All-round development strategy of quality education makes primary and secondary school students not only pursue the improvement of achievement but also carry out physical exercise. Physical training is the material basis for students to study other disciplines, and the core is to improve students’ own physical quality and increase their physique. Having a strong body helps students have certain physical strength to study in other courses. In recent years, in the background of the scientific era, college students in China obviously have some problems, such as insufficient awareness of physical exercise and serious decline in physical fitness. Nowadays, teenagers are addicted to games and go out to become members of the low-headed people. Nowadays, it is very unhealthy for teenagers to go out with their mobile phones as “low-headed people.” In order to avoid college students getting rid of this living condition, colleges and universities carry out physical fitness tests every year to promote contemporary college students to strengthen exercise. College students, as the main force in the future construction of the motherland, should not only master professional knowledge but also improve their physical fitness. Good health is the greatest capital in one’s life. Every year, some students fail to pass the physical fitness test in universities. It stands to reason that college students are in the age of high youth, and physical fitness test should be a piece of cake for them. In the face of the inconsistency between the predicted results and the actual results, this paper analyzes this. Based on the above situation, With the aim of improving students’ training efficiency and physical performance, the physical performance prediction model of deep learning is designed and analyzed to predict the performance, analyze the influencing factors of the model and how to reduce the influencing components of the factors, and analyze and compare the performance of various prediction models to find out the best model, so as to make the predicted value closer to the true value.

1. Introduction

Contemporary college students in China are the main force in revitalizing the Chinese nation and improving comprehensive national strength, and their physical quality is closely related to the prosperity and development of the country. Digital storytelling, student engagement, and deep learning are applied to geography [1]. This study aims to provide insight into the usefulness of integrating digital stories in teaching and learning activities in Geography in higher education [1]. Using convolution neural network, ion current is decoded in high-dimensional feature space, which can visually reflect the hidden signal of rapid translocation movement of objects in nanoscale catheter [2]. Deep learning classifies galaxy morphology into 3-way and 4-way CNNs [3]. In Deep Merge-II, robust deep learning algorithms are constructed for cross-domain merger galaxy identification [4]. The paper aims to address the tracking algorithm based on deep learning and four deep learning tracking models developed [5]. This paper presents a literature survey and discusses how SOA can be enabled by as well as can facilitate the use of deep learning approaches in different types of environments for different levels of users [6]. Deep learning reduces blindness due to retinopathy of prematurity [7]. In publisher correction, a convolutional neural network is used to convert tabular...
data into images for deep learning [8]. We believe that deep learning technology-based systems will be on the front line of monitoring and investigation of microorganisms [9]. Deep learning is the automatic segmentation of middle skull base structures in augmented navigation [10]. Deep learning is an artificial intelligence (AI) function that imitates the workings of the human brain in processing data and creating patterns for use in decision making. Deep learning is a subset of machine learning in artificial intelligence that has networks capable of learning unsupervised from data that are unstructured or unlabeled, and it also known as deep neural learning or deep neural network [11]. We present a comprehensive exploration of the use of GPU-based hardware acceleration for deep learning inference within the data reconstruction workflow of high energy physics [12]. Application of deep learning is detection of obsolete scaphoid fractures with artificial neural networks [13]. Deep learning now accurately predicts physicochemical properties of peptides from their sequence, including tandem mass spectra and retention time [14]. This reiterates the idea that even if ML/DL algorithms are trained to make some hydrologic predictions accurately, they must be designed and trained to provide each user-required output if their results are to be used to improve our understanding of hydrologic systems [15].

Deep learning methods are applied to genotype data to predict eye color and type-2 diabetes phenotypes [16]. Deep learning and machine learning are applied to sketch image retrieval [17]. Time series and deep learning algorithms are applied to predict the gold price in India [18]. The article considers the possibilities of using the deep learning convolutional neural network ResNet in computer vision and image classification problems [19]. The differences and common points are abstract from the classification, and it is found that there are sensitive points in the counter disturbance, and the fluctuation of the sensitive points affects the classification of the deep learning model [20]. A systematic literature search was undertaken of the Web of Science, PubMed, Cochrane Library, and Embase, with an emphasis on the deep learning-based diagnosis of precancerous lesions in the upper GI tract. The status of deep learning algorithms in upper GI precancerous lesions has been systematically summarized [21]. This paper also discusses the challenges and expected future trends in the application of deep learning to heart sounds classification with the objective of providing an essential reference for further study [22].

