per minute[14].

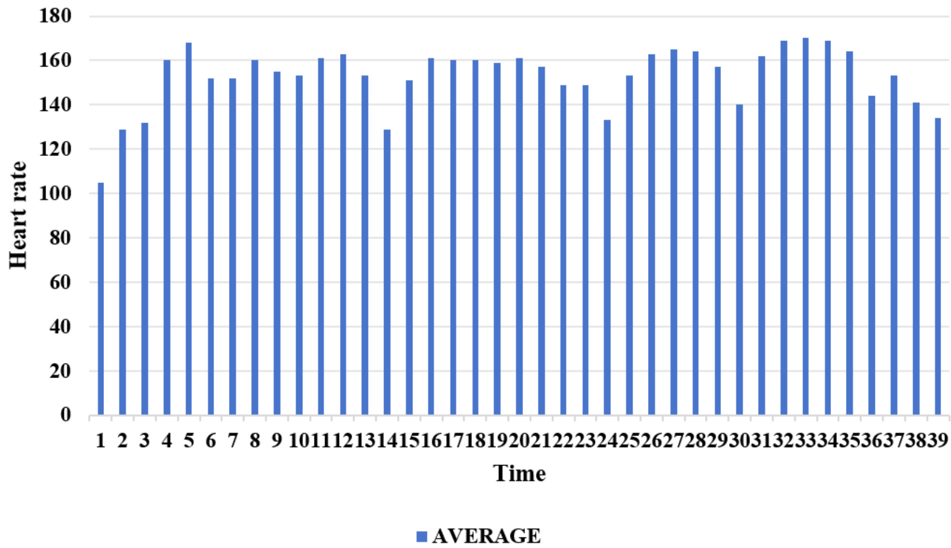

Figure 4. Analysis of the exercise heart rate chart.

d) Trend analysis of sports energy consumption

During the teaching process of this lesson, researchers tested students' exercise energy consumption every 5 minutes, totaling 8 times. This indicates that the intensity and density of students' exercise are directly proportional to their energy consumption, meaning that the higher the intensity and density of students' exercise, the greater the energy consumption, as shown in **Figure 5**.

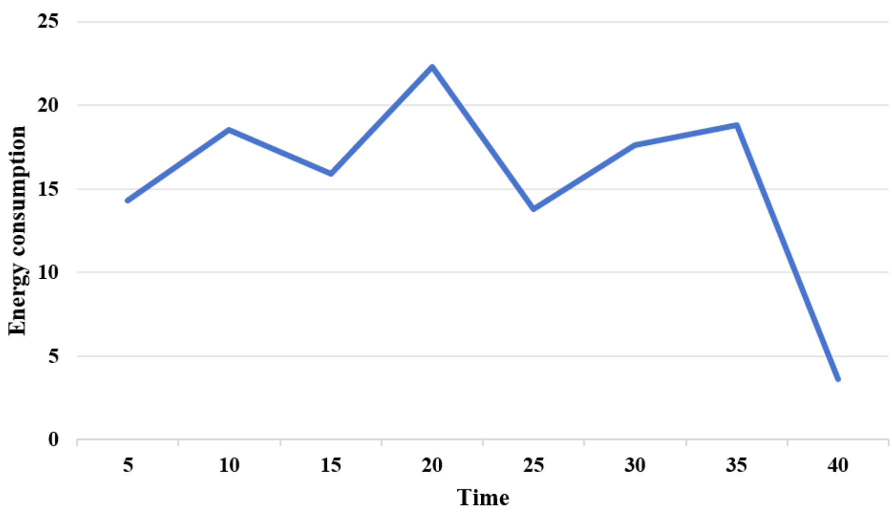

Figure 5. Analysis diagram of movement energy consumption trend.

e) Analysis of overall situation of motion monitoring data

The average exercise heart rate, average exercise duration, exercise density, exercise energy consumption, and exercise steps of male students are higher than those of female students, and the duration of high-intensity exercise for male students is also longer than that for female students, as shown in **Table 1**. This indicates that boys have a higher love for basketball than girls, and their enthusiasm for participating in basketball is also higher than that of girls[15].

Table 1. Overall situation analysis of the movement monitoring data.

