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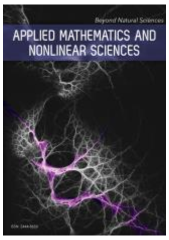

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Research on the Quality Assessment Model of “Dual-Teacher” Teachers in Higher Vocational Colleges and Universities Based on Big Data Technology

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Abstract

To further analyze the content of “dual-teacher” teacher team construction in higher vocational colleges and universities, this paper focuses on teacher moral construction, teacher training, assessment and evaluation, and incentives for in-depth investigation. It is clear that higher vocational colleges and universities should distinguish between “dual-teacher” teacher quality assessment and ordinary teacher assessment, and put forward the gradient “dual-teacher” teacher quality team construction. Improve the support vector machine, use the binary tree to propose an evaluation model based on incomplete DBT-SVM, and combine multiple binary classifiers to solve the multi-classification problem of “dual-teacher” teacher quality evaluation. The optimal parameter combinations, i.e., $C = 2^8$ and $\gamma = 0.0534$, are obtained using the kernel function and parameter tuning experiments, and the accuracy of the model prediction results reaches 94.325%, taking the “dual-teacher” teachers in a university in Y province as the specific evaluation object. This shows that the accuracy of this DBT-SVM-based evaluation method of “dual-teacher” teacher quality is good.

Keywords: Support vector machine; DBT-SVM evaluation; Classifier combination; Kernel function; “Dual-teacher” teachers.
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1 Introduction

“Dual-teacher” teachers play a crucial role in higher vocational education; they not only teach professional knowledge but also guide the practical skills of students, which has an important impact on the development of students’ comprehensive quality and vocational ability [1]. Dual-teacher” teachers in higher vocational colleges and universities refer to teachers who have both professional and technical skills and educational and teaching abilities. With the development of education informatization, building an effective “dual-teacher” teacher quality assessment model based on big data technology has become an important issue in the field of higher vocational education [2-3].

Big data technology provides a scientific basis for educational decision-making by collecting, processing, and analyzing massive amounts of data. In the “dual-teacher” teacher quality assessment, big data technology can help analyze teachers’ teaching behavior, student feedback, teaching effect, and other aspects of information, providing comprehensive data support for teacher quality assessment [4-5]. The “dual-teacher” teacher quality assessment model based on big data technology should include collecting and analyzing students’ feedback on teachers’ teaching, evaluating teachers’ teaching effect, examining teachers’ professional knowledge and practical ability, and analyzing teachers’ teaching plan, teaching method, and teaching content [6-7].

When constructing and applying big data-based assessment models, they may face challenges such as difficulty with data collection, data privacy protection, and the accuracy and fairness of the model [8-9]. In the future, the “dual-teacher” teacher quality assessment model based on big data may develop towards the use of artificial intelligence technology to improve the intelligence of the assessment model, achieve more accurate data analysis, and provide personalized assessment and feedback according to the characteristics of different teachers and the needs of students [10-11]. The “dual-teacher” teacher quality assessment model of higher vocational colleges and universities based on big data technology is of great significance for improving the quality of education and optimizing the teaching force [12]. Through continuous research and practice, a more scientific and reasonable assessment model can be constructed to promote the development of higher vocational education [13-14].

This paper puts forward a specific path for the construction of a “dual-teacher” teacher team by fully combining the situation of “dual-teacher” teacher team construction in a higher vocational college in S province. Starting from three parts, the “dual-teacher” teacher quality construction atmosphere is clearly identified as the standard, improving the training mechanism and establishing the teacher assessment mechanism together to form a gradient “dual-teacher” teacher team construction path. Using the factor analysis method for the initial Screening and finalization of the “dual-teacher” teacher quality evaluation standard, combined with the improved support vector machine algorithm, construct the “dual-teacher” teacher quality evaluation model of the DBT-SVM algorithm and carry out the evaluation model example. Analyze.

2 Preliminary study on the construction of “dual-teacher” teachers

2.1 “Two-Teacher” Teaching Team Building

A school in province Y is a national key higher vocational college and university, provincial and ministerial key general higher vocational, with a school network teaching platform and network learning resources to realize class access, so the teaching place is equipped with multimedia equipment. The school has electromechanical technology application, automobile use and maintenance, CNC machining technology, electrical and electronic technology, computer technology and application, accounting, marketing, pre-school education, national defense education, chemical technology, landscape gardening, and eighteen other majors.

Aiming at the characteristics of this higher vocational college in Province Y and the research needs of this study, we conducted a survey and research on the status of “dual-teacher” teacher team building. In order to grasp the deeper status of the construction of “dual-teacher” teachers in this school, in-depth interviews were conducted with the school management, general teachers, and “dual-teacher” teachers, with a view to exploring the shortcomings of the school in the management of “dual-teacher” teachers through the interviews. The purpose of the interviews is to explore the deficiencies in the school’s management of “dual-teacher” teachers and to make suggestions for their development.

