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# Construction of the College Counselor Network Education Evaluation System based on the BP Neural Network Model

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**ABSTRACT**

*Education is an important component of the education system for college students and a key link in cultivating core socialist values. Under the influence of Internet applications, college students are more susceptible to various ideological and value influences. Colleges and universities continuously innovate and reform the ideological and political education model to strengthen students' education. However, traditional evaluation methods cannot comprehensively and effectively assess the effectiveness of new educational models. Therefore, this paper constructs a college counselor network ideological and political education evaluation model based on the BP neural network and introduces the GA algorithm to optimize the model. Experimental results show that the model has good performance stability, with a small error between educational and actual results, and can derive a scientific evaluation grade based on the results.*

**Keywords:** BP Neural Network, Counselor, Conceptual Education, Education Evaluation

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## 1. Introduction

Curriculum is an important part of college education and an important way to cultivate successors of socialism. It significantly impacts the thinking, values, and worldview of college students. While the widespread use of the Internet provides college students with more sources of information, exposure to different opinions, and the world's diversity, it also continuously influences and challenges college students' values and judgment abilities [1]. Therefore, to strengthen students' education, to better bridge the gap between students and educators, as well as to gain a more authentic and comprehensive understanding of the world from the student's perspective, colleges and universities have been committed to innovating and reforming education in recent years. Many universities have constructed network education classrooms through the Internet and information technology, significantly different from traditional ideological and political education models. Cultivating students' thoughts is no longer limited to offline classrooms but is achieved through more online avenues, expanding the scope of education.

Education evaluation is an indispensable method for achieving the goals of education. Education evaluation can provide educators with effective and authentic feedback information, enabling them to promptly make targeted adjustments to education models and content, thus improving education quality and effectiveness. Traditional education evaluation methods rely on expert evaluations and student assessments, which have strong subjectivity or adopt general education evaluation models. However, traditional models' linear relationship between evaluation indicators and influencing factors does not conform to the non-linear relationship between network education and evaluation indicators [2]. BP neural network algorithm is a non-linear, dynamic information processing system with high processing capability for network data. Unlike linear relationship algorithms, BP neural networks can easily represent highly non-linear mapping relationships between data variables when the relationship and distribution of data between variables are uncertain. Therefore, in an in-network education evaluation, the non-linear characteristics of the BP neural network can construct corresponding models when the cause of data generation is unclear. Through sample data learning and training, the network can achieve the expected results and effectively reduce the impact of human subjective factors on the final evaluation results, thus obtaining more comprehensive, reasonable, and scientific results.

This paper constructs a college counsellor network education evaluation system based on a BP neural network. The genetic algorithm (GA algorithm) is introduced to optimize the BP neural network, reduce the influence of special individuals and randomness, and avoid problems such as local optima. This improves the authenticity and accuracy of the evaluation results of the counsellor network education.

## 2. Education Evaluation System in Universities

Education has always been a focal point in the education system and is highly valued in various countries' education sectors. To better cultivate talents that conform to core socialist values, many countries usually combine education with citizenship education, moral and legal education, religious education, and historical education to solidify students' ideologies during their daily learning and knowledge acquisition processes [3]. With the application of Internet technology in the education field, education mode has broken away from the constraints of traditional education models. Through new media such as campus websites, mobile apps, QQ groups, etc., universities' education dissemination has higher professionalism and credibility [4]. Based on this, some scholars have discovered that college students are in a stage of shaping their values, worldview, and outlook on life. Their thoughts are easily influenced and changed by other ideologies and emotions. Therefore, they propose using education evaluation to measure the effectiveness and quality of education. Early ideological and political education evaluation methods mainly relied on questionnaire surveys, interviews, expert evaluations, and student evaluations [5]. Some scholars believe these evaluation methods have strong subjectivity and cannot serve as authoritative results for ideological and political education. Therefore, mathematical models such as weighted averaging methods have been introduced as education evaluation models [6]. However, these mathematical models cannot reflect the correlations between evaluation indicators and influencing factors, leading to significant errors between evaluation and actual results. In the subsequent development, a combination of evaluation models and expert evaluations became the primary approach for education evaluation in universities.

