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Research Article

Application of C4.5 Decision Tree Algorithm for Evaluating the College Music Education

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Music courses in colleges and universities have undergone significant changes as the new curriculum reform has proceeded. As a result, student evaluations in the classroom are changing, and a diversified evaluation paradigm is gradually developing. Numerous new and more effective teaching concepts and teaching methods have been developed for revitalizing the state with science and education. This interrupts the standard instructional activities' backward teaching pattern. Online teaching has become more significant in the area of education as technology, science, and Internet technologies have advanced. Music instructors at universities and colleges are continually updating their teaching methods and utilize several techniques to provide in-depth instruction in the classrooms. To expand students' enthusiasm and involvement while also developing their musical creative talents, a web-based information educational administrations management system has been widely used in many universities and colleges. This study utilizes the C4.5 algorithm to create a decision tree model for establishing an evaluation system of classroom teaching to enhance the quality. The proposed algorithm evaluates the model's accuracy and practicability using performance information from 125 teachers' music classroom teaching. Finally, it identifies the decision-making attributes that affect the teachers' evaluation. The quality of classroom teaching is evaluated, and some useful suggestions are provided based on the experimental results, which can support college and university decision-making by motivating teachers to improve their classroom teaching quality.

1. Introduction

Music courses at colleges and universities have seen significant changes in teaching techniques and strategies as a result of new curriculum reform, prompting classroom evaluation of students to change thoroughly by gradually forming a diversified evaluation model [1]. The CPC central committee and the state council recently published a policy agenda aimed at promoting the development of aesthetic education in schools and learning aesthetic education evaluation. The CPC central committee and the state council recently published a policy agenda aimed at promoting the development of aesthetic education in schools and learning aesthetic education evaluation improvement [2]. Music is attracting more and more attention in universities and colleges, and music teaching is becoming more specialized, which addresses the issue of teacher evaluation. Currently, the evaluation of music classroom teaching is not effective and mature enough to fully reflect the function and function of the evaluation system. The music classroom evaluation system should be able to intuitively reflect the teacher's teaching effectiveness, students of the existing music level, and other factors such as being more progressive than before [3]. However, the current evaluation system is still very superficial. The questionnaire of music teachers simply follows the evaluation system of other disciplines, with slight changes in application, so it may not be applicable. In the assessment process, students are often given "water," even if the students' music level or progress level is not up to standard, also counted as qualified. As a result, of the development of this phenomenon, or did not pay any attention to the importance of music education to students, given a series of problems in the music class evaluation system, teachers should actively seek solutions [4]. In essence, evaluation is a kind of assessment, through which we can know the existing music level of students and the progress of

students in music learning and help teachers understand the status quo and needs of students. On this basis, formulate a more suitable for students and better help students grow up teaching plan. In the evaluation of music classroom teaching, students are the evaluated party, which is called the evaluation object, while teachers are the evaluated party, which is also the evaluation subject [5]. In the evaluation procedure, it is essential to take a certain standard as the yardstick of whether the assessment reaches the standard or not. Under the unified assessment standard, the students who can reach the standard are qualified, and the students who cannot reach the standard are unqualified. This kind of student needs to continue to learn and exercise [6].

According to these authors, music education uses a variety of methods to allow students to learn. This study focuses on the impact of machine learning approaches on the development of automatic music categorization models to obtain category classifications [7]. Therefore, this technique can be simulated as a learning problem based on instances. By first building a medium-sized sample collection for the well-recognized genres and then evaluating the results of various learning algorithms, we evaluated the influence of different musical parameters on inductive reliability [8]. This research focuses on music therapists and specialists' holistic music educational strategy for young children, which combines technology with music, integrates it into local culture, and frames it for holistic education. The results suggest that including a comprehensive music education method may greatly improve the abilities of students with special educational needs, as well as that supporting training has a positive impact [9]. This paper proposes a novel vertical partitioning approach based on the principles of the music rhythm tree in this paper. Before dividing the feature set, it arranges the features according to their average correlation strength. The suggested method outperforms C4.5, AdaBoost, Random Forest, Bagging, an ensemble methodology, and a vertical segmentation strategy on average, demonstrating greater classification accuracy. Finally, certain common numerical tests are used to verify the numerical consequence of the suggested method's results [10].

Music education is a significant part of quality education and a vital way of promoting the implementation of aesthetic education, and evaluation is very meaningful in the teaching of a process. If the teacher teaches and does not organize regular evaluation activities, the teacher cannot fully understand the student's existing level of music and how they compared with before the foundation of the progress, etc. Teachers do not know enough about students, so they cannot make clear how to carry out music teaching [11]. With scientific and systematic teaching evaluation, teachers can know students' knowledge of music through the evaluation and use of the situation, naturally can understand how to carry out music teaching, and can let students get maximum progress. Through the evaluation, some students show great progress, and some students make very little progress. Then, the teacher can clearly distinguish the students' learning attitude which is positive and which is negative. Teacher can determine which barriers and challenges students have during the learning process to support them in improving their attitude, reducing obstacles, and improving their musical skills. The evaluation of music classroom teaching includes not only the evaluation of students' academic achievement but also the assessment of teachers' learning outcomes. However, teaching evaluation is not the only standard to evaluate the teaching quality of teachers; after all, each student's learning ability is different [12, 13]. For students with poor learning ability, even if the teacher's teaching methods are excellent, the students are just like insulators, being unable to absorb the essence of the classroom content. In this case, if the students' evaluation is not up to standard, it does not mean that the teacher's teaching quality is bad [14].