The data on the construction of “dual-teacher” teachers are shown in Table 1. Except for the dimension of teacher training, the standard deviations of the other four dimensions are all within a relatively close range, indicating that the sample data used in this study are representative to a certain extent. From the column of the mean value of the five dimensions, it can be seen that the mean value of the other three dimensions is less than 3, except for the dimension of making construction, which is 3.122>3. This shows that there are some deficiencies in the construction of the “dual-teacher” teacher team in the aspects of teacher training, assessment and evaluation, and incentives in this school at present. It can be seen that the sample school needs to improve the construction of a “dual-teacher” teacher team further.

Table 1. Data on the construction of teachers’ teams

Dimension	Sample size	Mean	Standard deviation
Construction of teachers and ethics	165	3.122	0.673
Faculty culture	165	2.093	0.925
Appraisal	165	2.356	0.916
Incentive measure	165	2.275	0.817
Population mean	165	2.4615	0.83275

2.1.1 Teacher training

The rationalization and scientificization of the teacher structure is a powerful guarantee for the smooth progress of education and teaching in schools and an important foundation for improving the quality of education and teaching.

Among the 165 “dual-teacher” teachers, 79 have the title of assistant lecturer, 53 have the title of lecturer, 30 have the title of senior lecturer, and 3 have the title of senior lecturer. It can be seen that most of the “dual-teacher” teachers have the titles of Assistant Lecturer and Lecturer, and the proportion of Senior and Full Senior Lecturer is small.

ANOVA was used to explore the differences in titles in the four dimensions of teacher moral development, teacher training, assessment and evaluation, and incentives. The ANOVA data on teachers’ titles are shown in Table 2.

The significance coefficients, i.e., P-values, of the four dimensions of teacher moral construction, teacher training, Appraisal and evaluation, and incentives are 0.567, 0.488, 0.603, and 0.353, respectively, which are greater than 0.05, indicating that there is no significant difference between these four dimensions in terms of job titles. It indicates that the views of teachers with different titles, whether they are assistant lecturers, lecturers, or senior lecturers, on these four dimensions are basically the same.

Table 2. Variance analysis data on teacher's title

Job title	Construction of teachers and ethics		Teacher culture		Appraisal		Incentive measure	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Assistant lecturer	3.005	0.652	2.130	0.992	2.131	0.974	2.233	0.890
Lecturer	2.934	0.691	1.922	0.893	1.939	0.865	2.138	0.749
Senior lecturer	2.989	0.753	1.846	0.702	1.858	0.901	1.976	0.710
Positive level lecturer	2.688	0.635	1.725	0.680	1.821	0.831	1.834	0.635
F	1.365		1.855		2.421		2.661	
P	0.567		0.488		0.603		0.353	
LSD	-		-		-		-	

2.1.2 Appraisal and evaluation

The assessment and evaluation of teachers in schools help them to understand the development of the teaching force and urge them to continuously improve their professionalism and teaching ability. The scientific assessment mechanism plays a vital role in the construction of "dual-teacher" teachers. The assessment and evaluation of "dual-teacher" teachers is shown in Table 3.

In the aspect of "whether the assessment and evaluation standard of the school is different from that of ordinary teachers," the average value is 1.968, which is lower than the other three aspects, and more than 70% of the teachers think that the current assessment and evaluation is not in line with the construction of "dual-teacher" teacher quality. This indicates that the university's "dual-teacher" teacher quality training is not differentiated in the assessment, and the assessment and evaluation standards are generalized.

Table 3. "Double teacher" teacher evaluation situation

Project	Sample	Mean value	Standard deviation	Frequency				
				Complete mismatch	Discrepancy	General	Coincidence	Perfect coincidence
The evaluation is consistent in time	165	2.251	1.233	52	70	22	11	10
The evaluation and evaluation of multiple subjects	165	2.136	1.157	65	42	32	15	11
Unlike ordinary teachers	165	1.968	1.120	75	42	24	15	9
Evaluation can highlight your professional characteristics	165	2.011	1.208	66	56	26	5	12

2.2 Path of "dual-teacher" teacher team building in higher education institutions

Dual-teacher teachers are a feature of the construction of higher vocational colleges and universities' teaching force, which can effectively promote the development of higher vocational colleges and universities and further improve the comprehensive quality of higher vocational students.

In view of the deficiencies in the construction of a "dual-teacher" teaching force in schools, as mentioned above, and in order to achieve the purpose of cultivating applied teaching talents, this paper puts forward the design idea of constructing a graduated dual-teacher teaching force. The idea of a gradient dual-teacher-teacher team is shown in Figure 1. Gradient dual-teacher teacher teams can help teachers continuously improve their teaching ability, stimulate teachers' enthusiasm for self-improvement, and overall improve the quality of higher vocational colleges and universities teacher teams so as to cultivate a group of applied talents in line with the requirements of society.

Firstly, the identification standard of graded dual-teacher teachers should be clarified.

