ISSN 2522-6398 Vol. 6, Issue 9: 139-145, DOI: 10.25236/FER.2023.060923

Research on Neural Network Prediction System in Loose-leaf Textbook Course Assessment

Liu Xing[1,2], Wu Sheng[1,2], Chen Li[1,2], Mei Jing[1,2], Hu Dong[1]

[1]College of Mechanical Engineering, Sichuan Vocational College of Chemical Industry, Luzhou, 646300, China
[2]The Key Laboratory of Mechanical Structure Optimization & Material Application Technology of Luzhou, Sichuan Vocational College of Chemical Industry, Luzhou, 646300, China

Abstract: *The unique advantages of flexible and novel loose-leaf textbooks have become a new development direction, but the diversified assessment system of loose-leaf textbooks is still relatively imperfect, and the application of traditional curriculum assessment systems in loose-leaf textbooks is subject to certain constraints. Therefore, in order to improve the diversified assessment system of loose-leaf textbooks, this paper proposes a machine learning algorithm applied to the loose-leaf textbook assessment system. By comparing various neural network algorithms, a prediction model suitable for the diversified assessment system was found. The results show that the application of SVM radial basis function neural network in the assessment and prediction system for loose-leaf courses has high prediction accuracy and small error, can effectively play a prediction and reminder role, improve the diversified assessment system, and promote the application and promotion of loose-leaf textbooks.*

Keywords: *neural network algorithm; loose-leaf teaching materials; course assessment system*

1. Introduction

With the formulation of the "Fourteenth Five Year Plan", which focuses on quality and technology as the national priorities, and aims to strengthen education and talent, the goal of strengthening education and talent has become the direction of the country's future development. In the context of the development of artificial intelligence and big data, traditional engineering majors are required to transform and upgrade to new engineering majors. Scientific and systematic engineering majors require more automation and intelligence. In the curriculum reform of vocational education, the state clearly states that "it is advocated to use new loose-leaf and workbook-style textbooks and develop supporting information resources". Scientific and systematic curriculum innovation requires the construction of professional evaluation systems and standards, ensuring the effectiveness of the implementation of engineering education professional courses and evaluating the quality of students' learning. The new loose-leaf teaching material is a product of the transformation and reform, and has also attracted more attention and exploration from secondary and vocational colleges. For example, the author Li Xiaoyin and others took the course "Comprehensive Practical Training in Finance and Accounting" as the research object, and based on the comprehensive practical training courses in the book, explored the educational mech-anism of vocational colleges from multiple aspects such as team practice, modular loose-leaf teaching materials, and teaching methods[1]; The author, Zhu Haihui, et al., explored the knowledge and skill needs of the "3+2" five-year college and ordinary classes based on the starting point of "Automobile Maintenance" and the development of a loose-leaf teaching material[2]. From the above references, it can be seen that the new loose-leaf teaching material has flexible and novel characteristics, diverse forms, and vivid appearance. Combined with flipped classroom methods, it can completely subvert traditional teaching methods.

Throughout the existing research and exploration results, the development of loose-leaf teaching materials mostly focuses on the distribution of teaching projects, the style design of teaching materials, and the exploration of implementation methods and means. The exploration of the curriculum assessment system and methods for the new loose-leaf teaching materials is relatively small.This article will take the loose-leaf assessment system as a foothold, take the "Mechanical Processing" course of Sichuan Vocational and Technical College of Chemical Industry as an example, and through the application and research of neural network data in the new loose-leaf teaching material curriculum assessment system, aiming to establish a diversified curriculum assessment prediction model,

ISSN 2522-6398 Vol. 6, Issue 9: 139-145, DOI: 10.25236/FER.2023.060923

scientifically and effectively ensuring the effectiveness of teaching implementation and the quality of students' learning.

2. Establishment of Assessment System

The new type of loose-leaf teaching materials for engineering majors are highly professional and practical, and the general way to evaluate students' learning effectiveness is to add their usual scores to their final exam scores. Such an evaluation system has the characteristics of being rough, one-sided, and unreasonable; Due to the delayed nature of the assessment method, it is only after obtaining the usual and final grades that you can know whether you have mastered the course. In addition, due to the weak relevance of the new loose-leaf teaching material modules, students are required to learn flexibly and pay attention to the learning of various modules, which also prompts students to have greater doubts about the degree of mastery of the curriculum[3]. Therefore, it is of great significance to study and explore an intelligent assessment system with diversified assessment methods and early warning functions.

