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The application of improved backpropagation neural network in college student achievement prediction

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CHRONICLE

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ABSTRACT

Educational institutions generate a large amount of digital data in their daily operations, which is stored in servers, forming a substantial educational data set. Extracting valuable information through practical data analysis has become a critical problem that needs to be solved urgently. Students' examination results are an essential basis for evaluating their learning status, which reflects the effect of school education to some extent. Therefore, we propose a model based on the BP network and Pandas to construct a prediction model for Pandas' performance in the first year and their successful graduation to explore the potential relationship between Pandas' performance in the freshman year and graduation, thus realizing the principle of early guidance and improvement of teaching quality. Through the random prediction experiment of 9,424 scores data of 304 students in 2017 and 2018 majoring in network engineering at a university, the accuracy rate is 96.71% after the experimental data analysis and verification, which has proved that there is a potential correlation between the students' first-year course scores and graduation. Meanwhile, the improved BP network proposed in the present research exhibits reasonable practicability and extensibility in the college student achievement prediction model.

1. Introduction

Teaching quality has always been an essential part of teaching management in colleges, and it is the lifeline for a college to survive (Aaron, 2023). Academic achievement is a crucial index for evaluating the comprehensive score of students' learning and teachers' teaching quality (Chavez et al., 2993). Therefore, improving students' performance has become essential for colleges to enhance teaching quality. Predicting student achievement can help schools and educational institutions better understand students' academic performance and potential and provide students with targeted educational guidance and support (Li et al., 2023). However, predicting student achievement is a complicated problem that many factors affect. Traditional prediction methods often fail to consider these factors' complex relationships fully. Therefore, it is necessary to explore new techniques and models to enhance the accuracy and reliability of student achievement prediction (Chavez et al., 2023).

Traditional student achievement prediction methods mainly rely on statistical analysis and regression models. Still, these methods often fail to capture complex nonlinear relationships and potential feature interactions, resulting in limited prediction accuracy (Mouti et al., 2023). The student achievement prediction model based on the backpropagation network exhibits higher flexibility and expression ability, which can help learn more complex feature representation through many sample data and predict student achievement (Di et al., 2023).

In this study, we will conduct pre-processing and feature engineering of students' performance data based on the panda's library, and we will establish a student performance prediction model with a backpropagation neural network. This paper investigates using an improved Backpropagation neural network model in college student achievement prediction and

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verifies its validity and feasibility through empirical research. It is hoped that the results of this study can provide a more accurate and personalized student achievement prediction model for colleges and educational institutions, to promote students' academic growth and advance the cultivation of students and the teaching quality.

2. Application of Panel Data Analysis

Panel Data Analysis is a typical method used to process data with time series and cross-sectional characteristics, also known as long-format data (Kumar et al., 2023; Yi et al., 2023; Zhao & Liu, 2022a). It is suitable for research that requires consideration of the temporal and individual dimensions of the data, and Pandas provides a range of capabilities when dealing with credit scores (Zhao & Liu, 2022b). First, student performance data is loaded into a DataFrame object using Pandas's functions and methods for data processing and analysis. Pandas' functions, such as read_csv() and read_excel(), allow you to read data from a file or other data source and convert it into an easy-to-handle tabular form. Next, functions and methods of Pandas are employed to clean and transform the data, which includes dealing with issues such as missing values, duplicate values, and outliers, ensuring data integrity and consistency by using functions such as dropna() and fill () to delete or fill in missing values (Chen et al., 2022), and functions and methods are used such as apply() and map() to perform custom transformation operations on the data or map specific values to other values to meet analysis requirements. After data processing is completed, the functions and methods used in Pandas are utilized for data calculation and analysis, for example, the groupby() function used to group data, and functions such as aggregate(), mean(), and sum() used for statistical calculation, such as calculating the average score and total score. These calculations can provide essential features and inputs for subsequent prediction model construction (Ai & Feng, 2022; Lan & Fan, 2022; Li, 2022). In conclusion, Pandas are crucial in predicting college students' performance based on the Backpropagation neural network. It provides robust data processing and analysis functions so that the student achievement data can be loaded, cleaned, converted, and calculated conveniently. This offers the necessary data foundation and preprocessing steps for constructing an accurate prediction model.

