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Effect Evaluation of Ideological and Political Education Based on Genetic Algorithm and DBN

Gao-Li Wei

The School of Culture and Communication
Anhui Xinhua University
Anhui 230088, P. R. China
geqian329@sina.com

Li Chen*

The School of Arts
Anhui Xinhua University
Anhui 230088, P. R. China
412235417@qq.com

Ying-Ying Zhang

Jose Rizal University
Mandaluyong 1552, Philippines
173487205@qq.com

*Corresponding author: Li Chen
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Abstract. *Civic and political education effect assessment is an essential measure to ensure the quality of ideological and political teaching. Aiming at current issues of incomplete and overly subjective indicators of the validity of ideological and political education, a method for assessing the effectiveness of ideological and political education relied on Genetic Algorithm (GA) and DBN is offered. Firstly, the indicators in the index system for assessing the validity of ideological and political education are divided into first-level and second-level metrics, and the weights of the metric system are determined by the Analytic Hierarchy Process (AHP). The AHP is improved by using GA to automatically search for the judgment matrix with consistency close to the optimum, which makes the assignment of matrix elements more objective and reasonable. Then the weighted indicators with lower correlation are eliminated using the Pearson correlation coefficient method, and the weighted indicators with higher correlation coefficients are introduced into the assessment model. By using Gauss-Bernoulli Restricted Boltzmann Machine (RBM) to improve the binary constraint issue of the RBM nodes in the DBN, the distributional features in the evaluation indicators are effectively extracted. Finally, a softmax classification layer is added to the top layer of the DBN as the output layer of the model. The weighted metrics with high correlation are used as inputs to the DBN, and the softmax's output is the assessment outcome. The experimental outcome indicates that the evaluation accuracy and F1 value of the offered method are improved by 4.56%–15.63% compared with other approaches, which has a good evaluation effect.*

Keywords: Educational effectiveness evaluation; Genetic algorithm; Analytic hierarchy process; Deep belief network; Pearson correlation coefficient

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1. **Introduction.** Since the reform and opening up, the civic and political knowledge coaching reform in colleges across the country has continued, in spite of the fact that substantial achievements have been reached. However, in bygone times, the teaching content of ideological and political teaching was much focused on learning objectives and program outline, while the reform of the assessment of the impact of Civic and Political education appeared to be quite lagging behind [1]. The effect of civic and political teaching is straightly associated with the training and development of personnel. The education effect assessment is to assess the quality of educational activities in terms of educational goals, and to assess and decide the value of teaching [2, 3]. Despite a lot of teachers participated in the education of civics give great weight to the study and summarization of educational experience and approaches, there are few research outcome on the assessment of the effectiveness of Civics education that have any weight [4, 5]. Thus, the evaluation research of civic and political education effect is of immense value to improve teaching quality, promote teachers' professional growth, support students' learning effect, assist teaching management decision-making, and promote educational research and reform.

1.1. **Related work.** At present, many scholars have performed extensive studies on the methods and systems of evaluating the effect of ideological education and achieved a lot of results [6, 7]. Lucas et al. [8] used Analytic Hierarchy Process (AHP) for evaluating the effect of ideological education, but the evaluation results are susceptible to the influence of subjective factors. Qin et al. [9] used dynamic variable-weight hierarchical analysis to assess the state of Civics teaching effectiveness, but the evaluation indexes were incomplete. Saeed et al. [10] used Principal Component Analysis (PCA) method to extract the effective index features from the original index information, and used multilevel Sigmoid Neural Networks to evaluate the effectiveness of undergraduate teaching. Liu and Chen [11] used the fuzzy comprehensive assessment approach to evaluate the effectiveness of multidisciplinary teaching, but the evaluation process is complicated. Gu [12] used the association rule and weighted simple Bayesian algorithm to evaluate the effectiveness of Civics and Politics teaching, but the evaluation effect is not satisfactory.

Assigning weights to the indicators manually can only indirectly reflect the teaching effect. How to dig out the intrinsic factors reflecting the effectiveness of Civics teaching from a large number of indicators, and how to establish an accurate correlation image between the indicators and the quality of teaching, is difficult to do by relying on traditional experience. Machine learning (ML) has the ability to discover patterns and establish implicit associations from data, making it possible to fully mine teaching effectiveness assessment metrics. Haining et al. [13] introduced the SVM algorithm into the process of teaching evaluation, constructed an educational effect evaluation model, and realized the automation of the teaching evaluation process. Zhang et al. [14] utilized genetic algorithm (GA) and gradient descent method to derive a scientific teaching evaluation model, contributing to the development of teaching evaluation system for research. Zhao [15] used simulated annealing algorithm (SA) to optimize the weights of teaching evaluation indexes and used the indexes with a high weight share as inputs to the decision tree to predict the effect of Civics teaching and improve the assessment effect. Zhao [16] used the Decision Tree (DT) algorithm to calculate the information entropy of teaching evaluation indexes, constructed a decision tree, determined the evaluation rules, and obtained the comprehensive evaluation results of teaching effectiveness through multi-layer composite calculation. Wang [17] suggested a BP neural network-based quality evaluation model for Civics teaching, using AHP to construct teaching quality evaluation indexes to make the evaluation results more explanatory and scientific.

Most of the traditional ML algorithms are semi-supervised learning, which requires a large amount of labeled data and cannot handle a large amount of evaluation index data, while Deep Belief Network (DBN) is an unsupervised learning algorithm, which not only learns the high-level features in a more abstract way but also can deal with high-dimensional data and complex large amount of data, which has attracted the close attention of scholars. Di et al. [18] screened the influence indicators of the effect of ideological education through PCA and realized the output of the evaluation results of educational effect by using DBN. Feng and Dong [19] used AHP with PSO optimization to analyze the indicators impacting the evaluation of educational effectiveness and used them as input variables for DBN to achieve the prediction of the three kinds of teaching effectiveness evaluations, namely, average, good and excellent.

