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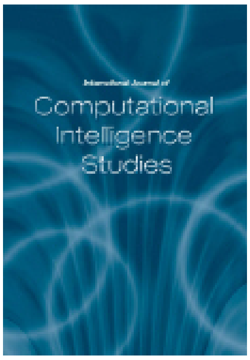

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Performance prediction analysis of college aerobics course based on back propagation neural network

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Abstract: To solve the problem of low accuracy of the performance prediction method of aerobics courses, the study proposes to combine the partial least squares regression (partial least squares – PLS) method with the multilayer feedforward (back propagation – BP) neural network to form a method. A new partial least squares-back propagation (PLS-BP) score prediction model, which uses the PLS method to analyse and extract the principal components, which improves the prediction accuracy of the model. It is then compared with the principal component analysis-back propagation (PCA-BP) prediction model and the partial least squares-support vector machine (PLS-SVM) prediction model. The results show that the accuracy of the PLS-BP score prediction model is 94.5%, which is better than the PCA-BP model and the PLS-SVM model. In the performance test of the constituted prediction system, the relative error value of the new score prediction system is 0.042, which has high accuracy. The experimental results show that the PLS-BP algorithm combining the PLS method and the BP neural network can improve the performance of the score prediction system, and provide a new idea for the performance improvement of the course score prediction system.

Keywords: score prediction; BP neural network; relative error value; partial least squares regression.

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1 Introduction

With the attention of all walks of life to the physical fitness of college students, college students' aerobics performance in schools has been paid more and more attention. And a method that can accurately predict the aerobics performance of college students can help college students improve their aerobics performance. Therefore, it is of great significance to find a method that can accurately predict the aerobics performance of college students (Feng, 2020). With the further development of information technology, more and more algorithms are applied in the field of forecasting. Among them, the BP algorithm is a relatively common prediction algorithm, which is relatively mature in theory and performance, and can meet most of the needs of neural networks (Yu et al., 2020). However, its prediction accuracy is insufficient, and the PLS method is a mathematical optimisation technique, which can find the best function matching for a set of data by minimising the sum of squares of the errors, so the combination of the PLS method and the BP algorithm can better Improve the prediction performance of the BP algorithm (Mehmood and Iqbal, 2021). In order to better predict the performance of aerobics in colleges and universities, the study adopts the PLS component extraction to optimise the relevant variables that affect the performance of aerobics courses, and then input the optimised variables into the BP neural network to construct a performance prediction model. Predict the performance and obtain the main factors that affect the performance, and provide a reference for designing a reasonable and efficient aerobics course teaching plan.

2 Related works

As various optimisation methods of the BP algorithm are gradually developed, the BP algorithm and its improved algorithms are applied in many fields. In order to improve students' learning efficiency, AFY and BFWBL propose a classification-based BP neural network student evaluation tool, and carry out an empirical analysis of the evaluation tool. The results show that the evaluation tool can effectively improve students' learning efficiency, which has great practical significance (Yang and Li, 2018). In order to better control non-affine nonlinear systems, Liu et al. (2021) proposed a hysteretic disturbance composite control framework based on linear active disturbance rejection control and BP network. The framework was simulated and verified, and the results showed that it can guarantee. The target signal can be tracked in a small original domain (Liu et al., 2021). Aiming at the problem of low identification accuracy of traditional intrusion detection systems, Lu et al. (2021) proposed a new algorithm based on adaptive clone genetic algorithm and BP algorithm. The model is applied to simulation experiments, and the results show that the detection accuracy of the model is much higher than that of traditional intrusion detection systems, and it has good global searchability (Lu et al., 2021). In order to better estimate the minimum deviation of the nucleate boiling ratio, Safavi et al. (2020) introduced and compared the BP algorithm and the radial basis function neural network. The comparison results of the two networks show that the training process of the radial basis function neural network is faster than that of the BPN. and its maximum network error is smaller than that of the BP algorithm (Safavi et al., 2020).

With the development and expansion of algorithms, there are also many algorithms used in the field of prediction. Hussain et al. (2019) used ANN, support vector machine (SVM), logistic regression, and classification tree algorithms to predict students' performance in digital design courses for the problem that students' classroom performance is difficult to predict. The results show that ANN and SVM are more accurate than other algorithms with higher utility (Hussain et al., 2019). In order to solve the problem of the low accuracy of the student dropout prediction model, Gray and Perkins (2019) proposed a student dropout prediction model based on machine learning tools. Effectively predict student withdrawal behaviour (Gray and Perkins, 2019). In order to make better use of music to improve the effect of aerobics, Zhang and Tian (2021) proposed an adaptive recommendation algorithm based on recurrent neural network and deep neural network. In order to better predict students' final performance, Alejandrino et al. (2020) proposed a prediction model based on the C4.5 algorithm, which achieved 98.64% accuracy in ten-fold cross-validation, 70% training and 30% testing percentages obtained 96.97% accuracy in segmentation (Alejandrino et al., 2020). Aiming at the problem that the prediction system of college students' sports performance is not effective, Zhang (2020) proposed a model of college sports teaching evaluation based on recurrent neural network, and applied the model to practice. The results show that the model shows good performance in the prediction and evaluation of college students' sports performance (Zhang, 2020).

