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Research on Vocational Education Students' Development Prediction and Personalized Learning Path Planning Based on Support Vector Machine Algorithm

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Abstract There is a significant trend of diversification in the development of vocational education students, and the traditional prediction methods have insufficient accuracy to meet the needs of personalized learning. The support vector machine algorithm has a unique advantage in the prediction of small-sample high-dimensional data, which provides a new idea to solve this problem. In this study, we constructed a support vector machine prediction model based on the optimization of differential evolution algorithm, and explored the methods of predicting the development trend of vocational education students and personalized learning path planning. The study adopts SVM algorithm to deal with nonlinear high-dimensional data, introduces differential evolution algorithm to solve the problem of SVM parameter selection, and realizes regression prediction through insensitive loss function. The experiment selects 500 sample data for training and 60 sample data for testing, and the student development trend prediction model reaches the accuracy requirement of absolute error limit value 1 after 115 steps of training. An empirical study was conducted on 804 valid student data of a vocational college, and the overall accuracy of the prediction model reached 98.13%, of which the highest accuracy was 94.3% for the item of “employment” and 91.6% for the item of “higher education”. The results of this study show that the student development prediction model based on support vector machines can effectively predict the development direction of vocational education students and provide data support for vocational colleges to develop personalized learning paths. The study further proposes a personalized learning path design framework, including four key aspects: data collection and management, learning portrait and demand orientation, learning goal and path planning, and learning resources and support services construction, to provide precise guidance for vocational education students' development.

Index Terms support vector machine, differential evolutionary algorithm, vocational education, student development prediction, personalized learning, learning path planning

I. Introduction

In recent years, with the importance attached to vocational education in various countries and the increasing call for social demand, vocational education is also undergoing continuous development and reform. Under the development of social economy, vocational education needs to pay more attention to the diversification and pertinence of talent cultivation [1]. In addition to the traditional training of skilled personnel, it is also necessary to cultivate new talents oriented to informationization, digitalization and intelligence [2]. In addition, it is also necessary to better utilize the specialties of vocational colleges and universities, strengthen the close cooperation with industries, and cultivate human resources adapted to the market demand [3], [4]. However, because most of the students in vocational colleges and universities have low entrance scores, students' learning ability and quality are more different, and some of them are seriously biased, limited by their majors and teaching environments, and the unified cultivation mode ignores students' individual differences and individual needs, which leads to students' professional skill level and professionalism are generally low [5]-[8]. And in the dynamic needs of the modern labor market, vocational education talent training mode and teaching mode is relatively single, education and employer demand is out of touch, and can not achieve accurate personalized training in the teaching classroom, further hindering the development of students, deviating from the training concept of vocational education, reducing the quality of vocational education [9]-[12]. This has also become a key factor affecting the employment quality of students graduating from vocational colleges. In addition, students in vocational colleges and universities are generally in a state of passive education, students are accustomed to passively accept the knowledge and skills taught by teachers in the classroom process, there is no clear understanding of the future direction of development and employment, there is no clear learning plan and learning tasks in the learning stage, which leads to vocational colleges and universities to cultivate students to the knowledge of this profession are involved in, broad but not precise, unable to High-quality employment by virtue of professional skills [13]-[16]. Therefore, it is necessary to predict the development trend and plan personalized learning path (PLP) for vocational education students.

Traditional student development prediction often uses psychometric scale methods such as the Hollander Career Interest Scale, and the shortcomings of scale prediction are obvious, i.e., lack of objectivity, low accuracy, and static characteristics [17]. With the development of intelligent algorithms in education, various algorithmic techniques have been used for student developmental prediction and PLP planning. Literature [18] proposed an Emperor Penguin Search Assisted Artificial Neural Network to predict students' career preferences based on considering their academic performance. Literature [19] not only considered students' academic performance, but also added factors such as students' choice of major and participation in academic activities, and predicted students' career inclination through a k-mean clustering algorithm, which showed better accuracy compared to mainstream convolutional neural networks and other factors. Literature [20] introduced multi-topological graph neural networks and clustering search algorithms, graph neural networks, knowledge graphs, and other techniques to predict students' trends and plan students' PLPs, with better accuracy and validity of prediction. These research methods are limited to single-dimensional influencing factors and lack the career-rigid factors such as students' problem-solving ability, practical ability, and collaborative ability.

