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Portrait Technology in Campus Recruitment

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Abstract: A significant limitation in campus recruitment lies in recruiters' inability to swiftly and accurately assess students' comprehensive qualities, leading to challenges such as low signing success rates, talent misjudgments, and suboptimal post-placement decisions. Traditional statistical approaches, which rely on small sample sizes, struggle to address these complexities effectively. This study proposes an intelligent solution leveraging artificial intelligence (AI) and big data technologies to optimize campus recruitment processes. By integrating clustering algorithms and neural networks, the research focuses on labeling student behavior data to establish a dual evaluation system that combines subjective and objective criteria. This framework enables the creation of detailed talent portraits tailored to campus recruitment scenarios, which synthesize academic performance, behavioral patterns, and soft skills into actionable insights. The results demonstrate that talent portrait technology mitigates existing inefficiencies by providing recruiters with data-driven tools to improve candidate evaluation, role alignment, and hiring outcomes. This approach offers a scalable and precise methodology to enhance recruitment accuracy while reducing human bias.

Keywords: practice campus recruitment, talent portrait, fuzzy c-means, general regression neural network

1. Introduction

The 21st century is an era of artificial intelligence (AI); in the process of enterprise development, machine learning [1], natural language processing [2], big data [3], and other technologies have been widely used in enterprise human resource management. Campus recruitment is an important part of enterprise human resources management. How to make campus recruitment intelligent and adapt to the development of The Times plays an important role in the sustainable development of enterprises and the improvement of economic benefits.

Based on AI and data mining technology, this paper takes the behavior data generated by the digital management system of colleges and universities as the core and constructs the "talent portrait" evaluation model suitable for the campus recruitment scene of enterprises. Using intelligent means to solve the enterprise HR personnel cannot quickly and accurately evaluate the comprehensive quality of students in the process of campus recruitment, resulting in the low success rate of signing, talent misjudgment, unreasonable post arrangement after successful signing, and other problems [4].

2. Related Work

The concept of user portrait was proposed by the software inventor Alan Cooper [5]. The concept has been widely used in business, finance, medical care, media, and many other fields [6]. With the advancement of digital construction in colleges and universities in recent years, the data accumulated by student behavior in the campus information system are also growing rapidly, and the application environment of campus big data is becoming increasingly mature. The research on the application of portrait technology based on big data in university management is also gradually increasing, mainly around scholarship evaluation [7], ideological management [8], personalized book recommendation [9], individualized learning [10], and other fields.

However, there are few studies on the application of portrait-based technology in campus recruitment, mainly using some small sample data analysis technology based on traditional statistics. For example, Chen [11] helped students find their vocational interests through the Holland Vocational Preference Inventory (VPI) scale and self-rating depression scale (SDS) scale based on Holland's vocational interest theory. Du [12] used education, psychological measurement, multivariate statistics, and other methods to quantitatively analyze the two-way accurate matching of talent supply and demand. Yang [13] used the dynamic decision tree algorithm model to analyze the behavior of graduates and provide the guidance for students' employment. The ability of traditional statistics in obtaining and processing massive data from multiple sources has gradually become difficult to apply and the practical effect is not good. Therefore, how to design and realize the portrait based on data-driven ideas and the application of AI technology, combined with management and other related disciplines, is an effective way to solve the existing problems in campus recruitment and the direction of research and development.

3. Talent Portrait Construction Method

3.1. Construction idea

In this paper, the method of data-driven portrait is adopted. First, the whole data of students in school are pre-processed, and then the data model is established by statistical analysis, machine learning, and other algorithms, and the labeled expression is obtained, and the "talent portrait" is finally formed. In order to give

