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Research on the Construction of Higher Education Ecosystem Model under the Empowerment Development Strategy of Higher Education

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Abstract: The construction of a higher education ecosystem model is a crucial research direction for enhancing the quality and management efficiency of higher education. Based on the empowerment development strategy of higher education, this study adopts graph neural networks (GNNs) combined with genetic algorithms (GAs) for system modeling and optimization. A complex dynamic system model encompassing multiple elements such as teachers, students, courses, and teaching resources is constructed. Experimental results demonstrate that GA-GNN exhibits outstanding performance across multiple key indicators. In the robustness analysis, the performance score of GA-GNN gradually increases from an initial 0.509 to 0.891 after 800 iterations, showcasing a consistent and stable improvement trend. In terms of generalization ability, GA-GNN achieves a score of 0.895 on the university performance dataset and 0.942 in the direction of curriculum design improvement, indicating its broad adaptability across different datasets and application scenarios. Furthermore, GA-GNN also performs exceptionally well in convergence, with an initial convergence score of 0.440 and reaching 0.950 after 800 iterations, far surpassing the performance of other algorithms.In summary, GA-GNN demonstrates wide applicability and excellent performance in higher education management, possessing efficient modeling capabilities and application value within the complex and dynamic higher education ecosystem.

Keywords: empowerment development in higher education; higher education ecosystem; genetic algorithm; dynamic system model; teaching quality optimization

Introduction:

With the continuous development of higher education, empowering the higher education ecosystem has emerged as a crucial strategic direction for enhancing educational quality and optimizing resource allocation. In recent years, fueled by rapid advancements in information technology, the modeling and optimization of educational ecosystems have become a hot topic in educational research. Traditional approaches to educational management have struggled to cope with the demands of multi-variable, multi-layered complex systems, necessitating the intelligent modeling and optimization of educational ecosystems [1-3]. Currently, modeling and optimization methods for higher education ecosystems primarily focus on data analysis and the application of machine learning techniques. However, traditional statistical methods and machine learning models exhibit significant limitations when dealing with complex systems characterized by nonlinearity and multi-variable interactions. While methods such as regression analysis, random forests, and support vector machines can capture individual characteristics and local relationships within the educational ecosystem to some extent, they struggle to effectively address the construction of multi-layered, complexly interacting system models. Furthermore, existing research often focuses on the analysis of single elements or local relationships, lacking a description of the system's overall dynamic changes, particularly in capturing the complex relationships between nodes and the evolution of system states over time. These issues lead to a lack of globality and dynamics in modeling higher education ecosystems, which fails to fully meet the needs of empowerment development in higher education [4-6].Graph neural networks (GNNs), as a type of deep learning model suitable for non-Euclidean spatial data, have emerged as a significant method for modeling educational ecosystems due to their ability to effectively capture complex relationships between nodes. By iteratively updating node features on a graph structure, GNNs enable efficient information propagation and aggregation in unstructured data, making them well-suited to tackle the complexities of multi-layered, multi-variable interactions in higher education ecosystems [7-9]. However, the performance of GNNs is highly dependent on the model architecture and hyperparameter configuration, posing a critical challenge in optimizing these parameters to enhance model performance across diverse educational scenarios. Therefore, the integration of genetic algorithms with graph neural networks aims to deeply mine hidden patterns within the system, providing scientific decision support and improvement directions for the development of higher education.

1. Construction of the Model for the Higher Education Ecosystem

The higher education ecosystem is a sophisticated and dynamic system that encompasses various participating elements and intricate interrelationships. The pivotal variables within this system primarily consist of teachers (T), students (S), courses (C), teaching resources (R), and evaluation feedback (F). These variables intertwine through multiple interactive relationships to form a complex network, where, for example, students' learning performance is influenced by the quality of courses and the teaching proficiency of teachers, teachers' instructional content and methods are constrained by course syllabuses and teaching resources, and the overall evaluation feedback of the system, in turn, shapes future teaching improvements. To address this, a directed graph $G=(V,E)$ is utilized to describe this ecosystem, where V represents the node set, embodying all participating elements within the system, and E denotes the edge set, signifying the interactive relationships between these elements. Each node $v \in V$ possesses a corresponding feature vector X_v , while an edge $e_{i,j} \in E$ signifies the interactive relationship from node i to node j , accompanied by a weight w_{ij} that quantifies the strength of this interaction. Furthermore, the higher education ecosystem can be conceptualized as a state-space model, where the system state is defined as a vector $X(t)$, with each component representing the state of a node (e.g., teacher, student) within the system at time t . The evolution of the system state over time is articulated by the following state equation.