Secondly, with the gradualization of dual-teacher-teacher identification standards, the introduction of corresponding training policies from the school level to promote the integration of industry and education, improve the incentive system so as to ensure the quality of dual-teacher-teacher training, to create a happy-to-teach, suitable for teaching, good at teaching dual-teacher teacher team.

Finally, the appraisal system in the graded dual-teacher-teacher recognition standard is the basis for teacher promotion, and a reasonable appraisal system is conducive to teachers to stimulate potential and mobilize enthusiasm for work. It helps teachers to recognize and measure themselves objectively, reflect constantly, summarize their work experience, and improve the quality of education.

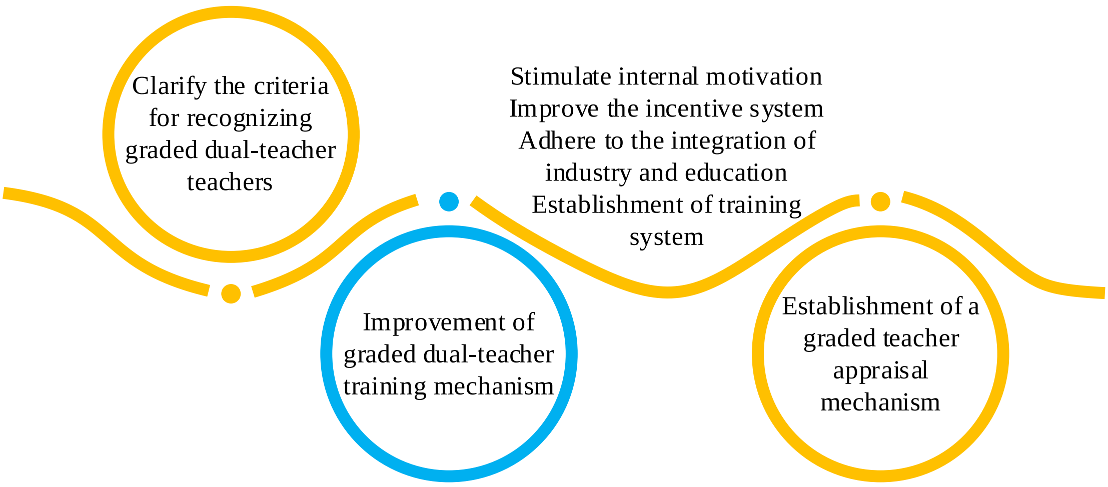

Figure 1. The idea of a two-teacher teacher team

3 Construction of a model for assessing the quality of "dual-teacher" teachers

3.1 Indicators for evaluating the quality of "dual-teacher" teachers

The acquisition of the elements of the qualification standard for dual-teacher teachers is the basis for the establishment of the indicator system. In order to ensure that the acquired elements are comprehensive, reliable, and scientific, the behavioral event interview method has been used to carry out targeted research.

Combined with the reading of policy documents about higher vocational colleges and universities, dual-teacher type, and other policy documents, as well as the existing research data, we obtained 48 elements of qualification standards for dual-teacher teacher quality. In order to extract the qualification standard elements more scientifically, accurately, and effectively, the STAR method was used to conduct behavioral event interviews with the staff of the Department of Education of Province Y, the administrators of higher vocational colleges and teachers, and the initial selection of qualification standard elements was further supplemented and improved with the data from the interviews.

3.1.1 Screening of indicator elements

The data collection involves people including 6 people from the Department of Education of Province Y and 35 people from the management of higher vocational colleges and universities, including some of the principals, the Academic Affairs Office, the Personnel Office, and the excellent teachers with the background of industry and enterprise.

In order to guide the interviewees to a fuller description of the whole picture of the event and a deeper excavation of the details of the event, the complete elements of so can be extracted through the behavioral events.

Combined with the interview structure, the initial Screening of dual-teacher quality standards was modified and improved, and qualified standard elements of dual-teacher quality in higher vocational colleges and universities were obtained. Among them, a total of 30 qualified standard elements are involved, i.e., innovation ability, ideological and moral cultivation, ability to transform scientific research achievements, caring for students, awareness of school-enterprise cooperation, teacher moral quality, advanced teaching methods, fairness and impartiality, advanced teaching concepts, love of work and dedication to their work, academic communication skills, sense of responsibility, classroom teaching ability, organizational and managerial skills, degree qualifications, professional knowledge, social service ability, business and industry backgrounds Knowledge mastery, participation in professional training, lifelong learning ability, curriculum reform ability, initiative, level of scientific research ability, professional and technical titles, dedication, practical teaching ability, guiding students to participate in innovation and entrepreneurship competitions, wide range of interests, communication and collaboration ability, psychological endurance.

3.1.2 Identification of indicators

With the support of the relevant universities, the data survey and collection were carried out in 15 higher vocational colleges and universities within the scope of Y province, and the main people involved included the relevant personnel of the personnel department of each school and the relevant teachers of each school.

