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Article

Analyzing the Effect of Blended Instructional Models for Accounting on Academic Achievement Based on Multilayer Perceptron Modeling

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Abstract: Blended teaching provides a flexible and personalized solution for teachers' teaching by integrating online resources and offline interactions. The purpose of this paper is to explore the impact of accounting blended teaching mode on academic achievement, for this purpose, data mining of students' online learning behaviors is carried out, and then the Gray Wolf Optimization Algorithm is improved to propose a multilayer perceptron model based on IGWO, and the performance of the model is examined, and it is applied to the practice of academic achievement prediction. The experimental results show that the proposed method can obtain higher classification accuracy, and the mean classification accuracy AVG is about 1.04%, 1.08% and 1.28% higher than that of the GWO algorithm, FF algorithm and FPA algorithm, respectively, and the standard deviation of the indexes is small, which is of good stability. Introducing the dynamically changing learning style identification results into the blended teaching mode academic achievement prediction model, its prediction accuracy is improved from 0.819 to 0.847, which is a significant increase in accuracy. The prediction model constructed in this paper has important practical reference value for improving the accounting blended teaching model.

Keywords: data mining; gray wolf optimization algorithm; multilayer perceptron; academic achievement prediction; blended teaching

1. Introduction

In recent years, with the rapid development of information technology and the popularization and application of the Internet, blended teaching is gradually emerging and receiving widespread attention. Blended teaching is a kind of teaching mode based on traditional face-to-face teaching and integrating a variety of teaching methods such as online learning, independent learning and cooperative learning [1-2]. In accounting professional courses, the use of blended teaching mode can improve the teaching effect, stimulate students' learning enthusiasm, satisfy students' differentiated learning needs, and have a significant effect on academic achievement [3-5]. Literature [6] examined the impact of blended teaching mode on the learning outcomes of accounting majors, and pointed out through a questionnaire survey that although the students had different levels of knowledge, all of the blended teaching modes effectively improved their learning outcomes. Literature [7] compared the impact of two blended instructional models on the performance and satisfaction of accounting students, based on a survey of accounting students indicating that the choice of instructional model varied depending on the students' learning objectives. Literature [8] designed a blended teaching model for accounting majors, which was proved to be effective in increasing the interest and enthusiasm of accounting students and improving the learning effect through practical teaching of accounting majors. Literature [9] describes the application of blended teaching mode in accounting courses, pointing out that this teaching mode provides good teacher-student interaction environment, learning flexibility and other advantages, which can effectively improve the efficiency and effectiveness of students.

In improving the learning effect, the traditional face-to-face teaching method exists classroom time is limited, students' attention is not focused and other problems, the blended teaching mode can make full use of the online learning platform to record the lecture content into a video for students to learn independently after class is conducive to the students to fully digest and understand the knowledge points [10-14]. Students can learn anytime and anywhere through the network, further deepening the understanding of the knowledge points and the cultivation of application ability [15-16]. Literature [17] examined the application of blended learning model in engineering, design and other majors, and evaluated the application cases, and the results showed that the blended learning model can improve the academic level of students. Literature [18] introduced the advantages of blended teaching mode in enhancing teacher-student interaction, pointed out the disadvantages of the traditional "duck" teaching method, and based on comparative experiments, revealed that the blended teaching mode played an important role in improving the learning effect and enthusiasm for learning. Literature [19] aims to evaluate the effectiveness of blended teaching programs by comparing the use of blended teaching modes with traditional classroom teaching, and found that the learning effect of students in the blended mode is significantly higher than that of traditional teaching forms. Literature [20] systematically describes blended learning and its advantages and examines the benefits of the model in teaching and learning with the aim of helping students to improve their learning outcomes.

In terms of motivation, traditional face-to-face teaching, teachers are usually active in imparting knowledge students are passive acceptance, this teaching method is prone to make students feel tired of learning interest and motivation gradually decline [21-23]. The blended teaching mode is characterized by focusing on students' independent learning and cooperative learning and more emphasis on students' participation and initiative [24-25]. Students can flexibly choose the learning time and learning mode according to their own learning progress and interest cultivates students' independent learning ability and cooperative spirit, and enhances the initiative and enthusiasm of learning [26-28]. Literature [29] explored the impact of blended learning on students' motivation to participate in the course and their learning experience, based on a questionnaire survey that showed that blended learning was effective in improving students' experience and increasing their motivation. Literature [30] aimed to analyze the impact of using technology on self-directed learning and student motivation, based on which a blended learning approach was adopted in the course, and the results showed that the blended learning model significantly improved student motivation. Literature [31] compared the difference between direct and blended learning modes on students' motivation and achievement, and improved controlled experiments pointed out that students' motivation to participate in learning and achievement were significantly higher in the blended learning mode than in the direct learning mode. Literature [32] pointed out the problem of insufficient cultivation of students' innovation ability in the current blended teaching mode, and put forward the offline classroom theory teaching based on the four-stage and problem-oriented teaching and the practical teaching method based on the "entrepreneurial mindset", and verified that this method effectively improves students' innovation ability and practical ability.

In terms of students' differentiated needs, as each student learns in a different way and at a different pace, some students may need more time to digest and understand the knowledge points, while others may have already mastered part of the knowledge [33-35]. The traditional face-to-face teaching mode is difficult to meet these different learning needs, while the blended teaching mode is able to personalize the teaching according to the actual situation of the students [36-37]. Literature [38] analyzed teachers' strategies and philosophies for implementing differentiated instruction in blended learning, and the study showed that some teachers believed that changes should be made to the blended learning arrangement to accommodate student diversity. Literature [39] emphasized the potential of blended learning to meet diverse learning needs, provided key challenges such as technology access and teacher preparation are addressed. Literature [40] aimed to assess students' experience, satisfaction and engagement with e-learning resources and blended learning, and the analysis of the survey pointed out that the vast majority of students incorporated e-learning resources into their teaching and learning, and the majority affirmed the benefits of e-learning. Literature [41] examined the impact of personalized intervention approaches on students' course performance and learning behaviors in a blended course, and a comparative experiment pointed out that personalized interventions in in a blended course were able to increase students' motivation, attitudes, and self-efficacy. Literature [42] aims to provide insights into contemporary issues of personalized learning based on blended instruction and reveals the trend of transforming pedagogical models, methods, and tools for personalized learning under blended learning conditions.

In this paper, we establish an academic achievement prediction model by mining the data of students' online learning behaviors under the blended teaching mode to provide data support for improving the accounting blended teaching mode based on students' academic achievement. The prediction model is established based on multilayer perceptron (MLP), the Cauchy variational operator is introduced into the gray wolf optimization algorithm, and at the same time, balancing the development ability, adding cosine convergence factor, an improved Cauchy variational gray wolf optimization algorithm, IGWO, is proposed, and optimization of the prediction model is achieved by using IGWO to train the MLP. On this basis, model performance evaluation experiments and model application experiments are designed in this paper.

2. Data Mining Analysis of Students' Learning Behavior in Blended Teaching Mode

Given the availability of data, this chapter conducts a data mining analysis of students' online learning behaviors under the blended teaching model of accounting, so as to provide data support for analyzing the impact of the blended teaching model of accounting on academic achievement. The big data mining analysis process is divided into 2 steps: data acquisition and characterization and data preprocessing and feature selection.