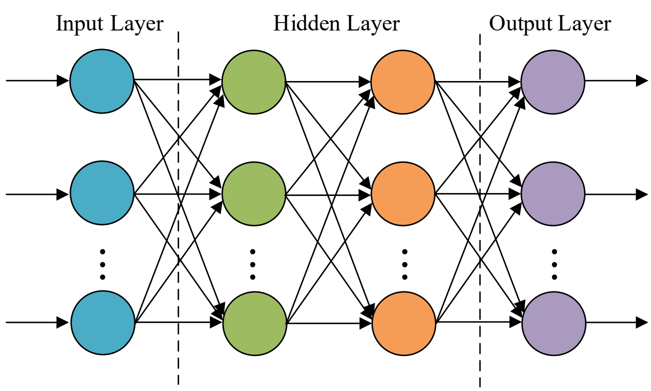
The above research shows that the BP neural network algorithm has been effectively used in many fields, and the methods applied to the performance prediction are also emerging one after another, but the research on the application of the BP neural network algorithm to the performance prediction is still relatively lacking. Therefore, the research applies the BP neural network algorithm to the aerobics score prediction system in colleges and universities, and combines the BP neural network algorithm and the PLS principal component extraction to form a new PLS-BP score prediction model, and embeds it in the aerobics score prediction system to improve the inaccurate problem of college students' aerobics score prediction.

3 Research on aerobics performance prediction system based on back propagation neural network

3.1 Back propagation neural network technique

Because of the ease of operation and high prediction accuracy of BP neural network algorithm, it has a good performance especially in the field of information processing, such as the collection, acceptance, transmission and processing of information, etc. The performance of BP neural network is excellent. Therefore, BP neural network was chosen to build aerobics performance prediction system (Xu et al., 2020). BP neural network is mainly composed of three modules: input layer, hidden layer and output layer, and the composition model of BP neural network are shown in Figure 1.

Figure 1 BP neural network model diagram (see online version for colours)



The main module hidden layers in BP neural networks can be classified according to the number of layers, which are divided into single hidden layers and multi-hidden layers. Among them, multi-hidden layer has better prediction ability, but requires longer training time. Since the mapping relationship in predicting aerobics course performance is not complicated, the single hidden layer BP neural network with shorter training time can be used. In the BP neural network, the output value transmitted from the input layer to the hidden layer net_1 is expressed as shown in equation (1).

$$net_1 = w^T x + b_1, h = g_1(net_1) \tag{1}$$

In equation (1), the initial value of neurons is represented by x, the intercept term is represented by b_1, the weight value of inter-layer connections is represented by w^T, and g_1 is the sigmoid function. The result transmitted from the hidden layer to the output layer net_2 is expressed as shown in equation (2).

$$net_2 = v^T x + b_2, y = g_2(net_2) \tag{2}$$

In equation (2), b_2 denotes the intercept term, and v^T denotes the weight value of the connection between the hidden layer and the output layer. g_2 is also the sigmoid function. The specific expression of the sigmoid function is shown in equation (3).

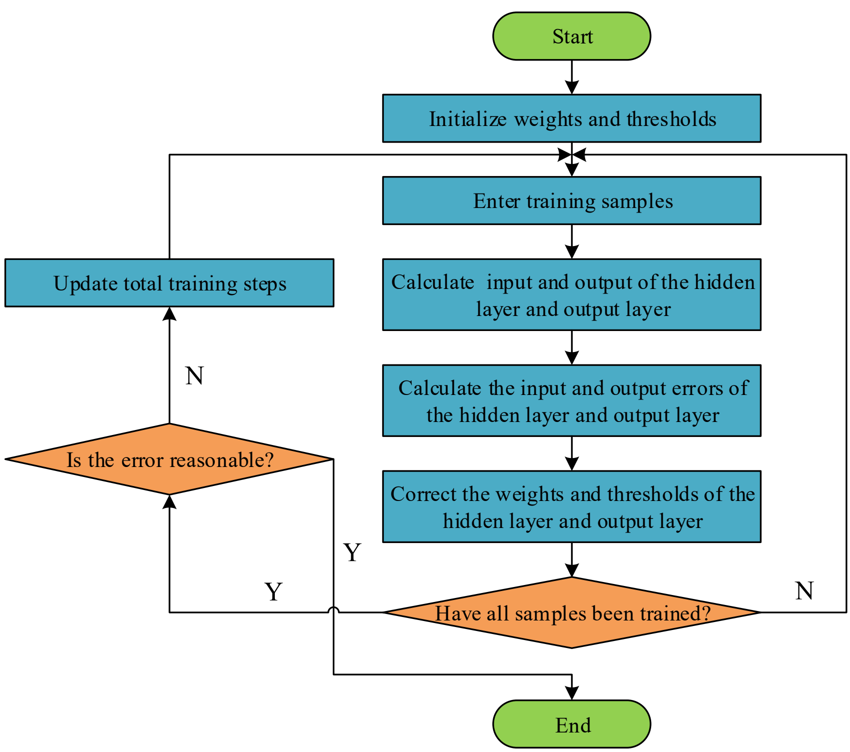
$$\hat{y} = g_2\left(net_2\right) = g_2\left(v^T g_1\left(net_1\right) + b_2\right) = g_2\left(v^T g_1\left(w^T x + b_1\right) + b_2\right) \tag{3}$$

