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Retraction

Retracted: Random Algorithm and Skill Evaluation System Based on the Combing of Construction Mechanism of Higher Vocational Professional Group

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] W. Jia, "Random Algorithm and Skill Evaluation System Based on the Combing of Construction Mechanism of Higher Vocational Professional Group," *Advances in Multimedia*, vol. 2022, Article ID 8378997, 9 pages, 2022.

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Research Article

Random Algorithm and Skill Evaluation System Based on the Combing of Construction Mechanism of Higher Vocational Professional Group

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At present, the employment situation in China is very severe, and there are both recruitment and employment difficulties in the society. There are many reasons for this problem, among which, the incompatibility between talents training and social demand in higher vocational colleges is one of the main reasons, and it is necessary for higher vocational colleges to effectively evaluate students' skills training with the real demand. Based on this, this paper studies the study of stochastic algorithm and skill evaluation system based on the combing of the construction mechanism of higher vocational professional clusters and builds a higher vocational skill evaluation system based on a simple analysis of the skill evaluation system and related evaluation algorithms in higher vocational institutions. Principal component analysis was selected to realize the quantitative processing of skill evaluation indexes, and random forest algorithm was used to realize skill evaluation. The simulated annealing algorithm is introduced to realize parameter selection, parameter optimization, and weight setting, and experiments are designed to analyze the performance of the algorithm. The simulation results show that the random forest algorithm is applied to skill evaluation with high accuracy, small error, and better generalization ability.

1. Introduction

Talents are necessary to promote social progress, and how to cultivate high-quality talents is the key factor to promote industrial upgrading and innovation [1]. With the surge of talent demand, the form of employment is also getting severe. Higher vocational colleges and universities aim to cultivate students' skills, and with the increasing requirements of the society for employment, the strategy of talent cultivation is also changing; so, higher vocational colleges and universities need to make corresponding changes in the evaluation of talent skills [2, 3]. In the current evaluation system, most of the existing studies explore the deficiencies in skills from a theoretical perspective, and the conclusions are not objective enough [4]. Although artificial intelligence techniques are beginning to be applied to the evaluation process, the research perspectives are not broad enough, mostly from the perspective of a specialized field, and the conclusions obtained are not broad enough to analyze skill mastery as a whole [5]. Scientific evaluation mechanism, as an effective carrier to promote the construction of high-level professional groups, plays an important leading role in key links such as the adjustment of professional structure, the optimization of curriculum and teaching, and multiparty collaborative education. From the current practice, the evaluation of professional groups needs to focus on solving the problems of concept, management, and technology.

The construction of specialty groups is one of the endogenous driving forces and main signs of the continuous development of higher vocational colleges, an important starting point for the promotion of the national "double high plan" and an effective way to improve the quality of vocational education in China. In February 2019, the State Council issued the national vocational education reform implementation plan, which proposed to "implement the high-level higher vocational schools and professional construction plan with Chinese characteristics." In December 2020, the Ministry of Education and the Ministry of Finance issued the

Interim Measures for the performance management of high-level higher vocational schools and specialty construction plans with Chinese characteristics, which incorporated the construction of specialty groups into the performance management and evaluation of "double high plan" colleges, continued to promote the "double high plan," and promoted the construction and research of specialty groups. Based on this background, this paper analyzes the study of stochastic algorithm and skill evaluation system based on the combing of construction mechanism of higher vocational professional clusters, which is divided into four main chapters. Chapter 1 first makes a brief introduction to the construction skill evaluation of higher vocational institutions and the chapter arrangement of this study; Chapter 2 introduces the domestic and foreign evaluations on teaching aspects and the applications of various data mining algorithms and summarizes the shortcomings in the current study. Chapter 3 constructs a skill evaluation model for combing the construction mechanism of higher vocational professional clusters, using principal component analysis to quantify the process and random forest algorithm to realize skill evaluation. In view of the shortcomings of the random forest algorithm, it is proposed to use RF algorithm and simulated annealing algorithm to improve and optimize the algorithm parameters and heart stems. Chapter 4 simulates and analyzes the skill evaluation system constructed in this paper based on the mechanism of combing the construction of higher vocational clusters, optimizes the system parameters, determines the accuracy of the algorithm, and analyzes the factors affecting the skills. The experimental results show that at each index level, the improved randomized algorithm proposed in this paper shows obvious advantages, with small error values, strong generalization ability, and high prediction accuracy when compared and analyzed with real skill scores.

