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Research Article

Prediction of Sports Performance Combined with Deep Learning Model and Analysis of Influencing Factors

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Physical education class helps students develop whole-body and fine motor skills and improve their strength, balance, and cardiovascular health. Sports also provide students with numerous social, psychological, and emotional benefits, which in turn improve their learning status and academic achievements. Nowadays, sports achievements are becoming more and more important, and many schools pay more and more attention to the development of sports. In order to improve sports achievements and predict sports achievements, we can combine them with relevant deep learning models to analyze sports achievements from multiple angles and factors, so as to improve sports achievements and predict sports achievements according to relevant influencing factors. Combined with the experimental part in this paper, the gradient compression algorithms under the deep learning model are compared. According to the data, the compression ratio of the AdaComp algorithm model is 1%, the training time is 5839 s, the average accuracy rate is about 90.9%, and the average loss value is 0.324. The compression ratio of the ProbComm-LPAC algorithm model is 1%, the training time is 5505 s, the average accuracy rate is about 91.8%, and the average loss value is 0.271. The compression ratio of the LAQ algorithm model is approximately 1%, the training time is 5467 s, the average accuracy rate is about 90.8%, and the average loss value is 0.554. When the number of training rounds increases from 20 to 5000, the accuracy of the three algorithm models is on the rise, but the accuracy of ProbComp-LPAC model is higher among the three models. When the number of training rounds increases, the data set loss rate of the three models is declining, indicating that the more the training times, the higher the correct rate, the smaller the loss value, and the higher the efficiency. Through four dimensions related to the influence of sports achievements-interest in seeking knowledge, ability pursuit, altruistic orientation, and reputation acquisition, this paper studies the influencing factors of sports achievements. According to the research data, most people think that the interest in seeking knowledge accounts for a large proportion of the factors affecting sports performance, with an average of 38.6709, accounting for 32% in the four dimensions. Through the study of students' gender and origin, this paper explores the analysis of the four dimensions of sports performance. It is believed that interest in knowledge is the most important factor. The average values of the four dimensions are 48.98, 52.37, 48.12, and 51.34, respectively. In order to accurately predict sports achievements, the characteristics of sports achievements prediction are sorted, among which the maximum number of action exercises is 0.24, the average score of sports action tests is 0.16, the video viewing time is 0.13, the sign-in rate is 0.09, and the minimum homework completion rate is 0.03. Predicting sports achievements through these characteristics can improve the accuracy of prediction. When the number of features in sports performance prediction gradually increases, the accuracy of sports performance prediction is also increasing. When the number of features is 8 and 9, the prediction accuracy is about 0.64.

1. Introduction

In order to better improve sports achievements, this paper studies and analyzes the prediction process and model of sports achievements and then analyzes the influencing factors of sports achievements through experiments, combined with the gradient compression model algorithm of deep learning to improve sports achievements. Through four dimensions to analyze the influencing factors of sports performance, it can use the analysis of sports characteristics to predict sports performance and improve the prediction accuracy.

In the paper [1], the structure and function of protein are understood in detail by deep learning. This method makes a great breakthrough in protein research, and this method is greatly superior to the existing methods. Combined with the latest CASP, it can obtain the highest $F1$ score of the free modeling target, so that it can better study protein. In literature [2], the deep hidden neurons in physiological features are extracted separately, so as to construct a set of deep classifiers. Experiments show that the proposed method improves the classification rate by 5.26% compared with the previous method, and its performance superiority has been proved. Literature [3] combining deep learning model with breast cancer can further improve the automatic classification of breast cancer by pathological images under computer and further distinguish breast cancer categories. It provides a better method for the classification of breast cancer in clinical environment. Literature [4] in order to solve the problem of facial attraction prediction, we will discuss it with the method of deep learning. Literature [5] uses the kinect model to provide data to identify human physical activities. Nowadays, human activity recognition is an active field. Kinect model and CAD-60 database are used to identify human activity, which reduces the time of preprocessing and data collection and improves the efficiency. At the same time, this method also has a high accuracy, which proves that this method is very effective in recognizing human activities. In literature [6], in order to extract useful features for fault detection, we combine standard fault detection with the FDC model. However, through research, it is found that this method will have some defects such as information loss and loud interference. Therefore, we build the FDC model through SdA to reduce noise interference. In literature [7], the AdaMix model is used to improve the convergence degree of deep learning to reconstruct the error. The convergence of deep learning under different learning strategies is verified by combining autoencoder with MNIST database, so as to minimize the reconstruction error. Experiments show that this method can significantly improve the convergence of deep learning model. Literature [8] proves the effectiveness of the forecast through various forecasts, such as environment, stock price and weather. At the same time, through three prompters and league samples, we can find that the method of random prediction is slightly lower than that of prompters. Through further testing, only one of the three prompters successfully utilized the relevant results and other unspecified information, which was better than a single prompter. In literature [9], we propose a whole learning algorithm to classify attributes and study their performance through the prediction model and data collection model. Through the simulation experiment on Hadoop platform, the rainfall forecast model is developed, which improves the accuracy and efficiency of rainfall forecast." Literature [10] predicts the anxiety state of domestic shooters by SMMU. We compare SMMU with SAS, SAI, and TAI scores for better results. Through the research and results comparison, we know that SMMU is better in predicting anxiety degree of domestic shooters. In literature [11], accurate prediction of business and sports performance is an essential part. Through research, we know that the accuracy of FIFA World Cup prediction is better than that of world ranking prediction by comparing the accuracy of FIFA World Cup prediction with that of ranking prediction. Literature [12] shows that dynamic characteristics have a positive effect on our sports endurance. Lactic acid is produced for high-intensity exercise, which reduces the efficiency of exercise. Literature [13] studies chronobiology for repetitive testing of athletic performance. Most of the components of motor performance, such as physical flexibility and muscle strength, change in a sinusoidal way every day and peak in the evening. Through 24-hour continuous monitoring, it is verified whether the motion control task changes with time during the day. Literature [14] tested whether the average correlation between self-efficacy and athletic performance was 0.38 by meta-analysis. The results show that variable control, univariate, and multivariate adjustment analyses are needed to improve efficiency and performance indicators in order to carry out more accurate test. Literature [15] developed and verified the exercise anxiety scale in order to show that anxiety in the exercise performance environment is mostly a measurement. In order to make the exercise focus scale can also be reflected in children, alternative items of level 4 or below have been prepared. The anxiety table can alleviate the anxiety of children and parents.

2. Prediction and Influencing Factors of Sports Achievements under Deep Learning

2.1. Neural Network. Neural network DNN model is also called perceptron, which is composed of many parts. The general input layer is in the first layer, the middle layer is the hidden layer, and the last layer is the input layer [16]. However, with the increase of the number of network layers, the more the network parameters, the more time it takes as shown in Figure 1.

