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Research Article

Big Data Analysis Model for Vocational Education Employment Rate Prediction

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Vocational education is an important means to promote the development of the national manufacturing industry. To correctly grasp the relationship between vocational education and the labor market, we start with the quality of vocational education and employment rate and study the interconnection between them. To this end, we propose a vocational education employment rate prediction method based on a big data model and build a vocational education quality assessment and employment rate prediction system. We draw on the big data cross-learning model to improve the model hyperparameters by using generalized intersection sets on the joint loss function to compensate for the shortcomings of dense vocational education datasets. We use the GSA algorithm to enhance the local features of different vocational education quality assessment index data series. To scientifically assess the recognition of vocational education, we evaluate the vocational education assessment indexes at the student level and the parent level to verify the reliability of the experiment. The experimental results prove that our method performs best in the prediction accuracy of vocational education quality assessment indicators, and the prediction accuracy rate stays above 91%. In the prediction of vocational education employment rate, the difference between the predicted and actual values of our method is the smallest, and the difference stays within 1%. Compared with other big data models, our method has higher prediction accuracy and better robustness.

1. Introduction

Vocational education is a powerful driver of manufacturing and plays an important role in the country's economic development. The integration of vocational education with secondary education can solve the contradiction of a single form of secondary school and provide more options for young people of school age. Diversified vocational education can not only improve the pressure for further education in the general education system but also address the pressure on employment rates in higher education [1, 2]. The more developed a city is, the more importance it places on vocational education, and the spread of vocational education can help rationalize the distribution of urban economies, can reduce youth unemployment, and is a necessary tool to guarantee skill acquisition for school-age youth [3]. For the general education system, vocational education offers multiple options for young students. Students with insufficient academic abilities can make voluntary choices about their future development according to their situation, fully guaranteeing their willingness to learn skills and advance to higher education [4].

Despite the important role of vocational education in socioeconomic mediation, the association between vocational education and employment rates is not supported by data. The feedback period of vocational education is long, and the linear correlation between economic feedback and the cost-effectiveness of vocational education is not strong enough for enterprises. After a large number of vocational education employment rate data analyses in which the employment rate of vocational education does not match the actual employment rate, the vocational education employment rate is in urgent need of a predictive model to enhance the economic benefits of vocational education [5]. The poor feedback on the economic benefits of vocational education has led society as a whole to hold a high and low opinion of vocational education. However, it is worth affirming that vocational education is by no means the only way out for working-class people. Most studies on vocational education have discussed this issue, and the level of individual ability has a dominant role in the future development of students, followed by the financial background of the family. Statistics show that most students with strong family financial backgrounds do not choose vocational education because it is the immediate choice for students whose families do not have enough financial resources, and they do not represent a continuous low labor output after choosing vocational education. In fact, the vocational education system also provides reasonable promotion channels for students in the vocational job promotion system to prevent the occurrence of class differentiation problems [6, 7].

For capable vocational education students, they can also be promoted to engineering positions through their practical efforts, which is a reflection of the advantages of diversified vocational education [8, 9]. Vocational teaching was created as a powerful measure to balance the large differences in general learning in the financial background of families and to prevent class differentiation. Although the current economic feedback benefits of vocational education are influenced by several complex factors, students trained in vocational education occupy a significant employment advantage in terms of age, given the reduced labor market advantage due to aging [10, 11]. Some developed countries investigating the impact of vocational education have focused on the way the vocational education system is organized, for example, with a clearer division of labor and a specific vocational training model for different types of occupations. Vocational teaching schools will provide basic vocational theoretical and practical training in school and will also provide factory internships for corresponding jobs with one-on-one training and assessment by skilled workers in which those who pass the assessment can choose a variety of jobs [12, 13]. In addition, vocational education is based on the student development model in terms of curriculum, teaching mode, and teacher expertise. Although some studies have shown that there is some variation in the link between vocational education preparation models and the labor market, most studies can use data analysis and computer science methods to compensate for this variation.