Supervised multitask deep learning with convolutional neural networks (CNNs) on frontal chest radiographs was able to predict many underlying patient comorbidities represented by hierarchical condition categories (HCCs) from the International Classification of Diseases, Tenth Revision, including those corresponding to diabetes with chronic complications, morbid obesity, congestive heart failure, cardiac arrhythmias, and chronic obstructive pulmonary disease [23]. This article reviews deep learning applications in biomedical optics with a particular emphasis on image formation [24].

2. The Importance of Physical Quality Education

2.1. Physical Training. Physical fitness is the material basis of energy output based on the three functional systems of human body, and physical fitness is improved through repeated movements of skeletal muscles. Physical training is an important part of sports training, which is divided into general physical training and special physical training. General physical training is the basis of special physical training. Physical training refers to improving the basic quality, extension ability, and sports level of the body to make it a skill of the trainees. The core task is to strengthen one’s own physique, improve the technical level of physical training projects, and obtain high scores. The fundamental purpose is to promote college students to take physical exercise, improve their life types, and make them develop good exercise habits. Its core significance lies in participating in training to improve their physical fitness and improve the performance level of physical fitness test, so as to achieve the three views of shaping their own posture, cultivating good temperaments, and establishing positive and healthy in this process. This paper takes college students as the main body, including archery, yoga, running, rope skipping, and other sports training.

2.2. Sports Attitude. In fact, the formation of sports attitude is that people get their own sports concepts and corresponding lifestyles under the environment of social development by observing the imitation of people’s actions around them. Among them, sports attitude is mainly to learn from other people’s life experience as a third party to gain their own insights. Sports attitude is parents’ expectation for their children’s physical training. First, parents’ actual support attitude towards children’s physical training, parents’ and children’s motivation to participate in sports together, the attitude of parents to support their children’s sports equipment, the guidance and support of parents to their children’s sports events, and the process support attitude of parents to their children’s physical training during the epidemic. Second, the different attitudes include the attitude support of parents accompanying together, the different attitude support of unilateral parents accompanying, and the potential attitude support of children participating alone. It also explores the direct attitude relationship between children’s performance and parents accompanying in physical training outside school. Third, the linkage attitude includes the attitude synergy between parents and their children’s education. There are four aspects of sports attitude support: attitude adjustment of children’s mutual assistance and growth in peer relationship, attitude guidance of teacher-student relationship to children’s physical education assistance, attitude integration of family relationship in parent-child relationship, and attitude coordination of family and society synergy in parent-coach relationship.
3. Prediction Algorithm and Model

3.1. Logistic Regression Model. Logistic regression is based on linear regression model with sigmoid function, and the output value is the same as the input value.

Sigmoid function is as follows:
\[ f(z) = \frac{1}{1 + e^{-z}}. \]  
(1)

The conditional probability calculation formula is as follows:
\[ p(Y = 1|x) = \frac{\exp(w \cdot x + b)}{1 + \exp(w \cdot x + b)} \]  
(2)
\[ p(Y = 0|x) = \frac{1}{1 + \exp(w \cdot x + b)} \]

The input training set is as follows:
\[ D = [(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)], \]  
(3)
where the likelihood function of \( x_i \in \mathbb{R}, x_i \in [0, 1] \) is as follows:
\[ \prod_{i=1}^{n} \left[ \psi(x_i) \right]^{y_i} \left[ 1 - \psi(x_i) \right]^{1-y_i}. \]  
(4)

Logarithmic expression of the above function is as follows:
\[ L(w) = \log \left\{ \prod_{i=1}^{n} \left[ \psi(x_i) \right]^{y_i} \left[ 1 - \psi(x_i) \right]^{1-y_i} \right\}, \]  
(5)
\[ = \sum_{i=1}^{N} \left[ y_i \log \pi(x_i) + (1 - y_i) \log(1 - \pi(x_i)) \right]. \]

The final model result is as follows:
\[ p(Y = 1|x) = \frac{\exp(\bar{w} \cdot x + \bar{b})}{1 + \exp(\bar{w} \cdot x + \bar{b})} \]  
(6)
\[ p(Y = 0|x) = \frac{1}{1 + \exp(\bar{w} \cdot x + \bar{b})} \]

3.2. KNN Classification Algorithm. KNN judges whether the new target prediction point belongs to this category by calculating the existing sites closest to it and the category to which the most sites belong.