$$X(t+1) = f(X(t),U(t)) + e(t) \quad (1)$$

Herein, f represents the state transition function of the system, $U(t)$ denotes the external input vector (e.g., policy changes or resource inputs), and $e(t)$ signifies the noise term, which captures unpredictable disturbances within the system. The state transition function f relies on the interactive relationships between nodes and can be further modeled using graph convolutional operations, as demonstrated in Equation (2).

$$X` = \sigma(AXW) \quad (2)$$

In Equation (2), $X`$ represents the updated node feature matrix, A denotes the adjacency matrix, which signifies the relationships between nodes, W is the weight matrix, indicating the degree of influence between nodes, and σ is the activation function, introduced to incorporate nonlinearity.

The optimization goal of the system is to enhance the overall health of the educational ecosystem, which can be achieved by maximizing or minimizing certain objective functions. An objective function L can be defined as the evaluation metric of the system, comprehensively considering factors such as student performance, teacher evaluations, and course quality, as shown in Equation (3).

$$L = \alpha_1 \cdot F_S + \alpha_2 \cdot F_T + \alpha_3 \cdot F_C$$

Where F_S is the comprehensive score of student performance, F_T is the score of teacher evaluations, F_C is the score of course quality, and α represents the weighting coefficients, reflecting the importance of each factor. The optimization problem can be formalized as Equation (4).

$$\min_{W,X} L(X,W) \quad (4)$$

The constraints encompass data integrity, system stability, and resource limitations, among others.

Graph Neural Networks (GNNs), as a deep learning model tailored for non-Euclidean spatial data, can effectively capture complex relationships between nodes. By iteratively updating node features over the graph structure, GNNs facilitate efficient information propagation and aggregation. They are well-suited for modeling the multi-layered and complex interactive structures within the higher education ecosystem, reflecting the dynamic relationships among various elements within the system through continuous updates of node states. The working principle of GNNs involves each node updating based on its own features and those of its neighboring nodes, with the core idea being the aggregation of information through graph convolutional operations. This approach captures local structural information while transmitting global information, making it an ideal choice for modeling educational ecosystems [10-11]. The GNN model architecture primarily comprises three parts: the input layer, the graph convolutional layer, and the output layer. The input layer is responsible for receiving the initial feature vectors X_v and edge features W_{ij} of each node in the system. These features can encompass factors such as teachers' teaching proficiency, course difficulty levels, and students' learning abilities. The adjacency matrix A defines the connectivity between nodes.

$$H^{(0)} = X \quad (5)$$

Where $H^{(0)}$ denotes the initial feature matrix. The graph convolutional layer serves as the heart of GNNs, updating node features layer by layer through information aggregation and update formulas. The aggregation process involves a weighted average of neighbor node features followed by a nonlinear activation, as exemplified in Equation (6).

$$H^{(l+1)} = \sigma(D^{-1/2}AD^{-1/2}H^{(l)}W^{(l)}) \quad (6)$$

Where D is the degree matrix, $H^{(l)}$ represents the node feature matrix at the l -th layer, $W^{(l)}$ is the weight matrix for that layer, and σ is the activation function. This process iterates continuously, fusing information from neighboring nodes layer by layer. The output layer generates system state predictions or optimization decisions based on the final node feature vector $H^{(L)}$. The structure of the output layer depends on the specific task requirements, producing numerical outputs for regression tasks or probability distributions for classification problems.

