

Research Article

Student's Physical Health Prediction Model Based on the Deep Neural Network

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The arrival of the Internet of Things era has brought us a series of conveniences, but it is also devouring the physical and mental health of most of us. Especially students, as the future main force of the motherland, their health cannot be ignored. To more accurately and appropriately predict the physical health of students, this paper establishes a deep convolutional neural network (CNN) model and uses its own strong function mapping ability, and using the general physical index of students' physical health to obtain the total score as the input parameter and the total score of physical health as the output parameter, so as to establish a deep CNN prediction model for students' physical health. The model firstly overcomes the shortcoming of singleness brought by a simple NN, and it more accurately and clearly reflects the relationship between various physical measurement indicators and the overall physical health score. Secondly, the specific ROC curve and the R-P curve are obtained by comparing the traditional gray EGM prediction model. Finally, from the comparison results of the R-P curve, it can be seen that the AUC of the deep convolutional network is 0.98, while the AUC of the gray EGM prediction model is only 0.89, which shows that the data of the deep convolutional network model is more accurate.

1. Introduction

Rapid economic development, the abundance of material products, not only meets people's life needs and spiritual needs in terms of comfort, convenience, enjoyment, entertainment, etc., but also eats up health in the fast-paced era. Up to now, students of different age groups are mostly troubled by learning. Due to the long study time and heavy academic tasks, they have problems such as lack of exercise and unbalanced nutrition, which make their bodies gradually appear subhealthy. According to relevant data, whether it is college students, high school students, or even primary school students, subhealth problems are common. Students' physical health generally shows a downward trend. If this situation continues in this way, it will have a profound impact on society, families, and even individuals. Therefore, to reduce this unfavorable trend, it is necessary to learn to take targeted countermeasures

such as using a gray EGM model or a deep convolutional neural network model to help students enhance their physique and grow healthily.

At present, the related research on the analysis of physical fitness prediction models is relatively scarce, including Fisher discriminant method, gray EGM prediction model, multilayer perceptron model, and other models. Although these models can make relevant predictions about the constitution of people at different ages, the effect is not satisfactory. Due to its own structure, the deep convolutional network can perform translation-invariant classification of the input information through the hierarchical structure, thereby minimizing the amount of computation. Therefore, in this situation, this paper establishes a deep CNN model, taking advantage of the complexity of the internal structure of the model, which can be used to accurately, sensitively, and efficiently evaluate the overall physical condition of students.

In the past, most of the prediction models of physical fitness used traditional prediction models, such as the gray EGM prediction model. However, these models need to calculate more data, and the data results obtained are not very accurate. It can be known through the traditional EGM prediction model and Fisher's discriminant method. A CNN model also has a convolutional layer because it has an input layer, a hidden layer, and an output layer. Therefore, this method is not only more predictive but also more widely applicable. The main innovation of this paper is that it provides a new method for predicting students' physical health.

2. Related Work

DNN is a technology in machine learning, and many people have in-depth research on its application. Among them, A Li et al. pointed out that in terms of image data analysis, it is crucial to select appropriate feature extraction and granulation methods for continuous 3WD-based image data analysis. While among the existing feature extraction methods, DNN has been widely considered due to its powerful representation ability [1]. According to Wang et al., the existing traffic mode detection from global positioning system (GPS) trajectories is highly complex and does not always work well [2]. Yan et al. proposed that to improve the efficiency of computing the similarity between images, deep CNN can be realized by proposing a single-stage supervised deep hashing framework (SDHP) to learn high-quality binary codes, which makes the similarity between the calculated images to be improved to a certain extent [3]. To reliably detect, track, and classify marine life in an underwater video without human intervention, Siddiqui et al. proposed a CNN model that not only requires a small amount of data but also has an accuracy rate close to 100% [4]. Quan et al. constructed prediction intervals (PIs) by implementing a neural network (NN)-based method. He applied and extended a newly introduced method, called lower upper bound estimation (LUBE), to develop PI using a NN model, which can more effectively address the uncertainty of power systems compared to the cost function [5]. Although there are a large number of literature studies on how to apply DNN to image processing, audio and video processing, etc., there are only a handful of applications in the physical health detection of students. Nowadays, most students are in a subhealth state due to high pressure and unbalanced nutrition. As the main force of the motherland in the future, their physical health is particularly important.

