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Retraction

Retracted: Application of Support Vector Machine Model Based on Machine Learning in Art Teaching

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

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

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

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

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

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

References

[1] Y. Hua, F. Li, and S. Yang, "Application of Support Vector Machine Model Based on Machine Learning in Art Teaching," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 7954589, 10 pages, 2022.

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Research Article

Application of Support Vector Machine Model Based on Machine Learning in Art Teaching

YongMing Hua,[1] Fang Li ,[2] and Shuwen Yang[3]

[1]*Department of Fine Arts, Changji University, Changji, 831100 Xinjiang, China*
[2]*Department of Computer Engineering, Changji University, Changji, 831100 Xinjiang, China*
[3]*Department of Fine Arts, Chongqing Normal University, Chongqing 401331, China*

Correspondence should be addressed to Fang Li; cjxy_lf@cjc.edu.cn

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The purpose of the evaluation is to reflect on whether education provides a good environment and conditions for the development of students and to reflect on the effect of teaching and the practicability of the talents cultivated by teaching to the society. When art education is evaluated, a number of positive outcomes have been achieved in terms of the development of art education, including the improvement of art education as a whole, the development of art talent, and a stronger role for the educational and social communities concerned about the quality of art education. Machine learning-based support vector machine (SVM) can better tackle issues like nonlinearity, high dimensionality, and local minima, which have been effectively implemented in the area of teaching quality evaluation (TQE) with the fast growth of information technology and the Internet. The main work of this paper is as follows: (1) it briefly expounds the research progress of TQE and multiclassification algorithm based on SVM at home and abroad and introduces the relevant basic theories of these two aspects. (2) One-to-one combination method is used in this research, reducing training time to a certain degree. Tests prove the procedure to be objective and equitable. (3) This research claims that an art TQE approach based on SVM is suited for limited professional assessment sample data and provides a method for this purpose.

1. Introduction

For a long time, my country's art universities and art colleges have cultivated many well-known domestic and foreign artists, educators, and specialized talents for the country and created a large number of fine works of art, which have made great contributions to the prosperity of my country's cultural and art market and economic construction [1, 2]. With the development of economy and culture and the progress of social civilization, the public's attention to art is constantly increasing. The number of students applying for art colleges and universities has doubled every year, which is a good illustration of this problem. At present, the number of undergraduate and junior college students in national art colleges has increased by about 5 times compared with 20 years ago. As an emerging applied discipline and an intellectual resource, art education has been increasingly valued by the government, society, and enterprises [3, 4]. There exist various learning theories in art education which help in seamless conduction of the teaching-learning process. The most popular theories in art education are psychoanalytic theory, gestalt theory, behaviorist theory, and cognitive theory. These theories help to get a varied perspective of human nature reflecting the underlying psychology behind human creativity and its source and objective. After entering the 21st century, the country's higher art education has developed tremendously, a thriving scene has emerged, and it is moving towards a new height require. In order to grasp the teaching situation of various higher art colleges, deepen the teaching reform, and improve the teaching quality and teaching management level, the Ministry of Education has officially launched the undergraduate TQE work in higher art colleges since 2003 [5]. Due to the particularity of art disciplines, it adopts the same teaching evaluation system as ordinary disciplines. Therefore, there is a lot of controversy over the current opinions on the teaching evaluation of art disciplines. Some experts believe that the evaluation of art subject teaching has further clarified the thinking and positioning of art colleges and universities, greatly promoted teaching investment, strengthened the central position of teaching work, standardized teaching management, deepened teaching reform, and made teaching work better. With unprecedented attention, the majority of students and teachers have gained tangible benefits from the evaluation [6]. Various studies have been conducted in the academic sector emphasizing on analyzing various factors that impact the functioning of its teaching-learning process. But majority of the studies use traditional statistical modelling techniques for factor analysis and generation of inferences from the results. The traditional statistical modeling techniques use statistics to develop representation of data and then analyzes the relationships existing among the variables concerned to discover insights. Machine learning uses both mathematical and statistical models to gain general understanding of the data in order to make predictions. Hence, machine learning helps various degrees of interpretability from the results generated from the impenetrable neural network models. The present study thus uses machine learning techniques to perform teaching quality evaluation (TQE) in art teaching. Modern intelligent technology relies heavily on data-based machine learning. There are a lot of things in the actual world that people cannot identify but can nonetheless witness. Samples and particular statistics may be used to derive internal laws, which can then be used to study objective objects and forecast future data or data that cannot be seen. As a result, the potential uses of this technology are many [7]. Based on statistical learning theory and the notion of structural risk reduction, SVM is a data mining approach. A better solution for real challenges such as tiny samples, nonlinearity, and high dimensionalities is sought, as well as the best compromise between model complexity and learning ability in order to attain the greatest generalization ability [8]. Based on the above background, this paper constructs a small-scale evaluation mode of TQE on the basis of introducing a new measurement method SVM and then forms a new art TQE system. The system uses new measurement methods, more detailed observation points, and multidimensional and multilevel evaluation data. Based on the SVM method, the evaluation index system was established by combining the basic theory of art TQE building a new art TQE platform. Through the systematic testing and assessment of the teaching level of the school's art department, the teaching effect and the realization of the teaching objectives are evaluated, and the corresponding value judgment and the process of improvement are made. Provide decision-making basis for the development of education and teaching for leaders at all levels. It is conducive to promoting the progress of teaching, scientific research, teaching management, and educational reform and is conducive to the improvement of the level of running schools.