Genetic Algorithm (GA), as a global optimization algorithm that mimics the biological evolution process, is widely used in solving complex problems, particularly in optimization scenarios involving multiple variables, nonlinearity, and multimodalities. GA simulates the natural selection process through operations such as selection, crossover, and mutation, continuously optimizing individuals within the population to gradually approach the optimal solution to the problem. In the modeling and optimization of higher education ecosystems, research has explored the use of Graph Neural Networks (GNNs) to simulate the complex relational structures within the system. However, the performance of GNNs depends on the configuration of multiple critical hyperparameters, including the number of layers in the network, the number of nodes per layer, the learning rate, etc. The choice of these parameters significantly impacts the model's accuracy, convergence speed, and other aspects. Genetic Algorithm, through its evolutionary optimization strategy, automatically tunes these parameters to search for the optimal GNN structure, thereby enhancing the performance of the higher education ecosystem model. In optimizing GNNs, the objective of GA is to adjust the hyperparameters to minimize the system's loss function L or maximize the system's fitness function F. The optimization problem can be formulated as Equation (7).

$$\max_{g} F(g) = -L(\theta(g)) \quad (7)$$

Where $\theta(g)$ represents the parameter configuration of the GNN, which is determined by the individual encoding g. To optimize the architecture and hyperparameters of the GNN, they need to be encoded into a form that can be processed by the Genetic Algorithm. The fitness function is utilized to evaluate the quality of an individual, reflecting the performance of the GNN under the current configuration. The fitness function can be defined in terms of the model's accuracy, loss function value, or other metrics. For optimizing the higher education ecosystem model, the research selects a specific form of the fitness function as defined in Equation (8).

$$F(g) = -\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Where y_i represents the true output, $\hat{y}_i$ denotes the predicted output, and N is the number of samples. Consequently, in the Genetic Algorithm-based optimization of the GNN model, an initial population is first generated, with each individual representing a configuration of the GNN architecture. The population size is set to P, and individuals are generated through random initialization of parameters, as exemplified in Equation (9).

$$Population = \{g_1, g_2, g_3, \square, g_P\} \quad (9)$$

Subsequently, for each individual g_i, a GNN model is constructed and trained, and the fitness value $F(g_i)$ is calculated based on the test set data. The fitness proportionate selection method is then employed to select parental individuals from the population, with the selection probability p_i computed as per Equation (10).

$$p_i = \frac{F(g_i)}{\sum_{j=1}^{P} F(g_j)} \quad (10)$$

The selection operation ensures that superior individuals have a higher chance of reproducing offspring. The crossover operation performs genetic recombination on the selected parents to generate new offspring. Following this, minor adjustments are made to the parameters of the new individuals. The mutation operation further increases the diversity of the population by fine-tuning the parameters of individuals. However, the optimization effectiveness of the Genetic Algorithm is influenced by parameter settings, with key parameters including the crossover rate, mutation rate, and selection strategy. The crossover rate is set to $0.7 \le p_c \le 0.9$, and the mutation rate is set to $0.01 \le p_m \le 0.1$. yy adjusting these parameters, the performance of the Genetic Algorithm in searching for the optimal GNN architecture is optimized, with the values determined as 0.8 and 0.05, respectively.

2. Experimental Analysis

2.1 Experimental Setup

To validate the effectiveness of the Graph Neural Network optimized by the Genetic Algorithm in the modeling of higher education ecosystems, the experimental setup employed a hardware environment comprising an Intel processor released in 2019 and a high-performance GPU, ensuring efficient model training and reliable results. The dataset was sourced from a comprehensive university's teaching management system, encompassing multi-dimensional data such as student grades, teacher evaluations, course resources, and spanning multiple semesters from 2021 to 2023. The dataset is segmented into University Performance Data (UPD), Educational Resource Utilization Data (ERUD), and Student Engagement and Feedback Data (SEFD). The data underwent preprocessing to ensure its integrity and consistency. The software environment for the experiment was built on a Linux operating system, using Python as the programming language. The core algorithms were implemented with the PyTorch deep learning framework, and the Scikit-learn library was integrated for data processing and model evaluation. The hardware and software configurations are summarized in Table 1.