The characteristics in the sample set are as follows:
\[ x = (x^1, x^2, \ldots, x^n). \]  
(7)

The Euclidean distance between samples is as follows:
\[ d(x^1, x^2) = \sqrt{\sum_{i=1}^{m} (x^1_i - x^2_i)^2}. \]  
(8)

The shortest distance sample of 1 is as follows:
\[ X[X_1, X_2, X_{kl}] = \min_{kl}(d(x_i, y)). \]  
(9)

3.3. Support Vector Regression Model. Assume that the training data set is \( D = [(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)] \).

Expression of planning problem is as follows:
\[ \min \frac{1}{2} w^2 + C \sum_{i=1}^{n} \delta_i. \]  
(12)

Constraints are as follows:
\[ \text{s.t. } y_i (w \cdot x_i + b) \geq 1 - \delta_i, \quad \delta_i \geq 0, 1, \ldots, n. \]  
(13)

Introducing Lagrange multipliers and transforming them into dual problems,
\[ \min L(w, b, \alpha) = \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i \left( x_i \cdot x_j \right) - \sum_{i=1}^{n} \alpha_i, \]  
(14)

Constraints are as follows:
\[ \text{s.t. } \sum_{i=1}^{n} \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C, \quad i = 1, 2, \ldots, n. \]  
(15)

The optimal solution problem is transformed into the optimal solution:
\[ w = \sum_{i=1}^{n} \alpha_i y_i x_i, \]  
(16)
\[ b = y_j - \sum_{i=1}^{n} \alpha_i y_i (x_i \cdot x_j). \]

The optimal hyperplane obtained is
\[ f(x) = \text{sign} \left( \sum_{i=1}^{n} \alpha_i y_i (x_i \cdot x_j) + b \right). \]  
(17)

Output real value as
\[ y_j = \sum_{i=1}^{n} \alpha_i y_i (x_i \cdot x_j) + b. \]  
(18)

3.4. Deep Neural Network. The structure of the deep neural network is shown in Figure 1.

The input of each moving track is enhanced after summation, and the correlation function is as follows.

The Sigmoid activation function takes the form of
\[ f(z) = \frac{1}{1 + \exp(-z)} \]  
(19)

The corresponding derivative function is
\[ f'(z) = f(z)(1 - f(z)). \]  
(20)
The Tanh activation function takes the form of

\[ f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}. \]  

(21)

The corresponding derivative function is

\[ f'(z) = 1 - (f(z))^2. \]  

(22)

The ReLU activation function takes the form of

\[ f(z) = \max(0, z). \]  

(23)

The corresponding derivative function is

\[ f'(z) = \begin{cases} 1, & z > 0, \\ 0, & z \leq 0. \end{cases} \]  

(24)

4. Experiment

4.1. Influence of Various Factors on Model Performance

4.1.1. Effect of Quantity Set on Model Performance. In this experiment, the ADFM model is trained on the above three data sets. Data set 1 represents the experimental results of 5 skipping groups, data set 2 represents the experimental results of 5 archery groups, and data set 3 represents the experimental results of 10 running groups. The analysis of the above results shows that on the three data sets, the more data, the better the prediction effect of the ADFM model. The experimental results of the ADFM model on three data sets are shown in Figure 2.

In the data set, the physical performance of 5 groups of students participating in different projects is randomly selected to predict the prediction accuracy of the model, as shown in Table 1.

<table>
<thead>
<tr>
<th>Group</th>
<th>Sports</th>
<th>Predicted value (%)</th>
<th>Actual value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3 km long-distance</td>
<td>90.12</td>
<td>88.3</td>
</tr>
<tr>
<td>2</td>
<td>Running</td>
<td>92.2</td>
<td>89.1</td>
</tr>
<tr>
<td>3</td>
<td>100-meter sprint</td>
<td>93.1</td>
<td>90.2</td>
</tr>
<tr>
<td>4</td>
<td>Skipping rope</td>
<td>95.21</td>
<td>91.1</td>
</tr>
<tr>
<td>5</td>
<td>Archery yoga</td>
<td>94.23</td>
<td>89.7</td>
</tr>
</tbody>
</table>

Table 1: Comparison of predicted and true values.