With the development of artificial intelligence technology, big data, and information technology, some scholars have introduced machine algorithms into the field of education evaluation. By collecting and analyzing big data, they search for correlations between evaluation indicators and influencing factors and use them for ideological and political education evaluation [7]. Some scholars have constructed student behavior recognition models through deep learning, evaluating ideological changes based on changes in student behavior and emotions, thus assessing educational effectiveness [8]. Considering the characteristics of information dissemination on the Internet, some scholars have built a network information recognition system using natural language processing technology and neural network models to evaluate students' ideological learning by identifying and detecting keywords [9]. Furthermore, some scholars have constructed student psychological evaluations based on psychological theories and big data technology to assess students' ideological changes and the effectiveness of education [10].

# 3. College Counselor Network Education Evaluation Model based on the BP Neural Network Model

## 3.1 BP Neural Network

The BP neural network algorithm is the most fundamental and important neural network algorithm. It not only has characteristics such as adaptability, self- organisation, and self-learning but also has advantages in terms of simplicity of structure, maturity of the algorithm, and precise optimization [11,12]. The structure of the BP neural network is topological and includes input layers, output layers, and hidden layers. It belongs to the feedforward network structure in classifying neural network structures. Information transmission in this neural network structure is unidirectional, without any information feedback. Each layer of neurons contains input unit nodes and computing unit nodes. The computing unit nodes can form input relationships with multiple arbitrary nodes in the previous layer, but only one output point exists. There is no connection between nodes in each layer, and the connection between layers is fully interconnected [13]. After connecting neurons in different quantities, the overall performance is not simply the sum of individual contributions but shows highly complex nonlinear relationships. The mapping relationship between the output values and input values demonstrated by the BP neural network can be expressed as follows:

$$Y = F(x) \qquad F : R^{n_1} \to R^{n_2} \tag{1}$$

Constructing an ideological and political education evaluation model based on the BP neural network algorithm can fit the function relationship between evaluation results and corresponding training indicators and reflect their intrinsic features accurately. Thus, feedback can be provided to college counsellors to help them rectify deficiencies in ideological and political education [14,15]. However, before conducting education evaluation, the BP neural network needs to undergo empirical learning, self-adaptation, and self-organization based on input learning samples to determine the weights and thresholds of each neuron. The information propagation in the BP neural network algorithm comprises two alternating propagation processes. The forward propagation process is presented in Formula (2):

$$y_j^k = \varphi_j^k(\sum W_{ij}^{k-1} y_j^{k-1} - \theta_j^k) \qquad j = 1,2,...,n_k; k = 1,2,...,M \tag{2}$$

Wherein the weight value from the $i^{th}$ neuron in the layer with sequence number to the $j^{th}$ neuron in the next layer is expressed as, the corresponding neuron threshold value is expressed as, representing the Activation function in the BP neural network, representing the number of neurons contained in the Presentation layer, representing the total number of neuron layers in the entire BP neural network model.

Another type of propagation process is error back propagation, where there is a computational error between the input vector, output vector, and actual output in general. Therefore, if the square error of the unit is expressed as the total instantaneous value of the square error present in the output section, it is shown in formula (3):

$$E(n) = \frac{1}{2}\sum_{j \in cj} e_2^j(n) \tag{3}$$

All output units are included in the above formula. If it is expressed as the total number of BP neural network learning samples, then shown in formula (4), it is the average value of the square error:

$$E_{AV} = \frac{1}{N}\sum_{n=1}^{N} E(n) \tag{4}$$

Among them, the learning objective function that minimizes itself is the function of all weights, thresholds, and input vectors in the BP neural network. As shown in Formula (5), the iterative formula is obtained by modifying the weight value through the Gradient method:

