Research on Quality Evaluation and Feedback Mechanism of Engineering Management Education Based on Artificial Intelligence

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Abstract. Aiming at the problem of quality evaluation of engineering management education, this study proposes a dynamic weight adaptive evaluation algorithm (DWAEA) to construct an intelligent evaluation and feedback mechanism. The algorithm is based on the multi-dimensional data characteristics of engineering management education, and uses adaptive weight theory to achieve accurate evaluation through data preprocessing, dynamic weight adjustment and comprehensive evaluation calculation. In the experimental stage, 1,200 student data from 5 colleges and universities were collected to construct a data set. In the Python environment, the simulation was carried out in combination with Scikit-learn and TensorFlow libraries, and the DWAEA algorithm was compared with the traditional weighted average method, BP neural network algorithm, and random forest algorithm. The results show that the accuracy of the DWAEA algorithm is 92.3%, which is 18.7% higher than the traditional method and 12.4% higher than the BP neural network algorithm; the recall rate is 89.6%, which is 15.3% higher than the traditional method and 10.2% higher than the BP neural network algorithm. After the feedback mechanism constructed based on this algorithm was piloted in a certain college, the rate of excellent student grades increased from 18% to 27%, and the course satisfaction increased from 68% to 85%. The study shows that the DWAEA algorithm and feedback mechanism significantly improve the accuracy of education quality assessment and management efficiency, providing a new path for the development of engineering management education.

Keywords: artificial intelligence; engineering management education; dynamic weight adaptive evaluation algorithm; quality assessment; feedback mechanism

1 Introduction

As an interdisciplinary field integrating engineering technology and management science, the quality of engineering management education directly affects the talent supply and project management level of the engineering construction industry. With the deep penetration of digital and intelligent technologies in the engineering field, the traditional education quality assessment model based on fixed indicators and manual scoring

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A. Y. M. A. Islam et al. (eds.), *Proceedings of the 2025 4th International Conference on Science Education and Art Appreciation (SEAA 2025)*, Advances in Social Science, Education and Humanities Research 952,
https://doi.org/10.2991/978-2-38476-452-5_27

can no longer meet the requirements of engineering management education for dynamics and accuracy. The current evaluation system has problems such as single evaluation indicators and limited data dimensions. In addition, the feedback mechanism relies heavily on manual summary and has significant lag, resulting in a long teaching optimization cycle and difficulty in quickly adapting to the needs of industry technology iteration [1].

This study proposes a dynamic weight adaptive evaluation algorithm (DWAEA). The algorithm is based on the machine learning adaptive weight theory and combines the multi-source and dynamic characteristics of engineering management education data to achieve real-time adjustment of evaluation indicator weights. At the same time, a complete mechanism of "data collection - intelligent evaluation - accurate feedback" is constructed [2]. Through experiments on multi-source data of 1,200 students from 5 colleges and universities, the superiority of the algorithm in indicators such as accuracy and recall rate, as well as the actual effectiveness of the feedback mechanism in improving teaching quality, is verified, providing technical support and practical paths for optimizing the quality of engineering management education.

2 Dynamic Weight Adaptive Evaluation Algorithm

2.1 Algorithm Principle Description

Assume that the set of engineering management education quality evaluation indicators is $\mathcal{X} = \{x_1, x_2, \cdots, x_n\}$, where x_i represents the i evaluation indicator. In the traditional evaluation model, the evaluation result Y can be expressed as:

$$Y = \sum_{i=1}^{n} w_i x_i \tag{1}$$

Where w_i is a fixed weight, satisfying $\sum_{i=1}^{n} w_i = 1$. However, in the dynamic scenario of engineering management education, the contribution of each indicator to education quality is not constant [3]. DWAEA introduces time series t as a variable and defines the weight as a function $w_i(t, x)$ of time t and data feature x. Then the evaluation result can be expressed as:

$$Y(t) = \sum_{i=1}^{n} w_i(t, x) x_i(t) \tag{2}$$

Where $x_i(t)$ represents the value of the i evaluation indicator at time t. Through this model, DWAEA can capture the dynamic changes in the importance of each evaluation indicator in the teaching process, making the evaluation results more in line with the actual education quality.