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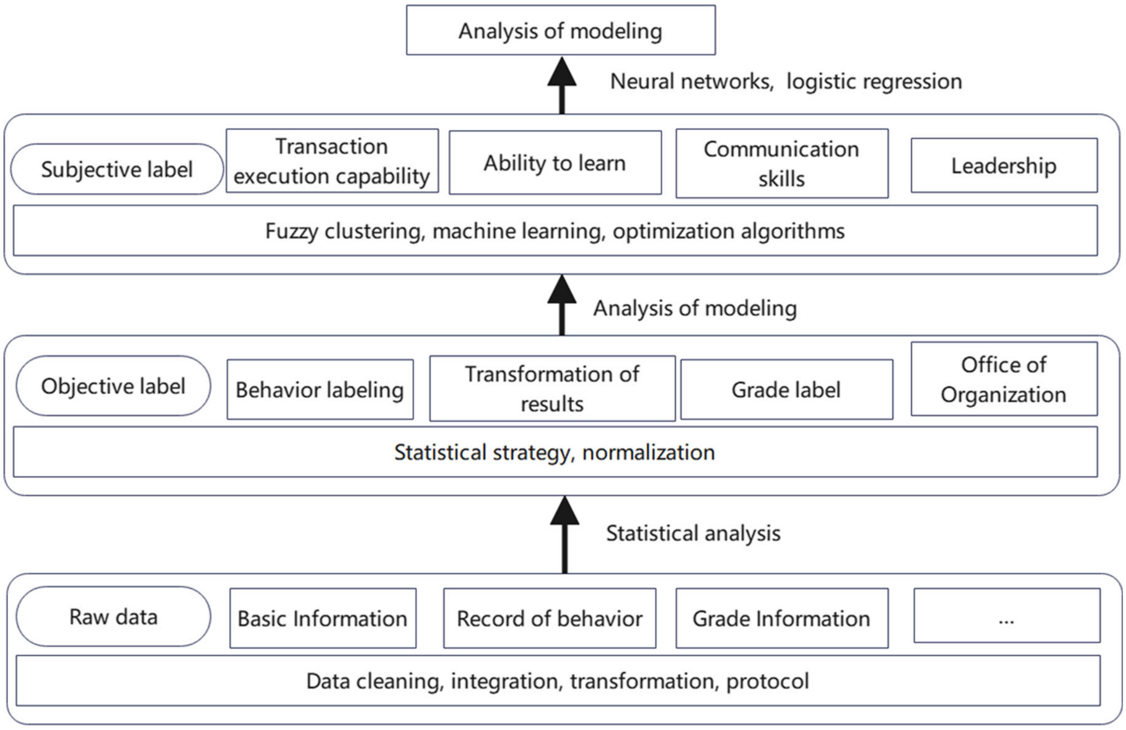
Figure 1
Talent portrait modeling knowledge map



enterprises a comprehensive understanding of the candidates, the researchers divided the labels into objective and subjective categories. Objective labels mainly include labels such as behavior, achievement transformation, organization and community, and achievement. This kind of label corresponds to real data, which can be realized by data pre-processing and simple statistics. In this paper, the subjective labels are set as the executive ability, learning ability, leadership ability, and communication ability that enterprises are more concerned about, which are the evaluation of students' ability in a certain aspect and are highly general. Subjective labels require further modeling and analysis of objective labels to obtain subjective labels [14]. The specific portrait modeling idea is shown in Figure 1.

3.2. Data acquisition

The data source of this paper is the campus digitization system. In this paper, the data on student behavior in the school register, educational administration, scientific research, and student system are directly exported from the database to obtain the data of each system.

3.3. Data pre-processing

Due to the different production teams of each subsystem in the digital system, the databases are independent of each other, and the data are seriously heterogeneous. Therefore, the data collected in the system need to be pre-processed to improve the quality of data to meet the needs of modeling. The specific data pre-processing flow chart is shown in Figure 2.

3.4. Objective label

The basic information label, achievement label, achievement label, and community organization label are selected as the objective labels of the talent portrait. Most of the objective labels can be obtained through data pre-processing, such as students' scholarship records, competition records, and paper records in achievement labels. Some objective labels need simple statistical analysis, such as grade ranking and average grade in grade labels.

3.5. Subjective label

In addition to determining the objective labels of students, talent portraits also need to obtain subjective labels that can be intuitively understood by recruiters. This paper will give a label rating method for the subjective label, which will rate the learning ability, transaction execution ability, communication ability, and leadership in the subjective label. These four abilities can well summarize a student's comprehensive ability, so as to more intuitively reflect the comprehensive quality of students. The subjective label rating algorithm model consists of two parts: subjective label range determination and subjective label prediction. The determination of the range of subjective labels is based on the cluster analysis of the 4-year data of students to obtain the classification standard of subjective labels. However, the subjective label prediction is to predict the subjective label value of the new student sample.