2.2. Influence of Sports Performance. The influence of learning motivation on academic performance is analyzed concretely. From the image analysis, we can see that the combination of learning motivation and learning effect when learning motivation is too low or too high will have a small impact on the learning behavior effect. Appropriate motivation will promote the increase of learning effect. Therefore, too low or too high motivation level in physical education learning will not have a great impact on sports achievements, while medium motivation level has a better effect on sports achievements [17] as shown in Figure 2.

2.3. Sports Achievement Prediction. The neural network prediction model diagram of sports performance is shown as follows. First, select the indicators that need to be predicted, input the relevant network parameters, and then input the data of sampling samples after the input, in which the sample data is a new sample [18]. After the sample input is completed, the data are preprocessed, which includes network prediction and output prediction results [19]. Carrying out network self-learning mode after pretreatment, judging

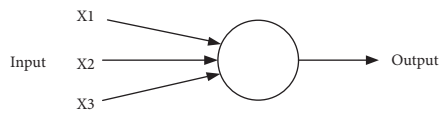

Figure 1: Perceptron.

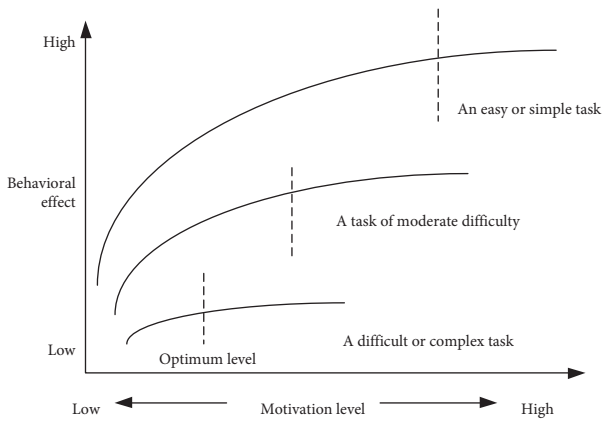

Figure 2: Motivation and behavior effect.

whether the learning efficiency of the network is satisfied after self-learning is completed, if not, returning to the step of inputting network parameters, and then carrying out circulation again. If the efficiency of network learning is met, save the results and exit as shown in Figure 3.

The accuracy of sports performance prediction is compared, and the data are normalized by the mean smoothing method [20]. Then, the sports test action is decomposed, and the sample data of the decomposed action are divided into two types: training set and test set. Train the training set data by W-LSTM model, judge whether the target standard rate is reached after training, updating relevant training parameters if the standard rate is not reached, and then retrain by the W-LSTM model. If the accuracy rate is reached, enter the test set type, use convergent neural network to test, then output the relevant test results, and compare the results and finally draw a conclusion. W-LSTM can usually achieve excellent results for predicting time data, and now, it has become one of the most popular algorithms to deal with this kind of problems. An efficient time series analysis method based on wavelet decomposition is presented. By separating the signals of different frequency bands from the data, the multiangle observation of the data can be realized as shown in Figure 4.

3. Correlation Formula

3.1. Deep Learning Model

3.1.1. CNN Neural Network Model. In formula (1), S is the output of $N \times N$ convolution kernel, w_{ij} is the weight in convolution kernel, b is the offset, x_{ij} is the pixel in the input image, and f is the nonlinear activation function.

Convolution layer formula:

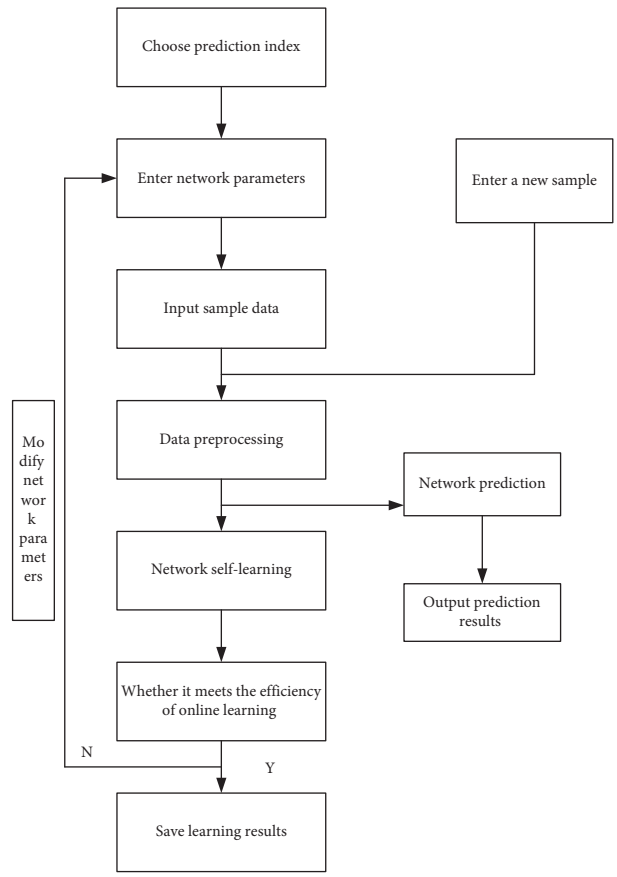

Figure 3: Performance prediction process.

$$S = f\left(\sum_{i,j} w_{i,j} x_{i,j} + b\right). \tag{1}$$

Activation function:

$$\begin{aligned} \mathrm{ELU}(x) &= \left\{\begin{matrix} x, & x > 0 \\ \alpha\left(e^{x} - 1\right), & x \le 0 \end{matrix}\right\}, \\ \mathrm{sigmoid}(x) &= \frac{1}{1 + e^{-x}}, \\ \tanh(x) &= \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}. \end{aligned} \tag{2}$$

3.1.2. RNN Cyclic Neural Network Model

$$\begin{aligned} O_i &= g\left(W_2 H_i\right), \\ H_i &= f\left(W_0 I_i + W_1 H_{i-1}\right). \end{aligned} \tag{3}$$

In order to solve the gradient disappearance and gradient explosion problems in the neural network, the formula is improved [21].

