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College student employment prediction based on machine learning and improved rate neural networks

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Abstract As an important part of improving the employment rate of college students, the current employment guidance work in colleges and universities suffers from problems such as lack of relevance and formality. In this paper, we start from the perspective of college students' employment prediction, integrate the data mining method with college graduates' employment prediction, and design the operation process of the employment prediction model. Then, we process the performance data and employment data of N college graduates separately, and use the Pearson correlation coefficient to analyze the correlation between graduates' employment destinations and their demographic characteristics. Then the hybrid feature selection algorithm based on mutual information and weights (HMIGV) is introduced for the elimination of redundant information in the feature set. On this basis, the XGBoost algorithm is used to predict the employment of graduates, and a college student employment prediction model based on the HMIGV algorithm and the XGBoost algorithm is established. Compared with similar model algorithms, the model has the highest prediction efficiency on different college graduates' datasets, with the lowest training time of 38.46 s and the lowest testing time of 6.82 s. By predicting college students' employment with high efficiency, the model is able to provide powerful technical support and reference for graduates' employment guidance work.

Index Terms employment prediction model, data mining, HMIGV algorithm, XGBoost algorithm

I. Introduction

As higher education is in full swing, the number of college students in China is increasing, the employment pressure on college students is getting bigger and bigger, and the situation of college employment is not optimistic [1]. The employment rate of college students is an important evaluation index of “harmonious society”, which is directly related to the stability of the society and the sustainable development of the economy, and at the same time, the employment rate of college students is directly related to the level, quality and reputation of a university [2], [3]. How to model and predict the number of college students' employment, accurate analysis of the number of college students' employment, and provide an important reference basis for the employment guidance work of colleges and universities is particularly important.

At present, colleges and universities have begun to use information technology to collect, store and manage students' personal data, school learning data and employment data, so a large amount of information data with important value has been accumulated in the employment management system of the employment guidance department of colleges and universities [4]. Although most university employment management systems have management and analysis functions, these functions only stop at simple statistics and presentation of a large amount of employment information, and do not really dig out the inherent laws and values behind these important data, not to mention the inability to predict the future employment of students based on the existing data to provide appropriate employment intervention and guidance [5]-[7]. Therefore, mining and extracting the relationships and rules implicit behind these data from a large amount of student employment information, and constructing a prediction model based on them to predict the future employment of students, so as to provide decision support for college employment guidance is an important problem that needs to be solved urgently [8]-[10].

Around the problem of college students' employment prediction, in order to effectively improve the quality of employment, some scholars use machine learning technology to predict and analyze the employment situation of college students. Literature [11] constructed employment prediction models based on decision trees, random forests and artificial neural networks using college students' employment information and other data, and used them to evaluate the prediction results of each model. Literature [12] also compared the accuracy of multiple machine learning models in performing the task of predicting the employability of graduates, and found that the random forest classifier exerted a high prediction performance, which provided assistance in carrying out targeted college student employment guidance. Literature [13] proposes a hybrid prediction model incorporating the Improved Bat Algorithm and Support Vector Machines to generate highly accurate and explanatory career guidance programs by extracting features of college students' data related to education, family, and career planning. Literature [14] analyzes the factors that may affect the employment process of college students in different subjects, and inputs the calculated factors into the integrated algorithm W_voting to construct a college student employment classifier, whose prediction results will provide effective support for the career development path of college students. Literature [15] applies the decision tree algorithm to the field of college students' employment management, and constructs a prediction model by extracting valuable characteristic factors from the employment data, which can accurately guide students to choose the positions that match their own employment ability, thus significantly improving the employment rate of college students. In order to improve the global search ability of the prediction algorithm and avoid local optimization, literature [16] introduced the communication mechanism and Gaussian skeleton mechanism to form the augmented butterfly optimization method (CBBOA), which constructs the employment prediction model of college students and can provide a reference to the relevant departments in career decision-making and policy formulation. In general, machine learning algorithms are increasingly used in college employment guidance work, although the depth of research is not deep enough and there are no particularly sensational results, but the trend of its development is getting stronger and stronger, and has received widespread attention from all walks of life. How to obtain information of reference value and its related attributes from the existing data, so as to build a more realistic model, has become the next focus of attention.