2. Related Work

In western developed countries, research on educational evaluation started relatively early. In 1864, the British first proposed and developed a standard for scoring on a five-point scale. It was with the publication of "Introduction to Psychological and Social Measuring" by reference [9] that educational measurement reached its full maturity and a firm theoretical framework for standardization. After 1905, the invention and publication of some measurement methods such as "Bina-Simon Scale" and TCBE measurement method marked the further maturity of measurement technology [10, 11]. Classroom teaching quality assessment has long been an essential aspect of the American educational and teaching evaluation system in the United States [12]. The method of teaching evaluation in American universities is mainly the student discussion method, followed by the examination method. The information that may be gleaned from these two methodologies can be used as a point of reference by educators in their pursuit of educational and instructional improvement. There has always been a significant deal of attention given in the United Kingdom to the quality of classroom instruction at colleges and universities. The internal management model of academia was initiated by Oxford University and Cambridge University in the Middle Ages. At that time, the goal of teaching evaluation was to evaluate teachers. After entering the 21st century, in order to promote the development of teachers and improve the teaching ability of teachers, the British educational circles, together with the British government, carried out a thorough reform of the teacher's classroom teaching evaluation system and implemented a developmental teacher evaluation system [13]. This new teacher evaluation system requires teachers to keep relevant materials and teaching evaluation results confidential, with the purpose of protecting teachers participating in the evaluation and not frustrating teachers' enthusiasm for teaching. For my country, the development of education evaluation started later than that of western countries. The real period of education evaluation was in the 1980s. Evaluation activities have developed rapidly. According to incomplete statistics, from 1981 to 1990, there were more than 680 articles on school education evaluation [14]. One of the hallmarks of China's educational model since the turn of the twenty-first century is its emphasis on student-centered instruction, with professors evaluating how well their classes are working by asking students for feedback. This allows teachers to make adjustments to their own teaching methods as necessary to meet the goal of improving student learning. Although substantial progress has been achieved in the investigation of methodologies for evaluating the quality of domestic classroom instruction, there are still certain issues. Reference [15] analyzed the characteristics of the tendency of the evaluation subject of the teaching quality of college teachers to be relatively single. Specifically, only students are allowed to participate in the evaluation, and the teachers themselves, leaders, and peers who are participants in teaching activities have no chance to participate at all. Teaching quality assessment findings cannot accurately represent instructors' abilities, and personal and subjective elements in students will also have an influence on evaluation outcomes. Reference [16] said that it is quite frequent in my nation for schools and institutions to focus on the outcomes and disregard the process of teaching assessment. Students' opinions on instructors' performance in the classroom are the only thing considered, with no thought given to the way teachers conduct themselves throughout the actual teaching process. As a final consequence, the link between instructors' teaching process behavior and students' learning impact cannot be identified, let alone the objective of enhancing teaching effectiveness by evaluating the teaching process itself. Since SVMs offer special benefits for dealing with nonlinear, small-sample, and high-dimensional patterns, numerous researchers in the United States and elsewhere have applied them to many elements of education and produced excellent results. Reference [17] applied SVM to the teaching design of text classification and achieved good results. According to the particularity of teaching activities in reference [18], SVM is used in the evaluation of teaching quality indicators, which can not only weigh the teaching process of teachers according to the actual situation but also improve the teaching activities of teachers according to the teaching process. In reference [19], SVM can help with a few issues in the assessment of classroom teacher quality. In the experiments, SVM performed well in terms of both assessment and generalization. However, when using the SVM to classify the samples, it does not consider that the samples may have inseparable regions, or as the number of categories of the samples increases, the number of constructed classifiers will also increase. Therefore, some scholars have improved the algorithm and then applied it to teaching quality evaluation. Reference [20] used the shortest distance method to improve the SVM algorithm and applied it to the TQE model. The improvement principle is to calculate the average distance between this class and other classes. According to the principle of priority classification of the category with the shortest difference, the binary tree is constructed in turn by classification. The results fulfil two objectives. Firstly, the method objectively evaluates errors caused by human factors in the evaluation results, and on the other hand, it improves the learning speed and evaluation accuracy. Reference uses the hypersphere method to improve the SVM and then applies it to the TQE model. The improvement principle is to first calculate the distribution range of various sample groups and then use the distance formula to calculate the distance of various sample groups, according to the sample with the largest distance. According to the principle of group priority separation, the binary tree is constructed in turn by classification. The results show that the improved method not only improves the accuracy of TQE but also improves the generalization of the improved method. Reference [21] uses the nearest sample distance method to improve the binary tree SVM and applies it to the evaluation system of colleges and universities. The improvement principle is to compare the sample distances with the closest distances between the two classes and then classify and construct a binary tree according to the principle of prioritizing separation with the largest distance value. The results show that the improved method not only improves the accuracy of TQE but also optimizes the traditional teaching model. Although they all use binary tree SVMs in teaching evaluation, this method avoids the problem of inseparable regions to a certain extent, but they all generate partial binary trees when generating binary trees. If there are more classifications, the depth of the binary tree will be greater. If it is large, it may be necessary to traverse the entire tree when testing samples and the training cost is relatively high.