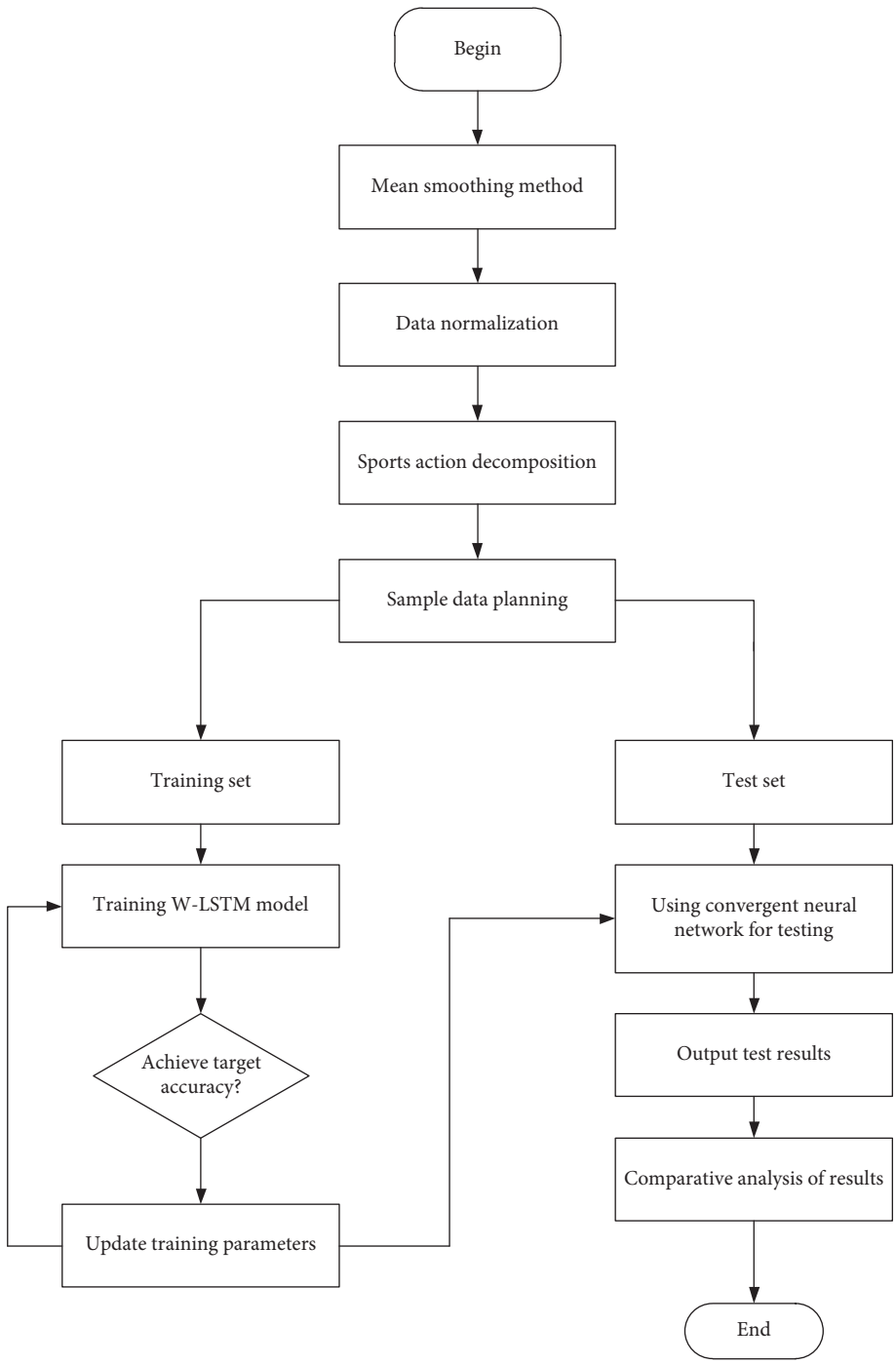

Figure 4: Comparison of performance predictions.

$$\begin{aligned}
\text{input}_t &= \text{Sigmoid}\left(W_{ix}x_t + W_{ih}h_{t-1} + b\right),\\
\text{forget}_t &= \text{Sigmoid}\left(W_{fx}x_t + W_{fh}x_{t-1} + b_f\right),\\
c_t &= \text{forget}_t * c_{t-1} + \text{input}_t\\
&\quad * \ \tanh\left(W_{cx}x_t + W_{ch}h_{t-1} + b_c\right),\\
\text{output}_t &= \text{Sigmoid}\left(W_{ox}x_t + W_{oh}h_{t-1} + b_o\right),\\
h_t &= \text{output}_t * \ \tanh\left(c_t\right).
\end{aligned} \tag{4}$$

3.1.3. GRU Cyclic Neural Network Model

$$\begin{aligned}
r_t &= \text{Sigmoid}\left(W_r x_t + U_r h_{t-1}\right),\\
z_t &= \text{Sigmoid}\left(W_z x_t + U_z h_{t-1}\right),\\
h_t' &= \tanh\left(W_h x_t + r_t U_h h_{t-1}\right),\\
h_t &= \tanh\left(W_h x_t + r_t U_h h_{t-1}\right).
\end{aligned} \tag{5}$$

3.2. Sports Achievement Prediction

3.2.1. Time Series Model Method. Proportional change practice:

$$C_{t+1}^{\wedge} = C_t\left(1 + \frac{C_t - C_{t-1}}{C_{t-1}}\right). \tag{6}$$

Moving average model:

$$C_{t+1}^{\wedge} = \frac{C_t + C_{t-1} + \cdots + C_{t-n+1}}{N} \; t \geq N. \tag{7}$$

Weighted moving average model:

$$C_{t+1}^{\wedge} = \frac{a_0 C_t + a_1 C_{t-1} + \cdots + a_{N-1} C_{t-n+1}}{N} \; t \geq N, \tag{8}$$

where a_0, a_1, and a_{N-1} are weighting factors [22].

Exponential smoothing model:

$$C_{t+1}^{\wedge} = aC_t + (1-a)C_t^{\wedge}. \tag{9}$$

3.2.2. Evaluation of Prediction Methods of Sports Achievements. Evaluation criteria:

$$\begin{aligned} MAPE &= \frac{\sum_{i=1}^{N} \left|(x_i - y_i)\right| / y_i}{n} \times 100\%, \\ R &= \frac{\sum_{i=1}^{n} (x_i \times y_i)}{\sum_{i=1}^{n} (x_i)^2 \times \sum_{i=1}^{n} (y_i)^2}, \end{aligned} \tag{10}$$

where x_i represents the model analog input value and y_i is the actual value [23].