2.1. Data Acquisition and Characterization

2.1.1. Data set description

The MOOC online learning behavior data of Accounting collected from the MOOC platform describes a learner's learning record of the course, with each column item as a description of the learner's learning behavior, providing a dozen or so dimensions, which are mainly divided into 3 categories, namely, the course information, the basic information of the learner such as the student number, name, and gender, as well as the learner's learning behavior including video viewing length, number of accesses, percentage of task points completed, total discussions , reply discussion, post discussion, course video score, course quiz score, assignment score, MOOC composite grade, MOOC composite grade five-level scale grade, whether MOOC composite grade is passing or not, and final grade, among other learner behavior information.

2.1.2. Data acquisition

Using Python data analysis module pandas to read and merge the learning behavior information of 400 students majoring in accounting in the class of 2022 on the MOOC platform, including quiz and homework grades, number of discussions, video viewing hours and other index data, and associated and merged with the final written examination grades according to the student number to complete the data extraction work.

2.1.3. Learner behavior analysis

Statistical mapping through single feature analysis, multivariate statistical analysis, and statistical mapping led to the following conclusions.

The MOOC comprehensive grade consists of the completion of watching videos in online learning, online quiz and online homework grades, which are divided into five grades A-E, with grade A being 90 and above, grade B being 80-89, grade C being 70-79, grade D being 60-69, and grade E being less than 60. The relationship between the MOOC comprehensive grade level and the passing grade of the final written exam is shown in Figure 1. It can be seen that the proportion of the number of people failing the final written exam in the MOOC composite grade increases as the grade decreases.

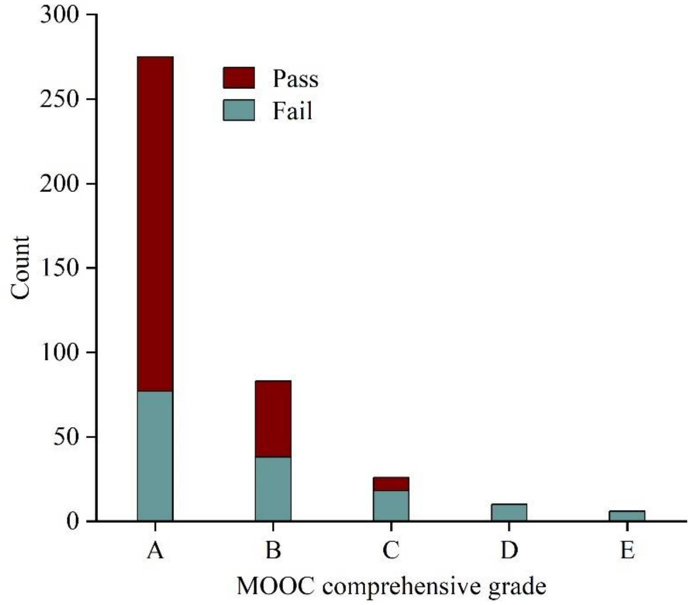

Figure 1. The relationship between the MOOC comprehensive grade and the final test score.

The relationship between MOOC composite grade level, gender and passing rate of the final written examination is shown in Figure 2, where All indicates the situation of passing rate of the final written examination for males and females among all students. Comparison shows that there is a significant difference between different genders in the final written test scores when the MOOC composite achievement level is the same: the passing rate of female students is significantly higher than that of male students. And the overall passing rate of female students in the final written examination is 76.47%, much higher than that of male students, which is 25.10%.

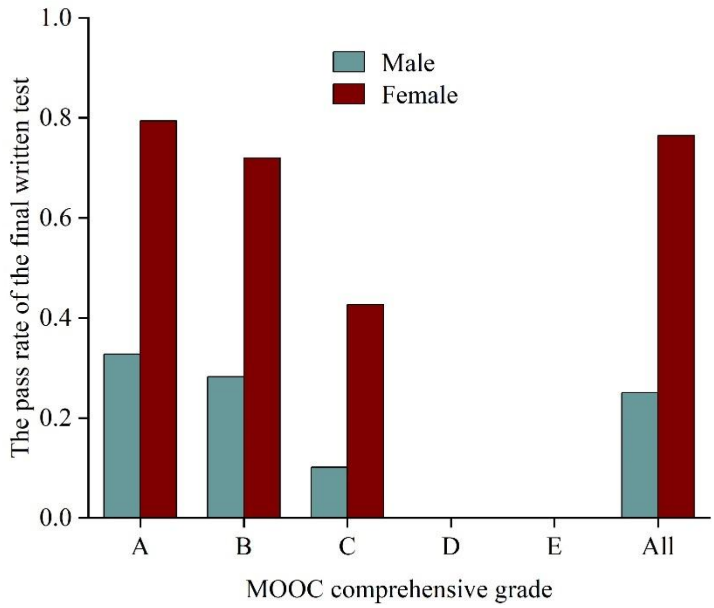

Figure 2. Relationship between the MOOC comprehensive grade, gender and final test grade.

The effects of the total number of discussions, the number of visits and the length of watching videos on the final written examination grade in different gender situations are shown in Figures 3~5 respectively. The median data of the total number of discussions and the number of visits show that female students are higher than male students, but the distribution of the total number of discussions and the number of visits and the distribution of whether the final written examination grade is passed or not show a regional imbalance, and in general the total number of discussions and the number of visits of the students who have passed the examination are higher. The median data on the length of time spent watching videos are higher for girls than for boys, and in general, students who passed the exam watched videos for a longer period of time.

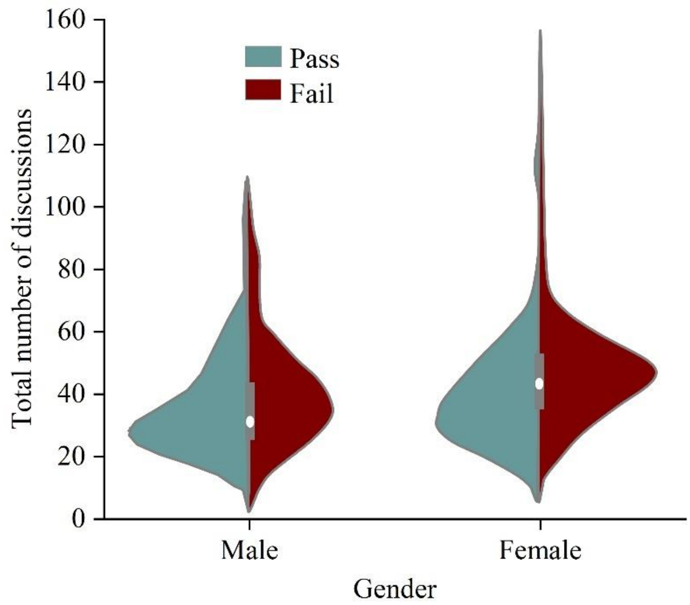

Figure 3. The influence of gender and the total number of discussions on the final test scores.

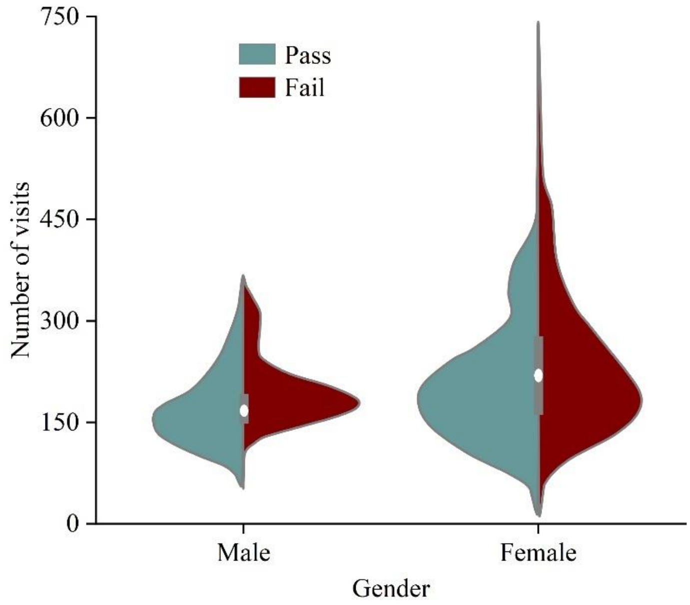

Figure 4. The influence of gender and the number of visits on the final written test scores.