In recent years, due to factors such as students' learning pressure and environmental pollution, the physical health of adolescents has attracted increasing attention. Many people have put forward their own opinions on how to more efficiently and accurately detect the model of students' physical health. Among them, Xu established a prediction model based on BP neural network (BPNN) to more accurately predict the risk of hypertension, with a relative error of 2.418%. And it was demonstrated that a system with a

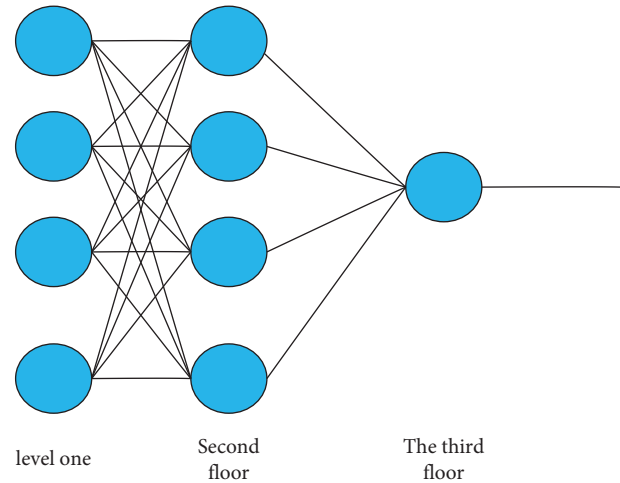


FIGURE 1: BPNN structure model.

decision tree BP model can be a useful tool for more accurate health assessments and recommendations for individual students [6]. Yin believed that the physical and mental health of adolescents is the foundation of all-round development of society and the key to improving people's health quality [7]. Li et al. proposed IoT-assisted physical activity monitoring devices to track students' physical activity and improve outcomes [8]. Wang et al. pointed out that with the accelerated pace of life and increased pressure, the physical quality of students has generally declined, and the incidence of health diseases has continued to rise. To reduce the occurrence of this trend, he believes that this purpose can be achieved by storing and analyzing the data of students' health [9]. Sortwell and Ramirez-Campillo combined examples of the 2019 coronavirus disease (COVID-19) delta variant to detect physical health indicators in children [10]. For students' physical health detection, there is a small amount of literature based on neural network research, but because the factors affecting students' physical fitness are diverse, to measure more accurately and effectively, it is obvious that DNN can meet this demand.

3. Prediction Method of Students' Physical Health

3.1. Basic Structure of NN. NN is mainly composed of neural units. If there are more neural units, the structure will be more complicated. The simpler structure is BPNN, which consists of three layers of neural units. The more complex one is DNN, whose neural unit layer composition is uncertain [11]. Figure 1 is NN composed of three layers of neural units.

Although BPNN has only three layers of neurons, each layer of neurons can have m inputs. After the calculation of neurons, the results are output to the next layer of neurons. The specific calculation process is as follows: the first step is a weighted summation of the m input values; the second step is through the activation function, the final result is obtained, which is then output to the next layer of neurons [12]. The calculation formula is

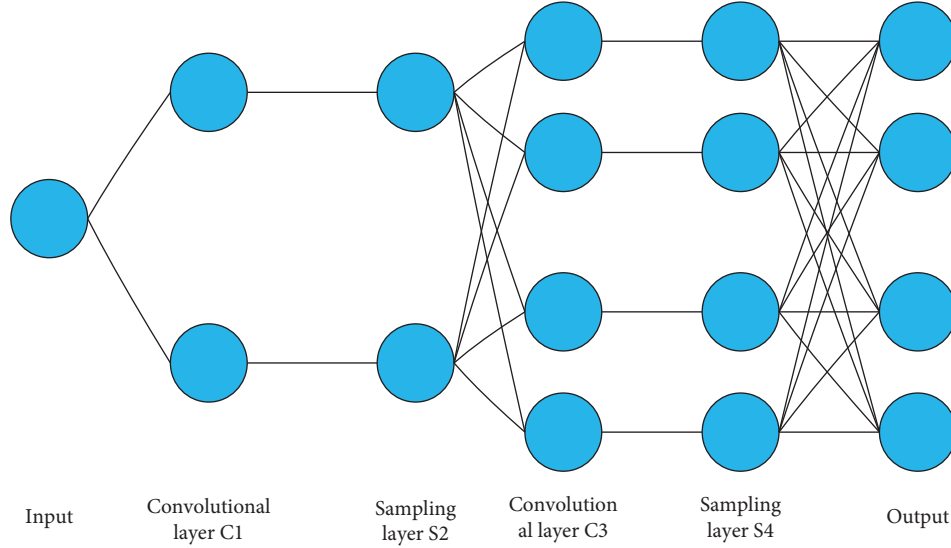


FIGURE 2: NN model structure.