3.2.3. Metaregression Model. The logarithm of the effect quantity index of each study is established as the dependent variable to carry out regression analysis on sports activities [24].

$$Y_i = \beta_0 + \sum_{k=1}^{n} \beta_k X_{ki} + \varepsilon_i. \tag{11}$$

3.2.4. Improved BP Neural Network Algorithm Based on MATLAB

$$\Delta X(k+1) = mc \times \Delta X(k) + lr \times \frac{\partial E}{\partial X} \; 0 < lr < 1. \; \partial. \tag{12}$$

K is the training times, mc is the momentum factor, lr learning rate, and e is the error function [5].

$$\begin{aligned} \Delta X &= lr \times \frac{\partial E}{\partial X}, \\ \Delta X(k+1) &= mc \times \Delta X(k) + lr \times mc \times \frac{\partial E}{\partial X}. \end{aligned} \tag{13}$$

After formula optimization,

$$lr(k+1) = \begin{cases} 1.05 lr(k) \mathrm{mse}(k+1) < \mathrm{mse}(k), \\ 0.7 lr(k) \mathrm{mse}(k+1) > 1.04 \mathrm{mse}(k), \\ lr(k), \quad \text{others}. \end{cases} \tag{14}$$

4. Prediction and Analysis of Sports Achievements under Deep Learning

4.1. Analysis of Deep Learning Model

4.1.1. Comparison of Performance Prediction of Frequency Division Multiple Access Deep Learning Model. Compared with the traditional model, the FDPN model has higher accuracy, precision, recall, $F1$, AUC, and other performance. Compared with other algorithms, the ProbComm-LPAC gradient compression algorithm has higher average accuracy, lower average loss, and higher efficiency. Through the analysis of the factors affecting sports achievements, we can have a deep understanding of the composition of sports achievements, so as to improve sports achievements. The accuracy, precision, recall, $F1$, AUC, and other performances of FDPN model are compared under different neuron numbers. Through the observation of relevant experimental data, it is known that when the number of neurons is 256, its performance is the best, and the accuracy is 0.8668 (accuracy: 0.8680; recall rate: 0.9499; $F1$: 0.9071; AUC: 0.8179). When the number of neurons in the hidden layer is 32, 64, 128, 256, 512, and 102, the FDPN prediction model analyzes its accuracy, precision, recall, $F1$, and AUC data. It is found that when the number of neurons in the hidden layer is 256, the research values reach the highest, and its FDPN prediction performance is the best.

According to Table 1 and Figure 5, each performance data reaches the peak when the number of neurons is 256, which shows that the FDPN model has the best prediction performance when the number of neurons is 256. FDPN model includes three parts: FM, DNN, and PNN, which is a model for predicting grades. The prediction effect of the model is related to the activation function setting of hidden layer neurons. When the activation function is ReLU, the prediction accuracy, recall rate, $F1$, and AUC of FDPN model are improved by about 2%, and the prediction effect is better.

4.1.2. Comparison of Gradient Compression Algorithms for Deep Learning Models. In order to solve the problem of gradient disappearance in deep learning function, we compare gradient compression algorithms through AdaComp, ProbComm-LPAC, and LAQ models. The compression ratio of the three models is approximately 1%, and the longest training time of AdaComp model is 5839s, the shortest training time of ProbComm-LPAC model is 5505s, and the shortest training time of LAQ model is 5467s. The average accuracy of the AdaComp model and ProbComm-LPAC model is similar, which is 90.9% and 90.8%, respectively, and the average accuracy of ProbComm-LAPC model is 91.8%. In terms of average loss value, the lowest average loss value of ProbComm-LPAC model is 0.271, and the average loss value of AdaComp model is 0.324, while the highest average loss value of LAQ model is 0.554. Therefore, from the comprehensive analysis of compression ratio, training time, average accuracy, and average loss value, it is concluded that the average accuracy rate of ProbCom-LPAC

Table 1: Performance comparison of FDPN models.

Hidden layer neuron number	Accuracy	Precision	Recall rate	$F1$	AUC
32	0.8532	0.8593	0.9395	0.8976	0.8025
64	0.8590	0.8621	0.9453	0.9018	0.8082
128	0.8619	0.8634	0.9483	0.9039	0.8111
256	0.8668	0.8680	0.9499	0.9071	0.8179
512	0.8607	0.8656	0.9431	0.9027	0.8124
1024	0.8578	0.8647	0.9395	0.9005	0.8099

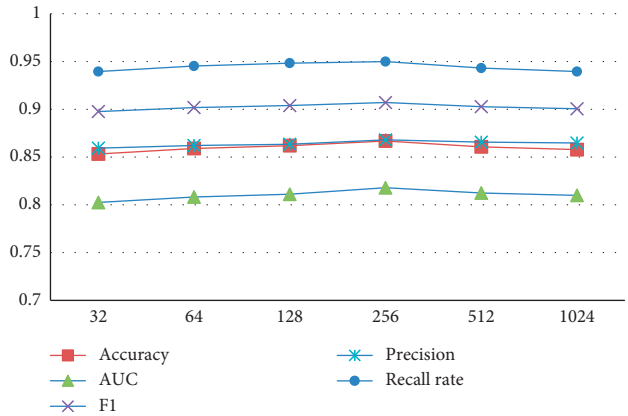

Figure 5: Performance comparison of the FDPN model.

model is higher and the average loss value is lower, which shows that the ProbComm-LPAC model has more advantages in comparison, and the gradient compression algorithm for deep learning model is more efficient, so it should be preferred when selecting the deep learning model.

According to the Table 2, when the number of training rounds is 1000, 2000, 3000, 4000, and 5000, when the number of training rounds is less than 1000, the accuracy of data sets of the three deep learning models is approximately 0. When the number of training rounds is 1000, the accuracy of ProbComm-LPAC model is higher than 0.87, followed by AdaComp model with 0.72 and LAQ model with 0.72. When the number of training rounds is 2000, the accuracy of the data set is 0.89, 0.80, and 0.75 in turn, and the corresponding models are ProbComp-LPAC, AdaComp, and LAQ models; when the number of training rounds is 3000, 4000, and 5000, the accuracy of ProbCom-LPAC model is 0.9, 0.91, and 0.95 respectively. The accuracy of the LAQ model was 0.77, 0.8, and 0.83 when the number of training rounds was 3000, 4000, and 5000. However, from the overall data of the accuracy of the three models, with the increase of the number of experimental rounds, the accuracy of the data sets of the three models is on the rise, which shows that the more the experiments, the high the accuracy.

From the Figures 6 and 7, when the number of training rounds is close to 0, the data set loss values of the three models are all high, the data set loss values of LAQ model are 4.2, AdaComp model are about 4, and ProbComp-LPAC model are 3.7, which are relatively low. When the number of training rounds is 1000, 2000, 3000, 4000, and 5000, the loss value of ProbComp model is 0.5, 0.44, 0.4, 0.37, and 0.27, respectively. Through the observation of the whole data, with the increase of the number of training rounds, the loss values of the three models all decreased, but the ProbComp-LPAC model decreased the most.