This paper introduces data mining algorithms into the employment prediction of college graduates based on the different performances of college students on multiple characteristics. It describes in detail the workflow of data mining analysis methods in employment prediction and forms the idea of constructing employment prediction model. Subsequently, we processed the achievement data and employment data of the graduates of college N to obtain the demographic characteristics of the graduates of the college. The Pearson correlation coefficient method is used to analyze the correlation between the relevant features and employment. Aiming at the characteristics of large number, complex structure and high dimensionality of the graduates' feature data, the HMIGW algorithm is used to judge and propose the redundant information in the feature set. And XGBoost algorithm is chosen to predict the employment destination of college students based on the processed feature data set, so as to construct the college students' employment prediction model. Finally, the model is used to analyze and extract the features that are most relevant to college students' employment, and the overall performance of the model is examined by comparing with similar algorithm models.

II. The idea of constructing an employment forecasting model

Classification, as an important branch in the field of data mining, is an example of pattern recognition. This study combines the data of the influencing factors of graduates' employment to establish an employment prediction model, which can find exactly the factors and the proportion of the factors affecting graduates' employment in the employment guidance work of graduates, so as to facilitate the specific adjustment and optimization of the employment guidance work of colleges and universities. The basic process of data mining classification method in the application of college students' employment prediction is shown in Figure 1.

(1) Pre-analysis: Understand the relevant background, determine the research object and the goal of data mining. For example, the background of the research is the employment of college students, based on the analysis of the background and the problem can determine the object of data mining as well as the goal, this step is the key link in the whole data mining process, with a clear pre-analysis, in order to lay the foundation for subsequent research.

(2) Data preparation: data preparation is a complex process, including data collection and data pre-processing processes, such as integration of data, data normalization, as well as the use of correlation analysis or principal component analysis and other methods to find the redundancy of attributes in the data, in order to delete, to form a more accurate data set.

(3) Data mining: this is the actual data mining stage of the work, in the preliminary problem analysis and data preparation based on data mining. First of all, the output of data mining needs to select the appropriate mining method, and then determine the specific mining algorithm for the actual data mining, to get the final results.

(4) Result interpretation and pattern evaluation: After obtaining the data mining results, in order to facilitate the user's understanding and acceptance, visualization tools are used to express and interpret the results. Secondly, in

order to verify whether the obtained data mining results meet the expected requirements, pattern evaluation is also required.

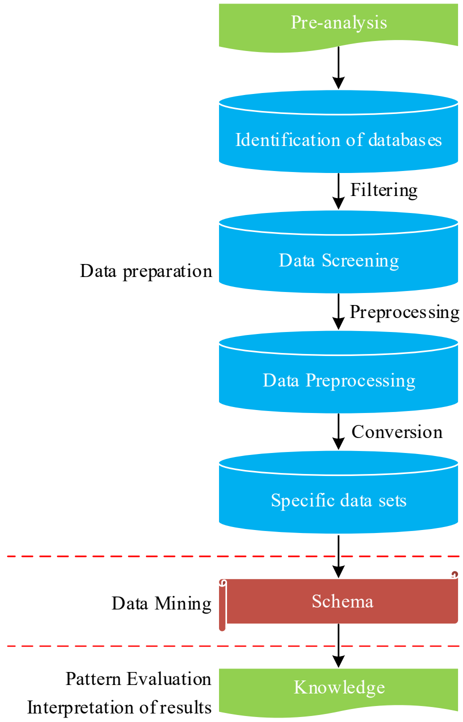


Figure 1: The construction process of the employment prediction model

III. Construction of an employment forecasting model for university students

This chapter analyzes the demographic features after completing the preparation of the research data based on the real dataset provided by Colleges and Universities N. Combined with the data characteristics, the HMIGW feature selection algorithm is used to screen the subset of features that meet the prediction needs. XGBoost algorithm is introduced to construct the college student employment prediction model.

III. A. Data collection and processing

III. A. 1) Achievement data

The total number of grade data is 195,777, of which there are 1,603 courses. The grade data mainly consists of two parts, one part is the grade related data, such as, nature of examination (normal/remedial/repeat), examination grade, examination status (normal/postponed/remedial/cancelled/absent/default/cheating), and so on. The other part is course-related data, such as, course type (general/practical/laboratory/physical education), course type (compulsory/elective), course category (professional foundation course/professional core course/general education course/practical course/teacher education orientation course), class mode (theoretical/practical/laboratory/lab/computer-based/others), and so on.

