Evaluation Model of Electrical Control Teaching Mode Reform Effect Based on Deep Convolution Neural Network

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Abstract. In view of the results obtained by introducing neural network into the evaluation model of the reform effect of the existing teaching model, the paper proposes an evaluation model of the effect of the reform of the electrical control teaching mode based on the deep convolution neural network. The corresponding weight in the rating system is established, the weight is obtained by using the deep convolution neural network, and finally, the data is extracted by the multiple collinear regression method to complete the evaluation of the reform effect of the electrical control teaching mode. The experimental results show that the evaluation model of the teaching model reform effect evaluation model of the design method is more quality and feasible.

Keywords: Teaching mode · Evaluation model · Neural network · Multicollinearity

1 Introduction

The key problem faced by the reform of teaching mode at the teaching level is the low efficiency of the classroom, which will greatly affect the level of personnel training. Therefore, an important routine content of teaching management in Colleges and universities is to analyze and evaluate the teaching mode of teachers. The establishment of the evaluation model of teaching mode reform effect can not only provide reference for other universities to carry out course teaching effect evaluation, but also apply this kind of evaluation thinking to other types of evaluation [1–3]. Help teaching managers or teachers to identify whether a teaching reform achievement has achieved the purpose of improving quality through vertical and horizontal comparison, and provide data reference for determining whether to continue this reform practice [4–6].

In developed countries, the evaluation of the effect of teaching mode reform is divided into three stages, namely, preliminary formation, punitive evaluation and developmental evaluation, which focus on students and carry out teacher performance evaluation of students, but this kind of evaluation is controversial [7]. Most colleges and universities in China have established their own teaching effect evaluation index system, including teaching objectives, methods, effects and attitudes, etc. the evaluation contents and versions of colleges and universities have little difference. Some people understand that the

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whole of teaching quality evaluation is to evaluate the quality of classroom teaching, which leads to the relatively single content of evaluation [8]. Subsequently, people began to study the effect evaluation of teaching mode reform towards the direction of operation model, but the quality of the evaluation results is not ideal.

2 Design of Evaluation Model for the Reform Effect of Electrical Control Teaching Mode Based on Deep Convolution Neural Network

2.1 Establishment of Evaluation System Weight

The importance of two indicators in the evaluation index system can not be reflected, and the weight analysis and calculation can express the relative importance of an indicator in the overall evaluation [9, 10]. A group of evaluation index system corresponding to the index weight constitutes the weight system. In this paper, the indicators of teaching evaluation are divided into different levels, such as target level, criterion level, indicator level, scheme level, etc. [11–13]. In this paper, all indicators have been divided into first level indicators, second level indicators and third level indicators, and their internal subordination has been determined. Based on this, the importance of corresponding evaluation indexes is analyzed, and the corresponding evaluation system indexes can be obtained, as shown in Table 1.

Table 1. Index allocation of evaluation index system

Evaluation criterion	Extremely important	Very important	Iimportant	Commonly	Unimportance
Inquiry activities	15	39	27	8	6
Explore knowledge	21	61	24	19	
Emotional attitude	29	30	25	11	9

In Table 1, the evaluation importance is assigned as follows: extremely important is 1, very important is 0.75, important is 0.5, general is 0.25, unimportant is 0. Then multiply and add the data of importance of each index with the corresponding assignment, and divide the result by the total number to calculate the average score. Finally, the average score of the two indicators is subtracted to form a matrix according to Saaty method. When the importance score of A_i and A_j of two indicators at the same level (i.e. average score), and construct the judgment matrix R, and stipulate that when $0.025 < A_i - A_j \leq 0.05$, A_i is slightly more important than A_j, and the value of satty is taken as 3. When $0.075 < A_i - A_j \leq 0.1$, A_i is more important than A_j, and satty is 5. When $0.125 < A_i - A_j \leq 0.15$ and A_i are more important than A_j, satty value is 7. When

$0.175 < A_i - A_j$, A_i is more important than A_j, satty is 9. Using the example in Table 1, the corresponding matrix of student evaluation index system is obtained as follows (Table 2):

Table 2. First level index matrix of student evaluation index system

First level indicators	Explore knowledge	Inquiry activities	Emotional attitude
Explore knowledge	1	1/5	1/2
Inquiry activities	5	1	5
Emotional attitude	2	1/5	1

Namely:

$$R = \begin{Bmatrix} 1 & \frac{1}{5} & \frac{1}{2} \\ 5 & 1 & 5 \\ 2 & \frac{1}{5} & 1 \end{Bmatrix} \tag{1}$$

At the same time, the indexes are sorted in a single hierarchy, and the weight value of the indexes is calculated, and the relative importance level and the relative importance level in matrix R are obtained, such as $V_1 = 1 + 1/5 + 1/2 = 1.7$, $V_2 = 5 + 1 + 5 = 11$, $V_3 = 2 + 1/5 + 1 = 3.2$, The sum of all levels is: $\sum_{i}^{n} V_i = V_1 + V_2 + \ldots.. + V_n$.