In the research process of this paper, the data of some college teachers about the quality of music classroom teaching are taken as the research basis. The classification technology of data mining technology decision tree methods is utilized to process and analyze the data. The key point is to use the C4.5 algorithm to assess the main factors affecting classroom teaching quality, intending to establish a theoretical framework for future classroom teaching quality improvement.

The following are some of the present research's significant contributions:

(i) To propose a music teaching evaluation package from an educational administration platform that is used to improve classroom teaching quality and reduce education costs in the future

(ii) A proposed model for this study, where the samples to be evaluated will be produced utilizing information from the teaching quality index system of music classes at colleges and universities

(iii) The proposed model evaluates the entropy increment value of all indicators to build a decision tree and theoretical evaluations based on the data mining technology

(iv) The association rule method is used to evaluate the classification rules of music teaching quality evaluation developed using the proposed model based on the C4.5 decision tree.

The remainder of this paper is organized in the following order: Section 2 depicts relevant work, Section 3 depicts model establishment, and Section 4 depicts the experiment and results. Finally, the research work is concluded in Section 5.

2. Relative Work

In this part, we discuss some of the most significant related research for vertical segmentation to address the instability and class imbalances problems of decision tree approaches that have been suggested in the literature. Segmentation methods based on data categories of features were originally used by the technical profession [15]. In this work, feature segmentation is done utilizing meta-learning, where the classifier identifies features based on the data set's properties.

This research uses the feature set decomposition approach to enhance manufacturing quality. To choose the features, it employs the Breadth-Oblivious-Wrapper research methodology [16]. Furthermore, in other research, web page categorization is done using feature segmentation and the co-training approach, which employs both labeled and unlabeled data instances. To identify the features and dimensions constrained to assign the attributes to a particular segment, an evolutionary technique such as a genetic algorithm is utilized. Multiview ensemble learning (MEL), an ensemble approach, enhances classification precision for both high-dimensional and low data sets [17]. To categorize data instances, the MEL technique employs the (NB) naive Bayes, (KNN) k-Nearest Neighbours, and Support Vector Machine (SVM) algorithms. In another paper, the characteristics of data sets are divided into subject-based classification. Themes are identified based on domain expertise, for example, if we identify study and effort experience as themes in the teacher enrollment data set. The study is focused on the number of national and international publications, R&D projects, and consulting activities, among other things, which are all assigned to the same block [18, 19]. Authors who studied music, noises, or something connected to the subject should be included. This study presents a method for classifying radio broadcast data based on music and speech. The challenge in employed with this type of data is developing a reliable model for detecting music signals. The suggested approach combines six characteristics with the C4.5 algorithm, which creates a binary decision tree with the least amount of classification error. The findings of the testing demonstrate that the decision tree approach enhances the outcomes of specific features by highlighting their complementarity, resulting in a gain of more than 10% over the most discriminative feature [20, 21]. A decision tree is used in this article to categorize films into distinct genres and generate a set of choice rules. Given to the authors, qualities may be used to categorize media into distinct genres since videos belonging to one type have comparable features that distinguish them from others such as music genres. Therefore, decision trees have an accuracy of approximately 75%, and they may be considered promising for classification [22]. The outcomes of five major experiments utilized to categorize eight traditional Malay music genres are presented in this research. The authors conduct the research by changing the parameters such as data set size, music start point, track duration, and cross-validation numbers, as well as using two classifiers, One R and J 48 decision tree algorithm. In this last experimentation, J 48 outperformed the One R classifier in terms of accuracy. They conclude that some classifiers are appropriate for solving classification problems while others are not [23].

3. Establishment of the Model

3.1. Establish an Evaluation Index System. Multicultural education has long been a phenomenon, and the process of the globalization of multicultural education has become increasingly complex; from a new angle of understanding, the multicultural education phenomenon is a good way to its further development [24]. College teaching evaluation refers to a certain method, the way of curriculum and teaching plan, activities and results, and related problems or characteristics to judge the value of the process. Its main functions include determining objectives, diagnosis course, and revisions and predicting the education results. Multicultural evaluation mode is various, such as target evaluation model, process evaluation, the evaluation model, the main body evaluation mode, and background mode. These processes are involved in the evaluation object, evaluation standard, and evaluation method and way [25].

The index system includes students' music subject learning goals and general development goals. This requires that we must not just focus on students' academic success but also on discovering and developing their musical talent; learn from too much focus on results to focus on students' learning in the procedure of exploration and hard work; and support students, form a positive learning attitude and scientific exploring spirit, and realize "music knowledge skill and music ability," "emotional attitude and values," and "process and method" of development. Teaching must face all students, must conform to the student psychology and personality development, and the need to each student line is connected to the knowledge state translation to my point of view, and thus stimulate students' interest in learning music [26]. Teaching should be emphasized in the rich emotional experience of students to improve the students' aesthetic taste and aesthetics as the core. In the cultivation of music knowledge and music skills, teachers should pay attention to the cultivation and improvement of students' innovation ability, thinking ability, and aesthetic ability. Table 1 shows the summary of an evaluation of the teaching quality index system for music classes in colleges.

