J. COMBIN. MATH. COMBIN. COMPUT. 125 (2025) 3213--3227

Journal of Combinatorial Mathematics and Combinatorial Computing
www.combinatorialpress.com/jcmcc

Combinatorial Press

Research on Optimizing Vocational Education Curriculum System through Machine Learning to Enhance Students' Employability

Yumin Wang[1,✉]

[1] *Department of Economic Management, Luohe Institute of Technology, Henan University of Technology, Luohe, Henan, 462002, China*

ABSTRACT
In today's deepening education reform, promoting the deep integration of technology and education has facilitated the process of informatization of school education. Vocational education shoulders the important responsibility of cultivating “high-quality laborers and technical talents”, and the reform of informatization of vocational education has gradually become the focus of attention. In this study, we construct a prediction model of learning achievement based on machine learning to optimize the vocational teaching curriculum system. In this paper, before constructing the prediction model, the basic information data and learning behavior data of students are firstly subjected to feature extraction and feature selection. Then CNN combined with BiLSTM and Attention is used to construct the student performance prediction model CNN-BiLSTM-Attention. Finally, based on the performance prediction model, this study proposes the optimization path of the vocational education curriculum system to solve the problem of student employment. The model in this paper achieved the best prediction results in the performance comparison with both the single model and the integrated model, and the indicators were 0.961, 0.953, 0.985, 0.966, and 0.957, respectively. Moreover, it was found that the model had better prediction results in the process of vocational education courses at 80% and above. Among the features, the importance of the relevant features about honor acquisition is higher, all of them are above 0.8, which is an important factor affecting students' performance. In the actual application of grade prediction, only one student had only 61.6 points in the final semester's grade prediction, which had the risk of not being able to successfully graduate and proceed to employment. The study shows that the prediction model based on machine learning in this paper has good performance and can provide a strong basis for the reform and optimization of the vocational education curriculum system and promote the informatization process of vocational education.

Keywords: machine learning, CNN-BiLSTM-Attention, performance prediction model, vocational education, curriculum system optimization

✉ Corresponding author.
E-mail address: weibaosmile@163.com (Y. Wang).
Received 03 March 2024; Revised 10 May 2024; Accepted 25 November 2024; Published Online 15 April 2025.
DOI: 10.61091/jcmcc127a-182

1. Introduction

The employment and entrepreneurship situation of college students has become the focus of attention and concern of various colleges and universities, and the Chinese government has also formulated a series of relevant measures for the employment and entrepreneurship situation of college students [1-2]. According to statistics, in 2014, the number of graduates from national colleges and universities has reached 7.27 million, which is a record high. Meanwhile, under the influence of some comprehensive factors such as national economic and industrial structural adjustment and enterprise employment structural adjustment, the recruitment demand of a part of employing units began to decrease, so the employment situation of graduates is quite severe [3-5]. For vocational colleges and universities, the employment rate of graduates directly affects the rise and fall of the school, so it is imperative to utilize the reform of vocational education curriculum in vocational colleges and universities to improve the employment and entrepreneurship ability of college students [6].

Currently, the cultivation goal of higher vocational education. The view that it should be centered around the core of vocational ability and vocational quality development has been recognized by more and more vocational educators, and the resulting training model should also be a system designed around the core of vocational ability and vocational quality development [7-9]. In the daily teaching process, the curriculum is an important carrier and expression of the cultivation mode, and the reform of the curriculum and curriculum system with the overall goal of “student-oriented, employment-oriented, enterprise participation, competence-based, quality synchronization” plays a very crucial and fundamental role in achieving the ultimate cultivation goal of higher vocational education [10-11]. The specific method of curriculum competency-based reform is that teachers work together with enterprise experts to formulate job competency standards by going to enterprises for research, and then formulate the implementation rules and implementation plan of curriculum teaching with the main line of cultivating technical application ability [12-13]. These measures not only fully consider the main position of students in vocational and technical education, teach students according to their aptitude, and fully mobilize students' learning initiative and enthusiasm, but also actively implement the basic principle of "employment-oriented", fully consider the basic adaptability of students and the good development of vocational ability, and also attach importance to school-enterprise cooperative teaching, let enterprises participate in the formulation of curriculum standards, and implement quality requirements into all aspects of teaching [14-15].

On the other hand, higher vocational colleges and universities focus on cultivating professional and skilled talents, focusing on creating specialties and improving the quality of graduates so as to increase the employment rate. This is the biggest difference with ordinary undergraduate colleges and universities, so it needs to be reformed and innovated in the curriculum system, teaching mode, teaching concept and teaching evaluation system [16-17]. Only in this way can higher vocational colleges survive and develop, and students graduated from higher vocational colleges can be more competitive and advantageous in the society.

Vocational education is an important part of the education system, and scholars' research on vocational education mainly involves the content and development of vocational education, the optimization and innovation of vocational education model and teaching design, and the impact of vocational education on students' career development and the social labor market. Literature [18] examines the relevance of vocational education, vocational training and vocational practice, and examines how the composition and development of vocational knowledge affects the design of vocational teaching curricula, and the study points out that vocational education is formed by the underlying logic of the theoretical foundation of vocational knowledge and practical application. Literature [19] examines the trends and pathways for the future development of vocational education, including the significance of technical education, the purpose of vocational qualifications, trade unions and employers, etc., which contributes to reform and innovation in vocational education. Literature

[20] examined the reform and optimization of teaching and learning in vocational courses using literature analysis and concluded that in the new paradigm of vocational education, the teacher should act as a motivator of learning and encouragement to students and stated that vocational courses should be designed by integrating the views of the students, the industry, and the governmental departments of education, among others. Literature [21] used semi-structured interviews and in-depth analysis of information data provided by vocational education and training students to identify themes related to the establishment of a framework for vocational education and to clarify the differences between the apprenticeship training system and the vocational education system. Literature [22] explored the association between school curriculum tracking and social inequality and how socioeconomic status affects students' vocational placement, and found that curriculum tracking reduces socioeconomic inequality to a certain extent in an education system with a high social division of labor. Literature [23] examines the differences between formal and non-verified vocational education based on three dimensions: curriculum, forms of learning, and quality of teaching and learning, which helps to deepen the understanding of the core and role of vocational education. Literature [24] discussed the behavior of school tracking, pointing out that school tracking is conducive to students' access to high-quality vocational education and training, clear career paths to achieve self-worth, and the earlier the school tracking, the better the effect, but based on the analysis of the Matthew effect and the theory of prioritized attachment, school tracking is very detrimental to the early performance of students, and therefore put forward a targeted proposal to optimize vocational education.