$$c1 = p1u1 + p2u2 + p3u3 + \dots + pmum$$

$$y = f(c1). \quad (1)$$

Among them, $f \sum_1^m (piui)$ is the activation function of the neuron, and y is the output value of the neuron. The specific calculation process is

$$c_1^{(2)} = f(p_{11}^{(1)}u1 + p_{21}^{(1)}u2 + p_{31}^{(1)}u3 + d_1^{(1)})$$

$$c_2^{(2)} = f(p_{11}^{(1)}u1 + p_{21}^{(1)}u2 + p_{31}^{(1)}u3 + d_2^{(1)})$$

$$c_3^{(2)} = f(p_{11}^{(1)}u1 + p_{21}^{(1)}u2 + p_{31}^{(1)}u3 + d_3^{(1)})$$

$$hp, d(u) = c_1^{(3)} = f(P_{11}^{(2)}c_1^{(2)} + P_{21}^{(2)}c_2^{(2)} + P_{31}^{(2)}c_3^{(2)} + d_1^{(2)}). \quad (2)$$

3.2. Deep CNNs. As one of the DNN methods, CNN is a kind of feedforward NN with a computational and deep structure, which is mainly composed of input layer, hidden layer, convolutional layer, and output layer. Moreover, deep CNNs can establish two learning methods, supervised learning and unsupervised learning [13]. The difference between the two learning methods is that: supervised learning gives both data and results in samples; non-supervised learning only gives data and no results. The CNN structure model is shown in Figure 2.

As can be seen from the figure, the object is first input and then processed through the C1, C2, C3, and C4 layers, and finally the result is output.

3.2.1. Convolution Operation. The structure of the convolutional layer and the input layer is shown in Figure 3. Since the work in this paper is based on digital images for training, this section only describes the discrete convolution operation, which is expressed as follows:

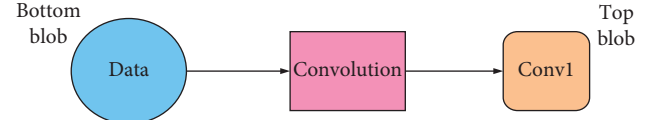


FIGURE 3: Convolutional layer and input layer.

$$S(i, j) = (F * K)(i, j) = \sum_m \sum_n F(m, n)K(i - m, j - n). \quad (3)$$

In formula (7), (i, j) represents the input data, and the “kernel function” is represented by $F(m, n)$, the size of the filter is represented by m and n , and the result value of the feature map is $S(i, j)$.

3.2.2. Pooling Operation. The pooling layer is generally divided into an average pooling layer and a maximum pooling layer. The average pooling layer propagates the average value of all input values in the receiving area to the next layer, and the maximum pooling layer transfers the maximum value in the receiving area. The values are propagated to the next layer [14]. Assuming that a is a pooling layer, the operation formula of pooling is as follows:

$$Hi = \text{subsampling}(Hi - 1). \quad (4)$$

3.2.3. Network Training. CNNs, like NNs, to get the desired network output, most people employ learning algorithms to alter their parameters (such as biases and weights). The backpropagation method is the most often utilized algorithm for this purpose [15]. Backpropagation computes the gradient of the loss function to determine how to tune network parameters to minimize errors that affect the performance.

$$MSE(w, q) = \frac{1}{|U|} \sum_{j=1}^{|U|} (U(j) - \hat{U}(j))^2 \quad NLL(w, q) = \sum_{j=1}^{|U|} \log U(j). \quad (5)$$

Among them, w refers to the weight and q refers to the bias.

3.2.4. Full Connection Operation. Convolution is utilized to extract features, pooling is used to reduce dimensionality, and the fully connected layer is used as the final data output layer in the above analysis [16]. Therefore, as a “classifier” in deep CNN, it can achieve the role of a projection space mapping, projecting the extracted results from a feature space to a different feature space. The formula is as follows:

$$R = Wmn\lambda + q. \quad (6)$$

Wmn , $\lambda = \{\lambda_0, \lambda_1, \lambda_2, \dots, \lambda_n\}$, $q = \{q_0, q_1, q_2, \dots, q_n\}$, and $z = \{z_0, z_1, z_2, z_n\}$ represent the weight coefficient, input vector bias, value and output vector, respectively.