Music ability and level can only be reflected in music practice, so the assessment of students can only be carried out in practice. Therefore, we should pay attention to the evaluation of music teaching in practice. Fourth, the principle of integrity: students only evaluate music learning. Teachers must make a comprehensive and all-round evaluation of music education, music curriculum management, and the field of music learning and music teaching covering all levels. On just one side, the entire development of musical skills should be promoted (in the evaluation of students, the teacher should pay attention to the overall evaluation of the student's ability of music, not from a single skill of vocal music or piano) to evaluate students. On the other side, the teacher should pay consideration to improving students' overall quality [27]. Higher normal music education's goal is to support a high quality of the all-around development of music teachers. So, diversified teaching evaluation should start from the whole, the comprehensive development of students' quality structure is reasonable, and say, education teaching ability and communication ability should be within the scope of the evaluation [28].

Based on the world's multicultural music education, the idea of music teaching in normal universities needs to follow the principle of the new evaluation view. First, the developmental principle: the education process is a dynamic process, as a person is thinking by education, has the active part of the

Table 1: Evaluation of teaching quality index system of music classes in colleges.

First level	Second level	Third level
The quality of teaching	Teaching content	The arrangement is reasonable and scientific
		Key points highlight difficult breakthroughs
		The teaching process is scientific and compact
		The design is profound and creative
	Teaching method	Respect students and pay attention to their individual differences
		Outstanding music discipline characteristic aesthetic as the core
		The effective application of modern education technology means.
	Teaching attitude	Double-base teaching effectively
		Preparing fully
		Explain carefully
		Strict requirements
		Innovative teaching
	The teaching effect	Test scores
		Knowledge goal achievement
		Ability goal achievement
		Emotional goal achievement

object, and should use the dynamic, positive view of the development of students, music teachers, and music curriculum management. Second, the scientific principle: to evaluate the scientific principle, the evaluation must conform to the music education teaching laws and embody the characteristics of the music subject. The evaluation industry needs music education teaching based on regularity and music discipline characteristics, reflecting the nature and value of music courses and conforming to the student body and mind development characteristics and the rule of music aesthetic education [29]. Evaluation and test must have higher reliability and validity, the difference degree, to ensure accurate, objective, and fair evaluation. Third, the practical principle: music discipline with very strong practicality.

3.2. C4.5 Algorithm Theory. C4.5 is a collection of algorithms for classification techniques in machine learning and data mining. Its purpose is supervised learning, in which each tuple in a data collection may be described by a set of attribute values, and each tuple belongs to one of many different and incompatible classes. C4.5's purpose is to learn a mapping from attribute values to categories that may be used to categorize unknown items into new categories. J. Rossi Quinlan suggested C4.5 based on ID3. A decision tree is built using the ID3 algorithm. A decision tree is a tree structure that is like a flowchart, with each internal node (nonleaf node) representing a test on an attribute, each branch representing a test outcome, and each leaf node holding a class label [28]. After building a decision tree for tuples that do not provide classification labels, we select the path from the root node to the leaf node, and the path saves the prediction information of the tuple. The decision tree has the benefit of requiring no domain information or parameter configuration, making it ideal for exploration extracting information.

C4.5 algorithm is based on ID3 added to the continuous attributes, attribute values, and information processing, by generating a tree for building a decision tree pruning in two stages. In each attribute by the calculation of C4.5 algorithm information, we can know the information gain rate Gain Ratio. Finally, it is chosen with the highest information gain rate of a given set s test attribute to set up branches. According to the test attribute value using a recursive algorithm, get a preliminary decision tree. C4.5 algorithm-related computation formula as follows [30]. First, the expected value required for sample classification is given as follows:

$$Info(S) = -\sum_{i=1}^{m} \frac{s_i}{s} \log_2 \frac{S_i}{S}. \tag{1}$$

The information gained by property A divided into subsets of information for

$$E(A) = Info_A(S) = \sum_{j=1}^{v} \frac{S_i}{S} Info\left(S_{ij}\right). \tag{2}$$

The difference between the original information requirement and the new requirement is the information gain.

$$\text{Gain, }(A) = Info(S) - E(A). \tag{3}$$

The C4.5 algorithm incorporates information gain rate, and the formula for computing the information gain rate of an attribute is as follows:

$$\begin{aligned} \text{GainRatio}(A) &= \frac{\text{Gain}(A)}{\text{Split}E(A)}, \\ \text{Split}E(A) &= -\sum_{i=1}^{k} \frac{|S_i|}{|S|} \log_2 \frac{|S_i|}{|S|}. \end{aligned} \tag{4}$$

To reduce the generated decision tree and build a decision tree model, the C4.5 algorithm employs postpruning technology. According to the established model, a series of IF-THEN rules are generated to achieve the classification of training sets.