In this paper, there are a total of 30 standard elements of dual-teacher quality, and factor analysis is utilized to describe the connection between the 30 elements with fewer factor areas. The condition for conducting factor analysis is that there is a correlation between the qualification standard elements. Statistically, the KMO sampling adequacy test and Bartlett's spherical test can be performed to determine whether a set of indicators is suitable for factor analysis. The data show KMO=0.921>0.9, the chi-square value is 12352.238, the degree of freedom is 492, the level of significance is 0.000, and the significance is obvious. Thus, the data in this paper can be factor analyzed.

Principal component analysis was used to factor analyze the data. In principal component analysis, each principal component serves as a common factor, and the basis for determining whether it is a principal component factor is the eigenvalue. Generally, factors with eigenvalues greater than 1 are extracted. A total of five principal components in the analysis have eigenvalues greater than 1, and the percent sum of variance of these five principal components reaches more than 70%. Usually, in character social science research, if the cumulative variance contribution rate of the extracted principal components is above 70%, it indicates that the extracted public factors can accept most of the information of the original elements, so the five public factors extracted in this paper are able to represent the 30 qualified standardized elements, which is more in line with the expected constructed dimensions.

Five public factors are extracted according to the results of the factor extraction. Organize to get the evaluation index of the quality of dual-teacher teachers in higher vocational colleges, and the weights of the dimensions of the evaluation indexes are shown in Table 4. The five dimensions of the quality of dual-teacher teachers in higher vocational colleges and universities are professional moral cultivation, practical application ability, curriculum teaching ability, theoretical knowledge level, and personality and mentality characteristics, and their weight indices are 0.2269, 0.2159, 0.1885, 0.1865, 0.1822 respectively.

Among them, professional moral cultivation includes teacher moral quality, ideological and moral cultivation, love and dedication, caring for students, fairness and justice, dedication, and responsibility.

Practical application ability includes guiding students to participate in innovation and entrepreneurship competitions, the ability to transform scientific research results, social serviceability, participation in professional training, awareness of school-enterprise cooperation, and innovation ability.

Course teaching ability includes practical teaching ability, curriculum reform ability, organization and management ability, communication and collaboration ability, advanced teaching philosophy, and classroom teaching ability.

Theoretical knowledge level includes scientific research ability level, professional and technical title, degree qualification, academic communication ability, enterprise industry background knowledge mastery ability, and advanced teaching methods.

Character and mentality characteristics include positive enterprising, lifelong learning ability, psychological tolerance, a wide range of interests, and professional knowledge.

Table 4. The evaluation indexes are weighted in each dimension

Sort	Qualified standard	Variable number	Variable score	Standard score	Weighting
1	Moral cultivation	7	32.65	4.52	0.2269
2	Practical ability	6	30.52	4.38	0.2159
3	Curriculum teaching ability	6	29.35	4.22	0.1885
4	Theoretical knowledge level	6	24.71	4.12	0.1865
5	Characteristics of personality mentality	5	21.56	4.03	0.1822

3.2 Introduction of Support Vector Machines

3.2.1 Linearly differentiable SVMs

For a given sample data $\{(x_i, y_i), i = 1, 2, \ldots l$ of size l, it is divided into class I and class II with corresponding labels $y_i = \begin{cases} 1, & x_i \text{ is class I} \\ -1, & x_i \text{ is class II} \end{cases}$. For linear data, the samples can be divided into two classes using the classification hyperplane $f(x) = wx + b = 0$. Samples with the same characteristics are said to be linearly divisible, i.e., satisfied, when they are divided to the same side:

$$\begin{cases} wx_i + b \geq 1, y_i = 1 \\ wx_i + b \leq -1, y_i = -1 \end{cases}, i = 1, 2, \cdots, l \tag{1}$$

Define the distance from sample point x_i to the classification hyperplane as:

$$\varepsilon_i = y_i \left(wx_i + b \right) = \left| wx_i + b \right| \tag{2}$$

Normalizing the w and b parameters in Eq. (1), i.e., replacing w and b in Eq. (1) with $\frac{w}{\|w\|}$ and $\frac{b}{\|w\|}$, respectively, redefines the distance from sample point x_i to the classification hyperplane as:

$$\delta_i = \frac{wx_i + b}{\|w\|} \tag{3}$$

The distance from each sample point in the sample set to the classification hyperplane is obtained, and the smallest distance interval recorded is simultaneously defined as the interval from the sample set to the classification hyperplane, as in equation (4):

$$\delta = \min \delta_i, i = 1, 2, \cdots \tag{4}$$

For some special sample points, which may be misclassified, the relationship between the number of misclassifications N of a sample and the distance δ of the sample set to the classification hyperplane is defined as:

$$N \leq \left(\frac{2R}{\delta} \right)^2 \tag{5}$$

Where $R = \max \left\| x_i \right\|, i = 1, 2, \cdots l$ is the vector value with the longest length in the sample set.