Gender	Male	Female
Number of people/person	22	18
Heart rate target completion rate/%	100	100
Density target completion rate/%	100	94
Average heart rate/beats/minute	155	151
Maximum heart rate/beats/minute	197	199
Minimum heart rate/beats/minute	83	81
Exercise duration/minute	32	30
Motion density	83	78
Medium intensity duration/minute	15	17
High intensity duration/minute	16	13
Sports energy consumption/kcal	144	100
Exercise Steps/Step	3443	2975

4. Experimental results

A total of 40 students from the ninth grade administrative class of compulsory education in a certain school were selected, and another 10 test results were selected as the proofreading of the convolutional neural network. The proofreading samples are detailed in **Table 2**. The test scores of height, weight, lung capacity, endurance, flexibility and strength, and speed and dexterity were respectively composed into an input matrix P, and the total test scores were formed into an objective matrix t[16]. The test scores of each indicator in **Table 2** were formed into a validation sample matrix PP, with a training display interval of 50, a maximum training frequency of 20,000, and a minimum mean square error of 10-4. Run the program and obtain the test results and absolute errors as shown in **Figure 6**.

Table 2. Check the sample data.

Number	Height	Weight	Vital capacity	Endurance project performance	Achievements in flexibility and strength projects	Achievements in speed and dexterity projects	Total test score
1	164.8	55.7	3013	56	20.3	2.15	71.6
2	169.3	56.1	3940	55	20.3	2.00	74.3
3	165.6	59.3	2576	67	19.8	2.15	68.1
4	156.8	46.8	2247	60	19.3	2.10	60.5
5	158.8	43.1	2681	63	19.1	2.00	61.5
6	165.5	53.5	2938	73	18.3	2.05	74.5
7	165.7	56.9	4192	51	18.2	2.00	70.5
8	163.8	51.9	3479	53	18.2	1.80	63.0
9	166.0	51.3	2288	51	17.6	1.98	53.2
10	165.7	57.9	2188	55	17.3	2.10	60.2

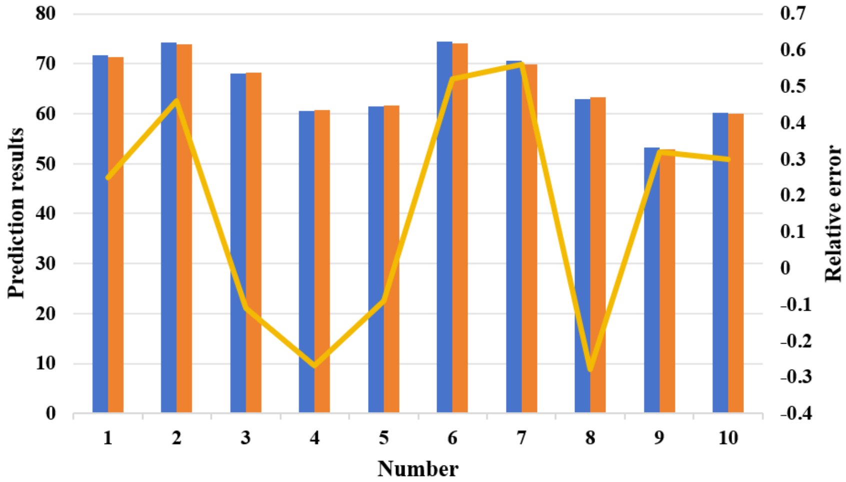

Figure 6. Prediction results and relative error conditions.

From **Figure 6**, it can be seen that the convolutional neural network-based model for evaluating college students' physical fitness can better reflect the nonlinear mapping relationship between the total score of college students' physical fitness and the scores of various indicators, making it a relatively reasonable model for evaluating college students' physical fitness.

Using a multiple linear regression model and the least squares method to fit the relationship between college students' physical fitness indicators and total test scores, the obtained mathematical model is:

$$y = 0.069x_1 - 0.052x_2 + 0.008x_3 + 0.475x_4 + 0.317x_5 + 14.423x_6 - 28.03 \tag{9}$$

Height (x_1), weight (x_2), lung capacity (x_3), endurance performance (x_4), flexibility and strength performance (x_5), speed and dexterity performance (x_6); The output layer only has one neuron y, which represents the total score of college students' physical fitness tests; According to empirical formula (5), the standard error of the prediction is 3.096, $R^2 = 0.862$. By using this mathematical formula, the predicted physical fitness scores of college students can also be calculated[17,18]. Then, in the same Cartesian coordinate system, a graph of the actual total physical fitness scores of 10 test students and the predicted scores predicted using the above two methods can be drawn. The results are shown in **Figure 7**.