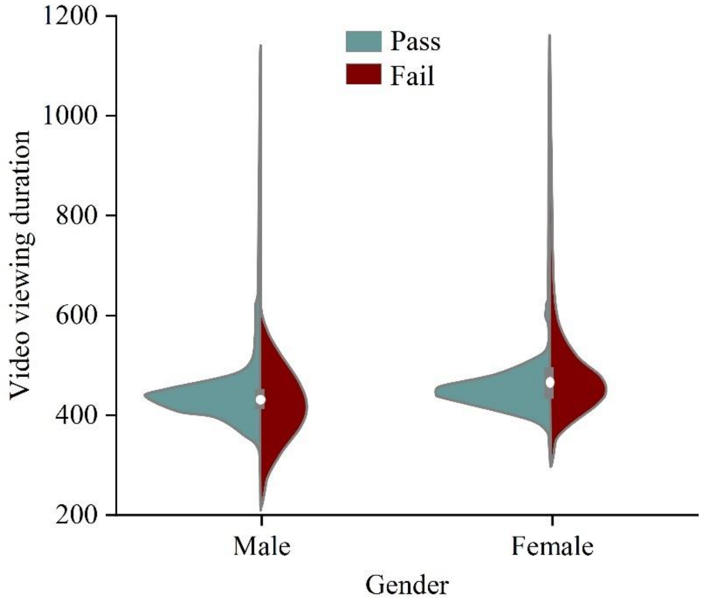

Figure 5. The influence of gender and video viewing durations on the final written test scores.

2.2. Data Preprocessing and Feature Selection

By checking the missing values and filling them in, and then standardizing the feature data, the feature heat map is established as shown in Figure 6 to filter the correlation of each feature. Among them, A1~A15 denote: video viewing duration, number of visits, percentage of task point completion, total discussion, posting comments, replying to comments, course video score (100%), course quiz score (100%), homework score (100%), MOOC composite grade, MOOC composite grade on a five-point scale, whether the MOOC composite grade is qualified, gender, and final grade, Pass or fail final written exam grade.

Through the standardized feature data heatmap, some positively correlated features and some negatively correlated features can be observed. Remove the five features of "course video score", "final grade", "reply and discussion", "MOOC comprehensive grade five-level system", and "course test score".

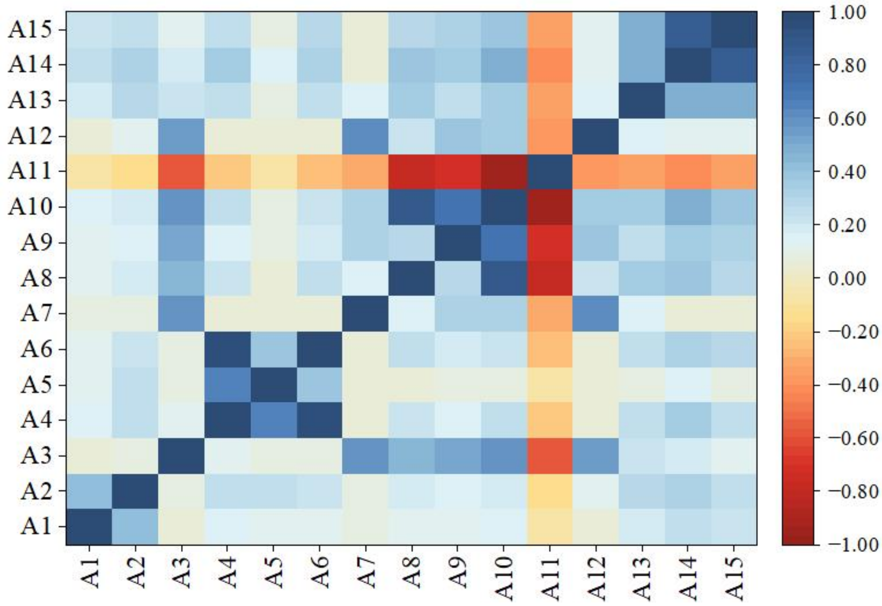

Figure 6. Feature heat map.

3. Multilayer perceptron model construction based on gray wolf optimization algorithm

In order to investigate the impact of accounting blended teaching model on academic achievement, this paper adopts multilayer perceptron (MLP) neural network as the main carrier of academic achievement prediction, and proposes a multilayer perceptron model, IGWO-MLP, which is trained by using Improved Gray Wolf Optimization (IGWO) algorithm.

3.1. MLP Neural Network Model

MLP [43], as a kind of forward neural network with deep learning capability, contains a large number of neurons in a multilayer network, which can map a set of input vectors to a set of output vectors, and can theoretically approximate any linear continuous function with arbitrary accuracy, and this advantage facilitates the development of the application of MLP neural networks in speech analysis, image analysis, intelligent devices, etc.

The structure of MLP model is shown in Fig. 7, which is generally three-layer or multi-layer.

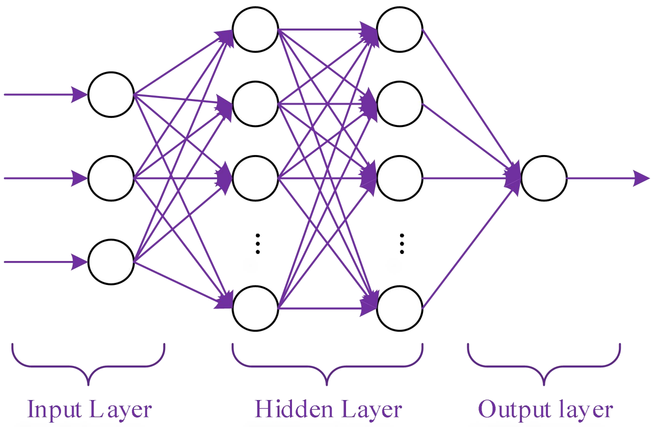

Figure 7. Structure diagram of MLP model.