3. Backpropagation Neural Network

Backpropagation Network is a forward network with multiple layers of error feedback mechanism, which belongs to the supervised learning method and is often used to solve classification and regression problems (Liu, 2022; Zhang & Wen, 2022; Zhu, 2022; Zhang, 2022). This model is shown in Fig. 1.

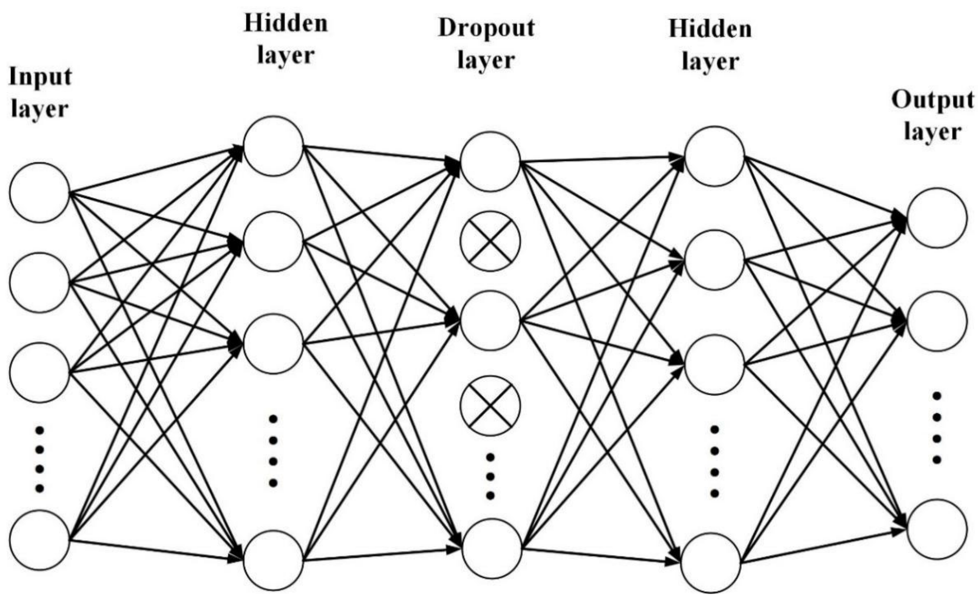

Fig. 1. Backpropagation neural network model

The construction process of a Backpropagation neural network includes two stages: signal forward and error backpropagation. In the former stage, the input signal propagates layer by layer through each neural network layer and generates the output signal through nonlinear transformation. The neuron state of each layer can only affect the neuron state of the next layer, which is transmitted and transformed by the connection weight between layers. The later stage is entered if the network's actual output has an error. At this stage, errors are distributed layer by layer to individual neurons by backpropagating error signals from the output layer to the input layer (Sun & Zhang, 2022; Shi, 2022; Gu, 2022). In this way, the contribution of each neuron to the error can be calculated, and the connection weight and threshold can be adjusted according to these contributions so that the output error is gradually reduced. The gradient descent method was applied to minimize the prediction error. It calculates the error and adjusts the connection weight of each neuron based on the error gradient. Specifically, it uses the chain rule to calculate the error contribution of each neuron and updates the weights and thresholds based on the contribution size. The construction process requires several iterations of training until the network error meets the preset conditions or reaches the preset training times. By constantly adjusting the connection weight and threshold value, the Backpropagation neural network gradually optimizes its prediction ability and can predict student achievement more accurately. In other words, a backpropagation neural network uses the gradient descent method to optimize the connection weight using signal forward and error backpropagation to minimize the prediction error. This process is realized through iterative training so that the network can gradually strengthen its prediction accuracy.