2.2 Algorithm Implementation Steps

2.2.1 Data preprocessing.

In the data cleaning stage, the outlier detection method based on density peak clustering is adopted. Let the local densityρ_j of the data point x_j be:

$$\rho_j = \sum_{i=1}^{m} \exp\left(-\left(\frac{d_{ij}}{d_c}\right)\right) \tag{3}$$

Where d_{ij} is the Euclidean distance between data points x_i and x_j, d_c is the cutoff distance, and m is the total number of data points [4]. If ρ_j exceeds the normal density range, x_j is determined to be an outlier and is removed. For missing value processing, a filling method based on matrix decomposition is used. The original data matrix $\mathbf{X}$ is decomposed into low-rank matrices $\mathbf{U}$ and $\mathbf{V}$, that is, $\mathbf{X} \approx \mathbf{U}\mathbf{V}^T$, and $\mathbf{U}$ and $\mathbf{V}$ are solved through iterative optimization to fill in the missing data [5].

The data standardization adopts the improved Z-score standardization formula:

$$x_{ij}^{*} = \frac{x_{ij} - \mu_i}{\sigma_i + \epsilon} \tag{4}$$

Wherex_{ij} is the original data, μ_i and σ_i are the mean and standard deviation of the i indicator respectively, and ϵ is a very small positive number to avoid the denominator being zero.

In terms of feature extraction, combined with the characteristics of engineering management education, the method of combining principal component analysis (PCA) with mutual information is adopted. By calculating the mutual information $MI(x_i, x_j)$ between each indicator:

$$MI(x_i, x_j) = \sum_{x_i} \sum_{x_j} p(x_i, x_j) \log \frac{p(x_i, x_j)}{p(x_i)p(x_j)} \tag{5}$$

Filter out the core features that contribute most to the evaluation of education quality, reduce the data dimension and retain key information.

2.2.2 Dynamic Weight Adjustment.

At each time step t, the algorithm selects an action $a_t \in A$ according to the current state $s_t \in S$, and obtains a new weight vector $\mathbf{w}_{t+1}$ after performing weight adjustment. Calculate the reward r_t:

$$r_t = \alpha(\text{Accuracy}_{t+1} - \text{Accuracy}_{t}) + \beta(\text{Recall}_{t+1} - \text{Recall}_{t}) \tag{6}$$

Where Accuracy $_t$ and Recall t are the evaluation accuracy and recall rate at time t, respectively, and α and β are reward coefficients [6].

At the same time, the attention mechanism is introduced to dynamically adjust the weight update priority of different indicators according to the teaching objectives. Let the attention coefficient $\alpha_i(t)$

$$\alpha_i(t) = \frac{\exp(f(x_i(t)))}{\sum_{j=1}^{n} \exp(f(x_j(t)))} \tag{7}$$

Where $f(\cdot)$is the feature importance evaluation function. In the weight adjustment process, the indicators with high attention coefficients are given a larger weight update step to enhance the algorithm's responsiveness to key evaluation indicators and make the evaluation results more in line with teaching needs.

3 Experimental Design and Simulation

3.1 Construction of Experimental Dataset

To evaluate engineering management education quality comprehensively, data from 1,200 students across five colleges in different regions (east, middle, west, south, and north) and levels (key comprehensive universities, specialty colleges, and ordinary undergraduate colleges) were collected. Data included student grades, classroom performance records, and practical project results. After data screening, the dataset was divided into a training set (840 students) and a test set (360 students) in a 7:3 ratio [7].

3.2 Experimental Environment and Parameters

The experiment was conducted in Python, using libraries like Scikit-learn and TensorFlow. The hardware included an Intel Core i9-12900K processor, 64GB DDR5 memory, a 2TB NVMe SSD, and an NVIDIA GeForce RTX 3090 GPU. Software versions were Python 3.9.7, Scikit-learn 1.0.2, and TensorFlow 2.8.0 [8].

3.3 Comparative Experiment Design

3.3.1 Comparison of Traditional Methods.

The traditional weighted average method was used for comparison. It assigns fixed weights to evaluation indicators, with advantages of simplicity but inflexibility. The DWAEA algorithm and this method were compared on the same dataset using accuracy, recall, and F1 value as indicators.

3.3.2 Comparison of Intelligent Algorithms.

The BP neural network and random forest algorithms were chosen for comparison. BP neural network has strong nonlinear mapping ability, while random forest improves performance by combining multiple decision trees. For BP neural network, the hidden layer nodes were set to 20, learning rate to 0.01, and training rounds to 200. For random forest, the number of decision trees was set to 150 [9].

3.4 Experimental Results Analysis

Figure 1 shows the accuracy curves of different algorithms under different training rounds. The horizontal axis is the number of training rounds, and the vertical axis is the accuracy. As can be seen from the figure, the accuracy of the DWAEA algorithm improves rapidly in the early stage of training, and reaches a high accuracy after a small number of training rounds.