At the same time, the importance level and the ratio of the sum of the index weights are determined. The weight vector is calculated as follows:

$$W_i = \frac{V_i}{\sum V_I} \tag{2}$$

According to formula (2), the weight calculation in the matrix can be completed, and the corresponding ranking can be carried out to complete the establishment of index weight.

2.2 Weight Convergence of Deep Convolution Neural Network

In order to calculate the function form in the weight system of the rating index, this paper uses the deep convolution neural network to learn the meridional basis function and deal with the weight of the evaluation index. Radial basis function is usually defined as a monotone function of Euclidean distance between any point a and x center c in space, and its effect is local, that is, when c is far away from c, the value of the function is relatively small [14, 15], as shown in Fig. 1:

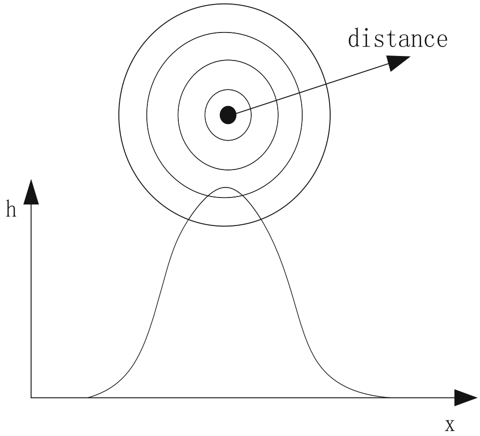

Fig. 1. Radial basis function diagram

The formula of radial basis function is as follows:

$$h(x) = \exp\left(-\frac{(x-c)^2}{r^2}\right) \tag{3}$$

In formula (3), r represents the corresponding radial basis function index. The birth of radial basis function is mainly to solve the problem of Multivariable Interpolation.

For the reform and evaluation of teaching mode, the evaluation index can be used as the basis function and processed by radial basis function. The RBF interpolation is to construct a function $F(x) = \sum_{i=1}^{N} w_i \varphi_i(\|x - x_i\|)$, and let the curve pass through the corresponding sample points, and keep the space dimension N, where the evaluation difference is φ. Given the sample points, the corresponding radial basis function matrix format is determined:

$$\begin{bmatrix} \varphi_{11}, & \varphi_{12}, & \cdots, & \varphi_{1N} \\ \varphi_{21}, & \varphi_{22}, & \cdots, & \varphi_{2N} \\ \cdots & \cdots & \cdots & \cdots \\ \varphi_{N1}, & \varphi_{N2}, & \cdots & \varphi_{NN} \end{bmatrix} \begin{bmatrix} w_1 \\ w_1 \\ \vdots \\ w_N \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} \tag{4}$$

At the same time, deep convolution neural network is used to map the input of low dimensional space to high dimensional space by using hidden element RBF, and then the curve is fitted in this high dimensional space. It can be equivalent to finding an optimal surface in a certain hidden high-dimensional space, which can fit the training data. In the process of training, the network parameters are used as the weight value of the output layer, and the center is determined by clustering algorithm. The empirical formula $\sigma^2 = \frac{d\max}{\sqrt{h}}$ can be used for variance, where d max represents the maximum Euclidean distance in the center of the neural network, h represents the number of network centers, and the weight convergence of the output value can be directly given in the network without iteration. Let T represent the period in the training sample Expected output, Y represents the actual output of the sample. Φ represents the output value of RBF function in the hidden layer of neural network:

$$\begin{aligned} E &= \frac{1}{2}(T - Y)^T(T - Y) = \frac{1}{2}(T - \Phi V)^T(T - \Phi V) \\ &= \frac{1}{2}\left(T^T T - 2T^T \Phi V + V^T \Phi^T \Phi V\right) \end{aligned} \tag{5}$$

Formula (5) represents the linear equations of output layer weights. When the number of samples is large (more than the number of weights), the equations are contradictory equations without exact solutions. In this case, the least square method can be used to transform them into the following normal equations:

$$\begin{aligned} &\frac{\partial E}{\partial V} = 0 \Rightarrow -\Phi^T T + \Phi^T \Phi V = 0 \\ &\Rightarrow V = \left(\Phi^T \Phi\right)^{-1} \Phi^T T \end{aligned} \tag{6}$$

Formula (6) can be solved by Jacobi iterative method.