The study in [22, 23] proposes a machine learning-based approach to enhance the effect of music teaching. The paper develops an intelligent music teaching system using machine learning and SVM wherein the framework initiates with a simple three-layered structure back propagation neural network to a multilayered structure. The study conducts training tests on music teaching dataset and then evaluates the teaching effect of the system on actual needs of the stakeholders.

Various studies have been conducted using machine learning approaches in education. Also, multiple studies have been conducted using SVM emphasizing on teaching quality evaluation. In case of the traditional SVM approach, if the technique is used on classification problems with a large number of categories, the training speed gets reduced compromising the classification efficiency.

The unique contribution of the proposed approach lies in conducting an exhaustive review of TQE using multiclassification algorithms, namely, SVM. The associated challenges of the traditional SVM multiclassification approaches are identified, and considering the same, a one-to-one combination mode is adopted in the classification process. It constructs a classification function between each category which further reduces the training time, human participation, and chances of human errors [24, 25].

3. Method

3.1. Support Vector Machine. Vapnik introduced a novel classification technique based on statistical learning theory: SVM. Structural risk minimization is at the heart of it. Model generalization and robustness in small samples distinguish SVMs from more standard machine learning approaches. Essentially, SVM is based on the following: assuming there are practice datasets available $\{(x_i, y_i)\}$, $i = 1, 2, \cdots, m$, which can be separated by a certain hyperplane $w \bullet x + a = 0$ without error, where $x_i \in R^n$, $y_i \in \{-1, 1\}$, m is the number of samples, and R^n is an n-dimensional real number space. This is known as the ideal hyperplane, which is defined as the distance between the two kinds of sample locations. H is the best hyperplane, as indicated in Figure 1. The support vector (SV) refers to the heterogeneous vector that is closest to the ideal hyperplane. Sample points closest to the ideal hyperplane will be used to establish the hyperplane's optimal value, with no additional

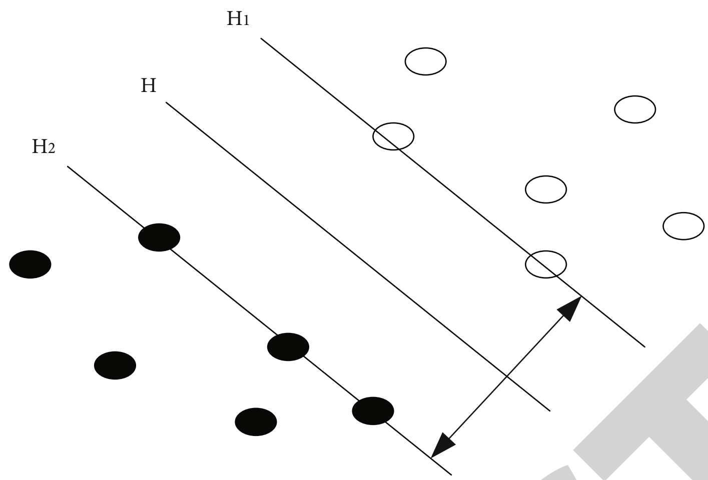

Figure 1: The concept of optimal hyperplane.

samples considered. For the best generalization, the best hyperplane is needed.

The classification hyperplane with sample interval Δ is described in the following form:

$$S = w \cdot x + a, \tag{1}$$

where $\|w\| = 1$, if $w \cdot x + a \geq \Delta$, $y = 1$.

Vapnik gave a theorem about the upper bound on the VC dimension of the Δ-spaced classification hyperplane: if the vector x is in the range of a hypersphere of radius R, then the VC-dimension h of the set of Δ-spaced classification hyperplanes satisfies the following bound.

$$h \leq \min\left[\left[\frac{R^2}{\Delta^2}\right], m\right] + 1. \tag{2}$$

As a result, the SVM ensures a low empirical risk and manages the VC dimension of the function set by picking the hyperplane with the most edges. Thus, increasing the classification interval is equivalent to controlling the SVM's generalization ability.