1.2. **Contribution.** Through the in-depth analysis of the above educational effect assessment methods, it can be found that the assessment indexes of the existing methods have problems such as being incomplete and being constrained by subjective factors, etc. For the goal of addressing the above issues, this paper suggests an approach of assessing the impact of civic education relied on GA and DBN, and the innovative work of this method is implied in the following four respects.

(1) Referring to the teaching effect evaluation framework of domestic colleges, the paper constructs the assessment metric system of civic and political education in colleges by AHP. The indicators in the index system are classified to first-level metrics and second-level metrics, and the weight ratio of the standard system is determined by AHP to form a complete evaluation index system.

(2) Aiming at the issue that the selection of judgment matrix in AHP is subject to the constraints of subjective factors, GA is used to improve AHP by automatically searching for the decision matrix and identifying a decision matrix that exhibits a consistency level nearing the optimal one, which will significantly ease the task of resolving the decision matrix and enhance the objectivity and rationality in assigning matrix elements.

(3) The Pearson correlation coefficient method is utilized to eliminate the weighted indicators with low correlation, and the RBM in DBN is improved by utilizing Gauss-Bernoulli Restricted Boltzmann Machine (RBM) to improve the binary constraints problem of the RBM nodes, and to efficiently extract the distributional features in the weighted indicators.

(4) Add a softmax classification layer to the topmost layer of the DBN as the output layer of the model. The weighted indicators with high relevance are used as inputs to the DBN, and the output of the softmax layer is the assessment result. The experimental outcome indicates that the suggested approach can greatly enhance the precision of evaluating the impact of civic and political education in colleges, and offer a novel approach for evaluating the quality of education.

2. Theoretical analysis.

2.1. **Genetic algorithm.** GA simulates natural selection and evolution through a series of genetic operations, which is essentially an iterative process [20], starting from a set initial solution and evolving iteratively to improve the current solution and obtain the optimal solution. GA has been widely used in statistical analysis, ML and other fields due to its simplicity and versatility, as well as its robustness, and has shown good optimization performance.

(1) **Genetic coding**. The process of converting the feasible solution of the problem to be optimized into chromosomes in the GA. Since the GA cannot process the feasible solution directly, the nonlinear mapping from the solution space to the genetic space is

the key problem for the implementation of the algorithm. Commonly used genetic coding methods include real number coding, symbolic coding, and binary coding.

(2) **Initial population selection**. Individuals randomly generated from the optimization problem to be solved constitute the initial population for the iteration of future generations.

(3) **Calculation of individual fitness**. The fitness of an individual in GA can present to a certain extent the degree of excellence that this feasible solution can reach the optimal solution in the actual optimization problem [21]. If the individual fitness is to be obtained, the value of the objective function needs to be determined first, and then the individual fitness is derived from it.

(4) **Genetic operations**. Selection, crossover, and mutation of individuals for the purpose of population evolution. At the level of optimization search for a real problem, performing genetic operations leads to a feasible solution that is optimized over and over again, thus approaching the optimal solution.

2.2. **Deep belief network.** DBN is a ML method that is a fusion of probabilistic statistics, machine learning, and neural networks, and its constituent element is the RBM, the core of which lies in the continuous updating and optimization of connection weights in DBN through a layer-by-layer greedy learning method [22], and the network structure is shown in Figure 1.