In the decision tree classification, there may be some missing attribute values in the test sample data, the traditional decision tree algorithm in dealing with missing attribute values. Generally, the uses abandoned the missing

attribute value of the sample or give the training sample a common value of this attribute. C4.5 algorithm and the probability distribution of the filling method are adopted to deal with missing attribute values. The specific implementation process: first, each possible value of some unknown attribute gives a probability, according to a certain node property on different values of frequency, the probability to estimate. Although the C4.5 algorithm has a strong ability to deal with noise data, when the lack of training set attribute value rate is high, it uses the algorithm to construct the decision tree model of knot points more and more complex models. Because Naive Bayes classification has a solid theoretical foundation and a small error rate, the classification accuracy will decline. This paper presents a method based on Naive Bayes theorem to deal with the value attribute classification of vacant real estate [31].

Suppose the data sample is an n-dimensional vector space, $V-\{V, V2, V3, V_i\}$. If the data sample has $C1, C2, G3, \ldots$ Cm category attribute values, then basic Bayes will classify the sample V of unknown category into category C if and only if

$$\frac{p(c_i)p(v|c_i)}{p(v)} > \frac{p(c_j)p(v|c_j)}{p(v)}. \tag{5}$$

If m properties of V are independent of each other, then

$$p(v|c_i) = \prod_{k=1}^{n} p(v_k|c_i). \tag{6}$$

Followed by

$$p(c_i)\prod_{k=1}^{n} p(v_k|c_i) > p(c_j)\prod_{k=1}^{n} p(v_k|c_j), \frac{s_i}{s}\prod_{k=1}^{n} p(v_k|c_i) > \frac{s_j}{s}\prod_{k=1}^{n} p(v_k|c_j). \tag{7}$$

The processing of multidimensional vacancy attributes can be realized according to the above principles.

$$\frac{s_i'}{s}\prod_{k=1}^{n} p\left(v_k'|c_i'\right) > \frac{s_j'}{s}\prod_{k=1}^{n} p\left(v_k'|c'\right). \tag{8}$$

Processing of empty attribute values. In this paper, the above algorithm is used to process the vacancy attribute, and the general process is as follows:

(1) Read test data.

(2) If there is no vacant attribute value in the data set, the data are pushed into the Di set. If there are vacancy attribute values in the test data set, insert them into the $D2$ set according to the principle of "the number of vacancy attributes in the sample is sorted, the less the vacancy attributes are, the higher they are; otherwise, the lower they are."

(3) Return to the first step until all data in the test data set have been checked. Finally, two sets Di and $D2$ are formed, where Di stores the value of the vacant attribute and $D2$ stores the information containing the vacant attribute.

(4) Fetch the recorded data in $D2$ and assign the missing attribute to Di.

(5) Step 4 above is recursively called until 0 is recorded in $D2$.

Even though the C4.5 algorithm has the benefits of fast model speed, high precision, ease of understanding, flexibility, and simplicity, it must perform sequential scanning and sorting of data sets many times during the tree construction process and is frequently called during computation because of the above shortcomings [32]. The calculation formula of the C4.5 method was reduced and optimized in this research, and a better algorithm termed the C4.5 algorithm was presented to reduce calculation time. The formula is simplified as follows:

Suppose S is an n-dimensional finite discrete data set, and there are only positive and negative cases in S, which are represented as YS and NS, respectively. The number of records of positive example YS is M and that of negative example NS is N. According to formula (9), the expected value required for data set S classification is

$$\text{Info}(S) = -\frac{m}{m+n}\log_2^{m/m+n} - \frac{n}{m+n}\log_2^{n/m+n}. \tag{9}$$

The value of attribute A is (A1, A2, A3):

$$I(S_i) = -\frac{m_i}{m_i+n_i}\log_2\frac{m_i}{m_i^i n_i} - \frac{n_i}{m_i+n_i}\log_2^{n_i/m_i+n_i}. \tag{10}$$

The information entropy formula of attribute X calculated in data set D is

$$\text{Info}_A(S)\& = \sum_{i=1}^{v}\frac{m_i+n_i}{m+n}I(S_i)$$

$$= \frac{1}{(m+n)\ln 2}\sum_{i=1}^{v} -m_i\ln\frac{m_i}{m_i+n_i} - n_i\ln\frac{n_i}{m_i+n_i},$$

$$\text{Info}_A(S)\& = \sum_{i=1}^{v}\frac{m_i+n_i}{m+n}I(S_i) \tag{11}$$

$$= \frac{1}{(m+n)\ln 2}\sum_{i=1}^{v}\left(-m_i\ln\frac{m_i}{m_i+n_i} - n_i\ln\frac{n_i}{m_i+n_i}\right),$$

$$\text{Info}_A(S) = \sum_{i=1}^{v}\left(-m_i\ln\frac{m_i}{m_i+n_i} - n_i\ln\frac{n_i}{m_i+n_i}\right).$$

According to the infinitesimal principle, $\ln(1+x)x$, then

$$\ln\frac{m_i}{m_i+n_i} = \ln\left(1-\frac{n_i}{m_i+n_i}\right) = -\frac{n_i}{m_i+n_i}. \tag{12}$$

