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RESEARCH ARTICLE

The Employment Management for College Students Based on Deep Learning and Big Data

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ABSTRACT College graduates face increasing employment pressure due to the continuous expansion of colleges and universities' enrollment scales. It highlights the shortcomings of college students' employability, and these deficiencies can be improved and enhanced through the role of ideological and political education. Firstly, this paper summarizes the current situation of college students' employment management at this stage and finds countermeasures to improve their employability to help them correctly understand their employment situation. Secondly, the reasons for the lack of ideological and political education in cultivating college students' employability are emphasized to clarify the relationship between ideological and political education and college students' employment management. Besides, specific suggestions are put forward on the issue of cultivating college students' employability. Finally, the deep learning (DL) recommendation model is used to effectively connect the correlation between student data and enterprise information to improve the employment rate and employment satisfaction of colleges and universities, and the two are jointly trained. The experimental results show that: 1) The proposed model can mine the characteristics of students and enterprises and conduct feature interaction with a good hit rate; 2) The proposed model can interact with the two tasks and mine the relationship information to improve the performance of the recommended task. This paper aims to use DL methods to analyze and construct the portrait of college students' employability needs and study the accurate recommendation system based on the employment matching degree of college students to improve employment management and ideological and political education methods.

INDEX TERMS Employment of college students, employment management, ideological and political education, deep learning, recommendation system.

I. INTRODUCTION

In recent years, the number of fresh graduates from colleges and universities across the country has only increased. In addition, graduates who have not been employed in the past have led to increased employment numbers and increasingly fierce competition for employment. In general, the employment situation of college students is becoming increasingly severe. It can be seen that the employment pressure of fresh graduates will stay relatively high for a rather long time in the future [23]. Ideological and political education can help college students establish a correct world outlook, outlook on life, and values. It allows college students to correctly understand their employment situation and establish a proper concept of employment. It helps students to thoroughly and objectively understand themselves, build self-confidence in employment, and continuously improve their employability [21]. How to give full play to the role of ideological and political education in cultivating college students' employability and find countermeasures to improve college students' employability have become the most critical issue to be solved in the work of ideological and political education.

It is imperative to use recommendation algorithms to achieve accurate employment to reduce the employment pressure on graduates and improve the employment rate. With

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the development of deep learning (DL), some studies have applied DL methods to recommendations [8]. DL architectures have the following advantages. Its overall model is end-to-end derivable and conducive to integrating multiple network structures. For multimodal data, DL frameworks are a good structure. It can incorporate network structures that process text, images, speech, and other data types into the same framework, which is difficult to achieve under other frameworks [17]. Therefore, this paper aims to design a DL recommendation system for employment recommendation that integrates the behavioral characteristics of college college students to provide students with personalized job recommendations and improve the employment rate and satisfaction of graduates.

Based on the above problems, the current college student employment management situation is summarized first, and countermeasures to improve college students' employability are found. Meanwhile, the reasons for lacking ideological and political education in cultivating college students' employability are emphasized. Specific suggestions are put forward on the issue of developing college students' employability. Finally, this paper uses a DL recommendation model to effectively connect the correlation between student data and enterprise information and jointly trains the two to improve colleges and universities' employment rates and satisfaction. It is hoped that the research here can reduce the employment pressure on college graduates and provide a solid and reliable theoretical foundation for future discussion on graduate employment recommendation algorithms and ideological and political education methods.

II. LITERATURE REVIEW

Many research papers and literature are on strengthening college students' ideological and political education on employment. However, there are different research directions at different times, which makes this topic always innovative. Yu discussed the current problems in college employment guidance and the main ways to strengthen the ideological and political education of college students in career guidance, highlighting ideal and belief education, personality education, entrepreneurship education, and psychological quality education [29]. Liu discussed establishing the correct career ideals for college students, helping students develop correct life values, guiding college students to change their concept of career choice, establishing specialized institutions, and strengthening the employment guidance of college students [15]. In his article, Liu analyzed the psychological situation of college students in the context of career selection and discussed the adaptability and consciousness of self-psychological adjustment of college students in combination with social practice [16].