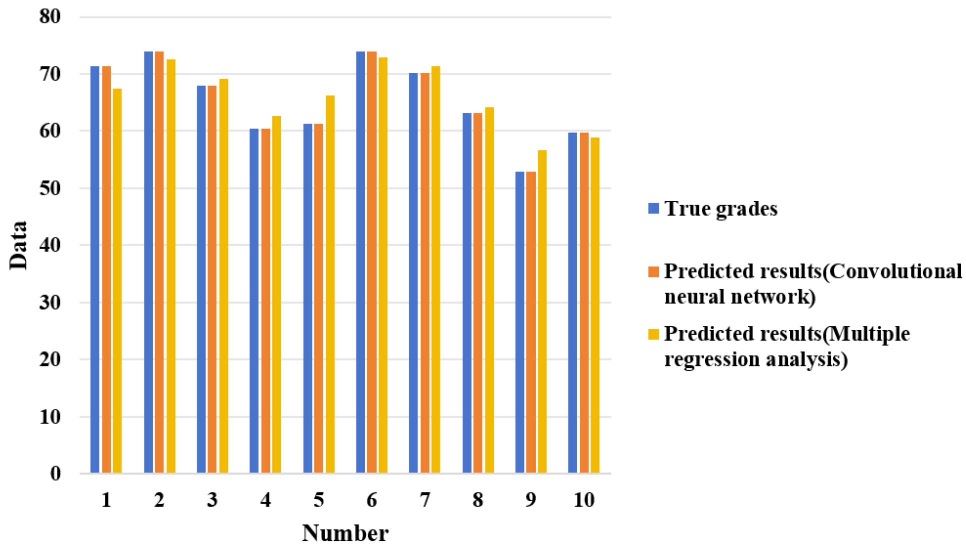

Figure 7. Comparison of the two results.

The blue in the diagram represents the actual total score, the orange indicates the prediction score of the convolutional neural network, and the yellow indicates the prediction score of the multivariate regression analysis. From **Figure 7**, we can see that the fitting precision of the convolutional neural network is better than that of the multi-linear regression. In other words, the CNN model can better reflect the function relation of each index and the total test result, which can provide a more rational mathematical model[19,20].

5. Conclusion

The BP neural network algorithm based on genetic algorithm is not only capable of calculating neural network functions, but also uses genetic algorithm to optimize the weights and thresholds of BP neural network, which avoids the negative effects of long-term training and easily enters the local network. extremum and is implemented by MATLAB software. Case studies show that this model has better prediction and performance than many other evaluation models, and does not require prior decisions on mathematical model maps. The operation is simple and the test results are scientifically sound. This can be used as a good model for assessing the physical safety of future college students. In this study, there may be limitations such as difficulty in data collection, insufficient data samples, and the generalization ability of the model. By increasing the number and diversity of research samples, further optimizing the model structure and algorithm, the accuracy and reliability of physical fitness evaluation can be improved. Future work can explore more methods for collecting sports data and improving models to enhance the accuracy and practicality of student physical fitness evaluation.

Author contributions

Conceptualization, HZ and CS; methodology, Chuan Shu; software, HZ and CS; validation, HZ; formal analysis, CS; investigation, HZ and CS; resources, HZ; data curation, CS; writing—original draft preparation, HZ; writing—review and editing, HZ and CS; visualization, CS; supervision, CS; project administration, HZ; funding acquisition, HZ. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