In terms of PLP planning, literature [21] designed a knowledge network based on learning resource nodes and knowledge points, determined the order of knowledge points, and combined the time boundaries of different learning scenarios of students to form relevant learning materials as a way of realizing students' PLP. Literature [22] extracted the students' learning patterns of different modalities through the Transformer model, adversarial training, and quantum state classification, and combined them with the self attention mechanism to obtain PLP, which considers students' learning behavior and dynamic interests. Literature [23] collects data features such as students' personal learning, background information, and interests, and uses a deep Q-network algorithm, combined with a reward mechanism of reinforcement learning, to realize real-time dynamic planning of PLP. Literature [24] mentions in its study that adaptive learning system applies artificial intelligence, machine learning techniques, and data analytics to plan PLPs for students by collecting and analyzing student data, as well as real-time learning feedback.

In the above study, it was observed that PLP planning mostly focuses on students' interests, academic performance, learning scenarios, personal information, etc., and lacks unstructured data such as students' practical training, and in the actual application, most of the algorithmic models are poorly interpretable and have a low rate of practical use. In contrast, Support Vector Machine (SVM) seeks the best compromise between the complexity of the model and the learning ability based on the limited sample information, in order to obtain the best generalization ability [25]. Literature [26] evaluated the accuracy of SVMs in predicting students' career paths, with higher accuracy in predicting career paths in academic and governmental orientations compared to entrepreneurship and freelance career development. SVMs show many unique advantages in solving small sample, nonlinear, and high-dimensional pattern recognition, and can be utilized for developmental prediction and path planning.

Vocational education, as an important part of China's education system, bears the important responsibility of cultivating high-quality technical and skilled talents. With the rapid development of social economy and the continuous adjustment of industrial structure, the development path of vocational education students is becoming more and more diversified, and it is difficult for the traditional unified cultivation mode to meet the individualized development needs of students. How to scientifically predict the future development direction of students and provide them with personalized learning path planning has become an important issue in the reform and development of vocational education. Accurate prediction of students' development trend is the prerequisite for personalized learning path planning, while traditional prediction methods are often difficult to ensure the prediction accuracy due to the characteristics of high data dimensionality, small sample size, and complex nonlinear relationships. Support vector machine (SVM) provides a new technical path for student development prediction due to its superior performance in solving nonlinear, small sample, and high-dimensional problems. However, the parameter selection of SVM directly affects its prediction performance, and how to determine the optimal parameter combination becomes a key challenge in applying SVM for prediction. Based on this, this study introduces the differential evolution (DE) algorithm to optimize the SVM parameters, constructs a student development prediction model based on DE-SVM, and explores the personalized learning path planning method on this basis. This study first analyzes the principle of SVM algorithm and its application in regression prediction, focusing on the influence of kernel function selection and parameter setting on prediction performance, second, the differential evolution (DE) algorithm is introduced to solve the problem of SVM parameter selection, and the global optimization of parameters is achieved through the operations of variation, crossover, and selection, then, based on the data of students from vocational colleges and universities, the prediction model of students' development is constructed and the model is verified through the empirical research prediction performance, finally, combined with the prediction results, a personalized learning path design framework is proposed, including four key aspects: data collection and management, learning portrait and demand orientation, learning goal and path planning, and construction of learning resources and support services. By combining advanced machine learning algorithms with vocational education practice, this research aims to break through the limitations of traditional prediction methods, improve the accuracy of student development prediction, and provide data support and decision-making references for vocational colleges and universities to formulate personalized training programs. Meanwhile, the research results are expected to provide theoretical guidance and practical paths for promoting the high-quality development of vocational education, improving the quality of talent cultivation, and enhancing the ability of vocational education to serve the economic and social development, which is of important theoretical value and application significance.