3.5.1. Input index of label generation algorithm

This paper needs to give important indicators of subjective label rating as input for clustering. According to the research

Figure 2
Flow chart of data pre-processing

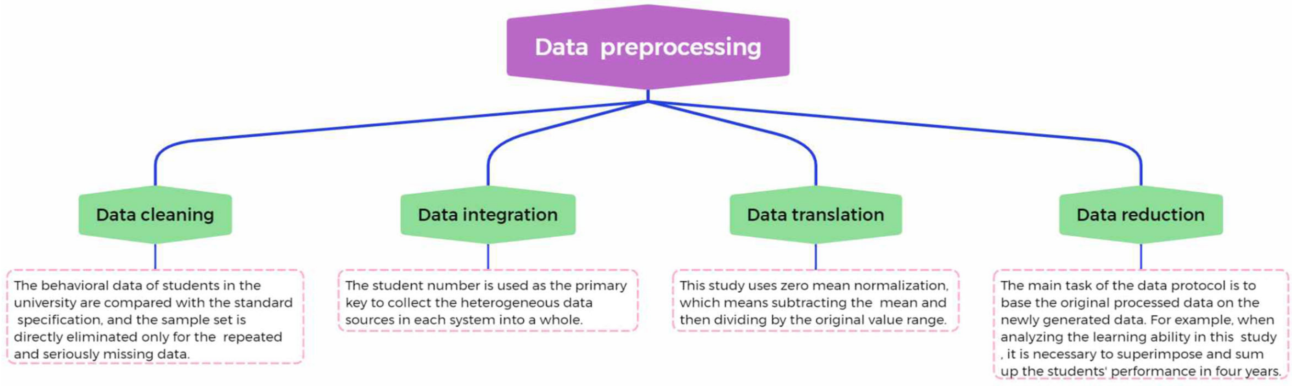


Table 1
Meaning of indicators in RFM

Rating label	R	F	M
Ability to learn	Last year grade label average percentage	Average percentage of 4-year college grade tags	The total number of achievements is the basis in the achievement transformation label
Transaction execution force	Total number of behavior tags in the last year	Total number of behavioral labels in 4 years of college	Total number of achievement transformation labels
Communication skills	Total number of behavior tags tagged for the team in the last year	Total number of college years labeled as team behavior tags	Mark as a team
Leadership	In the behavior label and organization and community label of the last year, the position is the total duration of the person in charge (unit: month)	In the behavior label and organization association label of 4 years in college, the position is the total duration of the person in charge (unit: month)	Total number of deliverable marked as teams with the title of leader

results of literature [15] on the RFM model in measuring customer value and customer profitability, as well as its application value in many customer relationship management models, the input indicators are selected with reference to the RFM model, where R is the closeness, representing the behavior status of the students in the recent period; F is the frequency, representing the comprehensive behavior status of the students in tp indicators in learning ability, leadership ability, transaction execution ability, and communication ability, which are shown in Table 1.

From Table 1, the various input indicators for label generation through cluster analysis can be obtained. Before data entry, data transformation, that is, data normalization, needs to be performed. This paper takes transaction execution as an example to demonstrate, and other indicators will not be described here.

In the context of transaction execution force, the behavior label count fields P_Count_2017, P_Count_2018, P_Count_2019, P_Count_2020, and the result transformation label count fields A_Count_2017, A_Count_2018, A_Count_2019, A_Count_2020 were selected from the constructed label database in this research. Then

R = P_Count_2020
F = P_Count_2017 + P_Count_2018 + P_Count_2019 + P_Count_2020
M = A_Count_2017 + A_Count_2018 + A_Count_2019 + A_Count_2020

The above data are cleaned and pre-processed, which can be directly normalized. After zero-mean normalization, the mean of the data is 0 and the standard deviation is 1, and the equation is as follows:

$$x^* = \frac{x - \mu}{\sigma} \tag{1}$$

where μ represents the average value of the sample data, and σ represents the standard deviation of the sample data. Some normalized data are shown in Table 2.

3.5.2. The range of subjective labels is determined

In this paper, fuzzy c-means (FCM) algorithm is used to realize the clustering of subjective labels [16]. The performance of FCM algorithm depends on the selection of the initialized cluster center. A good initialized cluster center can get a better solution, while a poor initialized cluster center will lead to the local optimal solution. In this paper, the density method [17] is used to select the initial clustering center. This process does not require a lot of complex operations to obtain relatively reasonable initial clustering centers.