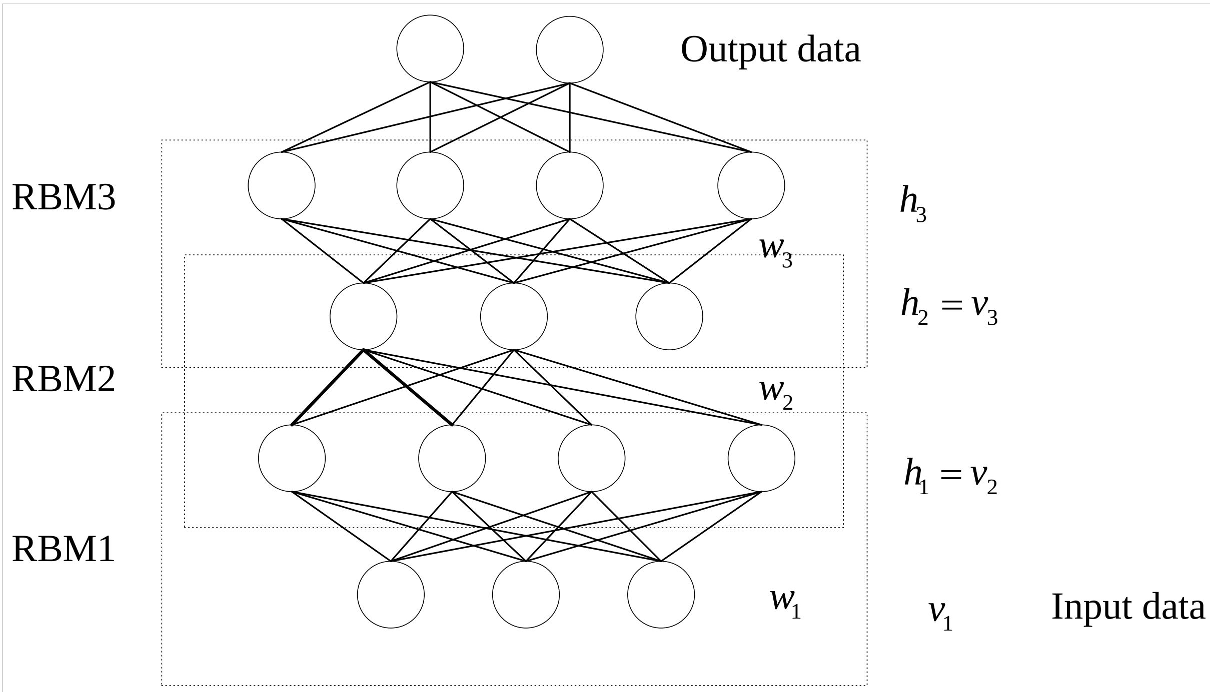

Figure 1. The network structure of DBN

Assuming that $\mathbf{v}$ is the visible level, $\mathbf{h}$ is the obscured level, and $(\mathbf{v}, \mathbf{h})$ is the state given by the DBN, the energy functions E of the binary variables i and j of all visible and obscured level units in the DBN network are as follows:

$$E(\mathbf{v}, \mathbf{h} \mid \theta) = -\sum_{i=1}^{n} a_i v_i - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n} \sum_{j=1}^{m} v_i w_{ij} h_j \tag{1}$$

where w is the connection weight of $\mathbf{v}$ and $\mathbf{h}$, a, b is the bias of $\mathbf{v}$ and $\mathbf{h}$, and θ is the set consisting of w, a, b. Let K be the number of training samples, the stochastic gradient method is used to solve the maximum value of the log-likelihood function $L(\theta)$ to determine the value θ^* of parameter θ:

$$\theta^* = \arg_\theta \max L(\theta) = \arg\max \sum_{k=1}^{K} \ln p(v^{(k)} \mid \theta) \tag{2}$$

After the parameters are decided, the joint distribution of probabilities function for each state $(\mathbf{v}, \mathbf{h})$ of $\mathbf{v}$ and $\mathbf{h}$ can be obtained from the energy function as below:

$$\begin{cases} p(v, h|\theta) = \dfrac{e^{-E(v,h|\theta)}}{Z(\theta)} \\ Z(\theta) = \sum\limits_{v} \sum\limits_{h} e^{-E(v,h|\theta)} \end{cases} \tag{3}$$

The activation probability p of the visible level cell and the obscured level cell are shown in Equation (4) and Equation (5), respectively:

$$p(h_j = 1 \mid \mathbf{v}, \theta) = \text{sigmoid}\left(b_j + \sum_{i=1}^{n} v_i w_{ij}\right) \tag{4}$$

$$p(v_i = 1 \mid \mathbf{h}, \theta) = \text{sigmoid}\left(a_i + \sum_{j=1}^{m} h_j w_{ij}\right) \tag{5}$$

3. Establishment of Civic Education Effectiveness Assessment Indicator System Based on GA and AHP.

3.1. Construction of civic education effectiveness assessment indicator system based on AHP. Correct and reasonable assessment indexes are crucial for model accuracy. In the actual Civics teaching there are many aspects that affect the educational effect but in general they are designed from the perspective of teachers and students. Specifically, it includes teachers' teaching content, teaching attitude, teaching ability and teaching methods, as well as students' learning attitude, interest, initiative and quality development. In this paper, we draw on the teaching effect assessment system of domestic universities [23], and use AHP [24] to construct a structural model for the evaluation of the impact of efficient civics education as shown in Figure 2.

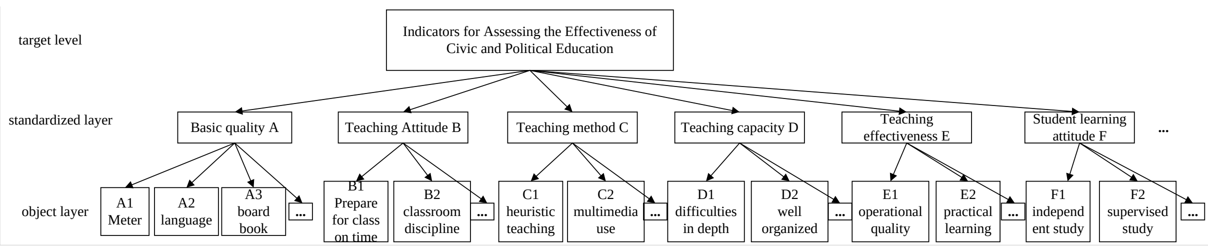

Figure 2. The structural model for the evaluation of the impact of efficient civics education

It can be concluded that the evaluation index system is classified into m first-level metrics and n subdivided second-level metrics, which are numbered $x_1, x_2, \ldots, x_n$. Due to the different importance of each evaluation indicator, this paper uses the most commonly used AHP to determine the weight of each indicator. The steps in detail are as below.

(1) Construct the judgment matrix of the indicator system. For AHP, the metrics in the indicator framework are classified into first-level metrics and second-level metrics,

the criterion level is the level where the first-level indicators are located, and the target level is the level where the second-level metrics are located. Taking the decision matrix B at the criterion level as an example, and using b_i and b_j to stand for the significance of the first-level metric instances B_i and B_j at the criterion level to the effectiveness of education, one of the judgment matrices created is

$$B = (b_{ij})_{n\times n}, \quad b_{ij} = \frac{b_i}{b_j}.$$

(2) Compute the eigenvectors of the decision matrix. After establishing the decision matrix, its largest eigenvalue $\lambda_{\max}$ and the related eigenvector W' are also required, and the vector after standardizing W' is the weight vector W of each index in the decision matrix.