Figure 2 shows the changes in recall rates of different algorithms under different data scales. The horizontal axis is the data scale, and the vertical axis is the recall rate. As the data scale increases, the recall rate of the DWAEA algorithm remains at a high level

and shows a stable growth trend. The recall rates of other comparison algorithms grow more slowly, and even fluctuate after the data scale reaches a certain level.

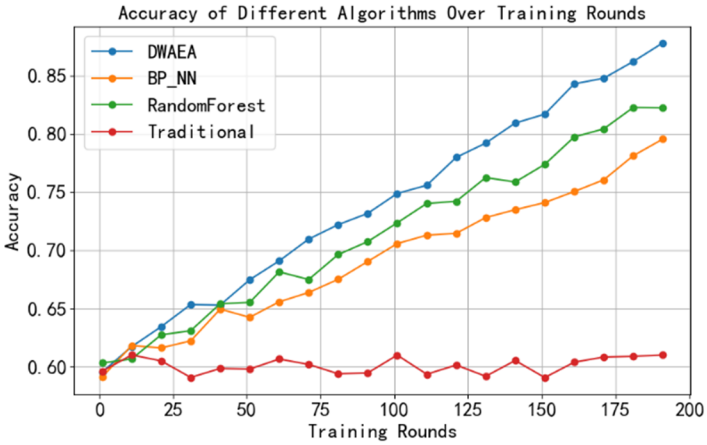

Fig. 1. Accuracy curves of different algorithms under different training rounds

Fig. 2. Changes in recall rates of different algorithms under different data scales

Figure 3 shows the adjustment curves of dynamic weights under different data scenarios. The horizontal axis is the change in data scenarios, and the vertical axis is the weight value. It can be seen that the dynamic weights of the DWAEA algorithm can be adjusted in time according to the changes in data scenarios.

Figure 4 shows the changes in the error rate of evaluation results of different algorithms when the weight adjustment amplitude changes. The error rate of the DWAEA algorithm shows a clear downward trend as the weight adjustment amplitude increases, and tends to stabilize after the adjustment amplitude reaches a certain level.

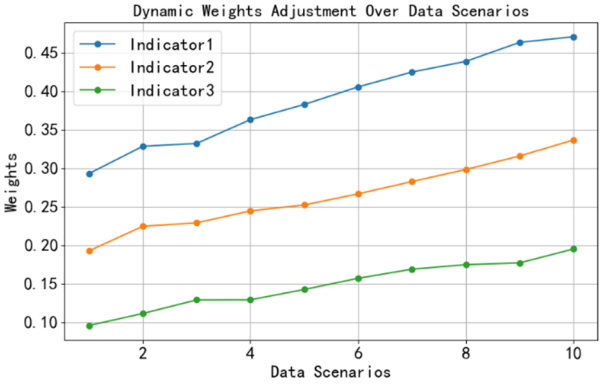

Fig. 3. Adjustment curve of dynamic weights in different data scenarios

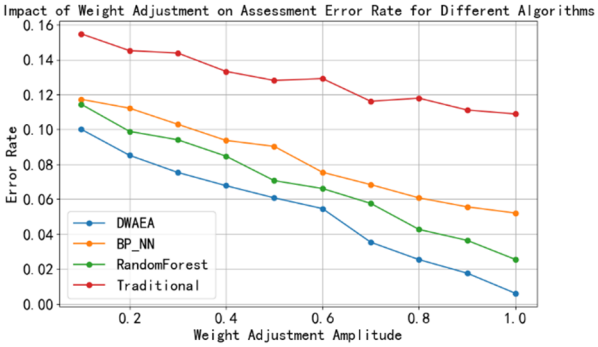

Fig. 4. Changes in the error rate of evaluation results of different algorithms when the weight adjustment range changes

4 Conclusion

This study successfully designed and verified the dynamic weight adaptive evaluation algorithm (DWAEA) and its supporting education quality feedback mechanism. By constructing an experimental data set containing multi-source data, simulation experiments have proved that the DWAEA algorithm is superior to traditional and common intelligent evaluation algorithms in core indicators such as accuracy and recall rate, and its dynamic weight adjustment mechanism can effectively respond to changes in engineering management education scenarios. Actual case applications show that the algorithm and feedback mechanism significantly improve key indicators such as student grades and course satisfaction.

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