3.1 Rectified Linear Unit

The Rectified Linear Unit (ReLU) function is commonly used in the hidden and output layers of neural networks (Feng & Feng, 2022; Dai & Yang, 2022; Qi et al., 2022). It can be expressed in a simple form.

$$f(x) = \max(0, x) \tag{1}$$

where x and $f(x)$ refer to the input and output values, respectively. ReLU functions have simple but efficient properties: when the input is above zero, the output equals the input, or the output is zero. The nonlinear transformation enhances the ability of the neural network to express itself. Compared to traditional activation functions (such as Sigmoid and Tanh), ReLU functions have efficient computational performance, especially when processing large amounts of data. In addition, the ReLU function can effectively alleviate the gradient disappearance problem, thus improving the stability of the backpropagation process. Therefore, ReLU functions are widely used in neural networks, providing a compelling choice for improving network performance and accelerating the training process.

3.2 Sigmoid

The sigmoid function is a commonly used classification function, also known as the Logistic function (Xu & Xia, 2022; Peña-Ayala, 2014; Francis Bindhia & Babu, 2019). It maps the input value to a range of 0 -1. The mathematical expression of the Sigmoid function is as follows:

$$f(x) = \frac{1}{1+e^{-x}} \tag{2}$$

where x and $f(x)$ are defined in Eq. (1). The main characteristic of the Sigmoid function is that its output approaches one as it approaches positive infinity and 0 as it approaches negative infinity. This property makes the Sigmoid a helpful function for binary classification problems. It can interpret the output as a probability value that the sample belongs to a particular class. In the training stage, the Sigmoid function increases the nonlinear expression ability of the model by introducing nonlinear transformation, which helps to fit the complex relationship in the data better. In the present research, that function is applied as the activation function of the output layer of the neural network, and its primary function is to convert the continuous output of the network into probability values for classification prediction. By applying the Sigmoid function, we can obtain the predicted probability of each student corresponding to different categories (such as pass/fail, excellent/good/pass/fail, etc.) to classify and evaluate student achievement.

3.3 Cross-Entropy

Cross-entropy is an ordinary loss function, particularly applicable to classification problems. In neural networks, cross-entropy measures the degree of difference between model predictions and accurate labels (Roshani, 2019). For the binary classification problem, the mathematical expression of the cross entropy loss function is as follows:

$$H(y, y') = -\left[y\log(y') + (1-y)\log(1-y')\right] \tag{3}$$

where y is the actual label, with a value of 0 or 1, and y' is the model's predicted output, with a value between 0 and 1. This function measures the model's performance by comparing actual label and production differences. When the prediction results are precisely consistent with the actual label, the value of this function is 0, indicating that the model prediction is accurate. However, when the prediction result is different from the actual label, the value of this function is significant, indicating that the model prediction is wrong.

This model was applied in the study to measure the difference between predicted and actual student achievement. By reducing this loss function to a minimum, the neural network parameters are adjusted to enhance the precision of the model's prediction of student achievement. This approach helps ensure that the model can more accurately predict student achievement.

4. Graduation prediction model and method

Constructing a graduation prediction model is a complex and challenging task involving the comprehensive consideration of many factors (Qin, 2020a, 2020b). Although individual psychological changes, industry development, and other factors impact students' learning process, these factors, which cannot be directly quantified, have not been considered for the time being in constructing the prediction model. We will focus on the relationship between courses because of course continuity. For example, there is an apparent relationship between the introductory courses of advanced algebra and probability theory, C language programming and data structure, and the majors' core courses. The learning state of students in the pilot course directly affects the learning effect of the follow-up course and further affects the graduation result. While general courses, such as college students' mental health, ideological and moral cultivation, and legal basis, have no direct correlation with other courses, they play a positive role in cultivating students' learning ability, thinking mode, and innovation ability, thus indirectly affecting other courses and graduation results. Therefore, excluding other factors and considering only the curriculum factors, the results of most students should show a particular trend. For example, their grades may improve as students gradually get into the learning mode. When individual demands are relaxed, performance may decline, Or grades may remain stable within a specific range. Therefore, it is feasible to predict graduation grades using the grades of courses offered during the first year. In addition, because of its hidden layer structure and dynamic adjustment of weight parameters, the BP neural network is more suitable for mining the potential relationship between some courses and graduation results. Through the training and optimization of students' performance data, the BP network can study the complex patterns and rules between courses and grades from abundant data. It can be used to predict students' graduation results.