In equation (3), $\hat{y}$ is the output value of the neural network. During the operation of the neural network, there is always an error, and the total error generated during the operation of the BP neural network $E(\theta)$ is expressed in equation (4).

$$E(\theta) = \frac{1}{2}\sum_{i=1}^{2}\left(y_i - \hat{y}_i\right)^2 \tag{4}$$

In equation (4), y_i represents the actual value and $\hat{y}_i$ represents the output value. The BP network algorithm consists of two processes: forward propagation of the data and backward propagation of the error. The BP neural network first propagates the data forward to the end, and then compares the output value with the expected output to determine whether the error signal needs to be backward propagated. The initial weights and thresholds are continuously adjusted during the process until the error value is reduced to a reasonable value. The flow chart of this neural network operation is shown in Figure 2.

Figure 2 BP neural network operation flowchart (see online version for colours)



In the BP neural network for forward propagation, firstly, the neurons make inputs to the hidden layer, and the expressions of the input values of each neuron at the time of n are shown in equation (5).

$$I_j(n) = \sum_{i=1}^{n} w_{ij}(n)x_i(n) + \theta_j(n) \quad j = 1, 2, \cdots, p \tag{5}$$

In equation (5), p denotes the total number of neurons in the hidden layer, and $\theta_j(n)$ is used to denote the threshold value of j neurons in the hidden layer at the moment of n, and $w_{ij}(n)$ denotes the weights of i neurons in the input layer and j neurons in the hidden layer. Then the input values are substituted into the activation function for activation, and the output value of each neuron in the hidden layer at n $y_j(n)$ is calculated, and the expression is shown in equation (6).

$$y_j(n) = f\left(I_j(n)\right) \quad j = 1, 2, \cdots, p \tag{6}$$

In equation (6), p also represents the total number of neurons in the hidden layer. Similarly, the input value $I_t(n)$ of each neuron in the output layer at the time of n is expressed as shown in equation (7).

$$I_t(n) = \sum_{j=1}^{p} w_{jt}(n)y_j(n) + \theta_t(n) \quad t = 1, 2, \cdots, q \tag{7}$$

In equation (7), q represents the total number of units in the output layer, $\theta_t(n)$ represents the threshold value of neurons at t n, and $w_{jt}(n)$ represents the weights of j neurons in the hidden layer and t neurons in the output layer. The output value of each unit in the output layer n $y_t(n)$ at is shown in equation (8).

$$y_t(n) = \vartheta\left(I_t(n)\right) \quad t = 1, 2, \cdots, q \tag{8}$$

The output value obtained by forward propagation is back-propagated with the error, and the variance between the target output and the actual output at $e(n)$ at the time of n is expressed as shown in equation (9).

$$e(n) = \frac{1}{2}\sum_{t=1}^{q}\left(d_t - y_t(n)\right)^2 \tag{9}$$

In equation (9), $y_t(n)$ represents the output value of each cell at the time of n. The calculated error e is compared with the predicted error maximum, and if the calculated error value is greater than the allowed error value, the model adjusts the initial weights as well as the threshold value to reduce the error value to the allowed error value. Neural network algorithms generally determine the initial weights and thresholds through model training. By calculating the output value of each layer neuron, and then comparing the output value with the desired output to obtain the error value, the weights and thresholds are adjusted according to the obtained error value until the error reaches the appropriate range to end the training. Traditional algorithm learning generally uses error correction algorithm, competition algorithm, Hebb algorithm and other algorithms, but due to the traditional learning algorithm has slow learning speed and slow convergence speed and other problems. For this problem, gradient descent method, Newton-like method, and LM algorithm are commonly used to solve it. The LM algorithm is obtained by combining the gradient descent method and the Newton-like method, and the correction process is shown in equation (10).

$$x(k+1) = x(k) + \Delta x \tag{10}$$

In equation (10), $x(k)$ represents the vector of weights and thresholds after performing k iterations. Where Δx expression is shown in equation (11).

$$\Delta x = -\left(J^T(x)J(x) + \mu I\right)^{-1} J^T(x)e(x) \tag{11}$$

In equation (11), I is the unit matrix and μ is the adjustment factor where $J(x)$ is the expression shown in equation (12).