II. Support vector machine-based model for predicting student development

II. A. Support vector machine model

Support vector machine SVMs have the advantages of high accuracy and low risk of overfitting [27], [28]. SVMs perform better in solving problems with nonlinearity, small samples, high dimensionality and local minima. In the beginning, support vector machine models are mainly used to solve pattern recognition and classification problems. After the introduction of the insensitive loss function, support vector machines were able to start solving regression problems, which can also be notated as SVR. Prediction using SVMs is done by making all sample points close to the regression hyperplane so that the total deviation between the sample points and the regression hyperplane is minimized. Since the principles of SVM modeling are structural risk minimization and statistical theory, it is possible to use the limited information on balancing the complexity of the model and the learning ability, and optimization between the two, as a way to achieve the application in time series forecasting, regression estimation forecasting and so on.

(1) SVM algorithm

When dealing with regression problems using SVM, the input sample x is mapped into a high-dimensional space by a nonlinear mapping of $u(x)$. Next, a linear model is built in the feature space: $f(x)=\omega\cdot\varphi(x)+b$, where ω is the weight vector, and b is the value of the offset.

The use of a new loss function ε in a given training dataset $\{(x_i,y_i),i=1,2,\cdots,n\}$ is called insensitive loss function. The constrained optimization problem is represented as follows:

$$\min\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}\left(\xi_i+\xi_i^*\right) \tag{1}$$

$$s.t\begin{cases} y_i-\omega\cdot\varphi(x)-b\le\varepsilon+\xi_i \\ \omega\cdot\varphi(x)+b-y_i\le\varepsilon+\xi_i^* \\ \xi_i,\xi_i^*\ge 0 \\ i=1,2,\cdots,n \end{cases} \tag{2}$$

where C is the penalty term coefficient, ξ_i, and ξ_i^* are slack variables that measure the deviation of the training samples outside the ε insensitive region. This optimization problem can be transformed into a pairwise problem by introducing a Lagrangian function:

$$\begin{aligned} &\max-\frac{1}{2}\sum_{i,j=1}^{n}(a_i-a_i^*)(a_j-a_j^*)K(x_i,x) \\ &-\varepsilon\sum_{i=1}^{n}(a_i+a_i^*)+\sum_{i=1}^{n}y_i(a_i-a_i^*) \end{aligned} \tag{3}$$

$$s.t\begin{cases} \sum_{i=1}^{m}(a_i-a_i^*)=0 \\ 0\le a_i,a_i^*\le C,i=1,2,\cdots,n \end{cases} \tag{4}$$

where a_i and a_i^* are Lagrange multipliers, the samples corresponding to $a_i\neq 0$ or $a_i^*\neq 0$ become support vectors, and $K(x_i,x)$ is the kernel function, and the following solution is obtained by solving the dual problem:

$$f(x)=\sum_{i=1}^{n_{sv}}(a_i-a_i^*)K(x_i,x)+b \tag{5}$$

where n_{sv} is the number of support vectors.

The common kernel functions in SVM are RBF kernel function, polynomial kernel function and Sigmoid kernel function as shown below:

Polynomial kernel function:

$$K(x,x_i)=\left[g(x,x_i)+coef\right]^d \tag{6}$$

RBF kernel function:

$$K(x,x_i)=\exp\left(-g\left\|x-x_i\right\|^2\right) \tag{7}$$

Sigmoid kernel function:

$$K(x,x_i)=\tanh\left(g(x\cdot x_i)+coef\right) \tag{8}$$

where d is the degree of the polynomial, $coef$ is the deviation, and g is the parameter of the kernel function.

(2) Parameter effects

The key issue of regression using SVM is to choose a good set of parameters to realize the excellent performance of the support vector machine, according to the parameters regulated in this paper, the parameter C and the parameter g are selected for introduction.

The penalty term coefficient C can balance the training error and complexity of the model, and it is unique, the penalty term coefficient C is different for different data. In the process of parameter optimization, if C is too small, the range of allowable error becomes larger, and the penalty for samples beyond the ε insensitive band becomes smaller, then the phenomenon of underlearning will occur. And when C is taken too large, the overlearning phenomenon occurs. Therefore, in the SVM modeling in this paper, an appropriate value of the parameter C is chosen according to the sample data set in order to make the best generalization performance of the SVM. The parameter g, as a parameter of the kernel function, has an implicit decision on the distribution of the data after mapping to the new feature space. The larger the g, the less the support vector. And the smaller the value of g, the more support vectors there are. The number of support vectors affects the speed of training and prediction. Therefore it is especially important to choose an appropriate parameter g to train the SVM model.