4.2. Analysis of Sports Achievements

4.2.1. Analysis on the Proportion of Sports Achievements. The boys' sports test items are 1000-meter running, standing long jump, 50-meter running, pull-ups, and throwing solid balls. Girls' sports test items are 800-meter running, standing long jump, 50-meter running, sit-ups, and throwing solid balls. According to the proportion of total scores of each project, the total scores of students' related sports are calculated. According to the data, 1000/800-meter running accounts for 30% of the total sports achievements, standing long jump and solid ball account for 15% of the total sports achievements, and 50-meter running and sit-ups/pull-ups account for 20% of the total sports achievements. According to the proportion analysis, we know that, to make sports achievements, we should mainly improve the achievements of 1000/800 meters running because the achievements of 1000/800 meters account for a large proportion in the total sports achievements as shown in Tables 3 and 4.

From Figure 8, it can be seen that the scores of 1000/800 meters running are relatively large in sports test items, followed by solid ball and sit-ups/pull-ups, and finally standing long jump and solid ball items.

4.2.2. Analysis on the Influence Factors of Sports Achievements. In order to analyze the influencing factors of sports achievements, the influencing factors are analyzed

Table 2: Gradient compression algorithm.

Gradient compression algorithm	Compression ratio	Training time (s)	Average accuracy (%)	Average loss value
AdaComp	1%	5839	90.9	0.324
ProbComm-LPAC	1%	5505	91.8	0.271
LAQ	Approximately 1%	5467	90.8	0.554

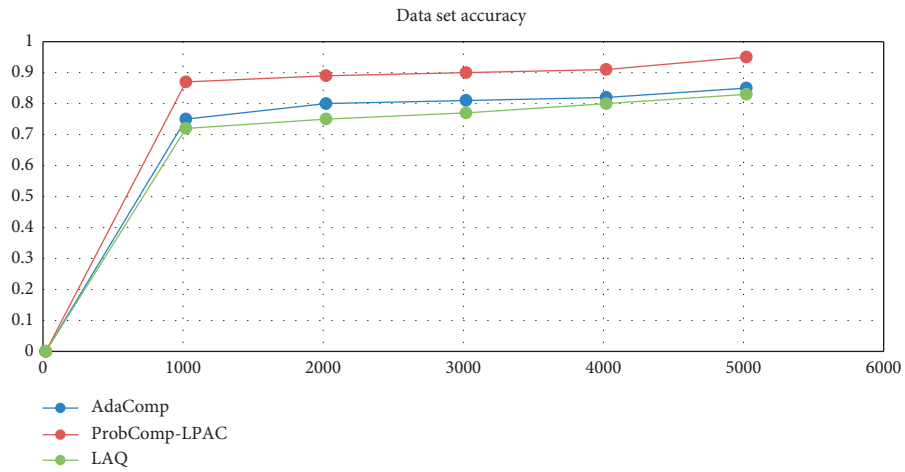

Figure 6: Accuracy of the four-dimensional data set.

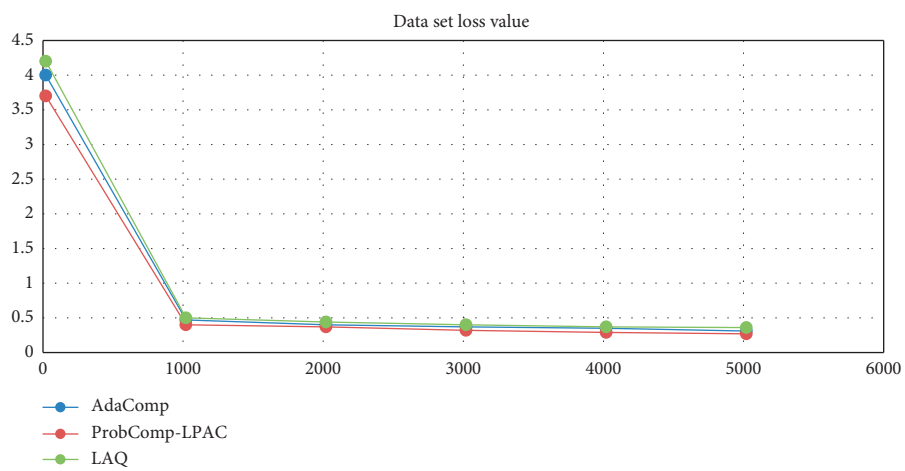

Figure 7: Loss value of the four-dimensional data set.

Table 3: Distribution of sports achievements (male).

Item score	1000 meters running (minutes and seconds)	Standing long jump (CM)	Run 50 meters (seconds)	Pull-up (times)	Throw solid ball forward (m)
100	3′40″	250	7.3	15	9.6
90	3′50″	240	7.5	13	9
80	4′05″	225	7.7	11	8.4
70	4′30″	205	8.7	9	6.9
60	4′55″	185	9.7	6	5.4
50	5′15″	180	9.9	5	5.1

from four dimensions: interest in seeking knowledge, ability pursuit, altruistic orientation, and reputation acquisition. As can be seen from Table 5, in the following four dimensions, the average value of choosing interest in seeking knowledge is 38.6709, and its standard deviation is 9.0268. The average value of selection ability pursuit is 30.6582, and the standard

Table 4: Distribution of sports achievements (female).

Item score	800 meters running (minutes and seconds)	Standing long jump (CM)	Run 50 meters (seconds)	Sit-ups	Throw solid ball forward (m)
100	3′10″	1.97	8.1	50	6.70
90	3′20″	1.89	8.3	46	6.30
80	3′30″	1.81	8.5	42	5.90
70	3′40″	1.73	8.7	38	5.50
60	3′50″	1.65	8.9	34	5.10
50	4′00″	1.57	9.1	30	4.70

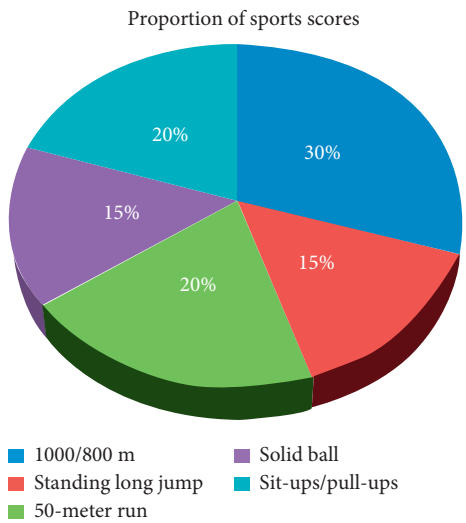

Figure 8: Proportion of sports scores.

Table 5: Influencing factors of four dimensions of sports achievements.