$$J(x) = \begin{bmatrix} \frac{\partial e_1(x)}{\partial x_1} & \frac{\partial e_1(x)}{\partial x_2} & \cdots & \frac{\partial e_1(x)}{\partial x_i} \\ \frac{\partial e_2(x)}{\partial x_1} & \frac{\partial e_2(x)}{\partial x_2} & \cdots & \frac{\partial e_2(x)}{\partial x_i} \\ \cdots & \cdots & \cdots & \cdots \\ \frac{\partial e_i(x)}{\partial x_1} & \frac{\partial e_i(x)}{\partial x_2} & \cdots & \frac{\partial e_i(x)}{\partial x_i} \end{bmatrix} \tag{12}$$

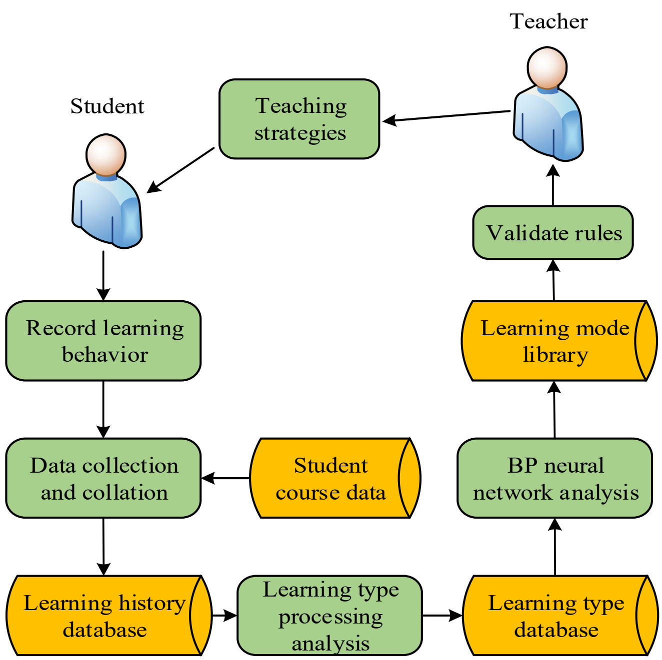
In Eq. (12), denotes the error of the first network node, and denotes the Jacobi matrix. When the value of μ is close to 0, equation (11) is the Gaussian Newton method; when the value of μ tends to positive infinity, equation (10) is the gradient descent method. The weights and thresholds are adjusted by the above methods until the error value meets the prediction output range and the training is terminated. BP neural network has been mature in both theory and performance. Compared with convolutional neural network and feedforward neural network, BP neural network has strong nonlinear mapping ability and flexible network structure. The number of intermediate layers and the number of neurons of BP neural network can be set arbitrarily. With the difference of its structure, the performance is also different, which can meet most of the needs of neural network.

3.2 Back propagation neural network optimisation and overall design of aerobics performance prediction system

Students' aerobics scores not only reflect the true level of students' aerobics, but also are an important indicator to evaluate the quality of teachers' teaching (Chen and Zhu, 2021). Therefore, it is very important to predict students' aerobics performance accurately. In most cases, the degree of influence of different causes on students' performance varies, and traditional methods of performance prediction only use linear models to predict scores, which often differ significantly from the correct values (Terlapu, 2020). In the past, the prediction of a student's performance was usually done with reference to the student's past performance, without taking into account that the student's behaviour also affects the performance, which has limitations and leads to inaccurate prediction results. In order to avoid these problems, the study includes the student's learning behaviour as a reference, and the architecture of the designed aerobics performance prediction system is shown in Figure 3.

The prediction system mainly consists of an extraction module, an analysis module, and an output module. The extraction module is mainly a system to record students' learning behaviours and aggregates the collected data for processing. The student's course data and the collected data are combined to create a database of the student's learning history. The analysis module analyses the learning history of each student and stores the results in the learning type database. The output module mainly saves the output values from the analysis module in the learning pattern database and outputs the prediction results to the teacher. Finally, the teacher develops corresponding teaching strategies to improve students' performance based on the output results. The structure diagram of this prediction system is shown in Figure 4.

Figure 3 Architecture of aerobics performance prediction system



The specific structure of the aerobics performance prediction system can be clearly seen in Figure 4, which is mainly divided into four parts: user management, student information management, student performance prediction, and student performance warning. The user management section mainly includes the basic system of users, such as the setting of user rights and the editing of user information. The student information management section is mainly for keeping records of various information of students. It includes students' learning information, students' learning history database, learning type database and other data. The student performance prediction section mainly includes the prediction of students' exam actions and students' performance prediction. The BP neural network algorithm is used in the prediction process to analyse some key information of students to ensure the accuracy of the prediction. The student performance warning section is mainly for adding and modifying the warning conditions. In the aerobics performance prediction system, in order to make the accuracy higher, the study uses the PLS method to extract the components of the aerobics course indexes, and the extracted effective components are used as the input values of the BP neural network. The brief schematic diagram of PLS-BP structure is shown in Figure 5.