If the interval $\varepsilon_i = \left| wx_i + b \right| = 1$, the distance between the two classes of sample points is $2\frac{\left| wx_i + b \right|}{\|w\|} = \frac{2}{\|w\|}$. Thus the function is that seeks the optimal classification surface under the constraint of satisfying Eq. (1), such that $\frac{2}{\|w\|}$ takes the largest value even if $\frac{\|w\|^2}{2}$ is minimized, i.e., it is:

$$\begin{cases} \min \frac{\|w\|^2}{2} \\ s.t. y_i \left(wx_i + b \right) \geq 1 \end{cases}, i = 1, 2, \cdots, l \tag{6}$$

Based on the Lagrange dyadic theory to transform Eq. (6) into a dyadic problem to solve, the final optimal classification function is:

$$f(x) = \operatorname{sgn}\left[\sum_{i=1}^{l} \alpha_i^* y_i (x x_i) + b^*\right] \tag{7}$$

Where the optimal solution is $\alpha^* = \left[\alpha_1^*, \alpha_2^*, \cdots \alpha_i^*\right]^T$, w^* and b^* are $\begin{cases} w^* = \sum_{i=1}^{l} \alpha_i^* x_i y_i \\ b^* = -\frac{1}{2} w^* (x_r + x_s) \end{cases}$, and x_r and x_s are any pair of support vectors in the two categories.

For the possible existence of a few samples that may be outliers resulting in failure to find the optimal classification hyperplane, slack variables are introduced, and the optimization function and conditions of Eq. (6) are modified, i.e.:

$$\begin{cases} \min \frac{\|w\|^2}{2} + C\sum_{i=1}^{l} \xi_i \\ s.t. \begin{cases} y_i (w x_i + b) \geq 1 - \xi_i \\ \xi_i > 0 \end{cases}, i = 1, 2, \cdots, l \end{cases} \tag{8}$$

In Eq. (8), C is the penalty factor, which indicates the degree of tolerance for misclassification of samples, and the larger C is, the more intolerable the occurrence of misclassification of samples. The corresponding constraints after the introduction of the penalty factor are transformed into:

$$\begin{cases} \sum_{i=1}^{l} \alpha_i y_i = 0 \\ 0 \leq \alpha_i \leq C \end{cases}, i = 1, 2, \cdots l \tag{9}$$

3.2.2 Linear Indivisible SVMs

In practice, there are a variety of problems, and many cases are nonlinearly differentiable, when linearly differentiable support vector machines cannot be applied to such problems. In the case of linear indivisibility, SVM can not accurately classify the features described in the low-dimensional space, then we need to map the low-dimensional space to the high-dimensional high-dimensional feature space H through the nonlinear mapping $\Phi : R^d \to H$, and establish the optimal classification hyperplane to achieve the classification effect in H . When solving the pairwise problem, the dot product operation under linear differentiability is replaced by using a kernel function $K(x_i, x_j)$ that satisfies Mercer's condition, i.e., the kernel function:

$$K(x_i, x_j) = \Phi(x_i)\Phi(x_j) \tag{10}$$

Mapping to the high-dimensional eigenspace, the counterpart of the solved dyadic problem becomes:

$$\begin{cases} \max Q(\alpha) = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K\left(x_i, x_j\right) \\ s.t. \begin{cases} \sum_{i=1}^{l} \alpha_i y_j = 0 \\ 0 \le \alpha_i \le C \end{cases}, i = 1, 2, \cdots, l \end{cases} \tag{11}$$

Let $\alpha^* = \left[\alpha_1^*, \alpha_2^*, \cdots \alpha_i^*\right]^T$ be a solution of Eq. (11), then:

$$w^* = \sum_{i=1}^{l} \alpha_i^* y_i \Phi\left(x_i\right) \tag{12}$$

Based on the transformation derivation, the optimal classification function is found to be:

$$\begin{aligned} f(x) &= \operatorname{sgn}\left(w^* \Phi(x) + b^*\right) \\ &= \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i^* y_i \Phi\left(x_i\right) + b^*\right) \\ &= \operatorname{sgn}\left(\sum_{i=1}^{l} \alpha_i^* y_i K\left(x_i, x\right) + b^*\right) \end{aligned} \tag{13}$$

Different inner product kernel functions in SVM algorithms correspond to different algorithms, and the main kernel functions that are currently more widely used are:

Linear kernel function:

$$K(x, y) = x \cdot y \tag{14}$$

Radial basis functions:

$$K(x, y) = \exp\left(-\gamma \left\| x_i - y_i \right\|^2\right) \tag{15}$$

Polynomial kernel functions:

$$K(x, y) = (x \cdot y + 1)^d, (d = 1, 2, \cdots) \tag{16}$$

Sigmoid kernel function with parameters k and θ:

$$K(x, y) = \tanh(k(x \cdot y) - \theta) \tag{17}$$

3.3 Improved binary tree SVM multiclass classification algorithm

3.3.1 Improvement steps

Although the SVM multiclass classification algorithm based on a binary tree has achieved certain research results, the structure of the tree is directly related to the performance of the algorithm. In reality, due to the limited number of samples, training samples are usually used to estimate the degree of easy separation of all classes. Therefore, how to make the structure of the binary tree tend to an ideal state so that it is easy to separate the categories in the upper nodes earlier, and ultimately make the structure of the binary tree constructed to achieve as complete as possible is the key problem to be solved. In this paper, the improved algorithm is specifically the Euclidean distance-based binary tree support vector machine (DBT-SVM) multiclass classification algorithm.