The innovation of this paper lies in the construction of the skill evaluation model for combing the mechanism of higher vocational professional cluster construction. The random forest algorithm is introduced and improved, the RF method is used to process the feature importance, and the weighting is calculated according to the classifier performance. Combined with simulated annealing algorithm to select the important features and optimize the parameters, the parameters are binary coded to improve the accuracy of the algorithm.

2. Materials and Methods

The talent training goal is an overall description of the career and professional achievements that graduates can achieve in about 5 years after graduation. The main basis for formulating talent training objectives is education laws, school orientation, industry and employer needs, national and social needs, and other factors. To formulate talent training objectives, we should proceed from the internal development laws of education, combine the current and long-term needs of the state, society, industry, and employers, determine the final talent training objectives according to the school's school running ideas, and make appropriate adjustments to the specific requirements of the talent training objectives according to the development of the times and the needs of the country and society.

In recent years, as the expansion of universities has gradually shrunk and the national focus on talent has shifted from quantity to quality previously, talent training has received widespread public attention, and research on the evaluation of talent learning has emerged. For example, Guo et al. proposed an integrated model based on statistical modeling and integrated learning, using computer vision and intelligent speech recognition, and proposed a metric system that combines traditional assessment scales with new values derived from CV and ISR-based artificial intelligence analysis to design classroom teaching assessment models using hierarchical analysis method entropy weights and integrated learning-based methods [6]. Yz et al. proposed a model that combines network structural features with graph neural networks in a hybrid recommendation model that describes students, courses, and other entities by using student ratings, review texts, ratings, and interpersonal relationships, using a random walk-based neural network to generate a vectorized representation of students by learning their own relational structure, with personalized features identified as the third dimension of the rating tensor [7]. Lin et al. proposed two vocabulary approaches, specifically a knowledge-based approach and a machine learning-based approach for automatic opinion extraction from brief comments, which achieved 78.13% and 84.78% accuracy in the student review sentiment classification task, respectively [8]. Liu et al. developed an instructional assessment model using deep convolutional neural networks and a weighted plain Bayesian algorithm, proposing the use of category attributes of correlation probabilities to estimate the weight of each assessment feature and assign the corresponding weights, and producing an instructional assessment model that promotes standardization and comprehensibility [9]. Based on an in-depth study of the theory of Markov chain algorithm, Yuan proposed an improved Markov chain hybrid instructional quality assessment model and designed comparative experiments to validate its effectiveness through experiments [10]. Liu et al. applied the classification algorithm in machine learning to the construction of the evaluation model, used the empirical algorithm as the basic algorithm for evaluating teaching quality, took the subject word distribution obtained from the joint model training as the original knowledge, and analyzed the performance of the system in this study through controlled experiments [11]. Chen, in his study of English teaching evaluation, constructed the parametric model of constrained English teaching level and the big data analysis model and used big data information fusion and clustering processing methods for ELT proficiency assessment to improve the quantitative prediction ability of the assessment [12]. Although modern quantitative statistical methods have achieved certain results in different degrees in the evaluation of teaching quality in colleges and universities, there are still many imperfections in these methods. Most of them study specific technologies from the microscopic perspective, such as fuzzy comprehensive evaluation, AHP, and Markov chain method. They have some difficulties in determining the weight of each secondary index.

Usually, they rely on the evaluation of expert experience, resulting in a large subjective randomness of the evaluation. There is a certain error between the evaluation result and the actual value. However, from the perspective of system engineering, there are still insufficient research on identifying the key factors of teaching quality evaluation in colleges and universities, determining the status of various factors, thus proposing evaluation models and methods, and making a comprehensive evaluation of college teachers through the evaluation system (the evaluation should not be a simple evaluation of the excellent, medium, and poor teaching quality of teachers, but also be embodied in the evaluation results).

In summary, it can be seen that there are many studies in student learning assessment, and the early studies are survey-based and highly subjective. With the development of data analysis techniques, new data mining algorithms have been introduced in the assessment of competencies, and the algorithms are constantly being updated and improved. However, these studies themselves are similar in analysis, the research angle is narrow, the objects targeted are mostly school students, and the indicators used along are mostly those of achievement evaluation, which cannot reflect the skill mastery in higher vocational institutions. Therefore, it is of great practical significance to carry out research on stochastic algorithm and skill evaluation system based on the combing of construction mechanism of higher vocational professional clusters.