It consists of three parts: input layer (one layer), hidden layer (one or more layers) and output layer (one layer). Neurons located in the same layer are not directly connected to each other, and full connectivity is achieved by summing the weights between neurons in neighboring layers. After the data enters the MLP from the input layer, the neurons in the hidden layer analyze and transfer it, and finally the data is output from the output layer, thus realizing the multilayer optimization of the data.The MLP neural network can have more than one input and more than one output, and the number of neurons in the input layer and the output layer is determined according to the demand objectives. As for the number of layers in the hidden layer and the number of neurons in each layer, it is based on the set error requirements.In the MLP model, the output of the previous layer is the input of the next layer, and for the neurons in the hidden layer and the output layer, the output of the j neuron in the i layer is given by the formula:

$$y_j^{(i)} = f_j^{(i)}\left(W_j^{(i)} \cdot y^{(i-1)} + b_j^{(i)}\right) \tag{1}$$

Where $W_j^{(i)}$ is the weight vector of the i th layer, j th neuron, with the direction pointing from the $i-1$ th layer to the i th layer, j th neuron. $y^{(i-1)}$ is the output vector of the $i-1$ layer. $b_j^{(i)}$ is the bias vector of the i th layer, j th neuron. $f_j^{(i)}$ is the activation function of the i th layer, the j th neuron. The activation function $f_j^{(i)}$ is chosen to be the tansig function with the following expression:

$$\text{tansig}(n) = \frac{2}{1+e^{-2n}} - 1 \tag{2}$$

Assuming that the MLP neural network has m layers $(m \geqslant 3)$ the output layer has only one neuron, analogous to Eq. (1) shows that the output formula of the output layer is:

$$Y = f^{(m)}\left(W^{(m)} \cdot y^{(m-1)} + b^{(m)}\right) \tag{3}$$

where Y denotes the output, $W^{(m)}$ is the weight vector of the m th layer, $y^{(m-1)}$ is the output vector of the $m-1$ th layer, and $b^{(m)}$ is the bias vector of the m th layer.

Except for the neurons in the input layer, the rest of the neurons are multiple-input-single-output and with nonlinear activation functions. The weight vector W and bias vector b are determined by the training process of the MLP, and the MLP neural network is capable of self-learning and feedback adjustment during the training, so as to correct and adjust the weight and bias of each neuron, and this process can be used to optimize the weight and bias of the MLP by using algorithms, so that the output values of the MLP are closer to the real values, and the prediction accuracy of the MLP model in the later stage is improved.

3.2. Gray Wolf Optimization Algorithm

In a gray wolf pack, the wolf that takes the primary leadership role is known as the α wolf, the wolf that is in the 2nd leadership echelon, i.e., the one that assists the α wolf in making decisions and leading the pack as a whole, is known as the β wolf, and the 3rd leadership echelon that assists the α and β wolves is known as the δ wolf, and the rest of the pack is known as the ω wolves and are under the leadership and direction of the previous 3 leaders. The Gray Wolf Optimization (GWO) algorithm [44], as a swarm intelligence optimization algorithm, is based on the unique predatory behavior of gray wolves, i.e., the encircling attack predation method.

In the GWO algorithm, assuming that the population size of gray wolves is N and the search space is d -dimensional, the position of the i th gray wolf in the space is $X_i = \left(x_1, x_2, \cdots, x_d\right)$ and the spatial position of the prey, i.e., the global optimal solution.

Gray wolves are commanded and controlled by α wolf, β wolf and δ wolf in the predation process and encircle the prey by encircling attack, so the position of gray wolves encircling the prey is updated as in equation (5):

$$D = \left| C \cdot X_p(t) - X(t) \right| \tag{4}$$

$$X(t+1) = X_p(t) - A \cdot D \tag{5}$$

where t is the current iteration number, $X_p = \left(x_1, x_2, \cdots, x_d\right)$ is the prey position, $A \cdot D$ is the encircling step, and the vectors A and C are defined as:

$$A = 2\left(r_1 - E\right) \cdot a \tag{6}$$

$$C = 2r_2 \cdot a \tag{7}$$

where r_1 and r_2 are 1-row d -column random vectors between the intervals $[0,1]$, E is a 1-row d -column vector where every element is 1, and a is a vector of convergence factors that decreases linearly from 2 to 0 as the number of iterations increases, i.e:

$$a = 2\left(1 - t / t_{\max}\right) \cdot E^{\mathrm{T}} \tag{8}$$

From Eqs. (4) to (8), the predation positions of other individual gray wolves guided and directed by α wolves, β wolves, and δ wolves during predation are updated as in Eqs. (9) to (11):

$$D_\alpha = \left| C_1 \cdot X_\alpha - X \right|, D_\beta = \left| C_2 \cdot X_\beta - X \right|, D_\delta = \left| C_2 \cdot X_\delta - X \right| \tag{9}$$

$$X_1 = X_\alpha - A_1 \cdot D_\alpha, X_2 = X_\beta - A_2 \cdot D_\beta, X_3 = X_\delta - A_3 \cdot D_\delta \tag{10}$$

$$X(t+1) = \frac{X_1 + X_2 + X_3}{3} \tag{11}$$

3.3. Improved Cauchy Variant Gray Wolf Optimization (IGWO) Algorithm

3.3.1. Cosine convergence function

The convergence factor a affects the global and local search ability of Wolf. Different deceleration rates of $a(t)$ correspond to different search performance of the algorithm. The convergence factor a decreases linearly in the gray wolf optimization algorithm, and the convergence rate changes from slow to fast as the number of iterations increases, which balances the algorithm's global exploration and local exploitation. In training the MLP, this paper cites a cosine-based formula for the convergence factor, as shown in equation (12):

$$a(t) = 2\times\cos\left(\left(t / t_{\max}\right)*(\pi / 2)\right) \tag{12}$$

where $a(t)$ is the t th generation convergence factor and $t_{\max}$ is the maximum number of iterations.

Using a cosine convergence factor instead of a regular linear convergence factor ensures that there is a large convergence factor that facilitates global exploration. Conversely, a small convergence factor favors local exploitation. Using a cosine convergence factor balances the global exploration and local exploitation capabilities of the GWO algorithm.

3.3.2. Introducing the Kersey Variation Operator

The gray wolf optimization algorithm is prone to premature maturity and falling into local optimality, so this paper introduces the Cauchy variation operator into the algorithm. According to the characteristics of the Cauchy distribution, the Cauchy variation factor is to search the local area of the potentially optimal gray wolf individual, generating a random perturbation within a certain range of the potentially optimal solution, which enhances the algorithm's ability to search locally and tests its optimal position. The Cauchy variance is based on the Cauchy probability density function, as shown in equation (13):

$$g\left(x;x_0,\gamma\right) = \frac{1}{\pi\gamma\left[1+\left(\frac{x-x_0}{\gamma}\right)^2\right]} \tag{13}$$

where x_0 is the location parameter, γ is a random variable greater than 0, and x is a real number. In this paper, we take $x_0 = 0, \gamma = 1$, which is a standard Cauchy distribution. By analyzing its probability density function, it can be seen that it does not have a specific mean and variance, but the multitude and median are equal to the location parameter, x_0. Its distribution function is shown in equation (14):

$$G(x) = \frac{1}{2} + \frac{1}{\pi}\arctan(x) \tag{14}$$

Comparing the Cauchy distribution with the normal distribution, the overall distribution of the Cauchy distribution is more uniform, the maximum of the axis of symmetry is flatter relative to the Gaussian distribution, and the trailing probability corresponding to the 2-sided curve is larger. Such distributional characteristics give the Cauchy distribution greater scattering properties. The perturbation formulas that will be incorporated in this paper are shown in Eqs. (15) and (16):

$$X_{ibest}(t) = X_i(t) + X_i(t)*G(x) \tag{15}$$

$$X_i(t+1) = \begin{cases} X_{ibest}(t), f\left(X_{ibest}(t)\right) > f\left(X_i(t)\right) \\ X_i(t), f\left(X_{ibest}(t)\right) \leqslant f\left(X_i(t)\right) \end{cases} \tag{16}$$

where $f\left(X_i(t)\right)$ denotes the fitness value of the i wolf at the t th iteration. The algorithm is guided to jump out of the local optimum through local perturbations.