3.2.5. Softmax Regression Function. The Softmax regression function is proposed to solve the multiclassification problem [17], and its specific expression formula is as follows:

$$P(v|u) = \frac{e^{h(u, v_i)}}{\sum_{j=1}^m e^{h(u, v_j)}}. \quad (7)$$

3.3. Gray System Theory (EGM). The gray system theory is mainly used to deal with incomplete information, because this theory is to sort out the original data, to find the law of data change [18]. Therefore, using this theory can predict the laws in a certain period and solve a large number of practical problems. The reason this method is used for physical health prediction is also based on the fact that it can predict the laws in a certain period. Suppose the original data sequence collected through the actual test is

$$W^0 = \{W^0(j) \geq 0, j = 1, 2, \dots, m\}. \quad (8)$$

The relevant formula is obtained by performing an accumulation generation operation (1-AGO accumulating generation operation) on the above formula:

$$W^1 = \{W^1(j) \geq 0, j = 1, 2, \dots, m\}. \quad (9)$$

Among them, $W^1(j) = \sum_{m=1}^j w^0(m)$, the background value of the gray model GM(1,1) is

$$z(\lambda) = 0.5(w^{(1)}(\lambda) + w^{(1)}(\lambda - 1)). \quad (10)$$

In which, $\lambda = 2, 3, \dots, n$.

The equation of the first-order gray model is

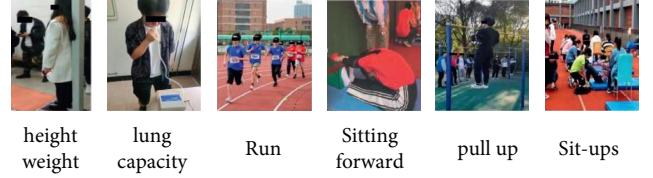


FIGURE 4: Physical health testing items.

$$\frac{dw^t}{dt} + pw^t = q. \quad (11)$$

Among them, the development coefficient is represented by p and the gray action is represented by q . The two variables represent the development trend of the estimated value of the behavior sequence and the data mined from the behavior sequence. The formula reflects the relationship between data changes [19]. Let $\hat{p} = [p, q]^T$, B , V be the parameter series.

$$B = \begin{bmatrix} U^{(0)}(2) \\ U^{(0)}(3) \\ \dots \\ U^{(0)}(n) \end{bmatrix} Y = \begin{bmatrix} -Z^{(0)}(2) & 1 \\ -Z^{(0)}(3) & 1 \\ \dots & \dots \\ -Z^{(0)}(n) & 1 \end{bmatrix}. \quad (12)$$

The parameter estimates can be obtained by the least squares method:

$$\hat{p} = (B^T B)^{-1} B^T V. \quad (14)$$

The solution to the equation of the gray model is

$$\hat{w}^{(1)}(\lambda + 1) = \left[w^{(1)}(0) - \frac{q}{p} \right] e^{-p\lambda} + \frac{q}{p}. \quad (15)$$

Among them, $\lambda = 0, 1, \dots, n$.

Taking $w^{(1)}(0) = w^{(0)}(0)$, the restoration value of the gray model is

$$\begin{aligned} \hat{w}^{(1)}(\lambda + 1) &= \hat{w}^{(1)}(\lambda + 1) - \hat{w}^{(1)}(\lambda) \\ &= (1 - e^p) \left(w^{(0)}(1) - \frac{q}{p} \right) e^{-p\lambda}. \end{aligned} \quad (16)$$

Among them, $\lambda = 0, 1, \dots, n$.

When $\lambda > n$, $\hat{w}^{(0)}(\lambda)$ is the predicted value of the original data series; and when $\lambda \leq n$, $\hat{w}^{(0)}(\lambda)$ is the fitted value of the original data series $w^{(0)}(\lambda)$ [20].

4. Students' Physical Health Prediction Experiment

4.1. Data Collection. The experimental subjects of this article are students. The following is a specific illustration of the process of monitoring their physical fitness, as shown in Figure 4.

TABLE 1: Basic information of a middle school boys sample in 2020.

	Index	Height/ cm	Body mass/kg	Vital capacity/ mL	100 m run time/s	Sit and reach/cm	Standing long jump/cm	Pull up	1000 m run time/ min
Schoolboys	Min	165	50	450	19.8	-20	110	0	2'50
	Max	188	86	5932	32.3	43	295	36	3'45
	Mean	173	75	4365	21.5	13	265	24	3'01

TABLE 2: Basic information of a sample of girls from a middle school in 2020.

Gender	Index	Height/ cm	Body mass/kg	Vital capacity/mL	100 m run time/s	Siting forward bend/cm	Standing long jump/cm	Sit up (number·min ⁻¹)	800 m run time/min
Schoolgirls	Min	148	37.5	230	18.9	-20	105	0	3'02
	Max	176	82	5365	35.7	35	275	12	4'09
	Mean	159.5	60.5	2465	28.6	12	223	8	3'59

TABLE 3: Basic information of a sample of boys from a primary school in 2020.

Gender	Index	Height/ cm	Body mass/kg	Vital capacity/mL	100 m run time/s	Siting forward bend/cm	Standing long jump/cm	Sit up (number·min ⁻¹)	1000 m run time/min
Schoolboys	Min	119	27.5	130	30.9	-20	85	0	5'02
	Max	150	50	365	40.7	10	175	9	6'09
	Mean	135	43.5	255	35.6	8	135	6	5'59

TABLE 4: Basic information of a sample of girls from a primary school in 2020.