The purpose of vocational education is to cultivate students' employment skills and realize students' career aspirations, and the current research on students' employment education skills mainly focuses on the assessment and prediction of students' employment skills, as well as the design of teaching methods for the development of employment skills and the analysis of employment practices, which is a broader direction of the research, but the depth of the research is a little insufficient. Literature [25] analyzes the effect of Australian universities' employability policy practice, which builds a framework for students' future career development and provides professional services and consulting without students' career development, aiming to improve students' employability. Literature [26] explains the kernel of students' employability and proposes the use of data mining technology to analyze the data related to students' employability in order to achieve accurate prediction, which helps to clarify whether the students' employability matches with the needs of the applying enterprises, and at the same time, it can also help the students to identify their own vocational skills proficiency, and carry out targeted learning to improve. Literature [27] takes student development theory and Bloom's adaptation taxonomy as the underlying logic, builds a model for assessing the maturity of employability skills, and conducts relevant analysis, pointing out that students show great differences in employability skills, and arguing that educational institutions need to reshape the graduates' sense of identity and vocational cognition in order to adapt to the fast-changing labor market. Literature [28] collected and analyzed the participation of undergraduate and postgraduate students in employability development activities at a university in Australia and the United Kingdom, pointing out that students' participation in these employability development activities and related courses somewhat enhanced their employability and attractiveness to employers. Literature [29] investigated the attitudes and understandings of marine sport science students towards professional employment during their professional studies through a mixed methods approach, and found that students' views changed from what employers wanted to what students had to offer employers.

This study uses machine learning to construct an achievement prediction model to assist the optimization of vocational education curriculum system. Through data analysis and feature extraction of students' learning behaviors, on the basis of machine learning, CNN is introduced to improve the predictive ability of the model, and BiLSTM and Attention are integrated to construct an achievement prediction model for vocational education schools. After the model is constructed, it is compared with different single and integrated models, so as to verify the effect of the model in this paper. On this basis, combined with empirical analysis, the value of this paper's prediction model for vocational education is investigated to assist in the optimization of the vocational education curriculum system, to promote the improvement of the teaching curriculum, and to improve students' employability.

2. Machine learning-based forecasting for vocational education

With the development of advanced manufacturing industry and emerging industries, the requirements for the comprehensive ability and quality of practical talents are also increasing, and the requirements for composite talents are getting stronger and stronger. The reform of vocational education curriculum has become an important content to realize the teaching objectives, and the construction of the curriculum system that adapts to the development of the school and meets the needs of the society and the enterprises should be aimed at improving the vocational ability and employability of the students. In the process of vocational education curriculum development and construction, schools must pay attention to the cultivation of professional talents' skills and professional ethical norms, improve students' professional skills level, and ensure the effective realization of the cultivation objectives. Vocational education curriculum is to job employment needs as an important basis for adjustment, therefore, in the construction of vocational education curriculum system, based on the students' learning status, learning achievement is to adjust the curriculum structure and intervention is to realize the adjustment of the timeliness of the need for means. The traditional vocational education is difficult to track students' performance, so in order to pay attention to preventing the school students and society from derailment, this paper constructs a vocational education prediction model based on machine learning for predicting and tracking students' performance and situation in vocational education, and optimize the vocational education curriculum system based on it, and ultimately realize the purpose of enhancing students' employability.

2.1. Mechanical Learning and Learning Behavior Feature Extraction

Machine Learning (ML) is a cross-discipline originating from statistics. It analyzes and searches for laws from experience through the study of computer algorithms, involving knowledge of many disciplines such as system identification, theory, computer science, approximation theory, etc. It is used to analyze and sort out the existing data information and continuously optimize its own structure in order to obtain the relevant information for the new goal. Machine learning contains three basic elements: data, algorithm and model, it selects appropriate algorithms according to specific research objectives and real data, summarizes the law from data through algorithms, and predicts unknown objects according to this law (machine learning model) and new data. The problems solved by machine learning can be categorized into classification problems and regression problems. Classification models can map a sample in a dataset to a class in a given category, and the output of this type of model is a discrete value for the category to which the sample most likely belongs. The regression model is based on the input sample data, summarize and generalize the laws and trends of the data, through training to get a specific model for determining the target predictive value of the unknown sample, the output of this type of model is a certain characteristic value of the sample, is a continuous value. Common mechanical learning algorithms are Support Vector Machines (SVM), KNN, Logistic Regression Analysis, Integrated Learning and so on.

Before constructing the prediction model, it is necessary to analyze the basic information data of students and learning behavior data for feature analysis and feature selection, and the feature extraction and selection in the dataset will have an important impact on the prediction results. In the process of data analysis, the selection of factors influencing learning achievement is reflected in the selection and determination of data features. In the original dataset, it usually contains some irrelevant or redundant attributes, for example, there is obviously no correlation between the student's school number and the student's academic achievement. Removing redundant and irrelevant features improves the accuracy of the prediction results and the predictive model learned on a subset of attributes is better understood.

The information gain rate is a method used to determine and classify attributes, and the magnitude of its value reflects the extent to which the features affect the prediction results, which in this study can be used to analyze the impact of each feature on student learning outcomes. In order to determine the information gain rate of the features, the information entropy of each feature must be calculated first.