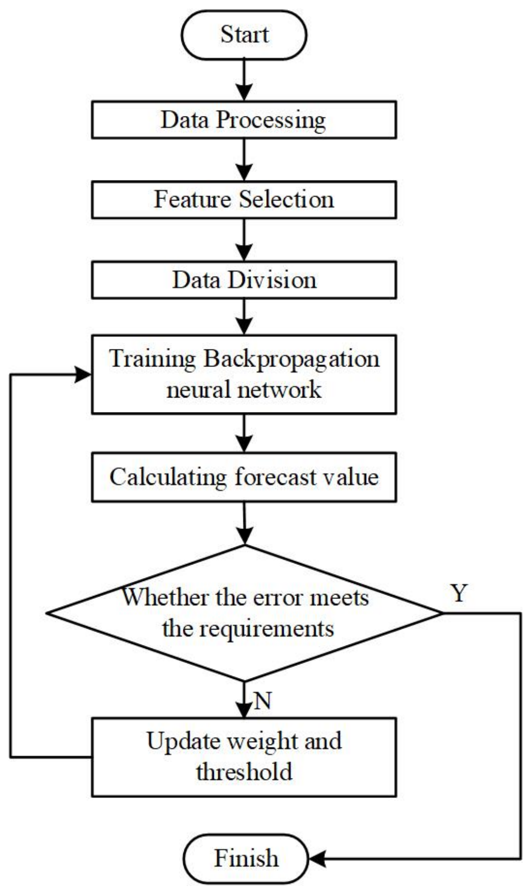

Fig. 2. Grade prediction method

The prediction method is shown in Fig. 2 and covers a series of critical steps:

(1) Data preprocessing. Use the Pandas library to load student performance data, including students' personal information, course grades, and credits. Clean and process the data to ensure its accuracy and integrity.
(2) Feature selection: Features related to student achievement are selected from the data, including credits as an essential feature and graduation as a target variable.
(3) Data division: the selected features are standardized or normalized to ensure the uniformity of scales of different features and avoid the impact of differences between features on model training.
(4) Construction of BP model: We will use the Sequential model to build a BP neural network. In this network, we explicitly specify the neurons in the input, hidden, and output layers and how they are connected. The input layer will receive features related to student achievement, the hidden layer will be responsible for extracting nonlinear features, and the output layer

will generate predicted student achievement. We chose the ReLU function as the activation function because it performs well in extracting nonlinear features and can better fit the nonlinear relationship of student achievement.
(5) Selection of loss function: To assess the precision of the out results, the cross entropy loss function is usually selected as the loss function. This loss function effectively measures the model error and optimizes the model to better fit the data by minimizing the loss function. Using such a function helps to ensure that the model fits the data more accurately, as it can accurately reflect the gap in the output value and the actual value and adjust the model parameters based on minimizing loss function, thereby improving the performance and prediction accuracy of the model.
(6) Model training and optimization: We will use labeled training data to train and optimize the model. We will define appropriate loss functions and optimizers to measure the model error and utilize backpropagation algorithms to update the network's connection weights. By evaluating the performance of the training set and the validation set, we will adjust the hyperparameters and structure of the model to improve its accuracy and generalization ability in predicting student achievement.
(7) Model prediction and verification. The trained model is used to predict the graduation, and the actual graduation situation is compared and verified. The performance and validity of the model are evaluated by comparing the consistency and accuracy of the predicted results with the exact problem.

5. Prediction model construction and result analysis

5.1 Experimental data

The data used in this paper are 304 students who graduated from the class of 2022 and the class of 2021, majoring in network engineering, obtained from the educational administration system of a university. Each student takes 31 courses during the first year, with a minimum graduation credit of 164 credits and a total score of 56.5 points for the courses offered in the first year. Because the graduation situation of students is known, there is no need for students or teachers to fill in additional questionnaires or organize score entries, which makes it easier to be accepted by colleges, teachers, and students. Experimental data were processed as follows:

(1) The five-level scores recorded in the educational administration system as excellent, good, medium, pass, and fail are replaced with 95, 85, 75, 65, and 50, respectively;
(2) The scores of the two-level system recorded in the teaching administration system as qualified and unqualified are replaced with 80 and 50;
(3) The score of missing or missing the course shall be treated as 0.