In the process of network training, the selection of training parameter μ directly affects the performance of the algorithm. If the value is too large, it is approximate to gradient descent method, and the convergence speed is slow. If the value is too small, it is approximate to Gauss Newton method, which easily leads to irreversible operation. In essence, neural network training problem can be attributed to optimization problem, which can be described as the problem of finding the extremum of multivariate function. As we all know, at the beginning of the optimization process, the search should take a big step, which is never conducive to the global search. At the end of the optimization process, the search should take a small step, so that the algorithm will not miss the global optimal solution. It is reflected in the deep convolution neural network. In the early stage of training, the value of μ should be relatively small to make the algorithm approximate the optimal solution with the second-order convergence rate of Gauss Newton, while in the later stage, the value of μ should be relatively large to make the algorithm approximate

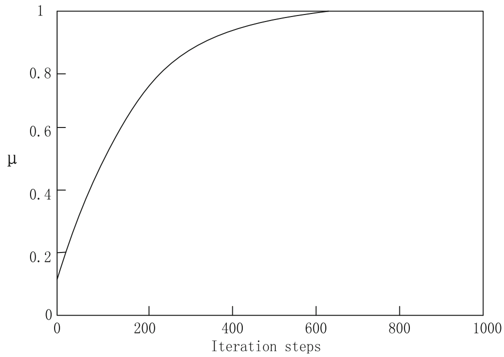

Fig. 2. Iterative change of deep convolution neural network

the optimal solution with the first-order convergence rate of approximate gradient descent method. As follows (Fig. 2):

After training, the data is imported into the deep convolution neural network to complete the weight convergence.

2.3 Multicollinearity Regression Method

By using the estimation method of multiple linear regression, the regression coefficients form the distribution characteristics of statistics. Use these methods to analyze the factors that affect students' learning efficiency and teachers' teaching level.

Assuming conditions, the least square estimator is set and the corresponding multiple linear regression model is established as follows:

$$y_t = \beta_0 + \beta_1 x_{t1} + \beta_2 x_{t2} + \ldots + \beta_{k-1} + u_t \tag{7}$$

In formula (7), y_t represents the explained variable, that is, the dependent variable. x_{tj} stands for explanatory variable, that is, independent variable. u_t is the random error term and β_k is the regression parameter.

Heteroscedasticity method was used for analysis. On the basis of the linear relationship between residual and explanatory variables, the square and cross terms of explanatory variables are added to get the auxiliary regression model. Testing the heteroscedasticity of the original model is equivalent to testing whether the regression parameters of the auxiliary regression model are significantly zero except for the constant. When H_0 holds, it is equivalent to the constant in $\hat{u}_t^2$. In multiple linear regression method, multicollinearity is common, and the consequences are complex, so the test of multicollinearity is particularly important. There are multiple explanatory variables in this method. One explanatory variable can be used for linear regression of all other explanatory variables, and goodness of fit can be calculated. The one with the largest goodness of fit and close to the one with the largest goodness of fit indicates that the linear relationship between the corresponding explanatory variable and all other explanatory variables is significant. This method has multicollinearity. At the same time, multicollinearity only affects the estimated values of the corresponding parameters of some unimportant explanatory variables, which can be omitted from the method. According to the front-end method, the modified Frisch method (stepwise regression method) was used in this method. There is a certain degree of linear correlation between $0 < \left|r_{xixj}\right| < 1$ explanatory variables. This situation is often encountered in practice. With the enhancement of collinearity, the accuracy and stability of parameter estimation are affected. When calculating, the goodness of fit of $\left(R^2\right)$ is very high, F is very high, and the variance $Var\left(\beta_j\right)$ of each regression parameter estimation is large, which indicates that the variable has multicollinearity. Extract the data with multiple collinearity, and take it as the final result of the evaluation factor index to complete the evaluation.

3 Experimental Analysis

In order to verify the feasibility of the designed teaching mode reform effect evaluation model. Using the class of electrical control major in a university to evaluate the teaching effect reform. The model designed in this paper and the model in literature [1], literature [3] and literature [4] are compared.

3.1 Experimental Class Information

The experimental results are based on the sophomore electrical class 3, class 4 and class 6 after the implementation of teaching reform in the University (Table 3).