Gender	Index	Height/ cm	Body mass/kg	Vital capacity/mL	100 m run time/s	Siting forward bend/cm	Standing long jump/cm	Sit up (number·min ⁻¹)	800 m run time/min
Schoolgirls	Min	125	24	125	29.9	-20	98	0	4'58
	Max	156	43	365	35.7	12	165	11	6'19
	Mean	136	35.5	285	31.6	10	158	9	5'48

It can be seen from the figure that the system health monitoring items are as follows: height, weight, vital capacity, running, sitting forward, bend, pull-up, and sit-up. The data studied in this paper are derived from the physical data of boys and girls in a primary and secondary school, including all registered students of the school in 2020. Among them, there are 512 boys and 398 girls in primary school; 1,535 boys and 1,729 girls in secondary school. The total score is calculated from the scores of boys and girls in the test items and is used to reflect the physical health of boys and girls in school. The specific sample information is shown in Tables 1–3, and 4.

4.2. Prediction of Students' Physical Health Based on CNN

4.2.1. Model Construction of Student Detection Projects.

The DNN structure used in this paper for the physical health prediction of middle school students has 8 input branches, which, respectively, receive 8 indicators and parameters from different sources. These 8 parameters are height, weight, vital capacity, 50 m and 1000 m, sitting forward, flexion, standing long jump, and the last test item is pull-ups for boys and sit-ups for girls. The input dimension of each branch is determined by the number of index parameters of each category. The eight categories of

TABLE 5: Dividing physical measurement indicators into eight categories.

Types	Index parameter
Class 0	Height
Class 1	Body mass
Class 2	Vital capacity
Class 3	50 m run time
Class 4	Sit and reach
Class 5	Standing long jump
Class 6	800 m run time/1000 m run time
Class 7	Pull up/sit-up

parameters used in this paper are shown in Table 5 and Figure 5.

To better know that this method is effective for predicting students' physical health, this paper uses the vital capacity of high school students as a variable, and the specific variation range is 2000 mL–4500 mL. The boy's physical condition is as follows: height 175 cm, weight 75.5 kg, standing long jump 200 cm, 50 m running time 19.2 s, pull-up 21/min, sitting body forward bending -10 cm, and 1000 m running 4 min30 s. The girl's physical condition is as follows: height 161 cm, weight 50 kg, standing long jump 1.5 m, 50 m running time 21.3 s, sit-