5.2 Performance Evaluation Index

The Loss Function is applied to measure the difference between model output and actual value. The choice of it depends on the type of problem being solved and the type of output of the model. When the model is applied for training, the loss value of each training step is usually monitored and recorded. The model adjusts the weight and bias by minimizing the loss function to make the predicted result closer to the actual value. The loss function is negatively related to model prediction precision. The training set is a loss function item to optimize and train the model. The convergence is shown in Fig. 3.

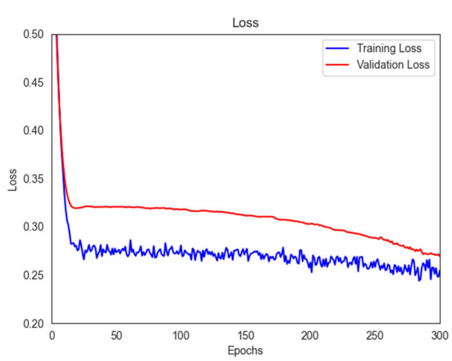

Fig. 3. Training loss function graph

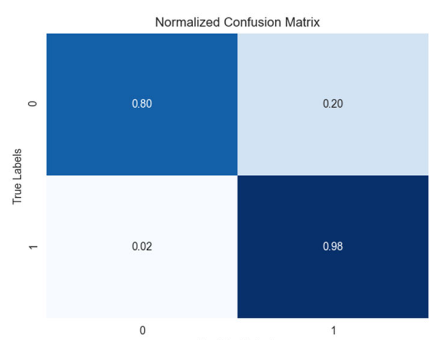

Fig. 4. Confusion matrix graph

Blue represents the test set loss function, and red represents the verification set loss function. The verification set converges faster than the test set, and within the exact training times, the loss value is lower, and the model is more convergent. After normalization, the confusion matrix graph can be seen in Fig. 4. The horizontal axis represents the prediction result, and the vertical axis represents the actual situation. The standard method of normalization confusion matrix is to divide the number or proportion of samples in each category by the total number of samples in this category to obtain the classification accuracy of each category. In this way, the influence of sample quantity imbalance on the confusion matrix can be eliminated, and the performance of different categories can be more comparable. It can be seen from Fig. 4 that the accuracy rate of the sample number in which the model is predicted as a positive example and the actual label is also a positive example is 98%. The accuracy of the number of samples predicted by the model as negative cases and the actual label as negative cases was 80%. It shows that the prediction performance of the model is worthwhile.

5.3 Experimental results and analysis

PyCharm Community Edition 2020.3.3×64 was used in this paper, and Epoch is 2000 times the training in this setting. To prevent interference with subsequent experiments caused by considerable data differentiation, the remaining data was specially normalized and uniformly mapped to the interval [0,1]. Part of the data results can be seen in Fig. 5. The students' number is 304, and each student has 31 courses.

	Grade_1	Grade_2	Grade_3	Grade_4	Grade_5	Grade_6	Grade_7 \
0	0.456637	0.073451	0.396460	0.283186	0.424779	0.533628	0.237168
1	0.461947	0.074336	0.532743	0.272566	0.456637	0.581416	0.279646
2	0.456637	0.073451	0.427434	0.350442	0.440708	0.669027	0.258407
3	0.461947	0.073451	0.446018	0.350442	0.403540	0.254867	0.237168
4	0.467257	0.073451	0.495575	0.290265	0.424779	0.477876	0.272566
..	...	...	...	...	...	...	...
299	0.456637	0.062832	0.476991	0.293805	0.446018	0.326549	0.187611
300	0.456637	0.061062	0.377876	0.332743	0.472566	0.350442	0.304425
301	0.467257	0.060177	0.402655	0.304425	0.461947	0.477876	0.191150
302	0.461947	0.058407	0.408850	0.286726	0.435398	0.477876	0.180531
303	0.456637	0.058407	0.309735	0.315044	0.467257	0.493805	0.272566

Fig. 5. Graph of data processing results

During operation, the first 100 times of data were exhibited in Table 1.