Given that the geometric mean approach for determining the approximate weights of a matrix boasts the benefits of a straightforward process and straightforward programming execution, this article utilizes the geometric mean approach to solve the eigenvectors as shown in Equation (6), where $i = 1, 2, \ldots, n$.

$$W_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}} \tag{6}$$

For Equation (6), the product $A_i = \prod_{j=1}^{n} a_{ij}$ of each instance of the rows of the decision matrix is computed, while $w = (w_1, w_2, \ldots, w_n)^T$ is normalized to obtain:

$$W_i = \frac{w_i}{\sum_{j=1}^{n} w_j} \tag{7}$$

Combining each W_i, the resulting

$$W = (W_1, W_2, \ldots, W_n)$$

is the estimated eigenvector associated with the maximum eigenvalue, where W_i is the weight value. The approximation of the maximum eigenvalue can be calculated by:

$$\lambda_{\max} \approx \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} \tag{8}$$

3.2. **GA-based AHP judgment matrix indicator weight calculation.** Decision matrix is an essential calculation object of AHP, and the good or bad decision matrix straightly impacts the objectivity and logicality of index weights [25]. However, since the method of constructing the AHP is subjective and assigns values to the elements, it is tough to gain absolute consistency in the decision matrix. Therefore, this paper applies an easy-to-implement GA to improve AHP, automatically searching for judgment matrices and identifying judgment matrices that exhibit near-optimal consistency, which will significantly ease the task of resolving decision matrices and enhance the objectivity and rationality in assigning matrix elements.

(1) **Encoding of the judgment matrix.** The judgment matrix only needs to encode the upper triangular elements, and this paper uses real-valued encoding, encoded as chromosome $b' = b_{11}b_{12}\ldots b_{mn}$.

(2) **Establishment of fitness function.** The fitness function is the only criterion for judging the degree of chromosome superiority or inferiority in the GA population. Take the decision matrix B as an instance, and let the amount of level 1 metrics in B be m. Then the vector of weights of the metrics in B for the evaluation of educational

effectiveness is W, where $W_i > 0$ and $\sum_{i=1}^{n} W_i = 1$. If each element b_{ij} in B satisfies $b_{ij} = W_i/W_j$, then B has full consistency, which leads to:

$$\sum_{j=1}^{n} b_{ij} W_j = \sum_{j=1}^{n} \frac{W_i}{W_j} \cdot W_j = nW_i \tag{9}$$

Equation (9) can be reorganized as:

$$\sum_{i=1}^{n} \left| \sum_{j=1}^{n} (b_{ij} W_j) - nW_i \right| = 0 \tag{10}$$

As the judgment matrix may differ from one case to another, a lower value on the left-hand side of (10) indicates a higher degree of consistency in the judgment matrix, and perfect consistency is achieved when the value equals zero. Thus, the objective function can be written as:

$$\min f_{Cl}(n) = \frac{\sum_{i=1}^{n} \left| \sum_{j=1}^{n} (b_{ij} W_j) - nW_i \right|}{n} \tag{11}$$

where $W_j > 0$, $\sum_{j=1}^{m} W_j = 1$. When the goal is to reduce to a minimum, the definition of the ultimate fitness function is as below, the maximum estimation of $f_{CI}(n)$ is given by $C_{\max}$:

$$F(n) = \begin{cases} C_{\max} - f_{CI}(n), C_{\max} > f(n) \\ 0, C_{\max} \le f(n) \end{cases} \tag{12}$$

(3) **Genetic operation.** The same principle of genetic operation as that of GA is used, where selection, crossover and mutation act together in order to generate a new population and find the optimal solution through iterative optimization.

(4) **Obtain the optimal judgment matrix.** From the establishment of the fitness function, it can be seen that the smaller the value of $f_{CI}(n)$, the better the consistency of the decision matrix, so the closer the value of $F(n)$ is to $C_{\max}$, the better the corresponding solution. The algorithm terminates when the current population optimal solution satisfies $|C_{\max} - F(n)| \le \sigma$. This optimal solution is used as the optimal decision matrix. By solving the eigenvectors of the optimal decision matrix, the final indicator weight W' can be obtained, so as to get the weighted Civic Education Effectiveness Assessment Indicator $x' = W'x$.

4. Evaluation of civic education effectiveness based on optimized DBN.

4.1. Redundant indicator removal based on person's correlation coefficient approach. After obtaining the weighted indicators for assessing the effectiveness of civic education, redundant indicators were first removed using the Person correlation coefficient method. Then, the Gauss-Bernoulli distribution RBM [26] was introduced to improve DBN, and forward unsupervised layer-by-layer training was carried out on DBN, and the optimal parameters of the model were simulated to determine the optimal network structure for the assessment of ideological and political education effect and improve the evaluation effect of the model. The screened weighted assessment indicators are used as inputs to improve the DBN, and the results of the evaluation of the effectiveness of civic education are outputted through the softmax layer, corresponding to excellent, good, qualified, and unqualified, respectively. The model of the proposed assessment methodology is shown in Figure 3.