Considering the differences between the vocational education system and the labor market, we refer to studies related to vocational education and find a compensatory relationship between selectivity bias, age effectiveness, and vocational education training model. Compared to the employment rate of general education students, the employment rate of vocational education students is oriented to different recruitment demands. However, according to the available data, the demand for vocational education jobs is much greater than the demand for jobs of general college graduates, which is a great advantage of the vocational education system. Depending on the length of the work cycle, vocational education students have a wider range of choices, with short-term company training, medium- and long-term factory practical work, and a long-term promotion system for engineers, giving vocational education students more room for development [14].

The rest of the paper is organized as follows. Section 2 presents the history and research results of vocational education quality research. Section 3 introduces the relevant principles and implementation details of the LSSVR-based vocational education quality and employment rate prediction model. Section 4 shows the experimental datasets and the analysis of the experimental results. Finally, Section 5 summarizes our research and reveals some further research work.

2. Related Work

Vocational education, which directly corresponds to manufacturing production jobs, can facilitate the renewal iteration of manufacturing and also maintain a steady increase in manufacturing output. Despite the poor feedback benefits of vocational education employment, the relationship between vocational education systems and socioeconomics is only a temporary mismatch in terms of macroeconomics [15–17]. The data on employment rates in vocational education are only temporarily inadequate, and with the intervention of scientific management and job planning tools, the vocational education system will become more relevant to students' situations in career training planning, employment rates will be more accurately predicted, and cooperation between companies and vocational education schools will increase substantially. Most economists, when considering the role of vocational education in the socioeconomy, give priority to the ability and substitutability between the vocational teaching system and manufacturing production jobs. The desired outcome of vocational education is the training of a pool of directly applicable skilled people for each skilled workplace, and the quality of vocational education training is indirectly reflected by the assessment of the competencies of skilled people at the firm level [18, 19]. The higher the quality of vocational education, the higher the economic benefits it generates for the company, which will indirectly increase the future employment rate of vocational education. This model of assessment in cooperation with companies tends to bring a more substantial employment rate increase than that of general higher education. In addition, researchers in the literature [20] argue that vocational education is an important measure to increase national manufacturing productivity, reduce youth unemployment, and reduce poverty. The literature [21, 22] in studies on vocational education found that vocational education is an important tool for national transformation and can achieve a smooth transition from developing to developed countries. Developing countries strongly advocate the training of industrialized and skilled personnel in vocational education to improve the vocational education system and promote the transformation of industrialized countries.

In labor market projections, some researchers have compared vocational education with general education in a hierarchical manner, taking into account the ability weights, cognitive weights, the ability to learn new knowledge among students, and other factors. However, in the data comparison of hands-on practical scores and efficiency of enterprise rotations, vocational education students performed more superiorly. To equalize the differences in learning and cognitive abilities of vocational education students, some scholars have developed vocational education student development systems that aim to balance learning ability differences through skill acquisition for student ability prediction in employment rates [23, 24]. There are also researchers who have developed studies from students' family backgrounds, which provide great value for vocational education development based on students' family social status, family financial resources, family education, and family cohesion [25]. In addition, the development of students from different family backgrounds in the vocational education system strictly limits the development of student's abilities and indirectly predicts their future employment and development potential [26]. Some researchers started with the quality of vocational education, studied the distribution of vocational courses in different vocational schools, the strength of teachers, the arrangement of enterprise practice, and other key factors, and then established a prediction model for vocational education development system, which can effectively predict the development of students in different vocational education systems, providing a solid basis for the prediction of vocational education employment rate and providing detailed vocational training for enterprises that choose to cooperate with rules [27, 28].

Different countries have different planning systems and development orientations for vocational education. Compared to general higher education, the curriculum and delivery methods of the vocational education system are determined by the country's basic industrial model. Most industrially developed countries use a dual vocational education training system. For students who choose vocational education, vocational classroom studies and on-the-job training in companies Dei are alternatives to compulsory education, which is similar to the academic guidance courses offered by an academic education. In this case, researchers, to assess the educational quality and employment rate of vocational education, mostly use deep neural network models to capture the key influences from the multiple vocational education systems. The learning model of neural networks is used to integrate a large amount of vocational education data to effectively predict the trends of quality and employment rates of vocational education. For agricultural developing countries, which advocate vocational education similar to developed countries, but considering the weak industrial base due, the focus of vocational education training is more on theoretical education of vocational courses. In this case, to assess the quality and employment rate of vocational education, researchers mostly use data analysis and machine learning models due to the inability to capture a large amount of information on vocational education and employment rates in real time [29–31]. The data is limited, the trend of employment rate data can only be predicted by data analysis, and then machine learning is used to complete the learning of vocational education quality factors. The vocational education employment rate prediction results obtained in this way are less accurate and less preferable for the overall socioeconomic prediction.