Table.1 Software and hardware configurations

Environment type	Detailed configuration
processor	Intel Core i9-9900K

GPU	NVIDIA GeForce RTX 2080 Ti (11GB)
Internal memory	32 GB DDR4 RAM
store	1 TB SSD
Operating system	Ubuntu 18.04 LTS
Programming language	Python 3.7
Deep learning framework	PyTorch 1.3.1
Data processing library	Scikit-learn 0.21.3
Archive	MySQL 5.7

2.2 Analysis of Algorithm Effectiveness and Robustness

In the modeling and optimization process of higher education ecosystems, algorithm robustness serves as a crucial metric for evaluating model performance. To validate the performance of the proposed GA-GNN algorithm across different iterations, the experiment compares it with other classical algorithms, including Random Forest, Support Vector Machine, K-Nearest Neighbors, and Decision Trees. Through a comparative analysis of performance scores, the focus is on assessing the advantages of GA-GNN in complex system optimization, particularly its outstanding performance in multi-variable interactions and dynamic adaptation. The robustness comparison of the GA-GNN model is illustrated in Figure 1.

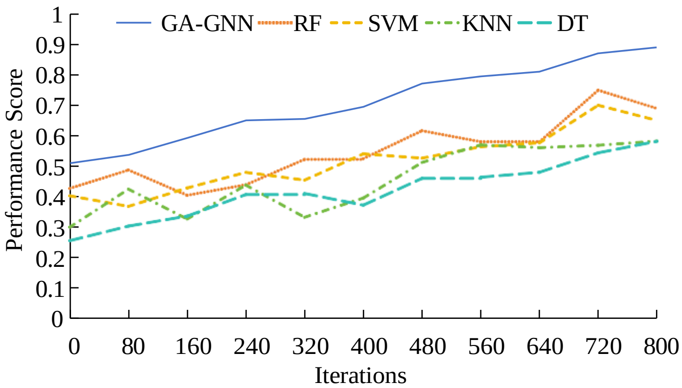
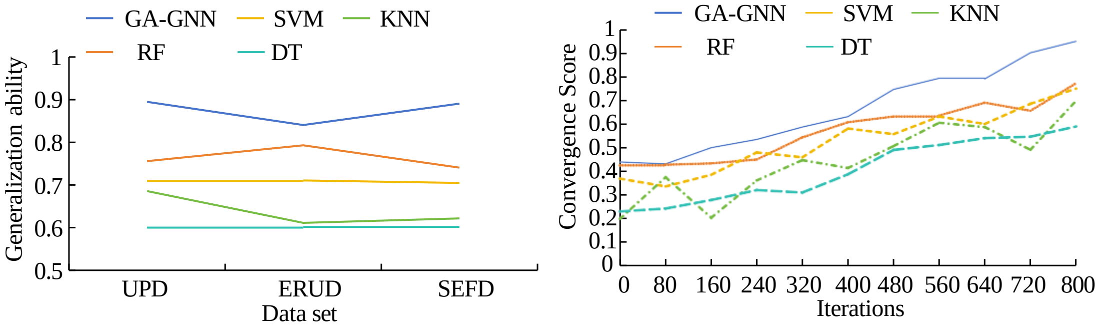


Fig.1 Comparison of robustness of different algorithms

As evident from the data in Figure 1, GA-GNN demonstrates remarkable superiority across various iteration counts, with its performance score gradually increasing from an initial 0.509 to 0.891 at 800 iterations, showcasing a consistent and stable upward trend. In contrast, the performances of other algorithms exhibit slight fluctuations and lesser improvement margins. Random Forest lags significantly behind GA-GNN in early iterations, peaking at 0.748 after 720 iterations but failing to maintain sustained growth. SVM exhibits significant fluctuations in its early performance and a relatively slow rate of improvement, ultimately reaching only 0.649 at 800 iterations, indicating inadequate adaptability to system dynamics. KNN displays marked instability throughout the iterations, with notable declines at 240 and 400 iterations, ending at 0.582 at 800 iterations, suggesting its limitations in handling complex multivariable relationships. DT shows the flattest overall performance, starting with a low initial performance and ending with only a slight improvement to 0.581, failing to demonstrate significant advantages. It is clear that the advantage of GA-GNN lies in its ability to more stably optimize system states in each iteration, reflecting greater robustness and adaptability in modeling higher education ecosystems, particularly those with multivariable and complex relationships, where it exhibits significant advantages.