3. Results and Discussion

3.1. Higher Vocational Professional Cluster Construction Mechanism to Sort Out Skill Evaluation Index. The professional group mainly refers to a professional cluster composed of several related majors or professional directions with similar technical basis and occupation positions, centering on a certain technical field or service field, according to its own unique advantages and service orientation, with the key or characteristic (advantage) majors of the school as the core. Carrying out the evaluation of specialty group construction is conducive to guiding higher vocational colleges to determine the direction and focus of school specialty development according to their own industry and local economic development needs and improve the overall efficiency of specialty construction. It is convenient to form a joint force among specialties and improve the matching degree between specialty layout and industrial development. It is helpful to enhance the post adaptability and career transfer ability of graduates and lay a solid foundation for their sustainable development.

With the problem of data from higher vocational institutions, collate school records, questionnaires, and grades to obtain students' data. In the skill evaluation of higher vocational institutions, there are many indicators covered, and the connotations are crossed; in the construction of the evaluation index system, it should follow the principle of targeting, which can provide reference opinions for students' development and can provide feedback mechanism for higher vocational institutions [13]. Skill evaluation indexes should follow the principle of combining subjective and objective; in addition to objective achievements, there are subjective feelings. The selected indicators should have accuracy and validity and be able to be quantified. In addition, each skill evaluation index should have independence and avoid overlap [14].

In constructing the evaluation index system, following these principles, it is also necessary to combine the requirements in terms of national engineering certification and select an index system that is convenient for evaluation [15]. Combining the actuality of higher vocational majors themselves with the existing evaluation models and methods, the index system is established and divided into three levels. The first level is skill evaluation index, and there are six secondary indexes, respectively: professional skills, innovation and entrepreneurship, knowledge and skills, practical ability, comprehensive development ability, and sustainable development. Professional skills are represented by class performance and innovation, innovation representative indicators include competition, thesis publication, innovation projects, and patent situation, knowledge learning ability includes various certificates, management practice ability includes club participation, instructing, participation in research, and volunteer situation, comprehensive development ability is represented by various scholarships and titles, and sustainable development ability includes salary package and enterprise satisfaction.

In constructing the evaluation of students' ability, it is necessary to collect data and clean and fill the data, etc. Combining with the national requirements, the skill evaluation index system of higher education institutions is established and quantified, and the evaluation of skills is realized by using the improved random forest algorithm, as shown in Figure 1.

Combined with the requirements of national education, the indicators established for the evaluation of professional skills in higher education should cover professional skills, innovation ability, learning ability, sustainable development, and other indicators. In the indicator processing stage, different processing methods need to be used to improve the evaluation accuracy. In the student professional skills rating, the principal-form analysis method is used to calculate it, and the raw data are first standardized [16]. Assuming that there are n participants in the evaluation, the matrix is formed by combining the evaluation competency indicators and calculating the matrix correlation coefficient eigenvalues, with the formula.

$$
\begin{aligned}
y_1 &= u_{11}x_1 + u_{21}x_2 + + u_{m1}x_m, \\
y_m &= u_{1m}x_m + u_{2m}x_m + + u_{mm}x_m.
\end{aligned}
\tag{1}
$$

The principal component is selected to calculate the comprehensive evaluation value, and the contribution rate is calculated. When the principal component contribution rate is close to 1, the principal component is substituted for the evaluation index, and then the comprehensive analysis is performed. The score of each principal component was calculated with the following formula.

$$
Z = \sum_{j=1}^{p} b_j y_j. \tag{2}
$$

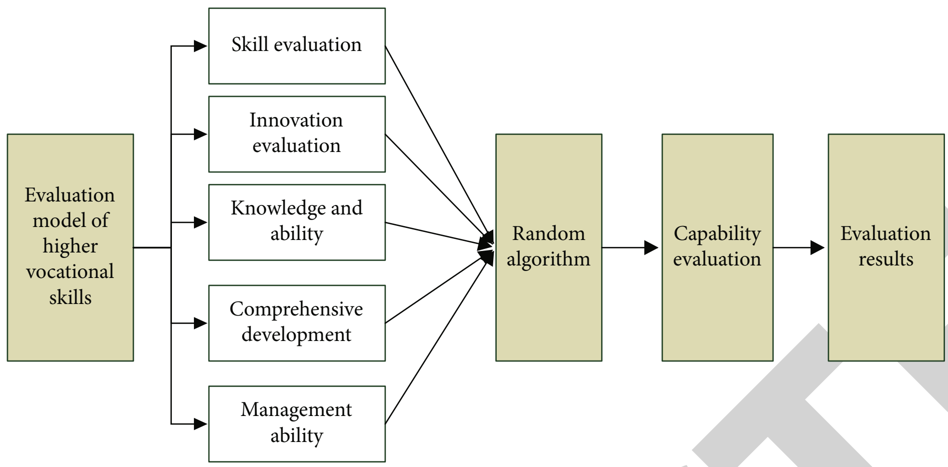

Figure 1: Evaluation model of higher vocational skills.