3. Method

3.1. Mainstream Model. The demand for vocational education is closely related to employment rate and economic development, and we innovatively use vocational education employment rate and economic indicators as transition variables. We investigated the literature related to vocational education employment rate prediction research methods, among which the least square support vector regression (LSSVR) model performed the best in the research of employment rate prediction; therefore, we chose this model as our base network. To improve the employment rate prediction accuracy of the vocational education model, we proposed the gravitational search algorithm (GSA) to optimize the LSSVR model. The model contains three parts, as shown in Figure 1; the data preparation part represents the data input from various aspects of vocational education. The GSA part represents the additional part with the model parameters adjustment and the model structure optimization. LSSVR represents the backbone network of the vocational education employment rate prediction model.

3.2. LSSVR Mathematical Principles. In the literature research, it was found that the literature [32] proposed the support vector machine approach, which the authors applied to structural risk optimization with the main principle of statistical planning learning theory. In planning learning of large-scale data samples, the support vector machine causes the model to take a long time to process the data due to its complex structure. To solve the time-consuming problem, we take inspiration from the literature [33], and we use a nonlinear function $\varphi(y_t)$ based on the LSSVR model, assuming that the original data is y_t, and we try to map the original data into the high-level feature map by the nonlinear function. The linear regression is then performed on the mapping results, and the mathematical function relationship is shown as follows:

$$\overline{y_t} = w^T \varphi(y_t) + b, \tag{1}$$

where w represents the vocational education parameter weights and b represents the employment rate forecast bias. The values of these two parameters represent the prediction estimates with the least structural risk. The mathematics is calculated as follows:

$$\begin{gathered} \mathrm{Min}\frac{\left(w^T w\right)}{2} + \frac{\left(\gamma \sum_{t=1}^{T} e_t^2\right)}{2}, \\ \text{s.t. } \overline{y_t} = w^T \varphi(y_t) + b + e_t,\ (t = 1, 2, \ldots, T), \end{gathered} \tag{2}$$

where γ represents the weight parameter and e_t represents the estimation error in time t. Based on the above solution equation function, to obtain the optimal solution to the optimization problem, we used the following mathematical equation to obtain the solution:

$$\overline{y} = \sum_{t=1}^{T} \alpha_t K(y, y_t) + b, \tag{3}$$

where $K(y, y_t) = \exp(-\|y - y_t\|^2/\sigma^2)$ is a kernel function with a Gaussian operator.

In the design of the network structure of LSSVR, we tried to set the parameter values of hyperparameters γ and σ^2 in advance by migration learning. After experimental tests, it was found that the parameter settings of migration learning could not reach the optimal values of data simulation, and for this reason, to enhance the similarity of data simulation, we borrowed the heuristic optimization algorithm proposed in the literature [34], and the GSA algorithm can achieve the optimization of large-scale data simulation with the assistance of the heuristic optimization algorithm, which takes the simulation of universal gravity as the main principle. The GSA algorithm is based on the main principle of simulating gravity, treating the search particles as a set of relative numbers in the universal gravity, and learning the gravitational optimal distance under the action of universal gravity by simulating the trajectory of this set of particles in space. The mutual attraction between particles follows the laws of dynamics, and the attraction between the host particles is positively related to their mass.