3.1.1. Linear SVM. Normalize the classification hyperplane in the SVM optimization problem: let $\Delta = 1$, while w and a are scaled. The sample closest to the hyperplane satisfies the following: if $y = 1$, then $w \cdot x + a = 1$; if $y = -1$, then $w \cdot x + a = 1$. The distance from the support vector to the hyperplane is $1/\|w\|$. The problem is transformed into a constrained nonlinear programming problem:

$$\begin{aligned} &\min_{w,a} \frac{1}{2}\|w\|^2 \\ &\text{s.t.} \quad y_i(w \bullet x_i + a) \geq 1, i = 1, 2, \cdots, m. \end{aligned} \tag{3}$$

"Original" refers to the first attempt at solving optimization issue (3). According to optimization theory, this issue has a single global minimum solution since the objective function and the constraints are both convex. Its Lagrange function is

$$\text{Lag} = \frac{1}{2}\|w\|^2 + \sum_{i=1}^{m} \mu_i [1 - y_i(w \bullet x_i + a)], \tag{4}$$

where $\mu \geq 0$ is the Lagrange multiplier that constrains $y \geq 1$.

For the linearly separable problem, the optimal hyperplane that can correctly divide the training set is found, and now, we will discuss the linearly inseparable problem. When the training sample set is linearly inseparable, a slack variable $\delta_i \geq 0$ is introduced, and the constraints are relaxed as follows:

$$y_i((w \bullet x_i) + a) \geq 1 - \delta_i, i = 1, 2, \cdots, m. \tag{5}$$

At the same time, a penalty term is introduced to the objective function:

$$\lambda(w, \delta) = \frac{1}{2}\|w\|^2 + P\sum_{i=1}^{m} \delta_i. \tag{6}$$

The original question (3) is changed to

$$\begin{aligned} &\min_{w,a,\delta} \frac{1}{2}\|w\|^2 + P\sum_{i=1}^{m} \delta_i \\ &\text{s.t.} y_i(w \bullet x_i + a) \geq 1 - \delta_i, \delta_i \geq 0, i = 1, 2, \cdots, m. \end{aligned} \tag{7}$$

where P is the penalty parameter, and the larger the P, the greater the penalty for misclassification.

Obviously, the original problem (7) is not only suitable for solving linear inseparable problems but also for solving linearly separable problems. We now discuss applying it to linearly separable problems and compare with the original problem of linearly separable SVMs. It is to be noted that optimization problems (3) and (7) are not the same, so in general, different decision functions result. In fact, the decision function obtained from the original problem (3) of the linearly separable SVM is not necessarily the best, because a "wild point" in the training set, such as a mislabeled point or a noise point, may seriously affect the final obtained partition hyperplane, and the original problem (7) can overcome this shortcoming to a certain extent. In addition, when the parameter $P \longrightarrow \infty$, the original problem (7) degenerates into the original problem (3) of the linearly separable SVM. In this case, the two algorithms can be considered to be the same.

3.1.2. Nonlinear Separable SVM. A really valuable application of the SVM method is to solve nonlinear problems. On the nonlinear separable problem, by introducing the kernel space theory, which uses a nonlinear mapping function to move data from a low-dimensional input space to a high-dimensional feature space, Vapnik et al. have made significant progress in resolving the classification issue. High-dimensional feature spaces may be used to translate linearly inseparable input space issues into linearly separable high-dimensional features. The reason lies in the inner product operation between the training samples being involved in both the optimization and classification functions. High-dimensional feature spaces only need inner product operations. Kernel functions are used to perform this inner product operation, which may then be applied to the original input space, that is, the kernel function $K(x_i, x_j) = \lambda(x_i) \bullet \lambda(x_j)$. The solution of this problem makes the SVM classifier officially become one of the general classifiers.

In general, for nonlinear problems, the difficulty of transforming to a linear problem in a high-dimensional space through a nonlinear mapping is that the transformation can be very complex. However, according to the relevant theory of functionals, we do not need to know the specific form of the transformation, as long as the kernel function $K(x_i, x_j)$ satisfies the Mercer condition, and it must correspond to the inner product in a certain space. Now, a linear classification after a nonlinear transformation can be achieved as long as an appropriate kernel function $K(x_i, x_j)$ is used. In this way, the problem of high-dimensional transformation calculation is avoided and the problem is greatly simplified.

3.1.3. Properties of Kernel Functions. The kernel function's computation quantity is independent of the feature space's dimension. Kernel function avoids direct operation in the modified high-dimensional feature space, which significantly decreases the amount of computation and avoids the catastrophe of dimensionality. Some kernel functions may be used to make the feature space endless in order to enhance pattern categorization. The nonlinear transformation function and its parameters need not be known. The kernel function calculation in the original input space is basically an operation that implicitly corresponds to the high-dimensional feature space transformed by the nonlinear transformation function, which overcomes the determination of the nonlinear function structure and its parameters in the general mapping method and the limitation of feature space dimensionality. Kernel functions have a variety of nonlinear transformation functions. SVMs may be generated by changing the shape and parameters of the kernel function. This, in turn, alters the attributes of the feature space. It is possible to create a number of algorithms based on kernel function technology by combining it with other approaches that use the kernel function method. It is also possible to construct these two components individually and to use alternative kernel functions and algorithms depending on the application. A kernel function may be any arbitrary symmetric function that meets the Mercer requirement. The following is a list of the most frequently used kernel functions.