According to the characteristics of engineering majors, on the one hand, curriculum assessment can start from loose-leaf teaching materials, with the characteristic indicators P1 (p1, p2, p3, p4) for loose-leaf exercises, loose-leaf expansion, loose-leaf reflection, and loose-leaf practice; On the other hand, starting from the process assessment, a neural network mathematical model is established to achieve a diversified assessment and early warning system by taking the preview effect, classroom attendance, classroom discipline, homework, and final paper score as the characteristic indicators P2 (p5, p6, p7, p8), and whether the final examination is passed as the output expected value T.

3. Research on Algorithm of Early Warning System for Diversified Assessment System

Multiple assessment systems based on neural networks have unique advantages over commonly used assessment methods. In this section, a prediction model is built to analyze and detect students' academic performance, and the multiple assessment system is endowed with the function of machine learning. Through the practical teaching of loose-leaf teaching materials, a large number of students' academic achievements were found. The scores of each section of the loose-leaf, the process assessment scores, and the final paper score were used as the input variables, and whether the final examination was passed was used as the output. Using SVM support vector regression, BPNN neural network, and other algorithms, mathematical models were established to obtain a relatively fast and reasonable prediction model.

3.1 Division of Sample Sets

According to the characteristics of neural network algorithms in deep learning, it is necessary to use a large amount of test data for sample training. As the number of samples increases, the error and reliability of neural network algorithms will be improved, and more reliable detection models can be obtained. However, a large amount of data will undoubtedly greatly reduce computational efficiency. Therefore, extracting superior data from big data will effectively improve the efficiency of data operations. Currently, the commonly used data sampling algorithms include KS sampling algorithm and SPXY sampling algorithm. After consulting relevant literature[4], this article adopts KS sampling algorithm, whose basic principles are: ① Calculate the Euclidean distance dx (p, q) [5] of all sample data, and then compare the maximum two sets of Euclidean distances of all samples as sample input data. ② According to the samples selected in the previous step, calculate the minimum Euclidean distance between the remaining samples and select the sample data corresponding to the maximum value as training data Repeat the previous two steps to make the training data reach the set threshold. The formula for calculating the Euclidean distance dx (p, q) mentioned therein is shown in Equation (1).

$$d_y(p,q)=\sqrt{\sum_{j=1}^{J}\left[y_p(j)-y_q(j)\right]^2}=\left|y_p-y_q\right|, \quad p,q\in\left[1,N\right] \tag{1}$$

Where, $d_x(p,q)$ is a European distance, $y_p(j)$&$y_q(j)$ is a sample p q the jth dependent variable of y.

According to the "Mechanical Processing" course, there are 5 classes, including 90 people in 3 classes of electromechanical integration, and 90 people in 2 classes of mold design and manufacturing.

ISSN 2522-6398 Vol. 6, Issue 9: 139-145, DOI: 10.25236/FER.2023.060923

The total number of elective students in this course is 150. Through the KS sampling algorithm, 50 input samples and 20 test samples were finally selected, as shown in Table 1 and Table 2, respectively.

Table 1: Input Samples

student	Loose leaf exercise	Soose leaf expansion	flip sheet reflection	loose leaf practice	class attendance	classroom discipline	home work after class	final exam	passed or not
sample 1	19	9	7	16	0	5	7	61	1
sample 2	18	7	7	16	0	9	3	64	1
sample 3	11	3	6	15	-5	6	-6	59	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
sample 48	26	7	7	16	-5	8	5	77	1
sample 49	20	4	4	16	-5	8	5	41	0
sample 50	18	4	7	17	0	4	-1	53	1

Table 2: Test Samples

student	Loose leaf exercise	Soose leaf expansion	flip sheet reflection	loose leaf practice	class attendance	classroom discipline	home work after class	final exam	passed or not
sample 1	31	9	8	17	0	8	7	60	1
sample 2	23	5	5	17	0	7	-2	59	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
sample 19	19	7	4	17	0	8	3	42	0
sample 20	21	0	8	17	0	6	7	50	1

3.2 Normalization of Assessment Sample Data

The assessment scores obtained through the KS sampling algorithm have been reduced in terms of data dimensions, but due to inconsistent orders of magnitude, there are certain constraints in calculating relevant parameters. Therefore, before training neural networks, data normalization processing methods are generally used; That is, by converting all data into values between [0,1]. Such a processing method can effectively avoid the difference in the magnitude of neural network factors, which leads to excessive prediction error of the neural network. Call the function [inputn, inputps]=mapminmax (input_train) in MATLAB to complete it. Its local parameters are shown in Table 3.