3.3. Model Optimization Principle. Assuming that there are N_a impact factors in the vocational education system, the data dimension of the i-th impact factor is defined as follows:

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right), \tag{4}$$

where n represents the dimensionality of the i-th vocational education quality factor and x_i^d represents the data mapping performance of the i-th vocational education quality factor in the d-th dimension, $i = 1, 2, \ldots, N_a$. The mathematical definition between the vocational education quality factors i and j in the d-th dimension at time t is as follows:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t) \times M_{aj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right), \tag{5}$$

where, at time t, $G(t)$ denotes the vocational education quality constant, $M_{pi}(t)$ denotes the i-th passive quality factor variable, $M_{aj}(t)$ denotes the j-th active quality factor variable, ε denotes a constant, and $R_{ij}(t)$ denotes the Euclidean distance between two employment rate variable factors i and j. The mathematical expressions are as follows:

$$R_{ij}(t) = \left\|X_i(t), X_j(t)\right\|_2. \tag{6}$$

The i-th employment rate variable factor in dimension d is defined as

$$F_i^d(t) = \sum_{j=1, j\neq i}^{N_a} \mathrm{rand}_j F_{ij}^d(t), \tag{7}$$

where rand_j denotes a random variable whose data series are uniformly distributed within the ideal interval. Then, according to the gravitational acceleration formula of gravity, we migrate its mathematical expression to the vocational education employment rate prediction model. It is shown as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)}, \tag{8}$$

where $M_{ii}(t)$ denotes the i-th employment rate inertia quantity. Suppose $M_{ai}(t) = M_{pi}(t) = M_{ii}(t) = M_i(t)$. The mathematical expression of the i-th employment rate variable for the vocational education curriculum and practice factors at time t is as follows:

$$\begin{aligned} m_i(t) &= \frac{\mathrm{fit}_i(t) - \mathrm{worst}(t)}{\mathrm{best}(t) - \mathrm{worst}(t)}, \\ M_i(t) &= \frac{m_i(t)}{\sum_{j=1}^{N_a} m_j(t)}, \end{aligned} \tag{9}$$

where $\mathrm{fit}_i(t)$ denotes the fitness value of the i-th employment rate variable factor at time t. To optimize the hyperparameters of the LSSVR model, we introduced the GSA algorithm, and to facilitate the experimental validation of hyperparameter ablation, we adopted a cross-validation grid search method for hyperparameter introduction.

3.4. Optimization Model. The GSA algorithm is mainly used to filter the best solution from the mixed trajectory by predefined data mixture search. To be able to get the best learning result, the algorithm is set up to automatically loop iteratively through the vocational education assessment range system, and the best predictor of employment rate is obtained by clustering algorithm during the iteration process. The main steps of GSA are shown in Figure 2.

The LSSVR model is used in the prediction of static samples of large data, the pretraining dataset is mainly used to determine the initial parameters of the predefined model in one stage, and the formal model training is performed after the initial parameters are determined. Finally, a test dataset is used for model evaluation.

To compare the predictive performance of the models, we used three metric items at the performance evaluation level. The root means square error (RMSE) is mainly used to measure the deviation between the predicted and true values and is more sensitive to outliers in the data. Mean absolute percentage error (MAPE) represents the relative error metric, which avoids positive and negative errors from canceling each other by absolute values. The Willmott's Index of Agreement (WIA) rated the accuracy and predictive power of the regression formulas, and the regression formulas for each parameter had good generalizability.

$$\begin{aligned} \mathrm{RMSE} &= \sqrt{\sum_{t=1}^{N}\frac{\left(y_t - \overline{y}_t\right)^2}{N}}, \\ \mathrm{MAPE} &= 100 \times \sum_{t=1}^{N}\frac{\left|1 - \left(\overline{y}_t/y_t\right)\right|}{N}, \\ \mathrm{WIA} &= 1 - \frac{\sum_{t=1}^{N}\left(\overline{y}_t - \overline{\overline{y}}\right)^2}{\sum_{t=1}^{N}\left(\left|\overline{y} - \overline{\overline{y}}\right| + \left|y_t - \overline{\overline{y}}\right|\right)^2}, \end{aligned} \tag{10}$$