Linear kernel function:

$$K\left(x_i, x_j\right) = x_i \bullet x_j. \tag{8}$$

Polynomial kernel function:

$$K\left(x_i, x_j\right) = \left[\left(x_i \bullet x_j\right) + 1\right]^b. \tag{9}$$

Radial basis function:

$$K\left(x_i, x_j\right) = \exp\left(-\alpha \left\| x_i - x_j \right\|^2\right). \tag{10}$$

Multilayer perceptron: the SVM uses the sigmoid function as the inner product. At this time, a multilayer perceptron including a hidden layer is realized, and the number of hidden layer nodes is automatically determined by the algorithm. The sigmoid function satisfying the Mercer condition is as follows.

$$K\left(x_i, x_j\right) = \tanh\left(v\left(x_i^T * x_j\right) + p\right). \tag{11}$$

3.2. SVM Multiclassification Method

3.2.1. 1-a-r Method. The 1-a-r SVM classification algorithm is the earliest multiclass classification SVM algorithm, which needs to construct M two support vector machine classifiers. There are two ways to train the i-th SVM binary classifier. When you train it, the samples that belong to the i-th category are marked positive, and those that do not belong to the i-th category are marked negative. The corresponding optimization problem is as follows:

$$\begin{cases} \min\limits_{w^i, a^i, \delta^i} \dfrac{1}{2} \left\| w^i \right\|^2 + P^i \sum\limits_{j=1}^{m} \delta_j^i \\ \text{s.t.} \quad w^i \bullet \lambda\left(x_J\right) + a^i \geq 1 - \delta_j^i, \text{if } y_j = i \,; w^i \bullet \lambda\left(x_j\right) + a^i \leq -1 + \delta_j^i, \text{if } y_j \neq i \\ \delta_j^i \geq 0, j = 1, 2, \cdots, m. \end{cases} \tag{12}$$

Solving M, such optimization problems yield M decision functions:

$$\begin{cases} f_m(x) = \operatorname{sgn}\left(w^m \bullet \lambda(x) + a^m\right), \\ \cdots\cdots \\ f_M(x) = \operatorname{sgn}\left(w^M \bullet \lambda(x) + a^M\right). \end{cases} \tag{13}$$

During testing, the sample x is substituted into the M decision functions in formula (13), and the class with the largest function value is the class of the sample x to be classified.

$$\text{Class}(x) = \arg \max_{i=1,\cdots,M} w^i \bullet \lambda(x) + a^i. \tag{14}$$

The advantage of the 1-a-r method is that the number of combined two-classifiers is small and the decision-making speed is fast, so it has been widely used. However, this method also has many shortcomings; one is that there is an unclassifiable area; the other is that the training of each SVM requires all training samples, and the repetition rate of the training samples is high. Third, the number of positive examples in each SVM considerably exceeds the number of negative samples, resulting in a poor classification accuracy for the class being studied.

3.2.2. 1-a-1 Method. The 1-a-1 SVM classification algorithm builds a binary SVM for any two categories, so a total of $M(M-1)/2$ binary SVMs need to be built. When training the classifiers corresponding to the i-th class and the j-th class, the data belonging to the class i and class j are selected as training samples in the sample set, and the samples belonging to the i-th class are marked as positive classes, and the samples belonging to the j-th class are marked as positive classes. Samples are marked as negative class. The corresponding optimization problem is as follows:

$$\begin{cases} \min\limits_{w^{ij},a^{ij},\delta_t^{ij}} \dfrac{1}{2}\left\|w^{ij}\right\|^2 + P^{ij}\sum\limits_{t=1}^{m}\delta_t^{ij} \\ \text{s.t.}\ w^{ij} \bullet \lambda(x_t) + a^{ij} \geq 1 - \delta_t^{ij}, \text{if}\, y_t = i\,; \\ w^{ij} \bullet \lambda(x_t) + a^{ij} \leq -1 + \delta_t^{ij}, \text{if}\ y_t = j, \delta_t^{ij} \geq 0. \end{cases} \tag{15}$$

Solving these $M(M-1)/2$ optimization problems, we can get $M(M-1)/2$ decision functions:

$$f_{ij}(x) = \operatorname{sgn}\left(w^{ij} \bullet \lambda(x) + a^{ij}\right) \quad i, j = 1, 2, \cdots, M \text{ and } i \neq j. \tag{16}$$

When using the 1-a-1 SVM algorithm to classify the samples to be classified, each classifier f_{ij} must judge it and "cast a vote" for the corresponding category, and the category with the most votes is the category of the sample to be classified. The 1-a-1 algorithm tends to have higher classification accuracy. However, this method also has many shortcomings: one is that there are unclassifiable regions; the other is that the number of SVMs to be constructed is large. For classification problems with a large number of categories, the training speed is low and the classification efficiency is not high.