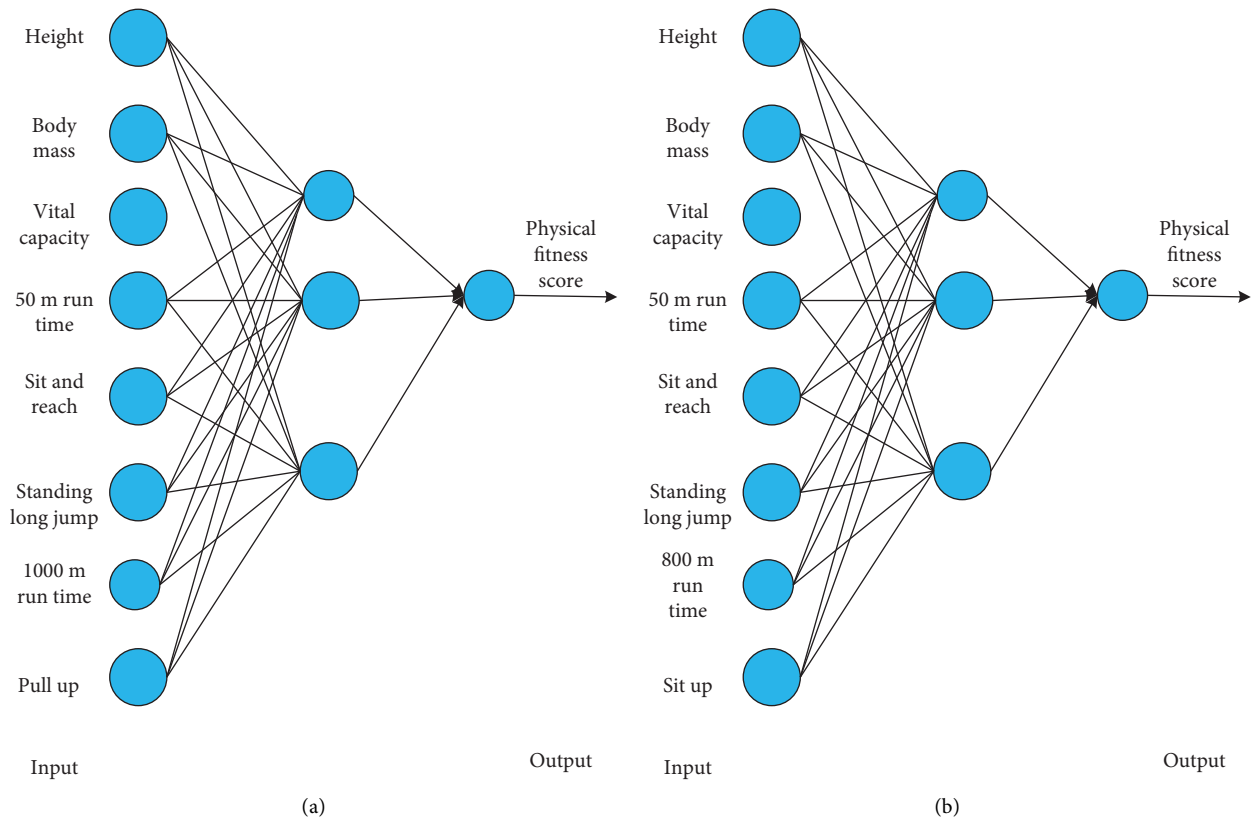


FIGURE 5: DNN architecture. (a) Physical examination of boys. (b) Physical examination of girls.

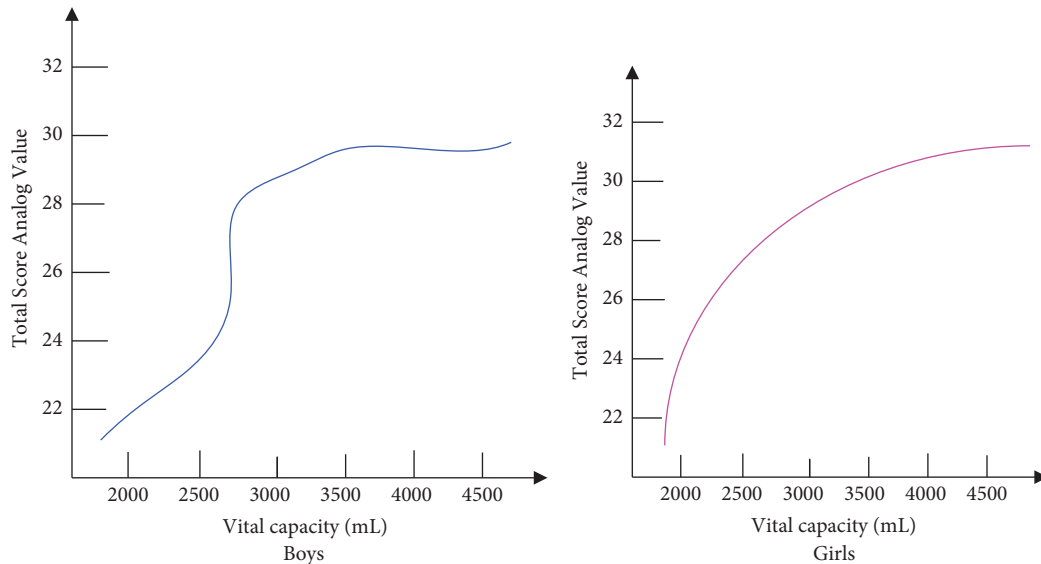


FIGURE 6: The amount of change in the system with different lung capacity.

ups 50/min, sitting forward flexion 16 cm, and 800 m running 3 min53 s.

It can be seen from Figure 6 that both boys and girls, with the continuous increase of lung capacity, their physique is also steadily improving. Although the physical health of each

student may be more or less different, the simulation results produced by each student are also different. However, the overall results of the graph show that the method can predict the physical condition of students under the condition of different variables. Therefore, this method is feasible.