References

1. Wang C. Acute Teaching Method of College Physical Skills Based on Mobile Intelligent Terminal. Journal of Interconnection Networks. 2022, 22(Supp05). doi: 10.1142/s0219265921470071
2. Liu W. RETRACTED: Beach sports image detection based on heterogeneous multi-processor and convolutional neural network. Microprocessors and Microsystems. 2021, 82: 103910. doi: 10.1016/j.micpro.2021.103910
3. Zhang Y, Zhang Y. Sports Training System Based on Convolutional Neural Networks and Data Mining. Ahmed SH, ed. Computational Intelligence and Neuroscience. 2021, 2021: 1-9. doi: 10.1155/2021/1331759
4. Zhu D, Zhang H, Sun Y, et al. Injury Risk Prediction of Aerobics Athletes Based on Big Data and Computer Vision. Nazir S, ed. Scientific Programming. 2021, 2021: 1-10. doi: 10.1155/2021/5526971
5. Geng L. Evaluation Model of College English Multimedia Teaching Effect Based on Deep Convolutional Neural Networks. Khan F, ed. Mobile Information Systems. 2021, 2021: 1-8. doi: 10.1155/2021/1874584
6. Zhang CK. Design and Implementation of Student Physical Fitness Analysis System Based on Data Mining Technology. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. Published online 2023: 85-96. doi: 10.1007/978-3-031-23950-2_10
7. Chandler L, Lee JW, Lesniak KT, et al. Fitness Assessment Feedback May Lower Intrinsic Motivation for Physical Activity among College Students. Californian Journal of Health Promotion. 2021, 19(1): 54-63. doi: 10.32398/cjhp.v19i1.2649
8. Wang L, Chen S. Student Physical Fitness Test System and Test Data Analysis System Based on Computer Vision. Wu W, ed. Wireless Communications and Mobile Computing. 2021, 2021: 1-8. doi: 10.1155/2021/5589065
9. Wu ZJ, Wang ZY, Gao HE, et al. Impact of high-intensity interval training on cardiorespiratory fitness, body composition, physical fitness, and metabolic parameters in older adults: A meta-analysis of randomized controlled trials. Experimental Gerontology. 2021, 150: 111345. doi: 10.1016/j.exger.2021.111345
10. Fu Y, Lin M, Zhang Y, et al. Slope stability analysis based on big data and convolutional neural network. Frontiers of Structural and Civil Engineering. 2022, 16(7): 882-895. doi: 10.1007/s11709-022-0859-4
11. Guo J, Wan B, Zheng S, et al. A Teenager Physical Fitness Evaluation Model Based on 1D-CNN with LSTM and

Wearable Running PPG Recordings. Biosensors. 2022, 12(4): 202. doi: 10.3390/bios12040202
12. Li C yan, Zheng L. Analysis of Tai Chi Ideological and Political Course in University Based on Big Data and Graph Neural Networks. Nazir S, ed. Scientific Programming. 2021, 2021: 1-9. doi: 10.1155/2021/9914908
13. Gao J, Song J, Han L. Research on Analysis and Prediction of Elderly Medical Satisfaction Based on Convolutional Neural Network. Journal of Physics: Conference Series. 2021, 1944(1): 012013. doi: 10.1088/1742-6596/1944/1/012013
14. Liu Y, Ji Y. Target recognition of sport athletes based on deep learning and convolutional neural network. Wagner N, Sundhararajan, Son LH, Joo M, eds. Journal of Intelligent & Fuzzy Systems. 2021, 40(2): 2253-2263. doi: 10.3233/jifs-189223
15. Subbiah S, Dheeraj R. Twitter Sentimentality Examination Using Convolutional Neural Setups and Compare with DCNN Based on Accuracy. ECS Transactions. 2022, 107(1): 14037-14050. doi: 10.1149/10701.14037ecst
16. Brumann C, Kukuk M, Reinsberger C. Evaluation of Open-Source and Pre-Trained Deep Convolutional Neural Networks Suitable for Player Detection and Motion Analysis in Squash. Sensors. 2021, 21(13): 4550. doi: 10.3390/s21134550
17. Luo X. Three-Dimensional Image Quality Evaluation and Optimization Based on Convolutional Neural Network. Traitement du Signal. 2021, 38(4): 1041-1049. doi: 10.18280/ts.380414
18. Chen T, Grabs E, Petersons E, et al. Multiclass Live Streaming Video Quality Classification Based on Convolutional Neural Networks. Automatic Control and Computer Sciences. 2022, 56(5): 455-466. doi: 10.3103/s0146411622050029
19. Chen Z, Wang Y, Wu J, et al. Sensor data-driven structural damage detection based on deep convolutional neural networks and continuous wavelet transform. Applied Intelligence. 2021, 51(8): 5598-5609. doi: 10.1007/s10489-020-02092-6
20. Greco A, Saggese A, Vento M, Vigilante V. Effective training of convolutional neural networks for age estimation based on knowledge distillation. Neural Computing and Applications. 2021, 78(7): 9619-9641.