Figure 4 Structure diagram of aerobics performance prediction system (see online version for colours)

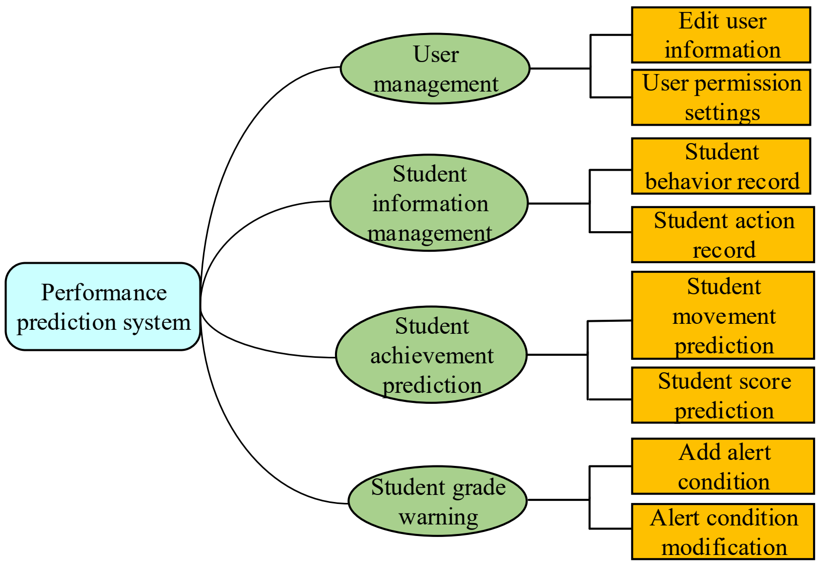
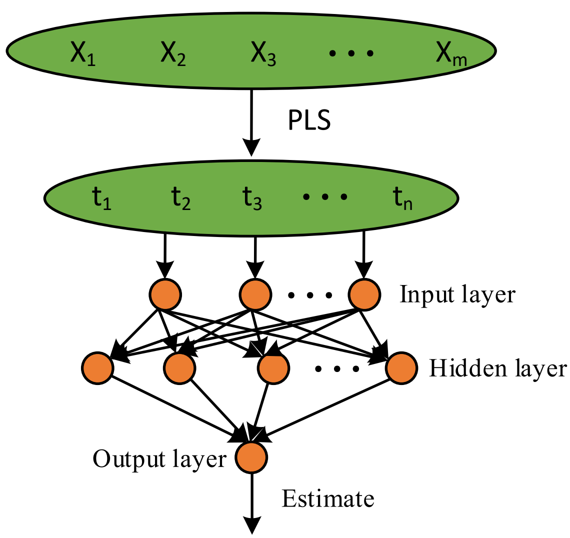


Figure 5 PLS-BP structure diagram (see online version for colours)



PLS method is a statistical method used for principal component analysis (PCA), and the basic idea is to study the relationship between the dataset of m independent variables $X = \{X_1, \ldots, X_m\}$ and the dataset of n dependent variables $Y = \{Y_1, \ldots, Y_n\}$. Firstly, the first component of $t_1 = k_1x_1 + k_2x_2 + \ldots + k_mx_m$ is selected in the independent variable dataset, and the information of the variance in the dataset is obtained as comprehensively as possible. Then, the first component of the dependent variable set $u_1 = k_1y_1 + k_2y_2 + \ldots + k_nx_n$ is extracted, and the correlation between the first component of the independent variable set t_1 and the first component of the dependent variable set u_1 is maximised by the Lagrange multiplier method. t_1 if the accuracy of the regression equation can meet the requirements, the algorithm is terminated; if the accuracy of the regression equation cannot meet the expectations, the second component is extracted based on the remaining information until the accuracy meets the expectations. To extract the components using the PLS method, the first i observation ($i = 1, 2, \ldots, p$) is removed each time, and the PLS method is applied to model the remaining $p - 1$ observations, observe the regression equation fitted after selecting the h component, and bring the previously removed i observation into the established regression equation to obtain the predicted value of $y_k(k = 1, 2, \ldots, n)$ at the i observation $\hat{y}_{(\iota)k}(h)$ (Kumar, 2021). The above steps were repeated for $i = 1, 2, \ldots, p$ and subsequently the expression for the sum of squared prediction errors for the k^{th} dependent variable when the $y_k(k = 1, 2, \ldots, n)$ h^{th} component was extracted was obtained as shown in equation (13).

$$PRESS_k(h) = \sum_{i=1}^{n} \left(\hat{y}_{\iota k} - \hat{y}_{(\iota)k}(h)\right)^2 \quad (k = 1, 2, \ldots, n) \tag{13}$$

$Y = (y_1, \ldots, y_p)^T$. The expression of the prediction error sum of squares is shown in equation (14).

$$PRESS(h) = \sum\nolimits_{k=1}^{n} PRESS_k(h) \tag{14}$$

Using all sample points, a regression equation with h components is created. By noting the predicted value of the i^{th} sample point as $t_{(\iota)k}(h)$, the error sum of squares expression for y_k is obtained as shown in equation (15).

$$ss_k(h) = \sum_{i=1}^{p} \left(\hat{y}_{ik} - \hat{y}_{ik(h)}\right)^2 \tag{15}$$