Dimension name	Number of items	Mean value	Standard deviation
Summary of influencing factors	34	123.9367	9.0268
Interest in seeking knowledge	12	38.6709	5.1058
Ability pursuit	9	30.6582	3.3673
Altruistic orientation	8	30.0759	3.1813
Reputation acquisition	7	21.2152	4.4712

deviation is 3.3673. The mean value of altruistic orientation is 30.0759, and the standard deviation is 3.1813. The average value of reputation acquisition is 21.2152, and the standard deviation is 4.4712. According to the data, the most important factor affecting sports performance is interest in knowledge, and the influence of reputation acquisition on sports performance is less. This shows that most students affect their sports achievements because of their love for sports. Among them, the number of people who think that ability pursuit and altruistic orientation are also more, and their average value is about 30.

It can be seen from Figure 9 that the interest in seeking knowledge accounts for a large proportion of sports achievements, and the reputation acquisition accounts for the smallest proportion, with 18%. The research shows that interest is an important factor to achieve higher grades in a subject.

From Table 6, we can see that, through different genders, we can explore the specific situation of the influence of these four dimensions on sports achievements. Through the random investigation of 75 male masses and 26 female masses, it can be seen that the female masses choose to think that the interest in seeking knowledge has a great influence on sports achievements, with an average value of 52.37 and a standard deviation of 3.670. Female people think that reputation acquisition has a relatively small impact on sports performance, with an average of 32.66 and a standard deviation of 4.778. Male people think that the interest in seeking knowledge has the greatest impact on sports performance, accounting for 48.98, and the standard deviation is 5.235. Male people think that reputation acquisition has little influence on sports performance, with an average of 32.54 and a standard deviation of 4.454. It can be seen that male and female people think that interest in seeking knowledge is the relative main factor affecting sports achievements. T value is the value obtained by testing independent samples, and P value represents significant difference. When P is less than or equal to 0.05, there is significant difference.

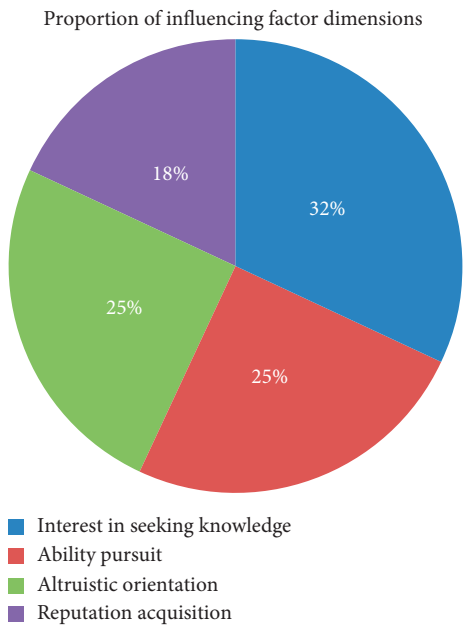

Figure 9: Proportion of four-dimensional influencing factors.

Table 6: Analysis of influencing factors by different genders.

Dimension name	Gender	Sample size	Mean value	Standard deviation	*T* value	*P* value
Total factor score	Male	75	123.67	9.186	−2.825	0.026
	Female	26	129.70	7.954		
Interest in seeking knowledge	Male	75	48.98	5.235	−2.963	0.006
	Female	26	52.37	3.670		
Ability pursuit	Male	75	41.56	3.358	−1.263	0.231
	Female	26	42.76	2.976		
Altruistic orientation	Male	75	40.99	3.103	−0.872	0.235
	Female	26	41.57	3.879		
Reputation acquisition	Male	75	32.54	4.454	−0.067	0.996
	Female	26	32.66	4.778		

It can be clearly seen from the curve trend in the Figure 10 that the highest proportion of factors affecting sports achievements is interest in seeking knowledge, followed by ability pursuit and altruistic orientation, and finally reputation acquisition.

By dividing the types of students into rural areas and cities, this paper analyzes these four influencing factors. From the data in Table 7, it can be seen that students from rural areas think that the dimension of interest in seeking knowledge has the greatest impact on sports achievements, with an average value of 51.34 and a standard deviation of 1.141; the influence of reputation acquisition on sports achievement is 31.21, and its standard deviation is 4.447. Students from cities think that interest in knowledge is the biggest influence factor on sports achievement, with an average of 48.12, and its standard deviation is 5.532.

It can be seen from the Figure 11 that the average value of choosing interest in seeking knowledge as a major factor affecting sports achievements is larger, while the proportion of those who think that reputation acquisition has a greater impact on sports achievements is relatively small.

It can be seen from the data in Table 8 that there is a big gap between boys and girls in theoretical subjects and special subjects. The average score of women in theoretical subjects is 87.264, while that of boys is 81.936. Girls' scores in theoretical subjects are higher than those of boys, which shows that girls have better scores in a series of subjects that need to calm down, such as thinking and recitation, while boys are more active and easily influenced by external factors, so their scores are lower than those of women as can be seen from Table 8.

Combined with the analysis of tables and Figure 12, it can be seen that boys are more susceptible to external factors than girls, so girls' scores in theoretical subjects are relatively higher.

4.3. Prediction and Analysis of Sports Achievements. As can be seen from Figure 13, the prediction of sports achievements is analyzed from several aspects, such as homework completion rate, classroom interaction amount, sign-in rate, video viewing time, average score of sports action test, and

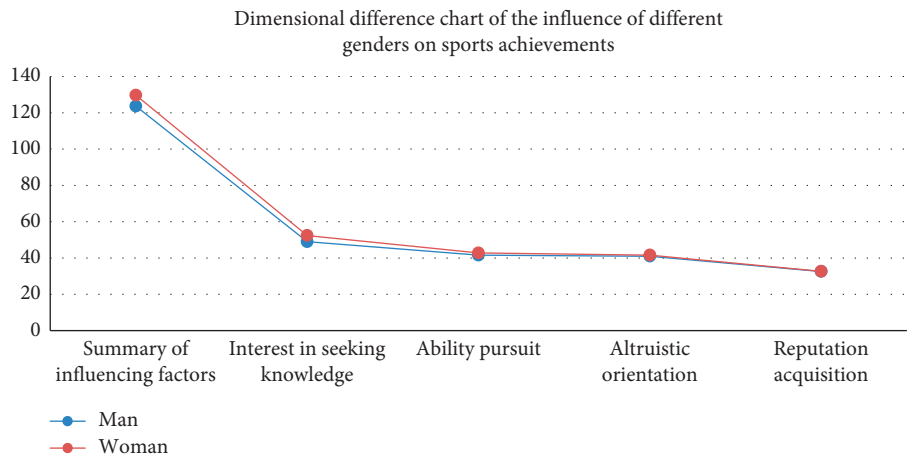

Figure 10: Influence of different genders on sports performance.

Table 7: Analysis of influencing factors of different places of origin.