Table 3: Data Normalization Samples

student	Loose leaf exercise	Soose leaf expansion	flip sheet reflection	loose leaf practice	class attendance	classroom discipline	home work after class	final exam	passed or not
student	0.423	0.222	0.400	0.750	0.666	0.555	0.625	0.180	1
sample 1	0.423	0.666	0.600	1	1	0	0.812	0.194	1
sample 2	0.538	0.555	0	1	1	0.333	0.562	0.108	0
sample 3	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
⋮	0.692	0.777	0.800	1	1	0.555	0.875	0.251	1
sample 48	0.538	0.333	1	0.750			0.187	0.064	0
sample 49	0.923	1	0.600	0.750	1	0.777	1	1	1

3.3 Algorithm for building prediction models

The diversified assessment and prediction system uses a regression model based on support vector bases. Its basic idea is to seek a better classification surface, minimizing the distance between all diversified assessment performance samples and the optimal surface. Assuming that the number of samples to be trained is l, the sample set pair is {(xi, yi), i=1, 2, 3... l}, xi represents the input column vector with the sample number i, and yi represents the output value of the sample data. The linear regression function established in the characteristic space of the diversified assessment sample data is[6]:

$$f(x) = w\Phi(x) + b \tag{2}$$

Where, $\Phi(x)$ is a nonlinear mapping function. The regression function of the neural network model can be obtained as follows:

ISSN 2522-6398 Vol. 6, Issue 9: 139-145, DOI: 10.25236/FER.2023.060923

$$f(x) = w^*\Phi(x) + b^* = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\Phi(x_i)\Phi(x) + b^* = \sum_{i=1}^{l}(\alpha_i - \alpha_i{*})K(x_i, x) + b^* \quad (3)$$

On the other hand, the basic idea of a diversified assessment and prediction system, such as using neural networks, is to train and learn a certain sample of diversified assessment results. The loose-leaf section, process assessment, and final paper scores are input as samples to each divine element of the neural network input layer, and then transmitted to the output layer through the weight calculation of the hidden layer to obtain the corresponding prediction values for each input layer. Assuming that there is a significant error between the predicted diversified assessment result and the expected value, which does not meet the accuracy requirements, the neural network will feed back the error results to the input layer, readjusting the weights and thresholds of each neuron, so that the error value of the entire neural network model meets the set accuracy[7]. Set a sample pair of multiple assessment scores (X, Y) (X=[x1, x2, x3,... xm] ', Y=[y1, y2, y3,... ym]'), and the hidden layer neurons of the model are O=[o1, o2, o3,... om] '. W-1 is the network weight matrix between the input layer and the hidden layer neurons of the evaluation and prediction system, and W-2 is the network weight between the hidden layer and the output layer neurons. θ 1 is the threshold value of hidden layer neurons, *θ* 2 is the threshold value of the output layer neuron. The number of neurons in the input layer is m, the number of neurons in the hidden layer is l, and the number of neurons in the output layer is n. The output of the hidden layer neuron is:

$$O_j = f(\sum_{i=1}^{m} w_{ji}{}^1 x_i - \theta_j{}^1) = f(net_j), \qquad j = 1,2,\cdots,l \quad (4)$$

According to the algorithm construction of the prediction model, the preparation process of the prediction algorithm for the diversified assessment system is determined, as shown in Figure 1. Firstly, the sampled and normalized assessment results are used as sample data for data input. Compile two different neural network algorithms (SVM, BPNN) and train the data until the error and accuracy meet the requirements. After training the neural network model, input the test data into the neural network model for prediction and analysis. Finally, compare SVM and BPNN algorithms to determine the application of a better neural network prediction model in a diversified assessment prediction system.

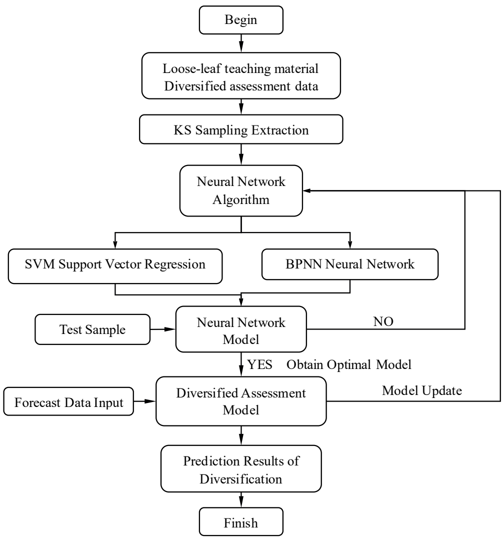


Figure 1: Flow Chart of Diversified Assessment Prediction Algorithm

4. Prediction System result Analysis

After the algorithm of the prediction model is built, the test data are input into the prediction model to obtain the error and confidence parameters of the neural network. The commonly used indicators of neural network algorithms in the detection of error, accuracy, and reliability are root mean square error