III. A. 2) Employment data

The employment data was collected in 2023 and included 2,345 students in 10 colleges (College of Educational Sciences and Technology, College of Chemistry and Life Sciences, College of Physical Sciences and Technology, College of Foreign Languages, College of Music, College of Fine Arts, College of Business, College of Social Development, College of Mathematics and Information Sciences, and College of Arts and Letters) with 65 majors (15 teacher education majors and 50 non-teacher education majors) . During the data cleaning process, some (196) students with incomplete information were excluded. Therefore, this paper uses the employment data of 2,149 students, of which 1,573 are employed and 576 are not employed, and among the employed students, 990 go to work in enterprises and 583 go to work in schools.

There are two main parts in the employment data, one part is the demographic information of the students, such as province, gender, date of birth, major, and college. The other part is employment-related data, such as the name of the employment organization, the province where the employment organization is located, the mark of the employment organization (1: enterprise, 2: school), and the mark of whether or not they are employed (1: employed, 0: not employed).

In this paper, company_mark is used as the label to be categorized, which is mainly divided into two major categories, employed and unemployed (using the number 0 to indicate), of which employed can be divided into going to work in enterprises (using the number 1 to indicate) and going to work in schools (using the number 2 to indicate), so that the prediction of the students' employment direction is converted into a three-categorization problem.

The most commonly used datasets or characteristics to predict students' academic performance and employability are their cumulative grade point average (CGPA), gender, major, communication, problem solving, analytical, critical thinking and decision making skills, extracurricular activities and age, as well as psychomotor factors such as behavioral and attendance, and training, and internship placements, with academic performance being the main determinant of employability. The characteristics used in this paper to predict students' employment destinations are primarily demographic information and curricular knowledge networks, and the analysis of this characteristic follows.

III. B. Demographic characterization

In addition to academic performance, students' demographic information, such as age, gender, major, and other characteristics are also factors that influence employment. The demographic information of students in the dataset includes province, gender, age, major, and college, and in this paper, we filter the characteristics by calculating the Pearson's correlation coefficient between the demographic characteristics and employment destinations.

III. B. 1) Pearson's correlation coefficient

Pearson's correlation coefficient, also known as Pearson's product-moment correlation coefficient, is one of the most commonly used correlation coefficients, denoted as r, which is used to reflect the degree of linear correlation between the two variables X and Y, with the value of r ranging from -1 to 1, and the larger the absolute value indicating a stronger correlation.

The overall correlation coefficient ρ is defined as the ratio of the product of the covariance and the standard deviation of the two variables X and Y, and is calculated as in equation (1):

$$\rho_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E\left[(X-\mu_X)(Y-\mu_Y)\right]}{\sigma_X \sigma_Y} \tag{1}$$

The Pearson correlation coefficient reflects the strength of the linear correlation between two variables, and when $r > 0$, it indicates that the two variables are positively correlated. When $r < 0$, the two variables are negatively correlated. When $r = 0$, it indicates that the two variables are not linearly correlated, but may be correlated in some other way. When $r = 1$ and -1, it means that the two variables X and Y can be well described by a linear equation, when all sample points fall nicely on a straight line.

III. B. 2) Analyzing results

The results of the correlation calculation are shown in Figure 2. The characteristics with the highest to the lowest correlation with the students' demographic information and the employment destination are (zydm) major, (xydm) college, (nl) age, (xbdm) gender, and (sfdm) province, with the corresponding correlation coefficients of 0.457, 0.371, 0.325, 0.232, and 0.115, respectively. Therefore the demographic characteristics used in this paper are (zydm) major, (xydm) college, (nl) age, and (xbdm) gender.

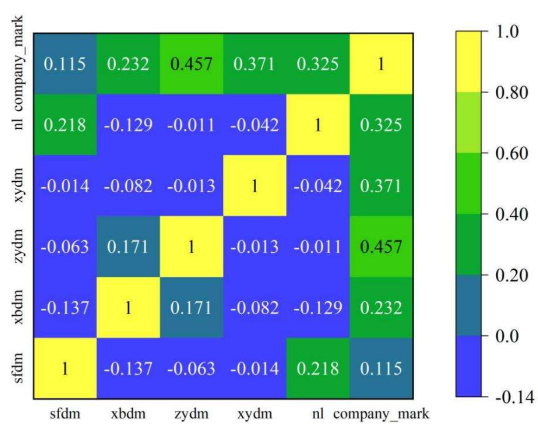


Figure 2: Demographics and employment correlation coefficient

III. C. Feature selection algorithm HMIGV

Compared with the simple forward and backward search, the above method first performs descending sorting of features, and on the basis of the current feature subset classification prediction accuracy as an evaluation index, recursively removes redundant features and features with lower classification accuracy, which effectively reduces the feature volatility.