The leading role of the recommendation system is users and projects. The recommendation system gives a small collection of items to a specific user, filters out the items the user is not interested in with a high probability, and reduces the search burden when the user is satisfied. Deldjoo proposed a content-based job recommendation system. It was aimed at Facebook and Linked In users. It used data from multiple domains, such as user interaction, social data, and job descriptions, to measure user similarity to work [7]. Based on the need for two-way selection between jobs and job seekers, Shao proposed a recommendation system based on probabilistic models to find a good match between job seekers and jobs [26]. Zhang proposed a job recommendation system based on a hybrid recommendation method, which used job profiles, user profiles, and user behaviors to generate personalized job recommendations. It constructed the collected network network information graphically, used the ranking algorithm to rank the work related to the target user, and generated the target user's job recommendation set [30].

To sum up, the literature and treatises of various experts and scholars in China on strengthening ideological and political education in the employment of college students have a great reference and help for the research of this paper. However, much of the literature focuses solely on employment situation responses. Or, it analyzes the methodological response to the employment problem from a certain angle of strengthening ideological and political education. This paper strives to further study these aspects. Besides, DL theory is introduced to construct an employment recommendation system for college students, improve the employment rate and satisfaction, and summarize the methods and measures to strengthen the ideological and political education under the new employment situation.

III. METHODS AND MATERIALS

A. EMPLOYABILITY OF COLLEGE STUDENTS AND THE CURRENT SITUATION OF IDEOLOGICAL AND POLITICAL EDUCATION

Employment is the foundation of people's livelihood, which is related to the interests of college students and thousands of families and affects the country's and society's development [3]. Employability is a comprehensive competency, a person's ability to obtain, maintain, and do well the job he desires. It allows individuals to work smoothly and play a better role in the workplace and is the sum of the skills that can continuously improve their professional ability. College students must strengthen their adaptability of comprehensive quality correspondingly with changes in the environment to realize their career aspirations [9]. Regarding the employability structure, the employability structure of college students mainly includes the following aspects (Figure 1).

First, practical execution ability refers to the ability of an individual to achieve the desired effect after receiving knowledge indoctrination. Second, self-learning means that individuals continue to broaden the scope of their theoretical knowledge in their development and can effectively apply theories to social practice. Third, social adaptability refers to individuals' reaction speed and ability to accept digestion when they perceive the stress or difficulties caused by their

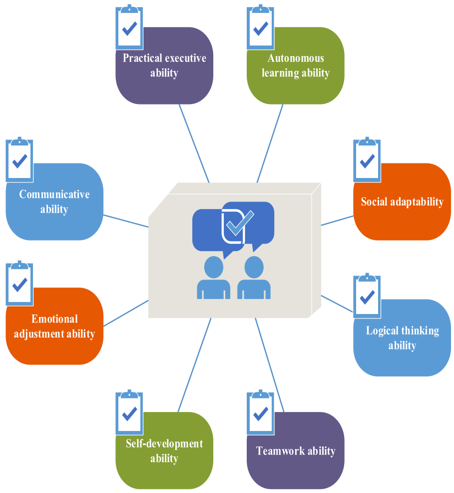

FIGURE 1. **Employability structure of college students.**

surroundings. Fourth, logical thinking ability refers to the ability of individuals to keep a clear mind when doing and thinking about things and have a strong ability to grasp the logical order of things. Fifth, teamwork ability refers to the ability of an individual to successfully complete a thing with others and achieve certain results. Sixth, self-development ability refers to the individual's ability to expect and predict his development and continuously improve his skills in various ways. Seventh, emotional adjustment refers to the psychological regulation ability of individuals in the face of the pressure of what has happened or is about to happen. Eighth, communicative competence refers to individuals' ability to communicate and get along with others [2].

Compared with the discussion of college students' employability, the aspects of college students' employability at this stage and the reasons for this phenomenon can be summarized, as shown in Figure 2.

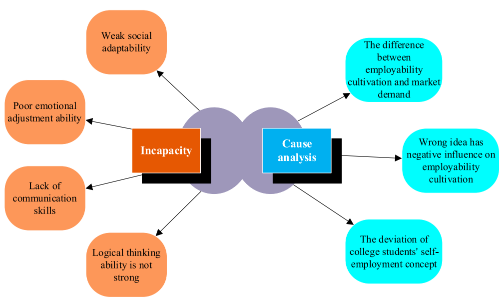

FIGURE 2. **Analysis of employability defects and causes of college students.**

Employment and career selection is an important turning points in the life of college students. At this stage, college students are facing huge employment pressure. Many college students face employment pressure and have various confusions about employment. Some college students are even worried that they cannot face employment rationally and produce self-isolation, irritability, and low self-esteem, which has caused great harm to the body and mind of college students [22]. Given this situation, colleges and universities must strengthen ideological and political education and employment guidance for students. Ideological and political education plays a vital role in cultivating students' healthy personalities, helping students form correct values and outlooks on life by transmitting correct ideas [13]. Under the new employment situation, the strategy for improving the ideological and political education methods of college students is proposed here, including the aspects shown in Figure 3.