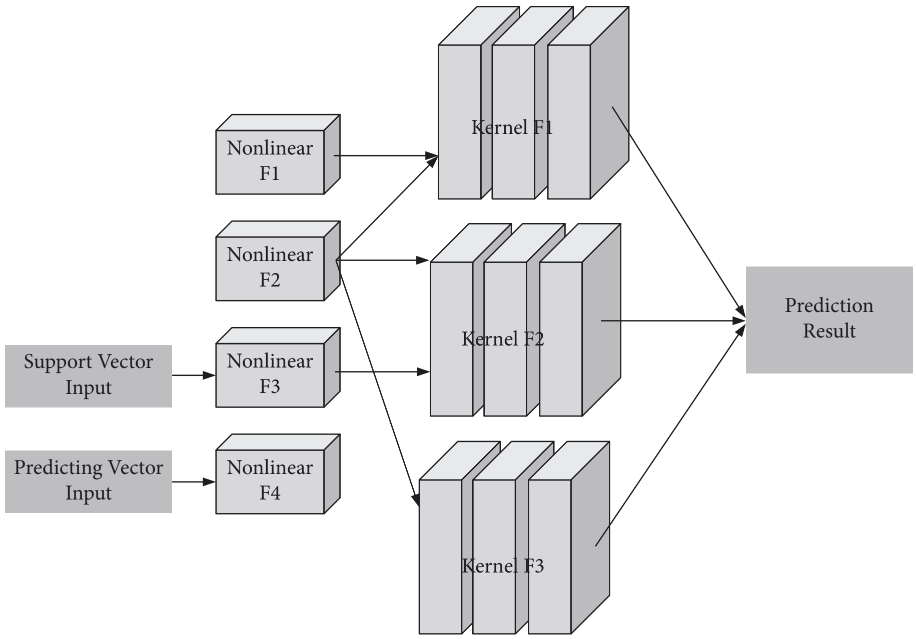

FIGURE 1: LSSVR model structural.

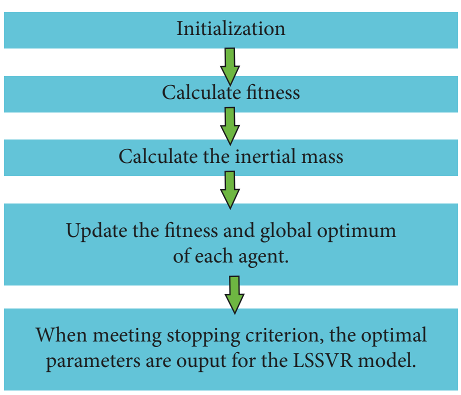

FIGURE 2: The main steps of GSA.

where N denotes the employment rate detection factor in the test set. In the assessment of vocational education employment rate prediction performance, RMSE and MAPE are used to predict the test accuracy. WIA is used to measure the peripheral prediction ability of the vocational education employment rate prediction model, so WIA is used to assess the generalization ability of the model. The Improved LSSVR for vocational education quality assessment and prediction system is shown in Figure 3.

4. Experiment

4.1. Data Preparation. Vocational education data collection was carried out with the support of professional data analysts. In the work of vocational education data collection, we referred to the data keyword collection methods mentioned in the literature [35–37]. We obtained data on vocational education in terms of curriculum data, faculty strength, training mode, and enterprise cooperation methods through keyword search on educational websites. For all the acquired data, we performed uniform preprocessing operations to integrate the data differences between mobile and PC to prevent the problem of training inapplicability due to data format mismatch during the model training. The data preprocessing process is shown in Figure 4.

To unify the orders of different types of vocational education data, we use the keyword of lag order $l\,(l = 0, 1, \ldots, L)$ to encode x, where the number of interrelationships between the vocational education quality series and the employment rate series y is calculated as follows:

$$r_l = \frac{\sum_{t=1}^{T-l}(x_t - \overline{x})(y_{t+l} - \overline{y})}{\sqrt{\sum_{t=1}^{T-l}(x_t - \overline{x})^2 \sum_{t=1}^{T-l}(y_{t+l} - \overline{y})^2}},$$
$$\overline{x} = \sum_{t=1}^{T-l} \frac{x_t}{(T-l)}, \overline{y} = \sum_{t=1}^{T-l} \frac{x_{t+l}}{(T-l)}, \tag{11}$$

where $l < T$. We set the number of interrelationships in the keyword search process to prevent the search from exceeding the bounded range and causing the problem of data inflation. After data collection, we added data cleaning and transformation work to match keywords as word labels relative to economic indicators and to build a vocational education database. The data details are shown in Table 1.