4.1.2. Influence of Physical Fitness on Model Performance. Self-physical quality is an important feature that affects physical performance. Therefore, in this experiment, different students’ physical quality and the potential characteristics of different courses have different weights and different influences on students’ performance. The experimental results are compared with those in Table 2.

The data in the above table are counted into a two-dimensional bar chart, as shown in Figure 3.

4.1.3. Effect of Liking for Sports Events on Model Performance. Different students have different affection for sports events, which also has certain influence on the performance of the model. We study and analyze the performance of the model with three different affection degrees: special affection, general affection, and disaffection. The experimental results are as shown in Table 3.

The data in the above table are counted into a two-dimensional bar chart, as shown in Figure 4.

4.2. Model Comparison

4.2.1. Effect of Activation Function on Model. Because this paper is a combined and single-structure model and because ReLU and Tanh are better applied in the deep learning
Figure 3: Comparison of experimental results.

Table 3: Comparison of experimental results.

<table>
<thead>
<tr>
<th>Degree of liking</th>
<th>Rmse</th>
<th>Mae</th>
<th>Mape</th>
</tr>
</thead>
<tbody>
<tr>
<td>Especially liking</td>
<td>1.208</td>
<td>0.886</td>
<td>0.332</td>
</tr>
<tr>
<td>Generally like</td>
<td>1.084</td>
<td>0.621</td>
<td>0.219</td>
</tr>
<tr>
<td>Dislike</td>
<td>0.651</td>
<td>0.449</td>
<td>0.105</td>
</tr>
</tbody>
</table>

Figure 4: Comparison of experimental results.

Table 4: Comparison of the prediction of skipping rope by the number of activated culverts.

<table>
<thead>
<tr>
<th>Activation function</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tanh</td>
<td>0.912</td>
<td>0.886</td>
<td>0.923</td>
<td>0.752</td>
<td>0.802</td>
</tr>
<tr>
<td>ReLU</td>
<td>0.890</td>
<td>0.885</td>
<td>0.943</td>
<td>0.771</td>
<td>0.819</td>
</tr>
</tbody>
</table>
model, this experiment only compares the hidden layer neuron activation function with ReLU activation function and Tanh activation function. The experimental results of the prediction model for skipping rope, archery, running, and yoga by activation function are shown in Tables 4–7.

The data comparison table of the overall impact of the two activation functions on the four projects is counted as a bar chart, as shown in Figure 5.

### Table 5: Comparison of prediction of archery events by activation function.

<table>
<thead>
<tr>
<th>Activation function</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tanh</td>
<td>0.932</td>
<td>0.876</td>
<td>0.915</td>
<td>0.789</td>
<td>0.823</td>
</tr>
<tr>
<td>ReLU</td>
<td>0.880</td>
<td>0.885</td>
<td>0.945</td>
<td>0.799</td>
<td>0.854</td>
</tr>
</tbody>
</table>

### Table 6: Comparison of prediction of running events by activation function.

<table>
<thead>
<tr>
<th>Activation function</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tanh</td>
<td>0.905</td>
<td>0.891</td>
<td>0.941</td>
<td>0.738</td>
<td>0.844</td>
</tr>
<tr>
<td>ReLU</td>
<td>0.911</td>
<td>0.902</td>
<td>0.952</td>
<td>0.747</td>
<td>0.865</td>
</tr>
</tbody>
</table>

### Table 7: Comparison of yoga project prediction by activation function.

<table>
<thead>
<tr>
<th>Activation function</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tanh</td>
<td>0.918</td>
<td>0.876</td>
<td>0.954</td>
<td>0.763</td>
<td>0.802</td>
</tr>
<tr>
<td>ReLU</td>
<td>0.895</td>
<td>0.892</td>
<td>0.949</td>
<td>0.799</td>
<td>0.819</td>
</tr>
</tbody>
</table>

### Table 8: Comparison results of hidden layer number on skipping project prediction.

<table>
<thead>
<tr>
<th>Number of layers</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.75</td>
<td>0.86</td>
<td>0.95</td>
<td>0.91</td>
<td>0.81</td>
</tr>
<tr>
<td>2</td>
<td>0.76</td>
<td>0.85</td>
<td>0.94</td>
<td>0.88</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>0.61</td>
<td>0.65</td>
<td>0.73</td>
<td>0.72</td>
<td>0.69</td>
</tr>
</tbody>
</table>