3.3.3. Adaptive position update formulation

In this paper, an adaptive adjustment strategy is cited to use the inverse of the fitness value as the weight coefficient of the updating formula, which increases the positional advantage of the 3 head wolves, so that the positional updating of the wolves whose fitness value is higher than the average fitness value of the population tends to the optimal solution, and improves the convergence speed of the algorithm. Therefore, Eq. (17) is used instead of Eq. (11) as the wolf position update formula:

$$X_i(t+1)=\begin{cases}\dfrac{\dfrac{1}{f_\alpha}X_\alpha+\dfrac{1}{f_\beta}X_\beta+\dfrac{1}{f_\delta}X_\delta}{\dfrac{1}{f_\alpha}+\dfrac{1}{f_\beta}+\dfrac{1}{f_\delta}}, f\left(X_i(t)\right)\leqslant f_{\text{avg}}\\ \dfrac{X_\alpha+X_\beta+X_\delta}{3}, f\left(X_i(t)\right)>f_{\text{avg}}\end{cases} \tag{17}$$

where $f\left(X_i(t)\right)$ represents the acclimatization value of i wolves at generation t, and f_α, f_β and f_δ represent the acclimatization values of α,β and δ head wolves at generation t, respectively. f_{avg} represents the mean value of acclimatization for all wolves in the t th generation population.

3.3.4. Algorithmic Implementation of IGWO

In summary, the implementation process of the IGWO algorithm proposed in this paper is shown below:

Step1: Initialization of algorithm parameters, gray wolf population size N, maximum number of iterations $t_{\max}$, variable spatial dimensions M, upper and lower bounds of spatial variables ub and lb.

Step2: Initialize the population.

Step3: Make the number of iterations $t=1$.

Step4: When $t<t_{\max}$ or when the iteration stopping condition is not satisfied:

Step5: Calculate the adaptation value $\left\{f\left(X_i\right), i=1,2,\ldots,N\right\}$ in the wolf pack, where the individuals with the highest adaptation value are α wolves, β wolves & δ wolves.

Step6: Update the convergence factor $a(t)$ using equation (12).

Step7: Update the position of each wolf in the current iteration number using Eq. (9), Eq. (10) and Eq. (17).

Step8: Calculate the fitness value $\left\{f\left(X_i(t)\right), i=1,2,\cdots,N\right\}$ for each wolf in the current iteration number.

Step9: Find α wolf, β wolf & δ wolf after position update.

Step10: Update the wolves according to equation (17) such that $t=t+1$.

Step11: If the maximum number of iterations is reached, end. Otherwise jump to Step4.

The flow of training multilayer perceptron using IGWO algorithm is shown in Fig. 8.

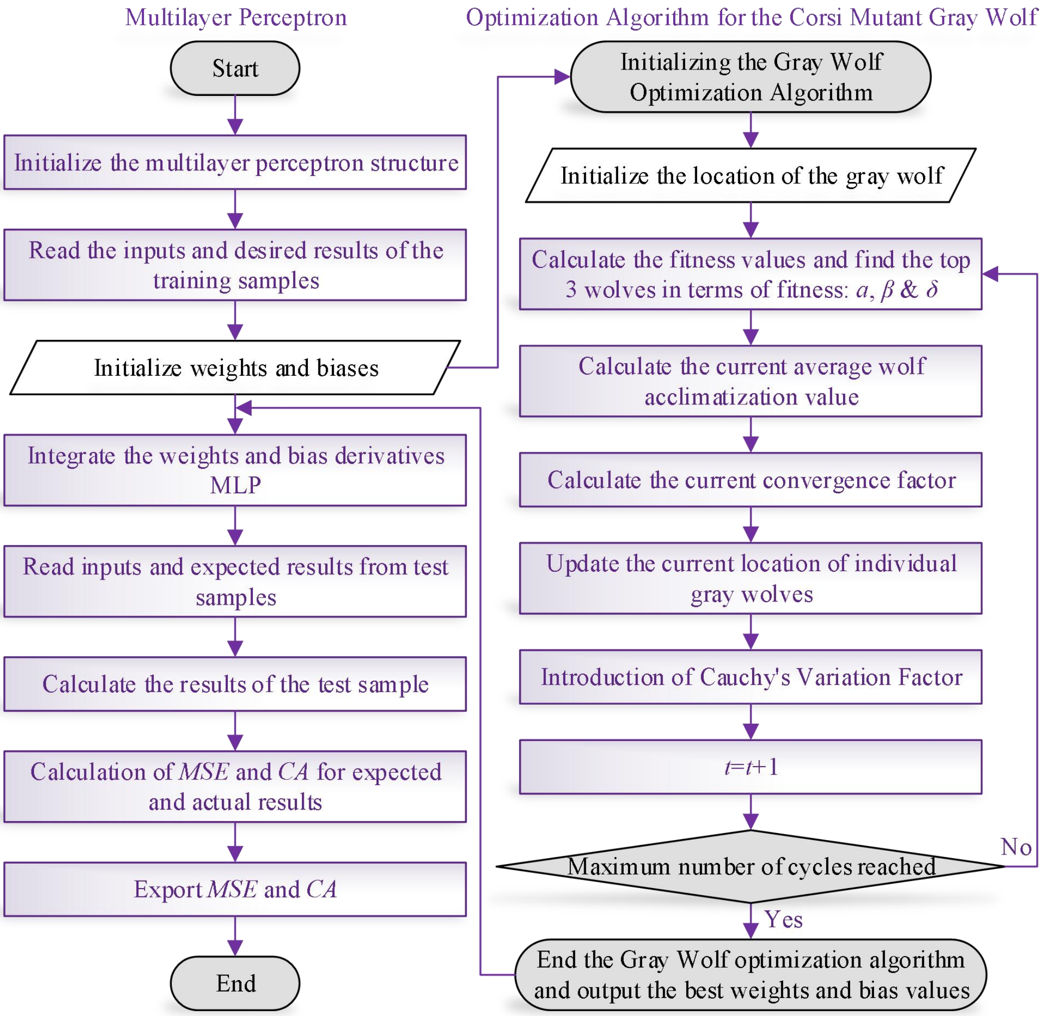

Figure 8. MLP trained by IGWO algorithm.

3.4. Multilayer perceptron trained based on IGWO algorithm

For the multilayer perceptron MLP, there is a possibility of having redundant data and data loss due to the fact that the data space samples are mostly high-dimensional and multi-modal, and there is also a possibility of data being interfered by noise. The main purpose of training the MLP is to update the weights and biases, which is a challenging optimization problem. In this paper, we use an intelligent optimization algorithm to optimize the training of MLP by encoding the weights and biases of each node as an input vector V as shown in equation (18):

$$V=\{W,\theta\}=\left\{w_{1,1},w_{1,2},\cdots,w_{n,n},\theta_1,\theta_2,\cdots,\theta_n\right\} \tag{18}$$

where $w_{i,j}$ denotes the weights connected for node i and node j. θ_j denotes the bias of node j and n is the total number of nodes.

3.5. Experimental results and analysis

3.5.1. Experimental setup

The experimental platform is 64-bit Windows 10 OS+ Matlab R2017a, with a CPU main frequency of 2.4G and 8GB of RAM.In order to verify the performance of the improved algorithm, the IGWO-MLP algorithm is tested using five student learning behavior datasets A~E from the corpus of a MOOC platform. The datasets involve a total of five types of learning behavior recognition problems, and each dataset focuses on the recognition of one specific learning behavior.