II. B.Support vector machine prediction model based on differential evolutionary algorithm

II. B. 1) Mechanism of differential vector support vector machine prediction

Although the SVM method provides a good idea and method for the prediction of the development and evolution process of some things, but due to the selection of different parameters in the support vector machine will have different effects on its application, the selection of a suitable and effective parameter or a group of parameters has become an important issue in the application process. Nowadays, the selection of parameters has become a major problem in many SVMs, and many scholars have introduced a large number of optimization algorithms to optimize the parameter selection problem, the most representative of which is the genetic algorithm. The introduction of genetic algorithm makes the traditional evolutionary algorithm in the support vector machine face some problems, such as the slower speed of calculation, the optimization function is particularly complex, and the local extreme value convergence problem, the introduction of DE algorithm in this paper is a very good solution to the problem of parameter selection of SVM.

In 1995 Storn and Price proposed Differential Evolution (DE) for intelligent optimization algorithms. This algorithm adopts the direct operation of real numbers, without encoding and decoding, with fast convergence speed and better stability, and is suitable for the solution of multivariate complex problems.DE calculates each population with real parameters, and it mainly varies according to the difference of a pair of randomly selected target vectors. But most of its target vector distributions have a good dependence on the properties of the objective function, in this way, the DE algorithm can make the objective function more clear and explicit.

II. B. 2) Differential evolutionary algorithms

The Differential Evolutionary Algorithm (DE) is a relatively new evolutionary optimization algorithm [29], [30], and like all evolutionary optimization algorithms, the Differential Evolutionary Algorithm operates on a population of candidate solutions, but not just on a single solution. DE utilizes real-valued parameter vectors as the population for each generation. Its self-referential population breeding scheme differs from other evolutionary optimization algorithms, where the new parameter vector is created by adding a weighted difference vector between two members of the population to a third member. This process is referred to as "mutation." Then, the parameters of the mutation vector are mixed with a predefined target vector's parameters according to certain rules to generate a trial vector, commonly known as "crossover." If the cost function of the trial vector is lower than that of the target vector, the trial vector replaces the target vector in the next generation, this operation is called "selection." By using random perturbations to generate new individuals in this manner, a highly convergent adaptive program can be obtained.

Unlike other evolutionary algorithms where the mutation operation mainly relies on random distribution functions, the differential evolution algorithm relies on the difference of a pair of randomly selected target vectors for mutation. The distribution of the target vectors largely depends on the characteristics of the target function, so this variation makes the differential evolution algorithm search more suitable for the target function and has stronger robustness and global search capability.

To summarize, the DE algorithm mainly contains the following important elements:

(1) Initialization. DE utilizes NP real-valued parameter vectors of dimension D as the populati.on in each generation, and each individual is denoted as $Individual_{i,G}$, with $i = 1, 2, \cdots, NP$, where $Individual$ denotes the sequence of an individual in the population, and G denotes the number of generations to which the population generation to which it belongs, and NP is kept constant during the optimization process. In order to establish the initial point of the optimization search, the population must be initialized and its initialization should cover the entire solution space.

(2) Variation. For each objective vector $x_{i,G}$, the generation of the variation vector can take the following form:

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}) \tag{9}$$

where the randomly selected ordinates $r1$, $r2$, $r3$ are different from each other and the ordinates i of $r1$, $r2$, $r3$ and the target vector should also be different, so NP must be greater than or equal to 4 in order to fulfill the above condition. The factor $F \in [0,2]$ is a real factor that controls the amplification of the deviation variable.