Compared with the pure use of Filter or Wrapper method, HMIGW algorithm first filters and then recursively wraps according to the filtering results, which ensures that the number of redundant information in the obtained feature subset is reduced to a certain level, and its prediction performance for the results is optimal.

The method includes two stages of Filter and wrapping Wrapper, which are as follows:

(1) Filtering for redundant irrelevant features: for each feature, calculate its information measure in turn to find the relevance valuation I_x.

For the data sequence $X=(x_1,x_2,\cdots x_i,\cdots x_m)$, the entropy finding formula is as in equation (2):

$$H(X)=-\sum_{x_i\in X}p(x_i)\log(p(x_i)) \tag{2}$$

where $p(x_i)$ denotes the probability density of x_i in its parent data series.

The magnitude of joint entropy between two different data series indicates the degree of non-determinism that occurs when they are with each other. Conditional information entropy denotes the magnitude of information entropy calculated for the case of another variable $Y=\left(y_1,y_2,\cdots,y_i,\cdots,y_m\right)$ in the premise that a certain variable in the data series is deterministic, and the formulas for both are in Eqs. (3)-(4):

$$H(X,Y)=-\sum_{x_i\in X}\sum_{y_j\in Y}p(x_i,y_j)\log(p(x_i,y_j)) \tag{3}$$

$$H(Y\mid X)=-\sum_{x_i\in X}\sum_{y_j\in Y}p(x_i,y_j)\log(p(x_i,y_j)) \tag{4}$$

where $p(x_i,y_j)$ in Eq. (3) refers to the combined probability density of the two variables, and $p(x_i,y_j)$ in Eq. (4) denotes the conditional probability density of $p(x_i)$ if the value of y_i is determined.

Equation (5) can be obtained from equations (2) and (4):

$$H(X,Y)=H(X)+H(Y\mid X)=H(Y)+H(X\mid Y) \tag{5}$$

Entropy magnitude is positively correlated with the degree of stabilization between the variables, whereas a larger mutual information means that the variables are more similar.

Mutual information is defined as expressed in equation (6) below:

$$I(X;Y)=\sum_{x_i\in X}\sum_{y_j\in Y}p(x_i,y_j)\log\frac{p(x_i,y_j)}{p(x_i)p(y_j)} \tag{6}$$

where $I(X;Y)$ denotes the shared information measure between X, Y.

The value of $I(X;C)$ can visualize the correlation between the two, and large indicates strong correlation. Equation (6) is transformed by equations (2) and (3), and the mutual information can be expressed in the form of entropy as in equation (7):

$$I(X;Y)=H(X)+H(Y)-H(X,Y) \tag{7}$$

Denote $I(X;Y)$ as the relevance valuation I_x of feature X.

(2) Adopt forward feature addition and backward recursive deletion strategy for feature selection

According to the relevance valuation I_x obtained in stage (1), the features in the feature space are sorted in descending order, and the feature space is traversed using the forward add strategy, with a feature added each time, one by one, and the corresponding set of features is $X_1,X_2,\cdots,X_m$ (m is the number of features contained in the subset of features), and then the current feature set is classified by the XGBoost algorithm for predicting the result accuracy. The accuracy of the classification prediction result is calculated by the XGBoost algorithm on the current set of features, which is obtained as a_i. If $a_i<a_{i-1}$, then the feature x_i is removed from the feature set X, and so on until the end.

The advantage of the above strategy is that by first finding the correlation valuation I_x, then based on the value of I_x, and then using the classification accuracy to secondly evaluate the weight of each feature's contribution to the prediction result, it can effectively reduce the feature volatility without sacrificing the prediction accuracy, and according to the evaluation result, delete the features with smaller weights. Each time a feature is deleted, the feature set is re-traversed to generate a new feature set, and the above steps are repeated to obtain a feature set with minimal redundancy and optimal performance.

IV. Application and Analysis of Employment Prediction Models for University Students

This chapter applies the college student employment prediction model designed above to preliminarily extract the more relevant features of employment and analyze their significance as important indicators for model prediction. Comparison experiments with similar modeling algorithms on different datasets are designed to assess the feasibility and reliability of the model in this paper.