In order to test the performance of the IGWO algorithm, the following classical intelligent optimization algorithms are introduced for comparative analysis: the standard gray wolf optimization algorithm GWO, the firefly algorithm FF [45], and the flower pollination algorithm FPA [46]. The population sizes were all set to N=100, and the number of algorithm iterations was set to 400.Among the relevant parameters of the FF algorithm, the initial fluorescein was 5, the perception radius was 10, the volatilization factor was 0.4, the medium absorption coefficient was 0.6, the diffusion number was 15, and the division ratio was 50%, and among the relevant parameters of the FPA algorithm, the conversion probability was 0.8.

3.5.2. Assessment of indicators

The performance of the algorithm is evaluated using six metrics, the first four of which are obtained from the confusion matrix of the data classification model.TP denotes the number of samples that are correctly classified as positive instances, i.e., the number of samples that are actually positive and categorized as such.FP denotes the number of samples that are incorrectly classified as positive instances, i.e., the number of samples that are actually negative and categorized as such.FN denotes the number of samples that are incorrectly classified as negative instances, i.e., the number of samples that are actually positive but categorized as such.TN denotes the number of samples that are TN denotes the number of samples correctly classified as negative, i.e., the number of samples that are actually negative and categorized as negative.

(1) Classification accuracy rate ACC : indicates the proportion of accurately classified samples to the total number of samples, calculated as:

$$ACC = \frac{TP + TN}{TP + FN + FP + TN} \tag{19}$$

(2) Specificity SP : indicates the proportion of predicted negative samples to the total number of negative samples. It is calculated as:

$$SP = \frac{TN}{FP + TN} \tag{20}$$

(3) Sensitivity SE : indicates the ratio of predicted positive samples to the total number of positive samples. Higher sensitivity indicates that the classification model is more accurate in identifying learned behaviors, calculated as:

$$SP = \frac{TP}{FN + TP} \tag{21}$$

(4) G -mean $G - mean$: denotes the joint index of sensitivity SE and specificity SP , calculated as:

$$G - mean = \sqrt{SE + SP} \tag{22}$$

(5) AUC : denotes the region under the ROC curve of the subject's operating characteristics, which is a valid classification metric for categorizing datasets with uneven distribution of positive and negative samples, computed as:

$$AUC = \int_0^1 \frac{TP}{P} d\frac{FP}{N} = \frac{1}{PN}\int_0^1 TPdFP \tag{23}$$

where $P = TP + FP, N = TN + FN$.

(6) Mean square error MSE : by inputting the data of the sample into the input layer of the MLP, the output data of the MLP is compared with the target result, if the output data is closer to the target result, the better the training effect is, and vice versa the worse the training effect is. MSE is defined as shown in equation (24):

$$MSE = \frac{\sum_{i=1}^{PP}\left(o_i^k - d_i^k\right)^2}{PP} \tag{24}$$

where o_i^k is the desired output of the output node, d_i^k is the actual output, and PP is the total number of training samples.

3.5.3. Experimental analysis

The dataset A is selected as an example for experimental analysis, and the metrics test results of dataset A are shown in Table 1, which demonstrates the mean AVG, standard variance STD, as well as the optimal value BEST, and the worst value WORST for each metric.

Overall, the IGWO algorithm in this paper is slightly better than several other algorithms in most of the metrics, and the mean AVG of the classification accuracy is higher than the GWO algorithm, the FF algorithm, and the FPA algorithm by about 1.04%, 1.08%, and 1.28%, respectively. Except for the SE metric, the standard variance of the remaining metrics IGWO algorithm is the smallest among all algorithms, indicating that the algorithm stability is also better.

Table 1. The metric test results of dataset A.

Statistical indicators	Algorithms	AUC	ACC	SP	SE	G-mean
AVG	FPA	0.9855	0.9685	0.9621	0.9726	0.9676
	FF	0.9955	0.9704	0.9479	0.9818	0.9644
	GWO	0.9951	0.9708	0.9438	0.9795	0.9616
	IGWO	0.9978	0.9809	0.9534	0.9804	0.9667
STD	FPA	0.0162	0.0089	0.0279	0.0099	0.0125
	FF	0.0011	0.0081	0.0247	0.0058	0.0122
	GWO	0.0012	0.0064	0.0191	0.0034	0.0096
	IGWO	0.0010	0.0052	0.0143	0.0057	0.0070
BEST	FPA	0.9969	0.9818	0.9988	0.9859	0.9864
	FF	0.9978	0.9781	0.9878	0.9937	0.9809
	GWO	0.9965	0.9745	0.9749	0.9864	0.9749
	IGWO	0.9969	0.9781	0.9749	0.9868	0.9786
WORST	FPA	0.9263	0.9493	0.9140	0.9488	0.9406
	FF	0.9943	0.9532	0.9028	0.9675	0.9409
	GWO	0.9945	0.9519	0.9041	0.9755	0.9406
	IGWO	0.9946	0.9560	0.9258	0.9604	0.9494

The convergence curves of the MSE metrics for each algorithm and their violin plots are shown in Figures 9 and 10, respectively. The violin plot can illustrate the situation of the degree of data dispersion, and its top horizontal line and bottom horizontal line indicate the upper quartile and lower quartile, respectively, and the dashed line in the middle is the median value. Observation of the convergence curves shows that the IGWO algorithm has the fastest convergence rate among all algorithms. The violin plot reflects that the IGWO algorithm possesses the smallest MSE mean value, which has the smallest volume, indicating that the algorithm has the best stability.

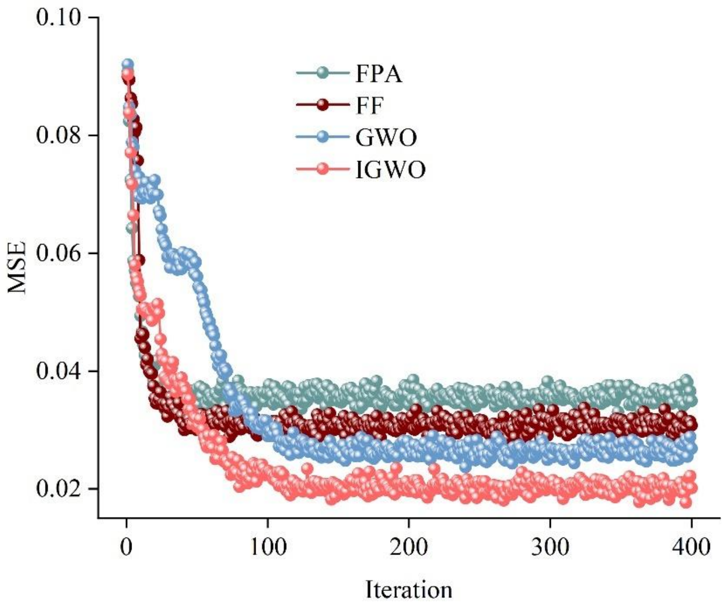

Figure 9. The convergence curve of MSE.