In section 3.2, this paper has assigned weights to the assessment indicators, and the indicators with a low weight share are non-key indicators, but it is also necessary to consider the two-by-two correlation between the assessment indicators. The Person correlation coefficient method is suitable for measuring the linear relationship between two variables and has the advantage of being simple and easy to use, allowing the correlation coefficient between two variables to be calculated quickly. Therefore, this paper utilizes the Pearson correlation coefficient method [27] to calculate the degree of influence of each weighted indicator on the assessment results, and introduces the weighted indicators with higher correlation coefficients into the assessment model. The equation of the Pearson correlation coefficient method is as follows.

$$\mu_{xz} = \frac{\sum_{j=1}^{M}(x_i - \bar{x})(z_i - \bar{z})}{\sqrt{\sum_{j=1}^{M}(x_i - \bar{x})^2} \cdot \sqrt{\sum_{j=1}^{M}(z_i - \bar{z})^2}} \tag{13}$$

where μ_{xz} denotes the correlation coefficient between indicator x and indicator z, M is the amount of indicators, $\bar{x}$ denotes the average value of x_i, and $\bar{z}$ is the average value of z_i.

μ_{xz} takes values in the range of $[-1, +1]$. Larger values of $|\mu_{xz}|$ indicate a stronger correlation between the indicators. Where $\mu_{xz} = 0$ is no correlation between the two indicators, $|\mu_{xz}| < 0.3$ stands for a weak correlation, $0.3 \leq |\mu_{xz}| < 0.5$ stands for a moderate correlation, and $|\mu_{xz}| \geq 0.5$ stands for a high correlation. This paper takes the weighted metrics of $|\mu_{xz}| \geq 0.3$ as the final input metrics, denoted as $X' = \{x_1, x_2, \ldots, x_k\}$.

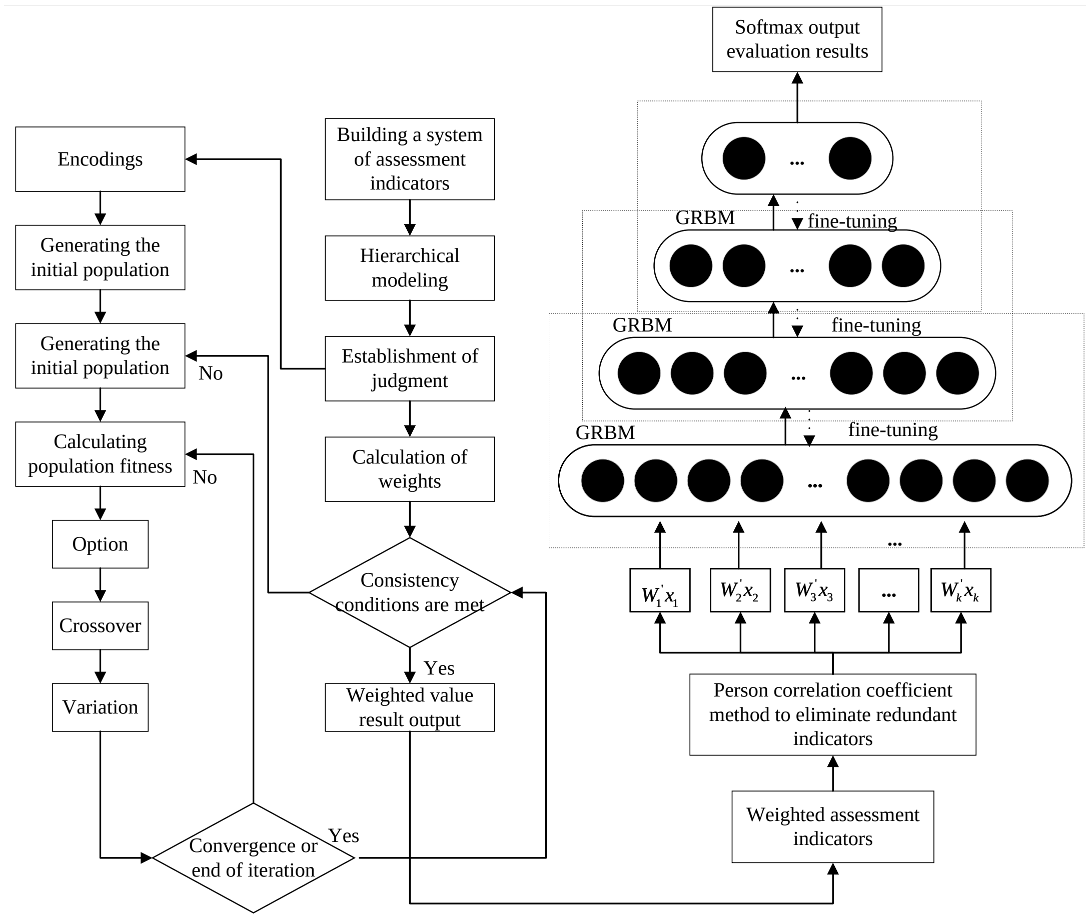

Figure 3. The model of the proposed assessment methodology

4.2. **Evaluation of the effectiveness of civic education based on improved DBN.** After obtaining the final input indicators, to gain the precise assessment of the effect of ideological education and ensure the objectivity and fairness of the assessment, this paper utilizes the powerful learning capability of DBN to carry out the effect of ideological education. As shown in Section 2.2, the core of DBN is RBM, and since the traditional restricted RBM takes the value of binary numbers, which is not adept at handling uninterrupted data, GRBM is introduced to make the metrics continuous in [0,1]. In GRBM, the traditional binary nodes in the visible units of RBM are substituted by linear variable nodes that incorporate independent Gaussian noise. These nodes follow a Bernoulli distribution for the obscured level variables, while they adhere to a Gaussian distribution for the variables in the visible level. The GRBM's energy operation is as bellow.

$$E(v, h \mid \theta) = -\sum_{i=1}^{n} \frac{(v_i - a_i)^2}{2\sigma_i^2} - \sum_{j=1}^{m} b_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{v_i}{\sigma_i} W_{ij} h_j \tag{14}$$

where σ_i represents the standard deviation for Gaussian noise of visual level v_i; a_i is the bias of v_i; b_j is the bias of implicit layer h_j; $\theta = \{W_{ij}, a_i, b_j\}$ is the structural parameter; and W_{ij} stands for the linked value of implicit level and visual level.