Define the error sum-of-squares expression for Y as shown in equation (16).

$$ss(h) = \sum_{k=1}^{p} ss_k(h) \tag{16}$$

When $PRESS(h)$ is the smallest, at this point h is the number of components to be selected. The study tested the model performance with relative error and coefficient of determination. Relative error is often used to reflect the difference between predicted and true values. The specific formula is shown in equation (17).

$$error = \frac{|yi - y|}{y} \times 100\% \tag{17}$$

In equation (17), y is the true value and y_i is the predicted value. The formula of the judgment coefficient is shown in equation (18).

$$R^2 = \frac{\left(l\sum_{i=1}^{l}\hat{y}_i y_i - \sum_{i=1}^{l}\hat{y}_i \sum_{i=1}^{l} y_i\right)^2}{\left(l\sum_{i=1}^{l}\hat{y}_i^2 - \left(\sum_{i=1}^{l}\hat{y}_i\right)^2\right)\left(l\sum_{i=1}^{l} y_i^2 - \left(\sum_{i=1}^{l} y_i\right)^2\right)} \tag{18}$$

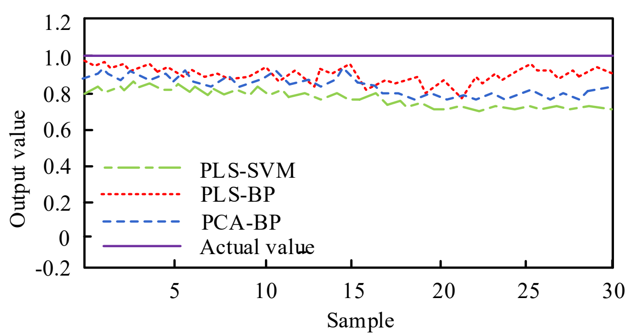
In equation (18), $\hat{y}_i$ represents the first i predicted value and y_i is the first i true value. The larger the value of the coefficient of determination, the better the performance of the system, and the smaller the relative error, the better the performance of the system.

4 Performance comparison of back propagation neural network model and result analysis of performance prediction system

4.1 Back propagation neural network model performance comparison

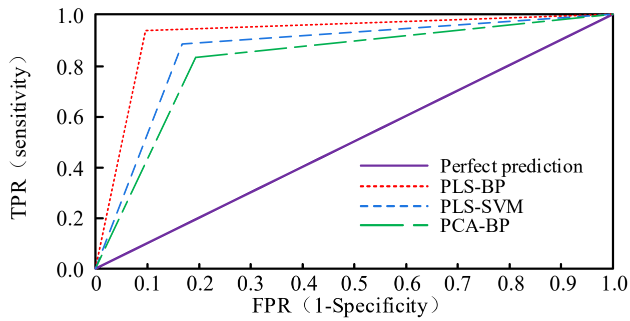
The study adopted PLS PCA for component extraction of aerobics course indexes to achieve variable optimisation of BP neural networks. A novel PLS-BP score prediction model was constituted. In order to test the performance of the optimised model, PLS combined with SVM and PCA combined with BP were used to test the sample set, respectively. Neural network to construct the models, and three models, PLS-SVM, PLS-BP, and PCA-BP, were used for the test sample set, and the training prediction accuracy results of the three models are shown in Figure 5.

Figure 6 Comparison of prediction effects of models (see online version for colours)



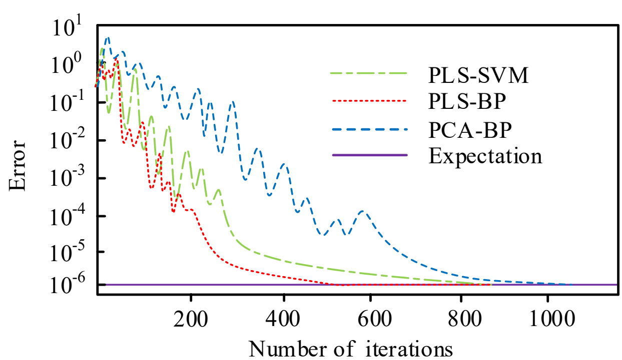
From Figure 6, it can be obtained that the PLS-BP model constructed in the study has the highest accuracy for aerobics performance prediction among the three models with an accuracy of 94.5%; the PLS-SVM model has a slightly lower accuracy than the PLS-BP model for aerobics performance prediction with an accuracy of 89.2%; and the PCA-BP model has the lowest accuracy for aerobics performance prediction with an accuracy of 86.5%. The average prediction accuracy of the BP neural network model using the PLS approach improved by 9.1% compared to the BP neural network model using the PCA approach and by 5% compared to the SVM model using the PLS approach. This result indicates that the BP neural network model using the PLS method has the best performance among the three models. Defining the false positive rate (FPR) as the X-axis and the true positive rate (TPR) as the Y-axis, the ROC curves based on the results of the PLS-BP model, PLS-SVM model, and PCA-BP model for aerobics performance prediction are shown in Figure 5.