Let X be the set of samples including k categories and X_i denote the set of training samples for category i, the existing definitions are as follows:

Definition 1: The Euclidean distance of the nearest sample between category i and category j is:

$$d_{i,j} = \min\left\{\left\|x_i - x_j\right\|\right\} \tag{18}$$

Where $i = 1, 2, \ldots\ldots, k$, then, there is $d_{i,i} = 0, d_{i,j} = d_{j,i}$.

Definition 2: The sample center of the class i is:

$$c_i = \frac{1}{n}\sum_{x \in X_i} x \tag{19}$$

Where n is the number of samples in category i.

Definition 3: If c_i and c_j are the sample centers of class i and class j, respectively, then the Euclidean distance between the centers of class i and class j is:

$$d'_{i,j} = \left\|c_i - c_j\right\| \tag{20}$$

The process of constructing a binary tree is explained below using a concrete example:

Suppose that the five species form a matrix as follows:

$$D = \begin{bmatrix} 10.1 & 12.2 \\ 1.3 & 2.2 \\ 8.2 & 9.5 \\ 4.3 & 5.7 \\ 5.3 & 7.4 \\ 2.3 & 4.1 \\ 6.5 & 8.3 \\ 7.2 & 9.4 \\ 3.2 & 4.6 \\ 9.2 & 10.4 \end{bmatrix} \tag{21}$$

Eq. (21) consists of 10 rows and 2 columns, with the first column of numbers representing the Euclidean distance of the nearest samples between the two categories $d_{i,j}$ (where i and j denote the class labels of the two categories, respectively), and the second column of numbers representing the Euclidean distance of the center of the samples between the two categories $d'_{i,j}$ (where i and j denote the class labels of the two categories, respectively). The following is the procedure for constructing a binary tree for that specific example:

Step1: Store all the class labels into the root node SVM T0, and select the two classes with the largest Euclidean distance of the nearest samples between the two classes from the above matrix D. At this point $\max d_{i,j} = d_{1,2} = 10.1$, then add class label 1 and class label 2 to each of the two newly created nodes SVMT1 and SVMT2.

Step2: For the categories other than 1 and 2, traverse all the Euclidean distances of the sample centers to find out the smallest Euclidean distances min1 and min2 between each category and the sample centers in the node SVM T1 and the node SVM T2, and if $\min 1 \le \min 2$, then let the category be attributed to the node T1, and if not, then attribute it to the node T2, and finally, let the nodes T1 and T2 become upper level left and right subtrees of the node. For category 3, $\min 1 = d'_{1,3} = 2.2, \min 2 = d'_{2,3} = 7.4$, and hence $\min 1 < \min 2$, attribute category 3 to T1. For category 4, the Euclidean distance $\min 1 = d'_{1,4} = 9.5, \min 2 = d'_{2,4} = 4.1$, i.e. $\min 2 < \min 1$, between it and the smallest sample of categories 1, 3 in node T1, places category 4 in node Tree2. Similarly for category 5, its Euclidean distance to the smallest sample of categories 1, 3 in node T1 $\mathrm{minl} = d'_{1.3} = 2.2$, $\min 2 = d'_{2,5} = 8.3, \min 1 < \min 2$, so category 5 is added to node T2. Finally, the left subtree of the root node is categories 1, 3 and 5 and the right subtree of the root node is categories 2 and 4.

Step3: Similarly, count the two categories 1 and 5 in node T1 that have the largest Euclidean distance of the nearest samples between the two categories and make them put to the two new nodes T3 and T4, due to $d'_{1,3} = 2.2, d'_{3,3} = 4.6$, $d'_{1,3} < d'_{3,5}$, so category 3 will be grouped into node T3.

Step 4: Let the two categories 2 and 4 in node T4, in turn, be divided into the new nodes T5 and T6; the new nodes contain only leaf nodes, and the algorithm ends. Otherwise, go to STEP1.

Step 5: Divide categories 1 and 3 in node T3 into two new nodes, T7 and T8. The new nodes contain only leaf nodes, and the algorithm ends. Otherwise, go to step1.

3.3.2 Algorithm description

The DBT-SVM multiclass classification algorithm is also divided into two main parts, and the following describes the algorithmic process in the training and testing phases, respectively:

Step 1: Put the existing category numbers into set C in ascending order.