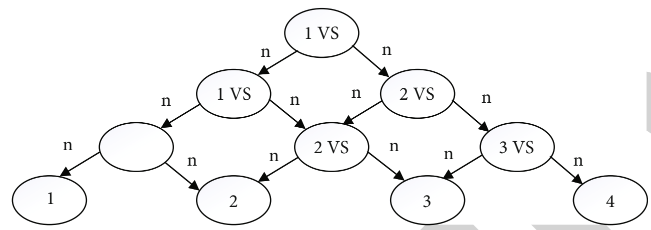

Figure 2: Directed acyclic graph SVM.

3.2.3. DAGSVM Method. DAGSVM was first proposed by Platt. The training stage of DAGSVM is exactly the same as that of 1-a-1 SVM; that is, a binary classifier is constructed for any two classes, and a total of $M(M-1)/2$ subclassifiers are obtained. The difference between the DAGSVM method and the 1-a-1 method is that the DAGSVM method arranges these subclassifiers into a directed acyclic graph of M layers, and the subclassifier judges the samples as "nonpositive examples" and "nonnegative examples." The classification process begins with the root node and progresses down the tree, classifying the lower nodes based on their classification results, until it reaches a leaf node, at which point the sample to be categorized is placed in the class determined by the leaf node. For a 4-class classification problem, the classification process using the DAGSVM method is shown in Figure 2.

3.3. The Evaluation Index System of Art Teaching Quality. The art TQE system is a complex system. To clearly describe the nature and laws of the entire teaching process, it is important to set up a huge index system, which is unrealistic. An indicator can only reflect a certain attribute of the TQE system. Therefore, only by selecting its main indicators in a reasonable way to form a reasonable curriculum evaluation index system can teaching quality be evaluated within a reasonable cost range. Art teaching pays attention to teachers' demonstration guidance and students' practical interaction ability in learning. As a consequence, the effectiveness of a teacher's instruction depends on a variety of elements, some of which are difficult to measure up front. The performance of teaching quality needs to be communicated with students' future achievements. Therefore, these long-term influencing factors should be considered when evaluating teaching quality. The teaching of teachers' artistic ideas and the performance of artistic accomplishment can affect nonintellectual factors such as students' psychological personality for a long time and at the same time can eliminate the phenomenon that teachers and students pay more attention to skills than literature. The quality evaluation indicators of the effect are, respectively, expounded. In addition to requiring teachers to clarify teaching objectives, they also make detailed evaluations of scientific, cutting-edge, relevance, and balance of teachers' teaching content and require teaching activities to focus on the improvement of students' learning quality. In the teaching method, it is proposed to

Table 1: Art teaching quality evaluation index system.

Primary indicator	Secondary indicators	Label
Teaching objectives	Express clearly and specifically	X1
	It is very hierarchical and scientific	X2
	Fully feasible and operable	X3
	Reflect students' personality and professional characteristics	X4
Teaching content	To impart the spiritual essence of art to students	X5
	Guide students to understand new achievements and trends in art	X6
	High degree of connection between technique operation and art theoretical knowledge	X7
	The depth and breadth of art theory in different directions are well balanced	X8
Teaching methods	Pay attention to the teaching of learning methods and the inspiration of creative thinking	X9
	Comprehensive cross-over of knowledge in all aspects of art	X10
	Design different teaching methods according to the characteristics of art courses	X11
	Timely reflection on the validity of each teaching link	X12
Teaching effect	Students have a comprehensive grasp of the concepts and skills in art teaching	X13
	Students develop artistic thinking, artistic observation, and artistic creation ability	X14
	Students develop positive emotions and attitudes towards art	X15
	The planning and effectiveness of teaching activities are consistent with the goals	X16

implement teaching in accordance with students' aptitude according to the characteristics of students' commonality and personality, thereby increasing the breadth and depth of students' learning. The evaluation of the teaching effect should include teachers' formation of artistic thinking, art observation, and the cultivation of art creation ability of students, which also reflects the difference between art teaching effect and other disciplines. Through the quantitative analysis of teachers in the process of organizing classroom teaching, clarifying teaching objectives, guiding students' personality development, and ensuring the smooth progress of large-scale organizational teaching, teaching quality presents a causal relationship through four aspects: teaching objectives, teaching content, teaching methods, and teaching effects. The improvement of teaching quality is a comprehensive reflection of their combined effects (see Table 1 for details).

Using a three-tiered system, the quality of instruction may be rated as exceptional, good, or bad. To begin, an expert panel selects 500 samples from which 400 are used to train the SVM and 100 are used for testing. Of these, 100 are utilized for training and the remaining 400 are used for testing. There are 16 assessment variables in the index system that are utilized by different assessors to rate instructors' teaching quality. The range of scores for each assessment component is set to [0, 100] in order to make measuring easier and to align with commonly used evaluation techniques. There are three degrees of teacher evaluation: bad, good, and exceptional, based on a combination of scores, expert judgment, and the instructor's regular performance. It is then possible to score the data in accordance with the assessment indicators, resulting in 400 distinct sets of rather accurate sample data for use in the final analysis. According to the formula (x/80), the data is standardized into the training sample table in the database, where it may be used for assessment and data concentration.