Figure 7 Comparison of prediction results and ROC curve of models (see online version for colours)



According to Figure 7, among the three prediction models, the PLS-BP model has the largest area under the curve, with an area under the curve of 0.839; the PLS-SVM model has a slightly lower area under the curve than the PLS-BP model, with an area under the curve of 0.757; and the PCA-BP model has the smallest area under the curve, with an area under the curve of 0.695. This result indicates that using the PLS method for component extraction can effectively improve the accuracy of the prediction model and can make the BP neural network model achieve better prediction results. The data of PLS-BP model, PLS-SVM model, and PCA-BP model in the model training process were compared, and the results are shown in Figure 7.

Figure 8 Training effect comparison (see online version for colours)



As can be seen from Figure 8, among the three different prediction models, the PLS-BP model has the most obvious downward trend in training error, reaching the desired accuracy at 564 iterations; the PLS-SVM model has a slightly slower downward trend in training error than the PLS-BP model, reaching the desired accuracy at 852 iterations; the PCA-BP model has a more moderate downward trend in training error overall, reaching the desired accuracy at 1,086 iterations. The PCA-BP model achieves the desired accuracy at 1,086 iterations. This result indicates that the PLS-BP model constructed in the study has better training performance, the fastest convergence speed, and better performance. From these three results, it is clear that the PLS-BP model performs better than the PLS-SVM model and PCA-BP model, and has better prediction results.

4.2 Analysis of the results of the aerobics performance prediction system

After installing the prediction system designed by the study, in order to determine the performance of the aerobics performance prediction system, the study selected students who took the aerobics exam at the university to conduct real tests on the performance of the prediction system. The system was tested in three dimensions of accuracy, relative error, and coefficient of determination, respectively, and the prediction system was used in two groups of students, and the comparison graphs of the real and predicted scores of the two groups are shown in Figure 8.

Figure 9 Curves of predicted and actual scores for the two groups of students, (a) curve between predicted score and actual score of the first group of students (b) curve between predicted score and actual score of the second group of students (see online version for colours)

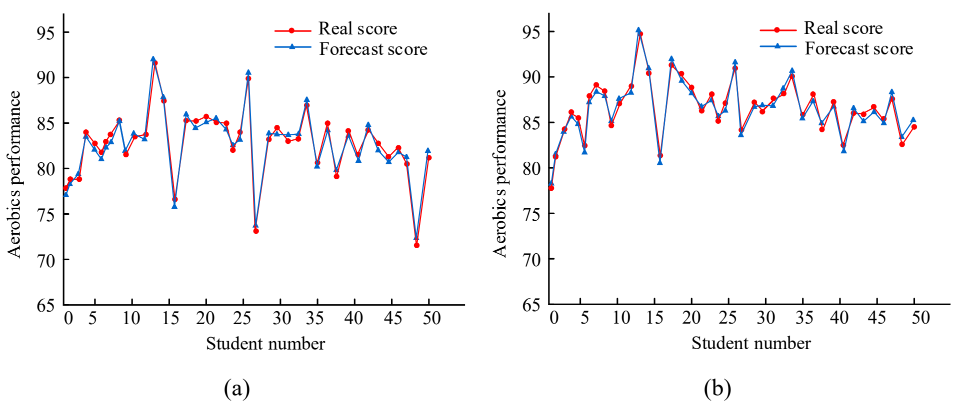


Figure 9 shows the comparison between the true and predicted scores of students in aerobics in two groups, where the red dots indicate the true scores of students and the blue triangles indicate the predicted scores of students. From the figure, it can be seen that the difference between the students' true scores and the predicted scores of the model in both groups is small, and the average accuracy rate in both groups is 93.7%, which is higher than the accuracy rate of the traditional prediction system. This result indicates that the prediction system designed in the study is more accurate and possesses better performance. The performance prediction system was applied to 80 students participating in aerobics, and the relative error plot of student performance is shown in Figure 9.

Figure 10 shows the relative errors of the real and predicted aerobics scores of 80 students, where the red line (error1) indicates the relative error value of the prediction system that only considers students' scores; the blue line (error2) indicates the relative error of the prediction model that takes into account students' past scores as well as their learning behaviours. It is clear from Figure 9 that the blue line as a whole tends to be below the red line, and only a very small number of blue lines are above the red line. The lowest value of the blue line is 0.032 and the highest value is 0.061. The average value of the relative error in this dataset is 0.042, which is much lower than that of the conventional prediction model. The above results indicate that this prediction model performs significantly better than the traditional prediction model and that considering students' learning behaviours in the prediction system would be helpful in predicting performance accuracy. The gymnastics performance prediction system was applied to two groups of students, one group of students in which only the student's performance was considered, and the other group of students in which both past performance and learning behaviour were considered together. The graphs of the true and predicted grades obtained for the two groups are shown in Figure 10.