Although a reasonable initialization of the clustering center can reduce the fluctuation of the clustering results, the FCM algorithm is still easy to fall into the local optimal solution. In order to avoid FCM algorithm falling into local optimal solution, researchers combined FCM algorithm, simulated annealing (SA) algorithm [18], and

Table 2
Part of the sample normalizes the data

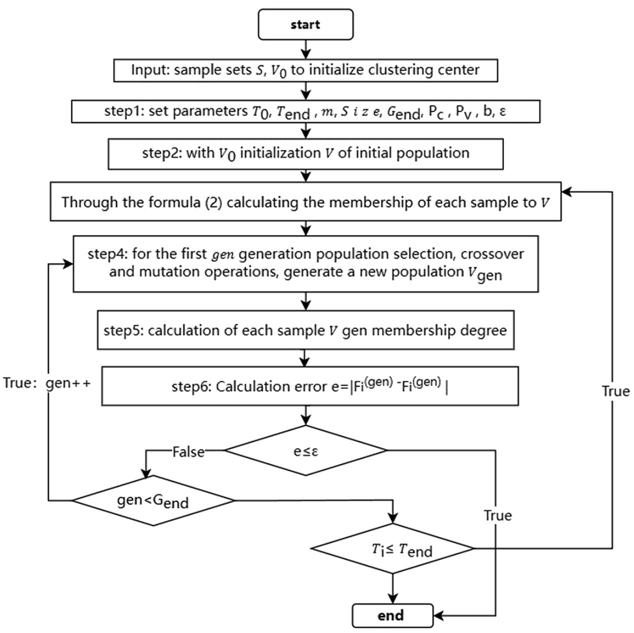
Sample serial number	ZR	ZF	ZM
1	1.18711	2.301231	4.875612
2	1.18711	2.301231	4.415709
3	1.18711	2.301231	4.121810
4	1.18711	2.301231	4.121810
5	0.32112	1.209123	3.172381
6	1.18711	1.209123	4.415709
7	1.18711	2.301231	2.623171
8	1.18711	2.301231	3.108294
9	1.18711	1.209123	2.1263114

genetic algorithm (GA) [19] to design the FCM-SAGA algorithm. The improved FCM algorithm can effectively converge at the global optimal solution and obtain a reasonable cluster center. The algorithm flow is shown in Figure 3. Among them, SAGA algorithm takes GA as the main body, performs annealing operation only for the chromosomes in the population, and then uses Metropolis criterion to continuously adjust the old and new chromosomes, so as to reduce the probability of premature occurrence. The number of cluster centers C is selected by comparing the size of the objective function for each experiment, and the one with the smallest objective function value is the best experimental setting.

The formula for calculating the membership degree of sample x_i to category A_i in the FCM algorithm is defined as follows:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \frac{d_{ik}^{\frac{2}{b-1}}}{d_{jk}}} (1 \neq k) \tag{2}$$

Figure 3
Flow chart of range determination algorithm for subjective labels. Where SA parts: initial annealing temperature T_0, the termination of annealing temperature T_{end}, cooling coefficient m; GA parts: population size $Size$, maximum evolution algebra G_{gen}, crossover probability P_c, mutation probability P_v; FCM part: termination iteration error ε, weighting parameter b



where is the ambiguity index $b \in (1, \infty)$ and d_{ik} is the Euclidean distance.

3.5.3 Subjective label prediction

Subjective label prediction is the process of label prediction for new samples, which is carried out on the basis of the result of the range determination of subjective labels. It can be regarded as the classification problem that the range sample of subjective labels is trained. For solving classification problems, naive Bayes model, support vector machine, generalized regression neural network (GRNN), and other algorithms are classical. Combined with the characteristics of uncertainty and relevance of student behavior data in the application scenario of this paper, this paper selects GRNN as the prediction model [20]. GRNN is structurally composed of four layers: input layer, pattern layer, summation layer, and output layer, as shown in Figure 4.