In the same way,

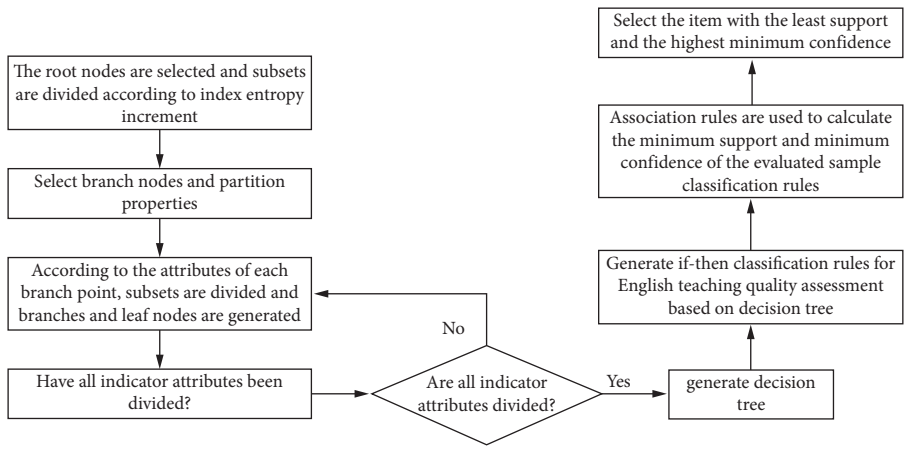

Figure 1: The teaching quality assessment process.

$$\begin{aligned}\mathrm{Info}_A(S)\& &= \sum_{i=1}^{v}\left(-m_i \ln\frac{m_i}{m_i+n_i} - n_i \ln\frac{n_i}{m_i+n_i}\right),\\ &= \sum_{i=1}^{v}\left(\frac{m_i n_i}{m_i+n_i} + \frac{m_i n_i}{m_i+n_i}\right) = \sum_{i=1}^{v}\frac{2m_i n_i}{m_i+n_i}.\end{aligned} \tag{13}$$

Information gain:

$$\begin{aligned}\mathrm{SplitE}(A)\& &= -\frac{n_i}{m_i+n_i}\log_2^{n_i/m_i+n_i} - \frac{m_i}{m_i+n_i}\log_2^{m_i/m_i+n_i},\\ &= \sum_{i=1}^{v}\frac{2m_i n_i}{\ln 2\left(m_i+n_i\right)^2},\\ \mathrm{Split}E(A) &= \sum_{i=1}^{v}\frac{m_i n_i}{\left(m_i+n_i\right)^2}.\end{aligned} \tag{14}$$

The improved calculation formula uses four mixed operations instead of the original logarithm operation, which can improve the calculation efficiency. The time complexity of the original C4.5 algorithm is O ($n2$ log2), while the time complexity of the improved algorithm is O ($n2$). The new algorithm eliminates logarithm operation and optimizes the time complexity.

4. Experiment and Results

The highest index in Gain (A) value was selected as the root node, and the second-highest value of Gain (A) was selected as the branch node; we constructed classification rules in the form of IF-THEN and finally used association rules to verify the consistency of teaching quality assessment. The specific process is as follows:

(1) Obtain an English teaching evaluation package from the educational administration platform.

(2) Initialize the data according to the indicators in Table 1 to generate the samples to be evaluated.

(3) Calculate the entropy increment value of all indicators to generate a decision tree.

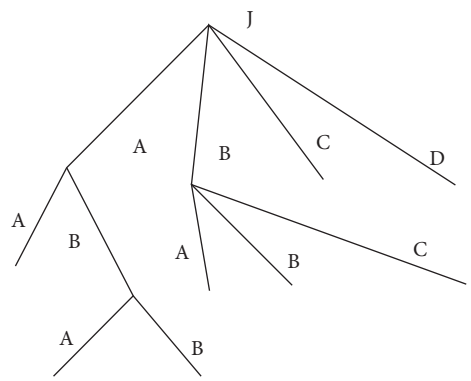

Figure 2: To construct a teaching evaluation decision tree, use the C4.5 algorithm.

(4) The association rule method is adopted to verify the classification rules of English teaching quality assessment generated by the decision tree. The teaching quality assessment process is shown in Figure 1.

The evaluation of multimedia network teaching is divided into 6 system indexes, namely, $J1$ (teaching method), $J2$ (teaching attitude), $J3$ (teaching quality), $J4$ (teaching efficiency, benefit), $J5$ (teaching efficiency), and $J6$ (teaching evaluation) as shown in Table 1. A represents a 90~100-point score, B represents an 80~89 point score, C represents a 70~79-point score, D represents a 60~69 point score, E represents a score of less than 60, F represents a score of less than 40, and Js denotes the conclusion.