Figure 10 Plot of relative error data of aerobics performance of 80 students (see online version for colours)

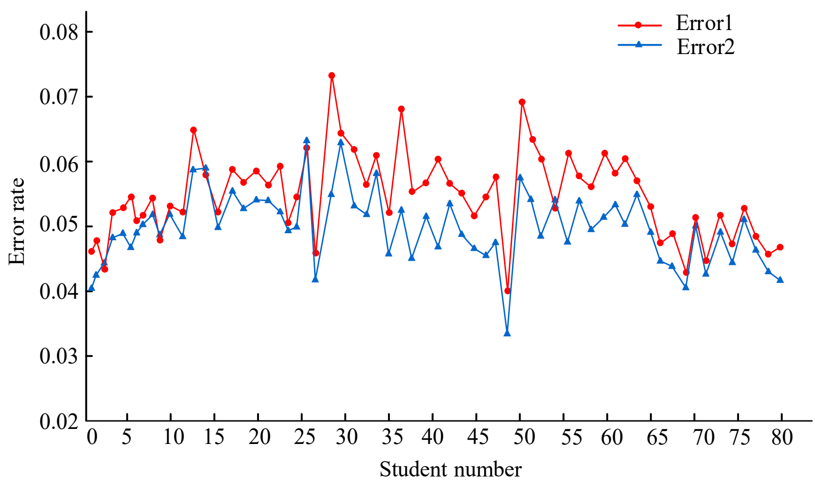
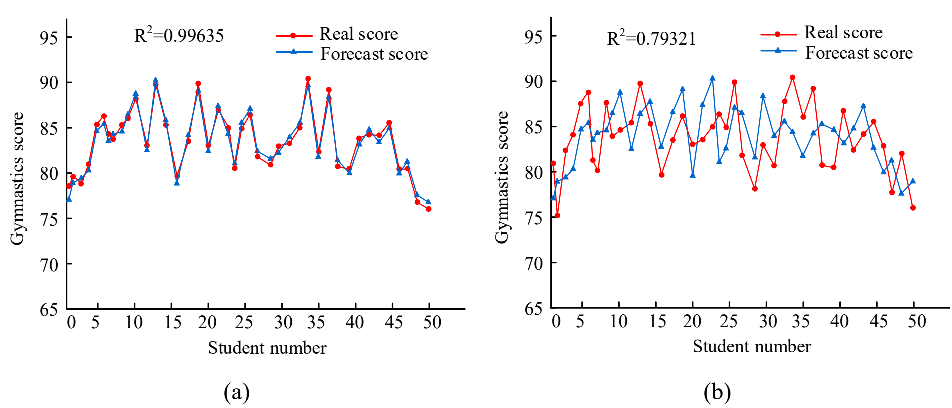


Figure 11 True and predicted scores and coefficients of determination for the two groups of students, (a) comparison of prediction results considering both performance and behaviour factors (b) comparison of prediction results considering only student performance factors (see online version for colours)



In Figure 11, the graph of the predicted and true grades of the system that takes into account both students' past grades and learning behaviours is shown in Figure 11(a). It can be seen that the difference between the true and predicted grades in this dataset is small, and the coefficient of determination is 0.99843, which is extremely close to 1 and has a good prediction performance [Figure 11(b)]. The graph of the predicted and true grades of the prediction system that only takes into account students' grades is shown in Figure 10. It can be seen that the difference between the true and predicted grades in this set of data is large, and the value of the coefficient of determination is 0.79424, which is much less effective than the model of the system that considers both students' past grades and learning behaviours. This result indicates that adding students' learning behaviours to the factors that affect students' grades will increase the coefficient of determination and improve the performance of the prediction system. In summary, the prediction performance of the model designed in the study is very good in terms of three dimensions: accuracy, relative error, and coefficient of determination, and it is also found that adding students' learning behaviours to the achievement prediction model greatly improves the accuracy of the prediction model.

5 Conclusions

In view of the low accuracy of current course performance prediction methods, the paper studies the optimisation of BP algorithm by using PLS method to obtain PLS-BP performance prediction model, which improves the prediction accuracy of the model by extracting the principal components. Comparing the performance of the optimised PLS-BP prediction model with PCA-BP prediction model and PLS-SVM prediction model, the results show that the accuracy of PLS-BP model is 94.5%, which is better than that of PCA-BP model (86.5%) and PLS-SVM model (89.2%); The offline area of PLS-BP model is 0.839, which is better than 0.695 of PCA-BP model and 0.757 of PLS-SVM model; The offline area of PLS-BP model is 0.839, which is better than 0.695 of PCA-BP model and 0.757 of PLS-SVM model. In addition, the system composed of PLS-BP model is also empirically analysed. The results show that the accuracy rate of the system is 93.7%. The relative error is 0.042. The determination coefficient is 0.99843. The above results show that the performance of PLS-BP score prediction model is better than that of PLS-SVM model and PCA-BP model, and the overall prediction performance of the score prediction system composed of PLS-BP model is very good. However, due to data limitations such as data volume and data quality, the experimental data is relatively small, which may make the experimental results unilateral. How to break through the data limitations is the next research direction.

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