Based on the structural features of GRBM, this article obtains the conditional probabilities for both the obscured and visible levels as detailed below.

$$P(h_j = 1 \mid v, \theta) = \sigma\left(b_j + \sum_i \frac{v_i}{\sigma_i} W_{ij}\right) \tag{15}$$

$$P(v_i \mid h, \theta) = N\left(a_i + \sigma_i \sum_j W_{ij} h_j, \sigma_i^2\right) \tag{16}$$

Similarly, where $\sigma(x) = 1/(1 + e^{-x})$ is the sigmoid activation operation; $N(\mu, \sigma^2)$ represents a Gaussian function with a mean μ and a difference σ^2.

The stochastic gradient ascent method is employed to attain the peak value of the likelihood function [28], and the parameter updating rules for the GRBM network are thus obtained as follows.

$$w_{ij} = w_{ij} + \eta\left(\left\langle \frac{v_i h_j}{\sigma_i} \right\rangle_{data} - \left\langle \frac{v_i h_j}{\sigma_i} \right\rangle_{model}\right) \tag{17}$$

$$a_i = a_i + \eta\left(\left\langle \frac{v_i}{\sigma_i^2} \right\rangle_{data} - \left\langle \frac{v_i}{\sigma_i^2} \right\rangle_{model}\right) \tag{18}$$

$$b_j = b_j + \eta\left(\langle h_j \rangle_{data} - \langle h_j \rangle_{model}\right) \tag{19}$$

where η is the studying rate and $\langle\cdot\rangle_{data}$ and $\langle\cdot\rangle_{model}$ are the output and expected values, respectively.

Since DBN can get stuck in the local minimum problem during batch training, the momentum factor incorporates the gradient estimate from the previous iteration into the algorithm, which helps the algorithm to converge quickly with better performance, and the parameter update equation is as bellow.

$$\theta_{t+1} = \theta_t + \Delta\theta_t \tag{20}$$

$$\Delta\theta_t = m_b + \Delta\theta_{t-1} + \varepsilon \times \frac{\partial \ln L}{\partial \ln \theta} \tag{21}$$

where $\partial \ln L/\partial \ln \theta$ is the gradient of the log-likelihood function and m_b is the momentum factor.

The improved DBN combines GRBM and DBN, fully absorbing the advantages of both, avoiding overfitting and improving studying performance. The training data is input into the visualization layer of the underlying GRBM, which then proceeds to complete the forward, unsupervised, layer-wise training of GRBM, RBM1, and RBM2, along with the subsequent backward fine-tuning of the model parameters. At the same time, the optimized DBN is capable of extracting the distributional characteristics within the assessment indicators more comprehensively, create the intricate nonlinear connection among the characteristic information and the assessment results, and enhance the accuracy of the assessment.

Then a softmax classification level is added to the top layer of DBN as the output layer of the model. Important weighted ideological and civic education impact evaluation indicators are served as the input of the DBN, and the output of the softmax classification level is the evaluation result, corresponding to excellent, good, qualified and unqualified respectively.

5. Performance testing and analysis.

5.1. Results of civic and political education effectiveness evaluation. To estimate the evaluation performance of the offered method, this article conducts experiments under Window 10 (64-bit) operating system, Intel Core i5-5200U CPU @ 3.6 GHz, 8 GB RBM, Python 3.5 environment. The population size of GA in the experiment was set to 10, the maximum number of epoches was 100, the crossover probability was 0.7, the variance probability was 0.1, and the studying rate of DBN was set to 0.001. The dataset is based on the teaching evaluation data of college students and teachers in the civic and political discipline of a university from 2008 to 2017, and selects important indicators for the assessment of the impact of civic and political education, mainly involving teaching content, teaching attitude, teaching ability, teaching and learning methods, and the quality training of students, including 52,178 teaching evaluation data. Students and teachers use machine-readable cards to fill in four grades of evaluation one by one for each major aspect of the small indicators, in which 85–100 is excellent, 70–85 is good, 60–70 is qualified, and less than 60 is unqualified. The proportion of different evaluation scores is shown in Figure 4.

The SA_AHP model from the literature [15], the BP_AHP model from the literature [17], and the AHP_DBN model from the literature [19] were chosen for the experimental comparison models. The median, mean and standard deviation of 10 independent runs of the first and second order matrix data for the different models are shown in Table 1, where the bold values indicate the best values of the judgment matrix. The standard deviation of AHP_DBN is small so the AHP method for PSO optimization can be optimized to a certain extent, so this may be caught in a state of local convergence that cannot be jumped out to get the subsequent global optimal results. SA_AHP optimizes the AHP method by SA algorithm, but the optimization is not large; BP_AHP does not optimize the AHP in any way, so the judgment matrix obtained cannot converge. Therefore, from the analysis of the overall results, the hierarchical system of GA_DBN can reach the optimal effect.