Dimension name	Type of students	Sample size	Mean value	Standard deviation	T value	P value
Total factor score	City Rural	52 49	134.15 135.79	10.876 6.0571	−7.95	0.425
Interest in seeking knowledge	City Rural	52 49	48.12 51.34	5.532 1.141	−2.914	0.004
Ability pursuit	City Rural	52 49	41.61 41.76	3.767 3.012	−1.313	0.986
Altruistic orientation	City Rural	52 49	41.13 41.03	3.115 3.487	0.132	0.875
Reputation acquisition	City Rural	52 49	33.15 31.21	4.403 4.447	1.944	0.056

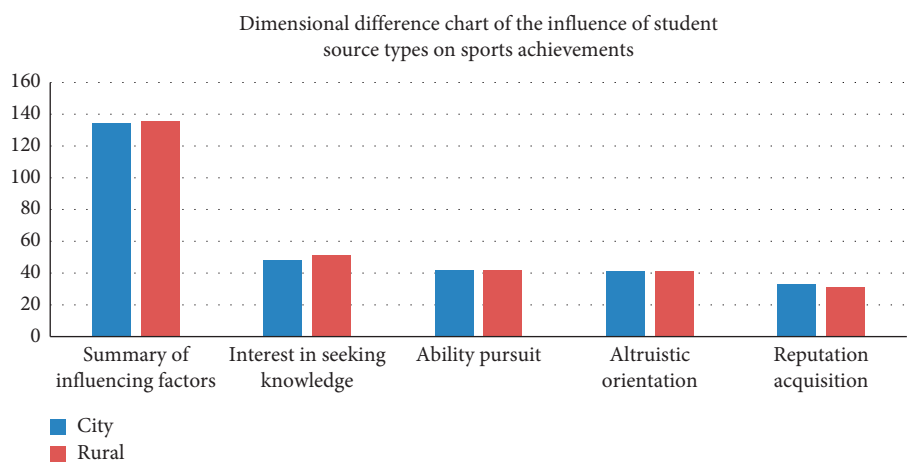

Figure 11: Influence of different places of origin on sports achievements.

number of action contact times. Among them, the number of movement exercises ranks first, which shows that the number of movement exercises is of great importance to the prediction of sports achievements.

With the number of features gradually increasing from 1 to 9, the accuracy of sports performance prediction is slightly improved. When the number of features is 9, the highest accuracy of sports performance prediction is 0.635. From the experimental data, it can be seen that the correct rate of sports performance prediction is related to the number of reference features as shown in Figure 14.

Table 8: Analysis of gender achievements.

Name of academic achievement	Gender	Sample size	Mean value	Standard deviation	*T* value	*P* value
Achievements in theoretical subjects	Male	75	81.936	6.065	−3.287	0.002
	Female	26	87.264	2.979		
Scores of special subjects	Male	75	89.908	6.065	−1.105	0.323
	Female	26	90.926	2.711		

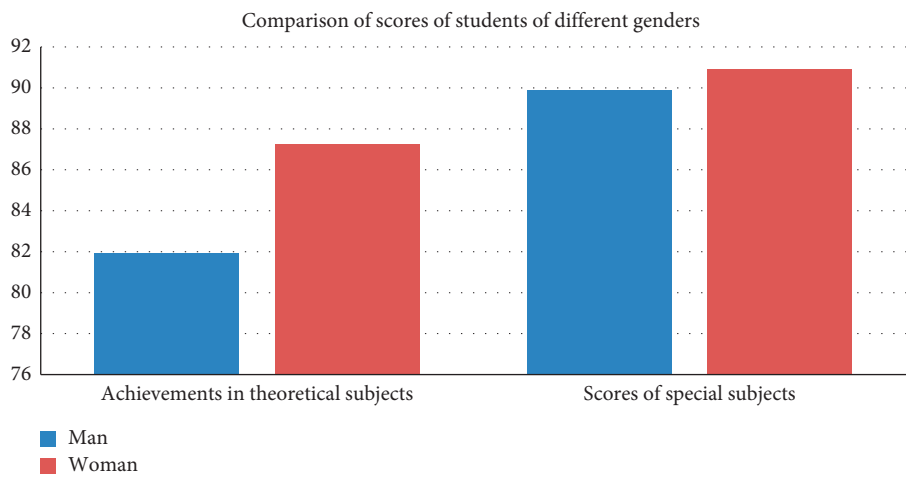

Figure 12: Comparison of gender achievements.

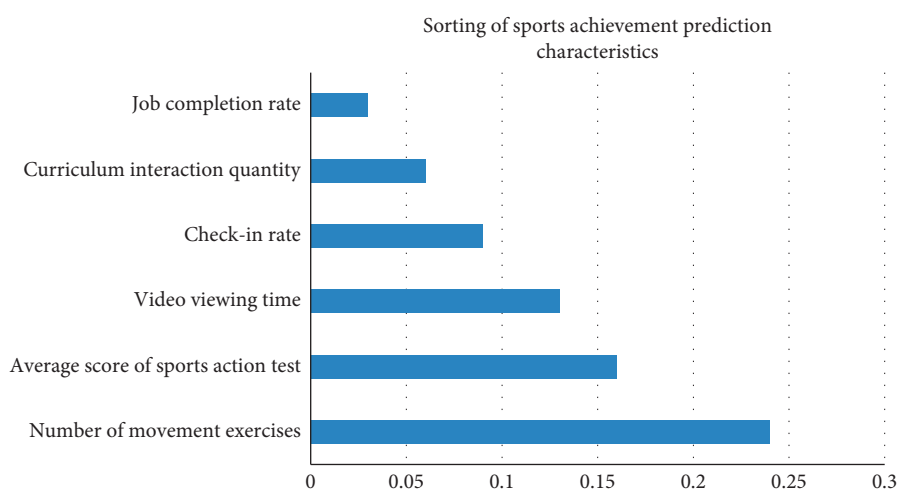

Figure 13: Ranking of sports performance prediction characteristics.

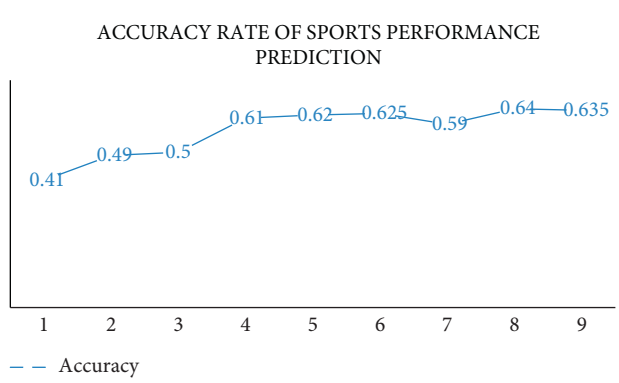

Figure 14: Accuracy rate of sports performance prediction.