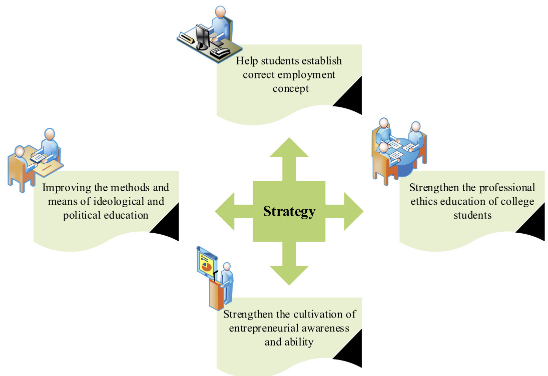

FIGURE 3. **Ideological and political education strategies for college students.**

At present, the employment situation of college students is very grim. In the employment management and ideological and political education of college students, teachers should carry out ideological and political education work concerning the new employment situation, help students master the employment situation and employment policies, and strengthen students' professional ethics education. Teachers should help students form correct concepts of employment and career choice and improve ideological and political education methods to help college students find employment smoothly [28].

B. CONSTRUCTION OF AN EMPLOYMENT RECOMMENDATION SYSTEM BASED ON DL

DL is a class of Machine Learning (ML) methods that can be instantiated as a deep learner. The corresponding design, training, and use methods are called DL. A deep learner consists of several processing layers. Each layer contains at least one processing unit. Each layer of output is a representation of the data, and the level of representation increases as the processing level increases [25]. DL is another important Artificial Intelligence (AI) method in the era of big data. It is an ML model of a deep neural network. It has become the direction of modern AI research [27]. The technical route of DL application to the employment recommendation system is illustrated in Figure 4.

The problems graduates face in employment are the personal unsuitability of information and information overload. It is of practical significance for the recommendation system to be applied to the employment of graduates, which

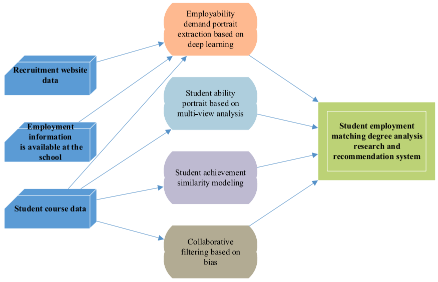

FIGURE 4. The technical route of DL.

can recommend a personalized collection of enterprises for graduates to reduce their employment pressure and improve employment rate and employment satisfaction [24]. The architecture of DL can implement end-to-end derivability of the overall model, which is conducive to integrating multiple network structures. It enables high-order fitting of the data. In particular, the emergence of residual networks dramatically reduces the risk of overfitting of deep networks, increases the data fitting efficiency and robustness of the network, and enables the network to be further deepened [14]. The design of the recommendation algorithm here is centered on extracting and processing features. Figure 5 displays the specific framework.

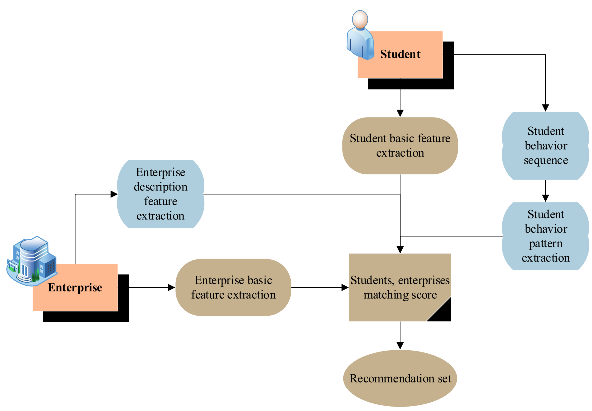

FIGURE 5. Framework diagram of the employment recommendation algorithm.