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) y_i(n) \tag{5}$$

In the formula, the learning step size of the BP neural network is expressed as representing the momentum factor. When it grows to a certain extent, the momentum factor will avoid the instability caused by it. According to the purpose and demand of ideological and political Educational assessment, this paper selects the Activation function as an *S*-type Activation function that can compress any input data into the range of (0,1). Its functional relationship is shown in Formula (6):

$$f = \frac{1}{1 + \exp(-n)} \tag{6}$$

The input of the Activation function changes with time and needs to be expanded into a spatial variable. At the same time, to reduce the randomness of the input vector, it needs to be standardized before input, as shown in Formula (7):

$$\overline{y_i} = (y_i - y_{\min}) / (y_{\max} - y_{\min}) * \mu + \nu \tag{7}$$

In the formula, the minimum value in the unit input vector is represented as, the maximum value is represented as, and the parameter relationship is.

According to the above formula, the BP neural network algorithm has a flat error area. That is, the error is still in a slow decline state when the weight value is extremely large, thus significantly increasing the number of training times and affecting the Rate of convergence [16]. In addition, the BP neural network algorithm has a high probability of falling into the local minimum problem, resulting in a certain gap between the training convergence results and the expected error.

## 3.2 Educational Assessment based on Improved BP Neural Network

Due to the shortcomings of the BP neural network, such as the rate of convergence not meeting the actual needs and poor generalization performance due to the greater uncertainty and randomness in the assignment, this paper uses the GA algorithm to optimize it. GA algorithm is a search algorithm based on the evolution law of nature to find the global optimal solution, which includes Natural selection, mating, mutation and other operators. Through continuous iteration, the conditions that can finally meet the algorithm are obtained

[17,18]. The reference of the GA algorithm can enable the BP neural network to obtain the optimal threshold and initial value weight and make its convergence condition reach a minimum adjustment value. In addition, the excellent global optimization performance and parallelism of the GA algorithm can also enable the BP neural network to have a certain degree of dynamic adaptability, effectively avoiding significant error problems caused by local optima in the BP network, simplifying the structure of the BP neural network, and improving its generalization ability. The GA algorithm steps mainly include six steps:

Firstly, it is necessary to record the diagnostic information of each individual in the population and transform it into an encoding that the GA algorithm can recognize.

Secondly, initialize the population so that each individual has corresponding hierarchical weights and bias values, defining the population's size.

Thirdly, evaluate the fitness of each individual in the population, the absolute value of the error trained by the BP neural network algorithm, and the individual fitness value, as shown in formula (8):

$$F = k\sum_{i=1}^{n}(y_i - o_i) \tag{8}$$

Among them, the number of outputs is represented by the corresponding ideal output value, the coefficients represent the predicted results after training, and the coefficients represent the coefficients. Randomly search and select individuals based on the roulette wheel selection method. Reorganize the selected excellent individuals into a new population and perform cross-hybridization to obtain better genes, as shown in formula (9):

$$\begin{cases} a_{kj} = a_{kj}(1-b) + a_{lj}b \\ a_{lj} = a_{lj}(1-b) + a_{kj}b \end{cases} \tag{9}$$

Among them and represent the excellent genes of an individual, which are parameters. Genetic variation occurs in the population, as shown in formulas (10) - (11):

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) \times f(g) & r > 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) \times f(g) & r \le 0.5 \end{cases} \tag{10}$$

$$f(g) = r(1 - g/G_{\max})^2 \tag{11}$$

Among them, it represents a random number between 0 and 1, the current number of iterations, and the maximum number of iterations. Figure 1 shows the flow chart of the educational assessment based on an improved BP neural network.