The b in the formula indicates the information contribution of the principal components.

3.2. Skill Evaluation Model Based on Stochastic Algorithm. The random forest algorithm is an integrated learning algorithm. It uses multiple decision trees to train, classify, and predict samples. It is mainly used in classification and regression. On the basis of building bagging ensemble with decision tree-based learners, random forest further introduces the selection of random attributes in the training process of decision tree. The random forest algorithm is simple, easy to implement, and has low computational cost. It has shown strong performance in many real tasks.

The stochastic algorithm belongs to the relatively novel machine learning algorithm, combined with the characteristics of skill evaluation, the random forest algorithm is used to constitute the evaluation model, in building decision trees, and all decision trees are independent of each other to improve the training efficiency [17]. The random algorithm covers two random processes, and bagging randomly generates the training set and selects a subset of features. The bagging algorithm does not depend on the computational process and is randomly selected from the original data for independent computation; so, the algorithm classification accuracy is relatively high and can avoid the problem of overfitting. Of course, the random forest algorithm also has many shortcomings. The random forest algorithm uses the mechanism of average voting when making decisions, without considering the difference between strong and weak classifiers. Too many weak classifiers participate in the decision-making process, which will reduce the accuracy of decision-making. In addition, due to the use of random selection to select sample features, it is impossible to eliminate the impact of sample data when processing unbalanced data.

In the application, data are randomly extracted from the dataset D to form a new training set, the training set is subjected to classification regression, and the final output is obtained after weighted calculation and arithmetic average calculation [18]. The dataset of the decision tree can be effectively enhanced by this step, and the generalization ability is improved. Using bootstrap sampling, samples are drawn by putting back from the original data to form a sample set, and the probability that each sample is not able to be every drawn is expressed as the following equation.

$$p = \left(1 - \frac{1}{N}\right)^{N}. \tag{3}$$

When N takes an infinite value and P takes a value of 0.368, 37% of the data in the training set will not be drawn, and this part of the sample is represented by OOB, a metric that can be used to analyze the error and can also respond to the importance [18]. Based on the submodel of the randomized algorithm when there is the CART model, the Gini index is used as a splitting metric when the decision tree nodes are split to generate a bifurcated decision tree, and each division divides the sample into two subsets. The impurity of the data set is calculated using the Gini index with the formula.

$$\mathrm{Gini}(D) = 1 - \sum_{1}^{m} p_i^2, \tag{4}$$

where the probability of p belonging in the sample is represented C, and if the sample D is based on a A binary division that becomes a subset of 2, the exponential calculation based on this division is expressed as follows:

The p in the formula denotes the probability of belonging to C in the sample, if the sample D becomes 2 subsets based on the binary division of A, then the exponential calculation based on this division is expressed in equation (5).

$$\mathrm{Gini}_A(D) = \frac{|D_1|}{D}\mathrm{Gini}(D_1) + \frac{|D_2|}{D}\mathrm{Gini}(D_2). \tag{5}$$

After this calculation, the binary division impurity based on A can be obtained as the following equation.

$$\Delta\mathrm{Gini}(A) = \mathrm{Gini}(D) - \mathrm{Gini}_A(D). \tag{6}$$

In CART calculation, it is necessary to choose maximizing impurity. The CART model divides the dataset by this method until the dataset of each node is of the same class. Regression trees are generated when the dataset features are transformed into continuous values [19]. Based on the bagging method to extract the data, some of the data will not be extracted, and in the actual randomized algorithm execution, the OOB is able to detect the value of the decision tree, and the smaller the value, the better the classification [20]. The average OOB of the decision tree is generally used to calculate the error, and the formula is as follows.

$$\text{OBBerror} = \frac{\sum_1^k \text{OOBerror}_i}{k}. \tag{7}$$

For each training subset, the CART method is used to generate a dichotomous recursive decision tree, which constitutes a random forest, and is tested. For the classification results, majority voting method and weighting method are used to determine the final results. The decision tree is weighted, the total number of votes is calculated, and the formula is expressed as the following equation.

$$S_c = \sum_1^k [T_{c,X}(X) W_t]. \tag{8}$$

The value of T in the formula is 0 or 1. If the sample is classified as having c categories, the value is 1; otherwise, the value is 0. After weighted statistics, the one with more categories is selected as the final classification result. Compared with other classification algorithms, the randomized algorithm operates more efficiently, but the default parameters are not optimal, the OOB error is large, the objective function needs to be determined, and the number of predefined features may also affect the calculation accuracy [21–24].