(3) Crossover. In order to increase the diversity of disturbance parameter vectors, the crossover operation is introduced in DE, then the test vector becomes:

$$u_{ji,G+1} = \begin{cases} x_{ji,G} & if\left(randp(j) > CR\right)\ or\ j \neq rnbr(i) \\ v_{ji,G+1} & if\left(randp(j) \leq CR\right)\ or\ j = rnbr(i) \end{cases} \tag{10}$$

where $randp(j)$ is the j th value that generates a random number between $[0,1]$, $rnbr(i) \in 1, 2, \cdots, D$ is a randomly chosen sequence that ensures that $u_{i,G+1}$ obtains at least one parameter from $v_{i,G+1}$, and GR is the crossover factor, taking values in the range $[0,1]$.

(4) Selection. To decide whether the test vector $u_{i,G+1}$ will be a member of the next generation, the test vector is compared with the target vector $x_{i,G}$ in the current population, and the current vector is replaced if the test vector has a smaller objective function value than the current vector.

The steps of the differential evolution algorithm are as follows:

① Determine the control parameters of DE and the specific strategy for selection. ② Generate the initial population randomly with evolutionary generation k=l. ③ Evaluate the initial population, i.e., calculate the objective function value. ④ Determine whether the abort condition is reached. If yes, the best individual at this point is output as the solution, otherwise, continue. ⑤ Perform mutation and crossover operations on the boundary solution to obtain the temporary population. ⑥ Evaluate the temporary population and calculate the objective function value. ⑦ Perform selection operation to get new population. ⑧ Evolutionary algebra refresh k=k+l, go to step ④.

II. B. 3) Support vector machine training based on differential evolution

The key parameters of the support vector machine can be easily mapped to each individual of the differential evolutionary algorithm population (encoding process).

The process of selecting the parameters of the technical support vector machine based on the differential evolutionary algorithm is actually the process of using the differential evolutionary algorithm to seek the optimal support vector machine parameters, and the objective function is defined as:

$$MSE_G = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{11}$$

where y_i is the actual output value of the training sample, and $\hat{y}_i$ is the predicted value of the regression performed by the support vector machine with the specific parameters chosen. Let θ be the vector representing the parameters of the support vector machine, then it is actually solving the following optimization problem:

$$Min(MSE) \tag{12}$$

$$s.t\ L \leq \theta \leq U \tag{13}$$

where L and U denote the lower and upper limits of the support vector machine parameters, respectively. The specific process is shown in Figure 1.

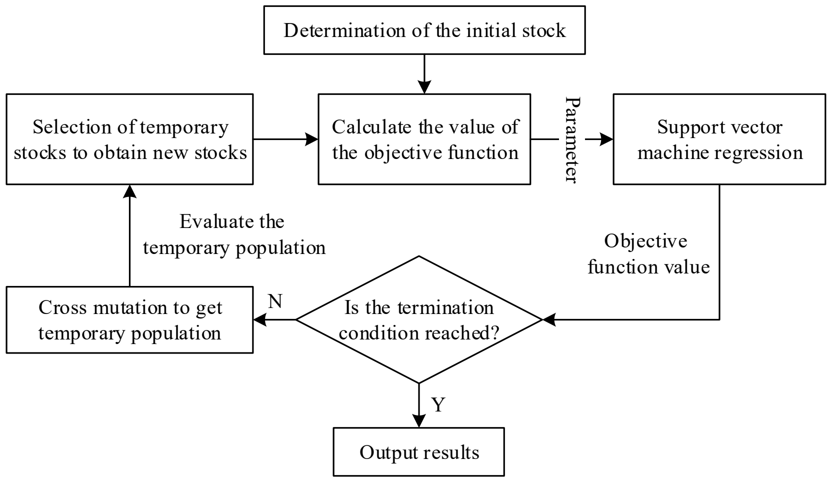

Figure 1: Support vector machine training schematic based on differential evolution