Firstly, the definition of student behavior attributes is proposed. Based on using the basic attributes of enterprises, enterprise description text data is introduced. Then, the multi-head self-attention mechanism is used to extract the features of student behavior attributes and enterprise description attributes. Multi-layer feature crossover networks and multi-layer feed-forward networks are used to accurately predict the matching degree of students and enterprises. Finally, according to the matching degree, the enterprise collection is selected for the student to get the enterprise recommendation set for the student [5].

It is assumed that the student set is S={s1, s2, …, sI}. I represents the total number of students. The enterprise set is C={c1, c2, …, cN}. N represents the total number of enterprise types. Student attributes are divided into student basic attributes and student behavior sequence attributes to effectively represent the characteristics of students and enterprises. Enterprise attributes are divided into enterprise basic attributes and enterprise description attributes [12]. The basic attribute of students is si, and the basic attribute is:

$$G_i = [(g_{i,1})^T, \ldots, (g_{i,L_G})^T, (g_{i,dense})^T] \tag{1}$$

In Eq. (1), gi represents a discrete characteristic in a student's basic attributes. LG represents the number of discrete features in a student's basic attributes. gi,dense represents dense vectors and consists of continuous features in the student's basic attributes. The basic attributes of enterprise cn are:

$$Q_n = [(q_{n,1})^T, \ldots, (q_{n,L_Q})^T, (q_{n,dense})^T] \tag{2}$$

In Eq. (2), qn stands for the discrete feature. qn,dense means composed of continuous features.

In the employment recommendation scenario, the attributes of students and enterprises have many discrete characteristics, such as "college" and "place of origin." These features are generally encoded as one-heat vectors. However, this often leads to too large vector dimensions, resulting in more useless neurons. Embedding modules are used to convert high-dimensional sparse vectors into low-dimensional dense vectors to reduce the vector dimension. In the module of the student's basic attributes, the embedding vectors of discrete features are stacked with continuous features to obtain the student's basic attribute embedding.

$$G_i^{embed} = [(W_{G,1}^{embed} g_{i,1})^T, \ldots, (W_{G,L_G}^{embed} g_{i,L_G})^T, (g_{i,dense})^T] \tag{3}$$

In Eq. (3), $W_{G,1}^{embed}$ represents the matrix of embedded parameters. The same method is used to get the basic attributes of the enterprise embedding Q_n^{embed}. Student behavior sequence attribute embeddings are different from basic attribute embeddings. It is an embedded representation of the same class of features, and the embedded parameters for each item in the sequence are shared parameters. The student behavior sequence attribute is embedded as:

$$A_i = [W_A^{embed} e_{i,1}, W_A^{embed} e_{i,1}, \ldots, W_A^{embed} e_{i,L_A}^m] \tag{4}$$

In Eq. (4), $W_A^{embed} \in R^{d_A^{embed} \times |E|}$ represents an embedded parameter matrix.

The embedding of the basic attributes of students and enterprises is spliced with the output through the multi-head self-attention mechanism. Then, the interaction between features is further generated through the deep prediction layer. The feature crossover network is to realize the interaction between features. For the recommendation system with a large set of features, the feature intersection can reduce the model fitting pressure and the risk of overfitting [10]. Feature intersection networks can automatically and efficiently implement feature interaction, which contains a total of V sublayers. The input of v+1 layers is represented as:

$$x_{v+1}^c = x_0 (x_v^c)^T W_v^c + b_v^c + x_c^v \tag{5}$$

In Eq. (5), x_v^c represents the input of layer v. W_v^c and b_v^c represent the trainable parameters of the feature crossover network. x_0 represents the input of the depth prediction layer. The layers have residual connections, which can be expressed as:

$$x_0 = Concat(G_i^{embed}, A_i^{trans}, Q_n^{embed}, J_n^{trans}) \tag{6}$$

In Eq. (6), $\boldsymbol{G_i^{embed}}$ represents the embedded presentation layer output of the student's basic attributes. $\boldsymbol{Q_n^{embed}}$ represents the embedded presentation layer output of the basic attributes of the enterprise. $\boldsymbol{A_i^{trans}}$ represents the student behavior sequence attribute. $\boldsymbol{J_n^{trans}}$ represents the sequential semantic layer output of the enterprise description attribute.