Table 3. Participants

Class	Number of males	Number of women	Total number (person)
Electrical class 3	38	11	49
Electrical class 4	29	8	37
Electrical class 6	33	7	40
Involving teachers	8	6	14

3.2 Evaluation Index Weight Distribution

Before evaluating the effect of teaching mode reform in the University, the influencing factors of teaching mode reform in the university are determined and the weight is allocated (Table 4).

3.3 Experimental Calculation Basis

In order to verify the advantages and disadvantages of the design evaluation model, this paper tests the relative weight and consistency of the elements of the evaluation model. According to the sorting weight calculation formula:

$$w_i = \frac{\sqrt[n]{\prod_{j=1}^{n} a_{ij}}}{\sum_{j=1}^{n} \sqrt[n]{\prod_{j=1}^{n} a_{ij}}} \tag{8}$$

In formula (8), a_{ij} represents the weight value of the element in the model. After the relative weight is determined, the relative weight of all elements in the model is calculated by MATLAB software to obtain the maximum eigenvalue λ max. The higher the eigenvalue value is, the more obvious the characteristics of each element in the model are. After expert analysis, the maximum eigenvalue of the model should be $\lambda \max \leq 2.896$. At the same time, the consistency index $C.I$ is used to calculate the consistency:

$$C.I \triangleq \frac{\text{S-}c}{c - 1} \tag{9}$$

Table 4. Experimental evaluation index weight distribution

Serial number	Evaluation factors	Key points of evaluation	Factor weight	Weight score
1	Instructional objective	Determine the teaching task	0.16	3
		Implementation of teaching objectives	0.3	1/2
		The feasibility of teaching purpose	0.21	1
2	Content of courses	Understand theory and master skills	0.41	1/5
		The content is primary and secondary, highlighting the key points	0.15	2
3	Teaching structure	The logic of teaching	0.22	1
		Combination of teaching links	0.36	1.5
		Scientific organization of teaching	0.27	2.5
4	Teaching method	Optimizing teaching methods	0.41	3
		Logic and appeal of teaching language	0.29	2
		Arousing students' enthusiasm	0.11	1

In formula (9), c represents the order of the evaluation model and S represents the maximum eigenvalue of the model. The lower the consistency of the model, the better the quality of the model. After expert analysis, the consistency of the model should be $C.I \geq 0.0192$.

3.4 Model Evaluation Results

According to the model, the teaching mode reform effect is evaluated, in which the largest eigenvalue λ max and consistency $C.I$ are used to judge the advantages and disadvantages. First of all, the evaluation results of teaching purpose factors of teaching mode are calculated:

In Table 5, evaluation model 1 is the evaluation model designed in this paper, evaluation model 2 is the evaluation model in literature [1], evaluation model 3 is the evaluation model in literature [3], and evaluation model 4 is the evaluation model in literature [4].

Table 5. Evaluation index of teaching purpose

Scoring index		Implementation of teaching tasks	The feasibility of teaching purpose
Evaluation model 1	λmax	3.786	3.857
	C.I	0.0116	0.0108
Evaluation model 2	λmax	3.127	3.542
	C.I	0.0186	0.0179
Evaluation model 3	λmax	3.127	3.542
	C.I	0.0191	0.0168
Evaluation model 4	λmax	3.364	3.172
	C.I	0.0183	0.0188

The maximum eigenvalue λ max and consistency $C.I$ of the four models meet the requirements of expert analysis, but the comparison shows that the model parameters in this paper are better. The evaluation results of teaching content are as follows (Table 6):

Table 6. Evaluation index of teaching content

Scoring index		Understanding theory	Highlight the key points
Evaluation model 1	λmax	3.892	3.846
	C.I	0.0126	0.0115
Evaluation model 2	λmax	3.077	3.174
	C.I	0.0158	0.0189
Evaluation model 3	λmax	3.117	3.012
	C.I	0.0132	0.0151
Evaluation model 4	λmax	3.222	3.187
	C.I	0.0126	0.0134

In order to ensure the reliability of data, the evaluation indexes are calculated in the same way. The evaluation indexes of teaching results are as follows (Table 7):

The model evaluation factors of teaching structure and teaching method are calculated as follows (Table 8):

In the above table, except that the maximum eigenvalue of evaluation model 2 is lower than the required value, the other results meet the requirements of the minimum evaluation model. However, according to the comparison of the values in the table, it can be found that in this experiment, the designed evaluation model is better than the other evaluation models in evaluating the same factors.