Most of the traditional algorithms in skill evaluation are randomly selected and weighted according to expert opinions, which are too subjective, do not consider the influence of the environment, and are inefficient. Standard random algorithms are random in selecting features, but the probability of occurrence and the importance of sample features are also different, which also affects the evaluation results. To avoid this situation, the sample importance is chosen as the selection index to reduce the impact caused by the classifier. A certain basic feature X is selected, and random noise data is introduced to calculate the OOB error. Assuming that there are N decision trees present in the randomized algorithm, the importance of the feature is calculated as

$$I_x = \frac{\sum_j^N \left(\text{errOO}B2_j - \text{errOO}B1_j\right)}{N}. \tag{9}$$

Based on the data features, 75% of the features are selected, the later features are deleted, and the steps are repeated until the number is reduced to a set value. The traditional stochastic algorithm uses an average majority method in classification decisions, and the result obtained is the class with the most output, but in practice, there may be cases where the decision tree has the same voting weight and the classifier is not used. In the decision tree weighting calculation, the confusion matrix calculation method is used, and the formula is expressed as follows.

$$\begin{aligned} \text{Recall} &= \frac{\text{TP}}{\text{TP} + \text{FN}}, \\ \text{ACC} &= \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}, \end{aligned} \tag{10}$$

where TP denotes the number of people predicted as high skill scores, TN denotes the number of people with poor skill scores, FP denotes the number of people predicted as high misclassified skill scores, FN denotes the number of people misclassified as poor skill scores, recall denotes is recall rate, and ACC denotes accuracy rate. The value of the decision tree is calculated according to the F-measure calculation method, and the formula is expressed as the following equation.

$$F - \text{measure} = \frac{2 \times \text{recall} \times \text{precision}}{\text{recall} + \text{precision}}, \tag{11}$$

where recall denotes recall rate, and precision denotes accuracy rate. The data from the validation set is input in each decision tree, and the predicted values are calculated and compared with the real results for analysis. The improved algorithm reduces the impact caused by the averaging regime and improves the overall performance. In the stochastic algorithm improvement, in addition to feature selection, weight calculation and parameter optimization are covered to remove useless feature information and also analyze the different weight settings to find the best combination.

In the stochastic algorithm, there are two parameters that affect the execution efficiency, which are the number of decision trees and the attribute feature subset size. A larger number of decision trees indicate more classifiers, which helps to improve the performance but is costly and affects the computational efficiency. If K is too small, it affects the accuracy of the results. Attribute feature subset size responds to attribute size. Too large a value of this will affect the similarity of the decision tree, and too small a value will lose many important features. In the same stage of the decision tree, weighting calculation is needed to introduce the concept of weighting weights to improve the classification results.

For the optimization of the feature value parameters and the adjustment of the weights, a comprehensive optimization improvement method is used to obtain the optimal feature decision tree size and weights by incorporating the simulated annealing algorithm in the stochastic algorithm. The simulated annealing algorithm is an optimization algorithm of serial structure that can effectively avoid falling into local minima and eventually reach global optimization by giving the search process a time-varying and eventually zero probability jump. Theoretically, the algorithm has probabilistic global optimization performance and has been widely

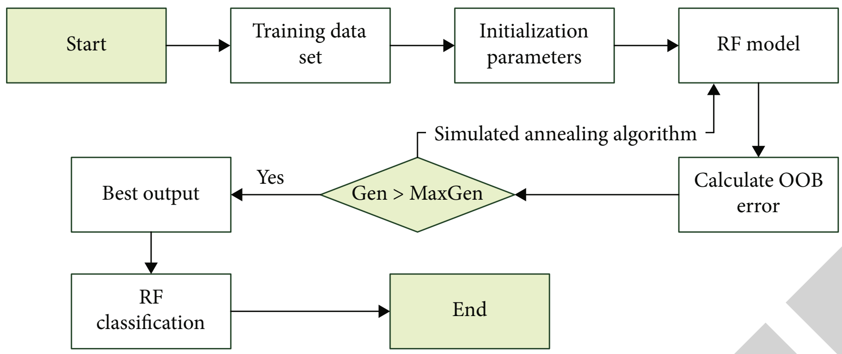

Figure 2: Irfc process of improved algorithm.

used in engineering, such as VLSI, production scheduling, control engineering, machine learning, neural networks, and signal.