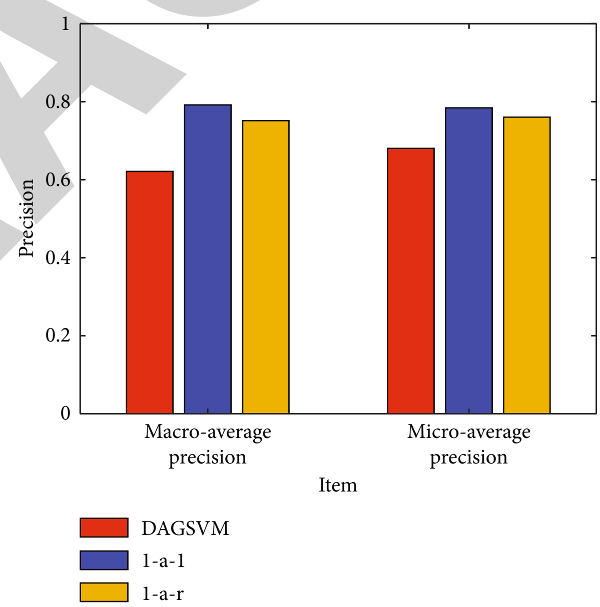

Figure 3: Precision comparison of different algorithms.

4. Experiment and Analysis

4.1. Dataset. X is a normalized evaluation index value, and Y is the teacher's assessment result based on expert and normal performance, respectively, for the index system outlined in Chapter 3: $X = (x1, x2, \cdots, x16)$ is an output index that corresponds to X, and X is the evaluation result. Select the training samples in the sample library, query the corresponding data from the database, and call the classifier SVM Train in the system for training. The training results are stored in the corresponding table of the database and stored in the predetermined model file, which can be called directly by the SVM toolbox. It can be seen that the training results include various parameters and support vectors selected in the training. The radial product kernel function that can obtain better classification results is selected in the parameters. The remaining sample data in the database is extracted, and SVM Predict is used to train the three groups. The results are verified and a better matching ratio is obtained. In the system, three two-class classifiers are constructed, and the radial product function is used to collect data for training. First, two kinds of sample data, excellent and good, are trained. In the sample data, the data belonging to the excellent and good categories are collected, and one-half of them are obtained, respectively. According to the two types of samples, the excellent and good classifier is called for training. Secondly, the two types of sample data, excellent and poor, are trained. In the sample data, the data belonging to the excellent and poor categories are collected, and the remaining half of the excellent and poor sample data are obtained, and one half of the poor sample data is obtained. The two types of samples are called the excellent and poor classifier for training. Then, train on good and poor sample data. In the sample data, collect the data belonging to the good and poor categories, and obtain the remaining half of the good and poor data, respectively. According to the two types of samples, call good and poor classifiers are trained. After several trainings, the three classifiers obtained from the training and the selected parameters and the support vectors obtained from the training are verified by the remaining 100 sample data. According to the verification results, the constructed classifier can achieve better matching effect. It can be used to evaluate new data. Therefore, the corresponding parameters and support vectors are stored in the database and written to the corresponding configuration file, which is called when testing and evaluating new data.

4.2. Experimental Results and Analysis. It is the precision and speed with which a text categorization system can map data that should be looked at when assessing the system. The intricacy of the mapping rules affects the mapping speed, and the classification result of the text after expert thought and judgment is the reference for measuring the correctness of the mapping. The closer it is to the manual classification result, the higher the classification accuracy. Two metrics for evaluating text classification systems: precision and recall.

The accuracy rate is the proportion of correctly classified texts among the classified texts. Its mathematical formula is expressed as follows:

$$\text{Pre} = \frac{\text{Number of correctly classified texts}}{\text{The actual number of classified texts}}. \tag{17}$$

The recall rate is the proportion of correctly classified texts in the texts that should be classified by manual classification. Its mathematical formula is expressed as follows:

$$\text{Rec} = \frac{\text{Number of correctly classified texts}}{\text{The number of texts that should be}}. \tag{18}$$

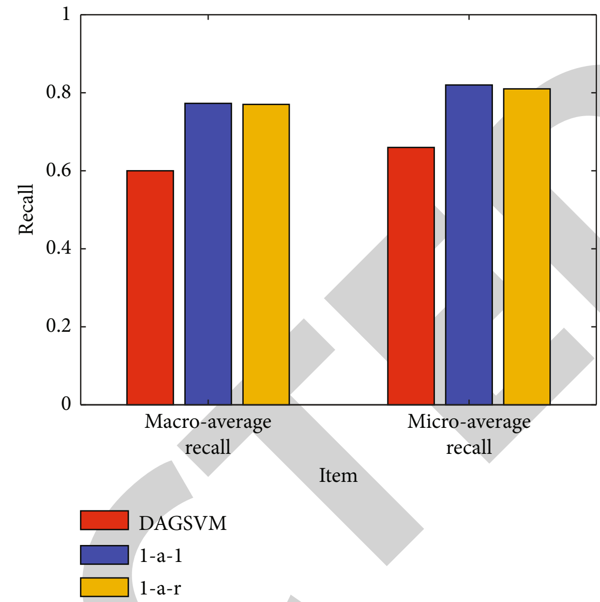

Figure 4: Recall comparison of different algorithms.