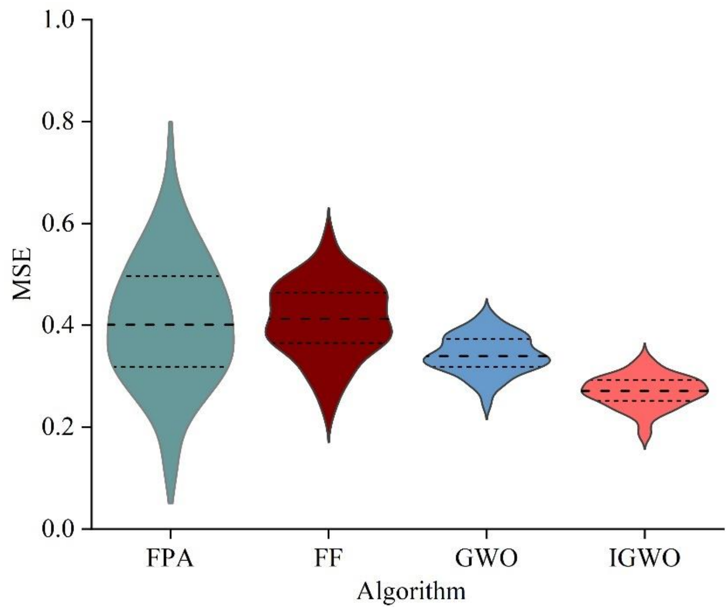

Figure 10. Violin picture of MSE.

The results of the Wilcoxon rank sum test of IGWO relative to the three comparison algorithms on the MSE metrics are shown in Table 2, which is a nonparametric test that replaces the sample value with the sample rank, specifically, it refers to the test of whether there is a significant difference between the median value of the two sets of data of the proposed algorithms and the comparison algorithms at a significance level of 5 percent. The P-value in the table represents the probability of significance of whether the two data sets are the same overall, and H represents the result of hypothesis testing, with H=1 representing the existence of a significant difference and H=0 representing the absence of a significant difference.

It can be seen that there are significant differences on the data obtained by IGWO relative to the three comparison algorithms on the five data sets, while the P-value is less than 1.00E-10, which indicates that the IGWO algorithm has a higher search accuracy, which improves the MSE index very well, and the performance of the search for excellence has been improved.

Table 2. The result of the Wilcoxon rank sum test.

Dataset	Indicator	FPA	FF	GWO
A	*P*	2.204E-10	2.204E-11	2.204E-11
	H	1	1	1
B	*P*	1.812E-11	2.648E-11	2.648E-11
	H	1	1	1
C	*P*	1.735E-10	2.204E-11	2.204E-11
	H	1	1	1
D	*P*	2.204E-10	2.204E-11	2.204E-11
	H	1	1	1
E	*P*	2.204E-10	2.204E-11	2.204E-11
	H	1	1	1

The performance comparison of different prediction models is shown in Figure 11, including the standard BP neural network model, the standard MLP model, the MLP model GWO-MLP optimized by the standard GWO algorithm, and the IGWO-MLP model in this paper. It can be seen that compared to the poor performance of the mean square error of the standard BP network model and the MLP model without optimization, the differences of the IGWO-MLP model of this paper on the five datasets are 19.75%, 30.52%, 20.86%, 10.52%, and 37.23% and 12.60%, 37.33%, 14.95%, and 1.03%, respectively, 34.03%. Obviously, the introduction of Gray Wolf Optimization algorithm GWO to optimize the MLP model has improved the prediction performance better. And compared with the standard GWO algorithm, the improved IGWO algorithm is more effective for MLP optimization, and due to the improved accuracy and speed of population search, it is bound to build a better MLP prediction model, and the classification accuracy of the dataset will be further improved.

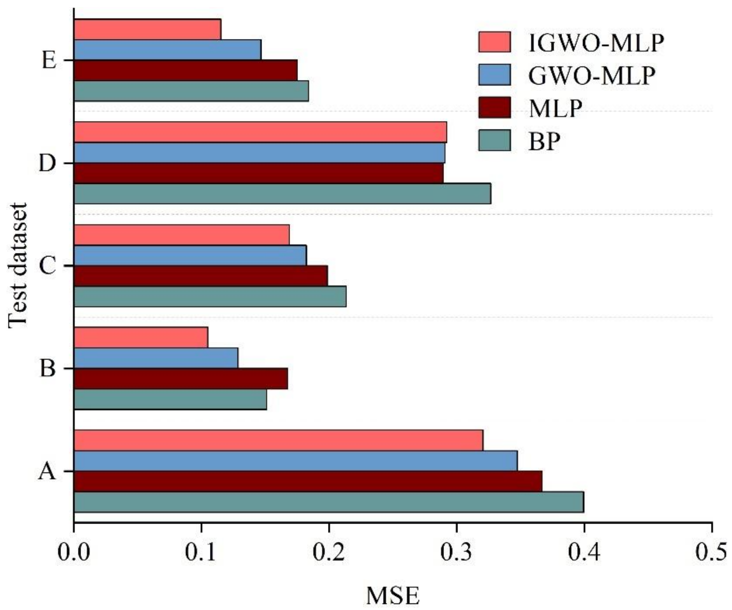

Figure 11. Performance comparison of different prediction models.

4. Prediction of Academic Achievement in IGWO-MLP Based Blended Instructional Models

This chapter examines the impact of a hybrid model of accounting instruction on academic achievement by using the IGWO-MLP model to predict the academic achievement of students in a hybrid model of accounting instruction.

4.1. Forecasting process

The flowchart for predicting students' academic achievement in the blended teaching model of accounting using IGWO-MLP is shown in Figure 12.

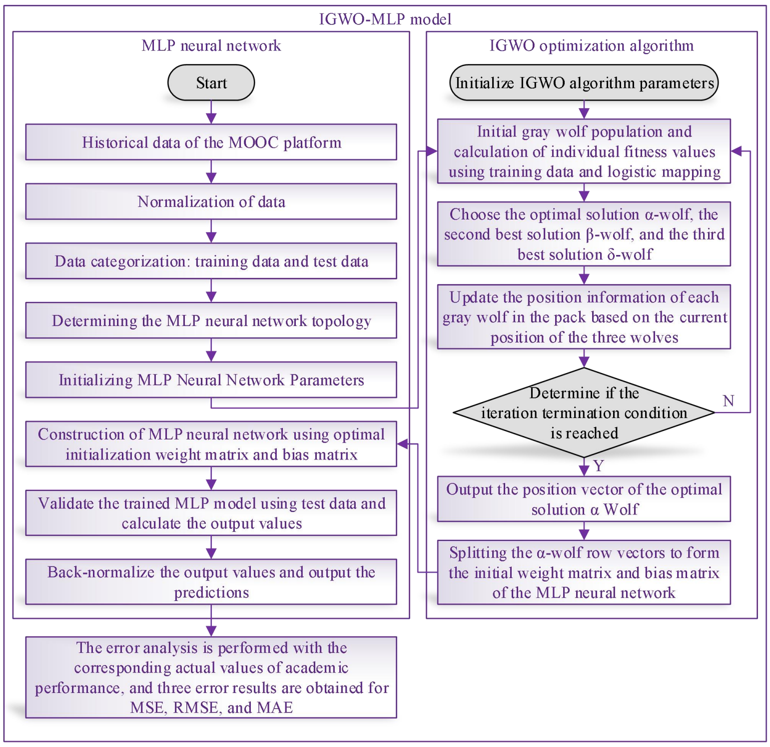

Figure 12. Flowchart of the IGWO-MLP model prediction.

The prediction process is as follows:

(1) Normalize the historical data of MOOC platform:

$$\overline{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{25}$$

Where $\overline{x}$ is the normalized data, $x_{\min}$ is the minimum value and $x_{\max}$ is the maximum value.

Accordingly, at the end of the MLP neural network training and testing process, the output values are back-normalized to obtain the predicted values of students' academic achievement. The inverse normalization expression is as follows:

$$x = \overline{x} \times \left(x_{\max} - x_{\min}\right) + x_{\min} \tag{26}$$

(2) Divide the normalized MOOC platform historical data into training data and test data in the ratio of 7:3.