### Table 9: Comparison results of hidden layer number on archery project prediction.

<table>
<thead>
<tr>
<th>Number of layers</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.74</td>
<td>0.86</td>
<td>0.92</td>
<td>0.88</td>
<td>0.81</td>
</tr>
<tr>
<td>2</td>
<td>0.76</td>
<td>0.85</td>
<td>0.84</td>
<td>0.85</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>0.68</td>
<td>0.65</td>
<td>0.85</td>
<td>0.78</td>
<td>0.69</td>
</tr>
</tbody>
</table>

### Table 10: Contrast results of prediction of running events by hidden layer number.

<table>
<thead>
<tr>
<th>Number of layers</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.77</td>
<td>0.86</td>
<td>0.95</td>
<td>0.98</td>
<td>0.86</td>
</tr>
<tr>
<td>2</td>
<td>0.73</td>
<td>0.88</td>
<td>0.86</td>
<td>0.88</td>
<td>0.84</td>
</tr>
<tr>
<td>3</td>
<td>0.75</td>
<td>0.75</td>
<td>0.73</td>
<td>0.87</td>
<td>0.76</td>
</tr>
</tbody>
</table>

### Table 11: Comparative results of hidden layer number on yoga project prediction.

<table>
<thead>
<tr>
<th>Number of layers</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.78</td>
<td>0.68</td>
<td>0.85</td>
<td>0.95</td>
<td>0.83</td>
</tr>
<tr>
<td>2</td>
<td>0.79</td>
<td>0.73</td>
<td>0.87</td>
<td>0.90</td>
<td>0.82</td>
</tr>
<tr>
<td>3</td>
<td>0.68</td>
<td>0.75</td>
<td>0.88</td>
<td>0.72</td>
<td>0.79</td>
</tr>
</tbody>
</table>

4.2.2. Influence of the Number of Hidden Layers on the Model. For DNN and PNN single-segment neural networks, we set the number of hidden layers and the number of neurons in each layer to be the same and change the number of hidden layers. The experimental results of the prediction model of hidden layer number for skipping rope, archery, running, and yoga are shown in Tables 8–11.
Compare the overall model performance indicators of the above projects with different hidden layers, such as Figure 6.

4.2.3. Influence of Model Structure on Model. In this paper, seven mixed structures are used to predict the results of physical fitness test. In this experiment, we compare different feature combinations and observe the influence of structure on model performance. The experimental results are shown in Table 12.

According to the influence of different structures on the model, it is compared and counted into a bar chart, as shown in Figure 7.

4.3. Contrast Experiment. The model presented in this chapter is compared with the traditional methods used in predicting students’ physical performance including KNN,
MF, NCF, and DMF. The test was carried out on the sample set, and the final experimental results are shown in Figure 8.

Different parameters affect the performance of FDPN, DNN + PNN, and FM + PNN models. Through a large number of experiments with different neuron numbers, the learning comparison of students’ physical fitness performance prediction models is obtained, as shown in Figures 9–11.

5. Conclusion

With the development of social intelligence, our research on the prediction of students’ physical performance has made great significance in the aspects of accurate management and scientific decision making. This paper discusses a variety of prediction models to study and analyze the prediction of physical fitness test scores in colleges and universities. The results are as follows:

(1) In the experiment of the influence of data set on the model, the amount of training data in data set 2 and data set 3 is obviously lower than that in data set 1. The analysis of the above results shows that on the three data sets, the more data, the better the prediction effect of the ADMF model.

(2) Taking students’ physical quality and students’ love for sports as independent variables, students with good physical quality and love for sports will naturally have better physical test scores.

(3) In the comparative experiment, we select different numbers of neurons to carry out the experiment. It can be seen that when it comes to deep neural network training, the number of neurons needs to be continuously compared by model training and learning, and the optimal number of neurons should be selected.

(4) In the experiment of exploring the influence of model structure on the model, the results show that the effect of single structure is slightly worse, and the combined feature learning of two structures is slightly better than that of single structure. The FDPN model has a good prediction effect and can improve the performance of performance prediction.

Data Availability

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

The authors declare that they have no conflicts of interest regarding this work.

References