5. Conclusion

In order to solve the gradient disappearance problem of the deep learning DNN model, we compare gradient compression algorithms through three models. Through experimental data, it can be seen that ProbComm-LPAC model has higher average accuracy, lower average loss rate, and the best performance. And, through the number of hidden layer neurons to FDPN model accuracy, precision, recall, $F1$, AUC experimental analysis, according to the experimental data, when the number of hidden layer neurons is 256, FDPN model prediction performance is the best. According to the sports test items and the proportion of project scores, this paper analyzes the students' sports scores, and the analysis results show that the proportion of 1000/800 meters in sports test is larger than other items. Through four dimensions to analyze the influencing factors of sports performance and improve the correct rate of sports performance prediction according to sports characteristics, we analyze the influencing factors of sports performance and predict sports scores to better improve sports performance. In order to improve the accuracy of sports performance prediction, we should analyze the performance of relevant prediction models and experiment from various factors, so as to achieve the highest performance value. At the same time, we should also strengthen physical exercise in peacetime and enhance our interest in sports, so as to improve sports performance.

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 author declares no conflicts of interest regarding this work.

References

[1] W. Sheng, S. Sun, and L. Zhen, "Accurate de novo prediction of protein contact map by ultra-deep learning model," *PLoS Computational Biology*, vol. 13, no. 1, Article ID e1005324, 2017.

[2] Z. Yin, M. Zhao, Y. Wang, J. Yang, and J. Zhang, "Recognition of emotions using multimodal physiological signals and an ensemble deep learning model," *Computer Methods and Programs in Biomedicine*, vol. 140, pp. 93–110, 2017.

[3] Z. Han, B. Wei, Y. Zheng, Y. Yin, K. Li, and S. Li, "Breast cancer multi-classification from histopathological images with structured deep learning model," *Scientific Reports*, vol. 7, no. 1, p. 4172, 2017.

[4] J. Xu, L. Jin, and L. Liang, "A new humanlike facial attractiveness predictor with cascaded fine-tuning deep learning model," *Computer Science*, vol. 70, no. 1, pp. 45–79, 2015.

[5] M. J. Barnes, "Alcohol: impact on sports performance and recovery in male athletes," *Sports Medicine*, vol. 44, no. 7, pp. 909–919, 2014.

[6] H. Lee, Y. Kim, and C. O. Kim, "A deep learning model for robust wafer fault monitoring with sensor measurement noise," *IEEE Transactions on Semiconductor Manufacturing*, vol. 301 page, 2016.

[7] Y. Y. He and B. Q. Li, "A combinatory form learning rate scheduling for deep learning model," *Acta Automatica Sinica*, vol. 7, pp. 23–42, 2016.

[8] D. Forrest and R. Simmons, "Forecasting sport: the behaviour and performance of football tipsters," *International Journal of Forecasting*, vol. 16, no. 8, pp. 24–37, 2000.

[9] W. Zhu, W. Ma, Y. Su et al., "Low-dose real-time X-ray imaging with nontoxic double perovskite scintillators," *Light: Science & Applications*, vol. 9, no. 1, pp. 112–123, 2020.

[10] N. Hu, C. Chen, and Y. Jin, "Shooters' anxiety prediction and the relationship with sports performance," *China Journal of Health Psychology*, vol. 5, no. 2, pp. 12–31, 2010.

[11] S. Luckner, J. Schröder, and C. Slamka, "On the forecast accuracy of sports prediction markets," *Negotiation, Auctions, And Market Engineering*, vol. 7, no. 8, pp. 56–81, 2006.

[12] M. Burnley and A. M. Jones, "Oxygen uptake kinetics as a determinant of sports performance," *European Journal of Sport Science*, vol. 7, no. 2, pp. 63–79, 2007.

[13] G. Atkinson and T. Reilly, "Circadian variation in sports performance," *Sports Medicine*, vol. 21, no. 4, pp. 292–312, 1996.

[14] G. Chen, L. Wang, and M. M. Kamruzzaman, "Spectral classification of ecological spatial polarization SAR image based on target decomposition algorithm and machine learning," *Neural Computing & Applications*, vol. 32, no. 10, pp. 5449–5460, 2020.

[15] R. E. Smith, F. L. Smoll, S. P. Cumming, and J. R. Grossbard, "Measurement of multidimensional sport performance anxiety in children and adults: the sport anxiety scale-2," *Journal of Sport & Exercise Psychology*, vol. 28, no. 4, pp. 479–501, 2006.

[16] M. A. Fredericksen, Y. Zhang, M. L. Hazen et al., "Three-dimensional visualization and a deep-learning model reveal complex fungal parasite networks in behaviorally manipulated ants," *Proceedings of the National Academy of Sciences*, vol. 114, no. 47, pp. 12590–12595, 2017.

[17] Z. Yin and J. Zhang, "Cross-session classification of mental workload levels using EEG and an adaptive deep learning model," *Biomedical Signal Processing and Control*, vol. 33, pp. 30–47, 2017.

[18] Y. X. He, S. T. Sun, and F. F. Niu, "A deep learning model enhanced with emotion semantics for microblog sentiment analysis," *Chinese Journal of Computers*, vol. 26, no. 3, pp. 31–58, 2017.

[19] B. Chen, Y. U. Qiuting, and T. Chen, "On deep-learning-model-based sensor activity recognition," *Journal of Zhejiang University of Technology*, vol. 31, no. 2, pp. 112–131, 2018.

[20] X. Ning, K. Gong, W. Li, and L. Zhang, "JWSAA: joint weak saliency and attention aware for person re-identification," *Neurocomputing*, vol. 453, pp. 801–811, 2021.

[21] F. Pappenberger, K. Bogner, F. Wetterhall, Y. He, H. L. Cloke, and J. Thielen, "Forecast convergence score: a forecaster's

approach to analysing hydro-meteorological forecast systems," *Advances in Geosciences*, vol. 29, pp. 27–32, 2011.

[22] C. M. Bailey, R. J. Echemendia, and P. A. Arnett, "The impact of motivation on neuropsychological performance in sports-related mild traumatic brain injury," *Journal of the International Neuropsychological Society*, vol. 12, no. 4, pp. 475–484, 2006.

[23] A. J. Braakhuis and W. G. Hopkins, "Impact of dietary antioxidants on sport performance: a review," *Sports Medicine*, vol. 45, no. 7, pp. 939–955, 2015.

[24] S. J. Haake, "The impact of technology on sporting performance in Olympic sports," *Journal of Sports Sciences*, vol. 27, no. 13, pp. 1421–1431, 2009.