Table 1: Three groups comparison of experimental results

Number	The first group		The second group		The third group	
	Predict value	Real value	Predict value	Real value	Predict value	Real value
1	3.042	3.839	1.905	2.496	4.370	3.926
2	2.393	2.319	4.708	5.372	5.136	5.358
3	2.850	2.510	0.430	1.198	5.255	4.811
4	4.619	4.134	3.086	3.086	5.873	4.960
5	4.457	3.631	3.233	4.001	1.153	1.036
6	1.581	1.537	5.122	4.960	2.908	3.159
7	1.286	1.537	5.623	4.841	3.882	3.070
8	3.587	4.118	3.779	4.134	3.468	4.118
9	3.706	3.617	1.109	1.567	5.608	5.608
10	4.221	4.370	5.388	5.594	1.935	2.805
11	0.370	0.091	1.169	1.212	4.074	4.015
12	0.931	0.343	4.251	3.454	4.399	5.106
13	4.619	4.562	2.834	3.706	3.292	2.805
14	1.610	1.626	5.683	5.845	4.649	5.388
15	5.816	5.816	5.859	5.653	4.974	4.797
16	3.720	3.720	4.118	3.130	1.654	2.407
17	4.827	4.605	4.914	4.665	4.118	3.573
18	4.340	5.255	4.267	3.779	5.608	5.919
19	2.642	3.145	4.546	3.956	5.196	4.267
20	3.013	3.912	1.375	0.741	4.104	3.587

III. Forecasting performance and empirical analysis

III. A. Predictive performance analysis

After completing the student development trend prediction model, the author used the data from the preliminary research to analyze the dataset, and designed relevant data experiments to verify the performance as well as the accuracy of the prediction model of the development trend of vocational education students, with the purpose of providing guiding suggestions for the student training methods in vocational colleges and universities as well as for the students' independent learning. In this thesis, 500 samples of data are selected as training data, 60 samples of data are selected as test data, and the 60 samples are divided into 3 groups. After 115 steps of training, the data accuracy of the prediction model of the development trend of higher vocational students basically reaches the accuracy requirement of the absolute error limit value of 1. In this paper, a comparison experiment was designed to compare the experimental data of the prediction model of student development trend with the sample data of the actual study. The results show that the prediction model of vocational education student development trend based on support vector machine has high accuracy, and the specific experimental results of the three groups are shown in Table 1. As can be seen from the data in Table 1, the maximum error between the predicted value and the actual value of the samples in the first group, the second group and the third group are 0.915, 0.988 and 0.929, respectively, and the maximum error is zero.

Through the analysis of the experimental results, found that some data still exist errors, the above obtained three groups of experimental data comparison results and then calculate, we can get the absolute error between the experimental data and the sample data, the specific calculation of the absolute value of the error as shown in Table 2.

This article further analyzes the experimental data. Overall, the maximum absolute error obtained from the student development trend prediction experiment in this article is 0.139, which is within an acceptable error range. Therefore, the student development prediction model based on support vector machines constructed in this paper can accomplish the task of predicting student development directions. It can preliminarily solve the problem of student development prediction, meet the needs of predicting the development of vocational education students, and assist vocational colleges in planning the future development directions for their students.

Table 2: Absolute error value map of experimental results

Number	Absolute error	Number	Absolute error	Number	Absolute error
1	0.004	21	0.022	41	0.079
2	0.099	22	0.078	42	0.001
3	0.000	23	0.139	43	0.002
4	0.111	24	0.000	44	0.068
5	0.084	25	0.133	45	0.063
6	0.106	26	0.131	46	0.091
7	0.022	27	0.094	47	0.076
8	0.126	28	0.014	48	0.086
9	0.057	29	0.000	49	0.000
10	0.097	30	0.019	50	0.079
11	0.067	31	0.011	51	0.099
12	0.072	32	0.118	52	0.092
13	0.124	33	0.000	53	0.009
14	0.026	34	0.117	54	0.011
15	0.045	35	0.059	55	0.000
16	0.000	36	0.104	56	0.054
17	0.106	37	0.026	57	0.108
18	0.076	38	0.057	58	0.005
19	0.106	39	0.083	59	0.004
20	0.099	40	0.000	60	0.009

III. B. Analysis of forecast results

In order to make this study more realistic and this experiment more applicable and operable, this paper selects S vocational college students, predicts the development of vocational education students through the student development prediction model based on support vector machine constructed in this paper, and empirically analyzes the prediction results for the student users to predict the direction of career development according to their own data in school.