The expected information quantity is calculated first to calculate the decision attribute's information gain.

$$\begin{aligned}&I\left(r_1, r_2, r_3, r_4\right)\\ &= -\frac{4}{10}\log_2\frac{4}{10} - \frac{2}{10}\log_2\frac{2}{10} - \frac{3}{10}\log_2\frac{3}{10} - \frac{1}{10}\log_2\frac{1}{10} = 1.8465.\end{aligned} \tag{15}$$

Then, the single expected information amount is calculated as follows:

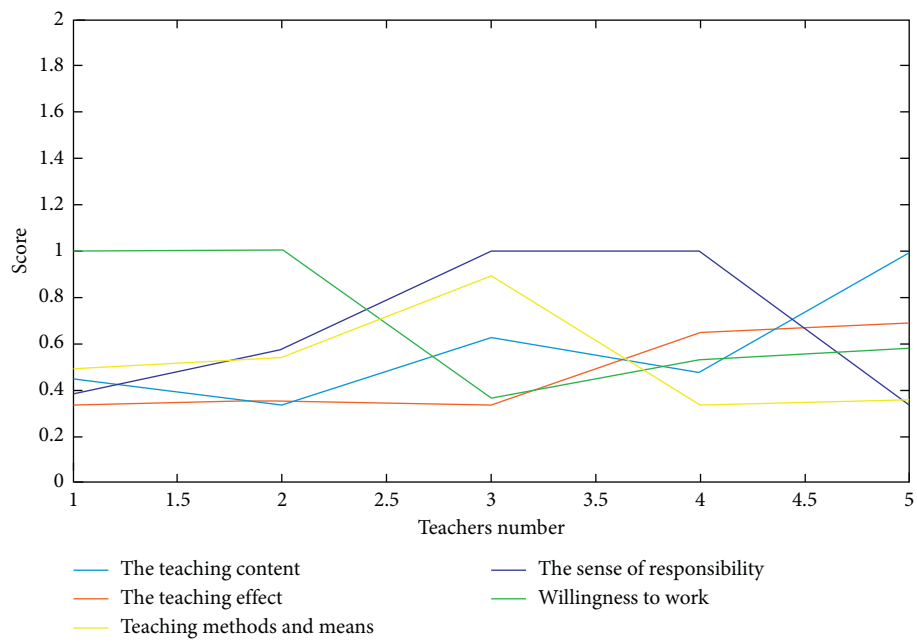

Figure 3: The correlation coefficient between each index and the best index in the reference index.

$$E(\mathrm{S},\mathrm{J}_1) = \frac{3}{10} \times E(\mathrm{S}_\mathrm{A}) + \frac{4}{10} \times E(\mathrm{S}_\mathrm{B}) + \frac{1}{10} \times E(\mathrm{S}_\mathrm{C}) + \frac{2}{10} \times E(\mathrm{S}_\mathrm{D}) = 1.0755,$$
$$\mathrm{Gain}(\mathrm{S},\mathrm{J}_1) = I(r1, r2, r3, r4) - E(\mathrm{S},\mathrm{J}_1) = 1.8465 - 1.0755 = 0.771. \tag{16}$$

Therefore, the information gain rate of attribute $J1$ is

$$\mathrm{Ratio}(J_1) = \mathrm{Gain}(J_1)/E(S, J_1) = 0.771/1.0755 = 0.7169. \tag{17}$$

In the same way,

$$\mathrm{Ratio}(J_2) = \mathrm{Gain}(J_2)/E(S, J_2) = 1.0465/0.8 = 1.3081,$$
$$\mathrm{Ratio}(J_3) = \mathrm{Gain}(J_3)/E(S, J_3) = 0.8465/1 = 0.8645,$$
$$\mathrm{Ratio}(J_4) = \mathrm{Gain}(J_4)/E(S, J_4) = 0.9135/0.9510 = 0.9606,$$
$$\mathrm{Ratio}(J_5) = \mathrm{Gain}(J_5)/E(S, J_5) = 0.989/0.8755 = 1.1296. \tag{18}$$

Further association analysis was carried out by setting min support = 5% and min confidence = 30% to obtain a frequent set of the two attributes. As can be seen from Table 1, educational background, professional title, teaching attitude, and course category have a significant influence on English teaching quality, while teaching experience and multimedia proficiency have little influence on English teaching quality. According to the item set generated in Table 1, conditions are further strengthened, min support = 5%, min confidence = 45%, and the set meeting the conditions can be obtained. C4.5 algorithm to construct a teaching evaluation decision tree is shown in Figure 2.

The results show that master's and doctoral teachers with a good teaching attitude are more likely to obtain higher evaluation scores, which is highly consistent with the if-then results. This indicates that professional title and educational background have a great impact on the quality of English teaching, and more teachers with high educational backgrounds and rich teaching experience should be equipped for English teaching. Furthermore, a good teaching attitude has a significant impact on the quality of English instruction. As for the selection of confidence threshold, in practical application, the selection should be reasonable. The selected value is too high; although the properties with very strong correlation are selected, it is easy to ignore the medium-correlation index attributes, which may affect the teaching quality because the accumulated errors of calculation may miss some of them. The correlation coefficient between each index and the best index in the reference index set is obtained by using the formula as shown in Figure 3.