As the core part of GRNN model, pattern layer is composed of radial basis neurons, and its calculation equation is as follows:

$$p_i = \exp\frac{(x - x_i)^{\mathrm{T}}(x - x_i)}{2\sigma^2}, i = 1, 2, \cdots, n \tag{3}$$

where x_i is the learning sample corresponding to the first neuron; σ is the smooth factors, namely the standard deviation of Gaussian function.

In Equation (3), σ is a hyperparameter called the smoothing factor, which corresponds to the standard deviation of the Gaussian function. σ has a significant influence on the model. As σ increases, the model's output becomes more similar to the mean of all sample variables, resulting in a smoother approximation of the sample data by the Generalized Regression Neural Network (GRNN) and stronger generalization ability. Conversely, as σ decreases, the model's output becomes closer to the training samples, leading to weaker generalization ability. To obtain an appropriate smoothing factor, an experimental method can be employed to determine the optimal σ value, although it may be prone to local optima. In order to get good smooth factor, this paper, by using GA algorithm optimization σ value, build the subjective label for prediction of GRNN-GA algorithm and can realize prediction of new samples, specific algorithm process as shown in Figure 5.

Figure 4
Graph of generalized regression network structure

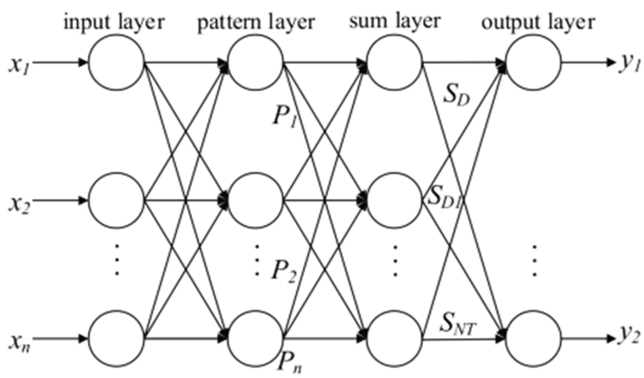
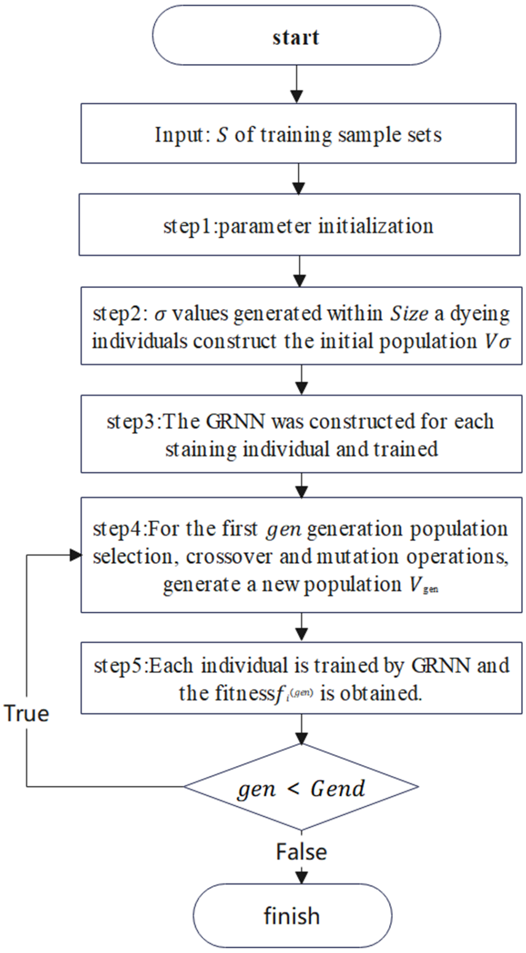


Figure 5
Flow chart of subjective label prediction algorithm



4. Experiment

4.1. Experimental analysis of range determination of subjective labels

4.1.1. Experimental scheme

The data source of the experiment is the behavioral data generated during the period from 2017 to 2020 (specifically for the four majors of computer science and technology, software engineering, network engineering, information management, and information system) provided by a college in Sichuan Province, China.