In this paper, the student development prediction model inputs all kinds of data during the student's school period, such as academic performance, English proficiency, political civilization activities, science and technology innovation activities, cultural, sports and art activities, social volunteer service, etc., and then after this paper's support vector machine prediction model based on the differential evolution algorithm calculates, the final prediction results of the student user's career development direction are obtained. According to the prediction results of this paper's prediction model, the existing data samples are compared and analyzed. There are a total of 924 pieces of student data, and 804 pieces of valid data are obtained after processing, of which, the prediction results of the career development direction of some students are shown in Table 3.

Table 3: Predictive results (part)

No.	Grade point	English level	Political civilization	Technological innovation	Culture, sports and art
1	1365	0.2	5.4268	0	0.63
2	1456	0.4	7.9356	0.868	2.68
3	1726	0.4	7.1253	0	2.03
4	1512	0.3	8.456	8.064	3.84
5	1658	0.2	7.1523	7.54	0.45
6	1744	0.2	5.4826	0	0.65
7	1406	0.3	6.4152	0	4.05
8	1547	0.4	4.8467	4.385	0.43
9	1786	0.4	8.9468	5.162	3.11
10	1503	0.3	5.1625	0.35	0.65

No.	Social volunteering	Forecast development	Actual development	Congruity
1	0	Further study	Further study	Yes
2	0.34	Work	Work	Yes
3	0	Further study	Further study	Yes
4	0.42	Work	Work	Yes
5	0.22	Work	Work	Yes
6	0	Work	Work	Yes
7	0	Work	Work	Yes
8	0	Further study	Further study	Yes
9	0.34	Work	Work	Yes
10	0	Work	Work	Yes

After comparing the statistics of all the prediction results with the employment situation of actual students, it is concluded that the correct data of the overall data sample prediction results are 789, the overall prediction accuracy is 98.13%, and the error rate is 1.87%. The single prediction data of various types of career development directions are counted, and the single prediction results are obtained as shown in Table 4, in which the accuracy of the single result prediction is calculated by the ratio of the number of correct predictions to the total number of this number. Comprehensive overall experimental data, this prediction model fine single direction prediction effect is the best “employment” item, the prediction accuracy rate of 94.3%. The item of “higher education” is in the second place, with a prediction accuracy of 91.6%. The worst one-way prediction is “not graduated”, followed by “not employed”. In this case, this paper makes the following analysis:

Table 4: Development direction predictive results

Development direction	Predict sample number	Real sample number	Prediction accuracy
Work	425	402	94.3%
Further study	251	274	91.6%
Go abroad	44	52	84.6%
Freelancing	31	36	86.1%
Unemployment	40	32	75.0%
Ungraduated	13	8	37.5%

1) Students' own quality. Due to the experimental data selected from the student sample of personal quality or learning quality is better, and the students studied the profession and the current employment of popular professions, so most of the students in the post-graduation successful employment or further study is also reasonable.

2) Family factors interfere. The future career development of college students is not only a matter of personal choice, but also related to the wishes of parents and family factors. A small number of students will follow their parents' wishes or change their career plans according to their own family conditions.

3) The amount of data for individual prediction items is small. Since the algorithm used in this experiment is the differential evolutionary support vector machine algorithm, which is characterized by the fact that the larger the

training set is, the better the effect is, and in this experiment, for example, there are only 8 people in the item "not graduated", which accounts for only 0.995% of the valid data, so the training effect of this item is not good.

4) Overall, the prediction algorithm and model are better, but there is still room for optimization and improvement.

IV. Ideas for designing personalized learning paths

IV. A. Data collection and management

Data collection and management is a fundamental part of personalized learning path design, the core of which lies in comprehensively obtaining information on students' learning behaviors, performance, interests, knowledge mastery, and learning progress through multi-channel and multi-dimensional data collection. These data not only come from students' performance inside and outside the classroom, homework and assessment scores, but also include students' online learning trajectory, interactive participation, and learning data generated by digital tools such as intelligent learning platforms. Higher vocational colleges and universities should build a comprehensive and accurate data collection mechanism to guarantee the breadth and diversity of data and ensure that it can reflect the real needs and learning status of students. The design of personalized learning paths requires a reasonable configuration of data collection tools and technology platforms, as well as the design of reasonable data storage and processing processes to ensure real-time updating and efficient processing of data.