Table 7. Evaluation index of teaching structure

Scoring index		The logic of teaching	Combination of teaching links	Scientific teaching
Evaluation model 1	λmax	3.692	3.799	3.695
	C.I	0.0119	0.0104	0.0114
Evaluation model 2	λmax	2.961	3.045	3.015
	C.I	0.0162	0.0178	0.0144
Evaluation model 3	λmax	2.917	2.982	2.988
	C.I	0.0142	0.0151	0.0183
Evaluation model 4	λmax	3.041	3.211	3.115
	C.I	0.0158	0.0152	0.0187

Table 8. Evaluation index of teaching structure

Scoring index		Optimizing teaching methods	Logicality and appeal of language	Enthusiasm mobilization
Evaluation model 1	λmax	3.815	3.912	3.783
	C.I	0.0139	0.0115	0.0109
Evaluation model 2	λmax	2.876	3.014	3.115
	C.I	0.0172	0.0188	0.0184
Evaluation model 3	λmax	2.961	2.992	2.981
	C.I	0.0172	0.0165	0.0144
Evaluation model 4	λmax	3.061	3.041	2.915
	C.I	0.0168	0.0183	0.0187

4 Conclusion

This paper, the deep convolution neural network is used to design the evaluation model of teaching mode reform effect. Although the model can improve the efficiency of evaluation and the objectivity of evaluation results, there are some shortcomings, such as the poor universality of the model, and the well-trained model for one type of university is not suitable for other types of universities. Therefore, how to improve the universality of the evaluation model is the key problem to be solved in the next step.

References

1. Li, C., Wang, J., Yang, S.: Construction of psychiatric nursing skill teaching model based on blending-learning concept and its effect evaluation. Chin. J. Mod. Nurs. **24**(16), 1961–1965 (2018)

2. Liu, S., Bai, W., Zeng, N., et al.: A fast fractal based compression for MRI images. IEEE Access **7**, 62412–62420 (2019)
3. Jin, X., Qi, H.: Construction of quality evaluation index system in practical teaching based on quality stereoscopic model—a case study of internship program. J. Nanjing Radio Telev. Univ. (2), 55–58 (2019)
4. Feng, B.: Research on multi-evaluation mechanism of blended teaching based on CoI model. J. Guangdong Univ. Educ. **39**(4), 14–19 (2019)
5. Liu, S., Li, Z., Zhang, Y., et al.: Introduction of key problems in long-distance learning and training. Mob. Netw. Appl. **24**(1), 1–4 (2019)
6. Zhu, J., Chen, G., Xiang, H., et al.: Evaluation model of study behavior of blending teaching based on random forests. Comput. Knowl. Technol. **15**(29), 118–120 (2019)
7. Bai, C., Wang, F., Wang, B.: Construction of the practice teaching evaluation indicator system of electrical engineering based on the CIPP model. Comput. Knowl. Technol. **15**(27), 118–121 (2019)
8. Zhang, Y.: Research on teaching evaluation based on topic model. Comput. Knowl. Technol. **15**(7), 32–34 (2019)
9. Hu, Q., Su, B.: Evaluation of informatization teaching quality in higher vocational colleges based on dynamic CIM comprehensive model. J. Sci. Teach. Coll. Univ. **39**(3), 24–29 (2019)
10. Liu, S., Glowatz, M., Zappatore, M., et al. (eds.): e-Learning, e-Education, and Online Training, pp. 1–374. Springer, Heidelberg (2018)
11. Chen, X.Q., Zhao, W.T., He, F.J., Chen, Y.C., Song, Q.M.: Practice and exploration of mixed teaching reform of human anatomy based on rain classroom. Chin. J. Anat. **42**(1), 98–100 (2019)
12. Ouyang, G.H., Shen, X.Y.: Teaching quality assessment in higher education from the perspective of learning paradigm: a practical investigation based on the practice of teaching excellence framework in the United Kingdom. Univ. Educ. Sci. **6**(6), 81–88 (2019)
13. Li, F., Zhang, W., Lv, Z.: On theoretical construction and characteristic of higher engineering education system. Res. High. Educ. Eng. **14**(5), 180–186 (2019)
14. Lu, Y., Xue, T.Q., Chen, P.H., Yu, S.Q.: A study on the system design and key technologies of an ai-driven ed ucational robot: taking the "smart learning partner" as an example. Educ. Res. **26**(2), 83–91 (2020)
15. Lin, L.: Educational action forms in german systematic pedagogy: a study based on educational theories of Immanuel Kant, Johann Friedrich Herbart and Friedrich Schleiermacher. **16**(3), 149–159 (2019)