The FCM-SAGA algorithm model is designed in label generation to perform cluster analysis on student data. The model parameters are set as follows: population size $Size = 20$, maximum evolution number $G_{end} = 80$, crossover probability $P_c = 0.8$, mutation probability $P_v = 0.01$, initial temperature T_0=100, termination temperature T_{end}= 0.5, cooling coefficient $m = 0.9$, termination iteration error of objective function $\varepsilon_0 = 1.0 \sim 6.0$, weighting parameter $b = 2.0$, and cluster center c$\in$ [3, 6]. In order to evaluate the clustering effect of each time, this paper uses compactness (CP) [21] to evaluate the accuracy of FCM-SAGA algorithm, and the compactness equation is as follows:

$$\overline{CP_i} = \frac{1}{|\Omega_i|} \sum_{x_i \in \Omega_i} \|x_i - w_i\| \tag{4}$$

$$\overline{CP} = \frac{1}{K} \sum_{K=1}^{K} \overline{CP_K} \tag{5}$$

where *CP* calculates the average distance between each point in each class and the cluster center, and the smaller the *CP* is, the closer the clustering distance within the class is.

4.1.2. Experimental results and discussion

By using the density method, the relationship between the number of cluster centers and the value of the objective function is shown in Table 3.

As can be seen from Table 3, when clustering center $c = 4$, the objective function value of the minimum is$j_b = 4.0921$. Therefore, the number of cluster centers can be determined to be 4. The corresponding FCM-SAGA clustering results are shown in Table 4.

Table 3
Relation between the number of clustering centers and the value of the objective function

The objective function value j_b	4.5981	4.0921	4.2124	4.6075
The number of cluster centers C	3	4	5	6

For the above clustering results, it can be seen that there are hierarchical differences in students' transaction completion ability, with cluster 1 being the strongest and cluster 4 the weakest. It allows for a clear rating of student achievement. In order to make people better understand, the researchers use "excellent," "good," "average," and "poor" to express the four cluster categories, respectively. For the other three rating labels, the same treatment is applied.

At the same time, the researchers obtained the CP value of the label through three experiments, and the results are shown in Table 5. From the experimental results, it can be seen that the CP value of the clustering results fluctuates less and is very stable, which does not easily fall into the local optimal solution, thus verifying the accuracy of the algorithm.

4.2. Evaluation of subjective label prediction algorithm

4.2.1. Experimental scheme

The cluster result samples obtained by FCM-SAGA are used to train GRNN-GA, so as to predict the new sample data. The researchers divided the experimental data into training set and validation set in a ratio of 4:1. The transaction execution capability is analyzed as an example.

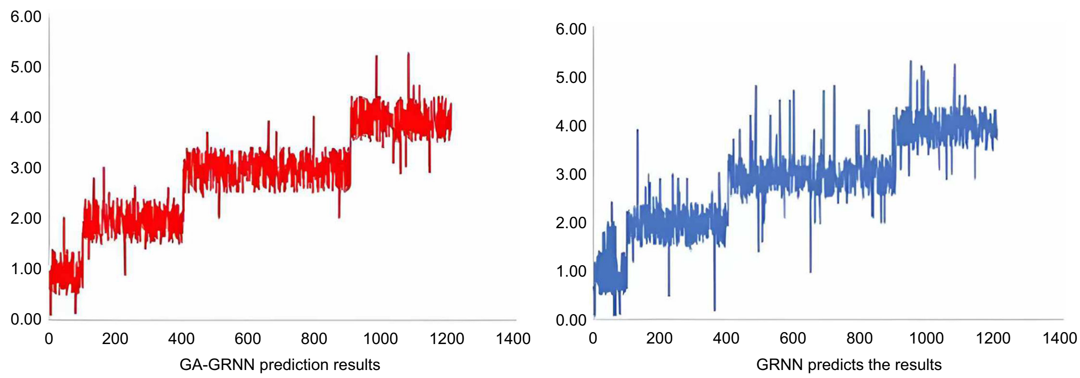
Table 4
Transaction execution capability clustering results

Classification results		Cluster 1	Cluster 2	Cluster 3	Cluster 4
Proportion of samples		9.70%	24.57%	40.87%	24.86%
Center of clustering	R	− 1.101136	− 0.901241	− 0.782318	0.357609
	F	3.810212	2.789971	0.781291	− 0.209781
	M	8.712831	1.832641	− 0.126198	− 0.472112