Information entropy is used to measure the purity of the dataset. Assuming that the current sample set D has a proportion of type k samples of $p_k(k=1,2,\cdots,|y|)$, the information entropy of D is defined as:

$$Ent(D) = -\sum_{k=1}^{|y|} p_k \log_2 p_k \tag{1}$$

Then the information gain of the feature can be calculated, the information gain is the purity enhancement value of the dataset after dividing the feature attributes, the difference of the information entropy obtained after dividing the original dataset with the attributes is the purity enhancement value. The formula for information gain is:

$$Gain(D,a) = Ent(D) - \sum_{v=1}^{v} \frac{|D^v|}{D} Ent(D^v) \tag{2}$$

D is the dataset, a is the selected attribute, a there are a total of V values, with this V value to divide the dataset D, respectively, to get the dataset D^I to D^V, the information entropy of the V dataset, and its weighted average, the difference between the two obtained is the information gain. After obtaining the dataset, the size of the information gain value can be used to decide whether to use this attribute a to divide the dataset D or not, if the information gain obtained is larger, it means that this attribute is a better attribute to be used for dividing the dataset D or else it is considered that this attribute is not suitable for dividing the dataset D, which is of great help in building the decision tree, and it can also be used to analyze the impact of each feature on the prediction results. The impact of each feature on the prediction result is analyzed.

The metric value, i.e., the rate of information gain. Information gain has some drawbacks since it can favor attributes with more values. To avoid this drawback from adversely affecting the feature analysis, the information gain rate was chosen to analyze the importance of the features. The information gain rate is calculated as:

$$Gain\_ratio(D,a) = \frac{Gain(D,a)}{IV(a)} \tag{3}$$

where $IV(a)$ is calculated as follows:

$$IV(a) = -\sum_{v=1}^{v} \frac{|D^v|}{|D|} \log_2 \frac{|D^v|}{|D|} \tag{4}$$

2.2. *Machine Learning Based Prediction Model for Vocational Education*

The workflow of the model is shown in Fig. 1.The purpose of this study is to predict students' academic performance through their potential behavioral characteristics.In this study, it is argued that the cumulative click data obtained on a weekly basis, which leads to the students' time-series behavioral data.A new student performance prediction model, CNN-BiLSTM-Attention, is proposed.The model consists of two important components, namely, 1D- CNN, BiLSTM, and Attention.In time-series data processing, 1D-CNN has strong ability in feature extraction, and the introduction of CNN can enhance the prediction ability of the whole model.BiLSTM has the function of forward and backward data relevance mining.BiLSTM network is introduced to mine the temporal and periodic features embedded in the data. It is based on the principle of giving different levels of attention to different features, i.e., using different weights to increase or decrease the importance of features to the overall data.

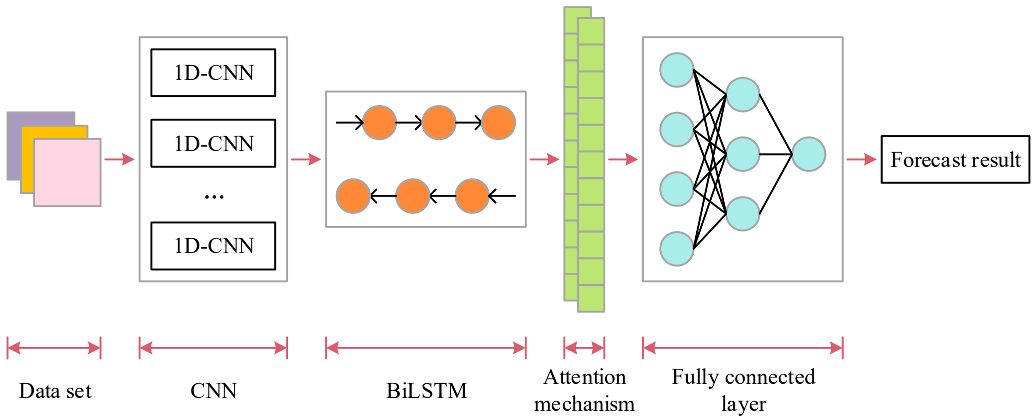

Fig. 1. Model frame

In this model. First, a lightweight ID-CNN structure is used, which can significantly reduce the network complexity. Each ID-CNN network processes only one week of temporal behavioral information. This approach enhances the predictive power of the model while ensuring a concise network structure. The study categorized the overall behavioral data of the students on a weekly basis into 32 weeks of behavioral data. Then the 32 weeks of behavioral data were fed into 32 1D-CNN networks in parallel, from which high-dimensional features of the behavioral data were obtained, and then the ID-CNN output was accessed in the BiLSTM network, which obtained weekly time-series behavioral correlation features, and, finally, the output attention mechanism of the BiLSTM network, as well as the fully-connected layer, were processed to obtain the final results.

Convolutional layers are an important component of CNN. Each convolutional layer has a number of convolutional kernels that are convolved to the input information to capture the hidden features and form the feature map. The feature map is used by a nonlinear activation function to produce an output at the convolutional layer. The convolutional layer can be expressed as:

$$m_i = f(w_i * x_i + b_i) \tag{5}$$

Inside the formula w_i denotes a weight matrix, * denotes dot product operation, b_i denotes a bias vector, f denotes an activation function, there is more than one CNN activation function, generally ReLU function is used as an activation function, and m_i is a feature map. Mathematically ReLU is defined as:

$$m_i = f(k_i) = \max(0, k_i) \tag{6}$$

Inside the formula k_i is the element of the feature map in the convolution operation.