4.2. Preexperimental Evaluation. With the Ministry of Education's strong support for vocational education, the number of vocational teaching schools is increasing year by year, as shown in Figure 5. According to a large number of vocational education needs, the Ministry of Education sets up assessment norms for other types of vocational education by assessing successful vocational education models.

In the process of developing student training programs, vocational education usually refines the assessment

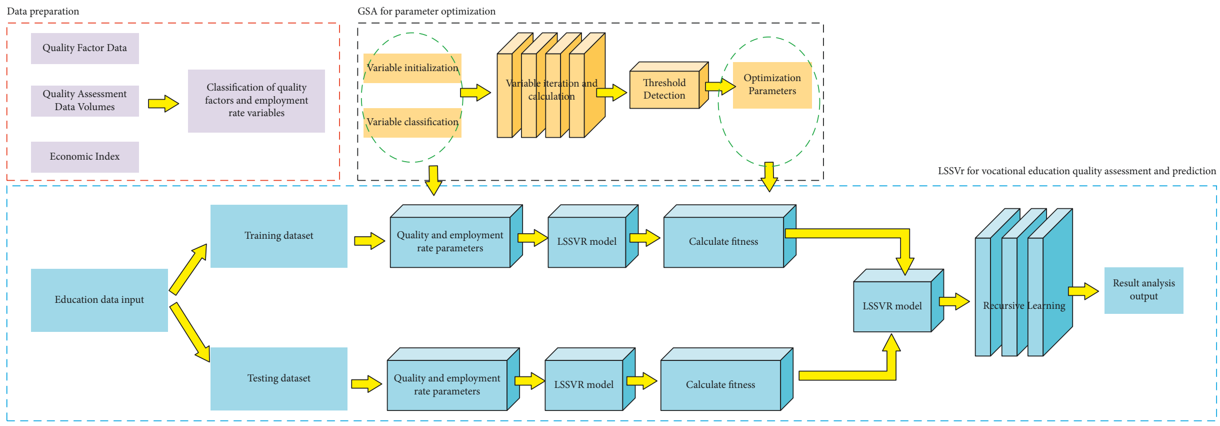

Figure 3: Improved LSSVR for vocational education quality assessment and prediction.

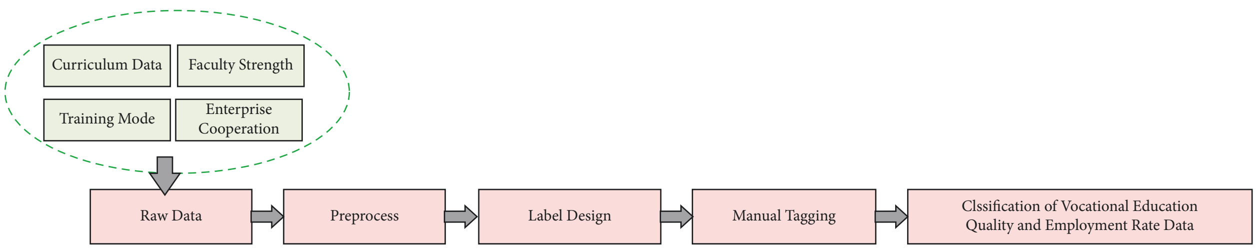

Figure 4: Data preprocessing process.

Table 1: Vocational education dataset classification and quantity.

	Train	Test	Total
Curriculum data	2981	1363	4344
Faculty strength	3635	2653	6288
Training mode	3453	1941	5394
Enterprise cooperation	3530	1696	5226

indicators to the purpose of vocational education (PVE), school enrollment (SE), professional settings (PS), education costs (EC), and employment rates (ER). To investigate the views of students and parents on the assessment indicators, we randomly interviewed 4 parents and 4 students, and each assessment indicator was evaluated with a score out of 100. The results of the survey are shown in Table 2. The quality construction of each assessment index helps to improve the employment rate of vocational education, which is a key aspect of vocational school construction.