The results show that subtropical high-title teachers have a better teaching attitude than Thurber teachers and that if the consistency is strong, the title and degree influence the performance of English instruction. In the English teaching, the teachers have high degrees and teaching with more experience. In addition, a good teaching attitude also affects the teaching quality key factors, on the confidence threshold choice; in practical application, the choice should be reasonable and should choose the value too high. Although the selected attributes of the correlation are very strong, they are easy to ignore the medium-correlation index properties. Possibly calculating the accumulative errors will miss part of

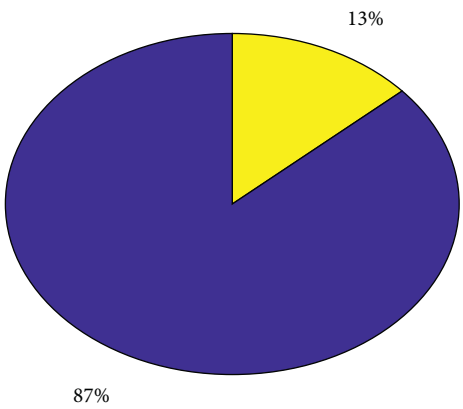

Figure 4: Accuracy of classification results.

the teaching quality assessment of key indicators, which is not conducive to the comprehensive evaluation of teaching quality. However, if the selected value is too low, there will be too many related indicators, and the evaluation of indicators will lose practical significance. The accuracy of the classification results of the C4.5 is shown in Figure 4.

Figure 4 shows this point, using the decision tree and associative analysis method used in the study of English teaching quality evaluation, association rules are generated by decision tree teaching evaluation, and then confidence gets frequent set. Through the calculation of association rules, the analysis of the teaching evaluation of the two methods got similar teaching quality evaluation results so that the efficiency of the technique to evaluate teaching quality is good as a strong price shall be applied to the value. In the next step, the index attributes and attribute categories can be further added to improve the comprehensiveness of teaching evaluation indicators. The decision tree algorithm can be optimized to improve the efficiency of constructing the tree based on entropy gain and improve the quality prediction and evaluation applicability of large-scale teaching evaluation samples.

5. Conclusion

This paper uses the C4.5 decision tree algorithm in data mining technology to build an evaluation decision tree model of classroom teaching quality of teachers in colleges and universities based on the classroom teaching quality of teachers in colleges and universities. The following are the main themes addressed in the research. The implementation plan for applying data mining classification technology to the evaluation system of classroom teaching quality of teachers in colleges and universities is presented based on the characteristics of the teaching process and data scale of classroom teaching quality of teachers in colleges and universities. The expert consultation approach and analytic hierarchy were used to create the classroom teaching quality evaluation index system. Processes can combine quantitative and qualitative features. The evaluation indexes included, among other things, addressing the major elements impacting the quality of teachers' classroom teaching, obtaining a multilevel and all-around measure of instructors' classroom teaching quality, and building a decision tree model of classroom teaching quality evaluation for teachers at colleges and universities using the C4.5 decision tree algorithm. To evaluate the quality of education, this study utilizes a decision tree technique based on fuzzy clustering. To categorize instructors in general, first, this study uses the fuzzy clustering approach. This will make people integration easier, and the key will be identified organically by utilizing the decision tree approach for qualitative and quantitative evaluation. So according to different classifications into the best various decision tree analyses to optimize the excavation of remarkable abilities, people, objects, and the overall level of the school may be improved. It has been proven that the approach is simple to comprehend, that the evaluation results are objective and fair, and that it is useful in analyzing depth problems so that appropriate steps can be implemented to improve the overall quality of teachers.

Data Availability

The data sets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

References

[1] J. Shafer, R. Agrawal, and M. Mettha, "SPRINT: a scalable parallel classifer for data mining," in *Proceedings of the U. S: IBM Almaden Research Center*, pp. 44–555, San Francisco, CA, USA, September 1996.

[2] B. Hssina, A. Merbouha, and B. Bouikhalene, "Predicting learners' performance in an E-learning platform based on decision tree analysis," *Int. Arab Conf. Inf. Technol*, pp. 1–5, 2016.

[3] G. Muhiuddin, A. Mahboob, and M. E. Elnair, "A new study based on fuzzy bi-Γ-ideals in ordered-Γ-semigroups," *Journal of Computational and Cognitive Engineering*, pp. 42–46, 2022.

[4] Y. Zhou, T. Zhang, and Z. Chen, "Applying Bayesian approach to decision tree," *Lecture Notes in Computer Science*, LNAI-II, vol. 4114, pp. 290–295, 2006.

[5] J. Gehrke, R. Ranakrishnan, and V. Ganti, "RainForest: a framework for fast decision tree construetion of large datasets," *Proceeding of International Conference on Very Large Data Bases*, vol. 4, 1998.

[6] X. Xiongjun and D. Lv, "The evaluation of music teaching in colleges and universities," vol. 2022, Article ID 2678303, 7 pages, 2022.

[7] E. Budiman, Haviluddin, N. Dengan, A. H. Kridalaksana, M. Wati, and Purnawansyah, "Performance of decision tree C4.5 algorithm in student academic evaluation," *Lecture Notes in Electrical Engineering*, vol. 488, pp. 380–389, 2018.

[8] R. Basili, A. Serafini, and A. Stellato, "Classification of musical genre: a machine learning approach," in *Proceedings of the Univ. Pompeu Fabra*, Barcelona, Spain, October 2004.

[9] L. Lee and Y.-S. Liu, "Training effects and intelligent evaluated pattern of the holistic music educational approach for children with developmental delay," *International Journal of*

Environmental Research and Public Health, vol. 18, no. 19, pp. 10064–19, 2021.