Pooling operations have the effect of reducing the dimensionality of the feature map, avoiding overfitting, and so on. Among them, maximum pooling is the most common. By calculating the maximum value in a prescribed region on the feature map based on the equation:

$$\mu(m_i, m_{i-1}) = \max(m_i, m_{i-1}) \tag{7}$$

$$c_i = \mu(m_i, m_{i-1}) + \eta_i \tag{8}$$

Inside the formula μ is the sampling function in the pooling layer. η_i is the offset, and c_i is the pooling layer output. Finally the features obtained by convolution and pooling operations are transferred to the fully connected layer and then the final output vector is computed:

$$y_i = f(v_i c_i + \lambda_i) \tag{9}$$

In the formula y_i denotes the final output vector, λ_i is the offset and v_i is the weight matrix.

LSTM is a kind of RNN.LSTM is very suitable for time-series data modeling due to its design characteristics.It is a combination of forward LSTM and backward LSTM.Each LSTM cell has three types of gating structures: forgetting gate and input gate and output gate.

Each LSTM cell has a forgetting gate, input gate and output gate a total of 3 gating structures. Each gating structure of the LSTM cell, the output of the hidden layer, the cell state transfer process.

Oblivion gate inside the formula:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{10}$$

Enter the formula inside the door:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)\tilde{c}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)C_t = f_t^* C_{t-1} + i_t * \tilde{c}_t \tag{11}$$

Output gate inside formula:

$$o_t = \sigma(W_0[h_{t-1}, x_t] + b_0) \tag{12}$$

$$h_t = o_t * \tanh(C_t) \tag{13}$$

where x_t denotes the input timing data, f_t, i_t, o_t denotes the output of the oblivion gate, the input gate and the output gate, respectively. W_f, W_i, W_0 is the weight matrix of the three gates, b_f, b_i, b_c is the corresponding three bias cells, σ is the sigmoid function, tanh is the hyperbolic tangent function, * denotes the inner product operation, $\tilde{c}_t$ denotes the candidate vectors created through the tanh layer, W_c, b_c corresponds to the weight matrix and bias cells of this layer, respectively, C_t is the cell state, and h_t denotes the hidden state.

However, LSTM only feeds the information in the forward sequence into the neural network for prediction, and it is difficult to perceive the backward content of the data during the training of the model. The emergence of Bidirectional Long and Short-Term Memory Network (BiLSTM) technique solves the problem of insufficient attention to backward information. By bi-directional, it means, there are forward LSTM units, backward LSTM modules set up within the said BiLSTM, each LSTM unit conforms to the construction of the LSTM described above and the two units of forward and backward shift are independent of each other.

The attention mechanism utilizes the input feature values to help the model filter out valid and significant features. To filter out significant features, the attention module combines the attention score module with the attention focus module to filter out significant features. For the hidden layer state of the neural network, different weight vectors are assigned to the features based on their influence on the final prediction results. In this study, important student behavioral features were given more weight based on the effect of different student time-series behavioral data on performance prediction.

The input to the Attention layer is the hidden layer state $h_{t'}$ computed by the BiLSTM layer, m_t represents the value of the probability distribution of attention determined by $h_{t'}$, a_t is the value of the attention weights, and the output of the Attention layer at the moment of t is s_t, as specified in Eq:

$$m_t = s_{t-1} \times h_t' \tag{14}$$

$$a_t = \frac{exp(m_t)}{\sum_{j=1}^{t} exp(m_j)} \tag{15}$$

$$s_t = \sum_{i=1}^{t} a_i h_i^{'} \tag{16}$$

The fully connected layer is chosen as the output layer and sigmoid is chosen as the activation function to output the predicted value of the score at the $t+1$st moment, denoted as $y^{'}$, which can be expressed as:

$$y^{'} = sigmoid(\omega_{st} + b) \tag{17}$$

where ω is the weight matrix and b is the bias.

3. Prediction of learning achievement and curriculum optimization in vocational education

3.1. Comparative analysis of the performance of learning achievement prediction models

In order to evaluate the accuracy of the prediction model constructed in this chapter, this study uses machine learning algorithms commonly used in grade prediction to assess the prediction performance of this prediction model in the task of student grade prediction. In this experiment, five types of metrics, namely, accuracy, precision, recall, F1-Score, and AUC, are used as indicators to evaluate the performance of the student achievement prediction model. The comparison of the metrics can more accurately describe the strengths and weaknesses of the algorithms. Commonly used machine learning algorithms include LR, KNN, DT, NB, SVM, RF, Adaboost, GBDT, respectively, while sklearn toolkit is used to implement these algorithms during the experiment. The performance comparison results with a single machine learning algorithm are shown in Figure 2. It can be found that the NB algorithm achieves the worst results in the single algorithm model, with accuracy, precision, recall, F1-Score, and AUC of 0.802, 0.925, 0.680, 0.790, and 0.813 for each metric respectively. This is because the NB algorithm assumes that each feature in the sample is independent of each other, whereas during the learning process, there is often a correlation between different types of student interactions that are not completely independent. Compared with a single algorithm, the model in this paper achieved the best prediction results, with the indicators of 0.961, 0.953, 0.985, 0.966, and 0.957, respectively, which were improved by 0.144 to 0.305 for each indicator compared with the NB algorithm, and by 0.008 to 0.031 for each indicator compared with the better-performing SVM model.