(a) Comparison of generalization ability (b) Convergence contrast

Fig.2 Comparison of generalization ability and convergence performance

As shown in Figure 2(a), for the generalization capability analysis and comparison, GA-GNN significantly outperforms other benchmark algorithms across the three datasets, demonstrating strong generalization ability. On the University Performance Data (UPD), GA-GNN achieves a performance score of 0.895, far exceeding RF's 0.756, SVM's 0.709, KNN's 0.686, and DT's 0.600, indicating a clear advantage in learning from student performance and teacher evaluation data. In the Educational Resource Utilization Data (ERUD) test, GA-GNN's performance slightly drops to 0.841 but still maintains the highest score, exhibiting better stability compared to RF's 0.793 and SVM's 0.711, while KNN and DT decline to 0.611 and 0.602, respectively, indicating weaker adaptability to resource utilization data. For the Student Engagement and Feedback Data (SEFD), GA-GNN scores 0.891, significantly higher than RF's 0.741 and SVM's 0.705, showcasing its good learning effect and adaptability in processing student behavior and feedback data. Overall, GA-GNN's high scores and stable performance across all datasets prove its robust adaptability and consistency in handling diverse educational data, demonstrating its superior generalization capability in multi-faceted teaching scenarios.From Figure 2(b)'s comparison of convergence performance, GA-GNN exhibits notable convergence advantages at various iteration counts. At the initial iteration, GA-GNN's convergence score is 0.440, slightly higher than RF's 0.426, SVM's 0.370, and KNN's 0.200. When the iteration count reaches 400, GA-GNN's score improves to 0.632, indicating a faster performance enhancement rate. In later iterations, GA-GNN's convergence score rises to 0.794, while RF and SVM score 0.637 and 0.632, respectively. Although both show decent convergence to a certain extent, they consistently fail to match GA-GNN's level. At 800 iterations, GA-GNN achieves 0.950, far surpassing RF's 0.773 and SVM's 0.750. Overall, GA-GNN not only achieves rapid improvement in the early stages but also maintains sustained performance advantages in the later stages, exhibiting excellent convergence characteristics.

After implementing GA-CNN in practical applications, a questionnaire survey was conducted and scored on a 10-point scale, where a higher score indicates better performance. The scoring results are presented in Table 2. It can be observed that GA-GNN achieved the highest score of 0.947 in the direction of personalized learning. For course design, it scored 0.942. In comparison, the score for student performance prediction was slightly lower at 0.879, but still demonstrated a high level of application effectiveness. Other directions such as resource optimization and teaching effect evaluation received scores of 0.894 and 0.890, respectively, reflecting the broad applicability and outstanding performance of GA-GNN in these application scenarios.

Table.2 Score results of different application directions

Application direction	Score
Personalized Learning	0.946632
Resource Optimization	0.894306
Student Performance Prediction	0.879092
Teaching Effectiveness Evaluation	0.889832
Curriculum Design Improvement	0.942427

3. Conclusion

To enhance the health of university education ecosystems, a study was conducted to develop a dynamic model based on Graph Neural Networks (GNNs) and Genetic Algorithms (GAs). Experimental results demonstrate the superiority of GA-GNN across multiple dimensions. In the robustness analysis, GA-GNN's performance score gradually rose from an initial 0.509 to 0.891 at 800 iterations, significantly outperforming traditional algorithms such as Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Decision Tree (DT). Furthermore, GA-GNN excelled in convergence performance, ultimately achieving a convergence score of 0.950, far surpassing other comparative algorithms, showcasing rapid improvement and sustained optimization capabilities.In terms of generalization ability, GA-GNN outperformed other algorithms on all three datasets, particularly scoring 0.895 on the University Performance Data (UPD), indicating its adaptability and consistency across diverse educational data. In the practical application direction scoring, GA-GNN surpassed 0.89 in areas such as personalized learning, course design improvement, and resource optimization, with a particularly impressive score of 0.947 in personalized learning, demonstrating its widespread applicability in various educational scenarios.A limitation of the study is the high computational complexity of the model when dealing with large-scale graph data, necessitating further research into distributed computation methods to enhance efficiency. Overall, this research, by constructing a GA-GNN-based model for university education ecosystems, provides an effective tool for optimizing the dynamic relationships among various elements of the education system, offering a reference for the intelligent and personalized development of future university education ecosystems.

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