IV. B. Learning Profiles and Needs Targeting

Learning portrait and demand orientation are the key links of personalized learning path design, and its core task is to accurately depict students' learning characteristics and needs through in-depth analysis of students' multi-dimensional data. Learning portrait is a comprehensive description of students' cognitive level, learning style, interest tendency, ability and strengths, which is the foundation of personalized learning path design. In the process of demand orientation, based on the multi-dimensional analysis of students' portraits, educators can identify students' learning bottlenecks, knowledge gaps and personalized needs, and then make fine adjustments to learning objectives, learning styles and learning contents to ensure that teaching activities can maximally meet students' personalized needs. This process requires higher vocational colleges and universities to take advantage of data mining technology, combined with students' academic performance and psychological characteristics, to adjust the configuration of learning resources and teaching strategies in real time, and to customize the most suitable learning path for each student, so as to maximize the educational effect.

IV. C. Learning objectives and pathway planning

The key to learning goals and pathway planning is to combine students' learning profiles and needs to formulate personalized and actionable learning goals and pathway planning. Through in-depth analysis of students' learning behaviors, performance data and development potential, we can scientifically set short-term and long-term learning goals for students, which should be differentiated according to their cognitive levels, interests and academic needs, so as to avoid a homogeneous teaching mode. Pathway planning is based on the setting of goals, and customized curriculum arrangements and learning routes are designed according to students' learning progress, learning habits, learning styles and other factors, to ensure that each student learns in a pathway that suits his or her individual needs and maximizes his or her learning potential. In this process, the path planning not only includes the hierarchical distribution of knowledge points and the systematic arrangement of learning content, but also takes into account the dynamic adjustment of the learning rhythm and the improvement of the feedback mechanism to ensure that students can obtain timely learning support and feedback at different stages, and continuously optimize the learning effect.

IV. D. Construction of learning resources and support services

The construction of learning resources and support services is an important part of the design of personalized learning paths, and its main goal is to provide students with diversified and personalized learning resources and all-around learning support, so as to ensure that students can obtain resources and assistance that suit their needs at different learning stages. The construction of learning resources should include digital teaching content, online courses, experimental platforms, virtual simulation and other forms to ensure that students can flexibly choose and use resources in the personalized learning path. At the same time, educational institutions need to establish a comprehensive online learning support system based on students' learning needs, providing intelligent tutoring, personalized Q&A, learning progress tracking and other services to ensure that students receive timely feedback and support in the learning process. Such support services are not limited to the academic level, but should also cover psychological counseling, career planning, skills training and other comprehensive services to help students improve their overall development.

V. Conclusion

In this study, a support vector machine prediction model optimized based on differential evolutionary algorithm was constructed to achieve high-precision prediction of the development trend of vocational education students.

The experimental results show that after 115 steps of training, the maximum absolute value of the prediction error of the model is only 0.139, and the overall prediction accuracy reaches 98.13%, which is significantly better than the traditional prediction methods. Among the single-item predictions, “employment” has the highest prediction accuracy of 94.3%, “further education” has the second highest accuracy of 91.6%, and “going abroad” and “freelancing” have prediction accuracies of 84.6% and 86.1%, respectively. Based on the prediction results, the study proposes a personalized learning path design framework that includes four aspects: data collection and management, learning profile and demand orientation, learning goals and path planning, and construction of learning resources and support services. It is found that students' personal qualities, family factors and the amount of training data affect the accuracy of the prediction results, especially the “not graduated” item, which has a lower prediction accuracy because the sample size only accounts for 0.995% of the total data. The study confirms that the student development prediction model based on support vector machine can effectively solve the problem of predicting the development direction of vocational education students, provide a reliable data basis and algorithmic support for the realization of personalized learning path planning, and have important theoretical and practical value for promoting the quality of vocational education personnel training.

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