From the above table, it can be seen that students and parents are more concerned about the details of the cost of vocational education among the assessment indicators stipulated by the Ministry of Education for vocational education. In the preliminary research, it was found that most of the students who choose vocational education have insufficient family financial resources; therefore, parents and students always rank first in terms of cost consideration for vocational education, and the cost-performance comparison between vocational education and general higher education is the key point to determine the enrollment volume. Besides, students and parents are most concerned about the employment rate of vocational education. The employment rate determines the stability of students' jobs after graduation, and for most students, the ultimate goal of choosing vocational education is to find a stable job. Employment rate data can directly reflect the economic benefits of vocational education in social development, and the higher the employment rate, the better the enrollment situation. The professional setting of vocational education is also the assessment index that students are more concerned about. The professional setting of vocational schools directly connects with social production, and different professional choices determine different employment positions. Therefore, for vocational schools, the broader the specialties set, the more choices students have, and the better their employment quality is.

4.3. Experimental Results. To verify the effectiveness of our vocational education employment rate forecasting system, we compared three different big data forecasting models. The autoregressive integrated moving average model (ARIMA) [38] is a well-known time series forecasting method, the main principle of which is to obtain a random series through time-lapse and then use a mathematical model to achieve an approximate description of this data series. The method is more widely used in a variety of economic segments and has a better effect on the prediction of economic trends. Backpropagation neural network (BPNN) [39] is based on a neural network and uses the principle of error backpropagation to apply supervised learning to batch data and finally generates a prediction model for trend prediction of characteristics among data. The BPNN model performs better in the prediction of economic risk control. The radial basis function (RBF) [40]

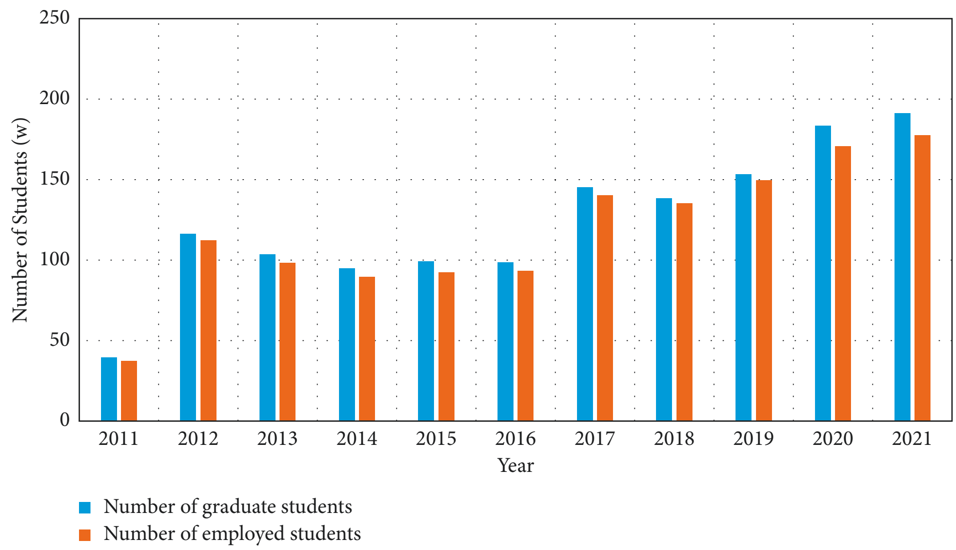

FIGURE 5: Number of graduates and employment over the years.

TABLE 2: Students and parents' evaluation of vocational education assessment indicators.

		PVE	SE	PS	EC	ER
Students	1	72	70	86	96	99
	2	76	74	85	94	98
	3	77	73	88	96	99
	4	71	71	89	93	99
Parents	1	78	72	85	98	96
	2	79	73	89	97	97
	3	75	72	90	92	96
	4	76	71	91	95	99

TABLE 3: Comparison of vocational education quality assessment of different methods.