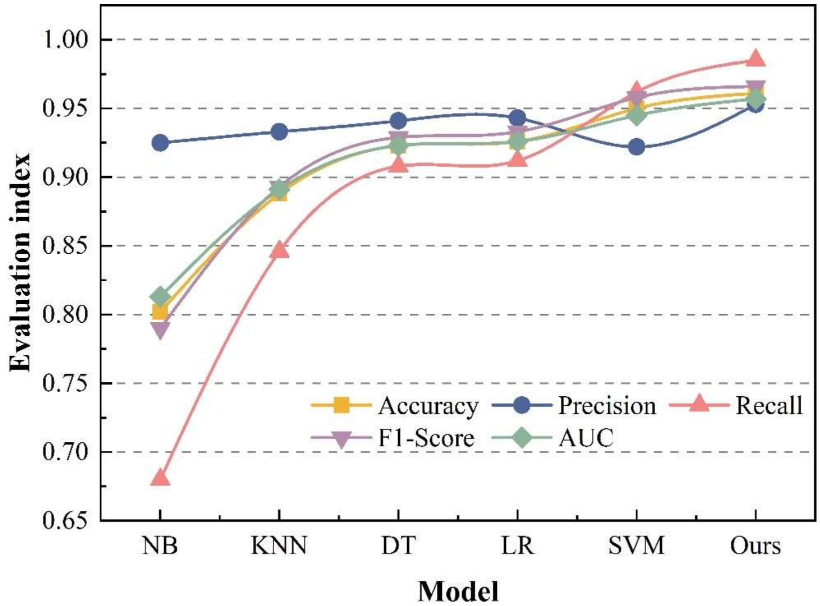

Fig. 2. Performance comparison results with single machine learning algorithm

The results of the performance comparison with other integrated learning methods are shown in Figure 3.In this experimental comparison, integrated learning algorithms commonly used in student performance prediction studies were used to make predictions about whether students could pass the course. These integrated algorithms are all implemented based on decision trees, of which Random Forest belongs to the extension algorithm of Bagging in the integrated learning algorithms, while AdaBoost and GBDT belong to the Boost type of integrated learning. Compared with other integrated algorithms, the model in this paper still achieves the best performance results, compared with the better performance of the GBDT model each index is improved by 0.028~0.060, which shows that the model in this paper has excellent performance, and it will have a better performance in the prediction of academic performance.

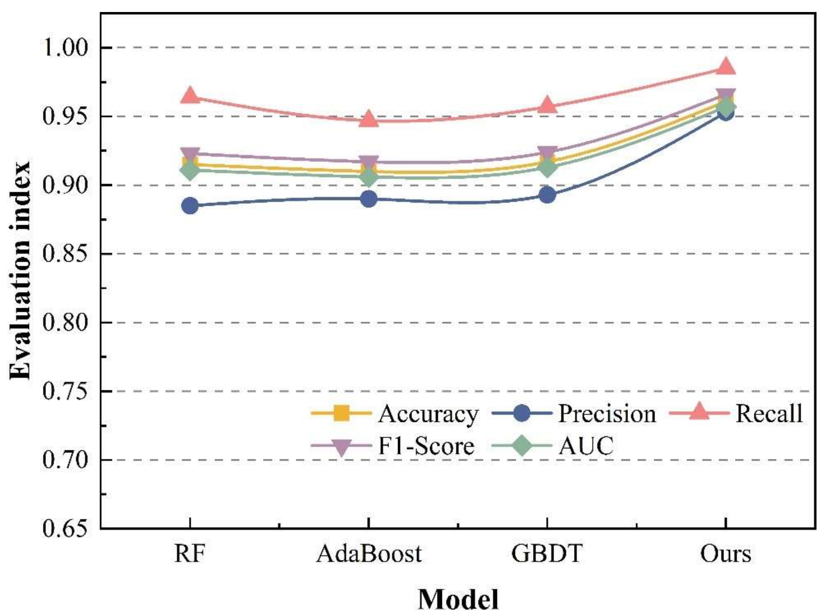

Fig. 3. Compare results with its integrated learning methods

To ensure the reliability and accuracy of the predicted scores in this paper, vocational education courses were divided in this study. According to the time when the course is conducted, it is divided into 10%, 20%, ... , 100% and other 10 different course progress, and then use the prediction model of this paper to predict the students' grades under different course progress respectively, and the results of the grade prediction of different course progress are shown in Figure 4. It is easy to find that with the deepening of the course progress, the prediction accuracy of students' grades will gradually increase from 0.624 to 0.954, indicating that the higher the course progress can help the model to predict more accurately. Therefore, when the course progresses to 80% and above, more accurate prediction of students can be made.

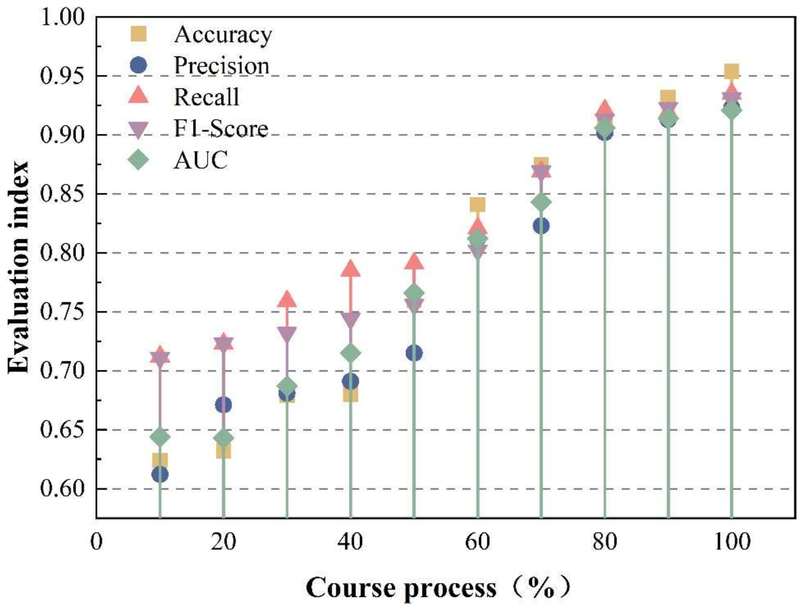

Fig. 4. Results of the results of different courses

3.2. *Predictive analysis of student performance in vocational education*

This paper takes S vocational school as the research object, obtains first-hand information through collection, survey and other methods, and carries out strict desensitization processing at the beginning of data collection and integration to ensure that the data information does not involve personal privacy. On this basis, information entropy is used to process the data, and the information of students' employment data is added to study the practical application value of the model of this paper through empirical analysis. The prediction effect of the model in this paper has been verified through the results of the model experiment. As the importance of various prediction indicators is not the same in different prediction problems, and machine learning can obtain different prediction effects by adjusting the parameters, this ability can be used as an efficient and low-cost alternative to apply in the actual higher education intervention.