## 4. The College Counselor Education Evaluation Model based on BP Neural Network

To validate the application effectiveness of the college counsellor ideological and political education evaluation model based on the BP neural network, this study compares the traditional BP neural network ideological and political education evaluation model with the improved BP neural network model. Fifteen college counsellors from a certain university were selected as the sample data for evaluating their education. The comparison results are shown in Figure 2. The data results in the figure show that the improved BP neural network model has relatively smaller errors between its ideological and political education evaluation results and the ideal values. In contrast, the BP neural network model obtained significant errors compared to the ideal values. On an individual basis, the BP neural network evaluation model resulted in a substantial increase in error for some individuals. In contrast, the improved BP neural network model showed smaller variations in individual errors, with only a few individuals having larger errors than others. This indicates that the improved BP neural network model exhibits better performance stability, both in overall and individual evaluation results, with higher accuracy and better alignment with actual values, making it more valuable for practical applications in real environments.

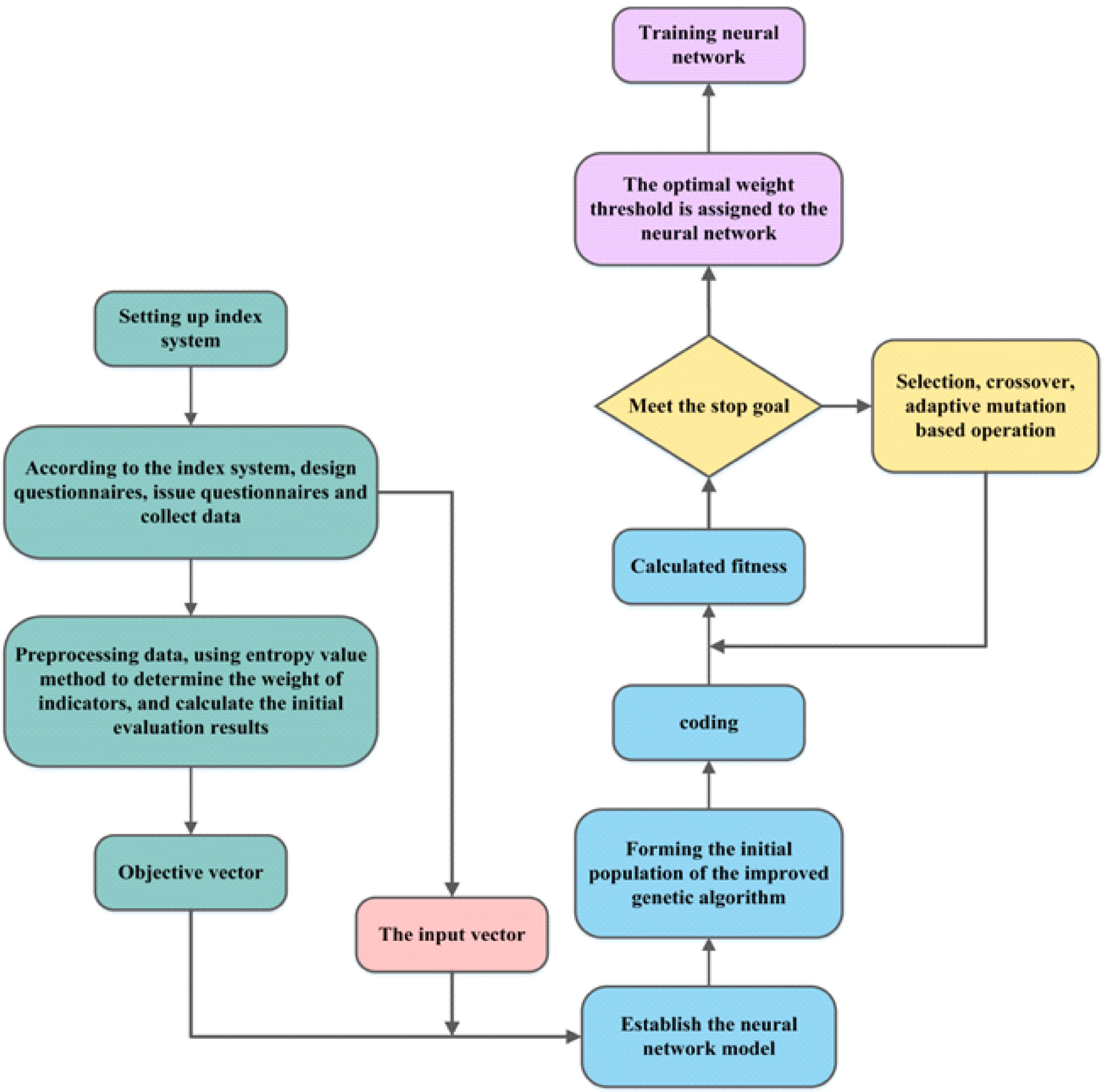


Figure 1. Flowchart of Ideological and Political Education Evaluation based on Improved BP Neural Network

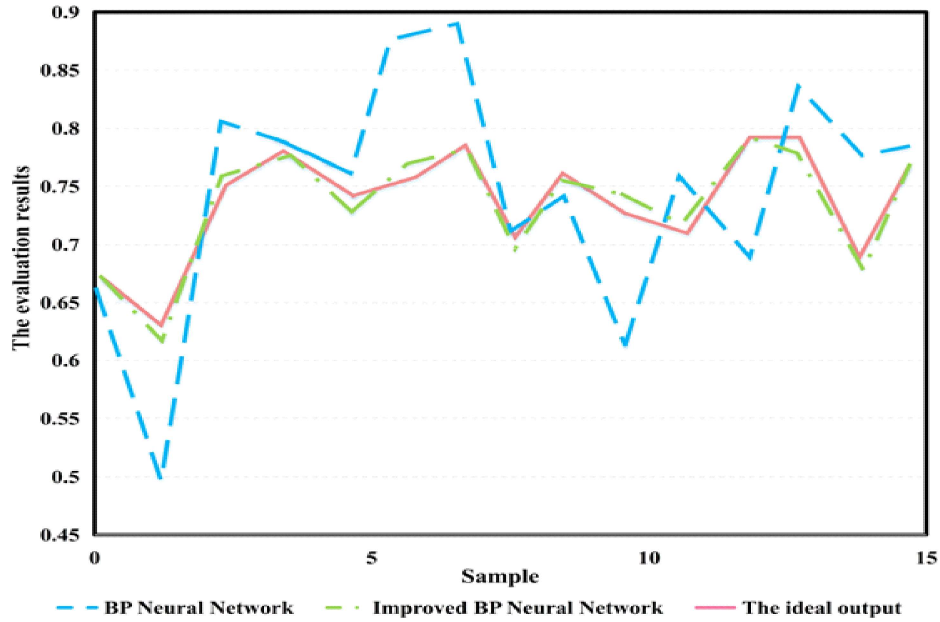


Figure 2. Comparison of Ideological and Political Education Evaluation Results between BP Neural Network and Improved BP Neural Network