The objective function of the improved algorithm is set as the following equation.

$$f\{k^*, o^*(\text{Attribute}i|i = 1, 2, \cdots, M)\} = \arg\min(\text{acgooBerror}). \tag{12}$$

Optimization is performed for parameters K and O. K ranges from 0 to 500, and W ranges from 0 to 15. Attribute with a value of 0 indicates that the feature is not selected, and a value of 1 indicates that it is selected. A binary code is used to represent the optimization variables, and the number of coding bits is fixed at 22.

Based on the binary encoding of variables, a random forest improvement algorithm is used to calculate the optimal solution of the objective function, as shown in Figure 2. Assuming an initial problem of t and a maximum number of iterations maxgen, the initial solution is randomly generated and computed in conjunction with RF classification. If the termination condition is reached within this temperature, it ends; otherwise, the solution is randomly selected from the current solution, the objective function value is calculated, the optimal solution is updated, and the formula is expressed as the following equation.

$$X_{\text{best}} = \begin{cases} X_{\text{new}}, \Delta F < 0, \\ X_{\text{new}}, \Delta F < 0, qnde^{-\Delta F/t_k > \text{random}}, \\ X_{\text{best}}, \textit{else}. \end{cases} \tag{13}$$

It terminates the calculation when the termination condition is met; otherwise, the operation continues.

4. Result Analysis and Discussion

4.1. Data Processing and Simulation Analysis. The process of talent quality evaluation is to select talents with the best comprehensive quality from various indicators of students' performance in school, which can be regarded as a classification problem of unbalanced data sets. If we do not consider the balance of indicators and directly model the original data, it is difficult to get a more ideal model. We can need to train data to improve the imbalance rate. The main way is to measure the importance of data indicators through the measurement of feature importance, which is the standard for indicator weighting. The selection of feature samples and the voting process of decision tree are the main aspects that affect the application of RF algorithm in talent training evaluation. This paper proposes the following improvement schemes in these two aspects.

Students from higher education institutions are selected as an example, these students come from any major, including computer, software engineering, and electrification, and there are more than 30,000 records. The collected data are arranged according to the academic number. In the evaluation of student employment indicators, there are many information covered, except for the nature of the enterprise and the data of the examination, other data are difficult to distinguish effectively, and there is a lack of effective salary data. Therefore, the more common enterprises in China are selected for matching analysis, and enterprises such as entering listed companies and foreign enterprises are considered as high-tech enterprises. In terms of examinations and research, famous universities are taken, and classification labels are set.

The quality of the data will directly affect the data analysis results. The data collected from the academic affairs system is not complete enough, there is noise, and there will be redundant data; so, the data needs to be preprocessed. The preprocessing of student skills data starts with data cleaning, removing the results of the existence of double degrees, and the make-up exams are based on the results of the first exam. Then, the data simplification process is performed. There are many numbers of data attributes collected, but not all of them are necessary, data related to the study are selected, and irrelevant data, such as semester, academic year, and class, are proposed.

The traditional method of processing student evaluation indicators is to select and weight the indicator points according to the literature and expert opinions. This method is greatly affected by subjective factors and does not consider the different influence of indicators in different environments. There are two main problems with this method: first, this method is not only inefficient but also affects the final result due to factors; second, because the feature selection in the standard random forest algorithm is completely random, the probability of sample features being selected is

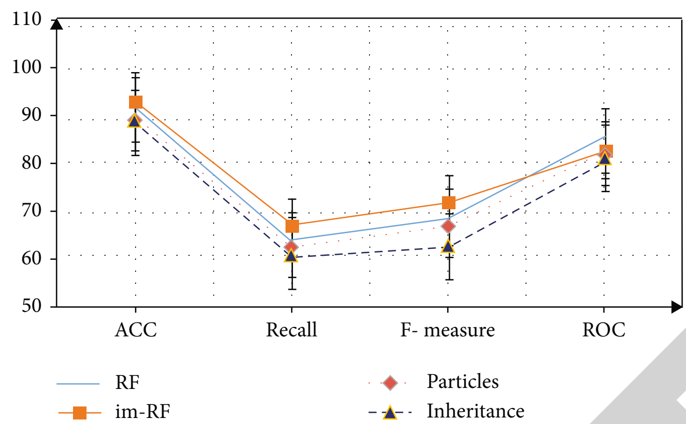

Figure 3: Effect of feature importance on algorithm performance.