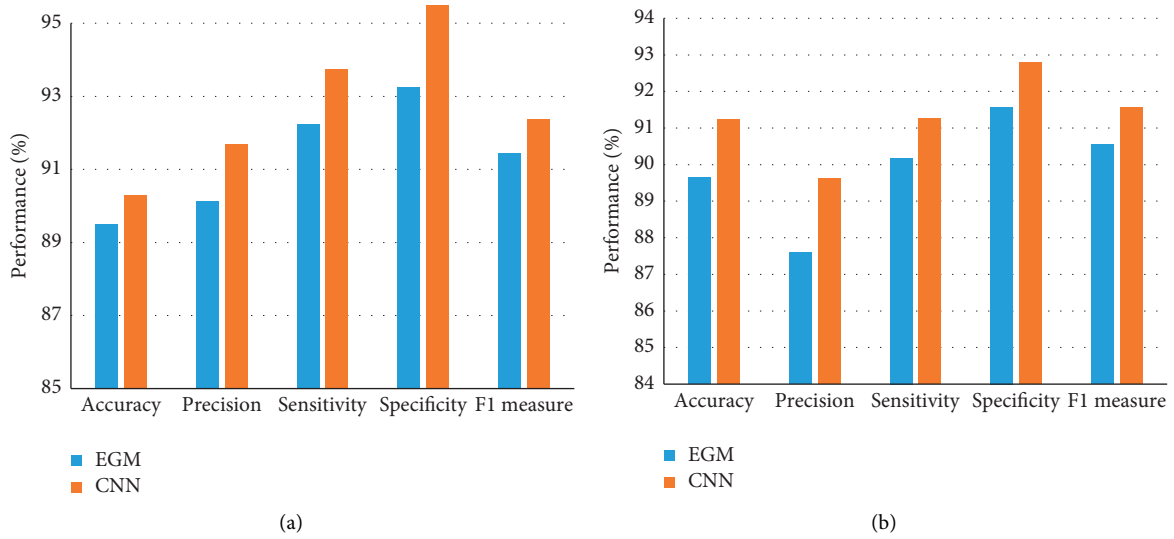


FIGURE 7: Performance comparison of EGM and CNN on different data. (a) Performance comparison of boys EGM and CNN on different data. (b) Performance comparison of girls EGM and CNN on different data.

TABLE 6: Performance comparison of EGM and CNN.

Classifier		Accuracy/%	Precision/%	Sensitivity/%	Specificity/%	F1 measure/%
Boys	EGM	86.12	89.38	85.42	91.56	89.98
	CNN	92.03	95.41	96.06	98.19	96.54
Girls	EGM	91.25	93.29	94.43	91.56	87.98
	CNN	92.03	96.23	95.98	97.56	95.23

To evaluate students’ physical health prediction methods, this paper uses six performance measures, including accuracy, precision, sensitivity, specificity, F1 measure, and receiver operating characteristic (ROC), the area covered under the curve, namely, AUC (Area under the ROC curve). The relevant calculation formula is

$$\begin{aligned}
 Precision &= \frac{TP}{TP + FP} \\
 Sensitivity &= \frac{TP}{TP + FN} \\
 Specificity &= \frac{TN}{TN + FP} \\
 F1 &= \frac{2TP}{2TP + FP + FN} \\
 Accuracy &= \frac{TP + TN}{TP + TN + FP + FN}
 \end{aligned} \tag{17}$$

Among them, in the above formulas: the full English name of T is true and the full English name of F is false. Therefore, TP is the number of correct predicted physical test items for students; TN is the number of correct predicted nonstudent physical test items; FP is the number of non-student physical test items that are predicted to affect

students’ physical health; FN is the number of students’ physical test items that are predicted to affect students’ physical health.

The size of the area under the ROC curve is proportional to the size of AUC. The larger the area covered under the curve, the better the performance of the body measurement indicator. As one of the methods commonly used to predict students’ physical health, the gray EGM model will be devoted to compare it with deep CNNs under these five performances.

4.2.2. *Experimental Results and Analysis.* Figure 7 shows the performance comparison between EGM and CNN for boys and girls. As can be seen from the data in the figure, from the perspective of accuracy, whether it is EGM or CNN, girls are higher than boys. Table 5 compares the performance of deep CNN and the gray prediction model based on the feature vectors extracted in this paper for boys and girls in middle school. It can be seen from Table 6 that accuracy, precision, specificity, and F1 metric of deep CNN constructed in this paper are all optimal, of which the accuracy rates are 91.25% and 92.03%, which proves that the performance of deep CNN is better than the gray prediction model.

On the basis of Table 6, Figures 8 and 9 show the ROC curve and the P-R curve of EGM and CNN, respectively,