IV. A. Importance analysis of features

Using the model of this paper to select the preliminary selection of 50 features that are more relevant to the employment of graduates, the results of the correlation analysis of the 50 features with the direction of employment are shown in Figure 3. 50 features are centered on the behavioral characteristics of four different dimensions (academic performance, comprehensive practical performance, life performance, ideological performance) to carry out (e.g., changes in the frequency of weekly breakfast in the performance of life, etc.), of which the academic performance dimension contains characteristic points 1-15, academic practice performance contains characteristic points 16-30, life performance contains characteristic points 31-40, and ideological performance contains characteristic points 41-50.

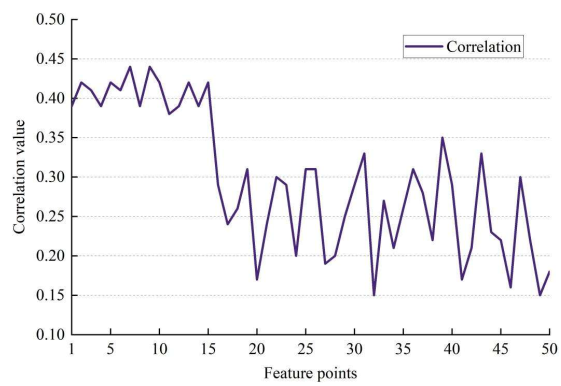


Figure 3: The correlation ranking of features

It can be clearly seen that the correlation of academic performance characteristics is high at 0.38 and above, so the importance of academic performance characteristics and students' employment direction is shown in Fig. 4.There are (a) average course grades, (b) practical grades, (c) English grades (Grade 4/6), (d) graduation design grades, among which (a) average course grades has the highest importance of 0.847, indicating that students' graduation is most significantly associated with their professional knowledge reserves and learning performance. 0.847, indicating that students' graduation is most significantly associated with their professional knowledge reserves and academic performance.

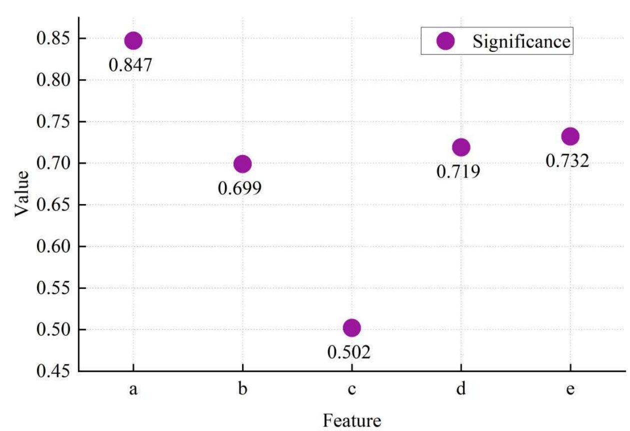


Figure 4: Feature importance ranking

IV. B. Feature vector extraction

The values of the attributes of the employment units are categorized into three types: state-owned enterprises (SOEs or institutional units), foreign enterprises (foreign-funded enterprises or Sino-foreign joint ventures) and private enterprises. The same bars of data were taken as training samples in each of the three categories. The set of 15 students' training samples is selected as shown in Table 1, and the student characteristics described are (a) average course grade, (b) practical grade, (c) English grade (grade 4/6), (d) graduation design grade, and (e) type of employment unit (SOE/private/state-owned enterprises).

Table 1: Training sample set

Number	(a)	(b)	(c)	(d)	(e)
1	60	70	Level Four	98	State-owned enterprise
2	66	83	Level Six	92	Foreign company
3	85	85	Level Four	94	State-owned enterprise
4	70	69	Level Six	94	State-owned enterprise
5	73	89	Level Six	94	Private enterprises
6	88	95	Level Four	88	Private enterprises
7	79	80	Level Four	83	Private enterprises
8	61	69	Level Six	98	Foreign company
9	94	88	Level Six	99	State-owned enterprise
10	73	79	Level Four	92	Private enterprises
11	79	86	Level Four	95	Private enterprises
12	97	63	Level Six	82	Foreign company
13	87	85	Level Six	99	Foreign company
14	65	86	Level Four	99	State-owned enterprise
15	87	89	Level Four	92	Private enterprises

Since the values of some feature attributes are non-numerical, in order to facilitate the implementation of the algorithm, the English grades therein are numerically processed, i.e., Grade 6 is replaced by 95, and Grade 4 is replaced by 85. The processed data of the training sample set is shown in Table 2.