Step2: If a categorization problem contains k category, then follow Definitions 1-3 to compute the matrix D of Euclidean distances for categories i and $j(i \ne j)$:

$$D = \begin{bmatrix} d'_{1,2} & d'_{1,2} \\ d_{1,3} & d'_{1,3} \\ \cdots & \cdots \\ d_{k,(k-1)} & d'_{k,(k-1)} \end{bmatrix} \tag{22}$$

Then, the first and second columns each represent the labels of category i and category j, the third column is the Euclidean distance of the nearest samples of categories i and j, and the fourth column is the central Euclidean distance of the samples of categories i and j.

Step3: Find the two classes i and j from matrix D that contain the largest distance between samples in set C and put them into $C1$ and $C2$ in ascending order, at this point make an SVM classifier at the place of the corresponding node in the binary tree, followed by updating $C = C - (C1 \cup C2)$.

Step 4: If $C = \phi$, go to Step 6.

Step5: Find the minimum class-centered Euclidean distance $D_{i,m}$ and $D_{j,m}$ from matrix D for each of class m (where $m \in C$) to each of the classes in $C1, C2$. If $D_{i,m} \leq D_{j,m}$, then put m in $C1$, otherwise put it in $C2$ and skip to Step 3.

Step 6: Make the above $C1$ and $C2$ become the left and right subtrees of the binary tree respectively, and complete a two-class classification.

Step7: Update $C = C1$ so that the left subtree is further split into 2 sub-trees until each sub-tree contains only one category that cannot be subdivided, and the algorithm ends, at which point this category is used as a leaf node of the binary tree, otherwise, go to Step3.

Step 8: Update $C = C2$, divide the right subtree into 2 sub-trees, until each sub-tree has one and only one category; the algorithm ends; at this time, the category is the leaf node of the binary tree; otherwise, go to Step 3.

Test phase:

Step 1: First, calculate the function value X of the root node of test sample a in the binary tree constructed above.

Step 2: If $X > 0$, then step to the left subtree of the root node; otherwise, step to the right subtree of the root node.

Step 3: Calculate the value of the decision function Y, if $Y > 0$ then step to the left subtree of the root node else step to the right subtree of the root node. Week after week, until the node contains only one category, at this time the output of the test sample a class labeling is the leaf node belongs to the category.

Step 4: End of test.

3.4 Example analysis

3.4.1 Evaluation model

Combined with the evaluation indexes of “dual-teacher” teacher quality in higher vocational colleges selected in the previous paper, using the improved SVM algorithm in this paper, a basic incomplete DBT-SVM evaluation model is constructed, which utilizes the binary tree technology and the idea of relative distance, and combines multiple binary classifiers to solve the multi-classification problem of “dual-teacher” teacher quality evaluation, in order to improve the efficiency and accuracy of “dual-teacher” teacher quality evaluation. The model utilizes binomial tree technology and relative distance ideas to combine multiple binary classifiers to solve the multi-classification problem of “dual-teacher” teacher quality evaluation in order to improve the efficiency and accuracy of “dual-teacher” teacher quality evaluation.

The basic incomplete DBT-SVM “dual-teacher” teacher quality evaluation model is shown in Figure 2. The model mainly includes an evaluation module and classification module, and the figure shows the total workflow of the whole “dual-teacher” teacher quality evaluation system, in which the basic data set contains basic information about teachers, course information, and an achievement table. The evaluation result data set includes the score of each evaluation item of individual teachers, the overall score of teachers, and the final evaluation result.

1) The evaluation module is mainly responsible for recording the evaluation subject’s scores for each item of the teacher and processing the data. This module first obtains the scores of the evaluation subject, then counts the individual teacher’s scores for each item, and then preprocesses the data to make it meet the data requirements of the classifier.

2) The main work of the classification module is to automatically classify the evaluation results of teachers’ teaching quality using the classifier. This module first constructs a classifier using the incomplete multiple classification algorithm proposed in this paper and then automatically categorizes teachers’ teaching results according to the decision function to improve the efficiency of evaluation.

The advantage of this model is reflected in the fact that it combines the technique of binary tree and the idea of relative distance in the classification module, combines several binary support vector machine subclassifiers, overcomes the inseparable problem of the traditional multi-classification algorithm, and reduces the occurrence of error accumulation in the binary tree structure.

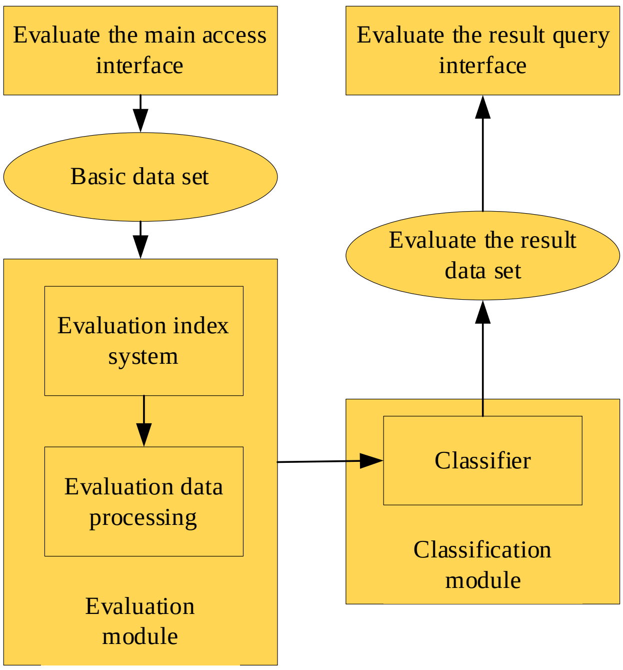

Figure 2. The basic incomplete dbt-svm “two-teacher” teacher quality evaluation model