Table 5
CP values of the results of the FCM-SAGA experiment

	CP value			
Number of experiments	Transaction execution	Communicative competence	Leadership	Ability to learn
1	2.9101	3.8821	2.8791	3.0124
2	2.8991	3.8741	2.8782	3.0122
3	3.0001	3.8797	2.8922	3.0211
Average	2.9364	3.8786	2.8832	3.0152

Figure 6
Comparison diagram of GA-GRNN and GRNN prediction results



Set population size $Size = 20$, maximum evolution algebra $G_{end} = 30$, crossover probability $P_c = 0.8$, the mutation probability $P_v = 0.01$, to adapt to the function for selecting type (5), the scope of σ as [0.05, 1].

$$f = \frac{1}{\sqrt{\sum (y_i - \hat{y}_i)^2}} \tag{6}$$

where y_i represents the true category of the sample and $\hat{y}$ represents the observed value; the larger the error, the smaller the function value and the smaller the fitness value.

4.2.2. Experimental results and discussion

Through experiments, the fitness value of traditional GRNN is 1.18, and that of GRNN-GA is 1.32. It can be seen that GRNN-GA has lower error rate, higher fitness value, and better model prediction effect than traditional GRNN, which greatly reduces the training cost.

Through Figure 6, GRNN-GA by the GA algorithm to select σ, more stable than traditional GRNN prediction results, can achieve better prediction effect.

Figure 7
Generate sample renderings

Student: XXX

	事务执行能力:优秀 Executive ability: Excellent
	学习能力:一般 Learning ability: Average
	交际能力:良好 Communication ability: good
	领导力:良好 Leadership ability: good

1.成果：发表论文 1 篇，参与专利 1 项
1. Achievements: 1 paper published and 1 patent participated

2.竞赛:ACM 区域比赛一等奖,2020/11
2. Competition: First prize of ACM regional competition, 2020/11

3.成绩：成绩排名全年 21 名，平均成绩 88.7
3. Score: Ranked 21st in the year, with an average score of 88.7

4.担任过一年班长，学生会体育部副部长、参加了摄影、营销协会。
4. Served as monitor for one year, vice minister of sports department of student union, and participated in photography and marketing association.

Note: In order to show the real generation effect, Chinese characters are retained in the picture

4.3. Experimental results and discussion

After pre-processing the new student sample data, the label expression of student information is adopted by GRNN-GA algorithm. It constitutes a talent portrait suitable for assessing the comprehensive quality of students and preliminarily screening out unqualified applicants during campus recruitment. The generated example is shown in Figure 7.

5. Conclusion

In this paper, we have presented a method for constructing a "talent portrait" using clustering and neural network algorithms to label and express students' behavior data. This approach addresses the needs of employers, universities, and students in campus recruitment, providing a comprehensive and accurate representation of a student's skills, interests, and experiences. Our results demonstrate the effectiveness of this method in generating a talent portrait that can serve as a valuable tool for employers and universities in identifying and recruiting the most suitable candidates. Further research is needed to explore the potential applications of this approach in other domains and to refine the algorithms used in the construction of the talent portrait.

Recommendations

Talent portraits provide a way for employers to understand a student's overall ability during the recruitment process. The recruiter can quickly complete the comprehensive understanding of the applicant in a very intuitive way, preliminary screen out the unqualified applicant, and preliminary determine the position that the applicant is suitable for, which reduces the consumption of material resources and manpower and saves the cost of recruitment of employers [22]. The portrait provides a way of thinking for colleges and universities to optimize the formulation of talent training plans [23]. Colleges and universities use portraits to divide students into groups and make different plans for different groups to improve students' comprehensive ability, so as to improve the employment rate of schools. Portraits provide a way for students to build self-awareness for the job search process. On the basis of identifying their own positioning and understanding, students should rationally choose the applicant units and positions, increase the success rate of application, reasonably plan their career path, and improve their professional quality [24].

This study also has some shortcomings, such as talent portrait label selection; there is a certain degree of subjectivity, so that the portrait objectivity is insufficient. Data collection is not comprehensive enough, such as the campus card consumption records, campus network access information, and other dynamic data acquisition; these data can reflect the comprehensive quality of students to a certain extent and increase the richness of the portrait. In the follow-up research process, researchers will gradually improve these problems.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Huang Yu: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Cecilia Mercado:** Conceptualization, Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision, Project administration.

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