The results of evaluating the effectiveness of Civic Education in different models are shown in Figure 5 and Table 2. From the overall evaluation results, GA_DBN outperforms the other three models, with the smallest RMSE and the largest correlation coefficient R, on both the training and test sets, indicating that GA_DBN has the highest degree of correlation between the evaluated values and the actual values, and the best prediction

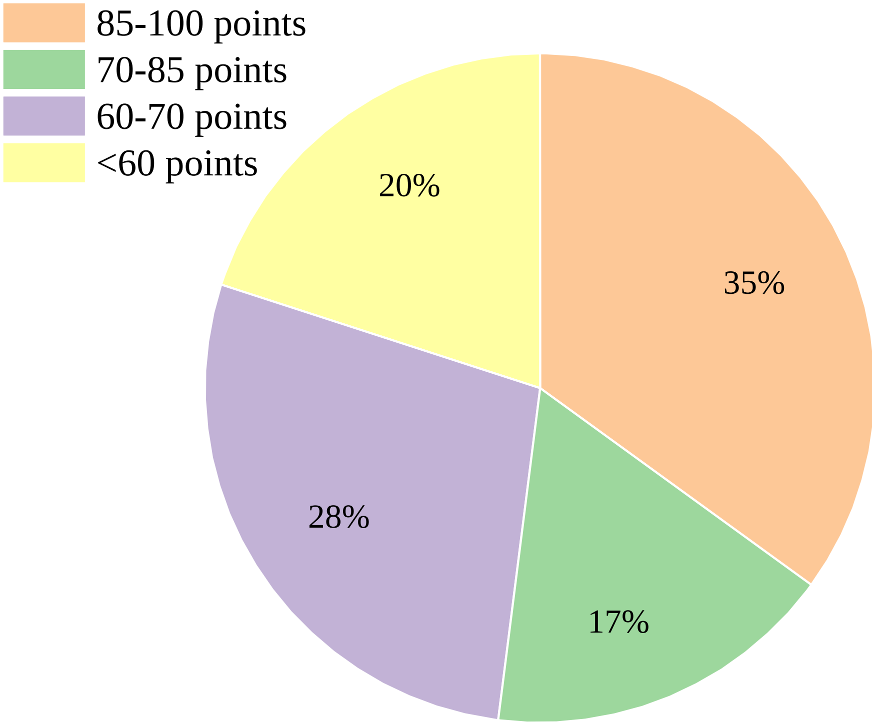

Figure 4. The proportion of different evaluation scores

Table 1. Results of 10 independent runs with different model matrix data

Matrix	Value	BP_AHP	SA_AHP	AHP_DBN	GA_DBN
	Median	0.0242	0.0167	0.0148	**0.0134**
B1	Mean	0.0269	0.0170	0.0164	**0.0156**
	STD	0.00358	0.00214	0.00196	**0.00057**
	Median	0.0125	0.0073	0.0061	**0.0035**
B2	Mean	0.0149	0.0082	0.0062	**0.0042**
	STD	0.0025	0.0012	0.0007	**0.0004**

results. SA_AHP, AHP_DBN and GA_DBN evaluation accuracy is better than BP_AHP, mainly because all three algorithms optimize AHP and optimize the evaluation accuracy of the approach.

Table 2. Comparison of assessment outcome of various methods

Method	Train set RMSE	Train set R	Test set RMSE	Test set R
SA_AHP	0.0176	0.9452	0.0472	0.9456
BP_AHP	0.0168	0.9632	0.0459	0.9642
AHP_DBN	0.0112	0.9786	0.0392	0.9711
GA_DBN	**0.0089**	**0.9956**	**0.0373**	**0.9893**

5.2. **Comparative experiments on obstacle avoidance with different algorithms.** To further compare the performance of various methods, this paper analyzes the evaluation metrics Accuracy (AC), Recall (RC), Precision (PC), F1 and also AUC values of each method. The AC of GA_DBN was 94.68%, which was improved by 4.56%–13.59% compared to SA_AHP, BP_AHP, and AHP_DBN. It indicates that GA_DBN has the best

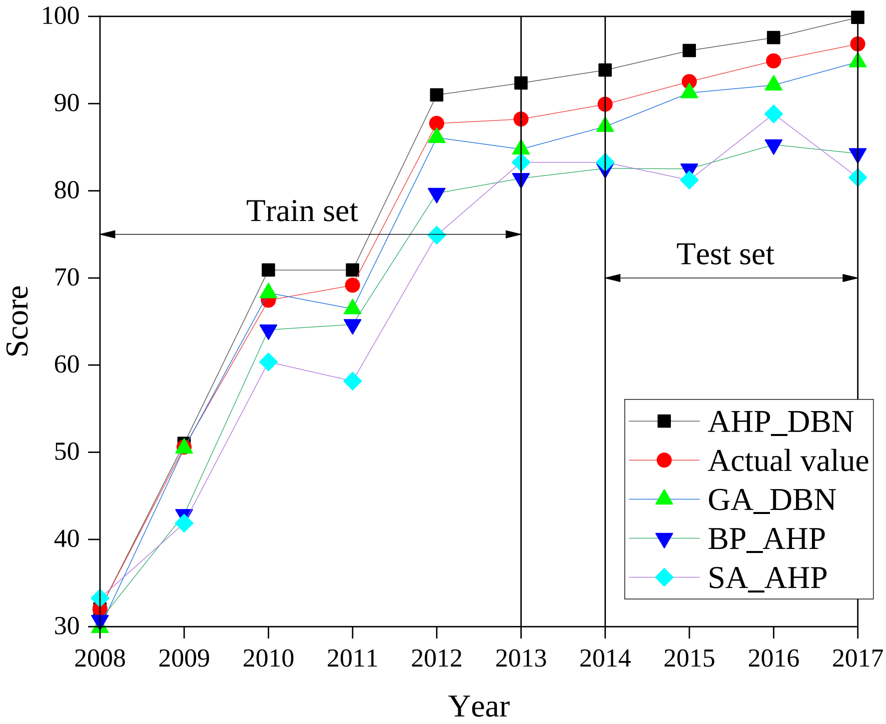

Figure 5. Results of evaluation of the effectiveness of different methods of civic and political education

assessment accuracy. F1 is the reconciled mean of RC and PC, which best reflects the evaluation accuracy of the model, and the F1 of GA_DBN is 94.01, which is improved by 15.63%, 7.76%, and 4.72% compared with SA_AHP, BP_AHP, and AHP_DBN, respectively. GA_DBN not only uses GA to optimize AHP and eliminate redundant indicators, but also introduces GRBM to improve DBN, which greatly improves the evaluation efficiency of the model.