C. EMPLOYMENT RECOMMENDATION SYSTEM DATA COLLECTION AND PREPROCESSING

The original dataset contains data on the activities of graduates during their four years in school and data on where they are employed. It contains the following information: basic information about the student, students' grades and overall grades and rankings of all courses, students' grade test scores and time, data on competitions in which students participate, data on intramural activities in which students participate, data on students' positions on campus, data on students' awards, name of the student's employment enterprise, place of file receipt, and employment category [1]. The above data is information obtained by collecting employment data of students in a university. Table 1 describes the primary fields corresponding to student data fields.

TABLE 1. Fields corresponding to students' data information.

Information classification	Data field	Corresponding field
Basic information	Personal information	Gender, age, place of origin College and major Political affiliation
Information about the student's school presence	Grade information	Course grades Grade test results Grade point ranking Examination time
	Cadre experience	Institute-level and university-level positions Duration
	Awards	Awards of scholarships and grants Award time
	Participation in the competition	Category of participation Results of various competitions
Job search information for students	Employment information	Name of employer File receiving place Postal code of receiving place

The above questions are designed into a survey form, which is distributed and filled out by relevant researchers to college students, indicating that the collection of this survey data is used for the research and use of college students' employment management under deep learning.

The original dataset lacks detailed data on the enterprise. Therefore, the crawler is used for enterprise data collection, and the web automation testing tool Web Driver is used to access and query. The main access and query page is Aiqicha, an enterprise credit query tool launched by Baidu [18]. Table 2 shows the main fields corresponding to enterprise data fields.

TABLE 2. Corresponding fields for enterprise data information.

Data attributes	Corresponding fields
Description attributes	Name Company enrollment brochure
Basic attributes	Establishment time of the enterprise Enterprise type and scale The registered capital of the enterprise The address of the enterprise Industry

In collecting employment enterprises in the original data, filtering, modifying, and integrating are based on regular expressions. Then, query and crawl the data. The original data may have missing values, inconsistencies, redundant, and uselessness. In addition, the collected data needs to be preprocessed to provide more reasonable and effective data input to the model. It mainly includes the processing of basic attributes, the extraction of student sequence data, and the processing of enterprise description text.

The 2022 students of a university are taken as the research object. The dataset includes basic student information (gender, grade, and place of origin), student performance information, student cadre information (position and tenure), student employment destination, student scholarship information, and student competition information. The original grade of each course is normalized. The overall grade variance and grade point ratio of this course are used to form the calculated weight of this course. The weights are sorted by size, and the first 20 courses are selected as the basic attribute input of students. The original dataset was split into two to test the robustness of the model. The statistics are given in Figure 6.

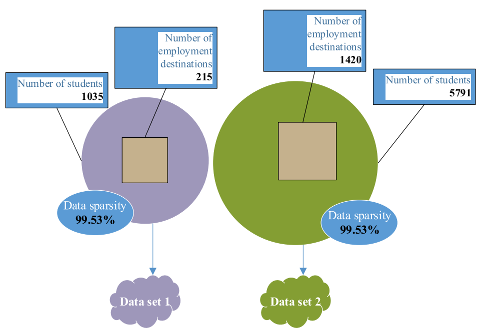

FIGURE 6. Dataset statistics.

The original dataset is divided into two to test the robustness of the model. In Figure 6, a dataset is the data of 1035 students from Communication College and Computer College, including 215 graduation destinations, and its data sparsity is 99.53%, and the data is sparse. The second dataset is 5791 students' data, including 1420 different employment destinations, and its data sparsity is 99.93%, which is extremely sparse data. Because this extremely unbalanced dataset makes the model learning process biased, negative samples are randomly selected and positive samples are resampled to balance the dataset.

The college student employment recommendation model based on DL proposed here will be compared with the following representative recommendation methods. The first is Random Forest (RF) algorithm [19]. It first extracts the characteristics of students and enterprises. Then, it calculates whether students and enterprises are matched. The second is the Personalized Preference Collaborative Filtering (P2CF) algorithm [6]. It is a personalized preference collaboration algorithm. The algorithm recommends jobs for graduates through massive campus records, which can identify students' personal preferences for jobs. The third is Ability-aware Person-Job Fit Neural Network (APJFNN) algorithm [20]. Recurrent neural networks and hierarchical attention mechanisms are used to process text data and predict enterprise resume-matching problems. The parameter settings for the experiment are revealed in Table 3.

TABLE 3. Parameter settings.