Indicators	ARIMA (%)	BPNN (%)	RBF (%)	Ours (%)
Curriculum data	75	81	86	91
Faculty strength	73	83	85	92
Training mode	69	85	87	95
Enterprise cooperation	78	86	82	94

model works on the principle of mapping interoperability between low-dimensional data features in the hidden space and high-dimensional data features. The model is more commonly used in studies of predicting serial trajectories and data trends. To ensure independent validation relationships between the methods, five sets of experiments were conducted during the training process, and each set of methods was independently validated for different vocational education assessment indicators. The test results of each method were directly input to the statistical calculation part of the dataset, and the final evaluation results were obtained by balancing the total number and quality factors of the dataset. In the first stage of the experiment, we validated all vocational education quality feedback datasets and compared the efficiency of our methods with those of other methods. The experimental results are shown in Table 3.

From the experimental results in the above table, it can be seen that the ARIMA model does not perform well in the vocational education quality assessment index. Since the model is more suitable for predicting the trend direction of data in data prediction by hyperparameter addition, it is slightly insufficient in the accurate prediction of vocational education quality assessment indexes. The performance of BPNN and RBF models in the prediction accuracy of vocational education quality assessment indexes is not very different, maintaining around 85%. The overall prediction accuracy of our method stays above 90%, which is significantly better than other methods and proves the effectiveness of our method.

In the employment rate prediction experiment, we verified the proportion of different vocational education quality assessment indicators in the employment rate separately and subdivided the association between each vocational education quality assessment indicator and the employment rate. Before the start of the experiment, we performed preprocessing operations on vocational education feedback data to standardize the input format and sampling frequency of assessment index data to prevent the influence of data discrepancies on the experimental results. The results of the second phase of the experiment are shown in Table 4.

From the table above, we predict the employment rate of vocational education in the past five years and compare it with the actual employment rate. The experimental results found that the ARIMA model has a larger gap between the employment rate prediction and the actual employment rate. The BPNN model employment rate prediction is lower than the actual employment rate, but the difference between the predicted and actual values stays within 5%. The RBF model employment rate prediction is higher than the actual value because the mapping relationship between its implicit

Table 4: Comparison of predicted results of vocational education employment rates.

Years	Actual rate (%)	ARIMA (%)	BPNN (%)	RBF (%)	Ours (%)
2017	75	65	70	80	74
2018	86	78	80	88	85
2019	85	79	79	88	85
2020	70	63	66	75	71
2021	73	66	79	78	74

functions leads to a better match between the assessment indicators, so the predicted value is higher than the actual value, but the difference between both of them stays within 5%. The predicted employment rate of our model is closer to the actual value, and the difference between the predicted and actual values remains within 1%. This shows that our method is superior in vocational education employment rate prediction compared with other methods, which proves the effectiveness of our method.

5. Conclusion

In this paper, we propose a vocational education employment rate prediction method based on a big data model and build a vocational education quality assessment and employment rate prediction system. We draw on the big data cross-learning model to improve the model hyperparameters by using generalized intersection sets on the joint loss function to compensate for the shortcomings of dense vocational education datasets. We use the GSA algorithm to enhance the local features of different vocational education quality assessment index data series. In addition, we use the minimum outer matrix algorithm to extract the features of assessment index sequences of different dimensions to improve the accuracy of the model for vocational education quality index assessment. To scientifically assess the recognition of vocational education, we evaluate the vocational education assessment indexes at the student level and the parent level to verify the reliability of the experiment. The experimental results prove that our method performs best in the prediction accuracy of vocational education quality assessment indicators, and the prediction accuracy rate stays above 91%. In the prediction of vocational education employment rate, the difference between the predicted and actual values of our method is the smallest, and the difference stays within 1%. It proves that our method performs well in both vocational education quality assessment and employment rate prediction. Compared with other big data models, our method has higher prediction accuracy and better stability.

Although our method performs well in vocational education quality assessment and employment rate prediction, the number of assessment indicators of vocational education quality is huge, and only five assessment indicators are covered in our study. In our future research, we will try to add generative adversarial neural networks to the adversarial network as an auxiliary classification, optimize the reasonable segmentation of data sequences of different dimensions, and improve the model's inclusiveness of more vocational education quality assessment indexes.

Data Availability

The dataset can be accessed upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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