3.2.1. Predictive Characterization of Vocational Education Students. In this study, based on the prediction of students' performance, we tracked and surveyed students' data up to May 2023, tagged the students' data with data characteristic attributes including gender (X1), ethnicity (X2), political affiliation (X3), students' majors (X4), grades in the submission (X5), whether or not they have received any school honors (X6), whether or not they have received any provincial honors (X7), whether or not they have received any national honors (X8) scholarships received (X9), and academic performance scores (X10). Thus, the effect of student characteristics on the prediction of student performance was investigated. The distribution of the importance of each feature is shown in Figure 5, and the experimental validation analysis can be used to find out which features are more important in the prediction of students' performance. It can be seen that the importance of whether or not to receive school honors (X6), whether or not to receive provincial honors (X7), whether or not to receive national honors (X8) scholarships received (X9), and academic performance scores (X10) are higher than 0.8, 0.855, 0.896, 0.932, 0.912, and 0.895, which are all higher than 0.8, respectively. In particular, the importance of “receiving national honors or not” is the highest. At the same time, several of the characteristics related to the acquisition of honors were high. Secondly, students' academic performance ranked third. The analysis shows that these characteristics are important factors affecting students' performance, therefore, in the construction of vocational education curriculum system focusing on the performance of students, we should encourage students to participate in different levels of events, cultivate students' practical ability, and comprehensively improve students' personal ability.

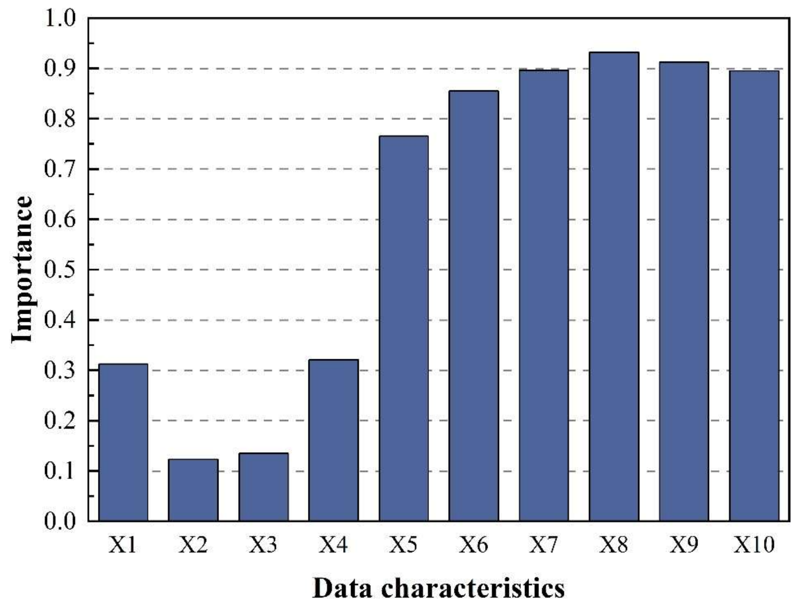

Fig. 5. The importance of each feature

3.2.2. Employment analysis based on the prediction of academic performance. Student achievement is not only a measure of the outcome of vocational education, but also an important basis for the reform of the vocational education curriculum system, and at the same time, it also affects the graduation and employment of students. In this study, for example, five students (S1~S5) enrolled in the year 2023 were predicted for their grades in college S. We analyzed whether the students could graduate and be employed by the predicted results of the grades, so as to judge whether the school needed to make teaching interventions or not, and the predicted results of the students' grades are shown in Fig. 6.There are 8 semesters in college S, in which the first 5 semesters have already been carried out, and the students' grades are the really grades, and the 5~8 semesters are predicted grades. Observations show that the overall predicted grades of the four students, S1, S2, S4, and S5, were on an upward trend and all of them were able to achieve a score of 70 or more in the final semester's predicted grades. On the other hand, the performance of S3 student traveled a significant decline, only 61.6 points in the final semester's grade prediction, which means that the student has the risk of not being able to successfully graduate and carry out employment, and the school should carry out timely instructional interventions to improve the student's learning situation, so as to ensure that the student is able to successfully graduate and carry out employment. The study proves that the grade prediction model based on machine learning in this paper can be effectively applied to actual teaching, and through grade prediction, it can intervene with students with poor grades in advance to prevent these students from not graduating on time, to improve students' employability, and to realize the development of students' employment.

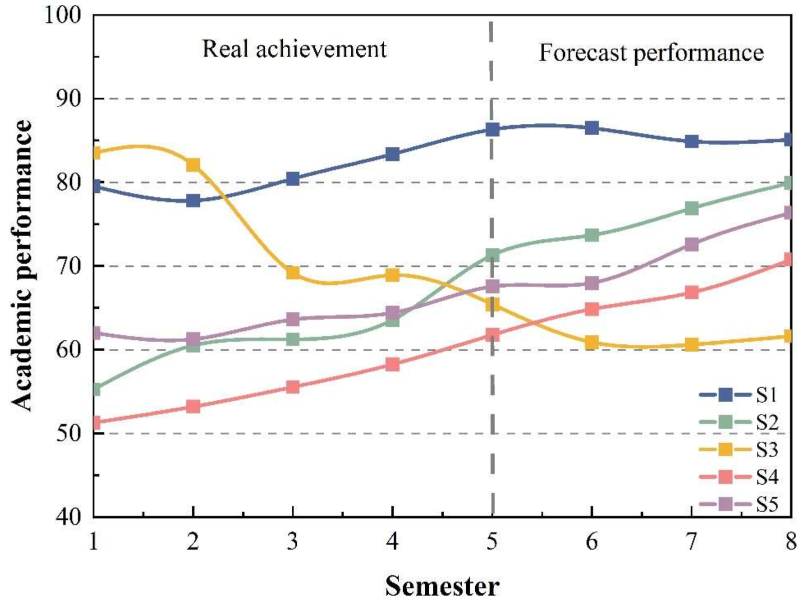

Fig. 6. Student performance prediction results

3.3. *Optimization of vocational education curriculum system based on learning prediction*