(3) Determine the topology of the MLP neural network.

(4) Initialize the MLP neural network parameters.

(5) Optimize the initial weight matrix and bias matrix of the MLP neural network using the IGWO optimization algorithm.

(6) Validate the trained IGWO-MLP model using test data and calculate the output values.

(7) Inverse normalization is performed on the output values to obtain the PV output power prediction value, and ACC, Precision, Recall, F1, AUC are used as the prediction accuracy evaluation criteria, and the error results are compared and analyzed with the corresponding real data of academic achievements.

4.2. Model parameterization

In the IGWO-MLP model, data such as video viewing length, number of visits, percentage of task point completion, total discussion, published comments, assignment score, MOOC composite grade, and gender in the historical data of the MOOC platform are selected as inputs to the model, and the output is the students' final written test scores predicted by the IGWO-MLP model. Therefore, the number of neurons in the input and output layers of the MLP model is set to 8 and 1, respectively, and the number of layers of the hidden layer is set to 3, with each hidden layer containing 8 neurons.The maximum number of training times of the MLP model is set to 2000, the training error is 1e-8, and the training algorithm is the Levenberg-Marquardt algorithm.The number of populations of the IGWO is 20, and the maximum number of iterations is 2000.

4.3. Evaluation indicators

The evaluation indexes used in the experiments in this chapter include Precision, Recall, and F1 in addition to ACC and AUC used in the previous section.

(1) Precision (P):

$$Precision = \frac{TP}{TP + FP} \tag{27}$$

From Equation (27), the precision rate is concerned with the proportion of samples in which the prediction is Positive that the prediction is correct.

(2) Recall:

$$Recall = \frac{TP}{TP + FN} \tag{28}$$

Comparing equations (27) and (28), it can be found that the recall rate and precision rate are calculated in a more similar way, but the recall rate is more concerned with the proportion of samples with correct predictions in samples where the actual value is Positive.

(3) F1-score:

$$F_1 = \frac{2 \cdot precision \cdot recall}{precision + recall} \tag{29}$$

In order to better balance precision, recall, the F1 score was obtained by integrating their weighting.

4.4. Analysis of experimental results

4.4.1. Comparison of the Effectiveness of Single-Period and Multiple-Period Predictions of Academic Achievement

This study is based on the quantitative characteristics data in the accounting blended teaching model for academic achievement prediction, using correlation analysis and other methods to screen the behavioral characteristics that have a greater impact on academic achievement, and using the IGWO algorithm to optimize the MLP model. Secondly, in order to avoid the influence of some extreme samples on the experimental effect, this study adopts the method of five-fold cross-validation, taking the accuracy rate, precision rate, etc. as the evaluation indexes, and taking the average of its five results as the final model index results. The results of multi-period prediction of academic achievement are shown in Table 3.

The experimental results show that among the single-term and multi-term academic achievement prediction models, the multi-term model has higher prediction accuracy. Specifically, the accuracy of academic achievement prediction for the whole semester is 0.694, the accuracy of the first half of the semester is 0.742, and the accuracy of the second half of the semester is 0.768, the accuracy of which has been improved by 0.048 and 0.074, respectively. 0.051, i.e., with the inclusion of students' historical academic achievements can effectively improve the performance of the prediction model.

Table 3. Multi-period prediction results of academic achievements (50% Cross-validation).

Time	ACC	P	R	F1	AUC
The entire semester	0.694	0.721	0.694	0.707	0.625
The first half of the semester	0.742	0.769	0.744	0.756	0.648
The second half of the semester	0.768	0.801	0.767	0.784	0.716
The second half of the semester + the first half	0.819	0.835	0.813	0.824	0.748

4.4.2. Impact of Learning Styles on the Prediction of Academic Achievement

Previous studies have shown that different learning styles have a significant impact on individual performance in academics, and understanding students' learning styles under the blended teaching model of accounting and providing corresponding educational resources in a targeted manner can improve students' academic achievement performance. At the same time, it can also help teachers make timely adjustments to the teaching mode according to the actual situation of different types of students in order to achieve the best results. Based on the above research, this experiment incorporates the results of learning style identification as a new feature into the academic achievement prediction model and observes its prediction effect in different learning cycles, and the results of academic achievement prediction based on learning styles are shown in Table 4.

Overall, the inclusion of learning styles has a certain enhancement effect on the prediction effect of academic achievement in the blended teaching mode of accounting. In terms of the accuracy index, taking the whole semester academic achievement prediction effect as an example, its prediction accuracy after incorporating the new features of learning styles increased from 0.694 to 0.725, an increase of 0.031, and there is a similar enhancement effect on other learning cycles. In addition, this study compares the effect of academic achievement prediction based on learning styles and analyzes the best model for academic achievement prediction, and it can be found that the best prediction effect is achieved after incorporating learning style features into a multi-period academic achievement prediction model considering historical information, and its prediction accuracy is 0.847, compared with that of a multi-period academic achievement prediction model that does not incorporate learning styles with an accuracy of 0.819, which is a 0.028 increase in accuracy. The accuracy of the model was 0.847, compared with the accuracy of 0.819 of the model without learning styles, which was 0.028 higher.

Table 4. Academic achievement prediction results based on learning styles.

Time	ACC	P	R	F1	AUC
The entire semester	0.694	0.721	0.694	0.707	0.625
The entire semester + learning style	0.725	0.748	0.725	0.736	0.634
The first half of the semester	0.742	0.769	0.744	0.756	0.648
The first half of the semester + learning style	0.793	0.824	0.793	0.808	0.728
The second half of the semester	0.768	0.801	0.767	0.784	0.716
The second half of the semester + learning style	0.825	0.865	0.825	0.844	0.763
The second half of the semester + the first half	0.819	0.835	0.813	0.824	0.748
The second half of the semester + the first half + learning style	0.847	0.906	0.844	0.874	0.791

5. Conclusion

In this paper, we propose an improved Cauchy variant gray wolf optimization algorithm IGWO, combined with multilayer perceptron to realize the construction of academic achievement prediction model in accounting blended teaching mode, and verify the practical effect of the model.

By mining students' online learning behavior data, the study found that: there is a significant difference between different genders in the final written test scores. The total number of discussions, the number of visits and the length of watching videos are higher for female students than for male students, and the corresponding passing rate of the final written examination is also higher.

Combining the metrics of classification accuracy ACC, specificity SP, sensitivity SE, G-mean G-mean, AUC, and MSE, as well as the model iteration convergence speed and error level, the IGWO-MLP model constructed in this paper performs the best among all the compared models in terms of classification accuracy and stability.

In addition, compared with the single-period academic prediction model, the multi-period academic prediction model has a better prediction effect, and its accuracy is improved from 0.768 to 0.819, an increase of 0.051. Learning styles have a certain enhancement effect on the prediction effect of academic achievement, and after incorporating learning style features, the accuracy of the multi-period model is improved from 0.819 to 0.847, and its prediction effect is improved by 0.028.

The IGWO-MLP constructed in this paper can effectively predict students' academic achievement, which can help teachers adjust their teaching plans, guide accounting blended teaching, and focus on students who are warned. However, the accuracy of the model needs to be improved because only 400 students' MOOC feature data are selected in this paper, and the training data is small. In the future, a large amount of learning behavior data of different learners can be collected to further train the model, further improve the model accuracy, and better predict the academic achievement of learners, so as to tailor the teaching to the students' needs and thus comprehensively improve the quality of teaching.

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