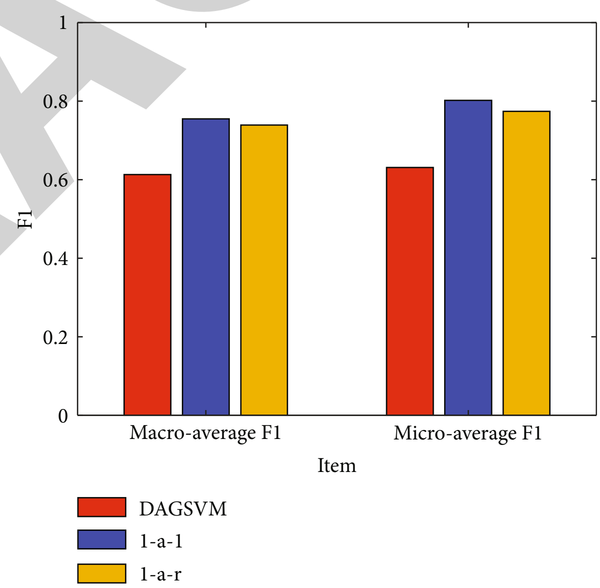

Figure 5: F1 value comparison of different algorithms.

Table 2: Comparison of training time and test time of three algorithms.

Algorithm	Training time	Test time
DAGSVM	198	192
1-a-1	198	185
1-a-r	416	171

Precision and recall reflect two different aspects of classification quality, and they must be considered comprehensively and cannot be neglected. Therefore, there is a new evaluation index, F1 test value, whose mathematical formula is as follows:

$$F1 = \frac{\mathrm{Pre} \times \mathrm{Rec} \times 2}{\mathrm{Pre} + \mathrm{Rec}}. \tag{19}$$

Three types of SVM multiclassification algorithms are employed for experimental study to compare the performance of the algorithms. Comparison of the three algorithms' macro- and microaverage precisions can be seen in Figure 3, and comparison of the algorithms' macro- and microaverage recall can be seen in Figure 4. The macroaverage F1 value and the microaverage F1 value of the three methods are shown in Figure 5. There is a comparison of the training and testing times for the three methods in Table 2.

The results of the experiments show that all three algorithms are capable of determining a teacher's proficiency level. This method's macroaverage precision, recall, macroaverage F1 value, and microaverage precision rate are all higher than those of the DAGSVM algorithm and 1-a-r algorithm, although its training speed is somewhat lower than that of 1-a-r and DAGSVM, respectively. In other words, the 1-a-1 method is the most accurate and fastest for assessing the quality of art instruction.

The number of classifiers that the 1-a-r method algorithm needs to construct is the number of categories of training samples, which is suitable for training sample sets with small scale and large number of categories. The 1-a-1 method and the DAGSVM method need to build a binary classifier for any two categories, so they are suitable for training sample sets with a large scale and a small number of categories, but the classification process using the DAGSVM method involves recursion, so the evaluation speed is slower than the 1-a-1 method. In TQE, the training set has fewer categories and larger scale, so the 1-a-1 method is the most suitable, and the experiment also proves the effectiveness of this method.

5. Conclusion

The so-called art evaluation culture refers not only to the values and attitudes of art school leaders, teachers, and students towards teaching evaluation but also to the way art schools treat teaching evaluation. Support vector functions, which can better tackle issues like nonlinearity, high dimensionality, and local minima, have emerged as a new machine learning research hotspot as a result of the fast growth of information technology and information networks. In high-dimensional pattern recognition issues, several distinct benefits have been shown and have been effectively implemented in the area of TQE. In general, the main work of this paper is as follows: (1) it briefly expounds the research progress of TQE and multiclassification algorithm based on SVM at home and abroad and introduces the relevant basic theories of these two aspects. (2) After in-depth analysis of the shortcomings of the existing SVM multiclassification algorithm, this paper adopts a one-to-one combination mode in the classification process and constructs a classification function between each category, thereby reducing the training time to a certain extent. Experiments show that this method has certain objectivity and fairness, and the professional TQE data after sample data training does not require too much human participation, which reduces some human errors and mistakes. (3) This paper proposes an SVM-based art TQE methodology and shows that it is suited for small professional assessment sample datasets, with the ultimate objective of finding the ideal answer based on all available data, not only on a few representative examples. When the number of data is approaching infinity, this is the best value. Although the results of the study are promising, it could be further enhanced to achieve better acceptability in real-time implementations. Also, the results of the study are evaluated based on recall, training time, and test time. As part of future research, other precision, accuracy, and other relevant metrics could be included to justify the superiority of the proposed approach.

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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