Experimental platform	Number of samples	Positive and negative sample ratios	Regularization parameters
Python3.7 PyTorch1.5	300	1	0.001
Batch size	Dropout	Embedding dimensions	Feed-forward layer scale
128	0.2	100	1024

Students and businesses have only one interaction. In the case of a successful recommendation, there will only be one positive sample in the entire recommendation set. In this case, it is not appropriate to describe model performance with indicators' accuracy and recall rate in the traditional recommendation scenario. Therefore, the evaluation of recommendation sets mainly calculates Hit Ratio (HR) and Mean Reciprocal Rank (MRR) indicators. HR indicates whether the student's employment choice is in the recommendation set. MRR uses the ranking of the correct results in the recommendation set to evaluate recommendation performance.

IV. RESULTS

Experiments are performed on real datasets to verify the validity of the model. The experimental results of the recommendation model based on DL and three other comparison methods under the performance index HR are plotted in Figures 7 and 8.

Compared with the dataset 1, the algorithm performance of the experiment on the dataset 2 has been greatly reduced, mainly because the data in the dataset 2 is sparser, and because the dataset 2 contains students with different majors, their employment types have different preferences, which is more challenging for the model.

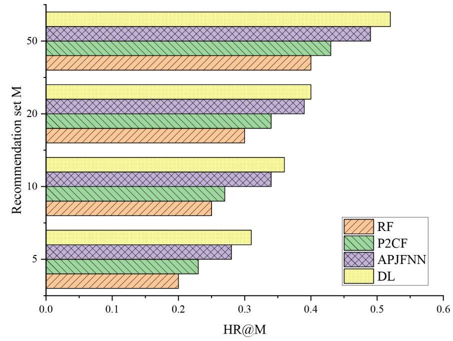

FIGURE 7. The relationship between HR and the number of neighbors of each model on dataset 1.

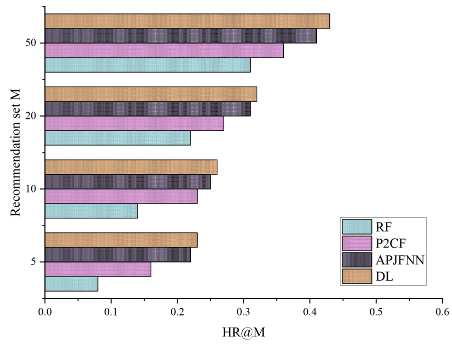

FIGURE 8. The relationship between HR and the number of neighbors of each model on dataset 2.

In the figure, DL represents the employment recommendation model based on DL proposed here. As the recommendation set size M increases, the HR value of the algorithm increases. It can be seen that the HR of all methods is relatively low, which is due to the very sparse student employment dataset. This is consistent with the experimental results of most mainstream employment recommendation algorithms. The recommendation model achieves the best performance on both datasets because the structure of the proposed model can effectively extract the characteristics of students and enterprises and can effectively alleviate the problem of data sparseness.

At present, there are three related recommendation algorithms: Random Forest (RF) recommendation method first extracts the characteristics of students and enterprises, and then calculates whether students and enterprises match; Personalized Preference Collaborative Filtering (P2CF) recommendation method is a personalized preference collaborative algorithm, which can identify students' personal preferences for work by recommending jobs for graduates through massive campus records. Ability-Aware Person-Job Fit Neural Network (APJFNN) uses RNN and hierarchical attention mechanism to process text data and predict the problem of enterprise resume matching.

Experiments are performed under the university dataset and the graph data to verify the model's validity. The relationship between the recommendation model proposed here and the number of neighbors under the performance index MRR is shown in Figure 9.

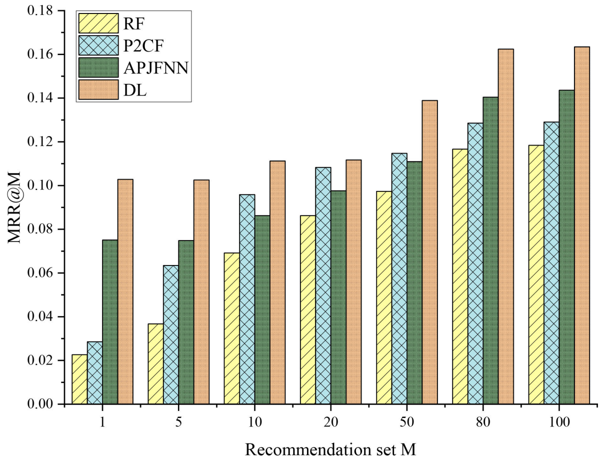

FIGURE 9. The relationship between MRR and the number of neighbors for each model.