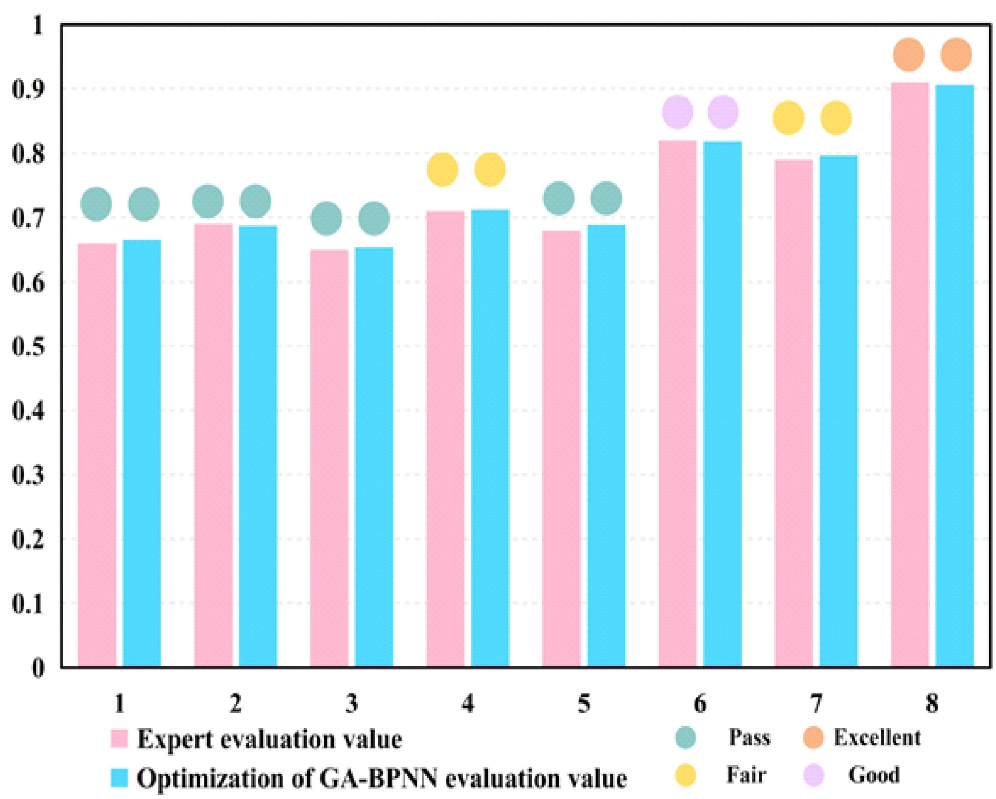


Figure 3. Comparison between the Results of the Improved BP Neural Network Ideological and Political Education Evaluation Model and Expert Evaluations

Certain differences exist between ideological and political education and other disciplines' education, and its educational outcomes have strong subjectivity. Therefore, in the past, expert evaluations were generally used as the standard and widely recognized. Its results were compared with expert evaluations to verify the practical applicability of the evaluation model proposed in this study. Figure 3 compares the results of the improved BP neural network ideological and political education evaluation model and expert evaluations. The results in the figure indicate that the expert evaluations and the evaluation model results from this study are very close. The numerical errors between the overall evaluation results and the expert evaluations are very small and within an acceptable range. Moreover, there were no significant errors in individual evaluation results, demonstrating the stability of the model's performance. Additionally, the ideological and political education evaluation results are presented at four grade levels. In the experimental results, the output of this study's model is consistent with the expert evaluation grades, and there is no significant gap between the grades. This indicates that the evaluation model produces minimal errors that do not affect the determination of evaluation grades, providing scientific, reliable, and authentic evaluation results and information for practical applications.

## 5. Conclusions

Ideological and political education is crucial for cultivating university students' core ideology, values, life outlook, and world outlook, and it plays a vital role in nurturing future socialist successors. With the advent of the information age, university students have greater exposure to diverse ideologies and opinions through the Internet, which may impact their original thoughts and values. In order to strengthen students' ideological education, universities have integrated the Internet and information technology to implement online ideological education, and counselors use various mobile devices to achieve the goals of ideological and political education. However, traditional evaluation methods do not align with online ideological and political education characteristics, resulting in subjective judgments and errors in evaluation outcomes, making it difficult for counselors to obtain accurate and reliable evaluation information. Therefore, this study proposes a high-level counselor ideological and political education evaluation model based on the BP neural network and introduces the GA algorithm to optimize the BP neural network, avoiding issues related to local optima and enhancing the model's accuracy. The experimental results demonstrate that the improved BP neural network ideological and political education evaluation model yields smaller errors between evaluation results and actual outcomes and exhibits good stability, providing more accurate evaluation information. Moreover, the model consistently presents evaluation grades that align with the actual grades, indicating that the errors are within a reasonable range and do not affect the determination of evaluation levels. As a result, the model offers counselors scientifically effective and authentic evaluation information from multiple perspectives.