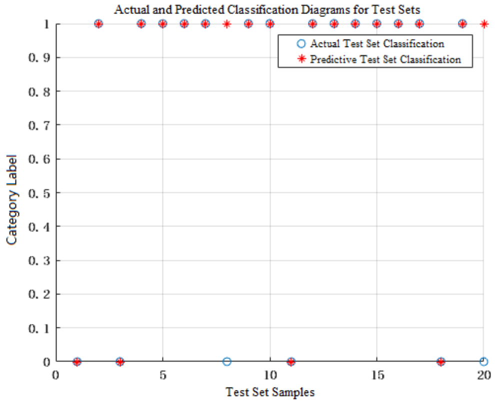
ISSN 2522-6398 Vol. 6, Issue 9: 139-145, DOI: 10.25236/FER.2023.060923

(RMSE) and determination coefficient (R2). Wherein the root mean square error is a parameter that measures the performance of the model, reflecting the difference between the estimated quantity and the estimated quantity[8]; The determining coefficient is the proportion of the sum of squares of the regression model to the total sum of squares. It is a statistic that measures the degree of fitting in the regression equation, reflecting the proportion explained by the estimated regression equation in the variation of the dependent variable. The root mean square error (RMSE) and determination coefficient (R2) of the diversified assessment prediction model are shown in Table 4.

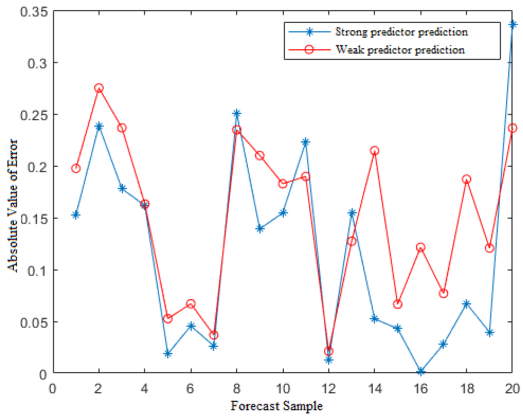
Table 4: Root Mean Square Error and Determination Coefficient of Prediction Model

input characteristics	sample Set Partitioning Method	regression model	training set		test set	
			R2	RMSE	R2	RMSE
number of samples(50)	KS	SVM	0.9986	0.0029	0.8304	0.0619
		BPNN	0.8878	0.0036	0.9322	0.0952

The fitting effect of SVM support vector regression training set and test set is shown in Figure 2 (a). The fitting effect of the BPNN neural network training set and test set is shown in Figure 2 (b).



(a) SVM Test Set Model Effects



(b) BPNN Test Set Model Effects

Figure 2: Prediction of diversified assessment of loose-leaf teaching materials

From Table 4, it can be seen that the prediction accuracy of SVM and BPNN neural networks is relatively ideal. Comparing the statistical results of modeling effects between SVM and BPNN, the R2 of SVM is slightly higher than that of BPNN. Among the above two modeling algorithms, the optimal prediction model algorithm for the diversified assessment system is SVM. In summary, the prediction model of the diversified assessment system established using the SVM support vector basis neural network algorithm has the best effect.

5. Research and Development of Diversified Assessment and Early Warning System

The research and development of a diversified assessment and early warning system allows teachers to grasp the learning effects of students at any time during the teaching process, effectively reminding students of their learning in various areas. For students, during the development process, the software has the functions of inputting and modifying prediction samples, displaying student performance

ISSN 2522-6398 Vol. 6, Issue 9: 139-145, DOI: 10.25236/FER.2023.060923

prediction results, and so on; through the early warning system, you can remind yourself to consolidate the knowledge points in the missing areas, so that students can better form corresponding summaries. For the relatively independent knowledge points of loose-leaf textbooks, a diversified assessment and early warning system can effectively connect them. Therefore, through the combination of matlab and C # [9], the neural network model for diversified assessment and prediction is generated by matlab into a dynamic link library. dll file [10]. C # performs interface development, completes function calls, data input and output, and results display settings, to achieve the development and debugging of a loose-leaf teaching material diversified assessment and prediction system. The prediction system software interface is shown in Figure 3.