Table 3. Comparison of evaluation performance indicators for different methods

Model	AC (%)	RC (%)	PC (%)	F1 (%)
SA_AHP	81.09	79.18	77.59	78.38
BP_AHP	85.64	84.61	87.96	86.25
AHP_DBN	90.12	88.14	90.48	89.29
GA_DBN	**94.68**	**93.15**	**94.87**	**94.01**

AUC is the area under the ROC curve, and the ROC curves of different models are shown in Figure 6. The closer the ROC curve is to the point (0,1) and the more it deviates from the 45-degree diagonal, the better the prediction is. From the ROC curves, GA_DBN has the best curve, while SA_AHP has the worse. To further quantitatively analyze the effectiveness of the assessment, the ROC curve was quantified using AUC. The AUC value of DBN is 0.9156, which is the largest among these models, indicating that the model is the most effective. The AUC of SA_AHP is 0.7236, the AUC of BP_AHP is 0.7826, and the AUC of AHP_DBN is 0.8256, and the prediction effect of these models is average. Although SA_AHP uses PSO to optimize AHP, the computational complexity of the decision tree is high, and the evaluation results are average. BP_AHP is not optimized for AHP, and the metrics analyzed by AHP are directly used as inputs to BP, which reduces the predictive performance of the model. AHP_DBN did not improve on AHP and DBN,

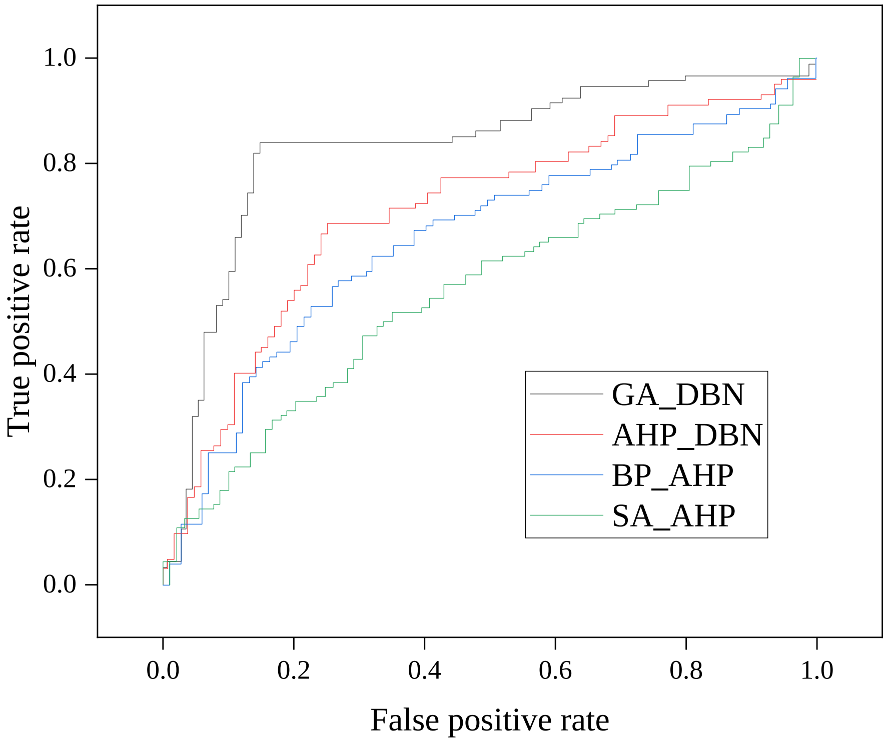

Figure 6. The ROC curves of different models

so the assessment was not as effective as GA_DBN. Therefore, GA_DBN had the best performance in the assessment of Civic Education.

6. **Conclusion.** Civic and political education is the basis of powerful education. Aiming at the problems of incomplete evaluation index and lack of objectivity in the current evaluation methods of civic and political education effect, this article offers an evaluation approach based on GA and DBN. Firstly, AHP was used to optimize and reconstruct the assessment system of efficient civic education, and the weights of the standard system were determined through AHP to form a complete evaluation index system. Improvement of AHP by using GA to search the decision matrix automatically and identifying a decision matrix that exhibits a level of consistency close to the optimal one can significantly streamline the process of resolving the decision matrix, and can achieve a more objective and logical assignment of matrix elements. The Pearson correlation coefficient method is introduced to eliminate the weighted indicators with low correlation, and the RBM in DBN is improved by utilizing the GRBM to improve the binary constraint problem of the RBM nodes, and the distributional features in the assessment indicators are effectively extracted. A softmax classification level is added to the DBN as the output layer of the model. The weighted metrics with high correlation are used as inputs to the DBN, and the output of the softmax level is the assessment outcome. The experimental outcome indicates that the assessment accuracy and F1 value of the proposed model are 94.68% and 94.01%, respectively, which effectively improves the accuracy of the assessment of the effect of Civic Education. At present, the limited data of the experiment makes the accuracy and reliability of the assessment of the proposed method still need to be improved, and the next step needs to gather a substantial quantity of classroom data of civic Education and assessment information, so as to train a more stable and more generalized model.

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