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## References

[1] Gan, Tian. (2021). Research on the quality evaluation of distance education in colleges and universities is based on a decision tree classification algorithm. *Modern Electronic Technology, 44*(9), 171-175.

[2] Ren, Youqun., Wan, Kun., Feng, Yangcun. (2019). Promoting the sustainable development of Artificial

Intelligence Education - Interpretation and Enlightenment of “artificial intelligence in Education: challenges and opportunities for sustainable development” of the United Nations. *Modern Distance Education Research, 31*(5), 3-10.

[3] Fawns, T., Aitken, G., Jones, D. (2021). Ecological teaching evaluation vs the datafication of quality: Understanding education with, and around, data. *Post Digital Science and Education, 3*, 65-82.

[4] Gao, Y., Yang, J., Liu, F. (2009). The research on the comprehensive assessment of higher engineering education based on fuzzy comprehensive evaluation method. In *2009 Second International Conference on Future Information Technology and Management Engineering* (pp. 124-127). IEEE.

[5] Liu, J., Huang, J., Sun, R., et al. (2020). Data Fusion for Multi-Source Sensors Using GA-PSO-BP Neural Network. *IEEE Transactions on Intelligent Transportation Systems, 99*, 1-16.

[6] Sadollah, A., Sayyaadi, H., Yadav, A. (2018). A Dynamic Metaheuristic Optimization Model Inspired by Biological Nervous Systems: Neural Network Algorithm. *Applied Soft Computing, 71*, 747-782.

[7] Saito, K., Nakano, R. (2002). Extracting regression rules from networks. *Neural Networks, 15*, 1279-1288.

[8] Hizlisoy, S., Yildirim, S., Tufekci, Z. (2020). Music emotion recognition using convolutional long short term memory deep neural networks. *Engineering Science and Technology an International Journal, 24*(3), 760-767.

[9] Jugo, I., Kovaèiæ, B., Slavuj, V. (2016). Increasing the Adaptivity of an Intelligent Tutoring System with Educational Data Mining: A System Overview. *International Journal of Emerging Technologies in Learning, 3*, 423-425.

[10] Yang, Yumei., Li, Jina. (2015). Research on Employment Quality Evaluation of College Graduates Based on AHP and BP Neural Network. *Journal of Chinese Education, 11*, 148-149.

[11] Gupta, T. K., Raza, K. (2020). Optimizing deep feedforward neural network architecture: A tabu search based approach. *Neural Processing Letters, 51*, 2855-2870.

[12] Karsoliya, S. (2012). Approximating number of hidden layer neurons in multiple hidden layer BPNN architecture. *International Journal of Engineering Trends and Technology, 3*(6), 714-717.

[13] Liu, L., Chen, J., Xu, L. (2008). Realization and application research of BP neural network based on MATLAB. In *2008 International Seminar on Future BioMedical Information Engineering* (pp. 130-133). IEEE.

[14] Jiang, Z., Shen, G. (2019). Prediction of house price based on the back propagation neural network in the Keras deep learning framework. In *2019 6th International Conference on Systems and Informatics (ICSAI)* (pp. 1408-1412). IEEE.

[15] Luo, X. J., Oyedele, L. O., Ajayi, A. O., et al. (2020). Genetic algorithm-determined deep feedforward

neural network architecture for predicting electricity consumption in real buildings. *Energy and AI, 2*, 100015.

[16] Ansari, H. R., Zarei, M. J., Sabbaghi, S., et al. (2018). A new comprehensive model for relative viscosity of various nanofluids using feed-forward back-propagation MLP neural networks. *International Communications in Heat and Mass Transfer*, 2018, 91: 158-164.

[17] Jiang., Z., Shen, G. (2019). Prediction of house price based on the back propagation neural network in the keras deep learning framework, 2019 6th International Conference on Systems and Informatics (ICSAI). *IEEE, 1408-1412*.

[18] Huang., G B. (2003). Learning capability and storage capacity of two-hidden-layer feedforward networks. *IEEE transactions on neural networks, 14(2): 274-281*.