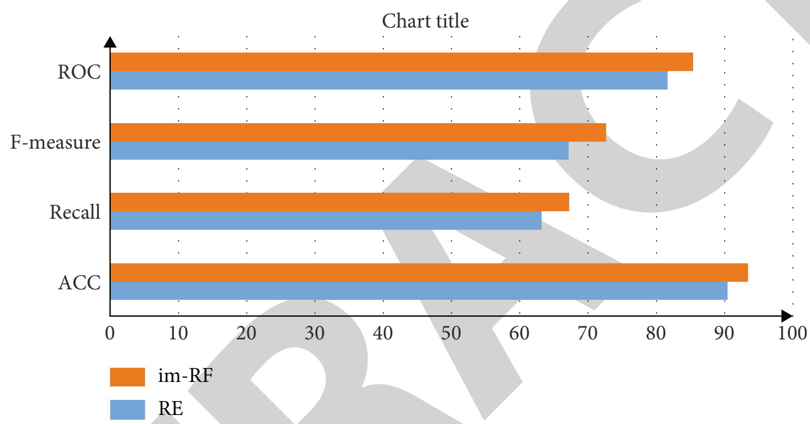

Figure 4: Effect of weight improvement on algorithm performance.

the same, but in fact, the importance of each feature is different, that is to say, in the process of talent training quality evaluation, unbalanced data is involved. In order to solve the above problems, this paper selects the selected sample features with high importance based on the importance of each sample feature to reduce the possibility of weak classifier generation.

In the evaluation using the stochastic algorithm, the algorithm is improved, and the performance of the algorithm needs to be verified first. The algorithm proposed in this paper is simulated and analyzed with the stochastic algorithm without weighting. Both algorithms were simulated and analyzed on the UCI dataset, taking the same parameters, and this dataset is one of the most widely used datasets, which facilitates the parallelization process. The results in the determination are shown in Figure 3. In this dataset, the accuracy of the improved randomized algorithm is significantly improved, and the selection of the improved randomized algorithm is able to select representative indicators on its own during feature selection, reducing the impact brought by the classifier.

The traditional random forest method uses the average majority voting method when making classification decisions. Each decision tree outputs its own classification label, and the final result is the class with the most output. However, in the process of classification, the classification effect of decision trees is different. If each decision tree has the same voting weight according to the average voting method, the classifier with good effect will not play a better role, and the classifier with poor effect will have a negative impact on the result.

Next, the impact of the weighted improvement strategy on the performance of the algorithm is analyzed, and the simulation analysis is also performed under the UCI data set to determine the performance of the randomized algorithm with the ordinary voting mechanism and the improved randomized algorithm with the weighted mechanism, and the measurement results are shown in Figure 4. From the data in Figure 4, we can see that the accuracy of the weighted improved randomized algorithm is improved, which indicates that the improvement strategy used in this paper can improve the performance of the randomized algorithm.

The improved stochastic algorithm proposed in this paper is applied to higher vocational skills evaluation, and it is compared and analyzed with classical algorithms such as particle swarm stochastic optimization algorithm, hybrid genetic algorithm, hybrid fish swarm algorithm, and primitive forest algorithm. Student data are selected for analysis, and the sample set is analyzed by 4-fold crossvalidation to determine the accuracy and recall rate. The results of the determination are shown in Figure 5. From Figure 5, it can be seen that compared with the classical algorithm, the

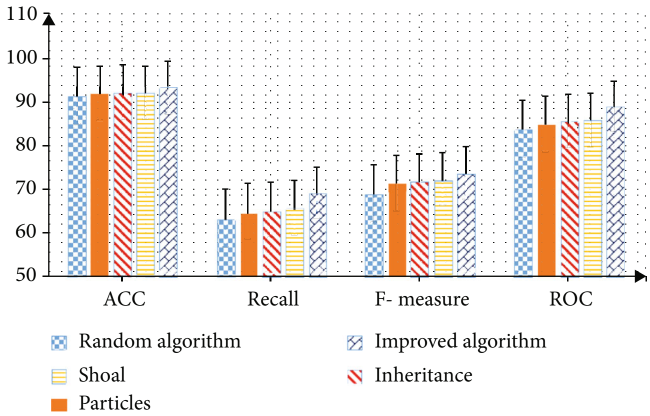

Figure 5: Performance comparison of different algorithms.