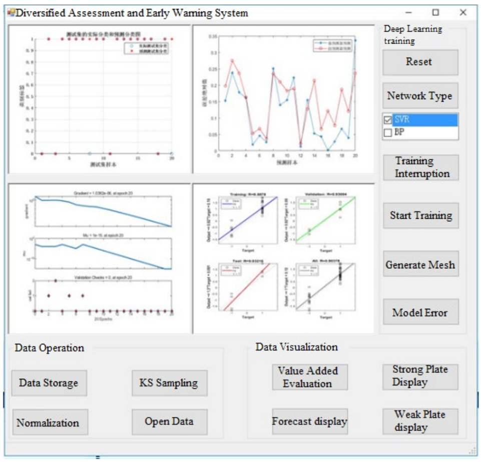


Figure 3: Loose-leaf Teaching Material Diversified Assessment and Prediction System

6. Summary

In the context of the "three education" reform, the diversified assessment system is one of the highlights of the loose-leaf teaching material, and the improvement of the assessment system is an important link in the teaching material reform. This article applies neural prediction models to the assessment of loose-leaf teaching materials and courses through machine learning under the analysis of big data; And through the combination of matlab and C #, a diversified assessment and early warning system for loose-leaf teaching materials has been designed and developed. For the design and development of new textbooks, it effectively solves the problem of relatively independent knowledge points in loose-leaf textbooks, which prevents students from knowing whether they have mastered the knowledge points in loose-leaf textbooks, and improves the content of the evaluation system for loose-leaf textbooks; For students, it achieves the goal of promptly detecting and filling in gaps, and solves the problem that students cannot predict whether they will pass the course due to the delayed impact of the assessment method; For teachers, we can timely adjust the loose-leaf teaching material assessment system by collecting a large number of diversified assessment performance samples, making the assessment system more diverse and scientific.

Acknowledgements

Fund Project: Key R&D Project of Sichuan Provincial Department of Science and Technology (2023YFG0241); The Key Laboratory of Mechanical Structure Optimization & Material Application Technology of Luzhou (SCHYZSB-2022-07); Sichuan Province 2022-2024 Vocational Education Talent Training and Education and Teaching Reform Research Project (No. GZJG2022-449).

References

[1] Li Xiaoyin. Exploration of Curriculum Construction in Vocational Colleges under the Background of "Three Education" Reform—Taking the Course of Comprehensive Practical Training in Finance and Accounting as an Example [J]. Accounting Learning, 2021 (29): 163-164

[2] Zhu Haihui. Practice and Thinking on the Development of Loose-leaf Textbook Based on Automobile Maintenance Course [J]. Automotive Maintenance and Repair, 2021 (20): 17-19

[3] Cui Chenghong, Xia Jianwei, Wang Jing. Practical exploration on the development of

ISSN 2522-6398 Vol. 6, Issue 9: 139-145, DOI: 10.25236/FER.2023.060923

three-dimensional new loose-leaf teaching materials for pharmaceutical technology specialty courses in higher vocational colleges [J]. Journal of Qingdao Vocational and Technical College, 2020, 33 (3): 5.

[4] Wu Lei, Fang Bin, Diao Liping, et al. A Resampling Method for Unbalanced Data Combining Oversampling and Undersampling [J]. Computer Engineering and Applications, 2013, 49 (21): 6.

[5] Ding Yi, Yang Jian. Comparison of Euclidean distance and normalized Euclidean distance in k-nearest neighbor algorithm [J]. Software, 2020, 41 (10): 3.

[6] Zhang Qian, Yang Yaoquan. Soft Measurement of Oxygen Content in Flue Gas of Thermal Power Plants Based on Support Vector Machine Regression [J]. Information and Control, 2013: 10.

[7] Zhou Kaili. Neural Network Model and MATLAB Simulation Program Design [M]. Tsinghua University Press, 2005.

[8] Zheng Fengxia. Research on Prediction Methods and Applications Based on Neural Networks and Time Series [D]. University of Electronic Science and Technology, 2013.

[9] Kouser R R, Manikandan T, Kumar V V. Heart Disease Prediction System Using Artificial Neural Network, Radial Basis Function and Case Based Reasoning[J]. Journal of Computational and Theoretical Nanoscience, 2018, 15(9):2810-2817.

[10] Lu Bo. Research on engine/aircraft integrated modeling and parameter estimation technology based on Matlab [D]. Nanjing University of Aeronautics and Astronautics 2013.