Table 2: The set of training samples after numerical processing

Number	(a)	(b)	(c)	(d)	(e)
1	60	70	85	98	State-owned enterprise
2	66	83	95	92	Foreign company
3	85	85	85	94	State-owned enterprise
4	70	69	95	94	State-owned enterprise
5	73	89	95	94	Private enterprises
6	88	95	85	88	Private enterprises
7	79	80	85	83	Private enterprises
8	61	69	95	98	Foreign company
9	94	88	95	99	State-owned enterprise
10	73	79	85	92	Private enterprises
11	79	86	85	95	Private enterprises
12	97	63	95	82	Foreign company
13	87	85	95	99	Foreign company
14	65	86	85	99	State-owned enterprise
15	87	89	85	92	Private enterprises

IV. C. Overall performance test of the model

IV. C. 1) Comparison of the accuracy of employment forecasts for university graduates

Using (M1) SVM, (M2) CNN, (M3) ACO-BPNN 3 kinds of university graduates' employment prediction models and (M4) this paper's model, based on the sample data above, the graduation employment status of 4 universities (numbered in order: No. 1, 2, 3, 4) was modeled and analyzed, and the prediction accuracy was obtained as shown in Fig. 5.

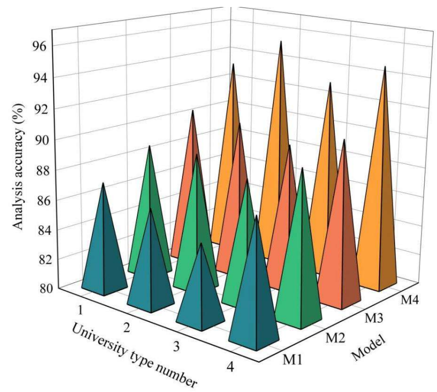
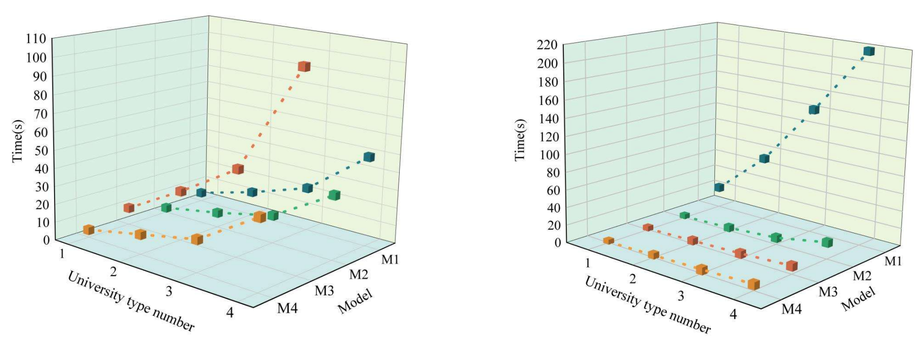


Figure 5: Comparison of Employment Prediction Accuracy for University Graduates

(M1) SVM model of college graduates employment prediction accuracy is the lowest, are lower than 88.00%, indicating that (M1) SVM model can not accurately describe the characteristics of the employment changes of college graduates, resulting in the largest analytical error. (M4) The prediction accuracy of university graduates' employment of this paper's model is substantially higher than that of the remaining three comparative models, reaching a maximum of 95.41% in No.2 universities, and the overall accuracy is 93.00% and above. This shows that (M4) the model in this paper better overcomes the large prediction error of college graduates' employment existing in the current model, describes the characteristics of college graduates' employment changes well, and verifies the superiority of (M4) the model in this paper.

IV. C. 2) Comparison of the efficiency of employment forecasting for university graduates

The training time of the university graduate employment prediction model designed in this paper is shown in Fig. 6(a) and the testing time is shown in Fig. 6(b) with the three comparison models. (M3) ACO-BPNN has the longest total time for college graduate employment prediction, which is as high as 106.76s on No.4 colleges and universities, which is less efficient for college graduate employment prediction. (M1) SVM model has the longest total test time, up to 218.15s on No.4 college.The highest efficiency for predicting the employment of college graduates of 4 universities is (M4) model of this paper, the shortest training time and test time used are 38.46s and 6.82s, respectively, which speeds up the prediction of college graduates' employment.