Today, vocational education is difficult to adapt to the development of the times, due to the aging of its specialties and the obsolete and lack of skills in the knowledge system. Vocational education must optimize and adjust the curriculum system, establish a new curriculum system, and improve the teaching means to support the curriculum system. This study uses machine learning to construct a performance prediction model for vocational education, through which the performance prediction model can effectively reflect the problems in the teaching curriculum and provide timely teaching interventions for students, so as to build a personalized and modernized vocational education system. The optimization path of vocational education curriculum is shown in Figure 7. The optimization path of this paper is always based on the fact that ability cultivation is always the core position, and in vocational education, secondary vocational education cannot become simple vocational training, and at the same time, it cannot take “advancement to higher education” as the main index of running schools. In the special professional courses of specific occupations, the principle should be to cultivate the core competitiveness of the workplace, through the construction of a reasonable curriculum education system, to cultivate technical talents who can be applied to different positions, so that the graduates of the school will have the knowledge, quality and ability to participate in the practical work of the corresponding level. In the process of curriculum construction, the school needs to ensure that the theory and practice of education system, to ensure that to meet the needs of society for the grass-roots work orientation of the duties. This not only expands the cultivation of students' practical ability, but also broadens their theoretical knowledge and improves their comprehensive quality. At the core of capacity building, schools must always pay attention to the characteristics of vocational education talents (application-oriented talents). Students need to expand the proportion of practical classes, replace the traditional classroom-centered teaching model, develop a modern education model that focuses on cultivating students' abilities, and strengthen students' practical skills. This will improve the goal of education and the employment rate of the society, and guarantee the security and stability of the society.

In a word, the establishment of vocational curriculum system enables students not only to master the basic knowledge and skills of their specialties, but also to innovate knowledge and skills, so as to enhance their comprehensive ability, solve the problem of cultivating talents needed for social development, gain advantages in the fierce competition for employment, and enhance their employability.

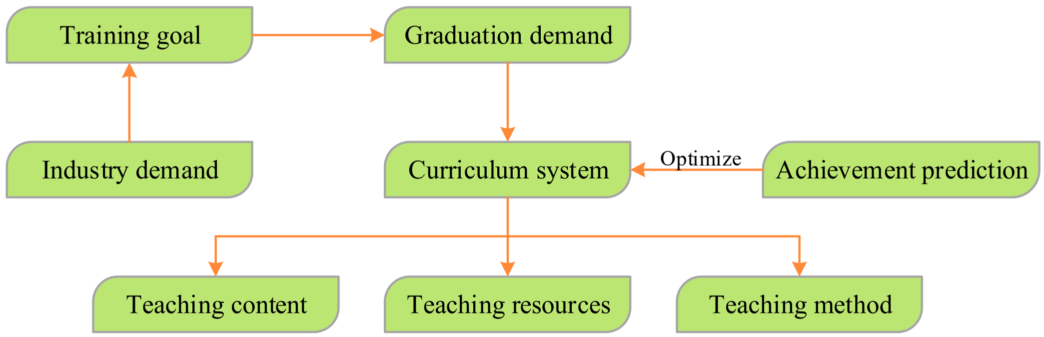

Fig. 7. Career education course optimization path

4. Conclusion

This study constructs a CNN-BiLSTM-Attention grade prediction model for vocational education on the basis of machine learning, and applies it in practice to assist the optimization of vocational education curriculum system. The research results of this paper are as follows:

1) The accuracy, precision, recall, F1-Score, and AUC of this paper's model are 0.961, 0.953, 0.985, 0.966, and 0.957 for each metric, respectively. In the single model comparison, the improvement over the poorer performing NB algorithm is 0.144 to 0.305 for each metric, and 0.008 to 0.031 for each metric compared to the better performing SVM model. In addition, comparing with the integrated model, the model in this paper still achieves the best performance results, with an improvement of 0.028~0.060 in each metric compared with the better performing GBDT model. Second, as the course progress deepens, the accuracy of this paper's model improves from 0.624 to 0.954, which means that the higher the course progress predicts the grades more accurately, further verifying that this paper's model has a better performance in predicting students' grades.

2) The importance of whether or not they received school honors (X6), whether or not they received provincial honors (X7), whether or not they received national honors (X8) Scholarships received (X9), and academic performance ratings (X10) were all higher than 0.8. “Receiving national honors” was the most important at 0.932, and students' academic performance ranked third at 0.895. Therefore, while paying attention to students' performance in the construction of the vocational education curriculum system, it is necessary to cultivate students' practical ability, increase the opportunities for learning participation, and comprehensively improve students' personal ability and employability.

3) In the practice prediction, S3 students showed a significant decline in their grades, scoring only 61.6 in the final semester grade prediction, while the other four students were on an upward trend in their overall predicted grades, all scoring 70 or higher in the final semester grade prediction. This indicates that S3 students are at risk of not being able to graduate and pursue employment compared to the other students. The study proves that the machine learning-based grade prediction model in this paper can actually predict student grades. The prediction can provide timely intervention for students with poor grades and risks, thus preventing these students from failing to graduate on time, improving students' employability, and providing a strong guarantee for the optimization path of vocational education curriculum system.

Acknowledgements

2024 Higher Education Reform Research and Practice (Key) Project (Employment and Entrepreneurship Guidance Category) of Henan Provincial Department of Education, “Exploration and

Practice of Enhancing Employment Ability of Students in Vocational Colleges and Universities in the Context of Integration of Industry and Education” (Project No.: 2024SJGLX1086);

2023 Research and Practice on Teaching Reform of Vocational Education in Henan Province (Key) Project “Research and Practice on Talent Cultivation Mode of “Staring Chain and Building Cluster, Four Dimensions and Ten Communities” in Shuanghui College in the Context of Development of Leading Industries in the Municipal Areas” (Project No.: YUJI [2024]). 05752).