[10] S. Guggari, V. Kadappa, V. Umadevi, and A. Abraham, "Music rhythm tree based partitioning approach to decision tree classifier," *Journal of King Saud University - Computer and Information Sciences*, 2020.

[11] R. Rajeev and S. Kyuseok, "PUBLIC: a decision tree that integrates building and Pruning," in *Proceedings of the 24 International Conference on vevy large Databases*, New York, USA, August 1998.

[12] W. Xiaohu, W. Lele, and L. Nianfeng, "An application of decision tree based on ID3," *Physics Procedia*, vol. 25, pp. 1017–1021, 2012.

[13] J. Zhang, "Music feature extraction and classification algorithm based on deep learning," *Scientific Programming*, vol. 2021, pp. 1–9, Article ID 1651560, 2021.

[14] G. M. Bressan, B. C. F. de Azevedo, and E. A. S. Lizzi, "A decision tree approach for the musical genres classification," *Applied Mathematics & Information Sciences*, vol. 11, no. 6, pp. 1703–1713, 2017.

[15] A. Kusiak and N. Larson, "Decomposition and representation methods in mechanical design," *Journal of Mechanical Design*, vol. 117, no. B, pp. 17–24, 1995.

[16] L. Rokach, "Decomposition methodology for classification tasks: a meta decomposer framework," *Pattern Analysis & Applications*, vol. 9, no. 2-3, pp. 257–271, 2006.

[17] A. Blum and T. Mitchell, "Combining labeled and unlabeled data with co-training," *Proceedings of the eleventh annual conference on Computational learning theory - COLT' 98*, Morgan Kaufmann Publishers, in *Proceedings of the eleventh annual conference on Computational learning theory - COLT' 98*, July 1998.

[18] V. Kumar and S. Minz, "Multi-view ensemble learning: a supervised feature set partitioning for high dimensional data classification," in *Proceedings of the Third International Symposium on Women in Computing and Informatics*, pp. 31–37, Kochi, India, August 2015.

[19] K. West and S. Cox, "Features and classifiers for the automatic classification of musical audio signals," *Proceedings of the Int. Soc. Music Inf. Retr. Conf*, pp. 1–6, Barcelona, Spain, October 2004.

[20] V. Kumar and S. Minz, "Multi-view ensemble learning using optimal feature set partitioning: an extended experiments and analysis in low dimensional scenario," *Procedia Computer Science*, vol. 58, pp. 499–506, 2015.

[21] V. Kadappa, S. Guggari, and A. Negi, "Decision tree classifier using theme based partitioning," in *Proceedings of the IEEE International*, Trivandrum, India, December 2015.

[22] D. Cast´an, A. Ortega, and E. Lleida, "Speech/music classification by using the C4.5 decision tree algorithm," *FALA 2010 - VI Jornadas en Tecnolog´ıa del Habla and II Iberian SLTech Workshop*, vol. 4, pp. 197–200, 2010.

[23] X. Chen, "Compensated fuzzy neural network-based music teaching ability assessment model," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–11, Article ID 3865190, 2021.

[24] N. M. Norowi, S. Doraisamy, and R. Wirza, "Factors affecting automatic genre classification: an investigation incorporating non-western musical forms," in *Proceedings of the International Conference on Music Information Retrieval (ISMIR)*, pp. 13–20, London, United Kingdom, September 2005.

[25] T. Gong, "Deep belief network-based multifeature fusion music classification algorithm and simulation," *Complexity*, vol. 2021, pp. 1–10, Article ID 8861896, 2021.

[26] J. Wu and J. Lu, "Construction and simulation of music style prediction model under improved sparse neural network," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1–10, Article ID 6268224, 2022.

[27] B. Ibeka, C. Wka, and B. Lbra, "PRUCARS: improved association rule-based social recommender systems using overlapping community detection," *Procedia Computer Science*, vol. 176, pp. 956–965, 2020.

[28] X. Xia and J. Yan, "Construction of music teaching evaluation model based on weighted naïve Bayes," *Scientific Programming*, vol. 2021, pp. 1–9, Article ID 7196197, 2021.

[29] M. Ünver, M. Olgun, and E. Türkarslan, "Cosine and cotangent similarity measures based on Choquet integral for Spherical fuzzy sets and applications to pattern recognition," *Journal of Computational and Cognitive Engineering*, vol. 1, pp. 21–31, 2022.

[30] C.-L. Hsu, "A multi-valued and sequential-labeled decision tree method for recommending sequential patterns in cold-start situations," *Applied Intelligence*, vol. 51, no. 1, pp. 506–526, 2020.

[31] W. Li, "Multimedia teaching of college musical education based on deep learning," *Mobile Information Systems*, vol. 2021, pp. 1–10, Article ID 5545470, 2021.

[32] Y. Cai, H. Zhang, S. Sun, and X. Q. Wang, "Axiomatic fuzzy set theory-based fuzzy oblique decision tree with dynamic mining fuzzy rules," *Neural Computing & Applications*, vol. 32, no. 15, pp. 11621–11636, 2020.