(a) Training time (b) Test time

Figure 6: The training time and testing time of the four models

V. Conclusion

This paper proposes a college employment prediction model by mining and analyzing the different performances of college students on multiple features, selecting the optimal subset of features using a machine learning algorithm (HMIGV), and predictively modeling the employment of graduates based on the improved rate neural network algorithm (XGBoost). The model predicts the employment direction of a student by mining the student's feature information, which provides an effective guideline and reference for university employment guidance.

The proposed employment prediction model has an overall accuracy of 93.00% and above for the employment prediction of college students in four colleges and universities, and the highest accuracy is 95.41%. The shortest training time and prediction time for multiple datasets are 38.46s and 6.82s, respectively, which is both accurate and efficient.

References

[1] Gao, W., Tang, W., & Wang, J. (2025). Relationship Between Career Adaptability and Competitive Attitudes Among Chinese College Students. Journal of Adolescence.

[2] Hsieh, T. L. (2025). Comparative analysis of career aspirations among STEM college students: social-cognitive model across college years. International Journal of Adolescence and Youth, 30(1), 2460604.

[3] Li, Y., & Zhao, L. (2025). Application of Support Vector Machine Algorithm in Predicting the Career Development Path of College Students. International Journal of High Speed Electronics and Systems, 2540230.

[4] Wei, Y., Zheng, Y., & Li, N. (2023). Big Data Analysis and Forecast of Employment Position Requirements for College Students. International Journal of Emerging Technologies in Learning, 18(4).

[5] Al-Alawi, L., Al Shaqsi, J., Tarhini, A., & Al-Busaidi, A. S. (2023). Using machine learning to predict factors affecting academic performance: the case of college students on academic probation. Education and Information Technologies, 28(10), 12407-12432.

[6] Rosenzweig, E. Q., Song, Y., Chen, X. Y., Baldwin, A., Barger, M. M., Cotterell, M. E., ... & Lemons, P. P. (2025). Switching within STEM: Examining the motivational concerns that college students report considering when changing career plans within STEM fields. Journal of Educational Psychology.

[7] Zayed, Y., Salman, Y., Awad, M., & Hasasneh, A. (2023). Employment Recommendation System for Graduates Using Machine Learning. International Journal on Engineering Applications, 11(5).

[8] ElSharkawy, G., Helmy, Y., & Yehia, E. (2022). Employability prediction of information technology graduates using machine learning algorithms. International Journal of Advanced Computer Science and Applications, 13(10).

[9] Huang, Y. (2025). Individualized career planning intelligent teaching system for college students based on adaptive artificial intelligence. Journal of Computational Methods in Sciences and Engineering, 14727978251315731.

[10] Krishnaiah, V., & Kadegowda, Y. H. (2022). Undergraduate engineering students employment prediction using hybrid approach in machine learning. International Journal of Electrical and Computer Engineering, 12(3), 2783-2791.

[11] Lee, D. H., & Kim, T. H. (2020). Study on the Prediction Model for Employment of University Graduates Using Machine Learning Classification. The Journal of Information Systems, 29(2), 287-306.

[12] Baffa, M. H., Miyim, M. A., & Dauda, A. S. (2023). Machine learning for predicting students' employability. UMYU Scientifica, 2(1), 001-009.

[13] Wei, Y., Rao, X., Fu, Y., Song, L., Chen, H., & Li, J. (2023). Machine learning prediction model based on enhanced bat algorithm and support vector machine for slow employment prediction. Plos one, 18(11), e0294114.

[14] Su, J., & Sun, X. (2023, August). Research on the Employment Prediction Method of College Students Under the Background of Mass Entrepreneurship and Innovation Education. In International Conference on E-Learning, E-Education, and Online Training (pp. 341-353). Cham: Springer Nature Switzerland.

[15] Meng, Z. (2023, July). Analysis and Prediction of College Students' Employment Based on Decision Tree Classification Algorithm. In 2023 World Conference on Communication & Computing (WCONF) (pp. 1-6). IEEE.

[16] Wang, Z., Liang, G., & Chen, H. (2022). Tool for predicting college student career decisions: an enhanced support vector machine framework. Applied Sciences, 12(9), 4776.