3.4.2 Evaluation results

A school was randomly selected as a pilot school among 15 higher vocational colleges and universities in Province Y, and the evaluation data of “dual-teacher” teachers in the school were obtained, which were used as the data set of the evaluation model. The data after the assessment and evaluation by the evaluation team of the school were organized to obtain the vector table of teacher indicators. This time, only the specific vector data of the first-level indicators of professional ethics and cultivation are listed, and the specific vector data of professional ethics and cultivation are shown in Table 5. These teacher data are divided into two parts, in which about 2/3 of the data are used as the training sample set, and the remaining 1/3 of the data are used as the prediction sample set to be evaluated. Each part generates a text file as a sample data set for the system according to the data format previously described. The most suitable parameter combinations, i.e., $C = 2^8$ and $\gamma = 0.0534$ found after the experiments of kernel function and parameter adjustment, are used to build the “dual-teacher” teacher quality evaluation model. The model file is obtained by training the training module of the evaluation model using the training sample set. The model file is trained, and the prediction module, i.e., the decision function derived from the classification algorithm being evaluated, is used to make predictions on the prediction sample set.

In the process of teacher evaluation, the “dual-teacher” teacher quality evaluation system in this paper uses the teacher number or teacher name as <label> when predicting sample data so as to determine the identity of teachers when outputting results to databases or files. However, when the accuracy of the evaluation results needs to be obtained, the <label> item of the teacher number or teacher name needs to be converted into the category label of the teacher. As a reference for prediction accuracy, the prediction results of the evaluation system can be compared with the original category labels in this data to obtain the accuracy of the prediction results.

Through the evaluation of the obtained sample data, it is found that using the DBT-SVM-based “dual teacher quality evaluation model” and adjusting the experiment according to the previous parameters, a good parameter combination has been obtained, and the accuracy of the prediction result is 94.325%. This indicates that this DBT-SVM-based “dual teacher type” teacher quality evaluation method has good accuracy and has certain further research value.

Table 5. Specific vector data for professional ethics

Number	Categories	Moral cultivation						
1	0	Master quality	Moral cultivation of thought	Volunteer professionalism	Love student	Fair and fair	Dedication	Responsibility
2	0	0	0	0	5	6	2	5
3	0	3.1	2.2	1.2	1.8	2.1	2	4
4	0	1.3	2	2.5	4.2	8	6	7
5	0	3.5	2	0	2	3	7	5
6	0	2.3	4	3	8	9	1	4
7	0	4.5	8	6	7	4	3.2	2
8	0	3.2	9	2	3	0	1.2	2
9	0	3.5	6	3	2	0	4.3	0
10	00	4.2	5	4	2	3	3.5	0
11	1	3.7	7	5	4	2	2	0
12	1	2.3	4	1	0	1	3	6
13	1	2.5	3	2	7	1	4	2
14	1	2.9	2	0	6	2	8	4
15	1	3.1	1	5	1	0	6	3
……								
n	3	0	0	0	2	2	2	1

4 Conclusion

This paper combines the deficiencies in the construction of “dual-teacher” teachers in higher vocational colleges and puts forward the path of “dual-teacher” teacher construction in higher vocational colleges and universities based on gradualization in terms of teacher cultivation and, assessment and evaluation. The factor analysis method is used to screen out the indicators that meet the standard of “dual-teacher” teacher quality, and the weights of the indicators are calculated. The five dimensions of the quality of dual-teacher teachers in higher vocational colleges and universities are professional moral cultivation, practical application ability, curriculum teaching ability, theoretical knowledge level, and personality and mentality characteristics, and their weight indexes are 0.2269, 0.2159, 0.1885, 0.1865, 0.1822, respectively. Combined with the insufficiencies of the Support Vector Machine (SVM), the SVM multiclass classification algorithm of the Improved Bifurcated Tree (IBT) is designed, and the improvement steps of the algorithm are described in detail. Describe the algorithm improvement steps. A certain higher vocational college in Y province is selected as the research object, and the DBT-SVM “dual-teacher” teacher quality evaluation model is applied; its accuracy rate reaches 94.325%, which indicates that the DBT-SVM “dual-teacher” teacher quality evaluation model proposed in this paper has certain research value. This shows that the DBT-SVM “dual-teacher” teacher quality evaluation model proposed in this paper has certain research value.

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