References

[1] Cheng, M., Adekola, O., Albia, J., & Cai, S. (2022). Employability in higher education: a review of key stakeholders' perspectives. Higher Education Evaluation and Development, 16(1), 16-31.

[2] Behle, H. (2020). Students’ and graduates’ employability. A framework to classify and measure employability gain. Policy reviews in higher education, 4(1), 105-130.

[3] Bennett, D., Knight, E., & Rowley, J. (2020). The role of hybrid learning spaces in enhancing higher education students’ employability. British Journal of Educational Technology, 51(4), 1188-1202.

[4] Irwin, A., Nordmann, E., & Simms, K. (2019). Stakeholder perception of student employability: does the duration, type and location of work experience matter?. Higher Education, 78(5), 761-781.

[5] Thakar, P., & Mehta, A. (2017). A unified model of clustering and classification to improve students’ employability prediction. International Journal of Intelligent Systems and Applications, 9(9), 10.

[6] Rosina, H., Virgantina, V., Ayyash, Y., Dwiyanti, V., & Boonsong, S. (2021). Vocational education curriculum: Between vocational education and industrial needs. ASEAN Journal of Science and Engineering Education, 1(2), 105-110.

[7] Azman, A., SIMATUPANG, W., Karudin, A., & Dakhi, O. (2020). Link and match policy in vocational education to address the problem of unemployment. International journal of multi science, 1(07), 76-85.

[8] Mbarushimana, N., & Allida, D. (2020). Curriculum change and teacher participation in technical and vocational education training programs (TVET): experiences of Groupe Scolaire Aiper Nyandungu, Rwanda. Education, 2021.

[9] Audu, A. (2022). Role of entrepreneurship education and vocational education in the management of education. Journal of Advances in Education and Philosophy, 6(7), 377-382.

[10] Fix, G. M., Ritzen, H. T. M., Pieters, J. M., & Kuiper, W. A. J. M. (2019). Effective curricula for at-risk students in vocational education: a study of teachers’ practice. Empirical research in vocational education and training, 11, 1-17.

[11] Billett, S. (2020). Perspectives on enhancing the standing of vocational education and the occupations it serves. Journal of Vocational Education & Training, 72(2), 161-169.

[12] Terblanche, T., & Bitzer, E. (2018). Leading curriculum change in South African technical and vocational education and training colleges. Journal of Vocational, Adult and Continuing Education and Training, 1(1), 104-125.

[13] Rageth, L., & Renold, U. (2020). The linkage between the education and employment systems: Ideal types of vocational education and training programs. Journal of Education Policy, 35(4), 503-528.

[14] Casuat, C. D., & Festijo, E. D. (2019, December). Predicting students' employability using machine learning approach. In 2019 IEEE 6th international conference on engineering technologies and applied sciences (ICETAS) (pp. 1-5). IEEE.

[15] Maryanti, R., & Nandiyanto, A. B. D. (2021). Curriculum Development in Science Education in Vocational School. Online Submission, 1(3), 151-156.

[16] Pambudi, N. A., & Harjanto, B. (2020). Vocational education in Indonesia: History, development, opportunities, and challenges. Children and Youth Services Review, 115, 105092.

[17] Tentama, F., & Abdillah, M. H. (2019). Student Employability Examined from Academic Achievement and Self-Concept. International Journal of Evaluation and Research in Education, 8(2), 243-248.

[18] Hiim, H. (2017). Ensuring curriculum relevance in vocational education and training: Epistemological perspectives in a curriculum research project. International journal for research in vocational education and training, 4(1), 1-19.

[19] Young, M., & Hordern, J. (2022). Does the vocational curriculum have a future?. Journal of Vocational Education & Training, 74(1), 68-88.

[20] Munir, M., Sinambela, E. A., Halizah, S. N., Khayru, R. K., & Mendrika, V. (2022). Review of vocational education curriculum in the fourth industrial revolu-tion and contribution to rural development. Journal of social science studies (jos3), 2(1), 5-8.

[21] Rintala, H., & Nokelainen, P. (2020). Vocational education and learners' experienced workplace curriculum. Vocations and Learning, 13(1), 113-130.

[22] Sevilla, M. P., & Polesel, J. (2022). Vocational education and social inequalities in within-and between-school curriculum tracking. Compare: A Journal of Comparative and International Education, 52(4), 581-599.

[23] Handoyono, N. A. (2022). Comparative study of curriculum, learning models, and quality assurance in vocational education. Journal for Education and Vocational Future, 1(2), 1-8.

[24] Ozer, M., & Perc, M. (2020). Dreams and realities of school tracking and vocational education. Palgrave Communications, 6(1), 1-7.

[25] Campbell, M., Cooper, B., Rueckert, C., & Smith, J. (2019). Reimagining student employability: A case study of policy and practice transformation. Journal of Higher Education Policy and Management, 41(5), 500-517.

[26] Bharambe, Y., Mored, N., Mulchandani, M., Shankarmani, R., & Shinde, S. G. (2017, September). Assessing employability of students using data mining techniques. In 2017 international conference on advances in computing, communications and informatics (icacci) (pp. 2110-2114). IEEE.

[27] Griffiths, D. A., Inman, M., Rojas, H., & Williams, K. (2018). Transitioning student identity and sense of place: future possibilities for assessment and development of student employability skills. Studies in Higher Education, 43(5), 891-913.

[28] Jackson, D., & Tomlinson, M. (2022). The relative importance of work experience, extra-curricular and university-based activities on student employability. Higher Education Research & Development, 41(4), 1119-1135.

[29] Gedye, S., & Beaumont, E. (2018). "The ability to get a job": student understandings and definitions of employability. Education+ Training, 60(5), 406-420.