From Figure 9, in the MRR indicator test, the recommendation model here achieves the best performance because its structure can be jointly trained by graph embedding and recommended tasks. During joint training, the feature interaction between graph and attribute information can be performed, making the model extract the information in the graph conducive to recommending tasks.

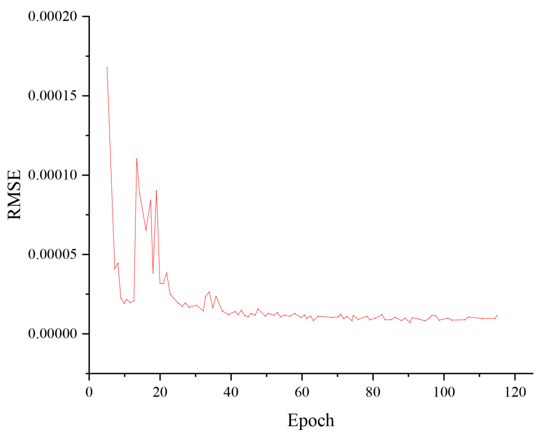

FIGURE 10. Model time complexity.

In Figure 10, when the number of training rounds exceeds 40, the error tends to be stable, which proves that the model has good convergence. Because the size of the training set has a significant impact on the training time, a larger dataset usually takes longer to complete the training. In the future, parallelization and distributed training techniques can be used to spread the training time to multiple computing units, thus reducing the overall training time.

V. DISCUSSION

Chen & Yu proposed an employment recommendation model that integrated behavioral characteristics. For the sparsity of interactive data, the student behavior sequence attribute and the enterprise description attribute were first defined to better explore the characteristics of students and enterprises. Then, the basic features and sequence features were extracted. Finally, the feature interaction and deep fitting of the data were carried out to obtain the matching degree between students and enterprises to make recommendations [4]. By using deep learning technology, this algorithm can more accurately analyze the multi-dimensional data of college students' personal characteristics, academic performance, hobbies and internship experience, and provide more personalized and accurate employment recommendations for each student. Compared with the traditional method based on rules or simple data analysis, this personalized recommendation can better meet the needs of students and improve employment matching. Jin objectively analyzed the current situation of college students' employability and discussed the relationship between ideological and political education and college students' employability training. The shortcomings and causes of ideological and political education in cultivating college students' employability were expounded through empirical investigation. Some specific suggestions were put forward on the cultivation of college students' employability from the perspective of ideological and political education [11]. Based on the conclusions of the existing papers, this paper designs a college student employment recommendation model based on DL. On the one hand, college students' employability is cultivated based on improving ideological and political education. On the other hand, from the perspective of model prediction, the interaction characteristics between students and enterprises are explored to enhance employment HR. Compared with the existing research, this algorithm pays more attention to the fusion of multi-source data. It can integrate students' academic data, social media activities, internship experience and other data sources to understand students' comprehensive situation more comprehensively. This helps to provide more comprehensive employment advice, taking into account more factors, such as academic ability, social skills and practical experience.

VI. CONCLUSION

Research to improve college students' employability is necessary with the increasing employment pressure. This is not only an unavoidable practical demand but also a political demand from top to bottom. This long road requires long-term preparation, exploration, and research. Ideological and political education is undoubtedly an effective means of struggle at present. Through the cultivation of college students' mental health, ideological concepts, and comprehensive quality, the employability of college students is effectively improved to escort the employment prospects of college students. In the face of the torrent of employment pressure, many parties must persevere and positively impact college students through various channels at different stages and levels to increase their ability to adapt to social practice and life. Additionally, the employment recommendation algorithm model based on DL proposed here has certain advantages, which can mine the characteristics of students and enterprises and conduct feature interaction with a good HR to improve the performance of recommendation tasks. However, there are also shortcomings. Here, the employment recommendation algorithm of fusion behavior sequence and relationship graph is studied, but it has not been studied from the data distribution perspective. Therefore, future research will continue to conduct in-depth analysis on the dataset. Future research should focus more on data intelligence and personalized recommendation. With the rapid development of big data and artificial intelligence technology, students' data can be collected and analyzed more comprehensively, including academic achievements, hobbies and social activities to generate more intelligent employment advice. Personalized recommendation will consider the multi-dimensional characteristics of students and provide each student with more customized development paths and employment opportunities.

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