Table 1
The result is the first 100 times

Numble	loss	acc	PRauc	val_loss	val_acc	val_Prauc
1	0.5026	0.9218	0.9218	0.4926	0.9016	0.9016
2	0.4629	0.9218	0.9218	0.4572	0.9016	0.9016
3	0.4286	0.9218	0.9218	0.4270	0.9016	0.9016
4	0.3976	0.9218	0.9218	0.4028	0.9016	0.9016
5	0.3741	0.9218	0.9218	0.3820	0.9016	0.9016
…	…	…	…	…	…	…
98	0.2717	0.9218	0.9218	0.3180	0.9016	0.9016
99	0.2736	0.9218	0.9218	0.3179	0.9016	0.9016
100	0.2807	0.9218	0.9218	0.3178	0.9016	0.9016

The first 100 times of operation results, loss and val_loss data decreased gradually, while val_loss tended to be flat. In the first 100 times of operation data, acc, PRauc, val_acc, and val_PRauc did not change significantly. The final result is shown in Figure 6, with an accuracy rate of 96.71%. Recall rate is 100%.

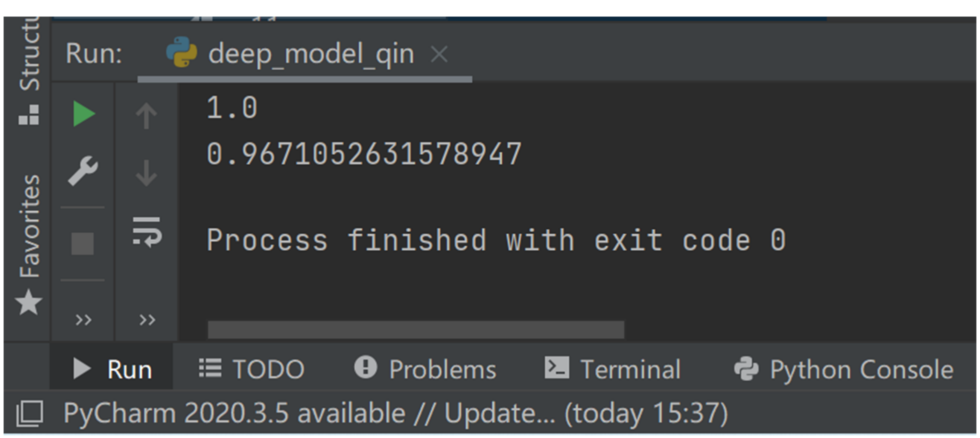

Fig. 6. Running result graph

6 Conclusion

In the study, an improved BP neural network is proposed and applied to predict college students' academic ability. Based on the prediction of college students' academic performance in the first year, a graduation prediction model is established. By dividing students into different groups and combining them with the predictive ability of the BP neural network, decision support, and personalized guidance can be provided, which plays a positive role in promoting the education management of colleges and the progression of students. Using the Pandas library for data processing and feature engineering, this paper successfully compiled and prepared student performance data and used them as input for training and testing the BP model. A sequential model with an appropriate number of layers and nodes was designed. ReLU was chosen as the activation function of the hidden layer to capture the non-linear relationship between student achievement better. Meanwhile, a sigmoid is adopted in the output layer to map the prediction result to the probability value. Cross-entropy was used as a loss function to improve the model, and the backpropagation algorithm and gradient descent optimizer were employed to train the model. The weight and bias of the model are gradually optimized to enhance the prediction accuracy through repeated training of the training set and test set. This paper uses an actual data set containing many students' grades and graduation in the experiment. After training and testing, the model has performed well in predicting students' achievements, with an accuracy rate of 96.71%. This shows that the method used in this paper can predict students' academic performance with high accuracy and provide valuable reference information for schools and educational institutions. However, we should also be aware that the model has certain limitations; the model can only provide prediction and analysis, and academic performance is also affected by various factors. Therefore, when the model is applied to the actual situation, multiple factors should be considered comprehensively, and the guidance of education experts and actual needs should be combined to make decisions.

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