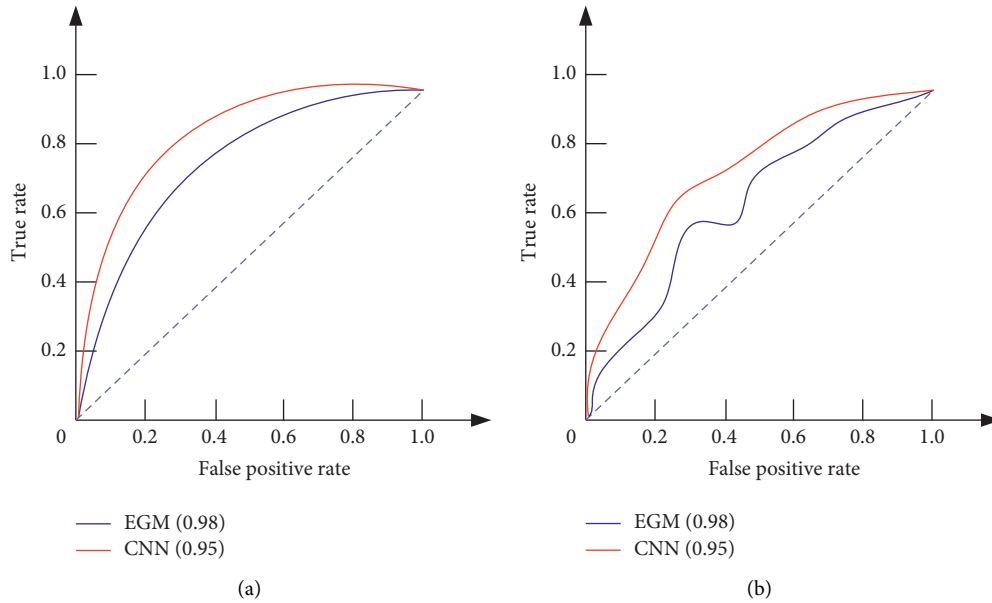


FIGURE 8: ROC curve graph. (a) Complete ROC curve. (b) Local ROC curve.

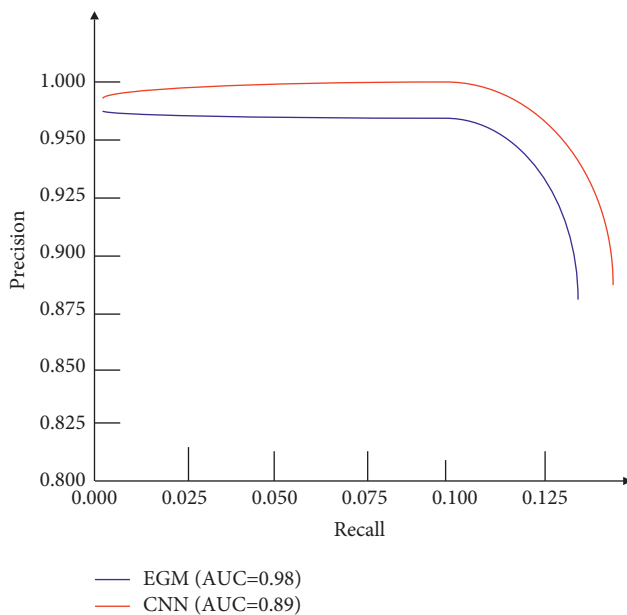


FIGURE 9: R-P curve graph.

where P refers to precision, and R refers to recall; P is the vertical axis, and R is the horizontal axis.

It can be seen from Figure 8 that the average AUC value of deep CNN is higher than that of the gray EGM model. Figure 8(b) is a partial enlarged view of the upper left corner of the ROC curve of deep CNN. It can be seen that the ROC curve of deep CNN can almost completely “envelope” the gray EGM model. Similarly, the P-R curve of the deep network in Figure 9 is also outside the gray EGM model. Clearly, deep CNNs outperform gray EGM models.

As can be seen from the above chart, whether it is the ROC curve or the R-P curve, all performances of CNN are higher

than the gray EGM model. It can be seen that the CNN model can better predict the physical health of students.

5. Conclusion

This paper mainly conducts experiments on the application of CNN in the prediction of students’ physical health. And a single neural network and a deep neural network are used to predict and analyze the physical health of primary and secondary schools. First, the basic principles of single NN and deep CNN are briefly introduced, and then CNN, one of the methods of DNN, is used to study the physical health of a middle school and to make relevant predictions. Students’ physical health prediction is of a great significance to a family or a country. Their physical health is related to the future of the family and the country, and it is the future talent pool. Only when the physical health of young people is guaranteed, the family can be fulfilled and the country gain the corresponding value. Therefore, this paper proposes a framework for predicting students’ physical fitness based on deep CNNs. Secondly, using weight, height, vital capacity, and other physical indicators of boys and girls in middle school to construct a related physical fitness prediction model and to provide a reference for the physical fitness evaluation of middle school students and other age groups. Finally, through the analysis of the comparative results, it can be seen that the CNN model has absolute advantages compared with the gray EGM model in terms of accuracy or other performance. Therefore, although the CNN model is somewhat complicated in application, this defect is acceptable compared to the ability to more accurately predict the physical health of students. It is believed that in the near future, by using this model, it can provide a better reference for the prediction of the student’s physique model and enhance the students’ physical health.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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