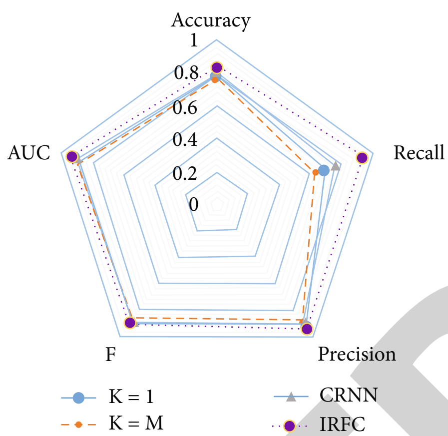

Figure 6: Student skill evaluation scores.

improved randomized algorithm proposed in this paper has improved both accuracy and recall in skill evaluation.

The improved random forest algorithm reduces the impact of the average voting mechanism, reduces the impact of weak classifiers on the results, and improves the overall performance of the algorithm. It can be applied in talent quality evaluation or other applications.

4.2. Skill Evaluation in Higher Education Institutions. In the evaluation using the improved stochastic algorithm, the max-gen parameter is set to 20, and the tmax parameter is set to 10. In the evaluation, the values of each index are used in a 4-fold crossvalidation method. In the students' dataset, the data of the first two years were used as the training set and trained using the improved stochastic algorithm, and the data of the latter year were used as the test set and compared with the real performance for analysis. The corresponding results are shown in Figure 6. From the data in Figure 6, it can be seen that at each index level, the improved stochastic algorithm proposed in this paper shows significant advantages with small error values and strong generalization ability.

The improved stochastic algorithm proposed in this paper is applied to higher vocational skills evaluation, and it is compared and analyzed with classical algorithms such as particle swarm stochastic optimization algorithm, hybrid

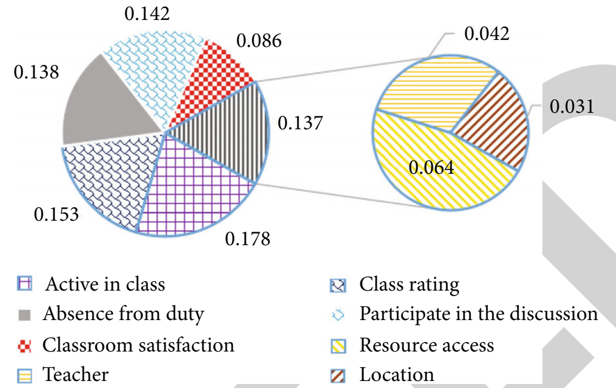

Figure 7: Analysis of influencing factors of students' skill evaluation.

genetic algorithm, hybrid fish swarm algorithm, and primitive forest algorithm. Student data are selected for analysis, and the sample set is analyzed by 4-fold crossvalidation to determine the accuracy and recall rate. The results of the determination are shown in Figure 7.

It can be seen from Figure 7 that compared with several classical modified random forest algorithms, the improved random forest algorithm proposed in this paper has little difference in accuracy and recall when used in talent training evaluation, but it has improved in accuracy to a certain extent, meeting the design requirements.

5. Conclusion

The random forest algorithm is an algorithm developed based on the decision tree algorithm, which performs well on data sets, can handle high-dimensional data, has strong adaptability, can handle discrete and continuous data, is very efficient, easy to explain the application, and is an important mining algorithm in the field of machine learning. Based on this, this paper studies the stochastic algorithm and skill evaluation system based on the combing of the construction mechanism of higher vocational professional clusters, combining the national demand about higher vocational skills and the existing research, constructing a higher vocational skill evaluation system, determining skill evaluation indexes, and using stochastic algorithm to conduct index analysis. The simulated annealing algorithm is used to optimize the design of the stochastic algorithm, and the accuracy and effectiveness of the stochastic algorithm in skill evaluation are confirmed through simulation experiments. It should be noted that there are many data in the database of higher vocational schools, and the parallelization of processing on the data platform can be considered in the application of the stochastic algorithm, and the stochastic algorithm can be optimized from other aspects to improve the accuracy. In student skill evaluation, there are various classification algorithms, the stochastic algorithm can be combined with other classification algorithms to speed up the training, and these aspects need to continue to be studied.

As a new thing, the professional group skill evaluation system has no mature experience to learn from at the initial stage of construction. It needs to constantly try and innovate in management and technology in practice to promote the renewal and development of the evaluation concept of professional groups in higher vocational colleges. Therefore, it is necessary to base on the practice of professional group construction in higher vocational colleges, form a scientific concept of professional group evaluation construction, and guide the development and innovation of professional group evaluation at the management mechanism and technical design level, so as to create a high-level professional group evaluation system with Chinese characteristics in higher vocational colleges.

Data Availability

The figures used to support the findings of this study are included in the article.

Conflicts of Interest

The author declares no conflicts of interest.

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